Composite Indicators for Incorporating Environmental Externalities into On-farm Economic Decision-Making using Farm Management Information Systems

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Thesis Overview

This document presents an argument for the value of well-developed and validated composite indicators in agricultural software and their potential to promote conservation through informed on-farm decision making.

Chapter 1 discusses the motivation for composite indicators in the age of computerized agriculture. I examine ecosystem services in agriculture and how they are used to promote conservation practices through regulations and subsidies. In this age of rapid agricultural computerization, composite indicators provide an essential tool for integrating economic and environmental variables in the farm management process and allow for a better understanding of the relationship between farm systems and ecosystem services. Composite indicators provide farmers with farm-specific metrics that help them make informed decisions and aid in complying with regulations and qualifying for government payments for ecosystem services. I give an overview of composite indicators and discuss their necessity in the development and application of complex farm system models that could someday be integrated with precision agriculture and variable rate technology.

Chapter 2 provides three examples of widely used composite indicators: Milk per Acre, the Phosphorus Index, and the Revised Universal Soil Loss Equation, Version 2 (RUSLE2) and briefly discusses their development and use.

Chapter 3 demonstrates a current working example of the coordinated use of composite indicators through software. Three popular agricultural composite indicators are used to assess site-specific benefits of winter rye cover crops in a corn silage system.

Chapter 4 concludes that continued efforts by academia must be made to keep agricultural composite indicators valid and relevant in the age of agricultural computerization to ensure the continued consideration of environmental externalities in on-farm decision making.

Chapter 1. Motivation for Composite Indicators in Modern Farm Management

Introduction

Agriculture accounts for roughly half of the land use in the United States (USDA 2012), making it one of the primary ways we interact with the environment. The negative environmental externalities of agriculture are substantial, including nutrient and sediment loading into surface waters leading to coastal hypoxic zones, greenhouse gas emissions from soils, livestock, and machinery operations contributing to anthropogenic climate change, and leached pesticides and fertilizers contaminating ground waters (Diaz and Rosenberg 2008, IPCC 1996, Cohen et al 1984). The high level of interdependency between agricultural systems and the environment implicates farm management as environmental management.

Farm management presents tradeoffs between the potential outcomes of many decisions. The economic and environmental value gained or lost from agricultural practices can be understood in terms of ecosystem services, some of which can be monetized. However, when environmental effects are involved, the expected outcomes are often non-marketable and not easily comparable. Environmental tradeoffs are then oversimplified due to countless unknown variables. In these situations, concise metrics that inform farmers about the effects of their decisions can prove useful. As farmers become familiar with such metrics they will be better able to understand the overall balance of marketable and non-marketable ecosystem services produced on their farms.

Advancements in agricultural research and technology have allowed substantial progress in both improved productivity, as well as reduced negative externalities (Tilman et al. 2002). Technological advancements are central to the efforts of research in sustainable agriculture, specifically technologies that help to conserve ecosystem services and improve environmental conditions while maintaining farm profitability. These technologies often increase the complexity and demand of farm management. Highly integrated methods of farm management will become imperative for agricultural production to move towards a more sustainable agroecosystem that is both sufficiently productive and free of unaddressed negative externalities.

Farm Management Information Systems (FMIS), software developed to aid on-farm management decisions, has emerged as a result of the increased complexities of farm management. Constant innovation in agriculture presents farmers with an increasing set of management decisions at every stage of the production system. Compounded by the significant influence of a largely uncertain environment and the undeterminable interaction effects of the decision variables, the farmer’s process of making the best collection of choices for achieving their objectives proves daunting and often impossible. Public and private development of FMIS is accelerating in response as a possible solution to the need for more comprehensive management of these increasingly complex systems.

Farm profitability will predictably be the primary objective of FMIS. Efficiency of production will be a direct consequence of this objective, but environmental conservation is not an inevitable result. Rather, indicators of environmental quality must be a deliberate consideration of FMIS development.

Thus, we find agricultural innovation at the confluence of two major developments that will provide us with a crucial opportunity to revolutionize how we produce food, fuel, and fiber. Improved understanding of the interactions between agriculture and the environment through composite indicators integrated into FMIS that are able to utilize a variety of data streams of controlled and uncontrolled variables affords us a unique prospect of transitioning towards a more sustainable agriculture. The purpose of this paper is to: (1) identify the need for composite indicators in modern farm management to address externalities of farming, (2) show that combining several composite indicators can provide a comprehensive understanding of the economic and environmental consequences of farm management decisions, and (3) to provide an example of using a combination of composite indicators to test the hypothesis that adding winter cover crops to a common cropping system in Wisconsin can reduce environmental externalities without increased risk of lost profits.

Ecosystem Services

Humans rely entirely on ecosystem services for their survival and wellbeing. Historically, we have largely taken these services for granted, but due to the finiteness of the planet and a growing population with growing resource demands, a firm understanding of anthropogenic impacts on the environment is essential to the sustainability of humanity. The United Nations commissioned an assessment of these impacts at the turn of the millennia – the *Millennium*

Ecosystem Assessment. This assessment represents a joint effort among a majority of the world's nations to understand and respond to the anthropogenic degradation of our ecosystems. It represents a consensus of the world population that efforts must be made to counter this degradation in consideration of sustainability and future generations. The assessment included the report "Ecosystems and Human Well-Being: Synthesis" which defines *ecosystem services* as "the benefits people obtain from ecosystems" (Millennium Ecosystem Assessment 2005). Although this definition is broad, it highlights the breadth of these services and motivates attention to the fact that at some level the entirety of human utility, welfare, and existence relies on ecosystem services.

Ecosystem Service Valuation and Policy

A folly of humanity is to view ourselves outside or above our environment. Our entire existence, as with all life, is a dynamic and integrated ecosystem. We found ways to substantially improve the human condition in the last two centuries, but these improvements come at the cost of substantial changes to the ecosystem we rely on. Recently, we are beginning to recognize and appreciate that these changes, over time, may be damaging to human well-being. Humans must address ecosystem changes and understand the trade-offs of our choices. This process will require a highly informed valuation of ecosystem services and a mindful consideration of those services that are not directly valuable.

Understanding the effects of human activity on ecosystems has proven difficult. Methods of preemptively determining these effects are deficient (Costanza et al. 1997, Costanza et al.

2014). Consequently, assessment of these effects has been primarily retrospective and often only in response to highly consequential events that are far removed from the activity that caused them. For example, the significance of nutrient loading in the Mississippi River watershed has only been fully considered in response to the large hypoxic zone in the Gulf of Mexico and its ramifications on fisheries (Rabotyagov et al. 2014).

The ability to incorporate the externalities affecting ecosystem services through valuation will, on its own, likely be insufficient to change production practices for marketable goods. This effort inevitably necessitates well informed policies and institutions that can guide and regulate these processes. There are examples of this throughout US history. The National Environmental Policy Act of 1969 started the Environmental Protection Agency and lead to widespread assessment of human driven effects on the environment. The Soil Conservation and Domestic Allotment Act of 1935 created of the Soil Conservation Service (subsequently renamed the Natural Resource Conservation Service), which currently administers the Conservation Title of the Farm Bill, funding programs to aid farmers in conservation practices. To this end, methods of understanding and addressing the effects of policies and the industry practices they influence need functional methods of evaluating the ecosystem services that are impacted.

Valuation of Ecosystem Services

The value humans derive from ecosystems can be categorized in many ways. One important distinction is whether the service is directly marketable. While this division is not an indication of the level of value humans gain from the service, it is historically the primary determinant of the effort humans are willing to make to conserve the service. Consequently, the focus on conserving a marketable ecosystem service often comes at the cost of degrading another, more indispensable, non-marketable service. Continuing with the prior example, in agriculture we work to conserve the productivity of farmland through fertilization at the expense of affecting ground and surface water quality. More generally, we are presented with trade-offs but often do not include the full ramifications of our choices in the decision-making process.

The *Millennium Ecosystem Assessment* divides ecosystem services into four categories: provisioning services, regulating services, cultural services, and supporting services (Millennium Ecosystem Assessment 2005). Much of the directly marketable services are categorized under provisioning services, which encompasses natural capital, but humans receive value from each type of ecosystem service. From the esthetics of natural surroundings to the natural filtration of our water systems, ecosystem services are essential to human existence. The notion that an ecosystem service only has value as long as it can be capitalized has proven flawed, and significant effort must be made to advocate for the functionality of the environment as a whole.

The widespread effort to incorporate environmental valuation into economic analysis has come under a sharp, yet justified, critique. These concerns must be central considerations in the valuation process to ensure that humans are not deluded in believing we have somehow solved the issue of sustainability. There is concern that economic rationale will become the sole driver of conservation, and equally-important noneconomic reasoning will lose its intrinsic merit

(Matulis 2014). Equally as problematic is a feature inherent to ecosystem services as I have defined them, that if an aspect of the environment does not evidently benefit humans, then it is not worth conservation (Redford and Adams 2009). In many cases, rather than being beneficial, essential ecosystem processes are directly detrimental to humans, for example, wild fires or floods. The converse of this is also true, that just because an ecosystem service gives benefit to humans does not mean it is natural or beneficial to the environment, such as the increased clarity of Midwestern lakes due to the invasive introduction of zebra mussels (Redford and Adams 2009).

In the attempt to better understand the environment and give value to ecosystem services, additional apprehension surrounds a trajectory of increased human control over these services. This control could lead to engineered ecosystems, market dependent decisions for conservation, conflict over control of ecosystem services, or fixation on the status quo of ecosystem services despite drastic changes due to a changing climate (Redford and Adams 2009). As we begin to recognize the full magnitude of ecosystem services and their roll in not only our economy and welfare, but our existence, the equitable distribution of benefits from ecosystem services must also be a central consideration (Cobrera 2014). This distribution will be hindered by the prevailing imbalance of power to control allocation of, access to utilize, and ability to influence the markets of ecosystem services (Matulis 2015).

Ecosystem Services and Agriculture

Agriculture dominates the landscape at the interface between humans and the rest of the environment. Consequently, agriculture is not only highly dependent on ecosystem services, but maintenance of ecosystem services is also highly dependent on agricultural practices (Tilman et al. 2002). This relationship is a feedback loop where agroecosystems that promote conservation of ecosystem services will benefit from those sustained ecosystem services. Conversely, agriculture will suffer from practices that degrade ecosystem services. Many instances of this relationship have been observed such as improved yields and pest suppression due to diversified crop rotations (Berzsenyi et al 2000).

To this end, we must begin to consider the agroecosystem as a whole, where field-level decisions are made in consideration of the effects at the landscape level and beyond. A greater understanding of how farm operations cultivate both marketable and nonmarketable ecosystem services is needed. More specifically, agriculture, as with any natural capital, is thought to be a provisioning service as it provides food, fuel, and fiber. Moving towards a sustainable agroecosystem will be driven by an expanded consideration of the regulating, supporting, and cultural services that are affected as well (Swinton et al. 2007). In this sense, farmers are the stewards of many of the landscape's ecosystem services that deliver value whether or not that value can be harvested.

Currently commodity support policies reward maximizing production, especially in the presence of small or negative profit margins. As policy changes due to concerns of anthropogenic climate change, conserving ecosystem services will become one of the primary objectives of agriculture, but this does not necessitate a loss in productivity. For example, in a comprehensive review of literature comparing diversified to conventional farming systems, Kremen and Miles (2014) found that the diversification of farming systems is essential to improving ecosystem services, and it need not result losses to productivity. They further suggest that this perception of lost productivity in diversified systems stems from a lack of funding for agroecological research and posit a need for increased research of integrated whole-system studies to better understand the interactions between farming practices and ecosystem components and services.

Policies Promoting Ecosystem Services in Agriculture

Many types of policies have been employed in the United States to promote conservation of ecosystem services in agriculture, both federally and at the state level. Broadly, these can be categorized as regulations and conservation programs. Often the two categories are linked, where conservation programs are administered to aid farmers in meeting regulation criteria or regulation criteria must be met to receive government transfers.

There are several varieties of conservation programs including direct payments for ecosystem services, information dissemination through conservation support programs, as well as mandatory monitoring of agricultural practices associated with negative environmental externalities. At the federal level, support for ecosystem services are primarily provided through conservation programs administered by the USDA. The motivation for these programs is to provide financial incentives for conservation promoting practices that reduce onsite and offsite environmental impacts. These incentives may be necessary to mitigate perceived losses to productivity due to the adoption of the practice or to overcome the initial investment costs of implementing the practice.

