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REVIEW

Applied Turfgrass Science

A review of precision management for golf course turfgrass

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Abstract

Precision turfgrass management (PTM) is a combination of methods and technologies proposed to increase the resiliency of golf courses by improving input efficiency while maintaining the function and aesthetics of the playing surface. However, there is no recent review describing the status of precision management in turfgrass. The objectives of this review were to (a) summarize peer reviewed research on precision technology for turfgrass management, (b) describe adoption of PTM-based tools, and (c) propose an agenda of research priorities to advance and promote PTM adoption. Of the articles reviewed, 94% documented the accuracy of sensors to detect turfgrass performance and stressors before or during visual symptoms. Only 6% of the research reviewed focused on developing models or decision support systems to quantify the relationship among reflectance, nitrogen uptake, visual quality, biomass production, and irrigation which are required for precision management by golf course superintendents. Efficacy or value of using PTM methods and technologies have not been reported. Golf course superintendents lack of knowledge about PTM, and lack of quantification of benefits of PTM pose limitations to promote adoption. Increasing the adoption of PTM will require research to focus additionally on automating sensor data processing; quantifying costs, benefits, and value of adopting PTM; and simplifying input applications in a PTM system. This review described the status of precision management in golf course turfgrass and shed light into the need for research to develop models and decision support tools for precision management of golf course turfgrass.

1 | INTRODUCTION

Turfgrass is defined as a plant system that remains green for 6 or more months while maintaining a dense contiguous ground cover during dormancy (Steinke & Ervin, 2013). Golf course turfgrass is managed to maintain specific function and aesthetics that vary depending on the intensity of use (Throssel et al., 2009). The intensity of management required on golf course turfgrass drives demand for turfgrass care products and economic expenditures (Haydu et al., 2006). The U.S. golf course turfgrass sector employs more than 300,000 people and produces an estimated 44% of the total economic output of the turfgrass industry at the time of this review, or US$24 billion annually (Haydu et al., 2006). The number of golf courses in the United States, estimated to be 16,000 (National Golf

Abbreviations: DGCI, dark green color index; EC_a, soil apparent electrical conductivity; GIS, geographic information systems; GPR, ground penetrating radar; GPS, global positioning system; IPM, integrated pest management; NDVI, normalized difference vegetation index; PTM, precision turfgrass management; SSMU, site specific management unit; UAV, unmanned aerial vehicle; VARI, visible atmospherically resistant index.

Foundation, 2021) is comparable to the number of golf courses in the rest of the world (Specialty Products Consultants, 2009). Even as the number of golf courses have decreased in the last two decades, the remaining facilities have invested a total of $3.8 billion in renovations during the same period (National Golf Foundation, 2021), suggesting that the golf course turfgrass sector is a large industry willing to invest in improving play for golfers.

Golfers expect the superintendent to maintain turfgrass with lush color, manicured surfaces, and long ball roll on putting greens due to the influence of televised manicured golf courses (Breuninger et al., 2013). Golfer's expectations often increase the use of water, fertilizer, fuel, and pesticides on golf courses. Golf course turfgrass is primarily located in urban areas competing for water with other urban uses and can be viewed as a luxury, making it an easy target for restrictions (Breuninger et al., 2013). New products, technologies, and management methods are needed to increase the resiliency of golf course turfgrass and efficiency of input applications to manage turfgrass function (Breuninger et al., 2013). Precision turfgrass management, defined as precise field applications to target irrigation, fertilizer, pesticide, or cultural applications to meet turfgrass function and aesthetics, offers one such possibility.

Deficit water can reduce the function and aesthetic value of turfgrass, whereas extreme drought can result in complete loss of turfgrass stands. Water, applied through irrigation, is the largest and most important input for golf course turfgrass growth (GCSAA, 2015a). Golf courses in the United States were estimated to use 1.9 million acre-ft of water in 2013, a 22% decrease in water applied from 2005 (GCSAA, 2015a). The median amount of water applied on golf courses ranges annually from 400 acre-ft in the arid and warm Southwest United States to 37 acre-ft in the cool and rainy Northeast (GCSAA, 2015a). Increasing the efficiency of irrigation with precision management would help golf courses reduce cost and environmental impact while maintaining function and aesthetics (Straw et al., 2018).

