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FARM LANDSCAPE DESIGN DECISION SUPPORT TO INCREASE ECONOMIC, ENVIRONMENTAL AND SOCIAL BENEFITS USING STAKEHOLDER ENGAGEMENT, SUSTAINABILITY ASSESSMENT AND SPATIAL ANALYSIS

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ABSTRACT

Sustainable agriculture is essential for improving rural economies and remediating environmental challenges like air, water, and soil pollution. Perennial bioenergy grasses can be one of the approaches to improve water and soil quality and increase farmer profits on lower-yielding parts of the land. The challenge that this dissertation tackles is to identify where in a field or a landscape might perennial grasses best meet producer priorities and needs, in the context of fluctuating market prices for agricultural commodities and biomass, policy uncertainty, and the changing nature of US Midwest agriculture. The approaches that this dissertation takes to supporting the landscape design decisions include an agricultural sustainability assessment based on stakeholder engagement, economic and market analysis of perennial biomass and annual commodity crops, and generation of a landscape layout using spatial data analysis based on a range of sustainability indicators.

Agricultural sustainability and its indicators for assessment can be defined differently by different stakeholders, which is why this dissertation first studies what sustainability indicators matter most to agricultural producers and how they prioritize those indicators for further decision-making. The results suggest that producers have diverse priorities including profitability, soil quality, water quality, positive image, independence, financial stability and many more. Furthermore, the research shows that all producers consider multiple time horizons and spatial boundaries, that these boundaries vary depending on the sustainability indicators and stakeholder type, and that the different indicators need to be modeled at the varying space and time boundaries relevant to each specific indicator and stakeholder type.

One of the primary sustainability indicators that agricultural producers in this dissertation prioritize is profitability. To inform their decisions around incorporating perennial grasses into the landscape, this dissertation assesses whether and where there may be a business case for perennial grasses relative to the status-quo of annual crops like maize. To make that comparison, this study identifies and evaluates several biomass markets that either currently exist or will become available in the future, estimates the biomass prices associated with those markets, and uses published yield estimates and perennial crop production budgets for switchgrass to estimate the possible biomass profit. For annual crops, the study evaluates the historic profitability of corn using yield estimates based on high-resolution remote sensing imagery, and historic crop budgets, market prices, and subsidies. That analysis is carried out on two example watersheds in some of the most productive maize cropland in the world – the headwaters of the North Raccoon River watershed located in Buena Vista county, Iowa, and the South Fork River watershed located in Hardin county, Iowa. The results indicate that perennial grasses can be more financially viable on as much as 80% of productive Iowa land with biomass prices of $150/Mg assuming a high switchgrass yield of 10 Mg/ha, or over 25% of land if a low switchgrass yield is assumed of 5 Mg/ha. If the low price of $50/Mg is assumed, between 6% and 22% of land depending on the watershed and the scenario could be profitably converted to switchgrass. The fact that perennial grasses can be more profitable than maize on highly yielding Iowa cropland even with low-paying biomass markets suggests that biomass production can scale up to supply large-scale markets like biorefineries even if those markets are highly uncertain.

Profitability is an important factor, but not the only one that impacts the decision-making process. As illustrated through producer interviews, stakeholders consider a multitude of priorities when designing their landscapes. In this study, a framework is developed that can help design farm landscape plans according to those diverse priorities, with a range of outcomes estimated and evaluated through a sustainability assessment. The framework incorporates individual producer values, goals and preferences as the user selects priorities that matter most to them, assigns them a utility score, and weights them according to the level of priority that best describes the value of that indicator to the decision-maker. To demonstrate how that framework can be applied, a decision support tool was developed to optimize farm plans for prioritized sustainability objectives. Based on the stakeholder input and historical or modeled spatial data, the tool generates raster map layouts suggesting where to plant switchgrass or maize/soybeans and uses a smoothing algorithm to improve the operability of the farm layout. The selected model runs illustrate that with transitioning from economic-only to diversified priorities, the farm landscape transforms to include a higher percentage of perennial grasses. Overall, this dissertation fills a knowledge gap about producer priorities for sustainable bioenergy systems and demonstrates techniques that integrate stakeholder engagement and spatial data processing to inform perennial bioenergy crop decision-making.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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"Starting with people counters the tendency to see people as the problem. People can be helped, invested in, connected to others, taught, empowered, and cared for. They cannot be "fixed" or "solved."

TD **McGuinnes** and AM **Slaughter**, 2019. Spring Stanford Social Innovation Review p.29

Programming sticks upon the shoals
Of incommensurate multiple goals,
And where the tops are no one knows
When all our peaks become plateaus
The top is anything we think
When measuring makes the mountain shrink.

The upshot is, we cannot tailor
Policy by a single scalar,
Unless we know the priceless price
Of Honor, Justice, Pride, and Vice.
This means a crisis is arising
For simple-minded maximizing.

MD **Mesarovic**, 1964. Views on General Systems Theory

Chapter 1

Introduction

Agricultural status quo and the opportunity for herbaceous biomass

Corn and soybean farms in the US Midwest are a significant source of feed for animal farms and feedstock for first generation bioenergy plants across the U.S. and globe. However, these millions of acres of annual crops have also resulted in severe environmental pollution due to soil erosion and nutrient runoff, leading to algal blooms and eutrophication (Vitousek et al. 1997, Tilman et al. 2002, Hladik et al. 2014). Over time, this water and soil degradation can lead to social problems because of the loss of workable land and little space for innovation and profitability for future generations. Without significant action, agricultural pollution problems will increase with time (Sinha et al. 2017). As climate change impacts intensify, precipitation patterns will be changing and will lead to more nutrient runoff from the fields as well as greater stress on sensitive cropland from both floods and drought. Sinha et al. (2017) indicate that rivers in the US Midwest will receive nearly 28 percent more nitrogen the end of the 21st century if agricultural practices do not change. Such projections increase the need to take rapid action in adopting sustainable agricultural practices. Conventional management practices used in US agriculture function on a scale too large to ensure the most efficient use of the resources, as they fail to address field heterogeneity. High-resolution subfield farm planning can be used to suggest sustainable intensification options like placing perennial grasses in parts of the field to reduce the field nutrient runoff and establish wildlife habitat. These practices can help manage the economic, social and environmental challenges of both sustainable agriculture and sustainable bioenergy systems and provide a new approach for managing the land to reach its full economic and environmental potential.

Perennial grasses can help overcome a range of environmental challenges (Dale et al., 2014). For example, buffer strips have been shown to reduce nutrient runoff from fields, especially when these strips were placed downslope from row crops (Heathwaite et al. 2006; Zhou et al. 2010). Zhou et al. (2010) illustrated that strategic transitioning of even ten percent of farmland to perennial vegetative buffers decreased nutrient runoff, while Asbjornsen et al. (2014) pointed out that perennial buffers help also maintain soil, stream and groundwater levels during drought, the can also prevent floods, increase field biodiversity to aid in pest control, and increase pollination. Furthermore, perennial plant buffers capture carbon, thus reducing the greenhouse gas (GHG) footprint of the farming operation and sequestering atmospheric CO_2 as soil carbon (Zan et al. 2001).

Even when the environmental benefits of perennial biomass-based production are demonstrated, critics argue against such environmentally-friendly agricultural practices due to the cost of production and lost productivity. There is a widespread assumption that floodplain soils are highly profitable, and that farmers will lose the opportunity to make a profit from the seemingly productive land. Contrary to this assumption, emerging research indicates that many subfield areas (small parts of the fields conceptualized as separate units for economic, environmental or social analysis of farms) of fields are unprofitable, especially in low valleys during flooding and on steep hillslopes during drought. Bonner et al. (2014) illustrated the low profitability of maize across many subfields, even on fertile soils in Hardin County Iowa at typical grain prices (Figure 1-1). Based on multi-year average prices, conventional farm operations on this land would hardly sustain farmers’ livelihoods had there been no subsidies or insurance on crop loss. These losses on parts of fields have become quantifiable because of satellite data, precision agriculture tools, and GPS-tracking of agricultural machinery. Thus, with the correct software, a farmer could see that they might be losing money from parts of fields and take corrective action, which may include planting perennials. Since the net revenue farmers receive for growing soybeans and maize has not been financially attractive for several years, farmers may be more open to changing to their practices and evaluating biomass or other perennial crop production.

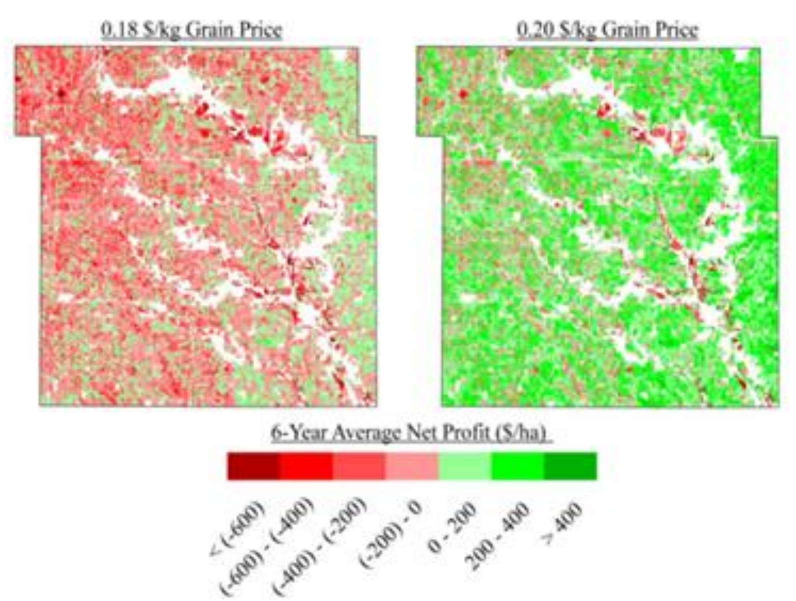


Figure **1-1**: Subfield economic analysis of land profitability depending on the market grain price (Bonner et al. 2014).

Contrary to the common assumption that sustainable farming practices require public or private investment without providing a return (Babcock et al. 2007, Motallebi et al. 2016, O'Connell et al. 2017), some companies and farmers have proposed and, in some cases, demonstrated ways to create commercial products from crops grown for environmental remediation. For example, studies like the report from National Renewable Energy Laboratory (Biddy et al. 2016) suggest that there is a myriad of uses for biomass. As these technologies mature and commercialize, perennial grasses could help supply these new markets and generate jobs across the region wherever the perennial crops are grown and processed. Perennial grasses and the bioenergy and bio-based products that can be made from those grasses create an environmentally friendlier alternative to the resource-intensive status quo (Georgescu et al. 2011, McLaughlin and Walsh 1998). These products are of interest to multiple stakeholders, including farmers, bioenergy industry representatives, environmental organizations, and consumers, and offer environmentally friendly energy and materials from renewable sources. To verify the benefits of biomass-based systems, sustainability or life-cycle assessments are required, and these assessments can be challenging because of the different concerns and interests of the stakeholders involved.

Sustainability assessment and optimization in agriculture

The term ‘sustainability’ became widespread in international policy language in the late 20th century with the discussions of society’s environmental footprint (Kidd 1992, Caradonna 2014). Many common definitions of sustainability are derived from the “Brundtland” report (Brundtland et al. 1987), stating that sustainability is an approach to development that does not limit the resources and choices of future generations but still satisfies the needs of the present population. This definition of sustainability can be directly applied to farming by inserting the term “agricultural practices” instead of “development.” This definition of agricultural sustainability can help conceptualize and evaluate multifunctional and productive agriculture systems. Hansen (1996) suggested that the most useful way to define sustainable agriculture is “agriculture that can continue”, meaning that sustainable agricultural is such set of practices that conserves soil, water, nutrients, economic resources, social fabric and other relevant resources for the future generations.

Most definitions of sustainability consider environmental, economic, and social dimensions. These three dimensions of sustainability were termed the “triple bottom line” by Elkington (1994) and have also been called the three “P”s: People, Planet, and Profit. Most agricultural enterprises, whether biofuel producers or small-scale farmers, depend on the profit from their activities to be sustainable. In addition, environmental and socio-cultural factors need to be considered to ensure system resilience to resource shortages or market and weather fluctuations. Sustainability assessments can help conceptualize the three categories of sustainability in a measurable way.

Sustainability assessment is one technique used to compare agricultural landscape design scenarios. Evaluating indicator outcomes from multiple scenarios or optimized solutions can help identify a design that performs best according to an agricultural producer’s priorities but does not limit the opportunities of surrounding communities and future generations for work and recreation. The popularity of sustainability assessment is increasing as more and more organizations choose to evaluate the performance of systems using indicators and measures that include but are not exclusively financial. Singh et al. (2009) reviewed the different techniques international organizations, academics, and research societies have used to evaluate sustainability, and discuss the wide range of tools that have been used. Sustainability and life-cycle assessment techniques and studies are diverse and are often not comparable because of different indicators, assumptions, and base cases (Ness et al. 2007, Cherubini and Stromman 2011). The goal of this section is not to detail all the techniques that can be used in sustainability assessment, but instead to highlight those most useful in agriculture and bioenergy research.

Sustainability assessments normally reflect the three dimensions embedded in the definitions of sustainability: economic, environmental, and social. Usually such assessments are multidimensional and consider indicators across the triple bottom line. Useful assessments are usually characterized as holistic and transdisciplinary, providing feedback and explaining uncertainty to stakeholders including decision-makers (Sala et al. 2015). Furthermore, sustainability assessment is an integrated assessment that reflects the nature-society relation, impact across spatial levels, and short- and long-term timeframes (Ness et al. 2007). Because agriculture is a coupled human-natural system, the appropriate assessment should be conscious of the value judgment that it is carrying (Gasparatos and Scolobig 2012). For agricultural decision-making purposes, such diverse characteristics of sustainability assessment can be summarized as interdisciplinary and informed by stakeholder opinion, as well as measurable and reflective of diverse spatial and temporal boundaries (Marchand et al. 2014).

Sustainability indicators can represent the decision variables for agricultural production and bioenergy crop sustainability, and are the foundation upon which sustainability assessments are built (Bell and Morse 2012). To be useful, sustainability indicators need to be easily measurable, sensitive and responsive to stress, correlated to other indicators, and be at least partly representative of the state of the system (Dale et al. 2015). A set of clearly defined indicators provides a way to simplify and represent a complex system. Sustainability indicators are often used to measure or model the current state of a system as a baseline but can also be used for simulation and modeling of system performance for alternative current or future scenarios. Current measures (for example, of nitrate concentration in water) can be classified as 'state' indicators (Bell and Morse 2012). Hansen and Jones (1996), in one of the pioneer agricultural sustainability assessment studies, point out that if sustainability assessment is future-oriented, the assessment should include simulations of how current decisions impact the future because of the definition of such assessment. Simulated values can be used in the assessment, either representing the rate of change or describing the result of the actions, thus serving as either 'driving forces' or ‘response indicators’ according to Bell and Morse (2012). Different types of sustainability indicators that represent agricultural systems and their performance have been integrated into several decision support and optimization tools (Bonner et al. 2016, Balezentiene et al. 2013, Parish et al. 2012, Dantsis et al. 2010).

Landscape planning for sustainable long-term agricultural operations has been attempted and documented in multiple case studies. Parish et al. (2012) developed a multiobjective optimization tool that identifies candidate locations for switchgrass placement on a farm and takes into account economic and environmental factors. That model’s operation was Geographic Information Systems (GIS)-based and carried out within the Biomass Location for Optimal Sustainability Model (BLOSM). The model considered a range of environmental and economic factors but did not include social factors in the assessment. Mendecka et al. (2020) sought an optimal biodiesel production scenario using several sustainability parameters but represented each pillar of sustainability with only one aggregated indicator without including the diversity of sustainability indicators. Human health has been also used as an indicator to signify the social influences. A study by Tien et al. (2018) incorporated the need for coupled human-nature assessment as suggested in Ness et al. (2007) by combining several models for a more holistic sustainability assessment. The authors argue that by both evaluating the ecosystem services and the economic implications of agricultural decisions could better inform regional decisions in agriculture. However, like many before them, Tien et al. (2018) did not consider social indicators.

Predicting and quantifying a decision’s impact on complex and dynamic systems including agroecosystems and other managed landscapes at either local or global scales can be challenging. Frameworks of analysis have included limits to growth (Meadows et al. 1972), ecosystem services and natural capital (Costanza and Daly 1992, Costanza et al. 1997), ecological footprint relative to planetary carrying capacity (Rees 1992), planetary boundaries (Rockström et al. 2009), and sustainable development goals (Griggs et al. 2013); these and other frameworks have been used to estimate the impacts of natural resource decisions on the future. Many of these frameworks discuss and quantify ecological boundaries or amounts of resources that people cannot exceed in their use. While all of the frameworks mentioned above can be useful for agricultural decision-making, some of them, like planetary carrying capacity or planetary boundaries, focus on large geographic areas that could be difficult to relate to on-field decisions. In contrast, ecosystem services could a concept that could help evaluate the impact of a decision on-the-ground.

Ecosystem services have been commonly used in agricultural studies to quantify the impact of agricultural practices and can serve as inputs for sustainability indicators. Ecosystem services are products of nature that can be used for improving human livelihood (Boyd and Banzhaf 2007). They include, among others, cleanliness and security of access to water and air, pollution mitigation, climate stabilization, biodiversity, recreation opportunities and the aesthetics of the surroundings. Ecosystems, including agroecosystems, can "provision" these services to humans either naturally or with human management, which is why this framework has been widely developed in the agricultural context (Robertson et al. 2014, Costanza et al. 2017). Ecosystem service studies quantify the value a specific practice or service could have to the community, often by estimating the costs of providing that same service by artificial means. Because the focus is on provisioning humans, the ecosystem service approach has sometimes been named as anthropocentric (Silvertown 2015), and that is why such services are quantified to assist stakeholders as they decide between alternative management strategies and their associated sustainability indicators and outcomes.

