Quantifying the Efficiency of Golf Course Resource Use

By

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doctorate and nor did I ever feel any pressure from them to do so. While I did not discount the idea; I simply had not thought that far ahead. Nonetheless, I was fascinated by the world they worked in, but I also remember many of their stories about the trials and tribulations of advising graduate students. I remember them saying that a doctorate tested everyone, and that it tested the whole person, not just the scientist. Dad often framed a doctorate in terms of the personal growth that occurred as much as he did in scientific terms. I remember wondering and being curious about what going through that gauntlet would be like and whether I could do it. How might I be tested? In what ways might I change? I know the answers to those questions now, and I could fill another dissertation with them because I know that completing a doctorate has been the most challenging endeavor I have tackled thus far. It challenged me personally and professionally more than I thought it would, but it left me a stronger, more resilient, and confident person. In the last five years, I experienced genuine struggle, genuine success, and every emotion in between. Thank you, Mom and Dad, for always being there for me.

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With great appreciation,

Michael, July 26, 2022

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Abstract

The goal of this study was to develop a method to quantify the efficiency of water, energy, fertilizer, and pesticide use on golf courses. Information on golf course resource use, best management practices, and basic facility demographics were collected through a survey, which were received from five regions of the US (Midwest, Northeast, Northwest, East Texas, and Florida) and three countries in Europe (Norway, Denmark, and UK). With these data, seven ecosystem models were used to quantify water and fertilizer requirements, evaluate pesticide risk, and calculate energy use and carbon footprints. The Tipping Bucket model, which uses a soil moisture-based approach to determine water requirements, accurately predicted golf course water usage when averaged across all regions of the study. The Growth Potential Nitrogen (N) Requirement model was used to predict N use on golf courses; it overpredicted golf course N requirements and was recalibrated to predict mean N use for golf courses in the study. The Environmental Impact Quotient (EIQ) and Hazard Quotient (HQ) models showed that, despite a wide range of climates, pesticide risk for each of the five regions studied in the US were not statistically distinguishable. Pesticide risk in the UK, Norway, and Denmark was significantly lower than in all regions of the US. Carbon footprint analyses revealed that 63 percent of golf course greenhouse gas (GHG) emissions originate from fuel and electricity use. Economic factors such as maintenance budget and environmental factors such as grass and soil type were limited in their ability to predict resource use efficiency. The rate of adoption of a range of resource efficiency best management practices was not predictive of water, energy, fertilizer, or pesticide use efficiency. Lastly, an eco-efficiency model, the ratio of social or economic outputs

to resource inputs, was developed to score a golf courses ability to turn resource inputs into rounds played and profit generated.

Chapter 1 – Introduction and extended acknowledgment

1.1 A history of the project

The ideas that led to this project formed while working for the Golf Environment Organization (GEO) in 2016. GEO certifies golf courses for their commitment to sustainable practices, but, at the time, the assessment process used for certification was entirely qualitative. Golf course personnel who applied for certification were required to report and make public their resource use, but that information was not yet systemically analyzed by GEO's employees, who were interested in exploring quantitative tools that would allow them to determine the resource efficiency of a given course. As part of this inquiry, I began searching both peer reviewed and industry literature for methods by which the efficiency of water, energy, fertilizer, and pesticide use on golf courses could be quantified. There were methods for quantifying the efficiency of some resources used on golf courses (i.e., water budgeting) but these methods were at an early stage of development. More importantly, I could not find a study that presented an overarching framework for how to evaluate the resource use efficiency of a golf course. The prevailing assumption was that such a comparative method was not achievable given the myriad site-specific factors that characterize golf courses (e.g., climate, soil, course area, course type and so on), and that analyzing resource use across courses within a given region, much less across climates, would not yield results that could be used to develop an evaluative tool. However, it seemed that creating a method for which the efficiency of golf course resource use could be compared across climates would be possible if all the relevant normalizing factors were considered. Believing that this was at least worth an attempt, I began to outline how such a project could work in a proposal that I eventually sent to several university turfgrass programs across the US. Dr. Doug Soldat was supportive of the idea, agreed to fund it, and the project began to take shape at UW-Madison in the fall of 2017.

The objective of the project was to create a framework within which we could quantify golf course resource use, estimate the efficiency of a given resource's use while considering site specific factors (e.g., climate, soil, area of the golf course etc.), and identify those factors that explain the variance in a given resource's use efficiency across golf courses.

Originally, my plan was to use the GEO certified database to build such a framework. However, after exploring the resource use data in the GEO database during the first year of this project, we determined that data collected by GEO was of insufficient quality or detail on which to build a reliable foundation for this project.

Instead, we decided to build our own database of golf course resource use information so that we could collect the exact data needed. These efforts resulted in the *UW-Madison Resource Efficiency Survey*. The survey, which was designed for golf course superintendents, requested detailed facility information (e.g., course type, maintenance budget, number of rounds etc.), best management practice uptake information, and comprehensive data on water, energy, fertilizer, and pesticide use. An initial draft of the survey was developed in the spring of 2018. During the summer and fall of 2018, I met with superintendents individually with the goal of their providing feedback to improve the survey. While I had experience with surveys from my work at GEO, I could never have anticipated how challenging and time-consuming a task it became to administer this survey. I was constantly changing the wording, the questions, the order of the questions, adding questions, and removing others. The survey evolved after every round of data collection beginning that first summer and continued throughout the next three years.

In the fall of 2018, the survey was uploaded to Qualtrics so that it could be distributed via email and taken online. Survey distribution occurred primarily between January and April at a time when most golf course superintendents in the northern US and Europe, where the majority of the data originated, are not as busy as they are during the growing season.

The first survey distribution attempt in this project was made through the Wisconsin Golf Course Superintendents Association (WGCSA). I presented the project at the 2019 WGCSA spring business meeting, which was followed by an email blast to all WGCSA members. These initial efforts yielded only ten responses out of the 198 golf course superintendents in the association, a far lower response rate than we had hoped for and a sobering moment.

Admittedly, the survey was long with 131 questions; it often took several hours for superintendents to complete, which limited the number of superintendents willing to take the survey. However, all the information in the survey was useful and most of it was critical to the success of this project. As a result, we decided to slightly reduce the level of detail and extended the data collection period.

During the summer of 2019 I visited golf course superintendents in the greater Madison area in person to help them complete the survey. I also traveled to New York to visit the New York State Park golf courses which have a long history of working with the Cornell Turfgrass Program and committee member on this project, Dr. Frank Rossi. These efforts yielded nine more responses.

In the fall of 2019, we continued to tweak the survey with the help of the UW Survey Center in an effort to make the survey easier to navigate, more user friendly, and to refine our distribution strategy without compromising the content gathered. From January to April 2020, more emails were sent asking the WGCSA membership to take the survey. The Minnesota Golf Course Superintendents Association (MSGA) also distributed the survey to their membership. These approaches yielded 33 responses. The increased number of responses compared with our initial attempts perhaps were aided by a greater awareness of the project. While many of these responses were incomplete, the dataset from the Midwest and New York was determined to be of sufficient size for the objectives of the project.

In January to April 2021, we expanded our efforts by building partnerships with turfgrass extension specialists in five additional US states, Montana, Oregon, Texas, Arizona, and Florida, and four European countries where English is either a primary or secondary language because the survey was written in English: Norway, Denmark, Sweden, and the UK. The survey was distributed to golf course personnel in each region via the extension specialists who live and work within that region. To encourage superintendents to respond to a detailed survey run by a research group they were likely unfamiliar with, we awarded up to $100 for a completed survey response in this final year of data collection. Our goal was to achieve at least five survey responses from each region. This was achieved in Texas, Florida, Norway, Denmark, and the UK, but unfortunately not in Montana, Oregon, Arizona, and Sweden. After three years of effort, we closed survey data collection in April 2021. We had received a total of 149 responses, 64 of which were greater than 95% complete.

Equally critical to the success of this project was the development of ecosystem models that could estimate the efficiency of golf course resource use. The pesticide risk indicator models that we used, Environmental Impact Quotient (EIQ) and Hazard Quotient (HQ), are mathematically simple and were constructed in Microsoft Excel. Dr. Paul Koch and Kurt Hockemeyer were incredibly helpful in setting up these models. We decided to calculate pesticide risk for each golf course component over a three-year period using a range of absolute (total) risk and area normalized risk metrics. We also calculated pesticide use intensity with the area treatment model. Calculating pesticide risk and pesticide use intensity on every golf course component, breaking pesticide risk into fungicide, herbicide, insecticide, and plant growth regulator risk within each component, calculating risk using both EIQ and HQ, and doing all of this over a three-year period resulted in over 1,200 pesticide metrics calculated for every golf course, which were summed, weighted, and averaged in various ways to generate the metrics of pesticide risk presented in Chapter 1 and 2. However, the hardest part of the pesticide risk calculation was not the model construction, but the recording of golf course pesticide records. Golf course pesticide records were uploaded to our survey in nearly as many formats as there were golf courses in the study, and few were in a format that could be directly entered into our model. Thus, pesticide applications at a golf course had to be entered manually into spreadsheets in a format the model could read. Pesticide risk was calculated over a three-year period on 68 golf courses. Each year of pesticide data entry took an average of three hours of effort. Pesticide data entry for this project alone took over 800 hours. I am grateful to the many undergraduate students who helped during this pursuit, and I strongly advocate that superintendents shift to a software-based pesticide recording system. Lastly, we had to build a database that included information on active ingredients, toxicity, and use rate for every pesticide applied on the 68 golf courses in the study. Dr. Paul Koch and Kurt Hockemeyer lent me the database they had used for a similar project on golf courses, which included approximately 250 products. At the completion of this project, the pesticide database contained over 500 products.

I began developing the life cycle analysis model that I used to estimate energy use and carbon footprint of a golf course while working at GEO. However, by the time that I left GEO, the model was still incomplete, and I finished constructing it in Microsoft Excel during this project. The model is mathematically simple, but as with pesticide modeling, there were many input and output variables to manage. For both the energy model and carbon footprint model there were 110 input metrics and approximately 250 output metrics, which were summed, weighted, and averaged in various ways to generate the results in Chapter 4.

Determining how to develop models to predict golf course water and fertilizer use was significantly more challenging. Previous attempts to predict golf course water use used outdated water budgeting approaches from the EPA Water Sense Program. For fertilizer, the Growth Potential N Requirement Model, which was developed collaboratively by PACE Turf and the Asian Turfgrass Center, estimates the N fertilizer requirement of a golf course. Unfortunately, there were no published results describing how the model performed as a predictive tool for golf course N requirements.

To understand how to improve the water and N budgeting methods, I met with many experts across the UW campus. Unfortunately, the results of these early meetings were largely unproductive. The approaches suggested involved coding new models from scratch, which, given the breadth of this project, was beyond what I could reasonably learn to do within the time frame of this project. Everything changed when I enrolled in Dr. Chris Kucharik's Environmental Biophysics class in the fall of 2018. I met with Chris early in the semester and described the approaches that had been taken to predict water and N requirements on golf courses. Chris became interested in the project, and to my great delight offered to collaborate. He recommended that we use the water and nutrient balance capability in the Agro-IBIS model. Agro-IBIS is a process-based ecosystem model that simulates a wide range of ecosystem processes. However, even though the model existed, we quickly realized that I would not have the time to parameterize and validate Agro-IBIS for use on golf course turfgrass. Thus, I led an effort to write both a United States Golf Association (USGA) and Scandinavian Turfgrass and Environment Research Foundation (STERF) grant proposal to support a post doc to complete this work. Unfortunately, the USGA and STERF were not as excited about this project as I was. When the USGA decided not to fund the grant, STERF backed out as well. Thus, in the spring of 2020, nearly three years into the project, I did not know how we were going to model water or N. Our fortunes changed in the summer 2020 when Doug received a USDA grant and used the funds to hire a post-doctoral researcher to parameterize Agro-IBIS so that it could predict water and N requirements for golf course turfgrasses. Dr. Dimitris Pavlou joined Doug's lab group in

January 2021. Parameterizing Agro-IBIS for golf course turfgrass is no small undertaking because the golf course turfgrass system is significantly different from natural and agricultural ecosystems for which the model was developed. As of this writing, the effort to parameterize Agro-IBIS to simulate the water requirement of golf course turfgrass is nearly complete.

After taking Dr. Jingyi Huang's Soil Physics class in the Fall of 2020, it occurred to me that it may be possible to develop a relatively simple soil moisture-based model that could predict a golf course's water requirement. This model would still be more realistic and complex than any previous attempts at modeling golf course water needs, but still relatively simple in that it would be a single layer model that did not differentiate between golf course components. In the fall of 2021, Jingyi lent his coding expertise in R to the development of such a model. This model is referred to as the Tipping Bucket model in Chapter 5 and its success as predictive tool was critical to the timely completion of this project. Chapters 7 and 8 relied on results from the Tipping Bucket model.

To model the nitrogen (N) requirement on golf courses within the allotted timeframe of this project, we relied on the previously created but largely unvalidated Growth Potential Nitrogen Requirement Model. The model overpredicted N use on golf courses, but results suggest how the model can be best calibrated for use on golf courses in the future (Chapter 6). At this writing, I hope that the Agro-IBIS model can be successfully reconfigured and used to predict the N requirement on golf courses, though those developments will mostly likely occur after I leave UW-Madison in early August 2022.

Figuring out what might cause variance in resource use efficiency between golf courses is one of the central goals of this project. Climate clearly causes variance in resource use, but the goal was to calculate resource use efficiency on golf courses in such a manner that the effect of climate is normalized. Thus, given climate normalized resource efficiency metrics for golf courses, what might cause variance in golf course resource use? I put a great deal of thought into this question early in the project. Initially I thought that golf course quality would be the variable with the strongest correlation to golf course resource use. It seemed to me that a perfectly manicured high end country club would use more resources than a public golf course that costs $20 to play. To evaluate this idea, I worked with Dr. Frank Rossi and his lab manager Carl Schimenti to learn how to evaluate golf course quality using a scoring methodology they had created. The method used both qualitative and quantitative metrics to assign a quality score to each golf course component. I spent part of the summer of 2018 learning the method and visiting golf courses to evaluate their quality. However, the method was time consuming and given the number of golf courses that I needed to complete my survey, I realized that measuring turfgrass quality across all golf courses in the study would be too time-consuming and costly. Furthermore, course quality is not stable because quality varies throughout the year. Measuring course quality on each golf course only once would be insufficient. Measuring course quality multiple times on courses throughout the US and Europe was not logistically feasible. Lastly, the course quality assessment, while using as many objective quantitative metrics as possible, ultimately required a qualitative rating scheme. In the summer of 2018, I traveled to Scotland and used the methodology to assess the quality of courses there and completed the course quality assessment on five Scottish golf courses. What I learned was that what constitutes course quality also varies by culture. What the average Scottish golfer views as high course quality is not the same as what an average American golfer views as high course quality. For example, greens speeds above 10 on the stimpmeter are not sought after in Scotland the way they are in the US.

By the fall of 2018, we abandoned the attempt to directly evaluate course quality and decided to use economic variables as a proxy for golf course quality. Economic variables, such as green fees, could be collected on the survey quickly and easily and we assumed could be just as effective in stratifying golf courses with respect to playing quality. Thus, I added questions to the survey related to the basic economics of the golf course, including but not limited to course type, maintenance budget, water, fertilizer, energy, and pesticide budget, green fee, initiation fee, yearly membership fee, number of full-time employees, number of seasonal employees, and rounds played per year.

Another important component of this project was to determine whether resource use efficiency best management practices (BMPs) actually lead to greater resource use efficiency. Quantifying the adoption of best management practices was something that I knew would be incredibly challenging. The uptake of one BMP is often related to the uptake of another, not all BMPs are the same level of importance, and each BMP is adopted at a varying frequency. Fortunately, Dr. Paul Mitchell had developed a mathematical method in 2015 that addressed all of these complications and quantified the bulk adoption of a wide range of BMPs by a practitioner. Paul helped design our survey so that we asked superintendents to report their BMP uptake in a manner consistent with Paul's methods of BMP quantification.

By the fall of 2021, nearly four years into the project, I had finally collected the data that I needed and with the help of every committee member on this project, determined how all the data would be analyzed. This left me just under a year to finish the analysis and write the majority of this dissertation. While the project took a long time to materialize, the results have been worth the wait.

1.2 The original proposal for this PhD project – from 2016

The original proposal for this project was written while working at GEO in 2016. The project commenced in the fall of 2017 under the direction of Doug Soldat in the Department of Soil Science at UW-Madison.

The Environmental Sustainability of Golf Courses:

Quantifying and Analyzing the Performance of Golf Course Systems

A quick google search of "golf courses and environment" is dominated by hits describing the environmental degradation caused by excessive resource use on golf courses underscoring the public's environmental perception of golf course management. Given this response, one might expect that a similar search among peer-reviewed scientific journals would return a large number published studies reporting analyses of the efficiency of resource use in the golf industry. Surprisingly, this is not the case; peer-reviewed publications documenting research on golf courses tends to focus on a specific research question appropriate to a specific discipline, such as ecology, water quality, toxicology, soil science, agronomy, and environmental engineering. These studies are primarily insular to their disciplines and do not adopt the vantage point that golf course management is a complex, interconnected system. While such interdisciplinary studies may exist, they have eluded this literature review to date, highlighting the lack of interdisciplinary research into just how efficiently a wide range of resources are used on golf courses.

Golf industry professionals' claim that resource use on golf courses cannot be compared systematically because golf courses vary globally in size, shape, climate, play quality, and player expectations. Additionally, data for such a study have been hard to obtain given that golf superintendents have traditionally not shared resource consumption figures, with one notable exception: the Environmental Institute for Golf Environmental Profile Reports. Beyond these reports, however, the industry literature is effectively devoid of studies analyzing the efficiency of resource use on golf courses. In an age of increased competition for finite resources, analytical studies of this nature are precisely what the golf industry needs to do, especially given a challenging political climate. It is surprising that the golf, academic, and environmental communities have not fully and systematically developed a means for addressing questions of sustainable resource use on golf courses. Developing a flexible model that would allow golf course professionals to set realistic targets for resource sustainability will not only maximize resource use efficiencies but will also highlight the ecological benefits of golf course green spaces. The goal of this research project is to develop an integrated model that can contextualize, score, and compare the efficiency of water, fertilizer, pesticide, and energy use both within and across golf courses globally. This model will assign a resource efficiency score (RES) to analyzed golf courses, which will allow golf managers to target specific resources that could be trimmed to their economic and local environment's benefit.

Background

To address a lack of baseline data for resource use on golf courses, the Environmental Institute for Golf (EIFG), a branch of the Golf Course Superintendents Association of America (GCSAA), instituted a series of survey-based studies in 2006. From 2007 to 2012 the EIFG published reports on environmental stewardship, water use, nutrient use, pesticide use, and energy use on US golf courses. Survey response rates were poor, ranging from ten to sixteen percent. Despite low response rates from the four surveys, the data were assumed to be statistically representative and were extrapolated to all US golf courses. The resulting reports provide baseline data on management practices, property features, and environmental stewardship of US golf courses. Phase II of the survey (2014 to 2017) is currently underway in an effort to measure trends in each area of study over time.

The research project proposed herein will differ from the EIFG approach in a number of key areas. First, the EIFG reports are categorized by resource, which makes sense as a general organizational structure, but potentially overlooks inter-relationships and synergies between resources used on golf courses. Second, the reports summarize data collected by region of the US, which, while effective for their reporting purposes, does not provide individual golf courses with a measure of their resource use performance. Third, while the reports do make an effort to contextualize resource use for some resources (e.g., water budgeting used in the Phase II Water Report), other resources, such as fertilizers and pesticides, are not contextualized. In other words, predicted use is not compared with actual use. Finally, the EIFG reports analyze resource use as industry-wide trends, which, while useful for the industry, does not indicate a minimum level of sustainable resource use nor set a targeted use level for improved sustainability.

Methodology

To analyze the efficiency of resource use on golf courses world-wide, I will use published analytical models to define minimum levels of sustainable resource use based on specific characteristics of a given course. While many models will be considered as the project progresses, the following models will be used initially to contextualize and compare resource use across golf courses: 1) water use will be analyzed using water budgeting equations (US EPA, 2014), 2) fertilizer use will be contextualized using the Minimum Level of Sustainable Nutrients (MLSN) fertilizer model (Woods, 2016), 3) pesticide use will be contextualized using either the Environmental Impact Quotient (EIQ*) model or the risk quotient approach (Kovach, 1992; Peterson and Schleier, 2014; Kniss and Coburn, 2015), and 4) energy consumption will be contextualized using carbon footprinting methodologies for golf courses (Bartlett, 2011; Selhorst and Lal, 2011; Ng et al. 2014). To better understand variations in resource efficiency across golf courses globally, the courses analyzed will be categorized according to country, climatic region, course ownership model (e.g. public or private), and cost of play/ membership.

Research Questions

This study will use a data-oriented approach to ask the following questions:

1. Based on the resource efficiency scores produced can a minimum sustainable level of resource use be defined for all relevant golf course categories?
2. What proportion of courses analyzed are utilizing resources at or close to a minimum sustainable level for a given golf course category?
3. What are the interrelationships between resources used on golf courses?

4. How do resource efficiency scores vary between pre-certified (Golf Environment Organization Certified, GEO-certified) and post-certified courses? Which interventions of the GEO-certified standard lead to a more favorable Resource Efficiency Scores (RES)?
5. Is there a correlation between a course's best management practices and RES?
6. Does the RES vary systematically with course category?

1.2.1 Answering the original research questions

1. Based on the resource efficiency scores produced can a minimum sustainable level of resource use be defined for all relevant golf course categories?

We decided not to try to define 'minimum sustainable level' and instead focused on generated resource efficiency scores for pesticide (Chapter 2 and 3), energy (Chapter 4), water (Chapter 5), and nitrogen (Chapter 6). These resource efficiency scores were then combined into a single overarching score of resource use efficiency (Chapter 8).

2. What proportion of courses analyzed are utilizing resources at or close to a minimum sustainable level for a given golf course category?

We did analyze resource efficiency by golf course category via the eco-efficiency model (see Chapter 8). Golf course resource efficiency did not vary to the degree anticipated by golf course category.

3. What are the interrelationships between resources used on golf courses?

Of the 144 golf courses that took the UW-Madison Resource Efficiency Survey, only 28 of them gave us complete water, energy, and fertilizer data. Thus, our dataset was not large enough to address this question.

4. How do resource efficiency scores vary between pre-certified (Golf Environment Organization Certified, GEO-certified) and post-certified courses? Which interventions of the GEO-certified standard lead to a more favorable Resource Efficiency Scores?

After working with the GEO certified database for nearly a year at the start of this project, we determined that the database did not have sufficiently detailed data to generate resource efficiency scores in all categories. Thus, this question was not able to be answered.

5. Is there a correlation between a course's best management practices and RES?

The uptake of a great majority of BMPs had no correlation resource efficiency scores (Chapter 7). We found it was more common that the uptake of a BMP was correlated to higher resource use than to lower resource use.

6. Does the RES vary systematically with course category?

Yes, but not to the degree that I originally hypothesized (Chapter 8).

1.3 Future Work

The findings and conclusions of this project were limited by a relatively small dataset of golf course resource use. The Golf Course Superintendents Association of American (GCSAA) has a far larger dataset of golf course water, energy, and fertilizer use. Analyzing that dataset with the framework developed in this project would likely inform many of the questions that this study has left open.

Continuing to parameterize ecosystem models for golf courses, such as Agro-IBIS, to predict water and nitrogen requirements for golf courses is an important direction of future research because it will improve the accuracy of golf course resource use efficiency estimates. Currently Agro-IBIS is being set up to run across 76 golf courses in this study. With the help of the USGA, who have digitally mapped every component (greens, tees, fairways, and roughs) of every golf course in the US, Agro-IBIS could run water and nitrogen requirement simulations on every golf course in the US over the next 100 years under a variety of future climate scenarios. Such a study would allow the golf industry to better plan and prepare for the future.

The greatest potential value of this project will likely not be derived from peer reviewed scientific publications, or traditional extension articles or talks, but from the implementation of the models presented in this study into software tools that could be used by practitioners to guide their management. Whether these software tools are built by governments to regulate pesticide risk, as in Denmark, or built by private companies to allow superintendents to use water or nitrogen more efficiently, the models presented in this study have the capacity to make tangible improvements to resource use efficiency on golf courses, and perhaps other forms of managed turfgrass as well. It is not hard to imagine that a model similar to the tipping bucket model presented in Chapter 5 could automatically control the irrigation system of a golf course, with little oversight needed by the superintendent.

The metrics presented in this study may also be of interest to golf course general managers (GMs). The business structure of US golf courses seems to be responsible, in part, for the resource inefficiencies highlighted in this study. Superintendents are commonly given a maintenance budget that they can either spend entirely or lose the money in following year if they do not. This practice may discourage golf course personnel from testing new and innovative approaches to using resources more efficiently. Future work could analyze these social and financial dynamics and elucidate their contribution to lagging resource efficiency. In addition, GMs often lack basic agronomic knowledge, and therefore are unable to recognize when a superintendent is using resources inefficiently. The metrics in this study, which quantify how efficient one golf course is in comparison to another within or across climates, could encourage GMs to become more knowledgeable about the efficiencies associated with water, energy, fertilizer, and pesticide use at their golf course.

Lastly, findings from this study suggest that there may be a disconnect between the expectations of golfers and those of superintendents. In some cases, the heuristics that superintendents use to manage golf courses appear to be misaligned with golfer expectations, which could also lead to resource use inefficiency in golf. For example, this study found that pesticide risk on golf courses showed no correlation to the number of rounds played on or the profit generated by the golf course. In the US Midwest, fungicides are often sprayed on fairways to control dollar spot. These applications, which contribute greatly to the overall pesticide risk of the golf course, are made because the superintendent assumes that golfers recognize and dislike dollar spot infection on fairways. However, it is unclear whether dollar spot infections in fairways, especially at low rates, affect a golfer's impression of course quality.

In summary, resource use efficiency estimates need to be continually improved by better parameterizing, calibrating, and validating ecosystem models on golf courses. These models need to be distributed to golf courses in the form of usable software to guide and aid management decisions. Finally, developing a better understanding of the social and business dynamics that may correlate with golf course resource use inefficiencies is also a promising area of future research.

1.4 Scientific (and personal) reflections

This doctoral project was purposefully broad in scope. The objective was to create a single, consistent, overarching framework for quantifying golf course resource use efficiency across a wide variety of climates. However, the drawback to pursuing such a project is that inevitably less time and attention can be given to any one part of the project. This project poses many questions and was able to answer many questions, but some only at a relatively low confidence level.

Future work could tackle modeling energy, water, fertilizer, and pesticide at a finer level of detail, or could focus on surveying golf course resource use more completely in any given region. However, I hope that range of topics explored in this study opens up possibilities for future turfgrass research.

I think one of the key insights of the project was demonstrating that there is a difference between the scientific characterization of turfgrass and how turfgrass is managed on golf courses. For example, even though annual bluegrass is typically thought of as requiring more resource than creeping bentgrass, data from this study shows that these grass types received a statistically indistinguishable level of resource inputs.

Survey work is difficult, time consuming, and all of us are overwhelmed with surveys in our modern digital lives. But I think that turfgrass research would be more impactful if fewer studies were completed at research stations and more studies focused on analyzing how turfgrass systems function in society.

As a lifelong and dedicated golfer, pursuing this project was as much a passion as it was a scientific goal. In the world of turfgrass science, because of their much larger area, lawns have far greater environmental impact than golf courses. However, I felt that given the knowledge I had of the game, my interest in the environmental sciences, and the experience that I had working in the golf industry as a young professional, I thought I might be uniquely positioned to help make the game I love a little healthier for ourselves and our planet.

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Madison, WI

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Chapter 2: Quantifying golf course pesticide use efficiency

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Published title: A novel framework for estimating and analyzing pesticide risk on golf courses.

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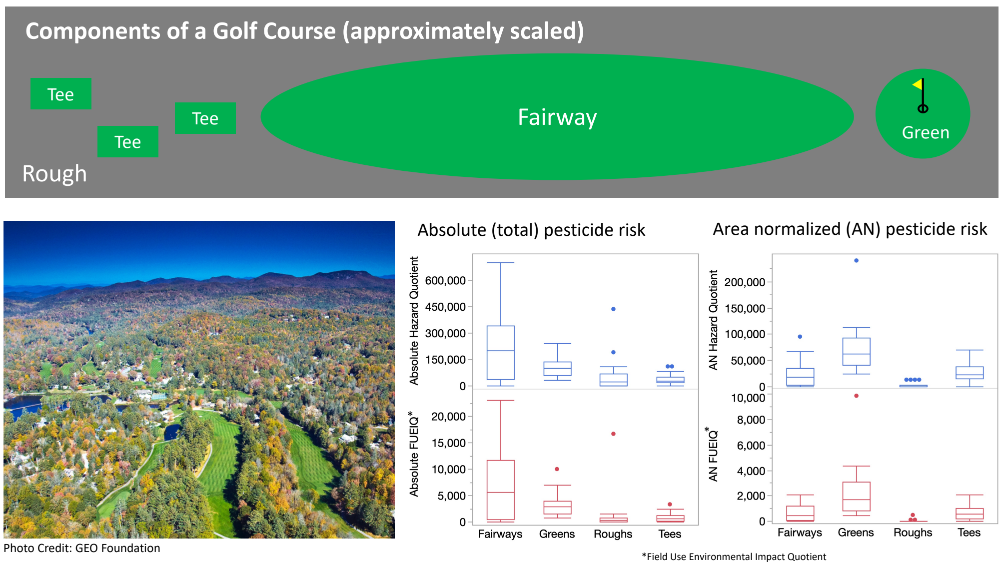
Abstract

This study develops a framework that quantifies golf course pesticide risk, explores environmental and economic factors that may be responsible for the observed risk, develops a method to compare golf course pesticide risk to other agricultural crops and investigates how pesticide risk on golf courses can be most effectively reduced. To quantify pesticide risk, we adapt the Environmental Impact Quotient (EIQ) and hazard quotient models for use on golf courses. The EIQ model provides an estimate of overall environmental risk, while the hazard quotient model, as applied here, provides an estimate of pesticide risk to mammals. This novel framework was applied to twenty-two courses in Wisconsin and New York, USA. Using both pesticide risk models, all twenty-two golf courses showed a high coefficient of variation of pesticide risk (<0.76). Within a golf course, mean absolute pesticide risk was at least two times higher on fairways than on greens, tees, or roughs. Mean area normalized risk was at least three times higher on greens than the other three golf course components. Pesticide risk of a component-weighted aver- age of greens, tees, fairways and roughs on each course were within the range of pesticide risk calculated for five other agricultural crops. Our data suggest that variation in pesticide risk on golf courses is related to economic fac- tors, such as maintenance budget, and can be effectively lowered by reducing pesticide use on fairways and selecting

products of lower risk. To assist golf course superintendents in developing programs that lower pesticide risk, a new metric was developed: the Risk to Intensity Quotient (RIQ). The RIQ is the ratio of pesticide risk to use intensity and quantifies the average risk of product selection by a golf course superintendent.

Graphical Abstract



Highlights

- A method for measuring pesticide risk on golf courses was developed.
- Pesticide risk was highly variable both within and across golf courses.
- Fairways had the highest risk while greens had the highest area normalized risk.
- Parameterizing pesticide risk models for petroleum derived spray oils is unknown.
- Product selection and economic factors are important determinants of risk.

Abbreviations

AAR, average application rate; AN, area normalized; AT, area treatment; B, beneficial arthropod toxicity; C, chronic toxicity; CWA, golf course component-weighted-average; D, bird toxicity; DT, dermal toxicity; EIQ, Environmental Impact Quotient; EIQ_{ai}, Environmental Impact Quotient of an active ingredient; F, fish toxicity; FUEIQ, Field Use Environmental Impact

Quotient; GCC, golf course component; L, leaching potential; LD_{50}, lethal dose at which 50% of the experimental population dies; NASS, National Agricultural Statistics Service; NYSIPM, New York State Integrated Pest Management; P, plant surface half-life; PDSO, petroleum derived spray oil; PGR, plant growth regulator; PMEP, Cornell Pesticide Management Education Program; R, surface loss potential; Rfd_{ai}, reference dose of a pesticide active ingredient; Rfd_{p}, reference dose of a pesticide product; RIQ, Risk to Intensity Quotient; S, soil half-life; SY, systemicity; W_{ai}, weight of pesticide active ingredient; WGCSA, Wisconsin Golf Course Superintendents Association; W_{p}, weight of pesticide prod- uct; Z, bee toxicity.

1. Introduction

With 38,864 courses worldwide, golf is ubiquitous in modern society (R&A, 2019). Globally, golf courses cover an area of approximately 23,600 km^2 or 0.02% of earth's land surface (based on the median area of a US golf course (Gelernter et al., 2017)). But golf courses are not distributed evenly; golf courses are often purposely built in and around housing developments to boost both property and housing values. Economic analyses indicate that golf courses can increase the sale price of adjacent homes by 8 to 26% (Nicholls and Crompton, 2007; Do and Grudnitski, 1995). Thus, golf courses are heavily concentrated in urban and suburban areas and are often scrutinized for their environmental impact, especially for the use or overuse of pesticides, water and fertilizers (Hiskes, 2010; Wheeler and Nauright, 2006). Pesticide use on golf courses is particularly concerning to governments (Toxic Fairways, 1995), environmental groups (Beyond Pesticides, 2021), and concerned citizens (Garris, 2018), both because of the real or perceived toxicity of chemicals used and potential exposure to those living on and around golf courses. In fact, several European countries have either entirely banned (e.g. Spain and the Wallonia region of Belgium) or severely restricted (e.g. Italy and Norway) pesticides available to golf course managers (R&A, 2020). However, despite widespread societal concern over golf course pesticide use, few rigorous scientific studies have addressed the topic in peer reviewed journals.

The majority of previous scientific work investigating the environmental impact of golf course pesticide use has been completed by taking field-based measurements of water, soil, flora, and fauna. Such studies indicate that golf course pesticide use can negatively impact non-target organisms including aquatic life (Baris et al., 2010; King and Balogh, 2010; Haith and Rossi, 2003) and beneficial soil biota (Gan and Wickings, 2017; Harman et al., 2006). However, these studies can be time consuming and costly while also possessing limited external validity.

Conversely, there is only one peer reviewed scientific study that could be located that has surveyed golf course superintendents to estimate pesticide risk directly from pesticide application records. This one study, completed in Northern Ireland, found that mean annual pesticide application rates on forty-four golf courses were two times higher than on adjacent agricultural grasslands (Kearns and Prior, 2013). Considering that this study found golf course pesticide application rates to be significantly higher than in agriculture, combined with an increasing public desire to reduce the risks of pesticide use on amenity grasslands, it is surprising that only one published study in the scientific literature could be located that attempts to quantify the environmental risk associated with golf course pesticide application programs.

Simply measuring the weight of pesticides applied, as completed by Kearns and Prior (2013), fails to consider differences in toxicity between pesticides (Barnard et al., 1997). Kniss (2017) argued that a more accurate measure of the environmental risk posed by pesticides can be determined through the use of pesticide risk indicator models. Pesticide risk indicator models are mathematical equations which produce risk scores based the two primary components of risk: toxicity and exposure (Greitens and Day, 2006). For this analysis, a framework was built to measure pesticide risk on golf courses around the world using two existing pesticide risk indicator models: Environmental Impact Quotient (EIQ) and hazard quotient. This framework was then applied to a sample of twenty-two golf courses in Wisconsin and New York, USA over a three-year period.

The EIQ model (Kovach et al., 1992) has been used widely to estimate the environmental risk of agricultural pesticide programs such as Glycine max (soybean), Zea mays (maize), Brassica napus (canola) and Gossypium (cotton) (Brookes and Barfoot, 2016; Oliver et al., 2016; Hudson and Richards, 2014; Gallivan et al., 2001). These studies provide a point of comparison for analysis of golf turf systems. Greitens and Day (2006) tested the EIQ model and seven other pesticide risk models for their statistical validity and reliability. The authors found that the EIQ model was one of three models that performed consistently and gave statistically valid results. In addition, Rossi and Grant (2009) used the EIQ model to evaluate environmental risk from turfgrass pesticide use on a single golf course subjected to a variety of management systems.

The Environmental Impact Quotient (EIQ) model is composed of the Base EIQ value assigned to pesticide active ingredients and the Field Use EIQ (FUEIQ) that is used to estimate the environmental risk of agricultural pesticide applications (Kovach et al., 1992)(Eq. (1)).

$$(Eq. 1)\ Base\ EIQ = \{C[(DT*5)+(DT*P)]+[(C*((S+P)/2)*SY)+(L)]+[(F*R)+(D*((S+P)/2)*3)+(Z*P*3)+(B*P*5)]\}/3$$

where C is chronic toxicity; DT is dermal toxicity; P is plant surface half-life; S is soil half-life; SY is systemicity; L is leaching potential; F is fish toxicity; R is surface loss potential; D is bird toxicity; Z is bee toxicity; and B is beneficial arthropod toxicity. To determine a Base EIQ for a given active ingredient, each of these variables is scored on a 1, 3, 5 scale. Once the base EIQ value is determined, a Field Use EIQ (FUEIQ) rating can be calculated (Eq. (2)).

$$(Eq. 2)\ Field\ Use\ EIQ = Base\ EIQ * Active\ Ingredient\ Application\ Rate$$

Agricultural analyses using the EIQ model commonly report FUEIQ values as the final metric describing pesticide environmental impact.

Despite its common use, the EIQ model has been criticized for its discrete qualitative scaling methods (i.e., 1, 3, 5 scale) because the method is not able to adequately represent the inherently probabilistic and un- certain nature of risk (Peterson and Schleier III, 2014; Dushoff et al., 1994). For example, "medium risk" in the EIQ scaling system is given a discrete value of 3 on a 1–5 scale. However, "medium risk" could be more accurately represented by a range of numbers between 1 and 5 (e.g. 2.5 < x < 3.5, where x is "medium risk"). In addition, the FUEIQ rating has been criticized for being overly reliant on application rate in de- scribing pesticide environmental risk (Kniss and Coburn, 2015). Previous research highlighting the flaws of EIQ recommend the model no longer be used (Kniss and Coburn, 2015; Peterson and Schleier III, 2014). However, despite its technical flaws, EIQ remains appealing for extension applications and practitioners because it considers a wide variety of environmental factors and produces a single number.

The hazard quotient model is commonly offered as an alternative to EIQ (Kniss, 2017; Kniss and Coburn, 2015; Peterson and Schleier III, 2014). Hazard quotient is a quantitative framework with the ability to accurately rank the risk of various pesticides even when using highly conservative estimates of toxicity and exposure (Peterson, 2006). Hazard quotient is known by many other names such as risk quotient, hazard index, margin of safety, exposure-toxicity ratio, and margin of exposure.

A hazard quotient is simply the ratio of exposure to toxicity and the resulting value, the hazard quotient, provides an estimate of risk (Eq. (3)).

$$(Eq. 3)\ Hazard\ Quotient = \frac{Exposure}{Toxicity}$$

Estimates of exposure and toxicity can be made across varying levels of accuracy and refinement (i.e., tiers). Tier 1 estimates of exposure and toxicity are highly conservative, simple, and lower cost. Subsequent tiers of testing increase in specificity and cost and may not be available for all products as this testing is only required when previous tiers yield results indicating toxicity concerns. In tier 1 agricultural applications of hazard quotient, the exposure term commonly is quantified as the ap- plication rate of the pesticide, while the toxicity term commonly is quantified as the acute or chronic LD_{50} for a particular group of organisms, which is sometimes referred to as a toxicity endpoint value.

Hazard quotient is a flexible model adaptable to the researcher's needs and interests and has been used in various agricultural applications for estimating pesticide risk to a range of organisms. Kniss (2017) used hazard quotient for estimating the historical changes in US herbicide risk to mammals and Stoner and Eitzer (2013) used hazard quotient for estimating agricultural pesticide risk to honeybees in Connecticut, USA. Further, the hazard quotient is consistently used in the turfgrass literature as a reliable quantitative model to assess the human health risk of golf course pesticide applications to both golfers and applicators (Cooper et al., 2017; Wong and Haith, 2014; Murphy and Haith, 2007; Murphy et al., 1996).

As with the EIQ, there are drawbacks to the hazard quotient model. The researcher must choose a single toxicological value and the resulting metric and analysis is therefore limited to a single group of organisms (e.g., rats or fish) and cannot be used to understand the broader environmental impact using a single number. Multiple hazard quotients would need to be calculated to better understand overall environmental risk which cannot be combined into a single number under a strictly quantitative framework (Jepson et al., 2014).

In summary, both EIQ and hazard quotient use tier 1 toxicity and exposure data to estimate risk of pesticide applications. Hazard quotient uses a strict quantitative framework but estimates pesticide risk for only a single endpoint. As applied in this study hazard quotient measures pesticide risk specifically to mammals. Mammals were chosen as the endpoint for the hazard quotient model because they are a major wildlife group that inhabits golf courses (Hodgkison et al., 2007), mammalian toxicity data is widely available for pesticides used on golf courses, and mammalian toxicology has implications for human health. Conversely, EIQ uses a qualitative framework to weigh risk for eleven environmental endpoints and subjectively combines these risks into a single number.

The purpose of this study was to establish a framework for quantifying golf course pesticide risk to both the environment generally (EIQ) and specifically to mammals (hazard quotient). The framework purposely utilized publicly available data and pesticide risk models with relatively straight forward mathematics. This ensured the framework can be a tool available to a wide variety of stakeholders including governments, environmental groups, golf industry bodies, and other concerned communities. Additionally, in an effort to begin to explore potential predictors of pesticide risk on golf courses this study investigated possible connections between pesticide risk and various facility, environmental, and economic factors.

2. Material and methods

2.1. A framework for measuring pesticide risk and use intensity on golf courses

2.1.1. Components of a golf course

All golf courses are divided into four basic components: greens, tees, fairways, and rough. Each golf hole starts at the tee and ends on the green where the hole is located. The fairway is located between the tee and green and the rough is located around the periphery of each golf hole. Typical mowing heights on each golf course component are: greens 3–4 mm, tees 8–12 mm, fairways 10–15 mm, and rough 40–50 mm.

2.1.2. Absolute and area normalized metrics

To measure pesticide risk on golf courses, two levels of metrics were established: an absolute metric and an area normalized metric. An absolute metric refers to one that can be summed and does not consider the area of the golf course, such as annual weight of pesticide active ingredient applied (kg). Area normalized metrics take an absolute metric and divide by area, an example being application rate (kg ha^{-1}).

In golf course management, it is nearly universal that each golf course component (e.g. greens, tees, fairways, and rough) is managed independently. Therefore, the pesticide metrics as described in Eqs. (4)–(9) were calculated for each golf course component independently. To obtain a value that was representative of the entire course the absolute metrics were summed across all golf course components, and a component- weighted-average (CWA) was applied to the area normalized metrics. The CWA was calculated by first determining the percentage of the total golf course turf area that each component occupied. This was computed by dividing the area of each component by the sum of the areas of greens, tees, fairways, and roughs. The percentage of each component was then multiplied by a components area normalized metric and then summed for all components to produce the CWA.

Annual absolute FUEIQ and area normalized FUEIQ were computed in a manner consistent with methods established by Kovach et al. (1992) (Eqs (4) and (5)).

$$(Eq. 4)\ Annual\ Absolute\ EIQ = \sum_{1}^{n} EIQ_{ai} * W_{ai}$$

$$(Eq. 5)\ Annual\ Area\ Normalized\ FUEIQ = \sum_{1}^{n} \frac{EIQ_{AI} * W_{AI}}{GCC}$$

where n equals the number of pesticide applications to a given golf course component in an annual pesticide application program; EIQ_{ai} equals the Base EIQ of the active ingredient applied; W_{ai} equals the weight of active ingredients applied (kg) and GCC is the area of the golf course component (ha).

Hazard quotient was computed as a ratio of exposure and toxicity and summed annually. The absolute and area normalized hazard quotients were calculated on a product basis (Eqs. (6) and (8)) and on an active ingredient basis (Eqs. (7) and (9)).

$$(Eq. 6)\ Annual\ Absolute\ Product\ Hazard\ Quotient = \sum_{1}^{n} \frac{W_p}{Rfd_p}$$

$$(Eq. 7)\ Annual\ Absolute\ AI\ Hazard\ Quotient = \sum_{1}^{n} \frac{W_{AI}}{Rfd_{AI}}$$

$$(Eq. 8)\ Annual\ Area\ Normalized\ Product\ Hazard\ Quotient = \sum_{1}^{n} \frac{(W_p/GCC)}{Rfd_p}$$

$$(Eq. 9)\ Annual\ Area\ Normomalized\ AI\ Hazard\ Quotient = \sum_{1}^{n} \frac{(W_{AI}/GCC)}{Rfd_{AI}}$$

where n equals the number of pesticide applications to a given golf course component in an annual pesticide program; W_p equals the weight of product applied (mg); Rfd_p equals the reference dose associated with the pesticide product (mg pesticide product/kg rat); W_{AI} equals the weight of active ingredient applied (mg) and Rfd_{AI} equals the reference dose associated with the pesticide active ingredient (mg active ingredient/kg rat).

These annual area normalized metrics establish a risk per area value comparable between component surfaces present on a golf course (fair- ways vs. greens) or between components on different golf courses (e.g. greens on golf course A vs. greens on golf course B). The component-weighted-average (CWA) of the annual area normalized metric establishes a golf course wide risk value that is comparable between entire golf courses (golf course A vs. golf course B). Golf course FUEIQ and hazard quotient values reported in this study are three-year means (2016, 2017, 2018) of the area-normalized component-weighted-aver- age (AN-CWA) values, unless otherwise specified.

2.1.3. Area treatments

Pesticide area treatments were calculated for every golf course analyzed in the study. Area treatments quantify the intensity of pesticide use and were defined as the number of pesticide applications made at the average application rate (Kniss, 2017). The average application rate

(AAR) was defined as the average of the highest and lowest labelled rate for the pesticide product for golf turf (Eq. (10)).

$$(Eq. 10)\ Annual\ Area\ Treatment\ = \sum_{1}^{n} \frac{(W_p/AAR)}{GCC}$$

where n equals the number pesticide applications to a given golf course component in an annual pesticide program; W_p equals the weight of product applied (mg); AAR is the average application rate of the pesticide product and GCC is the area of the golf course component (ha). Area treatments were calculated for each golf course component. A component-weighted-average (CWA) was also applied to obtain a golf course wide area treatment value. All area treatment values reported in this study are three-year means (2016, 2017, 2018).

An area treatment value of 1 for the greens (or any golf course com- ponent) can be obtained by applying a pesticide at the average rate to all greens. An area treatment value of 0.5 for greens can be obtained either by applying the pesticide at a half rate, or by applying at the average rate to half of the greens area. An area treatment value of 2 for the greens can be obtained by applying a pesticide at double the average rate to all greens.

2.1.4. Pesticide weight

Pesticides are often formulated as liquids, however, hazard quotient, EIQ, and area treatments all require pesticide product and active ingredient (AI) weight. Pesticide product volume was converted to pesticide product weight by metrics available on the pesticide label (Eqs. (11) and (12)).

$$(Eq. 11)\ Product\ weight = product\ volume * \frac{weight\ AI}{product\ volume} * \frac{1}{AI\ concentration}$$

$$(Eq. 12)\ AI\ weight = product\ volume * \frac{weight\ AI}{product\ volume}$$

2.2. Pesticide risk model set up

2.2.1. Hazard quotient formula

In this analysis, rat acute oral LD50 (i.e. acute mammalian toxicity) was chosen as the toxicity value (reference dose) for the hazard quotient formula. Acute mammalian toxicity was chosen because it is one of the most widely available toxicological values and because it has implications for human health. However, the relevance of mammalian toxicity to human health is complex, variable, and often uncertain.

Others have applied the hazard quotient model with pesticide active ingredients (AI) not the actual pesticide products (Kniss, 2017). However, products with the same active ingredients at the same con- centration can have widely varying product toxicities due to inactive ingredients and product formulations (Damalas and Eleftherohorinos, 2011). Product hazard quotients are therefore likely a better representation of actual pesticide risk in the environment.

However, using AI's provides better toxicological data coverage. Our database of 356 turfgrass products had 15 products without the re- quired mammalian LD50 data, which required us to develop two different scenarios to deal with these missing data (see Missing Data section of Methods below). However, all of the 177 different AI's in our turfgrass pesticide database had published mammalian acute LD50 values. An additional advantage of calculating AI hazard quotients is that agricultural pesticide data from the USDA is reported in active ingredient use rates. Calculating AI hazard quotients on golf courses allows for direct com- parison to these agricultural data, which product hazard quotients do not. However, the AI hazard quotient method has several significant dis- advantages (see Results).

As such, both product hazard quotients and AI hazard quotients were applied in this analysis. Product hazard quotients, herein referenced to as hazard quotients, were primarily used but AI hazard quotients were used to compare golf course pesticide risk to agricultural pesticide risk. Product rat acute oral LD50 values were obtained from safety data sheets produced by product manufacturers. Where products had rat acute oral LD50 values listed as >5000 mg kg^{-1}, a value of 5000 mg kg^{-1} was assumed. AI rat acute oral LD50 values were obtained primarily from EPA registration documents and the Cornell Pesticide Management Education Program (PMEP) database.