Nitrogen (N) is the highest volume fertilizer applied on golf courses (Carey et al., 2012; Kussow et al., 2012). Although historically, some golf course superintendents have adjusted N fertilizer rates based on clipping volume or biomass, most continue to rely on seasonal scheduling or inherited knowledge that is not based on more precise quantitative measurements. Golf courses have reduced the N fertilizer applied by 35% from 2006 to 2014. Only 21% of this reduction can be attributed to a change in application rates, whereas 16% has been attributed to a reduction in total fertilized acreage (GCSAA, 2015b). Increasing the efficiency of nutrient applications is important as 24% of golf courses reported restrictions on nutrients in 2015, compared with 8% in 2006 (GCSAA, 2015b). Precision management of N fertilizer applications would increase N use efficiency reducing detrimental effects of overapplication on the surrounding environment.

Core Ideas

- Precision turfgrass management is proposed to increase golf course resiliency.
- Research has focused on measuring performance and stressors of turfgrass.
- Superintendents' lack of knowledge about precision turfgrass management poses a challenge toward future adoption.
- Future research should focus on developing precision turfgrass management decision support systems for golf course turfgrass.

Diseases, weeds, and insects reduce turfgrass playability and aesthetics, requiring pesticide applications to prevent or reduce the infected area. Fungicides are the most sold pesticide on golf courses accounting for more than $170 million of fungicides sold annually (Specialty Products Consultants, 2009). Herbicides are the second largest pesticide economic input on golf courses with more than $80 million of herbicides sold annually (Specialty Products Consultants, 2009). Insecticide sales account for $24 million of annual pesticide sales on golf courses (Specialty Products Consultants, 2009). Golf courses increased reliance on fungicides and herbicides by 4 and 2% from 2007 to 2015, respectively, and reduced insecticide usage by 4% during the same period (GCSAA, 2016). During the same time period, 2007–2015, golf courses reported an increase in their reliance on integrated pest management (IPM) practices by 66% (GCSAA, 2016). The IPM practices adopted included scouting for pests, monitoring weather, rotating pesticides, spot treatments, and improved plant health (GCSAA, 2016). Precision management of pesticides could increase the resiliency of golf courses by reducing overapplication of pesticides while controlling pest outbreaks.

Golf course superintendents manage areas of turfgrass such as roughs, tees, fairways, and putting greens differently, depending on the function. Precision turfgrass management (PTM) is suggested to improve the management of golf courses by increasing input efficiency throughout areas of the property (Carrow et al., 2010). The precision agriculture and conservation concept of applying inputs (i.e., water, fertilizer, pesticides, etc.) where, when, and in the amount needed is adopted in PTM. Geo-referenced sensors and geographic information systems (GIS) are used in PTM, precision agriculture, and conservation to develop management plans that address spatial and temporal variability to increase input efficiency (Corwin & Lesch, 2005; Delgado & Berry, 2008). Maintaining consistent function is a goal of PTM by using technology to increase the micromanagement of resources for efficient irrigation, fertilizer, and pesticide applications (Bell & Xiong, 2008; Bell et al., 2013; Krum et al., 2010). Economic, environmental, and societal factors are catalysts for research and adoption of PTM to increase the efficiency of input applications through site-specific management (Beard & Kenna, 2008; Carrow et al., 2010). There are no reviews of PTM methods and technologies which could help direct future research into precision management of golf course turfgrass.

The adoption of PTM can allow golf course superintendents to maintain playability and aesthetic goals of golf and increase the efficiency of input applications. Precision turfgrass management adopts the precision agriculture concept of applying inputs to increase the site-specific efficiency of irrigation, fertilizer, and pesticide applications to increase resiliency and reduce environmental impact on golf courses. Reflectance sensors and GIS technology research is needed to create adoptable methods and decision support systems to help golf course superintendents to increase management efficiency. The objectives of this review were to (a) summarize peer reviewed research on precision technology for turfgrass management, (b) describe current precision turfgrass research and adoption, and (c) propose an agenda of research priorities to promote PTM adoption.