Agricultural conservation programs provided by the USDA are authorized under Title II, The Conservation Title, of the Farm Bill. These programs are grouped by similarities as working land programs, land retirement programs, easement programs, partnership programs, conservation compliance, and other overarching provisions. Many of the programs receive mandatory funding which accounted for $58 billion, or roughly 6%, of the total ten-year mandatory funding authorized under the 2014 Farm Bill, The Agricultural Act of 2014. Every year since 2010, conservation spending has been between 5 and 6 billion dollars (USDA 2019).

Many of the programs authorized under the Conservation Title of the Farm Bill are aimed at removing environmentally sensitive lands from production. These programs play an important role in shaping a sustainable agroecosystem landscape. However, there has been a shift in funding towards working land payments since their introduction in 2006 in part due to improvements in production technology, high commodity prices, and variability in land rents (USDA 2019). While commodity prices have fallen in recent years, conservation-oriented production technologies continue to improve, and working land payments have become the predominant form of conservation related government transfers to farmers, accounting for over 50 percent of conservation payments since 2014 (USDA 2019). Ultimately a dynamic balance of land retirement and working land programs will be ideal, and the best solution may require a farm-specific, variable combination of these two types of aid.

Several working land programs work to promote sustainable agroecosystems by directly influencing the productive practices of farmers. Included in this category are the Environmental Quality Incentives Program (EQIP) which provides technical and financial assistance to design and implement new conservation plans, the Conservation Stewardship Program (CSP) which provides technical and financial assistance to improve upon existing conservation practices, and Agricultural Management Assistance (AMA) which provides technical and financial assistance to address specific on-farm environmental concerns (USDA 2019).

Increasing interest in addressing locally specific environmental concerns has led to the authorization of Regional Conservation Partnership Programs (RCPPs). These programs, involving plans tailored specifically to a geographic region, receive some mandatory funding under the Farm Bill, as well as redirecting a portion of funding from working land and easement programs. RCPPs also have the ability to leverage local and state funding to match federal contributions and address specific environmental concerns in well integrated and coordinated efforts (USDA 2019).

Conservation compliance as a condition for government transfers represent an important feature of agricultural aid. Such requirements take on various forms at both the federal and state levels, and generally are directed at farms that fulfill a set of criteria. For example, at the federal level compliance programs for highly erodible lands conservation and wetland conservation are authorized under the Agricultural Title of the Code of Federal Regulations with administration appropriations in the Conservation Title of the Farm Bill (USDA 2019).

State level conservation policies and programs also play an important role in promoting conservation of ecosystem services, since localized initiatives have greater potential to address specific concerns of environmental degradation and loss of ecosystem services. As example in Wisconsin, several standards administered and enforced by the Wisconsin Department of Agriculture, Trade, and Consumer Protection and the Department (DATCP) of Natural Resources (NR) layout regulations to mitigate negative environmental externalities of agriculture. For example, ATCP 50 and NR 151 outline regulations to control nutrient and sediment loading into surface and ground waters. These regulations are recommended for all farmers and are requirements for farmers meeting specific criteria such as concentrated animal feeding operations. Additionally, requirements must be met to participate in state sponsored cost share programs or to receive tax credits such as through the Farmland Preservation Program. Compliance with the Nutrient Management 590 Code published by the USDA NRCS is a requirement of these state regulations, requiring farmers to annually complete a nutrient management plan. These requirements have great potential to reduce nutrient and sediment loading but come at the cost of increased management obligations for the farmer.

Farm Management Information Systems

Farm System Complexity and Risk

As farmers, researchers, crop consultants, and politicians continue to develop and implement agroecosystems that balance profitability with ecosystem service maintenance, farm systems will increase in complexity. The number of interacting decision variables and the planning horizon they span will extend, creating intricate problems that require advanced management systems. This increased complexity is driven both by increased consideration of the effects of management decisions and by an increased number of options for technologies that determine these effects (Pannell 1999). For example, the farmer's choice of crop rotations has become a coordinated decision of utilizing beneficial cross year interactions between crops on individual fields and maintaining a diversified production in each year to exploit predicted market prices as well as alleviate environmental and financial risk. Farms such as dairies that utilize their produce on farm for feed have additional considerations in deciding how to manage rotations that best satisfy the needs of their herd while maintaining field health. Intercropping has become an option that can further benefit soil health and ecosystem diversity but has implications for rotations, necessary machinery, and production levels. Seed treatments can prevent detrimental pest damage and improve germination rates, but are sold at a premium, adding costs with return on investment that is difficult to determine. Precision agriculture has presented new options for fine tuning seeding, fertilizer, and pesticide rates with high levels of granularity and accuracy. Increased options for fertilizer application timing and location allows farmers to abate production limitations with unprecedented levels of specificity and efficiency.

However, coordinating all of these efforts and allocating labor and capital appropriately can be complicated.

The increased complexity of highly integrated farming systems can present a deterrent to farmers looking to uptake new technologies. Evidenced by lagging technology adoption, farmers are often assumed to be risk averse, and although technology and crop diversification will generally mitigate risk (Harwood et al. 1999), the added complexity may be internalized by the farmer as added risk.

There are many known sources of risk associated with farm systems: production risk such as variable yield, market risk such as variable commodity pricing, institutional risk such as variation in insurance and government support, and financial risk such as variation in credit and access to capital (Harwood et al. 1999). A farmer's reluctance to add to these risks is understandable. Although the farm is a production firm, in most cases it is also a household. Therefore, decision outcomes have personal effects. However, I believe that much of what researchers and consultants determine to be risk of technology adoption is actually internalized as uncertainty by the farmer. That is to say, a technology may prove beneficial most of the time in most places, but that doesn't give concrete evidence to a farmer that it will be beneficial in their field. This uncertainty results from a lack of trusted information available to the farmer about how the technology may specifically affect their system. While researchers attempt to abate this uncertainty through information dissemination and extension, empirically generated information will lack the farm specificity needed to assure farmers of a technology's benefits.

This increased complexity has potential to maintain farm profits while increasing ecosystem service maintenance and decreasing unwanted externalities, but it comes at the cost of more involved and multifaced management requirements (Pannell 1999). Additionally, more complex systems present increased difficulty in determining the true relationships between farm management decisions and the resulting environmental and economic effects. This increased complexity demands well-informed management that is able to integrate more information into the management process and accurately anticipate outcomes of changes to practice and technology. Methods of providing farm-specific effects of management decisions could help alleviate the uncertainty and improve understanding of the risk in complex systems. Providing this information will require an integrated analysis of the farm attributes, all available applicable data streams, and the farmer's preferences. Software to aid farm management must focus on the goal of providing farmers with sufficient information so that management decisions are truly based on objectives and risk, and not overly influenced by precieved uncertainty.

On-Farm Internet and Computer Access

The use of on-farm management software, referred to here as Farm Management Information Systems (FMIS), is quickly growing in response to the increased complexity of farm management in conjunction with increased rural access to internet services and the decreased cost of computers and smart phones. Although many farmers still lack interest in using digital resources in their farm management, as the demographics of farmers shift with an aging farmer population, we will see younger, more-educated farmers embrace these resources, a trend documented by Shutske et al. (2018) in a survey of digital technology use by Wisconsin farmers. Based on these trends, the agricultural landscape of the near future is expected to be a highly integrated production system with numerous information sources providing environmental and economic indicators, regulation and payment program guidelines, and research on best management practices, all interacting in a farm-specific system analysis and playing a substantial role in daily farm management decisions (Sorensen et al. 2010). These technologies also present the potential of interactive planning and innovation at levels higher than the individual farm, where crop choices can be made based on regional or national cropping rates and commodity demands; and environmental conservation and pest prevention can be locally and regionally coordinated to prevent devastating externalities and outbreaks while reducing input costs (Antle et al. 2017).

Software and Agriculture

With an increase in the complexity of farming systems, the need for well-developed, opportune, decision-making support using diverse and dynamic data streams has accelerated. Options for FMIS have proliferated in response to this need. Early examples of FMIS focused on record keeping and basic information access such as weather and soil data, and they have since advanced to include a diverse set of data streams and recommendations such as market information, application recommendations and regulations, statutory compliance, satellite imagery, and on-site sensory information (Fountas et al. 2015). This integration of real-time and historical data will continue to expand, creating a dynamic management system that motivates and responds to current management decisions and focuses on usability and human-computer interaction (Fountas et al. 2015).

Motivation for farmers to use FMIS will depend on a variety of factors. Primary features that are likely to drive uptake of FMIS include usability, cost-effectiveness, applicability, and compatibility with regulations (Rose et al. 2016). As a digital technology, FMIS have potential for diversified revenue streams, alleviating the initial uptake cost to farmers and encouraging their use. Privately developed FMIS will capture market surplus through user discrimination with tiered software, which will allow for gradual uptake and incorporation into farm management. Since the needs and preferences of every farmer are different, a dynamic marketplace of FMIS will allow farmers to integrate systems that meet their needs (Kaloxylos et al. 2014).

The functionality of FMIS is expanding in conjunction with several other technologies that facilitate access to geographically and temporally relevant data. As data access improves, farm system models at the farm and landscape level are being developed to improve data incorporation into the farm management process (Capalbo et al. 2017). Web-based systems with mobile platforms allow farmers to access and input information throughout their farm, and precision agriculture technology using timely satellite and drone imagery along with tractor mounted sensors provide farmers with up-to-date measurements allowing for opportune decisions and spatially varying input recommendations (Paraforos et al. 2016, Nikkila et al. 2010). As agricultural technology continues to evolve, reliable tools for holistic management will prove essential. FMIS offers an opportunity to integrate economic and environmental sustainability, but this combination of diverse data will rely on well-developed indicators to provide usable information to the farmer (Capalbo et al. 2017).

Indicators for On-farm Use

Indicators used in farm level decision making have potential to improve sustainability by incorporating environmental externalities into economic decision making. The use of sustainability indicators for reducing negative externalities and fostering positive externalities in agriculture should be at the forefront of agricultural developments. Indicators are becoming popular in agricultural research, and while they have been embraced in various regions and types of farms, they have not become standard agricultural practice (Van der Werf and Petit 2002).

Indicators can prove useful in understanding sustainability at the farm level (Rigby et al. 2001). Farm-level indicators can help us understand the mechanisms of sustainability and can drive the discussion of sustainability from a theory-based understanding to one that is methodological. Additionally, indicators improve our understanding of the role of scientific measurement in decision making, both for farmers and policy makers (Dale and Polasky 2007). It is necessary to develop logical and useful farm-level indicators in order to improve and implement our understanding of sustainability (Rigby et al. 2001).

The process of deciding which indicators to use and how those indicators should be constructed is of primary concern. Indicators can be direct measurements, but since monitoring and measuring the variable of interest is often problematic, indicators are typically latent metrics estimated from other direct measurements that encapsulate the characteristics of the desired indicator (Gómez-Limón and Sanchez-Fernandez 2010). The accuracy of estimators as proxies for latent variables is generally a tradeoff with their components' ease of measurement.

Base indicators, those collected directly from the system of interest, can provide useful data to recognize the effects of agriculture on the encompassing ecosystem. Examples include ecological indicators of farming effects and farming practice decisions (Dale and Polasky 2007) such as nitrate levels in the soil or percent field cover in the spring. From base indicators, composite indicators can be developed to help simplify their interpretation and mechanize their usefulness (Gómez-Limón and Sanchez-Fernandez 2010). Composite indicators allow for the user to consider a wide range of externalities without the loss of the underlying information.

Base Indicators

Base indicators, or more specifically ecological indicators, can help farmers understand the interaction of their agricultural system with the encompassing ecosystem. Dale and Polasky (2007) provide a framework for interpreting ecological indicators and layout criteria for the identification and selection of indicators that satisfactorily metricize the complex interactions within the system. They suggest three types of ecological indicators categorized by the manner of ecological feature meant to be estimated: structure, composition, and function. Additionally, they propose three scales at which they can be observed: landscape, ecosystem, and population. The criteria they outline provide guidance for deciding from which category and at which scale to choose appropriate and useful ecological indicators. These criteria can be generalized to all indicators.

