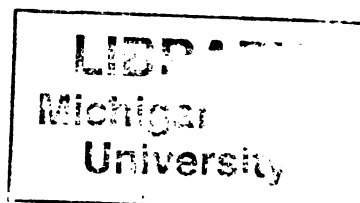


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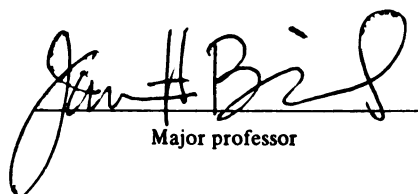
PREDICTION OF AVAILABLE WATER IN CREEPING BENTGRASS
AND ANNUAL BLUEGRASS USING VISIBLE AND NEAR INFRARED
SPECTROSCOPY

presented by

Beau James McSparin

has been accepted towards fulfillment
of the requirements for

M.Sci. degree in Crop and Soil Sciences



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**PREDICTION OF AVAILABLE WATER IN CREEPING BENTGRASS AND
ANNUAL BLUEGRASS USING VISIBLE AND NEAR INFRARED
SPECTROSCOPY**

By

Beau James McSparin

A THESIS

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ABSTRACT

PREDICTION OF AVAILABLE WATER IN CREEPING BENTGRASS AND ANNUAL BLUEGRASS USING VISIBLE AND NEAR INFRARED SPECTROSCOPY

By

Beau James McSparin

Site-specific management (SSM) of turfgrass based upon the specific water needs of the turfgrass plant has the potential to save money and water for waer resources that could be diverted for human use. Visible and near infrared spectroscopy (VIS/NIRS) was evaluated as a rapid and indirect analysis technique to determine water status of monostands of creeping bentgrass (*Agrostis palustris* Huds. cv. 'Penncross') and annual bluegrass (*Poa annua* var. *reptans*) grown in lysimeters containing either an Owosso sandy loam (fine-loamy, mixed, mesic Typic Hapludalfs) or a United States Golf Association (USGA) specification sand:peat (90:10, v/v). Field and greenhouse lysimeters were allowed to dry from field capacity to near-wilt. Every two days, volumetric soil moisture content (VSMC) and evapotranspiration (ET) were determined for each lysimeter by time domain reflectometry (TDR) and gravimetric analysis, respectively. At the same time, a field modified monochromator (NIRSystems 6500, Silver Springs, MD) measured reflectance from the turfgrass canopy from 400 to 2500 nm at 2-nm increments. The explained variance (R^2) for the relationship between reflectance and water status ranged from 0.59 to 0.92 for

TDR and 0.39 to 0.97 for ET. Higher R^2 values were obtained under greenhouse compared to field conditions where experimental error was minimized.

Wavelengths that contributed most to detection of water status occurred at 464 and 690 nm in the VIS region, and 1430 and 1900 nm in the NIR region which corresponds to absorption peaks for free water. These results indicate the potential for development of sensing technology using VIS/NIRS to detect turf water needs on a site specific basis thereby leading to more efficient water use.

To my parents, Harry and Wendy, for their continual support.

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Images in this thesis/dissertation are presented in color.

LIST OF ABBREVIATIONS

AOAC.....	Association of Analytical Chemists
CWSI	Crop Water Stress Index
EMS	Electromagnetic Spectrum
ET	Evapotranspiration
HPLC	High Performance Liquid Chromatography
IR	Infrared
IRT	Infrared Thermometry
MPLSR	Modified Partial Least Squares Regression
N	Nitrogen
NIR.....	Near infrared
NIRS	Near infrared Spectroscopy
PAR	Photosynthetically Active Radiation
SDD	Stress Degree Day
SNR	Signal to Noise Ratio
SOM.....	Soil Organic Matter
SSM	Site-specific Management
TDR	Time Domain Reflectometry
VPD	Vapor Pressure Deficit
VSMC	Volumetric Soil Moisture Content

INTRODUCTION

Turfgrass water use has recently become a highly debated issue due to limitations of water for human consumption. As human populations continue to grow, water for turf use becomes more limiting. Identifying when and how much water the turf plant needs becomes an increasingly important task. Currently, methods to determine plant water use can be tedious for the end-user.

Furthermore plant water status exhibits considerable variability that adds to the difficulty of managing large areas. Localized spatial variability is not effectively managed because management decisions are based on data from large geographic locations and cannot account for localized variability. Often times, the result is dead turf.

Over the years, scientists have searched for a fast, reliable, and non-destructive method to monitor and manage turf water requirements. Developing sensor technologies bring into possibility the use of localized data in a SSM program. Sensor development using VIS/NIRS is a concept currently being pursued for use in a SSM program. These sensors are very desirable because they can provide instantaneous information about localized conditions where variability is problematic. This approach would allow turf managers to more easily determine and manage problem areas before irreversible conditions occur.

The objectives of this research were to: 1) determine the relationship between turf spectral reflectance and water status as measured by VSMC and water loss; 2) determine if that relationship is affected by turf species and soil

type; and 3) determine the important wavelengths necessary for predicting moisture content.

Chapter 1

LITERATURE REVIEW

ELECTROMAGNETIC SPECTRUM

The electromagnetic spectrum (EMS) is composed of both electrical and magnetic forces and is divided into several regions including visible light (Fig. 1.1) (Kemp, 1991). The EMS can be defined in terms of wavelength (a measure of the length of the wave), frequency (number of waves per second), or amplitude (the magnitude of the vertical peak or valley of the wavelength signal) (Kemp, 1991). The EMS ranges from gamma rays, which have the shortest wavelengths, highest frequencies, and highest energy to radio waves, which have the longest wavelengths, lowest frequencies, and lowest energy. The three transition states depicted in Fig. 1.1 categorize the type of distortion caused by different magnitudes of energy exerted on an object.

As early as 1666, Sir Isaac Newton performed many basic experiments involving light and its properties. His most widely recognized experiment involved the separation of visible light into its component colors using a glass prism. From that point forward, scientists have discovered more about the properties of light and its effects on everyday life. Light is a form of energy that is described by two theories: the wave theory and the corpuscular or particle theory (Kemp, 1991). In the wave theory, the number of photons at that wavelength determines the energy or amplitude measured at a specific wavelength of frequency (f). In the corpuscular model, radiant energy is comprised of discrete

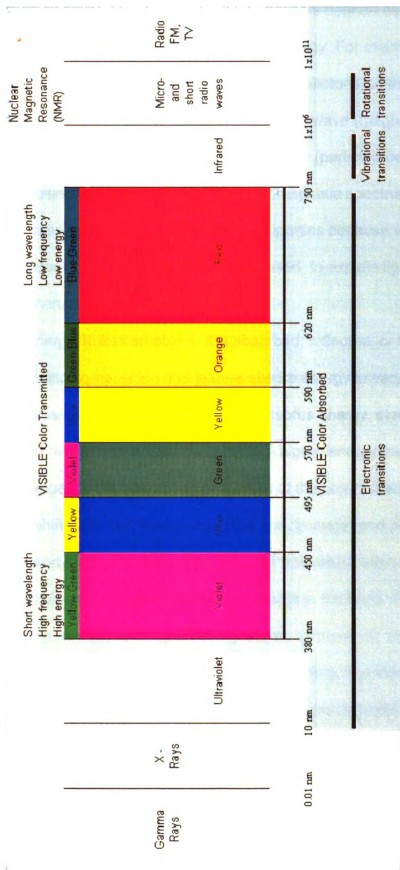


Figure 1.1. Electromagnetic Spectrum.

packets of energy called photons. A photon's energy is defined as $E=hf$ where h = Planck's constant and f is the frequency of the energy. For example, the amplitude (wave model) is equivalent to numbers of photons for the corpuscular model. Some properties are best explained using the wave (magnetic) theory while others are best explained using the corpuscular (particle) theory (Kemp, 1991) thus resulting in the nomenclature "electromagnetic spectrum." Neither theory alone completely explains all of light's properties because wave and particle forces coexist. When both theories are used to explain light's energy, all energy phenomena can be accounted for.

When energy strikes an object, it is absorbed, reflected, or transmitted. Surfaces of varying composition and texture absorb energy in varying magnitudes across the EMS. When an object absorbs energy, electrons may become excited resulting in an electron shift to a higher energy level thereby resulting in changes in the absorption properties of the object (Hatchell, 1999). These energy shifts can be measured using a spectrometer and plotted to produce an absorbance spectrum of the object. Peak absorbance regions indicate the location and intensity of the energy shift in the EMS. Absorbance spectra are often referred to as spectral signatures because the energy of that particular object has been recorded at that instant (Shenk and Westerhaus, 1990). Spectral signatures for inanimate objects such as ceramics are considered to be relatively stable and therefore constant and unchanging (Shenk and Westerhaus, 1990). These objects serve as standards by which instrumentation is calibrated while spectral information gathered from living

organisms such as plants often varies based on changing internal and external conditions. Measuring the spectral properties of a plant can yield data that directly correlates to laboratory derived values for protein, fat, nitrogen, or water (Wetzel, 1983).

Within regions of the EMS, defined ranges of wavelengths called bands have been found to represent specific chemical bonds and/or functional groups to which the energies of electrons are restricted (Kemp, 1991). For example, the NIR spectra may show absorption peaks that serve as indicators for functional groups such as water (1430 and 1900 nm), amines (1550 and 2000 nm), or carbonyl (1200 and 1780 nm) groups (Bowers and Hanks, 1965; Dalal and Henry, 1986; Hatchell, D.C., 1999). Each functional group behaves independently and absorbs energy at varying frequencies and in different amounts (Shenk and Westerhaus, 1990). Plants possess these same functional groups and therefore can be analyzed in a meaningful manner using spectroscopy.