2 | METHODS

More than 270 studies were selected for review based on following criteria: published in a peer-reviewed journal, available in the English language, conducted in the laboratory or field over the course of at least 1 year, precision management or technologies and remote sensing studied on turfgrass. This review includes studies conducted on plot-scale experiments, operational golf courses, and in the laboratory. Relevant studies researching remote-sensing technologies on turfgrass management on golf courses, sports fields, and lawn management systems were included. The time frame for articles were chosen from 2000 to 2022 to review turfgrass science articles concurrent to the start of research defining PTM up to current day.

Journal articles were collected from the Web of Science databased from Clarivate Analytics and Scopus on 17 Aug. 2021, with the search statement "TS = (turfgrass) AND (precision or remote sensing)" restricted to journal articles in English among all publication dates and database indices. The Web of Science search produced 85 unique journal articles, and the Scopus search produced 71 journal articles. The Turfgrass Information File (Michigan State University) was searched on 18 Aug. 2021, with the search statement "precision or remote sensing" restricted to journal articles in English among all publication dates and database indices. The Turfgrass Information File search produced 119 unique journal articles. Additional articles were selected based on their importance to the adoption of PTM or how they documented current PTM research. There was a total of 275 journal articles produced among all searches, after redundancies 170 journal articles were identified.

The peer-reviewed papers were ordered by publication date and selections started with the most recent published papers. Abstracts were read to determine if papers met the objectives of this review focused on precision management and technology. Papers that used remote sensing to document turfgrass occurrence for land classification or ecological analysis of water use were not considered and made up the majority of the 170 unique journal articles found in databases. After selection, 78 articles were used in this review including articles that were not found in the database searches. The experimental treatments, treatment levels, and statistically significant, as reported by authors, were summarized.

3 | RESULTS

In this review 78 studies were analyzed, and we arbitrarily grouped the literature into the following five groups: GPS, remote sensing, imagery, electrical conductivity, and acoustic sensors. The peer reviewed research was used to determine gaps in the research and suggest research priorities to increase PTM adoption on golf courses.

3.1 | Global positioning system research for precision turfgrass management

Increasing the efficiency of input applications requires georeferenced sensors to measure and locate turfgrass performance and stressors. Current GPS research quantified spatial variability of soil volumetric water content (Krum et al., 2010; Straw et al., 2016), variation of sports turfgrass fields (Straw & Henry, 2018), or soil EC_a (Ganjegunte et al., 2013; Grubbs et al., 2019). Straw et al. (2017) and Krum et al. (2011) reported the use of sensor technology to accurately describe the spatial variability of soil and plant parameters on sports turfgrass fields by defining the number of samples needed to document the variability. Georeferencing locations of insect populations could be used to develop precision insecticide applications. The spatial variability of annual bluegrass weevil (*Listronotus maculicollis*) limited the ability of McGraw et al. (2009) to detect statistical significance of nematode treatments and future research was needed to determine how to locate annual bluegrass weevils. Diaz and Peck (2007) reported that location of annual bluegrass weevil varied among the type of habitat on golf courses with higher populations in higher mown rough, than lower mown putting greens. Gireesh et al. (2021) reported that hunting billbug (*Sphenophorus venatus vestitus*) larval population exhibited 12.8 ft range of spatial dependence and suggested that georeferenced 13.1-ft samples should accurately quantify the spatial variability of hunting billbug population on sod farms.

Locating disease infestations with geo-referenced imagery or sensors can help reduce the negative effects diseases may have on turfgrass function or aesthetics. Dollar spot (*Sclerotinia homoeocarpa* Bennett) has been reported to exhibit a stable pattern of spatial aggregation throughout the growing seasons on creeping bentgrass and annual bluegrass (*Poa annua* L.) stands (Horvath et al., 2007), which is similar to the spatial aggregation of large patch (*Rhizoctonia solani* L.P.) on zoysiagrass (*Zoysia japonica* Steud.) (Spurlock & Milus, 2009). Booth et al. (2021) reported that unmanned aerial vehicle (UAV) imagery can classify areas of and control spring deadspot (*Ophiosphaerella* spp.) on fairways whereas sprayer hardware and spring deadspot image classification methods need to improve for individual nozzle control. Henry et al. (2009) documented the distribution of dallisgrass (*Paspalum dilatatum* Poir.) and bahiagrass (*Paspalum notatus* Fluegge) in fairway and rough turfgrass with a GPS unit and reported that both weeds had higher plant densities in moderately compacted soil. Adopting GPS sampling and sprayers enabled with individual nozzle control could reduce application time and product usage as the sprayer would apply inputs only where desired, whereas this has not been reported.