Assigning a value to ecosystems services can be tackled in three ways. First, the cost of not having the service could be estimated, either by calculating the price of a substitute (e.g., piping in clean water, filtering air, or treating people for ill health). Second, if a specific new method or crop can be shown to provide a service similar to a conservation practice that is already subsidized, the current value for that ecosystem service could be assigned to the new environmentally beneficial practice to make it more marketable. Third, if the difference between current traditional agricultural practices and the alternative can be determined, a subsidy can be provided to compensate for the difference. The second and third methods were used by Woodbury et al. (2018), where the authors propose a payment for N loading reduction by switchgrass. The payment could be based on amounts currently used to subsidize winter cover crops or could also equal the difference between the profitability of row crops that can be grown in the area and the profits from growing switchgrass for bioenergy and bio-products.

Instead of assigning a monetary value to ecosystem services, a stakeholder can establish the value function or the utility value of that service or indicator, as suggested by utility theory (Fishburn 1970, Tversky and Kahneman 1981). For each of the indicators or services, the initial unit of measurement would differ depending on the model or field data used. The utility or value function helps bring those different measures to a consistent range, for example, between 0 (least value) and 1 (highest value). Furthermore, the stakeholder can assign weight – priority – of the indicator to further specify the value of the service compared to other services. The utility values and weights can assist sustainability optimization by establishing a common unit of measure and allowing not only single-objective optimization but multi-objective optimization approaches.

Sustainability assessments can use similar inputs as ecosystem services studies but be more broadly inclusive of both inputs and indicators. For example, ecosystem services typically omit some social factors that are otherwise included in sustainability assessments (Dale et al. 2018). Assessments that have included social factors include social life cycle assessment (Dreyer, Hauschild et al. 2006) and corporate social responsibility assessment (Hopkins 2005). Social factors are often highly salient to stakeholders as they represent people’s well-being and community sustainability. Some of those factors might be hard to estimate, but proxy measurements can be used to find social indicator values like the measures in Dale et al. (2013). Given the diversity of factors that can be included in sustainability assessments, stakeholders need to be involved in the selection of the most important factors to ensure the usefulness of the assessment in a particular context.

Some researchers suggest adding multiple stakeholders to the sustainability and decision analysis to incorporate a full range of perspectives (Elghali et al. 2007). Such a multi-stakeholder approach is easily justified by the agricultural, industrial and institutional complexity of the bioeconomy problem, which spans the globe and where transitions are likely to take decades. Nevertheless, the sustainability indicators and assessments required for commercial growth of a bioeconomy are needed at different – smaller and shorter – dimensions of space and time to inform smallholders and other agricultural producer decisions, which will have different values and motivations than policymakers or business leaders operating at national or regional levels. To correctly represent the sustainability indicators and the spatio-temporal scales at which such indicators are measured, stakeholder engagement is necessary.

Stakeholder engagement

The influence and functioning of stakeholders, including organizations and agencies, varies between geographic and political scales. Thus, it is reasonable to anticipate their values and priorities, and the sustainability indicators that they find relevant would differ with scale as well. For farm-scale decision-making, some researchers have used agricultural producer profiles to represent the different opinions. Farm profiles are often generated from ethnographic studies in the region of interest. Several different approaches have been used for classifying farmer types. For example, Brodt et al. (2006) defined three groups of farm operators: “environmental stewards,” “production maximizers,” and “networking entrepreneurs.” Other classifications were presented in Bakker and van Doorn (2009), where the groups were “active,” “innovative,” “absentee,” and “old.” Still other classifications are presented in a paper by Darnhofer et al. (2005): “committed conventional,” “pragmatic conventional,” “environment-conscious but not organic,” “pragmatic organic,” and “committed organic.” These classifications are based on the findings that education and profit goals would result in similar choices, or that social position and age will determine decision-making. It is important to recognize that farmer profiles will not precisely predict farmers’ choices, which is why alternatively farms can be directly engaged to assign priorities to indicators, and such engagement can lead to empowerment.

The empowerment of stakeholders is closely linked to the concept of agency. Agency can be a way that authority is passed on to an executor, and the differences in interests between the agent and the principal can result in a conflict due to the so-called “agency problem” (Eisenhardt 1989, Bendickson et al. 2016). Agency can also have a definition that is more centered on one person’s power: of being able to act freely (Samman and Santos 2009), or having “process freedom” (Ibrahim and Alkire 2007). In the context of selecting indicators, agency can be related to having the freedom to choose indicators that reflect the person’s priorities. As Ibrahim and Alkire (2007) discuss in their paper, that empowerment increases a stakeholder’s ability to impact the system. This dissertation extends Ibrahim and Alkire’s argument to the spatial and temporal dimension, by considering how sustainability indicators can be adapted to the different spatial boundaries at which the stakeholders might be involved in decisions about bioenergy production. While the assessment in this dissertation is carried out for a 10-year average, stakeholder engagement results that are discussed in Chapters 2 and 4 indicate that decision support tools need to be flexible for multiple temporal boundaries.

By expanding the types of bioenergy sustainability indicators and adapting them to the spatial and temporal scales relevant to stakeholders, these stakeholders could acquire more decision-making power and agency (Reed et al. 2006). If indicators are selected by a research team without substantive stakeholder input, the analyst is holding power over the decision factors. Even though the analyst might offer the final decision-maker a range of scenarios and multiple outputs on which to make the decision, defining the decision parameters can profoundly impact the decision outcome. If the decisions around bioenergy and agroecosystems involve deciding where and how much bioenergy crop is grown, or what the payment for a product should be, the analyst is assuming the role of an agent without being formally delegated to do so. By returning to the farmers or industry representatives as a primary decision-maker and discussing their priorities, the power at least partially could return to those decision-makers. An example of such empowerment is the work of Fraser and colleagues in communities across different countries as discussed in Fraser et al. (2005).

Stakeholder engagement, like the engagement of agricultural producers, gives leverage to stakeholders in decisions that would affect them by including their opinions on the decision criteria. If researchers and policy-makers rely only on their expertise, they impose their power and biases onto the people that are affected by the decision (Slätmo et al. 2017). Such a top-down approach hinders the adoption of sustainable agricultural practices, as they may fail to address important goals and key performance indicators that are critical for specific stakeholders, such as financial or labor constraints. Stakeholders can have greater control over the decisions through interactive participation (Pretty 2008), and such interactive participation can be in the form of model co-development (Voinov and Bousquet 2010). Similarly, decision support can include the values and priorities of stakeholders, which has been named as “value-based decision support” (Tuana 2020). Agency and empowerment are advanced when stakeholders have the power to define decision criteria, and the method used for decision-making is transparent and accessible. These components of research and implementation are central elements to transdisciplinary approaches.

Empowering stakeholders can help increase the likelihood that they will carry through on decisions. Saam (2007) discusses how the stakeholder’s and the modeler’s perspectives are often substantially different with respect to risk perception and information access. Understanding which stakeholder takes most of the risk could help clarify whose indicators should be included in the analysis. For example, representatives of the industry and farming take most of the risk by changing their practices. That risk can be mitigated through subsidies or grants from the government or NGOs.

Samman and Santos (2009) suggest that agency and empowerment can be exercised at different levels – they mention micro, meso, and macro – and across different domains. These authors argue that different stakeholder categories (which parallel geographic extents) require different sets of skills. Such an approach recognizes that each level of stakeholders has decision-making authority within their level, even though it might be expressed differently in the organization chart of a hierarchical organization or among different businesses collaborating in a value chain. Following that logic, each level should also have a corresponding set of indicators, as using a set that might be relevant to a different level would take power from the groups of stakeholders who happened to work at the other levels. For example, if the sustainability of a bioenergy system is measured only at the landscape level, such analysis would miss the finer-detail priorities of those that put the bioenergy crops on the ground, and the resulting designs might not be readily applied on the field.

Exercising power across domains can be paralleled to the concept of agency of a profession. Agency through a profession can be a useful strategy to describe the relationship between the stakeholders – they have different roles and different personal priorities/goals tied to the profession, which frames where the information asymmetry could come from (beyond the physical distance to land). For example, if a researcher selects decision criteria for the farmer, they apply their agency to a decision that should instead have been determined using decision criteria coming directly come from the farmer. When defining stakeholders that should be engaged in the decision-making, researchers should consider who has the actual power over the decision and make sure that the method of engagement matches the capabilities of the stakeholders (Reed 2008).

As a result of engaging stakeholders, the solutions that analysts develop might be more readily accepted and implemented. Many project developers avoid stakeholder engagement out of fear of public resistance, attempting to maintain secrecy while permitting is underway. This practice is sometimes referred to as "announce and defend", and while it is sometimes effective in getting projects implemented it can also generate fierce opposition and project failure. In contrast, McGuinness and Slaughter (2019) argue that the stakeholders are part of the solution rather than the problem. Increasing numbers of companies now formalize stakeholder engagement early in the development of projects in order to obtain the social license to operate. Such a concept has been applied in industries like mining (Owen and Kemp 2013), but too often this still means engaging stakeholders to approve a plan, rather than to co-generate knowledge and decisions.

Bioenergy supply and processing is a complex system that involves multiple stakeholder groups with different goals. Multiple authors suggest that sustainability decision analysis should incorporate a full range of perspectives of stakeholders (Elghali et al. 2007), but such engagement would require consensus between the stakeholders. According to Fraser et al. (2006) each ‘element group’ (or, as this dissertation refers to, stakeholder group) has a different objective and thus different indicators and control mechanisms are needed if that objective is to be met. Farmers, government, NGOs, industry, the general public – all can be treated as element groups, and have different objectives. Hardin (1968), in his foundational paper on governing the commons, characterizes those differences as challenges because he sees the groups being locked in their own group paradigm and trying to improve their own ‘herd.’ However, Ostrom (1990) challenged this thinking by discussing that stakeholders can escape the “trap” of their group paradigm through effective strategies of engagement. While every group and person has a different set of “goods” and these “goods are incommensurable” (Hardin 1968), bringing stakeholders together can help establish common ground and create value for all participants (Horisch et al. 2014). Consensus can be reached through effective stakeholder engagement by “committing to a cooperative strategy that they themselves will work out” (Ostrom 1990).

The choice of whom to empower in the decision-making process, and through them the decision criteria that will eventually be evaluated, is clearly critical to sustainability assessments. As described above, there is a wide universe of potential stakeholders, and in most cases it will not be practical to include all of them. Downselecting the most relevant and necessary groups can be assisted by formal methods of stakeholder analysis. Garvare and Johansson (2010) define the stakeholders of sustainable development as those who have the power to act towards their needs. The authors themselves point to the challenges in identifying where that power lies, and determining what is a “need” compared to a “want.” Prell et al. (2009) suggested that stakeholder selection depends on the specific problem. Such an approach is practical and transdisciplinary in the way that it makes the research problem-driven. Stakeholders are interconnected through social relations, so it can be useful to map and analyze the network of the stakeholders to understand where connections are strong and where they are weak. As several authors have illustrated (e.g. Rowley 1997, Bendickson et al. 2016), network theory can also help understand the diversity of opinions that the stakeholders have. Beyond network analysis, and because many stakeholders are guided not only by economic benefits, social embeddedness theory can provide a framework to help analyze and explain these interactions (Le Breton-Miller and Miller 2009). Whichever path is selected for stakeholder analysis, it can help identify the key stakeholders that need to have a say in bioenergy decisions. This dissertation focuses on the agricultural producer, the most critical group involved in decision-making about agricultural landscapes and sustainability planning. However, the approaches developed here can be extended to other stakeholder groups and other natural resource decision problems.

Research goals and research area

This dissertation work borrows concepts and terminology from different scientific disciplines, including operations research, sustainability science, economics, agroecology and other fields. Sustainability science examines the interactions between the natural and social worlds in space and time, and through the multiple lenses of stakeholder values (Kates et al. 2001); this research attempts to do this as well. Stock and Burton (2011) describe sustainability research as a transdisciplinary approach that calls for cooperation and partnership, which may explain why sustainability has served as a driving force for global and regional policy-making (Triandafyllidou and Fotiou 1998). Although much of the sustainability literature has been multidisciplinary, including the formulation of Sustainability Development Goals, the Natural Capitals approach, or the triple bottom line, sustainability science borders between stakeholder consultation, policy-making and foundational science and calls for direct interaction with stakeholders.

Landscape ecology provides a useful terminology to understand scale and extent in decision-making. Taking the landscape ecology approach to decision-making, it is important to include considerations of natural components like topology, soil, and microclimate, and also the social interactions with those biophysical features – including not only the anthropogenic impacts, but also the value or connection that the inhabitants feel to the land (Tress et al. 2001). Inevitably, if the landscape is involved, so are people, including people that own/have a stake/have memories in that land. The connection between the social and natural components of the landscape becomes especially visible from the ecosystem or landscape services concept (Termorshuizen and Opdam 2009): that literature discusses the natural or landscape provisions as having a specific value to humans, and the natural resource decisions are made based on that value. Even the scale or extent at which a decision is made depends on human and natural constructs (Lebel et al. 2005). For example, if the government officials are deciding on the levels of nutrient reduction loads in the watershed, the 'watershed' is not only defined by the natural condition but also how those natural conditions were interpreted and altered by people.

As with landscape ecology, agroecology – which is another discipline within which this dissertation research could reside – is transdisciplinary (Mendez et al. 2013). This research approach integrates scientific ecological knowledge with local farmer knowledge, meaning that two-way learning and engagement are central to the inquiry. Furthermore, agroecology considers both on-farm impacts and also the broader impact on the environment and community, making it multiscalar.

This research project stands on the border of discovery science, helping to understand how agroecosystems and agricultural business are impacted by cropping system decisions with respect to various dimensions of sustainability, and translational science, applying this practical knowledge to inform decisions and enhance farm management. This border-spanning is another characteristic of transdisciplinary research. The management component applies the scientific concepts to current problems. The application of research in management, although possibly contrary to some philosopher's understanding of the role of scientists, answers the modern call for action from the scientific community (Brandt et al. 2013, Bornmann 2012). Such engagement can add a new layer to the transdisciplinarity when not only stakeholders are engaged in science, but when scientists are engaged in decisions and action.

Building upon the available literature across the disciplines and using input from stakeholders, this dissertation develops a decision support framework to assist producer decision-making about where to place perennial grasses relative to annual crops, with the objective to maximize the utility of sustainability indicator values using spatial decision analysis. To do so, it fills the research gap in establishing a decision support tool that is based on agricultural producer values and converts those values into actual field layouts that can be operable.

Chapter 2

Producer sustainability perspectives: conservation perennial grass, perennial bioenergy, and corn stover-harvesting producers and their values, geographic and temporal concerns

Abstract

Agricultural producer priorities and values strongly influence the actions and decisions that they take. In the bioenergy context, if society's sustainability goals require increasing bioenergy feedstock production, that will happen more rapidly if the planning and implementation of biomass supply holistically addresses producer needs and priorities. This paper discusses the priorities of stakeholders that are engaged in bioenergy crop production and considers their perspectives with respect to space and time. The goal of the study was to identify the priorities that can serve as the foundation for producer decision support on planting perennial grasses. A mixed-method approach of semi-structured interviews and quantitative priority elicitation was used to understand producer priorities. To include a broad array of perspectives, three producer groups were interviewed for this study: those that plant and harvest perennial biomass crops as part of bioenergy projects, those that harvest corn stover to supply bioenergy plants, and those that establish perennial crops for conservation purposes and are not currently marketing those crops for bioenergy. Results demonstrated that several key priorities, including profitability, financial stability, and soil quality, were important across all the producer groups. Other priorities like preventing soil erosion and improving water quality were more important to the conservation and perennial biomass crop growing groups compared to the corn stover growing group. Although the responses suggest that the conservation and perennial biomass crop growing groups may be more concerned with longer-term outcomes, all the producers

interviewed considered multiple spatial and temporal boundaries in their decision-making. This study provides insights as to the priorities that are particularly relevant to different producers that have planted perennial grasses or harvested biomass for bioenergy, including the spatial and temporal dimensions of indicator variables. This study can help inform which priorities can be measured and modeled to inform producer decisions about bioenergy crop production.

Introduction and research background

Biomass supply is one of the main requirements for expanding the bioeconomy – increasing the fraction of the economy that uses plant and animal waste materials as feedstocks for energy and materials production. Agricultural producers are the foundation to the bioeconomy supply chain, which means that their success is necessary for a healthy bioenergy and biochemicals industry, and bioeconomy-related decision-making would benefit from their perspectives (Schmid et al. 2012). Designing biomass supply systems that explicitly address producer needs could increase the chance of their buy-in, and as a result increase the rate of bioenergy crop expansion (Lewandowski 2015).