Base Indicator Selection

Dale and Polasky (2007) list seven criteria for the selection of indicators. The first is that an indicator should "be easily measured." This is important to both minimize cost and increase the frequency of data collection. Considerations for this criteria include what equipment is needed to measure the indicator and whether it can be measured remotely. The next criteria proposed are that indicators "be sensitive to changes in the system," "respond to change in a predictable manner," and "be anticipatory." Indicators must be dynamic and responsive to changes in the system in order to properly understand the farming effects on the system, and they must be predictive of these effects to be useful in deterring adverse externalities. Dale and Polasky (2007) aptly add the criterion that indicators "predict changes that can be averted by management actions." If the information received from the indicators cannot be used to effect change, then they do not have value in practice. Finally, they suggest the criteria that indicators "are integrative" and "have known variability in response." These last two criteria ensure that the indicator data lead to pertinent actions at the appropriate scale. Dale and Polasky (2007) focus on indicators that can be directly measured, but the criteria they present are helpful in considering what information should be collected when developing composite indicators and how composite indicators should be constructed to have the desired effect.

Composite Indicators

Composite indicators have great potential to monitor countless variables with just a few key metrics. However, their benefit comes with significant risk. Developing composite indicators must be a mindful and dynamic process. Gómez-Limón and Sanchez-Fernandez (2010) outline some key advantages and disadvantages of composite indicators. By reducing the set of indicators that the farmer has to consider, composite indicators make it easier to understand and monitor complex, multivariate systems and to observe their progress or deficits without losing the original observed data. Composite indicators provide a good tool for making comparisons at the farm, region, and country level. This comparison allows for realization at each of these levels of potential areas for improvement and helps place the onus for deficits in the achievement of sustainability benchmarks. Additionally, it encourages communication between farmers, consumers, and other stakeholders, which further adds to accountability at the various monitored levels (Gómez-Limón and Sanchez-Fernandez 2010).

Composite indicators have apparent potential value, but they must be developed and utilized with great care. If composite indicators are inadequately developed or misconstrued, they could draw false inferences or lead to poor policies. Composite indicators run the risk of being overly arbitrary and lead to debates about their appropriate interpretation and implementation. Additionally, poorly constructed composite indicators could lead to excessively focusing on one issue and overlooking other problems as a result, a problem which composite indicators also provide great potential to avoid.

Composite Indicator Construction

A variety of methods for constructing composite indicators from base indicators are potentially useful in practice. Gómez-Limón and Sanchez-Fernandez (2010) outline the basic premise that is common to many of these methods. As discussed previously, the base indicators must be selected, and the data gathered. The collected data need to be normalized to make them operational, which involves making the values unitless through a demeaning process and allows originally incomparable data to be aggregated. The normalized data are then weighted, which is the step where the concepts of sustainability are incorporated into the composite indicator's creation. Variables that are considered to diminish sustainability will be negatively weighted while those that are deemed to improve sustainability will be positively weighted. Ultimately, this step can be arbitrary and should be well-founded in evidence-based research to reduce this subjectivity. Finally, the data are aggregated into a composite indicator. This step must consider the possibility for incommensurable data and that multiple composite indicators should be used. In each step, Gómez-Limón and Sanchez-Fernandez (2010) advocate for accuracy and transparency. Throughout an indicator's use, each of these steps should be revisited frequently and updated as the science evolves.

Indicators of Effects and Indicators of Practice

Several considerations must be made when choosing base indicators and developing composite indicators. Van der Werf and Petit (2002) analyze twelve sustainability indicators and their methods of construction. The important considerations they deliberate are the tradeoff of the ease of data gathering with the complexity of the indicator, the concerns of the agroecosystem that need to be addressed, the most apt indicators to measure these concerns, whether the indicators are of practices or effects, and how to evaluate the effectiveness of the indicators. I will focus on their assessment of indicators of practice versus indicators of effects.

Indicators of practice are data on the decisions and operations of the farm. Examples include the percent cover left on the field at harvest or the tillage methods and depth. They prove to be much more common than indicators of effects. They are much easier to collect and consequently prove to be much cheaper. They can be collected in hindsight and can thus provide larger data sets for researchers. However, practice-based indicators do not provide certain causal correlation to ecosystem effects, and thus preferred changes in practice to correct for externalities are not always obvious. In the indicators assessed by Van der Werf and Petit (2002), those that were practice based were generally presented as values and without thresholds, which leads to ambiguity that may reduce appropriate responses by farmers.

Indicators of effects are data on the surrounding ecosystem. Examples include nitrate levels in the soil or point runoff rates for a field. These indictors often prove difficult and costly to collect. Consequently, the amount of data collected is often insufficient and inconclusive. As a benefit, relating these indicators to the concerns of environmental effects proves more transparent. Van der Werf and Petit (2002) found that indicators of effects are often presented with a threshold which gives a goal for changes in farming practices. However, similar to practice-based indicators, a causal relationship to methods of farming may prove difficult, and lack of culpability of environmental problems to specific practices could prevent remediation. Ultimately, a combination of indicators of practice and indicators of effects may prove to be the most useful in driving a change in agriculture towards sustainability.

Validation of Indicators

A validation method is essential for indicators to adhere to scientific standards. Bockstaller and Girardin (2003) provide a three-part framework for the validation of indicators. The first step is validating that an indicator is scientific by design. Design validation involves presenting the method of construction to a group of experts in the given field for assessment and gathering feedback.

The second step is to validate the reliability of the indicator's output, which ideally would involve a comparison of the indicator estimate to measured data of the conditions the indicator is intended to approximate. One provided example is to produce an expected graphical area where the indicator predicts a measured variable to be, analogous to a multidimensional confidence interval, and determine how often the measured data adheres to this prediction. This confidence interval can be difficult to define when the indicator is predicting sustainability, difficult to realize given the temporal implications of sustainability, and possibly meaningless given a unitless composite indicator. Furthermore, this validation requires measurement of the exact variables that are difficult to measure and need an indicator as a proxy. As an alternative Bockstaller and Girardin (2003) once again suggest a panel of experts to assess the validity of the output.

The last step for validation proposed by Bockstaller and Girardin (2003) is to determine the usefulness of the indicator in practice. This step is critical, for an indicator has no purpose if it is not used. They recommend that this evaluation can be accomplished with a survey of the users. This method seems appropriate and, in addition to validation, is essential to the development and maintenance of useful and dynamic indicators. Validating indicators must be a continuous process as the measurement and construction of indicators is itself continuous.

Composite Indicators in Agricultural Software

The usefulness of composite indicators for making on-farm decisions is facilitated by the uptake of software for aiding farm management. As this software uptake increases, composite indicators provide a way to implement concise methods of conveying the likely effects of management decisions. Already, vast amounts of data are available to farmers from sources such as satellites, drones, precision agriculture machinery, and on-farm sensors such as SPAD or NDVI. As management software evolves, the data streams from these technologies will be utilized to provide farmers with comprehensive delineations of all the processes taking place on their farm. Composite indicators provide a way to incorporate many types of data into more easily interpreted metrics, which will allow farmers to relate aspects of their farm to the surrounding environment that would not otherwise be easily comparable. For example, in determining the effect of adding winter cover crops to a field's rotation, changes to outcomes will be seen in economic concerns such as productivity, profitability, and resource demands as well as environmental concerns such as runoff, nutrient loading, and soil health. Software that is able to analyze the expected outcomes and deliver concise metrics to inform the farmer can help them determine the best field specific management practice.

Conclusion

Humans rely on ecosystem services. Farm management is ecosystem management. In an effort to reduce negative externalities from agriculture and to improve sustainability, farmers need efficient and effective methods of analyzing the effect of their practices on ecosystem services for the integration of environmental externalities into on-farm decision making. The increasing uptake of computerized technologies by farmers and the improved understanding of agroecosystems provides a unique opportunity for this integration. Composite indicators are a necessary way to provide accessible and useful analysis and interpretation of environmental externalities in farm management. Chapter 2 reviews three composite indicators which are current working examples available to farmers, and Chapter 3 uses these indicators to illustrate the incorporation of potential environmental externalities into an on-farm decision process.

Chapter 2. Three Examples of Composite Indicators Used in Agriculture

In this chapter I provide an overview of three composite indicators that have been incorporated into software and are used by Wisconsin farmers: Milk per Acre, the Phosphorus Index, and RUSLE2. All three are calculated from easily accessible data using free software, have gone through multiple revisions to remain consistent with the current research, and incorporate base indicators of effects and practice. Milk per Acre is retrospective and indicative of economic effects, and the other two are predictive and indicative of environmental externalities. Together, they provide a current working example of the potential for composite indicators to improve our understanding of how cropping decisions will affect profit as well as ecosystem services, and the tradeoffs being made with each decision.

Milk per Acre

The Milk per Acre metric was developed at the University of Wisconsin in an effort to provide a simple single metric that estimates milk produced per acre of forage (Undersander 1993). The measure combines forage quantity and quality to help compare forage production systems. Milk per Acre is a composite indicator of milk production at the field level that is easily measured and indicative of the effects of cropping decisions made on dairy farms. The accuracy of predicted Milk per Acre is variable, so the best use of the metric is for comparing various crops for a single herd. The metric should not be used to compare forage value across farms or herds.

The base indicators required for Milk per Acre include indicators of practice and indicators of effects. The indicators of practice include the type of forage and dairy attributes such as the size of the cows and the portion of the rations from forage. The indicators of effects include per area forage yield and forage analysis results with concentrations of dry matter, protein, fat, ash, starch, NDF, and ttNDFD. These base indicators are all easily accessible for a farmer and are generally already available through a dairy's standard practices.

The usefulness of Milk per Acre is evident in the consideration of cropping decisions for dairy farmers. Cropping decisions often present a tradeoff between forage quantity and quality, and both can affect profitability making it difficult to optimize. Additionally, forage pricing metrics such as Relative Feed Value (RFV) or Relative Forage Quality (RFQ) ignore important aspects that affect quality despite the recognized effect of these characteristics on feed rationing for milking cows. That is to say, these metrics are based on levels of dry matter, digestible dry matter, or total digestible nutrients (TDN) in the forage, calculated from lab analyses of neutral detergent fiber (NDF), acid detergent fiber (ADF), and organic matter (OM). They do not, however, factor in protein and fat concentrations in the feed. The original Milk per Acre metric (Undersander 1993), as well as more recent revisions. used equations developed by the National Research Council (NRC 1978, NRC 2001). The NRC publication on the nutrition requirements for cattle is central to the improved predictive capabilities of the Milk per Acre metric (Undersander 1993) and builds on decades of research and analysis with input from councils of the National Academy of Sciences, the National Academy of Engineering, and the Institute of Medicine. Central to the development of the NRC equations is the incorporation into a computer model allowing for a more accurate accounting of animal variation (NRC 2001). The equations published by the NRC give a more accurate measure of the value received from forage, which allowed farmers and researchers to rank different cropping systems (Eastridge et al. 1998).

The Milk per Acre metric has gone through multiple revisions since its advent to remain current with the information available from forage analyses and the improved understanding of the cow's digestion. It was originally designed in the early 90's for corn silage and hay and available for use in a Lotus 123 spreadsheet. Changes to Milk per Acre include updates with improved access to more advanced laboratory analyses, an adaptation to small grains, a user interface in Microsoft Excel, and the incorporation of total tract NDF digestibility (ttNDFD) (Undersander et al. 2006, Undersander et al. 2016). Milk per Acre can be easily calculated using Milk2006 for corn silage and Milk2016 for grass and legume forages. Milk2006 and Milk2016 are specially formatted Excel spreadsheets available for download from the UW Madison Extension website (https://fyi.extension.wisc.edu/forage/). With the aforementioned inputs, Milk2006 and Milk2016 return estimates of values including TDN, net energy of lactation (NE_L), milk per ton of dry matter (TDM), and milk per acre. The calculations for these metrics, as used in the Milk2016 spreadsheet, are shown in Table 2-1. Using the anticipated milk price, farmers can determine net yield and net profit per acre, allowing them to compare economic returns on various cropping systems.

Milk per Acre provides an example of how to better understand yields in the complex system of a dairy farm. It is important to note that the Milk per Acre metric is a retrospective indicator and can only give information on expected yield and profits after harvest. While the metric cannot be predictive of the effects of practices yet to be realized, it can help provide a thorough assessment of the previous season's practices. This assessment can prove very helpful in anticipation of supplemental feed purchases, cover crop planning, and planning for next year's crops. Milk per Acre has also proven useful in research such as corn hybrid comparison trials conducted at the UW Madison Agronomy Department (Lauer et al. 2000; Schwab et al. 2003). Laboratories serving farmers in Wisconsin, both private and University-affiliated, include estimates of Milk per TDM in forage and silage analyses reports.