2.2.2. EIQ formula

Base EIQ values were obtained from the New York State Integrated Pest Management (NYSIPM) program EIQ Calculator website (Eshenaur et al., 2020). The NYSIPM program periodically reviews and updates this database as new data becomes available, or new pesticide active ingredients become legal for use in New York.

2.2.3. Missing values: Scenario 1 and 2

For some pesticides, the EIQ value and acute mammalian toxicity was unknown. To account for these missing data, two separate scenarios were developed. Scenario 1 did not attempt to estimate pesticide risk for which the EIQ value or the mammalian toxicity of the pesticide being applied was unknown. In Scenario 2 pesticide products with an unknown mammalian toxicity were, if possible, assigned the LD50 value of a product that had the same active ingredient at a concentration ±5%. Otherwise, the product was assigned the average LD_{50} value of its corresponding pesticide type (fungicide, herbicide, insecticide, plant growth regulator) in our turf pesticide database. Missing EIQ values were similarly assigned the average EIQ value based on pesticide type.

2.3. Collecting data to test the framework

2.3.1. Survey

The data presented in this study is part of the University of Wisconsin- Madison Golf Course Resource Efficiency Study which attempts to quantify resource (water, energy, fertilizer, and pesticide) use on golf courses primarily in the northern USA. The associated survey, titled the University of Wisconsin-Madison Resource Efficiency Survey, collects information about facility economics, environmental conditions, and data on resource use over a three-year period from 2016 to 2018 (Bekken and Soldat, 2021).

Starting in the Spring of 2019, golf courses in Wisconsin were solicited to take the University of Wisconsin-Madison Resource Efficiency Survey through the Wisconsin Golf Course Superintendents Association (WGCSA). Forty-six of the 198 superintendents surveyed submitted full or partial responses to the survey (response rate of 23%). Additionally, New York State Park golf facilities were contacted for participation in the survey due to their involvement in the long-standing Cornell Integrated Pest Management Project. Eleven of nineteen New York State Park golf superintendents submitted full or partial responses to the survey (response rate of 58%).

2.3.2. Golf course pesticide application records

To be included in this study, golf courses from Wisconsin and New York needed to supply pesticide records from 2016, 2017, and 2018 that included the date of all pesticide applications, product name, rate of application, area applied, and the golf course component on which the application was made. Eleven survey respondents from Wisconsin and eleven respondents from New York fit these criteria. All pesticide risk and use intensity values reported in this study are a three-year mean for 2016, 2017, and 2018. The intent of this study is to establish a golf course's mean pesticide risk and use intensity.

2.3.3. USDA agricultural data

Data on pesticide use in agriculture were obtained from the National Agricultural Statistics Service (NASS) Agricultural Chemical Use Program database (USDA National Agricultural Statistics Service, 2020). This program surveyed farmers in various states to collect crop specific data on active ingredient usage. NASS publishes the mean state annual use rate (kg ha^{-1}) and mean state field applied area as a percentage of planted acres. These data were used to calculate FUEIQ and active ingredient hazard quotient values, under Scenario 1 assumptions.

Five comparison crops were selected from the USDA NASS database (USDA National Agricultural Statistics Service, 2020). Corn was selected because it is the most cultivated crop in the US (USDA, National Agricultural Statistics Service, 2019). Data on pesticide use in corn production were available for both New York (NY) and Wisconsin (WI). All other crops selected (potatoes and carrots in Wisconsin and grapes and apples in New York) are fruits and vegetables for which the appearance of the product is extremely important to consumers (Kays, 1999). Golf turf is similarly held to high aesthetic standards.

2.4. Data analysis software

All descriptive statistics, linear regression, and data visualization were completed in JMP Pro (Version 15.0, SAS Institute Inc., Cary, NC, 1989–2021). The assumptions made by linear regression models (linearity, homoscedasticity, independence, and normality) were met for all reported regressions. As such, no data transformations or statistical models more complex than linear regression were applied.

3. Results

3.1. Pesticide risk estimates in Scenario 1 and 2

In Scenario 1, the mean FUEIQ and hazard quotient of the twenty-two golf courses were 294 and 11,115 per hectare, respectively (Table 1). The standard deviation within the sample was 94% and 76% of the mean for FUEIQ and hazard quotient, respectively. In Scenario 2, the mean FUEIQ and hazard quotient increased to 626 per hectare and 14,402 per hectare. The standard deviation within the sample was 154% and 97% of the mean for FUEIQ and hazard quotient.

The large increase in pesticide risk scores from Scenario 1 to 2, especially in FUEIQ, was due to the use of a petroleum derived spray oil (PDSO) (Fig. 1). Golf courses that used PDSOs (defined as those golf courses that made at least three applications of a PDSO over the three- year period of the study) had increases in FUEIQ and hazard quotient scores of 5.3 and 1.8 and times values in Scenario 1, respectively. In addition to the PDSOs, Scenario 2 filled data gaps in mammalian toxicity and EIQ values to 15 products and 6 active ingredients, respectively. However, these additions to Scenario 2 made small differences in pesticide risk scores. For the sixteen golf courses in the study that did not use PDSOs, no golf course had more than a 10% increase in FUEIQ and hazard quotient scores under Scenario 2 assumptions. Because the actual pesticide risk that PDSOs pose are unclear given their high use rate but low product toxicity, Scenario 1 was used exclusively for the rest of the analysis.

TABLE 1 Mean annual pesticide risk and use values of twenty-two golf courses in New York and Wisconsin from the years 2016, 2017, and 2018. Calculations were made under two scenarios where data gaps in pesticide records were handled differently. *Component-weighted-average.

	Area-normalized metrics			Absolute metrics	
	Field Use EIQ	**Product Hazard Quotient**	**Area Treatments**	**Field Use EIQ**	**Product Hazard Quotient**
	------------------- mean (coefficient of variation) -------------------				
	Scenario 1 calculations				
Golf course component					
CWA*	294 (0.94)[a]	11,115 (0.76)[a]	8.1 (0.75)[a]	11,778 (0.94)[b]	436,031 (0.78)[b]
Greens	2,244 (0.90)	71,932 (0.64)	43.4 (0.54)	3,137 (0.69)	107,378 (0.52)
Tees	655 (0.79)	26,572 (0.64)	18.8 (0.59)	935 (0.93)	38,314 (0.82)
Fairways	665 (1.09)	23,602 (1.05)	18.4 (0.81)	6,593 (1.04)	235,050 (0.95)
Rough	37 (2.52)	2,428 (1.69)	1.4 (1.88)	1,114 (3.14)	55,289 (1.76)
	Scenario 2 calculations				
Golf course component					
CWA*	626 (1.54)[a]	14,402 (0.97)[a]	8.1 (0.75)[a]	24,822 (1.77)[b]	564,630 (1.07)[b]
Greens	2.724 (1.00)	77,174 (0.67)	43.4 (0.54)	3,873 (0.77)	115,608 (0.54)
Tees	1,363 (1.00)	33,316 (0.62)	18.8 (0.59)	2,430 (1.63)	51,772 (0.99)
Fairways	1,420 (1.74)	31,710 (1.22)	18.4 (0.81)	13,820 (1.48)	310,004 (1.03)
Rough	146 (3.54)	3,393 (2.10)	1.4 (1.88)	4,699 (4.16)	87,246 (2.68)

[a]CWA (Component-weighted-average), [b] Sum of components (greens, tees, fairways, and rough).

3.2. Areas of golf course components

The golf courses in our study covered an average area 75 ha, 40.4 ha of which were managed turfgrass (defined as grass that is mowed at least once per month during the growing season). Of this 40.4 ha greens occupied an average area of 1.6 ha, tees 1.4 ha, fairways 10.1 ha, and roughs 27.3 ha. The average size of greens in the US are 1.3 ha, tees 1.2 ha, fairways 11.4 ha, and roughs 19.4 ha (Gelernter et al., 2017). With the exception of roughs, the component areas of golf courses in this study are similar to the national averages.

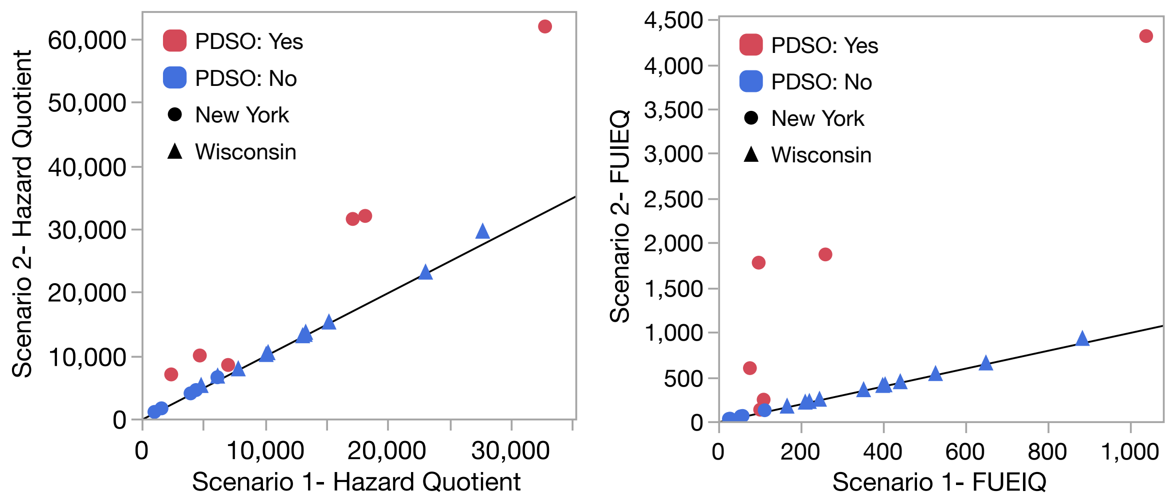


Figure 1 A) Scenario 1 and 2 area-normalized component-weighted-average (AN-CWA) hazard quotient. B) Scenario 1 and 2 AN-CWA FUEIQ (Field Use Environmental Impact Quotient). Black line is a 1:1 line.

3.3. Area treatment and pesticide risk

Mean area treatments (AT) on golf courses in the study were highest on greens (43), followed by tees (19), fairways (18), and then roughs (1). The mean component-weighted-average AT for golf courses in the study was 8, meaning that on average the entire turf area of the golf course was covered with eight pesticide treatments (applications at the average label rate) per year (Table 1).

Absolute pesticide risk was highest on fairways followed by greens, roughs, and tees (Fig. 2a). Absolute pesticide risk on fairways was more than twice that of greens and approximately four times that of roughs, according to both risk indices.

Greens had the highest area normalized (per hectare) risk followed by tees, fairways, and roughs (Fig. 2b). On average, greens had three times the per hectare pesticide risk of tees according to both risk indices and over twice the number of area treatments. Roughs had by far the lowest per hectare pesticide risk. Mean per hectare pesticide risk in roughs was less than 3% of greens mean per hectare risk.

Both the EIQ and hazard quotient models indicated that the pesticide risk on golf courses in the study primarily came from fungicide usage (Fig. 3). Fungicides accounted for 87 and 65% of the total pesticide risk on golf courses in the study according to the FUEIQ and hazard quotient, respectively.

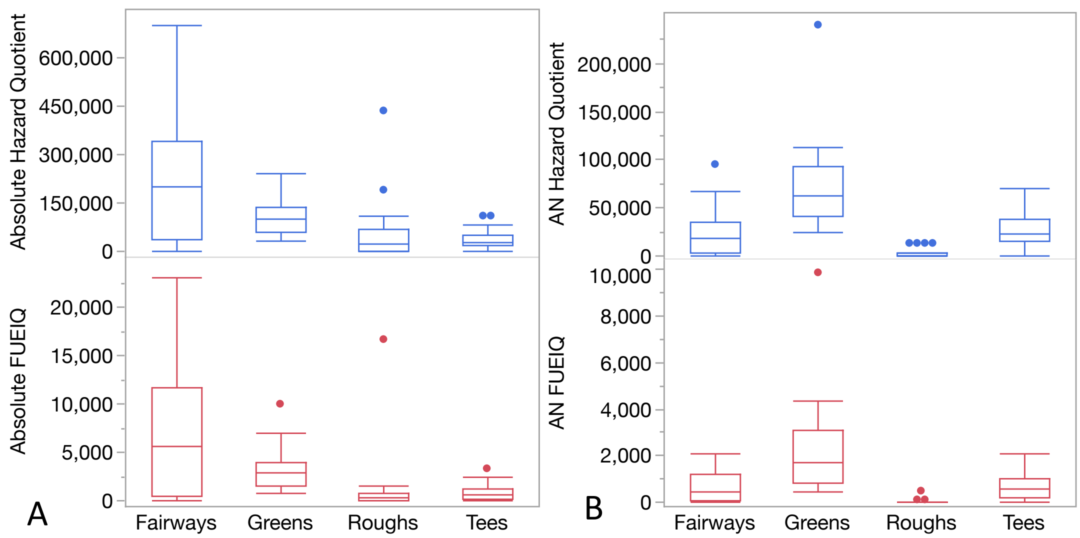


Figure 2 A) Absolute Field Use Environmental Impact Quotient (FUEIQ) and hazard quotient by golf course component on the twenty-two golf courses in the study. B) Area normalized (AN) FUEIQ and hazard quotient by golf course component on the twenty-two golf courses in the study.

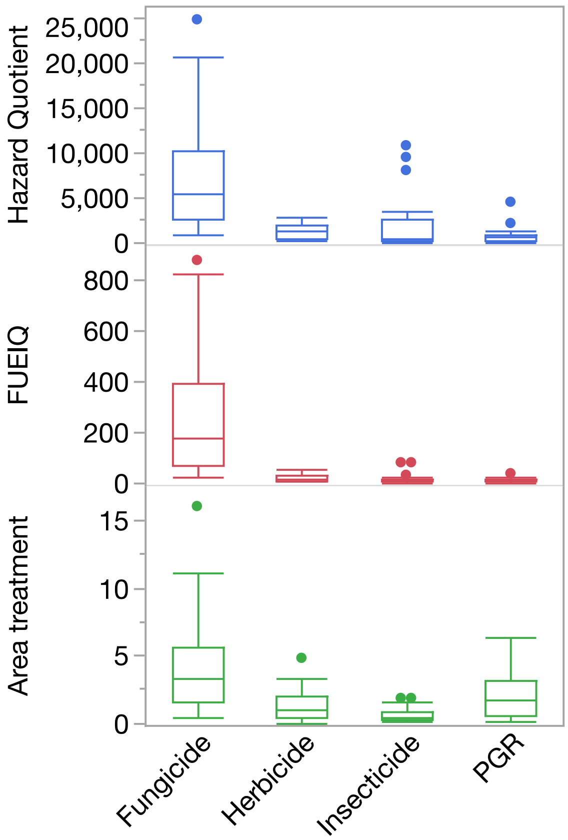


Figure 3 Area-normalized component-weighted-average (AN-CWA) Field Use Environmental Impact Quotient (FUEIQ), hazard quotient, and area treatment by pesticide type. PGR- Plant growth regulator.

The ratio of pesticide risk to pesticide use intensity quantifies the average risk of product selection by a golf course superintendent. This ratio is defined for the purposes of this study as the Risk to Intensity Quotient (RIQ). A lower RIQ indicates that on average, the superintendent selected products with lower risk. The RIQ is illustrated in Fig. 4, where courses below the correlation line used lower risk pesticides compared to average, while courses above the line used higher risk pesticides. Values for area treatment were correlated with FUEIQ ($r^2 = 0.49$) and hazard quotient ($r^2 = 0.71$).

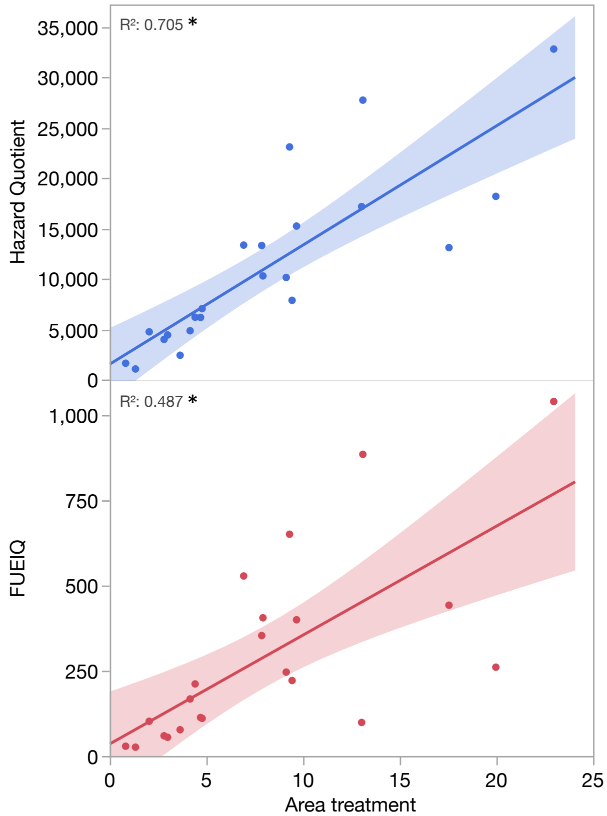


Figure 4 The Risk to Intensity Quotient (RIQ). Area-normalized component-weighted-average (AN-CWA) Field Use Environmental Impact Quotient (FUEIQ) and hazard quotient correlated with area treatment. Shaded areas represent 95% confidence interval for mean value of y for a given x value. *Indicates statistical significance at $\alpha < 0.05$.

3.4. Comparing golf pesticide risk to agriculture

The USDA does not report the actual pesticide products used on farms, making it impossible to calculate product hazard quotients with these data. Instead, active ingredients names and use rates are reported by the USDA, making it possible to calculate active ingredient (AI) hazard quotients. We calculated both product hazard quotients and AI hazard quotients for golf courses and found that the two metrics were highly correlated ($r^2 = 0.79$).

In New York and Wisconsin, mean per hectare pesticide risk in golf turf was approximately six to eight times higher than corn production, according to the AI hazard quotient and FUEIQ models, respectively (Table 2). Similarly, pesticide risk in golf turf was substantially higher than in carrot production in Wisconsin. However, mean per hectare pesticide risk in golf turf accounted for 8 and 12% the risk of potato pro- duction in Wisconsin, according to AI hazard quotient and FUEIQ, respectively. According to both models, mean per hectare pesticide risk of golf turf was less than 35% the risk of apple production and less than 80% the risk of grape production.

TABLE 2 Annual mean pesticide risk values by land use type. AN- Area Normalized. FUEIQ- Field Use Environmental Impact Quotient. *CWA (component-weighted-average)

	State	Year	Mean AN-FUEIQ	Mean AN Active Ingredient Hazard Quotient
Land Use Type				
Apples	NY	2017	1,007	21,324
Carrots	WI	2018	25	1,236
Corn	NY, WI	2018	42	906
Golf course turf*	NY, WI	2016, 2017, 2018	276	7,158
Grapes	NY	2017	648	8,906
Potatoes	WI	2016	2,543	91,345

3.5. Active ingredient and product toxicity discrepancies

Insecticides containing trichlorfon (LD_{50} = 136) and chlorpyrifos (LD_{50} = 95) had a large impact on AI hazard quotients. A New York golf course that made a single application of trichlorfon to fairways, tees, and rough increased their annual per hectare AI hazard quotient value by over 7 times. Applications of chlorpyrifos on another New York golf course more than doubled the annual per hectare AI hazard quotient. These active ingredients have relatively high application rates and have high acute mammalian toxicity. However, the actual products containing trichlorfon and chlorpyrifos have lower product toxicities: LD_{50} of 1098 and 654 mg kg^{-1} respectively.

3.6. Exploring variance in pesticide risk and use intensity

The golf courses analyzed in our study varied widely in management intensity and cost of play. Of the seventeen golf courses that filled in the general information portion of the survey, maintenance budgets ranged from $24,447 per hectare of managed turf to $2250. Cost of play (i.e., green fee) ranged from $150 for 18 holes to $18.

Pesticide risk as estimated by both EIQ and hazard quotient and use intensity as estimated by AT had little correlation with golf facility fac- tors such as rounds of golf played, or number of golf course maintenance employees (Table 3). All correlation coefficients (r^2 values) were less than 0.21 and were not statistically significant. Green fee correlated moderately with pesticide risk and use intensity. FUEIQ and green fee correlated at $r^2 = 0.31$ and AT and green fee correlated at $r^2 = 0.19$ and were both statistically significant at $\alpha < 0.05$.

TABLE 3 Correlation coefficient (r^2) between pesticide risk and use intensity values and golf facility factors. *indicates significance at $\alpha < 0.05$. CWA-AN: Area-normalized component-weighted-average.

	Pesticide risk and use values		
	AN-CWA FUEIQ	**AN-CWA Product Hazard Quotient**	**Area Treatments**
Golf facility factors			
Rounds of golf played	0.003	0.185	0.210
Full-time employees	0.008	0.077	0.140
Seasonal employees	0.026	0.011	0.010
Green fee	0.31*	0.15	0.19*

Notable correlations existed between pesticide use intensity and area normalized economic variables including gross revenue per hect- are, maintenance budget per hectare, and pesticide budget per hectare (Fig. 5). AT correlated well with revenue per hectare ($r^2 = 0.55$) and maintenance budget per hectare ($r^2 = 0.46$), indicating that pesticide use intensity increased on golf courses with higher revenue and maintenance budgets. Of all the economic factors tested, maintenance budget per hectare was the best predictor of both pesticide risk and use intensity. Correlations between FUEIQ, hazard quotient, AT and maintenance budget per hectare were all statistically significant at $\alpha < 0.05$.

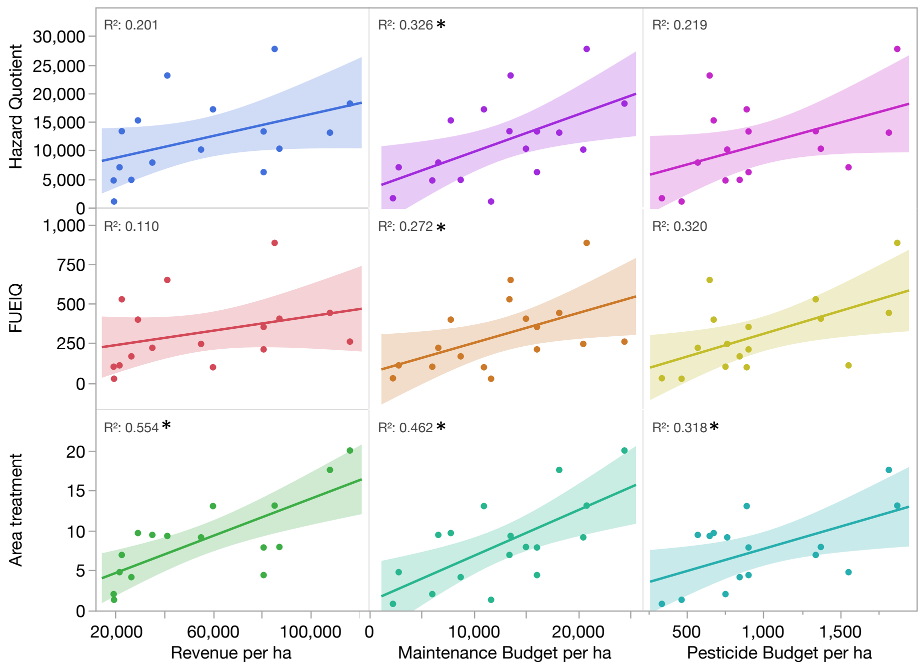


Figure 5 Area-normalized component-weighted-average (AN-CWA) Field Use Environmental Impact Quotient (FUEIQ), hazard quotient, and area treatment in relation to golf course gross revenue per hectare, maintenance budget per hectare, and pesticide budget per hectare. Shaded areas represent 95% confidence interval for mean value of y for a given x value. *Indicates statistical significance at $\alpha < 0.05$.

Golf courses in this study spanned three different climatic zones: cool humid, semicool humid, and transitional humid (Cook and Ervin, 2010). While the change from cool, to semicool, to transitional climate appeared to increase pesticide risk (data not shown), the small size of our dataset especially in the transitional climate precluded us from statistically analyzing the relationship between climate and pesticide risk in our study. Similarly, seventeen of the twenty-two golf courses in the study reported the primary and secondary grass types (data not shown) on each golf course component; however, the effect of grass type on pesticide risk was not analyzed because of the size of the golf course pesticide dataset compared to the relatively high number of grass types.

4. Discussion

4.1. The components of pesticide risk

When evaluating pesticide risk over space and time, the elements of pesticide risk - exposure and toxicity - are controlled by the following management practices: product selection (toxicity) and the associated application rate (exposure), application area (exposure), and application frequency (exposure). This novel framework incorporates FUEIQ, hazard quotient, and area treatment formulas to isolate how these management practices contribute to pesticide risk, which can then be used to recommend pesticide risk reduction strategies.

4.2. The Risk to Intensity Quotient (RIQ)

The area treatment formula quantifies only use intensity, while FUEIQ and hazard quotient as risk models consider both product selection and use intensity in their construction. This presents an opportunity through correlation to isolate product selection as a management practice in its contribution to overall risk. For example, when running correlations be- tween pesticide risk and area treatment, we can assume the unexplained variance is attributable to product selection. Area treatment accounted for 49 and 71% of the variation in FUEIQ and hazard quotient, respectively. The remaining variation in FUEIQ and hazard quotient, 51 and 29% respectively, is therefore attributable to product selection. These results suggest that product selection is equally as important as use intensity to reduce FUEIQ, while decreasing use intensity is more important to reducing hazard quotient.

The RIQ metric was created to assist a superintendent in reducing pesticide risk. As the ratio of pesticide risk to use intensity, RIQ quantifies the average risk of product selection made by a superintendent over an annual time period. To reduce a RIQ metric, a superintendent could choose products with lower risk, either by selecting products with lower toxicity or with lower use rates (exposure). In addition, the regression line of pesticide risk and area treatment (Fig. 4) could serve as a useful benchmark to compare pesticide risk between courses with similar use intensities.

4.3. Variance in pesticide risk across golf courses

In Scenario 1, the standard deviations of the FUEIQ and hazard quotient scores were nearly as large as the means themselves, indicating significant variability in pesticide risk among the twenty-two golf courses in our sample. The variability was even greater under Scenario 2. This suggests that pesticide risk on golf courses is not uniform and that some golf courses pose significantly more of risk to human and environ- mental health than others.

The high variance in pesticide risk among the twenty-two courses is best described by product selection (as measured by RIQ) and economic factors, though no single explanatory variable strongly explained pesticide risk. Other factors not accounted for may also play a role in pesticide risk and use intensity including irrigation and fertilizer management practices. Beyond broad climate categorizations, specific climatic factors that drive pest pressure were not considered in this analysis. There are various pest prediction models for turfgrass systems that may help explain variance in pesticide risk and use intensity.

4.4. Product and active ingredient (AI) hazard quotients

The majority of this study used product hazard quotients. However, to compare golf turf to agricultural data obtained from the USDA, active ingredient (AI) hazard quotients were calculated for golf courses as well. AI hazard quotients and product hazard quotients for the twenty-two golf courses in this study were highly correlated ($r^2 = 0.79$). AI hazard quotients then are a reasonable proxy for product hazard quotients, though are not a perfect replacement. In this analysis of mammalian AI toxicity in comparison to mammalian product toxicity, several pesticides have high AI toxicity but low product toxicities. Insecticides containing trichlorfon and chlorpyrifos had especially higher risk when calculated on an AI basis compared to a product basis. In both cases, the pesticide products were much less acutely toxic to rats compared to the isolated AIs, highlighting an underlying issue in using AI data to assess pesticide risk. Given the choice, product hazard quotients are preferable to more accurately model actual pesticide risk in the environment. Similar to AI hazard quotient, the EIQ model uses AIs to quantify pesticide risk, a limitation of the method.

4.5. Petroleum derived spray oils

Whether or not applications of petroleum derived spray oil (PDSO) were included in pesticide risk calculations had a large influence on pesticide risk estimates. The PDSO, Civitas Turf Defense by Intelligro™, used on six of golf courses in this study is an OMRI (Organic Materials

Review Institute) certified turfgrass fungicide composed of 89% white mineral oil. Civitas™ has not been assigned an EIQ value and has a mammalian LD50 value of 5000 mg kg^{-1}

Due to the missing EIQ value, the PDSO was removed from calculations in Scenario 1, as were other products where data gaps existed. In Scenario 2, the PDSO was included with its actual mammalian LD50 value of 5000 mg kg^{-1} but the average EIQ value for fungicides, 27. The median use rate according to the product label is approximately 40 kg ha^{-1}, much higher than conventional pesticides (Civitas Turf Defense by Intelligro™, 2020). Both hazard quotient and EIQ utilize the application rate of the pesticide in determining risk, and the extremely high use rate of the PDSO greatly increased the resulting risk scores from both models. Applications of the PDSO were responsible for 99% of the increase in mean FUEIQ values from Scenario 1 (Civitas™ not included) to Scenario 2 (Civitas™ included), and 90% of the increase in hazard quotient score. The environmental risks of PDSO's are unclear and have not been studied in golf environments. PDSO's generally have low acute toxicity and persistence, however they are applied at high rates, are fairly non-selective to insects, and can be harmful to bees and fish (Nile et al., 2019). Further research that studies the pesticide risk of PDSO's and how to represent them in pesticide risk models are critical to improving pesticide risk estimates on golf courses. In the meantime, we recommend that researchers clearly state whether PDSO's are included in risk estimates from golf courses.

4.6. Economic considerations

Considering data from both Wisconsin and New York, the AI hazard quotient and EIQ models suggest that pesticide risk in corn production is six to eight times lower than on golf turf. One explanation for this could be the difference in value generation for these two land-use types.

Estimated gross golf course revenue in this study ranged from $20,000 per hectare to over $100,000 per hectare, orders of magnitude higher than gross revenues from corn production that ranges from $1900 to $3000 per hectare (Schnitkey, 2018).

Golf turf is best compared to fruit and vegetable crops which are held to similar aesthetic standards as golf turf (Kays, 1999). Interestingly, golf course component pesticide risk values are comparable to the high and low ends of crop production, underscoring the heterogeneity in management of golf course landscapes. For example, in Wisconsin, mean per hectare FUEIQ values for potato production in the state are comparable to the golf course greens in this study, while mean per hectare FUEIQ values for carrot production are akin to golf course roughs in this study.

4.7. Golf course components and reducing risk

The framework allows for the estimation of pesticide risk on each golf course component. Roughs make up approximately 60% of turf area, are kept at longer heights of cut, and are meant to be peripheral to the main playing areas of the course. As such, pesticide use on roughs is lower which decreases component-weighted-average (CWA) risk values on golf courses compared to some crops despite intense usage of pesticides on other course components. Golf course greens had the highest area-normalized pesticide risk of any golf course component in the study. Greens occupy on average 4% of turf area at a golf course and are where the hole is located, necessitating low mowing heights that allow the golf ball to roll smoothly across the surface, which in turn requires higher pesticide inputs to maintain the health of the turf stand. However, absolute pesticide risk property wide was most influenced by fairway pesticide use. Fairways comprise 25% of turf area and are intensively managed, often receiving frequent pesticide applications.

Ultimately, this non-uniformity in management should be considered if a manager hopes to reduce pesticide risk. For golf courses in the north central to northeastern US with middle to high maintenance budgets, reducing fairway pesticide use, specifically fungicides, is likely the most effective option to reduce pesticide risk. Low budget golf courses in this region who are already not applying pesticides to fair- ways and wish to reduce risk, should likely examine fungicide applications to greens. However, for superintendents in all regions, evaluating the RIQ metric will help determine if altering product selection or reducing use intensity will be the most effective strategy for reducing pesticide risk.

4.8. Future work

Future work could replicate the methods of this study in different climatic regions across the world. The golf courses in this study were predominantly located in the semi cool-humid to cool-humid climatic regions of north central and northeastern US (Cook and Ervin, 2010).

Golf courses in warmer climates with longer growing seasons may have substantially different overall risk, risk by golf course component, and risk by pesticide type, than the golf courses in this study.

In addition to climate variability, political boundaries are likely to have a great influence on golf course pesticide risk. On the twenty-two golf courses in this study across a three-year period over 150 pesticide active ingredients were applied. Conversely, most European countries limit the number of pesticide active ingredients available to golf course superintendents to twenty or fewer (R&A, 2020). Analyzing the connections between pesticide availability and golf course pesticide risk across countries may yield valuable results for environmental policy.

Future work could also apply the hazard quotient model using toxicity data from birds, fish, and bees. This study only considered acute mammalian toxicity and therefore the hazard quotient values in this study are most applicable to mammals living in golf environments. The hazard quotient values are also applicable to those applying the pesticides (Kniss, 2017), in this case golf course superintendents. The hazard quotient values may to a lesser extent also be relevant to golfers. Future studies could also evaluate risk posed by the chronic toxicity of pesticides. Short of this work being completed on golf courses, the EIQ model provides a simple, if qualitative, estimate of overall environmental impact.

5. Conclusion

For governments, environmental groups, communities, golf industry organizations, and even individual golf course superintendents concerned with pesticide risk in golf course environments, the framework derived in this study allows for a quantification and analysis of golf course pesticide risk. Specifically, the framework develops a method to compare pesticide risk across golf course components and between golf courses. In addition, the framework allows for comparison of pesticide risk in golf to other land use types, potentially of value to those making future land use decisions. Finally, the framework makes clear how pesticide risk on golf courses can be most effectively reduced.

The sample of golf courses in this study indicates that pesticide risk is highly variable both among golf courses and across golf course com- ponents. According to both risk models, fungicides accounted for the majority of risk by pesticide type, while fairways accounted for the majority of risk by golf course component. Economic factors, such as maintenance budget, appear to be an important determinant of golf course pesticide risk and use intensity. Golf course superintendents interested in reducing risk could benefit from metrics that combine pesticide risk and use intensity (such as the Risk to Intensity Quotient - RIQ). Such metrics would allow a superintendent to determine the most effective means by which to reduce risk.

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CRediT authorship contribution statement

Michael Bekken: Conceptualization, Methodology, Formal analysis, Data curation, Writing – Original Draft, Visualization. Carl Schimenti: Conceptualization, Methodology, Formal analysis, Data curation, Writing – Original Draft. Douglas Soldat: Conceptualization, Methodology, Re-sources, Writing – Review & Editing, Supervision, Project administration. Frank Rossi: Conceptualization, Methodology, Resources, Writing – Review & Editing, Supervision, Project administration.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Michael Bekken, Carl Schimenti, and Douglas Soldat have no conflicts of interests to declare. Frank Rossi is employed part-time by Petro

Canada who own Intelligro, the maker of Civitas Turf Defense™, which is discussed in this article. This relationship had no influence on this manuscript.

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Chapter 3: Analyzing golf course pesticide risk across the US and Europe

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Abstract

This study quantifies golf course pesticide risk in five regions across the US (Florida, East Texas, Northwest, Midwest, and Northeast) and three regions across Europe (UK, Denmark, and Norway) with the objective of determining how pesticide risk on golf courses varied as a function of climate, regulatory environment, and facility-level economic factors. The hazard quotient model was used to estimate pesticide risk, which, as applied here, estimates risk to mammals specifically. Data from 68 golf courses are included in the study, with a minimum of at least five golf courses in each region. Though the dataset is small and representative of the population at confidence level of 75% with 15% margin of error, pesticide risk appeared to be similar across US regions with varied climates. The median golf course wide hazard quotient score was highest in the Northwest (13,686), followed by Florida (9818), East Texas (7893), Midwest (7404), and Northeast (4731). However, given the high variance in the sample, these risk scores were not significantly different from one another and normalizing for growing season length did not change this result. Median pesticide risk was significantly lower in the UK (2418), Norway (248), and Denmark (64). By golf course component, greens had the highest median absolute pesticide risk in East Texas and Florida, while fairways had the highest median absolute pesticide risk in the Midwest, Northwest, Northeast, Norway, Denmark, and UK. Facility-level economic factors such as maintenance budget were not predictive of pesticide risk, except in the Northern US (Midwest, Northwest, and Northeast). Regulatory environment appears to greatly influence pesticide risk. Norway, Denmark, and the UK limit the number of pesticide products

available to golf course superintendents to thirty or fewer, while in the US, many hundreds to thousands of pesticides products are registered for use on golf courses.

1. Introduction

Games similar to modern golf began to emerge around the European continent in the 14th and 15th centuries. The first of these games to require a cultivated field was the Dutch game colf (Keepers of Green, 2002). The cool and rainy European climate and native turfgrasses were conducive to cross-country ball and stick games, which were often played across grazed turfgrass on marginal agricultural land. In Scotland, where the game most similar to modern golf emerged in the early 16th century, the land deemed agriculturally marginal was commonly the thin strip of sandy soil along coastlines between the ocean and arable agricultural land further inland. By the late 18th century, golf in Scotland greatly increased in popularity and the first golfing societies were formed with rules of the game documented (A History of Golf, 1955). The turfgrass species native to Scotland along with grazing animals that kept the grass short, moving sand dunes that provided natural hazards, and periodic wind-blown sand topdressing primitive greens meant that golf courses required very little, if any, maintenance. One could argue that at this early stage of development golf reached peak sustainability; the courses required virtually no resource inputs.

Beginning in the late 19th century, golf's popularity increased exponentially, and the game spread out of Europe and around the world to different climates and geographies. Turfgrasses were shipped out from northern Europe to areas where no native turfgrasses existed. Not surprisingly, for these turfgrasses to grow successfully and survive foot traffic in climates for which they were not native, resource inputs such as water, fertilizer, pesticide, and fuel for mowing became both necessary and essential. As the game developed in the 20th century, golfers steadily demanded faster and smoother playing surfaces. This meant mowing turfgrass to ever shorter heights which increased the stress on the plant making it more susceptible to pests. Currently, golf greens, which are the most important component of the course, are mowed as low as 3mm leaving them even more vulnerable to a wide variety of insects and diseases.

Rossi and Grant (2009) found that golf greens in New York state, USA, struggled to survive without the application of pesticides. Thus, at least in the cool humid climate of the northeastern US, pesticides have become an essential tool for the golf industry's maintenance toolkit. Conversely, many European countries have severely restricted pesticide use on golf courses, and several have banned pesticide use entirely (R&A, 2020). The golf industry in Europe shows no sign of contracting (KPMG, 2019), indicating that, at least in some climates, modern golf courses can be successfully maintained without the use of pesticides.

In the US, a wide variety of pesticides are allowed on golf courses concerns environmental groups (Beyond Pesticides, 2020, Perfect Earth, 2022), as well as many people living near golf courses (Garris 2018; Hilson, 2017; Brenner, 2012). Previous research has indicated that chronic inhalation and dermal risk of pesticides to golfers was low (Murphy and Haith, 2007; Putnam, 2008; Wong and Haith, 2013); however, golf course pesticide application programs do pose ecological risks. Several studies have concluded that offsite transport of pesticides from golf courses routinely affects surrounding aquatic ecosystem health (King and Balogh, 2010; Metcalfe, 2007; Haith and Rossi, 2003). In addition, high levels of arsenic have been detected in golf course soils and groundwater because of arsenic containing pesticides that have been applied to courses (Pichler, 2008; Feng et al., 2005; Cia et al., 2002).

Bekken et al. (2021) developed a framework for estimating ecological risks from pesticides applied to golf courses using pesticide risk indicator models and applied the models to 22 golf courses in New York and Wisconsin. This study uses that same framework but applies the analysis to 68 golf courses in eight different regions. Five of these regions are in the US (Midwest, Northwest, Northeast, East Texas, and Florida) and three are in Europe (Norway, Denmark, and UK). The goal of this study is to compare pesticide risk on golf courses across climates and geographies to determine how pesticide risk varies both as a function of climate and regulatory environment. Within the US, we hypothesize that pesticide risk will be higher in warmer climates and lower in cooler climates because of the longer growing season in the warmer climates. In Europe, we hypothesize that pesticide risk will be lower than in the US because of laws which limit the number of pesticide available to golf course superintendents.

Despite the best efforts of all authors of this study to obtain a statistically representative sample of golf courses from each region, golf course superintendents were generally hesitant to voluntarily provide pesticide application information for this study. Thus, the sample size in each region of the study is smaller than originally intended. To the authors knowledge, this is the first study to compare golf course pesticide risk across geographies. As such, this research is an important first attempt to understanding how pesticide risk on golf courses varies as a function of climate and regulatory environment.

2. Methods

2.1 Survey

The data used for this study were collected via the *University of Wisconsin-Madison Resource Efficiency Survey*, which was conducted by the authors (Bekken and Soldat, 2021). All survey respondents were promised confidentiality and all data reported from the study would remain anonymous. The pesticide section of the survey asked golf course superintendents to submit pesticide application records from their golf course over a three-year period within a five-year window from 2016 to 2021. To be included in the study, pesticide applications records needed to include the name of the pesticide product applied, date of application, rate of application, and area of application. Fifty-nine golf courses supplied records over a 3-year period, five supplied records over a 2-year period, and seven supplied records over a 1-year period.

The original goal of this work was to achieve a sample that was representative of the population of golf courses within each region at an 85% confidence interval and 15% margin of error. Eighty-three percent of golf course superintendents in Norway, Denmark, and the UK who took the survey supplied pesticide records. However, only 47% of US-based golf course superintendents who took the survey shared pesticide records, underscoring the hesitancy of US golf course superintendents to share pesticide records on a confidential and anonymous survey.

Given the hesitancy to report pesticide information, the target confidence level and margin of error were adjusted to of 75% and 15%, respectively. To achieve this target, at least five survey responses were required in each region (Qualtrics, 2022).

Golf course superintendents in each region were asked to take the survey via an initial email solicitation from an author of this study that lives and works in that region. Three follow up emails were sent after the initial solicitation, and if necessary to achieve the desired sample size, superintendents were contacted by phone or met in person and asked to take the survey. The exact method of survey follow-up varied in each region and was based upon what the author in each region thought would return the greatest number of survey responses.

Table 1. Number of complete responses to the pesticide section of the UW Madison Resource Efficiency Survey by region.

Region	Complete responses*	Survey effort successful? (>5 responses)	State/country represented	Distributing Organization
US-Midwest	23	Yes	Wisconsin (21), Minnesota (1), Illinois (1)	UW-Madison Turfgrass Program, WGSCA, MGCSA
US-Northeast	11	Yes	New York (11)	Cornell Turfgrass Program
US-East Texas	7	Yes	Texas (7)	Texas A&M Turfgrass Program
Norway	6	Yes	Norway (6)	NIBIO, Norwegian Greenkeepers Association
Denmark	5	Yes	Denmark (5)	Danish Golf Union
US-Florida	5	Yes	Florida (5)	University of Florida Turfgrass Program
UK	5	Yes	England (4), Scotland (1)	GEO Foundation
US-Northwest	5	Yes	Oregon (2), Montana (2), Washington (1)	Oregon State Turfgrass Program, OGCSA, Peaks and Prairies GCSAA
Sweden	3	No	Sweden (3)	Swedish Golf Union
US-Southwest	1	No	Nevada (1)	Cactus and Pine GCSA

*A complete response was one in which the golf course superintendent supplied a pesticide application record that met all criteria for pesticide risk calculation (product applied, date of application, rate of application, and area of application).

2.2 Growing season length determination

Growing season length was determined using the Growth Potential model (Stowell and Gelernter, 2005) in a manner consistent with the methods of Bekken et al. (2022).

2.3 Component-Weighted-Average (CWA)

Golf courses are made up of four components (greens, tees, fairways, and roughs) all of which are managed independently and when the areas of each of these components are summed, they equal the total area of the course (Eq. 1).

$$(Eq. 1)\ A_{GCC} = A_G + A_T + A_F + A_R$$

Where A_{GCC} equals the combined area of all golf course components, A_G equals the area of greens, A_T equals the area of tees, A_F equals the area of fairways, and A_R equals the area of roughs. All areas were measured in ha. Dividing the area of each component by the total area gives the percent area that each component occupies on the course (Eq. 2-5).

$$(Eq. 2)\ P_G = \frac{A_G}{A_{GCC}}$$

$$(Eq. 3)\ P_T = \frac{A_T}{A_{GCC}}$$

$$(Eq. 4)\ P_F = \frac{A_F}{A_{GCC}}$$

$$(Eq. 5)\ P_R = \frac{A_R}{A_{GCC}}$$

Where P_G, P_T, P_F, and P_R equals the percentage of the total golf course area that is covered by greens, tees, fairways, and roughs, respectively.

Pesticide risk was calculated for each component of the course and then multiplied by the percent area of that component to determine the component-weighted-average pesticide risk (Eq. 6).

$$(Eq. 6)\ R_{CWA} = R_G * P_G + R_T * P_T + R_F * P_F + R_R * P_R$$

Where R_{CWA}, R_G, R_T, R_F, and R_R equals the pesticide risk on the golf course component-weighted-average for greens, tees, fairways, and roughs, respectively.

2.4 Pesticide Risk

This study applies the golf course pesticide risk framework of Bekken et al. (2021) using a hazard quotient model to quantify pesticide risk. The hazard quotient is the ratio of pesticide *exposure* to *toxicity* (Eq. 7). See Bekken et al. (2021) for a detailed discussion of the advantages and disadvantages of the hazard quotient model.

$$(Eq. 7)\ Hazard\ Quotient = \frac{Exposure}{Toxicity}$$

The annual absolute and area normalized product hazard quotient were both used to quantify pesticide risk in this study (Eq 8 and 9). The area normalized product hazard quotient was also divided by the season length (days) to determine a daily HQ score (Eq. 10).

$$(Eq. 8)\ Annual\ Absolute\ Product\ Hazard\ Quotient = \sum_{1}^{n} \frac{W_p}{Rfd_p}$$

$$(Eq. 9)\ Annual\ Area\ Normalized\ Product\ Hazard\ Quotient = \sum_{1}^{n} \frac{(W_p/GCC)}{Rfd_p}$$

$$(Eq. 10)\ Daily\ Area\ Normalized\ Product\ Hazard\ Quotient = \frac{\sum_{1}^{n} \frac{(W_p/GCC)}{Rfd_p}}{Season\ length}$$

Where n equals the number of pesticide applications to a given golf course component in an annual pesticide program; W_p equals the weight of product applied (mg), GCC is the area of the golf course component (ha), Rfd_p equals the reference dose associated with the pesticide product (mg pesticide product/kg rat), and where season length is measured in days. Consistent with Bekken et al. (2021), acute mammalian toxicity (i.e., rat acute oral LD_{50}) was used as the toxicity value (reference dose) in the hazard quotient model.

Henceforth, the annual absolute product hazard quotient (Eq. 8) was abbreviated as Abso-HQ. The annual area normalized product hazard quotient (Eq. 9) was abbreviated as AN-HQ. The component-weighted-average of the AN-HQ was abbreviated as CWA-HQ. Lastly, the daily area normalized product hazard quotient (Eq. 10) was abbreviated as Daily-HQ.

2.5 Pesticide Use Intensity

Also consistent with Bekken et al. (2021), the area treatment formula was used to quantify pesticide use intensity (Eq. 11).

$$(Eq. 11)\ Annual\ Area\ Treatment\ = \sum_{1}^{n} \frac{(W_p/AAR)}{GCC}$$

Where n equals the number pesticide applications to a given golf course component annually, W_p equals the weight of product applied (mg), AAR is the average application rate of the pesticide product, and GCC is the area of the golf course component (ha). Area treatments were calculated for each golf course component. A component-weighted-average (CWA) was also applied to obtain a golf course wide area treatment value.

An area treatment value of one for any golf course component (e.g. fairways) can be achieved by applying a pesticide at the average rate to all fairways. An area treatment value of 0.5 for fairways can be achieved either by applying the pesticide at half the average rate, or by applying at the average rate to half of the fairway area. An area treatment value of two for the fairway can be achieved by applying a pesticide at double the average rate to all fairways.

2.6 Risk to Intensity Quotient

The risk to intensity quotient (RIQ) was defined as the ratio between pesticide risk to area treatment (Eq. 12). Because the RIQ normalizes for that portion of risk attributable to pesticide use intensity, the RIQ quantifies the proportion of pesticide risk attributable to product selection (Bekken et al., 2021).

$$(Eq. 12)\ RIQ = \frac{Pesticide\ risk}{Area\ treatment}$$

2.7 Mean pesticide risk and use intensity

For golf courses for which multiple years of pesticide application data were provided, calculated pesticide risk and use intensity was averaged across years to obtain a value as representative as possible of mean pesticide risk and use intensity at a golf course.

2.8 Exploring variance in pesticide risk and use intensity

Linear regression was used to explore the correlation of five continuous variables (rounds of golf played, total number of maintenance employees, maintenance budget per ha, pesticide budget per ha, and revenue per ha) to pesticide risk and use intensity. To obtain a sufficient sample size to run correlations, golf courses in the eight regions were placed in one of three groups: northern US (Northeast, Midwest, and Northwest), southern US (Florida and East Texas), and Europe (UK, Norway, and Denmark).

2.8 Data Analysis software

All descriptive statistics, linear regressions, and data visualizations were completed in JMP Pro (Version 15.0, SAS Institute Inc., Cary, NC, 1989-2022).

3. Results

3.1 Pesticide availability by region

The number of pesticide products and active ingredients available to golf course superintendents in each region is listed in Table 2.

Table 2. The region, regulatory environment in which the majority of the courses in the region were located, and the number of active ingredients and products registered for use on golf courses in each regulatory environment in 2022.