INSTRUMENTS THAT MEASURE THE EMS

Several types of spectrometers can be used to measure the EMS. These instruments all convert energy into electrical units. These units can then be plotted to determine functional groups present or concentration of functional groups. Commercially available spectrometers that measure the UV, VIS, and NIR regions of the EMS are affordable and have proven extremely accurate. These spectrometers are available as filter instruments that measure pre-

determined wavelengths or as monochromators that measure across a series of wavelengths. Monochromators are more expensive and less common.

Spectrometers generally consist of a light source, dispersing element (grating), filter, detector, and a plotter. Typically, the light source and detector are composed of specific materials for the spectral region being analyzed. For example, when measuring the visible light spectrum, “white light” is provided by means of a tungsten quartz bulb while a sulfur diode is often used as the detector (Hatchell, 1999).

Spectrometers that measure the EMS are sensitive to fluctuations in power supply, humidity, scatter light and the path radiance angle. These variables must be calculated and instrumentation adjusted to provide accurate and repeatable measurements (Hatchell, 1999). Post-dispersive spectroscopy uses a supplemental light source to illuminate the target area. Light scattered off or transmitted through the sample is then collected and delivered to the detector. Ambient light that strays into the sample area is also measured. However, the stray ambient light represents a very small fraction of the total light signal measured by the detector (Hatchell, 1999).

The photosynthetically active radiation (PAR), between 400 and 700 nm, is frequently measured and reported because these wavelength regions are important for photosynthesis to occur. Energy that is absorbed by the plant can be redirected into the environment, used in plant functions, or released in the form of heat. Plant pigments, such as chlorophyll or carotenoids, absorb energy in differing amounts across the light spectrum. In the majority of plant species,

These pigments absorb more blue and red light. Plants appear green because the plant least utilizes green light. The result is a plant that most often appears green in color. By measuring the reflectance of a plant, a relationship with plant health can be determined (Salisbury and Ross, 1992).

NEAR INFRARED SPECTROSCOPY

The use of near infrared spectroscopy (NIRS) has many advantages over traditional laboratory analysis. These advantages include 1) little or no sample preparation; 2) rapid analysis of multiple functional groups from the spectra collected; 3) high precision, and 4) the absence of hazardous chemicals (Shenk and Westerhaus, 1993). Spectroscopy software used for data analysis in this paper is provided by Infrasoft International, Inc. (Port Matilda, PA) and is accepted for use by the Association of Analytical Chemists (AOAC). This particular software provides information about the key wavelengths chosen for prediction however, the software primarily operates through the creation of an algorithm that is based on all spectral data collected. In the research papers refereed here, few disclose the actual wavelengths chosen, but rather concentrate on the algorithm for equation performance.

Near infrared reflectance spectroscopy has been used by the forage industry for many years for prediction of plant nutrient content such as proteins, fats, and oils (Roberts et al., 1997; Shank et al., 1984, Wetzel, 1983). The NIRS has also been used to predict moisture, organic carbon, and N in soils (Dalal and Henry, 1986) as well as determining botanical composition of legumes in

monostands (Coleman et al., 1990) and of mixed samples of tall fescue and clover (Peterson et al., 1987). Roberts et al. (1997) concluded that NIRS could accurately quantify ergovaline in tall fescue with precision similar to that of high performance liquid chromatography (HPLC). Ergovaline is organic compound composed of alkaloids produced by endophytic fungi in certain grass species and has been shown to be disruptive to the digestive tracts of herbivores (Roberts et al., 1997).

The water molecule is a symmetrical bent molecule that gives rise to two absorption bands in the infrared spectrum. There is one band for each mode of vibration (or electronic transition): symmetrical stretching (1930 nm), asymmetrical stretching (1450 nm), and symmetrical bending (650 nm) (Wetzel, 1983). The O-H stretch is generally very broad in the near infrared spectrum due to the diversity of O-H configurations (Hatchell, 1999). These configurations can confound the characteristics of proteins, lipids, and nitrogen levels that possess lower intensity absorption properties.

As previously mentioned, NIRS has been utilized for soil moisture prediction. Within a narrow range of soil color and at moderate amounts of organic matter, NIRS was found to provide a rapid and nondestructive method for moisture measurement (Couillard et al, 1997; Sudduth et al., 1991). Couillard et al. (1997) demonstrated the ability of NIRS to predict soil moisture content with high accuracy using spectral bands at 1450, 1930, and 2200 nm. Soil samples that previously had not been measured with NIR spectra were used to quantify physical soil characteristics such as SOM and total N (Couillard et al., 1997).

Bowers and Hanks (1965) also reported these same wavelengths for determining soil water content. They examined the spectral reflectance of soils and found the moisture content of soils to be predictable at spectral reflectance levels of 1400, 1900, and 2200 nm. Sudduth et al. (1997) found that this spectral region provided a statistically more accurate analysis than traditional laboratory methods when analyzing soils thereby providing a reliable method of quantification. Couillard et al. (1997) concluded that expanding and developing a comprehensive database is necessary if NIRS is to be used across a broad spectrum of sample profiles. Finally, research conducted by Ben-Gera and Norris (1968) demonstrated that NIRS could be used to accurately measure and predict the moisture content of soybean leaves.

Fenstermaker-Shaulis et al. (1997) evaluated the usefulness of remotely sensed data to detect turf stress and found visible reflectance from tall fescue to be sensitive to stress caused by moisture content when using a multispectral scanner. In that study, moisture content was calculated through the use of lysimeters for determining evapotranspiration, clipping mass for determining percent tissue moisture content, and a neutron probe for measuring soil moisture content. An indice called the normalized difference vegetative index (NDVI) was used to correlate stress measurements with the spectral data using the red (600 – 650 nm) and near infrared (800 – 890 nm) regions. The NDVI was calculated as $(\text{NIR} - \text{red}) / (\text{NIR} + \text{red})$. Fenstermaker-Shaulis et al. (1997) found a linear correlation using the NDVI indice for both tissue moisture content and canopy temperatures. As tissue moisture increased, so did NDVI values ($R^2=0.90$) and

as canopy temperature increased, NDVI values decreased ($R^2=0.74$). A quadratic relationship was found to exist between NDVI and ET ($R^2=0.81$).

TURFGRASS WATER USE

Water use is defined as the amount of water required from rainfall and irrigation in addition to losses from ET to meet specific performance quality standards without consideration to yield standards (Waddington et al., 1992). Managing turfgrass irrigation is an attempt to balance root growth with canopy density and color without compromising aesthetics. Lack of water can result in the inability of the turf to withstand heat stress, traffic, soil compaction, nutrient allocation, and turgor pressure while too much water can result in increased disease pressure, lush growth, soil compaction, and anaerobic soil conditions (Waddington et al., 1992). Fry and Butler (1989) studied the ET rates of annual bluegrass and creeping bentgrass and found ET differences to be small and that water requirements did not vary considerably between the two species.

Three general factors affecting turf water use rates are: 1) evaporative demand of the air, 2) quantity of water supplied, and 3) evapotranspiration levels (Waddington et al., 1992). An understanding of the interaction of these three factors is critical if water use is to be evaluated by performance and quality standards, rather than yield standards. Replacement of soil water, regardless of the deficit level, saturates a portion of the soil profile from the surface downward. Even deficit irrigation that provides shallow applications of water, re-wets a substantial portion of the fibrous root zone, where much of the water uptake

occurs (Waddington et al., 1992). The turf manager must therefore take several environmental factors into consideration regarding when and how much water is needed to provide optimal turf conditions. Due to the large acreage of turf managed on golf courses, over-watering is a common occurrence which often times results in turf loss. Even with today's advanced irrigation systems that monitor changing environmental conditions, turfgrass problems still occur due to over-irrigation (Waddington et al., 1992).

MEASUREMENT TECHNIQUES FOR DETERMINING WATER USE

Several techniques have been utilized for measuring turf water use and soil water content. These techniques include the use of lysimeters, time domain reflectometry (TDR), and infrared thermometry (IRT).

A lysimeter is a closed-system containing both soil and turfgrass. Water can be added to the lysimeter and water loss calculated by measuring the amount of water applied and the amount of water lost from the lysimeter. Lysimetry is a relatively inexpensive method, however, lysimeters can be very labor intensive and bulky. Using lysimeters to calculate ET for turfgrass is, however, very common. Evapotranspiration is a measure of the total amount of water lost through transpiration and evaporation from the plant and soil surfaces (Waddington et al., 1992). Solar radiation is a major force causing evaporation and is a function of climate, season, altitude, and latitude. Data from all these measurements are used to estimate ET rates. Two common methods used to estimate ET are the open pan method and the Penman equation. The open pan

method is a measure of the evaporative loss of water from an exposed surface. When the water level drops below a pre-determined level due to evaporation, then irrigation is necessary. On the other hand, the Penman equation uses estimates to determine water use that are derived by additional factors as a means of calculating water loss from an exposed surface (Waddington et al., 1992). Factors in the Penman equation include wind speed, net radiation, temperature, and vapor pressure deficit (VPD). However, local calibration of the Penman equation is often required because VPD and net radiation are often estimated (Waddington et al., 1992). For estimating ET, the Penman equation has proven to be a very accurate and reliable method in dry, arid climates of the western United States.

Time domain reflectometry is a measure of the electrical conductivity of the soil and is used to calculate volumetric soil moisture content (VSMC) (Topp et al., 1980). To accomplish this, an electrical signal is transmitted through the soil by a series of probes and the velocity of the signal is determined by TDR as a measure of the dielectric soil constant. The dielectric constant is a measure of the ability of the soil to resist the formation of an electric field within itself. Water is the major factor that alters the dielectric soil constant (Topp et al., 1984). Also important, TDR measurements are independent of temperature, soil type, bulk density, or salt content (Waddington et al., 1992), Topp et al. (1980) found that on-site determination of water content could lead to improved efficiency in the characterization of soil properties. Research conducted by Saffel (1994) found TDR to be especially useful in monitoring the top 10 cm of the turf soil profile

since this soil volume has the greatest root mass and therefore the greatest root activity. Saffel (1994) also emphasized the ability of TDR to determine the water status of the soil for the application of the correct amount of water needed to restore turf to optimal performance conditions. Therefore, TDR is a useful tool for the measurement of soil water content. This technology is relatively new but affordable and highly reliable.