RUSLE2

The Revised Universal Soil Loss Equation, Version 2 (RUSLE2) is a composite indicator, built into a computer program, and used to estimate rill and interrill erosion for guidance in conservation and erosion control planning (Foster et al. 2002). It was constructed for a variety of applications, where soil is exposed to disruptions and erosive forces. The application of RUSLE2 to agriculture is unique since the disruptions are regular and vary throughout the year. The motivation behind RUSLE2 was to be a site-specific erosion estimator that would consider local climate conditions, field characteristics, and land use. The usefulness of RUSLE2 is in comparing the effects on erosion levels of different practices on a given parcel of land (Foster et al. 2001).

As indicated, RUSLE2 is the second version of revisions made to its predecessor the Universal Soil Loss Equation (ULSE), an empirically derived model first designed for cropland by

Wischmeier and Smith in 1965 and later adapted to other land uses (Renard et al. 1997). RUSLE1 was developed in the 1990s followed by RUSLE2 in the early 2000s (Foster et al. 2002). Both revised versions incorporate a number of process-based equations into the original equation (Foster et al. 2001). A full compendium of equations for RUSLE2 and references to their development literature is available in the "Science Documentation" for RUSLE2 from the USDA (USDA 2013).

The calculation of erosion by RUSLE2 is based on the concept of Hortonian overland flow and composed of three facets, each a fundamental process in rill and interrill erosion: sediment detachment, transport, and deposition. A detachment point calculation is empirically calculated using a daily indexed method derived from the original USLE model, while the transport and deposition are calculated using process-based equations from numerous sources. These three features are calculated for each day and each point over the area of concern, termed the overland flow path. Once calculated at each time and location, these values are integrated over time and space to determine annual levels of runoff (USDA 2013). RUSLE2 is able to account for multiple scenarios of varying rates of infiltration and deposition across the overland flow path (Foster et al. 2001).

Many of the base indicators necessary for RUSLE2 are incorporated into the RUSLE2 software database including soil and climate information, making it easier for farmers to compile the necessary data. Input requirements for farmers include field operations and cropping system management information, easily accessible from farm management records. The output of

RUSLE2 includes four variables, specific to an overland flow path, to aid in conservation planning: average annual erosion rate, average annual detachment rate, average annual erosion rate for the eroding portion, and average annual conservation planning soil loss. For a uniform overland flow path, these values will all be equal. All four are calculated on a temporal and spatial unit basis and integrated to determine annual rates. For example, the primary calculations for the average annual erosion rate is given in Table 2-2.

The amount of erosion in a field is based on several physical characteristics and processes determined by RUSLE2 using process-based equations from various fields of study. These equations are numerous and extensive and used to determine the influence of individual field features including weather, soil makeup, topography, cover-management, support practices, vegetation, and residue. Once calculated, these features are incorporated (Table 2-2) and then integrated. This process of utilizing a myriad of research from multiple disciplines in order to most accurately represent field conditions is exemplary of the potential for transdisciplinary research and cooperation to achieve useful composite indicators for agricultural management.

The usefulness of RUSLE2 is only applicable to rill and interrill erosion, which may seem to be a limitation, but incorporating other forms of erosion would likely detract from the reliability of the indicator. In practice, RUSLE2 will need to be used in conjunction with other metrics to fully understand the effects of management decisions. For example, the USDA has also developed the Wind Erosion Prediction System (WEPS) to estimate wind erosion from farm fields.

Together, these two indicators can give a more comprehensive picture of erosion prevention and conservation management.

Although the RUSLE2 computer program and databases are extensive, the model can be incorporated into other software as seen in the SNAPPlus nutrient management software developed at UW Madison. This consolidation of management tools reduces the need for farmers to learn different software user interfaces and prevents redundancy in record keeping for management practices. This trend of software consolidation will certainly be a theme in agriculture over the coming decades as it adds to efficiency and accuracy of recordkeeping and decision making. When developing composite indicators for on-farm use, partnering software, such as RUSLE2, that can be readily incorporated into any FMIS, such as SNAPPlus, should be a primary objective.

Phosphorus index

Eutrophication of surface waters caused by excessive phosphorus use in agriculture, predominantly intensive livestock production, is considered by the EPA to be the most widespread water quality problem in the US (EPA 2012). To address this concern the EPA and USDA worked to promote comprehensive nutrient management plans to ensure state specific guidelines for nutrient applications are met, assigning oversight to NRCS. The NRCS updated the NM 590 standard to require states to include phosphorus monitoring by 2008, giving the option to use one of three approaches – soil test P recommendations, soil test P thresholds, or P indices to determine risk for potential P loss (Sharpley et al. 2003). Most states (48) have developed a phosphorus index used to help farmers meet the NRCS 590 standard (Lemunyon and Gilbert 1993). While there is variation between calculation methods and entirely different data sets used for estimation, the objective of the information and the types of units used are consistent. The phosphorus index provides a metric for the risk of phosphorus runoff from fields in units of quantity of phosphorus per area of land per unit of time (e.g. lb/ac/yr or kg/ha/yr).

The phosphorus index (PI) is composed of three intermediate indices: risk of transport from field, phosphorus source levels, and site management. Depending on the specific PI these intermediates can be composed of various base indicators. Generally, risk of transport will include a metric of erosion risk such as RUSLE2, soil characteristics such as soil permeability and field slope, and distance to surface water; phosphorus source levels will include soil test phosphorus and application rates; and site management will include application methods and rates. This information is available with farm management records, a standard field soil test, and the NRCS soil survey (Sharpley et al. 2003).

Three major recommended changes to the calculation of the PI have been made with improvements in the understanding of how field management affects phosphorus loading. The interaction between source and transport factors changed from additive to multiplicative to improve representation of site vulnerability being dependent on both factors. Distance to surface water was added to the transport factor to improve estimation of the necessary magnitude of a rain event to cause loading. Finally, parameters for erosion, soil test P, and P application rate were made continuous and open ended to prevent small changes in base indicators leading to drastically different recommendations (Sharpley et al. 2003).

For this paper I will focus on the phosphorus index used in Wisconsin. An interim state technical committee, assembled in Wisconsin to determine a response to the updated 590 standard, agreed to allow farmers to either follow soil test recommendations (for those not using software for nutrient management) or to calculate a phosphorus index. The Wisconsin phosphorus index (WPI) was subsequently developed and incorporated into the SNAPPlus nutrient management software in 2005. While the phosphorus index in a majority of states is categorical, WPI attempts to numerically estimate annual P loads from each field. (Ward-Good et al. 2010)

The goal of the WPI was to provide a scientifically accurate index that was calculated using easily accessible base indicators. The required base indicators include nutrient application methods and rates, as well as soil test information. This information is used in conjunction with RUSLE2 to determine total P loading at the edge of the field due to surface runoff. The WPI is calculated by multiplying a total P delivery ratio by the sum of estimated particulate and dissolved P losses from the field edge (Ward-Good et al. 2010). These calculations are provided in Table 2-3. When accuracy is constrained by limited research or input imprecision, the index errs on the side of over-estimating.

Conclusion

The three assessed composite indicators, Milk per Acre, RUSLE2, and the Phosphorus Index, provide a current working example of how composite indicators incorporated into FMIS can aid farmers in making informed farm management decisions. This discussion highlights how a collection of base indicators and data streams, including field information, local weather data, chosen cropping systems, and cultural practices, can be consolidated into three concise and accessible metrics that can make farm management more informed. The future of FMIS is not clear, and which software will dominate the industry has yet to be seen. Researchers and developers of composite indicators must design their software as integrable APIs to allow for incorporation into any FMIS. To provide an example of the use of these composite indicators in farm management decision making, Chapter 3 tests the hypothesis that adding winter rye cover crops to a corn silage system can reduce environmental externalities without adding to the risk of yield losses.

Tables of Primary Calculations

Table 2-1. Calculations from Milk2016 Spreadsheet used to estimate expected Milk per Ton and Milk per Acre for grass and legume forages.

Milk2016			
Indicator	**Equations**	**Variables**	**Notes**
Total digestible nutrients	***TDN = tdCP + 2.25*tdFA + tdNDF + tdNFC – 7*** *tdCP = 0.93*CP* *tdFA = 0.97*(EE-1)* *tdNDF = 100*NDF/NDFD* *tdNFC = 0.98*NFC* *NFC = 100 – (NDF + CP + EE + ash – NDFCP)*	TDN = total digestible nutrients td = total digestible CP = crude protein (% DM) FA = fatty acids (% DM) EE = ether extract (% DM) NDF = neutral detergent fiber (% DM) NDFD = in vitro 48hr digestible NDF (% of NDF) NFC = non-fiber carbohydrate NDFCP = 1.3 (corn silage) or 3.8 (grasses and legumes) DM = dry matter	This is a standard calculation of TDN. NFC is calculated using summative equation modified to include starch and non-starch components. NDFD is measured over 48 hours rather than 30 hours as it is more consistent despite some arguments that it is less accurate.
Net energy of lactation	$\boldsymbol{NE_L = ((0.0245*TDN) - 0.12)/2.2}$	NE_L = net energy of lactation (Mcal/lbDM)	Calculated at 3x maintenance (NRC 1989)
Milk from forage	$\boldsymbol{M = ((NE_L*FI) - (0.08*613.64^{0.75}*PercF))/0.31}$	M = milk from forage (lb/ton DM) FI = forage intake (ton DM) PercF = percent forage in rations	M can be multiplied by forage yield per acre to give an estimate for milk yield per acre. This equation accounts for maintenance energy requirement.

Table 2-2. Example of primary calculations used by RUSLE2 software to calculate erosion.

RUSLE2			
Indicator	**Equations**	**Variables**	**Notes**
Detachment	$\boldsymbol{A = \left[\sum_{i=1}^{365m} a_i\right]/m}$ $\boldsymbol{a_i = r_i k_i l_i S c_i p_i}$	A = average annual erosion rate (mass/(area*year)) m = number of years in calculation r_i = erosivity factor (erosivity unit/(area*year)) k_i = soil erodibility factor (mass/ erosivity factor) l_i = slope length factor (dimensionless) S = slope steepness factor (dimensionless) c_i = cover-management factor (dimensionless) p_i = support practice factor (dimensionless)	Variables with subscript indicate long-term average for the *ith* day. $\boldsymbol{A}$ provides a numerical integration of erosion over all days in calculation. The cover-management and support practice factors are dependent on farm management practices.
Transport	$\boldsymbol{T_c = K_T \zeta q s}$	T_c = transport capacity (mass/(overland flow width *time)) K_T = coefficient of sediment transportability (mass/volume) ζ = coefficient of hydraulic resistance on transport capacity (dimensionless) q = overland flow rate (volume/(overland flow width *time)) s = steepness of overland flow path	This assumes that all sediment is equally transportable.
Deposition	$\boldsymbol{D_p = (\alpha_d * V_f/q)(T_c - g)}$	D_p = deposition rate (mass/(area*time)) α_d = deposition coefficient determined through calibration V_f= fall velocity of sediment in still water (length/time) q = overland flow rate (volume/(overland flow width *time)) T_c= transport capacity (mass/(overland flow width *time)) g = sediment load (mass/(unit overland flow width *time))	This is calculated for each sediment class and summed proportional to the distribution of total sediment load among classes. This equation assumes that total rill erosion is proportional to the difference between the runoff transport capacity and the sediment load.

Table 2-3. Calculations for the Wisconsin Phosphorus Index used in SNAPPlus (Ward-Good et al. 2010).

