Developing and Evaluating Turfgrass Growth Prediction Models with Machine Learning Techniques for Precision Nitrogen Management on Golf Course Greens

By

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Abstract

Nitrogen (N) fertilizer decisions are difficult for turfgrass managers because few tools or soil tests exist to assess N availability or requirements. This study proposed a new N fertilization strategy by building turfgrass growth prediction models using machine learning algorithms. The study was performed on two sand-based putting green root zones, and a series of experiments were conducted to quantify how foot traffic, soil moisture, and N fertilization affected bentgrass growth and tissue N content. Bentgrass tissue N ranged from 2.5% to 5% with an average of 3.9% across several years, root zones, and experiments. N fertilization was the most important factor for predicting bentgrass tissue N content, while weather and management practices were only weakly or not correlated with tissue N. Next, several inputs, including 7-day weather variables, traffic intensity, soil moisture content, N fertilization rate, and normalized difference red edge (NDRE) vegetation index were used to predict growth using machine learning techniques. The random forest (RF) algorithm was the most suitable among several. The best RF model had an R^2 of 0.64 on the training dataset and an R^2 of 0.47 on the validation dataset. The prediction model was not effective when used to predict growth from bentgrass grown at a different location, but training the model with growth data from that location resulted in accurate growth predictions (R^2 = 0.74). To test the ability of this growth prediction model for guiding fertilization decisions, a two-year study compared RF-guided N fertilization with three other N application strategies including 1) PACE Turf Growth Potential model; 2) an experience-based method for applying N fertilizer, and 3) the experience-based method guided by NDRE. The proposed machine learning method reduced fertilizer use compared to two of the three methods while maintaining acceptable or better turfgrass quality. In conclusion, golf courses can create customized growth prediction models using clipping volume and weather and other easy to obtain inputs. This model would be quite useful for determining N requirements of creeping bentgrass putting greens and has an advantage over other N fertilization methods because it is rooted in the N cycle.

Chapter One: Methods of Precision Nitrogen Management for Turfgrass

There are 34,011 golf courses in the world, and 45% of which are in the USA (Gelernter et al., 2016). An average course has about 30 hectares of maintained turf, and there are over one million hectares of maintained turf on golf courses in the USA. Managed turfgrass areas of golf courses provide important ecosystem services for communities, they offer valuable space for recreation and help to improve the quality of life under appropriate management (Colding and Folke, 2009; Dahl Jensen et al., 2017; Petrosillo et al., 2019; Lonsdorf et al., 2021). However, golf turf is intensively managed and receives heavier resource inputs compared with many other land uses. Fortunately, after decades of research on turfgrass input use efficiency and targeted education, the resources used to maintain golf course turfgrass are on the decline (Gelernter et al., 2015, 2016) and interest in optimizing resource use on golf courses exists. In order to appropriately manage the turfgrass areas while preserving the land, there is a need to develop better nitrogen (N) fertilizer application strategies to increase resource use efficiency, reduce management cost and minimize negative environmental impacts of golf courses.

N is often the most limiting nutrient and therefore it is an important nutrient driver of turfgrass growth. N inputs can affect many aspects of a golf course including turfgrass density, color, shoot and root growth, wear and temperature tolerance, thatch accumulation, and disease susceptibility (Beard, 1972; Carrow et al., 2002; Frank and Guertal, 2013). Relatively high annual N fertilization rates result in verdant and aesthetically pleasing playing surfaces. However, the rapid growth that results in increasing thatch and soil organic matter content which can reduce the function and aesthetics of putting greens (Meinhold et al., 1973; Murray and Juska, 1977; Throssell, 1981; Gaussoin et al., 2013). On the other hand, if N fertilization rate is too low, putting greens can be slow to recover from ball marks and wear damage which encourages weed invasion (algae, moss, annual bluegrass, etc.) (Beard, 1972).

“Where, when, and how much?” are questions that are frequently asked by turfgrass managers about N fertilizer used on golf courses (Carrow et al., 2009). The function of the playing surface is identified as the priority when maintaining the turfgrass on a golf course (Hammond and Hudson, 2007) as opposed to yield which is a major focus for production agriculture. Turfgrass managers are trained to apply N fertilization based on their experience and the observed turfgrass quality (shoot density, color and overall vigor). Of golf course components, putting green is one of the most important and they receive more N fertilizer per area than other components (Gelernter et al., 2015). The visual performance of putting green turfgrass is often quite similar when receiving optimum N and above optimum N rates, which explains the reason finding the optimum N fertilization rate is difficult. In terms of the purpose of management in a golf course, suboptimal N fertilization is unacceptable and risky, and above-optimal N application has fewer negative consequences; while above-optimal N application could cause the higher potential of N leaching and N gases emission that contaminate the environment.

Moreover, it is common that N fertilizer is applied in homogenous doses for the same components of a golf course. In reality, golf courses contain a series of landscapes that have a variety of spatial variables which generate several microclimates. In agriculture, there has been a progressive transformation from traditional agricultural management to technology- and data-based precision agriculture. Precision agriculture seeks to increase crop yield and profitability while lowering traditional resource inputs by allowing for site-specific management. Studies have shown that precision agriculture improves the environment, yields, and profits relative to traditional agriculture (Olson and Elisabeth, 2003; Bongiovanni and Lowenberg-DeBoer, 2004; Brown et al., 2016; Yost et al., 2017). In turfgrass systems, a parallel concept is precision turfgrass management, which seeks to provide optimum turfgrass performance while lowering human, natural, mechanical, and chemical resource inputs, and also allows site-specific management. Precision turfgrass management aims to provide decision support for the management of pests, fertilization, soil salinity management, cultivation and irrigation (Stowell and Gelernter, 2006; Carrow et al., 2007; Bell and Xiong, 2008; Krum et al., 2010), and it evolves requirement of on-site information about turfgrass areas in order to provide site-specific management support. For example, a golf course usually has multiple micro-climate zones; therefore, the irrigation plan should be specific to these zones in order to reduce water use and improve turfgrass quality (Carrow et al., 2009; Krum et al., 2010; Straw and Henry, 2018; Serena et al., 2020). The aforementioned studies have attempted to improve golf course irrigation strategies by observing soil attributes and conditions along with corresponding turfgrass performance data from sensors. Similar to precision irrigation on golf courses, N management can also be more effective and efficient by allowing managers to closely observe the turfgrass field condition and make decisions based on the real-time on-site data collection. The following sections review the current precision turfgrass management methods for N application and explore future opportunities.

Current Nitrogen (N) Application Strategies

Turfgrass Growth Potential to Make N Fertilization Decisions

There are two types of turfgrass including cool-season turfgrass and warm-season turfgrass which are distinguished by their unique growth requirements. Briefly, cool-season turfgrass or C3 turfgrass prefers growing in cool climates, and the optimum temperature for growth for these grasses is at 15.5-23.8°C, with growth decreasing dramatically as the temperature rises above 26.6°C or below 10°C. Warm-season turfgrasses or C4 turfgrass prefer temperatures between 26.6-35°C, the growth would decrease dramatically when the temperature is below 12.7°C, but are less hampered by temperatures above 35°C (Gelernter and Stowell, 2005). Clearly, temperature is one of the most important factors affecting cool-season or warm-season turfgrass growth. Therefore, the first turfgrass growth model was proposed by Gelernter & Stowell (2005) and focused on the role of temperature in the growth of both cool- and warm-season turfgrass. This model (expression (1)) was meant to estimate turfgrass growth potential instead of modeling the turfgrass growth rate as the authors recognized that other factors will affect turfgrass growth. This model is called the PACE Turf Growth Potential model. When the growth potential is 100%, then the turfgrass (both cool- or warm-season turfgrass) reaches the optimal growth and has the fastest growth rate, and when the growth rate is 0%, then no turfgrass growth is expected.

$$GP = \frac{1}{e^{0.5(\frac{T-T_0}{var})^2}} \quad (1)$$

Where,
e: 2.718
T: local average temperature; °C
T_0: optimal temperature for turfgrass growth; 20°C for cool-season grass, and 31°C for warm-season grass
Var: adjust the change in GP as temperature moves away from T_0; 5.5 for cool-season grass, and 343 for warm-season grass.

The PACE Turf Growth Potential model was first developed to help turfgrass managers to make decisions about the best time to schedule overseeding cool season grasses into warm season grasses. Later on, the growth model was endorsed by Woods (2013) for making decisions about N fertilizer applications. Woods (2013) illustrated that turfgrass N application rate should meet the turfgrass growth requirement, therefore, the amount of N needed can be estimated by multiplying turfgrass growth potential (estimated by PACE Turf Growth Potential model) by the maximum estimated N use over a period of optimal growing conditions (e.g. day, week). Turfgrass managers then could use temperature to decide the appropriate amount of N fertilizer to apply to their golf courses.

Because of the simplicity of using the model, the PACE Turf Growth Potential model has become the most commonly used turfgrass growth prediction model and used to guide N fertilization applications, time overseeding events, predict disease outbreaks, etc. However, temperature is not the only factor that influences turfgrass growth, and a growth model including other factors such as traffic (Carrow and Martin Petrovic, 1992), irrigation (Sills and Carrow, 1983) and disease (Vargas, 2018) may improve predictions of growth that could be useful for optimal management of turfgrasses. Moreover, different species of turfgrass, either cool- or warm-season grass, are likely to respond to differences in weather, soil, and management practices. The PACE Turf Growth Potential model does not attempt to explain plant growth to factors other than temperature.

Vegetation Index to Guide N Fertilization

In addition to the PACE Turf Growth Potential model, remote sensing and proximal sensing have been used in turfgrass research and management. Vegetation indices (VI) are obtained from sensing data which use a series of bands of light to detect plant health statuses such as nutrient status (Caturegli et al., 2016) and chlorophyll content (Bell et al., 2004). Guillard et al. (2021) conducted a study that used normalized difference vegetative index (NDVI) to estimate fall N fertilization. The study claimed that NDVI of turfgrass would reach a plateau when the N application reached and passed the maximum rate, and the authors developed NDVI-based methods to observe objective turfgrass quality and provide recommendations to achieve the optimal N application rate. This method requires users to seek out the plateau or the maximum N rate using reference strips that differ in the amount of N fertilizer received. The normalization process is called the sufficiency index (SI) (equation (2)). As the SI approaches 1, there is less demand for additional N since the soil N is likely to support turfgrass to a maximum NDVI.

$$\mathrm{SI} = \frac{Mean\ bulk\ reading}{Mean\ reference\ strip\ reading} \tag{2}$$

Where,
mean bulk reading: average NDVI reading of turfgrass
mean reference strip meaning: NDVI reading from “well-fertilized” reference plot.

Compared with making N application based on subjective turf quality observed by naked eyes, NDVI and other vegetative indices formulated based on spectral reflectance offered a more objective quality evaluation. While, it is known that the spectral reflectance indices can be affected by many variabilities in the field, such as canopy density (Bremer et al., 2011), turfgrass water status (Caturegli et al., 2020) and plant colorants (Obear et al., 2017). If properties like canopy density was affected by factors other than N fertilizer (such as abiotic and biotic stresses) using spectral reflectance to make N fertilization decisions could be misguided.

Data-Driven Decision Making

With the vast amount of data available, there is an increasing interest in exploiting data for competitive advantage. At the same time, computers have become far more powerful, and algorithms have been developed to understand the collected data. The benefits of data-driven decision making have been demonstrated, and therefore it has been rapidly adopted in industry and academia (Brynjolfsson and

McElheran, 2016; Tantalaki et al., 2019; Kamble et al., 2020). In agriculture, data-driven decision making has been adopted to overcome the challenges faced by conventional agriculture and help growers to have a more sustainable, profitable and environmentally friendly land (Olson and Elisabeth, 2003; Bongiovanni and Lowenberg-DeBoer, 2004; Brown et al., 2016; Yost et al., 2017). With the similarity between turfgrass and crops, there is a great opportunity to implement data-driven decision making in turfgrass system.

Machine Learning (ML) Techniques

ML is an application of artificial intelligence, which can learn and make predictions based on observing the data input via statistical methods. ML has rapidly developed in the past two decades and has been used in many fields to provide decision-making under a variety of uncertainties. Many ML techniques were first used in industries that had intensive data issues which are referred to as “Big Data”, and recently, these techniques have been widely used across empirical sciences for analyzing and understanding high-throughput experimental data in novel ways (Jordan and Mitchell, 2015). One of the main advantages of ML techniques is that they are capable of autonomously solving large non-linear problems using data from multiple sources. Simply put, ML can learn from experience (data input) and make predictions accordingly. For example, ML techniques have been widely used in agriculture to make detections, such as disease detection, weed detection, crop health status and quality and species recognition (Liakos et al., 2018). Besides evaluating crop health visual performance, ML techniques have been widely used for early estimation of yield production and to provide N application decisions (Tremblay et al., 2011; Cilia et al., 2014; Maresma et al., 2016; van Klompenburg et al., 2020). ML offers an opportunity to understand and unravel the intensive and complex process of plant growth under several management practices involved.

Applying ML in turfgrass research and management is still at an early stage. With large similarities between agricultural crop management and turfgrass management, turfgrass scientists and professionals have adopted ML aim to understand and learn the uncertainties of the process of turfgrass health status and visual performance and make management decisions accordingly under various spatial and temporal variables. Ding et al. (2016) applied ML to analyze RGB aerial imagines to evaluate turfgrass visual quality and color, and the ML models included linear regression models, support vector machine (SVM) and multilayer perceptron (MLP). Similarly, Phan et al. (Phan et al., 2017) applied deep learning technique to evaluate turfgrass quality and color. Yu et al. (2019a; b) demonstrated deep convolutional neural network (DCNN) models were able to accurately detect broadleaf weeds in bermudagrass and provided a precision herbicide decision support tool for weed control in bermudagrass. Moreover, Wang et al. (Wang et al., 2021) adopted ML techniques and unmanned aerial vehicle (UAV) derived NDVI (normalized difference vegetative index) to evaluate drought stress of zoysiagrass and demonstrated the potential of using ML and UAV phenotyping approaches to assist breeders in selecting hybrids. Turfgrass yield prediction has not yet been attempted using ML methods.

Yield Estimation and Nitrogen (N) Management

Yield prediction is an essential task for decision-makers at local and regional scales for rapid decision making. Accurate yield prediction models have been used on agricultural crop management to guide decisions about what to grow and when to apply, and match nutrient applications with crop demand. Yield prediction is critical for N management. A N fertilization strategy should be made to meet plant N demand. Accurate yield prediction can help growers with crop harvest, process and transport the crop (Zarate-Valdez et al., 2015). ML has been used in agriculture for decades (Liakos et al., 2018; van Klompenburg et al., 2020) for predicting crop yield and improving N application decisions. The top five the most commonly used ML models used for precision agriculture include artificial neural networks (ANN), ensemble learning (such as random forest), support vector machine (SVM), decision trees and regression (Benos et al., 2021). And among them, ANN was most widely used and usually performs better compared with the other four ML models. ANN is a deep learning technology that utilizes multiple hidden layers between input and output layers, which is meant to mimic the properties of brain neurons.

ANN is used to deal with non-linear models and to predict plant parameters and yield incorporated with remote sensing data (Farifteh et al., 2007; Kuwata and Shibasaki, 2015). Challenges with using ANN include selection of number and size of hidden layers, learning rate, the requirement for a large training dataset and the potential of overfitting (Chlingaryan et al., 2018). ANN requires expert knowledge and intensive computational costs (Sheykhmousa et al., 2020). Ensemble learning has also been widely used, and the most commonly used models include random forest (RF) (Chlingaryan et al., 2018). RF uses a decision tress as a base learner and generates many decision trees in parallel. RF has can produce results competitive with ANN (Mboga et al., 2017). SVM was the third most used ML model. While SVM is able to solve regression patterns called support vector regression (SVR), it is usually used for classification purposes in agricultural research settings (Benos et al., 2021). In this dissertation, we focused on investigating the feasibility of using ensemble learning (including RF, SVR, linear regression and decision trees) to predict yield and guide N fertilization of bentgrass putting greens.

An important component of building ML models and predicting plant yield is to identify which variables should be used for yield prediction. According to a review paper on ML used for crop yield prediction (van Klompenburg et al., 2020), based on 50 research papers published from 2010 to 2019 the paper had concluded that there were seven categories of feature inputs: 1) soil information, which including soil physical and chemical characteristics as well as nutrients in the soil; 2) crop information, including crop yield, crop density and crop varieties; 3) water, including information of rainfall and air humidity and soil water; 4) nutrients in the soil, including both soil and applied nutrients; 5) solar information, including information related to radiation and temperature; 6) field management, including irrigation and fertilization; and 7) other features, which includes wind speed, air pressure and vegetative indices including NDVI (normalized difference vegetative index), EVI (enlaced vegetative index) and NDRE (normalized different red edge). Because our study would be the first study on developing and evaluating ML models to predict turfgrass yield production, there is no research that has investigated which features should be used for building turfgrass ML growth prediction models. While as there is large similarity between crop and turfgrass, these features used for crop yield prediction would also be applied for turfgrass. Features unique to turfgrass management include traffic stress, which has been shown to affect turfgrass growth rate and visual quality (Shearman et al., 1974; Shearman and Beard, 1975; Bilgili and Acikgoz, 2007);

Despite significant development in ML techniques, fundamental limitations exist. As ML is a data-driven approach, it requires a large quantity of data input to train and evaluate the model to obtain relatively high accuracy. Therefore, the accuracy of the predictions and their uncertainties produced by the ML algorithms strongly depends on the data quality, model representativeness, and the dependencies between the input and target variables in the collected dataset. Input data with high noise and many outliers may largely reduce the predictive power and even cause overfitting, where the model does not apply to the new set of data. Strategies such as outlier detection, model selection and cross-validation should be applied and could be helpful to overcome these limitations.

Besides an accurate yield estimation, closely observing and understanding plant N status is also the key to precision N management. In precision agriculture, one of the approaches for making N fertilization recommendations for crops is commonly based on crop N status testing using remote sensing and in-situ data (Tremblay et al., 2011; Cilia et al., 2014; Maresma et al., 2016). Because of the unique management practices on golf course putting greens where the clipping are removed after each mowing event, if we can have a good estimation of clipping removal and clipping N status over time, we could estimate N removal from clipping, and N fertilization decisions could be linked to the N loss from clipping harvest.

With substantial similarities between agricultural crops and turfgrass, there is a great opportunity to investigate whether ML techniques could be used on turfgrass system for improving nutrient management. Although maximizing turfgrass yield is not a priority focus, the correlation between turfgrass quality and clipping yield has ultimately made turfgrass growth rate prediction a determinant in N fertilization management. An accurate estimation of clipping yield or clipping removal routinely would help turfgrass managers to estimate N removal, and N application decisions would be easily made to offset the N removal. Based on our knowledge, there is no study that investigates the feasibility of using ML to predict turfgrass growth and whether it is practical to help turfgrass managers to make N application decisions.

Summary and Research Objectives

N management is challenging as there is no reliable soil testing for guiding N fertilization application. With increasing pressure on golf courses reducing resource input, it is urgent to improve current N management for maximizing N fertilizer use efficiency. More precise N management is required to match N input with crop needs or growing demand. Currently, ML techniques and sensing technologies have been widely developed in many agricultural research and have been shown the ability to improve crop growth and nutrient management. With a large similarity between agricultural crop management and turfgrass management, there is an opportunity to improve current N management for turfgrass using ML algorithms. The objective of this research was to 1) determine turfgrass N status under different management practices (Chapter 2); 2) identify important growth factors affecting turfgrass growth that planted on golf course putting green, and decide the variable inputs when developing ML growth prediction model (Chapter 3,4); 3) develop ML growth prediction models for putting green turfgrass, with the goal of providing a short-term estimation of turfgrass clipping removal between each fertilization application events (Chapter 3,4); and 4) evaluate the feasibility of the developed turfgrass ML growth prediction model on improving N management by comparing with currently used N fertilization practices (Chapter 5).

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Chapter Two: Influence of Foot Traffic, Irrigation, Nitrogen (N) Fertilization, and Weather Factors on Creeping Bentgrass 'Focus' (Agrostis stolonifera L.) Tissue N Content

Abstract

Tissue nitrogen (N) content is an important indicator for estimating N removal in clippings from golf putting greens. To help managers determine average tissue N content, a better understanding of factors that control turfgrass tissue N content is needed. The objective of this study was to quantify how different N application rates, foot traffic intensities, soil volumetric water content (VWC) and weather factors influence tissue N content of creeping bentgrass 'Focus' (Agrostis stolonifera L.). Field experiment that investigated combined effects of foot traffic and nitrogen fertilizer on tissue N content were performed on two greens with 0.6 % and 0.9 % soil organic matter (SOM) in 2018, where N fertilizer was applied at 0, 10, or 20 kg N ha^{-1} $2wk^{-1}$, and foot traffic intensities were maintained at three rates: 0, 1800 and 3600 rounds wk^{-1} from 16 May to 28 Aug. Field experiment that investigated combined effects of VWC and traffic on tissue N content was conducted on the 0.9 % SOM green in 2019, where VWCs were maintained at low (VWC stayed at 12-15 %), medium (17-22 %) and high (25-29 %) levels by hand watering and with the assistance of time domain reflectometry (TDR) with 7.6cm rods, and foot traffic intensities were maintained at 0, 700 and 1400 rounds wk^{-1} from 31 May to 4 Oct. The tissue N content ranged from 2.5 to 5.0 % with an average of 3.9 %. N fertilizer rate was the main factor controlling the tissue N content. Foot traffic and VWC did not impact the tissue N content. Similarly, the impacts of temperature, relative humidity and estimated evapotranspiration on the tissue N content were minimal or non-existent.

Introduction

Nitrogen (N) is one of the most important essential nutrients for controlling turfgrass growth. Generally, turfgrass nutrient management plans are designed to supply a moderate N rate to limit turfgrass growth rate, essentially keeping the turfgrass in a state of N deficiency. While most turf managers make N application decisions based on their subjective assessment and usually do not quantify turfgrass growth, the use of area-normalized fresh clipping volume as a metric to quantify turfgrass growth has become popular with some greenkeepers in recent years. Fresh clipping volume can serve as a quantitative estimate of relative plant growth, but coupled with tissue N content, it may also be used to approximate N uptake and removal. Golf course putting greens are mowed several times each week, so analyzing tissue N content from each mowing event is not practical. Instead, the manager may wish to submit a few samples during the year and average or extrapolate the results, or simply assume a tissue N content without sending in a sample at all. Studies have documented how weather, traffic and water influence turfgrass growth (Biran et al., 1981; DiPaola and Beard, 1992), but there has not been much research on how these factors influence tissue N content.