Infrared thermometry (IRT) uses the infrared region of the energy spectrum to calculate the temperature difference of the canopy versus air temperature. This information is then used to determine the transpirational efficiency of the turf. Several methods have been developed to utilize IRT. One method involves the use of the NDVI. Unstressed turfgrasses were found to have lower canopy temperatures (high NDVI values) due to the cooling effect of transpiration, while stressed turfgrasses had higher canopy temperatures (lower NDVI values) due to lower levels of transpiration (Fenstermaker-Shaulis, 1997; Throssell, 1987). However when the cause of stress has been focused solely on water requirements, limitations exist. When using IRT, Hatfield (1990) found an increase in surface temperature variability as soil water decreased. This surface temperature variability was attributed to interference caused by different soil backgrounds. Stanghellini and DeLorenzi (1994) found IRT to be suitable for early detection of water stress, but added that sustained stress reduces the efficacy of IRT; in contrast, the accuracy of soil-based stress indicators such as TDR increased over IRT as the stress period progressed. Jackson et al. (1977) developed the stress-degree-day (SDD) concept utilizing IRT. This index uses

midday canopy temperatures that are summed until a pre-determined level is reached, whereby irrigation is required. Idso et al. (1981) developed the crop water stress index (CWSI) that was intended to normalize SDD for environmental changes in vapor pressure gradient. The use of IRT has proved that certain regions of the EMS can be used as indicators of plant water status.

Overall, the use of lysimeters and TDR is a highly accurate means for calculating available water for the turfgrass and determining irrigation scheduling. Although each method has its own shortcomings, each has unique advantages. Time domain reflectometry is becoming more widely utilized as it emerges from the developmental stage. Prices for TDR units have remained steady with units easily affordable, safe to use, and very mobile. Utilization of lysimeters is very inexpensive and reliable, however it remains a very labor intensive method. Qian and Fry (1997) compared soil water content with ET rate and found the resulting measurements closely associated. Also, IRT is easy to use however it is limited due to its shortcomings of determining the actual cause of stress. The use of IRT technology is very similar to the goals of this project with the exception that a broader region of the EMS will be examined. Examination of the NIR region will determine if a more direct relationship exists between spectral reflectance and water status. Ideally, this study will lead to the development of a sensor system that will simplify the input of environmental variables while increasing management reliability.

Chapter 2

PREDICTION OF AVAILABLE WATER IN CREEPING BENTGRASS AND ANNUAL BLUEGRASS USING VISIBLE AND NEAR INFRARED SPECTROSCOPY

ABSTRACT

Site-specific management (SSM) of water based upon the specific needs of the turfgrass plant has the potential to save money and water for human consumption. Visible and near infrared spectroscopy (VIS/NIRS) was evaluated as a rapid and indirect analysis technique to determine water status of monostands of creeping bentgrass (*Agrostis palustris* Huds. cv. 'Penncross') and annual bluegrass (*Poa annua* var. *reptans*) grown in lysimeters containing either an Owosso sandy loam (fine-loamy, mixed, mesic Typic Hapludalfs) or a United States Golf Association (USGA) specification sand:peat (90:10, v/v). Field and greenhouse lysimeters were allowed to dry from field capacity to near-wilt. Every two days, volumetric soil moisture content (VSMC) and evapotranspiration (ET) were determined for each lysimeter by time domain reflectometry (TDR) and gravimetric analysis, respectively. At the same time, a field modified monochromator (NIRSystems 6500, Silver Springs, MD) measured reflectance from the turfgrass canopy from 400 to 2500 nm at 2-nm increments. The explained variance (R^2) for the relationship between reflectance and water status ranged from 0.59 to 0.92 for TDR and 0.39 to 0.97 for ET. Higher R^2 values were obtained under greenhouse compared to field conditions where experimental error was minimized. Wavelengths that contributed most to detection of water

status occurred at 464 and 690 nm in the VIS region, and 1430 and 1900 nm in the NIR region which corresponds to absorption peaks for free water. These results indicate the potential for development of sensing technology using VIS/NIRS to detect turf water needs on a site specific basis thereby leading to more efficient water use.

Additional index words: *Agrostis palustris*, Evapotranspiration, *Poa annua*, Site-specific Management, Time Domain Reflectometry, Volumetric Soil Moisture Content.

Turfgrass water use has recently become a highly debated issue due to limitations of available water for human consumption. As a result of these limitations, identifying when and how much water the turf plant needs becomes an increasingly important task. Currently, methods to determine plant water use can be tedious for the end-user; furthermore plant water status exhibits considerable spatial and temporal variability which adds to the difficulty of managing large areas. Many times, water use information is not fully optimized because it is based on data from large geographic locations that cannot account for localized variability. Over the last few years, scientists have searched for a method to manage turf water use that is fast, reliable, and non-destructive. Current methods for determining water use are not universally feasible for turf managers due to time and budgetary constraints. Even with today's advancing technology, the problem of applying too much or too little water is still a problem that can result in loss of turf.

Several techniques have been utilized for determining turf water use and soil moisture content. These techniques include the use of lysimeters, time domain reflectometry (TDR), and infrared thermometry (IRT). A lysimeter is a closed-system containing soil and turfgrass whereby water can be added and water loss calculated in terms of evapotranspiration. By measuring the amount of water applied to the lysimeter, an estimate of water use can be determined. The use of lysimeters is a relatively low cost method, however, very labor intensive and bulky to maneuver or install. Evapotranspiration is a measure of the total

amount of water lost through transpiration and evaporation from the soil and plant surfaces (Waddington et al., 1992). Solar radiation is the major force behind evaporation and is dependent on climate, season, altitude, and latitude. Data from these four components are used to determine ET rates. Two common methods utilizing ET are the open pan method and the Penman equation. Time domain reflectometry (TDR) has been successfully used to measure the moisture content of soils. This technique is important in determining the amount of water in the turf rootzone. Time domain reflectometry uses parallel stainless steel rods inserted into the soil to measure the electrical conductivity of the soil (Topp et al., 1980). Electrical conductivity measurements are then used to calculate percent volumetric soil moisture content (VSMC). The advantages to using TDR are that all measurements are independent of temperature, soil texture, bulk density, and salt content (Waddington et al., 1992). Research conducted by Saffel (1994) found TDR to be especially useful in monitoring soil moisture in the top 10-cm of the turf profile since this area has the greatest root mass and therefore the greatest water absorption capabilities. Saffel emphasized the ability of TDR technology to determine the water status of the soil, thereby allowing for the application of the correct amount of water needed to restore a turf population to its field capacity.

The concept of remote sensing for application in a SSM program is not new. However, determining which wavelengths should be utilized in sensor construction has been a challenge. Sensors that have the durability and flexibility to be mounted on turf equipment could allow information about the current turf

status to be downloaded and viewed spatially on a computer so that golf course managers could more easily manage large properties at the localized level. In this specific application, sensor use in a site-specific management program has the potential to save water, money, and time for turf managers.

Near infrared reflectance spectroscopy has been used by the forage industry for many years for prediction of plant nutrient content such as proteins, fats, and oils (Roberts et al., 1997; Wetzel, 1983). Spectral energy shifts can be measured with a spectrometer and plotted to produce an absorbance spectrum of the object. The locations of peak absorbance regions serve as fingerprints of key components of the sample (turf) at that instant. These components can indicate turf variables such as water or nitrogen content. The advantages of NIRS include 1) a rapid analysis of functional groups within seconds requiring little or no sample preparation, 2) high precision, and 3) the absence of hazardous chemicals (Shenk and Westerhaus, 1993).

Research by Ben-Gera and Norris (1968) demonstrated that NIRS could be used to accurately measure and predict the moisture content of soybean leaves. Fenstermaker-Shaulis et al. (1997) evaluated the usefulness of remotely sensed data to detect turf stress and found visible reflectance from tall fescue to be sensitive to stress from tissue moisture content when using a multispectral scanner. A normalized difference vegetative index (NDVI) was calculated using the red (600 – 650 nm) and near infrared (800 – 890 nm) regions. The NDVI was calculated as $(\text{NIR} - \text{red}) / (\text{NIR} + \text{red})$. Fenstermaker-Shaulis et al. (1997) found a linear correlation for NDVI with tissue moisture content and canopy

temperature. The NIR spectrum has also been used to predict moisture, organic carbon, and nitrogen in soils (Dalal and Henry, 1986). Roberts et al. (1997) concluded that NIRS could accurately quantify ergovaline in tall fescue with precision similar to that of high performance liquid chromatography (HPLC).

Research by Coleman et al (1990) determined the botanical composition of legumes in monostands while Peterson et al. (1987) determined the composition of mixed samples of tall fescue and clover. Within a narrow range of soil color and at moderate amounts of organic matter, NIR spectroscopy was found to be a rapid and nondestructive method for soil moisture content (Couillard et al, 1997; Sudduth et al., 1991). Couillard et al. (1996) demonstrated the ability of NIRS to predict moisture content of soils with high accuracy at 1450, 1930, and 2200 nm. Soil samples that previously had not been measured with NIR spectrum were used to quantify physical soil characteristics such as soil organic matter (SOM) and total N (Couillard et al., 1997). Couillard et al. (1996) concluded that expanding and developing a comprehensive database is necessary for NIRS to be used across a broad spectrum of sample profiles. Bowers and Hanks (1965) reported these wavelengths for determination of water content in soils. Bowers and Hanks (1965) examined the spectral reflectance from soils and found the moisture content of soils to be predictable at spectral reflectance levels of 1400, 1900, and 2200 nm. Sudduth et al. (1997) found that this spectral region provided a statistically more accurate analysis than laboratory methods for analyzing soils thereby making a reliable method of quantification.