Region	Regulatory Environment	Registered Products for Golf Courses in 2022	Registered Active Ingredients for Golf Courses in 2022
Midwest	US-Wisconsin	726	*
New York	US-New York	1967	246
East Texas	US-Texas	*	*
Norway	Norway	18	12
Denmark	EU-Denmark	18	13
Florida	US-Florida	1419	241
UK	UK	74	17
Northwest	US-Oregon	1147	226

3.2 Golf course wide pesticide risk by region

Pesticide risk was highly variable in the five regions in the US, but comparatively much lower in the three European regions of the study (Figure 1). The median CWA-HQ in each region ordered from highest to lowest was: 13,686 in the Northwest, 9818 in Florida, 7893 in East Texas, 7404 in the Midwest, and 4731 in the Northeast, 2418 in the UK, 248 in Norway and 64 in Denmark. The range in CWA-HQ scores was highest in Florida (40,806), followed by the Northeast (31,736), Midwest (25,683), Northwest (17,658), East Texas (9,299), UK (5,703), Denmark (2,246), and Norway (547). The golf course with the highest CWA-HQ value was in Florida (42,507), and the golf course with the lowest value was in the Norway (15). All golf courses in the study applied at least one pesticide in each year of the study. No golf course had an HQ score of 0.

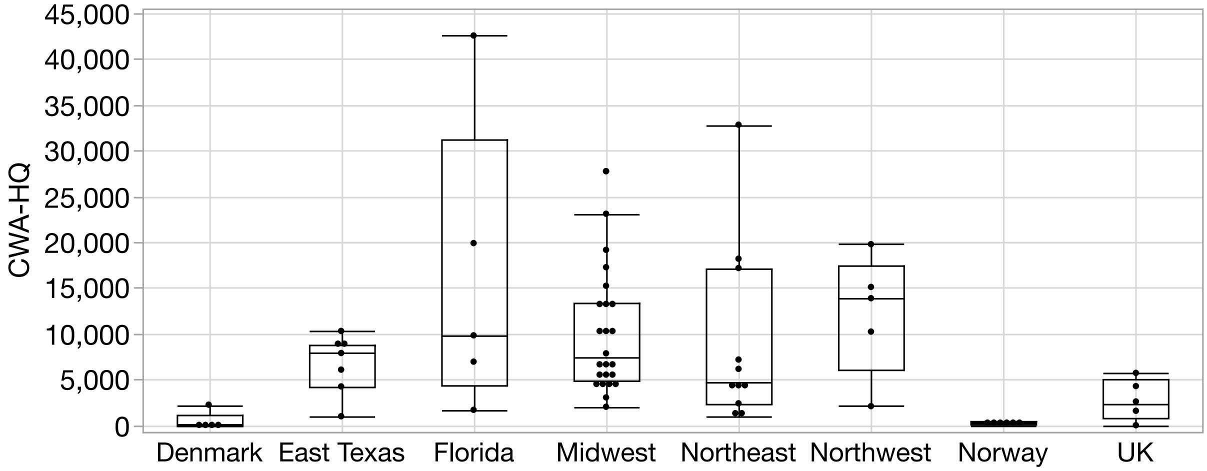

Figure 1. Component-weighted-average of the area normalized hazard quotient (CWA-HQ) in each region of the study. Black dots indicate pesticide risk for individual golf courses.

The median Daily-HQ was highest in the Northwest (62), followed by the Midwest (49), Florida (34), East Texas (28), Northeast (23), UK (12), Denmark (3) and Norway (2) (Figure 2).

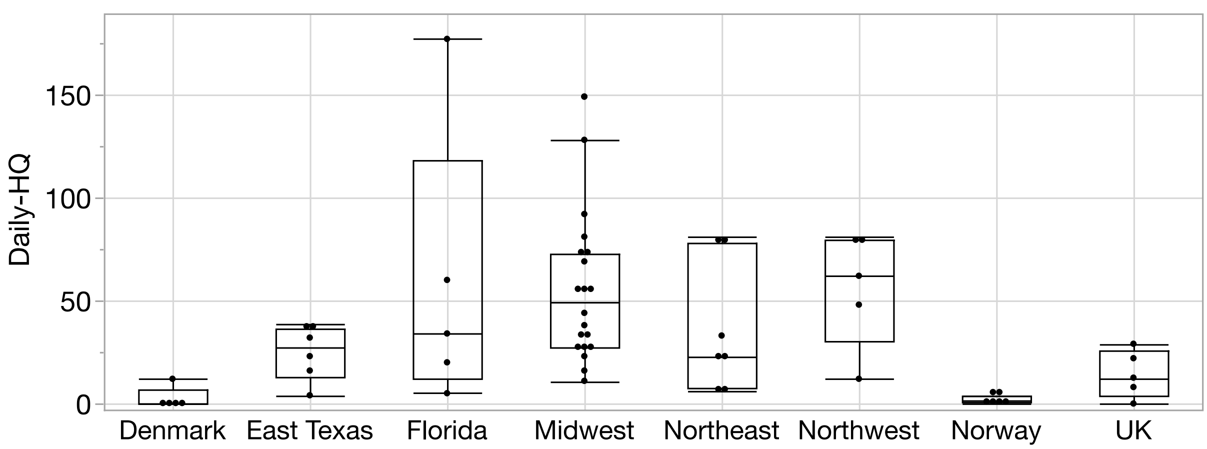

Figure 2. Daily component-weighted-average of the area normalized hazard quotient (Daily-HQ) in each region of the study. Black dots indicate pesticide risk for individual golf courses.

3.2 Golf course wide pesticide risk by region and pesticide type

Analyzing CWA-HQ scores by pesticide type, fungicides made up the greatest proportion of risk by pesticide categories in four out of eight regions: Florida, Midwest, Northeast, and Norway

(Figure 3). Herbicides contributed the most pesticide risk by pesticide type in East Texas, Northwest, and Denmark. In the UK, insecticides showed the most risk by pesticide type.

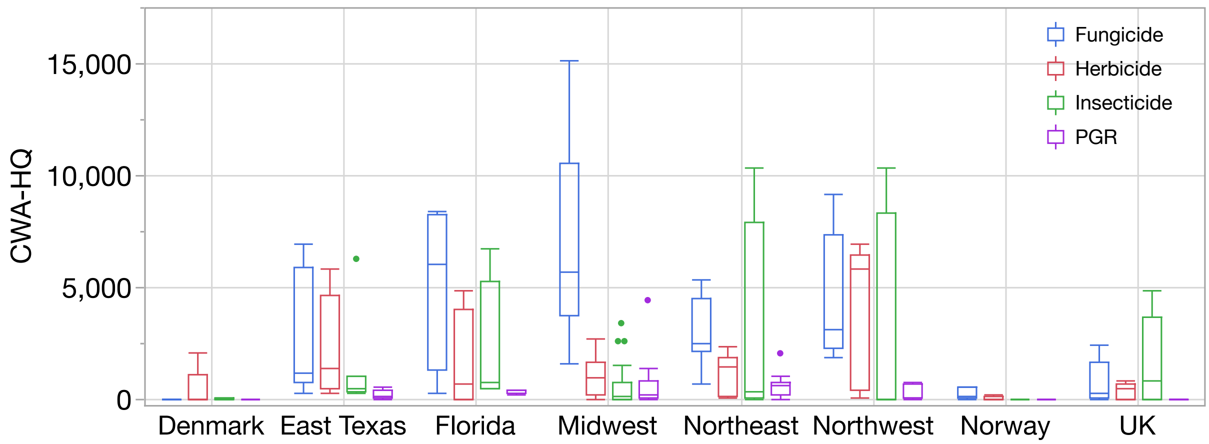

Figure 3. Component-weighted-average of the area normalized hazard quotient (CWA-HQ) of fungicides, herbicides, and insecticides, and PGRs in each region of the study. One golf course in Florida not shown on graph with an insecticide CWA-HQ of 35,602.

3.3 Golf course wide pesticide risk by region and component

The median AN-HQ score by golf course component was highest on greens in all regions of the study (Figure 4). East Texas and Florida had the highest median greens AN-HQ scores of 141,420 and 153,322, respectively. These pesticide risk values on greens were almost three times higher than the next highest regional value of 56,502 on greens in the Midwest. The Northeast and Northwest had similar greens AN-HQ scores as the Midwest. The median greens AN-HQ score was lower in the European regions: 8078 in the UK, 1525 in Norway, and 446 in Denmark.

Absolute pesticide risk was highest on greens in East Texas, Florida, Northeast, Denmark, and Norway (Figure 5). However, absolute pesticide risk was highest on fairways in the Midwest, Northwest, and UK.

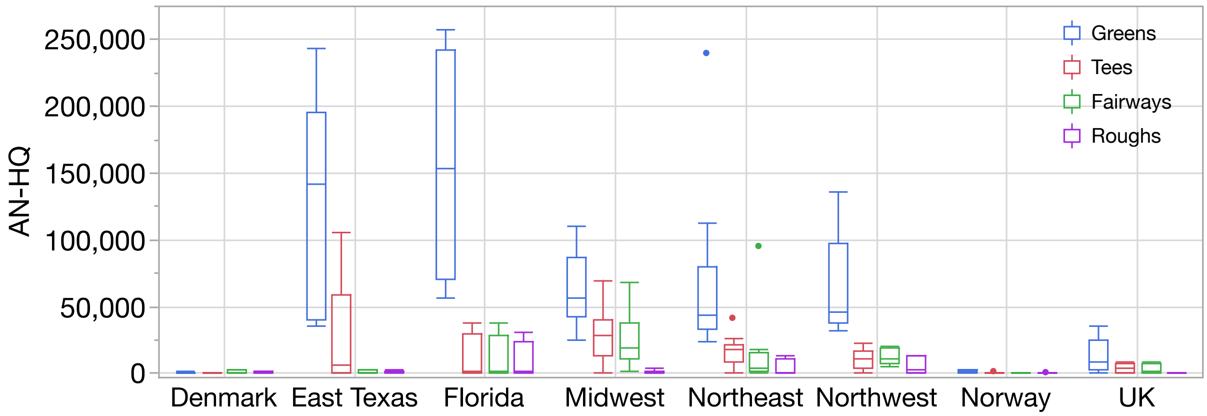

Figure 4. Area normalized hazard quotient (AN-HQ) on greens, tees, fairways, and roughs in each region of the study.

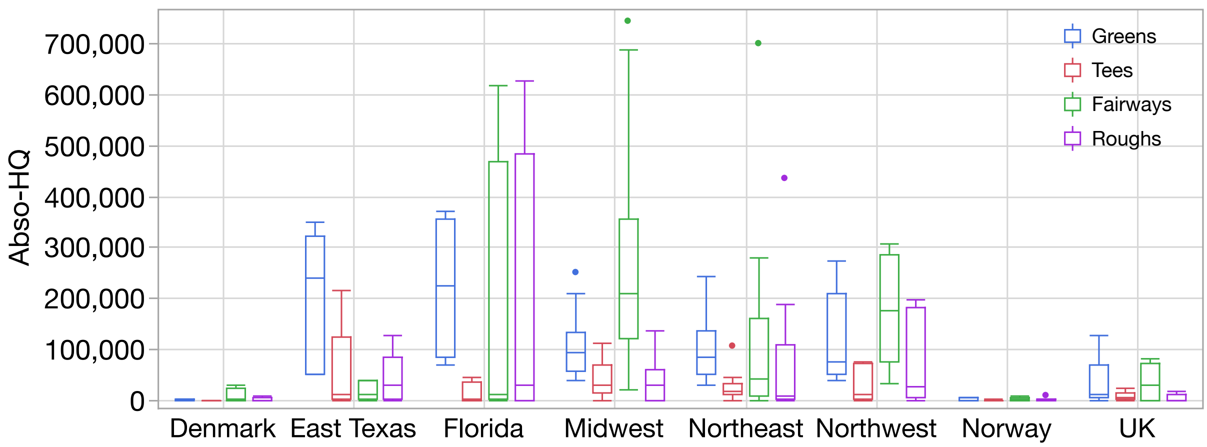

Figure 5. Absolute product hazard quotient (Abso-HQ) on greens, tees, fairways, and roughs in each region of the study.

3.4 Golf course wide pesticide use intensity by region

Golf course-wide pesticide use intensity as quantified by median CWA area treatment was approximately equivalent in the Midwest (7.8), East Texas (7.0), and Florida (6.8) (Figure 6). Median area treatment was slightly lower in the Northeast (3.6) and Northwest (3.2), and lowest in the UK (1.48), Norway (0.44), and Denmark (0.38).

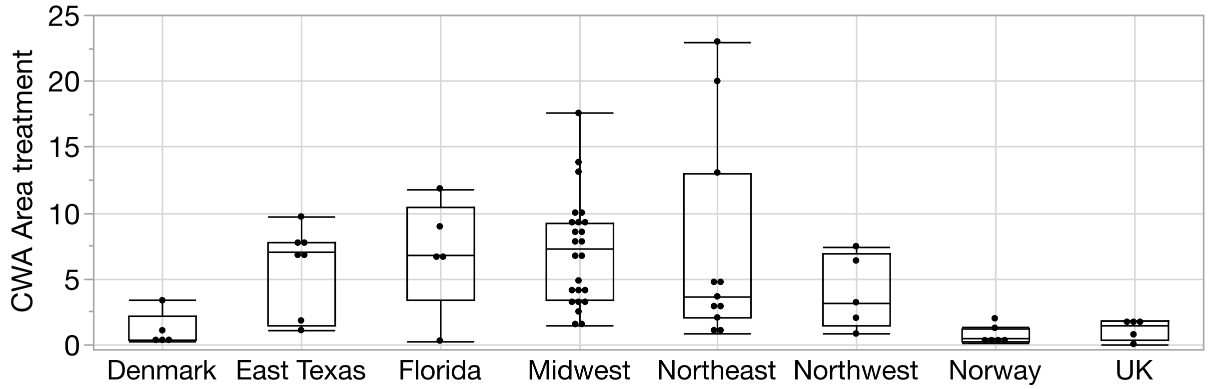

Figure 6. Component-weighted-average (CWA) area treatment in each region of the study. Black dots indicate pesticide risk of individual golf courses.

3.5 Golf course wide pesticide use intensity by region and pesticide type

In Denmark, East Texas, the Northwest, and the UK, applications of herbicides contributed the most to pesticide use intensity (Figure 7). In the remaining regions, Florida, Midwest, the Northeast, and Norway, fungicides contributed the most to pesticide use intensity. Insecticides had the lowest use intensity in all regions, except the UK, where the use intensity of PGRs was lower than insecticides.

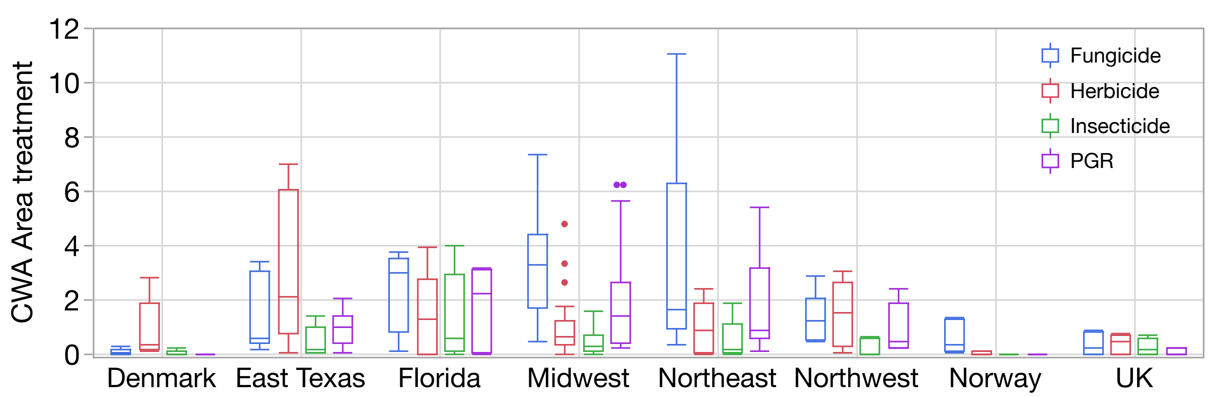

Figure 7. Component-weighted-average (CWA) area treatment of fungicides, herbicides, insecticides, PGRs in each region of the study.

3.5 Golf course-wide pesticide use intensity by region and component

Greens had the highest median area treatment value in all regions of the study (Figure 8). The median greens area treatment value was highest in Florida (91.8). However, values from Florida showed a high level of variation with greens area treatments ranging from 104 to 5.7. East Texas also showed a high level of variation in greens area treatments with a maximum of 83.6, a minimum of 15.0, and a median of 23.2. Greens area treatments in the Midwest, Northeast, and Northwest showed a lower range of variation. In all three regions, area treatments on greens ranged from approximately 15 to 60. The median number of annual area treatments on greens was much lower in all three regions in Europe: UK 6.8, Norway 3.3, and Denmark 2.3. The number of area treatments on tees and fairways was similar in all regions. Area treatments were lowest on roughs in all regions.

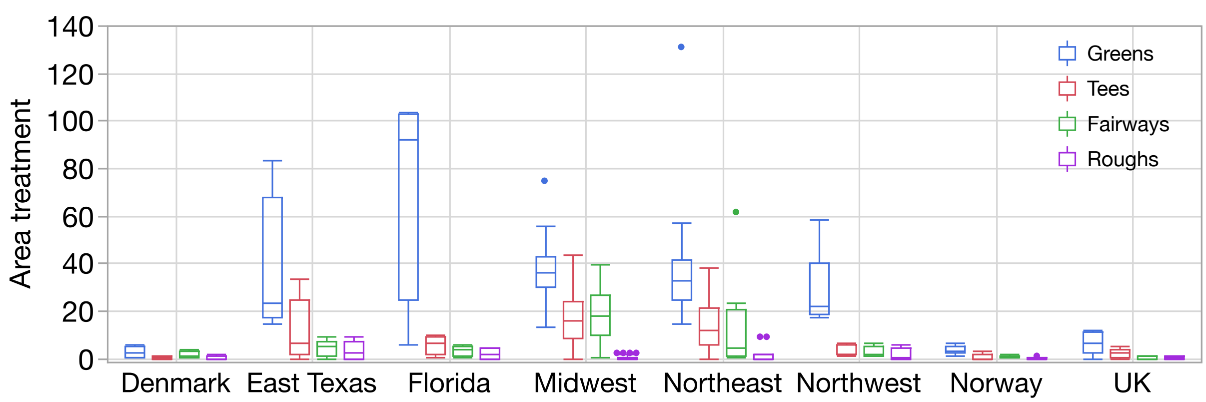

Figure 8. Area treatment of greens, tees, fairways, and roughs in each region of the study.

3.6 The Risk to Intensity Quotient

The Risk to Intensity Quotient (RIQ) correlation line defines average risk for every area treatment value (Figure 9). All golf courses in Norway and Denmark were below the correlation line, indicating that, on average, pesticide products used in these two countries are lower risk than the average as defined by all golf courses in the study. Despite having relatively low risk overall, two golf courses in the UK were above the RIQ correlation line, indicating that these golf courses used pesticides with higher-than-average risk. All golf courses in the Northwest used pesticides with higher-than-average risk. Of the 23 golf courses in the study from the Midwest, nine were above the correlation line and the remaining 14 were below.

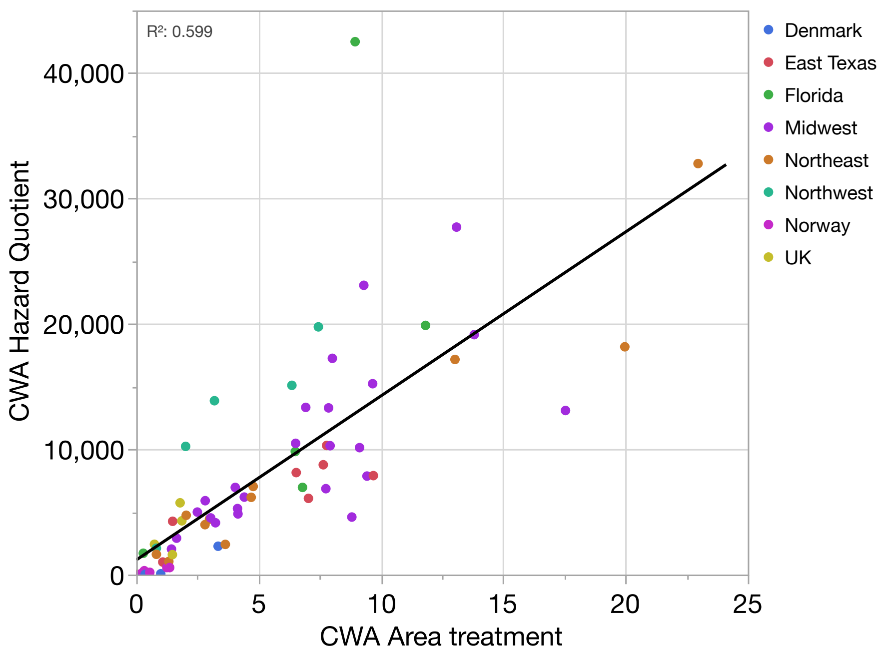

Figure 9. Component-weighted-average (CWA) hazard quotient and area treatment of each golf course in the study. Linear regression (black line) was statistically significant at $\alpha < 0.05$ with r^2 value of 0.599.

The Northwest and the UK region had the highest median RIQ values of all regions. Median RIQ values were lower and similar in Florida, the Midwest, Northeast, and East Texas. Norway and Denmark had the lowest and similar RIQ values.

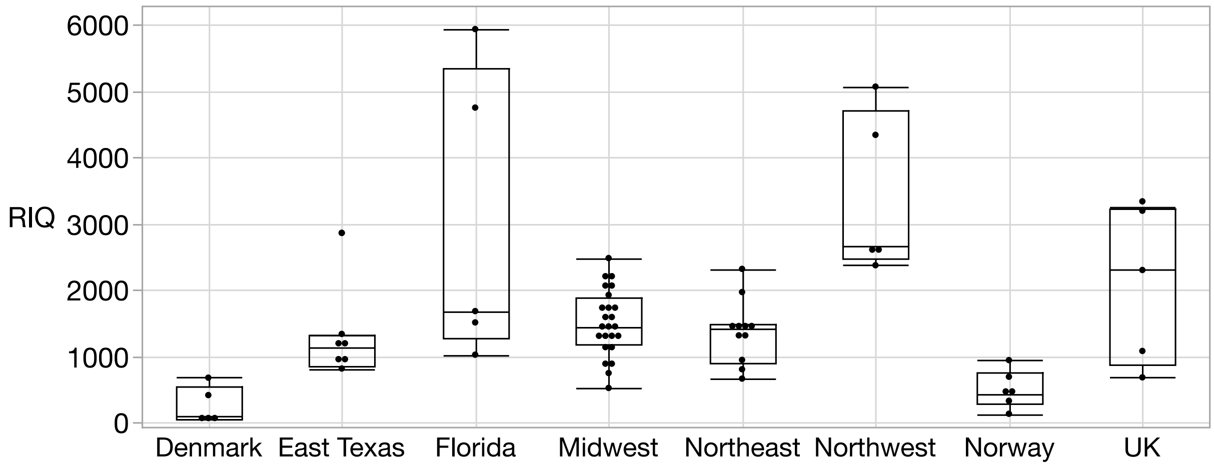

Figure 10. Risk to intensity quotient (RIQ) within each region of the study. Black dots indicate pesticide risk of individual golf courses.

3.7 Predictors of pesticide risk

None of the six possible explanatory variables tested correlated significantly with pesticide risk as quantified by HQ in all regions, in Europe, or in the southern US. In the northern US, maintenance budget per ha and pesticide budget per ha correlated with pesticide risk significantly, but the correlations were both weak (Table 3A).

Pesticide use intensity as quantified by area treatment correlated significantly with the total of all maintenance employees and pesticide budget per ha in all regions (Table 3B). The highest r^2 value observed (0.25) was between area treatment and pesticide budget per ha. Maintenance budget per ha, pesticide budget ha, and revenue per ha correlated weakly but significantly with pesticide use intensity in the northern US, but not in the southern US or Europe.

Table 3. Correlation coefficients between pesticide risk (A) and pesticide use intensity (B) and five economic variables: rounds of golf played, green fee, total maintenance employees, maintenance budget per ha, pesticide budget per ha, and revenue per ha.

A. Pesticide Risk	All regions (n=68)	Europe (n=16)	Northern US (n=40)	Southern US (n=12)
	r^2 value			
Rounds	0.03	0.009	0.09	0.30
Green fee	0.004	0.09	0.04	0.009
Total maintenance employees	0.05	0.07	0.01	0.0001
Maintenance budget per ha	0.02	0.04	0.17*	0.003
Pesticide budget per ha	0.03	0.003	0.15*	0.02
Revenue per ha	0.04	0.06	0.09	0.01
B. Pesticide Use Intensity	All regions (n=68)	Europe (n=16)	Northern US (n=40)	Southern US (n=12)
	r^2 value			
Rounds	0.02	0.01	0.10	0.17
Green fee	0.001	0.00	0.06	0.04
Total maintenance employees	0.14*	0.01	0.05	0.06
Maintenance budget per ha	0.05	0.07	0.22*	0.03
Pesticide budget per ha	0.25*	0.01	0.16*	0.14
Revenue per ha	0.02	0.01	0.16*	0.04

*Correlation coefficient significant at $\alpha < 0.05$.

4. Discussion

4.1 Limitations of a small dataset

The sample size and dataset in this study is small. Even though the sample size is representative of the population of golf courses in each region, it is representative at a low confidence interval with a high margin of error. As such, definitive statements about pesticide risk across regions of the study cannot be made. However, several patterns emerged from the dataset that are clear, while other trends require more data to confirm. This discussion clarifies our level of confidence in accepting some conclusions while arguing for additional data to clarify potential trends.

4.2 Trends across regions

Even when normalizing for season length, golf courses in Denmark and Norway had lower pesticide risk than golf courses in all other regions. The average daily-HQ score across all US regions was 46, 14 in the UK, 3 in Denmark and 2 in Norway. Thus, pesticide risk normalized for season length (Daily-HQ) was at least 15 times higher in the US than in either Norway or Denmark. Pesticide risk in the UK was at least 5 times higher than in Norway or Denmark, but approximately three times lower than in the US. Mean use intensity as quantified by area treatments was also lower in Norway and Denmark than all other regions. The number of pesticide products available to golf course superintendents in Denmark and Norway was less than 20, in comparison to the UK where 74 products were available and the US where, depending on the state, many hundreds to thousands were allowed. In addition, the Risk to Intensity Quotient (RIQ) values of pesticide programs on golf courses in Denmark and Norway were all below average, indicating that the products available in these two countries are low risk. Regulatory environment appears to be the single most important factor driving pesticide risk in our dataset.

In the US, where hundreds of pesticide products and active ingredients are available to golf courses across all regions, pesticide risk on golf courses in the southern US, with longer growing seasons, did not have higher pesticide risk than golf courses with shorter growing seasons in the northern US, refuting our original hypothesis.

4.3 Region specific summaries

Denmark

There are eight registered fungicide products (five of which are biological) that are allowed for use in Denmark. These fungicides are used primarily to control grey snow mold (*Typhula incarnata* and dollar spot (*Clarireedia* spp.) on greens. However, golf courses in Denmark had a median of just 2.3 area treatments on greens, and fungicide use overall only accounted for 3% of pesticide risk (Abso-HQ) on Danish golf courses. Meanwhile, seven herbicides were available to control broadleaf weeds. Herbicides accounted for 91% of pesticide risk on Danish golf courses. Herbicides in Denmark were mostly applied to fairways, because 71% of all pesticide risk (Abso-HQ) on Danish golf courses came from herbicide use on fairways. Only two insecticides were registered for golf courses to control leatherjackets (*Tipula* spp.) and June beetles (*Phyllophaga* spp.). Insecticides accounted for 6% of the pesticide risk on Danish courses. Overall, pesticide risk on Danish golf courses was low and resulted from herbicide applications to fairways.

In 2005, an agreement to phase out the use of pesticides on Danish golf courses was signed by the Danish Golf Union (DGU), the Danish Ministry of Environment (MoE), and the Municipalities Organization in Denmark. Subsequently, the MoE built an online tool which tracks pesticide risk using a model similar to HQ that all golf courses are required to use. The MoE sets a maximum allowable pesticide risk value for fungicides, herbicides, insecticides, and plant growth regulators that golf courses in Denmark cannot exceed. If a golf course exceeds their allowable pesticide risk for a given pesticide type, the course could be subject to a fine by the MoE. Periodically the MoE reduces the maximum allowable pesticide risk on golf courses.

According to the MoE, pesticide risk on golf courses has been reduced 97% since the agreement was signed in 2005. Ninety-eight percent of golf courses are compliant in tracking their pesticide risk with values below the maximum allowable. To remain under this threshold, golf course superintendents must tolerate higher levels of disease, weeds, and insects. Assessments completed by the DGU indicate that the majority of golfers surveyed were satisfied with the quality of golf courses and were not concerned by the higher pest thresholds; however, golfers with a ten handicap and below were less satisfied with course conditions, but only 7% of players are in this group.

Norway

The pests that cause the greatest economic damage on golf courses in Norway include Microdochium patch (*Microdochium nivale*) and grey snow mold (*Typhula incarnata*), which are most damaging to greens and fairways in the winter. To control for these diseases, Norwegian golf course superintendents apply one, two, or three applications of fungicides in the late fall. There are four fungicides registered for use on golf courses in Norway: azoxystrobin, fludioxonil, propiconazole, and trifloxystrobin. Fungicide use accounted for 94% of the total pesticide risk (Abso-HQ) on Norwegian golf courses in the study. Forty-one percent of total pesticide risk on golf courses in the Norwegian sample was from fungicide use on fairways, 26% was from greens, 22% from roughs, and 4% from tees.

UK

There are currently 17 pesticide active ingredients that are allowed on golf courses in the UK. Fungicides account for 46% of the overall risk, insecticides 42%, and herbicides 12%. Fungicides are primarily applied to greens on UK golf courses in the study. Thirty nine percent of total pesticide risk (Abso-HQ) came from fungicide applications to greens. These fungicides primarily target anthracnose (*Collectotrichum cereale*) and Microdochium patch (*Microdochium nivale*).

In this study, 38% of the total or absolute pesticide risk on UK golf courses came from insecticide applications to fairways making UK fairways higher risk than all other golf course components. Leatherjackets (Tipulidae family) and chafer grubs (*Amphimallon majale*) are primary insect pests on UK golf courses. Leatherjackets are the larvae of craneflies and live in soils with higher clay content. Chafer grubs are the larvae of chafer beetles and live in soils with high sand content. If both species of larvae are present in the soil at high enough numbers, badgers, birds, and other animals will dig through the soil to find and eat them. In the process these animals will often destroy large areas of turf. Currently, only acelepryn is the insecticide registered for use on golf courses in the UK.

Florida

In our study, the greens on all golf courses in Florida were planted with bermudagrass, and despite bermudagrass's reputation as a relatively disease tolerant turfgrass, median pesticide risk (AN-HQ) on greens in Florida was nearly three times higher than in the Northeast, Midwest, and Northwest. Greens on these Florida golf courses accounted for 4% of the total turfgrass area but were responsible for 40% of absolute risk (Abso-HQ). Pesticide risk attributable to fungicides was six times higher than risk attributable to insecticides on greens in Florida, and herbicides were not used on greens on any of the Florida golf courses studied. Golf courses in Florida averaged over 60 fungicide area treatments on greens each year. Fungicide applications in Florida commonly target anthracnose (*Collectotrichum cereale*), leaf and sheath blight (*Rhizoctonia* spp.), dollar spot (*Clarireedia* spp.), leaf spot (*Bipolaris sorokinia)* fairy rings, and occasionally pythium (*Pythium aphanidermatum*).

Despite high pesticide risk on greens in Florida, median pesticide risk on fairways was lower than any of the regions from the courses studied in the northern US. Superintendents in Florida commonly choose to fertilize fairways to recover from disease instead of applying pesticides frequently. When managers apply pesticides to fairways, they commonly apply fungicides and target leaf spot (*Bipolaris sorokinia)* and dollar spot (*Clarireedia* spp.).

East Texas

Median area normalized pesticide risk (AN-HQ) on greens studied in Texas was three times higher in East Texas than it was in the Midwest, Northeast, and Northwest and roughly equivalent to that in Florida. Fungicides in East Texas are applied preventatively and primarily to greens to control pythium diseases (*Pythium aphanidermatum*), take-all root rot (*Gaeumannomyces graminis*), and leaf spot (*Bipolaris sorokinia*).

In our study, golf course-wide median pesticide risk (CWA-HQ) from herbicides was approximately equivalent to risk from fungicides on golf courses in East Texas. Common weeds on the golf courses studied in the region included annual bluegrass (*Poa annua*), crabgrass (*Digitaria* spp.), goosegrass (*Eleusine indica*), and sedges (Cyperaceae family).

Midwest

Based on the courses in our study, dollar spot (*Clarireedia* spp.) is the most common disease on golf course turfgrass in the Midwest (Smiley et al., 2005; Salgado-Salazar et al., 2018) and is the primary driver of pesticide risk in the region. Grey snow mold (*Typhula incarnata*) and anthracnose (*Collectotrichum cereale*) also are common in the Midwest. Median absolute and area normalized pesticide risk on fairways in the Midwest study samples were higher than in any other sampled region of the study, likely because of fairway fungicide applications targeting dollar spot. Absolute and area normalized pesticide risk on greens was similar to courses studied in the Midwest to the Northeast and Northwest.

Northeast

Fungicides accounted for the greatest pesticide risk by pesticide type in sampled courses in the Northeast. Applications of fungicides in the Northeast on greens and fairways primarily target dollar spot (*Clarireedia* spp.). Median absolute pesticide risk (Abso-HQ) was highest on greens in the Northeast, which was unexpected given that fungicides are applied to fairways to control dollar spot. This finding may be an artifact of the dataset. The eleven golf courses in the dataset from the Northeast were all part of the New York State Park system. These courses are public with lower budgets than average for courses sampled in other regions. The average maintenance budget of a golf course in this study was $19,150 per ha, while golf courses in the Northeast region had an average maintenance budget of $8,740. Bekken et al. (2021) found that maintenance budget was the best predictor of pesticide risk and use intensity with risk increasing with maintenance budget. Thus, because the Northeast sample is limited to state run public courses, it is likely not representative of fairway fungicide use in the region.

While median risk from insecticides was the lowest of all pesticide types in the Northeast, for 2 of the 11 golf courses in the region, insecticides contributed twice as much to their overall pesticide risk as any other pesticide type. Annual bluegrass weevil has recently become a significant pest throughout the region. The asynchronous nature of their life cycle with multiple generations per year require frequent insecticide applications to large areas (e.g., fairways and roughs) to control the population. Additionally, annual bluegrass weevils' propensity to develop resistance to pyrethroid chemistries can lead to ineffective applications before golf personnel recognize that insecticide resistance may be an issue.

Northwest

The original intention for this region was to separate data collected on courses from Montana and Oregon. However, given a low survey response rate from both regions, we decided to group survey responses from the Northwest and Pacific Northwest together. Thus, the five golf courses in the Northwest region spanned a large geographic area and included golf courses east and west of the Cascade Mountain range. Three golf courses in the study were in eastern Oregon (2) and Washington (1), and two golf courses were in Montana. East of the Cascades, the primary pests included grey snow mold, billbugs, and broadleaf weeds. West of the Cascades, the primary pests included microdochium patch (*Microdochium nivale*), anthracnose (*Collectotrichum cereale*), leatherjackets (Tipulidae family), and again broadleaf weeds.

Contrary to expectations that fungicides would account for the majority of pesticide risk, herbicides contributed to pesticide risk more than any other pesticide type sampled in the region. Insecticide use was either zero or high (CWA-HQ > 5000). It is unclear whether this pattern would hold with a larger dataset, but pesticide risk (CWA-HQ) and daily pesticide risk (Daily-HQ) in the Northwest were the highest of all regions in the US.

4.4 Hesitancy of US-based superintendents to supply pesticide records

This study was primarily limited by the hesitancy of US-based superintendents to share pesticide records. Had all golf course superintendents who took the UW-Madison Resource Efficiency Survey agreed to share pesticide records, the sample size in this study would have more than doubled. Eighty-three percent of golf course superintendents in Norway, Denmark, and the UK supplied pesticide records, however only 47% of US-based golf course superintendents shared pesticide records. It is unclear as to why US superintendents hesitate to confidentially and anonymously share pesticide records but may be related to the concern that supplying records would damage the golf course's reputation in its community, if leaked or published. Perhaps of greater concern to golf course superintendents may be that higher levels of public awareness of golf course pesticide use could lead to regulation that could limit the wide variety of pesticides currently available for use on golf courses in the US.

4.5 Contextualizing golf course pesticide risk

Bekken et al. (2021) found that pesticide risk on golf courses sampled in Wisconsin and New York was within the range of agricultural crops grown in both states. With data from the National Agricultural Statistics Service (NASS) the authors found that mean pesticide risk on golf courses, as estimated by the hazard quotient model, was eight times higher in golf than in corn production. However, golf course pesticide risk was approximately equivalent to grape production, three times lower than apple production and twelve times lower than potato production.

Pesticides applied to golf courses do not appear to present acute toxicity risks to golfers (Murphy and Haith, 2007; Putnam, 2008; Wong and Haith, 2013). Less is known about the chronic risks of pesticides to golfers. Only one study could be located that analyzed the health effects of pesticide exposure to golf course superintendents (Kross, 1996). This study analyzed the death certificates of 686 deceased members of the Golf Course Superintendents Association of America (GCSAA) from 1970 to 1992. The study found elevated mortality from three cancers (non-Hodgkin's lymphoma, brain, and prostate) and diseases of the nervous system, which are common in other occupations that expose workers to pesticides. Whether this pattern will hold true for golf course superintendents living today is unknown.

The ecological effects of pesticide risk on golf courses are clearer. Pesticides applied to golf courses negatively affect beneficial soil biota, but the effect of pesticides applications on various functional groups of soil biota depend on the nature of a golf course's pesticide application program (Gan and Wickings, 2017). King and Balogh (2010) found that pesticides were regularly transported offsite by streams draining a golf course but did not exceed EPA guidelines. Finally, several studies suggest that pesticide applications to golf courses routinely affect surrounding aquatic ecosystem health negatively (Metcalfe, 2007; Haith and Rossi, 2003).

4.6 Regulating golf course pesticide use

Regulatory environment was the best predictor of pesticide risk in this study. Norway, Denmark, and the UK limit the number of pesticide products allowed for use on golf courses to fewer than thirty, and, as a result, golf courses in these countries have low pesticide risk. In the US, where hundreds to thousands of pesticide products are registered for use on golf courses, pesticide risk on golf courses was significantly higher. Denmark's system of limiting pesticide risk on golf courses is an example of how pesticide risk can be reduced beyond simply banning products. However, only golf courses in Denmark must limit their use of pesticides in this manner. All other forms of agriculture in Denmark are not required to track and limit pesticide risk in the same way as golf courses.

Limiting and regulating pesticide risk is a value-based decision within a society, culture, state or nation. Scientific evidence suggests that pesticide use on golf courses does not pose dramatic human or ecological consequences as suggested by some concerned citizens (Hilson, 2017), but neither is pesticide use on golf courses as harmless as some golf course superintendents maintain (Arcury-Quandt et al., 2011).

5. Conclusion

To the author's knowledge, this is the first study to compare pesticide risk on a sample of golf courses across varying geographical regions. Even though the sample size of this study is low, given the complete lack of data on golf course pesticide risk across regions in the existing literature, the sample size achieved in this study provides an initial indication of golf course pesticide risk across regions. Further data collection is needed to increase confidence in the results of this study.

Despite the small dataset, our analysis reveals that regulatory environment is the best predictor of pesticide risk. Contrary to our original hypothesis, it appears from our limited dataset that climate does not influence pesticide risk as hypothesized. Golf courses in the southern US, with longer growing seasons, did not have higher pesticide risk than golf courses in the Northern US.

Bekken et al. (2022) found that uptake of best management practice intended to reduce pesticide risk had no correlation with actual pesticide risk. This study found that maintenance budgets were weakly correlated to pesticide risk in the Northern US, but not in other regions. Lower maintenance budget in some circumstances could lead to lower pesticide risk. However, restricting pesticides available to golf courses, either through product bans (i.e., UK and Norway) or the implementation of mandatory software tools that impose limits on pesticide risk (i.e., Denmark) appear the most effective ways to reduce pesticide use, and therefore risk, on golf courses sampled in this study.

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Chapter 4: Quantifying golf course energy use efficiency

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Published title: Estimated energy use and greenhouse gas emissions associated with golf course turfgrass maintenance in the Northern USA

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Abstract

Carbon sequestration in golf course soils has received some attention, but energy use and greenhouse gas (GHG) emissions from golf course turfgrass maintenance are poorly quantified. This study developed a model to estimate energy consumption and GHG emissions from golf turf maintenance and applied the model to 14 golf courses located in the northern USA over a 3-yr period. Energy use and GHG emissions that result from golf course maintenance operations were divided into three scopes. Scope 1 consisted of onsite emissions (n = 14), Scope 2 consisted of offsite emissions (n = 7), and Scope 3 consisted of supply chain (upstream) emissions (n = 7). Scope 1 emissions primarily result from onsite fuel use, Scope 2 emissions primarily result from offsite electricity generation, and Scope 3 emissions primarily result from the production and transport of goods and materials (e.g., machines, fertilizers, pesticides) to the golf course. All scopes were combined to calculate total energy use and emissions (n = 4). Mean area-normalized Scope 1 energy use was 24 GJ ha^{-1} yr^{-1}, mean Scope 2 energy use was 7 GJ ha^{-1} yr^{-1}, mean Scope 3 energy use was 40 GJ ha^{-1} yr^{-1} and the mean of all scopes was 72 GJ ha^{-1} yr^{-1}. Mean area-normalized Scope 1 emissions were 1,599 kg CO_2e ha^{-1} yr^{-1}, mean Scope 2 emissions were 1,012 kg CO_2e ha^{-1} yr^{-1}, mean Scope 3 emissions were 1,847 kg CO_2e ha^{-1} yr^{-1} and the mean of

all scopes was 4,277 kg CO_2e ha^{-1} yr^{-1}. Fuel and electricity use accounted for 63% of all GHG emissions. Electrifying golf course maintenance equipment and sourcing electricity generated from renewable sources are likely the most effective ways for golf course turfgrass maintenance emissions to be reduced.

Core ideas

- Greenhouse gas emissions from golf course maintenance can be quantified using life cycle analysis.
- Mean emissions from golf course maintenance were 4,277 kg CO_2e ha^{-1} yr^{-1}.
- Fuel and electricity use together accounted for 63% of all GHG emissions.

Abbreviations

DEFRA, UK Department of Environment, Food and Rural Affairs; GHG, greenhouse gas; LCA, Life Cycle Analysis

1. Introduction

The United Nations Sustainable Development Goal 13 (United Nations, 2016) states that urgent action must be taken to address climate change. Mitigating climate change will require all sectors of society to sharply reduce greenhouse gas (GHG) emissions (IPCC, 2014). Golf is a global sport played in 209 of 249 countries on 38,864 courses (R&A, 2019). Golf courses sequester carbon through the turf-soil system, but they also emit greenhouse gases through their maintenance. This balance between emissions and sequestration determines the carbon balance of golf course maintenance operations.

Researchers have studied the ability of turfgrass systems to sequester carbon, and previous research indicates that transiting land use from agriculture to golf is associated with a rapid increase in soil organic carbon (SOC) concentration (Baird, 2011; Selhorst & Lal, 2013; Selhorst

& Lal, 2011 ; Yao & Shi, 2010; Bandaranayake et al., 2003; Qian & Follet, 2002). This increase in SOC concentrations sequesters atmospheric carbon dioxide and has the potential to offset carbon emitted in the maintenance of golf courses. Many short term (fewer than 10 yr) turfgrass studies on lawns and golf courses report linear carbon sequestration rates between 0.32 and 1.63 Mg C ha^{-1} yr^{-1} (Braun & Bremer, 2019; Law & Patton, 2017; Qian et al., 2010). However, longer term turfgrass studies indicate that approximately 30 yr after turfgrass establishment SOC concentrations in golf course soils slow, and after approximately 90 yr carbon sequestration rates near zero (Bandaranayake et al., 2003; Qian & Follet, 2002; Selhorst & Lal, 2011). Thus, previous research suggests that for golf courses over 30-yr-old carbon emissions from golf course maintenance, not carbon sequestration in golf course soils, is more important in determining the overall carbon balance of golf turf maintenance. Unfortunately, in-depth analyses of carbon emissions in turfgrass systems are rare.

Because energy is used in many different forms on golf courses, developing a carbon emissions model for golf courses is a promising method for measuring the climate impact of energy use at a golf facility. Two previous peer reviewed studies have developed Life Cycle Analysis (LCA) models to estimate energy consumption (i.e. joules) and greenhouse gas emissions (i.e. kg CO_2e) from golf course management operations (Barlett & James, 2011; Tidåker et al., 2017).

Barlett and James (2011) were the first to develop an LCA model capable of estimating both GHG emissions and sequestration from golf course components (greens, tees, fairways, roughs etc.). The authors applied their GHG footprint model on two golf courses in the UK during a single year. GHG emissions from all playing surfaces (greens, tees, fairways, and rough) of a links and parkland course were 1,400 kg CO_2e ha^{-1} yr^{-1} and 1,700 kg CO_2e ha^{-1} yr^{-1}, respectively.

Tidåker et al. (2017) also developed a LCA model to calculate total energy use and greenhouse gas (GHG) emissions from golf courses. The authors applied the model to two golf courses in Sweden. Energy use on the two golf courses were 14 and 19 GJ ha^{-1} yr^{-1}. GHG emissions from the management of the two courses were 1,600 kg CO_2e ha^{-1} yr^{-1} and 1,000 kg CO_2e ha^{-1} yr^{-1}, which were comparable but slightly lower than those found from the UK courses reported by Bartlett and James (2011).

Selhorst and Lal (2011) and Gillete (2014) both estimated emissions from golf course maintenance but stopped short of creating full LCA models for golf course maintenance GHG emissions. GHG emissions from the production and transport of sand, machinery, and energy sources were not included by either study. Selhorst and Lal (2011) estimated golf course maintenance emissions from fuel use, electricity used for irrigation, fertilizer use, and pesticide use on a single golf course in Ohio. Estimated emissions from the golf course totaled 1,109 kg CO_2e ha^{-1} yr^{-1}. Gillette (2014) estimated emissions from clubhouse and maintenance facility electricity, propane use, natural gas use, electricity for irrigation, production and application emissions from fertilizer, and fuel usage for golf course maintenance on 22 golf courses in Colorado, USA over a 3-yr period. Gillete (2014) divided results into two statistical groups and found that mean GHG emissions from golf course operations were approximately 8,450 kg CO_2e ha^{-1} yr^{-1} and 6,320 kg CO_2e ha^{-1} yr^{-1}, respectively. These high emissions rates in comparison to Bartlett and James (2011) and Tidåker et al. (2017) are mostly attributable to the inclusion of clubhouse electricity in the calculations of Gillete (2014) and not in the other two studies.

The studies that use LCA models to quantify the GHG emissions from golf turf maintenance (Bartlett & James, 2011; Tidåker et al., 2017) apply their models to a total of only four golf courses observed over a single year. In addition, the two studies were completed in the United

Kingdom and Sweden. No such peer-reviewed studies utilizing LCA models have been completed in the United States (US), the world's second largest emitter of greenhouse gases (USEPA, 2020) and the country with 43% of the world's golf courses (16,752 of 38,864) (R&A, 2019). The purpose of this study is to expand the calculation of GHG emissions from golf course maintenance operations to include more golf courses in the United States. This study reports on energy use and GHG emissions from US northern golf courses evaluated over a 3-yr period from 2016--2018.

2. METHODS

2.1 A framework for measuring energy use and GHG emissions on golf courses

2.1.1 Life cycle analysis

Life cycle analysis (LCA) is a methodology that quantifies both the direct and indirect environmental impact of economic activity. As applied in this study, an LCA methodology is used to estimate direct and indirect energy use on golf courses and, with the exception of emissions from fuel use, uses these estimates to calculate greenhouse gas (GHG) emissions. Emissions from fuel use are calculated directly from volume of fuel burned.

2.1.2 Absolute and area normalized metrics

To measure energy use and GHG emissions on golf courses, two types of metrics were established: an absolute metric, and an area normalized metric. An absolute metric refers to one that does not consider the area of the golf course, such as the annual weight of GHGs emitted (kg CO_2e). Area normalized metrics take an absolute metric and divide by area, for example, the weight of GHG emissions per hectare (kg CO_2e ha^{-1}).

2.1.3 Scoping

Golf course turf management operations were the subject of this study. Energy use and GHG emissions from golf course clubhouse operations were not included in this analysis and considered out of scope. Energy use and GHG emissions generated by golf course turfgrass maintenance were divided into three scopes following the UK Department of Environment, Food and Rural Affairs (DEFRA) (2019) scoping framework. Scope 1 energy use and GHG emissions were defined as energy used and emissions occurring on the property of a given golf course. This includes all fuels burned on the golf course, such as diesel and gasoline to power maintenance equipment and natural gas or propane used to heat the maintenance building. Emissions from the denitrification of nitrogen fertilizer were also included as a part of Scope 1 in the GHG emissions model. Scope 2 was defined as those emissions and energy use that resulted from onsite electricity use. The emissions caused by electricity generation happen offsite of the golf course, which is why emissions from electricity generation are not included in Scope 1. Scope 2 includes electricity used to run the golf course maintenance building, maintenance equipment and irrigation pumps (electricity from other parts of the golf facility such as the clubhouse are excluded in this study). Scope 3 was defined as energy use and GHG emissions that are an upstream result of the golf maintenance operations. Sources of Scope 3 emissions and energy use included in this study were the production and transport of energy sources to the facility, production of fertilizer and pesticides, production and transport of sand to the facility, and machinery production, repair, and maintenance.