Engaging producers through interviews is one of the approaches used to understand their needs and priorities. Typically, such interviews have focused on understanding producers' past decisions or management approaches (Busck 2002, Reimer et al. 2011). By then separating producer values into typologies or categories it may be possible to backcast decisions and develop predictive models of group behavior which can then be useful in designing new policies or economic incentives. In this study, interviews with producers were instead designed to help understand producer priorities in order to inform research and communication needs and support decision-making by a wide range of producers or landowners, regardless of their group, typology, or category. For consistency in this study, we use the term “producer” to refer to the groups that were interviewed, because this term includes both landowners and tenants as defined in the most recent Census of Agriculture (USDA NASS 2017). Participants were contacted for the interviews as part of one of the three production categories (i.e. growing perennial grasses for conservation or biomass production, or harvesting stover for bioenergy feedstock supply) based on the information that regional and research project collaborators have provided about the producers. Participants were only categorized by their production activity to ensure that different perspectives are represented, rather than being categorized into environmentally-minded or profit-oriented producers based on the outcomes of the interviews. This distinction was not intended for group modeling but rather to ensure that different types of participants are included for the interviews and that research, education, and decision support systems around biomass production, farm field planning, and the design of agricultural landscapes are responsive to the differing values and priorities.

Theoretical framework

Producer priorities and values, and the decisions that result from them are at the center of this study. The assumption that producer priorities will guide their decisions is based on the theory of planned behavior (Ajzen 1991, Senger et al. 2017). The theory states that a person’s beliefs lead to behavioral intentions which in turn lead to actions (Ajzen 1991). Value-belief-norm theory (Stern et al. 1999) suggests that environmental stakeholder values can be expected to lead to corresponding pro-environmental behavior (Oreg and Katz-Gerro 2006). For example, a study by Wensing et al. (2019) suggests that environmental values of farmers can make them more likely to have a positive attitude towards expanding a sustainable bioeconomy. Wensing et al. (2019) apply the value-belief-norm theory and theory of planned behavior to illustrate that farmers' interest in valorizing the by-products of vegetable production can be correlated with farmers' worldviews and values, where the interest was understood as behavioral intention.

Besides priorities themselves, this study evaluates the time and space dimensions of those priorities. The dimensions of time and space are frequently considered in scenario development and output analysis of bioenergy sustainability models. However, these dimensions rarely have been explicitly used to understand and frame stakeholder's priorities. Stakeholders have space and time boundaries within which they operate and influence (and which they are influenced by), and these are typically the geographies and timescales that they care strongly about. Adams (1995) discussed a person's space-time dimensions suggesting that actions can be used to place a person on a space-time diagram. By stating that "people's actions externalize their values, expectations, and knowledge", Adams connects the space-time boundaries of a person to the theory of planned behavior and value-belief-norm theory. When the priorities of a person are expressed and assessed within a specific space-time boundary, then the stakeholder would be more conscious of their decision's impact within those boundaries. For example, if a producer is concerned about shrimp farmers in the Gulf of Mexico (a value and priority), they might be more likely to change their practices and behaviors to minimize harm to shrimp farmers within that spatial boundary, especially if they understand the impact that individual farm decisions on distant places can have at that scale.

Given that a person has specific space-time boundaries for their actions and influences, it is not surprising that their concerns have space-time boundaries as well. But the spatial and temporal extents of concerns may not be the same for a given individual across all concerns. For example, one priority of a producer, such as food security, could be emphasized at a planetary level, but others, like soil quality or crop profitability, could be expressed and evaluated at a farm or even subfield level. Uzzell (2000) has studied how perceptions of environmental problems can vary depending on whether the problem is local or global. Interestingly, this study finds the inverse effect of distance relative to individual actors; the further away the problem is, the more important it seems. This finding may be because global problems seem larger or more overwhelming, but also because people feel like they as individuals can have less impact over those global problems, even though they seem more serious. In the context of climate change problems, Haden et al. (2012) found that adaptation is increased by close proximity to a specific climate change challenge (e.g., flooding, drought), but efforts at mitigation are increased when actors understand the massive scale of the global challenge (e.g., methane or nitrous oxide emissions, or increased soil carbon storage). That is why Haden and colleagues suggest framing mitigation strategies as global issues, but adaptation issues as local issues. Following that logic, by understanding producers' space-time concerns, sustainability indicators associated with bioenergy goals can be framed as either global or local depending on whether they are mitigation oriented (e.g., reduce greenhouse gas emissions associated with farming or transportation) or adaptation oriented (e.g., improve soil health, more resilient crops, and more stable income), respectively.

Previous studies

Several previous studies have investigated producer priorities and beliefs in relation to expanding bioenergy crop production. Frequently, such studies explored the willingness of producers to adopt bioenergy crops – both harvesting bioenergy crop residue and producing dedicated bioenergy crops - with results categorizing producers as pro-environmental/sustainable or conventional, and summarizing the common priorities of the producers (Eaton et al. 2018, Eaton et al. 2019, Gowan et al. 2018, Rossi et al. 2011, Skevas et al. 2016, Tyndall et al. 2011).

Tyndall et al. (2011) surveyed Iowa farmers about their willingness to harvest corn stover for bioenergy. They state that 17% of the surveyed farmers are interested in such harvesting, with most of them in North-Central Iowa. The authors asked interviewees about their environmental concerns and reported that farmers who were interested in harvesting stover had lower levels of environmental concerns about the process. Bergtold et al. (2014) surveyed Kansas farmers to produce cellulosic biomass, including corn stover, and suggest that over 80% of survey participants were willing to harvest corn stover. Instead of categorizing farmers by type, these authors explain the willingness to adopt new practices by geographic location, suggesting that farmers in dryer regions in Kansas (like western part of the state) can be less likely to harvest stover because they prioritize preserving soil moisture content. The authors suggest that interest in harvesting and selling corn stover, like other bioenergy crop production, could be explained by whether they perceive such operations as a source of additional income.

Several studies have considered how producer concerns and beliefs about specific agricultural practices could influence the likelihood of perennial bioenergy grass adoption. Skevas et al. (2016) found that assuming the same rental price, farmers in Michigan were more likely to rent land out for perennial grasses than poplar trees or corn. Furthermore, the authors suggest that the farmers who use their landscape for recreation and value it for the scenery, are more likely to adopt dedicated bioenergy crops. Eaton et al. (2018) studied socio-cultural concerns of farmers who are likely to adopt perennial grasses, and showed that while a farmer’s profit- and production-orientation did not predict whether a farmer is likely to adopt perennial crops, the symbolic meaning a farmer assigns to the farming practice or their own land could be an explanatory variable. For example, Eaton et al. (2019) found that the farmers who believe that dedicated bioenergy crops like willow or switchgrass are a way to solve environmental challenges and enhance the farm’s harmony with nature were more likely to adopt such crops. Gowan et al.

(2018) found that valuing profitability and soil preservation was correlated with the interest in growing perennial crops. The qualitative study by Rossi and Hinrichs (2011) suggests that potentially negative social impacts of bioenergy crops and the resulting bioeconomy could make producers more skeptical of bioenergy grasses like switchgrass. Overall, producer perceptions of perennial bioenergy crops and the factors that influence the likelihood they will adopt such crops are complex, and linked to sometimes conflicting social, economic and environmental priorities.

Although most of the studies referenced above were prospective studies of producer's potential "willingness to adopt", some studies have considered the relation between producer beliefs and the actual adoption of new practices. A study by Comer et al. (1999) explored how the beliefs of "sustainable" and "conventional" farmers correlated with their adoption of switchgrass production. The results of their survey found that the "sustainable" farmers believed more in the benefits of environmentally-friendly agricultural practices, and were two times more likely to adopt new practices than the "conventional" farmers. Categorizing producer groups by their values and priorities could predict the types of practices that producers adopt and their frequency, but also illustrates the diversity of perspectives of different individuals in the same occupation. Again, the goal of this study is not to classify the producers by their adoption interests, but rather to build on the producer priorities observed in the literature, to include diverse participants in the interviews, and thus to generate a range of sustainability indicators that reflect those diverse priorities that can help guide bioenergy research, education, and on-farm decision-making.

Building on the literature on producer values and their willingness to adopt bioenergy crops, the goal of this study is to highlight the diversity of producer priorities, and their conceptualization of space and time boundaries for those concerns to set the foundation for value-based decision support (Tuana 2020) of individual farm landscape designs.

Methods and study context

This study combines methods from two different disciplines – social sciences and operations research. Following the social science approaches, agricultural producers were interviewed using semi-structured interviews. During the next phase of the interviews, a select group of the same producers were asked to set priority weights and select time and space boundaries for sustainability indicators of their concern. Each of the approaches was implemented as a separate interview phase, as illustrated in Figure 2-1. These methods are discussed in more detail below.

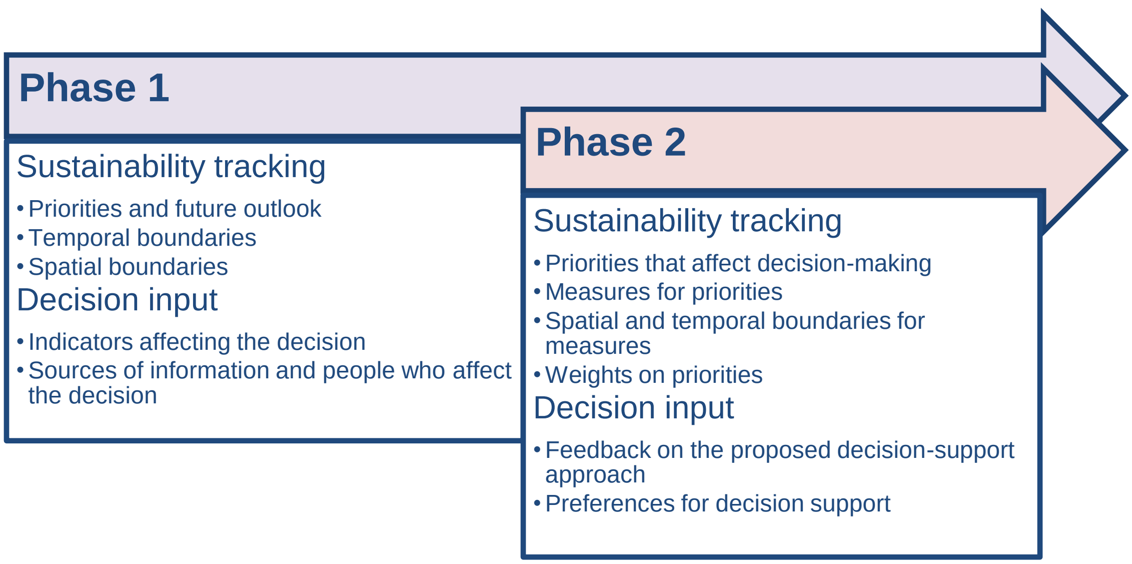


Figure **2-1**: Division of producer interactions into two phases.

Semi-structured interviews

The interviews were conducted with agricultural producers active in Iowa. All interviewees were landowners, yet some rented land for farming in addition to what they already owned. Most were actively farming their land, but many leased parts of their land to other producers. As mentioned earlier, we use the term “producers,” which represents the person(s) involved with on-farm decisions and includes landowners and tenants (USDA NASS, 2017) to account for and justify this mix of interviewees. The intent of this study is to identify priorities of producers across different groups that might grow and harvest biomass for the bioeconomy. With the goal of capturing a range of perspectives relevant to the study topic, three groups of producers were identified and interviewed: 1) those that have established perennial grasses for conservation; 2) those that harvest perennial crops (i.e., switchgrass or miscanthus) for biomass; and 3) those that harvest corn stover for bioenergy use.

Before beginning the interviews, the purpose of the study was presented to the participants as the effort to better understand producer priorities in decision-making about their production choices and design of their agricultural landscape. Interviews were conducted at the producers’ convenience in locations including their homes, machine workshops, or nearby businesses. During the first phase of interviews (February 2019), some participants who wanted to participate were traveling for the winter season, which is why four interviews were conducted over the phone.

Participants were selected using the key informant method, meaning that stakeholders familiar with agricultural practices on the ground in the study region were approached (Marshall 1996). They then recommended producers meeting the study’s producer sample criteria and who might be interested and willing to participate in the study. These prospective participants were in turn contacted by the researcher. Producers in the perennial grass conservation grower category have grown perennial grasses as a conservation practice to provide wildlife habitat and to improve local water quality: they were identified and contacted based on suggestions from local

Natural Resource Conservation Service (NRCS) officers. Producers in the crop residue-harvesting category had experience harvesting corn stover and marketing that stover to a cellulosic ethanol plant; they were identified and contacted through representatives of a local bioenergy facility. The third category was producers contacted through perennial grass bioenergy projects; they grow either switchgrass or miscanthus for bioenergy supply chain research and demonstration and were selected based on their participation in these bioenergy research projects. All participants were contacted by phone to set up a time for the interviews. Although most participants were identified before the interviews began, additional producers were added to the sample using the ‘snowball’ method. All interview participants were asked to offer recommendations of other agricultural producers for the interview. The method in which participants were selected and how the participant interview data were processed could be affected by the researcher characteristics and motivation. Possible researcher bias is described in Appendix A.

During Phase 1 of the study, 33 face-to-face and four phone interviews were conducted. Those 37 interviews included 46 different people, because some of the in-person interviews were conducted with both the husband and the wife present as producer pairs. On average, the interviews took 48 minutes. All interviews were conducted by the first author (Vazhnik). The corn stover-harvesting group interviews were supported by a note-taker (Jennett) during the interview. The interviews followed an interview guide with questions and protocol provided in Appendices A-1 and A-2. After the interview, a post-interview form was completed to summarize the first results.

During Phase 1, the interviews explored what priorities producers have for their operations. Furthermore, the researcher asked what “progress” would mean to producers and how they would measure it, over what period of time and at what geographic extent, and how that measure would impact their decisions. Exploring the decision process of the producers, the researcher asked what geographic boundaries and timespans producers were most concerned about, and what sources they used to inform their decisions.

Priority weight elicitation

Priority weight elicitation was done as an approach to quantify producers' priorities and was borrowed from similar approaches in decision analysis research. Several previous efforts have engaged stakeholders in developing decision support tools for land use change (Gladwin 1983, Bojórquez-Tapia et al. 2001, Jakku and Thorburn 2010, Rose et al. 2016, Ocampo-Melgar et al. 2017). However, such engagement has usually been limited to evaluating indicators and scenarios developed by the analyst, so that the stakeholders' role was simply to prioritize or choose. Kodikara et al. (2010) offered stakeholders several priorities and six preference functions (or, as they are named in this study, 'utility functions'). The weights for each priority were solicited using cards with the priorities, the participants were asked how many times one priority was more important than the other, and the results were recorded in a software for preference ranking (PROMETHEE).

Fifteen face-to-face interviews were conducted with a total of 19 people in the Phase 2. The participants were from the same groups that were interviewed during Phase 1, and no new producers were added. All participants from Phase 1 were contacted about their possible interest in participating in a follow-up interview, and the 15 interviews were held with those agricultural producers that were available. Six producers were interviewed from the corn stover harvesting category, five from the perennial biomass crop category, and four from the perennial grass conservation category. On average, the Phase 2 interviews lasted 61±23 minutes.

The Phase 2 interview aimed to achieve deeper exploration of the decision priorities and the dimensions of the priority indicator variables. Phase 2 interviews were guided by recognition that the weight (importance) might differ between each indicator, as might the temporal and geographic spatial extents that concern producers. Interviewees were asked to indicate their priorities by assigning a specific number of poker chips to the indicators that affect their decision, and to specify for each of the indicators what spatial and temporal boundary was of greatest concern or interest to them. Furthermore, participants were asked to explain the reasoning behind their choices. They were also asked to provide feedback about sample output from a decision support simulation of a typical Iowa farm. All participants were shown the same landscape design for consistency and commented about the information being useful or not as well as how it could be improved.

Spatial and temporal context of study

To reduce the possible correlation between the priority-related answers of the producers and the region where they operate, producers in each of the three categories were interviewed in several different regions across the state. However, the distribution was not uniform because some parts of the state are more suitable for larger operations or stover harvest (as reported in Tyndall et al. 2011), while others have greater need for perennial buffer strips because of the slopes of the fields. For confidentiality reasons, the regions of producers are not included as part of the producer demographics, even though the region may have some influence on producers' decision process, priorities and ultimately their choices (Bergtold et al. 2014).

Figure 2-2 presents a map of the areas where producers were interviewed. Central-West Iowa consisted of farms on rolling hills with some forested areas. The hilly terrain defines what practices many of the producers consider appropriate: no-till, cover crops, and prairie strips to prevent erosion. In that region, one is likely to see pheasants and deer cross the open fields between forested and shrubby areas. Several of the producers from this region noted they earned additional income by allowing hunting on their conservation plots and woodlands. The area has some beautiful lakes, which attract tourists and results in nature reserves and vacation homes with high property value. Many of the producers in that region are likely to have a side-job in Des Moines or in a smaller regional town or be retired. Most of the towns and houses have a suburban neighborhood character because of proximity to Des Moines.

North-Central Iowa is north of Des Moines and included producers that work on mostly flat land. Row crop related agricultural businesses thrive in this area because of high crop productivity. Several of the producers interviewed in the area not only grow corn and soybeans, but also keep cattle and use some of their crop residue as animal feed. All of the producers interviewed in that region were farming full-time, and the only diversification that some of the producers had was livestock. The producers in that region are used to interactions with media and researchers because of the proximity to Iowa State University's campus and because they are frequently visited by reporters.

South-East Iowa also included some higher-yielding farms, but many producers indicated that they have to diversify to survive. That often meant not only side-jobs and side-businesses, but also having hogs, vegetables, and fruit. The area was mostly flat, but the quality of the roads and the empty storefronts in small towns suggested that the region has not recovered as easily from the farming crises as communities in North-Central Iowa.