Foot traffic on golf courses putting greens is a major stress on turfgrass and usually has a negative effect on turfgrass performance (Carrow and Martin Petrovic, 1992). Excessive traffic stress can result in major turf damage and reduce turf quality and clipping yield significantly (Shearman et al., 1974; Shearman and Beard, 1975; Bilgili and Acikgoz, 2007). However, there is limited information on if or how foot traffic affects tissue N content. Water availability is another very important factor for plant growth. In some cases, water deficiency can be the primary growth-limiting factor (Stiles and Williams, 1965; Jordan et al., 2003). On the other hand, excessive irrigation has been shown to be detrimental for creeping bentgrass growth and visual quality (DaCosta and Huang, 2006) and may also result in increased vulnerability to traffic and disease stress. Understanding how water availability influences creeping bentgrass tissue N content is necessary for precision N management.

Tissue N content is an essential component for the accurate estimation of plant N uptake. As data-driven N management continues to grow, there is a need to thoroughly understand the factors affecting turfgrass N status. Therefore, this study was conducted to investigate the significance of weather, traffic, and management factors on creeping bentgrass tissue N content.

Materials and Methods

Two field experiments were conducted at the University of Wisconsin O.J. Noer Turfgrass Research and Education Facility located at Verona, WI, USA during 2018 and 2019. The research was conducted on two creeping bentgrass 'Focus' (Agrostis stolonifera L.) putting greens on sand root zones constructed following USGA (United State Golf Association) recommendations for putting green construction (US Golf Association, 2004a). The turfgrass was mowed five days per week and maintained at a height of 3.2 mm. The site was irrigated daily to replace ET as estimated by an on-site weather station (except when irrigation was a treatment), fertilized with 100 kg ha^{-1} split into 10 applications of 10 kg ha^{-1} of N as urea (except when N fertilizer was a treatment), topdressed with 0.6 m3 ha^{-1} of sand approximately every three weeks during the growing season. Hollow tine cultivation was conducted once a year at the end of the growing season and the holes were filled with topdressing sand. Diseases and other pests were controlled as needed.

Foot Traffic and Nitrogen (N) Fertilization Study

A study to investigate how foot traffic and N affect turfgrass tissue N content was conducted from 16 May to 28 Aug. 2018. The experimental design was a completely randomized design with three replications of nine treatments on two sand root zones, one with soil organic matter (SOM) of 0.6 % and the other with 0.9 % in the top 10 cm from which soil samples were collected and analyzed on 28 Aug. 2018. SOM was determined by igniting soil (first dried at 40 ℃) at 360 ℃ for 2 hours in a muffle furnace. Each plot measured 2.4 m by 1.2 m. The treatments consisted of three N rates (0, 10, or 20 kg ha^{-1} $2wk^{-1}$) and three traffic rates (none, medium, high). Traffic intensities were chosen based on an observational trial conducted by Hathaway & Nikolai (2005). The high traffic intensity represented 3600 rounds wk^{-1}, the medium traffic intensity was 1800 rounds wk^{-1} and the control treatment did not receive supplemental traffic. Traffic was applied by five researchers walking on the plots wearing golf shoes at a speed of 95 steps min^{-1} between 1300 and 1500h Monday through Friday until the treatments reached the assigned weekly traffic intensity requirements.

Clippings from each plot were collected three times a week between 900 and 1200h from 7 June to 31 July 2018 (weather permitting) by mowing a 1.9 m pass down the center of each plot using a 0.54 m wide green mower (Toro Co., Bloomington, MN). Before clipping collection, 0.27 m wide alleys were mowed at the top and bottom of each plot perpendicular to the collection pass. This was done to reduce the variability associated with starting and stopping the mower. The effective clipping collection area for each plot was 1.0 m2. Clippings were brushed from the mower bucket into paper bags, which were then placed in a 50 °C oven for at least 48 hours. Sand and other debris were removed from the dried clipping samples using the water method described in Kreuser et al. (2011). Then the clipping was ground into fine powder for determination of total N content using a combustion analyzer with thermal-conductivity-detection (TruSpec Micro, LECO Corporation, St. Joseph, MI).

Visual turfgrass quality for each plot was evaluated $2wk^{-1}$ from 7 June to 31 July 2018 using the National Turfgrass Evaluation Program's 1 to 9 scale, where 1 represents completely dead turf, 6 represents the minimally acceptable quality, and 9 represents a perfect or ideal turfgrass quality (Morris and Shearman, 1998). Normalized difference red edge (NDRE) for each plot was recorded on the same dates using a handheld device approximately 1 m above the canopy (Rapid SCAN CS-45, Holland Scientific Inc., Lincoln, NE).

Foot Traffic and Soil Moisture Study

A study designed to investigate the impact of soil volumetric water content (VWC) and foot traffic on creeping bentgrass 'Focus' (Agrostis stolonifera L.) tissue N was conducted from 31 May to 4 Oct. 2019. Due to the limitation of resources, this study was conducted on the root zone with the higher SOM content (0.9 %) of the two used in 2018. The experimental design was a randomized split-plot design with three replications, and VWC levels as the main plots (3.6 m by 2.4 m) and three different traffic intensities as the sub-plots (2.4 m by 1.2 m). VWC were maintained at 12-15 %, 17-22 % and 25-29 %. These VWCs were selected to represent low, mid-range, and excessive water for the sand-based putting green. VWCs were maintained by hand watering. Because we failed to maintain VWC at a low (12-15 %) rate in Sep 2019, clipping data collected from those plots in that month were omitted when making statistical analysis. VWC was measured using FieldScout TDR 350 Soil Moisture Meter with 7.6 cm long rod (Spectrum Technologies Inc. Aurora, IL) before each clipping collection event, with three measurements averaged to represent the moisture in each plot. If the VWC was below the assigned level, irrigation was applied by hand watering to meet the requirement. Foot traffic was conducted at a lower intensity range compared with the levels utilized in 2018, which represented more realistic traffic intensities allowable on the golf course. Traffic was applied as described above and included a medium traffic intensity at 1400 rounds wk^{-1}, a low intensity at 700 rounds wk^{-1}, and a treatment that received no supplemental traffic. Clippings were collected three times a week between 900 to 1200h from 1 Aug. to 18 Sep. 2019, and tissue N content was determined as described above. NDRE was recorded $2wk^{-1}$ as described above.

Statistical Analysis

Two-way ANOVA was used to determine statistical significance at P = 0.05, 0.01 and 0.001 with JMP software (version 14.0, SAS Institute Inc., USA). Means were separated using Fisher's protected least significant difference (LSD) test. N × traffic interactions were analyzed for clipping collected in 2018 on two research greens, and data from two research greens then were pooled and analyzed collectively. VWC × traffic interactions were analyzed for clipping collected in 2019. A simple linear regression model was used to estimate the relationships between weather factors and tissue N content which was collected from both 2018 and 2019.

Results and Discussion

The N fertilizer treatments caused significant differences in the tissue N content that were collected on two greens in June and July 2018 (n = 340) (Table 1). SOM, however, had no significant difference in the tissue N content (data not shown). The reason might be the difference of SOM between the two research greens is small. Future studies with a wide range of SOM would be needed to investigate the effect of SOM on turfgrass tissue N content. In this study, on both research greens, doubling the fertilization (from 10 kg ha^{-1} to 20 kg ha^{-1} 2wk^{-1}) increased tissue N content by 8 %; while increasing the fertilization from 0 to 10 kg ha^{-1} resulted in an increase of 6 to 7 % in plant tissue N content. Overall, there was a relatively strong relationship between tissue N content and N fertilization rate (R2=0.34), and N fertilization inherently improved turfgrass visual quality ratings and NDRE values.

Table 1. Statistical analysis of the effects of nitrogen (N) and foot traffic intensities on creeping bentgrass 'Focus' (*Agrostis stolonifera* L.) tissue N content, normalized difference red edge (NDRE) and turf visual quality collected from 7 June to 31 July 2018 on two research greens. Visual quality scaled from 1 to 9 where 1 represents completely dead turf, 6 represents the minimally acceptable quality, and 9 represents a perfect or ideal turfgrass quality. Means of two research greens were presented.

	Clipping N content % (June 2018)	Clipping N content % (July 2018)	NDRE (June-July 2018)	Turf quality (June-July 2018)
N rate (kg ha^{-1} 2wk^{-1}) (N)				
0	3.58 c[r]	3.65 c[r]	0.2017 c[r]	4.7 c[r]
10	3.83 b	3.86 b	0.2220 b	5.6 b
20	4.14 a	4.18 a	0.2431 a	6.1 a
Traffic rate (rounds wk^{-1}) (T)				
0	3.83	3.85	0.2443 a[r]	6.3 a[r]
1800	3.80	3.90	0.2177 b	5.4 b
3600	3.91	3.94	0.2049 c	4.7 c
Summary of ANOVA effect				
N	<0.0001***	<0.0001***	<0.0001***	<0.0001***
T	0.2736[ns]	0.2810[ns]	<0.0001***	<0.0001***
N × T	0.5931[ns]	0.5442[ns]	<0.0001***	0.0009***

[r]: Values in the same column followed by the same letter or not followed by any letter are not significantly different at $P = 0.05$; Tukey's post hoc test
***: Significant at $P < 0.001$.
[ns]: Not significant.

Foot traffic had no impact on the tissue N content (Table 1) from 2018's field study, despite a range from no to quite high traffic (3600 rounds wk^{-1}). Increasing traffic intensity decreased NDRE and turfgrass visual quality (Table 1). In 2019, traffic intensities maintained at 0, 700 and 1400 rounds wk^{-1}, also had no statistical influence on the tissue N content (n=54) (Table 2), and increasing traffic intensity decreased NDRE values. These results demonstrated that NDRE might not be an accurate tool for predicting tissue N content, especially across areas that were affected differently by traffic stress. VWC also had no impact on the tissue N content (Table 2).

Table 2. Statistical analysis of the effects of soil volumetric water content (VWC) and traffic intensities on creeping bentgrass 'Focus' (*Agrostis stolonifera* L.) tissue N content and NDRE collected from 1 Aug. to 18 Sept. 2019.

	Clipping N content % (Aug. 2019)	Clipping N content % (Sept. 2019)	NDRE (Aug. –Sept. 2018)
VWC (%) (W)			
Low (12-15 %)	4.17	N/A	0.2840 ab^{r}
Medium (17-22 %)	4.26	3.93	0.2811 b
High (25-29 %)	4.09	3.91	0.2967 a
Traffic rate (rounds wk^{-1}) (T)			
0	4.24	3.92	0.2971 a^{r}
700	4.10	3.87	0.2875 ab
1400	4.27	3.95	0.2772 b
Summary of ANOVA effect			
W	0.7596^{ns}	0.9065^{ns}	0.0193*
T	0.4335^{ns}	0.8934^{ns}	0.0153*
W × T	0.4667^{ns}	0.8343^{ns}	0.3319^{ns}

^{r}: Values in the same column followed by the same letter or not followed by any letter are not significantly different at P = 0.05; Tukey's post hoc test
*: Significant at P < 0.05.
^{ns}: not significant

Table 3 shows the impacts of weather factors, including average air temperature, evapotranspiration (ET) and relative humidity on the tissue N content collected in 2018 and 2019 (n=394). Overall, under the conditions of this study, weather appeared to play a small role in controlling the tissue N content. Temperature was slightly positively correlated with the tissue N content and particularly for days 4, 5, and 6 prior to the clipping collection. However, the R2 never exceeded 0.11. ET slightly negatively influenced the tissue N content except for five or six days prior to clipping collection; R2 values for this relationship never exceeded 0.04. Relative humidity had no impact on the tissue N content except there for a weakly positive correlation between tissue N content and the relative humidity on the third day prior to clipping collection. Because the data from this study were collected during summer in Wisconsin, USA, the range of values for the weather parameters was limited. Daily average temperature spanned 12 to 28 °C, mean relative humidity ranged from 57 to 98 % and ET ranged from 0.2 to 0.7 cm. Over this period, there was a relatively wide range in tissue N content from the individual plots, and the majority of samples fell between 2.5 and 5 %, with a mean value of 3.9 %.

Table 3. Impacts of average daily air temperature, evapotranspiration and relative humidity on creeping bentgrass ‘Focus’ (*Agrostis stolonifera* L.) tissue nitrogen (N) content collected from 7 June to 31 July 2018 and 1 Aug. to 18 Sept. 2019

Weather factors	Day(s) before clipping collection (n=294)	Tissue N content of creeping bentgrass	
		Slope	R^2
Air temperature	0	-0.020**	0.018**
	1	0.010^{ns}	0.005 ^{ns}
	2	0.041***	0.055***
	3	0.005 ^{ns}	0.001^{ns}
	4	0.023***	0.042***
	5	0.033***	0.110***
	6	0.038***	0.105***
Evapotranspiration	0	-0.485***	0.040***
	1	-0.143*	0.011*
	2	-0.128^{ns}	0.035^{ns}
	3	-0.443***	0.035***
	4	-0.101^{ns}	0.001^{ns}
	5	0.377***	0.029***
	6	0.071^{ns}	0^{ns}
Relative humidity	0	-0.005^{ns}	0.006^{ns}
	1	0.002^{ns}	0.001^{ns}
	2	0.004^{ns}	0.007^{ns}
	3	0.008***	0.044***
	4	-0.001^{ns}	0^{ns}
	5	-0.003^{ns}	0.005^{ns}
	6	-0.002^{ns}	0.001^{ns}

***: Significant at $P < 0.001$
**: Significant at $P < 0.01$
*: Significant at $P < 0.05$
^{ns}: not significant.

Conclusion

N fertilization was strongly related to creeping bentgrass ‘Focus’ (*Agrostis stolonifera* L.*)* tissue N content, while foot traffic, VWC and several weather factors including temperature, relative humidity and ET all had slight to no correlation with the tissue N content. The average tissue N content was 3.9 % under a wide range of management conditions and weather. Even when the N fertilization rate increased from 0 to 20 kg N ha^{-1} $2wk^{-1}$, the average tissue N content only increased from 3.6 to 4.1 % (i.e. a 14 % increase). This suggests that while tissue N content is critical for estimating the amount of nutrients removed during putting green clipping collection, the tissue N content of typically managed creeping bentgrass putting green turf can be assumed to be about 4 % as it is not strongly influenced by irrigation practices, foot traffic or weather factors. Turfgrass managers may be able to determine a robust average tissue N content for their creeping bentgrass putting greens by periodically (randomly) collecting samples and averaging them.

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Chapter Three: Creeping Bentgrass Yield Prediction with Machine Learning Models

Abstract

Nitrogen (N) is the most limiting nutrient for turfgrass growth. Instead of pursuing the maximum yield, most turfgrass managers use N to maintain a sub-maximal growth rate. Few tools or soil tests exist to help managers guide N fertilizer decisions. Turf growth prediction models have the potential to be useful, but the currently existing turf growth prediction model only takes into account temperature, limiting its accuracy. This study developed machine-learning-based turf growth models using the random forest (RF) algorithm for estimating short-term turfgrass clipping yield. To build the RF model, a large set of variables were extracted as predictors including 7-day weather, traffic intensity, soil moisture content, N fertilization rate, and the normalized difference red edge (NDRE) vegetation index. In this study, data were collected on two putting greens where the turfgrass received 0 to 1800 round/week traffic rates, various irrigation rates to maintain soil moisture content between 9 to 29%, and N fertilization rates of 0 to 17.5 kg ha^{-1} applied biweekly. The RF model agreed with the actual clipping yield collected from the experimental results. Temperature and relative humidity were the most important weather factors. Including NDRE improved the model's prediction accuracy. The highest coefficient of determination (R^2) of the RF model was 0.64 for the training dataset and was 0.47 for the testing data set when evaluating the model. This represented a large improvement over an existing growth prediction model (R^2=0.01). However, the machine-learning models created were not able to accurately predict clipping production at other locations. Individual golf courses can create customized growth prediction models using clipping volume to eliminate the deviation caused by temporal and spatial variability. Overall, this study demonstrated the feasibility of creating machine-learning-based yield prediction models that may be able to guide N fertilization decisions on golf course putting greens and presumably other turfgrass areas.

Introduction

There are 34,011 golf courses in the world, and 45% of them (15,372 golf courses) are in the USA according to a report in 2016. An average course has about 30 hectares of maintained turf, and there are over one million hectares of maintained turf on golf courses in the USA. Golf course turfgrass is usually intensively fertilized, and nitrogen (N) is applied in the greatest quantities of all nutrients. Gelernter et al. (2016) estimated that US golf courses use 55,333 Mg of N annually. These N inputs pose significant nonpoint source pollution risk (Bock and Easton, 2020). Hence, a need exists to optimize N management on golf courses.

N fertilization is one of the most important management practices that affect many characteristics of golf course putting greens, including density, color, shoot and root growth, wear and temperature tolerance, thatch accumulation, and disease susceptibility (Beard, 1972; Carrow et al., 2002; Frank and Guertal, 2013). N is often the most limiting nutrient on putting greens and is, therefore, an important driver of plant growth. Relatively high annual N fertilization rates result in verdant and aesthetically pleasing playing surfaces. However, the rapid growth that results in increasing thatch and soil organic matter content which can reduce the function and aesthetics of putting greens (Meinhold et al., 1973; Murray and Juska, 1977; Throssell, 1981; Gaussoin et al., 2013). On the other hand, if N fertilization is relatively low, putting greens can be hard to recover from ball marks and wear damage which encourages weed invasion (algae, moss, annual bluegrass, etc.) (Beard, 1972). N management is clearly of great importance to putting green quality, yet there are few quantitative methods for determining or estimating N requirements of putting green turf. Most turf managers make N application decisions based on visual turfgrass appearance, performance, environmental concerns, and budget (Throssell et al., 2009; Frank and Guertal, 2013), but rarely based on turfgrass growth rate and N removal from clipping harvest. Therefore, quantitative methods to assess N fertilization requirements would represent an important advance in precision N management of putting greens.

The N cycle of putting greens on sand root zones can be simplified. Potential N loss pathways including denitrification, volatilization, runoff, and leaching are typically negligible when best management practices are followed (Snyder et al., 1984; Morton et al., 1988; Gross et al., 1990; Miltner et al., 1996; Erickson et al., 2001, 2008). This leaves clipping removal as the primary output of N, and N fertilization as the primary input. When clipping removal exceeds N input, soil organic matter will decrease. When annual N fertilization exceeds clipping removal, soil organic matter will increase. This very simple conceptual model highlights the importance of quantifying N removal in clippings. Because tissue N content of creeping bentgrass is relatively stable, the annual N removal can be approximated by the dry matter removed from mowing (Kussow et al., 2012; Zhou and Soldat, 2021). Therefore, an accurate grass yield production prediction model could be useful for estimating N removal from putting greens.

Generally, two methods are often used for plant yield prediction: biophysical models and statistical models. Biophysical models predict plant growth by simulating plant growth, nutrient cycling as well as water and energy balance on regular time steps. Briefly, a biophysical model simulates plant growth based on physical and physiological processes. DAYCENT and CENTURY models (Bandaranayake et al., 2003; Qian et al., 2003; Zhang et al., 2013b) are two agroecosystem models that can be used for monitoring turf productivity, soil organic matter changes, and environmental impacts caused by different management practices. Despite the success, two major limitations still exist in biophysical models: (1) they usually make relatively long-term yield predictions. However, for turfgrass management on a golf course, especially on the greens, the prediction at a finer scale (daily or weekly) is essential to guide precision N fertilizer applications; (2) the model calibration is quite challenging and requires intensive data collection from the field to field, which is less practical to be widely used by turfgrass managers. Although biophysical models often fail to represent short-term turfgrass biomass production, they help to provide management decisions by successfully simulating soil organic carbon and N dynamic with various management practices (Bandaranayake et al., 2003; Qian et al., 2003; Chang et al., 2013) and tracing the fluxes of carbon and N gases (Parton et al., 1998; del Grosso et al., 2006, 2008; Zhang et al., 2013a).

On the other hand, statistical models are developed by establishing empirical relationships between input variables and ground reference data. The most commonly used turfgrass yield prediction model, the PACE Turf growth potential (GP) model was proposed by PACE Turf (Gelernter and Stowell, 2005). The PACE Turf GP model uses temperature to estimate the relative growth potential of both warm-season and cool-season grasses. The model assumes 20°C is optimal for cool-season grass growth. When the average daily temperature is 20°C, cool-season turfgrass growth potential is 100%, as temperature increases or decreases from 20°C, the relative growth potential decreases until it approaches 0% near 0 and 40°C. The model's disadvantage is that it requires users to make assumptions about the actual growth rate at 100% relative growth. In addition, this model fails to consider the factors that influence turfgrass growth aside from temperature. More complex statistical models can be constructed using more variables to fit historical data on plant yields and weather to build empirical predictive algorithms. The advantage of statistical models over biophysical models is that statistical models require less extensive information on plant characteristics, management practices, soil, and canopy conditions, and statistical models are easier to calibrate using existing data (Lobell and Burke, 2010).

