IMPACTS OF INCREASED PERENNIAL GRASS COVER AND REDUCED CROP NUTRIENT APPLICATIONS ON ECOSYSTEM SERVICES IN THE YAHARA WATERSHED, WISCONSIN

By

Tracy Alanna Campbell

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Table of Contents

Big Data and Ecoinformatics in Agricultural Research: Opportunities, challenges, and steps moving forward

Abstract

This article evaluates the use of big data and ecoinforamtics in agricultural research. I examine the growth of big data, its potential in agricultural research, and the challenges associated. Big data can be viewed as a tool to address new research questions resulting from an increase in the computational power related to data storage and analytics. In the last decade there has been a surge in discussion, investment, and research pertaining to big data and ecoinformatics, with recent developments in the agricultural sector. The use of big data techniques have the potential to transform agricultural research but come attached to a suite of challenges and concerns, and as a result, will require universities to adapt new research and educational practices.

Introduction

While physicists have been handling big data well before the term was coined, big data has now noticeably entered an array of academic disciplines as well as everyday life. Big data, a term that is often difficult to define, is often described by the volume, veracity, variety, and velocity at which it is generated and analyzed (Coble et al. 2006, Cukier and Mayer-Schonberger 2013). Ecoinformatics often falls within the realm of big data as it seeks to elucidate patterns and answer research questions through the analysis of large pre-existing data sets (Rosenheim and Gratton 2017). Others argue for the need to include value and visualization as defining features (Hashem et al. 2015, Kempenaar et al. 2016), further demonstrating the lack of consensus regarding a concrete definition (McKerlich et al. 2013).

With the parameters defining big data so broad, it is common for big data analytics to only encompass a few of the “4 V's”. Much of the power of big data stems from its heterogeneity, allowing multiple distinct sources of data to be aggregated. Similarly, the speed at which data is generated and analyzed allows for real time decisions and predictions to be made. However, the real value of big data comes from the new information and interpretations that can be gleaned from these sources of data (Porter et al. 2012). While we may lack a precise definition of the term, big data transforms the types of research questions we are able to ask, and as a result will heavily influence future research endeavors (Kitchin 2014). In addition, the interest and need to harness big data spans multiple sectors, encompassing academia, industry, and the government.

As with most new concepts, there is concern regarding the permanence of big data. Buzzwords generate a high-level of excitement that often quickly diminishes (Kathpalia 2016). However, there is strong support for the continued relevance of big data - and more importantly, the data intensive science it fosters (Sonka 2014, Kathpalia 2016). Using GoogleTrends, it appears that the relative frequency of searches using the term “Big Data” has remained consistently high over the last 3 years.

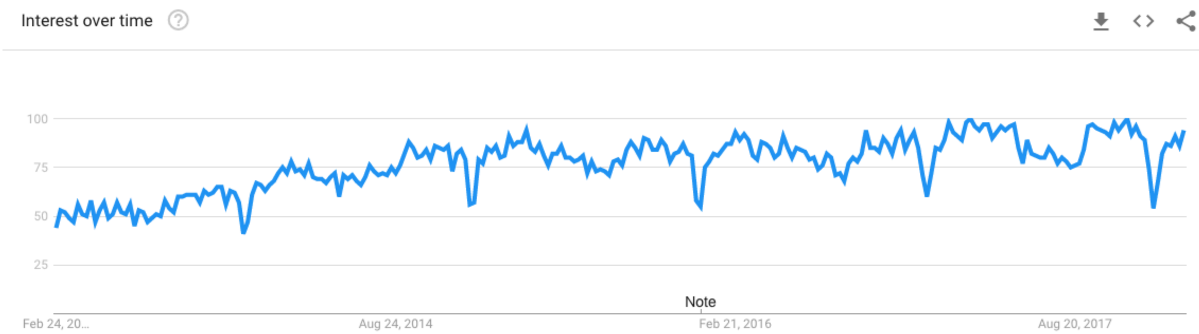

Figure 1. GoogleTrends search of the term "Big Data", Y axis indicates interest over time – with 100 corresponding to peak interest. Trend depicted spans from February 2014 to December 2017.

Big Data in Agricultural Research

Though the term "Big Data" has only gained in popularity over the last few years, big data analytics has been occurring for decades in certain fields, with progress in DNA sequencing, genome editing, and epidemiology (Cukier and Mayer-Schonberger 2013). However, until recently, big data techniques did not receive much application within the agriculture sector.

While the potential for big data approaches in agriculture is less developed compared to other disciplines, the last few decades are clear indicators of the utilization of big data to aid in solving on and off farm challenges. Within the agricultural sector, the influence of big data is evident in the growth of precision agriculture techniques, with use in the United States rising from 17% in 1997 to 72% in 2010 for fields dedicated to corn (Carolan 2017). Literature on the subject of big data in the field of agriculture has grown significantly; publications using the phrase "big data in agriculture" increased eightfold from the 2012 to 2015 (Kamilaris et al. 2017). Current literature reviews of agriculture research indicate weather and climate change, remote sensing, and farmers' insurance and finance as growing areas of publication utilizing big data approaches (Kamilaris et al. 2017). In addition, economic investment in the field has increased substantially - $661 million was invested into precision agriculture start-ups by private investors in the year 2015 alone (Pham and Stack 2018).

Some have even argued that agriculture is undergoing it's fourth revolution - smart farming (Walter et al. 2017). Smart farming, an overarching term, refers to data driven approaches to address agricultural challenges ranging from productivity, environmental impact, and economic gain (Wolfert et al. 2017). Agriculture is inherently risk prone - with economic gains and livelihood often dependent on weather, pest outbreaks, and other ecosystem variables that are constantly changing, especially under a changing climate (Schimel et al. 2013). Advances in the capabilities of big data and smart farming approaches have the potential to reduce risk and uncertainty (Kempenaar et al. 2016). Data intensive approaches allow us to form more accurate predictions and promote management options at a finer scale, aiding scientists, policy makers, producers and consumers in decision making (Zaks and Kucharik 2011).

Fueled by advances in big data analytics, the past decade has allowed for new questions to be asked and answered in regards to agricultural research. Areas of emphasized potential include improved crop yields, reduced environmental degradation, improved species distribution modeling, and a more comprehensive assessment of climate change and climate variability (Guerra et al. 2014, Sonka 2014, Butruille et al. 2015, Vitolo et al. 2015). Specific big data advancements that promote these areas include remote sensing and monitoring, use of unmanned aerial vehicles, machine learning and numerous additional developments (Friedl et al. 2002, Mulla 2013, Zhang et al. 2014, Sonka 2016).

However, gaps in current research are becoming more apparent, illuminating the need for continued investment within this field. Established areas of future research include supply chain management, yield prediction, and modeling of environmental phenomena (Kamilaris et al. 2017). Farm policy analysis is also an area where data-driven approaches have the potential to alter the field, provided that future research incorporates a policy perspective (Kamilaris et al. 2017). Specific to remote sensing, there is need for more research and development pertaining to sensor estimation of nutrient deficiencies, in addition to continued development of more complex spectral indices (Mulla 2013).

As with most advancements, there are areas of concern. Big data may profit larger scale operations disproportionately. Many of the cost investments related to technology associated with detailed data collection cannot be offset unless conducted across a larger scale. Rural areas are also restricted in their ability to collect and process data due to broadband limitations (Mark et al. 2016). In addition, smaller scale farm and feed operations are generally limited in the volume of data they have available which could hinder the potential of data driven approaches- and they may have less need to begin with (Carbonell 2016).

When advocating or incorporating data intensive approaches to farmers and the community, it will be necessary that possible limitations are openly acknowledged and discussed. Furthermore, concerns over privacy, security, and data ownership are expressed across all fields exploring big data approaches (Sykuta 2016, Leone 2017). We also must acknowledge the limitations of our report. Most of our review of the literature, and evaluation of challenges and solutions focuses on big data within developed countries. Developing nations have received fewer resources in regards to data collection (Mondal and Basu 2009) and face a greater economic hurdle when considering adoption of big data approaches (Kshetri 2014). These obstacles may limit the current potential of big data in these areas (Capalbo et al. 2017), alternatively, others point to greater potential for improvements (Zaks and Kucharik 2011, Walter et al. 2017).

Recently, the National Institute for Food and Agriculture (NIFA) of the USDA has established big data innovations as a priority research area. Specific goals established by NIFA stakeholders include: (1) Develop a culture that supports and rewards communities of researchers to build off one another's datasets, standardize protocols, harmonize experimental designs, and ensure that datasets can be usable over the long-term to minimize the number of "orphan" datasets; (2) Foster private-public partnerships while addressing tradeoffs among data availability, ownership, value, incentives for sharing, and privacy; (3) Build a robust infrastructure that houses and provides open access to publicly funded datasets; and (4) Train a workforce that can manage, analyze, and manipulate large datasets (NIFA 2016).

Considering the areas of concern summarized above and the aforementioned goals established at the national level through NIFA, it is essential that as researchers we examine and re-evaluate the current research and educational practices at our academic institutions. Based on our experience organizing a university wide symposium, *Big Data and Ecoinformatics in Agricultural Research*, at the University of Wisconsin – Madison (See Appendix A), we have prioritized key challenge areas and provided possible solutions that may be implemented across universities.

Challenges

Big data introduces a suite of challenges, ranging from the legalities of data ownership and data storage limitations, to struggles to form efficient collaborations. Moving forward, it will be critical for universities to address the institutional and organizational challenges outlined below.

I. Integrating Domain Experts and Data Scientists

As we increase reliance on data intensive approaches, it will be critical that we integrate both domain experts and data scientists. Domain experts, or those who can speak on the fundamentals of a specific aspect of agricultural sciences, such as entomologists, agronomists, and breeders will be vital for development of research questions and interpretation of data and results. On the other hand, data scientists will play an essential role in computational knowledge and statistics. It is only through a multidisciplinary approach, in which both data scientists and domain experts are interwoven, that we can harness the potential of big data. A case study conducted on the use of smart farming techniques in the milk production chain further supports this argument, emphasizing the critical role domain experts played in model development and data interpretation, and the need to pair this with the expertise of data scientists for the machine learning aspect (Kempenaar et al. 2016). The interdisciplinary research team was made out of experts in: drone and satellite imagery, cow genotype and phenotypes, and crop and dairy management. Others provide much needed guidance in relation to data protection, data management, and the tools and infrastructure needed to effectively harness big data for a socio-economic analysis. Findings reiterated the need for corporation across sectors and disciplines in order to overcome organizational challenges (Kempenaar et al. 2016). Similarly, a case study on applying technology science to biodiversity research illustrated the necessity of involving domain experts in design of data-intensive tools (Downey and Pennington 2009). To do so, early career scientists participated in a training programs designed to provide the skills needed to incorporate technical, data intensive, approaches into ongoing research (Downey and Pennington 2009). As a result of the history of research conducted in "silos", specific disciplines and departments have developed subject-specific vocabulary and data formatting techniques (Lokers et al. 2016), moving forward it will be critical to integrate these disparate habits. At the university level, we must find a way to bridge the divide between domain experts and data scientists. This will involve ensuring that both groups have resources that promote accessible conversation, as well as providing incentive to invest in collaborative efforts.

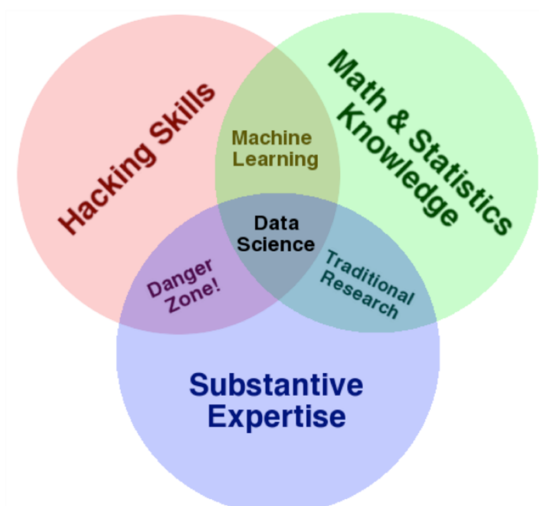

Figure 1. Venn diagram illustrating the dangers that can arise when any one domain is excluded from big data practices and developments (Conway 2010).

It is also vital that this approach span outside of the academic sector. We must recognize traditional expertise and knowledge - and work to foster partnerships that promote this knowledge while also incorporating analytical and computational skills. When communicating and involving farmers, we must seek to incorporate their firsthand, on-the-ground experiences with our newer, data-driven approaches. Some of this can be achieved by generating trust between all stakeholders of an interdisciplinary project, listening to farmer concerns, as well as developing protocols and guidelines upfront for data management.

II. Developing best-practices for discipline-specific use

As big data approaches continue to spread across agricultural disciplines, it will be necessary that researchers define a set of best practices. Agreed upon standards regarding data description and exchange will allow scientists to import, export, aggregate, and understand their data sets easier (Lynch 2008). In addition, discipline specific best practices will reduce both redundancies and discrepancies that develop when each data creator is forced to outline best practices for each set of data (Lynch 2008). Currently concerns exist around the correlative nature of big data approaches, in which causation is often difficult to determine (Rosenheim and Gratton 2017) – a framework of tools and best practices can be utilized to reduce such errors. In addition, the development of an agreed upon list of best practices and framework of tools will allow for easier replication of analysis (Porter et al. 2012). A proposed list of best practices in ecoinformatics research includes (1) determining the primary pre-existing data sets, (2) aggregating additional data sets, (3) evaluating any data privacy concerns, (4) finding out how the data was collected and determining if any bias exist, and (5) setting data management and workflows. For a complete list of proposed best practices and action items, see Rosenheim & Gratton (2017). Discipline collaboration and consensus will be crucial as best practice strategies are determined moving forward.