The use of the EMS has been shown to contain characteristics that correlate to chemical components of a sample. The advantage is a faster procedure reducing analysis cost. The importance of this information is realized when the data can be analyzed spatially for management in site-specific management (SSM). Remotely sensed data using the EMS can be a powerful tool to aid in water management practices while providing a means by which turf health is optimized.

The objectives of this experiment were to: 1) determine the relationship between turf canopy spectral reflectance and water status as measured by VSMC and percent water loss; 2) determine how the relationship is affected by turf species and soil type; and 3) determine the important wavelengths necessary for predicting moisture content.

MATERIALS AND METHODS

Plant Culture

Intact soil cores containing mature monostands of either Penncross creeping bentgrass or annual bluegrass were harvested at the Hancock Turfgrass Research Center (HTRC) in East Lansing, MI. The soil was an Owosso sandy loam soil (fine-loamy, mixed, mesic Typic Hapludalfs) containing 82.7% sand, 12.9% silt, 4.4% clay, and 6.8% organic matter with a pH of 7.4. The cores were placed into poly-vinyl chlorinated (PVC) lysimeters (22.5 cm tall x 25.0 cm dia) containing a plug in the bottom. In addition, a 90/10 (v/v) mixture of sand comprised of mainly medium sized particles and a sphagnum peat moss was packed into lysimeters to a bulk density of 1.45 g cc^{-1} . The pH and CEC of the sand mixture were 7.7 and $8.9 \text{ cmol(t) kg}^{-1}$, respectively. Penncross creeping bentgrass and annual bluegrass were harvested from a similar sand-based soil, washed, and transplanted onto the lysimeters.

Turf in the lysimeters received regular irrigation and fertilization prior to the initiation of the experiments in order to maintain adequate growth and color. Turf was mowed at 1.3 cm during the experiments.

Field Experiment

A field experiment was conducted from 6 August 1998 to 22 August 1998 at the HTRC. To provide a microenvironment similar to what might occur in the field, lysimeters were placed into sleeves (30.5-cm dia) in the turf. Lysimeters

were set so that the top of the canopy was even with that of the surrounding turf for mowing. Mowing was performed with a walking greensmower to the same height as the surrounding turf. Three replicates each of creeping bentgrass/soil, creeping bentgrass/sand, and annual bluegrass/soil were evaluated. Average daytime and nighttime air temperatures were 27.4 and 16.9 °C, respectively.

Greenhouse Experiment

A greenhouse experiment was conducted from 4 January 1999 to 9 February 1999 at the Plant Science Greenhouses in East Lansing, MI. Six replicates of the aforementioned species and soils in addition to annual bluegrass/sand were evaluated. Lysimeters were randomized on the greenhouse bench every other day. Mowing was performed with electrical clippers to the same height in the field experiment. Maximum and minimum air temperatures were 29.4 and 11.1 °C throughout the experiment. Supplemental lighting was provided through the use of two high-pressure sodium bulbs with lighting placed 110 cm above the turf canopy to achieve a 16-h photoperiod. Supplemental light intensity was measured with an integrating quantum sensor at $650 \mu \text{mol m}^{-2} \text{s}^{-1}$ (Licor 190-S; Lincoln, NE).

Dry-down

At the start of the experiment, the lysimeters were watered to field capacity (FC) and allowed to drain for three hours. Plugs were then inserted into the bottoms of the lysimeters and watering ceased for the duration of the

experiment. The experiment was terminated when the turf reached severe wilt. Lysimeter placement in the greenhouse was re-randomized every two days. Measurements of spectral reflectance, volumetric moisture content, and water loss by mass occurred every two days with mowing occurring after all measurements were recorded.

Volumetric Soil Moisture Content

Volumetric soil moisture content (VSMC) was measured using a TRIME-FM[®] (IMKO; Framingham, MA) time domain reflectometer (TDR). The TDR probes were inserted vertically into the soil for each measurement. Volumetric soil moisture content was measured across the soil profile to a depth of 11 cm.

Percent Water Loss

The lysimeters were weighed at field capacity and subsequently every two days during the dry-down period throughout the experiment using an electronic balance (Sartorius Corp., Bohemia, NY). Percent water loss by mass was calculated as $[(FC - \text{lysimeter mass}) / FC] * 100\%$.

Spectrometer

Spectral reflectance was obtained with a Model 6500 Spectrometer (NIRS Systems, Silver Spring, MD). Reflectance from the turf canopy was collected between 400 nm and 2500 nm at 2-nm increments and linearized in the form of $\log(1/R)$ reflectance to represent linear absorption values.

The spectrometer was modified in such a manner that the optics and light source were contained in a housing unit suspended 12.0 cm above the turf canopy. This setup provided a reduction in scatter radiation from the sun due to its shading effect from direct sunlight. This housing unit was 12-cm above the scanning surface. Within the spectrometer scanning unit, a tungsten-halogen light source provided supplemental and continual reflectance for a target area of 5 cm². A white calibration card was included in the housing unit. The calibration card was used to calibrate the instrument before and after spectral measurements to ensure integrity of the light source. To maintain spectral integrity, measurements were adjusted for instrument conditions at the time of recording. All measurements occurred between 1200 and 1400 h.

Data Analysis

Data were prepared for modeling using WINISI software (Infrasoft International; Port Matilda, PA). Data were analyzed using a Modified Partial Least Squares (MPLS) regression and transformed by a 1, 4, 4, 1 (derivative order, gap, 1st smoothing, and de-trend value) mathematical treatment (Shenk and Westerhaus, 1991). Analysis of the first derivative spectrum was performed to increase the signal to noise ratio (SNR) (Talsky, 1994). The derivative spectra indicate the locations where the most variability exists in the spectra with the lowest instrument variability.

Modified Partial Least Squares was performed using the procedures described as follows. Spectra for each treatment were randomly selected to

create the algorithm model while the remaining data were used in cross-validation (Shenk and Westerhaus, 1991). The algorithm was then tested against all spectra by treatment. The analysis provides an equation that best predicts the group to which the sample belongs. Only those spectra with the best fit were eligible for consideration in equation development. Outliers were included in the cross-validation statistics but removed from equation development. Performance statistics represent the performance of the equation against all data within the treatment group and are based on the number of terms incorporated into the equation algorithm. This algorithm was created using principle component analysis (PCA) based on analysis of the entire spectrum. The coefficient of determination represents the relationship of the spectra using the number of 'terms' (wavelengths) that were used to create the algorithm. First derivative spectra provided the best linear correlation between spectra and measured water values. Analysis of the raw spectral data and second derivatives provided lower correlation values than when using the first derivative.

Data were also separated by species and soil type and analyzed separately to determine whether either had an over-riding influence of the spectrum.

RESULTS AND DISCUSSION

The visible and NIR spectra of turfgrass show a wide range of absorbance ($\log 1/R$) with respect to water status. Spectra for each treatment group are shown in Fig. 2.1 – 2.4 and indicate that four regions of the spectrum (464, 690, 1430, and 1900 nm) varied greatly with changing water conditions. These four wavelengths appeared to be strongly related to moisture content. An example of transformed spectra is shown in Fig. 2.5 and its raw spectra in Fig. 2.6. Comparison of Fig. 2.6 with Fig. 2.1 - 2.4 show that spectral data in the VIS region do not always reflect a decreasing trend in water status while spectra in the NIR region are more consistent with decreasing water trends.

Volumetric soil moisture content and water loss by mass during the dry-down period ranged from 3.2 to 40.3% and 0.0 to 16.0%, respectively for all treatment groups (Tables 2.1 – 2.2). These data indicate a strong linear relationship between spectral reflectance and VSMC ($0.82 < R^2 < 0.91$) under controlled greenhouse conditions with $R^2 = 0.80$ across all treatment groups. During the greenhouse experiment, this relationship was $0.69 < R^2 < 0.92$ with a combined $R^2 = 0.59$. These data indicate a stronger relationship between spectral reflectance and percent water loss by mass ($0.91 < R^2 < 0.97$) under greenhouse conditions with a combined $R^2 = 0.91$. For the field study, the relationship was $0.39 < R^2 < 0.90$ with a combined $R^2 = 0.41$. Differences in the relationship between spectra and water status were attributed to: 1) a larger sample size and less introduced variability in the greenhouse when compared to the field data;

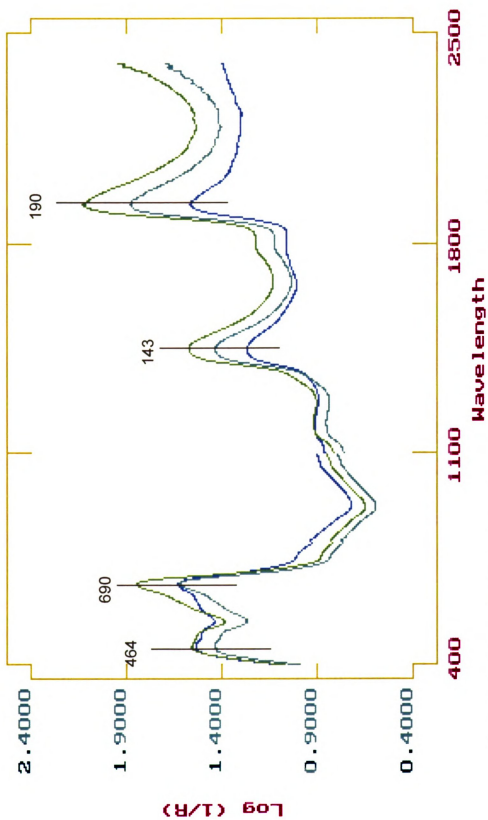


Figure 2.1. Comparison of spectra at different moisture levels as measured by time domain reflectometry for creeping bentgrass/sand.