Various machine learning models have been developed for agricultural crop yield prediction including linear regression model (Bolton and Friedl, 2013; Ramesh and Vardhan, 2015), support vector regression (Jaikla et al., 2008; Brdar et al., 2011), and decision tree (Veenadhari et al., 2011). These approaches only utilize a single regression model when making predictions, and some machine learning models are only capable of solving linear problems or are likely to occur overfitting when the number of training data is limited (Pal, 2007). Overfitting can cause the model to have high variance or make a poor prediction on the testing data. With the increasing demand for more accurate yield prediction and guidance for precision N management, studies have tested the machine learning models that build on several base learners to avoid overfitting and increase prediction accuracy (Zhang and Crawford, 2015). The ensemble methods, such as bagging and boosting, combine the predictions of several models and are capable of solving non-linear problems. These models also largely avoid overfitting and usually have higher prediction accuracy (Belgiu and Drăguţ, 2016). Recently, ensemble models, such as random forest (RF) model which is a representative of bagging ensemble method, have been developed to predict crop yield in response to climate variables (Lobell et al., 2007; Tulbure et al., 2012; Fukuda et al., 2013; Newlands et al., 2014; Zhang et al., 2019), and had been recognized as an important advancement for agricultural industries (Everingham et al., 2016; Chlingaryan et al., 2018; van Klompenburg et al., 2020). RF uses a decision tree as a base learner and generates many decision trees in parallel. Gradient boosting model is an example of boosting ensemble methods, which also use decision tree as a base learner, and has been used in agricultural crop yield prediction (Charoen-Ung and Mittrapiyanuruk, 2018). Compared to RF, gradient boosting model builds shallower trees, and these trees are generated based on the mistake of the previous tree. Extreme gradient boosting was introduced recently and has been recognized as an advanced gradient boosting method. Extreme gradient boosting has been a winning tool for several machine learning competitions (Phoboo, 2014) due to its high efficiency and accuracy, and has been tested on agricultural crop yield prediction (Herrero-Huerta et al., 2020). Agricultural and turfgrass production systems have many important differences, and therefore the ability of machine learning techniques to be useful in turfgrass management needs to be tested to determine their potential feasibility.

The goal of this study was to build and evaluate several machine learning models and to predict golf courses putting green creeping bentgrass yield. If successful, such models could become decision support tools for N fertilization in golf course management.

Materials and Methods

Study Sites

The clipping yield data used to build the growth model were obtained from a series of research trials conducted at the University of Wisconsin-Madison O.J. Noer Turfgrass Research and Education Facility located in Verona, Wisconsin, USA. The field experiments were conducted on two different sand-based putting green root zones from 2019 to 2020, both constructed according to USGA recommendations (US Golf Association, 2004). Root zone characteristics are reported in Table 1. The grass on both greens was '*Focus*' creeping bentgrass (*Agrostis stolonifera*), which is one of the most commonly used cool-season species for golf course putting greens. The research plots were maintained using practices typical of putting green maintenance at golf courses with creeping bentgrass in the northern USA. They were mowed five times a week at a height of 3.2 mm, irrigated daily to replace evapotranspiration (ET) as estimated by an on-site weather station (except when irrigation was a treatment) and fertilized with approximately 100 kg N $ha^{-1}yr^{-1}$ split into 10 applications of 10 kg N ha^{-1} as urea (except when N fertilizer was a treatment). The research areas were topdressed with 0.6 m^3 ha^{-1} of sand approximately every three weeks during the growing seasons. Hollow tine cultivation was conducted once at the end of each growing season and the holes were filled with topdressing sand. Diseases and other pests were controlled as needed. To examine the feasibility of the machine learning models for predicting creeping bentgrass clipping production at locations other than the site where the models were constructed, we evaluated the performance of the models for the creeping bentgrass yield production at a golf course within 20 km of Minneapolis, Minnesota, USA; Minneapolis is approximately 400 km northwest of the research site in Madison, Wisconsin.

Table 1. Soil chemical properties of two putting green root zones used for creating or evaluating the growth prediction models

	Depth	SOM [a]	P [b]	K	Ca	Mg	CEC [c]	pH
	(cm)	(%)			(mg kg^{-1})		(cmol kg^{-1})	
Research green 1	0 - 5	1.23	64.2	91.6	1210	295	8	7.5
	5 - 10	0.55	17.0	25.5	579	144	4	7.3
Research green 2	0 - 5	0.67	25.9	40.7	487	133	3	7.7
	5 - 10	0.51	24.1	17.2	430	102	3	7.5

[a] SOM, soil organic matter by loss on ignition (360°C for 2 hours)
[b] nutrients extracted via Mehlich-3 method (Mehlich, 1984)
[c] CEC, cation exchange capacity via summation of extracted cations

Management Practices Affecting Yield

To develop an accurate estimation of turfgrass yield with a machine learning model, it is critical to include the factors that affect creeping bentgrass growth rate, then data from a series of studies was used. The goal of this section is not to present the results of the individual studies, but rather to utilize the data from these studies for statistical model development. A brief and partial description of the experiments from which data were obtained follows.

Experiment 1. Creeping Bentgrass Growth Response to Soil Moisture Content, N Fertilization, and Traffic

The study was conducted in 2019 and on research greens listed in Table 1 and was designed to explore the combined effects of N fertilizer, walking traffic and soil moisture content on creeping bentgrass growth. The experimental design was a randomized split-plot (1.2 m by 2.4 m) design with soil moisture level as the main plots (3.6 m by 2.4 m) and sub-plots received three different traffic intensities. N fertilizer rates were applied as 0 and 5 kg N ha^{-1} biweekly. Soil moisture content were maintained at 9 to 15, 17 to 22, and 25 to 29% as measured by time domain reflectometry with 7.6cm rods (FieldScout TDR 350, Spectrum Technologies, Aurora, Illinois, USA). These soil moisture contents were selected to represent low, mid-range, and excessive water content for the sand-based putting green. Soil moisture was measured before each clipping collection event, with three measurements averaged to represent the moisture in each plot. If the soil moisture was below the assigned level, irrigation was then applied by hand watering to meet the requirement. Three traffic intensities (control, medium and high) were given based on an observational trial conducted by (Hathaway and Nikolai, 2005) at Forest Akers West Golf Course on the 13th green around the hole in East Lansing, Michigan, USA. Then traffic was applied by five researchers walking on the plots wearing golf shoes at a speed of 95 steps/min between 1300 and 1500 h Monday through Friday until the treatments reached the assigned weekly traffic intensities requirement. The high traffic intensity plot received around 760 steps/week which represented 1400 rounds/week, the medium traffic intensity plot received about 380 steps/week that represented 700 rounds/week and the control plot that did not receive traffic treatment.

Experiment 2. Creeping bentgrass growth response to a wider range of N fertilization

The study was conducted in 2019 and 2020 on the two research greens in Table 1 to monitor the creeping bentgrass growth when a wide range of N fertilizer was applied. The experiment was also completed randomized design with three replications and each plot was measured by 1.2 by 2.4 m. N fertilization rate ranged from 0 to 17.5 kg N ha^{-1} biweekly using urea as the N source. All the plots received a traffic intensity of 1000 rounds/week and obtained regular disease control and irrigation management as described above.

Clipping Data and Feature Selection

To build a machine-learning based creeping bentgrass yield prediction model, one of the essential elements is to have a database of historical clipping records from the field. We collected the creeping bentgrass clippings from the two research greens from 2019 to 2020 (Experiment 1 and 2). Clippings from each research plot were collected approximately every other day between 900 and 1200 h (weather permitting) by mowing a 1.9 m pass down the center of each plot using a 0.54-m wide walking greens mower (Toro Co., Bloomington, Minnesota, USA). Before clipping collection, 0.27 m wide alleys were mowed at the top and bottom of each plot perpendicular to the collection pass. This was done to reduce the variability associated with starting and stopping the mower. The effective clipping collection area for each plot was 1 m^2. Clippings were brushed from the mower bucket into paper bags, which were then placed in an oven set to 50°C for at least 48 hours. Sand and other debris were removed from the dried clipping samples using the water method described in Kreuser et al. (2011). Then dry clipping mass was weighed and recorded.

Soil moisture content and normalized difference red edge (NDRE) for each plot were recorded prior to each clipping collection event. Vegetative indexes such as NDRE and Normalized Difference Vegetation Index (NDVI) started to be widely researched and studies have shown its high correlation with turfgrass quality (Fitz–Rodríguez and Choi, 2002; Bremer et al., 2011). NDRE and NDVI rely on different wavelengths of light. NDVI uses near-infrared red light and red light, and can correlate with vegetative health status at the top of a plant canopy, but may not capture vegetative health when the canopy has several layers or the leaf area index of the canopy is high. Turfgrass on putting greens is maintained at a very high density. NDRE, which is collected by near-infrared light and a red-edge band (a narrow wavelength between red light and near-infrared red light), may result in a better indication of the vegetative index of the dense turf because the red edge band penetrates deeper into the turf canopy than the red band of NDVI. Therefore, in this study, we used NDRE to represent turfgrass health status. NDRE was collected using a handheld device approximately 1 m above the canopy (Rapid SCAN CS-45, Holland Scientific Inc., Lincoln, Nebraska, USA).

Variables that were used as inputs when predicting yield included (1) 3-day average soil moisture content which means the average soil moisture content on the clipping collection event and the one before; (2) average weekly traffic intensity; (3) NDRE; (4) root zone of two putting greens; (5) cumulative days of turfgrass growth prior to mowing; (6) daily weather variables which obtained from nearest weather station reported on Weather Underground (an open online real-time weather information repository). These variables included daily maximum temperature (Tmax), minimum temperature (Tmin), average temperature (Tavg), precipitation (precip), maximum relative humidity (RHmax), minimum relative humidity (RHmin), average relative humidity (RHavg) and average wind speed (Windavg), and ET which was from the UW-Extension Ag Weather station. A description of the weather variables utilized was presented in Table 2.

Table 2. Variables used in random forest (RF) models

RF variables	Variables names
Biweekly N rate	N rate (kg/ha/2wk)
Daily NDRE	NDRE
Three-day average soil moisture content	Moist avg (3 days)
Weekly walking traffic	Traffic (round/week)
Accumulative days turf grows	Days grow
Research green soil	Rootzone
Maximum, minimum, and average temperature/relative humidity on the clipping collection day	Tmax; RHmax Tmin; RHmin Tavg; RHmin
Maximum, minimum, and average temperature/relative humidity of x (1,2,3,4,5,6) days before the clipping collection day	Tmax (pre x days) Tmin (pre x days) Tavg (pre x days) RHmax (pre x days) RHmin (pre x days) RHavg (pre x days)
Accumulative maximum, minimum, and average temperature/relative humidity of x (2,3,4,5,6,7) days	Tmax (x days accu) Tmin (x days accu) Tavg (x days accu) RHmax (x days accu) RHmin (x days accu) RHavg (x days accu)
Accumulative precipitation/evapotranspiration of x (2,3,4,5,6,7) days	Precip (x days accu) ET (x days accu)
Accumulative difference between precipitation and evapotranspiration of x (2.3.4.5.6.7) days	Precip-ET (x days accu)
Average wind speed of x (1,2,3,4,5,6) days before the clipping collection day	Wind avg (pre x day)

Selection and RF Yield Prediction Model

In this study, we tested five machine learning models that have been used for agricultural crop yield prediction, which include RF, gradient boosting model, Extreme gradient boosting, decision tree and support vector regression. After comparing model performance, we eventually choose RF (Breiman, 2001). RF uses a decision tree as a base learner and includes a large set of decision trees, and each tree is independently trained by a random set of variables (listed in Table 2) and corresponding data from the training set. The algorithm first creates bootstrapped dataset, which requires randomly selected subsets of samples from the original dataset that have the same size, and numbers of decision trees would be created based on each subset of data. This step is repeated until the predefined number of trees is reached. In this study, the number of trees was set to 100. The yield prediction was calculated by averaging the predictions of each decision tree. The advantage compared with a single decision tree is that RF can help avoid overfitting (Friedman, 2017).

"Scikit-learn" RF package from Python (Pedregosa et al., 2011) was used in this study. Considering the availability of the input data from each golf course varies, we built three RF models with different intensities of data complexity and number of features. Three models were created for predicting the creeping bentgrass clipping production, which included (1) complete RF model, which includes all variables (Table 2) input, (2) simplified RF model, which included all variables except NDRE and 3-day average soil moisture water content; and (3) weather-only RF model, which contained all (and only) weather variables.

We used clipping yields collected from 2019 and 2020 (Experiment 1 and 2) to train and validate the model (n = 2190), and explored the predictors including daily weather variables, management practices (soil water content, historical N application rate and walking traffic), vegetative index data (NDRE) and other parameters that could potentially affect turfgrass physiology (i.e., turfgrass mowing frequency). In this study, to validate the model, we used 90% of the total data (n = 1897) to train the model during the training process and the remaining 10% of data (n = 293) was used to evaluate the model performance. We adopted four-fold cross validation to test the performance of the RF model (Fig. 1). The dataset was divided into four subsets, and each time one of four subsets was used as a validation set and the remaining three subsets were used as the training set. This way, every subset was used as a validation set once and as a training set three times.

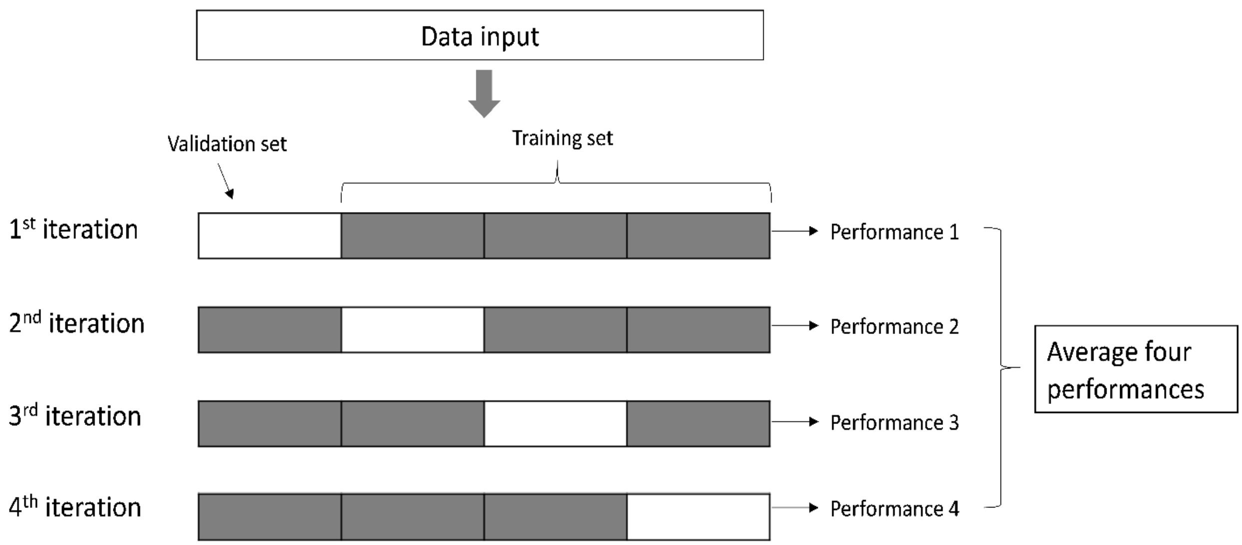

Fig. 1. Flow chart of four-fold cross validation

The hierarchy of important variables was also determined based on the "scikit-learn" package, which was expressed as feature importance score. Features with higher scores are important to model accuracy. The coefficient of determination (R^2) and root mean square error (RMSE) were statistical parameters used for evaluating the accuracy of the models by comparing the predicted values and actual values. Partial dependence plots (PDPs) were used to understand the result of the machine learning models. PDPs explain how each important variable affects the yield predictions by showing how the target variable partially depends on one or two input variables (Friedman, 2001); therefore, it also can help to visualize and understand whether the relationship between a target and a feature is linear, monotonic, or more complex.

Golf Course Data for Validating The Model

To test whether the models developed from the research greens data were useful for predicting yield on bentgrass putting greens from a different location, we gathered historical clipping records from a golf course in Minneapolis, Minnesota, USA. The putting greens were sand-based soil and constructed according to USGA recommendations (similar to our research greens). The clipping yield data were provided as fresh clipping volume instead of dried-and-cleaned clipping mass. However, we were able to convert fresh clipping volume to dried clipping mass via a linear relationship between the two (Suppl. Fig. S1). Measuring the fresh clipping volume is less time and labor-intensive than dried clipping mass. The turfgrass manager from the golf course provided the historical N application records. Weather data from the golf course were obtained from Weather Underground. The golf course used plant growth regulators occasionally, so the clipping data were categorized depending on if growth regulators were being used or not at the time of collection.

Results

Table 3 lists the performance of five machine learning models on turfgrass clipping production. The RF model (R^2 = 0.64) outperformed the single regression models which included decision tree (R^2 = 0.36) and support vector regression (R^2 = -0.15) and boosting ensemble models which included gradient boosting model (R^2 = 0.43) and Extreme gradient boosting (R^2 = 0.57). Therefore, in the following analysis and discussion section, we deeply investigate the RF model.

Table 3. Comparison of the performance of five machine learning models for training data set (n =1897). Full variable inputs were used when developing models

Machine learning method	R^2 with standard deviation	RMSE with standard deviation
Random forest (RF)	0.64 (0.08)	0.339 (0.06)
Extreme gradient boosting	0.57 (0.15)	0.366 (0.07)
Gradient boosting model	0.43 (0.13)	0.422 (0.07)
Decision tree	0.36 (0.17)	0.450 (0.09)
Support vector regression	-0.15 (0.15)	0.604 (0.08)

Table 4 three RF model performances on training dataset (n = 1897) collected from 2019 and 2020 at the University of Wisconsin research station, as well as PACE Turf GP model performance. During the study period, daily clipping yield spanned two orders of magnitude (0.09 to 4.1 g $m^{-2}d^{-1}$, with 95% of clipping at the range from 0.4 to 3 g m^{-2} d^{-1}). The complete RF model that included the entire suite of variables (listed in Table 2) had the best performance (columns 3 and 4 in Table 4, Fig. 2a). Regressed against the actual clipping yield, it had an average R^2 of 0.64 with standard deviation of 0.08 and had the lowest RMSE values compared with the other models created. The simplified RF model was similar to the previously described complete RF model but with no proximal sensing data (NDRE) or soil moisture content input. For the simplified model, the average R^2 was 0.57 with standard deviation of 0.09 (Table 4, Fig. 2c). The weather-only RF model only contained weekly weather data inputs, and had an average R^2 of 0.46 with standard deviation of 0.20 (Table 4, Fig. 2e). The model accuracy decreased with fewer variable inputs.

Table 4. Model performance on training and validation datasets of complete random forest (RF) model, simplified RF model and weather-only RF model

	Variables input	Training RMSE	Training R^2 with standard deviation	Evaluation RMSE	Evaluation R^2
Complete RF model	N fertilization Traffic intensity Categorized root zone Weather Days grow NDRE [a] Soil moisture content	0.339 (0.06)	0.64 (0.08)	0.489	0.47
Simplified RF model	N fertilization Traffic intensity Categorized root zone Weather Days grow	0.367 (0.06)	0.57 (0.09)	0.515	0.42
Weather-only RF model	Weather Days grow	0.406 (0.09)	0.46 (0.20)	0.567	0.30
PACE Turf GP model	Temperature	N/A	0.01	N/A	N/A

[a] NDRE, normalized difference red edge

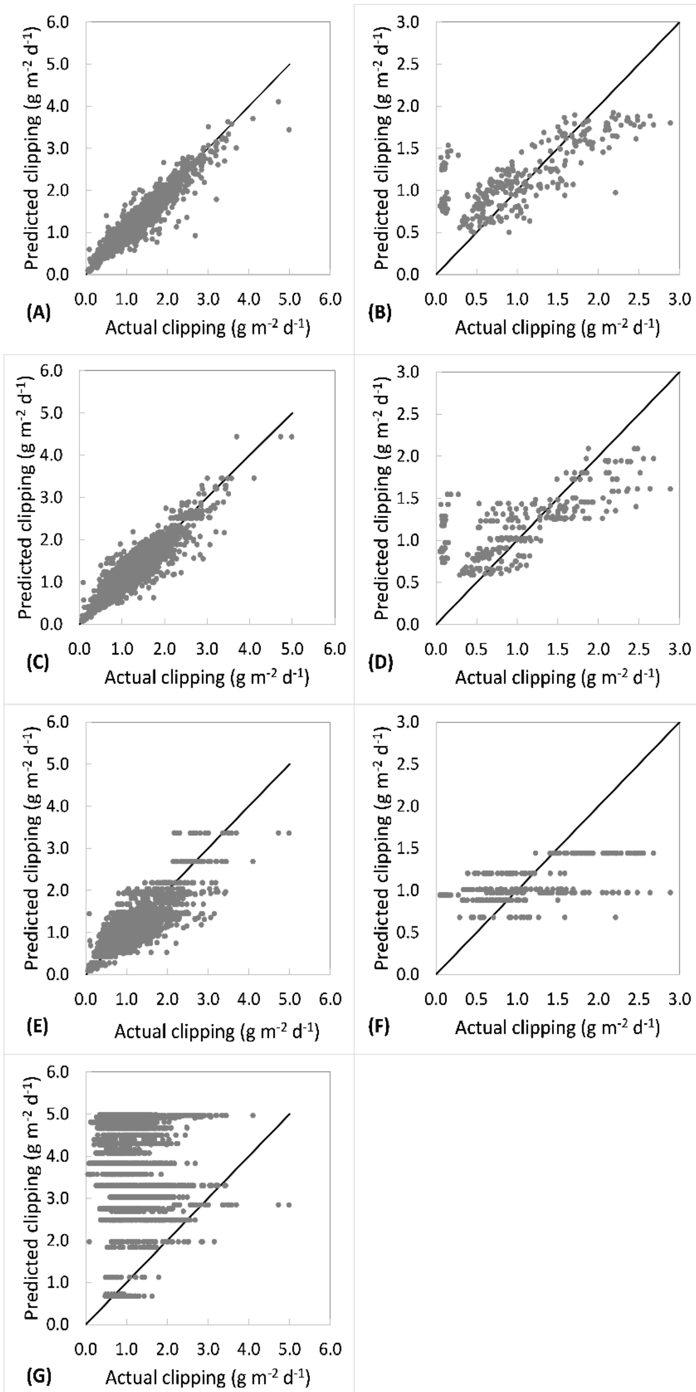

Fig. 2. Scatter plot of model performances with (a) complete random forest (RF) model with all variables inputs on training dataset; (b) complete RF model with all variables inputs on validation dataset; (c) simplified RF model with historical N rate record, traffic intensity and weather data on training dataset; (d) simplified RF model with historical N rate record, traffic intensity and weather data on validation dataset; (e) simplified RF model with only weather data input on training dataset; (f) simplified RF model with only weather data input on validation dataset; (g) PACE Turf GP model

Table 4 also presented the RF model performance on validation datasets (n = 293) where data spanned 0.10 to 2.89 g $m^{-2}d^{-1}$ (columns 5 and 6). Data were collected from 2019 and 2020 at the University of Wisconsin research station. Overall, the complete RF model had the highest coefficient of determination (0.42) and lowest RMSE of 0.49 (Fig. 2b). As the number of input variables decreased in the simplified RF model and weather-only RF model, the coefficients of determination also decreased to 0.42 and 0.27, respectively (Fig. 2d and 2f). We compared our statistical models to the PACE Turf GP model that uses only daily average temperature (Fig. 2g). The PACE Turf GP model had the lowest accuracy (R^2=0.01), which was unsurprising because that model only uses a single variable (temperature) to predict clipping yield.