III. Training students and researchers

Currently, one of the limiting factors in data intensive research is the lack of individuals with the computational and technical skills required for big data analytics. In order to remain competitive, it will be necessary that universities are able to train both current students and researchers as well as prospective students on data-driven skills, which will likely become increasingly necessary (Porter et al. 2012). As interdisciplinary research continues to grow along with the technological capabilities to utilize large-scale spatial and temporal data, universities must reevaluate their current curricula. Previous case studies have emphasized the new skill sets required to bridge the gap between biodiversity ecology and technology science, highlighting the need for emerging scientists who have the skills to analyze large heterogeneous data sets as well as the knowledge to collaborate with data scientists (Downey and Pennington 2009). Others have articulated the need to supplement core course requirements with computer science and non-traditional statistics courses, in order to increase the rate at which students can make meaningful contributions to their disciplines (Coble et al. 2018). Additionally, researchers have highlighted that students must not only learn data science skills, but also the ethics associated with data privacy and data ownership, and how it pertains to conducting research (Etter 2018). Besides offering degrees related to data science, courses teaching data management, analysis, and visualization at the undergraduate, graduate, and postgraduate level will be needed for those outside of data science degrees. Additionally, universities will need to provide resources in the form of data science consultations and data management workshops.

IV. Data Ownership and Data Sharing

A large portion of agricultural data is in the possession of major corporations who have the financial capital to invest in large-scale data collection and data storage (Coble et al. 2018). Agribusinesses have incorporated data collection into a fundamental center stone of their business models, collecting data through their marketable products. These approaches have evoked controversy, inciting sociopolitical concerns regarding unequal power distribution and increasing dependence on large corporations (Kamilaris et al. 2017). Those with access to the most data are disproportionately favored as they are granted greater opportunities to monetize data through insights gained from data aggregation and analysis (Carbonell 2016, Coble et al. 2018). As these practices have the potential to provide large financial gain, agribusinesses have little incentive to grant access to the data – restricting its users drastically, as evidenced by terms of services and contracts that prevent farmers from accessing their own data. Furthermore, privacy concerns have become an issue taking center stage. In a survey conducted by the American Farm Bureau in 2014, 77% of farmers surveyed expressed fear that government officials and regulators may receive access to their private information without permission (Carbonell 2016, Schuster 2017). Similarly, 76% of respondents indicated concern that their data would be used for market speculation without permission (Carbonell 2016). Despite high levels of concern regarding data ownership, widely accepted and implemented guidelines have not been established (Schuster 2017). There is ongoing debate over who owns the data generated on individual farms, which is likely to continue until standards are more widely set and accepted. Research universities must find a way to integrate and navigate within the complex challenges presented by data ownership and privacy concerns. Universities may need to seek collaboration with agribusinesses while striving maintain and promote trust with farmers, a process that will only be possible through clear communication of data ownership standards. At the university level, we have the opportunity to continue to emphasize open data sharing by setting a precedent for open access.

Moving Forward

Based on my evaluation of the emerging field, I have concluded that while big data provides valuable insights and improved agricultural practices across the supply chain, there are challenges that must be addressed. As a result, academic institutions need to develop new practices and strategies to address the organizational, technical, and ethical challenges associated with big data and agricultural research. I have prioritized four challenges that have direct relevance to educational institutions, and thus can be addressed at the university level. First, it will be crucial that we begin integrating data scientists and domain experts as we attempt to answer complex agroecological research questions. Second, we must develop best practices that are agreed upon across entire disciplines in order to promote both accurate and efficient research moving forward. Third, it is necessary that we re-evaluate the tools and training currently available to students and faculty alike, and strategize to determine key skills that must be incorporated into the curriculum, in addition to providing new resources that address data-intensive research challenges. Lastly, we advocate that universities, collaborators, and stakeholders must address discrepancies related to data ownership and data privacy standards. We hope that by recognizing, discussing, and addressing these challenges, researchers, educators, and students will have the skills and resources to conduct innovate, interdisciplinary research to address critical research questions in the agricultural sector.

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Transformative agricultural land management required to improve water quality in the Yahara watershed, Wisconsin

Abstract

Agricultural systems are currently experiencing heightened demands as we strive to increase food and feed production, generate fuel and fiber, and maintain ecosystem services. Moving forward, it is necessary we understand how varying ecological and societal drivers of change may mitigate or augment current stress on agricultural land. The Yahara Watershed, an agricultural and urbanizing watershed spanning 1,345 km^2 in southern Wisconsin, exemplifies many of the current challenges regarding the impact and interaction of climate change, land cover, and nutrient management. To evaluate the impacts of increased perennial grass cover and reduced crop nutrient applications on ecosystem services in a changing climate, we generated 48 scenarios projected to the year 2070 using the Agro-IBIS agroecosystem model. Tradeoffs associated with a transition from annual row crops to perennial grasses (0%, 10%, 25%, 50% transition) within the Yahara watershed, under varying manure and fertilizer applications (0% 10%, 25%, 50% reduction) and climate change were examined. Model output suggested inaction leads to further environmental degradation – with phosphorus yield increasing by 13%, 7%, and 23% under a baseline climate (BC), warmer and drier climate (WDC), and warmer and wetter climate (WWC) respectively. By incorporating transformative land management changes, P yield and N leaching could be reduced by 50%. However, reductions in P yield and N leaching of 50% only came after 50 plus years of investment in transformative land management changes. While water quality improvements were linked to soil retention, they came with tradeoffs to

other ecosystem services – particularly crop yield and freshwater supply. Our research highlights the potential for large-scale management changes to improve water quality under a changing climate, but indicates that improvements will require a long-term time investment and come at a cost to other ecosystem services. Current water quality improvement efforts are insufficient for combating the influence of climate change and legacy nutrients. Moving forward, it will be crucial policy decisions reflect the large-scale and time intensive approaches required for water quality improvements in the Yahara watershed.

Introduction

Across the Midwestern United States, agricultural watersheds are facing growing challenges as we strive to balance increasing food, fuel, and fiber demands with the maintenance of diverse ecosystem services. Despite increases in crop yield, malnutrition and food insecurity continue to persist – and as of 2013, 14% of those living in the Midwest (US) are considered food insecure (Coleman-Jensen et al. 2014). Simultaneously, historical and current agricultural intensification continue to degrade the environment through increased pollution, depletions in available freshwater, ecosystem biodiversity, and soil carbon (C) – in addition to exacerbating water quality problems (Foley et al. 2011, Zeng et al. 2014). Agricultural intensification is linked with the expansion of cropland, increased irrigation of croplands, increased application of nutrients like nitrogen (N) and phosphorus (P), and higher crop yields (Foley et al. 2011). Excess manure and fertilizer application are a known cause of nonpoint source pollution, as over-application leads to runoff events in which nutrients are carried from the soil into waterways (Sharpley et al. 1993, Pimentel et al. 2013). In addition, after manure and fertilizer is applied, 70-80% of phosphorus applied remains stored in soil or sediment (Jarvie et al. 2013, 2015). Stored P, often referred to as legacy P, can mobilize in the future, eventually polluting our freshwater systems (Jarvie et al. 2013, Chen et al. 2015, Motew et al. 2017). Recent research suggests N experiences similar legacies through soil accumulation (Van Meter et al. 2016, 2018), compounding the legacy nutrient challenge.

Ongoing and future climate change across the Midwestern United States has the potential to mitigate or exacerbate current agricultural challenges within the food-water-climate nexus. Increases in air temperature are likely to provide benefits to northern states, as longer growing seasons associated with a rise in temperature may allow for increases in crop yield (Bagley et al. 2015), but may reduce yields in other regions due to the occurrence of extreme heat (Lobell and Gourdji 2012). Extreme rainfall events resulting in flooding and soil saturation increase soil compaction, contributing to soil erosion, runoff, and leaching, contaminating surface and groundwater with excess N and P (Hatfield et al. 2011). Additionally, heavy precipitation events are found to be a leading cause of soil P mobilization, further emphasizing the potential for climate change to exacerbate current surface water quality challenges (Motew et al. 2017, 2018). Changes in soil freeze-thaw dates could impact water quantity and quality, especially in areas practicing winter manure application. A shorter duration of frozen ground may promote infiltration, allowing for increases in groundwater recharge and freshwater supply (Wisconsin Initiative on Climate Change Impacts 2011). However, if rainfall occurs on frozen ground, infiltration will not occur and instead runoff can increase delivery of excess nutrients to waterways (Wisconsin Initiative on Climate Change Impacts 2011, Kalkhoff et al. 2016).

Decades of research have demonstrated the role of excess manure and fertilizer application on water degradation, leading to the development of better management practices. However, numerous studies evaluating the efficacy of best management practices for water quality improvements have elucidated challenges. Often, improvements were muted and delays in mitigation occurred, if any were observed at all (Graham et al. 2017, Liu et al. 2017). These observations can be described as lag times, or the delays associated with the implementation of best management practices and measurable improvements in water quality (Dale et al. 2010, Van Meter and Basu 2017). Lag times are explained as a result of legacy nutrient concentrations, in which historical over-application of manure and fertilizer hinders current management strategies focused on improving water quality (Meals et al. 2010, Jarvie et al. 2013, Chen et al. 2015, Motew et al. 2017, Van Meter et al. 2018). In contrast, other studies across the Midwest utilizing field and plot level experiments to evaluate the effectiveness of vegetative buffer strips in improving water quality reflect successful results (Storm et al. 2010, Zhou et al. 2014). A meta-analysis completed by Zhang et al. (2010) reviewed 73 studies and determined the mitigating potential of vegetation to reduce sediment, nutrients, and pesticides from surface water runoff. Results indicated that on average, reductions of 72% and 68% were possible for P and N respectively (Zhang et al. 2010). Past modeling studies of wide spread deployment of perennial bioenergy crops also support the use of perennial vegetation for water quality improvement in both hypoxic (Costello et al. 2009, VanLoocke et al. 2016) and eutrophic conditions (Carpenter et al. 2015). The above findings indicate that perennial grass systems may overcome lag time effects by negating the role of legacy nutrients, providing a potential pathway towards mitigation of water quality problems.

Perennial grass systems are associated with promoting diverse ecosystem services while preventing further environmental degradation (Asbjornsen et al. 2014). Greater belowground biomass found in perennial systems increases soil retention, resulting in reduced soil erosion and decreased nutrient runoff. Year-long soil cover and reduced soil disturbance promote soil carbon sequestration (Qin et al. 2016). Past research supports the strategic placement of perennial grasses within cropland dominated by row crops, often referred to as perennialization, as a means of maximizing ecosystem service benefits (Asbjornsen et al. 2014). Furthermore, a transition from annual crops to perennial grass increases ecosystem services such as biodiversity and bird and pollinator abundance (Meehan et al. 2010, 2013, Werling et al. 2014, Landis et al. 2016). Aside from supporting numerous ecosystem benefits, perennial grasses can be used to provide a diversity of marketable products and services, including forage for livestock and as a cellulosic biofuel feedstock (Mitchell et al. 2016).

The Yahara Watershed, an agricultural and urbanizing watershed located in Southern Wisconsin, exemplifies many of the current challenges regarding the impact and interaction of climate change, land cover, and nutrient management experienced in the Midwest US. Cropland is dominated by corn, soybean, and dairy operations, and nutrient applications to the land through manure and fertilizer are common. Water quality of the Yahara watershed is of specific concern, as decades of research have established agriculture's impact on nutrient loading within the chain of lakes, which contributes to the development of algal blooms, decreased water clarity, and reduction in fish populations (Lathrop et al. 1996, Lathrop and Carpenter 2014, Motew et al. 2017). Water quality degradation is also linked to economic costs, loss of recreational activities, and human health concerns (Smith et al. 2006, Huisman et al. 2018). Due to the severity of the problem, many efforts over the last few decades have been directed at water quality improvement with a goal of a 50% reduction in phosphorus yield (Clean Lakes Alliance 2012). Achievement of this goal will double the number of days local beaches are open, increase water clarity, and significantly limit the development of algal blooms (Clean Lakes Alliance 2012).

Within the Yahara Watershed, and similar watersheds, it will be vital we understand how future societal and ecological drivers of change influence water quality metrics and the distribution of ecosystem services, especially under a changing climate. Scenario development serves as a method to reduce uncertainty, providing projections of potential futures - often across large spatial and temporal scales. Recent research utilized scenario development across the Yahara Watershed, incorporating qualitative storylines with biophysical models in order to generate a range of plausible but provocative future outcomes (Booth et al. 2016). Emphasis was placed on community members' concerns rather than specific environmental improvement goals, leading scenarios to reflect a slow, gradual shift in human values and priorities while simultaneously incorporating climate change and an increase in extreme weather events projected to the year 2070 (Carpenter et al. 2015). Analysis of changes in ecosystem services indicated a reduction in phosphorus yield, a major indicator of water quality improvement, across all scenarios, but requiring 50 years and not always meeting the 50% P yield reduction goals (Qiu et al. 2018). While water quality improvement was an unintended outcome considering the heterogeneity across scenarios, the results highlight the potential of scenario development to elucidate pathways towards water quality improvement.