3.2 | Remote sensing research on turfgrass

Spectral reflectance is a reliable, nondestructive method correlated with visual assessments to estimate turfgrass stressors (Trenholm et al., 2000). Measurements of canopy reflectance provide routine and frequent data which can be correlated to turfgrass health, visual quality, color, or function (Bell et al., 2004; Bell & Xiong, 2008). Canopy reflectance measurements reduce time spent rating visual quality by 58% compared with visual evaluation (Bell et al., 2009; Sullivan et al., 2017). Multispectral sensors typically measure wideband canopy reflectance whereas hyperspectral sensors measure narrowbands of canopy reflectance increasing the time for data processing. Hutto et al. (2006) reported that hyperspectral reflectance can differentiate between zoysiagrass, St. Augustinegrass (*Stenotaphrum secundatum* Walt.), common centipedegrass (*Eremochloa ophiuroides* Munro), and creeping bentgrass (*Agrostis stolonifera* L.) and the weed species: dallisgrass (*Paspalum dilatatum* Poir.), southern crabgrass (*Digitaria ciliaris* Retz.), eclipta (*Eclipta prostrata* L.), and Virgina buttonweed (*Diodia virginiana* L.) with 85% accuracy. The authors suggested future sensor research should focus on determining specific wavelengths to increase accurate classification among species.

Hyperspectral sensors detect critical soil water content 1 day before visual drought symptoms occur with an r^2 of .64 (Dettman-Kruse et al., 2008). An et al. (2015) suggested hyperspectral reflectance data can determine the most appropriate wavelengths to determine turfgrass stressors. The water band index measurements from hyperspectral sensors have been reported to exhibit a strong relationship to soil volumetric water content suggesting that the water band index can be used to monitor for turfgrass water stress aside other plant stressors measured by other vegetation indices (Badzmierowski et al., 2019; McCall et al., 2017; Roberson et al., 2021). Multispectral data are typically wideband measurements of canopy reflectance, often lacking the fine detail needed for differentiating stressors, whereas they are much easier to process because of the fewer number of bands measured.

Vegetation indices calculated from reflectance are universal methods of measuring turfgrass performance or stressors. Normalized difference vegetation index (NDVI) and red vegetation index are highly correlated with visual quality (r^2 of .71 and .73, respectively) (Fitz-Rodriguez & Choi, 2002). Vegetation index measurements of turfgrass from proximal, UAVs, or satellite sensors accurately discriminate among different cultivars or species and are highly correlated among sensor platforms with r^2 ranging from .83 to .99 (Caturegli et al., 2014; Caturegli, Lulli, et al., 2015). These findings suggest that turfgrass superintendents and researchers can use sensor platforms that best fit their operations. Multiple vegetation indices measured from different sensor platforms are reported to discriminate among N status which could be used to pinpoint areas that need varying rates of N to maintain consistent function (Baghzouz et al., 2006, 2007; Caturegli, Casucci, et al., 2015; Caturegli et al., 2016; Flowers et al., 2010; Guillard et al., 2021). Caturegli, Grossi, et al. (2015), Johnsen et al. (2009), and Kruse et al. (2006) reported that NDVI detects drought stress up to 47 hours before visual symptoms which could determine locations where irrigation is needed to maintain aesthetics. The water band index has been reported to be a better measure of plant water content than NDVI because it estimates the moisture limitations within a plant canopy (Badzmierowski et al., 2019; McCall et al., 2017; Roberson et al., 2021). Roberson et al. (2021) reported that water band index predicted moisture stress 12 hours before 50% visual estimation of wilt, compared with only 2 hours using NDVI. Vegetation indices can detect insect feeding on lawn-height turfgrass 10–16 days before visual damage symptoms which could be used to prescribe precision insecticide applications (Hamilton et al., 2009). Vegetation indices, like NDVI or red vegetation index, remotely can detect differences in turfgrass reflectance caused by moisture stress, N status, or insect