The RF algorithm identifies the relative influence of the factors that affect creeping bentgrass clipping production. In the complete RF model, the top five variables were found to be (1) average daily air temperature three days prior to clipping collection; (2) N fertilizer rate; (3) NDRE; (4) average relative humidity four days prior to clipping collection, and (5) three-day average soil moisture content (Fig. 3A). Among the three management practices we investigated in this study (soil moisture, N fertilizer rate and walking traffic), both N rate and soil moisture content were found to be more important than traffic for influencing creeping bentgrass clipping yield. This agreed with our previously reported findings that when the traffic intensity was maintained at a realistic intensity (0 to 1800 round/week), the effect on creeping bentgrass growth was small (Zhou and Soldat, 2021), but its influence was much more important than other weather variables like wind speed. In the simplified RF model, besides N fertilizer rate, temperature and relative humidity, root zone was another important variable (Fig. 3b). Briefly, although the golf course greens were sand-based soil and constructed based on USGA recommendations which had very similar soil texture and soil organic N, soil characteristics such as N mineralization rates could be very different among root zones, and those could potentially result in different plant-available N which would affect clipping yield. Finally, the key weather variables in the weather-only RF model agreed with the weather variables found to be important in the complete RF model and simplified RF model. Generally, relative humidity and temperature which were observed from a few days prior to the collection were the most important weather variables (Fig. 3c), demonstrating that weather has a delayed effect on creeping bentgrass clipping yield.

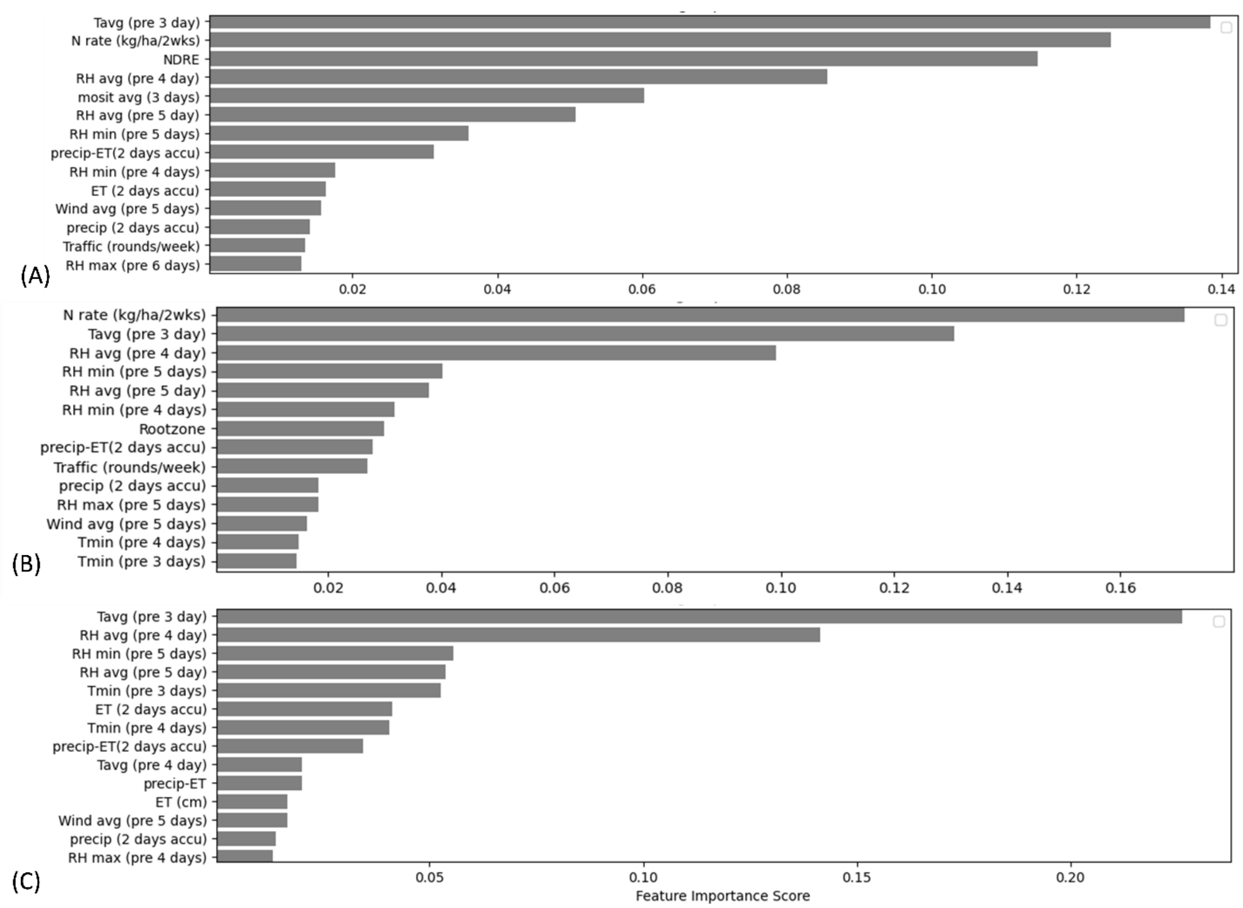

Fig. 3. Top important variables for (a) complete random forest (RF) model; (b) simplified RF model with N rates, traffic intensities and weather inputs; (c) weather-only RF model with all the weather variable inputs

A decision tree was created to visualize how the most important factors were used to predict creeping bentgrass yield (Fig. 4). The first node was split based on one of the most important variables, maximum relative humidity five days prior to the clipping collection event (list as *RH max (pre 5 days)* in Fig 4) with a threshold of 73%. The average clipping yield predictions were 2.68 and 1.04 g m^{-2} d^{-1} as the maximum relative humidity was below or above 73%. The decision tree was further divided based on

NDRE, RH avg (listed as *pre 4 day* in Fig 4), mosit avg (listed as *3 days* in Fig. 4), Tavg (listed as *5 days accu* in Fig. 4) and Rhavg (list as *4 days accu* in Fig. 4). Overall, this single decision tree presents an example of how RF algorithm would use decision tree as a base learner to predict creeping bentgrass clipping yield.

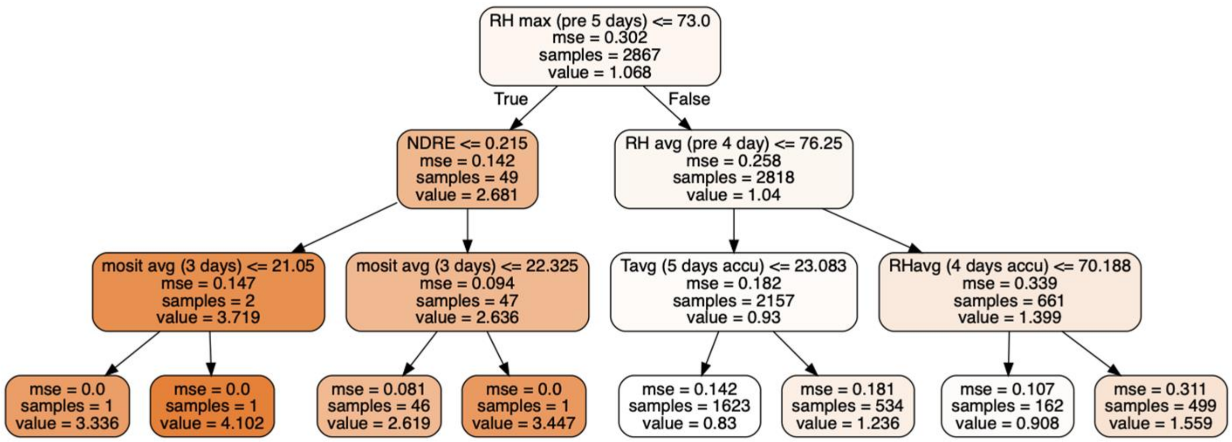

Fig. 4. A decision tree with three depths. Nodes with dark color have a higher estimated clipping yield

PDPs were created for the top five most important variables among three RF models (complete RF model, simplified RF model and weather-only RF model) to understand the relationship between the most important features and creeping bentgrass clipping production. Moreover, in this study, mowing frequency (or cumulative days that turfgrass grown between two mowing events) varied, the cumulative growing days include 1, 2, 3, 4, and 5 days. Therefore, we included cumulative turfgrass growing days and expected to find a relationship between mowing frequency and turf growth. N application rate and soil moisture content were positively correlated with creeping bentgrass clipping production (Fig. 5a and 5b). When the soil moisture tripled from 10 to 30%, the clipping production only increased about 10% (from 1.02 to 1.12 g $m^{-2}d^{-1}$). It agreed with our previous result that the influence of soil moisture content on creeping bentgrass growth rate was discernable but small (Zhou and Soldat, 2021). NDRE of the plots spanned 0.14 to 0.41, and it was also positively correlated with creeping bentgrass growth (Fig. 5e) especially when the NDRE spanned 0.28 to 0.41. We found little increase in the clipping yield when

NDRE was at the range of 0.14 to 0.28. Turf mowed more frequently had a lower clipping yield than turf mowed less frequently (Fig. 5d). This could be explained by one of the assumptions of the mechanism of plant defense that plants would grow fast to recover from the mowing damage (Stamp, 2003).

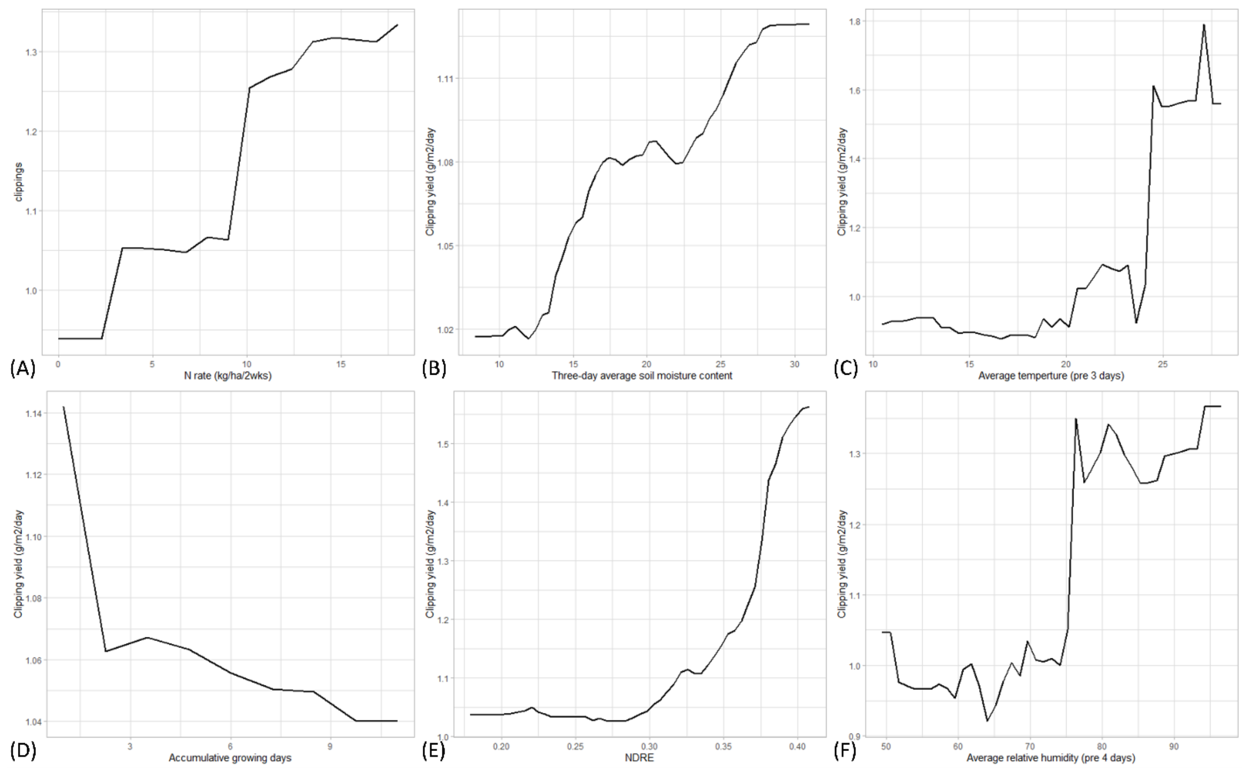

Fig. 5. Partial dependence of creeping bentgrass clipping production on N application rate (a); average 3-day soil moisture content (b); average temperature on the previous 3 days of clipping collection event (c); accumulative days that turf grew between mowing (d); normalized difference red edge (NDRE) (e); average relative humidity on the previous 4 days of clipping collection event (f)

The two important weather variables (temperature and relative humidity) displayed a more complex relationship with bentgrass yield. Creeping bentgrass growth peaked when the temperature on the third day prior to clipping collection was around 25 to 27°C (Fig. 5c), significantly higher than the 20°C assumed by the PACE Turf GP model assumes for cool-season grasses. As temperature increased from 10 to 23°C, the PDPs showed that there was a small increase in clipping production, but a larger increase in clipping yield when the temperature increased from 23 to 25°C. Similarly, there was a steep increase in clipping production when the relative humidity was above 75% (Fig. 5f). When the relative humidity was below or above 75%, we found very little impact on clipping yield.

RF models that were built based on the data collected from the University of Wisconsin-Madison research site in 2019 and 2020 were used to predict the clipping yield on bentgrass putting greens from a golf course located in Minnesota, USA. Since the golf course had access to only historical N fertilization rate and weather, we used the simplified RF model to make predictions. When converting fresh clipping volume to dried clipping mass, a conversion of 0.57 was used (Suppl. Fig. S1). The clipping yield overall was similar to the ranges we found on our plots and also spanned two orders of magnitude from 0.03 to 2.89 g m-2 d-1, (n = 2190, with 95% of clipping at the range from 0.3 to 2 g m-2 d-1). The simplified RF model built based on the data collected from the Wisconsin research putting greens also performed poorly with an R2 of 0.03 (Fig. 6b). The PACE Turf GP model had relatively low prediction accuracy (R2 =0.05) on the turfgrass clipping production (Fig. 6c). However, a customized RF model based on the Minnesota data was constructed using the clipping volume data collected from the golf course from Minnesota, USA. This model predicted clipping yield well with an R2 of 0.74 (Fig. 6a). While we failed to create a universal statistical bentgrass yield prediction model, we have demonstrated that it is possible to build accurate, customized growth models with local clipping data and readily available input variables like weather data and N fertilization rate.

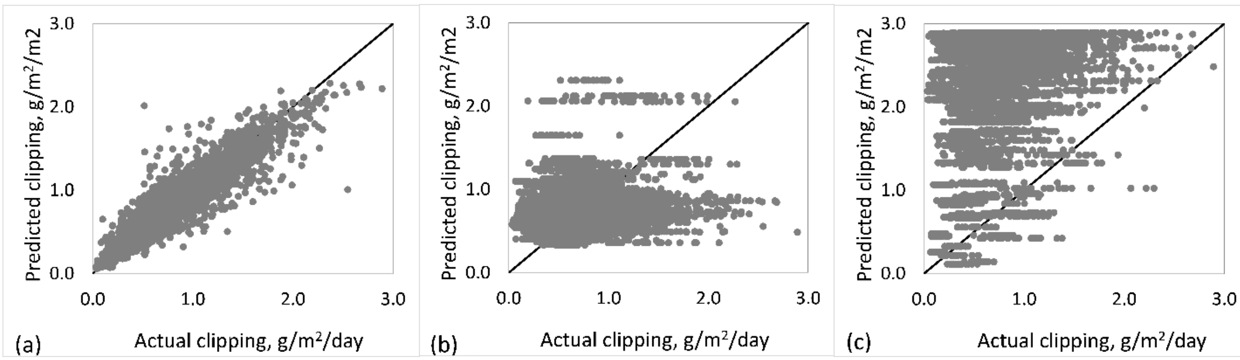

Fig. 6. Scatter plot with (a) random forest (RF) model performance on the golf courses that model was built on the on-site clipping data; (b) RF model built with clipping data collected from Madison, Wisconsin, USA perform on the clipping data collected from golf course from Minnesota, USA; (c) PACE Turf GP model

Discussion

Accurate turfgrass yield prediction would enable early and accurate decision-making and allow managers to more sustainably manage fertilizer resources. This study used clipping yield data from field experiments, and the results have shown that interactions among environmental factors, various management practices and clipping yield were rather complex and had non-linear relations. Three RF models were created based on the experimental results. Our results showed that the complete RF model with inputs of weather variables, NDRE, and management practices (N fertilization rate, mowing frequency, traffic intensity and irrigation plan) could provide a relatively high accuracy turfgrass clipping yield prediction model.

In this study, we found NDRE values were a critical parameter for creeping bentgrass yield prediction, and it represented the canopy information related to turfgrass density and vigor. The RF model also listed NDRE as one of the most important features. If mowers can be equipped with proximal sensors that collect NDRE and other vegetation indexes, it will become easier for managers to improve their own statistical models that are predictive of yield to more effectively manage N fertilization.

When evaluating the weather variables, temperature and relative humidity were all highly associated with the turfgrass growth rate or clipping production. The correlation between these weather variables with creeping bentgrass clippings was rather complex and weak compared with other variables it explained the failure of the existing growth rate prediction model. Solar radiation, an important factor influencing plant growth, was not included in this study because these data are not readily available to most turfgrass managers. Overall, weather had a delayed effect on creeping bentgrass clipping yield, demonstrating that weather factors prior to the clipping collection usually have a greater impact on growth compared to the impact of weather factors collected on the day of or the day prior to clipping collection.

The RF model has been used to predict annual or seasonal agricultural crop yield with high accuracy (Everingham et al., 2016; PS, 2019; Zhang et al., 2019). This study also verified that the RF model was able to provide high prediction accuracy compared with the other four commonly used machine learning models that include decision tree, gradient boosting model, extreme gradient boosting and supper vector regression. The RF model succeeded on short-term turfgrass clipping yield prediction for both plot-scale clipping data and golf course green-scale clipping data. The RF model is also computationally fast (Ziegler and König, 2014) and simple to operate. Moreover, the simplified RF model was also tested to have a relatively high prediction accuracy. This simplified model could provide valuable clipping yield prediction for golf courses that do not have access to some of the more intensive variables tested in this study like NDRE and soil moisture content.

With the increasing attention on resource use efficiency, more quantitative methods for guiding N application are required. Similar to agricultural crop management, yield prediction is also essential for decision making and N management for turfgrass managers. This study is the first to predict turfgrass clipping yield with machine learning approaches and found that RF algorithm was most useful. For future precision N management on golf courses, it is evident that future improvements such as incorporation with sensors could be beneficial. Although our goal of constructing a universal bentgrass yield prediction model was not achieved, individual golf courses could build customized yield prediction models with sound accuracy by using their own yield measurements. Therefore, for future research, there is a need to investigate the feasibility of using machine learning techniques, specifically this RF model, to guide nitrogen application decisions compared with existing nitrogen application strategies under field conditions. Additionally, a precision fertilization plan requires understanding plant nutrient needs, their response to different nutrient applications, and the supply of nitrogen from indigenous sources (Dobermann et al., 2003). Future studies should also seek to quantify soil mineralized nitrogen, which will provide a more complete understanding of soil-turfgrass-environment interactions and lead to more efficient use of fertilizer inputs.

Conclusion

Machine learning models were effective for turfgrass yield prediction. As the first study to develop machine learning models to predict turfgrass yield, we concluded that RF model resulted in the greatest accuracy to predict creeping bentgrass clipping yield. Three RF models with different intensities of data complexity were presented. The results demonstrated that the model with the greatest number of inputs had the greatest accuracy, models with reduced number of inputs, particularly those missing soil and vegetation sensed data, had lower yield prediction accuracy. However, all three RF models outperformed the current growth prediction model which used only temperature to estimate turfgrass yield. These findings suggest that golf course managers will be able to better estimate turfgrass growth, even with limited access to input variables. Additionally, our study showed that weather had a delayed effect on turfgrass growth, and use of one-day weather data would not result in the best yield prediction as inclusion of multi-day weather data. Using RF algorithm to build an accurate yield prediction model narrows the knowledge gap of for accurate N application guidance to achieve site-specific N management. The RF model was successful in providing an accurate estimation of clipping yield at a fine-scale which may assist turfgrass managers in more effectively allocate resources and modifying management practices site-specifically.

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Chapter Four: Soil CO_2 Burst on Sand Based Putting Green Soil and the Effects on Creeping Bentgrass Growth

Abstract

Precision fertilization requires understanding the supply of nitrogen (N) from soil. However, modern fertilization recommendations rarely include soil analysis as a component of potential N supply. In this study, we tested the ability of a soil CO_2 burst (SCB) test to estimate soil N supply on sand-based putting green soils. The objectives were to 1) investigate the correlation between SCB and turfgrass growth and N uptake; 2) observe the short- and long-term change of SCB on sand-based putting green soils; 3) test whether varying N fertilizer rates and soil depths affect the SCB results. The field experiment was conducted in Madison, WI, USA on four research greens with soil organic matter content of 1.0%, 0.9%, 0.6%, and 0.4% in the top 10 cm. The creeping bentgrass on these root zones was fertilized at 0, 10, 20 kg ha^{-1} of N every two weeks. Soil samples were collected at 0-5 and 5-10 cm depths every three weeks in 2020 and 2021. Soil respiration was estimated with the flush of CO_2 following rewetting of dried soil (1-day incubation at ≈50% water-filled pore space and 25°C). SCB was significantly affected by soil organic matter content and soil depths but not N fertilization rate. SCB significantly affected creeping bentgrass growth and had a positive, but weak correlation with clipping production (R^2 = 0.03 to 0.48) at both depths. SCB had no significant correlation with creeping bentgrass N uptake. Temperature and soil moisture conditions played major roles in affecting the rate of SCB, and both parameters were negatively correlated with SCB (R^2 = 0.50 to 0.57). Overall, this study has shown that SCB was not useful for predicting turfgrass growth response or guiding nitrogen fertilization decisions on sand-based putting green soil.