Our current research approaches scenario development with the specific goal of improving water quality in the Yahara Watershed considering immediate, transformative changes in land cover and nutrient application. Unlike the Yahara 2070 scenarios (Carpenter et al. 2015; Booth et al. 2016; Motew et al. 2017; Qiu et al. 2018a), a more traditional experimental approach to scenario development was undertaken. Incremental changes in land cover and nutrient management were implemented in an effort to identify thresholds required for achievement of water quality goals. To evaluate the impact and interaction of three drivers of change, namely land cover, nutrient management, and climate change on water quality, we answer the following questions: 1) What transformations to land cover and nutrient management are required to improve water quality under a changing climate? 2) If we change our actions today, what timeline is required for water quality improvements to occur? 3) What tradeoffs are associated with an increase in perennial land cover and reduction in inputs, in regard to ecosystem services (e.g. crop yield, soil carbon sequestration, water quality)? While past studies evaluate water quality at the watershed scale – few consider three drivers of change, and of those that do, many do not account for the interaction between drivers (March et al. 2012). We focus on land cover, nutrient management, and climate change as the key anthropogenic drivers of change – evaluating their impact and interaction by modeling changes and feedbacks of biogeochemical and biophysical processes through use of the agroecosystem model Agro-IBIS. Our research provides an estimate of the timespan and magnitude of transformations required to significantly improve water quality across the entire watershed while taking a systems approach in quantifying tradeoffs across a suite of ecosystem services.

Methods

2.1 Study Area

The Yahara watershed (Dane County, WI, USA) spans 1345 km² within south central Wisconsin, linking the chain of four Yahara lakes – Mendota, Monona, Waubesa, Kegonsa – together. The lakes are connected via the Yahara River, a tributary of the Rock River, which feeds into the Mississippi River, eventually reaching the Gulf of Mexico. Encompassing the Wisconsin state capital, Madison (43°6'N, 89°24'W), the Yahara watershed contains a population of 370,000 (U.S. Census Bureau 2017). As a watershed facing the challenges and stress of both an expanding urban footprint, increased population, and a large agricultural land base, the Yahara Watershed is representative of many urban watersheds around the agricultural Midwest United States. The Yahara watershed has gone through significant transitions and disturbances that have shaped the landscape, soils, and biogeochemistry of the region. Once covered by glaciers 11,000 years ago, the chain of lakes formed as the glaciers retreated with warming temperatures. Thus, the region has relatively little topographic relief and is comprised mostly of fertile Mollisol and Alfisol soils that are representative of the tallgrass prairie and oak savannah ecosystems that existed before European settlement in the early 1800s (Curtis 1959, Bockheim and Hartemink 2017). With European settlement for farming in the early to mid 1800s, the native ecosystems were transformed to row-crop agriculture, resulting in significant losses of soil C to tillage and disturbance (Kucharik et al. 2001). As agriculture intensified during the 19th and 20th centuries, more nutrients in the form of manure and inorganic fertilizers gradually built up in soils and have created a "legacy" nutrient problem that contributes to current water quality problems. Over the past 40 years, significant investments in improved management practices and other initiatives have failed to reduce the amount of P loading to Lake Mendota (Lathrop et al. 1998, Lathrop and Carpenter 2014, Gillon et al. 2016). Climate change has also been significant, with a trend towards warmer nights most prevalent in winter and spring, increased precipitation, and an increased frequency of heavy rainfall events (Gillon et al. 2016).

Today, agriculture in the Yahara watershed is a large economic driver and agricultural land accounts for 47% of the watershed, with dairy, corn, and soybean the dominant products (Expo 2014). Despite better management strategies, environmental challenges surrounding nutrient application are still present today. Within Dane County, the number of farms and land dedicated to cropland is shrinking – but overall farm size is growing, in addition to rises in total production (USDA 2018). Data for Dane County reflects a 50% increase in milk production per cow in the past 40 years (Bussler et al. 2017, USDA 2018). Cows producing more milk also generate more manure, and manure production per cow has increased by 20% since the 1980s (ASAE 2000, Gillon et al. 2016). Challenges surrounding nutrient management related to increasing manure production per cow are compounded by the simultaneous decrease in land available for manure application.

2.2 Agroecosystem modeling

Agro-IBIS (the Agroecosystem Integrated Biosphere Simulator), a process-based agroecosystem model, simulates the daily phenology and growth of natural (grasses and trees) and managed (corn, soybean, wheat) ecosystems and represents coupled carbon, water, energy exchange in the soil-plant-atmosphere system (Kucharik et al. 2000, Kucharik and Brye 2003). Agro-IBIS simulates complete nitrogen (N) and phosphorus (P) cycling for managed agroecosystems (Motew et al. 2017). The model was run on a regularly spaced terrestrial grid of 220m by 220m over the Yahara watershed using a 60 minute time-step to capture the rapid exchange of carbon, water, and energy between the land surface and atmosphere. The model requires inputs of gridded soil textural data, annual land cover and land use, annual nutrient management (manure and inorganic fertilizer), and daily weather (temperature, precipitation, specific humidity, solar radiation, and wind speed) which is interpolated to an hourly time-step using statistical and stochastic modeling (Kucharik et al. 2000). Agro-IBIS has been extensively calibrated and validated for the Yahara watershed (Motew et al. 2017, 2018) using a variety of biophysical and biogeochemical data. Most recently, the HYDRUS 1D soil physics model was incorporated into Agro-IBIS (Soylu et al. 2014), as well as the SurPhos model (Motew et al. 2017, 2018) to account for manure as well as the biogeochemical cycling of phosphorus and loss of dissolved and particulate phosphorus to runoff. For a more detailed description of the version of Agro-IBIS used in this study, please refer to Motew et al. (2017).

2.3 Scenarios of changing land cover, nutrient management, and climate

A series of scenarios of future watershed land management were created to understand whether replacement of row crops with perennial grass, reductions in nutrients (fertilizer and manure) applied to row crops, or a combination of both would lead to significant reductions in P yield and nitrate-N leaching given a changing climate. While the scenario development process builds on the original Yahara 2070 scenarios and modeling approach (Carpenter et al. 2015, Booth et al. 2016, Qiu et al. 2018), the important difference is that land cover and land management scenarios were created with the intent (goal) of understanding what specific changes would improve water quality and potentially reach a 50% reduction in P yield to the Yahara watershed. In contrast, the original Yahara 2070 scenarios developed four contrasting storylines of the future – including gradual biophysical and social changes – with no pre-conceived intent of improving water quality or any other ecosystem services from the onset.

Scenarios focused on three key drivers of change from 2014-2070: (1) increasing the proportion of cropland converted to perennial grass; (2) decreasing the amount of manure and fertilizer applied; and (3) long-term climate change. Land within the Yahara watershed classified as agricultural was the focus of scenarios of land cover and nutrient management change, with land classified as urban or natural ecosystems (grasses, forests) remaining unchanged. Land use and land cover changes transitioned traditional row-crops to perennial grass systems, containing a mix of C_3 (cool season) and C_4 (warm season) grass functional types. For all scenarios, traditional row-crops are defined as corn, soybean, small grains, and alfalfa.

The transitions from traditional row-crops to perennial grass were quantified by incremental changes (0% change baseline, and 10%, 25%, and 50% increases) in the proportion of row-crop area in the watershed replaced with a C_3 and C_4 grass mix. Transitions first focused on replacing row-crops that are currently classified as marginal using a continuum of suitability ratings for agricultural land. We argue that the land most likely to transition from row crops to perennial grass would be less than optimal for producing high crop yields based on challenging landscapes and soils. Identification of marginal land was based on the Land Capability Classification (LCC) created by the Natural Resources Conservation Service (NRCS) of the USDA (Helms 1991) and extracted from the USDA-SSURGO soils database (Soil Survey Staff, Natural Resources Conservation Service 2013). LCC categorizes land into a series of classes from I through VIII, based on considerations of landscape location, slope of field, and depth and texture of soil. Land in Class V and above suggests significant challenges to farming including erosion, excess wetness, rooting zone problems, and climate, and can be thought of as marginal. Due to the very small amount of land in the Yahara watershed planted in corn, soybeans, alfalfa, and small grains that is grown on marginal land, only Class I – the most productive cropland – was able to be completely excluded from conversion across all scenarios. A detailed description of our approach can be found in S1.

Annual rotation of row crops was simulated using a semi-random algorithm. Each grid cell containing a row crop was randomly reassigned a different row crop each year of simulation, while maintaining relative proportion of corn, soybean, alfalfa, and small grains on the landscape (Booth et al. 2016). To simulate the use of perennial grass as a crop for cellulosic biofuel in the future, 90% of aboveground biomass was harvested (Motew et al. 2017), and corresponding adjustments to both carbon and phosphorus budgets were modeled.

A second set of scenarios included a baseline (0% change) and incremental decreases – 10%, 25%, 50% - in the amount of manure and fertilizer applied to row crops, which directly impact the amount of P and N added to agroecosystems. Reductions in manure and fertilizer application rates were applied to land classified as corn, soybean, alfalfa, and small grains. No manure or fertilizer was applied to perennial grassland. Crop fertilizer application rates were estimated from University of Wisconsin extension recommendations (Laboski et al. 2012). Typical amounts of N and P fertilizer rates for corn grown in high yield potential soil are 194.1 and 39.1 kg ha^{-1}, respectively (Laboski et al. 2012). Actual fertilizer application rates may differ from the recommended rates; however, data on current farm level fertilizer applications are unavailable. Reductions in manure application rates were modeled assuming a corresponding decrease in watershed animal units on the landscape. Details regarding the recent development of an extensive database of manure application rates and spatial distribution across the Yahara watershed are provided by Booth et al. (2016). A third set of scenarios included a full-factorial approach, looking at all combinations of perennial cover and nutrient management.

Two scenarios of future climate to the year 2070 were taken from the core Yahara 2070 scenarios outlined in Booth et al. (2016), and are the same as those for the "Nested Watersheds" and "Connected Communities" scenarios. These two particular climate change scenarios were chosen as they present mild to moderate changes in comparison to the other Yahara 2070 scenarios. Additionally, the chosen scenarios both depict an increase in future air temperature – as past trends and climate models for this region have projected (Kucharik et al. 2010, Wisconsin Initiative on Climate Change Impacts 2011, Gillon et al. 2016) – but differ in annual average precipitation. A comparison allows us to better understand the role of future precipitation in altering ecosystem services. These climate scenarios were developed using downscaled General Circulation Model (GCM) projections and utilized a stochastic weather generator in order to depict daily weather and the occurrence of extreme weather events that matched the storylines in the Yahara 2070 scenarios. The climate scenarios used do not directly correspond to any individual long-term time series model results as part of CMIP3, but were subjectively pieced together using 20-year segments from GCMs that matched the general storyline and extreme weather events that are found within the Yahara 2070 scenarios. We also used a baseline climate (BC) for reference; this scenario uses cyclical, repeating historical weather data from 2004-2013 over the course of the entire simulation from 2014-2070. In comparison to the BC, the warmer drier climate (WDC) scenario includes an increase in annual average temperature of 4°C and a decrease in annual precipitation of 50 mm by 2070. The warmer wetter climate (WWC) scenario has an average annual temperature increase of 3.5°C, and about a 100 mm increase in annual average precipitation relative to the BC scenario, by 2070. For a detailed description of the climate scenarios and their development, please refer to Booth et al. (2016).

Collectively, a total of 48 different scenarios were simulated through the year 2070 with Agro-IBIS (Table 2). This includes a total of four possible land cover/land use scenarios, four potential nutrient reduction scenarios, and three climate scenarios. The land cover and nutrient management scenarios were simulated independently for each of the three climate scenarios. A full factorial approach was undertaken for the chosen incremental changes and climate scenarios. (See Table 2). For each year of the simulations (2014-2070), annual land cover and nutrient management databases were used as inputs to Agro-IBIS, along with the appropriate daily weather from the climate scenarios.

2.4 Ecosystem services assessment

We evaluated projected changes and trade-offs for several key ecosystem services. We focused on quantifying projected changes in surface water quality, groundwater quality, soil carbon content, crop yield, biomass yield, freshwater supply, and soil retention. A range of ecosystem services were selected in order to evaluate both provisioning and regulating services that have ecological and economic value. The assessment was performed using changes in watershed level averages. Temporal changes were examined using 9-yr moving averages. Refer to Table 3 for a list of indicators and metrics used.

2.5 Study Analysis

Quantified projections of water quality metrics are analyzed and discussed as watershed level averages. Emphasis is placed on evaluating projected ecosystem services in comparison to modeled historical quantities. In order to do so, we define the historical period to be the years 2004-2013, and focus on the last projected decade spanning 2061-2070 as a measure of future ecosystem services. The change in ecosystem services is often discussed as percent change – calculated as the difference between the average of the last projected decade and the average of the defined historical decade, divided by the average of the defined historical decade. Analysis and visualization were completed using Matlab v.2017a (Mathworks 2017).