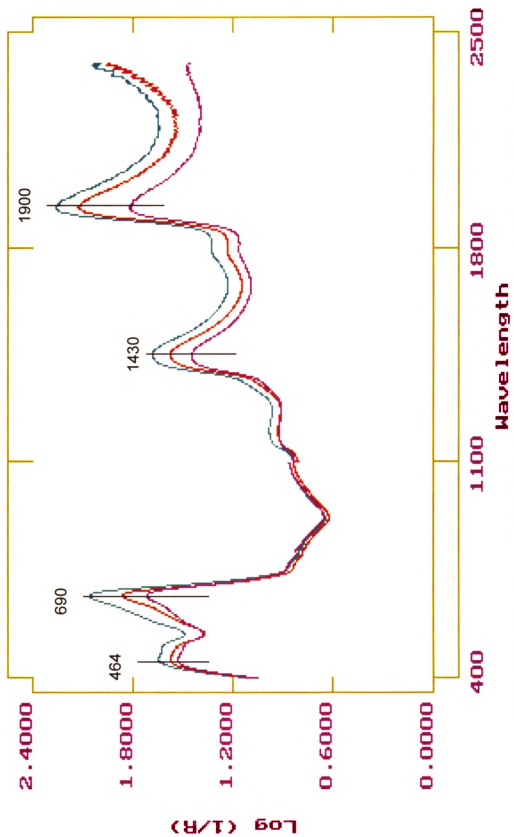


Figure 2.2. Comparison of spectra at different moisture levels as measured by time domain reflectometry for annual bluegrass/sand.

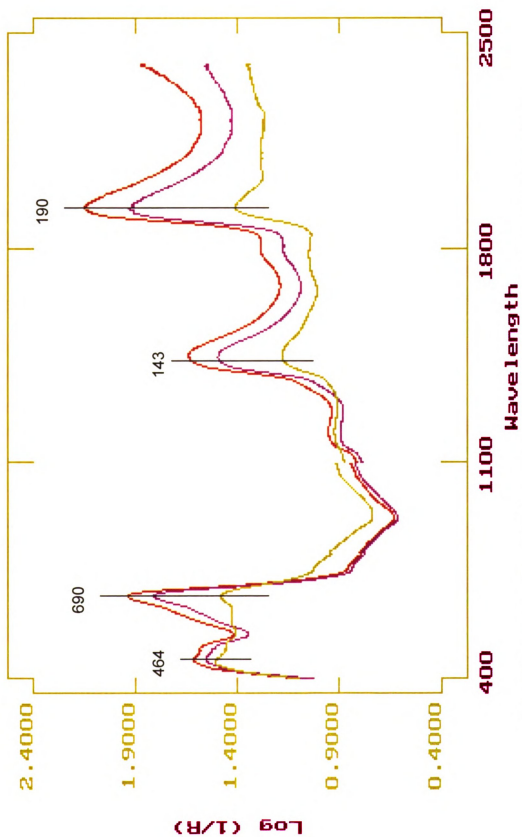


Figure 2.3. Comparison of spectra at different moisture levels as measured by percent water loss by mass for annual bluegrass/soil.

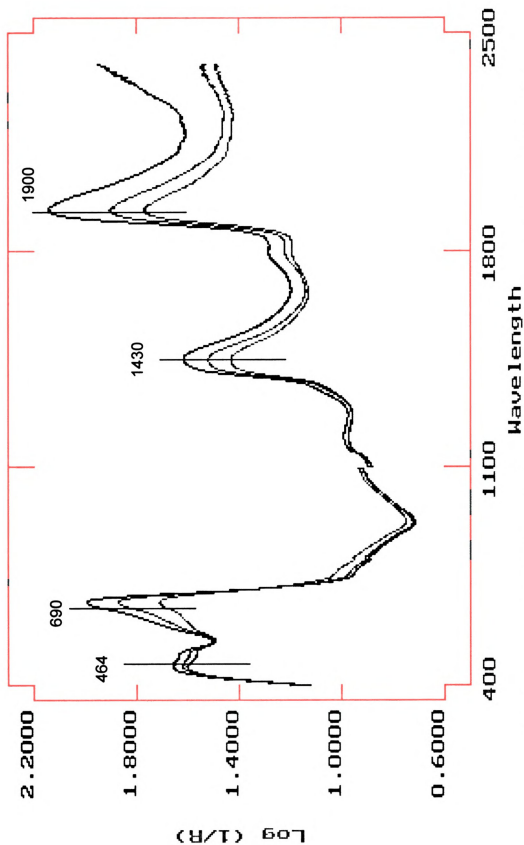


Figure 2.4. Comparison of spectra at different moisture levels as measured by water loss by mass for creeping bentgrass/soil.

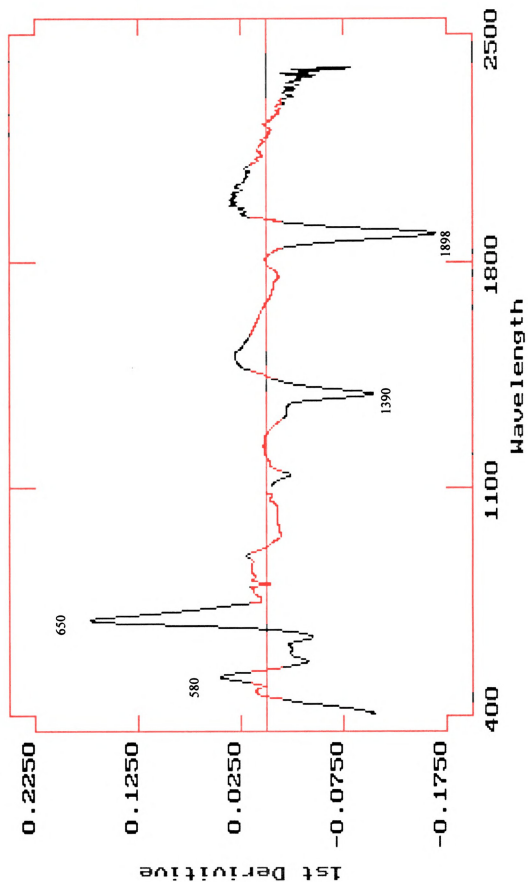


Figure 2.5. First derivative spectra for creeping bentgrass/sand.

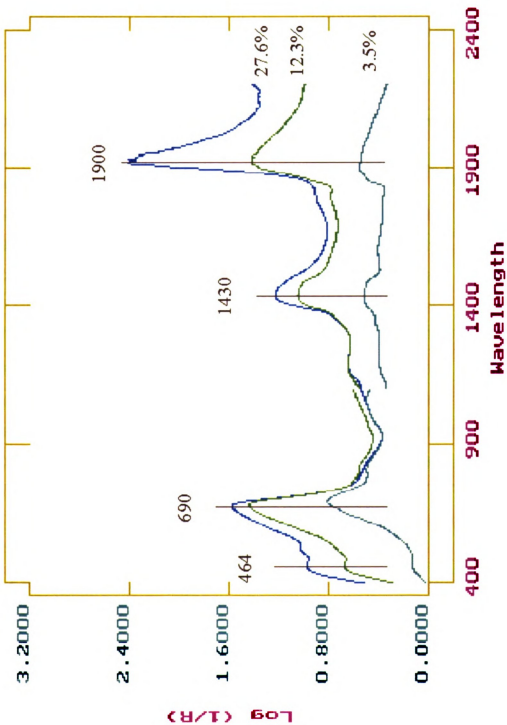


Figure 2.6: Spectra of creeping bentgrass/sand from the greenhouse experiment showing the relationship between volumetric soil moisture content and spectral reflectance.

Table 2.1. Calibration and validation statistics for quantification of volumetric soil moisture content using near infrared spectroscopy and modified partial least squares regression analysis using a 1, 4, 4, 1 math treatment†.

Treatment	Number of Terms	N‡	Range (%)	St. Dev§	Mean (%)	R ²	SEC¶
GREENHOUSE							
Sand: <i>Poa annua</i>	3	85	3.2 – 28.5	6.47	17.4	0.902	2.027
Sand: <i>Agrostis palustris</i>	7	95	4.2 – 28.6	5.84	16.7	0.906	1.789
Soil: <i>Poa annua</i>	5	83	15.8 – 38.6	5.16	27.7	0.874	1.833
Soil: <i>Agrostis palustris</i>	3	99	16.7 – 34.3	4.26	27.3	0.823	1.794
Combined	6	351	4.2 – 36.3	7.12	22.7	0.801	3.180
FIELD							
Sand: <i>Poa annua</i>	4	35	23.1 – 40.3	4.95	31.9	0.734	2.550
Soil: <i>Poa annua</i>	3	31	20.5 – 37.6	4.35	30.7	0.687	2.506
Soil: <i>Agrostis palustris</i>	3	23	30.3 – 37.6	1.45	38.5	0.924	0.612
Combined	3	93	16.5 – 39.10	4.62	32.4	0.586	2.975

† Mathematical treatment = derivative order, gap, first smoothing, and de-trend value.

‡ Number of Repeated Measures.

§ Standard deviation of the range.

¶ Standard Error of Calibration.

Table 2.2. Calibration and validation statistics for quantification of water loss by mass using near infrared spectroscopy and modified partial least squares regression analysis using a 1, 4, 4, 1 math treatment†.