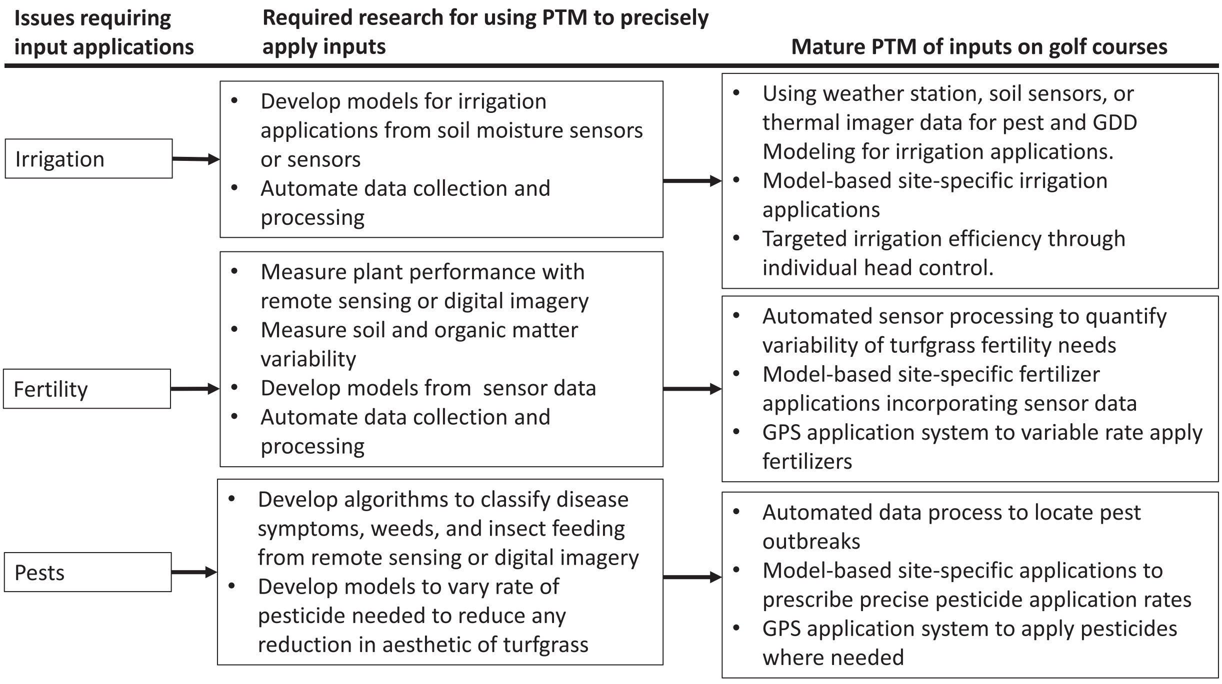

FIGURE 1 Workflow of proposed research to achieve mature adoption of precision turfgrass management (PTM) managing input applications on golf course turfgrass

feeding, whereas vegetation indices alone cannot distinguish among stressors.

Few publications developed models to quantify the relationship among reflectance, N uptake, visual quality, biomass production, and irrigation. Flowers et al. (2010) reported that a linear plateau model quantifies the relationship between N uptake and NDVI on perennial ryegrass seed fields. The authors suggested that developing a prescription N fertilizer model would be the next step, comparable to those developed for row crops (Scharf et al., 2011). Canopy reflectance measurements should be incorporated into breeding programs to aid golf course superintendents in selecting cultivars based on potential biomass production and salinity tolerance. Vines and Zhang (2022) suggested that canopy reflectance would allow turfgrass breeders to assess larger numbers of turfgrass genotypes to efficiently identify elite germplasm to cultivar development to meet the future demands of the turfgrass industry. Three derivations of NDVI and a red edge position vegetation index are positively linearly correlated with Kentucky bluegrass (*Poa pratensis* L.) biomass production (Poss et al., 2010). The authors reported that NDVI has a negative linear correlation between Kentucky bluegrass cultivars and salinity. Turfgrass water content and NDVI, soil adjusted vegetation index, and visible atmospherically resistant index (VARI) exhibit nonlinear relationships (Taghvaeian et al., 2013). Models of vegetation index response to turfgrass growth and stressors are required to develop decision support system tools for precision management.