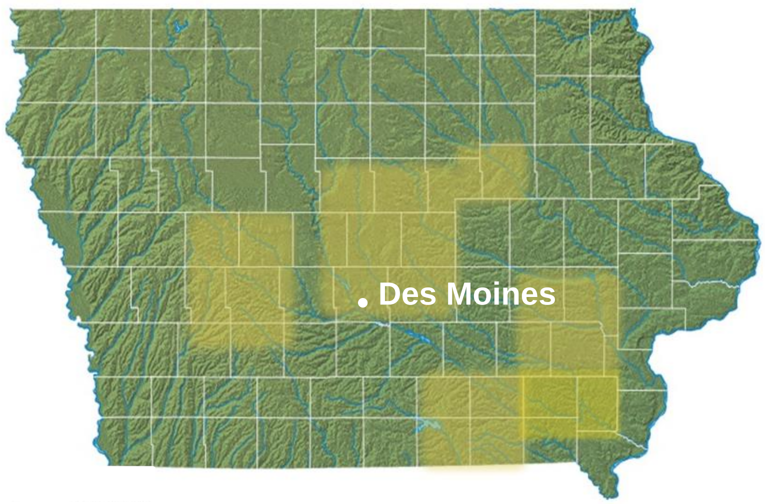


Figure **2-2**: Iowa regions where interviews were carried out (marked in light yellow).

Seasonal timing of the interviews could affect how producers discuss their priorities, which is why we briefly describe when the interviews were conducted. Both phases of the interviews were planned for the off-season – the time when producers are not actively planting or harvesting to make sure that interview times did not conflict with such work. Phase 1 interviews were carried out in February 2019 and Phase 2 interviews were conducted in November 2019. During February 2019 five snowstorms occurred within the 20 days that the researcher was conducting the interviews, which allowed for the “down time” for producers since they were not conducting any operations besides taking care of any animals they might have. Mid-November is usually the time when harvest is finished which is why the second phase of interviews was scheduled for that time. This assumption was partially correct because some producers had finished the harvest, and because there were several snowfalls and snowstorms during the period of the interviews. Still, some producers were still harvesting corn because the 2019 season had been delayed due excessive rainfall in the spring, summer and fall. The wet season not only delayed the planting by 2-4 weeks but also pushed the harvest dates back, forcing producers to be 1-4 weeks late with harvest.

Besides sub-optimal weather conditions, 2019 was a year with unstable crop commodity markets due to trade wars, which could have led producer participants to voice greater concern about trade at the planetary level because of the impacts of international trade disputes on their prices and profits for the year.

Analysis methods

Mixed method techniques, meaning a combination of qualitative and quantitative methods, were used both when collecting data and when analyzing the interview results. Mixed methods can be used to broaden and add detail to the research, as suggested by Johnson et al. (2008). Analysis was carried out by the same researcher who interviewed the producers and was done with the aid of online analysis software. The interviews were transcribed verbatim using Temi software (https://www.temi.com/) and coded using Dedoose software (https://www.dedoose.com/) using pre-selected codes for sustainability indicators and additional codes that emerged from the interview conversations. Initial categories for coding of priorities originated from a list of sustainability indicators generated by a literature review of agricultural and bioenergy sustainability indicators. As the interviews were analyzed, additional priority categories were added after a producer mentioned the priority two or more times during the interview. In addition to using direct participant quotes to inform the analysis, coded interviews were used to count the number of times the participants referred to an indicator or to the temporal and/or spatial extent. Another quantitative technique, used during the Phase 2 of interviews, was the quantitative weights (out of 100 poker chips) that participants assigned to priorities, time and space descriptors of those priorities.

Results and Discussion

Characteristics of study participants

The key demographic information for each of the interviewed producer groups for Phase 1 interviews is summarized in Table 2-1. The perennial grass conservation producer group included 12 interviewees with an average age of 68±10 years and average acreage of 979 ac (396 ha) of total land farmed (both owned and rented). Corn stover harvesting producers including nine participants with an average age of 49±14 years old and 3156 operated acreage (1277 ha). Perennial biomass crop producers were the largest group with 16 interviewees, with an average age of 71±10 years old and 1881 acres (761 ha) in operations.

Table **2-1**: Phase 1 interview participants' demographic information.

	Perennial grass conservation producers	**Perennial biomass producers**	**Corn stover harvesting producers**
Number of participants	12	16	9
Male/female	10/2	16/0	9/0
Average age	68±10	71±10	49±14
Average area of agricultural operation of all crops (both owned and rented for farming)	979 ac	1881 ac	3156 ac
Highest education attainment level (#):			
-High school diploma	3	6	1
-Additional courses and training beyond high school	3	2	2
-Bachelor's Degree	5	6	6
-Master's Degree	0	1	0
-Doctorate Degree	1	1	0

Priorities

Qualitative and quantitative analysis of the interviews illustrate the differences between different producer groups. The key priorities are listed in Table 2-2 in the order of how many producers mentioned the priority, repeat mentions by the same producer did not impact the order of how the priorities are listed in the table. The priorities provided in Table 2-2 are select priorities that could be most relevant for the decision-making. Tables 2-3 and 2-4 summarize the weights (adjusted to sum to 100%) that producers have assigned to the different priorities.

Table **2-2**: Producer priorities and the number of mentions by different producer groups.

	Conservation producers (n=12)	Perennial biomass producers (n=16)	Corn stover-harvesting producers (n=9)	All producers (n=37)
Profitability/cash flow	9	10	6	**25**
Freedom and independence (how independent is the decision of outside impacts)	8	8	5	**21**
Water quality	8	8	2	**18**
Erosion	6	9	1	**16**
Soil quality/Organic matter in soil/Soil health	7	5	4	**16**
Lifestyle/Type of work/Life and work with family	5	6	5	**16**
Stable markets and prices	5	6	3	**14**
Rural development	6	4	1	**11**
Young farmers and young families in farming	3	7	1	**11**
Developing a positive image of farmers among outsiders and city-dwellers	3	3	5	**11**
Diversified production and markets	1	7	2	**10**
Equal opportunity for small operations/Farms	5	4	1	**10**
Heritage/Tradition	4	4	1	**9**
Biodiversity/Presence of wildlife	6	2	-	**8**
Proximity to nature/Experience of pristine nature	2	4	2	**8**
“Feeding the world”	2	4	2	**8**
Yields	2	2	4	**8**
CO_2 emissions	1	1	-	**2***

***Note**: Because an important goal of identifying agricultural producer priorities is the further use of those priorities as sustainability indicators, CO_2 emissions were included in the subsequent assessment. Following a similar argument as in Reed et al. (2006) indicators were selected that are meaningful to the stakeholders but also validated them through expert-selected indicators. CO_2 emissions are one of the primary reasons why bioenergy solutions and thus markets for perennial crops are emerging, which is why this indicator was offered to stakeholders for assigning weight and time or space boundaries. In the subsequent interactions, producers could exclude this indicator entirely if it was not relevant to them. The complete list of producer priorities that have been identified are provided in Appendix A Table A-2.

Table **2-3**: Weights (out of 100) assigned to priorities based on the initial list of top 18 sustainability indicators

	Conservation producers (n=12)		Perennial biomass producers (n=16)		Corn stover-harvesting producers (n=9)		All producers (n=37)	
	Average weight	Standard deviation	Average weight	Standard deviation	Average weight	Standard deviation	Average weight	Standard deviation
Independence	2.05	4.1	1.46	2.55	3.05	3.4	2.25	3.18
Equal opportunity	-*	-	1.18	2.63	0.26	0.64	0.50	1.54
Financial stability	10.82	2.22	5.53	6.89	19.94	16.37	12.71	12.34
Profitability	16.51	3.8	26.63	28.86	16.37	6.52	19.83	16.76
Yield	9.72	6.68	6.58	8.18	10.33	11.24	8.92	8.76
Diversification	2.07	2.49	1.6	2.56	3.83	4.88	2.62	3.58
Water quality	12.14	2.62	6.07	2.54	5.7	3.27	7.54	3.93
Soil quality	10.4	0.91	12.43	13.38	6.87	4.77	9.67	8.11
Nature proximity	4.98	7.07	1.18	2.63	1.3	3.19	2.24	4.39
CO_2 emissions	4.46	5.23	-	-	-	-	1.19	3.17
Erosion potential	12.9	4.81	9.55	7.59	4.29	3.46	8.34	6.26
Wildlife presence	-	-	5.45	5.48	1.8	2.28	2.54	3.94
Food production	-	-	2.16	2.98	5.89	6.43	3.08	4.87
Rural development	-	-	1.8	2.65	0.78	1.91	0.91	1.96
Positive image	5.36	4.16	3.52	3.28	2.71	4.36	3.69	3.85
Farming lifestyle	6.53	2.98	3.33	3.05	10.21	19.69	6.94	12.34
Land inheritability	-	-	7.67	4.46	3.34	4.63	3.89	4.78
Young farmers	2.05	4.1	3.86	2.47	3.34	4.63	3.17	3.68

*Cells without values represent priorities for which no producers in that group assigned any weight (poker chips).

Table **2-4**: Weights (out of 100) assigned to priorities when three least-mentioned or confusing factors were removed.

	Conservation producers (n=12)		Perennial biomass producers (n=16)		Corn stover harvesting producers (n=9)		All producers (n=37)	
	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation
Independence	2.05	4.1	1.62	2.89	3.28	3.66	2.40	3.37
Financial stability	10.82	2.22	5.92	7.31	20.57	16.01	13.09	12.32
Profitability	16.51	3.8	27.82	29.66	17	6.21	20.47	17.24
Yield	9.72	6.68	6.99	8.6	10.46	11.18	9.11	8.82
Diversification	2.07	2.49	1.77	2.9	4.2	5.38	2.82	3.93
Water quality	12.14	2.62	6.36	2.48	5.97	3.33	7.74	3.84
Soil quality	10.4	0.91	12.83	13.25	7.27	5.12	9.96	8.11
Nature proximity	4.98	7.07	5.71	5.59	3.26	3.92	4.54	5.14
CO_2 emissions	4.46	5.23	1.33	2.98	-*	-	1.63	3.44
Erosion potential	12.9	4.81	9.94	7.55	4.51	3.62	8.56	6.25
Food production	-	-	2.35	3.26	6.29	6.93	3.30	5.24
Rural development	-	-	1.95	2.96	0.83	2.04	0.98	2.15
Positive image	5.36	4.16	3.81	3.55	2.96	4.8	3.89	4.07
Farming lifestyle	6.53	2.98	3.55	3.29	10.32	19.66	7.05	12.33
Young farmers and inheritability	2.05	4.1	8.03	4.46	3.65	5.12	4.68	5.01

*Cells without values represent priorities for which no producers in that group assigned any weight (poker chips).

The top priorities differ between the producer groups, but one must note that only a small sample of producers was interviewed, thus it is not possible to talk about statistically significant differences. Still, some patterns emerge from the interview counts during Phase 1 and the weights that were assigned during Phase 2 of the interviews. Profitability was the top priority both based on the number of mentions (25 out of 37) among producers and based on the weight assigned among the groups. Farming is a business, and being profitable is how the producers can maintain their land and operations, which is why it is natural to expect high priority on profitability. Several factors associated with profit were also high on the priority list. For example, financial stability was heavily weighted by both corn stover-harvesting producers and conservation producers, and it corresponded with frequent mentions about stable markets and prices across the producer groups. Yield, while an important factor, was not weighted or mentioned as frequently as profitability. It also was more highly prioritized by corn stover-harvesting producers than other groups. Some of the bioenergy producers explained the reason that they don't prioritize yield is because yield does not necessarily equal profitability. If producers use no-till equipment or otherwise reduce inputs and production costs, a lower yield could be more profitable because of these lower operating costs.

While profitability was an expected priority, the second most mentioned priority, independence and freedom, is seldom discussed in sustainability indicator literature. Independence signified that the producer could make independent decisions about operations and "be their own boss." That indicator was highly ranked based on the number of mentions, but not based on the amount of weight assigned to the priority. One explanation could be that independence is perceived as inherent to farming but producers do not often connect that indicator to their specific farming decisions.

A similar pattern of being a priority but not receiving a heavy weight in for decision-making was a "positive image" of the farming practice. That priority emerged during interview conversations and was most frequently brought up by corn stover-harvesting producers, although less so by the other two groups. Nevertheless, when weighting factors that impact their decisions, stover-harvesting producers did not assign much weight to positive image. That could, similarly, mean that they perceive the outsiders' view as important but do not consider their decisions having an impact on that view.

Several environmental factors were similarly prioritized, sometimes with differences between which priorities had been mentioned most frequently and the priorities that were heavily weighted for decision-making. For example, improving water quality and reducing erosion were frequently mentioned among conservation and bioenergy crop producers, and for that group these ideas were more heavily weighted for decision-making. Neither of those factors were mentioned much by corn stover-harvesting producers, but instead those producers discussed and assigned heavier weight to soil quality, possibly because of the more direct association with crop yield and profitability.

Although economic and environmental factors were more frequently discussed as producer priorities, social sustainability indicators including farming lifestyle and its synonym "type of work" were also important priorities to the interviewees. Farming lifestyle was mentioned across producer groups and was one of the more heavily weighted social indicators for their decision-making. Interestingly, the corn stover-harvesting producer group mentioned that priority more frequently than the other two groups. One possible explanation of that difference is that all stover-harvesting producers were on the farms full-time and did not have additional jobs, while many of the producers in the conservation and bioenergy crop category had additional outside income. Several interviewees commented that planting perennial grasses is like a "producer retirement plan," and thus may not be viewed as the sort of independent farming lifestyle that corn grain production and the associated stover harvest create.

Time and space views

Besides the priorities themselves, the interviewees were asked what space and time boundaries for those priorities are most meaningful for them. In Phase 1 interviews, the producers were asked about what spatial and temporal boundaries they were in general most concerned. Most producers framed the spatial and temporal dimensions of their decisions in terms of impacts on other people and were less concerned about the time duration or spatial extent of impacts on ecosystems. Producers were not always able to provide a direct answer and mostly conceptualized those boundaries by discussing people that they interact with or they affect (for example, some cared about the US geographic boundary, because they interact and hear from the opinions of people from across the coasts and from cities; or were concerned about 50-year horizon because they care about their children and grandchildren having a successful future). The spatial and temporal concerns of each producer were not within “solid walls” but rather were conceptualized as ripple effects – some had large-area concerns, but those concerns were weaker than the small-area concerns. The space-time boundaries of one specific producer are visualized in Figure 2-3, where the stronger concern is at 5 years and at the farm level, but there are still some general concerns at the county and 20-year levels.

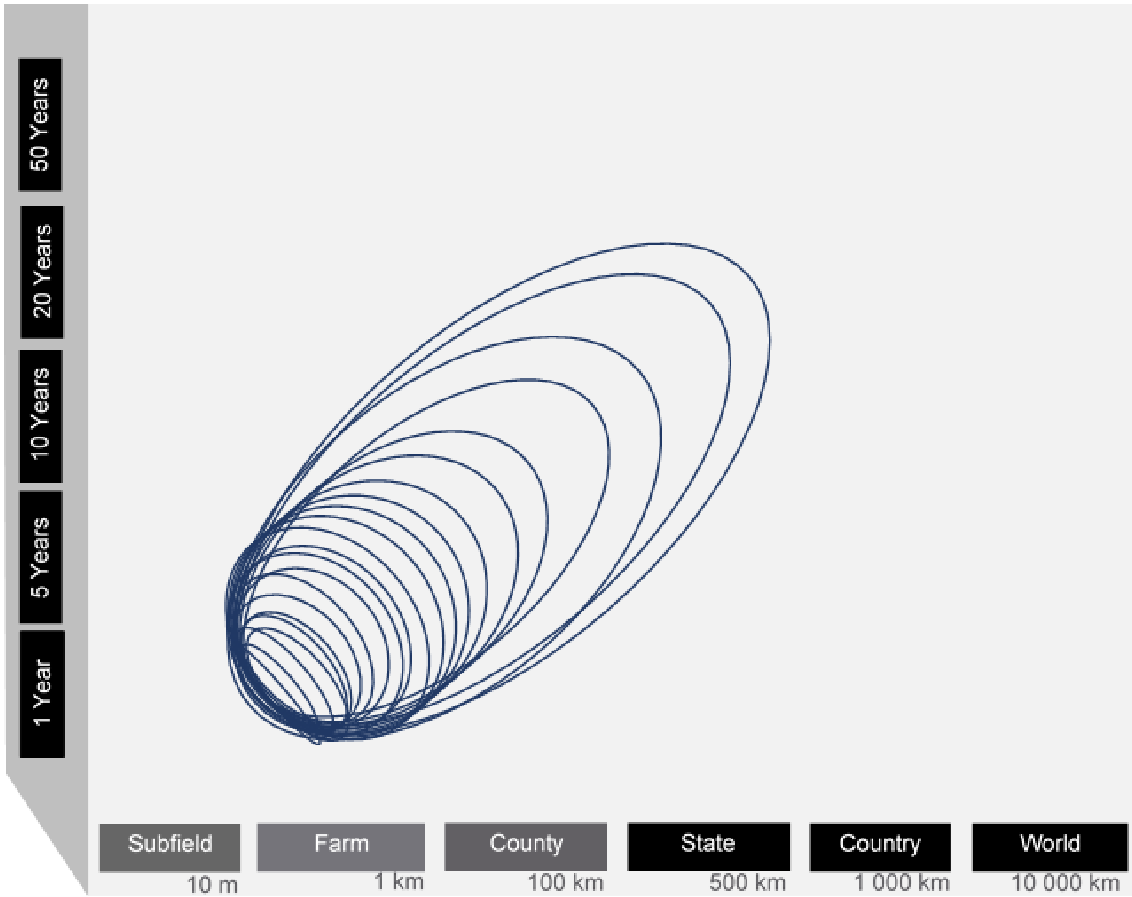


Figure **2-3**: Producer's space and time concerns (example of one corn stover-harvesting producer concerns).