Results

3.1 *Soil P losses from the landscape*

Baseline land management scenarios (e.g., no change in nutrient management or perennial grasses on the landscape) led to long-term P yield increases of 13%, 7%, and 24% under a BC, WDC, and WWC, respectively by the 2060s (Fig. 1). Even with 10% of row crops replaced with perennials, two climate scenarios (BC and WWC) still experienced small increases in P yield (Fig. 1a,b). A 25% conversion of cropland to perennial grass systems, absent of changes in nutrient management, resulted in a slight increase in P yield under a WWC, but under a WDC and BC– surface water quality improved by 5-10% (Fig. 1). With no reduction in nutrient applications, a conversion of 50% of row crop area to perennial grass systems led to P yield reductions of 11-22% across all three climate scenarios (Fig. 1).

In scenarios that kept current land cover consistent through 2070 (e.g., no increase in perennials), significant reductions in nutrient applications alone were needed to reduce P yield by the 2061-2070 time period. A 0-10% reduction in manure and fertilizer application rates was not enough to improve environmental condition; these nutrient management options led to increased P yields of 5-25% across all climate scenarios (Fig. 1). Similar to scenarios involving solely changes in perennial cover, a 25% reduction in manure and fertilizer application resulted in a small P yield increase (3%) under the WWC, but a decrease between 5% to 11% under the BC and WDC respectively. A 50% reduction in manure and fertilizer application resulted in P yield declines of 6-29% (Fig. 1).

Increasing the proportion of landscape dedicated to perennial grass with a corresponding decrease in manure and fertilizer application rates on the remaining row crops provided the greatest reduction in P yield. Across all three climate scenarios, a 35-50% P yield reduction was possible by the year 2070 (Fig.1). However, out of the 48 scenarios, only one scenario (50% perennials + 50% reduction in nutrient applications), under WDC, produced a P yield decrease of 50% or greater during last decade of projected results (2061-2070). Among all land cover and nutrient management changes, the largest magnitudes of P yield declines were consistently associated with the WDC scenario (Fig. 1c).

3.2. Sediment yield

In scenarios involving baseline conditions of land management (0% perennials, 0% reduction in manure and fertilizer application) sediment yield increased between 2-14% under a BC and WWC, but decreased by 5% under a WDC (Fig. 2). Keeping nutrient management constant, sediment yield decreased with increasing perennial cover, demonstrating increasing soil retention. A 10% transition of row crops to perennial grass led to sediment yield declines of 7% and 14% under BC and WDC respectively, and a 3% increase under a WWC (Fig. 2). A conversion of 25% of row crops to perennial grass was required for sediment yield to decrease significantly (10-25%) from current levels, across all climate scenarios (Fig. 2). A 50% conversion of row crops resulted in sediment yield declines of 27%, 34%, and 39% by the 2060s (Fig. 2).

When land cover remained at baseline conditions (0% transition to perennials), reduction in nutrient management alone was not sufficient for reducing sediment yield by 2070. For all incremental reductions in manure and fertilizer application (10%, 25%, 50%), sediment yield decreased by 5% under a WDC, increased by 2% under BC, and increased by 14% under a WWC (Fig. 2). Sediment yield did not vary with nutrient application reductions.

Similar to land cover change scenarios, a 10% transition to perennials paired with reduction in nutrient application (10%, 25%, 50%) did not reduce sediment yield across the BC and WWC (Fig. 2). Replacement of row-crops and simultaneous reduction in nutrient application of 25% produced sediment yield declines of 10%, 19%, and 25% for the WWC, BC, and WDC respectively (Fig. 2). By 2070, sediment yield was reduced between 27-39% (Fig. 2) when a 50% transition to perennial grass and a 50% reduction in nutrients occurred, but the majority of that was associated with transition to perennial grass. The WDC was associated with the greatest reduction in sediment yield across all land cover and nutrient management scenarios.

3.3. Soil drainage

Under current land cover and nutrient management conditions, soil drainage decreases ranged widely, declining by 3% under a BC, 22% under a WWC, and 50% under a WDC (Fig. 3). Across the three climates, drainage experienced the greatest reduction under baseline land cover scenarios, followed by 10%, 25%, and 50% perennial conversion scenarios – under no change in nutrient management. A 10% conversion to perennial grass led to declines between 3-49% (Fig. 3). A 25% transition of row crops to perennial grass produced a similar range in soil drainage reduction, 2-49% (Fig. 3). Under a BC, a 50% conversion to perennial grass increased soil drainage minimally (0.1%), and led to decreases of 47% and 20% for the WDC and WWC.

Holding land cover constant (0% perennials), soil drainage values varied little with manure and fertilizer application reduction. Under BC scenarios, a 0%, 10%, 25%, and 50% reduction in nutrient application led to soil drainage declines between 3.3-3.5% (Fig. 3a). For a WWC scenario, nutrient reductions between 0% and 50% resulted in soil drainage declines of about 22.0% (Fig. 3b). Scenarios under a WDC indicated a 49% decline in soil drainage across all reductions in nutrient application (Fig. 3c).

Scenarios incorporating both an increase in perennial land cover and a reduction in nutrient application led to similar results as scenarios solely focused on land cover. A 10% conversion of row crops to perennial grass paired with a reduction in manure and fertilizer led to declines in soil drainage of 3-50% (Fig. 3). A 25% transition to perennial cover combined with reductions in manure and fertilizer application resulted in a soil drainage reduction between 2-29% (Fig. 3). In scenarios involving a 50% transition to perennials and a 50% reduction in nutrients, soil drainage decreased by 47% and 20% for a WDC and WWC respectively, with no change under a BC scenario (Fig. 3). Across all land management transformations, climate was the largest driver, with variation in drainage only ranging 4% within scenarios utilizing the same climate.

3.4. Nitrate-N losses beneath the root zone

In the absence of any changes in land cover or nutrient management through 2070, watershed average nitrate-N leaching increased by 13% in the WWC scenario and 26% in the BC scenario (Fig. 4a,b). In the case of the WDC scenario, an 8% decrease in nitrate-N leaching occurred (Fig. 4c). When isolating the impacts of increasing perennial grass cover, nitrate-N leaching was reduced by 13% under a WDC when 10% of row crops were converted to a perennial grass system. Under a BC and WWC, a 10% conversion scenario still resulted in N leaching increases of 20% and 7% (Fig. 4a,b). When 25% of row-crops were converted to perennial grass, a WDC allowed for N leaching declines of 20%, but increases of 12% and 1% occurred under a BC and WWC. Under 50% conversion of row crops to perennial grass systems, N leaching was reduced by 29%, 12% and 1% for a WDC, WWC, and BC respectively (Fig. 4).

When holding current land cover constant through 2070, the contribution of nutrient management to NO_3-N leaching varied considerably depending on climate and magnitude of nutrient reductions. In the BC and WWC scenarios, increases in nitrate-N leaching still occurred with modest 10% application reductions (Fig. 4a,b). However, in both of the alternative future climates, 25% reductions in manure and fertilizer application led to an approximate 22% reduction in nitrate leaching (Fig. 4). A 50% reduction in manure and fertilizer application reduced nitrate-N leaching by 17-37%, depending on climate (Fig. 4).

Scenarios involving both land cover and nutrient management changes of 25% and 50% led to the most significant reductions in NO_3-N leaching, 34% and 53%, respectively, by 2070 (Fig. 4). Among all land cover and nutrient management changes, the largest magnitude of NO_3-N leaching declines were consistently associated with the WDC scenario (Fig. 4c).

3.5. Crop yield

Average crop yield over all cropping systems was significantly impacted by a changing climate in the absence of alterations to land cover or nutrient management. In these scenarios, crop yield increased from 7-33% (Fig. 5), with the most significant increase attributed to the WWC scenario. When holding nutrient application rates constant, a 10% replacement of row crops reduced average crop yield by 2% in the BC (Fig. 5a), but increased 15-23% by 2070 in the other two climate scenarios (Fig. 5b,c). With a conversion of 25% of row crop area to grasses, crop yield decreased by 16% and 1% under BC and WDC (Fig. 5a,c). Under a WWC, crop yield increased by 5% compared to the current average watershed yield (Fig. 5b). With a 50% transition of row crop area to perennial grass, watershed average crop yield decreased by 43%, 33%, and 29% under BC, WDC, and WWC conditions respectively (Fig. 5).

While holding watershed land cover constant through 2070, a reduction in nutrient application was associated with smaller crop yields in comparison to scenarios incorporating no reduction. However, yields increased by 20-26% relative to current values, even when manure and fertilizer application rates were reduced by 50% across the watershed (Fig. 5). A simultaneous decrease in manure and fertilizer application rates of 50% coupled with 50% replacement of row crops with grass led to results that were similar for just perennial grass increases (Fig. 5).

3.6. Biomass production from all vegetation

Holding land cover and nutrient management constant with current conditions, biomass of total vegetation increased between 26-38% across climates (Fig. 6). An increase in perennial cover, with no alterations to nutrient application, was associated with a reduction in biomass yield gain. A 10% transition of row crops to perennial grass led to biomass yield increases of 24% under BC, 34% under a WDC, and 36% under a WWC (Fig. 6). By 2070, a 25% conversion of row crops to perennial grass led to biomass yield increases ranging between 23-35% (Fig. 6). Scenarios incorporating a 50% transition to perennial grass experienced total biomass yield increases of 22-33% (Fig. 6).

When reductions in manure and fertilizer application occurred under no change in land cover (0% Perennial), scenarios indicate an increase in biomass ranging from 23-35% (Fig. 6). A 10%, 25%, and 50% reduction in nutrient application produced biomass yield increases ranging from 22-35% (Fig. 6). Reductions in nutrient management altered biomass yield only slightly across scenarios of the same climate. For manure and fertilizer reductions of 0-50%, increases in biomass only ranged 23-23.5% for BC, 34-35% for WWC, and 33-33.5% for WDC.

Considering both land cover and nutrient management alterations, increases ranged from 22 - 38% with climate, on average, serving as the main driver of change. Similar to crop yield, a WWC was associated with the greatest increase in biomass production (34-38%), followed by a WDC (33-34%), and then BC conditions (22-24%). A 50% conversion from row crops to perennial grass paired with a 50% decrease in nutrient application resulted in the smallest increase in biomass production across all three climates (22-33%).

3.7. Soil carbon

Under the BC with no changes in perennial grass cover or nutrient applications, soil C increased by 4.2% (Fig. 7a), whereas decreases of 1-5% occurred under a WDC and WWC (Fig. 7b,c). Incorporating incremental increases in perennial grasses with no change in nutrient application to row crops did not offset soil C declines associated with a warming future climate; a 50% transition from row crops to perennial grass resulted in a 2-5% soil C loss (Fig. 7), and represented the largest magnitude of loss. Although land cover changes were unable to alter the direction of change in soil carbon, a 10% to 25% transition to perennial grass with no reduction in nutrient application showed the smallest loss of soil carbon across all climate scenarios (Fig. 7b,c).

Maintaining current land cover (0% Perennials) and increasing the magnitude of manure and fertilizer reduction was associated with a smaller decline in soil C. Scenarios incorporating a 10% reduction in nutrient application led to soil C declines of 1.1% under WWC and 4.9% under WDC, and an increase of 4.1% under BC. A 25% reduction in nutrient application resulted in soil C changes ranging from -4.3% to +3.8% across the three climate scenarios (Fig. 7). When manure and fertilizer were reduced by 50%, soil C declined 4.9% under a WDC and 2.1% under a WWC, and increased 3.2% under BC conditions (Fig. 7).

When accounting for both an increase in perennial land cover and a reduction in nutrient application, projected soil C changed between -4.4% to +4.2%. Changes in land management at the 10% level resulted in soil C loss of 3.6% and 0.7% under WDC and WWC respectively, and soil C gains of 4.2% under the BC (Fig. 7). A 25% increase in perennial cover plus a simultaneous reduction in nutrient application lead to soil C changes ranging -3.7% to +3.7% (Fig. 7). Similar trends were evident at the 50% level (Fig. 7).

3.8 Temporal changes in surface water quality

Comparisons of change in P yield between the last modeled decade (2061-2070) and the baseline 10-year period (2004-2013) indicated a 50% reduction of P yield and nitrate leaching occurred in one of 48 scenarios. Under the WDC, a 50% transition of row crop to perennial grasses and a 50% reduction in manure and fertilizer application led to a 51% reduction in P yield and a 53% reduction in NO_3-N leaching by 2070 (Fig. 8, S1). However, decadal average changes in P yield indicate that the established 50% reduction goal for P yield may be met sooner. Under the BC scenario with 50% perennial transition and 50% reduction in nutrient application - decadal averages indicate the water quality goal could be achieved by 2050. Averaging annual watershed level P yield for the 2050's (2051-2060), P yield is projected to be 0.35 kg ha^{-1}, in comparison to the baseline average of 0.71 kg ha^{-1}, a 51% reduction. Considering the 2021-2030 period, average P yield was 0.36 kg ha^{-1}, representing a 48% reduction in P yield, and indicating that significant improvements in water quality could occur within 10 years of transformative land management change. Furthermore, a 30% reduction in P yield is possible by 2025 for scenarios under a BC and incorporating either perennial expansion or nutrient and manure reductions of 50%, or combined scenarios that have 25% change for each (Fig. 8a). However, for a WDC and WWC, a 30% reduction in P yield is not possible until 10 years later, during the year 2035, and is achieved under fewer land cover and nutrient management scenarios (Fig. 8b,c). Temporal analysis indicates that surface water quality changes fluctuate annually and per decade as a result of the influence of climate change and variability, and a P yield goal of 50% reduction could be attainable in 30 years under select scenarios.