3.3 | Imagery research for precision turfgrass management

Thermal imagers have been reported to detect turfgrass drought stress before visual symptoms. Hong et al. (2019a) reported that thermal imagers on UAVs detect drought stress 5 days before visual symptoms on creeping bentgrass. Thermal imaging detected rises in creeping bentgrass canopy temperature before visual silt using UAVs whereas all canopy reflectance vegetation indices other than the GreenBlue vegetation index, were not able to discriminate among rises in canopy temperature (Hong et al., 2019b). Taghvaeian et al. (2013) reported that thermal imagery measuring turfgrass canopy temperature can be used in the Grass Water Stress Index to identify both the timing and amount of irrigation needed similar to a complex surface energy balance model approach. Thermal imagers are another tool that golf course superintendents can use to monitor and schedule irrigation applications to mitigate drought stress and wilt. Geo-referencing thermal images would provide exact locations to increase the efficiency of water applied.

Visual cameras, or digital imagers, detect turfgrass disease stress and N status faster and more precisely than visual ratings. Richardson et al. (2001) reported that digital image analysis estimates of green bermudagrass turfgrass cover exhibited high correlation to calculated values of turfgrass cover (r^2 = .99) and reduced the mean error of percentage cover compared with traditional visual estimation methods.

Digital image-based Dark Green Color Index (DGCI) was also reported to have a strong relationship with visual quality ratings while reducing the mean error compared with the multiple ratings, and time spent processing to determine color (Karcher & Richardson, 2003). Analyzing turfgrass cover and color with digital image analysis was also reported to reduce processing time by more than 24 hours providing turfgrass breeders more efficient methods to assess cultivars (Karcher & Richardson, 2005). Zhang et al. (2019) reported that UAV-based camera images used to calculate NDVI and VARI predicted percentage ground cover with r^2 of .86 and .87, respectively. Camera-based digital image analysis is a tool that turfgrass breeders can use to quantify turfgrass cover and color more reliably while reducing time spent sampling, processing, or rating the turfgrass.

Visual cameras have been reported to provide accurate methods to locate disease symptoms on turfgrass and reduce total fungicides applied. Digital image analysis of camera images is more precise at estimating brown patch (*Rhizoctonia solani* L.) infestation on tall fescue (*Festuca arundinacea* L.) from 0 to 100% disease severity than visual estimation (Sykes et al., 2017). Booth et al. (2021) reported that UAV-based digital image analysis classifying spring deadspot on bermudagrass fairways resulted in 51 and 65% less fungicide applied while achieving similar control as the broadcast fungicide application. Cameras could be used to create prescription fungicide application maps based on the location of disease-infested areas.

Camera-based systems would provide turfgrass superintendents and researchers an affordable, time-saving tool to assess turfgrass performance. Image-based DGCI is highly correlated with N status of bermudagrass (*Cynodon dactylon* L.) and tall fescue with r^2 of .86 and .95, respectively (Caturegli et al., 2020). Visual quality of tall fescue is highly correlated with DGCI as r^2 ranges from .88 to .94 (Ghali et al., 2012). Lopez-Bellido et al. (2012) and Agati et al. (2015) suggested that camera-based analysis of N status is as precise as visual estimation. Richardson et al. (2010) quantified a digital image analysis-based method to quantify golf ball lie on fairway and rough turfgrass that had similar coefficient of variation as the manual Lie-N-Eye system, while reducing time measuring ball lie. The Lie-N-Eye system quantifies ball lie, or the amount of the ball exposed above the turfgrass canopy, using a caliper (Cella et al., 2004) making the system more labor intensive than imagery. Imagery can provide affordable data collection and could be used with reflectance to determine inputs needed to maintain turfgrass function.