While every producer's space and time concerns are complex, we summarize the categories of space and time boundaries and the number of mentions for each of those category in Tables 2-5 and 2-6. The tables list the average number of mentions of that space-time boundary per interview, and list the normalized values of how frequently the boundary was mentioned by producer group. The counts and normalized values were calculated using equations (1) and (2).

$$\overline{Mentions_{non-normalized}} = \frac{\sum Number\ of\ mentions\ per\ interview}{Number\ of\ interviews} \tag{1}$$

$$\overline{Mentions_{normalized}} = \frac{\sum \frac{Number\ of\ mentions\ per\ interview}{Total\ space\ or\ time\ mentions\ per\ interview}}{Number\ of\ interviews} \tag{2}$$

Categorizing space and time priorities by producer groups suggests that there are some differences in what spatial and temporal boundaries were most important to the groups. State and county were the dominant spatial boundaries that the producers discussed across the groups, but the stover-harvesting group frequently mentioned the world scale, especially in the context of markets and trade. Interestingly, 20 and 50 years were the time-frames most discussed by producers, with the exception of the stover-removing producers, who mostly mentioned the 1-year period.

Table **2-5**: Categories and mentions of space boundaries. Normalized row values represent the percentage of mentions of the space-related codes in each producer category.

Mentions Per Interview Per Category	Conservation producers (n=12)		Perennial biomass producers (n=16)		Corn stover-harvesting producers (n=9)		All producers (n=37)	
	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation
Farm	20%	17%	10%	25%	15%	25%	15%	23%
County	20%	15%	24%	28%	22%	33%	22%	25%
State	24%	23%	17%	18%	4%	7%	16%	19%
Midwest	11%	9%	8%	11%	7%	13%	9%	11%
The Gulf of Mexico and Mississippi River Basin	12%	14%	11%	16%	2%	7%	9%	14%
Country	8%	9%	15%	21%	10%	14%	12%	16%
World	6%	9%	15%	26%	39%	32%	18%	27%

Table **2-6**: Categories and mentions of time boundaries. Normalized row values represent the percentage of mentions of the time-related codes in each producer category.

Mentions Per Interview Per Category	Conservation producers (n=12)		Perennial biomass producers (n=16)		Corn stover-harvesting producers (n=9)		All producers (n=37)	
	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation	Averages weight	Standard deviation
1 Year	12%	18%	9%	18%	28%	31%	15%	23%
2-3 Years	13%	31%	5%	8%	6%	10%	8%	19%
5 Years	12%	21%	14%	14%	10%	17%	12%	17%
10 Years	18%	14%	11%	16%	10%	18%	13%	16%
20 years	14%	20%	31%	30%	23%	23%	23%	26%
50 Years	22%	19%	20%	18%	19%	15%	20%	17%
100 years	8%	13%	10%	13%	4%	7%	8%	12%

To gain an understanding of the space and time concerns beyond the general concerns of the individual producers, in Phase 2 the participants were asked to specify the space and time boundaries for each of the indicators. These results are presented in Table 2-7. Because fewer producers were interviewed per category in the Phase 2 interviews, we do not categorize the boundaries by producer type, but rather suggest which boundaries were most frequently mentioned and with what range. Note that the time average was calculated as the mode, or most frequently mentioned value, and not as an arithmetic average. In the case that all levels were mentioned equally among the participants, the median is selected instead of the mode. Most producers considered the entire range of the time and space levels in their answers, meaning that at least one factor mattered to them at a broader extent than their farm.

The results illustrate how diverse the spatial and temporal boundaries are across this set of priorities, with every level from 1 year to 100 years and from farm to world mentioned in the interviews. It is interesting that some heavily weighted economic priorities like profitability and yield had the smallest temporal and spatial boundary for producers, while other heavily weighted environmental factors had some of the largest spatio-temporal boundaries. These findings are consistent with the way Haden et al. (2012) reported sustainability strategies are conceptualized by farmers. Profitability can be considered a marker of adaptation towards the new climate, market and social conditions for their farm enterprise, while environmental indicators represent the mitigation of large environmental disasters like water pollution of an entire watershed, and demand action if the problem is perceived to be large. These results point to the complexity of the space and time concerns of the producers. While some producer groups categories have a characteristic space and/or time value for certain priorities as illustrated by the number of mentions in Tables 2-5 and 2-6, when looking across the full range of priorities, all interviewees discussed multiple spatial and temporal scales of concern.

Table **2-7**: Time and space boundaries of producer's concern for each of the key priorities.

	Time		Space	
	Most frequent	Range	Most frequent	Range
Independence	10	10 – 100	Farm	Farm – World
Equal opportunity	-	-	Midwest	Midwest – World
Financial stability	50	5 – 100	Farm	Farm – World
Profitability	1	1 – 50	Farm	Farm – World
Yield	1	1 – 10	Farm	Farm – Midwest
Diversification	10	10 – 100	Farm	Farm – World
Water quality	100	1 – 100	Gulf of Mexico and the Mississippi River Basin	Local watershed – World
Soil quality	100	5 – 100	Farm	Farm – World
Nature proximity	100	50 – 100	World	Local watershed – World
CO_2 emissions	10	10 – 20	State	State – Gulf of Mexico and the Mississippi River Basin
Erosion potential	100	1 – 100	Local watershed	Farm – World
Wildlife presence	20	1 – 100	World	County – World
Food production	50	10 – 100	World	US – World
Rural development	5	5	County	County – State
Positive image	50	1 – 100	US	Farm – World
Farming lifestyle	20	1 – 100	Farm	Farm – World
Land inheritability	100	10 – 100	Farm	Farm – US
Young farmers	10	5 – 100	US	Farm – World

Interviewees illustrated that their understanding of time is somewhat different from space, in that time is explicitly a continuum with a past and a future. When asked about the temporal extent that producers are concerned with, some discussed the range of time not only in one direction (present – to future as in next 5 years, 10 years, or 100 years), but in two directions, including the past and how it influences the current priorities and practices. Several participants discussed the past because of the heritage of their land and the perspectives of parents or previous farm operators, and they see themselves as a part of a historic flow of what was happening on the ground. Such a 2-directional axis of measurement is different from the spatial understanding, which is mostly in one direction of increasing extent (farm being the smallest extent and scaling all the way to the planetary boundaries.) This study focused on future-centered understanding of time, but it would be valuable to explore how explicitly considering the time dimension into the past might impact producers' priorities.

One of the challenges of looking at stakeholders' space-time boundaries is that they change. Adams (1995) conceptualizes such change by comparing a person to an "amoeba". Amoebas have a physical body and channels to explore the world, a social circle, and follow a specific hierarchy. Similarly, people interact with their surroundings through informal and formal channels, but also have "projects" that can span the initial personal boundaries. Farming can be perceived as one of those projects. Being project (farming) oriented implies that the person is dynamic and adaptive, which is required in pursuing a goal and a project whose context (market, community, climate) is changing. Similarly, Verbeke and Tung (2013) observe that stakeholder interests and positions change over time, which in this instance implies that bioenergy systems and solutions need to satisfy a range of interests if they are to grow and persist. Even during the interviews, several producers were mentioning how the priorities they were reporting are a function of their current state. We can expect that changing markets, weather, and other factors will change the boundaries, and that education and future experiences may shift boundaries of concern.

Bioenergy implications

Producer priorities and the temporal and spatial scales for which those priorities are most relevant can inform bioenergy research and education needs to improve the relevance of inputs to producer decision-making. Following the theory of planned behavior, which suggests that priorities reflect the actions that the stakeholder is likely to take, researchers can design decision support tools and communicate indicators and their measures at the spatio-temporal scales that are most relevant to the stakeholders. Figure 2-4 illustrates how understanding the priorities and the boundaries associated with them can be connected to the bioenergy-related behavioral change that could follow. As some of the most relevant priorities were profitability or soil quality, producers across different groups can be expected to select cropping systems and design agricultural landscapes where biomass production strategies improve farm profitability and soil quality. The most frequently mentioned time and space levels relevant to decisions about these two priorities were farm-level for space, and either 1-year for profit or 100-years for soil quality. Thus, to provide useful input to producer decision-making, profitability and soil quality should include modeling and analysis at those scales, while recognizing that other scales will be relevant for some producers as well as other types of stakeholders such as community members or government officials. Explicitly analyzing and reporting indicators over time, including both trends and variability, can help producer decision-making and assessment tools more effectively bridge between long-term and short-term impacts.

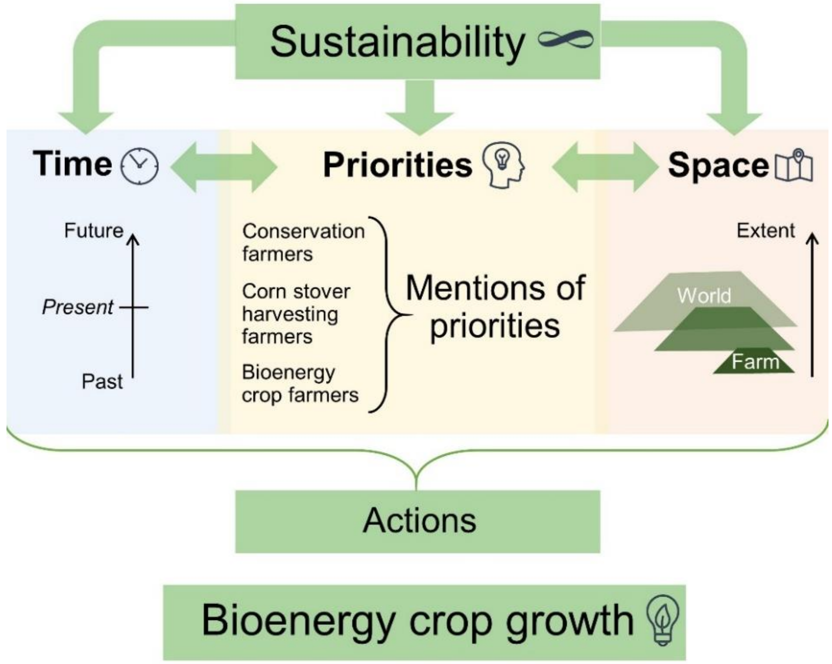


Figure **2-4**: Use of producer priorities, time and space boundaries to understand bioenergy sustainability and predict action towards bioeconomy.

The priorities that were most heavily weighted by producers can be expected to strongly affect producer behavior. Still, there were priorities that were frequently mentioned by producers during Phase 1 of the interviews but apparently not strongly associated with decisions and behavior based on the Phase 2 results. The difference between priorities that are frequently mentioned by producers, and those that are heavily weighted by them for decision-making, can point to a distinction of underlying values and business decision priorities. Priorities like creating a positive image, being independent, or encouraging young people to start farming are important to producers, but they may not consider these factors in their decision-making. Producers may see these factors as inherent in their activities, or they may not see the connection between their own farm operations and achieving these goals. Other factors, like profitability, preventing erosion, and improving water quality were both frequently mentioned as priorities and also heavily weighted for farm decision-making, and for these priorities it is especially important to provide meaningful decision support.

Beyond priorities and indicators that are frequently modeled quantitatively, including economic and environmental factors, the interviews indicate that descriptive goals like positive impact and independence are high on producer's lists. These factors are more complex to quantify and compare in scenarios, but could signal the types of bioenergy crops the producers would find most attractive – those that improve their image to outside stakeholders, and that also allow them to stay independent through profitable markets and business success. Research and education about the environmental impacts of bioenergy crops can help provide producers with a better understanding of those impacts and help those who choose the more environmentally sustainable systems gain recognition for their work to help the environment.

To the extent that bioenergy technology, cropping systems, and landscape designs address producer priorities and concerns, they can serve as attractive "new farming" strategies for producers and their communities. Perennial bioenergy crop producers can be similar to other niche producers, who are sometimes termed the "new American farmers" (Flachs and Abel 2019) because their interests and concerns are often distinct from conventional landowners. Currently, growers that supply biomass or grow perennial grasses are not a homogenous group; they have diverse motivations and backgrounds as illustrated within and among the three producer groups in this study. But there are common characteristics as well, and understanding and informing their priorities will help these new American farmers and producer-entrepreneurs (Nordin et al. 2005) be successful on their own terms, supporting themselves and their communities and enhancing rural development by adding a new element to the local producer "fabric".

Study limitations

All three groups of producers that were interviewed have adopted new agricultural practices – planting perennial grasses for bioenergy or conservation purposes, or harvested corn stover for bioenergy production. To understand the extent to which their priorities are more broadly shared, it would have been useful to compare the observed priorities of these groups to a “conventional” group of producers as categorized in Comer et al. (1999). Such a study would help inform individual decisions of farmers that have not tried the innovative bioenergy strategies, especially if their perspectives differ from the priorities found in this study. One might expect that the stover-harvesting group would be closest in their priorities, including their temporal and spatial outlook, to this “conventional” producer group that was not included in this study.

Further research

Because of the dynamic nature of producer perspectives, it would also be interesting to conduct a longitudinal study to learn whether the priorities and/or their most relevant time and space dimensions change. As perennial biomass planning can involve committing land to a decade or more of biomass growth, understanding how producer perspectives and decisions change over that period of time could lead to more robust agricultural landscape decision-making. Another area deserving of additional research is whether the spatial and temporal extents of these priorities is related to the producer’s feeling of agency and impact. A follow-up study that explores how the space-time-priority relationship is connected with perceived power of the producers in their decision-making could shine the light on why some priorities are weighted heavily, and why others were frequently mentioned but apparently not as relevant to the decision process.

Another topic that was frequently raised was improving the connections between landowners and land operators in landlord-tenant relationships. Many interviewees were concerned that there are many distanced landowners that do not have a strong connection to the land, and apparently are not interested in what happens to the soil, water, wildlife, and communities near their farms. Such concerns suggest that a separate series of interviews should be carried out with absentee landowners, who might have different concerns but might also be interested in growing bioenergy crops for a different set of goals and priorities.

Conclusion

Two sets of interviews were carried out with three types of producers: those that grow perennial grasses for conservation, those that grow perennial biomass for bioenergy markets, and those that harvest corn stover for bioenergy. The interviews identified key priorities, and for each of these priorities determined the spatial and temporal boundaries that these producers are most concerned about. Profitability, erosion control, water and soil quality were among the most mentioned and heavily weighted priorities across all the interviewees. Other priorities surfaced through the interviews that are not commonly measured or addressed in bioenergy models and simulations. Some of these priorities, including independence and a positive image, were of high concern to producers, although it was not clear how to incorporate them in the decision process. Expanding model frameworks to address these priorities could assist producer decision-making as they consider alternative cropping systems and agricultural landscape designs.

The initial Phase 1 interviews suggested that these three producer groups had different space-time priorities, with corn stover harvesters focusing on more local near-term issues and perennial grass being concerned about longer-term regional issues. However, the second set of interviews that questioned participants in more detail about the space-time boundaries for each priority indicated that all the producers considered multiple spatial or temporal boundaries, and for each producer the most important boundaries varied depending on the indicator. One implication of this finding is that decision models and tools intended to assist producer landscape decisions should be flexible to represent diverse spatial and temporal boundaries. A richer understanding of producer priorities and the associated space and time boundaries can help better inform the design of bioenergy systems, and help researchers more effectively collaborate with producers to establish bioenergy research and demonstration projects that address the indicators and measures most relevant to them.

Chapter 3

The economic case for perennial grasses: landscape designs for bioenergy production, water and soil quality create a financial opportunity at a subfield level

Abstract

Perennial bioenergy crops can not only improve water and soil quality and provide wildlife habitat but also be a more financially viable alternative to annual crops in low-yielding parts of crop fields. This study used a market assessment to project potential price levels for perennial biomass, paired historic yields with remote sensing imagery to model maize production at 10 to 30 m resolution, and applied crop production budgets to identify areas where switchgrass may be more profitable than maize. The analysis was run on three cases: two approaches for estimating corn stover yield paired with a high switchgrass yield, and one corn stover yield approach paired with a low switchgrass yield. Two Iowa watersheds were evaluated: the headwaters of the North Raccoon River watershed and the South Fork River watershed, located in Buena Vista and Hardin counties respectively. Averaged over the years 2013 to 2018, the subfield profitability of maize grain production ranged from a loss of $400/ha to a profit of $1500/ha. The results suggest that with biomass prices of $150/Mg (the high price scenario), perennial grasses could be more profitable on more than 80% of the cropland in these two watersheds in case of high switchgrass yield (10 Mg/ha) with or without corn stover harvest, or on more than 25% of the cropland in case of low switchgrass yield (5 Mg/ha). Even in the case of low-paying markets with biomass price of $50/Mg, between 6 and 22% of land depending on the scenario and watershed could be more profitably converted to perennial grasses. In this analysis, corn stover harvest was only profitable in the scenario when biomass price was $150/Mg. These results

illustrate that perennial grasses can be a more profitable agricultural choice on marginal lands than annual crops, especially when there are biomass markets to incentivize the establishment and harvest of perennial crops.