Wisconsin Phosphorus Index			
Indicator	**Equations**	**Variables**	**Notes**
Particulate P from field edge	***PP = C*CP + S*SP + L*LP*** *CP =3* SSTP* *SP =1* SSTP* *LP =0.7* SSTP* *SSTP = ISTP + ATP*8* *ATP = Pbroad + Pinc*0.4*	PP = particulate P C = clay content *(tons/(ac*yr))* CP = P concentrations in clay *(mg*P/kg)* S = silt content *(tons/(ac*yr))* SP = P concentrations in silt *(mg*P/kg)* L = large particle content *(tons/(ac*yr))* LP = P concentrations in large particles *(mg*P/kg)* SSTP = surface soil total P *(mg/kg)* ISTP = initial surface total P *(mg/kg)* ATP = total P added to surface *(lb/ac)* Pbroad = broadcasted P *(lb/ac)* Pinc = incorporated P *(lb/ac)*	Large Particles includes sand and small and large aggregates. The coefficient on Pinc of 0.4 is an empirically based estimate of the proportion of residue left on surface after incorporation of manure and is assumed to be an overestimate. SSTP equation assumes that 1 lb P equals 0.5 mg/kg in a 6-inch plow layer.
Soluble P from field edge	***SLP = SDP + DDP*** *SDP = (FR*FP + NFR*NFP)*0.2265*	SLP = soluble P *(lb/(ac*yr))* SDP = soil runoff dissolved P *(lb/(ac*yr))* DDP = direct dissolved P from applications *(mg P/L)* FR = frozen period runoff *(in)* FP = frozen period P concentration NFR = non-frozen period runoff *(in)* NFP = non-frozen period P concentration	DDP includes manure and fertilizer applications. The correction factor of 0.2265 in the SDP equation converts to units of lb/(ac*yr). Frozen period is designated as Nov 15 to Apr 15. To calculate frozen period runoff, a base volume is multiplied by a soil conditions factor that depends on field operations, contour, cover, and slope. Non-frozen period runoff is a sum of runoff from individual storms, predicted by local historic weather patterns. Dissolved P from applications is a function of all applications' soluble P with manure calculated using Bray P1 lab results.
Phosphorus index	***PI = (PP + SLP)*TPDR***	PI = Wisconsin Phosphorus Index PP = particulate P SLP = soluble P *(lb/(ac*yr))* TPDR = total P delivery ratio	TPDR is a constant determined by the field slope and distance to the nearest surface water.

Chapter 3. Application of Composite Indicators to a Key Wisconsin Cropping System

Introduction

Utilizing composite indicators for farm management presents potential for incorporating environmental externalities into on-farm economic decision making. However, due to the complexity of composite indicators, farm management information systems (FMIS) are necessary to overcome computational constraints and beneficially employ such indicators. To demonstrate the decision-making process with composite indicators, I provide a current working example using the three aforementioned composite indicators: Milk per Acre, the phosphorus index (PI), and RUSLE2, to assess the field specific effects of adding a winter rye cover crop to a corn silage system. Cover crops can preserve ecosystem services by mitigating soil degradation, erosion, and nutrient loading. Due to the heterogeneity in agricultural systems, the extent of environmental benefits realized from cover crops and the effect on farm profits will vary between years and locations. The lack of cover crop adoption by farmers indicates uncertainty of these benefits and risks. For farmers to make well-informed decisions about cover crops, they need field-specific expectations of the effects on revenue as well as the effects on externalities. For this analysis I focus on the use of winter rye cover crops in a corn silage system. This is a popular rotation for dairy farmers in Wisconsin, with both crops providing sources of feed for the herd. I hypothesize that using composite indicators integrated into farm management information systems can provide evidence for the environmental benefits of winter rye cover crops in a corn silage system without an added risk of economic loss.

Corn Silage for Feed

Using corn silage as feed on dairies and beef operations is common due to the forage's consistently high yields and energy content. Corn silage also has a low cost of production per ton relative to other forages, and while storage costs have decreased in recent decades due to advancements in bagging technologies, transport costs remain high. Therefore, there is not a large market for corn silage, and it is primarily produced for use onsite as feed. As a result, corn silage production is a standard practice for many farms with cattle, accounting for a large amount of cropland in the US, at over 6 million acres nationally each year for 2015 through 2019, with about 6.6 million acres harvested in 2019 (USDA 2018a; USDA 2020).

A major issue for corn silage production is the lack of soil protection after harvest, as most of the crop's above ground biomass is removed at harvest. Therefore, on highly erodible soils, soil conservation in these systems is an important concern. Maintaining field cover with crop residues is a simple way to reduce erosion impacts, however this is not feasible in a corn silage system. Winter cover crops present an alternative mode of maintaining field cover in corn silage production.

Ecosystem Services and Externalities of Corn Silage

In a corn silage system, the most evident ecosystem service being utilized is the provisioning service of the corn silage itself. Since markets for corn silage are sparse, comparison to more marketable forages allow it to be monetized. However, a fully informed decision of where and when to plant corn silage requires additional understanding of the other ecosystem services that are affected. Of primary concern in this system, where field cover after harvest is low, is erosion leading to nutrient and sediment loading (Blanco-Canqui and Lal 2009).

Erosion and soil degradation cost an estimated $44 billion per year in the U.S. due to lost productivity and environmental externalities such as nutrient loading (Pimentel et al. 1995). This cost of externalities is a prime example of how the utilization of one ecosystem service, crop production, can have unwanted effects on other ecosystem services: soil loss, well contamination, watershed eutrophication, and ocean hypoxic zones. Investment in conservation practices show great promise to reduce yield losses and unwanted environmental effects with as much as a five to one return (Pimentel et al. 1995).

For this example, we focus on sediment loss and phosphorus runoff. The extent of these externalities from corn silage production is reduced with an increase of residue left on the field at harvest (Grande et al. 2005a; Grande et al. 2005b). However, since the common practice for corn silage is to remove most of the above ground plant matter, winter cover crops are an alternative method of providing field cover and have been shown to substantially reduce soil and phosphorus losses (Siller et al. 2016).

Winter Rye Cover Crops

While the potential benefits of cover crops are well documented, the literature suggests the extent of these benefits can vary year to year. Ateh and Doll (1996) found that rye cover has the potential to control weeds without compromising soybean yields. However, this potential depended on soil moisture and the rye's groundcover, with below normal precipitation reducing the weed control effectiveness of the rye and leading to lower soybean yields. Kasper et al. (2001) showed in a three-year study that oat and rye cover crops can increase soil infiltration and decrease runoff and erosion. Nevertheless, in the first year of the study, there was less cover crop growth than in subsequent years, and the effects on runoff and erosion were not significant. Additionally, the cover crops had a significant effect on infiltration in only one year of the study. Many studies have been able to show the potential for benefits from cover crop use, but these benefits prove highly dependent on exogenous, uncontrolled variables and vary in extent across years and locations.

This high variability in the observed benefits from cover crops does little to address farmer concerns about uncertainty when using cover crops. Additionally, lack of farmer-accessible methods for determining the realized benefits of incorporating cover crops does little to encourage on-farm trialing. It is therefore essential to provide farmers with methods that allow them to quantify their own benefits and determine situations where cover crops prove beneficial to their operations and a key component of best management practices.

USDA SARE's report on their 2017 Cover Crop Survey suggest a steady increase in cover crop use among farmers both in the number of farmers using cover crops and the percentage of farmed acres planted with cover crops (USDA 2018b). However, winter cover crops have yet to become the standard in the US. In a survey of Corn Belt farmers, Singer et al. (2007) found that only 18% of respondents had ever used cover crops, and only 8% had used them in the year of the survey. These rates varied by state with Indiana and Illinois reporting higher rates of adoption at 15.9% and 15.7% respectively, while Iowa and Minnesota had lower adoption rates at 6.4% and 10.0% respectively. This low rate of adoption suggests that farmers are hesitant to include winter cover crops in their crop rotations.

There are many possible causes of deterred uptake of this technology, but they often relate to the farmer's perception of an associated increase in risk. Common perceived risks of implementing cover crop technologies are cover crop establishment difficulties due to time and weather constraints, negative yield impacts on the primary crop due to delayed planting and resource competition, and a lack of economic return on cover crop investments. Most noticeable is the uncertainty in the level of risk that cover crops pose. While there is general agreement in the perceived benefits of cover crops, it is not sufficient in outweighing the uncertainty of risk. Among non-adopters, many farmers indicate an interest in the technology but generally would like more information about how cover crops would benefit their farm (Arbuckle and Roesch-McNally 2015; USDA 2018b).

Central to farmers' concerns of added risks of winter cover crop use are the effects on the primary crop. These effects are often perceived to be negative and can be due to: delayed planting, increased soil moisture, delayed soil warming in spring, mechanical interference for planting equipment, or resource competition. However, in a comprehensive meta-analysis of 65 studies spanning 50 years that investigated the effects of winter cover crops, Marcillo and

Miguez (2017) found that grass cover crops did not have significant effects on yields for the following corn silage (n=140).

Winter rye provides a good option for a cover crop in a corn silage system in the northern Corn Belt. Rye is a hardy crop that provides good soil coverage, especially in no-till and minimum-tillage systems, providing as much as 5 tons of aboveground dry matter per acre. Rye can be planted relatively late in the season to not interfere with corn silage harvest and it is an effective weed and pest suppressor. Additionally, rye has the potential to capture substantial residual nitrogen after a corn crop (West et al. 2020).

On-farm technology adoption such as cover crops can prove daunting to farmers for many reasons. The barriers for uptake are usually more apparent than the benefits. To help abate this issue, researchers and crop consultants can provide farmers with methods of anticipating the field and farm specific results of a technology's adoption, as well as the methods of assessing these effects after a trialing period. Composite indicators in farm management software can provide farmers with a better understanding of the risks of incorporating cover crops into their rotation as well as the potential benefits received and reduce the uncertainty that prevents uptake of the technology. We will demonstrate this process using as an example the decision whether or not to adopt a winter rye cover crop in a corn silage system.

Data and Methods

Using research plot data from a study of winter rye cover crops in corn silage, we demonstrate the process of a dairy farmer using readily available data to access economic and environmental information from composite indicators employed via on-farm software to determine best management practices.

The Data

The data for this analysis are from West et al. (2020). Corn silage and corresponding winter rye cover forage yields were collected in a five-year (2012-2016) randomized complete-block, split-plot study at the University of Wisconsin's Arlington Research Center (43.304°, -89.383°) on a Plano silt loam soil. Three 43m x 9m plots of cover treatments: rye cover harvested as forage (RF), unharvested rye cover (RC), and no rye cover (NC), were split across three 43m x 3m plots of nitrogen rates: 67, 112, and 179 kg ha^{-1} (equivalently 60, 100, and 160 lb ac^{-1}). Nitrogen was sidedressed as ammonium nitrate. Additionally, each fall after corn harvest, all plots received applications of liquid dairy manure ranging from 90.7 to 115.0 kL ha^{-1}. The location of plot treatments was consistent over the five years.

Winter rye was drilled into the RC and RF treatments after the fall manure application at a rate of 110 kg ha^{-1}. The following spring, in late April or early May, the rye cover in RC treatment plots was terminated with a glyphosate burndown. The NC treatment plots were sprayed at the same time. The rye cover in the RF treatment plots was chopped and harvested in mid to late May and the stubble was then sprayed with glyphosate. Corn in all treatments was planted with a 0.76 m row spacing and a starter fertilizer of $6N – 16P_2O_5 – 47K_2O$ kg ha^{-1}. Corn silage was hand harvested at 65% moisture. The rye forage and cover as well as the corn silage were sampled from each plot for nutrient analysis and dry matter content. For additional details about the treatment practices, see West et al. (2020).

Partial Budget Analysis

Central to the decision to adopt new technology in farm operations is the consideration of its effect on profits. Farm budgets are extensive, so farmers generally use partial budgeting to simplify the analysis. Partial budget analysis involves calculating changes to cost and revenue from a change in operations to determine the effects on expected profits without creating a full cost of production budget. Expected profits, $E[\pi_i]$, were calculated on a per acre basis for each the NC, RF, and RC treatments ($i \in \{NC, RF, RC\}$).

$$E[\pi_i] = pE[Y_i] - W_i - C.$$

Here *p* is the price of milk (\$/cwt), $E[Y_i]$ is the expected milk produced from harvested forage calculated by Milk per Acre (cwt/ac), W_i is the treatment specific costs (\$/ac), and C is all other costs for the production system (\$/ac). The expected difference in profits between two treatments *i* and *j* is:

$$E[\Delta\pi] = E[\pi_j] - E[\pi_i] = pE[Y_j] - W_j - C - (pE[Y_i] - W_i - C)$$
$$= p(E[Y_j] - E[Y_i]) - (W_j - W_i) = pE[\Delta Y] - \Delta W.$$

In short, the expected profit difference is the milk price multiplied by the difference in milk per acre, minus the difference in costs for each treatment.