2.1.4 Country specific LCA model coefficients

The use of country specific energy and emission coefficients is encouraged by the Intergovernmental Panel on Climate Change (De Klein et al., 2006). Bartlett and James (2011) attempted to use UK specific GHG coefficients where possible. This study applies all US based GHG and energy coefficients with a few exceptions. GHG emission coefficients for the production, transport, and use of fuels are from DEFRA (2019). DEFRA emission coefficients for transport and production of fuels (Scope 3) were used because such coefficients could not be located from the USEPA. DEFRA emission coefficients were also utilized for fuel use because the coefficients are published in terms of carbon dioxide equivalents, meaning they account for the differing global warming potential of emitted greenhouse gases in addition to carbon dioxide. USEPA fuel emission coefficients only account for carbon dioxide emissions and not other greenhouse gases. Emissions coefficients for electricity, and all other input variables to the LCA model, came from US-based sources (Lal, 2004; Bowers, 1992; Mudahar & Hignett, 1987; Green, 1987; Pimentel, 1980; Cervinka, 1980; Boustead, & Hancock, 1979).

2.1.5 Energy coefficients

Scope 1 and 2 energy coefficients were primarily from Cervinka (1980). Scope 3 energy coefficients came from a variety of sources. Energy coefficients for the production of N, P, and K were from Mudahar and Hignett (1987). Several simplifying assumptions were made to estimate emissions from the production of fertilizers. All nitrogen was assumed to be urea and all phosphorus was assumed to be triple super phosphate. Energy coefficients for the production of pesticide active ingredients were from Green (1987). Energy coefficients for the mining and processing of sand were from Boustead and Hancock (1979) . The energy coefficient for the transport of sand by dump truck was from Pimentel (1980). This analysis assumes that sand travels an average of 200 km to reach the golf course. The 200 km travel distance assumption was derived from the average distance by road between the main quarry in Wisconsin that produces golf course topdressing sand and the golf courses in the state that participated in this study. The energy use of manufacturing, transporting and repairing machinery was estimated for golf maintenance equipment using methods of Bowers (1992). Golf course superintendents were asked to report the number of triplex mowers, triplex greens mowers, walk behind mowers, tractors, bunker raking tractors, aerators, light utility vehicles, heavy utility vehicles, motorized sprayers and spreaders, fairway mowers, rough mowers and banks and surrounds mowers. The weight of each machine was determined through the Toro equipment lineup. Bowers (1992) estimated that agricultural equipment required 87.6 MJ kg^{-1}, that transportation required 8.8 MJ kg^{-1} and that repairs over the course of the vehicle's lifetime are 55% of the manufacturing energy cost. All machines in this study were assumed to have a 20-yr lifetime. Total energy required for the production, maintenance and repair of each machine at the golf course was calculated and then annualized over its 20-yr lifetime.

2.1.6 GHG emission coefficients

All Scope 1 GHG emissions coefficients are standard emission coefficients from DEFRA (2019). Nitrous oxide emissions from the application of nitrogen fertilizer were estimated using the IPCC methods (De Klein, 2006). Of the nitrogen fertilizer applied as fertilizer 1% was assumed to denitrify. The global warming potential of N_2O was assumed to be 281 (De Klein, 2006). Scope 2 GHG emissions from electricity use were estimated using the average emission coefficient for the US grid (USEPA, 2016). Scope 3 emissions from the production and transport of fuels and electricity were from DEFRA (2019). The energy coefficients for the production of fertilizer, the production of pesticide, the production and transport of sand and the production, transport and repair of machinery were all converted to GHG coefficients using the energy to GHG conversion factor from Lal (2004).

2.1.7 Fertilizer and pesticide records

The annual weight of N, P, and K applied to the golf courses was calculated from golf course fertilizer records. The annual weight of fungicide, herbicide and insecticide active ingredients applied to the golf course was determined from pesticide records. Some participating golf courses declined to share fertilizer and pesticide records, which precluded calculation of Scope 3 emissions for these courses, and in turn prevented the calculation of energy use and GHG emissions from all scopes on these golf courses.

2.2 Collecting data

2.2.1 Survey

Data presented in this paper were obtained via the University of Wisconsin-Madison Resource Efficiency Survey which was conducted by the authors of this paper in an attempt to quantify resource (water, energy, fertilizer, and pesticide) use on golf courses (Bekken & Soldat, 2020). The survey collected information about facility economics, environmental conditions and data on resource use over a 3-yr period from 2016 to 2018. The survey was distributed through the Golf Course Superintendents Association of America (GCSAA) chapters in Wisconsin, Minnesota, and Montana. In addition, the survey was distributed in New York through the New York State Park Golf Course network. Golf course superintendents who completed the survey were individually contacted to ensure that the survey was filled in accurately.

Golf course superintendents were asked to report diesel, gasoline, electricity, natural gas, propane and heating oil use for 2016, 2017, and 2018 in three separate parts of their facility: the irrigation pump station, the maintenance building, and the maintenance equipment.

To calculate energy use and emissions from major inputs to golf turf systems, golf course superintendents were asked to provide pesticide and fertilizer records and sand use totals for 2016, 2017, and 2018. Superintendents were also asked to provide the number and type of all machines used at the facility.

2.2.2 Energy practices

To ensure the GHG emission and energy model accurately represented actual energy use for each golf course surveyed, questions in the survey were included to capture alternative practices such as green tariffing and onsite renewable energy generation. None of the golf courses in the study purchased or generated renewable energy; therefore, no modifications to the GHG and energy models were required.

2.2.3 Statistics

Energy use and emissions were calculated for three scopes over a 3-yr period from 2016 to 2018 for each golf course. From these years of data, a 3-yr mean of emissions and energy use within each scope was calculated for each golf course. These 3-yr averages are meant to approximate energy use and emissions at the golf course by integrating annual fluctuations caused by weather or other confounding factors. To determine an average value for each scope, emissions and energy use were averaged across all golf courses included in the study. The sample size within each scope differs, meaning that the sum of Scope 1, 2, and 3 emissions and energy use in Tables 5 and 6 will not equal the emissions and energy use reported in the *All scopes* column. Emissions and energy use for all scopes were calculated only from the four golf courses that provided data across all three scopes.

Statistical analysis and data visualization was completed in Microsoft Excel and JMP Pro (Version 15.0, SAS Institute Inc., Cary, NC, 1989--2020).

2.3 Models for GHG emissions and energy use on golf courses

2.3.1 Organization

GHG emissions and energy use models (Tables 1 and 2, respectively) were organized into eight categories: Fuel (Production and Transport or PT), Fuel (Use or U), Electricity (Production and Transport or PT), Electricity (Use or U), Fertilizer (Production and Application, or PA), Pesticide (Production or P), Sand (Production and Transport or PT), and Machinery (Production, Transport, and Repair or PTR). GHG emissions and energy use were also organized into three scopes, as described in section *2.1.3.*

2.3.2 GHG emissions model

$$Annual\ Absolute\ GHG\ Emissions\ =\ G$$

$$Annual\ Area\ Normalized\ GHG\ Emissions\ =\ \frac{G}{A_{Turf}}$$

where G is the annual total weight of carbon dioxide equivalents emitted for the golf course turfgrass maintenance operation in kg CO_2e yr^{-1}.

$$G\ = G_{Fuel\ (PT)}\ + G_{Fuel\ (U)} + G_{Electricity(PT)} + G_{Electricity\ (U)} + G_{Fertilizer\ (P)} + G_{Fertilizer\ (A)} + G_{Pesticide\ (P)} + G_{Sand\ (PT)} + G_{Machinery\ (PTR)}$$

where P is production, T is transport, U is use, A is application (i.e., denitrification), and R is repair. The total area of turf was defined as the sum of the areas of golf course components.

$$A_{Turf} = A_{Greens}\ + A_{Tees} + A_{Fairways} + A_{Rough}$$

where A_{Turf} is the total area of turfgrass, A_{Greens} is the area of greens, A_{Tees} is the area of tees, $A_{Fairways}$ is the area of fairways, A_{Roughs} is the area of rough in ha. Emissions were divided into three scopes.

$$Scope\ 1:\ G_{S1} = G_{Fuel\ (U)} + G_{Fertilizer\ (A)}$$

$$Scope\ 2:\ G_{S2} = G_{Electricity\ (U)}$$

$$Scope\ 3:\ G_{S3} = G_{Fuel\ (PT)} + G_{Electricity(PT)} + G_{Fertilizer\ (P)} + G_{Pesticide\ (P)} + G_{Sand\ (PT)} + G_{Machinery\ (PTR)}$$

where G_{S1}, G_{S2}, G_{S3} is the annual total weight of carbon dioxide equivalents emitted for the golf course turfgrass maintenance operation in kg $CO_2e\ yr^{-1}$ for Scope 1, 2, and 3, respectively.

$$G_{Fuel\ (PT)} = Q_D C_{D(PT)} + Q_G C_{G(PT)} + Q_{NG} C_{NG(PT)} + Q_P C_{P(PT)} + Q_{HO} C_{HO(PT)}$$

$$G_{Fuel(U)} = Q_D\ C_{D(U)} + Q_G C_{G(U)} + Q_{NG} N_{NG(U)} + Q_P C_{P(U)} + Q_{HO} C_{HO(U)}$$

$$G_{Electricity\ (PT)} = Q_E\ C_{E(PT)}$$

$$G_{Electricity\ (U)} = Q_E C_{E(U)}$$

$$G_{Fertilizer(P)} = Q_N C_{N(P)} + Q_P C_{P(P)} + Q_K C_{K(P)}$$

$$G_{Fertilizer(A)} = Q_N\ C_{N(A)}$$

$$G_{Pesticide(P)} = Q_H\ C_{H(P)} + Q_F C_{F(P)} + Q_I C_{I(P)}$$

$$G_{Sand(MT)} = Q_S\ C_{S(M)} + Q_S C_{S(T)}$$

$$\begin{aligned} G_{Machinery(PTR)} &= Q_{TM}\ C_{TM(PTR)} + Q_{TGM} C_{TGM(PTR)} + Q_{WBM} C_{WBM(PTR)} + Q_T C_{T(PTR)} + Q_{BRT} C_{BRT(PTR)} + Q_A C_{A(PTR)} \\ &+ Q_{LUV} C_{LUV(PTR)} + Q_{HUV} C_{HUV(PTR)} + Q_{MSS} C_{MSS(PTR)} + Q_{FM} C_{FM(PTR)} + Q_{RM} C_{RM(PTR)} + Q_{SM} C_{SM(PTR)} \end{aligned}$$

where $G_{Fuel\ (PT)}$ is the emissions from production and transport of fuels, $G_{Fuel\ (U)}$ is the emissions from combusting the fuel, $G_{Electricity\ (PT)}$ is the emissions from the production and transport of energy sources to generate electricity, $G_{Electricity\ (U)}$ is the emissions from the combusting fuels to generate electricity, $G_{Fertilizer\ (P)}$ is the emissions from producing fertilizer, $G_{Fertilizer\ (A)}$ is the emissions from the denitrification process after applying nitrogen fertilizer, $G_{Pesticide\ (P)}$ is the emissions from production of pesticides, $G_{Sand\ (PT)}$ is the emissions from the production and transport of sand, and $G_{Machinery\ (PTR)}$ is the emissions from the production, transport, and repair of machinery. Units for all equations are kg CO_2e yr^{-1}.

2.3.3 Energy model

$$Annual\ Absolute\ Energy\ Use\ = E$$

$$Annual\ Area\ Normalized\ Energy\ Use\ = \frac{E}{A_{Turf}}$$

where A_{Turf} is the total area of turfgrass in ha.

$$E = E_{Fuel\ (PT)} + E_{Fuel\ (U)} + E_{Electricity(PT)} + E_{Electricity(U)} + E_{Fertilizer\ (P)} + E_{Pesticide\ (P)} + E_{Sand\ (PT)} + E_{Machinery\ (PTR)}$$

where E is the annual total energy used for the turfgrass maintenance operation in gigajoules (GJ yr^{-1}).

$$Scope\ 1:\ E_{S1} = E_{Fuel\ (U)}$$

$$Scope\ 2:\ E_{S2} = E_{Electricity\ (U)}$$

$$Scope\ 3:\ E_{S3} = E_{Fuel\ (PT)} + E_{Electricity(PT)} + E_{Fertilizer\ (P)} + E_{Pesticide\ (P)} + E_{Sand\ (PT)} + E_{Machinery\ (PTR)}$$

where E_{S1}, E_{S2}, E_{S3} is the annual energy used for the turfgrass maintenance operation in GJ yr^{-1} for Scope 1, 2, and 3, respectively.

$$E_{Fuel\ (PT)} = Q_D K_{D(PT)} + Q_G K_{G(PT)} + Q_{NG} K_{NG(PT)} + Q_P K_{P(PT)} + Q_{HO} K_{HO(PT)}$$

$$E_{Fuel\,(U)} = Q_D\, K_{D(U)} + Q_G K_{G(U)} + Q_{NG} K_{NG(U)} + Q_P K_{P(U)} + Q_{HO} H_{HO(U)}$$

$$E_{Electricity\,(PT)} = Q_E\, K_{E(PT)}$$

$$E_{Electricity\,(U)} = Q_E K_{E(U)}$$

$$E_{Fertilizer(P)} = Q_N K_{N(P)} + Q_P K_{P(P)} + Q_K K_{K(P)}$$

$$E_{Pesticide(P)} = Q_H\, K_{H(P)} + Q_F K_{F(P)} + Q_I K_{I(P)}$$

$$E_{Sand(MT)} = Q_S\, K_{S(M)} + Q_S K_{S(T)}$$

$$\begin{aligned} &E_{Machinery(PTR)} \\ &= Q_{TM}\, K_{TM(PTR)} + Q_{TGM} K_{TGM(PTR)} + Q_{WBM} K_{WBM(PTR)} + Q_T K_{T(PTR)} + Q_{BRT} K_{BRT(PTR)} + Q_A K_{A(PTR)} \\ &+ Q_{LUV} K_{LUV(PTR)} + Q_{HUV} K_{HUV(PTR)} + Q_{MSS} K_{MSS(PTR)} + Q_{FM} K_{FM(PTR)} + Q_{RM} K_{RM(PTR)} \\ &+ Q_{SM} K_{SM(PTR)} \end{aligned}$$

where $E_{Fuel\,(PT)}$ is the energy used for the production and transport of fuels, $E_{Fuel\,(U)}$ is the energy used from combusting the fuel, $E_{Electricity\,(PT)}$ is the energy used from the production and transport of energy sources to generate electricity, $E_{Electricity\,(U)}$ is energy used as electricity, $E_{Fertilizer\,(P)}$ is the energy used from producing fertilizer, $E_{Pesticide\,(P)}$ is the energy used from production of pesticides, $E_{Sand\,(PT)}$ is the energy used from the production and transport of sand, and $E_{Machinery\,(PTR)}$ is the energy used from the production, transport, and repair of machinery. Units for all equations are GJ yr^{-1}.

2.4 Limitations

This study did not consider GHG emissions from the denitrification of grass clippings. The study also did not consider GHG emissions from the purchase of turf inputs outside of fertilizers, pesticides, sand, and equipment. Examples of some turf inputs not included in this study were wetting agents, seed, and soil amendments applied to golf courses. This study also did not account for the different rates of denitrification of various nitrogen fertilizers.

TABLE 1. Greenhouse Gas (GHG) Emission Model for Golf Course Turf Maintenance Life Cycle Analysis.							
Fuel (Production & Transport)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Diesel	Q_D (L)	$C_{D(PT)}$	0.617	kg CO2e/L	3	Well to tank emissions for diesel fuel.	DEFRA, 2019
Gasoline	Q_G (L)	$C_{G(PT)}$	0.598	kg CO2e/L	3	Well to tank emissions for gasoline.	DEFRA, 2019
Natural gas	Q_{NG} (L)	$C_{NG(PT)}$	0.265	kg CO2e/m^3	3	Well to tank emissions for natural gas.	DEFRA, 2019
Propane	Q_P (L)	$C_{P(PT)}$	0.191	kg CO2e/L	3	Well to tank emissions for propane.	DEFRA, 2019
Heating Oil	Q_{HO} (L)	$C_{HO(PT)}$	0.528	kg CO2e/L	3	Well to tank emissions for heating oil.	DEFRA, 2019
Fuel (Use)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Diesel	Q_D (L)	$C_{D(U)}$	2.63	kg CO2e/L	1	Average emissions for the combustion of diesel fuel.	DEFRA, 2019
Gasoline	Q_G (L)	$C_{G(U)}$	2.2	kg CO2e/L	1	Average emissions for the combustion of gasoline.	DEFRA, 2019
Natural gas	Q_{NG} (L)	$C_{NG(U)}$	2.05	kg CO2e/m^3	1	Average emissions for the combustion of natural gas.	DEFRA, 2019
Propane	Q_P (L)	$C_{P(U)}$	1.519	kg CO2e/L	1	Average emissions for the combustion of propane/butane.	DEFRA, 2019
Heating Oil	Q_{HO} (L)	$C_{HO(U)}$	3.18	kg CO2e/L	1	Average emissions for the combustion of heating oil.	DEFRA, 2019
Electricity (Production & Transport)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Electricity	Q_E (KWh)	$C_{E(PT)}$	0.071	kg CO2e/ kWh	3	Emissions from electricity transmission.	DEFRA, 2019
Electricity (Use)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope	Description	Source
Electricity	Q_E (KWh)	$C_{E(U)}$	0.5	kg CO2e/ kWh	2	Average value for US.	EPA eGRID, 2016
Fertilizer (Production & Application- Denitrification)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Nitrogen (production)	Q_N (kg)	$C_{N(P)}$	5.13	kg CO2e/kg	3	Emissions from the production of urea.	Mudahar and Hignett, 1987b In: Fluck, 1992; Lal 2004
Nitrogen (application)	Q_N (kg)	$C_{N(A)}$	2.81	kg CO2e/kg	1	Emissions from the application of nitrogen fertilizer.	De Klein et al. (2006)
Phosphorus	Q_P (kg)	$C_{P(P)}$	0.57	kg CO2e/kg	3	Emissions from the production of triple-super phosphate fertilizer.	Mudahar and Hignett, 1987b In: Fluck, 1992; Lal 2004
Potassium	Q_K (kg)	$C_{K(P)}$	0.47	kg CO2e/kg	3	Emissions from the production of potassium fertilizer.	Mudahar and Hignett,

							1987b In: Fluck, 1992; Lal 2004
Pesticide (Production)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Herbicide	Q_H (kg)	$C_{H(P)}$	19.5	kg CO2e/kg	3	Emissions from a kg of herbicide AI production.	Green (1987), In: Helsel 1987; Lal 2004
Fungicide	Q_F (kg)	$C_{F(P)}$	12.4	kg CO2e/kg	3	Emissions from a kg of fungicide AI production.	Green (1987), In: Helsel 1987; Lal 2004
Insecticide	Q_I (kg)	$C_{I(P)}$	15.8	kg CO2e/kg	3	Emissions from a kg of insecticide AI production.	Green (1987), In: Helsel 1987; Lal 2004
Sand (Production & Transport)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Transport of sand	Q_S (kg)	$C_{S(T)}$	52	kg CO2e/ tonne/200km	3	Assuming the sand is transported 200km from the quarry to the golf course.	Pimentel, 1980, Lal 2004
Production of sand	Q_S (kg)	$C_{S(P)}$	45.83	kg CO2e/ tonne	3	Emissions from the mining and processing of sand.	Boustead & Hancock, 1979, Lal 2004
Machinery (Production, Transport, and Repair)							
Parameter	Quantity (unit)	GHG Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Triplex mowers	Q_{TM} (#)	$C_{TM(PTR)}$	480	CO2e/ machine/year	3	Emissions from production, transport and repair of triplex mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Triplex green mowers	Q_{TGM} (#)	$C_{TGM(PTR)}$	261	CO2e/ machine/year	3	Emissions from production, transport and repair of triplex green mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Walk behind mower	Q_{WBM} (#)	$C_{WBM(PTR)}$	53	CO2e/ machine/year	3	Emissions from production, transport and repair of walk behind mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Tractor	Q_T (#)	$C_{T(PTR)}$	1588	CO2e/ machine/year	3	Emissions from production, transport and repair of tractors. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Bunker raking tractor	Q_{BRT} (#)	$C_{BRT(PTR)}$	232	CO2e/ machine/year	3	Emissions from production, transport and repair of bunker raking tractors. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Aerator	Q_A (#)	$C_{A(PTR)}$	365	CO2e/machine/ year	3	Emissions from production, transport and repair of aerators. Assume 20-year lifespan.	Fluck, 1992; Lal 2005
Light utility vehicle	Q_{LUV} (#)	$C_{LUV(PTR)}$	318	CO2e/machine/ year	3	Emissions from production, transport and repair of light utility vehicles. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Heavy utility vehicle	Q_{HUV} (#)	$C_{HUV(PTR)}$	529	CO2e/ machine/year	3	Emissions from production, transport and repair of heavy utility vehicles. Assume 20-year lifespan.	Fluck, 1992; Lal 2004

Motorized sprayer/ spreaders	Q_{MSS} (#)	$C_{MSS(PTR)}$	528	CO2e/ machine/year	3	Emissions from production, transport and repair of motorized sprayer/spreaders. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Fairway mowers	Q_{FM} (#)	$C_{FM(PTR)}$	445	CO2e/ machine/year	3	Emissions from production, transport and repair of fairway mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Rough mowers	Q_{RM} (#)	$C_{RM(PTR)}$	1059	CO2e/ machine/year	3	Emissions from production, transport and repair of rough mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
Surrounds mowers	Q_{SM} (#)	$C_{SM(PTR)}$	424	CO2e/ machine/year	3	Emissions from production, transport and repair of surrounds mowers. Assume 20-year lifespan.	Fluck, 1992; Lal 2004
TABLE 2. Energy Model for Golf Course Turf Maintenance Life Cycle Analysis							
Fuel (Production & Transport)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Diesel	Q_D (L)	$K_{D(PT)}$	8.08	MJ/L	3	Embedded energy of production and transport for diesel.	Cervinka, 1980. In Pimentel, 1980
Gasoline	Q_G (L)	$K_{G(PT)}$	9.12	MJ/L	3	Embedded energy of production and transport for gasoline.	Cervinka, 1980. In Pimentel, 1980
Natural gas	Q_{NG} (L)	$K_{NG(PT)}$	8.07	MJ/m^3	3	Embedded energy of production and transport for natural gas.	Cervinka, 1980. In Pimentel, 1980
Propane	Q_P (L)	$K_{P(PT)}$	6.16	MJ/L	3	Embedded energy of production and transport for propane.	Cervinka, 1980. In Pimentel, 1980
Heating Oil	Q_{HO} (L)	$K_{HO(PT)}$	9.12	MJ/L	3	Embedded energy of production and transport for heating oil.	Cervinka, 1980. In Pimentel, 1980
Fuel (Use)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Diesel	Q_D (L)	$K_{D(U)}$	38.66	MJ/L	1	Energy released in combustion of diesel fuel.	Cervinka, 1980. In Pimentel, 1980
Gasoline	Q_G (L)	$K_{G(U)}$	34.24	MJ/L	1	Energy released in combustion of gasoline.	Cervinka, 1980. In Pimentel, 1980
Natural gas	Q_{NG} (L)	$K_{NG(U)}$	41.38	MJ/m^3	1	Energy released in combustion of natural gas.	Cervinka, 1980. In Pimentel, 1980
Propane	Q_P (L)	$K_{P(U)}$	26.1	MJ/L	1	Energy released in combustion of propane/butane.	Cervinka, 1980. In Pimentel, 1980
Heating Oil	Q_{HO} (L)	$K_{HO(U)}$	38.66	MJ/L	1	Energy released in combustion of heating oil.	Cervinka, 1980. In Pimentel, 1980

Electricity (Production & Transport)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff -icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Electricity	Q_E (KWh)	$K_{E(PT)}$	0.96	MJ/KWh	3	Embedded energy for electricity generation.	DEFRA, 2019; Lal, 2004
Electricity (Use)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Electricity	Q_E (KWh)	$K_{E(U)}$	3.6	MJ/kWh	2	Direct conversion from watt-hours to joules.	
Fertilizer (Production)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Nitrogen	Q_N (kg)	$K_{N(P)}$	69.5	MJ/kg	3	Energy required for the production of urea.	Mudahar and Hignett, 1987b. In: Fluck, 1992
Phosphorus	Q_P (kg)	$K_{P(P)}$	7.7	MJ/kg	3	Energy required for the production of triple-super phosphate fertilizer.	Mudahar and Hignett, 1987b. In: Fluck, 1992
Potassium	Q_K (kg)	$K_{K(P)}$	6.4	MJ/kg	3	Energy required for the production of potassium fertilizer.	Mudahar and Hignett, 1987b. In: Fluck, 1992
Pesticide (Production)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Herbicide	Q_H (kg)	$K_{H(P)}$	264	MJ/kg	3	Energy from a kg of herbicide active ingredient production.	Green 1987, In: Helsel 1987
Fungicide	Q_F (kg)	$K_{F(P)}$	168	MJ/kg	3	Energy from a kg of fungicide active ingredient production.	Green 1987, In: Helsel 1987
Insecticide	Q_I (kg)	$K_{I(P)}$	214	MJ/kg	3	Energy from a kg of insecticide active ingredient production.	Green 1987, In: Helsel 1987
Sand (Production & Transport)							
Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Transport of sand	Q_S (kg)	$K_{S(T)}$	694	MJ/tonne/ 200km	3	Assuming the sand is transported 200km from the quarry to the golf course.	Pimentel, 1980
Mining of sand	Q_S (kg)	$K_{S(P)}$	620	MJ/tonne	3	Energy from the mining of sand.	Boustead & Hancock, 1979
Machinery (Production, Transport, and Repair)							

Parameter	Quantity (unit)	Energy Coefficient	Coeff-icient Value	Coefficient Unit	Scope (1,2,3)	Description	Source
Triplex mowers	Q_{TM} (#)	$K_{TM(PTR)}$	6,498	MJ/machine/ year	3	Energy from production, transport and repair of triplex mowers. Assume 20-year lifespan.	Fluck, 1992
Triplex green mowers	Q_{TGM} (#)	$K_{TGM(PTR)}$	3,532	MJ/machine/ year	3	Energy from production, transport and repair of triplex green mowers. Assume 20-year lifespan.	Fluck, 1992
Walk behind mower	Q_{WBM} (#)	$K_{WBM(PTR)}$	716	MJ/machine/ year	3	Energy from production, transport and repair of walk behind mowers. Assume 20-year lifespan.	Fluck, 1992
Tractor	Q_{T} (#)	$K_{T(PTR)}$	21,494	MJ/machine/ year	3	Energy from production, transport and repair of tractors. Assume 20-year lifespan.	Fluck, 1992
Bunker raking tractor	Q_{BRT} (#)	$K_{BRT(PTR)}$	3,145	MJ/machine/ year	3	Energy from production, transport and repair of bunker raking tractors. Assume 20-year lifespan.	Fluck, 1992
Aerator	Q_{A} (#)	$K_{A(PTR)}$	4,299	MJ/machine/ year	3	Energy from production, transport and repair of aerators. Assume 20-year lifespan.	Fluck, 1993
Light utility vehicle	Q_{LUV} (#)	$K_{LUV(PTR)}$	4,299	MJ/machine/ year	3	Energy from production, transport and repair of light utility vehicles. Assume 20-year lifespan.	Fluck, 1992
Heavy utility vehicle	Q_{HUV} (#)	$K_{HUV(PTR)}$	7,165	MJ/machine/ year	3	Energy from production, transport and repair of heavy utility vehicles. Assume 20-year lifespan.	Fluck, 1992
Motorized sprayer/spreaders	Q_{MSS} (#)	$K_{MSS(PTR)}$	7,150	MJ/machine/ year	3	Energy from production, transport and repair of motorized sprayer/spreaders. Assume 20-year lifespan.	Fluck, 1992
Fairway mowers	Q_{FM} (#)	$K_{FM(PTR)}$	6,018	MJ/machine/ year	3	Energy from production, transport and repair of fairway mowers. Assume 20-year lifespan.	Fluck, 1992
Rough mowers	Q_{RM} (#)	$K_{RM(PTR)}$	14,329	MJ/machine/ year	3	Energy from production, transport and repair of rough mowers. Assume 20-year lifespan.	Fluck, 1992
Surrounds mowers	Q_{SM} (#)	$K_{SM(PTR)}$	5,732	MJ/machine/ year	3	Energy from production, transport and repair of surrounds mowers. Assume 20-year lifespan.	Fluck, 1992

3. Results

Eighty-three golf courses responded to the University of Wisconsin-Madison Resource Efficiency Survey (Bekken & Soldat, 2020); however, only 14 golf courses provided Scope 1 energy and related data for 2016, 2017, and 2018. These fourteen golf courses are located in Wisconsin (9), New York (3), Montana (1), and Michigan (1). Of these, 7 golf courses also provided Scope 2 data and 7 golf courses provided Scope 3 data. Only 4 of the 14 golf courses provided Scope 1, 2 and 3 data. Twelve golf courses were 18-hole courses, one golf course had 9 holes, and one golf course had 27 holes. As a result, absolute GHG and energy data are largely representative of the total emissions from 18-hole golf courses.

Three-year mean absolute Scope 1 emissions were 62,760 kg CO_2e yr^{-1}, which was nearly double the mean Scope 2 emissions at 37,727 kg CO_2e yr^{-1}. Interestingly, mean Scope 3 emissions was the highest at 72,314 kg CO_2e yr^{-1} and the mean of all scope emissions was 153,089 kg CO_2e yr^{-1} (Table 4). Mean area normalized Scope 1 emissions was 1,599 kg CO_2e ha^{-1} yr^{-1}, mean Scope 2 emissions was 1,012 kg CO_2e ha^{-1} yr^{-1}, mean Scope 3 emissions was 1,847 kg CO_2e ha^{-1} yr^{-1}, and the mean of all scopes was 4,277 kg CO_2e ha^{-1} yr^{-1}. Scope 3 emissions were responsible for the largest GHG emissions of any of the three scoping categories, and also showed the largest standard deviation.

Three-year mean absolute Scope 1 energy use was 858 GJ yr^{-1}, which was nearly three times the mean Scope 2 energy use at 271 GJ yr^{-1}. Mean Scope 3 energy use was by far the highest of any scope at 1,524 GJ yr^{-1}. Absolute mean energy use from all scopes was 2,570 GJ yr^{-1}. Mean area normalized Scope 1 energy use was 24 GJ ha^{-1} yr^{-1}, mean Scope 2 energy use was 7 GJ ha^{-1} yr^{-1}, mean Scope 3 energy use was 40 GJ ha^{-1} yr^{-1}, and mean energy use from all scopes was 72 GJ ha^{-1} yr^{-1}.

For the four golf courses in this study that provided Scope 1, 2, and 3 data for three consecutive years (2016, 2017, 2018), total GHG emissions were consistent from one year to the next except for golf course D where emissions increased from 3,920 kg CO_2e ha^{-1} in 2016 to 5,611 kg CO_2e ha^{-1} in 2018 (Figure 1). For the other three golf courses GHG emissions varied no more than 13% from one year to the next.

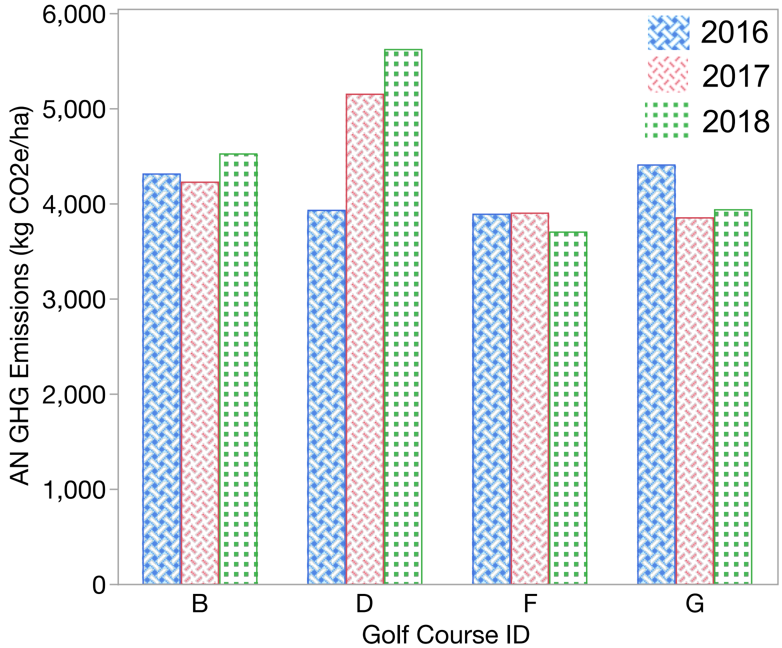

Figure 1. Area normalized (AN) GHG (greenhouse gas) emissions (Scope 1, 2, and 3) from four golf courses across three years (2016, 2017, 2018).

In addition to emissions and energy use being categorized by scope, emissions and energy use were also split into eight categories for the four golf courses that provided full data sets (Figure 2). These categories were electricity production and transport, electricity use, fertilizer production and application (denitrification), fuel production and transport, fuel use, machinery production, transport, and repair, pesticide production, and sand production and transport. Fuel use and electricity use accounted for 63% of total emissions. However, when accounting the energy expended (GJ), electricity use had the greatest GHG intensity of all categories at 139 kg CO_2e GJ^{-1}. Fertilizer use had the second highest GHG intensity of 120 kg CO_2e GJ^{-1}.

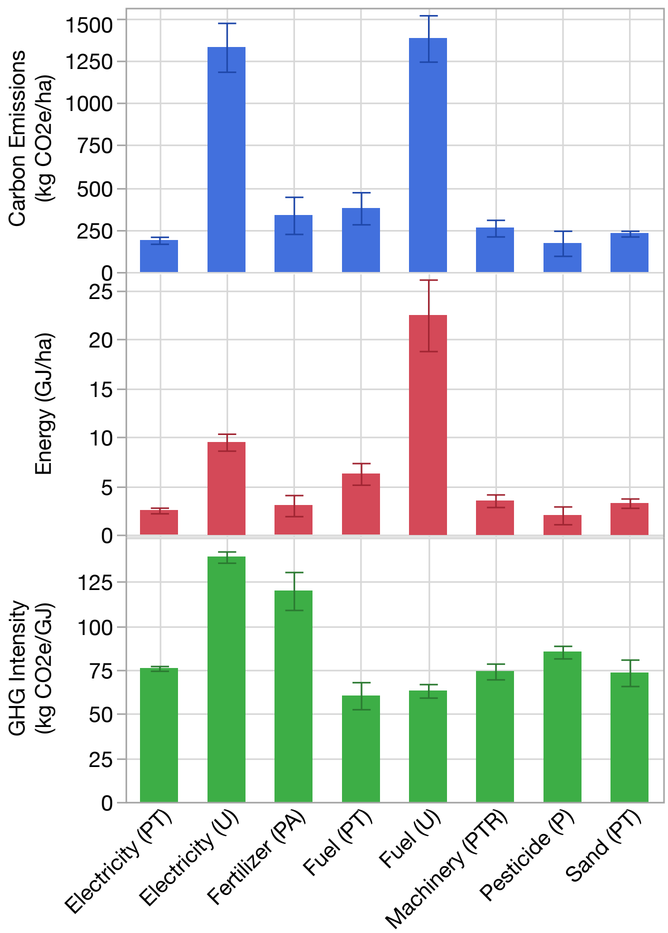

Figure 2. Mean and standard error of GHG emissions, energy use, and GHG intensity on the four golf courses that provided full data sets in eight categories: Fuel (Production and Transport or PT), Fuel (Use or U), Electricity (Production and Transport or PT), Electricity (Use or U), Fertilizer (Production and Application, or PA), Pesticide (Production or P), Sand (Production and Transport or PT), and Machinery (Production, Transport, and Repair or PTR).

Table 7 lists correlation coefficients for Scope 1 GHG emissions and energy use as compared with economic and facility variables such as per hectare revenue, green fee, per hectare maintenance budget, energy budget, full-time maintenance staff, seasonal maintenance staff, total maintenance staff (the sum of full-time and seasonal), rounds played, and age of the golf course. Per hectare revenue and full-time staff were the only variables to show a relationship with Scope 1 GHG emissions. Per hectare revenue correlated with Scope 1 emissions ($r^2 = 0.23$) and energy use ($r^2 = 0.30$) and full-time staff correlated with Scope 1 emissions ($r^2 = 0.27$) and energy use ($r^2 = 0.25$). These correlations were significant at $\alpha < .10$ but not significant at $\alpha < .05$.

Table 3. Demographic information of the golf courses analyzed in this study. Y= Yes, N= No.

Golf Course ID	State	Public/ Private	Holes	Turf Area (ha)	Maint-enance budget (USD/ha)	Estimated gross revenue (USD/ha)	Full time employees	Part time employees	18-hole green fee (if public), guest fee (if private)	Average annual rounds	Age (in 2018)	Previous land use	Scope 1	Scope 2	Scope 3	All scopes
A	WI	Private	18	38.5	7,797	29,177	2	8	48	30,000	103	Cropland	Y	N	Y	N
B	WI	Public	18	37.0	13,531	41,211	2	7	31	34,000	90	Cropland	Y	Y	Y	Y
C	WI	Private	18	49.8	16,059	80,715	5	15	135	16,000	90	Cropland	Y	N	Y	N
D	NY	Public	18	35.6	2,250	25,961	3	8	24	28,000	80	Pastureland	Y	Y	Y	Y
E	NY	Public	27	36.5	10,974	59,949	7	4	36	39,500	56	Undisturbed forest	Y	N	Y	N
F	NY	Public	18	33.21	6,022	19,223	3	8	26	15,000	56	Pastureland	Y	Y	Y	Y
G	WI	Private	18	37.3	13,419	22,560	2	14	75	12,000	96	Cropland	Y	Y	Y	Y
H	WI	Private	9	22.4	10,043	16,532	1	9	45	8,000	95	Cropland	Y	Y	N	N
I	WI	Private	18	68.6	8,745	26,484	4	13	85	11,000	88	Cropland	Y	Y	N	N
J	WI	Public	18	53.7	20,498	55,060	7	25	110	24,000	27	Pastureland & forest	Y	N	N	N
K	WI	Private	18	33.8	11,089	26,086	4	10	100	11,000	54	Pastureland & forest	Y	Y	N	N
L	MT	Private	18	37.7	10,620	55,181	3	11	-	16,000	74	Cropland & prairie	Y	N	N	N
M	WI	Private	18	33.6	20,824	85,229	7	20	80	16,000	119	Pastureland & marsh	Y	Y	N	N
N	MI	Private	18	40.5	14,815	31,931	5	9	100	14,000	91	Cropland & forest	Y	N	N	N

Table 4. Soils type and turfgrass species on the golf courses analyzed in this study.

Golf Course ID	Soils				Primary Turfgrass Species			
	Greens	**Tees**	**Fairways**	**Roughs**	**Greens**	**Tees**	**Fairways**	**Roughs**
A	Topdressing (push up)	Topdressing (push up)	Sandy loam, Loam	Sandy loam, Loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
B	Topdressing (push up)	Clay loam	Clay loam	Clay loam	Annual bluegrass	Annual bluegrass	Annual bluegrass	Kentucky bluegrass
C	Topdressing (push up)	Topdressing (push up)	Sandy loam	Sandy loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
D	Topdressing (push up)	Clay loam	Clay loam	Clay loam	Creeping bentgrass	Perennial ryegrass	Perennial ryegrass	Perennial ryegrass
E	Topdressing (push up), Sandy Loam	Clay loam	Clay loam	Clay loam	Creeping bentgrass	Perennial ryegrass	Perennial ryegrass	Perennial ryegrass
F	Topdressing (push up), Clay loam	Clay loam	Clay loam	Clay loam	Creeping bentgrass	Perennial ryegrass	Perennial ryegrass	Annual bluegrass
G	USGA, Topdressing (push up)	Sandy loam	Loam	Loam	Creeping bentgrass	Kentucky bluegrass	Kentucky bluegrass	Kentucky bluegrass
H	Topdressing (push up)	Topdressing (push up)	Sandy loam	Sandy loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
I	Topdressing (push up)	Sandy loam	Sandy loam, clay loam	Sandy loam, clay loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
J	USGA	Sand	Silt loam	Silt loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
K	Topdressing (push up)	Loam	Silt loam	Silt loam	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
L	Sandy loam	Silt loam	Silt loam	Silt	Creeping bentgrass	Creeping bentgrass	Creeping bentgrass	Kentucky bluegrass
M	USGA, Topdressing (push up)	Loam	Loam	Loam	Annual bluegrass	Annual bluegrass	Annual bluegrass	Kentucky bluegrass
N	Topdressing (push up)	Topdressing (push up), Silt Loam, Silt	Loam, Silt loam, Silt, Clay loam	Silt loam, Silt, Clay loam	Annual bluegrass	Annual bluegrass	Annual bluegrass	Kentucky bluegrass

TABLE 5 Three-year mean of absolute and area normalized GHG emissions across Scope 1, 2, 3, and all scopes combined.

	Absolute Metrics				Area-Normalized Metrics			
	GHG emissions (kg CO_2e yr^{-1})				GHG emissions (kg CO_2e ha^{-1} yr^{-1})			
	Scope 1	Scope 2	Scope 3	All scopes	Scope 1	Scope 2	Scope 3	All scopes
n	14	7	7	4	14	7	7	4
Mean	62,760	37,727	72,314	153,089	1,599	1,012	1,847	4,277
St. Dev.	20,644	16,006	37,443	19,834	442	453	782	462
Max	92,606	56,300	135,438	173,910	2,466	1,583	3,058	4,891
Min	29,606	10,055	34,567	126,864	769	449	898	3,820

TABLE 6 Three-year mean of absolute and area normalized energy use across Scope 1, 2, 3, and all scopes combined.

	Absolute Metrics				Area-Normalized Metrics			
	Energy Use (GJ yr^{-1})				Energy Use (GJ ha^{-1} yr^{-1})			
	Scope 1	Scope 2	Scope 3	All scopes	Scope 1	Scope 2	Scope 3	All scopes
n	14	7	7	4	14	7	7	4
Mean	858	271	1,524	2,570	24	7	40	72
St. Dev.	351	115	648	406	8	3	14	12
Max	1,401	405	2,575	3,155	36	11	53	89
Min	133	72	447	2,234	12	3	12	63

TABLE 7. Correlation coefficients for economic variables and Scope 1 GHG emissions and energy use. No correlation was significant at $\alpha < 0.05$. *Significant at $\alpha < 0.1$.

	Scope 1 GHG Emissions	Scope 1 Energy Use
	r^2	
Revenue ha^{-1}	0.23*	0.30*
Maintenance budget ha^{-1}	0.06	0.02
Energy budget ha^{-1}	0.22	0.26
Green Fee	0.003	0.001
Full time staff	0.27*	0.25*
Seasonal staff	0	0
Total staff	0.02	0.05
Rounds	0.20	0.05
Age of golf course	0	0.03

4. Discussion

The purpose of this study was to determine the energy use and GHG emissions that apply exclusively to golf turf maintenance without regard to clubhouse operations. The Environmental Institute for Golf (EIFG) conducted an energy use survey on over 500 golf courses in the United States; however, the survey collected energy use data from the entire golf facility. From these data, it is not possible to determine the energy use dedicated to golf turf operations. Clubhouse energy use can vary widely depending on the extent of dining, entertainment, and recreation that the golf facility offers (e.g., event spaces, pools, tennis courts). Thus, energy use as determined in this study, which focused exclusively on turf maintenance operations, cannot be directly compared to the EIFG energy use data.

Gillette (2014) measured energy use and emissions from both clubhouse operations and maintenance operations. The author found that clubhouse energy use accounted for over 60% of total golf facility (maintenance and clubhouse combined) GHG emissions, making clear that addressing clubhouse GHG emissions is important to reduce the overall GHG footprints of golf facilities. However, the purpose of this study was to estimate GHG emissions exclusively from golf turf maintenance operations.

Tidåker et al. (2017) developed a similar GHG emission and energy model to this study and applied the model to two golf courses in Sweden. The authors reported total energy use on the two courses to be 14 GJ ha^{-1} yr^{-1} and 19 GJ ha^{-1} yr^{-1}. Energy use in this study from all scopes was much higher and ranged from 63 to 89 GJ ha^{-1} yr^{-1}. GHG emissions from golf turf operations reported in this study were also significantly higher than both Bartlett and James (2011) and Tidåker et al. (2017). Bartlett and James (2011) found that GHG emissions from the turfgrass surfaces of two golf courses in the UK were 1,400 and 1,700 kg CO_2e ha^{-1} yr^{-1}, while Tidåker et al. (2017) found that GHG emissions from turfgrass surfaces of two golf courses in Sweden to be 1,600 kg CO_2e ha^{-1} yr^{-1} and 1,000 kg CO_2e ha^{-1} yr^{-1}. Total emissions from golf courses in this study were three to four times higher and ranged from 4,900 kg CO_2e ha^{-1} yr^{-1} to 3,800 kg CO_2e ha^{-1} yr^{-1} .

Energy use and emissions in this study were higher than Bartlett and James (2011) and Tidåker et al. (2017) in part because those studies did not consider GHG emissions or energy use from maintenance buildings, which this study included. Bartlett and James (2011) also did not consider indirect energy burden and GHG emissions from the production and transport of sand. Tidåker et al. (2017) considered the energy burden of GHG emissions from the transport of sand but did not include emissions from the production of sand. In addition, the electricity grid in the United States is significantly more GHG intensive (0.5 kg CO_2e kWh^{-1}) than in the UK (0.25 kg CO_2e kWh^{-1}) or in Sweden (0.017 kg CO_2e kWh^{-1}).

GHG emission figures found in this study are comparable to Gillete (2014), who calculated GHG emissions from golf course operations on 22 Colorado golf courses into two statistical groups. Mean GHG emissions from turf operations (i.e. maintenance facility emissions and land management emissions) and excluding clubhouse operations were approximately 4,120 kg CO_2e ha^{-1} yr^{-1} and 3,930 kg CO_2e ha^{-1} yr^{-1}. Gillete (2014) did not include Scope 3 emissions, such as the production and transport of sand, machinery, and energy use; thus the results are most comparable to Scope 1 and 2 emissions from this study. Mean Scope 1 and 2 emissions from this study were 2,549 kg CO_2e ha^{-1} yr^{-1}, and therefore slightly lower than the golf course maintenance emissions estimated at the 22 Colorado golf courses. Emissions in this study may be lower in part because Gillete (2014) used an electricity GHG emission coefficient specifically for Colorado of 0.9 kg CO_2e kWh^{-1}, higher than the US average used in this study of 0.5 kg CO_2e kWh^{-1}.

Only Scope 1 GHG emissions and energy use were tested for correlations with economic factors because the sample size for Scopes 2, 3 and all three scopes combined were determined to be too small to run a meaningful correlation test. Economic factors such as maintenance budget, energy budget, and green fee do not correlate with Scope 1 GHG emissions or energy use. Revenue per hectare, however, did correlate moderately with GHG emissions ($r^2 = 0.23$) and energy use ($r^2 = 0.30$), suggesting that golf courses with higher revenues tend to use more energy and emit more GHGs (correlation significant at $\alpha < .10$ but not at $\alpha < .05$). Energy use on golf courses may be more related to management style and practice than directly to these economic factors.

Energy use and GHG emissions on golf courses were remarkably consistent from one year to the next on three of the four golf courses that provided energy data for all scopes. Previous studies have only estimated GHG emissions for a single year, however, data from this study indicated that single year data could provide reasonable estimates of annual GHG emissions over a longer time period.

Golf course superintendents have limited control over Scope 3 emissions. Reducing Scope 3 emissions would require that the golf course manager either reduce inputs on the golf course or analyze his or her supply chain and purchase products with less embodied energy. For researchers, scope 3 GHG emissions and energy use are hard to estimate given the plethora of upstream energy burdens caused by golf course maintenance. Scope 3 factors not accounted for in this study included the manufacturing of wetting agents, of soil amendments and of other products applied to the golf course. This study also did not capture energy use by independent contractors on golf courses.

Superintendents have much greater control over Scope 1 and 2 emissions, which can be achieved through greater energy efficiency in golf course maintenance. Scope 1 and 2 emissions can also be more accurately estimated by researchers because there are fewer input variables to account for. The sum of Scope 1 and 2 are perhaps the most practical metric with which to track golf course energy use and emissions; though excluding Scope 3 emissions entirely will lead to an under estimation of actual energy use and emissions.