Introduction

Perennial grasses are an agricultural management option that can help control nutrient and sediment runoff, provide wildlife habitat, and provide biomass for bioenergy (Asbjornsen et al. 2014, Zhou et al. 2014). Perennial grasses can include prairie grass mixtures or monoculture bioenergy crops like switchgrass or miscanthus. The benefits of introducing perennial crops have been illustrated in multiple studies. For example, field trials reported by Schulte et al. (2017) found that perennial grasses help reduce nutrient and sediment runoff and increase species richness and diversity. Anderson-Teixeira et al. (2009) use statistical analysis on the results of 46 field trial studies and report that perennial grasses help build the soil organic carbon and thus improve the soil quality. Such positive qualities have encouraged some landowners to plant perennial grasses.

Perennial grasses have been installed across the U.S. Midwest either as designated bioenergy crops for harvest or as unharvested conservation mixtures. Companies like FDC Enterprises (2020) or organizations like The University of Iowa (2020) have worked with farmers to establish switchgrass and miscanthus to pelletize and co-fire with coal in hospitals and schools. For conservation purposes, research, private and government programs have encouraged planting of perennial grasses. For example, the Conservation Reserve Program (USDA 2020) has subsidized farmers to plant perennial grass mixtures as pheasant habitat, pollinator habitat and many other biodiversity-related purposes. Iowa State University has worked with stakeholders to establish perennial buffer strips on public and private land, with a goal to trap sediment and nutrients, as illustrated in the Science-Based Trials of Rowcrops Integrated with Prairie Strips (STRIPS) project in Iowa (ISU 2020). These projects were motivated by environmental quality goals rather than profitability. The present study will investigate whether these practices could prove economically beneficial as well.

Profitability and available markets are some of the main pre-requisites that farmers consider as they evaluate the potential of perennial crops, as suggested by farmer interviews (see Chapter 2 “Producer Sustainability Perspectives”). There are two sides to the economic opportunity of perennial grasses – 1) prices available in the marketplace from companies that can use perennial grasses biomass for production, relative to the cost of that biomass production, and 2) the lost profit, or in some cases the avoided loss, associated with annual crop production. This study included both sides of this economic question, but focused particular attention on the second factor which economists refer to as the opportunity cost. In field crop production this opportunity cost can either be positive or negative depending on commodity prices as well as the productivity of soil and other biophysical inputs and can also be effected by crop insurance and subsidies that may be available for conventional commodities and not biomass. Several studies have shown that planting perennial grasses on land that is economically marginal for annual crops can benefit farmers and landowners. For example, the Bonner et al. (2014) analysis found that up to 85% of corn producing fields in Hardin county Iowa may be losing money in some years, and these losses are a function of both the commodity price and biophysical productivity. In Bonner et al. (2014), the authors modeled crop yield based on soil quality indices. Also in Iowa, Brandes et al. (2018) take a similar approach of using a combination of biogeochemical and agroecosystem models to predict yield for the entire state. Their study found that 12 or 37% of Iowa cropland can be economically converted into switchgrass depending on the threshold of conversion. Finding such high percentages of cropland area that may be more profitable for perennial biomass than annual grain crops, especially in productive Iowa agricultural landscapes, indicates that perennial crops can create a financial opportunity for farmers.

Contrary to the common assumption that sustainable farming practices require public or private investment with little chance of any financial return, some companies and farmers have proposed and demonstrated ways to create commercial products from crops grown for environmental benefits. For example, switchgrass grown as vegetative filter strip to reduce nutrient and sediment runoff to streams can also be used as animal bedding, serve as feedstock for cellulosic ethanol, or serve as a material for composite construction materials. These and other markets that use perennial and cover crops are now emerging in many regions of the U.S., providing options for additional profit from crops that also improve soil and water quality, and create pollinator and other wildlife habitat. Market opportunities for lignocellulosic biomass resources are important because they could facilitate the adoption of perennial crops. The Conservation Reserve Program, while beneficial for the environment, provides both subsidies and constraints, and those constraints can limit whether the biomass can be harvested, if so how and when, and even prescribe which seeds should be in the mix. A market-driven biomass production system would allow the farmer to select how to manage the fields, allowing for freedom and independence as well as improve profitability – the most frequently mentioned priorities for farmers that grow biomass (see Chapter 2 “Producer Sustainability Perspectives”).

The potential economic opportunity from perennial crops can be simulated using detailed subfield yield data coupled with cost and price assumptions for inputs and products respectively. Using the subfield crop performance data at 10 m to 30 m resolution can inform both the precision agriculture techniques that allow for a more efficient use of resources, and also the larger question of field layout and design. Profitability indicators can be easily integrated with subfield analysis, with each subfield or each grid cell assigned a profitability value. Such detailed spatial analysis can be used to generate a profitability map, which is a practical decision-making tool for farm operators, and has previously been illustrated by Kitchen et al. (2005). With such a map, the decision-maker can identify zones of high and low profit and decide on agricultural management practices for different zones.

This study uses subfield economic assessment with remote sensing-derived yield estimation, location-specific cost calculation and possible perennial grass market prices to evaluate the conditions where perennial grasses can be a profitable alternative to annual crops in the U.S. Midwest. Unlike other studies that calculate yield and profitability based on crop modeling simulations using soil types and/or soil quality indices, this research uses historic yield data based on satellite imagery and historic prices to anchor the analysis in recent lived experience.

Methods

Biomass markets

Functioning biomass markets are one of the main assumptions for this profitability study. Diverse switchgrass markets that are currently available or are expected to become available in the future serve as the basis for price scenarios tested in the next section. Several of the industrial sectors that are likely to use biomass as feedstock are highlighted in Figure 3-1. Those markets are in no way exhaustive, but rather suggest how biomass could be valued based on the final end-use and illustrate the variety of uses and range of prices. For a more detailed description of biomass markets, please see Ruamsook and Thomchick (2014), who provide an overview of markets for lignocellulosic products including those listed in Figure 3-1 as well as mulch, biochar and animal feed products. Other potential future product streams for lignocellulosic biomass include commodity and specialty chemicals, as reviewed by Isikgor and Becer (2015).

Potential biomass markets can be categorized as either currently existing or future markets, with the prices for future markets estimated based on the prices for current feedstocks with a similar form factor in the supply chain. Figure 3-1 illustrates which markets can be considered existing (green) and emerging (tan). Current markets include bioethanol production, bio-based power pellets, animal bedding, and as filling for erosion control socks. Many of those markets are niche opportunities or are currently part of pilot-scale productions, demonstration projects or specialized products within larger organizations. Erosion control socks help control sediment runoff and are commonly made with wood chips. Several companies started using switchgrass because it can still trap the sediment but are much lighter and easier to install as erosion control socks. The future markets for lignocellulosic biomass include biochemicals, animal feed, pulp and paper and composite material production. Bio-based chemicals are currently based on corn starch or lactic acid but could in the future be made from cellulose or hemicellulose converted into simpler sugars. Such processing could be possible in a biorefinery but would require process refinement. Composite materials primarily use ground wood or wood waste today, but several small companies already use wheat straw or hemp when making decorative and structural composite boards. Even though switchgrass is not currently used commercially for composite materials, it would be possible to use such feedstock.

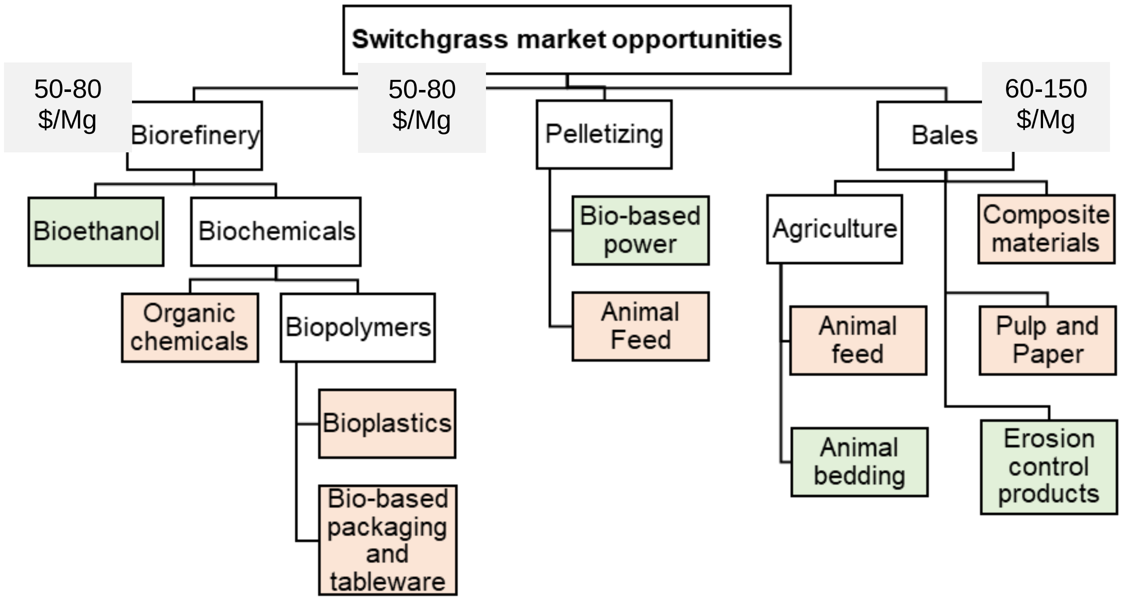


Figure **3-1**: Switchgrass current and future markets. Markets in green are those that are currently operating and those in tan are emerging markets.

The available and future biomass prices vary among the future and current markets. The highest-paying current market is the production of erosion control socks with the biomass price of $150/Mg (based on farmer and industry interactions). For both biochemicals and biofuels, the assumed feedstock price is typically $50-80/Mg based on assumptions in other bioenergy studies or the DOE Bioenergy Technology Office (Bioenergy KDF 2019). Technoeconomic studies on biomass pellets, which are used for biopower, have assumed a price of raw biomass as $55-60.6/Mg (Haase 2010). The prices on current animal bedding materials, which include straw, hay, or woodchips, vary between $70 and $130/Mg depending on quality (ISU 2020). Many companies producing composite materials and pulp and paper industry currently use woodchips or logs, with the raw woodchips being purchased for $60-130/Mg (Hoover’s 2017). Based on this wide variety of prices in existing and future markets, we select three price scenarios for biomass at the farm gate: $50/Mg, $100/Mg and $150/Mg of biomass.

Study case

To understand the economic viability of planting perennial crops, it is important to compare the profitability of biomass with the opportunity cost of growing a conventional crop. In the annual cropland-dominated study regions in Iowa, corn (*Zea maize*) is the most common current crop, while switchgrass (*Panicum virgatum L*.) is the most well-studied perennial biomass crop, so these two crops were selected for the comparison. Switchgrass is a perennial grass that is a popular choice among bioenergy crop growers because it is a native crop to the U.S. Midwest, it is planted from seed and therefore is cheaper to establish than miscanthus (rhizomes) or willow (cuttings), and it can be harvested using equipment that is already commonly available on the farm for hay harvest. Corn is the major commodity crop in the U.S. Midwest and is either planted every year ("corn on corn") or alternating with soybeans. Corn is generally more profitable than soybeans, so using it in this comparison is also conservative with respect to the opportunity cost for biomass.

To evaluate the economic case of switchgrass compared to corn, we select two watersheds in Iowa - the Headwaters of the North Raccoon and the South Fork watersheds (Figure 3-2). Historical cost and price county averages for Buena Vista County (North Raccoon) and Hardin county (South Fork) were used for corn (Iowa Farm Bureau 2019, ISU 2018, USDA 2019), and published crop production costs (Jacobs et al. 2016) and the previously described projected biomass market prices were used for switchgrass. The watersheds were selected because of their location on prime Iowa soils, with the expectation that if perennial grasses can be economically attractive on the highly productive land in Iowa, that case is even stronger on other lands in the state and across the Midwest. The watersheds are also located near cellulosic biofuel plants, justifying the bioenergy supply price assumption.

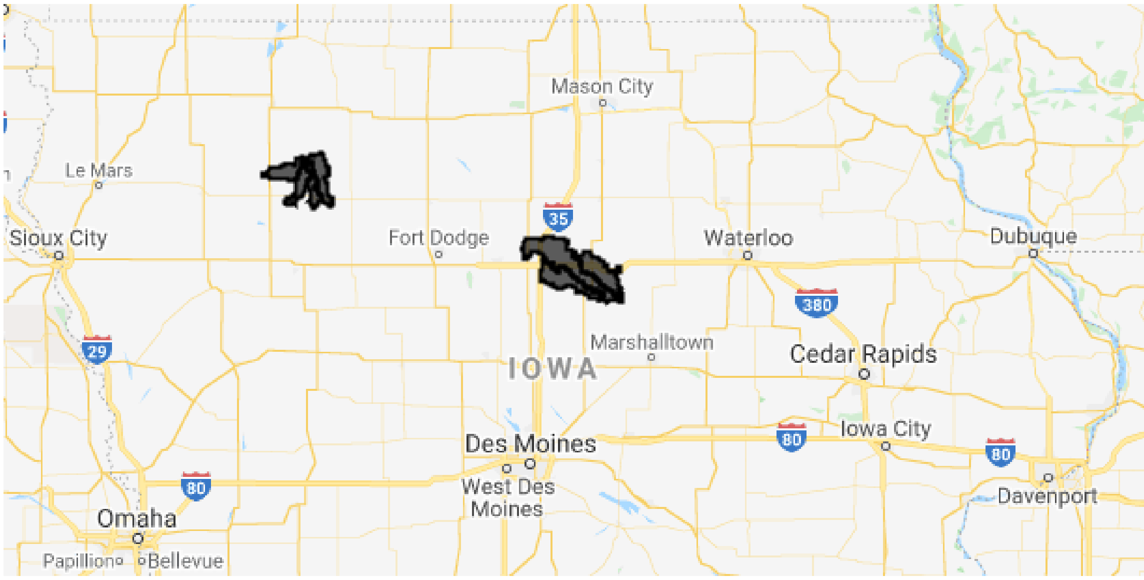


Figure **3-2**: Location of the Headwaters of North Raccoon River Watershed (top left corner on the map), and South Fork Iowa River Watershed (center of the map) in Iowa.

Yield, cost and profit analysis

Profitability calculations are based on production costs, yield and the price that is paid for the crop. This section describes each element for corn and switchgrass economic assessment. Spatially-explicit subfield yield and economic calculations were done using the Google Earth Engine online software, which allows access and processing of the satellite data online on the Google server (Gorelick et al. 2017). Google Earth Engine (GEE) operates in JavaScript, so the code for the analysis is provided in that language (Appendix B-1). GEE can be accessed using the Python language through Google Collaboration website, and the code would need to be adjusted for the different semantics. For the data processing code provided in Appendix B-1, the only input variables needed besides the remote sensing data were the year of assessment, historic county yields, production costs and the price on the product.

Two satellite data sources were used in this study – Sentinel 2A (accessed through the Google Earth Engine Copernicus collection[1]) and Landsat 8 (accessed through the Google Earth Engine Landsat 8 Tier 1 top-of-atmosphere collection with 8-Day Normalized Difference Vegetation Index (NDVI) composite[2]). Sentinel 2A is a satellite sensor launched by the European Space Agency's Copernicus Program in 2015 and has a comprehensive coverage of spectral bands, which is why this study uses these data for 2016-2018 yield evaluation (Gascon et al. 2016). One of the reasons for the installation of the Sentinel sensors was to monitor the change in vegetation in Europe, so it is well suited for yield estimation. The smallest spatial resolution of the data collected by the Sentinel 2A is 10 meters for the visible and near-infrared bands. Visible red data with Sentinel 2A are captured at wavelength 664.5 nm, and the near infrared is at 835.1 nm. Landsat 8 is a satellite program launched in 2013 and is the best public input data available for the 2013-2016 data (Roy et al. 2014). Landsat is a commonly used dataset, which already provides the calculated NDVI. Landsat 8 provides data at 30-meter resolution and captures the wavelengths of 640-670 nm for visible red, and 850-880 nm for near infrared light.

The satellite yield data is a primary input to the subfield economic analysis. Agricultural producers care not just about average profit, but whether that profit is stable year over year. Having a large profit one year and losing money for the next two years is not acceptable for most farmers, who often have large loans on machinery or land purchases, as well as family living

[1] Sentinel-2 MSI: MultiSpectral Instrument, Level-2A as accessed through the Google Earth Engine Copernicus collection using web address https://developers.google.com/earth-engine/datasets/catalog/COPERNICUS_S2_SR and ee.ImageCollection("COPERNICUS/S2_SR") in the in-line code as in Appendix 1.

[2] Landsat 8 Collection 1 Tier 1 8-Day NDVI Composite as accessed through the Google Earth Engine Landsat 8 top-of-atmosphere collection using web address https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C01_T1_8DAY_NDVI and ee.ImageCollection("LANDSAT/LC08/C01/T1_8DAY_NDVI") in the in-line code as in Appendix 1.

expenses. The profitability in this study is averaged over 6 years: from 2013 to 2018, which is when the Landsat 8 and Sentinel 2A datasets are available.