Treatment Specific Costs

In this example, treatment costs included direct costs associated with the cover crop treatment and nitrogen rate, as well as phosphorus and potassium removal by the forages. Direct costs from adding a rye cover crop consisted of rye seed as well as labor and machinery expenses for planting. If the cover crop is not harvested, the cost of materials and labor for an additional herbicide application for burndown is included. For rye planting, harvest, and burndown, the cost of labor and machinery is included. Since equipment and labor costs are variable and depend on the farmer's access to the necessary machinery, for this analysis the custom rates published in the 2017 Wisconsin Custom Rate Guide were used. Since the custom rate is the cost of bringing in a third party for the field operation, it is assumed to include labor and equipment costs, including upkeep and depreciation, as well as overhead costs. Additionally, using the custom rate allows us to ignore opportunity costs of the farmer's time and equipment, which would otherwise require additional considerations.

Nitrogen input costs were calculated for each treatment, but since application timings and methods did not change, the partial budget approach allowed for costs of labor and equipment for fertilization to be ignored. However, higher application rates may require additional trips to the field, and a farmer may choose to include these costs, so this assumption is a simplification for this analysis. Only the cost of the fertilizer itself was included, at $0.40 per pound of N. The amount of phosphorus and potassium removed by the corn and rye is also included in the cost calculation to account for lower yielding plots requiring less nutrient supplementation in subsequent years. Removal was calculated using the reported concentrations in the forage analysis multiplied by the measured per-acre yield. A dairy farmer may choose to ignore these fertilizer costs when a majority of credits come from manure applications. The added costs for the 2012 growing season at the 100 lb/ac nitrogen rate are summarized in Table 3-1 as an example.

Table 3-1. Example input costs ($/ac) for the partial budget analysis in 2012 with 100 lbs N/ac.

Input	No Cover (NC)	Unharvested Cover (RC)	Harvested Cover (RF)
Rye Seed	$ 0	$ 20	$ 20
Rye Planting	$ 0	$ 20	$ 20
Herbicide Burndown	$ 0	$ 26	$ 0
Rye Harvest	$ 0	$ 0	$ 110
Nitrogen	$ 40	$ 40	$ 40
P Removed by Rye	$ 0	$ 0	$ 16.07
P Removed by Corn	$ 22.01	$ 23.61	$ 18.36
K Removed by Rye	$ 0	$ 0	$ 55.13
K Removed by Corn	$ 45.53	$ 52.52	$ 33.72
Total Treatment Cost (W_i)	$ 107.54	$ 182.13	$ 313.28

Expected Yield

To determine the changes in revenues from adding rye cover crops, we used the composite indicator Milk per Acre, implemented with the decision support tools Milk2006 and Milk2016, available from UW Extension (https://fyi.extension.wisc.edu/forage). The necessary base indicators from the nutrient analysis reported for each treatment and yield measurement from each plot in each year from the West et al. (2020) data were entered into the Milk2006 and

Milk2016 spreadsheets. The spreadsheets returned fitted values for the predicted Milk per Acre, which is the production composite indicator.

Maximum Likelihood Yield Estimation

For maximum likelihood estimation of treatment effect parameters, yields were assumed to follow a normal distribution conditional on the treatments. Specifically, a linear model was assumed for the conditional mean (μ) and conditional standard deviation (σ) of milk per acre. The additive properties of normally distributed random variables allow for direct interpretation of the parameter estimates. The normal density function for yield (y) is:

$$\varphi(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu)^2}{2\sigma^2}}.$$

Hence, the log-likelihood function can be written as:

$$\ell_n(\mu, \sigma) = \sum_{k=1}^{n} log\ \varphi(y_k|\mu, \sigma) = \sum_{k=1}^{n} -\log(\sigma) - \frac{1}{2\sigma^2}(y_k - \mu)^2,$$

Where y_k is the measure of yield (TDM per acre or Milk per acre) for observation *k*, and the linear equations for the parameters μ and σ are:

$$\mu = \beta_0 + \beta_{RC}D_{RC} + \beta_{RF}D_{RF} + \beta_{N100}D_{N100} + \beta_{N160}D_{N160} + \sum_{t=2013}^{2016} \beta_t D_t,$$

$$\sigma = \delta_0 + \delta_{RC}D_{RC} + \delta_{RF}D_{RF} + \delta_{N100}D_{N100} + \delta_{N160}D_{N160} + \sum_{t=2013}^{2016} \delta_t D_t.$$

Here, D_τ are indicator variables equal to one for observations in treatment $\tau \in \{RC, RF, N100, N160\}$, where N100 and N160 indicate the nitrogen application rates of 100 and 160 lbs/ac. Additionally, since the data are from a longitudinal study, the data were pooled, and indicator variables were added to control for year fixed effects. Therefore, the coefficients give treatment effects for the conditional mean and standard deviation of the yield distribution.

In this case, when all indicators are zero, the intercepts give the mean and standard deviation of the no cover treatment at 60 lbs/ac of nitrogen in 2012. The estimation was also performed with added interaction terms between cover crop treatments and year. Log-likelihood ratio tests were used to compare models.

Estimation in R used the Newton-Raphson method with the ‘maxLik’ CRAN package. The $\hat{\beta}$ and $\hat{\delta}$ estimates are the mean ($\hat{\mu}$) and standard deviation ($\hat{\sigma}$) for each respective treatment. The expected change in milk yield per acre for the rye forage and rye cover treatments are then:

$$E[Y_{RF} - Y_{NC}] = \hat{\mu}_{RF} - \hat{\mu}_{NC} = \hat{\beta}_{RF},$$

$$E[Y_{RC} - Y_{NC}] = \hat{\mu}_{RC} - \hat{\mu}_{NC} = \hat{\beta}_{RC}.$$

Then the expected change in profit from adding rye forage (RF) and rye cover (RC) treatments to the no cover crop (NC) treatment are:

$$E[\Delta\pi]_{RF} = p\hat{\beta}_{RF} - (W_{RF} - W_{NC}),$$

$$E[\Delta\pi]_{RC} = p\hat{\beta}_{FC} - (W_{RC} - W_{NC}).$$

Using the additivity properties of independent and identically distributed normal random variables we can estimate the variance and standard deviation of yield differences:

$$\widehat{Var}(Y_{RF} - Y_{NC}) = \widehat{Var}(Y_{RF}) + \widehat{Var}(Y_{NC}) - 2\widehat{Cov}(Y_{RF}, Y_{NC}) = \hat{\sigma}_{RF}^2 + \hat{\sigma}_{NC}^2 - 2\hat{\sigma}_{RF,NC} = \left(\hat{\delta}_0 + \hat{\delta}_{RF}\right)^2 + \hat{\delta}_0^2 - 2\hat{\delta}_0\left(\hat{\delta}_0 + \hat{\delta}_{RF}\right) = 2\hat{\delta}_0^2 + 2\hat{\delta}_0\hat{\delta}_{RF} + \hat{\delta}_{RF}^2 - 2\hat{\delta}_0^2 - 2\hat{\delta}_0\hat{\delta}_{RF} = \hat{\delta}_{RF}^2,$$

$$\hat{\sigma}_{RF} = \sqrt{\hat{\delta}_{RF}^2}.$$

When year-treatment interaction terms are added, the calculation is similar. As an example, the estimated treatment effects and the variance and standard deviation for the harvested rye treatment (RF) in 2016 are:

$$E[Y_{RF\times2016} - Y_{NC\times2016}] = \hat{\mu}_{RF\times2016} - \hat{\mu}_{NC\times2016} = \hat{\beta}_{RF} + \hat{\beta}_{RF\times2016},$$

$$\widehat{Var}(Y_{RF\times2016} - Y_{NC\times2016}) = \left(\hat{\delta}_{RF} + \hat{\delta}_{RF\times2016}\right)^2,$$

$$\hat{\sigma}_{RF\times2016} = \sqrt{\left(\hat{\delta}_{RF} + \hat{\delta}_{RF\times2016}\right)^2}.$$

Risk

The economic risk of incorporating rye cover crops was assessed using the breakeven probability for each cover treatment. The breakeven probability is the probability that the expected change in profits is non-negative, $\mathbb{P}(\mathrm{E}[\Delta\pi] \geq 0)$. This probability can also be interpreted as the probability of recuperating the added costs of the rye cover crop. For example, the breakeven probability for adding an unharvested rye cover crop is:

$$\mathbb{P}\left(\mathrm{E}[\Delta\pi]_{rf} \geq 0\right) = \mathbb{P}\left(p\hat{\beta}_{rf} - \left(W_{rf} - W_{nc}\right) \geq 0\right)$$
$$= \mathbb{P}\left(\hat{\beta}_{rf} \geq \frac{W_{rf} - W_{nc}}{p}\right) = 1 - \Phi_{rf}\left(\frac{W_{rf} - W_{nc}}{p}\right).$$

Here $\Phi_{fc}(z) = \int_{-\infty}^{z} \varphi_{rf}(x)dx$ is the normal cumulative distribution function (CDF) with a mean and standard deviation given by the estimated treatment effects, $\hat{\beta}_{rf}$ and $\hat{\delta}_{rf}$. Normality of the coefficient estimates is ensured by the normality assumptions for the maximum likelihood estimation of the multivariate normal.

This characterization can provide additional insight prior to analysis. The cost of adding the rye forage cover crop $\left(W_{rf} - W_{nc}\right)$ has the units \$/ha and the price (p) has the units \$/Mg, so the term in the CDF has units of Mg/ha, which is the same as the units of the estimated treatment effects. In this sense, we can think of the term in the CDF as the change in milk production needed to offset the added cost of production. Additionally, this specification shows that as the price of milk increases, the breakeven probability increases, and as the cost of adding the cover crop increases, the breakeven probability decreases. This result will have implications for the decision to harvest or burndown an established rye cover crop.

Added costs were calculated for each cover treatment, at each nitrogen rate, and in each year. Since added nitrogen costs were in each cover treatment and differences in cost between cover treatments were similar across nitrogen rates and years, averages were taken across nitrogen rates for analysis. The analysis used a milk price of $429.90/Mg ($19.50/cwt), the average milk price reported by the USDA NASS Milk Production report for Wisconsin over the trial period (https://www.nass.usda.gov/Statistics_by_State/Wisconsin/Publications/Dairy).

Breakeven probabilities and the treatment effect on profit were calculated from the regression of total milk produced on the covariates including year-treatment interaction terms. Quartile estimates are calculated for treatment effects on per hectare profits using the NORM.DIST and NORM.INV functions in Microsoft Excel.

Assessment of Environmental Externalities

SNAPPlus was used to assess environmental effects by calculating composite indicators, the phosphorus index (PI) and RUSLE2. Management practices and field characteristics from the

West et al. (2020) study were entered into the SNAPPlus program. Values for the PI and RUSLE2 were returned for each treatment.

Results

Model Selection

A likelihood-ratio test between regressions with and without year-treatment interaction effects shows joint significance for the year-treatment interaction effects in all models (Tables 2-5). For the models with total milk production as the dependent variable, the log-likelihood ratio statistic was 42.89 (Table 3-2), which is significant at the 0.001% critical level in a chi-squared distribution with 16 degrees or freedom. Therefore, year interaction effects were included in the model used for the final analysis.

Treatment Effects

The most noticeable effect on yield in terms of magnitude and significance were the year fixed effects. Table 3-2 gives estimates for treatment effects on total milk production using the Milk per Acre metric. The intercept estimate, for milk production in 2012, with no cover, at 67 kg/ha nitrogen is 22.12 Mg/ha. The year fixed effects are all positive (9.85, 12.33, 18.22, 8.23) and highly significant ($\mathrm{p} \leq 0.01$) This is not surprising since these are the estimated additional milk per acre yields relative to 2012, a growing season with drought conditions (West et al. 2020).

In the model without year-treatment interaction terms, the effects on total milk production of adding a harvested and unharvested rye cover were -0.15 and 0.67 Mg/ha respectively, but neither were significant (Table 3-2). When year-treatment interaction terms were added, the harvested rye treatment estimate was -1.88 Mg/ha ($p = 0.09$). However, all year interaction terms for the harvested rye treatment were positive with the $D_{rf} \times D_{2016}$ coefficient estimate largest at 7.75 Mg/ha ($\mathrm{p} \leq 0.001$).

Harvested Rye

It should be noted that substantially higher rye forage yields were harvested in 2012 and 2016, averaging 3.44 and 3.08 Mg/ha dry matter. West et al. (2020) propose this may be due to higher than normal temperatures in those rye growing seasons. While this led to substantial increased profits from the rye treatment in 2016, the RF treatment performed poorly in 2012 due to a negatively affected subsequent corn yield. This corn yield loss could be a result of drought conditions through the 2012 growing season leading to increased competition between the rye and corn crops.