Introduction

Nitrogen (N) is typically the most limiting nutrient for turfgrass and N supply is well correlated with growth rate (Kussow et al., 2012), and this is also true for turfgrass golf course turfgrass (Throssell et al., 2009; Gelernter et al., 2016). Sand-based putting greens receive the most N per unit area compared with other components of a golf course (Gelernter et al., 2016), and the quality of this surface influences golfers' perception of the entire golf course quality. Optimizing N supply on putting greens is important, and precision fertilization requires understanding plant nutrient needs, their response to different nutrient applications, and the supply of N from indigenous sources (Dobermann et al., 2003). However, modern fertilization recommendations for golf course turf are based on empirical observations of turfgrass response to fertilizer applied on research plots and other study sites (Guillard et al., 2021), but rarely include soil analysis as a component of potential N supply.

The N cycle of putting greens on sand root zones can be simplified. Potential N loss pathways including denitrification, volatilization, runoff, and leaching are typically negligible under when best management practices are followed (Snyder et al., 1984; Morton et al., 1988; Gross et al., 1990; Miltner et al., 1996; Erickson et al., 2001, 2008). This implies that there are two primary N sources that drive turfgrass growth on sand-based putting greens: net N mineralization from soil organic matter, and N fertilizer inputs. Accurate estimation of plant-available N from soil is still a challenge due to the complex interactions among temperature, moisture, soil physical and biological properties, and management practices (Cabrera et al., 2005; Schomberg et al., 2009). Although many soil testing labs offer soil analysis with various forms of soil N (including total nitrogen, nitrate, ammonium and soil organic matter) these laboratory results are not used for making N fertilization recommendations to turfgrass.

Soil organic matter is a parameter that is related to soil N supply and is usually listed on routine soil analysis reports. Soil organic matter content affects turfgrass productivity and overall soil health, but it can be insensitive to management practices and is therefore not a good indicator for soil N supply (Wander, 2004). Predicting and quantifying net soil N mineralization is a high priority to improve N fertilization efficiency (Godwin and Singh, 1998; Dobermann et al., 2003; Wang et al., 2004). Soil net N mineralization can be conducted in the field but requires three to four months (Stanford and Smith, 1972).

Net N mineralization is a specific process controlled by soil biological activity, which implied that soil biological activity could be a useful indicator of potential N mineralization. In place of this time-consuming method of soil net N mineralization in the field, N mineralization potential involving 7-day anaerobic incubations under lab conditions have been introduced to evaluate soil organic matter quality (Drinkwater et al., 1997), and these lab-measured plant-available N are collectively called potentially mineralizable N (PMN). Currently, the 7-day anaerobic N mineralization method is considered as the best biological indicator of soil potentially available N (Schomberg et al., 2009).

A more direct expression of potential microbial activity is through soil incubation. Compare with chemical extraction, incubation would allow the naturally occurring of the interaction of chemical, biological and physical in the soil. Labile soil organic carbon serves as an energy source for soil microorganisms and has been connected to soil ecosystem changes (Culman et al., 2013) and soil N supply (Stevenson, 1994). Soils with abundant microbial activity are considered productive and biological active (Parkin et al., 1997), and certain microbes are known to be drivers of soil decomposition that promote soil N mineralization. While measuring soil microbes remains relatively challenging, measuring the soil organic carbon pools may be beneficial for assessing soil quality and crop productivity. Measurements of labile carbon estimating crop yield response and soil health have been received great attention due to their low cost and rapidity (Vahdat et al., 2010; Moore et al., 2019a). Studies over the past two decades (Haney et al., 2001; Ingram et al., 2005; Franzluebbers and Stuedemann, 2008; Franzluebbers, 2016; Rogers et al., 2018; Moore et al., 2019a) have shown that soil respiration measurements were highly correlated with soil N mineralization which was either measured under field conditions or lab incubations across a diversity of soils. This strong correlation between the two parameters suggests that soil respiration is a reliable test to predict soil N mineralization rate and estimate soil N supply. In addition, the labile soil organic carbon pool was shown to be sensitive to short-term changes in management practices (Schomberg et al., 2009). Studies have shown that soil CO_2 respiration was correlated with plant performance in agricultural soils and grassland soils (Agbim et al., 1977; Reichstein et al., 2003; Mureva and Ward, 2017; Chahal and van Eerd, 2018; Moore et al., 2019a; b). Particularly, there was a strong correlation between soil respiration and soil N mineralization on turfgrass-type native soils operating with Solvita® test kits (Moore et al., 2019b; a). Overall, this approach has currently only been tested on agricultural soils and turfgrass on finer textured soils. Because of the difference between constructed sand root zones associated with sand-based putting greens and the typically finer-textured native soils, there is a need to evaluate the relationship between soil respiration and plant performance on golf course sand-based putting green soils.

In this study, we tested the feasibility of using a soil respiration test, which is SCB, to estimate plant N availability and whether the test held promise for making more precise N application decisions. The objectives of this study were to 1) investigate the correlation between SCB with turfgrass growth and N uptake; 2) observe the short- and long-term changes of SCB on sand-based putting green soils; 3) test whether various N fertilizer rates and soil depths affect the SCB test results. We hypothed that greater SCB on the top 0-5 cm soil where potentially has higher soil organic matter content and microbial activity, and there was seasonal change of SCB on the sand-based soil and the seasonl change would affect turfgrass growth rate.

Methods and Materials

Study Site and Experimental Design

Field experiments were conducted on four different putting green root zones from May to October 2020, and May to September 2021 at the University of Wisconsin-Madison O.J. Noer Turfgrass Research and Education Facility in Verona, WI, USA. Root zone characteristics are reported in Table 1. These root zones were constructed according to USGA recommendations (US Golf Association, 2004), and planted with ‘Focus’ creeping bentgrass (*Agrostis stolonifera*), a commonly used cool-season species of golf course putting greens in this region. Turfgrass was maintained at 3.1 mm cutting height. Creeping bentgrass on two research greens (root zone B and C) were planted in 2011, and grass on the other two research greens (root zone A and D) was planted in 2019. Research greens were irrigated daily to replace 70% of reference evapotranspiration as estimated by an on-site weather station. Putting greens were topdressed with 0.6 m^3 ha^{-1} of sand approximately every three weeks during the growing season and hollow tine cultivation was conducted once a year in September with the cores removed and holes were filled with topdressing sand. Diseases and other pests were monitored and controlled as needed.

Table 1. Soil chemical properties of two putting green root zones used for creating or evaluating the growth prediction models

Root zone	Depth (cm)	SOM $^{\theta}$ (%)	P $^{\Phi}$ (mg kg^{-1})	K (mg kg^{-1})	Ca (mg kg^{-1})	Mg (mg kg^{-1})	CEC $^{\zeta}$ (cmol kg^{-1})	pH	C: N
A	0 - 5	1.2	16.4	39.1	566.2	145.4	4.0	7.7	13.2
	5 - 10	0.7	19.2	20.0	490.2	104.1	3.0	7.7	15.2
B	0 - 5	1.2	64.2	91.6	1210.0	295.8	8.0	7.5	18.7
	5 - 10	0.6	17.0	25.5	578.5	143.6	4.0	7.3	116.3
C	0 - 5	0.7	25.9	40.7	586.6	133.1	3.0	7.7	15.5
	5 - 10	0.5	24.1	17.2	429.9	101.6	3.0	7.5	20.7
D	0 - 5	0.4	9.6	17.7	378.7	97.0	2.0	7.6	13.0
	5 - 10	0.4	8.5	14.3	550.5	152.4	3.0	8.1	16.4

$^{\theta}$ SOM, soil organic matter by loss on ignition (360°C for 2 hours)
$^{\Phi}$ Nutrients extracted via Mehlich-3 method (Mehlich, 1984)
$^{\zeta}$ CEC, cation exchange capacity via summation of extracted cations

This experimental design was a completely randomized design with three replicates of three N treatments on the four root zones. Individual plots measured 2.4 by 1.2 m. N treatments included 0, 5, 10 kg N ha^{-1} applied every two weeks which represents an unfertilized control, medium-N rate, and high-N rate. The medium and high rates are within the range of normal variation for golf courses putting greens in the Midwest USA. Liquid urea (46-0-0) was used as the N source for all applications and was applied using a CO_2-powered backpack sprayer with air induction nozzles. No potassium was applied during the study period and 25 kg P_2O_5 ha^{-1} was applied to the plots in the spring of 2021 using phosphoric acid to prevent P from becoming growth limiting. N treatments were applied from May to September 2020 and 2021.

Soil Sampling and Soil Respiration

Soil samples on four root zones were collected approximately every three weeks. The first collection date from each year was approximately one week before the N treatments were initiated. Soil samples were collected to a 10 cm depth with a 1.5 cm diameter soil probe. Three soil cores were collected from random locations within each plot. Each core was separated into 0-5 cm and 5-10 cm depth increments and samples representing the same depth were combined for analysis. Collected soil samples were allowed to air-dry for at least one week, then passed through a 2 mm sieve after being gently ground with a mortar and pestle.

SCB was determined by measuring the flush of CO_2 24 hours after the rewetting of the dried soil (Franzluebbers et al., 2000). Briefly, 10 g of soil sample was placed in a 60 mL plastic cup, then deionized water was added until 50% water-filled pore space was achieved. Then, a plastic cup with soil (no cover) was placed into a 946 mL mason jar, and the jar was sealed and incubated in the dark for 24 h at 25 °C ± 1 °C. Released CO_2 was measured using a CO_2 analyzer (LI-820; LI-COR Biosciences, Lincoln, NE, USA) 24 h after initial wetting. Incubations were conducted in triplicate.

Turfgrass Sampling

Clipping yield was collected from each plot three to four times a week between 900 and 1200 h (weather permitting) by mowing a 1.9 m pass down the center of each plot using a 0.54 m-wide walking greens mower (GreensMaster 1000; Toro Co., Bloomington, MN). Prior to clipping collection, 0.27 m wide alleys were mowed at the top and bottom of each plot perpendicular to the collection pass. This was done to reduce the variability associated with starting and stopping the mower. The effective clipping collection area for each plot was 1 m^2. Clippings were brushed from the mower bucket into paper bags, which were then placed in a 50 °C oven for at least 48 hours. Sand and other debris were removed from the dried clipping samples using the water method (Kreuser et al., 2011). Dry clipping mass was measured and recorded. Next, the clippings were ground into a fine powder for determination of total N content using a combustion analyzer with thermal-conductivity-detection (TruSpec Micro, LECO Corporation, St. Joseph, MI). Turfgrass N uptake from the unfertilized control treatment represented the estimated net soil N mineralization since the N released from soil organic matter was the only substantial N source supporting turfgrass growth. The N uptake was calculated as the product of turfgrass tissue N content and the dry weight of clipping production.

Soil moisture content from each plot was measured three times a week using time-domain reflectance (TDR) probe with 7.6 cm rods (Field Scout 350, Spectrum Technologies Inc., Aurora, IL, USA). Three measurements were taken from each plot and averaged. The Normalized Difference Red Edge (NDRE) was also measured three times a week using a handheld device approximately 1 m above the canopy (Rapid SCAN CS-45, Holland Scientific Inc., Lincoln, NE). Soil moisture and NDRE were collected immediately prior to clipping collection.

Statistical Analysis

One-way ANOVA was used to determine statistical significance at 0.05, 0.01, and 0.001 with JMP software (version 15.0, SAS Institute Inc., USA). Means were separated using Fisher's protected least significant difference (LSD). Data collected from both years and the same root zone were combined when analyzed for the effect of soil depths on SCB. Data that represented the soil collected from different depths on the same root zone were combined when analyzed the effect of N fertilization on SCB. A simple linear regression model was used to estimate the relationships between SCB and creeping bentgrass daily clipping removal and three-week cumulative N uptake in 2020 and 2021. A simple linear regression model was also used to estimate the relationships between SCB and air temperature and soil moisture content.

Results

Weather and Soil Moisture Content in the Field

Air temperature at the research site from May to October 2020 and May to September 2021 are shown in Fig. 1. Both growing seasons had a similar temperature, except the average temperature in September 2021 was warmer than in 2020. May 2020 and 2021 were generally colder than the rest of the growing season.

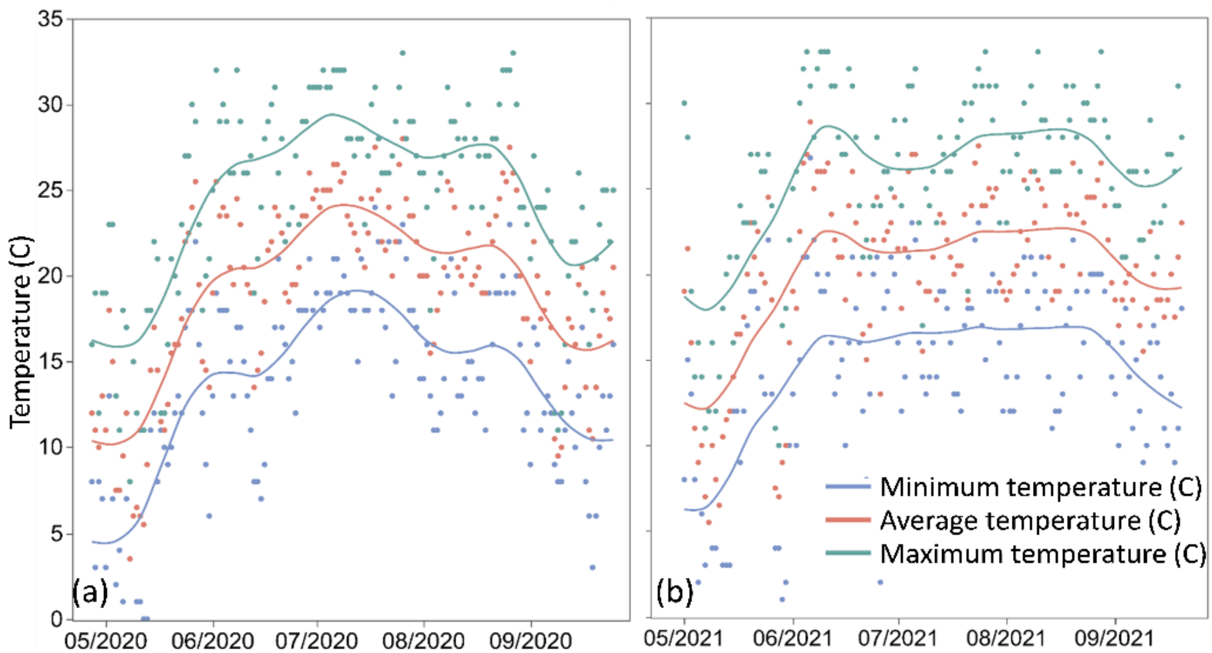

Fig. 1. Minimum, maximum, and average daily temperature at the University of Wisconsin – Madison turfgrass research facility, May to October 2020 (panel a) and May to September 2021 (panel b).

Soil volumetric water content of the four root zones is shown in Fig. 2. The soil water content in both years had similar trends, which started relatively dry in early May, then gradually climbed and stayed relatively stable from June to September. Root zones with higher soil organic matter content (Table 1) had greater soil moisture in both years, although all four root zones received the same irrigation amount over the study period.

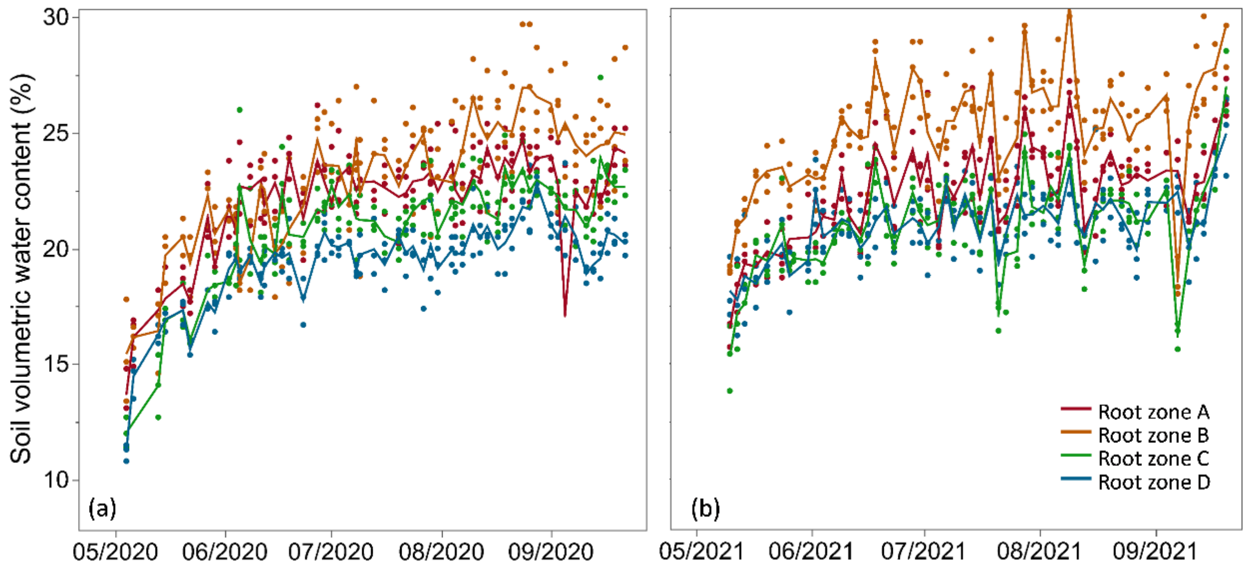

Fig. 2. Soil volumetric water content in the top 7.6 cm of four different sand-based putting green root zones from May to September 2020 (panel a) and 2021 (panel b).

Seasonal Change of Soil CO_2 Burst (SCB)

Despite a wide range of N fertilization rates in the study, no impact of N fertilization on SCB was observed on any of the four different root zones. Root zone A and B had similar soil organic matter content from 0 to 10 cm, and also had no significant differences in SCB. However, root zones C and D had no significant difference in SCB, but contained differing amounts of soil organic matter across the top 10 cm depth (Table 2), where the root zone C had slightly high SOM overall. This suggests that the SCB test is not sensitive to fertilization, and while clearly has a relationship with soil organic matter content, the SCB did not always follow the trends in soil organic matter among the root zones.

Table 2. Soil CO_2 Burst (SCB) across the soil collected from all depths (0-5 cm and 5-10 cm) received three N fertilizer rates. Data collected two-year growing season was combined.

N rate (kg ha^{-1} 2wk^{-1})	SCB (mg kg^{-1} d^{-1})			
	Root Zone A	Root Zone B	Root Zone C	Root Zone D
0	43.2 a	41.7 a	34.5 cd	31.8 d
5	44.1 a	40.9 abc	34.6 bcd	32.6 d
10	42.8 a	41.4 ab	34.1 cd	33.8 d

Soil organic matter accumulates most rapidly at the surface of putting green soils. Soil collected at 0-5 cm had significantly higher SCB than the soil collected at 5-10 cm on four root zones across two growing seasons (Fig. 3). Similar to Table 2, Root zone A and B had similar SCB at both depths but were significantly higher than the SCB on root zone C and D. Specifically, SCB on root zone A, B, C, D where the soil collected at 0-5 cm was averagely 58.7%, 56.7%, 63.1%, and 69.8% higher than the ones collected at 5-10 cm. This implied that surface soil could have a higher potential of elevated microbial activity and soil decomposition rates in the field on these four sand-based root zones.

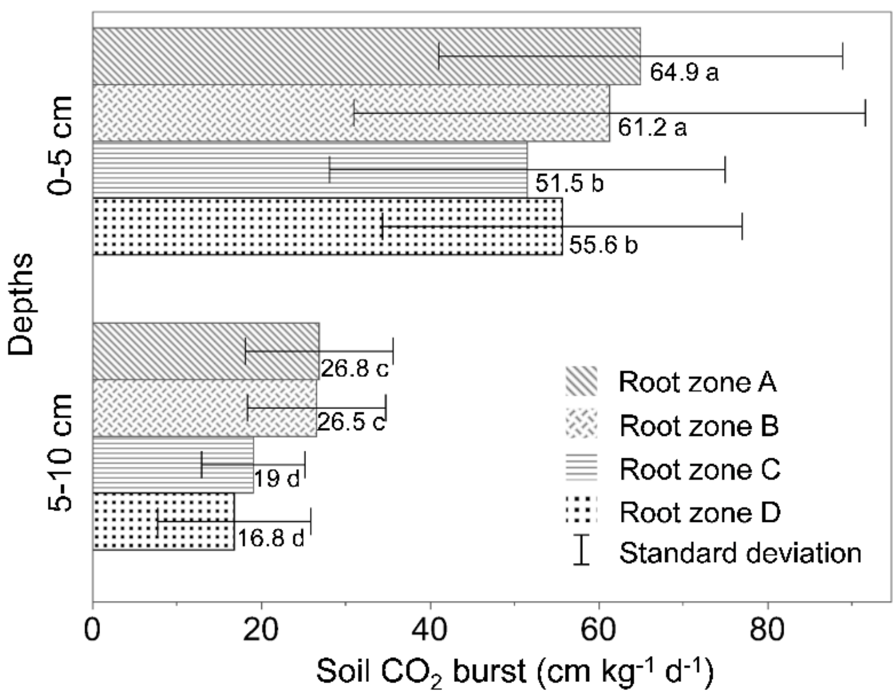

Fig. 3. Average Soil CO_2 Burst (SCB) across all N fertilizer at two depths on four research greens. The rank of soil organic matter content from high to low is root zone A, B, C, and D. The number list next to each bar is the mean value of SCB at different depths on different soil organic matter.