4. **Discussion**

4.1 Water quality improvements linked to improved soil retention and increased nutrient capture

Model results suggested that both surface and groundwater quality improve in tandem with soil retention. Past research supports the correlation of nutrient runoff and leaching with sediment transport rates - or yield quantities (Marshall and Randhir 2008). Our results indicate that P yield, NO_3-N leaching, and sediment yield are reduced most in the WDC scenario, in comparison to similar changes that occurred under the BC and WWC. Under a WDC, a reduction in rainfall and a lower frequency of extreme rainfall events potentially decreased the likelihood of soil particle disturbance, or sediment yield (Carpenter 2008). In turn, this reduces the opportunity for stored P in the soil, or legacy P, to mobilize and enter waterways (Sharpley et al. 2013, Lathrop and Carpenter 2014, Motew et al. 2017). Additionally, decreased annual precipitation in the WDC climate would support reductions of dissolved P runoff, which constitutes 60% of annual total P (Motew et al. 2018) and leaching of NO_3-N that occur under current manure and fertilizer application practices. Increases in annual temperature could increase evapotranspiration, reducing soil moisture and drainage that carry NO_3-N past the root zone to groundwater (Long and Ort 2010, Hatfield et al. 2011). Alternatively, decreased precipitation amounts and increased temperature under the WDC may increase plant water stress (Lobell and Gourdji 2012). Under conditions of water-stress, reduced uptake of nutrients increase the pool of available N and P susceptible to leaching and surface runoff. Furthermore, warmer soil temperatures can stimulate microbial activity – as simulated in Agro-IBIS (Kucharik et al. 2000)– leading to increased N mineralization (Ramankutty et al. 2002). Increased N mineralization can lead to reduced N stress and greater biomass production, or could potentially exit the system at nitrate during heavy precipitation events. However, simulated ET values for both the WDC and WWC indicate a 10% increase in ET by 2070, in comparison to baseline ET values. The increase in ET values suggest rising temperatures can reduce nutrient loss with increased photosynthesis, despite confounding factors such as increased N mineralization and plant water stress.

The greatest reductions in P yield and NO_3-N leaching occurred when the WDC was paired with a 50% transition from row-crops to perennial grass, in addition to a simultaneous 50% reduction in nutrient applications to row-crops. Previous research supports these findings, as perennial grass increases retention of P, N, and sediment through soil building and conservation mechanisms that reduce erosion (Zhang et al. 2010, Jackson 2017). Extensive root systems and year-long land cover associated with perennial grass systems promote physical soil stabilization through soil aggregation, and increase soil nutrient and water-holding capacity through infiltration and absorption (Asbjornsen et al. 2014). As our study focused on excluding transitioning land classified as optimal to perennial systems, results may suggest greater improvements in soil retention than can typically be achieved when converting highly-productive land to perennial grasses.

4.2 Ecosystem service tradeoffs will challenge future policy decision-making

Land managers and policy makers are faced with the challenge of managing for competing goals in addition to evaluating tradeoffs that arise, even when working towards a common goal. As a result, it is critical we evaluate not only water quality changes across scenarios, but the corresponding tradeoffs expressed among other ecosystem services.

Improvements in water quality were most often associated with a decline in freshwater supply, as represented by simulated drainage past the root zone. Drainage reduction varied widely, as climate change was the most significant driver of future trends (Fig. 9). The WDC had the largest increase in temperature and a simultaneous decline in annual precipitation; together these increased ET and decreased water storage in the system. However, because drainage also decreased under the wetter WWC scenario compared to the BC, model results highlight the important role that growing season expansion in mid-latitudes (Long and Ort 2010) has, elevating total photosynthetic uptake and increasing total net primary production (NPP) and ET, which can act to reduce soil drainage (Qiu *et al.* 2018). This can potentially exert a strong influence on freshwater supply at the expense of increased NPP.

Increases in atmospheric CO_2 concentrations in future climate scenarios likely influenced drainage changes, but to a lesser extent. Under a WWC, atmospheric CO_2 reached concentrations above 600 ppm during the last decade of mode scenarios (2061-2070), and levels of 625 ppm were reached by 2070 under a WDC. In contrast, simulated BC conditions had an average CO_2 concentration of 373 ppm (Table 1). Increased atmospheric CO_2 concentrations are associated with decreases in stomatal conductance and transpiration, increased rates of photosynthesis and aboveground growth, and improved water-use-efficiency (Rosenzweig and Hillel 1998, Drake et al. 2011). However, past research has highlighted differences in magnitude of response between C3 and C4 species due to their different photosynthetic pathways (Ainsworth and Long 2005, Leakey et al. 2009). Stomatal conductance decreases by a similar degree among both C3 and C4 plants (Ainsworth and Long 2005), but rates of photosynthesis were observed to be three times higher in C3 plants than C4 plants (Ainsworth and Long 2005), and Agro-IBIS has been calibrated to capture these responses using the most recent data from FACE experiments at Illinois for crops (Twine et al. 2013). Our results indicate that scenarios under the WDC and WWC experienced greater decreases in drainage in comparison to the BC (Fig. 9). Our findings highlight the potential for warmer atmospheric temperatures to reduce water-use-efficiency benefits associated with increased CO_2 concentrations, or alternatively, point to increased water-use as a result of greater productivity over a longer growing season.

Transitions to perennial grass landscapes were associated with smaller declines in drainage in a changing climate - possibly indicating a synergy associated with managing land cover for improved water quality and increased freshwater supply (Twine et al. 2004). Previous research has demonstrated higher annual evapotranspiration in perennial grass systems when compared to annual row-crops, leading to a reduction in water yield for the system (Berndes 2002, Schilling et al. 2008). Additionally, past modeling research for the broader Midwest demonstrated larger amounts of water usage in perennial grass systems in comparison to corn systems (VanLoocke et al. 2012). However, past findings have not reached a consensus, with other studies demonstrating no additional increase in water usage in perennial grass systems under a temperate humid climate (Hamilton et al. 2015).

Food production was adversely impacted as a result of managing land specifically for a goal of water quality improvement. Trade-offs were most significant for scenarios involving a 50% conversion of row crops to perennial grass, which reduced the amount of land available for crop production (Fig. 9). However, the elongated growing season and CO_2 fertilization effect associated with a changing climate boosted crop productivity to partially offset some reductions in crop area (Fig. 9b,c). Increases in temperature under the WWC and WDC impacted crops both phenologically and physiologically by expanding the growing season and increasing rates of photosynthesis (Hatfield et al. 2011, Sacks and Kucharik 2011). The elongated growing season provides additional time for crop and total biomass accumulation. However, warmer nights increase plant respiration during dark respiration, resulting in C loss (Ryan 1991, Kucharik et al. 2010). By 2070, scenarios under WWC and WDC reached atmospheric CO_2 concentrations of 620 ppm and 645 ppm (Table 2), producing a fertilization effect by increasing the rate of photosynthesis. Greatest increases in photosynthesis rates are expected in C3 plants such as soybean and cool season perennial grasses (Hatfield et al. 2011, Lobell and Gourdji 2012). However, past studies demonstrate reduced CO_2 fertilization effects under non-enclosed conditions, highlighting the possibility that crop yield gains could be lower than previously thought (Long 2006).

In the absence of land cover changes, crop yield and total vegetation biomass increased even under nutrient application reductions of up to 50% (Fig. 9). Biogeochemical processes do not remain static across time, even under consistent climatic and land management conditions leading modeled concentrations of soil NO_3 to increase by 20% under these scenarios. Higher concentrations of soil NO_3 signify an increase in available N for mineralization, supporting the observed increase in crop yield (Bundy 2005, Laboski et al. 2012, Van Meter et al. 2018). Some of this increase is supported by increases in soil C in the baseline climate scenario.

Among all climates, a 50% reduction in nutrient application accounted for marginal declines in crop yield compared to baseline scenarios (Fig. 5). Under all climate scenarios, a 50% reduction in manure and fertilizer resulted in modest crop yield gains (Fig. 9), and simultaneously reduced P yield by 18-29% (Fig. 1). While reductions in nutrient application limited increases in crop yield, the trade-offs may be less severe than anticipated (Varvel et al. 2008) allowing for an increase in yield relative to current conditions (Fig. 9). Biomass values followed similar trends to crop yield, with minimal tradeoffs associated with a reduction in manure and fertilizer as total biomass declined slightly (1-3%).

Trade-offs of improved water quality with soil C were minimal as little change in soil C occurred across all 48 scenarios through 2070. While there was little variation in soil C content, all scenarios incorporating a changing climate showed soil C losses when compared to contemporary values. Agro-IBIS simulates microbial biomass as a function of available substrate (Verberne et al. 1990), and microbial activity is simulated as dependent on hourly soil temperatures based on an Arrhenius function (Lloyd and Taylor 1994) and water-filled pore space (WFPS) (Linn and Doran 1984, Kucharik et al. 2000). The decomposition of carbon and litter is largely dependent in Agro-IBIS through microbial activity (Kucharik et al. 2000), which reaches a peak value at 60% water-filled pore space (Linn and Doran 1984).

Under the WDC, increased temperatures could increase soil microbial activity, and as a result increase decomposition and respiration rates - releasing C into the atmosphere (Davidson and Janssens 2006). Similarly, under the WWC, increases in precipitation could increase soil moisture content - promoting higher rates of soil respiration (Hursh et al. 2016). Alternatively, as the WWC is associated with greater increases in crop yield, increased precipitation may also be associated with increased NPP, which would contribute to returning C to the soil through litterfall. Depending on the amount of WFPS, C sequestration could then be enhanced. Our results depict the greatest amount of soil C lost under a WDC, indicating that increases in air and soil temperature likely increased microbial activity and soil respiration, overpowering potential C sequestration associated with increased NPP and reduced decomposition rates associated with a decrease in precipitation and lower WFPS.

Land cover and land management changes that could promote increased C uptake and soil C sequestration (e.g., longer growing seasons, CO_2 fertilization) are overwhelmed by the influence of climate (Bellamy et al. 2005), resulting in a net loss of soil C in all scenarios under simulated climate change. Model results are consistent with findings of Bellamy et al. 2005, which indicated that across England and Wales C was lost regardless of land management. Slight reductions in soil C, even under perennial grass systems are supported by ongoing long-term research (Sanford et al. 2012) and indicate that the soil of the Yahara Watershed may not support increased C sequestration despite best management practices. Additionally, the composition of perennial grass systems may influence C sequestration potential. Perennial grass systems containing a higher composition of C4 to C3 grasses may store more C (Spiesman et al. 2017). Our scenarios did not alter the ratio of C4 to C3 perennial grass which may have limited the potential for soil C sequestration.

4.3 Pathways for the greatest water quality improvement likely require transformative changes in farming and patience

Achievement of a 50% reduction in P yield – a watershed goal since the 1980s – and a comparable reduction in nitrate leaching only occurred in one scenario, specifically one incorporating both a 50% transition from row crops to perennial cover and a simultaneous 50% reduction in manure and fertilizer application. Although smaller reductions in nutrient losses were found in other scenarios, these still showed promise for improving soil and water quality over current conditions. Under BC, three key land use and nutrient management changes result in P yield reductions close to 20% (19-23%) by 2070: (1) a 50% reduction in manure and fertilizer application to row crops, (2) a transition of 25% of row crops to perennial grass paired with a 25% reduction in manure and fertilizer application rates, (3) and a conversion of 50% of row crops to perennial grass. Similar trends in P yield appeared across scenarios that considered two different climate change pathways. Under the WWC and WDC scenarios, P yield reductions were close to 15% (11-18%) and 25% (22-29%), respectively, and were achieved through the three aforementioned strategies. P yield varied across climates is a result of the biogeochemical and biophysical processes associated with differences in temperature, precipitation, and atmospheric CO_2 concentration. Based on our results, surface water quality is best improved under conditions supporting a warmer atmospheric temperature, increased atmospheric CO_2 concentration, and reduced precipitation amounts. Our results demonstrate a range of land cover and nutrient management strategies that elicit similar results, and will add to the growing body of literature supplying tools to aid land managers and policy makers in decision making (Sanford and Panuska 2015, Tayyebi et al. 2016a, 2016b). Among the above strategies and scenarios, the single management practice of reducing manure and fertilizer application consistently produced the largest reduction in P yield. For land managers with limited options and specific surface water quality goals, our findings indicate a possible path towards mitigation.

Groundwater quality improved under a range of management strategies. However, there was greater variability in nitrate leaching reductions in comparison to P yield reductions. As a result, projected changes in NO_3-N leaching can be used to determine management solutions that meet desired reduction thresholds under greater weather variability. To achieve an approximate NO_3-N leaching reduction of 35% by 2070, management changes under a WDC requires: (1) a 50% reduction in manure and fertilizer application, or (2) a 25% transition to perennial systems paired with a 25% reduction in nutrient application. Alternatively, under a BC scenario, both a 50% transition to perennial grass and a 50% reduction in nutrient application must be implemented. For a 15% reduction in NO_3-N leaching by 2070 under the WDC scenario, a 10% reduction in nutrient application is required, while the WWC scenario required that both a 25% perennial transition and 25% nutrient application reduction were needed. Alternatively, under BC condition, a 50% reduction in nutrient application is required to reach a 15% reduction in nitrate leaching. Agro-IBIS simulates nitrogen mineralization, nitrification, and denitrification, and has been used to evaluate nitrate export across the Midwest (Donner and Kucharik 2003). In addition to soil texture, the rate of nitrogen mineralization is simulated in response to amount of litterfall and fine root turnover (Kucharik et al. 2000), and accounts for changes in C:N allocation and N-fixation by legumes (Kucharik and Brye 2003). These varied results illustrate the complexities and feedbacks within the coupled carbon-water-nitrogen cycles, whereby changes in precipitation and plant growth can impact both the availability of N to leach out of the system as well as its rate of movement and cycling within the system. Crop demand for N is based on physiological requirements determined by tissue N and biomass yield, both of which are influenced by climate and land management (Cassman et al. 2002).