In all models with corn silage yield and milk from corn silage as dependent variables, the RF treatment had negative effects. For example, the RF treatment effect on total corn production without year treatment interaction terms was -3.49 Mg/ha ($p \leq 0.001$). This is consistent with research that points to resource competition between primary and secondary crops as a major concern for cover crops. These negative effects were not seen in the unharvested rye treatment, which in all models had a positive coefficient estimate, though not significantly different from zero.

Nitrogen Rate

In all regressions, nitrogen rates were positively correlated to production levels. The effect was larger and more significant for the 179 kg/ha rate than the 112 kg/ha rate. These effects were significant at varying critical levels. For example, increasing the nitrogen rate to 179 kg/ha increased the predicted milk production by 1.81 Mg/ha ($p = 0.059$) and increased total forage production by 1.20 Mg/ha ($p \leq 0.001$) relative to the 67 kg/ha rate. Increasing the nitrogen rate to 112 kg/ha increased the predicted milk production by 1.19 Mg/ha ($p = 0.193$) and increased total forage production by Mg/ha ($p \leq 0.05$) relative to the 67 kg/ha rate. Additionally, in the harvested rye treatment alone, higher nitrogen rates (112 kg/ha and 179 kg/ha) had positive effects on both the corn silage yield (1.22 Mg/ha ($p \leq 0.05$) and 1.35 Mg/ha ($p \leq 0.001$) respectively) and the total Milk per Acre value (2.70 Mg/ha ($p \leq 0.05$) and 2.01 Mg/ha ($p \leq 0.01$) respectively) (Table 3-7).

Breakeven Probability

Since the only variation in production costs within a treatment each year was the calculated P and K removal, added costs for the cover treatments were fairly consistent. The added milk production needed to break even for the two cover treatments averaged across years and nitrogen rates was 0.39 Mg/ha for the RC treatment, and 1.09 Mg/ha for the RF treatment. The breakeven probability (BEP), presented in Table 3-10, varied for both treatments from 0 to 1 showing a wide variation in the profitability of the cover crops between years. The RC treatment had BEP above 0.95 in three of the five years, but 0.05 or below for the other two. The RF treatment had a BEP of 1 in 2016 but it was 0 in 2012 and 2013 and less than 0.5 in the other two years. Despite this, the average expected change in profits across all five years for both cover treatments was positive. While the RC usually (60% of years) saw increased profits, the higher average for the RF treatment can only be attributed to the very high added profits in 2016.

SNAPPlus

Calculations from SNAPPlus of RUSLE2 and the Phosphorus Index (PI) for each treatment are presented in Table 3-8. The RUSLE2 value for NC treatments was 1.9 t/ac/year, higher than the RC and RF treatments' value of 1.1 t/ac/year. Since cultural practices remained consistent year to year, RUSLE2 gave the same results each year. Additionally, since harvesting a cover crop does not affect RUSLE2 or the PI, they are the same for the RC and RF treatments.

The PI values for the NC treatment were also higher than the cover treatments with a five-year average of 3.5 compared to 2.3 for the RC and RF treatments. Variation from year to year of the PI was due to variation in manure application rates. Differences in manure application rates also contributed to variability in the nitrogen credits.

Discussion

The preceding analysis provides a general framework for a farmer to make a well-informed decision about the use of winter rye cover crops in a corn silage system. The analysis presented verifies the potential of composite indicators incorporated into farm management information systems for including environmental externalities in on-farm decision making. This analysis strongly supports the planting of winter rye cover crops in the specified system but suggests the decision to harvest the rye is not always clear. A hybrid RC/RF system is likely optimal.

The estimated reduction in predicted phosphorus loading (34%) and soil erosion (42%) show substantial improvement in ecosystem service maintenance. This is consistent with findings in the literature, which is to be expected, since the predictions of SNAPPlus are based on published research findings. The changes in corn production, milk production, and profits from adding the unharvested rye cover crop were small, positive, and not significant. These findings should help encourage the planting of winter rye cover crops in this system. The farmer can get the benefits of reduced negative externalities without risking substantial losses to their primary crop.

While the decision to plant winter rye cover crops is well supported by this analysis, the decision to harvest the cover has more complexity. The predicted decrease in profits for four of the five years would likely dissuade a farmer's decision to harvest the rye cover crop. Fortunately for the farmer, this decision does not need to be made until the spring, when the rye yield can already be predicted. The added harvest costs are not realized unless the rye is actually harvested, and most of the environmental benefits are independent of the decision to harvest. Therefore, a farmer could plant a winter rye cover in the fall, and if the rye has a good year (e.g. 2016) then the farmer can decide to harvest the rye for feed. If the rye has a poor stand (e.g. 2013-2015), the farmer can do an early burndown, still receive the benefits of the cover crop, and not risk yield losses of the primary crop. The price of milk and the farmer's need for forage in the early season would affect these decisions.

The benefits of harvesting the rye cover will not always be clear. For example, in 2012, a high rye production was observed, however drought in the following growing season decreased the corn silage production following the harvest rye cover. A decision made in this scenario might consider that the rye is likely to return a high yield, but a forecasted dry summer may make the decision unprofitable. At this point the farmer could factor in other considerations such as the current on-farm demand for feed and the cost of buying alternatives. If the farmer is low on feed, and they have a diversified set of options for feed later in the season, then this could support the decision to harvest. In this sense, rye cover crops displace some of the risk of a single crop by utilizing the field throughout more of the year and diversifying the options for extracting marketable ecosystem services.

A final consideration for the farmer is the possibility of payments for ecosystem services. Specifically, through the working land payments discussed in Chapter 1.b.iv, a farmer can receive per-area transfers for implementing cover crops. These can be in the form of one-time adoption assistance or annual subsidies. Eligibility and access to these payments is not always guaranteed, but when awarded, can push the breakeven probability to certainty.

In this example, regression methods were used to estimate returns from each cropping system. In general, farmers will not have access to robust statistical methods that do not require extensive training. However, less contrived approaches, such as yield monitor data and historical averages can be used. As FMIS become more capable, much of this analysis can be incorporated to improve the decision-making process. Additionally, many important deliberations were incorporated into this analysis which must be central considerations of FMIS developers.

Conclusion

The decision to plant cover crops in a corn silage system of a dairy farm can depend on a variety of factors that can often be hard to coordinate. This is especially the case when not all of the benefits realized can be monetized. Useful composite indicators implemented through farm information management systems provide a framework for ensuring farmers have the necessary information to make well-informed, holistic farm management decisions. In conjunction with payments for ecosystem services, this technology can improve the maintenance of ecosystem services by agroecosystems.

Tables

Table 3-2. Total forage yields (Mg/ha) and predicted milk (Milk2006 and Milk2016, Mg/ha) yields by treatment and year, averaged across nitrogen rates (standard deviations in parentheses). Total forage is the corn yield for the NC and RC treatments and the sum of the corn and rye yields for the RF treatment. Treatments are NC for no cover crop, RC for a rye cover crop, and RF for a rye cover crop harvested for forage.

	Predicted Milk Yield			Total Forage Yield			RF Crop Yield	
Year	**NC**	**RC**	**RF**	**NC**	**RC**	**RF**	**Corn**	**Rye**
2012	**22.3**	**23.7**	**21.2**	**14.5**	**14.9**	**14.0**	**8.5**	**5.5**
	(3.4)	(2.6)	(2.2)	(2.2)	(1.4)	(0.8)	(0.8)	(0.3)
2013	**33.4**	**31.8**	**33.3**	**19.4**	**19.0**	**19.9**	**17.6**	**2.3**
	(2.9)	(2.5)	(2.9)	(1.4)	(1.1)	(1.5)	(1.6)	(0.1)
2014	**35.7**	**37.5**	**35.0**	**22.2**	**23.1**	**22.2**	**19.2**	**3.0**
	(5.7)	(5.4)	(2.6)	(2.1)	(2.2)	(1.4)	(1.2)	(0.3)
2015	**41.4**	**44.1**	**40.9**	**24.9**	**26.2**	**24.4**	**21.1**	**3.3**
	(4.1)	(2.6)	(2.7)	(2.6)	(1.8)	(1.4)	(1.4)	(0.2)
2016	**30.8**	**30.9**	**36.6**	**20.2**	**19.8**	**23.0**	**17.0**	**6.0**
	(3.4)	(3.7)	(3.1)	(2.1)	(2.3)	(1.6)	(1.6)	(0.3)

Table 3-3. Estimates for treatment effects on total milk production (Mg/ha) with and without treatment-year interaction effects.

	Mean Function		Std. Dev. Function		Mean Function		Std. Dev. Function	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Intercept	21.50 ***	0.87	2.56 **	0.79	22.12 ***	0.81	1.79	3.56
RC	0.67	0.77	-0.26	0.57	0.98	1.75	0.12	4.25
RF	-0.15	0.75	-0.74	0.57	-1.88 ·	1.12	0.44	5.69
N100	1.04	0.80	0.68	0.66	1.19	0.91	1.34	1.70
N160	1.29 *	0.66	0.27	0.55	1.81 ·	0.96	-0.29	0.93
2013	10.20 ***	0.83	0.12	0.64	9.85 ***	1.13	0.44	4.92
2014	13.74 ***	0.99	1.83 *	0.74	12.33 **	4.28	3.77	7.16
2015	19.55 ***	0.83	0.78	0.69	18.22 ***	1.70	2.54	6.31
2016	10.71 ***	1.14	1.94 *	0.83	8.23 ***	2.03	0.81	3.65
RC X 2013	-	-	-	-	-2.17	2.88	-0.47	5.63
RF X 2013	-	-	-	-	1.53	2.04	-0.59	7.36
RC X 2014	-	-	-	-	1.58	3.22	-1.06	8.95
RF X 2014	-	-	-	-	1.69	4.16	-3.84	9.39
RC X 2015	-	-	-	-	1.90	3.67	-1.56	6.65
RF X 2015	-	-	-	-	0.63	1.94	-3.34	9.08
RC X 2016	-	-	-	-	-2.13	7.80	0.76	4.49
RF X 2016	-	-	-	-	7.75 ***	2.04	-0.41	5.94
$\ell_n(\hat{\mu},\hat{\sigma})$:	-230.79				-209.35			

LLR = 42.89; df = 16; $P(>\chi^2)$ = 0.00029 ***

Significance level: *** = 0.001; ** = 0.01; * = 0.05; · = 0.1.

Table 3-4. Estimates for treatment effects on total forage production (Mg/ha) with and without treatment-year interaction effects.

	Mean Function			Std. Dev. Function			Mean Function			Std. Dev. Function		
Variable	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.
Intercept	13.86	***	0.47	1.46	***	0.42	14.05	***	0.69	1.82	**	0.56
RC	0.16		0.40	-0.29		0.30	0.20		0.76	-0.80		0.57
RF	0.11		0.40	-0.45		0.37	-0.70		0.77	-0.84		0.60
N100	0.62		0.40	0.27		0.36	0.85	*	0.34	0.29		0.28
N160	0.94	**	0.34	0.09		0.26	1.20	***	0.30	-0.09		0.30
2013	4.91	***	0.45	-0.08		0.36	4.58	***	0.80	-0.70		0.59
2014	8.07	***	0.44	0.56	·	0.34	7.52	***	1.02	0.34		0.73
2015	10.65	***	0.48	0.74	·	0.41	10.18	***	1.10	0.69		0.82
2016	6.68	***	0.63	1.07	*	0.44	5.58	***	0.89	-0.04		0.67
RC X 2013	-		-	-		-	-0.50		0.90	0.39		0.64
RF X 2013	-		-	-		-	1.14		0.98	0.89		0.73
RC X 2014	-		-	-		-	0.69		1.31	0.73		0.91
RF X 2014	-		-	-		-	0.71		1.21	-0.01		0.86
RC X 2015	-		-	-		-	1.09		1.38	0.34		0.96
RF X 2015	-		-	-		-	0.01		1.21	-0.77		0.99
RC X 2016	-		-	-		-	-0.84		1.24	1.17		0.87
RF X 2016	-		-	-		-	3.53	**	1.10	0.35		0.78
$\ell_n(\hat{\mu}, \hat{\sigma})$:	-140.60						-121.55					

LLR = 38.10; df = 16; $P(> \chi^2)$ = 0.0015 **

Significance level: *** = 0.001; ** = 0.01; * = 0.05; · = 0.1.

Table 3-5. Estimates for treatment effects on milk production from corn (Mg/ha) with and without treatment-year interaction effects.