In addition to categorizing GHG emissions and energy use by scope, this study also organized results by categories directly relatable to golf course maintenance: Fuel (Production and Transport), Fuel (Use), Electricity (Production and Transport), Electricity (Use), Fertilizer (Production and Application), Pesticide (Production), Sand (Production and Transport), and Machinery (Production, Transport, and Repair). Fuel use and electricity use together accounted for 63% of all GHG emissions. In addition, electricity use had the highest GHG intensity (the ratio of GHG emissions to energy consumed). In order for courses to significantly cut GHG emissions, emissions from fuel use and electricity generation need to be sharply reduced. Such GHG emission reductions can be achieved through the purchase of electric machinery and sourcing of renewable electricity that has a low GHG footprint. Golf courses can either purchase renewable energy through their energy provider, termed “green tariffing” (USEPA, 2018), or they can install onsite renewable energy sources such as solar panels.

The primary purpose of this study was not to estimate the overall carbon balance (emissions minus sequestration) of golf course turfgrass maintenance. However, using sequestration results from other golf course turfgrass studies, an estimate of the carbon balance of turfgrass systems on golf courses in this study can be achieved. Data on the vegetation type of non-turf areas was not collected, and therefore the analysis of carbon balances here is limited to golf course turfgrass systems and does not consider sequestration from non-turf areas of the course. Non-turf areas of golf courses can also sequester carbon (e.g., forests and grasslands at the perimeter of the course).

To estimate the carbon sequestered on golf courses in the study, information on the age and previous land use history was collected (Table 3). All four golf courses that provided complete energy use data were previously under agricultural use. This was similar to the golf courses studied in Selhorst and Lal (2011) where the authors provided quadratic functions that model SOC accumulation in golf course turfgrass soils (fairways and roughs) at four different soil depths after the transition from agricultural use. The authors also provide the time to SOC equilibrium. These equations were used to estimate carbon sequestration on the four golf courses in this study that provided complete energy data over their life cycle. GHG emissions over the golf courses life cycle were estimated to be linear and equal to the 3-yr mean found in this study. While golf course maintenance practices in recent decades have likely become more energy intensive, emission controls on modern equipment may counteract the increased intensity. Figure 3 estimates the life cycle carbon balance of golf courses B, D, F, and G.

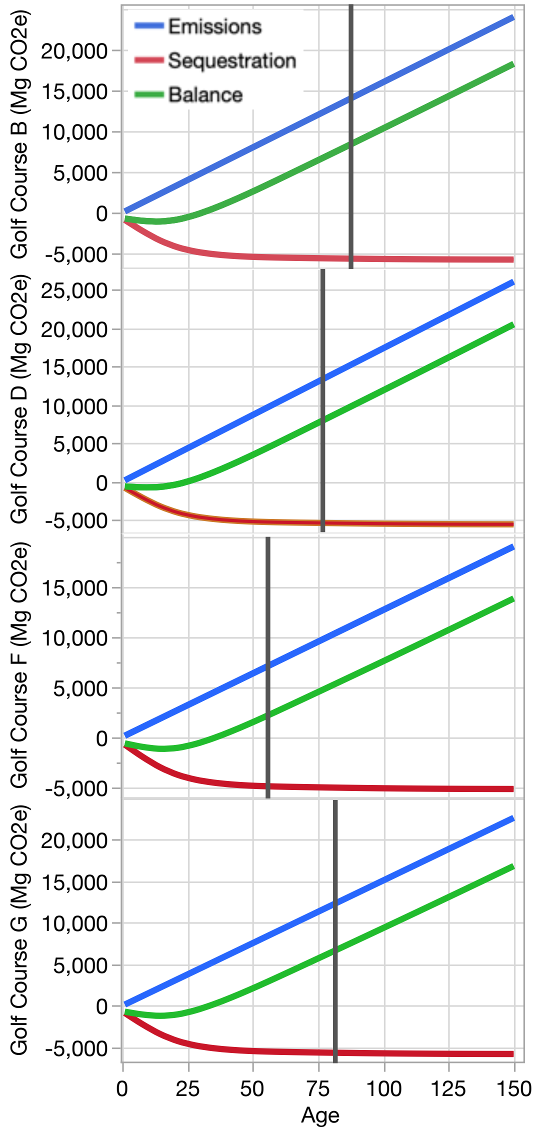

Figure 3. Estimated cumulative GHG emissions, sequestration, and balance of golf course B, D, F, and G (Mg CO_2e). Vertical lack line indicates the current age of each golf course. Sequestration modelling equations derived from Selhorst and Lal (2011). Values for emissions are defined as being positive, values for sequestration are defined as being negative, and the carbon balance is defined as emissions plus sequestration.

The turf system on golf courses in this study were carbon negative (cumulative sequestration greater than cumulative emissions) for the first 25 to 35 yr of operation, after which they became carbon sources. Over the turf systems lifetime carbon balances are strongly positive (cumulative emissions greater than cumulative sequestration). Golf course B (88 yr old) was estimated to have a life cycle carbon balance of +8,477,000 kg CO_2e, golf course D (78 yr old) +8,171,000 kg CO_2e, golf course F (54 yr old) +1,944,000 kg CO_2e, and golf course G (94 yr old) +8,491,000 kg CO_2e.

Thus, it is important for golf courses to reduce emissions at all stages of their life cycle. New golf courses that are able to effectively lower emissions from their inception may maintain negative carbon balances for longer periods of time than the golf courses in this study. However, for golf course turf systems to remain carbon negative throughout their life cycle, emission rates need to be much lower than current levels. According to the SOC modelling equations in Selhorst and Lal (2011) an average size golf course of 38 ha of maintained turf in the northern United States will sequester approximately 6,000,000 kg CO_2e assuming the land was converted from agricultural production. For a golf turf system to be carbon neutral over a 200-yr period (a rough estimate of a golf courses life cycle) then emissions would need to be 30,000 kg CO_2e yr^{-1}. Mean emissions rates for all scopes in this study were approximately 153,000 kg CO_2e yr^{-1}. Thus, emissions from turf maintenance need to be reduced greatly from current levels if golf turf systems are to be carbon neutral over their life cycle, much less carbon negative.

Recently published turfgrass studies have found turfgrass systems to be net carbon sinks (Braun & Bremer, 2019; Law & Patton, 2017), which may seem contradictory to the findings of this study. The carbon balance of the turfgrass systems in Braun and Bremer (2019) and Law and Patton (2017) ranged from -412 kg C ha^{-1} yr^{-1} to -1,290 kg C ha^{-1} yr^{-1}, equivalent to -1,511 kg

CO_2e ha^{-1} yr^{-1} and -4,730 kg CO_2e ha^{-1} yr^{-1}, respectively. Carbon sequestration was measured through soil organic carbon measurements while carbon emissions were estimated as the sum of soil and fertilizer N_2O emissions, and emissions from mowing, irrigation, fertilizer, and pesticide. However, both studies omitted various emissions sources associated with turfgrass management such as electricity and fuel consumption in maintenance buildings, and emissions associated with the production, transport, and repair of machinery. In addition, these studies were conducted on turfgrass that was established either at the start of the study (Braun & Bremer, 2019) or less than 3 yr prior (Law & Patton, 2017). Previous research indicates that turfgrass carbon sequestration rates are initially high but then level off after a period of approximately 30 yr (Selhorst & Lal, 2013; Selhorst & Lal, 2011; Bandaranayake et al., 2003 ; Qian & Follet, 2002). In summary, Braun and Bremer (2019) and Law and Patton (2017) underestimated carbon emissions associated with turfgrass maintenance, and overestimated turfgrass carbon sequestration if longer time horizons are considered.

5. Conclusion

The findings of this study on golf courses in the northern United States suggest that GHG emissions must be sharply reduced for golf courses to contribute to the United Nations Sustainable Development Goal 13 -- taking urgent action to address climate change and its impacts. Future work could use the carbon emissions and energy model presented here on golf courses outside of the northern United States, where the golf courses in this study were located.

This study was affected by the difficulty of collecting a comprehensive energy data set from a long and detailed voluntary survey. For example, in Wisconsin (one of four states surveyed), of the approximately 240 superintendents who are members of the Wisconsin Golf Course

Superintendents Association (WGCSA), 43 members responded to the survey, but only nine addressed the energy section and of those, only two superintendents completed all parts of the energy section. Further confounding responses was the fact that maintenance building energy use is generally not metered separately from clubhouse energy use meaning that several golf course maintenance operations included in this study could not provide Scope 2 electricity data. Without Scope 1, 2, and 3 energy data, a full GHG and energy footprint cannot be established for the golf maintenance operations. This is partly why the sample of full GHG and energy footprints were lower than any individual scope sample.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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Chapter 5: Quantifying golf course water use efficiency

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Abstract

This study tests three ecosystem models for their accuracy predicting water use on 76 U.S. golf courses, which were separated into five geographic regions (Northeast, Midwest, Northwest, East Texas, and Florida). The USGA, Tipping Bucket (TB), and Agro-IBIS (AI) models were used to estimate a given golf course's water requirements. To quantify golf course water use efficiency, actual water use at a golf course was divided by the model's predicted water requirement to generate a water efficiency score (WES). Each golf course in the study was assigned three WES's, one for each ecosystem model (WES_{USGA}, WES_{TB}, WES_{AI}). Mean WES_{USGA} by region ranged from 0.75 in the Midwest to 2.11 in Florida, meaning that the USGA water model overpredicted water use in the Midwest by 25% but underpredicted water use on golf courses in Florida by 2.11 times. Across all regions the mean WES_{USGA} was 1.32 with a coefficient of variation of 0.42. Mean WES_{TB} ranged from 0.85 in East Texas to 1.29 in Florida. The mean WES_{TB} across all regions was 1.00, meaning that on *average* the Tipping Bucket predicted water use on the 76 golf courses in the study accurately. However, the coefficient of variation of WES_{TB} was 0.46, meaning that the model overpredicted water use on some golf courses while underpredicting use on others. This study finds that rooting depth, irrigated area, and depth to water table are especially important modeling parameters for golf course water

requirement calculations. Economic variables such as green fee, maintenance budget, and cost of irrigation water were limited in their ability to predict WES.

1. Introduction

Golf is one of the most popular sports in the US by participation (Woods, 2017). Following a decline in popularity after the 2008 financial crisis, the popularity of golf has increased recently, in part, because of the game's appeal as an outdoor and socially distanced activity during the COVID-19 pandemic. Previous research has shown that golf promotes improved bodily and mental health (Murray et al., 2017; Farahmand et al., 2009; Parkkari et al., 2000). In 2020, 36.9 million Americans, or roughly 1 in 10 Americans played golf on at least one of the nation's 16,752 golf courses (NGF, 2021; R&A, 2019). In 2016, the golf industry employed 1.9 million people and had an approximate annual economic impact of $84 billion (Matuszeski, 2018).

Give golf's popularity, the resources required to maintain golf courses has led to widespread concern over the ecological and environmental consequences of golf course management (Garris 2018; Hilson, 2017; Brenner, 2012). Previous research has shown that golf course management can cause a decline in surface and groundwater quality from runoff and leaching of pesticides and fertilizers (Mallin and Wheeler, 2000; Davis and Lydy 2001; Winter et al. 2002; Metcalfe et al., 2007; King et al., 2007; Pichler et al. 2008, King and Balogh, 2010), that mowing commonly emits more carbon than turf can sequester (Bekken and Soldat, 2021), and that pesticides applied to the course pose a variety of ecological risks (Rossi and Haith, 2003; Bekken et al., 2021). However, golf courses can also be managed in such a way that they improve urban water quality

(Davis and Lydy 2001; Kohler et al., 2014), sequester more carbon than they emit (Bekken and Soldat, 2021), and enhance urban biodiversity (Hodgkison et al., 2007; Hodgkison et al., 2007b). Thus, the environmental impact of a golf course depends on how efficiently golf course managers use resources.

Water is perhaps the most vital resource that golf courses use, making it especially important to understand water use efficiencies on golf courses. Golf course water use is especially concerning in arid regions of the US where climate change is exacerbating water shortages causing state and local governments to impose water use restrictions on golf courses (Arizona Central, 2021; Golf Course Industry, 2014).

Water use on golf courses is an environmental concern, not only in the US, but around the world. The rapid development of golf courses in arid regions of Spain, Morocco, and elsewhere in the Mediterranean in the early 21st century sparked concerns that irrigating golf courses removed water intended for agricultural and domestic use (Rodriguez Diaz et al., 2007). This motivated a burst of water resource research in the region to determine how golf courses could be irrigated more efficiently including using effluent or reclaimed water (Salgot et al., 2012; García-González et al., 2015; Ortuno et al., 2015; Perea-Moreno et al., 2016; Benlouali et al., 2017).

Water use data on US golf courses has been collected primarily by a series of surveys conducted by the Golf Course Superintendents Association of America (GCSAA). These surveys revealed that the average US golf course used 131 million liters of water in 2013 (Gelernter et al., 2015), or the equivalent of what 314 US households would use in a year (US EPA, 2022). Golf course water use varies greatly by region. On average golf courses in the Southwest use the most water, 118 cm of irrigation a year, while golf courses in the transition zone of the US use only 18 cm of irrigation each year (Gelernter et al. 2015). In total, US golf courses used 2.29 billion cubic meters of water in 2013 across 4.85 billion square meters of irrigated golf turf (Gelernter et al., 2015; GCSAA, 2009) (Table 1). By comparison, US farms in 2013 used 109 trillion cubic meters of water across 226 trillion square meters of irrigated farmland (USDA National Agricultural Statistics Service, 2018). As such, the average depth of water applied to US golf courses and irrigated US farmland per year is essentially the same, 47 and 48 cm, respectively. However, 80% of US golf course turfgrass is irrigated (Throssell et al., 2019), but only 26% of US cropland is irrigated (USDA National Agricultural Statistics Service, 2018). Therefore, on a per area basis, US golf courses are more intensive users of water than US cropland.

Table 1. Comparing golf course water use to US farmland in 2013.

<table>
<tr><th>Annual Data from 2013</th><th>US golf course turfgrass</th><th>US cropland</th><th>Golf course/ cropland (%)</th><th>Citation</th></tr>
<tr><td>Area (m^2)</td><td>6.10×10^9</td><td>8.65×10^{11}</td><td>0.7</td><td rowspan="4">Gelernter et al. 2015; USDA NASS, 2018.</td></tr>
<tr><td>Area Irrigated (m^2)</td><td>4.85×10^9</td><td>2.26×10^{11}</td><td>2.1</td></tr>
<tr><td>Water Use (m^3)</td><td>2.29×10^9</td><td>1.09×10^{11}</td><td>2.1</td></tr>
<tr><td>Annual depth of water use (cm)</td><td>47</td><td>48</td><td>97.9</td></tr>
</table>

Given the increasing demand for freshwater resources as the climate warms (IPCC, 2014), it becomes imperative to develop methodologies capable of assessing how efficiently golf course managers use water. Golf courses that use water efficiently could be rewarded, and those that use water inefficiently could be encouraged to use less. One such method of measuring water use efficiency on golf courses is to compare a golf course’s actual water use to predicted requirement. Estimating the water requirement (commonly referred to as a water budget) of a golf course can be predicted with a wide variety of models of varying complexity. At the very least, models typically consider irrigated area and weather or climate data. Estimating the water requirement of a golf course allows owners or regulators to determine whether water is being used efficiently by golf course managers. Water requirements also allow interested stakeholders to determine whether climate or management practices are driving water use (Gelernter et al., 2015).

Golf organizations have recognized the need to supply water requirement tools to golf course managers, owners, and superintendents. Efforts to develop water requirements for golf courses have relied on the US EPA's landscape water requirement (LWR) equation (US EPA, 2014).

$$\sum_{12}^{1} LWR_M = \frac{1}{DULQ} * [(ET_o * K_L) - R_a] * A \qquad \text{(Eq. 1)}$$

where LWR_M is the monthly landscape water requirement summed over the year to generate an annual water requirement, DULQ is the lower quartile distribution uniformity, ET_o is the monthly reference evapotranspiration, K_L is the landscape or crop coefficient, R_a is the monthly allowable rainfall, and A is the turfgrass area.

As part of the Environmental Institutes for Golf's (EIFG) effort to track water use on US golf courses, Gelernter et al. (2015) calculated water requirements for 1,950 US golf facilities that responded to the 2014 water use survey using a modified and expanded form of the US EPA's water requirement equation. Gelernter et al. (2015) modified the US EPA's LWR equation by replacing the allowable rainfall coefficient with a daily water banking algorithm (R_{BA}) and added a leaching fraction (LF).

$$\sum_{365}^{1} LWR_D = \frac{1}{DULQ} * [(ET_o * K_c) - R_{BA}] * A * LF \qquad \text{(Eq. 2)}$$

Where LWR_D is the daily landscape water requirement summed over the year to generate an annual water requirement, DULQ is the lower quartile distribution uniformity, ET_o is the monthly local reference evapotranspiration, K is the crop coefficient, R_{BA} represents the rainfall water banking algorithm, A is the turfgrass area, and LF is the leaching fraction (the fraction of water that drains past the root zone). The authors used daily historical weather data queried by zip code to run the model. Additional assumptions made by Gelernter et al. (2015) are included in Table 1.

The daily water banking algorithm assumed a uniform rooting depth of 10 cm, and a plant available water content of 2.5 cm. This soil water holding capacity was held constant for all golf courses regardless of soil type. Rainfall exceeding the water holding capacity was not stored in the soil, while evapotranspiration (ET) was subtracted from soil water storage. Each day the soil water storage was filled by irrigation. This volume of irrigated water was summed over the year to determine the yearly irrigation requirement. Gelernter et al. (2015) found that most golf courses met their water requirement, although an exact percentage was not specified.

Table 1. Water requirement assumptions made by the 2015 EIFG Water Report (Gelernter, 2015).

Variable	Abbreviation	Value	Unit
Lower Quartile Distribution Uniformity	LQDU	0.7	Unitless
Local Reference Evapotranspiration	ETo	Hargreaves ET equation	Inches/day
Crop Coefficient	K	0.7	Unitless
Allowable Rainfall	Ra	Daily water banking algorithm	Inches/day
Leaching Fraction	LF	1.15 for facilities using recycled water	Unitless

The United States Golf Association (USGA) Water Resource Center (USGA, 2022) includes a spreadsheet-based water budget calculator that is also based on the US EPA's landscape water requirement equation (US EPA, 2014). However, instead of using the allowable rainfall coefficient from the EPA, or a water banking algorithm like Gelernter et al. (2015), the USGA uses an effective rainfall coefficient of 0.5 instead.

$$\sum_{1}^{12} LWR = [(ET_o * K) - R * R_e] * A \quad \text{(Eq. 3)}$$

if LWR < 0 then LWR = 0 for a given month.

Where LWR is the monthly landscape water requirement summed for each month of the year to generate an annual water requirement, ET_o is the monthly local reference ET, K is the crop coefficient, R is monthly rainfall, R_e is the effective rainfall coefficient, and A is area of irrigated turf.

In summary, previous attempts at calculating water requirements on golf courses, including the USGA method and the method used by Gelernter et al. (2015), rely heavily on the US EPA's water requirement equation (US EPA, 2014). In this study we used the USGA Water Budgeting Calculator as a baseline method of estimating a golf courses water requirement. We then introduce a Tipping Bucket model as an example of a model of intermediate complexity, which includes a representation of soil moisture based on soil texture. Finally, we used Agro-IBIS (the Agricultural-Integrated BIosphere Simulator), a complex process-based global dynamic agroecosystem model, to estimate golf course water requirements. Agro-IBIS uses a co-limitation water budgeting model, where water use is both limited by soil moisture and by stomatal conductance.

The purpose of this study was to develop a framework with which the water use efficiency of a golf course can be defined, and to explore the potential economic and environmental predictors of water use efficiency. An additional aim was to determine which ecosystem models (USGA, Tipping Bucket, or Agro-IBIS) could accurately predict golf course water requirements.

We hypothesize that: 1) model complexity will improve the accuracy of water requirement calculations, 2) golf courses with finer soil textures will use water less efficiently than golf courses with coarser textured soils, as was found to be the case on Nebraska farms (Gibson, 2019), and 3) that golf courses with higher playing quality expectations (quantified by maintenance budget) will use more water than golf courses with lower maintenance budgets.

2. Methods

2.1 UW Madison Resource Efficiency Survey

Golf course water use data presented in this study was collected via the *University of Wisconsin-Madison Resource Efficiency Survey,* which was conducted by the authors of this study (Bekken and Soldat, 2021). The water section of the survey asked golf course superintendents to report irrigation water volumes applied to the golf course over a three-year period from 2016 to 2018 and the area of irrigated land within each golf course component (e.g., greens, tees, fairways, and roughs).

From January to April of 2019 and 2020, golf course superintendents in Wisconsin and Minnesota were asked to take the *University of Wisconsin-Madison Resource Efficiency Survey* through the Wisconsin Golf Course Superintendents Association (WGCSA) and the Minnesota Golf Course Superintendents Association, (MGCSA). Twenty-six superintendents in Wisconsin and seven in Minnesota responded to the survey with complete water use data. Two complete survey responses were received from Illinois, and one complete survey response was received from Ohio. Survey responses from Wisconsin, Minnesota, Illinois, and Ohio make up the regional cluster of survey responses from the US-Midwest (n = 34).

From April through July of 2019 golf courses in New York were asked to take the survey through the Cornell Turfgrass Program. Six responses with complete water data were received from New York state golf courses through this effort. Additional responses from Maryland and Connecticut were also included with the New York courses to make a regional cluster of responses from the Northeast (n = 9). From January through April of 2021, golf courses in Texas, Oregon, Montana, Florida, and Arizona were solicited to take the survey. Partnering organizations in these regions that distributed the survey included the Texas A&M turfgrass program, the Oregon State turfgrass program, the Peaks and Prairie Golf Course Superintendents Association (Montana), the University of Florida turfgrass program, and the Cactus and Pine Golf Course Superintendents Association (Arizona).

Survey efforts was considered successful if at least five golf courses in the region responded to the survey. Regions which did not reach at least five responses were omitted (Table 1).

Table 2. Results from the UW Madison Resource Efficiency Survey by region.

Cluster Region	Responses	Survey effort successful? (>5 responses)	Distributing Organization	States represented in regional sample
Midwest	35	Yes	UW-Madison Turfgrass Program, WGSCA, MGCSA	Wisconsin (24), Minnesota (7), Illinois (2), Ohio (1)
East Texas	13	Yes	Texas A&M Turfgrass Program	Texas (13)
Florida	11	Yes	University of Florida Turfgrass Program	Florida (10), Mississippi (1)
Northeast	9	Yes	Cornell Turfgrass Program	New York (6), Maryland (1), Connecticut (1), New Jersey (1)
Northwest	6	Yes	Oregon State Turfgrass Program, Peaks and Prairies GCSA	Oregon (3), Montana (2), Washington (1)
Southwest	2	No	Cactus and Pine GCSA	Arizona (1), Nevada (1)

2.2 USGA Budget Approach

The United States Golf Association (USGA) Water Resource Center has a downloadable spreadsheet-based water calculator (Eq. 3), called the USGA Water Budget Calculator (USGA, 2021). The USGA describes water budgets as "an estimate of the amount of irrigation water that will be used by a golf course throughout the course of the year." The calculator includes links to monthly climate data for ET and rainfall. However, in this study, daily weather data was aggregated by month to run the USGA model, which accepts monthly reference ET and precipitation data. Daily weather data was supplied by GridMet (Abatzoglou, 2013). See section 2.7 for details.

The USGA calculator suggests a crop coefficient of 0.7 for warm season turfgrass and 0.8 for cool season turfgrass. Golf courses in the study were assigned a crop coefficient based on the type of turfgrass, warm or cool season, that was present on fairways. The allowable rainfall coefficient was set at 0.5 and is not adjustable by the user.

2.3 Tipping Bucket Approach

2.3.1 The Model

Following the approach of the *physical model* in Huang et al. (2017), a single layer tipping bucket model was developed for golf courses in the R software package (Eq 4-11) (Figure 1).

1. If $i = 1$, then $S(n) = \theta_{FC} * RD$, if $i > 1$ then $S(n) = S(n - 1)$
2. a) if $R \geq ET_O * K_c$, $\Delta S = R - (ET_O * K_c)$ then

   $S(n+1) = S(n) + \Delta S$

   b) if $R < ET_O * K_c$, $\Delta S = (ET_O * K_c) - R$ then

   $S(n+1) = S(n) - \Delta S$
3. If $S(n) > \theta_{FC} * RD$, then $S(n+1) = \theta_{FC} * RD$
4. If $S(n) < AWC * 0.5 + \theta_{WP}$ then

   $D = (\theta_{FC} * 0.8) - AWC * 0.5 + \theta_{WP}$ and $S(n+1) = \theta_{FC} * 0.8$
5. $I = D * RTM$

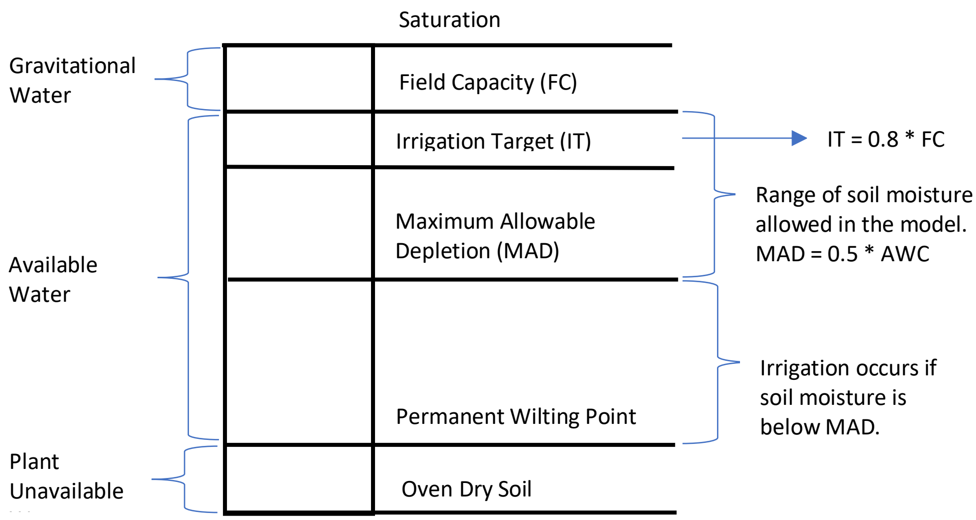

Figure 1. The Tipping Bucket model as defined in this study.

Where S is soil water storage (mm) on day n, θ_{FC} is volumetric water content at field capacity, θ_{WP} is volumetric water content at wilting point, RD is rooting depth, R is rainfall, ET_o is reference ET, K_c is the crop coefficient, ΔS is change in soil water storage (mm), AWC is the available water content, D is the water deficit (mm), I is irrigation (mm), and RTM is the run time multiplier (see section 2.3.5).

2.3.2 Input Data

The Tipping Bucket model was supplied data from GridMet (Abatzoglou, 2013). See section 2.7 for details.

2.3.3 Rooting Depth

Rooting depth was measured on a golf course in Corvallis, Oregon, USA in (October, 2021). Three samples were taken from three greens, tees, fairways, and roughs for a total of 36 samples. Rooting depths were averaged by component. The measured rooting depths were rounded to the nearest multiple of 5 cm for use in modeling, which resulted in rooting depths of 10 cm on greens, 15 cm on tees, 20 cm on fairways, and 25 cm in roughs. Co-authors of this study located in the Midwest, Northeast, East Texas agreed that these estimates were representative of rooting depths in their respective regions. However, the rooting depth estimates derived from the Oregon field samples were not representative of rooting depths in Florida. Therefore, superintendents of all golf courses in Florida were asked, via email, to share rooting depths from each of their courses. Three responses were received, averaged, and rounded to the nearest 1 cm (Table 3).

The Tipping Bucket model is a single layer model that does not distinguish between golf course components, and therefore a single rooting depth value must be chosen for each golf course. To determine a rooting depth for an entire golf course, an area weighted average rooting depth was calculated (Table 3). The area weighted average was determined based on the average size of each golf course component on US golf courses (Gelernter et al., 2017). Gelernter et al. (2017) found that the average area of greens was 1.6 ha (4% of turf area), tees 1.4 ha (3% of turf area), fairways 10.1 ha (25% of turf area), roughs 27.3 ha (68% of turf area). Applying our irrigated area formula (see section 2.5) to these averages, the irrigation of greens accounts for 8% of total irrigated area, tees 7%, fairways 48%, and roughs 38%. These percentages were multiplied by the rooting depth of each component to derive an area weighted average rooting depth, which was utilized in the Tipping Bucket model.

Table 3. Estimated rooting depths for each golf course component and an area weighted average for the entire golf course.

	Measured Rooting Depths in Oregon (cm)*	Rooting Depths for Modeling (cm)**	Estimated Rooting Depth in Florida (cm)***
Greens	8.7	10	5
Tees	13.5	15	10
Fairways	21.6	20	12
Roughs	25.3	25	15
Area weighted average	---	20.8	12.6

*Rooting depth in Oregon was measured on a golf course in Corvallis, Oregon.
**Rooting depths for modeling were rounded to the nearest 5 cm from the measurements taken in Oregon.
***Superintendents in Florida were surveyed via email to determine rooting depth there.

2.3.4 Crop coefficient

Like the USGA water budgeting approach, a crop coefficient of 0.7 was assigned to golf courses with warm season turfgrass fairways and a crop coefficient 0.8 was assigned to golf courses with cool season turfgrass fairways.

2.3.5 Soil Texture

Soil texture information was obtained from the Web Soil Survey (Natural Resources Conservation Service, 2021). The soil texture with greatest percent coverage over the golf course was assumed to cover the entire golf course. Seven soil textures were recognized in the model. Values for volumetric water content at field capacity (VWC_{fc}) and wilting point (VWC_{wp}) were taken directly from Campbell and Norman (1998), except for the sand textural class. Campbell and Norman list VWC_{fc} and VWC_{wp} for sand as 0.09 and 0.03, respectively. However, organic matter accumulation in golf course soils causes sandy soils to hold more water in a similar manner to sandy loam soils. As such, we used VWC_{fc} and VWC_{wp} for sandy loam soils for sand as well (Table 4).

Table 4. Volumetric Water Content at field capacity (VWC_{fc}) and wilting point (VWC_{wp}) for seven soil types used in the Tipping Bucket model. From Campbell and Norman (1998).

Soil Texture	VWC_{fc} (m^3/m^3)	VWC_{wp} (m^3/m^3)
Sand/Sandy Loam	0.21	0.10
Loam	0.27	0.12
Silt Loam	0.33	0.13
Silt	0.33	0.13
Clay Loam	0.32	0.20
Silty Clay Loam	0.37	0.21

2.3.6 Distribution Uniformity

All golf courses in the study were assigned a lower quartile distribution uniformity of 0.7, which is considered by Mecham (2005) to be "very good". Using this distribution uniformity, a run time multiplier (RTM) was calculated to Mecham (2010).

$$RTM = \frac{1}{0.4+(0.6*DU_{LQ})} \qquad \text{(Eq. 12)}$$

The RTM was multiplied by the water deficit to obtain the irrigation requirement (see Section 2.3.1- Step 5).

2.4 Agro-IBIS

Agro-IBIS (Integrated Biosphere Simulator) is a process-based model, meaning that it can represent several processes of managed and natural systems mathematically (Kucharik and Brye, 2003). It can simulate the exchange of energy, water, CO_2 and momentum balance between plants, soils and atmosphere at an hourly time step. Canopy and land surface depend on physiology, phenology, and carbon allocation so that coupled carbon and water exchange responds to potential stresses and management.

2.5 Calculating area irrigated

The UW-Madison Resource Efficiency Survey asked golf course superintendents to report the area of each golf course component (e.g., greens, tees, fairways, and roughs), and the area irrigated within each component. However, reported irrigated area data were determined to be unreliable because superintendents in the study commonly reported that all hectarage of roughs were irrigated. Previous studies indicate that 36% of rough is not irrigated (Throssell et al. 2009). Therefore, we devised a geometric method to approximate the area irrigated on golf courses in the study.

Irrigated area was estimated using Eq 13 for golf courses who reported irrigating roughs.

$Area\ irrigated = [Area\ (Greens) * 2] + [Area\ (Tees * 2)] + [Area\ (Fairways * 1.5)]$ (Eq. 13)

Irrigated area was estimated using Eq 14 for golf courses who reported not irrigating roughs.

$Area\ irrigated = [Area\ (Greens) * 2] + [Area\ (Tees * 2)] + [Area\ (Fairways)]$ (Eq. 14)

2.5.1 Geometric assumptions for area of irrigated buffers around greens, tees, and fairways

All greens, tees, and fairways in our study were irrigated. To simulate the overthrow of a modern irrigation system, we assumed that irrigation heads were placed on the edges of greens, tees and fairways (with double or triple line irrigation) and sprayed water 15 m beyond the edges of the component, creating a 15 m area surrounding the greens, tees, and fairways that is also irrigated (Figure 3). This additional irrigated area is modelled as a rough.

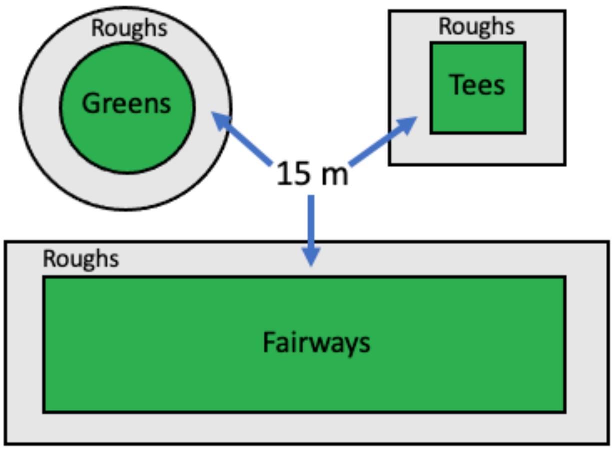

Figure 3. The 15 m buffer area surrounding greens, tees, and fairways (i.e., irrigated roughs).

To determine how much area the 15 m buffer covers (i.e., how much rough is irrigated), we made several geometric assumptions about each golf course component. We modeled greens as a circle. The average area of greens per 18-holes in our study was 16,117 m^2 or 895 m^2 per green. The average radius of a green was 16 m. Adding a 15 m buffer to a circle of this radius approximately doubled the area of the circle. Therefore, we doubled the area of greens to determine total area of irrigated land associated with greens. For example, a reported 1 ha of greens turned into a total of 2 ha of land irrigated (1 ha of greens and 1 ha of land surrounding the greens). We modeled greens' surrounds as roughs.

We modeled tees as a square. The average area of tees per 18-holes in our study was 18,523 m^2. Thus, the average area of tees per hole was 1029 m^2. The length of a square with this area was 32 m. Adding a 15 m buffer to a square of this size roughly doubled the area of the square.

Therefore, we doubled the area of tees to determine the total area of irrigation associated with tees. Two hectares of irrigated tees yielded a total of 4 ha of irrigated land (2 ha of tees and 2 ha of tees surrounds). We modeled tee surrounds as roughs.

To determine the average area of the 15 m buffer around fairways we made some simplifying assumptions about the size and shape of fairways in our study. The average golf course fairway width in the US is 32 to 40 m (Golf Course Industry, 2009). Therefore, we assumed the average fairway width in this study was 36 m.

The average length of the 18-hole golf courses in our study was 5560 m. Assuming the standard golf course set up of four par 3's, ten par 4's, four par 5's and staying within the range of USGA recommendations for hole lengths for each par, we assumed par 3's were on average 150 m, par 4's an average of 365 m, and par 5's an average of 460 m. We then assumed the fairway started 90 m from the tee which yields an average golf course fairway length of 230 m. Combining an average length of 230 m and width of 36 m, the average aspect ratio of the fairway is 6.38. Thus, we modeled the fairway as a rectangle with these dimensions.

In our study, the average area of fairways per hole was 7,190 m^2. Using the average aspect ratio of a fairway, 6.38, we find that the average fairway in our study had a dimension of 33 m by 214 m. A 15 m buffer around a fairway of these dimensions increased the area of the fairway by a factor of approximately 1.5. Therefore, we increased the area of fairways by 1.5 to determine total area of irrigation associated with fairways. Area of land irrigated for 10 ha of fairways meant a total of 15 ha of irrigated area (10 ha of fairways and 5 ha of fairway surrounds). We modeled fairway surrounds as rough.

2.6 The Water Efficiency Score

For the purposes of this study, the water efficiency score defined as:

$$Water\ Efficiency\ Score = \frac{Actual\ water\ use}{Model\ predicted\ water\ use} \qquad \text{(Eq. 15)}$$

A Water Efficiency Score (WES) greater than 1 means that the golf course used more water than predicted by their water budget, while a score below 1 means the golf course used less water than predicted their water budget. A lower WES is an indication of higher water use efficiency on a golf course.

WES's were calculated in this study using the USGA, Tipping Bucket, and Agro-IBIS budgeting methodologies and abbreviated as fellows: WES_{USGA}, WES_{TB}, WES_{AI}.

2.7 Weather vs. Climate Data in Predicting Water Requirements

The USGA Water Budget Calculator, when using data sources as suggested by the USGA, runs on climate normal (30-year average) data. This means that the model predicts water use in an average year but does not predict water use for the weather conditions of an individual year. In this study, we ran the USGA Water Budget Calculator with weather data from GridMet, which is also used in this study to run the Tipping Bucket and Agro-IBIS models. Thus, the water requirements generated by the USGA, Tipping Bucket, and Agro-IBIS models are dynamic from one year to the next.

GridMet provides daily weather data at 4 km (2.5 arc minute) resolution. Bands of the dataset utilized in this work included daily precipitation (mm), minimum temperature (C), and daily reference ET for grass (mm). These data were retrieved from GridMet via the Google Earth Engine R package 'rgee' (Version 1.0.9.999) for 2016, 2017, and 2018.

3. Results

3.1 Predicting Water Requirements

3.1.1 USGA Water Calculator

Using the USGA Water Calculator, a water requirement was determined for each of the 71 US golf courses participating in the study. The mean WES_{USGA} for all golf courses was 1.16, indicating that, on average, golf courses in the study used 16% more water than the USGA water budgeting method predicted. The median WES_{USGA} was 1.02.

In the Midwest, which included the largest regional cluster of golf courses (n=34), the mean WES_{USGA} was 0.75, indicating that water use in the region was slightly lower than predictions made by the USGA Water Calculator. The standard deviation was 0.51, indicating great variability among golf courses in WES_{USGA}.

On average, golf courses in Florida used 2.11 times what USGA Water Calculator predicted (Figure 2). The model also underpredicted water use in East Texas by 35% and the Northwest by 23%. In the Northeast, mean and median WES were 0.98 and 1.00, respectively, indicating that the model predicted water use in the region accurately. Variability of WES_{USGA} was high in all regions; the coefficient of variation was greater than 0.53 for all regions.

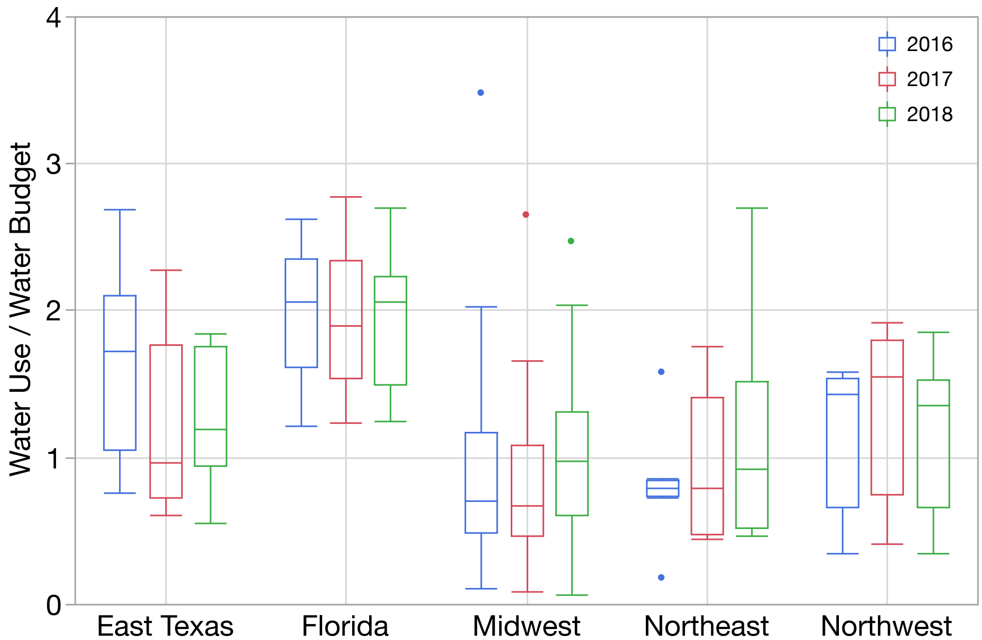

Figure 4. Water Efficiency Scores (WES) by region using the USGA water budgeting approach (WES_{USGA}).

Table 5. Descriptive statistics of mean Water Efficiency Scores (WES) from 2016-2018 for the USGA, Tipping Bucket, and Agro-IBIS water budget models.

	WES_{USGA}							WES_{TB}						
Region	Median	Mean	St dev	CV	Max	Min	Range	Median	Mean	St dev	CV	Max	Min	Range
Midwest	0.75	0.89	0.51	0.57	2.49	0.09	2.40	0.88	0.94	0.50	0.53	2.13	0.10	2.02
East Texas	1.23	1.35	0.51	0.38	2.16	0.64	1.52	0.78	0.85	0.36	0.42	1.48	0.39	1.09
Florida	2.11	1.97	0.47	0.24	2.74	1.38	1.36	1.41	1.29	0.38	0.30	1.76	0.61	1.16
Northeast	1.00	0.98	0.47	0.48	2.02	0.38	1.63	0.92	0.95	0.37	0.39	1.68	0.40	1.28
Northwest	1.50	1.23	0.53	0.43	1.66	0.37	1.29	1.39	1.16	0.53	0.46	1.61	0.33	1.28
All regions	1.02	1.16	0.62	0.53	2.74	0.09	2.65	0.91	1.00	0.46	0.46	2.13	0.10	2.02

	WES_{AI}						
Region	Median	Mean	St dev	CV	Max	Min	Range
Midwest							
East Texas							
Florida							
Northeast							
Northwest							
All regions							

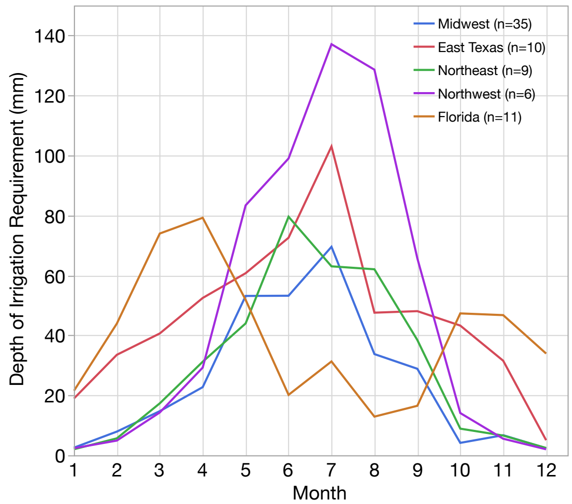

Figure 5. Average monthly irrigation requirement as determined by the UGSA Water Calculator for the five regions studied (Midwest, East Texas, Northeast, Northwest, and Florida).

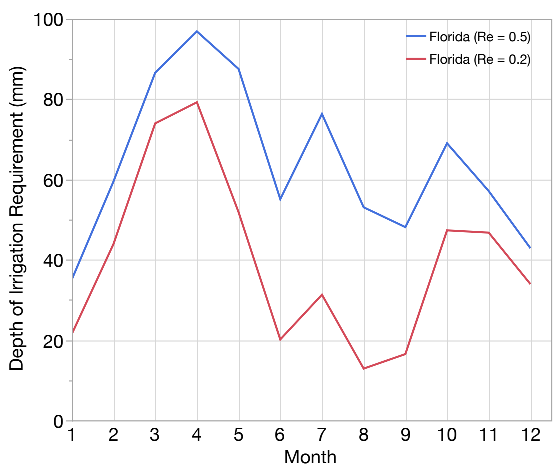

Figure 6. Average monthly irrigation requirement as determined by the USGA Water Calculator for Florida with an effective rainfall coefficient (R_e) of 0.5 (model default) and 0.2. A R_e of 0.2 is needed for the USGA Water Calculator to predict mean water use on Florida golf courses in this study.

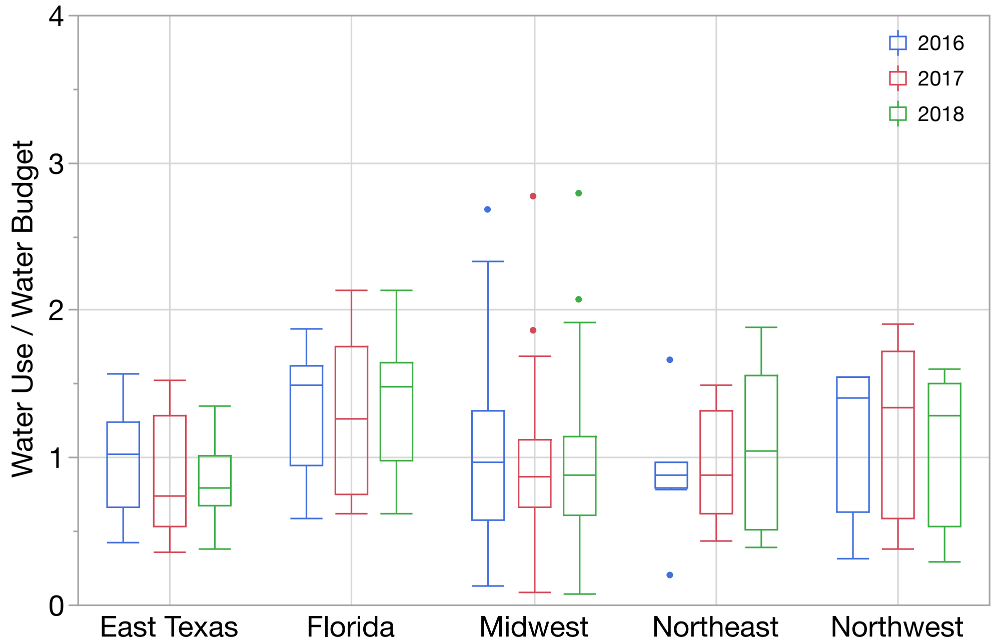

Figure 4. Water Efficiency Scores (WES) by region using the Tipping Bucket water budgeting approach (WES_{TB}).

3.1.2 Tipping Bucket Model

The mean WES_{TB} for all golf courses in the study was 1.00, indicating that mean water use matched the predicted water requirement. However, there was still a large standard deviation (0.46) and range (2.13) of WES_{TB} in the dataset.

The mean WES_{TB} for the Midwest region was 0.94, East Texas 0.85, Florida 1.29, Northeast 0.95, and Northwest 1.16. Of the 71 golf courses in the study 12 golf courses use less than 50% of the water that the Tipping Bucket model predicted. Of these 12 golf courses, 10 of them had a depth to water table of less than 1m (Web Soil Survey, 2022). Nine golf courses had a mean WES_{TB} of greater than 1.5 (Midwest 4, Florida 3, Northwest 2).

3.2 Variance in Water Efficiency Scores (WES)

Green fees (i.e., cost to play the golf course) varied widely in our study, ranging from \$16 to \$550 for an 18-hole round. Maintenance budgets ranged from \$2,300 to over \$100,000 per ha, revenues ranged from \$18,000 to over \$500,000 per ha, and irrigation budgets ranged from \$0 to \$4,056 per ha. However, despite all the variance in green fees, maintenance budgets, and irrigation budgets, none of these variables explained variance in the WES_{TB} (Table 6).

Golf courses in this study reported the dominant grass types on all four course components (greens, tees, fairways, and roughs). Because grasses on fairways and roughs account for the greatest percentage of irrigated area on a golf course, grass type on fairways and roughs was tested for correlation with WES_{TB} and WES_{AI}. Eight different turfgrass species were planted on the golf courses in the study: annual bluegrass, fine fescue, creeping bentgrass, Kentucky bluegrass, perennial ryegrass, bermudagrass, tall fescue, and perennial ryegrass. However, we found no significant relationship between grass type and WES (Table 6).

Golf courses in the study were underlain by seven different soil types: sand, sandy loam, loam, silt loam, silt, clay loam, and silty clay loam. No significant relationships were observed between soil type and WES (Table 6).

Table 6. Environmental and economic variables in relation to WES. Golf courses with shallow water tables were excluded from this analysis. Asterisk indicates statistical significance at $\alpha < 0.05$.

Economic factors	WES_{USGA}	WES_{TB}	WES_{AI}
	Correlation Coefficient (p-value)		
Green Fee (USD)[a]	0.02 (0.30)	0.00 (0.99)	
Maintenance Budget (USD/ha)[a]	0.25 (0.0001)*	0.06 (0.06)	

Irrigation Budget (USD/ha)[a,b]	0.18 (0.02)	0.00 (0.63)	
Revenue (USD/ha)[a]	0.14 (0.06)	0.01 (0.41)	
Total Employees[a]	0.06 (0.06)	0.00 (0.73)	
Cool season grasses (fairways)[c]	0.06 (0.06)	0.14 (0.39)	
Soil type (native soil)[c]	0.31 (0.0006)*	0.05 (0.90)	

[a]Linear regression
[b]Only golf courses that pay for water were included in this regression.
[c]One-way ANOVA

4. Discussion

4.1 Model Performance

The goal of the modeling in this study was to predict water use on individual golf courses as accurately as possible. The lowest mean WES_{USGA} was in the Midwest (0.89) and highest was in Florida (2.11), showing that the range in WES was 1.22 across all regions. The range of WES_{TB} was 0.45 across all regions.