Change of SCB over the two growing seasons was presented in Fig. 4. It is apparent that short-term N fertilizer overall had no impact on SCB on four root zones at both soil depths. Also, a similar trend of SCB existed for the two testing depths. Generally, elevated SCB rates were observed in spring of both years and decreased during the summer. While the peak was not observed in fall 2021, it is likely because the sampling ended earlier in 2021 than in 2020. This is supported by greater SCB observed in spring of 2020 and 2021, as the elevation of SCB in spring 2020 implies elevation in fall of 2019. The variability of SCB was greater at the surface soil than the deeper soil sample. Soil samples collected from different dates during the growing season would result in a different SCB value. Soil collected on different dates of a year would result in a different SCB rate at both soil depths. One-time samples collection on indicating yearly soil potential microbial activity and predicting soil N supply might not be accurate.

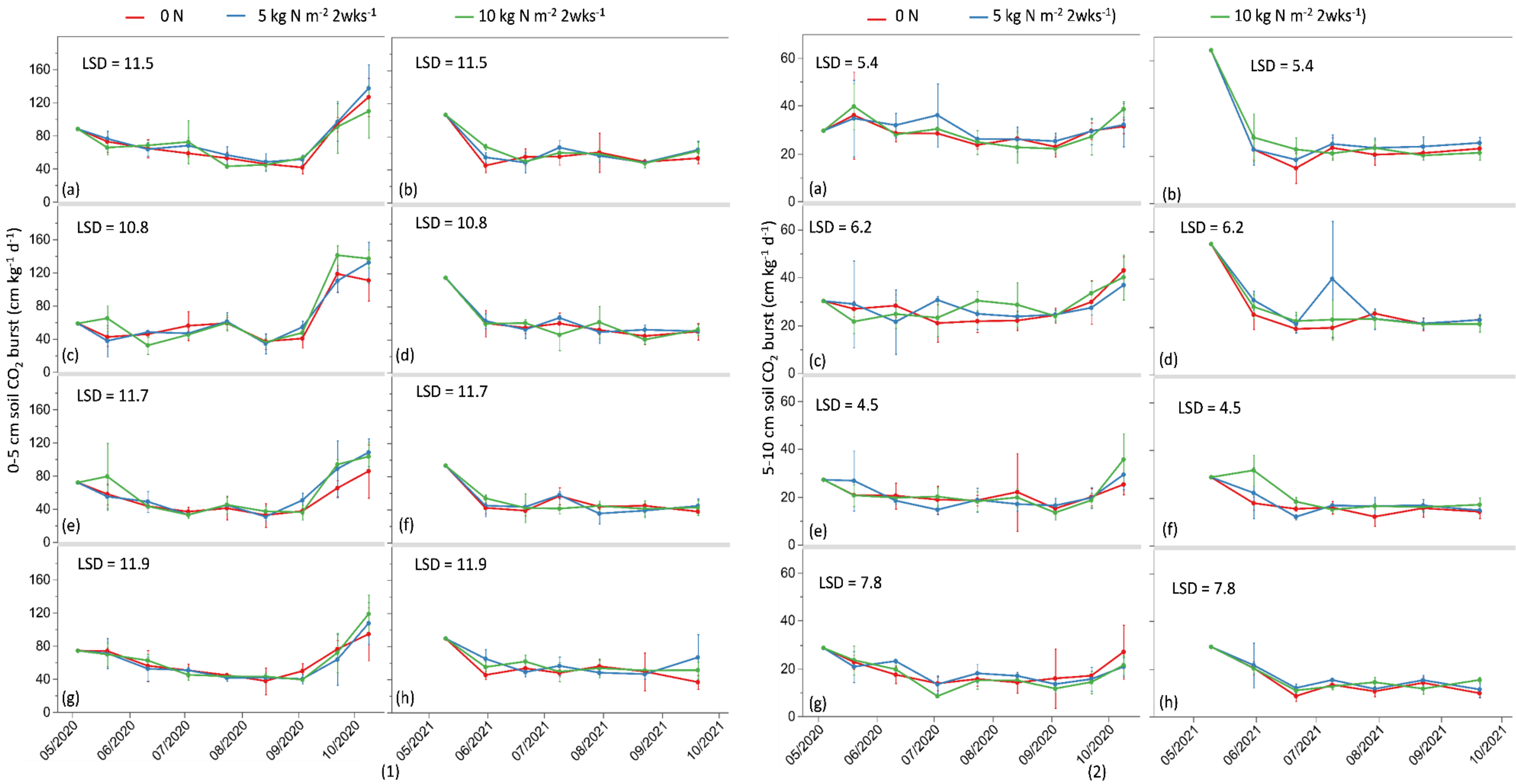

Fig. 4. Change of Soil CO_2 Burst (SCB) at 0-5 cm depth (1) and 5-10 cm depth (2) in response to N fertilization on four root zones. Data were collected from May to October 2020, and May to September 2021. Fig. (a)-(1) and (b)-(1): SCB of root zone A, where the soil was collected from 2020 and 2021 at 0-5 cm depth. Fig. (a)-(2) and (b)-(2): SCB of root zone A, where the soil was collected from 2020 and 2021 at 5-10 cm depth. Fig. (c)-(1) and (d)-(1): SCB of root zone B, where the soil was collected from 2020 and 2021 at 0-5 cm depth. Fig. (c)-(2) and (d)-(2): SCB of root zone B, where the soil was collected from 2020 and 2021 at 5-10 cm depth. Fig. (e)-(1) and (f)-(1): SCB of root zone C, where the soil collected from 2020 and 2021 at 0-5 cm depth. Fig. (e)-(2) and (f)-(2): SCB of root zone C, where the soil was collected from 2020 and 2021 at 5-10 cm depth. Fig. (g)-(1) and (h)-(1): SCB of root zone D, where the soil collected from 2020 and 2021 at 0-5 cm depth. Fig. (g)-(2) and (h)-(2): SCB of root zone D, where the soil was collected from 2020 and 2021 at 5-10 cm depth. LSD (least significant difference) is calculated by combining data collected in two years within the same depth and is the value by which any two means must differ for that difference to be significant at the $p < 0.05$.

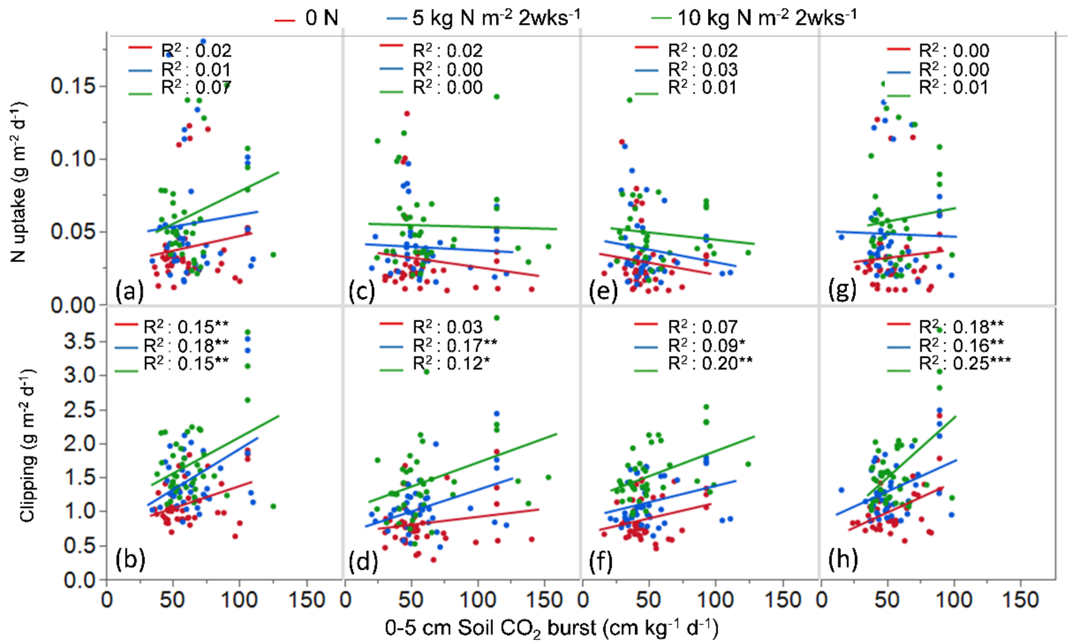

Fig. 5. Correlation between Soil CO_2 Burst (SCB) of 0-5 cm depth soil and creeping bentgrass clipping yield as well as corresponding tissue N content on four root zones. SCB from root zone A (panels (a) and (b)), root zone B (panels (c) and (d)), root zone C (panels (e) and (f)), and root zone D (panels (g) and (h)). R^2 values followed by *: significant at p <0.05; followed by **: significant at p < 0.01; followed by ***: significant at p <0.001.

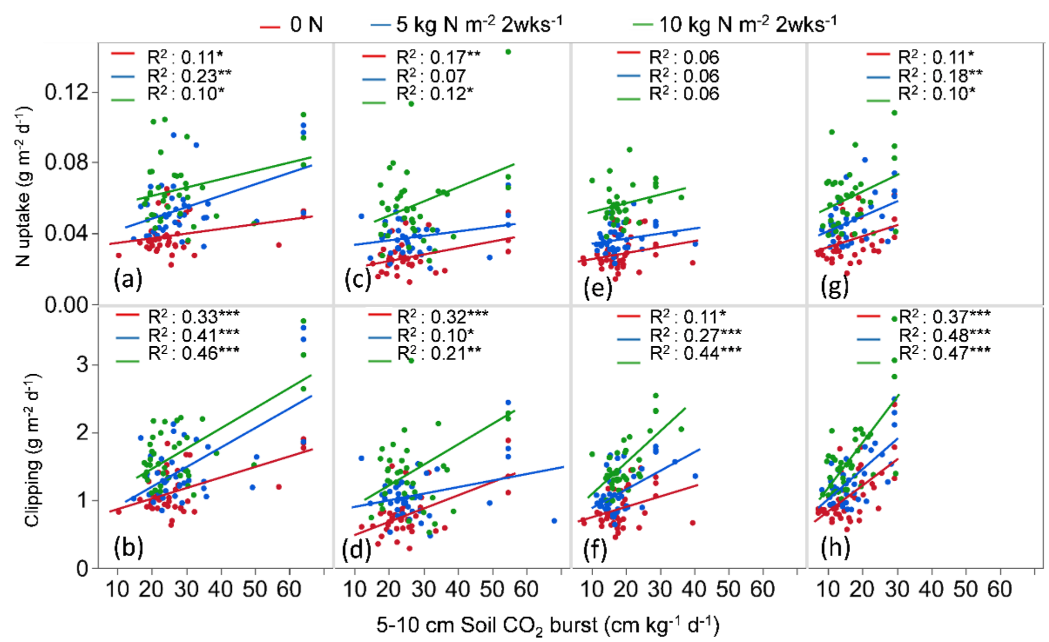

Fig. 6. Correlation between Soil CO_2 Burst (SCB) of 5-10 cm depth soil and creeping bentgrass clipping yield as well as corresponding tissue N content on four root zones. SCB from root zone A (panels (a) and (b)), root zone B (panels (c) and (d)), root zone C (panels (e) and (f)), and root zone D (panels (g) and (h)). R^2 values followed by *: significant at p <0.05; followed by **: significant at p <0.01; followed by ***: significant at p <0.001.

We observed no correlation between SCB of 0-5 cm soil and creeping bentgrass N uptake (Fig. 5), while the correlation between SCB of 5-10 cm soil and creeping bentgrass N uptake was apparent but weak (Fig 6). Similarly, the correlation between creeping bentgrass clipping yield and SCB of 5-10 cm soil was slightly stronger than 0-5 cm soil. SCB at both depths significantly affected creeping bentgrass clipping production in 22 of 24 of the correlations, but SCB was only significantly related to N uptake in 8 of the 24 correlations (Figs. 5 and 6).

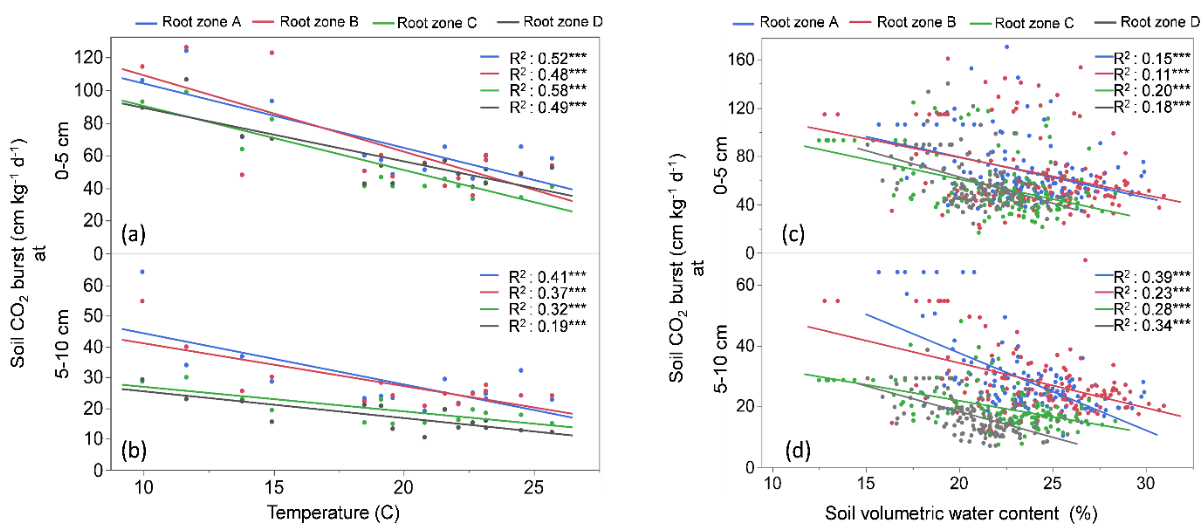

Fig. 7. The relationship between weekly average temperature in the field and Soil CO_2 Burst (SCB) of 0-5 cm (panel a) and 5-10 cm (panel b) soil on four root zones; and the relationship between average soil volumetric content in the field and SCB of 0-5 cm (panel c) and 5-10 cm (panel d) soil on four root zones.

The weekly temperature at the research field and SCB were negatively correlated on four root zones and two soil depths (Fig. 7). Both temperature and soil moisture content significantly affected SCB. Specifically, 0-5 cm SCB was better correlated with weekly temperature than 5-10 cm depth soil. Similarly, 0-5 cm SCB was better correlated with soil volumetric water content than the 5-10 cm soil samples. The results agreed with Fig. 4, where SCB spiked when the temperature and soil moisture in the field were both lower in both years.

Discussion

A precision N fertilization plan should be made with an understanding of the short- and long-term fate of N inputs. Generally, soil mineralization rate could change with additional organic and inorganic N sources adding to the soil (Kuzyakov et al., 2000), and this phenomenon is called the priming effect. The priming effect can either enhance or suppress soil mineralization process. For example, a study conducted on native grassland soil indicated that adding additional inorganic N sources could reduce soil mineralization rate (Jong et al., 1974; Ward et al., 2017); while a study conducted on a wheat farm concluded that addition inorganic N fertilizer enhances mineralization rate (Shen et al., 1984). Moreover, the N addition could have more complex and long-term impacts on soil carbon and N cycling. N additions could immediately raise soil mineralization rate, and the elevated rate would return to control level after a few months or years of chronic fertilization (Aber et al., 1993); or the elevated rates would decrease to have a slower decomposition rate compared with control levels (McNulty et al., 1996). Overall, additional N could have the ability to affect soil organic matter decomposition.

However, in this study, there was no clear evidence that N fertilization rate positively or negatively affected SCB from four sand-based root zones. Moreover, short-term and long-term N fertilization did not have a significant impact on the SCB as well. If the amount of N fertilization inputs exceed the turfgrass need, then soil microbes would consume the extra inorganic N. This would result in a slower soil mineralization rate than soil immobilization rate, and soil organic matter content would increase. On golf courses putting green soils, the turfgrass is usually managed to maintain at some level of N deficiency. The applied N fertilizer can easily be consumed by turfgrass, and not much inorganic N would be available for soil microbes. This may explain the reason that there was no priming effect observed.

Moore et al. (2019a) recently reported a good correlation between soil respiration and Kentucky bluegrass and tall fescue growth and nitrogen uptake on a Paxton fine sandy loam soil with Solvita® SCB test, where the soil incubation was conducted under room temperature. The authors used the relationship to provide guidance for N fertilization decisions according to a one-time soil sample collection each year. Moreover, the study contained a wide range of N fertilization rates included 22 nitrogen rates that ranged 50 to 2000 kg ha^{-1} yr^{-1}, it would result in larger variations in turfgrass growth rate and other plant responses. Our study has shown that SCB rates fluctuated during the growing season, with peaks in the spring and fall. Because there was seasonal change of SCB on sand-based putting green soil, it would be less accurate to seek the relationship between turfgrass growth and SCB only based on one-time soil sample collection each year, or make N application decision based on one-time SCB reading on sand-based putting green soil when N fertilizer was applied at a relatively lower rate.

Additionally, this study demonstrated that the collection depth strongly affected SCB. Soil collected in 0-5 cm had significantly higher SCB rates than the soil collected in 5-10 cm depth. In our study, the majority of root mass of creeping bentgrass was found at 0-3 cm depth. The percentage of total root mass in 0-3 cm accounted for 61-66% of total root mass, and the percentage of total root mass in 0-12 cm accounted for over 90% of total root mass based on different cultivars (Lyons et al., 2011). Additionally, although the 0-5 cm soil had greater SCB than 5-10 cm soil, it was interesting to observe that creeping bentgrass growth and N uptake were was slightly better correlated with SCB from the deeper soil sampling depth. Therefore, we would suggest testing SCB where the soil collected from 0-10 cm as a whole to eliminate the variations caused by root distribution

Temperature and soil moisture conditions played major roles in affecting the rate of SCB. These two parameters were also usually important growth factors affecting turfgrass growth. In this study, temperature and soil moisture content were both negatively correlated with the SCB. This is most likely explained by the difference in the microbial activity that occurred in the field and laboratory incubation conditions. As temperature and water are two important factors affecting microbial activity, when the temperature and soil water content in the field was lower than the laboratory incubation condition, then the microbial activity would be potentially suppressed in the field leading to an increase in labile carbon in the field. While the SCB was analyzed in the lab, if the incubation temperature and soil available water were higher than the field, the microbial activity would be enhanced. Specifically, surface soil was slightly better correlated with field temperature than deeper soil, as surface soil temperature would be more easily affected by air temperature than the deeper soil. It could cause larger differences in microbial activity under field and laboratory conditions. This can also explain the reason for spikes of SCB caused by temperature, which happened in September and October 2021, as well as May 2021. While, as the soil water content was measured with 7.6 cm rods, there was no clear explanation on the reason for the slightly better correlation between 5-10 cm SCB and field soil moisture content.

Overall, as temperature and soil moisture in the field mainly affected SCB, management practices such as irrigation water plans would result in different SCB values, moreover, whether the golf course putting greens were managed under shade or not would result in a different soil temperature in the field where the SCB would also be affected. This study presented that SCB cannot be solely used for making a prediction on turfgrass growth response and determining N fertilization application decision for sand-based putting green soil. However, SCB, which is recognized as a simple and effective soil test that is highly correlated with soil net mineralization (Franzluebbers et al., 2000), can be used as an effective soil health indicator for sand-based putting green soil, if future studies are conducted to have a better understanding of combined effects of management practices and weather on SCB.

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Chapter Five: Evaluation Precision Nitrogen Management on Golf Courses Using Decision Support Tools

Abstract

Nitrogen (N) is the most limiting nutrient for turfgrass growth. Few tools or soil tests exist to help managers guide N fertilizer decisions. Turf growth prediction models have the potential to be useful, but the lone turfgrass growth prediction model only takes into account temperature, limiting its accuracy. This study investigated the ability of a machine-learning-based turf growth model using the random forest (RF) algorithm (ML-RF model) to improve turfgrass N management by estimating short-term turfgrass clipping yield. This method was compared against three alternative N application strategies including 1) PACE Turf Growth Potential (GP) model; 2) an experience-based method for applying N fertilizer (experience-based method), and 3) the experience-based method guided by a vegetative index, normalized difference red edge (NDRE-determined). The ML-RF model was built based on a set of variables including 7-day weather, traffic intensity, soil moisture content, N fertilization rate, and NDRE. The field experiment was conducted on two sand-based research greens in 2020 and 2021. The cumulative applied N fertilizer was 281 kg ha^{-1} for the PACE Turf GP model, 190 kg ha^{-1} for the experience-based method, around 140 kg ha^{-1} for the ML-RF model and around 75 kg ha^{-1} NDRE-determined method. ML-RF model and NDRE-determined method were able to provide customized N fertilization recommendations on different root zones. The rank of methods resulted in the turfgrass quality and NDRE readings from highest to lowest were: PACE Turf GP model, experience-based, ML-RF model and NDRE-determined method, where the first three methods produced turfgrass quality over 7 and NDRE over 0.30. N fertilization guided by the ML-RF model resulted in a moderate amount of fertilizer applied, and acceptable turfgrass performance characteristics. This application strategy is rooted in the N cycle, and has the potential to assist turfgrass managers in making N fertilization decisions to creeping bentgrass putting greens.

Introduction

Natural resources, including soil, water, and air are negatively affected by the intensive use and production of agrochemicals. In turfgrass systems, especially on the highly maintained golf courses and athletic fields, agrochemicals are heavily used to achieve desired aesthetics and functions. Nitrogen (N) fertilizer is applied in amounts greater than all other nutrients. According to a 2016 report (Gelernter et al., 2016), US golf courses used 55,333 Mg N fertilizer annually. These N inputs pose potentially significant nonpoint source pollution risks (Bock and Easton, 2020). Optimizing the N application rate is one of the most effective ways to improve turfgrass management and reduce its potentially negative environmental impacts.

Maintenance of a high-quality playing surface of a golf course takes priority over maximizing the turfgrass yield as is common for agricultural crops. Specifically, golf course putting greens are the main focus for most golf course managers (Hammond and Hudson, 2007); therefore, putting greens usually receive the most resource inputs and energy use per unit area (Gelernter et al., 2016). N is the most limiting nutrient for turfgrass and is an important driver of plant growth and maintains great visual performance. Relatively high N fertilization rates result in verdant and aesthetically pleasing playing surfaces. However, the rapid growth induced by relatively high N fertilization increases thatch and soil organic matter content which reduces the function (e.g ball roll speed) and aesthetics of putting greens (Meinhold et al., 1973; Murray and Juska, 1977; Throssell, 1981; Gaussoin et al., 2013). On the other hand, putting greens receiving relatively low rates of N fertilization can be slow to recover from ball marks and wear damage from foot traffic which encourages weed invasion (Beard, 1972).