Treatment	Number of Terms	N‡	Range (%)	St. Dev§.	Mean (%)	R ²	SEC¶
GREENHOUSE							
Sand: <i>Poa annua</i>	7	90	0.0 – 11.0	0.03	4.7	0.966	0.006
Sand: <i>Agrostis palustris</i>	7	89	0.0 – 12.0	0.03	4.6	0.972	0.005
Soil: <i>Poa annua</i>	8	93	0.0 – 12.0	0.03	4.7	0.956	0.007
Soil: <i>Agrostis palustris</i>	9	104	0.0 – 16.0	0.05	6.7	0.969	0.008
Combined	10	368	0.0 – 16.0	0.04	5.0	0.908	0.011
FIELD							
Sand: <i>Poa annua</i>	3	20	0.0 – 6.1	1.94	1.9	0.903	0.604
Soil: <i>Poa annua</i>	1	18	0.0 – 7.4	2.43	2.5	0.387	1.679
Soil: <i>Agrostis palustris</i>	3	14	0.0 – 4.2	1.68	1.6	0.850	0.563
Combined	2	50	0.0 – 7.4	2.36	2.2	0.413	1.587

† Mathematical treatment = derivative order, gap, first smoothing, and de-trend value.

‡ Number of Repeated Measures.

§ Standard deviation of the range.

¶ Standard Error of Calibration.

rainwater that penetrated the field lysimeters during the course of the dry-down period (resulting in repeated measurements in modified partial least squares regression at field capacity with few measurements at wilt-point); and 3) the depth of water in the immediate rootzone during the experiment (Saffel, 1994). For all treatment groups, higher spectral absorbance corresponded to greater available water content levels while lower spectral absorbance corresponded to lower available water content levels (Fig. 2.1-2.4). The major absorbance fluctuations for raw spectra found at 464, 690, 1430, and 1900 nm were consistent across all treatment groups and data confirm the results of Bower and Hanks (1965) that absorbance increased as moisture content increased for soils.

Data were also separated and analyzed individually by soil and species type for their contributing effects to spectra. For comparison between spectral data and VSMC (Fig. 2.3), greenhouse data show a relationship of $0.75 < R^2 < 0.90$ while field data reveal a relationship of $0.57 < R^2 < 0.97$. When comparing spectral data with percent water loss by mass (Fig. 2.4), greenhouse data show a relationship of $0.90 < R^2 < 0.97$ with the field data showing a relationship of $0.26 < R^2 < 0.90$. Although greenhouse data indicate a strong relationship among soil and species type with the spectra, there was no factor that could be isolated as a main contributor to the changing spectral conditions.

Comparison of Soil Type and Species with Spectra

Under greenhouse conditions, creeping bentgrass ($R^2=0.90$, 0.90) was found to have a more consistent relationship than annual bluegrass ($R^2=0.77$, 0.97) for VSMC and percent water loss, respectively (Tables 2.3, 2.4). The 90:10 sand ($R^2=0.90$, 0.95) was found to have a more consistent relationship than the native soil ($R^2=0.75$, 0.95). Differences in spectral relationships were attributed to the textural consistency of a creeping bentgrass monostand as compared to the variability of annual bluegrass.

Under field conditions, creeping bentgrass ($R^2=0.97$, 0.73) showed a stronger relationship than annual bluegrass ($R^2=0.57$, 0.47) for VSMC and percent water loss, respectively. The USGA sand ($R^2=0.73$, 0.90) demonstrated a comparable relationship in the greenhouse ($R^2=0.72$) but did not show a strong relationship in the field (0.26).

During the course of the experiment, soil type appeared to play a role in affecting the dry-down time. Lysimeters containing native soils held water more tightly and restricted water uptake, causing a shorter dry-down period.

Lysimeters containing sand allowed the most water uptake as was observed by the rooting depth (12 cm) in the sand-based lysimeters while soil-based lysimeters contained very shallow roots (<5 cm). There were no noticeable differences in rooting depth between species, however no rooting data was collected in this study.

Table 2.3. Calibration and validation statistics for quantification of volumetric soil moisture content by mass using near infrared spectroscopy and modified partial least squares regression using a 1, 4, 4, 1 math treatment†.

Treatment	Number of Terms	N‡	Range (%)	St. Dev§	Mean (%)	R ²	SEC¶
GREENHOUSE							
<i>Poa annua</i>	4	159	5.1 – 38.6	6.87	23.767	0.777	3.247
<i>Agrostis palustris</i>	7	195	4.2 – 34.3	7.29	22.172	0.899	2.315
Sand	8	184	3.2 – 28.6	6.27	17.027	0.889	2.092
Soil	5	194	15.1 – 38.6	4.85	27.259	0.750	2.427
FIELD							
<i>Poa annua</i>	1	29	16.5 – 37.4	5.01	29.662	0.570	3.283
<i>Agrostis palustris</i>	8	44	25.7 – 38.6	3.48	33.268	0.965	0.651
Sand	4	35	23.1 – 40.3	4.95	31.949	0.734	2.550
Soil	5	58	23.0 – 38.5	3.55	33.105	0.723	1.866

† Mathematical treatment = derivative order, gap, first smoothing, and de-trend value.

‡ Number of Repeated Measures.

§ Standard deviation of the range.

¶ Standard Error of Calibration.

Table 2.4. Calibration and validation statistics for quantification of water loss by mass using near infrared spectroscopy and modified partial least squares regression using a 1, 4, 4, 1 math treatment†.

Treatment	Number of Terms	N‡	Range (g)	St.Dev§	Mean (g)	R ²	SEC¶
GREENHOUSE							
<i>Poa annua</i>	10	160	0.0 – 11.0	0.03	4.3	0.970	0.005
<i>Agrostis palustris</i>	6	190	0.0 – 16.0	0.04	5.4	0.899	0.009
Sand	8	184	0.0 – 12.0	0.03	4.4	0.945	0.007
Soil	10	202	0.0 – 16.0	0.04	5.9	0.951	0.010
FIELD							
<i>Poa annua</i>	1	18	0.0 – 9.0	2.43	3.182	0.456	1.788
<i>Agrostis palustris</i>	3	31	0.0 – 6.1	1.68	2.270	0.733	0.865
Sand	3	20	0.0 – 6.1	1.94	1.852	0.903	0.604
Soil	1	34	0.0 – 7.4	1.74	2.159	0.261	1.584

† Mathematical treatment = derivative order, gap, first smoothing, and de-trend value.

‡ Number of Repeated Measures.

§ Standard deviation of the range.

¶ Standard Error of Calibration.

Model Prediction

Prediction of soil moisture content with equations developed for each treatment group were generally successful ($0.79 < R^2 < 0.91$) when predicted with VSMC, however when predicting percent water loss, prediction models performed poorly ($0.36 < R^2 < 0.88$) as show in Table 2.5 – 2.6. This was interpreted as meaning that VSMC could be predicted with good accuracy, however prediction of percent water loss was slightly more complicated because loss was being measured, not the level of actual water present. Therefore, at field capacity, soils may appear to be identical when they may differ by a few moisture percentages. This would result in the formation of a more general equation with a much higher prediction error.

Prediction of soil or species using an equation developed for another treatment group was attempted to determined the closeness of spectral relationships (Tables 2.7, 2.8). Treatment groups were found to be too diverse to apply to another treatment group and no distinguishing trends were found that allowed for the spectra to be separated by soil or species type (Tables 2.9 – 2.12). Each treatment group was found to possess slightly different spectral signatures, thereby confounding interpretation. Examination of spectral similarities determined that the data could not be used in a general prediction equation for water content, species, or soil type. The relationship between spectral reflectance and water status was poor when one treatment group was used to predict another treatment group for comparisons among all treatment

Table 2.5. Prediction of water content in creeping bentgrass with creeping bentgrass equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		2.30		0.05
Means	22.00	21.96	0.07	0.06
Bias		0.04		0.01
Bias Limit		1.38		0.01
SEP (C)		2.31		0.05*
SEP (C) Limit		3.00		0.01
Stand Devs	7.36	6.99	0.06*	0.04*
Slope		1.00		1.01
RSQ		0.90		0.36*
Average H		1.00		1.00
N		196		184

* - Denotes values outside of range.

Table 2.6. Prediction of water content in annual bluegrass with annual bluegrass equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		3.22		0.01
Means	23.24	23.27	0.05	0.05
Bias		-0.03		0.00
Bias Limit		1.93		0.00
SEP (C)		3.23		0.01*
SEP (C) Limit		4.18		0.01
Stand Devs	7.14	6.40	0.03	0.03
Slope		1.00		1.04
RSQ		0.80		0.88
Average H		0.98		1.06
N		168		165

* - Denotes values outside of range.

groups of soil and species type. The poor predictability may be due to a number of factors including but not limited to: 1) a small sampling size (approximately 1000 to 2000 spectra are considered a good library size); 2) seasonal variability or sample textural inconsistencies; 3) instrument variability; and 4) that the statistical software utilized was developed for laboratory analysis of dried and ground forage tissue samples. Consequently, alternative methods of data analysis may be more appropriate for these data and need to be explored further.

Important Spectral Wavelengths

Several wavelengths were identified for prediction of water, species, and soil type. Utilizing five components for each prediction equation, wavelengths are shown by order of importance for prediction (Fig. 2.7 – 2.9). Wavelengths that explained the greatest overall variability were ranked by order of importance using the 1st derivative spectra. Data were combined for both water measurement techniques utilized in this study. Wavelengths found to be most important in equation development for water prediction were found to be located at 1838, 1394, 1898, 1498, 1906, 1938, and 1954 nm (Fig. 2.6). The most important wavelengths for prediction of species (Fig. 2.7) were determined to be located at 1846, 1898, 1906, 1918, and 1938 nm. The most important wavelengths for the prediction of soil type independent of species (Figure 2.8) were found to be located at 1394, 1846, 1906, 1894, 1498, 1938, 1874 nm. In terms of model development in all treatment combinations, the 1898-nm

wavelength region ranked as the most important wavelength region for water determination.