4.2 Model Evaluation and Comparison

The effective rainfall coefficient in the USGA Water Budget Model is currently set to 50%, which means that only half of all rainfall becomes plant available and subject to evapotranspiration (ET). A rainfall coefficient of 50% was representative of findings for the Midwest region; however, in all other regions, water use on golf courses was greater than the USGA Water Budget Model predicted. The USGA model underpredicted water use the most in Florida, where the average WES_{USGA} was 2.11, indicating that golf courses in Florida used approximately twice the amount of water than the USGA model predicted. From June through September in Florida, rainfall exceeds ET, causing the USGA model, when set with an effective rainfall coefficient of 50%, to predict that golf courses need little irrigation during these months. In fact, golf courses in Florida apply significantly more irrigation water during these months because rainstorms during this period deliver little plant available water, in part because the precipitation rate is so high that water either runs off or is not held by the predominantly sandy soils in the region. Based on our findings, for the model to predict mean water use on Florida golf courses (WES_{USGA} = 1), the effective rainfall coefficient would need to be reduced to approximately 20% (Figure 6).

4.3 Interpreting Variance in Water Efficiency Scores (WES)

For the Tipping Bucket model, a shallow water table (<1 m) seems to be a likely explanation for 10 of the 12 golf courses whose WES is lower than 0.5. In a follow-up email survey of the ten golf courses with shallow water tables, all eight superintendents who responded confirmed that a shallow water table allowed them to use less water. Six superintendents mentioned that they also use water conservation practices such as a preference to keep the course drier, use wetting agents frequently, apply water via spot irrigation and hand watering, water deeper and infrequently, and conduct soil moisture mapping of the golf course to customize irrigation programs.

4.4 The Role of Economic and Environmental Factors in Water Efficiency Scores (WES)

An initial motivation for this work was to investigate possible connections between water efficiency scores (WES) and various economic and environmental factors. Bekken et al. (2021) found that golf courses with higher maintenance budgets have, on average, higher pesticide risk.

Therefore, we hypothesized that maintenance budget may be predictive of water use. Maintenance budget was not predictive of WES_{TB} but was weakly predictive of WES_{USGA} (r^2 = 0.25). It is unclear why there was a discrepancy between WES_{TB} and WES_{USGA}. Regardless, irrigation budget was not strongly predictive of water use. This may be because golf course water use is not economically limiting in the five regions of the country for which this study was conducted. Maintenance and irrigation budgets may be predictive of WES in the Southwestern US, where golf course managers pay higher prices to irrigate their courses.

Both the Tipping Bucket and Agro-IBIS models accommodate many different soil types. Because sandy soils hold less available water, we hypothesized that superintendents would be more likely to overwater a golf course with a sandy soil, which may lead to less efficient water use on golf courses on sandy soils (i.e., have a higher WES value). However, this was not the case because WES_{TB} did not vary systemically by soil type. However, for the USGA model, which does not parameterize for different soil types, WES_{USGA} and soil type correlated significantly. This indicates parameterizing for different soil types is important and should be completed.

The Tipping Bucket and Agro-IBIS models only differentiate between either warm or cool season grasses and do not describe individual turfgrass species. Nearly all golf courses in the study with warm season grass were growing bermudagrass and, as such, the effect of warm season grass species on WES could not be tested. A wide variety of cool season grasses were grown on golf courses in the Northeast, Midwest, and Northwest, but the species of cool season grass did not significantly affect WES (Table 6). This suggests that, within the models, species specific parameterization for cool season grasses may not be necessary. If WES did vary systemically by grass species, then parameterizing both models for individual turf species would be necessary. Further, it is possible that the management style of a superintendent may be more important in determining water use efficiency than grass species or cultivar. Thus, efforts to breed more water efficient turfgrasses may be ineffective in reducing water usage on golf courses because cultivar efficiency could be dwarfed by the superintendent's irrigation decisions.

4.5 Important Modeling Parameters

Before any conclusions about a golf course's water efficiency can be derived from a WES, modeling parameters need to accurately represent each golf course. Rooting depth and irrigated area were two of the most important modeling parameters for the Tipping Bucket model to accurately predict water needs on golf courses.

Rooting depth is the depth over which turfgrass can obtain water from soil. A deeper rooting depth means that a greater percentage of rainfall becomes plant available. However, no comprehensive survey of golf course turfgrass rooting depths across the US could be found during this study. As such, we relied on a combination of field sampling, values from the literature (Suplick-Ploense and Qian, 2005; Lyons et al., 2011), and knowledge from golf course superintendents and turfgrass extension specialists to establish rooting depths for our study.

Estimating irrigated area accurately, especially in roughs, is incredibly important for all models to predict golf course water requirements. However, most superintendents in our study did not provide accurate estimations of rough irrigated area, likely because knowing this number is not critical to a superintendent's success. To maintain to a high aesthetic standard, roughs are the least important component of a golf course and receive the lowest management inputs per unit area. However, given their large size, roughs can use a significant amount of water on golf courses. Improving the water requirement predictions for golf courses will necessitate working with superintendents to map the amount of irrigated area more accurately on their courses, particularly with respect to the area of irrigated rough. Broadly, it is important to refine all model assumptions before drawing conclusions about the WES of any individual golf course.

There are two types of irrigated area, the area that is covered by the irrigation system and the area that the golf course superintendent chooses to irrigate in any given year. The latter will be smaller than the former; those interested in estimating a water requirement must be intentional about choosing the appropriate and useful definition of irrigated area.

4.6 Landscape Scale Factors Not Accounted for in Modeling

Landscape factors not accounted for in modeling must also be considered to make sure a WES is an accurate representation of water use efficiency at an individual golf course. The USGA and Tipping Bucket models do not consider groundwater as a possible water source, which likely leads both models to overpredict irrigation requirements on golf courses with near surface water tables. Therefore, we recommend only using the USGA and Tipping Bucket model on golf courses with water tables greater than 1m in depth. Agro-IBIS can simulate groundwater flow and the role that groundwater may play in reducing irrigation requirements. However, Agro-IBIS does not account for surface water runoff that is directed onto a golf course from the surrounding landscape.

4.7 Water Budgeting Role in Water Conservation on Golf Courses

Regulatory bodies, consultants, and turfgrass extension specialists working with golf courses on water use efficiency must check that the modeling assumptions made are appropriate for a particular golf course. However, if all assumptions discussed above are satisfied and parameters are accurately calibrated in the model, then one can have confidence in the WES to define water use efficiency. There are myriad ways in which to use water more efficiently and these are discussed at length in golf industry BMP manuals (GCSAA, 2016).

Water management districts in Florida already use water requirement calculations to cap allowable golf course water usage. However, water requirements have value beyond water use quotas. Water requirement calculations can be used to identify golf courses that are and are not using water efficiently considering their climate, soils, and grass. If graphical user interfaces were added to the Agro-IBIS and Tipping Bucket models, superintendents could use the models to predict water use at a variety of temporal scales, from annual water use efficiency evaluations to daily irrigation management. Water requirement estimation methods could also help developers in site planning for future golf courses, or to quantify the benefits of using golf courses as stormwater management sites.

4.6 Advantages and Disadvantages of the Three Models Used

Of the three models applied in this study, the USGA Water Budget Model is the most accessible model for practitioners to use. The links to climate data provided by the USGA allow a user to create a water budget for their course quickly and easily. As currently constructed, the USGA model is limited because the effective rainfall coefficient is not adjustable. Further research would be required to determine an appropriate effective rainfall coefficient for each region of the US.

The Tipping Bucket model is an open access model and accessible to those with coding experience in environmental sciences. As currently published, this model is not accessible to superintendents. Further work would be required to transform this model into an easily usable tool with a graphical user interface that superintendents could interact with via their mobile device or computer.

Agro-IBIS is the least accessible of the three models used in this study. This model is maintained by the Agronomy Department at University of Wisconsin-Madison and is only available to approved researchers.

4.8 Comparisons to Agriculture

Gibson (2019) quantified the efficiency of water use in maize and soybean fields in Nebraska over a three-year period from 2010-2012. The authors quantified water budgets in terms of water surplus (depth of irrigation applied minus depth of water budget). Water surplus values for 534 farm fields in the study ranged from -100 mm to 400 mm. In this study of 71 golf courses, water surplus values for the Tipping Bucket model ranged from -670 mm to 600 mm.

It is possible that resource use in golf course management is more variable because what constitutes yield in golf course management is not strictly defined. Yield may constrain management behavior in agriculture in a way that does not occur in golf, leading to a larger variance in golf course resource use inputs. In addition, golf courses in our study likely exist in a wider variety of hydrological environments than Nebraska farm fields, which adds uncertainty to our modeling. For example, golf courses often serve as stormwater retention sites for the surrounding urban area.

In addition, Gibson (2019) found that soils with higher available water holding capacity used less water in relation to their water budget, whereas we found no pattern between water budget (i.e. water surplus) and soil texture in this study. It is possible that this result reflects a limitation of using the Web Soil Survey to determine soil texture on golf courses. Soil texture was not directly measured in this study. In some regions of the U.S., the native soil on golf courses is amended to increase sand content.

5. Conclusion

Using the Water Efficiency Score (WES) has the potential to normalize for differences between area irrigated, climate, soil, and grass type. WES provides a quantitative measure of water use efficiency on golf courses that could be used by superintendents, golf industry bodies, and regulatory agencies to measure and encourage greater efficiencies across climates.

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Chapter 6: Quantifying golf course nitrogen use efficiency

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Abstract

Previous studies have surveyed golf courses to determine nitrogen (N) fertilizer application rates on golf courses, but no previous studies have attempted to quantify how efficiently golf courses use nitrogen. This study tests the ability of the Growth Potential (GP) N Requirement model as a benchmarking tool to predict a target level of N use on 76 golf courses in five regions of the US (Midwest, Northeast, East Texas, Florida) and three countries in Europe (Denmark, Norway, UK). The ratio of golf course-wide N application rate to the GP N requirement prediction (termed the Nitrogen Efficiency Score or NES) was 0.27, indicating that golf courses used 73% less N than predicted by the model. As such, the GP N requirement model needs to be recalibrated to predict N use on golf courses. This was achieved by adjusting the N_{max} coefficient in the model. N rates on golf courses were widely variable both within and across regions. All regions had a coefficient of variation in N rate of 46% or greater. This high degree of variation, which is largely unexplained by climate, economic factors, grass type, and soil type may be indicative of inefficient N use in golf course management.

Keywords: decision support tools, fertilizer, golf, golf course, growth potential, nitrogen, nitrogen use efficiency, modeling, turfgrass

Introduction

There are nearly 40 000 golf courses globally, approximately half of which are in the US (R&A, 2019). Golf courses are commonly located near urban centers and require inputs such as water, energy, fertilizer, and pesticide to maintain. Residents surrounding golf courses are often concerned about the effects of resource use on both environmental quality and their health (Garris, 2018). These concerns are not entirely unjustified. Concentrations of fertilizers and pesticides in outflowing streams from golf courses are commonly incrementally higher than inflowing water, though these concentrations rarely exceed US EPA water quality guidelines (King et al., 2007; King and Balogh, 2010).

Nitrogen (N) is the nutrient applied in the highest quantity to golf course turfgrass. While application rates of nutrients on golf courses vary based on the component of the golf course (i.e. greens, tees, fairways, or roughs), Gelernter et al. (2016) found that property-wide average N, P_2O_5, and K_2O application rates on US golf courses were 106, 15, and 72 kg ha^{-1}, respectively.

The application of N on golf courses can lead to increased dissolved concentrations of N bearing compounds in surface and groundwater (Cohen et al.; 1999; King et al., 2007). Documented ecological effects of increased NO_3-N and NH_4-N in surface waters downstream of golf courses include altered macroinvertebrate community structure, increased algal biomass, and eutrophication (Mallin and Wheeler, 2000; Davis and Lydy, 2001; Winter et al., 2002). Winter et al. (2002) found that golf course fertilizer application rates were an important predictor of aquatic ecosystem structure and function downstream of golf courses, with lower fertilizer application rates correlating to higher levels of ecosystem health.

Reducing N use on golf courses also decreases emissions of nitrous oxide (N_2O) from golf courses (Gillette et al, 2016), as well as maintenance costs for golf course owners and managers. However, eliminating or reducing N use can lead to turf thinning, soil erosion, and nutrient loss from the landscape (Kussow, 2011). Thus, there is an optimal level of N input on a golf course that maximizes environmental quality while maintaining the recreational benefits of the course. However, this optimal level is difficult to determine given the myriad factors that can influence the N requirement on a golf course, including but not limited to climate, soil and grass type, and utilization of the golf course.

Ecosystem models, which take a biophysical approach to simulating the N cycle, have been used to predict optimal N use on lawns, which are turf systems that are similar to golf courses. Using the DAYCENT model, Zhang et al. (2013) predicted the N requirement for high and medium quality Kentucky Bluegrass lawns in Colorado, USA. The quality of the lawn was defined by the annual net primary productivity (ANPP). Medium-quality lawns were defined as having an

ANPP of 1800 kg C ha^{-1} yr^{-1}, while high-quality lawns were defined as having an ANPP of 2800 kg C ha^{-1} yr^{-1}. The DAYCENT model predicted that during the first ten years after establishment, the turfgrass would require 80 and 140 kg N ha^{-1} yr^{-1} for medium and high-quality lawns, respectively. If clippings are returned to the grass, the model predicted that the N requirement 40 years after turfgrass establishment could be reduced to below 50 kg N ha^{-1} yr^{-1} to maintain both high and medium quality lawns.

In addition to biophysical modeling, N application rates on golf courses can be analyzed by comparing a given golf course's N rate to regional averages. Gelernter et al. (2016) carried out a nationwide survey to develop baseline data on nutrient use in seven agronomic regions of the US. The authors found that course-wide annual N rates ranged from 83 kg N ha^{-1} in the North Central region to 154 kg N ha^{-1} in the Southwest region. However, one issue with this approach is that regional average application rates do not necessarily represent optimal N use.

Analyzing golf course N rates by biophysical modeling or by regional comparison are methods of benchmarking. Benchmarking is the process of measuring against a standard or reference point to determine a level of efficiency (Malano et al., 2004). Efficiency, in this study, is defined as preventing the wasteful use of a resource. The goal of this research was to develop a benchmarking framework to determine the efficiency of golf course N use. This study uses both modeling and regional comparison as benchmarking tools to determine efficiencies. In addition, the study explores methods to normalize for differences in climate across regions. With climate accounted for, the efficiency of N use can be compared across regions directly. Lastly, by analyzing for potential connections between N use and economic and environmental factors, this investigation can begin to explain some golf courses may use N fertilizer more efficiently than others.

Methods

Survey

The golf course N use dataset was collected via the *UW-Madison Resource Efficiency Survey,* which was conducted by the authors of this study (Bekken and Soldat, 2021). The fertilizer section of the survey asked golf course superintendents to report N application rates on each golf course component (greens, tees, fairways, and roughs) in 2016, 2017, and 2018. Golf course superintendents were given the option to either upload N application records or enter average N application rates directly into the survey over the three-year period. The survey also asked superintendents to report the most common soil and grass type on each golf course component.

From January to April of 2019 and 2020, golf course personnel in Wisconsin and Minnesota were asked by Wisconsin Golf Course Superintendents Association (WGCSA) and the Minnesota Golf Course Superintendents Association, (MGCSA) to take the *UW-Madison Resource Efficiency Survey*. From April through July of 2019 golf course personnel in New York were asked by the Cornell Turfgrass Program to take the survey. From January through April of 2021, golf course personnel in Texas, Oregon, Montana, Florida, Arizona, Norway, Denmark, Sweden, and the UK were asked by a partnering organization in each region to take the survey (Table 1). Survey efforts were considered successful if at least five golf courses in each region responded to the survey. Regions that did not reach at least five responses were omitted from the study.

A follow up email survey was completed in the Spring of 2022 asking golf course superintendents in Florida and East Texas if they overseed with a cool season grass in the winter. A manager of one of the golf courses in East Texas reported that they had overseeded 18 of the 36 holes. The N rate for this overseeded course was removed from the dataset so that only golf courses that were not overseeded were included in the study. One exception was made for a golf course in East Texas that overseeded only on its tees. In our study, tees accounted for only 3.5% of golf course total turfgrass area on average.

Table 1. Results from the UW Madison Resource Efficiency Survey by region.

Region	Fertilizer Responses	Survey effort successful? (>5 responses)	Distributing Organization

US-Midwest	19	Yes	UW-Madison Turfgrass Program, WGSCA, MGCSA
US-Northeast	13	Yes	Cornell Turfgrass Program
US-East Texas	11	Yes	Texas A&M Turfgrass Program
US-Florida	9	Yes	University of Florida Turfgrass Program
US-Denmark	7	Yes	Danish Golf Union
Norway	7	Yes	NIBIO, Norwegian Greenkeepers Association
UK	5	Yes	GEO Foundation
US-Northwest	5	Yes	Oregon State Turfgrass Program, OGCSA, Peaks and Prairies GCSAA
Sweden	3	No	Swedish Golf Union
Southwest	2	No	Cactus and Pine GCSA

Growth Potential Calculations

The Growth Potential (GP) model is widely used in the turfgrass industry to predict turfgrass growth (Gelernter and Stowell, 2005).

$$\text{(Eq. 1) } GP = \frac{1}{e^{\frac{1}{2}\left(\frac{T_{obs}-T_{opt}}{var}\right)^2}}$$

where GP is the Growth Potential, T_{obs} is the observed temperature (typically a monthly average), and T_{opt} is the optimal temperature of the grass species of interest, and var is the variance of the distribution. When the growth potential is between 50 and 100% turf is likely to be actively growing. However, when the growth potential drops below 50% turf is likely to grow at increasingly restricted rates. When GP is below 10% turf growth is nearly halted.

Gelernter and Stowell (2005) recommends setting the variance to 10 for C_3 turfgrasses and 12 for C_4 turfgrasses. The authors also recommend setting the optimal temperature to 20 °C for cool season grasses and 31 °C for warm season grasses. These values for the variance and optimal temperature were used in this study. Golf courses were assigned as having either C_3 or C_4 turfgrasses based on the type of grass reported on their fairways.

Temperature Data for GP Model

Daily temperature data were obtained for all US based golf courses in the study from GridMet (Abatzoglou, 2013) via Google Earth Engine in the R package 'rgee' (Version 1.0.9.999) for the three years of the study: 2016, 2017, and 2018. GridMet does not report daily average temperature, but it does report minimum and maximum daily temperature. As such, minimum and maximum daily temperatures were queried for each golf course and averaged to determine mean daily temperature for 2016, 2017, and 2018. These three years of temperature data were then averaged to obtain a mean daily air temperature for each calendar day of the year. The 3-year mean daily air temperature results were then used in the GP model.

For golf courses in Norway, Denmark, and the UK, temperature data were obtained from Global Data Land Assimilation System (GLDAS) via Google Earth Engine. GLDAS provides instantaneous temperature every three hours, or eight temperature readings every day. These eight temperature data points were averaged each day to obtain a mean daily air temperature. Temperature data were again obtained for 2016, 2017, and 2018 and averaged over the three-year period to obtain a mean daily air temperature for each calendar day of the year during the 3-year period of the study.

Growing Season Length Determination

Using the 3-year mean daily air temperature dataset, the GP model was used to estimate the number of days in a calendar year that turfgrasses were actively growing on each golf course in our study. We defined a growth day as a day when GP was over 50%. N application rates were divided by growth days to normalize for the effect of season length.

Growth Potential N Requirement Calculations

Based on the Gelernter and Stowell (2005) GP model, Woods (2013) devised a method by which the N requirement of turfgrass could be calculated, henceforth referred to as the GP N Requirement model (Eq. 2).

$$\text{(Eq. 2) } F_N = N_{max} * GP$$

where N_{max} is the desired maximum nitrogen use rate of the grass, and where F_N is the N requirement. The GP N Requirement model was devised as a tool that golf course superintendents could use to scale N application rates in a manner commensurate with turfgrass growth, as predicted by the GP model.

As devised by Woods (2013), N_{max} of the GP N Requirement model is a qualitative parameter that a golf course superintendent can choose based on the maximum amount of N that the manager wants to apply in a day, week, or month. Woods (2013) gives a general recommendation for N_{max} of 35 kg N $ha^{-1}mo^{-1}$ for C_3 grasses and 40 kg N ha^{-1} mo^{-1} for C4 grasses. However, Woods (2013) makes clear that the value chosen for N_{max} is both site specific, species dependent, and dependent on the turf manager's goals.

In this study, N_{max} was initially set to 35 kg N $ha^{-1}mo^{-1}$ for C_3 grasses and 40 kg N $ha^{-1}mo^{-1}$ for C_4 grasses. N_{max} was then changed so that the GP N Requirement model predicted mean N use for C_3 golf course turfgrasses in our study. N_{max} was changed separately to predict mean N use for C_4 golf course turfgrasses.

Another strategy for choosing N_{max} is to base the parameter on the N harvest rate of research plot turfgrass (Zhou and Soldat, 2022). Zhou and Soldat (2022) chose an N_{max} value that matched the N being removed from the system via clippings. On research plots of bentgrass (*Agrostis stolonifera*) mowed at the height of a golf green and fertilized with 120 kg N ha^{-1} yr^{-1}, turfgrass N loss via clippings was 39 kg N $ha^{-1}mo^{-1}$. Thus, the authors chose a N_{max} value of 39 kg N $ha^{-1}mo^{-1}$ for C_3 turfgrass, a value slightly higher but within the range of that chosen by Woods (2013) for C_3 turfgrass.

Golf course components

For the purposes of this study, the area of the golf course turf surfaces were defined as the sum of the golf courses components (greens, tees, fairways, and roughs). Golf course superintendents commonly maintain practice areas, facility grounds, and even adjacent turfed recreational areas. However, this study focused exclusively on playing surfaces of the golf course (Eq. 3).

(Eq. 3) $A_{GCC} = A_G + A_T + A_F + A_R$

Where A_{GCC} equals the total area of the golf courses components, A_G equals the area of greens, A_T equals the area of tees, A_F equals the area of fairways, and A_R equals the area of roughs.

Because each golf course is managed independently, it receives a different N rate. N rates in this study are either reported specific to a particular component, or as an area-weighted-average of all golf course components, which we term a component-weighted-average (CWA) (Eq 4-8). To calculate a component-weighted-average N application rate, the percent area of each golf course component was determined.

(Eq. 4) $P_G = \frac{A_G}{A_{GCC}}$

(Eq. 5) $P_T = \frac{A_T}{A_{GCC}}$

(Eq. 6) $P_F = \frac{A_F}{A_{GCC}}$

(Eq. 7) $P_R = \frac{A_R}{A_{GCC}}$

Where P_G, P_T, P_F, and P_R equal the percentage of the total golf course area that is covered by greens, tees, fairways, and roughs, respectively.

(Eq. 8) $N_{CWA} = N_G * P_G + N_T * P_T + N_F * P_F + N_R * P_R$

Where N_{CWA} is the component-weighted-average N rate and N_G, N_T, N_F, and N_R are the N rates for greens, tees, fairways, and roughs, respectively.

Nitrogen Efficiency Score

For the purposes of this study, the N efficiency score was defined as (Eq. 9):

$$\text{(Eq. 9) } Nitrogen\ Efficiency\ Score\ (NES) = \frac{Component\ N\ Rate}{Model\ predicted\ N\ Rate}$$

Each golf course component was assigned a NES, as well as the golf course component-weighted-average, N_{CWA} (Eq. 10-14).

$$\text{(Eq. 10) } NES_G = \frac{N_G}{GP_N}$$

$$\text{(Eq. 11) } NES_T = \frac{N_T}{GP_N}$$

$$\text{(Eq. 12) } NES_F = \frac{N_F}{GP_N}$$

$$\text{(Eq. 13) } NES_R = \frac{N_R}{GP_N}$$

$$\text{(Eq. 14) } NES_{CWA} = \frac{N_{CWA}}{GP_N}$$

Where GP_N was the N requirement as predicted by the GP N Requirement model, and NES_G, NES_T, NES_F, and NES_R, and NES_{CWA} were the nitrogen efficiency scores on greens, tees, fairways, roughs, and the golf course component-weighted-average, respectively. A NES of greater than 1 means the N rate was higher than predicted by the GP N Requirement model, while a NES of less than 1 means that the N rate was lower than predicted by the GP N Requirement model.

N_{max} normalization

N_{max} was adjusted such that the mean NES on each golf course component was one. N_{max} was adjusted for C_3 and C_4 grasses separately.

Application Rate Notation

All N application rates in this study were annual application rates, kg N ha^{-1} yr^{-1}, unless otherwise specified. For simplicity annual application rates are abbreviated as kg N ha^{-1}.

Data analysis software

All descriptive statistics, linear regression, and data visualization were completed in JMP Pro (Version 15.0, SAS Institute Inc., Cary, NC, 1989-2022).

Results

N Rate

N rates were widely variable both within and across regions of our study. The coefficient of variation of N rate was highest in rough, followed by fairways, tees, and greens where the CV was the lowest (Table 2). Golf courses in Florida had the highest median component-weighted-average (CWA) N rate, 220 kg ha^{-1}. Median CWA N rate was the lowest in the UK, 17 kg ha^{-1} (Figure 1). The coefficient of variation of the CWA N rate was greater than 46% in all regions, indicating a high variability in N rate among golf courses (Table 2).

On golf courses sampled from all regions in this study, except for the Northwest US, N application rates were highest on greens, followed by tees, fairways, and roughs (Figure 2). N rates were highest on all golf course components in Florida, where median N rates were 341 kg ha^{-1} on greens, 244 kg ha^{-1} on tees, 224 kg ha^{-1} on fairways, and 122 kg ha^{-1} on roughs. Data from the Midwest showed the lowest median N rate on greens, 98 kg ha^{-1}. The UK had the lowest median N rate on tees 64 kg ha^{-1} and fairways 28.8 kg ha^{-1}. Denmark had the lowest N application rates in rough. None of the seven golf courses in Denmark that participated in the study applied N to their roughs.

Table 2. Mean N rate and coefficient of variation of N rate within each region of the study.

	N Rate (kg ha^{-1})				
Region	Greens	Tees	Fairways	Roughs	CWA
	Mean (coefficient of variation)				
US-Midwest (n=19)	97.7 (0.39)	97.3 (0.45)	72.9 (0.62)	38.2 (1.08)	51.1 (0.71)
US-Northeast (n=13)	123 (0.55)	99.0 (0.59)	89.5 (0.68)	57.4 (1.05)	72.2 (0.79)
US-East Texas (n=11)	252 (0.49)	202 (0.61)	183 (0.68)	144 (0.88)	159 (0.76)
US-Florida (n=9)	341 (0.31)	280 (0.57)	221 (0.41)	171 (0.61)	209 (0.48)
EU-Denmark (n=7)	116 (0.53)	109 (0.55)	45.4 (0.99)	0 (0)	34.6 (0.9)
Norway (n=7)	171 (0.54)	165 (0.63)	104 (0.72)	37.0 (1.66)	73.0 (0.91)
UK (n=5)	90.4 (0.43)	64.0 (0.32)	28.8 (1.05)	3.6 (2.24)	20.3 (0.65)
US-Northwest (n=5)	160 (0.34)	166 (0.45)	113.4 (0.16)	59.8 (1.08)	91.1 (0.46)
All regions	167 (0.45)	147 (0.52)	113 (0.66)	70 (1.07)	92.6 (0.71)

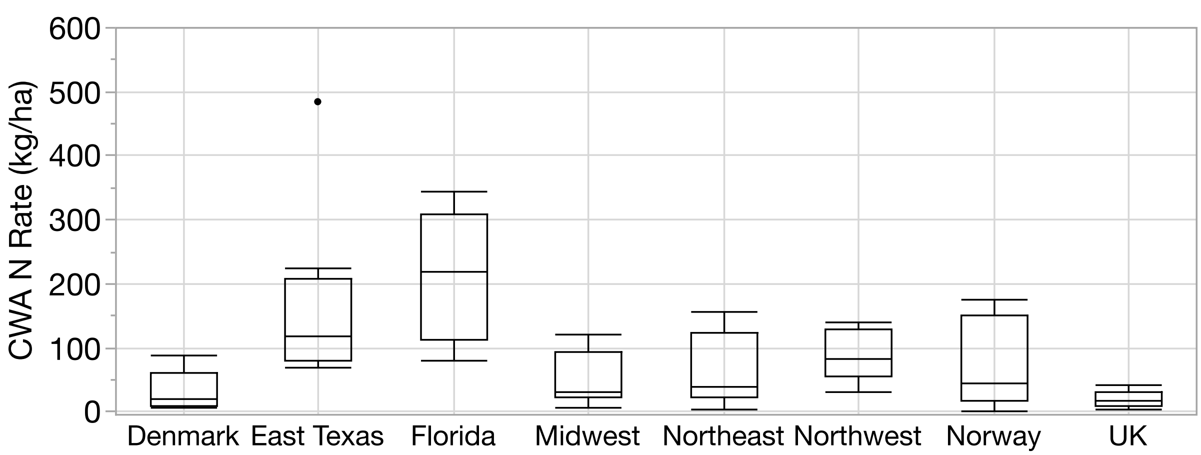


Figure 1. Component-weighted-average (CWA) N rate in each region of the study.

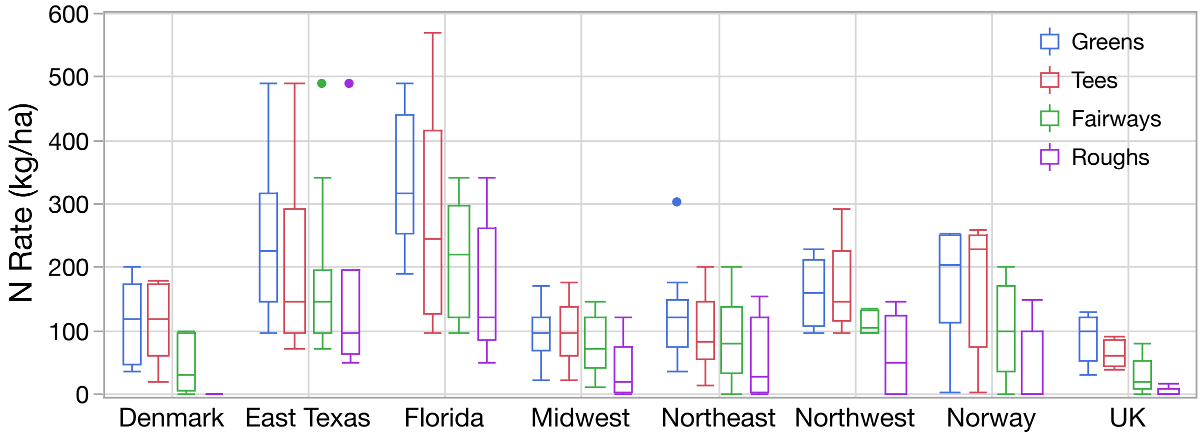


Figure 2. Annual N fertilization rate on the four golf course components in each region of the study.

N Rate Normalized by Turfgrass Growth days

The mean number of growth days in each region in 2016, 2017, and 2018 are listed in Table 3. Despite having the longest growing season, Florida golf courses still had the highest median CWA N rate normalized by turfgrass growth days, 0.6 kg ha^{-1} day^{-1} (Figure 3). East Texas had the second highest CWA N rate normalized by turfgrass growth days, followed by the Northwest, Norway, Northeast, Midwest, Denmark, and UK.

Norway had the second highest median N rate on greens normalized by growth days, and the highest median N rate normalized by growth days on tees (Figure 4). Six (East Texas, Midwest, Northeast, Northwest, Norway, UK) of the eight regions had similar N rates on fairways; median fairway N rate normalized by growth days were between 0.48 and 0.62 kg ha^{-1} day^{-1} in these regions. The UK, Denmark, and Midwest were below this range, with median N rate normalized by growth days of 0.10, 0.16, and 0.32 kg ha^{-1} day^{-1}, respectively.

Table 3. Mean turfgrass growth days in each region of the study. A growth day was defined when the growth potential was >0.50.

Region	Mean Growth Days (GP > 0.5)
EU-Denmark	186
US-East Texas	260
US-Florida	314
US-Midwest	184
US-Northeast	202
US-Northwest	228
Norway	159
UK	196

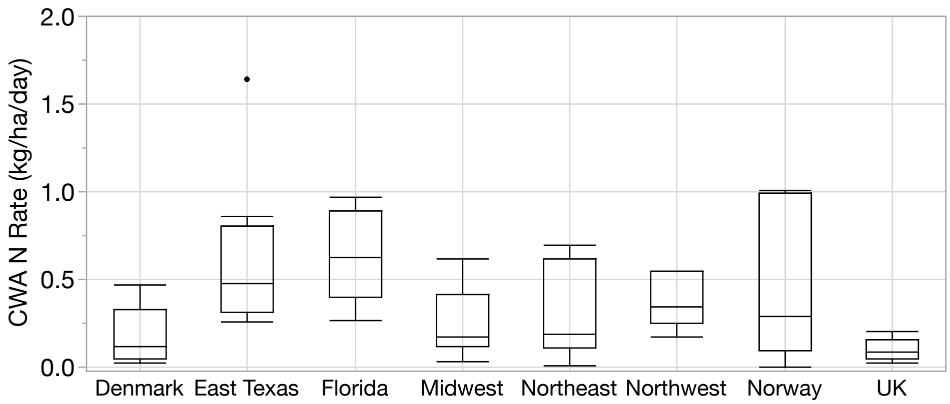


Figure 3. Component-weighted-average (CWA) N rate normalized by turfgrass growth days in the eight regions of the study.

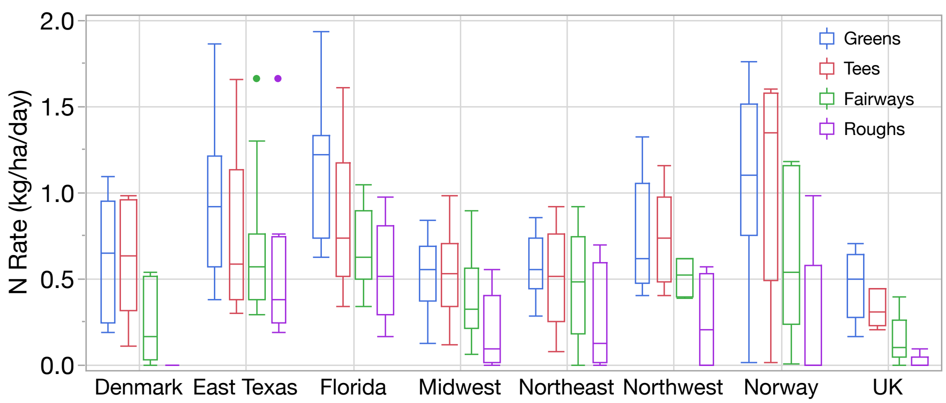


Figure 4. N rate normalized by turfgrass growth days on the four golf course components in the eight regions of the study.

Nitrogen Efficiency Score (NES)

The median CWA NES for all golf courses in the study was 0.27, indicating that golf courses used 73% less N across all components than predicted by the GP N requirement model. Florida and East Texas had the two highest median CWA NES, 0.55 and 0.37 respectively (Figure 5).

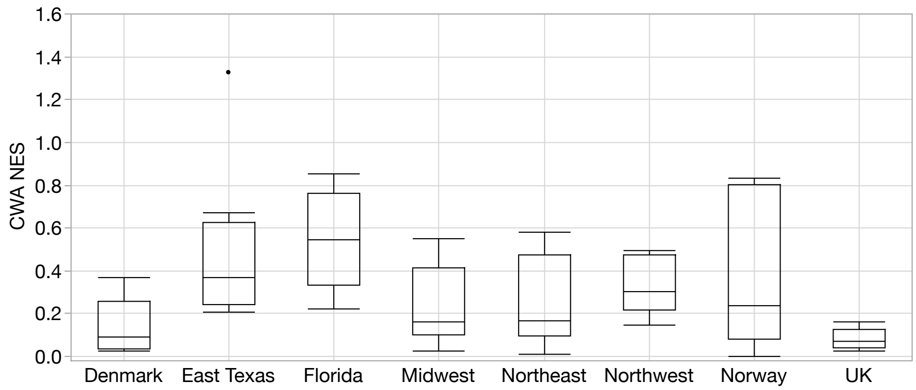


Figure 5. Component-weighted-average (CWA) NES across the eight regions of the study.

The median NES was less than one across all regions and all components (Figure 6). NES was highest on greens, followed by tees, fairways, and roughs. In East Texas, Florida, Northwest US and Norway, NES on greens and tees were greater than one on at least one golf course, indicating that these golf courses used more N than the GP N Requirement model predicted. However, in Denmark, the Midwest, Northeast US, and the UK, no golf course used as much N on any golf course component as the GP N Requirement Model predicted.

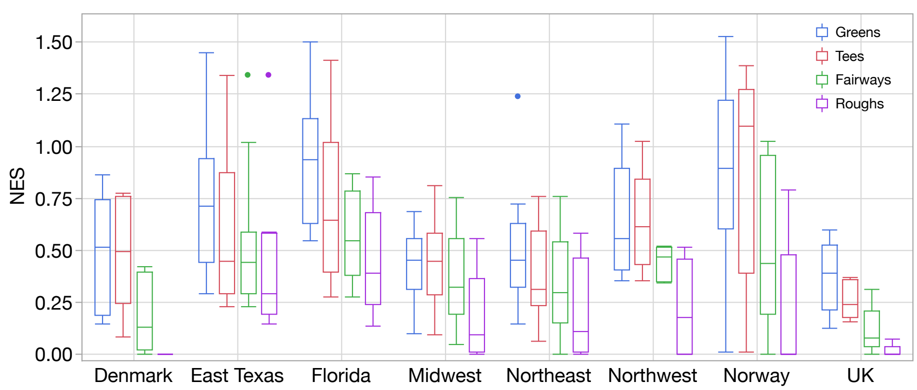


Figure 6. Component Nitrogen Efficiency Score (NES) across the eight regions of the study.

N_{max} Normalized Nitrogen Efficiency Score (NES)

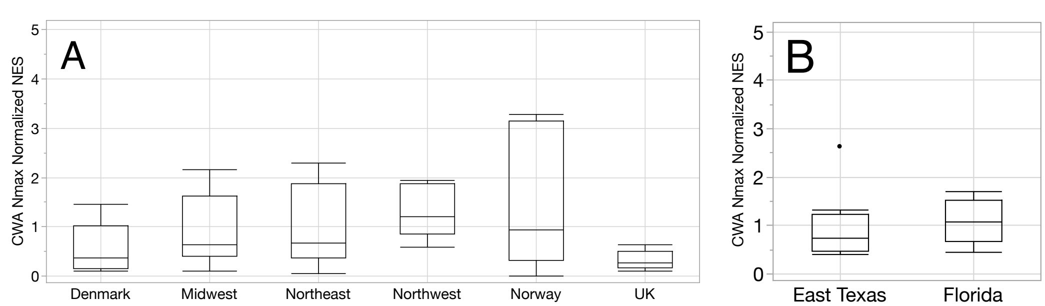
For each component, the N_{max} value that yielded a mean NES of one is listed in Table 4. The value of N_{max} needed for the GP N Requirement model to predict mean N use was highest on greens, followed by tees, fairways, and roughs.

Within the group of golf courses managing C_3 turfgrasses, golf courses in the Northwest and Norway had the highest median N_{max} normalized NES, indicating that they were the least efficient users of N (Figure 7). Golf courses in Denmark and the UK were the most efficient users of N and had the lowest N_{max} normalized NES. Golf courses in the Midwest and Northeast had median efficiency values that were in the middle of the high efficiency group (Denmark and UK) and low efficiency group (Northwest and Norway).

There were only two regions in this study with C_4 grasses, Florida and East Texas. The N_{max} values needed for the GP N Requirement model to predict N use in these regions were higher on each component than the C_3 regions; however, N_{max} values were still less than the 40 kg N ha^{-1} mo^{-1} suggested by Woods (2013) (Table 4).

Table 4. N_{max} values that allowed the GP N Requirement model to predict mean N use on golf courses for C_3 and C_4 turfgrasses.

Component	N_{Max} (kg N ha^{-1} mo^{-1})	
	C_3	C_4
Greens	18.4	33.4
Tees	17.0	27.0
Fairways	12.0	23.0
Roughs	5.7	17.0
CWA	8.9	20.2



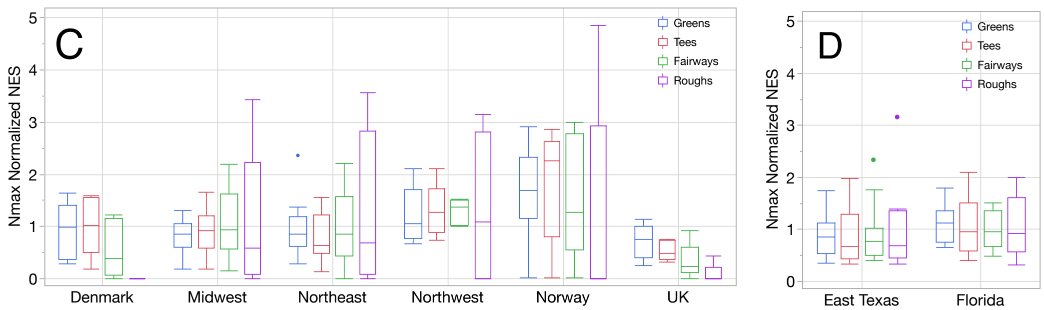


Figure 7. A) CWA N_{max} normalized Nitrogen Efficiency Scores (NES) for regions with C_3 turfgrasses. B) CWA N_{max} normalized NES for regions with C_4 turfgrasses, C) N_{max} normalized NES for regions with C_3 turfgrasses, D) N_{max} normalized NES for regions with C_4 turfgrasses.

Nitrogen Fertilization Rate and Economic Factors

Green free, revenue, and the number of maintenance staff employees did not correlate with N rate normalized by growth days (Table 5). Maintenance budget was weakly correlated to N rate normalized by growth days on fairways, roughs, and CWA. Fertilizer budget also was weakly correlated with N rate normalized by growth days on tees, fairways, roughs, and CWA. The number of rounds played weakly correlated to the N rate normalized by growth days on greens, fairways, and the CWA.

In the Midwest, the region with the largest sample size, maintenance budget and fertilizer budget correlated with N rate normalized by turfgrass growth days on all components of the course (Table 6). The strongest correlations were between fertilizer budget and N rate normalized by turfgrass growth days on roughs (r^2 = 0.41) and the CWA (r^2 = 0.55).

Table 5. Correlation coefficients between five economic factors and the N rate normalized by turfgrass growth days across all regions. *Indicates significance at α < 0.05.

Economic Factors	All regions- N Rate Normalized by Turfgrass Growth Days ($kg\ ha^{-1}\ day^{-1}$)				
	Greens	Tees	Fairway	Rough	CWA
Green Fee	0.00	0.00	0.00	0.01	0.00
Maintenance Budget (USD/ha)	0.01	0.03	0.07*	0.17*	0.15*

Revenue (USD/ha)	0.00	0.1	0.03	0.02	0.06
Fertilizer Budget (USD/ha)	0.02	0.08*	0.13*	0.14*	0.24*
Total employees	0.00	0.0	0.02	0.07	0.07
Rounds	0.06*	0.05	0.13*	0.04	0.07*

Table 6. Correlation coefficients between five economic factors and the N rate normalized by turfgrass growth days in the Midwest. *Indicates significance at $\alpha < 0.05$.

Economic Factors	Midwest- N Rate Normalized by Turfgrass Growth Days (kg ha^{-1} day^{-1})				
	Greens	Tees	Fairway	Rough	CWA
Green Fee	0.20	0.07	0.00	0.22	0.15
Maintenance Budget (USD/ha)	0.19*	0.21*	0.23*	0.22*	0.35*
Revenue (USD/ha)	0.02	0.04	0.00	0.07	0.05
Fertilizer Budget (USD/ha)	0.22*	0.19*	0.25*	0.41*	0.55*
Total employees	0.00	0.00	0.00	0.08	0.04
Rounds	0.09	0.06	0.20	0.01	0.06

3.7 Soil Type and N Rate

Soil type did not strongly influence annual N fertilization rate on greens, tees, or fairways (Table 7; Figure 8A-C). Sandy soils in roughs correlated significantly with increased N rates. Median N rate on roughs with sandy soils was 0.6 kg ha^{-1} day^{-1}, compared to 0.2 kg ha^{-1} day^{-1} or less in all other soil types (Table 7; Figure 8D).

Table 7. Results of a one-way ANOVA analyzing connections between soil type and N rate normalized by turfgrass growth days. *Indicates significance at $\alpha < 0.05$.

Component	r^2 (p-value)	Soil types
Greens	0.06 (0.05)*	sand, topdressing layer of sand over finer textured soil
Tees	0.02 (0.90)	sand, topdressing layer of sand over finer textured soil, sandy loam, silt loam, clay loam
Fairways	0.07 (0.19)	sand, sandy loam, silt loam, clay loam
Roughs	0.18 (0.008)*	sand, sandy loam, silt loam, clay loam

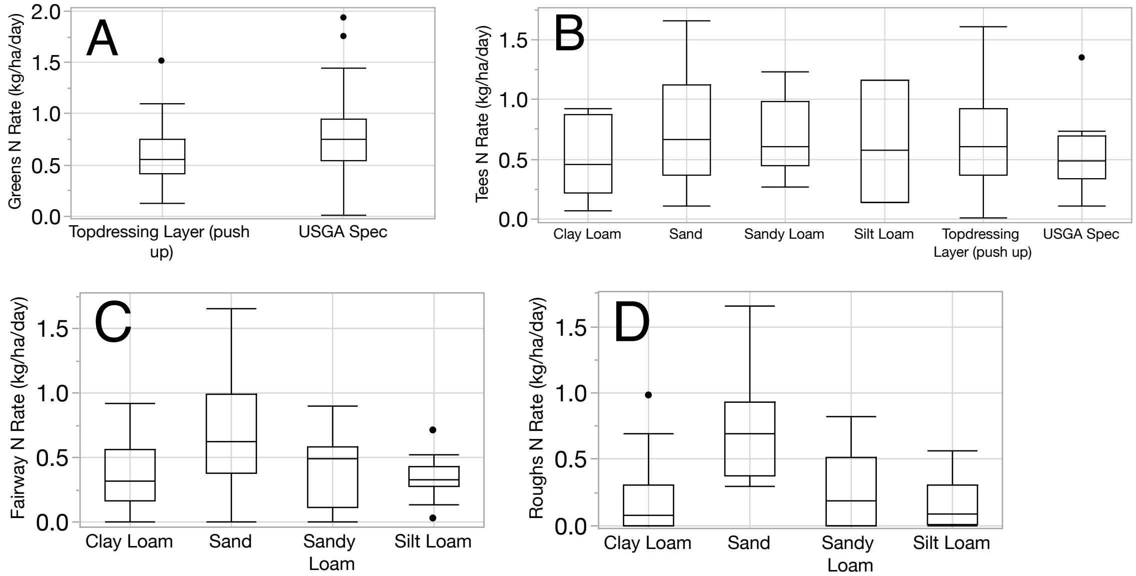


Figure 8. Soil type and N rate normalized by turfgrass growth days on greens (A), tees (B), fairways (C), and roughs (D).

Turfgrass Species and N Rate

Golf courses in the study had four different turfgrass species on greens and six different species of turfgrass on tees, fairways, and roughs (Figure 9). Grass type was not associated with significant differences in N rate normalized by turfgrass growth days on tees and fairways. On greens and roughs bermudagrass (*Cynodon dactylon*) received a significantly higher N rate normalized by turfgrass growth days than all other turfgrass species in the study (Table 8). On greens, N rates normalized by turfgrass growth days on creeping bentgrass (*Agrostis stolonifera*), annual bluegrass (*Poa annua*), and fine fescue (*Festuca spp.*) were statistically indistinguishable. On roughs, N rates normalized by turfgrass growth days on fine fescue (*Festuca spp.*), Kentucky bluegrass (*Poa pratensis*), perennial ryegrass (*Lolium perenne*), and tall fescue (*Festuca arundinacea*) were statistically distinguishable.