Other nutrient applications, such as potassium, phosphate, calcium and magnesium, etc., can be made according to soil testing (Murphy and Murphy, 2010; Landschoot, 2017). However, most commercial soil testing labs do not offer tests for estimating available N in soil. Tests for N exist, but they usually cannot be done quickly and cost-effectively because plant-available N in the soil is largely affected by weather and soil conditions, so the N release varies during the growing season. N application recommendations for golf courses putting green are mainly based on turfgrass managers' experience and observations of turf quality. The N fertilization rate for golf course putting greens recommended by universities was generally 49 - 195 kg ha^{-1} y^{-1} (Murphy and Murphy, 2010; Landschoot, 2017). Because soil conditions, changing weather, and customized management practices on each golf course would cause differences in N needs to achieve a performance goal, applying N fertilizer based on turfgrass visual performance might be warranted for turfgrass showing signs of inadequate N such as chlorosis, decreased density and growth, and slower recovery from abiotic and biotic stress. However, golf turf managers prefer to avoid these negative responses and therefore are regularly making fertilization decisions on turfgrass that is performing optimally, and this could result in over-application since optimally performing turfgrass may perform well with optimum and above-optimum N. It is clear that a more objective N application strategy is needed to maximize N fertilizer efficiency.

Turfgrass visual quality assessment has been widely used in turfgrass systems as a standard to evaluate the turfgrass response to various management practices. It involves a subjective visual evaluation of a turfgrass stand on a scale of 1 to 9 based on the evaluator's mental integration of turfgrass color, uniformity, and shoot density (Beard, 1972). With the recent development and increasing availability of sensor technology, turfgrass professionals are able to utilize spectral reflectance data obtained from proximal and remote sensors to subjectively quantify turfgrass quality and turfgrass growth response to various N fertilization. Spectral reflectance is measured with given wavelengths of light, and studies (Trenholm et al., 1999; Bell et al., 2002; Fitz–Rodríguez and Choi, 2002; Keskin et al., 2008) have shown that spectral reflectance could be well correlated to visual quality for turfgrass species maintained under different management practices. Spectral reflectance is sensitive to N fertilization of turfgrasses (Caturegli et al., 2016; Guillard et al., 2016) and therefore has the potential to serve as an objective measurement of turfgrass performance. For example, spectral reflectance has been used to detect chlorophyll content and has also been shown to have a good correlation with plant N status (Horler et al., 1983; Steven and Clark, 2013). However, few studies have evaluated the feasibility of making N application decisions solely based on spectral reflectance measurement of turfgrass on golf course putting greens, and these measurements are likely to play a larger role in the precision management of turfgrass in the future.

Precision turfgrass management aims to provide precise management of pests, fertilizer, salinity, cultivation and irrigation (Stowell and Gelernter, 2006; Carrow et al., 2007; Bell and Xiong, 2008; Krum et al., 2010). Precision N management is a branch of precision turfgrass management and seeks to match N supply with turfgrass N demand spatially and temporally to maximize turfgrass function and minimize resource loss to the ecosystem. On sand-based putting green soils, the N cycle can be simplified using a few assumptions. Potential N loss by denitrification, volatilization, runoff and leaching are expected to be negligible or quite low when best management practices are used (Snyder et al., 1984; Morton et al., 1988; Gross et al., 1990; Miltner et al., 1996; Erickson et al., 2001, 2008). This leaves clipping removal as the primary output of N, and fertilization as the primary input (assuming negligible input from irrigation water sources and atmospheric deposition). Moreover, Zhou and Soldat (2021a) concluded that tissue N content of creeping bentgrass was relatively stable during the growing season, and it can be reasonably assumed to be 3.9% for bentgrass putting greens under typical conditions. The optimal N fertilization rate (input), therefore, can be estimated by quantifying the N outputs (clipping mass x clipping tissue N content). This requires a need to measure or accurately estimate turfgrass clipping mass so that optimal N fertilizer inputs can be estimated.

The turfgrass growth potential (GP) model was developed by Gelertner and Stowell (2005) to aid decision-making related to fall overseeding on golf courses. Later, the turfgrass GP model was endorsed as a tool for determining monthly or annual turfgrass N requirements based on the turfgrass growth potential (Woods, 2013). The turfgrass GP model uses average air temperature to estimate turfgrass growth potential which spans 0 to 100%. For cool-season grasses, the model assumes the optimal average air temperature for growth is 20°C (growth potential = 100%); as the temperature drops below or passes 20°C, the growth potential will decrease correspondingly until the growth potential reaches 0% at 0 and 40°C. The turfgrass GP model assumes that N should be applied to match the turfgrass' growth potential. An obvious pitfall is that turfgrass growth is determined by complex physiological processes which include genetic potential, environmental, and edaphic factors in addition to air temperature. For example, foot traffic stress, which is one of the most common stresses on golf course putting greens (Beard, 1972; Carrow and Martin Petrovic, 1992), can result in major turf damage and reduce turf quality and clipping yield (Shearman et al., 1974; Shearman and Beard, 1975; Carrow and Martin Petrovic, 1992; Bilgili and Acikgoz, 2007). Moreover, water availability is another important factor supporting plant growth. Limited access to water would result in turfgrass with reduced root growth (Beard and Daniel, 1965); and excessive irrigation has been shown to also be detrimental for turfgrass growth and visual quality (Beard, 1972; DaCosta and Huang, 2006). Although the turfgrass GP model is useful for understanding how temperature may influence growth across regional or larger scales, at the local scale, a more detailed model could be useful for making more accurate predictions of turfgrass growth and corresponding N need.

In precision agriculture, crop growth models are widely used to guide N applications based on crop N demand to ensure increased N use efficiency. These models often estimate crop N need by accounting for soil-plant process, environmental conditions and interactions with various management practices. One of the approaches of using crop growth models is to use historical data to empirically predict crop yield production via machine learning (ML) models (Jaikla et al., 2008; Brdar et al., 2011; Fukuda et al., 2013; Kuwata and Shibasaki, 2015; Everingham et al., 2016; Zhang et al., 2019; van Klompenburg et al., 2020). Because of the differences in managing agriculture crops compared to turfgrass as well as the differing goals between agricultural production and turfgrass management, the utility of ML to aid turfgrass management needs to be tested. Zhou and Soldat (2021b) developed the first turfgrass growth model with a ML approach and reported that the random forest algorithm was the best among those algorithms that tested for predicting creeping bentgrass clipping production. The ML turfgrass growth model inputs included daily weather, evapotranspiration, soil moisture content, number of rounds of play, root zone type, N fertilization inputs, and NDRE. The aims of this study were to 1) evaluate the feasibility of the developed turfgrass ML growth prediction model on improving N management and 2) compare how various N application strategies and decision support tools in terms of N applied and turfgrass performance characteristics. Specifically, the study evaluated two turfgrass growth models: PACE Turf Growth Potential model and a ML (random forest) growth prediction model against two more traditional approaches to N fertilizer management: the standard experience-based approach (which is the current standard for putting green fertilization) and an experience-based approach that was modified by reflectance measurements.

Methods and Materials

Study Sites

The study was conducted at the University of Wisconsin-Madison O.J. Noer Turfgrass Research and Education Facility located in Verona, WI, USA. Field experiments were conducted on two different sand-based putting green root zones in 2020 and 2021, and both research greens were constructed according to USGA recommendations (US Golf Association, 2004). Root zones characteristics are reported in Table 1. Both greens were planted with ‘Focus’ creeping bentgrass (*Agrostis stolonifera*), which is the most commonly planted cool-season grass species used on golf courses putting greens in this region. Research plots were irrigated daily to replace 70% of reference evapotranspiration as estimated by an on-site weather station. The research greens were topdressed with 0.6 m^3 ha^{-1} of sand approximately every three weeks during the growing seasons. Hollow tine cultivation was conducted once at the end of each growing season (September) and the cores were removed and holes filled with topdressing sand. Disease and other pests were monitored and controlled as needed.

Table 1. Soil chemical properties of two putting green root zones

Root zones ID	Depth (cm)	SOM ⁰ (%)	P Φ	K	Ca	Mg	CEC ζ (cmol kg^{-1})	pH
			(mg kg^{-1})					
A	0 - 5	0.7	25.9	40.7	586.6	133.1	3.0	7.7
	5 - 10	0.5	24.1	17.2	429.9	101.6	3.0	7.5
B	0 - 5	1.2	64.2	91.6	1210.0	295.8	8.0	7.5
	5 - 10	0.6	17.0	25.5	578.5	143.6	4.0	7.3

⁰ SOM, soil organic matter by loss on ignition (360°C for 2 hours)
Φ Nutrients extracted via Mehlich-3 (Mehlich, 1984)
ζ CEC, cation exchange capacity via summation of extracted cations

Nintrogen (N) Application Strategies

Traditional N Fertilization Plan (Experience-based)

Traditionally, N fertilization rates are based on manager experience, observations, and recommendations from local services or organizations. In this region, golf course putting greens typically receive between 100 and 250 kg N ha^{-1} y^{-1}. At the O.J. Noer Turfgrass Research Facility, it would be typical for the station manager to apply 10 kg ha^{-1} every other week during the ~30 weeks growing season to putting green plots, for a total of approximately 150 kg ha^{-1} N per season. Therefore, for this study, we emulated this practice and the traditional N fertilization plan treatment utilized a 10 kg ha^{-1} application every other week during the growing season, which approximately spanned the period of May to October.

Turfgrass Vegetative Index (NDRE) (NDRE-determined)

In this study, we used the Normalized Difference Red Edge (NDRE) obtained from handhold proximal sensor (Rapid SCAN CS-45, Holland Scientific Inc., Lincoln, NE) to guide N application on the sand-based research greens. NDRE depends on the combination of near-infrared red light (±800nm) and red-edge band (±720nm). NDRE is designed for crops with relatively high canopy density where the red edge band is able to penetrate deeper through the plant canopy. To calibrate the sensor and use spectral reflectance to guide N fertilization, the spectral reflectance readings from the turfgrass area would need to be compared with the readings from reference strips, and then fertilizer decisions could be made according to the relationships (Blackmer and Schepers, 1995; Raun et al., 2008; Samborski et al., 2009; Holland and Schepers, 2013; Guillard et al., 2021). One of the types of reference strips for spectral reflectance is called the virtual-reference concept (Holland and Schepers, 2013). This method requires obtaining the spectral reflectance references from uniform research areas in the field where the turfgrass looks the greenest (well-fertilized) and the least green (under-fertilized) by visual observation. Based on the relationship between NDVI and nitrogen rate of well-fertilized and under-fertilized turf, a N fertilizer recommendation for turfgrass would be made based on the NDVI reading of an unknown area. In the study, we followed a similar approach but with some adjustments. Instead of finding the greenest and least green strip, we aimed to maintain the turfgrass at a minimally acceptable visual turfgrass quality. Therefore, the reference strips were the turfgrass research areas at an acceptable quality, which the visual turfgrass of approximately 6 (turfgrass visual color ranges from 1 to 9, and 6 is considered minimally acceptable). NDRE was used in this study, and the average NDRE on the four turfgrass areas of quality of 6 was 0.28. Therefore, if the biweekly average NDRE of the research plots was over 0.28 which means the turfgrass quality was likely above 6, then no additional N fertilizer was added; otherwise, additional N fertilizer was applied at 10 kg ha-1 every other week. NDRE was collected by scanning the research plot approximately 1 m above the canopy and was measured three times each week during the growing season.

Growth Potential (GP) Model (PACE Turf GP model)

The GP model was presented as equation (1) (Woods, 2013). N fertilization was applied every other week, and the N application rate was determined by the creeping bentgrass growth potential (equation (1)) multiplying maximum N fertilization rate that the creeping bentgrass need at the University of Wisconsin-Madison O.J. Noer Turfgrass Research and Education Facility, as the turfgrass GP model requires turf managers to make an assumption of maximum N rate turfgrass need or when turfgrass growth potential is 100%, and apply N fertilizer based on that potential. The maximum N rate would be determined according to the maximum clipping yield a golf course would collect, where the turfgrass growth potential reaches 100%. Therefore, the maximum N rate for our research plots was determined according to the maximum clipping production (3.2 g m^{-2} d^{-1}) of 2019's growing season multiplied by tissue N content (3.9%). N fertilizer was applied every other week.

$$GP = \frac{1}{e^{0.5(\frac{T-T_0}{var})^2}} \tag{1}$$

Where,
e: 2.718
T: local average temperature; °C
T_0: optimal temperature for turfgrass growth; 20°C for cool-season grass
Var: adjust the change in GP as temperature moves away from T_0; 5.5 for cool-season grass

Machine Learning Growth Model (ML-RF model)

We used the random forest (RF) algorithm for predicting turfgrass clipping yield using ML. The model was constructed using clipping yield data collected in 2019 and 2020, where clipping data collected in 2019 was used to train the model to predict for the year 2020's turfgrass clipping production and corresponding N application rate, and clipping yield data collected in 2019 and 2020 were used to train the model to predict the 2021 turfgrass clipping production. Variable inputs when making prediction included 1) three-day average soil moisture content which was the average soil moisture content on the clipping collection event and the one before, soil moisture content was measured by time-domain reflectometry with 7.6 cm rods (FieldScout TDR 350, Spectrum Technologies, Aurora, Illinois, USA).; 2) average weekly traffic intensities; 3) NDRE; 4) categorical value representing the root zone of the two putting greens; 5) days between mowing events; 6) daily weather variables obtained from the nearest weather station reported on Weather Underground (an open online real-time weather information site). These variables included daily maximum temperature (Tmax), minimum temperature (Tmin), average temperature (Tavg), precipitation (precip), maximum relative humidity (RHmax), minimum relative humidity (RHmin), average relative humidity (RHavg) and average wind speed (Windavg), and ET which was from the UW-Extension Ag Weather station. A detailed description of the processes of choosing the input variables and detail about building and validating the model was presented by Zhou & Soldat (2021b)

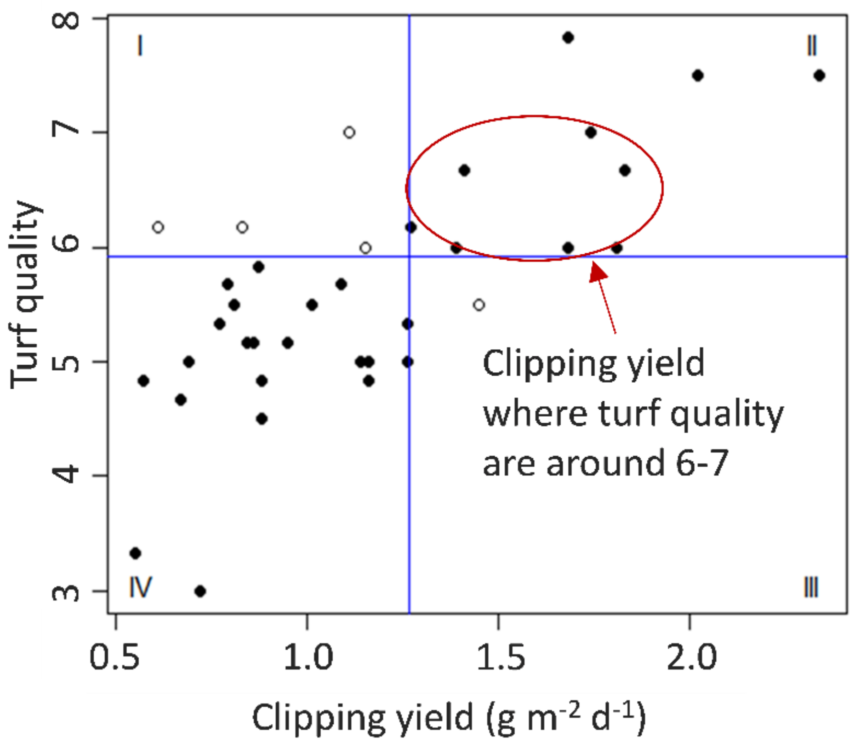

Fig. 1. Relationship between creeping bentgrass dry clipping mass and turf quality where the clipping and turf quality were collected in 2018 at the University of Wisconsin – Madison turfgrass research facilitate. Turf quality scaled from 1 to 9 where 1 represents completely dead turf, 6 represents the minimally acceptable quality, and 9 represents a perfect or ideal turfgrass quality

The goal of using machine learning-random forest growth model to guide N application was to accurately predict turfgrass clipping removal and maintain the clipping removal at a reasonable range. As maintaining a good quality of turfgrass is still the ultimate goal of turfgrass management, clipping removal range was determined by turf quality (Fig. 1). In this study, we aimed to maintain the turfgrass above 6 and below 8. From historical data, this meant that the daily clipping removal would be between the range of 1.25 to 1.6 g m^{-2} d^{-1}. Fig. 2 shows the flow chart of the N fertilization decision tree using the following logic: 1) if the estimated two-week accumulated clipping production was between 17.5 to 22.5 g m^{-2} $2wks^{-1}$, the N fertilization rate would replace the N removed as estimated by the model predicted clipping yield multiplied by the estimated average tissue N content (3.9%); 2) if the predicted clipping yield was less than 17.5 g m^{-2} $2wks^{-1}$ or over 22.5 g m^{-2} $2wks^{-1}$, then the N fertilization rate was determined using the median clipping yield (20 g m^{-2} $2wks^{-1}$) of the ideal clipping removal range multiplied the estimated average tissue N content (3.9%); Overall, the estimated clipping yield was in the range of 17.5 to 22.5 g m^{-2} 2wks^{-1} for the majority of the study except the beginning of each year's field experiment, where the estimated clipping yield was lower the target range.

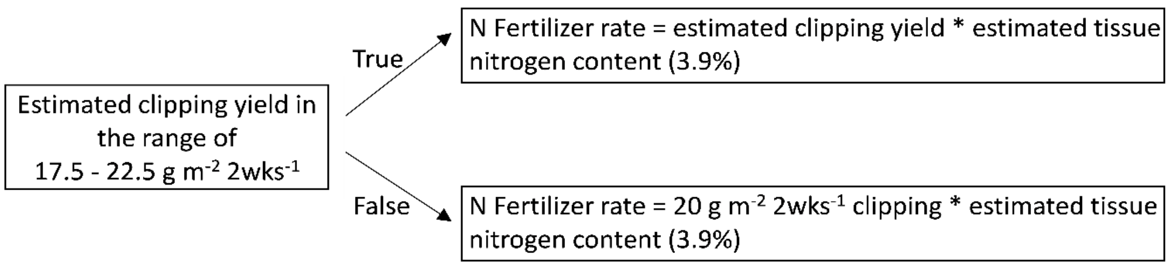

Fig. 2. Flow chart of making N fertilization decision based on creeping bentgrass clipping yield estimated by machine learning-random forest growth prediction model.

Turfgrass Data Collection

Clipping data was collected from both research greens during 2020 and 2021 approximately every other day between 900 and 1200 h (weather permitting) by mowing a 1.9 m pass down the center of each plot using a 0.54 m-wide walking greens mower (Toro Co., Bloomington, Minnesota, USA). Before each clipping collection, 0.27 m wide alleys were mowed at the top and bottom of each plot perpendicular to the collection pass. This was done to reduce the variability associated with starting and stopping the mower. The effective clipping collection area for each plot was 1 m^2. Clippings were brushed from the mower bucket into paper bags, which were then placed in an oven set to 50°C for at least 48 hours. Sand and other debris were removed from the dried clippings using the water method described in Kreuser et al. (2011). NDRE of each plot was also recorded prior to each clipping collection event.

Results

Two-year creeping bentgrass growth response to four N application strategies and corresponding N fertilizer inputs is presented in Fig. 3. Generally, there was greater clipping production when the turfgrass was received greater N fertilization rates. In this study, the PACE Turf GP model received the greatest amount of N fertilizer, followed by the experience-based method. The ML-RF model recommended the third most N fertilizer inputs, and creeping bentgrass clipping production from that method was also lower than the previous two N fertilization strategies. The NDRE-based strategy resulted in the least N fertilizer use and lowest clipping production on both root zones in both years. The creeping bentgrass growth response to four N application plans on both root zones had a similar trend, as nitrogen is one of the major contributions of turfgrass growth; while there was a different growth pattern in each year, differing weather and soil conditions (i.e. temperature, moisture) each year were most likely cause for these differences. Interestingly, as the research greens received identical N fertilizer inputs before this field experiment started, creeping bentgrass clipping yield response to the four N application strategies were similar during about the first 40 days of the experiment even though different N fertilization rates were applied. N fertilizer had a delayed effect on creeping bentgrass growth.