Increased extreme rainfall events, as occurred under the WWC, have been demonstrated to increase N loss (Maharjan et al. 2016) and may explain our findings. Alternatively, in an environment of water-stress, such as the WDC, plant nutrient uptake may be reduced (Ferguson et al. 1991), adding to the pool of available N for leaching (Oktem 2008). Additionally, differences in crop physiological requirements exist between C3 and C4 crops; C4 crops have greater physiological nitrogen efficiency due to their photosynthetic pathway (Cassman et al. 2002).

Despite diverse pathways offering a means to achieve water quality improvements, both a 50% reduction in P yield and a 50% reduction in N leaching are still only achieved under one scenario. Surface water and groundwater quality findings emphasize the role of legacy P (Jarvie et al. 2013, Chen et al. 2015, Motew et al. 2017), increased total precipitation and extreme rainfall events (Carpenter et al. 2017), and continued land nutrient inputs in hindering water quality improvements. However, if the climate were to remain steady, significant improvements in water quality could occur in the next 15 years (Fig. 8).

4.4 Limitations of study design

Agro-IBIS, like all models, serves as a representation of the complex environment we live in. As a result, Agro-IBIS simplifies or excludes certain processes that are associated with agroecosystems. Specific limitations that may restrict the scope of our results and analysis above include the simulation of microbial activity. Agro-IBIS is not designed to distinguish microbial community composition, but published research provides evidence for a relationship between specific microbial community composition and microbial phylogeny, such as nitrification (Balser and Firestone 2005). Agro-IBIS also does not simulate mycorrhizae, despite the critical role mycorrhizae play in soil biogeochemistry (Treseder and Allen 2000). Crop yield and biomass yield are modeled as direct functions of climate and weather, excluding the role of pests, disease, and weeds in altering yields. As the climate changes, it is likely insects will develop new life cycle spans and geographic ranges, possibly hindering crop production through range expansion, higher abundance, and increased crop vulnerability (Doll and Baranski 2011, Hatfield et al. 2011, IPCC 2014). Additionally, weeds are likely to increase in biomass under conditions of increased atmospheric CO_2 and elongated growing seasons, promoting increased competition of resources between weeds and crops (Wisconsin Initiative on Climate Change Impacts 2011, Zhao et al. 2017).

5. Conclusion

In an effort to improve water quality considering increasing demands for food, fuel, and fiber production under a changing climate, it is essential that we understand the biophysical and biogeochemical cycling that occur in response to changes in land cover and nutrient application. With a focus on the nexus of nutrient management, land cover, and climate change, our scenarios implemented immediate changes in land management in order to quantify and project changes in water quality to the year 2070. Our research demonstrates that water quality improvements are possible, but require transformative change. Additionally, these changes must be implemented immediately to combat the impact of legacy N and P in the land-water system. Only under the most extreme scenarios, a transition of 50% of row-crop agriculture to perennial grass, and a simultaneous reduction in manure and fertilizer of 50%, were water quality improvements of 50% achieved. Furthermore, a sole focus on water quality improvements resulted in tradeoffs with other key ecosystem services, some of which provide an income stream to producers. Improvements in surface water quality, groundwater quality and soil retention occurred simultaneously, but at a cost to freshwater supply, crop yield, total plant biomass, and soil carbon.

Our findings illustrate how climate change can act to enhance or diminish ecosystem services. The WDC promoted the largest improvements in surface and ground-water quality and soil retention. The WWC supported the largest increases in crop and biomass production and the BC results showed soil carbon and freshwater supply to be maximized. Our research emphasizes the need to reevaluate today's land management practices in order to alter our current trajectory – which projects continuing water quality degradation if no action is taken.

Figures and Tables

Time	Warmer Wetter Climate (WWC) Tmax (°C)	Tmin(°C)	Precip (mm)	CO_2 (ppm)	Warmer Drier Climate (WDC) Tmax (°C)	Tmin(°C)	Precip (mm)	CO_2(ppm)	Baseline Climate (BC) Tmax (°C)	Tmin(°C)	Precip (mm)	CO_2 (ppm)
2014-2020	16.07	5.01	899.97	412.24	16.43	5.47	1029.68	413.97	13.82	3.19	963.93	372.09
2021-2030	15.86	4.77	1075.21	439.35	16.70	5.67	1055.71	443.42	14.06	3.33	934.56	372.72
2031-2040	16.95	5.82	985.22	477.08	16.82	6.20	1004.57	484.29	14.06	3.33	934.56	372.72
2041-2050	17.08	5.87	933.23	517.40	17.72	6.74	1011.95	528.21	14.06	3.33	934.56	372.72
2051-2060	17.47	6.59	1089.37	561.59	18.24	7.09	795.14	576.54	14.06	3.33	934.56	372.72
2061-2070	17.59	6.65	962.99	605.36	18.16	6.97	845.87	624.88	14.06	3.33	934.56	372.72

Table 1. Annual weather data for all three climates, averaged across each decade. Weather data includes average maximum temperature, average minimum temperature, average annual precipitation, and average atmospheric CO_2 concentration.

Ecosystem Service	Indicator	Units
Surface Water Quality	Phosphorus Yield: the amount of phosphorus leaving the landscape through runoff, in both particulate and dissolved form	[kg ha^{-1}]
Groundwater Quality	Nitrate Leaching: N loss below the plant rooting zone, indicates the amount of N entering groundwater	[kg ha^{-1}]
Soil Retention	Measured as the inverse of sediment yield, as indicated by the amount of sediment present in runoff	[tons km^{-2}]
Freshwater Supply	Estimate of groundwater recharge	[mm]
Crop Yield	Annual Yield of traditional row crops (corn, soy beans, small grains, alfalfa)	[bu ac^{-1}]
Total Biomass	Total dry weight of all plant functional types (both natural and managed).	[kg m^{-2}]
Soil Carbon	Soil Carbon: estimates the amount of Carbon contained in the first meter of soil	[kg m^{-3}]

Table 2. Indicators and metrics used to assess seven ecosystem services based on watershed level

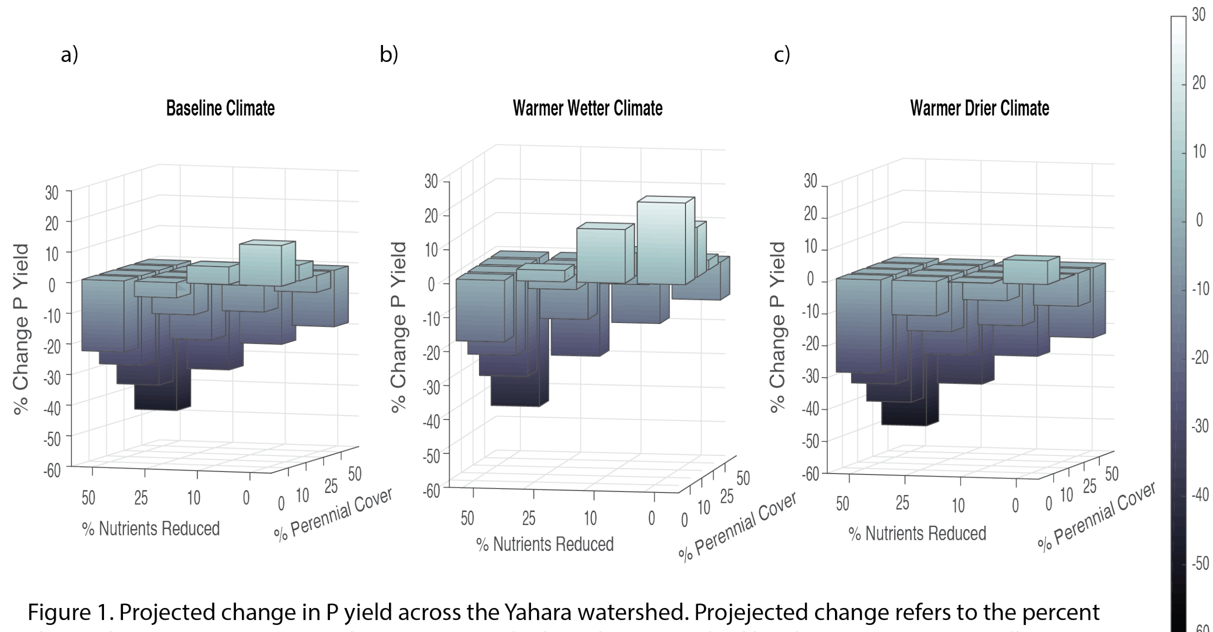

Figure 1. Projected change in P yield across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 1a illustrates % Change in P yield under BC, Figure 1b includes scenarios of a WWC, and Figure 1c illustrates changes under WDC.

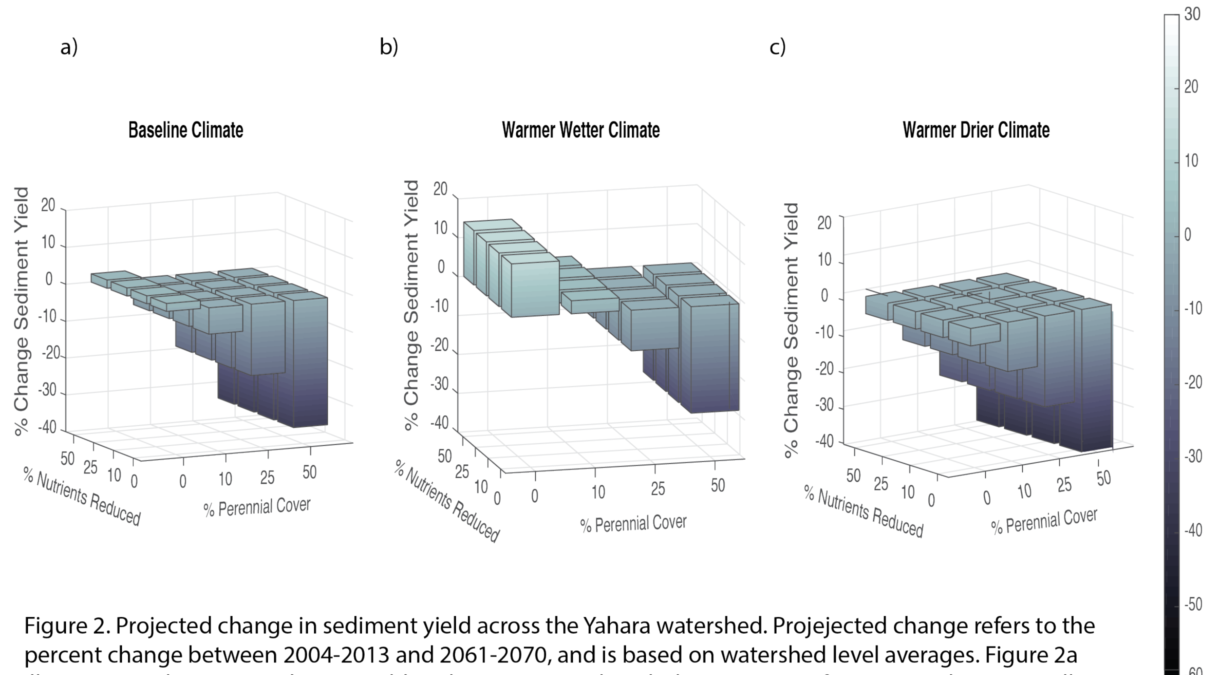

Figure 2. Projected change in sediment yield across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 2a illustrates % Change in sediment yield under BC, Figure 2b includes scenarios of a WWC, and Figure 2c illustrates changes under WDC.

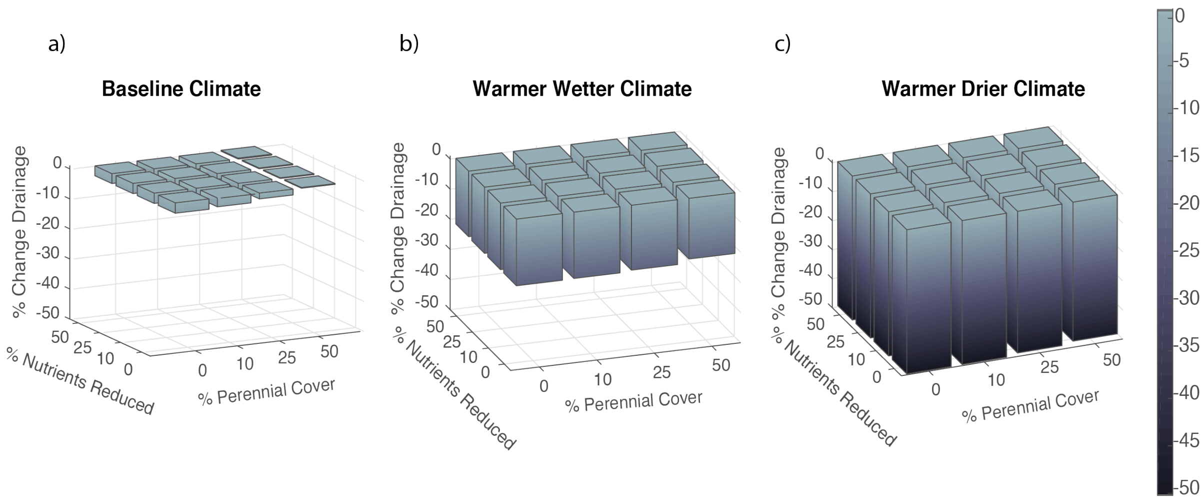

Figure 3. Projected change in drainage across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 3a illustrates % Change in drainage under BC, Figure 3b includes scenarios of a WWC, and Figure 3c illustrates changes under WDC.