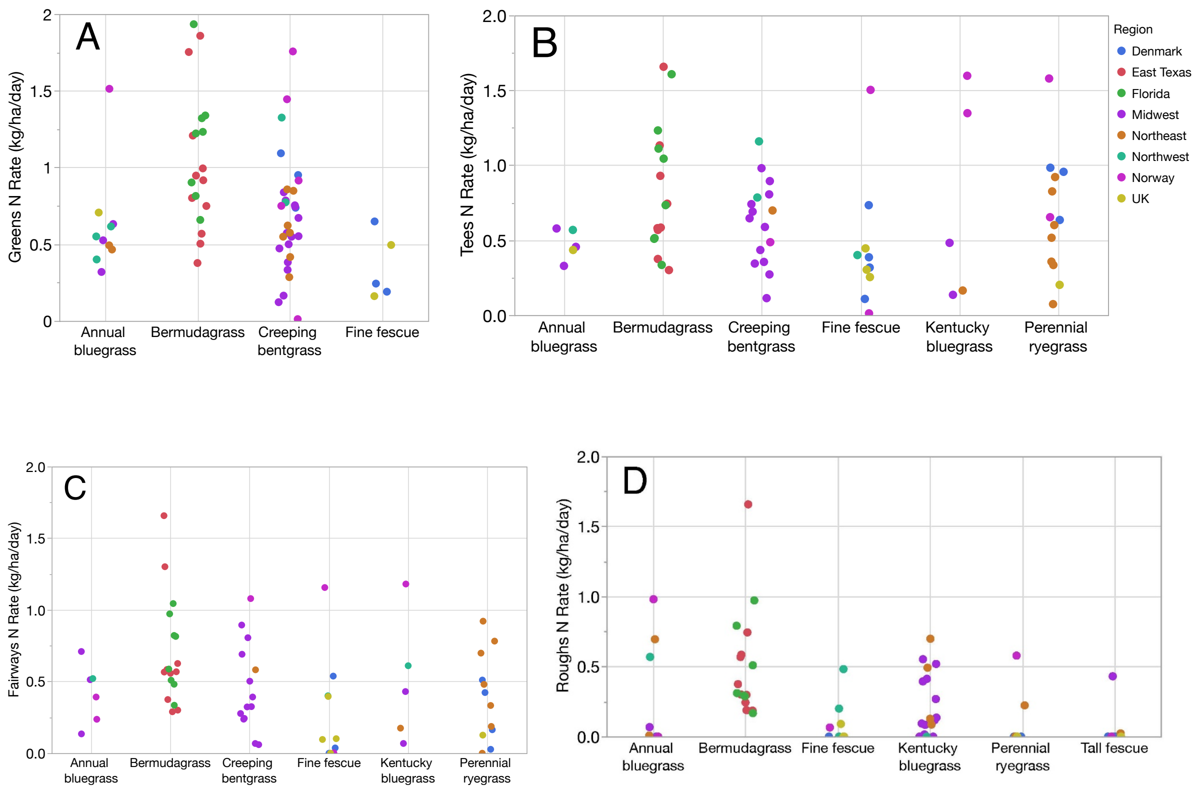


Figure 9. Grass type and N rate normalized by turfgrass growth days on greens (A), tees (B), fairways (C), and roughs (D).

Table 8. Results of means separation by protected Fishers least significant difference. No significant difference in daily N rate (kg N $ha^{-1}day^{-1}$) by turfgrass species was observed on tees and fairways. Different letters within a column indicate significant differences at $\alpha < 0.05$.

Turfgrass species	Mean Daily N Rate (kg N $ha^{-1}day^{-1}$)	
	Greens	Roughs
Annual bluegrass	0.62 B	0.29 AB
Bermudagrass	1.05 A	0.50 A
Creeping bentgrass	0.69 B	--
Fine fescue	0.35 B	0.10 B
Kentucky bluegrass	--	0.21 B
Perennial ryegrass	--	0.13 B
Tall fescue	--	0.06 B

Discussion

Defining N Use Efficiency on Golf Courses

In agriculture, yields underpin many definitions of efficiency. For example, nitrogen use efficiency is commonly defined as yield per unit nutrient uptake or nutrient supplied (Keating et al., 2010). Higher yield per unit of nutrient is indicative of more efficient production. However, in golf course management, there is no conventional yield and thus it becomes much harder to define resource efficiency in golf.

This study used comparative methods and modeling to estimate N use efficiency. Median N use rates were calculated based on survey data from each of the eight regions of the study. However, the difference in N rates among regions largely reflects differences in season length. For example, golf courses sampled in Florida had an average of 314 growth days (median CWA N rate 209 kg ha^{-1}), while golf courses in Norway had an average of 159 growth days (N rate 73 kg ha^{-1}). The difference in N use between these regions may not be reflective of differing efficiencies, but instead it may be a result of differences in growing season length.

As such, the first step in this study was to define the growing season length for each golf course and normalize the N rate based on growing season days, removing the effect of season length on N rate. N rate normalized by growing season length is more indicative of N use efficiency than N rate alone. However, and surprisingly, the ranking from highest to lowest N use by region did not change between the N rate normalized by growing season days and the non-normalized N rate (Table 9).

Table 9. Ranking of N Rate, N Rate Normalized by Turfgrass Growth Days, and Nitrogen Efficiency Score (NES) from highest to lowest.

Rank	N rate (kg ha^{-1})	N Rate Normalized by Turfgrass Growth Days (kg ha^{-1} day^{-1})	Nitrogen Efficiency Score (NES)

1 (highest)	Florida	Florida	Florida
2	East Texas	East Texas	East Texas
3	Northwest	Northwest	Northwest
4	Norway	Norway	Norway
5	Northeast	Northeast	Northeast
6	Midwest	Midwest	Midwest
7	Denmark	Denmark	Denmark
8 (lowest)	UK	UK	UK

The GP N Requirement model was subsequently used to calculate the N requirement of golf courses and to compare calculated N requirements to actual N use as a gauge of efficiency. Using the default N_{max} values as suggested by Woods (2013), 35 kg N $ha^{-1}mo^{-1}$ for C_3 grasses and 40 kg N ha^{-1} mo^{-1} for C4 grasses, the GP N Requirement model overpredicted the CWA N on golf courses in this study by 3.7 times. Thus, if superintendents surveyed in this study applied N as the GP N requirement model suggests when using the default N_{max} values, they would use N less efficiently than they are presently, not more. This highlights the importance of choosing an appropriate N_{max} value.

Woods (2013) does not specify where their N_{max} values are derived from. Zhou (2022) used the GP N Requirement model and derived the N_{max} parameter for greens by estimating the amount of N leaving the system in the form of clippings and then used this amount of N as the N_{max} value. The implicit assumption in this method of estimating N_{max} is that all N leaving the system is leaving through clippings, and that replacing this N will lead to a balanced N budget. Zhou (2022) found that the amount of N leaving a research green through clippings loss in the 2019 growing season was 230 kg N ha^{-1}, on a plot of creeping bentgrass that was fertilized with 120 kg N ha^{-1} which was the highest N rate in the study. This resulted in an N_{max} value of 39 kg $ha^{-1}mo^{-1}$, within the range of the values used by Woods (2013).

Thus N_{max}, as estimated by Woods (2013) and Zhou (2022), is an overestimate of the N required on golf courses from this study. This study finds that N_{max} values needed to predict golf course N use rates are lower than currently published N_{max} values. N_{max} values also need to be golf course component specific.

N_{max} normalized NES was the most reliable gauge of N efficiency in this study because N_{max} was parameterized based on the golf courses in this study, rather than the generic N_{max} values of Woods (2013). When using N_{max} normalized NES, C_3 regions need to be considered separately from C_4 regions. Within the C_3 regions of the study, Denmark and the UK have the lowest median CWA N_{max} normalized NES, and therefore we hypothesize that, based on the courses in this study, they are the most efficient users of N, whereas the Northwest and Norway have the highest CWA N_{max} normalized NES and are likely the least efficient users of N. Within the C_4 regions of this study, it appears that the East Texas golf courses in this study are a slightly more efficient user of N than the Florida courses, when considering CWA N_{max} normalized NES.

The influence of grass and soil type on N Rate

Soil type did not correlate strongly to N use rate on greens, tees, or fairways. N use on roughs underlain by sandy soils was significantly higher than on other soil types. On sandy soils, where N mineralization is generally lower, higher N fertilization may be required to maintain the level of primary production needed for golf course roughs. However, seven of the eleven golf courses in our study with sandy soils in roughs were in Florida or East Texas, where N rates were higher on all components of the golf course. It is unclear whether sandy soils may be a cause of higher N rates, or whether grass type and/or cultural practices in Florida and East Texas may cause an increase N rates in roughs.

As a warm season grass, bermudagrass is commonly thought of as a low N input grass, in part because the C_4 photosynthetic pathway is more nitrogen efficient per unit of dry matter produced than the C_3 pathway (Hallock et al., 1965; Wilson and Haydock, 1971). However, in this study, bermudagrass received the highest growing season length normalized N rate across all components (greens, tees, fairways, and roughs) in our study. Woods (2013) assigns C_4 grasses with a higher N_{max} parameter (40 kg N ha^{-1} mo^{-1}) than C_3 grasses (35 kg N ha^{-1} mo^{-1}). In addition, Beard (1973) listed bermudagrass as having the highest required N fertility level among the 24 commonly used turfgrass species. Beard (1973) listed 24 turfgrass species from ‘very low’ N fertility requirement (0-20 kg ha^{-1}growing $month^{-1}$) to ‘high’ (25-75 kg ha^{-1} growing $month^{-1}$)

and only one other warm season grass (St. Augustinegrass) is listed in the ten turfgrasses ranked as having a 'high' N requirement. Unfortunately, the authors were not able to locate more recent studies tracking N uptake and fate in warm season grasses. Despite prior evidence indicating that bermudagrass is physiologically efficient in processing N, managers appear to fertilize the grass at a higher rate than cool season grasses in our study.

Increasing N use efficiency on golf courses

Correlations between fertilizer budget and N rate were much stronger than correlations between N rate and soil type, grass type, and the number of rounds played. Thus, it appears that decisions on fertilization N rates by turfgrass managers are determined to a greater degree by the money spent on fertilizer than by the type of soil underlaying the turf, the type of grass being managed, or level of traffic on the golf course (i.e., rounds). This is a critical point should the golf industry seek to achieve its goal of a 25% resource use reduction by 2025, as stated by the USGA (USGA, 2022). Efforts to breed more N efficient turfgrasses may result in efficiency gains that are dwarfed by factors related to economic status and management styles of a given golf course superintendent.

The coefficient of variation of CWA N rate was above 45% in all regions of the study. In the Midwest, the coefficient of variation in CWA N rate was 71%. By comparison, Bierman et al. (2010) found that the coefficient of variation of N rate on corn in the Minnesota was 24%, approximately one half to one third the values found in this study.

Variance in the observed CWA N rate in this study for samples in the Midwest did not decrease when normalizing for the difference in season length; instead, the coefficient of variation increased slightly to 80%. Soil and grass type did not explain the variation either. Fertilizer budget explained 24% of the variance in N rate across all regions of the study, and over half of the variation in N rate in the Midwest, which leaves three quarters to half of the variation in N rate unexplained.

Because the wide variation in N efficiency remains unexplained by all methods of normalization and analysis, the golf industry should not only quantify N efficiency by mean and median, but also by variation in N use, because the wide variation in N use is a potential indicator of overuse of N on some golf courses.

Gelernter et al. (2016) and the *Environmental Profile* work of the Golf Course Superintendents Association (GCSAA) collected data on water, energy, and fertilizer use on U.S. golf courses and published primarily median resource use rates but did not report statistics of variance (e.g., standard deviation, standard error etc.) or thoroughly analyze possible causes of variation beyond climate. Analyzing the variation in resource use and considering its possible causes, or lack thereof, is essential to increasing efficiency. If the wide variation in resource use remains unexplainable by all possible methods of analysis or stratifying variables, this suggests that the golf course industry needs to increase resource efficiency.

The need for improved decision support tools

We hypothesize that high variation in N use on golf courses is indicative of inefficient N use that reflects a wide variety of manager skill. More skilled managers are able to achieve a lower NES (use N more efficiently), while less skilled managers overuse N. Decision support tools are thus needed to help less skilled managers use N more efficiently.

Determining how much N to apply to turfgrass is not easy because the goal of N applications is not to simply maximize growth. Instead, optimal N levels are those high enough to allow the turf to recover from damage and, but not so high as to require excessive mowing or cause N loss (i.e., N leaching to groundwater). The GP N Requirement model is a N decision support tool; however, the results of this study indicate that using this tool to guide N application decisions as it is currently constructed with the default N_{max} parameters would result in applying much higher levels of N. There are currently no other decision support tools that are publicly available to assist turfgrass managers in making N application decisions, though turfgrass researchers have proposed several models. Zhang et al. (2013) applied the process-based biophysical model, DAYCENT, to turfgrass lawns such that the model predicted a dynamic target of optimal N over

50 years of lawn management. Zhou and Soldat (2022) developed a machine learning algorithm that was able to make N requirement predictions for greens based on the clipping volume, weather data, soil moisture and type, foot traffic, and NDRE. Using both biophysical and machine learning approaches to develop N application decision support tools should be a major priority for the turfgrass community so that N use efficiency is improved.

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Chapter 7: Effectiveness of golf course resource efficiency best management practices

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Abstract

The US golf industry, especially the Golf Course Superintendents Association of America (GCSAA) and United States Golf Association (USGA), have relied heavily on the concept of best management practices (BMPs) to advance environmental sustainability initiatives. However, few previous studies test whether BMP uptake by golf course superintendents actually leads to improved environmental outcomes. This study tests whether resource efficiency BMPs lead to more efficient resource use on golf courses in four resource use categories: water, energy, fertilizer, and pesticide. Information on BMP uptake and resource use was collected via a survey from 96 golf courses across five regions of the US (Midwest, Northeast, East Texas, Florida, and Northwest) and three regions in Europe (Denmark, Norway, UK). Resource use efficiency on each golf course was estimated considering relevant factors specific to the resource (e.g., climate, soil type, grass type and area for water). BMP uptake was measured on a five point scale (never, rarely, sometimes, often, always) and adoption intensity of BMPs were quantified using a combination of principle component analysis and data envelope analysis. Linear regression revealed no correlation between water, energy, fertilizer, and pesticide use efficiency and adoption intensity of BMPs in that resource use category. Analysis of the effect of individual BMPs on resource use efficiency found that uptake of only 1 of 34 BMPs resulted in lower resource use. Avoiding fertilizing roughs was correlated with more efficient N use. Surprisingly, four BMPs correlated with higher resource use and 29 BMPs had no significant correlation to

resource use. As such, self-reported BMP uptake does not appear to be indicative of improved environmental performance, an important finding for future environmental initiatives by the golf industry.

1. Introduction

According to the National Golf Foundation, over 30 million Americans play golf making it one the most popular participation sports in the US. Multiple studies suggest that the physical and mental well-being outcomes from playing golf are positive and associated with reduce mortality (Murray et al., 2017; Farahmand et al., 2009; Parkkari et al., 2000). To support the game, there are 16,752 golf courses in the US, which cover approximately 10,200 km^2 of land (R&A, 2019). Despite golf's popularity, the golf industry is often criticized for its heavy use of resources that are applied to maintain its courses. Though resource use varies by climate, golf courses in the US require frequent irrigation, application of pesticides and fertilizers, and mowing that emits greenhouse gases and other airborne pollutants. Critics of the game also argue that these resources are unfairly invested in a sport that is predominantly played by higher socio-economic groups. In 2018, 13.4% of the American public with a household income of over $125,000 played golf, while only 3% of the American public with a household income under $30,000 played golf (NGF, 2018). To chart a more equitable and sustainable path forward, the challenge for the golf industry is to identify ways of reducing resource use that decreases environmental and economic costs, and, in doing so, makes the game more widely accessible and less ecologically impactful.

Sustainability indicators that track progress towards these goals can be categorized broadly as either practice-based or outcome-based (Dong et al., 2015). Practice-based indicators ask qualitative questions about how a practitioner achieves the course's management goals, such as whether a golf course superintendent uses a soil moisture sensor. Outcome-based indicators ask quantitative questions about a result, such as how much water a superintendent applied to a golf course in a given year. Practice-based metrics are viewed as less obtrusive and more easily communicated on surveys, than outcome-based metrics, which require more effort from practitioners to report. Golf practitioners generally prefer to communicate practice-based indicators because they are also viewed as less risky (i.e., by drawing less attention to current practices) than quantifiable outcome-based metrics (Dong et al., 2015).

In the past 10 years, the Golf Course Superintendents Association of America (GCSAA) and the United States Golf Association (USGA) have invested heavily in developing both practice-based and outcome-based sustainability indicators for the US golf industry. Practice-based indicators are termed best management practices (BMPs). Through the Best Management Practice (BMP) Initiative, the GCSAA and USGA created a national BMP Planning Guide and Template for U.S. golf courses and offered grants to states to complete customized state-level BMP documents. As of 2022, all 50 state level chapters of the GCSAA have completed a BMP document. Currently, golf course superintendents are encouraged to adapt the state level documents for use in their facilities.

Concurrently, the GCSAA and USGA led the Golf Course Environmental Profile (GCEP) survey, in which all superintendents in the U.S. were contacted and asked to develop baseline data on both outcome-based and practice-based indicators for US golf courses across five topics: water, energy, fertilizer, pesticide, and landscape features. Outcome-based indicators included metrics such as water use, fuel use, fertilizer application rates, and area of the facility. Outcome-based indicators were not collected for pesticide use. Practice-based indicators included metrics like soil nutrient testing, conducting an energy audit, use of soil moisture sensors, and use of biocontrol for pests. Project data were collected in several phases such that trends can be observed over time. Phase I of the project ran from 2007-2012, Phase II from 2014-2017, and Phase III from 2021-2024.

Some of the GCEP reports analyze connections between practice- and outcome-based indicators that show surprising results. The 2016 GCEP fertilizer report found that golf course superintendents who reported using soil tests applied fertilizer at higher rates than superintendents who did not test their soil (Gelernter et al., 2016). Fertilizer use rates are quantified based on the golf course component being fertilized (e.g., greens, tees, fairways, and roughs) and by nutrient type (e.g., nitrogen, potassium, and phosphorus). Together, this represents twelve combinations of individual fertilizer use rates (i.e., nitrogen use on greens, phosphorus use on tees, etc.). Those conducting soil tests applied significantly more fertilizer in 10 of the 12 categories, with the exception of phosphorus on fairways and roughs. The authors suspect that this finding may be due to soil testing guidelines that recommend applying fertilizer at rates higher than necessary for healthy turf growth. The GCEP reports on energy, water, and pesticides did not analyze connections between practice-based and outcome-based metrics (Gelernter et al., 2014; Gelernter et al., 2016; Gelernter et al., 2016b).

Analyzing connections between outcome-based indicators and practice-based indicators is important for determining the efficacy of practice-based indicators. Practice-based indicators are inherently subjective and may or may not be related to improving environmental outcomes. Improved understanding of the connections between outcome-based and practice-based indicators will likely impact and inform future golf industry initiatives and environmental policy recommendations for golf course management.

The objective of this research is to determine the impact of adopting a range of resource efficiency best management practices (BMPs) on achieving greater resource use efficiency outcomes. An additional aim is to determine which BMPs that are most effective in increasing resource use efficiency.

2. Methods

2.1 UW-Madison Resource Efficiency Survey

The data presented in this study were collected via the University of Wisconsin-Madison Resource Efficiency Survey, which was conducted by the authors. The survey asked superintendents to report both practice-based and outcome-based sustainability indicators over a three-year period, from 2016-2018. There were four sections of best management practices (i.e., practice-based metrics) in the survey: fertilizer, pesticide, water, and energy. The survey also asked superintendents to report outcome-based sustainability indicators in each resource use category. This included fertilizer application records to determine the nitrogen (N) application rate, pesticide application records to determine pesticide risk, volume of irrigation water and irrigated area to determine depth of irrigation water applied, and fuel use to determine emissions of carbon dioxide equivalents (CO_2e). Additionally, each golf course superintendent was asked to report the area of each golf course component, greens, tees, fertilizers, and roughs.

Golf courses in six regions of the US (Midwest, Northeast, East Texas, Florida, Northwest, Southwest) and three regions in Europe (Norway, Denmark, UK) were asked to participate in the UW-Madison Survey. Distributing organizations and the number of responses received in each region are listed in Table 1.

Table 1. The regions, number of responses, and distributing organizations in each region of the study.

Region	Responses	Distributing Organization
Midwest	34	UW-Madison Turfgrass Program, WGSCA, MGCSA
Northeast	12	Cornell Turfgrass Program
East Texas	12	Texas A&M Turfgrass Program
Florida	11	University of Florida Turfgrass Program
Denmark	9	Danish Golf Union
Norway	7	NIBIO, Norwegian Greenkeepers Association
UK	6	GEO Foundation
Northwest	5	Oregon State Turfgrass Program, OGCSA, Peaks and Prairies GCSAA
Southwest	2	Cactus and Pine GCSA

2.2 Outcome-based metrics

Four outcome-based metrics were calculated in this study, one metric for each of the four resource-use categories (fertilizer, pesticide, water, and fuel). Because golf courses in this study were located throughout the US and northern Europe, they were subject to a wide range of climates, soils, grass types, and maintained area. Resource use efficiencies were calculated for each golf course such that golf course resource use levels could be compared across geographies.

2.2.1 Nitrogen Efficiency Score

Nitrogen (N) application rates were calculated by taking an area-weighted-average of the N application rate across the four components of a golf course (i.e., greens, tees, fairways, and roughs); the resulting area-weighted-average by golf course component is referred to as the component-weighted-average (CWA). The CWA N rate was then divided by the N requirement of the golf course, which was calculated using the GP N Requirement Model (Woods, 2013). This ratio is defined as the Nitrogen Efficiency Score (NES) (Eq 1.). For a detailed description of these methods see Bekken and Soldat (2022).

$$Nitrogen\ Efficiency\ Score\ (NES) = \frac{CWA\ N\ Rate}{N\ Requirement}$$

2.2.2 Pesticide Efficiency Score

Consistent with the methods of Bekken et al. (2021), pesticide risk for every golf course in the study was estimated using the annual area normalized product hazard quotient (HQ). Pesticide risk was calculated for each golf course component, and a CWA was applied to obtain a pesticide risk value for the entire golf course. As constructed, the HQ model measured the acute pesticide risk to mammals (Bekken et al., 2021). The HQ was divided by the growing season length at each golf course to obtain a pesticide efficiency score (Eq. 2).

$$Pesticide\ Efficiency\ Score\ (PES) = \frac{Hazard\ Quotient}{Growing\ season\ length}$$

2.2.3 Water Efficiency Score

Water use efficiency was calculated by dividing irrigation depth (water use/irrigated area) at each golf course by a predicted irrigation requirement. The irrigation requirement at each golf course was determined by the Tipping Bucket model approach described in Bekken et al. (2022).

$$Water\ Efficiency\ Score\ (WES) = \frac{Irrigation\ depth}{Irrigation\ requirement}$$

2.2.4 Fuel Efficiency Score

Greenhouse gas (GHG) emissions from turfgrass maintenance equipment were determined by multiplying the volume of diesel and gasoline used at each golf course by their respective greenhouse gas coefficients. See Bekken and Soldat (2021b) for the GHG coefficients used. Total GHG emissions from each course, measured in carbon dioxide equivalents (CO_2e), were divided by the sum of the area of greens, tees, fairways, and roughs. This yielded an area normalized GHG emissions rate ($CO_2e\ ha^{-1}$), which was then divided by the growing season length at each golf course to obtain an energy efficiency score (Eq. 4).

$$Fuel\ Efficiency\ Score\ (FES) = \frac{GHG\ Emissions}{Growing\ season\ length}$$

2.2.5 Absolute values of Efficiency Scores

In all cases, a higher efficiency score value indicates less efficient resource use. The water and fertilizer efficiency scores compare water use and fertilizer use to a target set by a model. A higher efficiency score value for these two resources indicates that a golf course used more of the resource in comparison to the target level of resource use predicted by the model. With pesticide and fuel use, there are no models currently that can predict pest pressure or fuel use on golf courses. As a result, instead of comparing the use of these resources to a target set by a model, the level of resource use is calculated across each day of the growing season. A higher efficiency score value for these two resource use categories means that more of the resource is being consumed on each day of the growing season. Thus, more efficient use is still indicated by a lower efficiency score.

2.2.6 Growing season length determination

Growing season length was determined in a manner consistent with Bekken and Soldat (2022). A 3-year mean daily surface air temperature was used in the Growth Potential model (Stowell and Gelernter, 2005). We defined a growth day as a day when GP was over 50%. The growing season length was defined by the sum of growth days in a year.

2.3 Practice-based metrics (best management practices)

Superintendents who responded to the UW-Madison Resource Efficiency Survey between 2016 and 2018 were asked how frequently they adopted a range of best management practices (BMPs) within each resource use category. Each response used the same five-point scale: never (0), rarely (1), sometimes (2), often (3), always/very often (4) except for two responses in the fuel section which used a two-point scale: yes (1), no (0).

Nitrogen BMPs

N1. Before using a sprayer or spreader, how often did you calibrate it?

N2. When deciding on fertilizer application rates, how often did you consult your local land grant university or advisory service for recommendations on appropriate fertilizer application rates?

N3. When soils on your course were near or above field capacity, did you avoid applying fertilizer?

N4. Did you avoid fertilizing roughs?

N5. When applying nitrogen, how often did you apply slow release fertilizers or soluble nitrogen at low rates and more frequently (0.1-0.2 lbs/1000 square feet)?

N6. When determining nitrogen rate, how often did you utilize a model (e.g. growth potential) to determine nitrogen rate?

N7. When mowing greens, how often did you collect, measure, and record clipping volume from greens as an indication of turfgrass growth and nitrogen requirement?

Pesticide BMPs

P1. Over the previous three years, did you establish and/or update a course policy for disease thresholds on each area of the golf course (e.g., greens, fairways, tees, roughs)?

P2. Over the previous three years, did you establish and/or update a course policy for insect thresholds on each area of the course (e.g., greens, fairways, tees, roughs)?

P3. Over the previous three years, did you establish and/or update a course policy for weed thresholds on each area of the course (e.g., greens, fairways, tees, roughs)?

P4. How often did you use indicator areas to determine when spraying was required?

P5. How often did you use a model (e.g. Smith-Kerns Dollar spot model) to determine when spraying was required?

P6. How often did you use a GPS sprayer?

P7. When applying a pesticide, how often did you consider the toxicity rating of a pesticide when purchasing pesticides (e.g. pesticide label warning system, EIQ, or other risk management system)?

P8. When applying pesticides, how often did you rotate amongst pesticide classes to minimize development of pesticide resistance?

P9. How often did you utilize non-treated control (i.e. check) plots to demonstrate the efficacy of your pest management program?

Water BMPs

W1. Did you calculate an annual water budget (i.e. a predicated amount of water use) for the golf course?

W2. Did you use a soil moisture meter to determine a target soil moisture content on fairways?

W3. Did you utilize %ET (percent of evapotranspiration) to determine the depth of water to apply to fairways?

W4. When irrigating the golf course, how often did you avoid irrigating roughs?

W5. Did you inspect irrigation heads and nozzles to ensure optimal performance?

W6. Did you conduct catch can tests (or other tests) to determine the distribution uniformity of your irrigation system?

W7. Did you ensure that the central computer system contained updated information about the irrigation heads actually on the golf course?

W8. Did you percent-adjust irrigation heads (or use another method) to improve soil moisture uniformity?

W9. Did you arc-adjust irrigation heads to target desired areas?

W10. Did the irrigation system automatically shut off during rainfall events?

W11. Did you conduct a professional irrigation audit at least once every five years?

Fuel BMPs

F1. Did you purchase hybrid/electric machinery when possible? (yes/no)

F2. Did you utilize GPS trackers to determine high and low traffic areas? (yes/no)

F3. Did you 'naturalize'/reduce the management intensity in out-of-play areas whenever possible?

F4. Did you divide rough into maintenance levels, decreasing maintenance frequency farther from the fairway?

F5. Did you mow fairways 'Zamboni style'?

F6. Did you walk-mow greens?

F7. Did you frequently sharpen mower blades?

2.4 Quantifying adoption intensity

Measuring the uptake of best management practices by simply counting the number of best management practices undertaken is not an effective indicator of BMP adoption (Dong et al. 2015). This is because the impact of each practice in time, space and outcome differs; the practice may differ in its level of resource-reducing effectiveness, it may correlate with the uptake of another practice, or it may be undertaken at varying frequencies. A composite indicator (i.e., a single score) of BMP adoption intensity, was developed by Dong et al. (2015) and termed the adoption intensity index. Using this methodology, an adoption intensity index was calculated for each of the four resource use categories (fertilizer, pesticide, water, and fuel).

2.5 Analyzing connections between resource use efficiency and BMP adoption

The goal of this analysis was to determine whether varying levels of BMP adoption were related to changes in resource use efficiency, as quantified by the resource efficiency scores in section 2.3. To test whether the bulk uptake of resource efficiency BMPs resulted in higher resource use efficiency, linear regression was used to test for correlations between BMP adoption intensity index and the resource efficiency score within each resource use category.

To evaluate the effect of implementing an individual BMP on resource efficiency, one-way ANOVA tests were used to discern significant differences between resource efficiency means across the range of BMP uptake frequencies (never, rarely, sometimes, often, always/very often). For BMPs with significantly different resource efficiency scores across BMP uptake frequency (at $\alpha < 0.05$), protected Fishers least significant difference (LSD) was used to compare means to one another. To further test the effect of frequency of adoption on resource efficiency score, BMP uptake frequencies were grouped four different ways (Table 1). The two means within each group were analyzed for statistical difference again with one-way ANOVA at $\alpha < 0.05$.

Table 1. The four different ways in which the frequency of practice uptake was analyzed for its effect on resource use.

Abbreviation	Description
0 v 1234	Do golf courses that rarely, sometimes, often, or always/very often (1234) implement a practice use a resource more or less efficiently than those that never do (0).
01 v 234	Do golf courses that sometimes, often, or always/very often (234) implement a practice use a resource more or less efficiently than those that never or rarely do (01).
012 v 34	Do golf courses that often or always/very often (34) implement a practice use a resource more or less efficiently than those that never, rarely, or sometimes do (012).
0123 v 4	Do golf courses that always/very often (4) implement a practice use a resource more or less efficiently than those that never, rarely, sometimes, or often do (012).

3. Results

3.1 Results of one-way ANOVA

The number of golf course superintendents who responded to each section (fertilizer, pesticide, water, and fuel) of the survey differed, and thus the sample size of golf courses for which both resource use and BMP information was available differed across resource use categories. Seventy-one golf courses provided information on both fuel use and fuel BMPs, 65 provided N application rates and nitrogen BMPs, 58 provided volume of water used and water BMPs, and 52 provided pesticide application records and pesticide BMPs.

Linear regression revealed no correlation between the N BMP adoption intensity index and NES. For individual BMPs, Mean Nitrogen Efficiency Scores (NES) across the range of BMP uptake frequencies were not significantly different for five of the seven N BMPs (Table 2A). The degree to which a superintendent avoided fertilizing roughs (N4) had a significant effect on NES. Mean NES for superintendents that reported *never*, *rarely*, *sometimes*, or *often*, avoiding fertilizing roughs was not significantly different. However, golf course superintendents who reported *always* avoiding fertilizing roughs had significantly lower NES (Table 3 and Figure 1). Mean NES across the range of adoption frequencies for measuring clipping volume (N7) also differed significantly (Table 2A). Those who never measured clipping volume had the lowest NES (0.76), while those who rarely, sometimes, or often measured clipping volume had a higher NES (1.64, 1.15, and 1.32 respectively). Those who always measured clipping volume had a mean NES (0.81) similar to those who *never* measured clippings.

Linear regression found no correlation between the pesticide BMP adoption intensity index and pesticide efficiency score (PES). For individual BMPs, the mean PES was not significant across the range in BMP uptake frequencies for six of the nine pesticide BMPs (Table 2B). Disease thresholds (P1), insect thresholds (P2), and pesticide class rotation (P8) had a significant effect on mean PES. Those who answered that they *sometimes* or *always* set disease thresholds (P1) had higher PES (52.0, 50.5 respectively), while those who answered *never*, *rarely*, or *often* set disease thresholds had relatively lower PES (21.6, 17.8, 21.2, respectively). Thus, while there were significant differences in these mean PES across a frequency of disease threshold (P1) adoption, there was no discernable pattern. If anything, a higher adoption of this practice (P1) was related to a higher PES. The same was true for insect thresholds (P2), where there were significant differences between all means (Table 3). The highest mean PES were for those practices that *sometimes*, *often*, or *always* (59.4, 41.3, 36.0 respectively) adopted the practice and the lowest means were for those practices that were *never* or *rarely* adopted (16.1, 8.9 respectively). Pesticide class rotation was significantly correlated with a higher PES.

Linear regression found no correlation between the water or fuel BMP adoption intensity index and resource efficiency score in each category. For individual BMPs in both resource categories, the mean resource efficiency score was not significantly different across the range in BMP uptake frequencies for all of the water and fuel BMPs (Table 2C-D).

Table 2. Results of one-way ANOVA between a) Nitrogen Efficiency Score (NES) and Nitrogen Best Management Practices (BMPs), b) Pesticide Efficiency Score (NES) and Pesticide Best Management Practices (BMPs), c) Water Efficiency Score (WES) and Water Best Management Practices (BMPs), d) Fuel Efficiency Score (FES) and Fuel Best Management Practices (BMPs). All BMPs answered on a never (0), rarely (1), sometimes (2), often (3), always/very often (4) scale.

A. Nitrogen Best Management Practice	Nitrogen Efficiency Score (NES)
	r^2 (p-value)
N1 – Calibrate spreader	0.04 (0.53)
N2 – Fertilizer rate consulting	0.13 (0.09)
N3 – Avoid applications near field capacity	0.04 (0.61)
N4 – Avoid fertilizing roughs	0.18 (0.02)*
N5 – Slow-release N or low dose N	0.05 (0.20)
N6 – N rate determined by model	0.07 (0.35)
N7 – Measuring clipping volume	0.16 (0.04) *
Nitrogen BMP Adoption Intensity [a]	0.02 (0.19)
B. Pesticide Best Management Practices	Pesticide Efficiency Score (PES)
	r^2 (p-value)
P1 – Disease thresholds	0.19 (0.04)*
P2 – Insect thresholds	0.20 (0.03)*
P3 – Weed thresholds	0.04 (0.71)
P4 – Indicator area	0.05 (0.71)
P5 – Smith-Kerns model	0.06 (0.58)
P6 – GPS sprayers	0.05 (0.71)
P7 – Pesticide toxicity consideration	0.02 (0.90)
P8 – Pesticide class rotation	0.28 (0.004)*
P9- Control plots	0.03 (0.85)
Pesticide BMP Adoption Intensity [a]	0.02 (0.28)
C. Water Best Management Practices	Water Efficiency Score (WES)
	r^2 (p-value)
W1 – Water budget	0.12 (0.25)

W2 – Moisture meter fairways	0.03 (0.85)
W3 – ET fairways	0.14 (0.16)
W4 – Avoid irrigating roughs	0.11 (0.17)
W5 – Irrigation head inspection	0.04 (0.60)
W6 – Catch can test	0.09 (0.39)
W7 – Irrigation system update	0.03 (0.88)
W8 – Percent adjust	0.001(0.80)
W9 – Arc adjust	0.01 (0.84)
W10 – Irrigation rainfall shutoff	0.03 (0.78)
W11 – Irrigation audit	0.12 (0.25)
Water BMP Adoption Intensity Score [a]	0.007 (0.60)
D. Fuel Best Management Practices	Fuel Efficiency Score (FES)
	r^2 (p-value)
F1 – Electrification	0.01 (0.88)
F2 – GPS trackers	0.004 (0.59)
F3 – Naturalization	0.03 (0.12)
F4 – Rough maintenance levels	0.00 (0.99)
F5 – Zamboni fairways	0.01 (0.94)
F6 – Walk mow greens	0.12 (0.07)
F7 – Mower blades sharpening	0.02 (0.90)
Fuel BMP Adoption Intensity Score [a]	0.006 (0.13)

*Indicates statistical significance at $\alpha < 0.05$.
[a] Linear regression.

Table 3. Results of means separation by protected Fishers least significant difference. Different letters within a row indicate significant differences at $\alpha < 0.05$.

	Mean Nitrogen Efficiency Score (NES)				
	Never (0)	Rarely (1)	Sometimes (2)	Often (3)	Always/very often (4)
N4 – Avoid fertilizing roughs [a]	1.39a	1.24a	1.17a	1.17a	0.46b
N7 – Measuring clipping volume [a]	0.76c	1.64a	1.15abc	1.32ab	0.81bc
	Mean Pesticide Efficiency Score (PES)				
P1 – Disease thresholds [a]	21.6bc	17.8abc	52.0a	21.2c	50.5ab
P2 – Insect thresholds [a]	16.1c	8.9bc	59.4a	41.3ab	36.0abc
P8 – Pesticide class rotation [a]	1.67b	0.70b	18.6b	18.3b	47.8a

\[a] Mean Nitrogen Efficiency Score (NES) in the same row followed by the same letter are not significantly different according to protected Fishers least significant difference ($\alpha < 0.05$.).

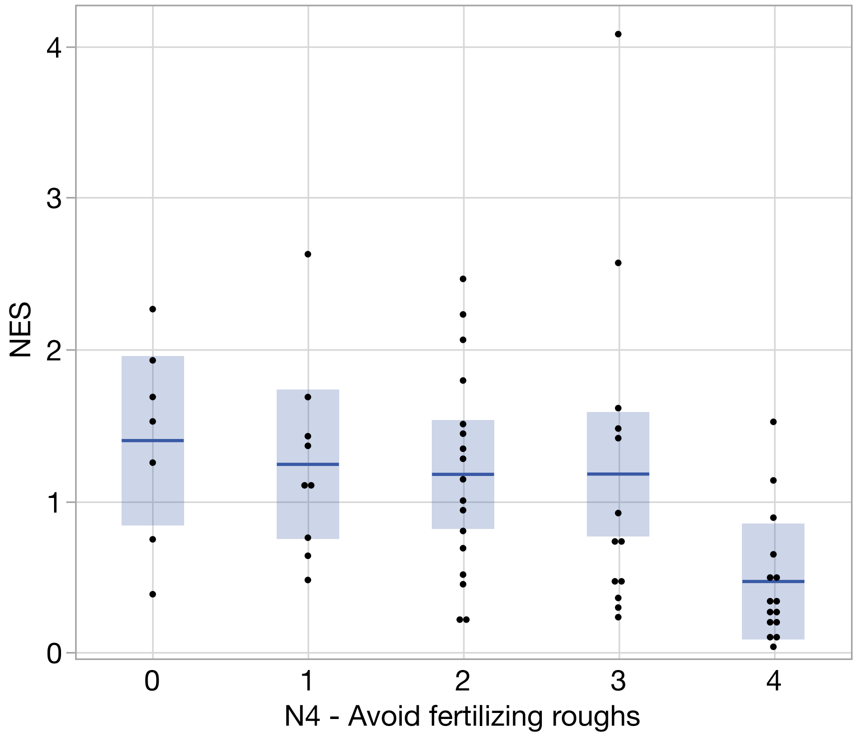

Figure 1. Nitrogen Efficiency Score (NES) for golf courses that never (0), rarely (1), sometimes (2), often (3), and always (4) avoided fertilizing roughs.

3.2 Frequency dependent regression analysis

Avoiding fertilizing roughs only reduced NES at high frequencies of adoption. Implementing insect thresholds appeared to increase PES at low uptake frequency, but this effect was not observed at higher uptake frequencies. Measuring clipping volume increased NES when the practice is implemented at any frequency (1234) as opposed to not being implemented at all (0). However, higher levels of implementation of this practice had no effect on NES. Pesticide class rotation was most strongly associated with higher PES at higher levels of adoption.

Table 4. Results of one-way ANOVA between the resource efficiency score of a given category to taking up a practice at a given or range of frequencies: 0 v 1234 - comparison of never taking up *to* taking up a practice at some frequency, 01 v 234 - comparison of taking up a practice never or rarely *to* sometimes or often or always/very often, 012 v 34 - comparison of taking up a practice never or rarely or sometimes *to* often or always/very often, 0123 v 4 - comparing taking up a practice always/very often *to* taking up the practice at any lower frequency.

	Resource Efficiency Score			
Best Management Practice	0 v 1234	01 v 234	012 v 34	0123 v 4

	r^2 (p-value)			
N4 – Avoid fertilizing roughs	0.13 (0.35)	0.04 (0.13)	0.09 (0.02)*	0.20 (0.0002)*
N7 – Measuring clipping volume	0.10 (0.01)*	0.02 (0.28)	0.01 (0.28)	0.005 (0.56)
P1 – Disease thresholds	0.03 (0.25)	0.05 (0.13)	0.001 (0.82)	0.06 (0.06)
P2 – Insect thresholds	0.10 (0.02)*	0.15 (0.004)*	0.027 (0.25)	0.001 (0.80)
P8 – Pesticide class rotation	0.06 (0.10)	0.14 (0.005)*	0.18 (0.002)*	0.26 (0.002)*

Table 5. Means and standard errors that one-way ANOVA revealed to be significantly different at $\alpha < 0.05$.

Best Management Practice	Mean (SE) Resource Efficiency Score							
	0 v 1234		01 v 234		012 v 34		0123 v 4	
	0	1234	01	234	012	34	0123	4
N4 – Avoid fertilizing roughs	-	-	-	-	1.2 (0.13)	0.73 (0.14)	1.2 (0.10)	0.41 (0.14)
N7 – Measuring clipping volume	0.68 (0.14)	1.20 (0.12)	-	-	-	-	-	-
P2 – Insect thresholds	16.1 (8.8)	40.5 (5.4)	14.8 (7.7)	43.4 (5.5)	-	-	-	-
P8 – Pesticide class rotation	-	-	1.1 (12.1)	39.0 (4.9)	9.2 (8.7)	42.3 (5.2)	12.4 (6.7)	47.8 (5.4)

4. Discussion

The GCSAA Best Management Practice Planning Guide states that BMP programs help superintendents manage golf facilities efficiently while providing quality playing surfaces and acting environmentally responsibly (GCSAA, 2007). This underscores a commonly held perception in the golf industry, that the adoption of BMPs will cause improved outcomes both environmentally and economically. However, our analysis of resource use efficiency BMPs and their effect on resource efficiency outcomes reveals that a higher adoption intensity index across a range of resource efficiency BMPs did not show any connection to resource efficiency outcomes in all four resource use categories: water, energy, fertilizer, and pesticide. Of the 34 individual resource use efficiency BMPs tested for their effect on resource efficiency, 29 had no effect, four BMPs had a significant effect on resource efficiency scores. Of these four, only one decreased resource use, while the three others either showed no discernable effect pattern or showed increased resource use. Thus, in our study of BMP uptake it was common that uptake of

BMPs had no effect on resource use or, in three cases, increased resource use, and in only one case, reduced it.

Because of the lack of observed connection between BMPs and resource efficiency scores (outcomes-based indicators) our results indicate that resource efficiency BMPs should not be used a proxy for actual resource use efficiency. Thus, reporting BMP uptake as a gauge of progress towards industry wide resource efficiency goals, is, according to this study, not a reliable method with which to assess industry BMP performance. Even though practitioners prefer to report practice-based indicators (Dong et al., 2015) to determine resource use efficiency levels, outcome-based indicators are needed to assess the effectiveness of BMPs in lowering resource use levels.

An initial motivating factor for this research was to determine which BMPs may be more effective at increasing resource use efficiency than others. The one practice that correlated to lower resource use levels involved reducing rough fertilizer inputs. Superintendents who reported avoiding fertilizing their roughs used less N than those who did not. However, beyond lower maintenance levels in roughs, our study found no other BMPs that correlated to lower resource use levels.

Higher frequency of adoption for three BMPs was correlated with higher resource use. BMPs are developed to make golf course maintenance operations more efficient, not less. This phenomenon may be occurring because BMPs are more relevant to higher resource users. For example, setting an insecticide threshold may not be needed if insecticides are not or cannot be used. Similarly, frequently rotating amongst pesticide classes is only necessary if pesticides are being frequently applied.

It is unclear exactly why the uptake of resource efficiency BMPs had no effect on resource use in the great majority of cases. BMPs, in this study and as commonly formatted, are short subjective statements, which may leave them open to interpretation. For example, what it means to "inspect" irrigation heads could be interpreted in a variety of ways. In addition, the interpretation of frequency could also differ amongst superintendents. What means *sometimes* or *often* to someone, may not means *sometimes* or *often* to someone else.

The UW-Madison Resource Efficiency Survey was a self-assessment of BMP adoption. Perhaps the results of this study would have differed if BMP uptake had been assessed using a more in-depth interview process, and the evaluation of BMP adoption frequency rested with the researcher and not the superintendent.

A much more detailed BMP survey would be required to determine exactly how each BMP is being implemented. For example, instead of asking if a golf course is using soil moisture meters, a more in-depth survey could ask for the number of times during each week that the meters are being used, what the target volumetric water content was, and ask for information on how many measurements are taken when they are used. However, testing the effect of a BMP at a narrower scope, would require a much larger database to achieve sufficient statistical power in the analysis. In addition, a longer and more detailed BMP survey would compromise the main advantage of using BMPs as sustainability indicators in the first place; they are less time consuming and cumbersome to report.

The term best management practice (BMP) was originally coined in the text of the 1972 Federal Water Pollution Control Act, which is also referred to as the Clean Water Act (EPA, 1993). BMPs were originally intended to describe strategies, both structural and practice-based, that were designed to protect and improve water quality, especially from non-point source or diffuse source pollution in both agricultural and urban settings. In agriculture, examples of structural BMPs include terracing, grassed waterways, constructed wetlands and buffer strips, while examples of practice-based BMPs include contour cropping, crop rotation, and no till, all of which aim to reduce the loss of nutrients and sediments (Tyndall and Roesch, 2014). Many previous studies have analyzed the effectiveness of BMPs in agriculture on improving water quality. The majority of these studies use a combination of monitoring and modeling approaches to determine BMP effectiveness (Easton et al., 2008). In a review of BMP effectiveness research, Lui et al. (2017) found that BMPs were generally effective in reducing sediment and nutrient loss at least over the short term (< 4 years), while longer term effectiveness is less well quantified. A BMP was originally intended to address only water quality although, more recently, the term has been adopted widely to refer to a range of management practices that may or may not be related to water quality. This analysis reveals that BMPs intended to target golf course resource use efficiency appear to be largely ineffective. Returning to the definition of a BMP as describing strictly those practices and structures targeting improved water quality may be warranted.

Given the results of this study, outcome-based metrics should be used to gauge resource efficiency in golf course management, not BMPs. However, collecting outcome-based metrics from practitioners is significantly more difficult. The UW-Madison Resource Efficiency Survey was conducted anonymously. Even with the guarantee of anonymity, of the 144 survey responses achieved by the BMP portion of the survey, the water section was filled in only 75 times, the fuel section 71 times, fertilizer 65, and pesticide 62. The disparity in these response rates underscores practitioner hesitancy about outcome-based metrics. It is unclear why practitioners are hesitant to report outcome-based metrics. Practitioners may be wary of outcome-based metrics because they fear that their reported numbers could be taken out of context, or simply because finding the appropriate records to report outcome-based metrics takes more time and energy. Efforts to standardize, automate, and make outcome-based metrics reporting easier and safer for practitioners are needed for the golf industry to collect sustainability indicators reflective of actual progress toward environmental goals.

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Chapter 8: An eco-efficiency model for golf

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Abstract

This study develops a framework for quantifying the eco-efficiency of a golf course. Eco-efficiency is the ratio of economic outputs to environmental inputs. On a golf course, environmental inputs are water, energy, fertilizer, and pesticides, but economic output cannot be measured by traditional means of agricultural yield. We hypothesize that, because efficiencies are tied to yield, the yield of a golf course is best defined as the profit made by a course or by the number of rounds hosted by a course. Which of these two yields is most important to a particular golf course likely depends upon the type of golf course (e.g., public, private, or a resort). In this study, the ratio of rounds of golf played to water, energy, fertilizer, and pesticide use is referred to a social eco-efficiency, and the ratio of profit generated to water, energy, fertilizer, and pesticide use is referred to as economic eco-efficiency. Mean social eco-efficiency of the 28 golf courses in the study was 207 rounds per kg CO_2e ha^{-1} emitted, 228 rounds per mm of irrigation water applied, 1157 rounds per kg N ha^{-1}, and 245 rounds per HQ ha^{-1} (where HQ is hazard quotient score quantifying pesticide risk). Mean economic eco-efficiency of the 28 golf courses in the study was \$425 per kg CO_2e ha^{-1} emitted, \$566 per mm of irrigation water applied, \$2489 per kg N ha^{-1}, and \$360 per HQ ha^{-1}. Social and economic eco-efficiency scores within each resource use category were then weighted equally to generate a social and economic eco-efficiency index for each golf course in the study. Mean social and economic eco-efficiency indices were higher on golf courses in Europe than golf courses in the US. Public golf courses

had higher mean social eco-efficiency indices than private golf courses, and resort courses had the highest mean economic eco-efficiency indices.

1. Introduction

Previous research indicates that excess fertilizer and pesticide use on golf courses can cause significant declines in urban and suburban surface and groundwater quality (Mallin and Wheeler, 2000; Davis and Lydy 2001; Winter et al. 2002; Metcalfe et al., 2007; King et al., 2007; Pichler et al. 2008, King and Balogh, 2010). Greenhouse gas emissions from maintenance equipment can turn golf courses from carbon sinks to carbon sources (Bekken et al., 2021; Bartlett and James, 2011) and excess water use on golf courses can strain local water supplies (Rodriguez Diaz et al., 2007). However, the use of water, energy, fertilizer, and pesticide are essential to the maintenance of nearly all golf courses. The challenge is to optimize resource inputs, so that a viable recreational space can be provided while minimizing environmental impact. Thus, there are both environmental inputs (i.e., resources) and social and economic outputs (i.e., recreation and economy) involved in the production process of a golf course. Eco-efficiency is the ratio of social and economic outputs to environmental inputs and is a framework which has been widely used by the business and agricultural communities (Keating et al. 2010).