	Mean Function			Std. Dev. Function			Mean Function			Std. Dev. Function		
Variable	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.
Intercept	19.95	***	0.93	2.93	***	0.82	22.20	***	0.72	1.72	*	0.67
RC	0.86		0.83	0.09		0.60	0.93		1.07	0.22		0.74
RF	-6.03	***	0.89	-1.25	*	0.63	-10.16	***	1.01	0.26		0.78
N100	1.12		0.77	0.72		0.69	1.31	.	0.71	1.49	**	0.53
N160	1.44	*	0.72	0.79		0.60	1.78	***	0.43	-0.36		0.34
2013	12.98	***	0.96	0.35		0.86	9.71	***	1.09	0.50		0.82
2014	15.71	***	0.96	0.97		0.75	12.18	***	2.15	3.85	*	1.52
2015	20.80	***	0.81	0.20		0.72	18.12	***	1.61	2.67	*	1.21
2016	11.25	***	0.96	0.43		0.90	8.20	***	1.18	0.88		0.91
RC X 2013	-		-	-		-	-2.05		1.62	-0.51		1.02
RF X 2013	-		-	-		-	6.09	***	1.58	-0.34		1.08
RC X 2014	-		-	-		-	1.72		3.02	-1.16		1.96
RF X 2014	-		-	-		-	5.36	*	2.37	-3.95	*	1.63
RC X 2015	-		-	-		-	1.95		2.12	-1.67		1.40
RF X 2015	-		-	-		-	3.08	.	1.79	-3.70	**	1.34
RC X 2016	-		-	-		-	-2.22		2.16	0.64		1.36
RF X 2016	-		-	-		-	7.19	***	1.75	-0.28		1.22
$\ell_n(\hat{\mu}, \hat{\sigma})$:	-230.37						-204.34					

LLR = 52.06; df = 16; $P(> \chi^2)$ = 1.07x10^{-5} ***

Significance level: *** = 0.001; ** = 0.01; * = 0.05; · = 0.1.

Table 3-6. Estimates for treatment effects on corn silage production (Mg/ha) with and without treatment-year interaction effects.

	Mean Function			Std. Dev. Function			Mean Function			Std. Dev. Function		
Variable	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.
Intercept	12.6	***	0.57	2.30	***	0.46	14.07	***	0.65	1.84	***	0.55
RC	0.36		0.45	-0.12		0.33	0.25		0.72	-0.78		0.56
RF	-3.49	***	0.45	-0.84	*	0.33	-6.33	***	0.71	-0.85		0.58
N100	0.67	·	0.39	-0.10		0.32	0.82	*	0.35	0.25		0.29
N160	1.03	**	0.40	0.05		0.30	1.18	***	0.29	-0.23		0.27
2013	7.09	***	0.65	-0.13		0.47	4.54	***	0.77	-0.62		0.59
2014	9.48	***	0.53	-0.22		0.40	7.44	***	0.96	0.37		0.73
2015	11.8	***	0.53	-0.11		0.41	10.18	***	1.06	0.76		0.81
2016	7.08	***	0.56	-0.23		0.43	5.59	***	0.85	-0.06		0.66
RC X 2013	-		-	-		-	-0.47		0.86	0.35		0.63
RF X 2013	-		-	-		-	4.54	***	0.93	0.90		0.70
RC X 2014	-		-	-		-	0.72		1.23	0.76		0.91
RF X 2014	-		-	-		-	3.45	**	1.10	-0.23		0.82
RC X 2015	-		-	-		-	0.97		1.33	0.28		0.95
RF X 2015	-		-	-		-	2.35	*	1.14	-0.90		0.97
RC X 2016	-		-	-		-	-0.97		1.18	1.17		0.86
RF X 2016	-		-	-		-	3.23	**	1.04	0.38		0.76
$\ell_n(\hat{\mu},\hat{\sigma})$:	-145.58						-118.89					

LLR = 53.38; df = 16; $P(>\chi^2)$ = 6.54x10^{-6} ***

Significance level: *** = 0.001; ** = 0.01; * = 0.05; · = 0.1.

Table 3-7. Estimates for Treatment Effects on Total Milk Production (Mg/ha) and corn silage production in the harvested rye (RF) treatment.

	Total Milk Production in RF Treatment						Corn Silage Production in RF Treatment					
	Mean Function			Std. Dev. Function			Mean Function			Std. Dev. Function		
Variable	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.	Estimate		Std. Err.
Intercept	19.83	***	0.97	2.42	***	0.70	7.45	***	0.46	1.24	***	0.33
N100	2.70	*	1.07	1.04		0.74	1.22	*	0.53	0.07		0.40
N160	2.01	**	0.71	-0.41		0.56	1.35	***	0.41	-0.50	.	0.30
2013	11.53	***	1.12	-0.44		0.76	9.24	***	0.55	0.17		0.37
2014	14.02	***	1.17	-0.03		0.82	10.98	***	0.50	0.05		0.35
2015	19.01	***	0.98	-1.08		0.71	12.68	***	0.43	-0.34		0.37
2016	16.01	***	1.39	0.43		0.95	9.08	***	0.62	0.30		0.41
$\ell_n(\hat{\mu},\hat{\sigma})$:	-25.94						-59.30					

Significance level: *** = 0.001; ** = 0.01; * = 0.05; · = 0.1.

Table 3-8. Annual RUSLE2 and PI values for each cover treatment.

Year	PI	NC	RC	RF
2012	Particulate	2.2	1.3	1.3
	Soluble	1.0	0.8	0.8
	Total	**3.2**	**2.0**	**2.0**
2013	Particulate	2.3	1.4	1.4
	Soluble	1.3	1.0	1.0
	Total	**3.6**	**2.3**	**2.3**
2014	Particulate	2.3	1.4	1.4
	Soluble	1.3	1.0	1.0
	Total	**3.6**	**2.4**	**2.4**
2015	Particulate	2.4	1.4	1.4
	Soluble	1.4	1.1	1.1
	Total	**3.7**	**2.5**	**2.5**
2016	Particulate	2.2	1.3	1.3
	Soluble	1.2	0.9	0.9
	Total	**3.4**	**2.2**	**2.2**
AVG	Particulate	2.3	1.4	1.4
	Soluble	1.2	1.0	1.0
	Total	**3.5**	**2.3**	**2.3**
RUSLE2 (t/ac/yr)		**1.9**	**1.1**	**1.1**

Table 3-9. Added treatment costs ($/ha) for cover and nitrogen treatments by year with averages across years and across rates.

		$W_{\tau} - W_{nc}$			
Year	**Tmt(τ)**	**N60**	**N100**	**N160**	**AVG**
2012	RC	175	184	178	179
	RF	509	508	517	511
2013	RC	187	152	149	163
	RF	438	422	444	435
2014	RC	163	196	183	181
	RF	424	426	397	416
2015	RC	187	178	123	163
	RF	457	446	434	446
2016	RC	108	163	167	146
	RF	519	521	547	529
AVG	RC	164	175	160	166
	RF	470	465	468	467

Table 3-10. Breakeven probabilities for cover treatments in each year. The added cost used was the treatment cost averaged across nitrogen rates.

Year	Tmt(τ)	$(W_\tau - W_{nc})/p$ (Mg/ha)	$E[Y_\tau - Y_{nc}]$ (Mg/ha)	σ_τ	BEP
2012	RC	0.42	0.98	0.12	1.00
	RF	1.19	-1.88	0.44	0.00
2013	RC	0.38	-1.20	0.35	0.00
	RF	1.01	-0.35	0.15	0.00
2014	RC	0.42	2.56	0.94	0.99
	RF	0.97	-0.19	3.40	0.37
2015	RC	0.38	2.88	1.43	0.96
	RF	1.04	-1.25	2.90	0.22
2016	RC	0.34	-1.15	0.89	0.05
	RF	1.23	5.87	0.03	1.00

Table 3-11. Quartile thresholds of added profits for RC and RF treatments calculated from breakeven probabilities in table 3-10.

		$\Delta\pi$ Percentiles ($/ha)		
Year	**Tmt(τ)**	**25%**	**50%**	**75%**
2012	RC	385.09	420.88	456.67
	RF	-935.73	-809.24	-682.75
2013	RC	-615.90	-513.98	-412.07
	RF	-194.01	-150.34	-106.66
2014	RC	827.37	1098.51	1369.65
	RF	-1069.71	-83.49	902.74
2015	RC	820.56	1236.08	1651.61
	RF	-1381.24	-538.90	303.43
2016	RC	-749.47	-492.66	-235.85
	RF	2514.03	2522.15	2530.26
AVG	RC	133.53	349.77	566.00
	RF	-213.33	188.04	589.40

Chapter 4. Concluding Remarks

The successful use of composite indicators will require well-coordinated development and implementation between farmers, researchers, ag-businesses, and policy makers. Each of these stakeholders has a different responsibility to achieve this end. The development of the three example composite indicators: Milk per Acre, the phosphorus index, and RUSLE2 demonstrate a working example of composite indicators that can be calculated using available farm management information systems (FMIS) and used to help farmers balance economic and environmental factors in farm management decision-making.

Researchers need to focus on the construction of composite indicators and how they can be utilized. As RUSLE2 and Milk per Acre illustrate, indicators require continuous effort with regular updates as knowledge of the agroecosystem increases. This effort includes updated selection and recalibration of empirical models used in the construction of composite indicators. Additionally, as understanding of the agroecosystem and data access improve, new composite indicators should be developed to continually improve the relevant information accessible to farmers. This process will require coordination with farmers to understand where in the management process the deficiencies in information access are, what data need to be collected to better understand these deficiencies, and how these data can be transformed into a small number of easily interpretable metrics. Additionally, researchers must work to improve holistic agroecosystem models to incorporate these metrics and expand the feature space of the decision-making processes for farmers.

Developers of FMIS and precision ag (PA) technologies need to integrate the composite indicators and their encompassing models into software that can be accessed and executed by the farmer. This integration will require coordination with researchers to optimize software performance and coordination with farmers to ensure efficiently operational user interfaces. RUSLE2 provides a good example of creating an indicator and accompanying software that is easily integrated into FMIS, as demonstrated by SNAPPlus. Since the future of the market for FMIS is uncertain, this approach allows developers of composite indicators to increase accessibility to a variety of platforms available to farmers. In general, working to create more comprehensive software to reduce the complexities of farm management is essential.

Researchers and developers must also work to improve aggregated analysis of crop conditions and expectations. Analyses at regional levels have the potential to prevent potentially severe run-off events or pest infestations that individual farmers cannot address on their own. Aggregated state information of production systems can also help reduce the market frictions driven by the high uncertainty of crop performance. However, concerns of user privacy and data security must be addressed by developers to ensure the safety and trust of the farmers.

Farmers and crop consultants must provide constant feedback to help ensure that the construction and development of composite indicators in FMIS are well-suited to improve their management. Their coordination with researchers and extension is required to determine where their decision-making process can be improved and coordination with developers to ensure that the software will efficiently improve farm management. Additionally, composite indicator and FMIS maintenance will be a constant and dynamic process that requires farmer feedback at every step. This feedback must address issues of the indicator's usability, effectiveness, and efficiency.

Policy makers need to help coordinate ecosystem service management at regional and national levels. Regional and national coordination will require aggregating data from FMIS and external sources to determine where there are environmental externalities and how to promote positive ecosystem services while averting negative externalities. Coordination with researchers is also necessary to determine the best way to allocate payments for ecosystem services to maximize their preservation.

The effective use of composite indicators will clearly require extensive coordination across agricultural stakeholders. It may seem daunting, but examples of this coordination already exist as outlined by this paper. To summarize, policy makers created the NPM 590 standard requirements to address aggregated negative externalities of agriculture such as nutrient loading in surface and ground waters. Adherence to NPM 590 is required for agricultural tax credits and can be fulfilled with the FMIS, SNAPPlus. SNAPPlus records cultural and fertilizer practices to calculate the composite indicators RUSLE2 and the phosphorus index. Farmers can utilize these indicators to incorporate nonmarketable ecosystem services into their decision-making process.

Composite indicators implemented through FMIS provide a powerful framework for reducing negative environmental externalities by improved information access in the on-farm decision making process. The usefulness and effectiveness of these indicators will rely on a well-coordinated effort between agricultural stakeholders. In the age of computerization and mechanization, composite indicators will be essential to the abatement of environmental degradation and anthropogenic climate change.

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