The analysis of digital images can discriminate between turfgrass and weeds to develop prescription herbicide applications reducing the environmental impact of herbicides. Convoluted neural networks, an advanced data science technique, classifies broadleaf and grass weeds in bermudagrass and perennial ryegrass (*Lolium perenne* L.) with between 51 and 99% accuracy (Yu et al., 2019a, 2019b; Yu, Schumann, et al., 2019; Yu et al., 2020). Xie et al. (2021) reported that a convoluted neural network algorithm classifying yellow and purple nutsedges (*Cyperus esculentus* L. and *C. rotundus* L., respectively) in a bermudagrass stand reduced processing time by 95% compared other convoluted neural network methods. Advanced data science techniques should be utilized for rapid image classification for see-and-spray application systems to increase herbicide efficiency. Hunter et al. (2019) used UAV-based imagery to classify weeds and create precision herbicide application maps. The authors reported that precision herbicide applications were 30–300% more efficient in identifying and treating weeds while reducing herbicide inputs by 20–60% compared with broadcast herbicide applications. Imagery can increase the precision of herbicide applications whereas user-friendly software needs to be developed to automate data processing.

3.4 | Electrical conductivity and ground penetrating radar precision turfgrass management research

Soil apparent electrical conductivity (EC_a) measured from electromagnetic induction or electrical resistivity sensors quantifies the distribution and variability of soil salinity, leaching, clay, and organic matter content. Soil salinity is a problem for golf courses that receive recycled water or in geographies with saline and/or sodic soils. Krum et al. (2011) reported that EC_a quantified the spatial variability of salinity and leaching potential on a Florida golf course and was highly correlated to laboratory saturated paste extract electrical conductivity with r^2 of .59 and .87 for salinity and leaching, respectively. Locating high levels of salinity in soils could help turfgrass superintendents to focus their remediation efforts to reduce the effect of the saline soils on turfgrass performance and aesthetics. Ganjegunte et al. (2013) reported that EC_a accurately quantifies soil electrical conductivity and reduces time and money spent compared with destructive soil tests. Geo-referenced EC_a quantified by measuring electrical resistivity is reported to have a location-dependent relationship with clay and organic matter content (Grubbs et al., 2019). The authors suggested that additional research is needed to understand how to use EC_a to develop soil-based site-specific management units (SSMUs).

Ground penetrating radar (GPR) research has been reported to map belowground drainage pipe systems on putting greens (Allred et al., 2005, 2008; Boniak et al., 2008; Freeland et al., 2014). Allred et al. (2016) reported that GPR can be used to quantify soil volumetric water content of putting green sand layers with strong spatial correlation in three of four dates sampled ($r > .70$), whereas the sand layer depth is needed to accurately map the sand layer water content on putting greens.

Allred et al. (2016) also reported that GPR systems reported similar soil volumetric water contents in the sand layer as time domain reflectometry. Sports turfgrass field compaction using a georeferenced GPR system produced similar maps of surface hardness of using a Clegg Impact soil tester (Freeland et al., 2008). Measuring soil compaction on golf courses using a georeferenced GPR system could provide superintendents locations of where irrigation of cultivation is needed to maintain function and aesthetics. Nondestructive sampling of soil volumetric water content and soil compaction using GPR is another technology adapted from precision agriculture with uses that can help reduce the variability of turfgrass function and aesthetics.

3.5 | Acoustic sensor research for precision turfgrass management

Acoustic sensors use sound to detect or estimate insect prevalence and are suggested to geolocate insect populations in turfgrass systems providing a method prescribe site-specific insecticide applications. Brandhorst-Hubbard et al. (2001) reported that using geostatistical analysis to map acoustic sensor measurements of soil invertebrates had significant positive correlations ($r^2 > .50$) suggesting that it was a potential tool detect insect pests in soils. Acoustic sensors estimate the number of insects feeding on roots with greater accuracy, 81–92%, than the cup-cutter method which had 38% accuracy (Zhang et al., 2003a). The acoustic sensors were also more accurate at quantifying the number of insects present at economic injury level requiring insecticide applications, providing an additional method to tailor prescription insecticide applications. Zhang et al. (2003b) reported that acoustic sensors monitoring white grub populations in bluegrass (*Poa arachnifera* Torr) reported detectable sounds 25% of the time at temperatures at or below 48.2 ˚F. Acoustic sensors can nondestructively monitor insect populations in turfgrass stands, but the accuracy of these measurements can be reduced at low temperatures.