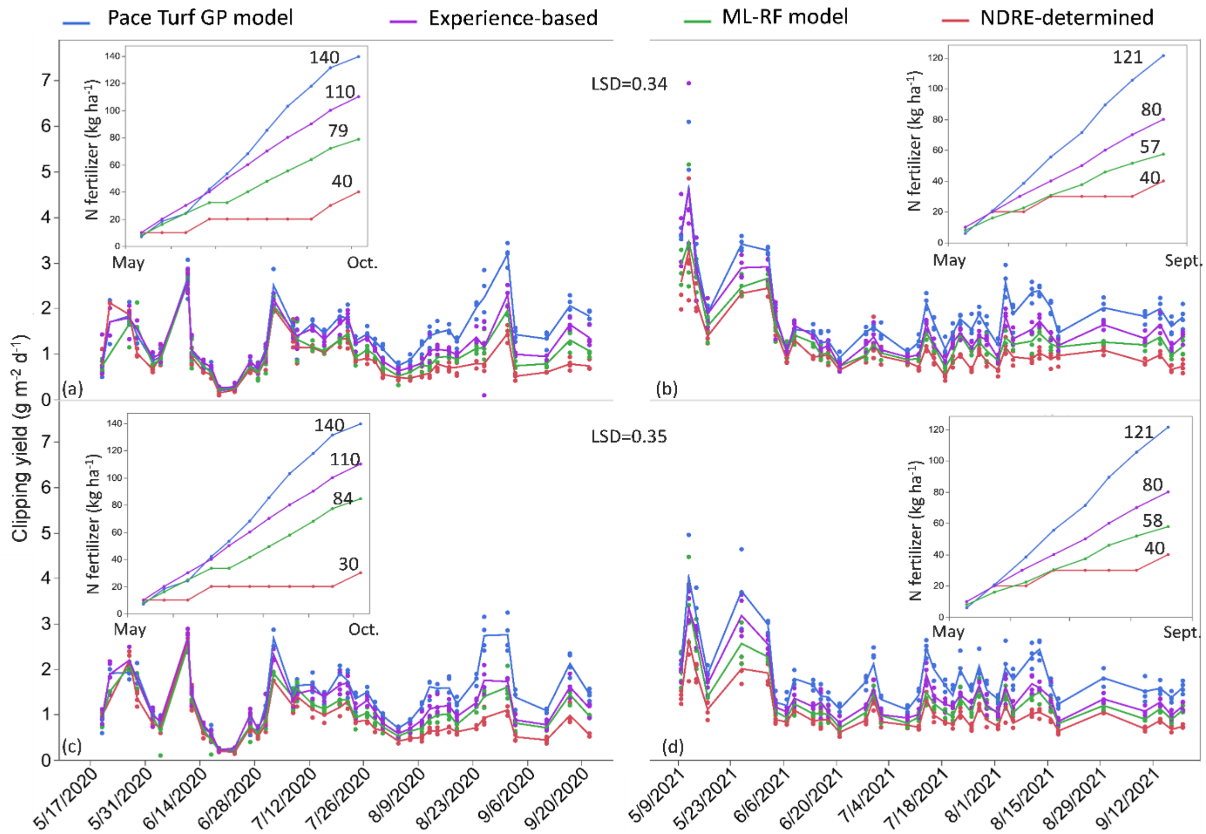

Fig. 3. Creeping bentgrass clipping dry mass response to four nitrogen (N) application strategies, which include PACE Turf Growth Potential model (PACE Turf GP model), traditional N fertilization plan (Experience-based), machine learning (random forest) model method (ML-RF model) and Turfgrass Vegetative Index based strategy (NDRE-determined). Panel (a): creeping bentgrass growth response on root zone A, and data collected in 2020. Panel (b): bentgrass growth response on root zone A, and data collected in 2021. Panel (c): bentgrass growth response on root zone B and data collected in 2020. Panel (d): bentgrass growth response on root zone B and data collected in 2021. Inserted figures in each panel presented the cumulative N fertilizer usage for each year on each root zones. LSD (least significant difference) is calculated by combining data collect from two years but the same research and is the value by which any two means must differ for that difference to be significant at the $p < 0.05$.

Creeping bentgrass NDRE readings under the four N fertilization treatments are presented in Fig. 4. Similar to growth response, plots that received N fertilizer recommendation following the PACE Turf GP model had the highest NDRE readings, followed by the experience-based method, ML-RF model, and the NDRE-based N fertilization strategy. The trends in NDRE readings on both greens and both years were similar, which implied N fertilizer inputs were the primary driver of differences in NDRE readings. At the end of each season, the GP model method had ~ 20% greater NDRE compared to the NDRE-based method, which represented the highest and lowest N fertilization amounts. The difference in the season-end NDRE readings between the PACE Turf GP model and ML-RF model was approximately ~9%, and the difference between the PACE Turf GP model and traditional N fertilization strategy was ~5%. Additionally, although there was no overall significant difference in creeping bentgrass clipping yield among the four N treatments in the early stage (first 40 days) of the field experiment, there were significant differences in NDRE readings suggesting that N fertilization had an immediate impact on creeping bentgrass NDRE response. Moreover, there were more days that the creeping bentgrass readings were above the reference reading (0.28) among the four N treatments in 2021 than in 2020.

Fig. 4. NDRE readings of creeping bentgrass on two research greens response to four nitrogen (N) application strategies, which including the PACE Turf Growth Potential (PACE Turf GP model), traditional N fertilization plan (Experience-based), machine learning (random forest) model method (ML-RF model) and turfgrass vegetative index (NDRE) based strategy (NDRE-determined). Panel (a): NDRE readings on root zone A in 2020. Panel (b): NDRE readings on root zone A in 2021. Panel (c): NDRE readings on root zone B in 2020. Panel (d): NDRE readings on root zone B in 2021. Dash line is where the NDRE reading at 0.28. LSD (least significant difference) is calculated by combining data collect from two years but the same research and is the value by which any two means must differ for that difference to be significant at the $p < 0.05$.

The two-year average creeping bentgrass clipping yield, NDRE and turf quality response to four N treatments, as well the two-year cumulative N fertilizer usage, clipping yield and N use efficiency (NUE) are presented in Table 2. There was no significant difference in clipping yield, NDRE and turfgrass quality between the two root zones. Similar to the periodical turfgrass response to the four N treatments, turfgrass that received N treatments followed by the PACE Turf GP model averagely produced significantly higher clipping yield, NDRE readings and turf visual quality. The experience-based model produced the second most clipping yield, NDRE and turf quality, then followed by ML-RF model and NDRE-based N fertilization plan. The two-year cumulative clipping yield from the non-fertilized control treatments on root zone A and root zone B were 64.9 and 60.4 g m^{-2} $2yrs^{-1}$ respectively. NUE were highest on both root zones receiving N fertilization according to NDRE-based method, which were near 70%. NUEs were around 45% on the root zones following ML-RF model N plan, and were about 40% following N fertilization plan with experience-based method. NUEs were lowest when using PACE Turf GP model method, which were around 34% on both root zones. According to Miltner et al. (1996) about 35% of the applied N fertilizer was recovered in turfgrass clippings, and the rest of the applied N was immobilized in thatch and soil. In this study, we recovered 34-71% of N in clippings, but did not attempt to quantify the fate of the remaining fertilizer N. The PACE Turf GP model and experience-based strategies were not able to customize N fertilization recommendations on different root zones, while the ML-RF model and NDRE-determined method were able to account for root zone properties. The experience-based resulted in 32% less N fertilizer than the GP method, and the ML-RF model applied 52% and 49% less N fertilizer on root zone A and B respectively. The NDRE-based method resulted in 72% and 75% less N fertilizer on root zone A and B respectively.

Table 2. Two-year average creeping bentgrass clipping yield, NDRE and turfgrass quality response to four nitrogen (N) application strategies on two research putting greens. Turf quality scaled from 1 to 9 where 1 represents completely dead turf, 6 represents the minimally acceptable quality, and 9 represents a perfect or ideal turfgrass quality.

Root zone ID	N app. strategies	Clipping (g m^{-2} d^{-1})	NDRE	Turf quality	Sum of N fertilizer (kg ha^{-1} $2yrs^{-1}$)	Sum of clipping (g m^{-2} $2yrs^{-1}$)	NUE$^{\mu}$ (%)
A	PACE Turf GP$^{\Theta}$	1.63 a	0.328 a	7.6 a	281	303	33.9
	Experience$^{\beta}$	1.38 b	0.315 b	7.4 ab	190	259	40.9
	ML-RF approach$^{\alpha}$	1.20 c	0.302 c	7.2 b	136	224	46.8
	NDRE-based$^{\Gamma}$	1.02 d	0.277 d	6.1 c	80	193	64.1
B	PACE Turf GP$^{\Theta}$	1.62 a	0.326 a	7.5 a	281	301	34.2
	Experience$^{\beta}$	1.32 b	0.318 b	7.4 ab	190	250	40.0
	ML-RF approach$^{\alpha}$	1.17 c	0.306 c	7.2 b	142	221	45.2
	NDRE-based$^{\Gamma}$	0.96 d	0.282 d	6.2 c	70	184	70.6

$^{\Theta}$ PACE Turf Growth Potential model-guided N application strategy

$^{\beta}$ Traditional N application plan

$^{\alpha}$ Machine learning (random forest) growth model guided N application strategy

$^{\Gamma}$ Turfgrass vegetative index (NDRE) determined N application strategy

$^{\mu}$NUE, nitrogen use efficiency, calculated by (N uptake by plant - N uptake by plant from non-fertilizer control plot)/two-year N fertilizer applied

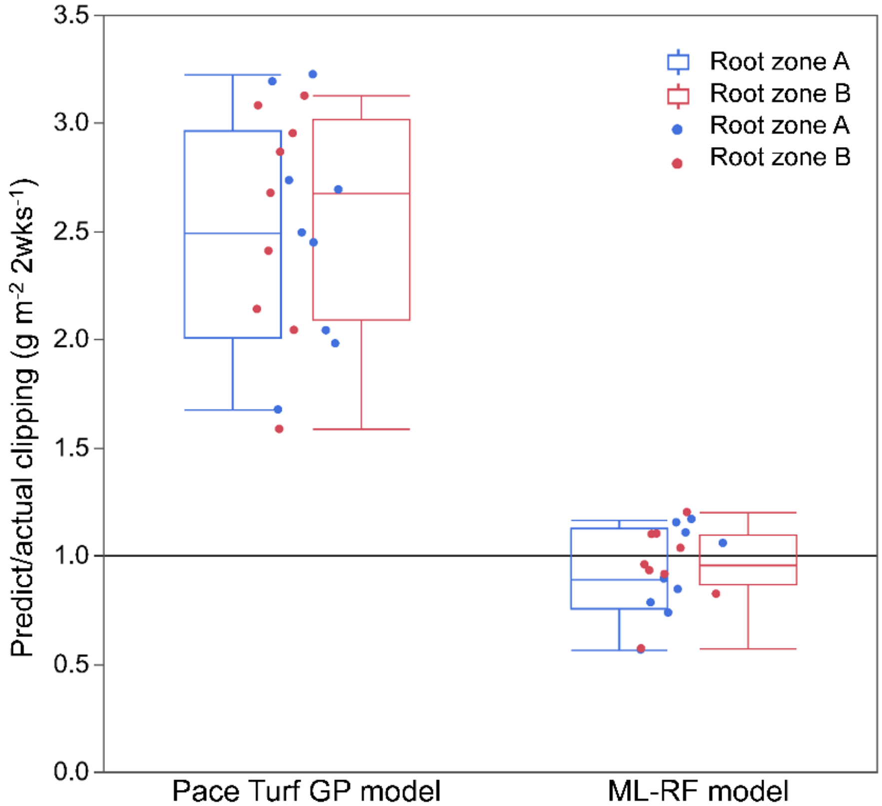

Fig. 5. Creeping bentgrass growth prediction accuracy of PACE Turf Growth Potential model (PACE Turf GP model) and machine learning-random forest model (ML-RF model). Blue boxes and dots represent data collected on root zone A, and red boxes and dots represent data collected on root zone B.

The PACE Turf GP model and ML-RF model were two approaches to making N application decisions based on turfgrass growth rate. As N fertilizer was applied every two weeks, Fig. 5 presented the prediction accuracy of two-week cumulative clipping yield using the two models. The predicted clipping of 2021 was generated based on the ML-RF model built and evaluated based on the data collected in 2019 and 2020. The ratio of predicted and observed clipping yield was close to 1 with by ML-RF model, and therefore it accurately predicted creeping bentgrass clipping yield on both research greens. The ratio of predicted to actual clipping yield with the PACE Turf GP method was significantly higher than random forest model ratio (2.5 and 2.7 for research root zone A and B respectively). The range of the ratio when using the PACE Turf GP model spanned 1.7 to 3.2 for root zone A, and 1.6 to 3.1 for root zone B. The range of the ratio when using ML-RF model spanned 0.6 to 1.2 for both root zones, and if the first clipping collection event was excluded, the range of the ratio improved to 0.8 to 1.2. The PACE Turf GP model treatment had a weak positive correlation between daily clipping yield and NDRE across two years (Fig. 6), while the clipping yield from treatments receiving N from the other three methods was not correlated with NDRE.

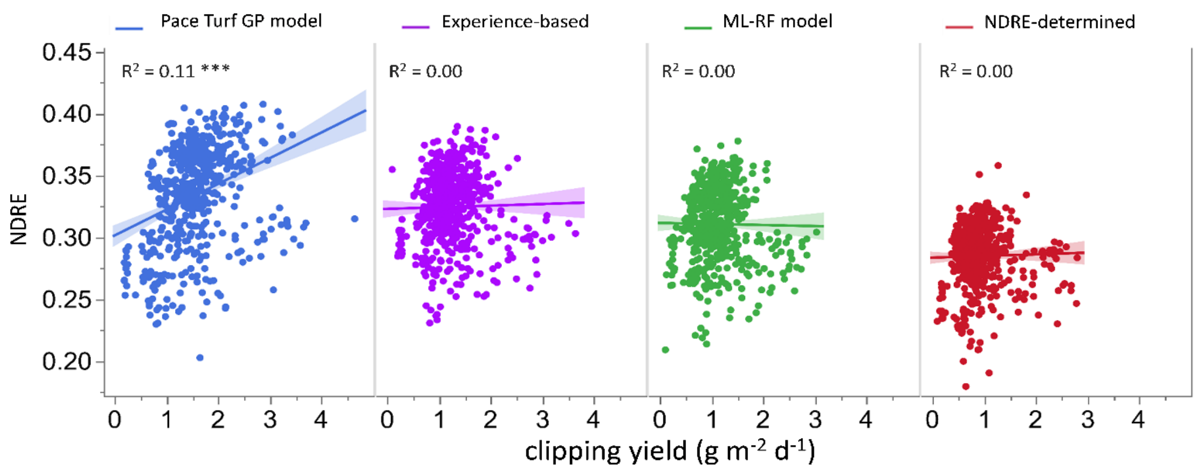

Fig. 6. Correlation between vegetative indices (NDRE) and corresponding creeping bentgrass daily clipping yield, where the turfgrass received four N treatments: 1. PACE Turf GP model: PACE Turf Growth Potential model; 2: experience-Based: traditional N fertilization plan that based on turfgrass quality and manager's experience; 3: ML-RF model: machine learning-random forest growth prediction model; 4: NDRE-determined: vegetative indices (NDRE) determined N fertilization. R^2 followed by ***: significant at p <0.001.

Discussion

Precision nitrogen management requires to satisfy nutrient needs for turfgrass. Vegetation indices like NDRE and NDVI, that formulated based on spectral reflectance have been evaluated as methods to guide N fertilization or quantify turfgrass response to fertilization (Kruse et al., 2006; Bremer et al., 2011a; Lee et al., 2011; López-Bellido et al., 2012a; b; Inguagiato and Guillard, 2016; Guillard et al., 2021). Our study demonstrated there was a weak (PACE Turf GP method) or no correlation between creeping bentgrass clipping yield and NDRE. It is known that NDRE and other vegetative indices can be affected by many variabilities in the field, such as canopy density (Bremer et al., 2011b), turfgrass water status (Caturegli et al., 2020) and plant colorants (Obear et al., 2017). If properties like canopy density was affected by factors other than N fertilizer (such as abiotic and biotic stresses), using NDRE to make

N fertilization decisions could be misguided. However, as NDRE was proved to obtain more objective turf quality than naked eyes when the turfgrass was not affected by the above-mentioned variabilities in a golf course, NDRE or other spectral reflectance could be more useful to improve N fertilization compared to using the traditional N fertilization plan that based on turfgrass visual quality observed by naked eyes, if the management purpose of a golf course is to have a uniform turfgrass quality but without the need of considering N cycle and the amount of resource inputs.

The PACE Turf GP model and ML-RF model were two approaches that attempted to guide N fertilization based on the N cycle. The ML-RF model better predicted creeping bentgrass clipping yield and therefore more accurately estimated N removal from mowing. As temperature is one of the major factors affecting turfgrass growth rate, the PACE Turf GP model can provide an estimation of clipping removal for golf courses in a similar climate zone, but it would not be able to account for other factors that impact turf growth. During the two-year field experiment in Verona WI, USA, the average air temperature during the growing season was 18.7 °C in 2020, and 20.1 °C in 2021 which both were near the optimum temperature for cool-season grass. Therefore, the N fertilization rates applied based on the GP model maintained the turfgrass growth at or close to the maximum growth rate that we selected based on the 2019 growing season (not necessarily the genetic maximum growth potential of the grass). A lower N rate would have resulted with this method if we had selected a lower "maximum" growth rate.

ML-RF model was built and evaluated relied on the previous years' clipping yield and corresponding growth factors, as well current year's weather data, management practices, and vegetative indices, it had been shown to accurately predict creeping bentgrass clipping yield on two research root zones and was able to provide site-specific N recommendation for turfgrass planted on different soil conditions, different micro-climates, and under different management practices. In a short term, the proposed ML approach cannot replace the experience-based method, as each turfgrass site need to build and calibrate the ML model based on the on-site clipping data (Zhou and Soldat, 2021b), but it certainly provides unique and supplementary value in a scalable way. In this study, using this ML-RF model could reduce N fertilization input compared to the traditional experienced-based method without resulting in unacceptable quality. The method is anchored in the N cycle but allows turfgrass managers to adjust clipping yield targets to achieve meet different performance goals. It also does not yet exist in a user-friendly graphical interface, so a decision support tool would need to be created for it to become widely used. With future support from cloud computing and database management, it is possible to expand this approach to every turfgrass field.

Conclusion and Future Work

The aim of the study was to evaluate different methods for deciding how to fertilize golf course putting greens. The results demonstrated that a ML random forest method was able to significantly reduce N fertilizer usage increase N use efficiency, and still maintain a good quality of turfgrass relative to the traditional method for fertilization. While the random forest and PACE Turf GP methods were based on turfgrass growth predictions, the more accurate random forest method was able to more accurately estimate N removal.

Sustainable turfgrass systems integrate the goals of environmentally friendly and economic profitability. Among many resource inputs on turfgrass systems, especially on golf courses, the efficient and effective use of N fertilizer is one of the main drivers for improving sustainability. Our proposed precision N management allows golf courses to use less N fertilizer, meanwhile, the turfgrass is still maintained at a uniform and satisfied quality. Many turfgrass managers of golf courses are beginning to recognize the benefits of regularly measuring grass growth by tracking clipping volume of golf course putting greens, and adjusting N fertilization based on the collected clipping. Precision N fertilization application has the potential to provide economic (i.e. reduced N fertilization input and other resource inputs, such as labor and energy) and environmental (i.e. reduced N leaching and N gases emission) benefits. However, there is not enough research, including economic research and environmental assessment, to evaluate precision N management. A well understanding of the outcome of precision N management could be able to help turfgrass managers to choose the suitable N fertilization methods for various management purposes, such as reduced resource inputs and maximal turfgrass quality

Turfgrass system including golf courses are needed that can provide many beneficial environmental services to our society (Lonsdorf et al., 2021). A more sustainable turfgrass system, then, would enhance the benefits. In the future, turfgrass managers need to embrace innovation, and precision turfgrass management is able to implement new concepts using new technologies. Moreover, while the random forest method is currently not able to be employed by turfgrass managers because a user-friendly application does not yet exist, it has the potential to be an effective strategy for guiding N decisions on golf course putting greens, and likely on other turfgrass areas with additional research and development. Future research should also focus on testing and evaluating the new technologies and concepts, and providing support to turfgrass managers on collecting robust and interpretable data on the users end.

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Summary and Future Work

Improving turfgrass quality while reducing resource inputs, operating costs and environmental pollution is the goal of precision turfgrass management. Turfgrass in golf courses is usually under intensive management to maintain the uniform and dark green color. Nitrogen (N) fertilizer is the most used nutrient in a golf course as it is usually a limiting growth factor for turfgrass. Because there is no reliable soil testing for guiding N fertilization, turfgrass managers mostly make N application adjustments based on turfgrass visual quality and experience. The aim of this study was to provide an alternative N application strategy of precision N management, which was conducted relying on a science-based growth prediction model. As turfgrass clipping is removal and there is a relatively simplified N cycle on the golf course putting green, a good estimation of N removal from mowing is important for making precise and efficient N fertilization applications.

Determining the tissue N content is an important step of precision N management. The first conclusion of this study is that creeping bentgrass tissue N content stay relatively stable during the growing season with various management practice including traffic stress and irrigation plan (expressed as soil moisture content). The creeping bentgrass tissue N content ranged from 2.5 to 5% with an average of 3.9% based on two field experiments in two years. Then this study developed machine learning models to quantify turfgrass clipping removal. Turfgrass growth is a function of soil, management and environment. Then the machine models were built based on interactions of soil, turfgrass, and environment and management practices. The variable input included real-time soil conditions (soil moisture content), weather data, turfgrass response (NDRE) and management practice (foot traffic and N fertilizer). As random forest model has the best performance overall. Three machine learning models were further developed with different intensities of data complexity and a number of features as some golf courses only have the access to limited variables. The best model has the prediction accuracy of $R^2 = 0.64$ which was much better than the existing turfgrass growth model ($R^2 = 0.01$). And the result showed that the proposed N fertilization strategy resulted in a moderate fertilizer applied, and acceptable turfgrass performance. This study also test the using SCB to quantify soil N supply, while we suggested that SCB was not useful for predicting turfgrass growth response, and therefore not considered as variable input for building the machine learning growth prediction model.

Precision N management, a branch of precision turfgrass management, offers the benefit of providing resource conservation by well-understanding turfgrass needs and associated adverse environmental impacts. As the first study to adopt machine learning techniques for improving N management for turfgrass, there is still a long way to go. First, the presence of within-field variability, spatial and temporal, is underlying argument for precision nutrient management. For example, this study found large spatial variability in yield across two different fields in Wisconsin and Minnesota. Yield mapping and soil mapping might be important tools in determining variable rate in the future study. Moreover, the routine of monitoring the soil-plant-environment system is a fundamental aspect of managing plant production for precision turfgrass management including precision N management. As sensing technologies are widely used in many aspects of research and the potential benefit of observing and characterizing the spatial-temporal soil and plant status. With limited research of using combined sensing technologies and growth prediction models on improving N management, there is a great opportunity for future studies to evaluate their applicability in precision turfgrass N management. Lastly, there is a need to develop a decision support system for N management that is built based on the developed machine learning model. It should provide a framework for incorporating various tools and techniques for use-friendly N decision-making.