Table 2.7. Prediction of water content in sand with sand equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		1.74		
Means	17.49	17.50		
Bias		-0.01		
Bias Limit		1.05		
SEP (C)		1.75		
SEP (C) Limit		2.28		
Stand Devs	5.71	5.42		
Slope		1.00		
RSQ		0.91		
Average H		1.00		
N		180		

Table 2.8. Prediction of water content in soil with soil equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		2.29		0.05
Means	27.12	27.05	0.07	0.06
Bias		0.06		0.01*
Bias Limit		1.35		0.00
SEP (C)		2.29		0.05*
SEP (C) Limit		2.93		0.01
Stand Devs	4.96	4.39	0.06*	0.04*
Slope		1.00		0.95
RSQ		0.79		0.39*
Average H		0.98		1.11
N		195		192

* - Denotes values outside of range.

Table 2.9. Prediction of water content in annual bluegrass with creeping bentgrass derived water equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		9.61		0.03
Means	22.58*	28.08*	0.05*	0.03*
Bias		-5.50*		0.02*
Bias Limit		1.38		0.01
SEP (C)		7.90*		0.03*
SEP (C) Limit		3.00		0.01
Stand Devs	7.86*	9.87*	0.03*	0.05*
Slope		0.50		0.63
RSQ		0.39*		0.72
Average H		1.96		2.13
N		181		176

* - Denotes values outside of range.

Table 2.10. Prediction of water content in creeping bentgrass with annual bluegrass derived water equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		8.07		0.06
Means	21.87*	27.35*	0.07*	0.09*
Bias		-5.47*		-0.02
Bias Limit		1.93		0.00
SEP (C)		5.94*		0.05
SEP (C) Limit		4.18		0.01
Stand Devs	7.39	6.15	0.06*	0.03*
Slope		0.76		1.37
RSQ		0.39*		0.30*
Average H		1.57		1.57
N		202		190

* - Denotes values outside of range.

Table 2.11. Prediction of water content in sand with soil derived water equation.

Statistics	Pair 1		Pair 2	
	VSMC	VSMC	PWLM	PWLM
SEP		10.84		0.04
Means	16.95*	27.22*	0.05*	0.03*
Bias		-10.27		0.02*
Bias Limit		1.35		0.00
SEP (C)		3.46*		0.03*
SEP (C) Limit		2.93		0.01
Stand Devs	6.19	5.49	0.04	0.04
Slope		0.94		0.66
RSQ		0.69		0.46*
Average H		1.65		1.64
N		189		177

* - Denotes values outside of range.

Table 2.12. Prediction of water content in soil with sand derived water equation.

Statistics	Pair 1	
	VSMC	VSMC
SEP	10.60	
Means	26.97*	17.04*
Bias	9.93*	
Bias Limit	1.05	
SEP (C)	3.71*	
SEP (C) Limit	2.28	
Stand Devs	5.11	5.95
Slope	0.68	
RSQ	0.62	
Average H	1.15	
N	199	

* - Denotes values outside of range.

Conclusions

This study demonstrates the feasibility for field use of VIS/NIR spectroscopy to predict water content for turfgrass. These data indicate that relationships exist between spectra and species/soil type for specific wavelengths and can be ranked by level of importance however, their exact interaction needs more study. From results in this study, NIRS has the potential to be a reliable method to monitor and manage turfgrass fairways for irrigation scheduling. Comparison of the standard deviation of the range with the standard error of calibration shows the ISI software to be a more accurate analysis method than traditional analysis methods. However collecting the large number of spectra necessary to build an accurate and reliable model is a major obstacle due to in large part to the variability of species and soil types utilized on golf courses throughout the country

Further research is needed to examine the combined effects of species, soils, and other associated factors on the spectral reflectance of the turf canopy. Although much more data will be required for model development than was collected in this study, this technology has the potential to aid turfgrass managers in a SSM program.

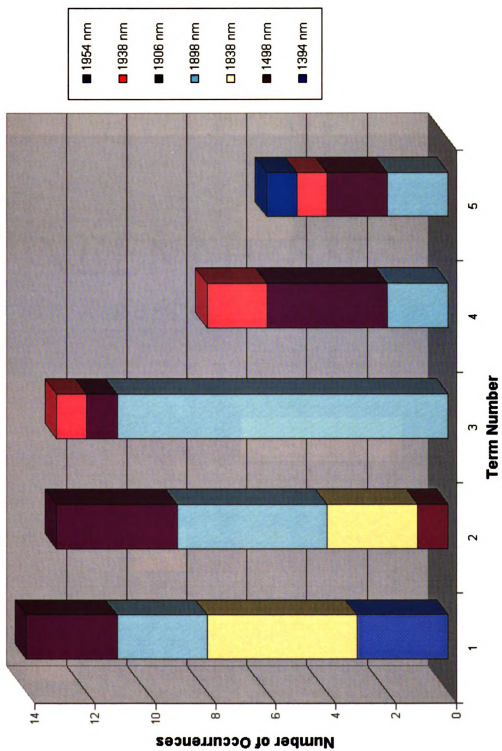


Figure 2.7. Occurrence of wavelength terms by order of importance for prediction of available water.

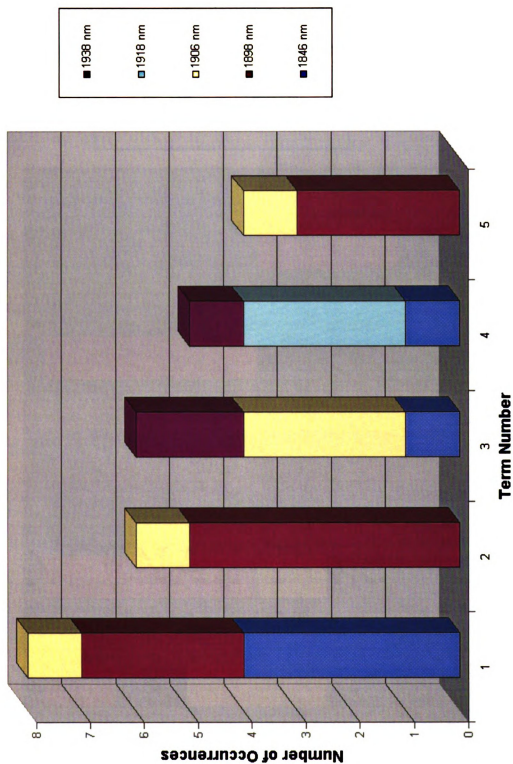


Figure 2.8. Occurrence of wavelength terms by order of importance for prediction of species type.

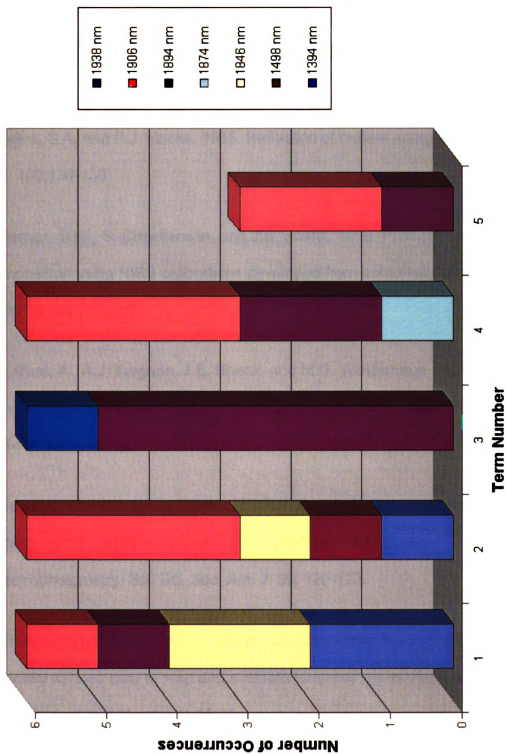


Figure 2.9. Occurrence of wavelength terms by order of importance for prediction of soil type.

References

- Ben-Gera, I. and K.H. Norris. 1968. Determination of moisture content in soybeans by direct spectrophotometry. *Isr. J. Agric. Res.* 18:125-132.
- Bowers, S.A. and R.J. Hanks. 1965. Reflection of radiant energy from soils. *Soil Sci.* 100:130-138.
- Coleman, S.W., S. Christiansen, and J.S. Shenk. 1990. Prediction of botanical composition using NIRS calibrations developed from botanically pure samples. *Crop Sci.* 30:202-207.
- Couillard, A., A.J. Turgeon, J.S. Shenk, and M.O. Westerhaus. 1997. Near infrared reflectance spectroscopy for analysis of turf soil profiles. *Crop Sci.* 37: 1554-1559.
- Dalal, R.C. and R.J. Henry. 1986. Simultaneous determination of moisture, organic carbon, and total nitrogen by near infrared reflectance spectrophotometry. *Soil Sci. Soc. Am. J.* 50: 120-123.
- Fenstermaker-Shaulis, L.K., A. Leskys, and D.A. Devitt. 1997. Utilization of remotely sensed data to map and evaluate turfgrass stress associated with drought. *J. of Turf Mgmt* 2(1):65-81.