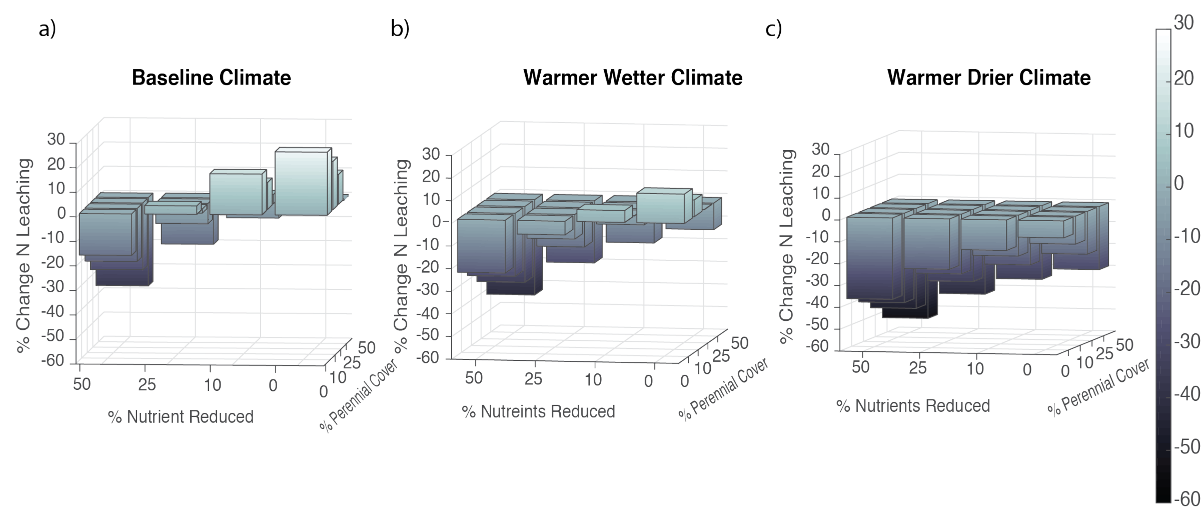

Figure 4. Projected change in nitrate across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 4a illustrates % Change in nitrate leaching under BC, Figure 4b includes scenarios of a WWC, and Figure 4c illustrates changes under WDC.

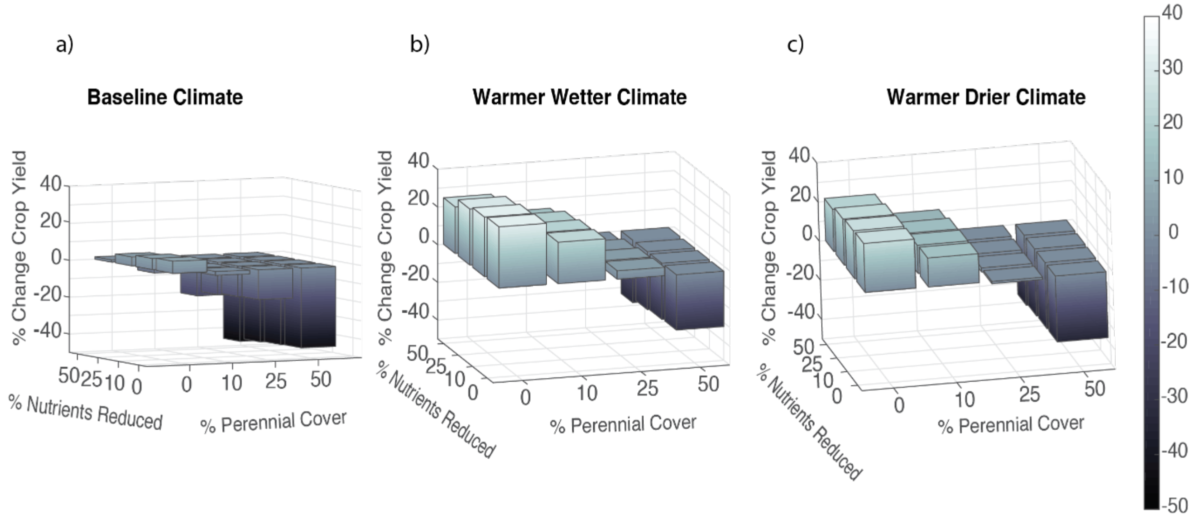

Figure 5. Projected change in crop yield across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 5a illustrates % Change in crop yield under BC, Figure 5b includes scenarios of a WWC, and Figure 5c illustrates changes under WDC.

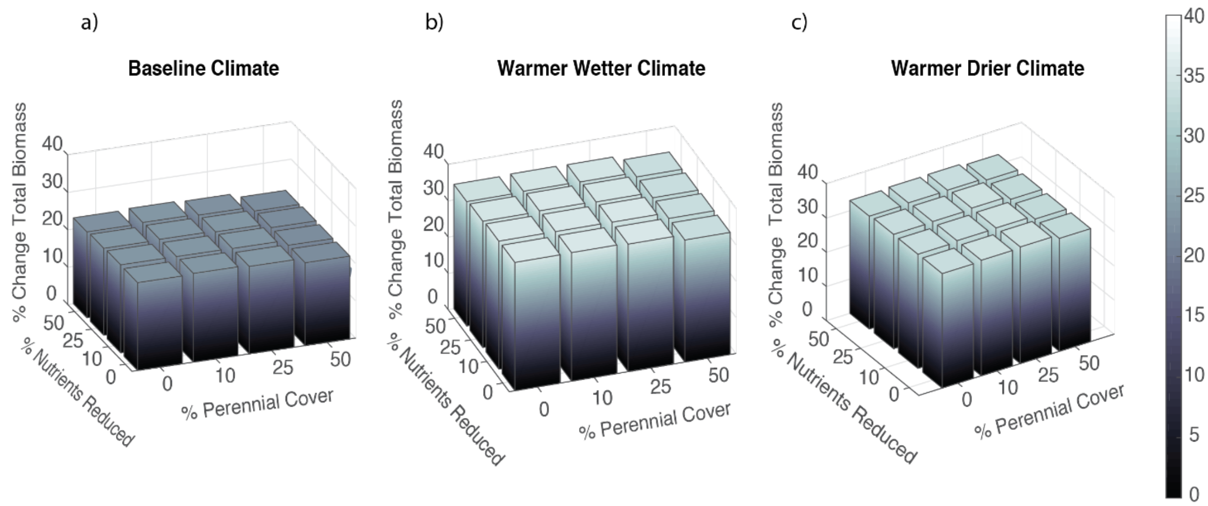

Figure 6. Projected change in total biomass across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 6a illustrates % Change in total biomass under BC, Figure 6b includes scenarios of a WWC, and Figure 6c illustrates changes under WDC.

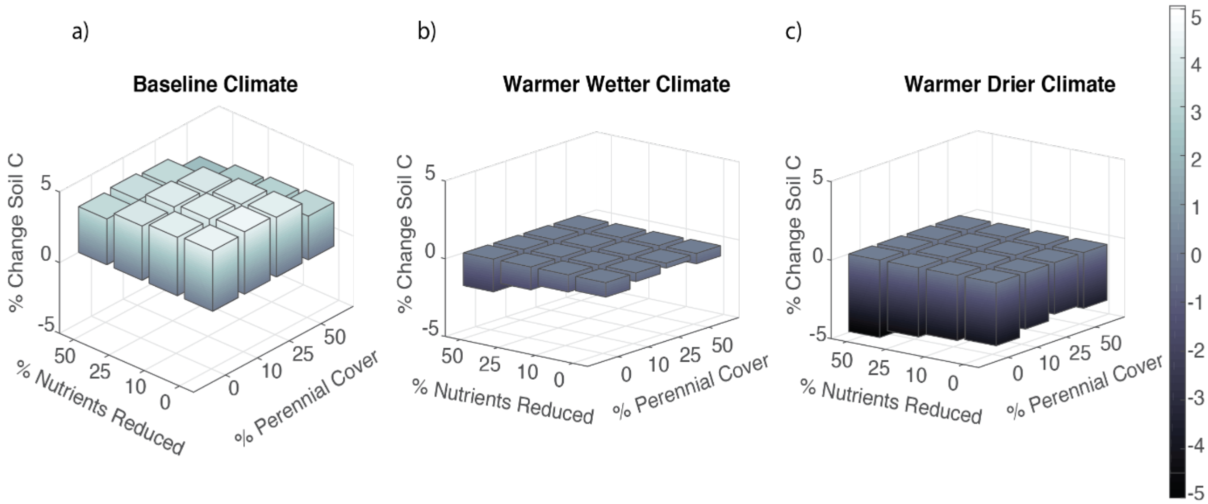

Figure 7. Projected change in soil carbon across the Yahara watershed. Projejected change refers to the percent change between 2004-2013 and 2061-2070, and is based on watershed level averages. Figure 7a illustrates % Change in soil carbon under BC, Figure 7b includes scenarios of a WWC, and Figure 7c illustrates changes under WDC.

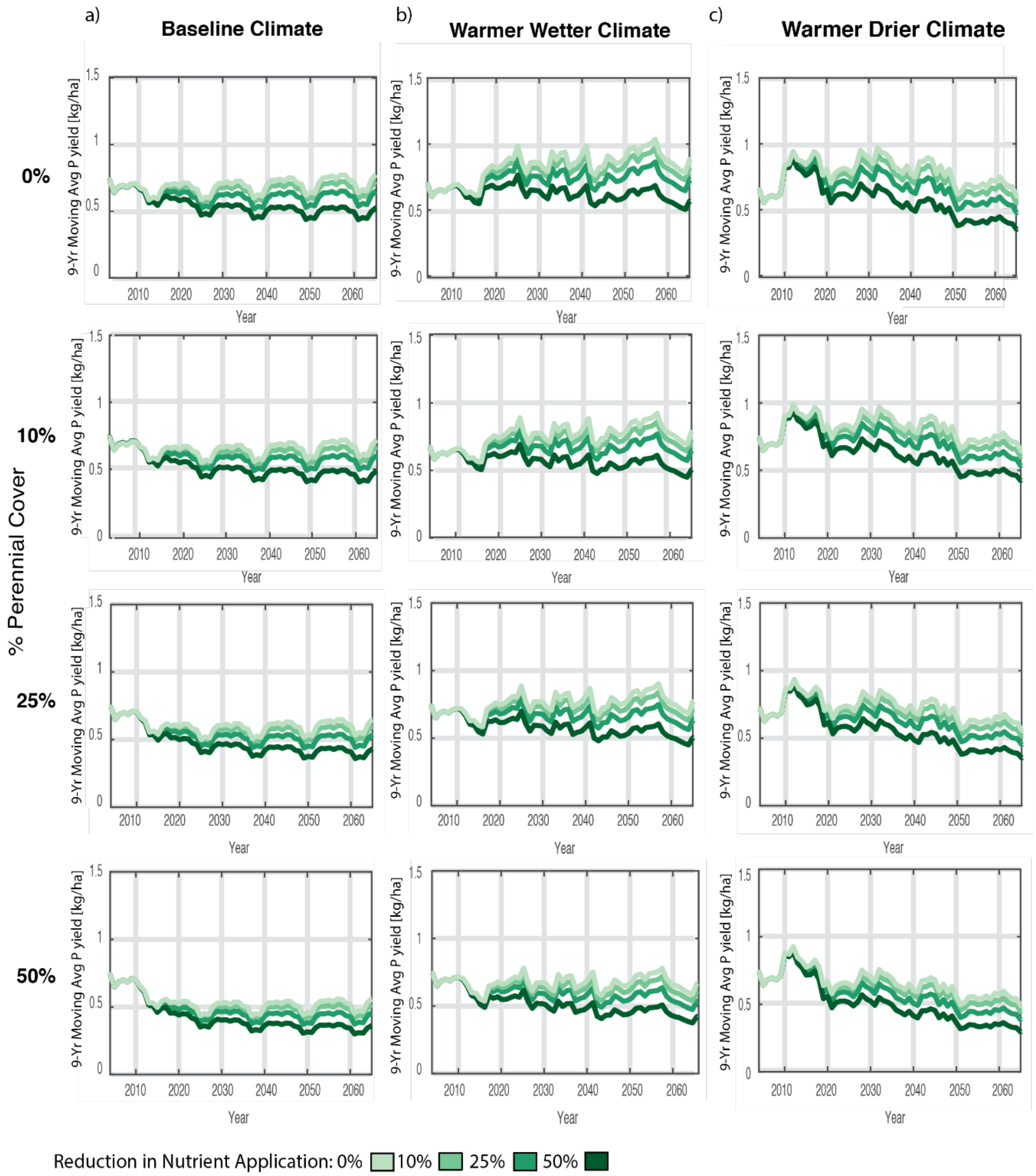

Figure 8. 9-Yr Moving Average of projected P yield [kg/ha] from 2004 to 2070. Climate is indicated by column and letter (a for BC, b for WWC and c for WDC), and perennial cover is indicated by row. Line color indicates