Landsat and Sentinel satellite data were used to estimate the crop yield based on the NDVI, which is the most widely used indicator for this purpose. NDVI represents the ratio between the visible red and near-infrared reflectance as in equation 1 and was first suggested by Rouse et al. (1973). NDVI is a particularly useful estimate because it can be calculated from several satellites that cover the entire planet.

$$NDVI = \frac{NIR - Red}{NIR + Red}\,, \tag{1}$$

Where NIR is the near-infrared reflection and Red is the visible red reflection. In this analysis, we used peak NDVI to estimate the subfield yield. We used Teal et al. (2006) to calculate the variability of yield within the field but corrected for the average county yield by changing the equation coefficient.

$$Yield = Coefficient \times e^{3.3525 \times NDVI} \tag{2}$$

The “coefficient” variable adjusts for the average yield, while NDVI is the Normalized Difference Vegetation Index. NDVI signifies how healthy a crop is – the healthier the crop, the more near-infrared radiation it reflects. The resulting raster files with yield were used directly in the model. NDVI changes during the season, and peak NDVI was used in this study’s calculations. Peak NDVI yield was the foundation for profitability analysis.

Corn stover, or the remaining biomass from corn grain harvest, is a possible feedstock for bioenergy and biomaterials production. The amount of stover that can be harvested sustainably has been suggested based on empirical and modeling studies. The present study uses two equations to estimate the possible corn stover yield. The first equation is based on the findings from Wilhelm et al. (2007) (Figure 1A) where the possible corn stover yield can be estimated as in equation (3):

$$Y_{stover} = 0.714 \times Y_{grain} - 5 \tag{3}$$

Equation (3) reflects the fact that the minimum amount of stover that has to remain on the ground depends on the subfield characteristics, which are inferred from the corn grain yield.

For the simplicity of use for agricultural producers, some researchers provide an estimate of how much corn stover should remain on the ground. Even though that number would depend on the exact field conditions like soil type and quality, some studies estimate that 6 Mg/ha of stover remaining on the ground is typical and has been recommended as a general guideline by Johnson et al. 2016. This estimate that a minimum of 6 Mg/ha stover should remain in the field was applied to the stover harvesting equation that was developed by Tan and Liu (2015) as shown in equation (4):

$$Y_{stover} = 0.61 \times Y_{grain} + 2.4 - Minimum\ Stover\ Remain \tag{4}$$

Where Y_{grain} is the estimated corn grain yield, and Minimum Stover Remain is the rate in Mg/ha of how much stover has to remain on the ground to conserve soil quality, and for this study is a constant fixed at 6 Mg/ha. This study assumes that stover is harvested only if it is profitable to do so. Cost of stover harvest was estimated based on the assessment in Thompson and Tyner (2014).

Switchgrass yield variation was simulated assuming a similar relationship as that between NDVI and corn yield, but with the magnitude of the variation reduced. Literature has shown that even though switchgrass yield also varies based on the temperature, precipitation and solar input, switchgrass yield is expected to be more stable than corn with respect to soil variability in Iowa and weather conditions in time (Varvel et al. 2008, Wang et al. 2010, Heaton et al. 2004), and this tolerance to a broad range of field and climate conditions is an important reason switchgrass is often recommended for marginal land (Stoof et al. 2015, Wullschleger et al. 2010). As detailed in more detail in Appendix B-2, the variability in switchgrass was estimated as three times lower than that of corn. The resulting variability of the two crops is visualized as in Figures 3-3 and 3-4. Switchgrass yield was simulated for both high and low yield scenarios by applying this reduced variability to two average values: 10 Mg/ha as suggested in the literature for high-yielding land (Wang et al. 2010), and 5 Mg/ha average yield which represents the yield on marginal land.

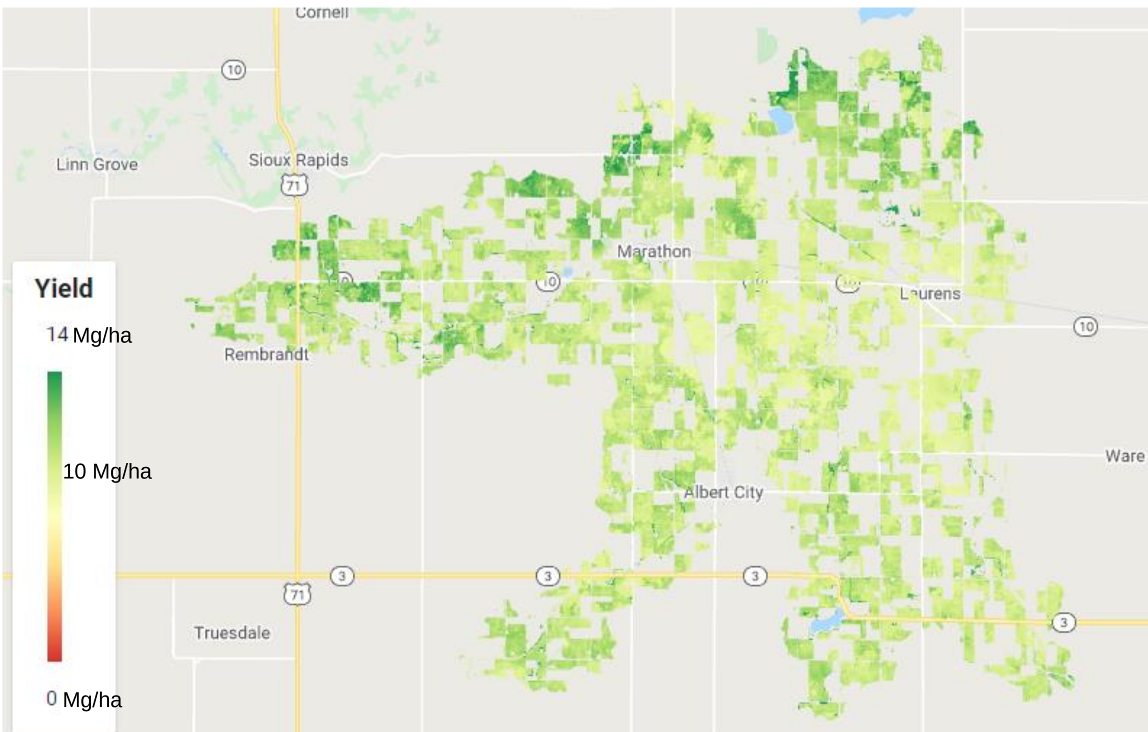


Figure **3-3**: Visualization of switchgrass subfield yield variability. The assumed mean yield was 10 Mg/ha, adjusted to reflect one third the subfield variability that was observed for corn grain in 2013. That corn grain yield variability is presented in Figure 3-4.

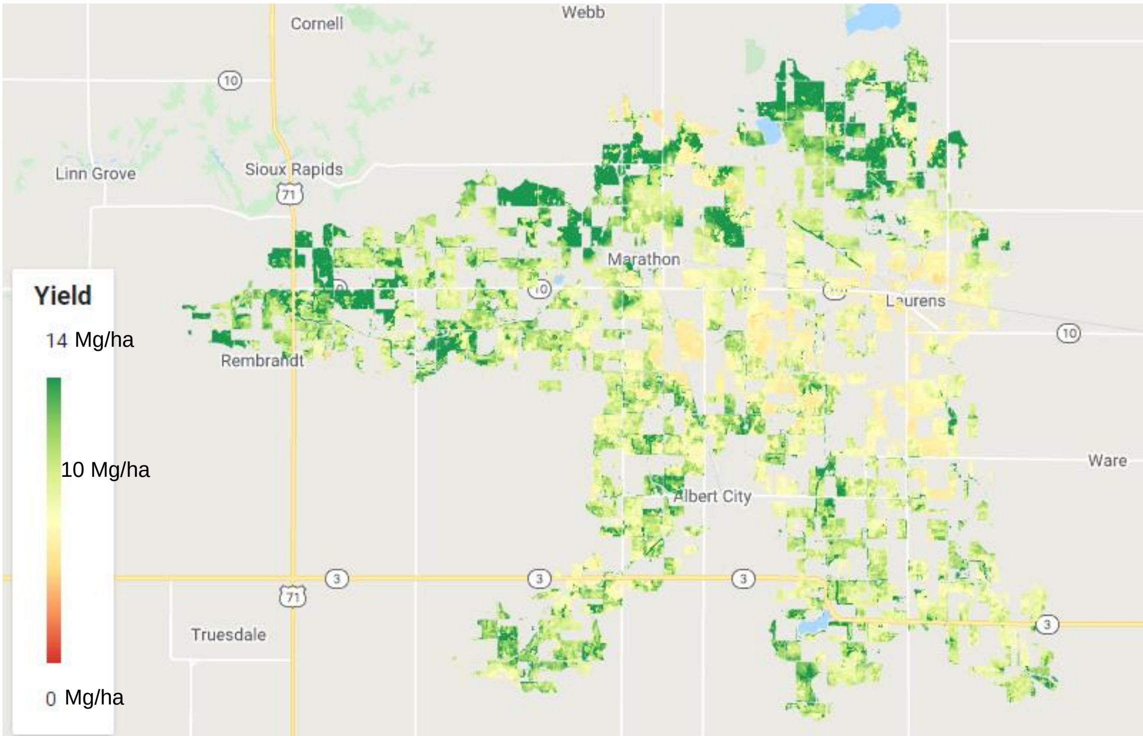


Figure **3-4**: Visualization of corn grain yield as calculated from NDVR data using equation (2). Mean corn grain yield in the North Raccoon watershed for 2013 was 10.1 Mg/ha. Corn grain yield variability is provided for reference, and can be compared with the yield variability for switchgrass in Figure 3-3.

The second step in the profitability calculations is accounting for production cost and calculating the profitability given the revenue from the harvested product. Switchgrass establishment costs were amortized over 10 years. The detailed production costs and assumptions are described in Appendix B, Table B-5 and are based on Jacobs et al. (2016). Although the size of a perennial buffer has been shown to affect the efficiency of machine operations and therefore the cost of production (Griffel et al. 2020), machine efficiency was assumed to be a constant 80% for this watershed scale assessment. A preliminary demonstration of the impact of subfield size and shape on production costs for perennial grasses is included in Appendix B, Table B-8. In the data outputs in Table B-8, an efficiency factor was calculated from the actual subfield area and shape, and this factor was applied to the machinery costs and the labor costs, including the fixed and variable costs. This preliminary study suggests that the machinery turns were more efficient in a larger area, and thus less time was used for breaking and turns. This is especially true if a large subfield area is coupled with a small subfield perimeter. However, more accurate estimates of the impact of subfield designs on harvest efficiency for each field in the watershed was beyond the scope of this study. Because the total harvest costs were a small part of the overall profitability assessment, the 80% harvest efficiency assumption is unlikely to have significantly affected the results.

Fertilizer application costs can vary from farm to farm as some of the agricultural producers are applying variable rate application of fertilizer to reduce excess fertilizer use and cost in low yielding areas of their fields (Nowatzke and Arbuckle 2016). Nevertheless, this study assumed a static fertilizer application rate because of the high average yields in the fields in the case studies. As reported in a study by Sawyer and Barker (2014), once the average yield reaches 180 bu/acre, applying more fertilizer beyond the suggested 185 lb per acre does not significantly increase crop yield.

In addition to the three market prices of $50/Mg, $100/Mg and $150/Mg, the Conservation Reserve Program (CRP) was also considered as a possible scenario. In the CRP case, the government program covers the perennial grass establishment costs, and also the rental cost if the land is rented. This CRP scenario serves as a base case for calculating the performance of the field if the markets are not functioning, or if there is overproduction relative to market demand. The percent land that is unprofitable for corn production, and thus may make sense to plant perennial grasses for conservation through the CRP program, is indicated in the results tables.

Corn cost and price assumptions are based on published crop budgets and historical prices for corn grain, and estimated harvest costs and projected biomass prices for corn stover. These assumptions are listed in Appendix B, Tables B-1 and B-3. The tables include corn grain price (USDA 2019), corn establishment cost (Duffy 2013 and 2014, Plastina 2015, 2016, 2017 and 2018), land rent price (Iowa Farm Bureau 2019), and corn grain subsidy, with the subsidy calculation described in Appendix B, Tables B-2 and B-4. The average per acre corn grain subsidy was calculated for each county based on the total dollar amount that was paid as corn grain subsidy in the county (EWG 2019) divided by the number of acres in corn (USDA 2019). The data are provided for Buena Vista and Hardin counties, because those counties are where most of the land of the Headwaters of North Raccoon River Watershed and South Fork River Watershed are located. The resulting profitability of corn is calculated by multiplying estimated corn grain and stover yields by historical corn grain price and the projected stover biomass farm gate price scenarios respectively, then subtracting the cost of corn establishment and grain and stover harvest (equation 5). Similarly, switchgrass profitability is calculated by multiplying estimated switchgrass yield and the projected switchgrass biomass farm gate price (switchgrass biomass is priced the same as the corn stover biomass in each biomass price scenario), and subtracting the cost of switchgrass establishment and harvest (equation 6).

$$Profit_{corn} = \left(Y_{grain} \times P_{grain} - C_{grain}\right) + i \times (Y_{stover} \times P_{biomass} - C_{stover}) + n \times S - m \times R \quad (5)$$

$$Profit_{switchgrass} = (Y_{switchgrass} \times P_{biomass} - C_{grain}) - m \times R \quad (6)$$

$$P_{biomass} = \begin{cases} 50, & Low\ value\ market\ scenario\ (\frac{\$}{Mg}) \\ 100, & Average\ value\ market\ scenario\ (\frac{\$}{Mg}) \\ 150, & High\ value\ market\ scenario\ (\frac{\$}{Mg}) \end{cases}$$

$$i = \begin{cases} 0, & Y_{stover} \times P_{biomass} < C_{stover} \\ 1, & Y_{stover} \times P_{biomass} > C_{stover} \end{cases}$$

$$n = \begin{cases} 0, & Scenario\ without\ subsidy \\ 1, & Scenario\ with\ subsidy \end{cases}$$

$$m = \begin{cases} 0, & Scenario\ without\ rent \\ 1, & Scenario\ with\ rent \end{cases}$$

Where Y is yield, P is price, C is establishment and harvest cost, S is corn grain subsidy, and R is rent. Stover is only harvested and sold when the biomass price exceeds the costs of harvesting the stover. For each part of the field, the profitability of corn grain and stover is compared to the profitability of switchgrass, and a final map is generated where the more profitable crop is selected; the corresponding average profit and percent area in perennial grasses from such map is reported. Rent is included in the calculation in some of the scenarios to illustrate that even leased land might be economically suitable for perennial grasses and to represent the opportunity cost of the land.

The cost, price and profit values are expressed in constant 2018 USD values. The actual costs for years 2013-2018 were obtained from crop budgets for the appropriate year and converted to 2018 equivalents using the Producer Price Index (farm products, commodity prices without seasonal adjustment) (Bureau of Labor Statistics 2020) so that the values could be compared and averaged. The Producer Price Index was selected because it represents the production purchasing power that is specific to the farming industry.

The economic scenarios described above were evaluated to understand the cases where perennial grasses like switchgrass could perform well or not relative to corn, the dominant annual crop in Iowa. Such scenarios included cost variation in switchgrass and stover biomass price ($50/Mg, $100/Mg and $150/Mg) and a conservation reserve program scenario as previously described, combined with other variables including whether the land is rented (or rent cost is included as the opportunity cost), and whether the producer is receiving corn subsidy. Two groups of scenarios are presented below for each watershed: the “best case” for corn, which assumes that the land is owned and that the producer has been receiving crop subsidies, and the “worst case” if the land rent is included and if no subsidy would have been received.

Results

Economic Profitability

The profitability of corn grain, corn stover, and switchgrass production varies within and between fields. Figures 3-5 and 3-6 are example model runs of field profitability of only corn production (both grain and stover harvest, where the stover harvest cost was less than the stover biomass price in a $/Mg basis and with a stover biomass price of $150/Mg) in 2013 to show the variability in profit across the watersheds. This simulation assumes that the corn grain subsidy is provided for corn and that rent is included, either as payment for farmers that lease cropland or as an opportunity cost for landowners. The resulting estimates of net profit, averaged over the years 2013 to 2018 for different subfield areas across these two watersheds, varied between a loss of $400/ha and profit of $1500/ha. As seen in figures below, some part of the watersheds had dramatically higher profits than others, and some parts had significant net losses, supporting the need for the subfield spatial economic assessment. The high prevalence of acres losing profit (marked in red in Figures 3-5 and 3-6) could be in part due to droughts in 2013 (NOAA 2013). For other years considered for this assessment, there were some low-profit areas that may be explained by low corn grain price in comparison with the 2013 prices. The average net profit used to allocate subfield areas to corn or switchgrass was a multi-year average, and would have been impacted by any variables that affected yield as well as these yearly price variations.