3.6 | Gaps toward adoption of precision turfgrass management

Generally speaking, golf course superintendents' lack of knowledge about PTM methods and technologies poses a challenge toward future adoption. Straw et al. (2020) reported that no members of a small group of superintendents interviewed understood the intricacies of processing data required to incorporate PTM methods on their course. The authors reported that the major barriers of PTM adoption were the lack of hands-on experience, attitude toward executing elaborate management schedules, insufficient management of physical resources, and skepticism of the proposed benefits. A decade earlier, Carrow et al. (2010) reported similar barriers to PTM adoption: lack of training, decision support systems, and criteria to assess the benefits. Both studies suggest the need to develop simplistic management methods using technologies that do not increase the number of input applications. Research assessing and quantifying the benefits and costs of adopting PTM need to be performed and reported to increase adoption.

More than 90% of articles reviewed focused on using sensors or imagers to detect differences, whereas <10% developed models or decision support systems for prescription applications. New research should develop models and decision support systems to determine correct product and application rates for desired function and aesthetic goals similar to how precision agriculture research has focused on developing models and tools for farmers. Guillard et al. (2021) developed fall-applied prescription N application models for lawn-height turfgrass in the Northeast United States, providing a PTM method for lawncare providers and homeowners to apply N more precisely to meet the turfgrass N needs. Straw et al. (2020) developed a method to create SSMUs from time domain reflectometry soil volumetric water content data. The author's method is the only report that provides superintendents a step-by-step guide to create SSMUs using free GIS software. Research that develops software to automate data processing and recommendations for superintendents should decrease the difficulty associated with adopting PTM.

Minimal research programs have focused on educating superintendents on using software to process and interpret geo-referenced sensor data for prescription input maps (Straw et al., 2020). The authors reported that no superintendents interviewed know how to perform processes for prescription input applications. Superintendents are unsure whether to dedicate an employee or hire a company to process and interpret sensor data for input applications (Straw et al., 2020). Educating superintendents on how to use GIS software to process and interpret sensor data is needed. Companies should develop software to automate data processing, thereby reducing time and labor required for data interpretation. Existing precision agriculture software companies could also tailor their software for golf course turfgrass markets. Decision support systems should be developed to use all available data to recommend the most appropriate inputs.

Although autonomous UAVs, sprayers, mowers, and reflectance data collection technology exists, replacement of labor-intensive management required to maintain function and aesthetics will only occur when these autonomous systems become more common. Automated sensor data processing for site-specific applications using GPS or see-and-spray systems are used in agriculture and could be used on golf courses when biological models are developed (Figure 1).

Machine learning or computer vision could decrease the time to classify pests (weeds, diseases, and insects), stress (drought, heat, or shade), and develop models for prescription applications (Figure 1). New equipment used in the future on golf courses will likely be autonomous and require technical knowledge to interpret data as PTM technology are adopted from precision agriculture technology which are becoming automated. Superintendents will need to learn about hardware, software, and data science to manage an automated and interconnected golf course.

Increasing the adoption of PTM will require research to focus on: (a) developing biological models and decision support systems to determine the most appropriate input and prescription input applications, (b) automating sensor data processing, (c) quantifying the costs, benefits, and value of adopting PTM, and (d) simplifying the input applications in a PTM system.

4 | CONCLUSIONS

Methods and technologies associated with PTM are proposed to provide golf courses with increased resiliency and provide protocols for end-users to lower inputs while maintaining function and aesthetics. Of the articles reviewed, 94% documented accuracy of sensors to detect turfgrass performance and stressors before or during visual symptoms. The remaining 6% of papers reviewed developed models or decision support systems from sensor data to guide management decisions. Current peer reviewed literature does not document adoption rates of PTM on golf courses. The literature does document the lack of knowledge among superintendents and lack of quantification of the benefits of PTM posing a limitation to promote adoption. Future research should develop decision support system tools that integrate sensors, models, and precision equipment for prescription input applications. Companies and researchers should focus on automating data collection, processing, and interpretation for input applications by GPS and computer guided sprayers.

AUTHOR CONTRIBUTIONS

Michael G. Carlson: Conceptualization; Data curation; Methodology; Project administration; Writing – original draft. Roch E. Gaussoin: Writing – review & editing. Laila A. Puntel: Supervision; Writing – review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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