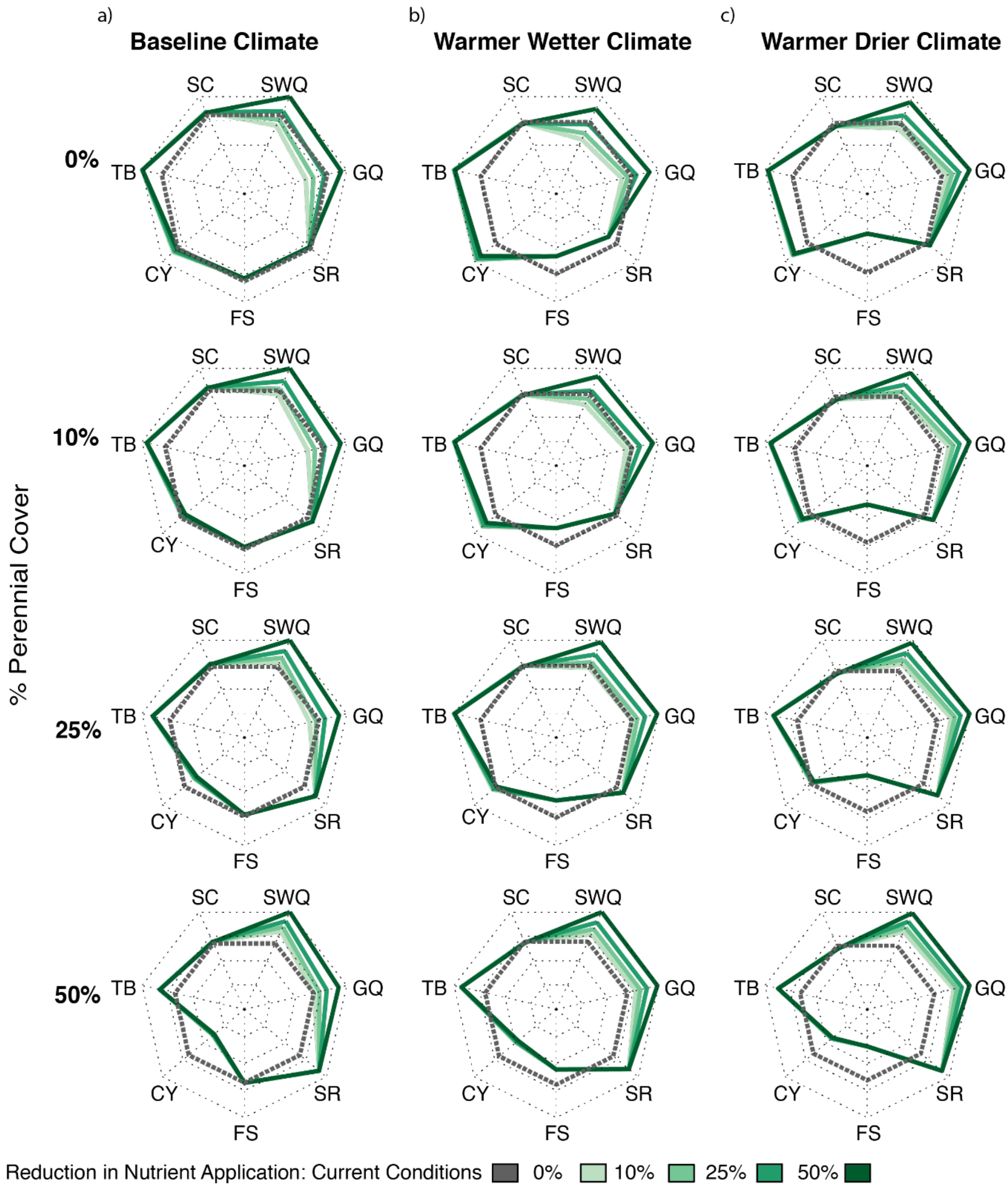

Figure 9. Tradeoffs of key ecosystem services expressed as propotion of change based on the averages of (2061-2070)/(2004-2013). The dotted gray line indicates current conditions (2004-2013), and any line expanding past indicates an improvemnt of labeled service. Abbreviations used: SWQ = Surface Water Quality, GQ = Groundwater Quality, SR = Soil Retention, FS = Freshwater Supply, CY = Crop Yield, TB = Total Biomass, SC = Soil Carbon

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Supplemental Information

Appendix A

8:00 a.m.	Introduction	Dr. Bill Barker (Associate Dean for Research)
8:15 a.m.	Opening Keynote	Drs. Chris Kucharik and Claudio Gratton (UW-Madison Agronomy, Entomology)
8:45 a.m.	Remote Sensing and Yield Forecasting	Dr. Mark Friedl (Boston University, Chief Science Officer/Co-founder Tellus Labs)
9:45 a.m.	Informatics, Data Sharing, Infrastructure	Dr. Ankur Desai (UW-Madison Atmospheric and Oceanic Sciences)
10:10 a.m.	Break	
10:25 a.m.	Algorithms and Machine Learning	Dr. Rebecca Willett (UW-Madison, Electrical and Computer Engineering and Wisconsin Institute for Discovery)
10:50 a.m.	Applications of Big Data in Agribusiness	Dr. Ravi Sripada (Senior Scientist, The Climate Corporation)

11:50 a.m. – 1 p.m. Lunch (Varsity Hall I & II)

Marquee Theater

1:00 p.m.	Academic Initiatives	Dr. Alfred Hero (University of Michigan, Michigan Institute for Data Science, Electrical Engineering and Computer Science)
2:00 p.m.	UW Big Data MS Program	Dr. Alex Smith (University of Wisconsin-Eau Claire)
2:25 p.m.	Enhanced Crop Breeding	Dr. Natalia de Leon (UW-Madison Agronomy)
2:50 pm.	Break	
3:05 p.m.	Human Behavior and Prediction vs Causation with Big Data	Dr. Paul Mitchell (UW-Madison Agricultural and Applied Economics)
3:30 p.m.	Policy and National Research Directions	Dr. Parag Chitnis (Deputy Director NIFA/USDA)
4:30 p.m.	Panel and Open Discussion	Symposium speakers and Gary Gabriel (Oracle-Big Data Industry Architect)

Table S1. List of speakers who presented at the symposium *Big Data and Ecoinformatics in Agricultural Research* in the spring of 2017.

Appendix B

Marginal Land Classification

Very few row-crops in the Yahara watershed are planted on Class V-VIII land. As a result, we needed to expand our transformations to include Classes IV – VIII, which still only accounted for 5% of row cropland. In order to reach our 10%, 25% and 50% replacement scenarios, we used a three-tiered approach. First, replacing all marginal cropland (Classes IV-VIII) with perennial grass – resulting in a transition of 5% of row crops. Second, we included a proportion of Class III (22% of all watershed row crops), using a randomized replacement of grid cells to reach the incremental transitions of 10%, and 25%. Last, we included Class II land (70% of watershed row crops) and randomized selection of grid cells to reach a 50% replacement of row crops with grasses. For all scenarios involving a 50% transition of cropland to perennial grasses, only Class I – the most productive cropland – was able to be completely excluded from conversion.

Scenario Number	**% Perennial**	**% N + P Reduced**	**Climate**
1	0	0	BC
2	0	0	WWC
3	0	0	WDC
4	0	10	BC
5	0	10	WWC
6	0	10	WDC
7	0	25	BC
8	0	25	WWC
9	0	25	WDC
10	0	50	BC
11	0	50	WWC
12	0	50	WDC
13	10	0	BC
14	10	0	WWC
15	10	0	WDC
16	10	10	BC
17	10	10	WWC
18	10	10	WDC
19	10	25	BC
20	10	25	WWC
21	10	25	WDC
22	10	50	BC
23	10	50	WWC
24	10	50	WDC

25	25	0	BC
26	25	0	WWC
27	25	0	WDC
28	25	10	BC
29	25	10	WWC
30	25	10	WDC
31	25	25	BC
32	25	25	WWC
33	25	25	WDC
34	25	50	BC
35	25	50	WWC
36	25	50	WDC
37	50	0	BC
38	50	0	WWC
39	50	0	WDC
40	50	10	BC
41	50	10	WWC
42	50	10	WDC
43	50	25	BC
44	50	25	WWC
45	50	25	WDC
46	50	50	BC
47	50	50	WWC
48	50	50	WDC

Table S2. List of all scenarios created, categorized based on % perennial cover (0%, 10%, 25%, 50%), % reduction in N + P (0%, 10%, 25%, 50%), and climate scenario (BC, WWC, WDC). Climate scenario acronyms: BC = baseline climate, WWC = warmer wetter climate, WDC = warmer drier climate

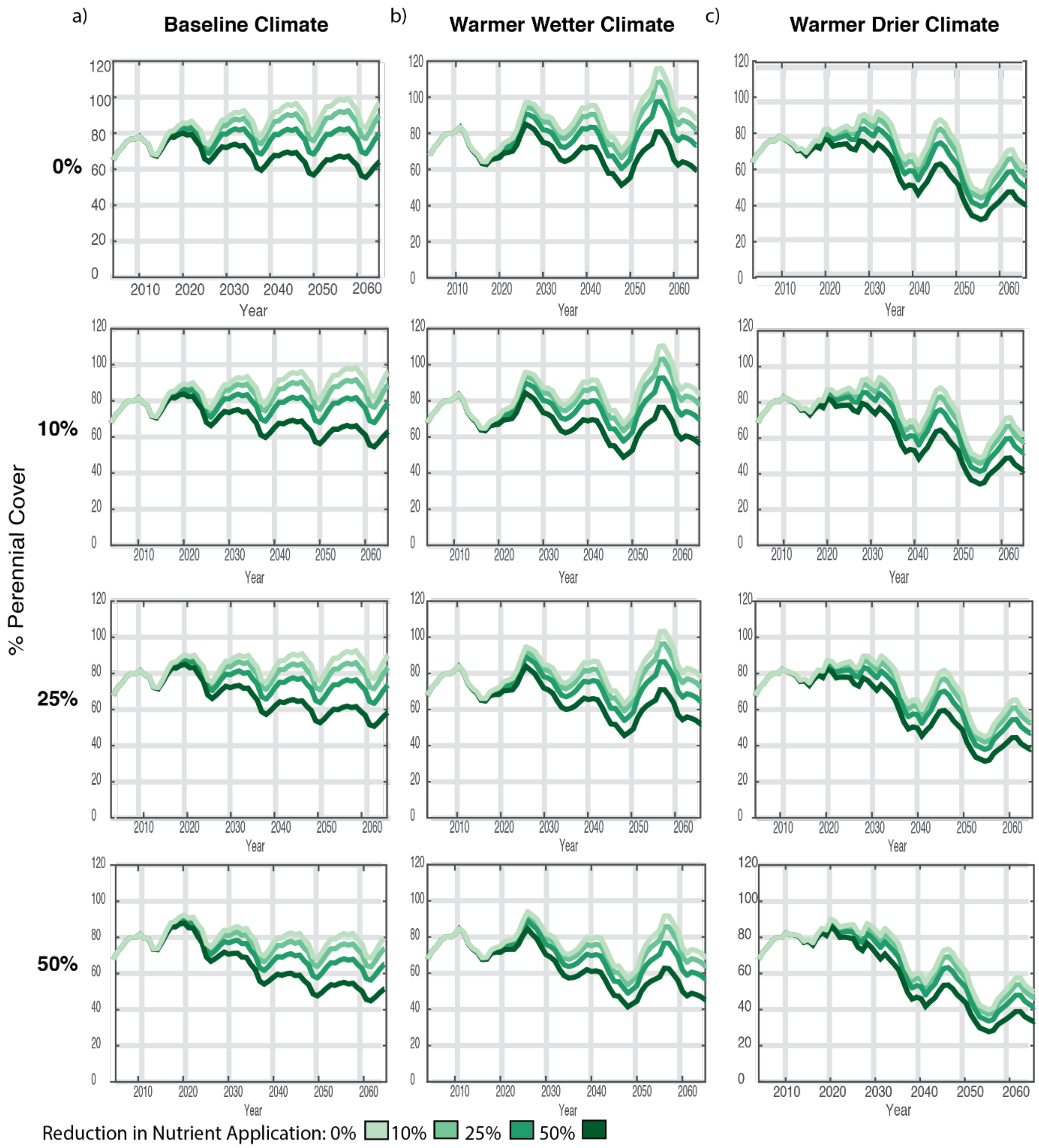

Figure S1. 9-Yr Moving Average of projected N03-N leaaching [kg/ha] from 2004 to 2070. Climate is indicated by column and letter (a for BC, b for WWC and c for WDC), and perennial cover is indicated by row. Line color indicates reduction in manure and fertilizer application.