The term eco-efficiency was coined by the World Business Council for Sustainable Development during the 1992 Rio Earth Summit and was originally intended for use as a business concept for sustainable development (Wiessner, 2010). Keating et al. (2010) define greater agricultural eco-efficiency as achieving more agricultural output (both quality and quantity) for less input of land, water, nutrients, energy, labor, or capital. Eco-efficiency metrics have been used extensively in agriculture long before the term was coined. The most used eco-efficiency metric is yield, the weight or volume of plant matter per unit area produced each year and measured in units such as bushels per acre or metric tons per hectare. Other agricultural eco-efficiency metrics include water use efficiency (yield per unit of water used), nutrient use efficiency (yield per unit nutrient uptake or nutrient supplied), radiation use efficiency (yield per unit radiation intercepted), labor efficiency (production per unit labor invested), and capital return on investment (profit as a fraction of capital invested) (Keating et al. 2010).

In agriculture, yield is the clear output of production and is important to defining agricultural resource use and efficiency (de Witt, 1992). Yield response curves allow farmers to determine the level of inputs (e.g., fertilizer) needed to obtain a desired output (i.e., yield). However, in golf course management, the output of production is far less clear because there is not a traditional agricultural yield. The turfgrass is not harvested or consumed. Thus, for the golf industry, it is important to define the output of production such that appropriate and optimal input levels of resources can be defined, and efficiencies determined. For example, if a farmer did not know crop yield, it would be hard for that farmer to determine an appropriate nitrogen application rate and thus determine an efficiency for that input. For golf courses, defining a yield or at least an output of production may assist efforts to optimize resource inputs.

Golf course managers must produce turf surfaces that are acceptable to golfers, of which the greens are the most important. Golfers prefer greens on which ball roll is smooth, consistent, and fast (Waters, 2020). However, producing a high-quality turf surface is a more qualitative pursuit than trying to maximize an easily quantifiable agricultural yield. Even if quantitative measures are used to evaluate the quality of greens (or tees, fairways, and roughs), such as using the USGA Stimpmeter to measure speed, or the STRI Trueness Meter™ to measure quality of roll, these measures must be subjectively weighed to produce a score of turf quality. Furthermore, unlike an agricultural yield, which is represented by one number each year, turf quality has a large intra-annual variability. These characteristics make turf quality a poor substitute for yield in a golf course setting.

The economic output of a golf course is perhaps better represented by the profit made by a golf course. All golf courses are businesses, and while the goal for every golf course may not be to maximize profits, ensuring that the golf course business generates sufficient profit to be economically sustainable is critical. Similarly, the social output of a golf course can be represented by the recreational space provided by the golf facility. The utilization of this recreation space by golfers is easily quantified by the number of rounds of golf that are played annually. Thus, we hypothesize that the economic output of a golf course is best represented by the profit the golf course makes, while the social output of the golf course is best represented by the number of rounds played each year. How directly a golf course pursues these proposed economic and social outputs depends upon the type of golf course, as defined by the PGA of America: public, private, and resort.

For public golf courses, which are owned and operated by local governments and commonly referred to as municipal courses, the primary motivator is to provide a recreational space for the public to play golf at a reasonable cost (City of Madison, 2020). The more rounds of golf that are played, the more recreational value that the community derives from the golf course. Some local governments are willing to subsidize golf course operational costs to provide the community with the recreational opportunity, but in recent years as the economic viability of municipal golf has declined, support for subsidizing public golf has also waned (Ingram et al., 2013; Friedman, 2019; City of Madison, 2020). As a result, it is increasingly important for municipal golf courses to ensure that golf course revenues cover maintenance and depreciation costs. For golf courses that are open to the public for play but are privately owned (commonly called daily fee golf courses), the primary motivating factor is slightly more profit-driven. These golf courses must generate sufficient profit to remain economically sustainable, unlike municipal golf courses that, in some cases, are or can be subsidized by local governments.

Private golf courses, which account for approximately 25% of US golf courses (NGF, 2022), operate under a markedly different set of motivating factors. Members of private golf clubs pay a higher price to access a course with a lower utilization rate and is commonly maintained to a higher standard. The average membership cost at a private golf facility in the US is approximately $6,000 annually, while the average cost of an 18-hole round at a public golf course is $40 (LPGA, 2019). Thus, one would have to play 150 18-hole rounds annually at a private golf course to equal the average price per 18 holes at a private golf course. The average US golfer played 18 rounds in 2019 (NGF 2022), indicating that, for the great majority of golfers, private golf is more expensive. Thus, through higher fees and membership caps, private golf clubs purposely limit the number of rounds that are played on the course. The motivating factor is to produce a golf course that is enjoyed by members at an acceptable cost to them. Generating profits may be appealing to private golf clubs in some circumstances; however, the goal of most private golf clubs is not to maximize profits or rounds played, but to maintain them at levels that are satisfying to their membership.

Generally, resort golf courses are owned by corporations that are obligated to maximize profits, or by a group of investors who are motivated by a return on their investment. In these scenarios, the number of rounds played is less important, and instead, maximizing the revenue and minimizing costs are primary motivating factors.

Therefore, we hypothesize that the social eco-efficiency, i.e., the ratio of rounds to resource inputs, will be highest on public golf courses, followed by resort courses, and lowest on private golf courses. Further, we hypothesize that economic eco-efficiency, i.e., the ratio of profit to resource inputs, will be highest on resort courses, followed by private courses, and lowest on public courses.

While we hypothesize that the motivating factors driving a golf course's economic output are affected predominantly by course type, previous research suggests that golf course water, energy, and fertilizer inputs are affected by climate, and to a lesser extent by course type (Gelernter et al., 2015; Gelernter et al., 2016; Gelernter et al., 2017). Overall pesticide risk within the US does not appear to vary greatly across US climates but does vary based on regulatory environment. Bekken et al. (2022) found that pesticide risk on golf courses in Europe was significantly lower than in the US.

Given the potential for climate to affect resource use, eco-efficiency scores in this study are calculated in two different ways. First, eco-efficiency scores are calculated with unnormalized resource use figures. Second, to compare eco-efficiency scores across climates, resource use is normalized for the effect of climate, which yields a climate normalized eco-efficiency score.

Understanding the relationship between resource inputs and economic or social outputs is critical to resource use efficiency in agriculture; however, the golf industry to date has not clearly defined such metrics, which may underpin the lack of resource use efficiency in golf. The objective of this research is to calculate the rate at which golf courses turn environmental inputs of water, energy, fertilizer, and pesticide into economic outputs of profits generated and social outputs of rounds played. Eco-efficiency scores are then analyzed to determine whether the scores vary systematically by golf course type. While the sample size of golf courses analyzed in this study is small, the framework of eco-efficiency, when applied to golf, may prove a valuable tool for increasing resource use efficiency within the industry.

2. Methods

2.1 The generic eco-efficiency model

In its most common form, eco-efficiency is a ratio of economic outputs to environmental inputs (Eq. 1). Greater eco-efficiency means less environmental input for greater social or economic output.

$$(Eq.1)\ Eco\text{-}efficiency\ Score = \frac{Social\ or\ economic\ output}{Environmental\ Input}$$

Table 1. A description of the environmental inputs, climate normalized environmental inputs, and economic outputs used to generate eco-efficiency scores in this study.

Category	Metric	Description	Reference
Environmental Inputs			
Water	Irrigation Depth (mm)	Water use for irrigating the golf course divided by golf course irrigated area.	Bekken et al. (2022)
Fuel	GHG emissions (kg CO_2e ha^{-1})	Volume of diesel and gasoline used for maintenance equipment multiplied by their respective carbon emissions coefficients.	Bekken and Soldat (2021)
Fertilizer	Nitrogen Application Rate (kg N ha^{-1})	The component-weighted-average (CWA) of the nitrogen on application rate on greens, tees, fairways, and roughs.	Bekken and Soldat (2022)
Pesticide	Pesticide Risk (HQ ha^{-1})	The area normalized component-weighted-average (CWA) hazard quotient (HQ) score.	Bekken et al. (2021)
Climate Normalized Environment Inputs			
Water	Water Efficiency Score (WES)	Irrigation depth divided by the irrigation requirement.	Bekken et al. (2022)
Fuel	Fuel Efficiency Score (FES)	GHG emissions divided by growing season length as determined by the growth potential model.	Bekken and Soldat (2021); Bekken et al. 2022; Stowell and Gelernter (2005)
Fertilizer	Nitrogen Efficiency Score (NES)	The component-weighted-average (CWA) nitrogen application rate divided by the N requirement as determined by the GP N requirement model.	Bekken and Soldat (2022); Woods (2013); Stowell and Gelernter (2005)
Pesticide	Pesticide Efficiency Score (PES)	The hazard quotient (HQ) score divided by the growing season length as determined by the growth potential model.	Bekken et al. (2021); Stowell and Gelernter (2005)
Economic Outputs			
Social output	Annual rounds	The number of 18-hole rounds played at a golf course in a year.	--
Economic output	Profit	Profit is defined as revenue from golfers minus maintenance budget needed to maintain the course.	--

2.2 Eco-efficiency score and index

Environmental inputs in this study are defined as the water, energy, pesticide, and fertilizer used to maintain the golf course playing surfaces (i.e., greens, tees, fairways, and roughs). The social output of a golf course is defined by the number of rounds that are played annually and the economic output by the profit in US dollars.

To normalize for differences in absolute values between the eco-efficiency scores in different resource use categories, each of the scores was normalized such that the mean equaled 100 (Eq 2). Then 100 was subtracted from the scores, so that the mean score equaled zero. Above average eco-efficiency scores are positive and below average eco-efficiency scores are negative.

$$\text{(Eq. 2) } NC = \frac{100}{\overline{EE}}$$

Where NC is the normalization coefficient and $\overline{EE}$ is the mean eco-efficiency score within a given resource use category.

$$\text{(Eq. 3) } EE_{100} = NC * EE$$

Where EE is the eco-efficiency of a given golf course within a given resource category, and EE_{100} is the eco-efficiency score transformed such that the dataset of eco-efficiency scores has a mean value of 100.

$$\text{(Eq. 4) } EE_0 = EE_{100} - 100$$

Where EE_0 is the eco-efficiency score transformed such that the dataset has a mean value of 0. EE_0 scores were used to generate all eco-efficiency indices.

Because eco-efficiency scores in each resource use category were normalized to a common mean of zero, the scores of any given golf course are relative to the mean of the dataset. If the golf course in the dataset changes, then the eco-efficiency scores also change. Eco-efficiency scores in this study were calculated for three course groupings: all golf courses combined, for golf courses in the US only, and for golf courses in the Europe only.

2.2.1 Social eco-efficiency (SEE)

$$\text{(Eq. 5) } SEE_W = \frac{Rounds}{Irrigation\ depth}$$

$$\text{(Eq. 6) } SEE_N = \frac{Rounds}{Nitrogen\ application\ rate}$$

$$\text{(Eq. 7) } SEE_F = \frac{Rounds}{Emissions\ rate}$$

$$\text{(Eq. 8) } SEE_P = \frac{Rounds}{Pesticide\ risk}$$

$$\text{(Eq. 9) } SEE_I = (SEE_{W0} * 0.25) + (SEE_{N0} * 0.25) + (SEE_{F0} * 0.25) + (SEE_{P0} * 0.25)$$

Where SEE_{W0}, SEE_{N0}, SEE_{F0}, SEE_{P0} were the social eco-efficiency scores for water, nitrogen, fuel, and pesticide, respectively, transformed to a have a mean value of 0. SEE_I is the social eco-efficiency index, which weights each of the four-resource specific eco-efficiency scores 25% each.

2.2.2 Economic eco-efficiency (EEE)

$$\text{(Eq. 9) } EEE_W = \frac{Profit}{Irrigation\ depth}$$

$$\text{(Eq. 10) } EEE_N = \frac{Profit}{Nitrogen\ application\ rate}$$

$$\text{(Eq. 11) } EEE_F = \frac{Profit}{Emissions\ rate}$$

$$\text{(Eq. 12) } EEE_P = \frac{Profit}{Pesticide\ risk}$$

$$\text{(Eq. 13) } EEE_I = (EEE_{W0} * 0.25) + (EEE_{N0} * 0.25) + (EEE_{F0} * 0.25) + (EEE_{P0} * 0.25)$$

Where EEE_{W0}, EEE_{N0} EEE_{F0}, EEE_{P0} were the social eco-efficiency for water, nitrogen, fuel, and pesticide, respectively, transformed to a have a mean value of 0. EEE_I is the economic eco-efficiency index, which weights each of the four-resource specific eco-efficiency scores 25% each.

2.3 Climate normalization of resource use

Golf courses exist in a wide variety of climates, and these climates influence resource use requirements (GCEP, 2017). To compare the efficiency of resource use on golf courses across climates, a variety of ecosystem modeling approaches were taken.

2.3.1 Water Efficiency Score

The irrigation requirement at each golf course was determined using the Tipping Bucket model approach in Bekken et al. (2022). The ratio of irrigation depth to irrigation requirement defined the water efficiency score (Eq. 14).

$$\text{(Eq. 14)}\ Water\ Efficiency\ Score\ (WES) = \frac{Irrigation\ depth}{Irrigation\ requirement}$$

2.3.2 Nitrogen Efficiency Score

The nitrogen (N) requirement of a golf course was determined by the GP N requirement model (Woods, 2013). Bekken and Soldat (2022) found that the GP N requirement model overpredicted N use on golf courses, and thus the Normalized Nitrogen Efficiency Scores (NES) from Bekken and Soldat (2022) were used in this study. The normalized NES scores were transformed using a normalization factor such that the mean NES value was one. The ratio of the component-weighted-average N rate to the N required as predicted by the GP N requirement model was defined as the nitrogen efficiency score (Eq. 15).

$$\text{(Eq. 15)}\ Nitrogen\ Efficiency\ Score\ (NES) = \frac{CWA\ N\ rate}{N\ requirement}$$

2.3.3 Fuel Efficiency Score

To normalize for the difference in season length that may cause climate-based differences in emissions between golf courses, GHG emissions (kg CO_2e) were divided by the growing season length measured in days of turfgrass growth per year (Eq. 16). Growing season length was determined in a manner consistent with Bekken and Soldat (2022). The growth potential (GP) model was used to estimate the number of days in a year the turf was actively growing. A turfgrass growth day was defined as a day in which the GP value was over 50%.

$$\text{(Eq. 16)}\ Fuel\ Efficiency\ Score\ (FES) = \frac{GHG\ emissions}{Growing\ season\ length}$$

Where GHG emissions were the greenhouse gas emissions (kg CO_2e ha^{-1}) from diesel and gasoline combustion to run golf course maintenance equipment. Growing season length was measured in days.

2.3.4 Pesticide Efficiency Score

The area-normalized component-weighted-average hazard quotient (AN CWA HQ) score of the golf course was calculated with the methods of Bekken et al. (2021). Growing season length was calculated in same way as it was to calculate the Fuel Efficiency Score (FES).

(Eq. 17) $Pesticide\ Efficiency\ Score\ (PES) = \frac{AN\ CWA\ HQ}{Growing\ season\ length}$

2.4 Climate-normalized eco-efficiency

The eco-efficiency metrics were recalculated with climate-normalized resource efficiency scores to produce a climate normalized eco-efficiency.

2.4.1 Climate-normalized social eco-efficiency (CNSEE)

$$\text{(Eq. 18) } CNSEE_W = \frac{Rounds}{Water\ Efficiency\ score}$$

$$\text{(Eq. 19) } CNSEE_N = \frac{Rounds}{Nitrogen\ Efficiency\ Score}$$

$$\text{(Eq. 20) } CNSEE_F = \frac{Rounds}{Fuel\ Efficiency\ Score}$$

$$\text{(Eq. 21) } CNSEE_P = \frac{Rounds}{Pesticide\ Efficiency\ Score}$$

$$\text{(Eq. 22) } CNSEE_I = (CNSEE_{W0} * 0.25) + (CNSEE_{N0} * 0.25) + (CNSEE_{F0} * 0.25) + (CNSEE_{P0} * 0.25)$$

Where $CNSEE_{W0}$, $CNSEE_{N0}$, $CNSEE_{F0}$, $CNSEE_{P0}$ were the climate normalized social eco-efficiencies for water, nitrogen, fuel, and pesticide, respectively, transformed to a have a mean value of 0. $CNSEE_I$ is the climate normalized social eco-efficiency index, which weights each of the four-resource specific eco-efficiency scores 25% each.

2.4.2 Climate normalized economic eco-efficiency (CNEEE)

$$\text{(Eq. 23) } CNEEE_W = \frac{Profit}{Water\ Efficiency\ score}$$

$$\text{(Eq. 24) } CNSEE_N = \frac{Profit}{Nitrogen\ Efficiency\ Score}$$

$$\text{(Eq. 25) } CNSEE_F = \frac{Profit}{Fuel\ Efficiency\ Score}$$

$$\text{(Eq. 26) } CNSEE_P = \frac{Profit}{Pesticide\ Efficiency\ Score}$$

$$\text{(Eq. 27) } CNEEE_I = (CNEEE_{W0} * 0.25) + (CNEEE_{N0} * 0.25) + (CNEEE_{F0} * 0.25) + (CNEEE_{P0} * 0.25)$$

Where $CNEEE_{W0}$, $CNEEE_{N0}$, $CNEEE_{F0}$, $CNEEE_{P0}$ were the climate normalized economic eco-efficiencies for water, nitrogen, fuel, and pesticide, respectively, transformed to a have a mean value of 0. $CNEEE_I$ is the climate normalized economic eco-efficiency index, which weights each of the four-resource specific eco-efficiency scores 25% each.

2.5 Eco-efficiency quadrants

Both social and economic eco-efficiency were illustrated in scatter plots. The boundaries between quadrants were defined based on the mean values of the social or economic output (y-axis) and environmental input (x-axis). Quadrant A represents the most eco-efficient golf courses, which have relatively low environmental inputs for high social or economic output (Figure 1).

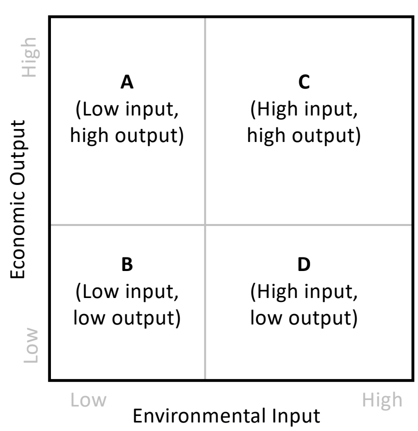

Figure 1. A conceptual diagram illustrating the four quadrants of eco-efficiency. Modelled after Gibson (2019).

2.6 UW-Madison Resource Efficiency Survey

The data presented in this study were collected via the University of Wisconsin-Madison Resource Efficiency Survey. This survey was conducted by the authors (Bekken and Soldat, 2021). The survey asked golf course superintendents to report water, fertilizer, pesticide, and fuel use in 2016, 2017, and 2018. The survey also asked superintendents to report economic information about their golf facility, including peak season green fee (if public), membership fee and number of members (if private), cart fee, rounds of golf played annually, overall maintenance budget and budget within each resource category, and number of seasonal and full-time employees.

Golf courses across the US and Europe were asked to participate in the survey via an organization in their region (Table 2). In total, 144 golf courses answered at least one section of the survey; however, only 29 golf courses supplied all the information required to calculate eco-efficiency scores.

Table 2. The regions the survey was distributed, the total number of responses from each region, the number of responses received for which all data needed to calculate an eco-efficiency score was provided, and the distributing organization in each region.

Region	Responses	Eco-Efficiency Responses	Distributing Organization
Midwest	68	5	UW-Madison Turfgrass Program, WGSCA, MGCSA
East Texas	15	5	Texas A&M Turfgrass Program
Northeast	13	3	Cornell Turfgrass Program
Denmark	10	1	Danish Golf Union
Florida	9	4	University of Florida Turfgrass Program
Northwest	9	4	Oregon State Turfgrass Program, OGCSA, Peaks and Prairies GCSAA

Norway	8	3	NIBIO, Norwegian Greenkeepers Association
UK	6	3	GEO Foundation
Southwest	2	0	Cactus and Pine GCSA

This study uses a simplified definition for golf course profit (Eq. 1) using information available from the UW-Madison Resource Efficiency Survey. Golf course superintendents were asked directly about their maintenance budget (rounded to the nearest $100,000), but they were not asked about revenue at the golf facility. We assumed superintendents would not know their course's gross revenues. Instead, superintendents were asked to report rounds played, green fee, cart fee, and number of members and membership fee (if private). Golf course revenue was estimated using these parameters.

Public golf course revenue was estimated by only considering the number of rounds played, the peak season green free, and the cart fee (Eq. 28). Private golf course revenue was estimated by only considering membership fee, the number of numbers, cart fee, and the number of rounds played (Eq. 29). We assumed that 69% of golfers use a cart, which is consistent with the US national average (NGF, 2022).

$$\text{(Eq. 28) } Revenue_{public} = (Green\ Fee * Rounds) + (Cart\ Fee * Rounds * 0.69)$$

$$\text{(Eq. 29) } Revenue_{private} = (Membership\ Fee * Members) + (Cart\ Fee * Rounds * 0.69)$$

Equations 28 and 29 are estimates of golf course revenue from playing golf. They do not account for dynamic pricing at golf facilities or other sources of revenue at a golf course such as the driving range or food and beverage service. Profit per ha of turf area was defined as revenue per ha minus the golf course maintenance budget per ha (Eq. 30). Turf area was defined as the sum of the areas of greens, tees, fairways, and roughs.

$$\text{(Eq. 30)}\ \frac{Profit}{Turf\ area} = \frac{Golf\ revenue}{Turf\ area} - \frac{Maintenance\ budget}{Turf\ area}$$

3. Results

3.1 Eco-Efficiency Scores

Golf courses varied widely in social eco-efficiency scores across all resource use categories. The most fuel eco-efficient golf course by rounds in the dataset achieved 3216 rounds for every kg CO_2e ha^{-1} emitted by maintenance equipment, while the least fuel eco-efficient golf course hosted 16 rounds for every kg CO_2e emitted (Table 3). Water eco-efficiency scores, measured in rounds per mm of irrigation applied, ranged from 3400 to 14. Nitrogen eco-efficiency scores, measured in rounds per kg N ha^{-1}, ranged from 10915 to 101. Pesticide eco-efficiency scores, measured in rounds per HQ ha^{-1}, ranged from 3,607 to <1.

Table 3. Descriptive statistics of social eco-efficiency scores in each resource use category.

Social Eco-efficiency	SEE_F (Fuel)	SEE_W (Water)	SEE_N (Nitrogen)	SEE_P (Pesticide)
	$\frac{Rounds}{kg\ CO_2e\ ha^{-1}}$	$\frac{Rounds}{mm}$	$\frac{Rounds}{kg\ N\ ha^{-1}}$	$\frac{Rounds}{HQ\ ha^{-1}}$
Mean (CV)	207 (2.9)	228 (2.77)	1,157 (1.9)	245 (3.5)
Median	48	72	507	4
Max	3,216	3,400	10,915	3,607
Min	16	14	101	<1

Golf courses also varied widely in economic eco-efficiency scores across all resource use categories. The most fuel eco-efficient golf course by profit in the dataset achieved \$6,334 ha^{-1} for every kg CO_2e ha^{-1} emitted by the maintenance equipment, while the least fuel eco-efficient golf course made \$38 ha^{-1} for every kg CO_2e emitted (Table 1). Water eco-efficiency scores, measured in profit per mm of irrigation applied, ranged from \$6,695 to \$16. Nitrogen eco-efficiency scores, measured in profit per kg N ha^{-1}, ranged from \$15,154 to \$137. Pesticide eco-efficiency scores, measured in profit per HQ ha^{-1}, ranged from \$6,822 to \$0.22.

Table 4. Descriptive statistics of economic eco-efficiency scores in each resource use category. All values in USD.

Economic Eco-efficiency	EEE_F (Fuel)	EEE_W (Water)	EEE_N (Nitrogen)	EEE_P (Pesticide)
	$\frac{Profit}{kg\ CO_2e\ ha^{-1}}$	$\frac{Profit}{mm}$	$\frac{Profit}{kg\ N\ ha^{-1}}$	$\frac{Profit}{HQ\ ha^{-1}}$
Mean (CV)	425 (2.8)	566 (2.3)	2,489 (1.5)	360 (3.7)
Median	141	199	817	11
Max	6,334	6,695	15,154	6,822
Min	38	16	137	0.22

The percentage of golf courses with a social eco-efficiency score in quadrant A for each resource-use category were fuel 29%, water 25%, nitrogen 25%, and pesticide 25%. The percentage of golf courses with an economic eco-efficiency score in quadrant A for each resource use category were fuel 7%, water 14%, nitrogen 14%, and pesticide 22%.

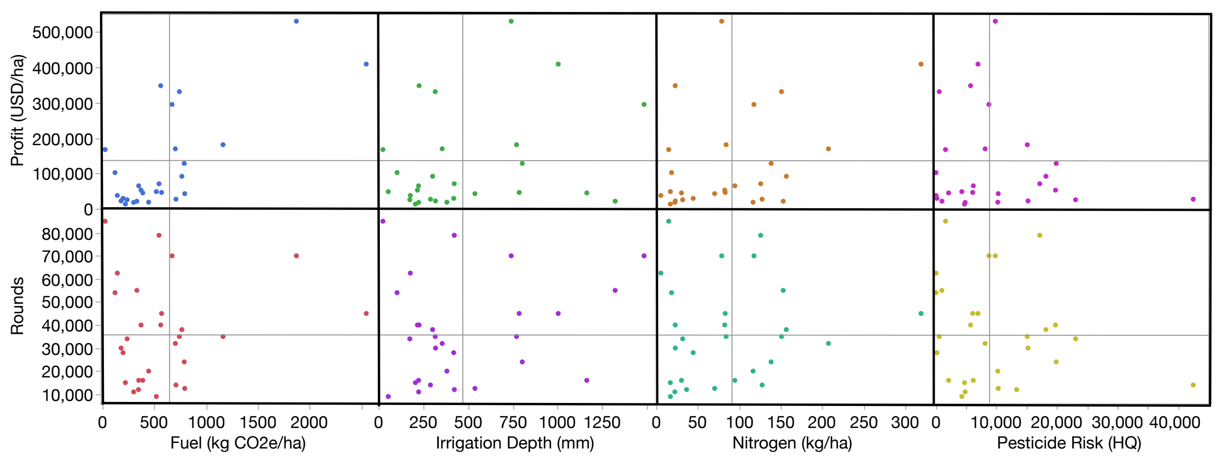

Figure 2. Profit in USD per hectare and rounds in relation to emissions from fuel use (kg CO_2e ha^{-1}), irrigation depth (mm), component-weighted-average nitrogen application rate (kg ha^{-1}), and area normalized component-weighted-average pesticide risk as quantified by hazard quotient (HQ).

The number of rounds played did not correlate significantly to resource inputs. Profit per ha correlated significantly with emissions from fuel use and N application rate, although the correlations were weak (Table 3).

Table 3. Correlation coefficients between economic outputs (rounds and profit) and environmental inputs (fuel, water, nitrogen, and pesticide).

Environmental	Economic Outputs

Inputs	Rounds	Profit (USD ha^{-1})
	r^2	
Fuel (kg CO_2e ha^{-1})	0.01	0.16*
Water (mm)	0.04	0.08
Nitrogen (kg N ha^{-1})	0.01	0.15*
Pesticide (HQ ha^{-1})	0.03	0.02

*Significant at $\alpha < 0.05$.

The mean social eco-efficiency index on US golf courses in the study was -73 with a standard deviation of 16, while the average in Europe was 218 with a standard deviation of 357 (Figure 3A). Three golf courses in Europe had high social eco-efficiency scores of 442, 517, and 788. The other four golf courses in Europe had a mean social eco-efficiency score of -55, just slightly higher than the mean social eco-efficiency score in the US.

The mean economic eco-efficiency index for US golf courses in the study was -71 with a standard deviation of 26, while the mean in Europe was 202 with a standard deviation of 289 (Figure 3B). Two golf courses in Europe had high economic eco-efficiency scores of 522 and 686. The other five golf courses in Europe had a mean economic eco-efficiency score of 41.

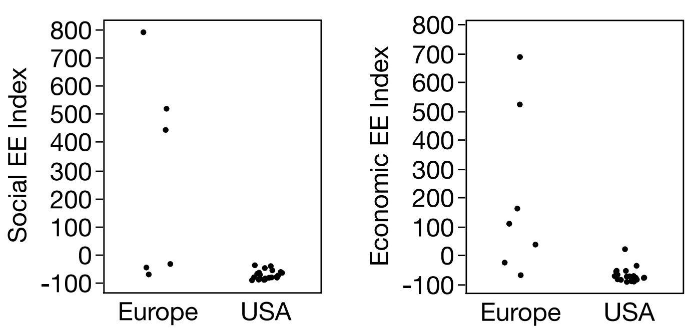

Figure 3. The social (A) and economic (B) eco-efficiency index on golf courses in Europe and in the USA.

The mean social eco-efficiency score on public US golf courses in the study was 27 (n=9), while the mean score for private courses was -28 (n=10), and for resort courses was 21 (n=2) (Figure 4A). The mean economic eco-efficiency score on public US golf courses in the study was -39 (n=9), while the mean score for private courses was -6 (n=10), and for resort courses was 204 (n=2) (Figure 4B). Golf courses in Europe were not tested for the effect of golf course type on eco-efficiency index because the number of golf courses in each course category was determined to be too low. Of the seven European golf courses in our dataset, five were public and two were private. There were no resort golf courses in the study in Europe.

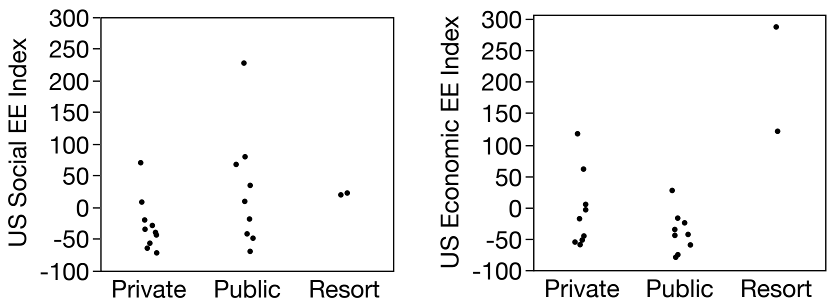

Figure 4. The social (A) and economic (B) eco-efficiency index on golf courses in the USA by course type (private, public, resort).

3.2 Climate Normalized Eco-Efficiency

The average coefficient of variation (CV) across the four climate normalized social eco-efficiency scores was 2.4 (Table 5). The average CV of the climate normalized economic eco-efficiency scores was 2.3 (Table 6). This level of variation was only slightly lower than the variation observed in the eco-efficiency scores that were not normalized for climate (section 3.1). The average CV of the unnormalized eco-efficiency scores was 2.8 for social eco-efficiency and 2.6 for economic eco-efficiency. The absolute value of climate normalized eco-efficiency scores does not have an easily interpretable meaning, but the values are comparable across climates (see Figure 6 and 7).

Table 5. Descriptive statistics of climate normalized social eco-efficiency scores in each resource use category.

Climate Normalized Social Eco-efficiency (CNSEE)	$CNSEE_F$ (Fuel)	$CNSEE_W$ (Water)	$CNSEE_N$ (Nitrogen)	$CNSEE_P$ (Pesticide)
	$\frac{Rounds}{FES}$	$\frac{Rounds}{WES}$	$\frac{Rounds}{NES}$	$\frac{Rounds}{PES}$
Mean	41,760 (2.8)	47,726 (1.27)	94,552 (1.85)	46,006 (2.69)
Median	11,408	31,058	38,314	828
Max	636,856	326,923	863,253	674,448
Min	3,405	6,906	11,191	79

Table 6. Descriptive statistics of climate normalized economic eco-efficiency scores in each resource use category.

Climate Normalized Economic Eco-efficiency (CNSEE)	$CNEEE_F$ (Fuel)	$CNEEE_W$ (Water)	$CNEEE_N$ (Nitrogen)	$CNEEE_P$ (Pesticide)
	$\frac{Profit}{FES}$	$\frac{Profit}{WES}$	$\frac{Profit}{NES}$	$\frac{Profit}{PES}$
Mean (CV)	87,762 (2.7)	140,742 (1.2)	214,681 (1.4)	67,444 (3.7)
Median	28,280	40,150	70,442	2,216
Max	1,254,059	642,758	1,237,897	1,275,772
Min	8,748	12,681	12,975	151

The percentage of golf courses with a quadrant A climate normalized social eco-efficiency score in each resource use category were fuel 21%, water 24%, nitrogen 24%, and pesticide 31%. The percentage of golf courses with a quadrant A economic eco-efficiency score in each resource use category were fuel 4%, water 14%, nitrogen 10%, and pesticide 25%.

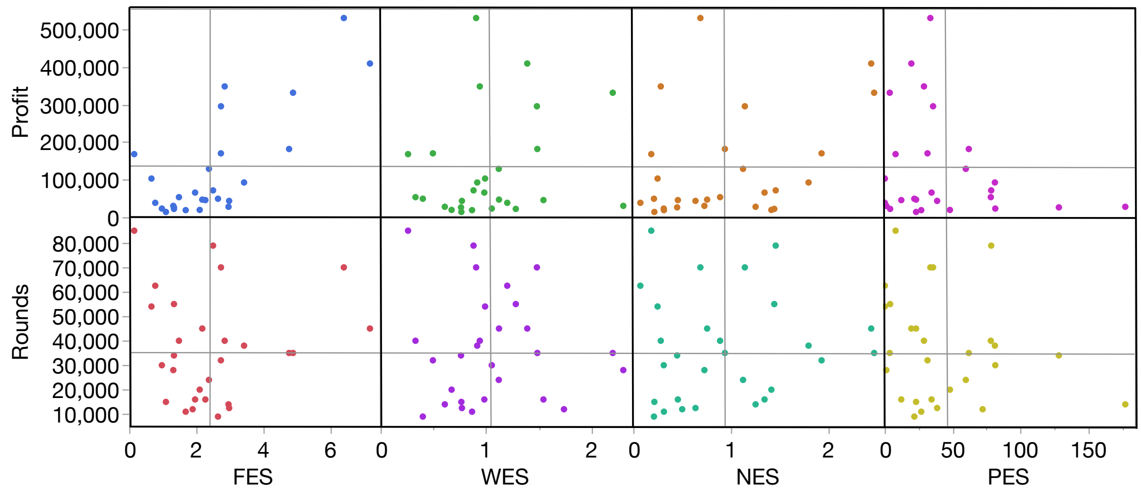

Figure 5. Profit in USD per hectare and rounds in relation to the fuel efficiency score (FES), water efficiency score (WES), nitrogen efficiency score (NES), and pesticide efficiency score (PES).

The number of rounds played did not correlate significantly to any of the resource efficiency scores. Profit per ha did not correlate significantly with the water efficiency score (WES), nitrogen efficiency score (NES), or pesticide efficiency score (PES). However, fuel emissions correlated with a higher fuel efficiency score (Table 4). A higher efficiency score is indicative of less efficient resource use. Thus, the majority of golf courses with higher profits also used more fuel to maintain their courses.

Table 4. Correlation coefficients between economic outputs (rounds and profit) and the efficiency scores of fuel (FES), water (WES), nitrogen (NES), and pesticide (PES).

Environmental Inputs	Economic Outputs	
	Rounds	Profit
	r^2	
FES	0.002	0.56*
WES	0.002	0.05
NES	0.003	0.11
PES	0.04	0.05

*Significant at $\alpha < 0.05$.

The mean climate-normalized social eco-efficiency index on US golf courses (n=21) was -59 with a standard deviation of 24, while the average in Europe was 177 with a standard deviation of 301 (Figure 3A). Like the pattern observed with the eco-efficiency scores not normalized for climate (section 3.1), three golf courses in Europe had significantly higher scores than the other four European courses, which were similar in their climate-normalized eco-efficiency to US golf courses in the study.

The mean climate-normalized economic eco-efficiency index on the US golf courses in the study was -54 with a standard deviation of 51, while the mean in Europe was 155 with a standard deviation of 238 (Figure 3B). Two golf courses in Europe had high economic eco-efficiency scores of 484 and 485. The other six golf courses in Europe had a mean economic eco-efficiency score of 24. Only one US golf course had a positive economic eco-efficiency score. This golf course showed the highest profit per ha of any golf course in the study at $530,939. However, the golf course also used high levels of resource inputs, even when normalizing for climate, and, as such, the course ranked fourth in economic eco-efficiency for all golf courses in the study.

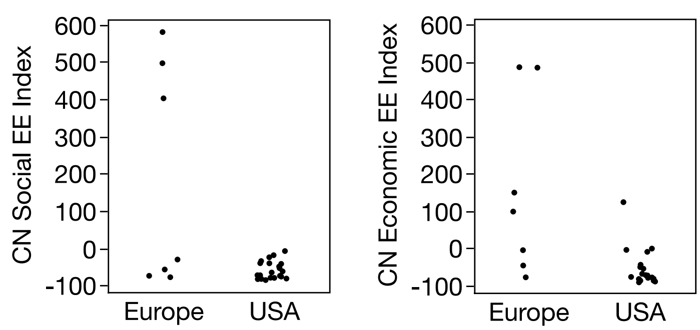

Figure 6. The climate-normalized (CN) social (A) and economic (B) eco-efficiency index on golf courses in Europe and in the USA.

The mean climate-normalized social eco-efficiency score on public US golf courses in the study was 21 (n=9), while the mean score for private courses was -30 (n=10), and resort courses 54 (n=2) (Figure 7A). The mean climate-normalized economic eco-efficiency score on public US golf courses in the study was -49 (n=9), while the mean score for private courses was -6 (n=10), and resort courses 246 (n=2) (Figure 4B).

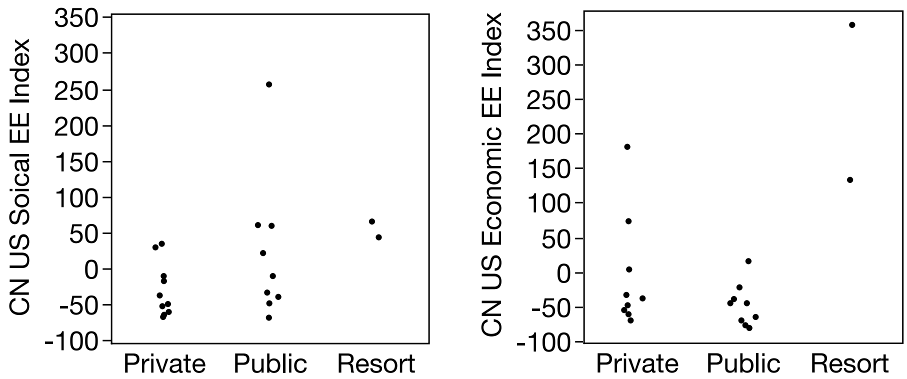

Figure 7. The climate-normalized social (A) and economic (B) eco-efficiency index on golf courses in the USA by course type (private, public, resort).

The three golf courses in Europe with high climate-normalized social eco-efficiency (CNSEE) indices scored high for slightly different reasons (Figure 8A). Golf course AB had high social eco-efficiency scores for fuel (1424), water (584), and nitrogen (388) and a slightly below average pesticide efficiency score (-77). Taken together, these four scores resulted in the highest social eco-efficiency index of any golf course (580). Golf course V had the second highest social eco-efficiency index and achieved this ranking through a high score for nitrogen (812) and pesticide (1068). Golf course Z had the third highest eco-efficiency score, achieved primarily through a high social eco-efficiency score for pesticides (1366).

Golf courses AB and Z were ranked first and second in climate-normalized economic eco-efficiency (CNEEE) for same reasons as their high CNSEE scores. Golf course AA was ranked seventh in CNSEE index, but third in the CNEEE index, indicating that this golf course, which is public, has relatively high profits in comparison to rounds played.

Figure 8C shows the CNSEE indices of seven golf courses in Europe, and Figure 8D shows the CNEEE indices in Europe. Golf course AB was the most socially and economically eco-efficient course of the European courses in the study. Golf course W was the least socially eco-efficient and golf course X was the least economically eco-efficient.

Figure 8E shows the CNSEE indices of the 28 US golf courses in the study, and Figure 8F the CNEEE indices of these same courses. Golf course L had the highest CNSEE index primarily because of high eco-efficiency scores in pesticide (851) and fuel (171). However, golf course L had a much higher number of rounds relative to profit. The course was ranked 12th in CNEEE. Golf course U had the highest ratio of profit to resource use and had positive CNEEE in nitrogen (566), water (395), pesticide (325), and fuel (143).

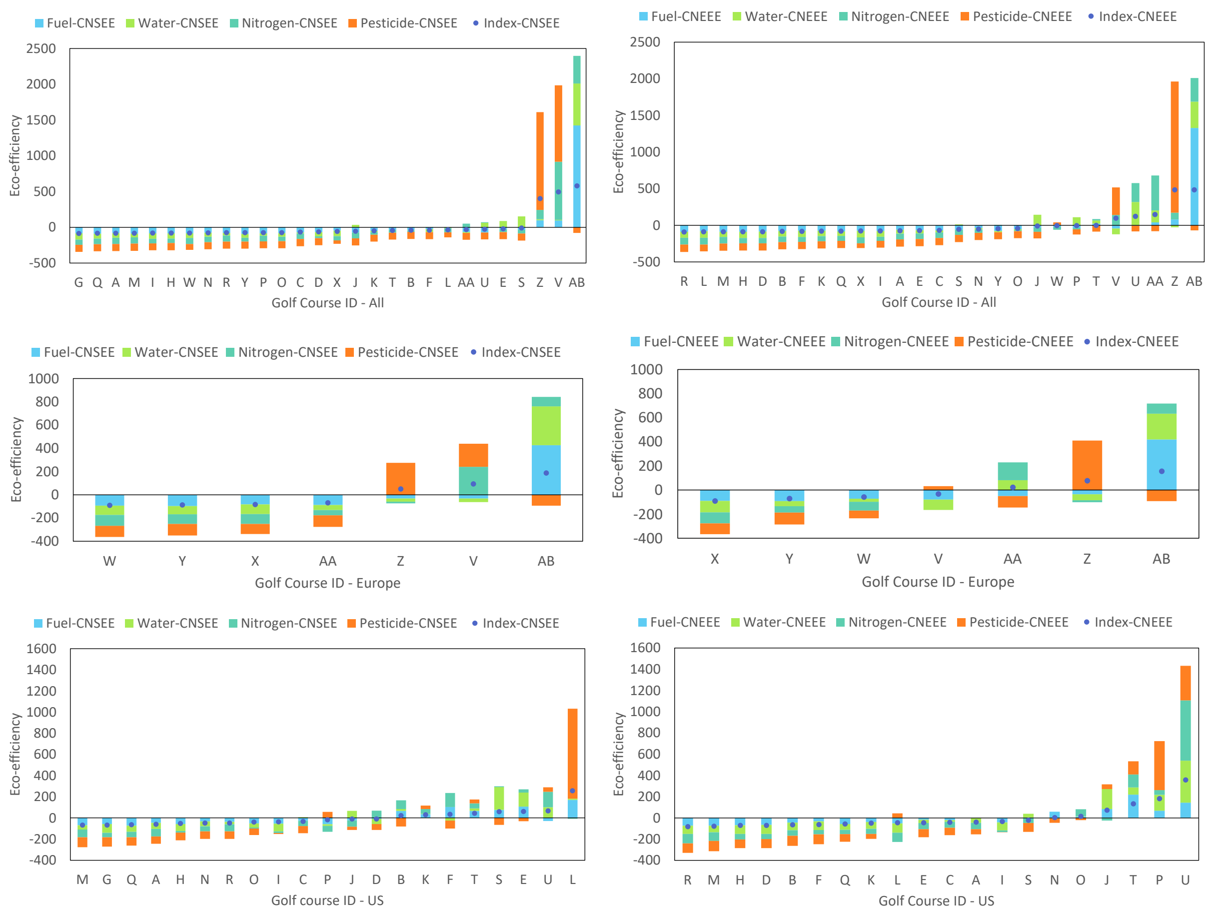

Figure 8. The climate normalized social eco-efficiency (A) and economic eco-efficiency (B) for fuel, water, nitrogen, and pesticide, and index for all golf courses in the study. These same parameters are shown for golf courses in Europe (C) and golf course in the US (D).

4. Discussion

The eco-efficiency framework derived in this study quantifies the ability of a golf course to turn resource inputs of water, energy, fertilizer, and pesticide into a social output of rounds played, and an economic output of profit generated. We anticipated that eco-efficiency would vary greatly by climate, which was not the case. Climate normalization only slightly decreased the coefficient of variation in eco-efficiency scores, indicating that the various climates in this study (continental US and northern Europe) did not affect eco-efficiency scores to the extent anticipated.

Regulatory environment, however, does seem to greatly impact a given golf course's eco-efficiency potential. Golf courses in Europe face greater regulatory pressure, especially in their use of fertilizers and pesticides (R&A, 2020). The average resource efficiency score (the average of WES, NES, PES, and FES) for golf courses in Europe was 3.2, whereas, in the US, it was 14.9. In our framework, a high resource efficiency score is indicative of less efficient use of the resource. However, higher resource use efficiency does not necessarily mean higher eco-efficiency scores, which also consider the output of production (i.e., rounds or profit in this study). In terms of social eco-efficiency, three of the seven golf courses in Europe hosted a high number of rounds, and combined with low resource use, had a high social eco-efficiency index (an average of 582). However, the other four courses in Europe hosted a lower number of rounds. Thus, despite low resource use, these courses had eco-efficiency scores similar to US golf courses in the study with comparatively higher resource use.

Given the difference between eco-efficiency scores in the US and Europe, and the relatively small dataset from European golf courses, we tested the effect of course type on eco-efficiency scores for US golf courses only. Our hypothesis that public golf courses would have the highest social-efficiency scores, that resort courses would have the highest economic eco-efficiency scores, and that private courses would have middling scores in both categories was mostly supported by the data. However, the dataset was small and there were only two resort courses for which we were able to calculate eco-efficiency scores. The two resort courses had the highest average economic eco-efficiency score, 246, in comparison to -49 for public courses and -6 for private courses. The two resort courses also had the highest social eco-efficiency score (54) but these scores did not exceed social eco-efficiency scores for public golf courses by much; public courses showed an average social eco-efficiency score of 21. As predicated, private golf courses had the lowest average social eco-efficiency score (-30). Private golf courses hosted relatively few rounds relative to the resources they consume, but also showed relatively higher profits in comparison to their resource use.

Only one previous study could be located that calculated an eco-efficiency metric in the golf industry (Rodriguez Diaz et al. 2007). Instead of defining the economic yield of individual golf courses, Rodriguez Diaz et al. (2007) defined the economic output of the golf industry based on the direct and total impact of the golf industry. The authors investigated golf courses in Spain where the direct economic impact of golf is €765 million and the total economic impact is €2.4 billion, annually. Then, using a survey and GIS modeling technique, the authors estimated that the 238 golf courses in Spain used 85 million cubic meters of water during the year of the study. Rodriguez Diaz et al. (2007) calculated the economic productivity of golf in Spain per unit of water at 28 €/m^3. The authors also calculated direct economic benefits (i.e., revenue from golf course fees only) of water use for golf in Spain to be 9 €/m^3. As a means for comparison, the authors stated that the highest value crop in Spain was strawberries grown in the southwest, which typically produce around 3 €/m^3 of direct economic benefit. Thus, the use of water on golf courses in Spain appeared to have a strong economic return in comparison to agriculture. Using direct or total economic impact as the economic output of production for golf makes sense on a nationwide industry level but it is perhaps less applicable to the economic or social sustainability of a single golf course.

Fuel use did not correlate with the number of rounds played but correlated significantly with profit (r^2=0.56). It seems plausible that to make a higher profit in golf, course quality must increase, which may be achieved through more frequent mowing, topdressing, tree trimming, leaf collection, and other similarly fuel-dependent activities. Our survey only asked for the total volume of fuel used for maintenance equipment and thus we cannot determine which maintenance activities increased on golf courses with higher profits.

This study found no correlation between the number of rounds played or the profit generated at a golf course in comparison to the amount of water, fertilizer, and pesticide used, suggesting that golf courses may be able to reduce use of these resources without experiencing declines in either output. Superintendents may be managing golf courses to their own levels of expectation, which may exceed that of the golfer. From our limited data, it appears that golf courses use more water, fertilizer, and pesticide than the majority of golfer's demand. Improving the alignment between environmental inputs and the intended outputs of a golf course and the may allow golf courses to minimize environmental impact while achieving greater social or economic value.

5. Conclusion

Yield is a critical concept in agriculture that underpins definitions of efficiency (de Wit, 1992). Agricultural researchers understand water use efficiency (yield per unit of water used) targets for all major crop types and how water use efficiency varies as a function of climate (Mbava et al., 2020). Agricultural researchers have also clearly delineated nitrogen use efficiency metrics (Congreves et al., 2021), quantified nitrogen use efficiency on farms around the world (Raun and Johnson, 1999), and thus can improve efficiencies (Quemada, 2020). However, such efficiency indicators have not been developed for the golf industry, in part, because the golf industry has not clearly defined yield. This study proposes that, for golf, defining yield is equally important to defining efficiency, but that the yield a golf course seeks may vary based on the type of golf course (e.g., public, private, resort).

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