- Peterson, J.C., F.E. Barton II, W.R. Windham, and C.S. Hoveland. 1987. Botanical composition definition of tall fescue – white clover mixtures by near infrared reflectance spectroscopy. *Crop Sci.* 27: 1077-1080.
- Roberts, C.A., R.E. Joost, and G.E. Rottinghaus. 1997. Quantification of ergovaline in tall fescue by near infrared reflectance spectroscopy. *Crop Sci.* 37:281-284.
- Saffel, M.T. 1994. Time domain reflectometry based turfgrass irrigation scheduling. M.S. thesis. Michigan State Univ., East Lansing, MI.
- Shenk, J.S. and M.O. Westerhaus. 1993. Near infrared reflectance analysis with single- and multiproduct calibrations. *Crop Sci.* 33:582-584.
- Shenk, J.S., S.L. Fales, and M.O. Westerhaus. 1993. Using near infrared product library files to improve prediction accuracy and reduce calibration costs. *Crop Sci.* 33:578-581.
- Sudduth, K.A., J.W. Hummell, and S.J. Birrell. 1997. The state of site-specific management for agriculture. pp. 183-210. ASA, CSSA, and SSSA, Madison, WI.
- Topp, G.C., J.L. Davis, and A.P. Annan. 1980. Electromagnetic determination of soil water content: Measurements in coaxial transmission lines. *Water Resour. Res.* 16:574-582.

Waddington, D.V., R.N. Carrow, and R.C. Shearman. 1992. Turfgrass. pp. 441-472. *In* Kneebone et al. Water requirements and irrigation. 1992. Agron. Monogr. 32. ASA, CSSA, and SSSA. Madison, WI.

Wetzel, D.L. 1983. Near-infrared reflectance analysis. Anal. Chem. 55:1165-1176A.

APPENDIX

WEATHER CONDITIONS FOR FIELD EXPERIMENT AT HTRC

Date	Relative Humidity (%)	Wind Velocity (mph)	Solar Radiation (Ly)	Rain (in)	Minimum Temp (°C)	Maximum Temp (°C)	Adjusted ET
8/9/98	93.5	1.38	318.6	0.16	20.3	27.5	0.10
8/10/98	90.0	2.78	426.9	0.23	19.3	29.5	0.15
8/11/98	84.8	5.50	410.5	---	16.9	24.3	0.14
8/12/98	77.4	3.16	548.7	---	12.9	25.4	0.18
8/13/98	76.6	1.74	554.4	---	13.4	26.1	0.17
8/14/98	76.7	2.24	493.3	---	14.0	26.8	0.17
8/15/98	85.9	2.06	318.3	0.13	17.9	26.5	0.11
8/16/98	80.7	4.46	495.6	---	16.1	27.8	0.17
8/17/98	83.8	3.35	413.2	---	16.8	29.2	0.15
8/18/98	86.7	5.14	425.9	1.13	18.6	27.0	0.14
8/19/98	71.2	3.56	595.9	---	9.4	23.9	0.19
8/20/98	75.5	3.10	461.5	---	12.2	26.9	0.16
8/21/98	80.7	1.95	375.9	---	19.7	30.1	0.14
8/22/98	75.2	3.69	516.0	---	19.4	28.8	0.18
8/23/98	N/A	N/A	N/A	N/A	N/A	N/A	N/A
8/24/98	72.7	6.54	442.8	---	22.7	31.5	0.21
8/25/98	80.8	6.43	397.9	0.40	19.7	27.9	0.17
8/26/98	74.3	2.86	519.4	---	15.9	27.2	0.18
8/27/98	75.6	1.52	525.2	---	14.9	29.4	0.17
8/28/98	86.2	1.93	165.5	0.12	18.8	23.4	0.07
8/29/98	80.9	5.87	414.0	0.01	18.8	28.4	0.17
8/30/98	69.5	3.59	419.6	---	16.5	27.0	0.17

Bibliography

- Ben-Gera, I. and K.H. Norris. 1968. Determination of moisture content in soybeans by direct spectrophotometry. *Isr. J. Agric. Res.* 18:125-132.
- Bowers, S.A. and R.J. Hanks. 1965. Reflection of radiant energy from soils. *Soil Sci.* 100:130-138.
- Coleman, S.W., S. Christiansen, and J.S. Shenk. 1990. Prediction of botanical composition using NIRS calibrations developed from botanically pure samples. *Crop Sci.* 30:202-207.
- Couillard, A., A.J. Turgeon, J.S. Shenk, and M.O. Westerhaus. 1997. Near infrared reflectance spectroscopy for analysis of turf soil profiles. *Crop Sci.* 37: 1554-1559.
- Dalal, R.C. and R.J. Henry. 1986. Simultaneous determination of moisture, organic carbon, and total nitrogen by near infrared reflectance spectrophotometry. *Soil Sci. Soc. Am. J.* 50: 120-123.
- Devitt, D.A., D.S. Neuman, D.C. Bowman, and R.L. Morris. 1995. Comparative water use of turfgrasses and ornamental trees in an arid environment. *J. of Turf Mgmt* 1(2): 47-63.

- Fenstermaker-Shaulis, L.K., A. Leskys, and D.A. Devitt. 1997. Utilization of remotely sensed data to map and evaluate turfgrass stress associated with drought. *J. of Turf Mgmt* 2(1):65-81.
- Fry, J.D. and J.D. Butler. 1989. Annual bluegrass and creeping bentgrass evapotranspiration rates. *Hort Sci.* 24(2):269-271.
- Hatchell, D.C. 1999. Analytical spectral devices technical guide. 3rd Edition. Analytical Spectral Devices, Inc., Boulder, CO.
- Hatfield, J.L. 1990. Measuring plant stress with an infrared thermometer. *Hort Sci.* 25(12):1535-1538.
- Idso, S.B., R.D. Jackson, P.J. Pinter, Jr., R.J. Reginato, and J.L. Hatfield. 1981. Normalizing the stress degree day parameter for environmental variability. *Agric. Net.* 24:45-55.
- Jackson, R.D., R.J. Reginato, and S.B. Idso. 1977. Wheat canopy temperature: A practical tool for evaluating water requirements. *Water Resour. Res.* 13:651-656.
- Kemp, W. 1991. Organic spectroscopy. pp. 1-29. New York, NY.

- Krishnan, P., J.D. Alexander, B.J. Butler, and J.W. Hummel. 1979. Reflectance technique for predicting soil organic matter. *Soil Sci. Soc. Am. J.* 44:1282-1285.
- Peterson, J.C., F.E. Barton II, W.R. Windham, and C.S. Hoveland. 1987. Botanical composition definition of tall fescue – white clover mixtures by near infrared reflectance spectroscopy. *Crop Sci.* 27: 1077-1080.
- Qian, Y. and J.D. Fry. 1997. Water relations and drought tolerance of four turfgrasses. *J. Amer. Soc. Sci.* 122(1): 129-133.
- Roberts, C.A., R.E. Joost, and G.E. Rottinghaus. 1997. Quantification of ergovaline in tall fescue by near infrared reflectance spectroscopy. *Crop Sci.* 37:281-284.
- Saffel, M.T. 1994. Time domain reflectometry based turfgrass irrigation scheduling. M.S. thesis. pp. 66-70. Michigan State Univ., East Lansing, MI.
- Salisbury, F.B. and C.W. Ross. 1992. *Plant physiology*. Fourth Ed. Wadsworth Publishing Company. Belmont, CA.
- Shenk, J.S. and M.O. Westerhaus. 1984. Accuracy of NIRS instruments to analyze forage and grain. *Crop Sci.* 25:1120-1122.

Shenk, J.S. and M.O Westerhaus. 1990. Monograph. Infracore International. Post Matilda, PA, pp. 11-54.

Shenk, J.S. and M.O Westerhaus. 1991. New standardization and calibration procedures for NIRS analytical systems. *Crop Sci.* 31:1694-1696.

Shenk, J.S. and M.O. Westerhaus. 1991. Population definition, sample selection, and calibration procedures for near infrared reflectance spectroscopy. *Crop Sci.* 31:469-474.

Shenk, J.S. and M.O. Westerhaus. 1991. Population structuring of near infrared spectra and modified partial least squares regression. *Crop Sci.* 31:1548-1555.

Shenk, J.S. and M.O. Westerhaus. 1993. Near infrared reflectance analysis with single- and multiproduct calibrations. *Crop Sci.* 33:582-584.

Shenk, J.S., S.L. Fales, and M.O. Westerhaus. 1993. Using near infrared product library files to improve prediction accuracy and reduce calibration costs. *Crop Sci.* 33:578-581.

Stanghellini, C. and F. DeLorenzi. 1994. A comparison of soil- and canopy temperature-based methods for the early detection of water stress in a simulated patch of pasture. *Irrig Sci.* 14:141-146.

Sudduth, K.A. and J.W. Hummel. 1991. Evaluation of reflectance methods for soil organic matter sensing. *ASAE* 34(4): 1900-1909.

Sudduth, K.A., J.W. Hummel, and S.J. Birrell. 1997. The state of site-specific management for agriculture. pp. 183-210. ASA, CSSA, and SSSA, Madison, WI.

Talsky, G. 1994. Derivative spectroscopy: Law and higher order. pp. 1-223. New York, NY.

Throssell, C.S., R.N. Carrow, and G.A. Milliken. 1987. Canopy temperature based irrigation scheduling indices for Kentucky bluegrass turf. *Crop Sci.* 27:126-131.

Topp, G.C., J.L. Davis, and A.P. Annan. 1980. Electromagnetic determination of soil water content: Measurements in coaxial transmission lines. *Water Resour. Res.* 16:574-582.

Topp, G.C., J.L. Davis, W.G. Bailey, and W.D. Zebchuk. 1984. The measurement of soil water content using a portable TDR hand probe. *Can. J. Soil Sci.* 64:313-321.

Waddington, D.V., R.N. Carrow, and R.C. Shearman. 1992. Turfgrass. pp. 441-472. *In* Kneebone et al. Water requirements and irrigation. 1992. Agron. Monogr. 32. ASA, CSSA, and SSSA. Madison, WI.

Wetzel, D.L. 1983. Near-infrared reflectance analysis. *Anal. Chem.* 55:1165-1176A.

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