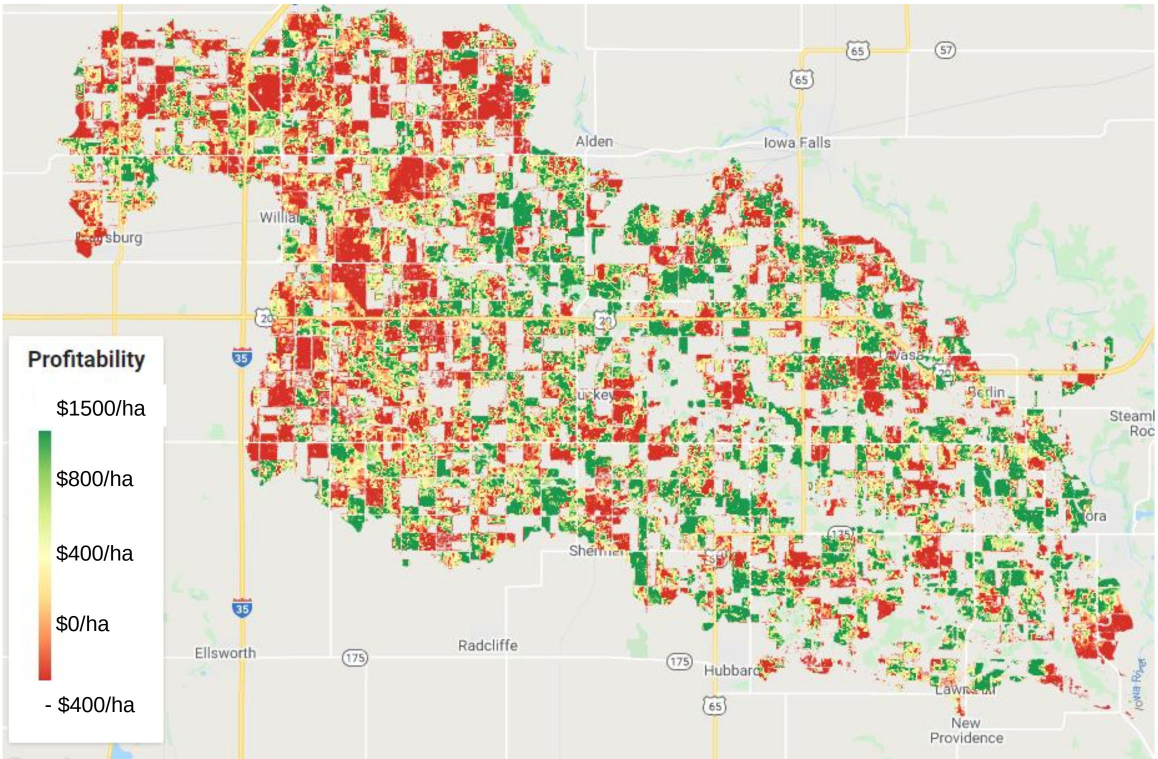


Figure **3-5**: Example run of the corn profitability analysis for 2013 (corn grain with corn stover harvest at \$150/Mg price scenario, without adding switchgrass) of the South Fork Iowa River watershed, including both land rent and corn subsidy.

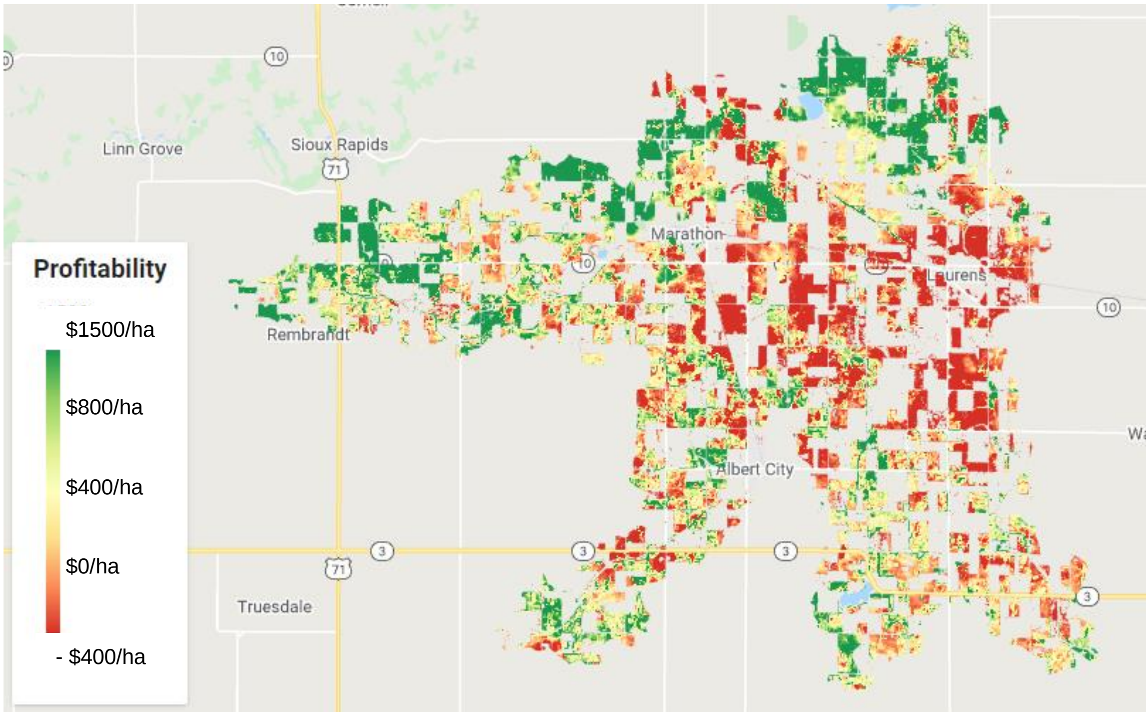


Figure **3-6**: Example run of the corn profitability analysis for 2013 (corn grain with corn stover harvest at $150/Mg price scenario, without adding switchgrass) of the Headwaters of the North Raccoon watershed, including both land rent and corn subsidy.

This study compared the possible subfield profitability of corn grain with and without corn stover harvest to the projected profitability of switchgrass in that subfield. The results as presented below and detailed in Appendix B, Tables B-6 and B-7, list the average profitability over the years 2013 - 2018 in two example watersheds with both only corn production and production of both corn and switchgrass when parts of the field are converted to the perennial grass if it is produces more profit or has a lower loss than corn. Both the South Fork Iowa River watershed and the North Raccoon River watersheds are located on highly productive Iowa soils, yet the analysis shows over 10% of the land in these watersheds was unprofitable for corn grain production even when the scenario includes corn subsidy and excludes land rent without considering any revenue for biomass (the CRP scenario, Appendix B Tables B-6 and B-7). Such land that is unprofitable for corn could be converted to the CRP grass mixtures, but the amount of land for perennial grasses increases even more if the biomass can be harvested and sold.

In all the scenarios that consider high switchgrass yield and $150/Mg biomass markets, switchgrass was more profitable on at least 69% of the land, and introducing switchgrass increases the average profitability of fields by at least $200/ha (Figure 3-7 to 3-10) when compared to annual crop production with corn stover harvest. Corn stover harvest increased average profitability only when biomass price was set to $150/Mg, as harvesting stover at a biomass price of $100/Mg or lower was unprofitable. Between 30% and 60% of acres across scenarios were more profitable with a switchgrass price of $100/Mg, but switchgrass was competitive on far fewer acres at $50/Mg of harvested biomass. Nevertheless, in all cases substituting switchgrass on the least profitable areas of these watersheds should equal or increase average farm profitability relative to the base case of corn. While conservation subsidies are sometimes more profitable for the farm than the lower price market incentives, a market-based approach would create spin-off companies and entrepreneurial producers who can take advantage of new markets as they emerge.

Looking beyond the average profitability over the full time period studied (2013-2018), the percent land that would have been more profitable for switchgrass production, and also the regional and farm specific profitability, varied across the years. In 2013, despite the lower average yields, the corn prices stayed high which led to high profitability of most acres and a low percentage of the field where switchgrass would have been more profitable than corn. This year-to-year variation is an important challenge to agricultural producers trying to maximize their profitability with switchgrass, as perennials take two or three years to get established. Thus, the percentage of acres cannot be adjusted in real time based on market price swings or weather variation. This reality may discourage farmers from planting switchgrass on cropland that is rarely less profitable, and focus on the subfield regions of fields where corn is unprofitable year after year. Even though both South Fork River and North Raccoon watersheds are in similar areas with average rent and yield, between 2017 and 2018, the percentage of land where switchgrass is more profitable than corn increased in North Raccoon River watershed, but decreased in the case of the South Fork Iowa River Watershed. Such results point to how the economic case for perennial grasses varies with location.

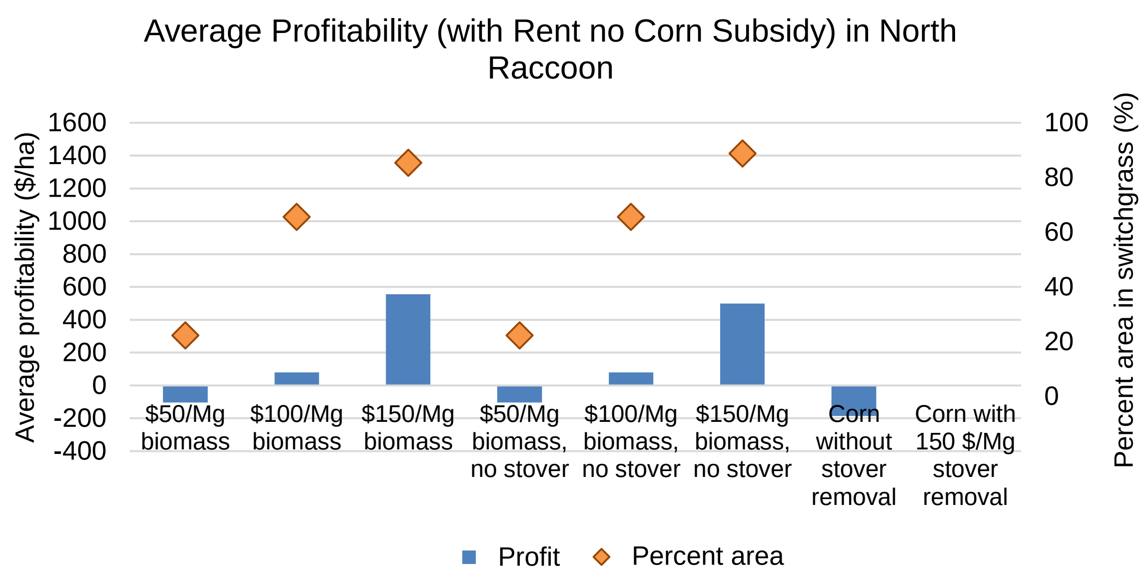


Figure **3-7**: Average profitability (2013-2018) in North Raccoon watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (3) given that rent is included in the profitability estimation, and the corn grain subsidy not included.

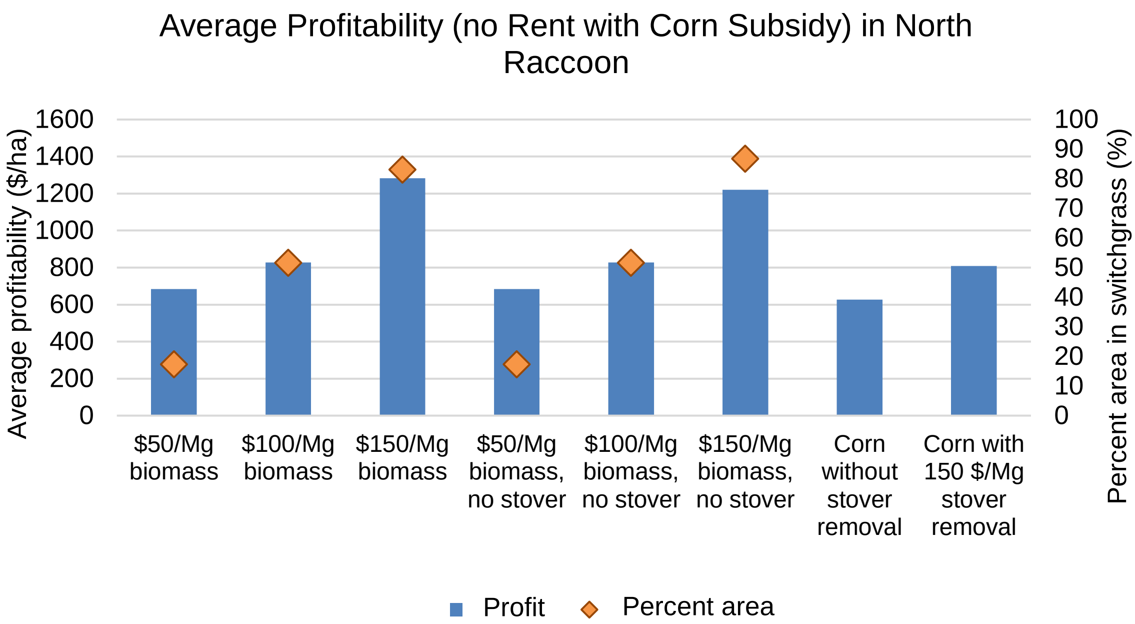


Figure **3-8**: Average profitability (2013-2018) in North Raccoon watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (3), with rent not included in the profitability estimation, and the corn grain subsidy included.

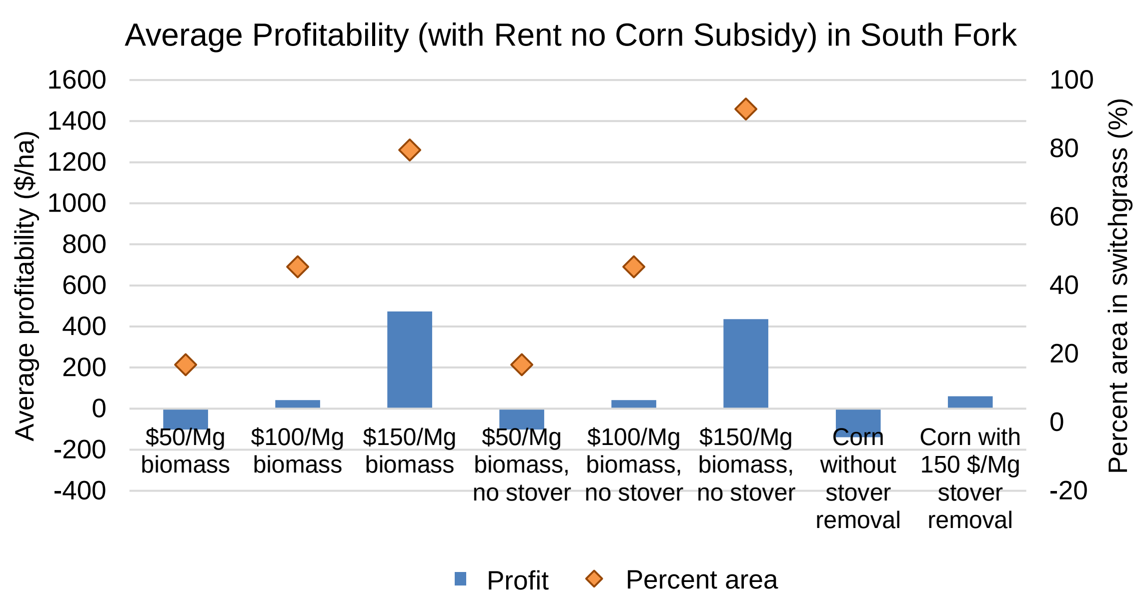


Figure **3-9**: Average profitability in South Fork watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (3) with rent included in the profitability estimation, and the corn grain subsidy not included.

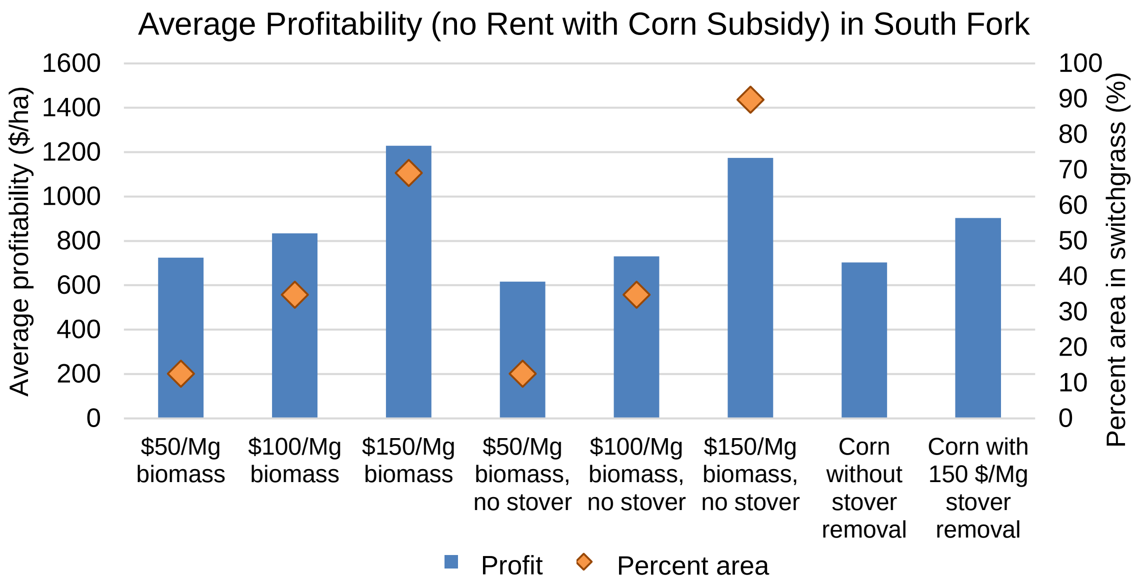


Figure **3-10**: Average profitability (2013-2018) in South Fork watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (3), with rent not included in the profitability estimation, and the corn grain subsidy included.

Results sensitivity

The results of this study are subject to the modeling assumptions of the estimated biomass yields, which is why two additional cases were tested to understand the sensitivity of the results to yield change (Figure 3-11 to 3-14). A second corn stover yield model was tested for a difference (corn stover yield based on Equation (4)) and a comparison indicated that both equations produce similar average profitability results. That result suggests that setting a fixed amount of corn stover to remain on the ground can provide a useful estimate of the resulting average crop profitability.

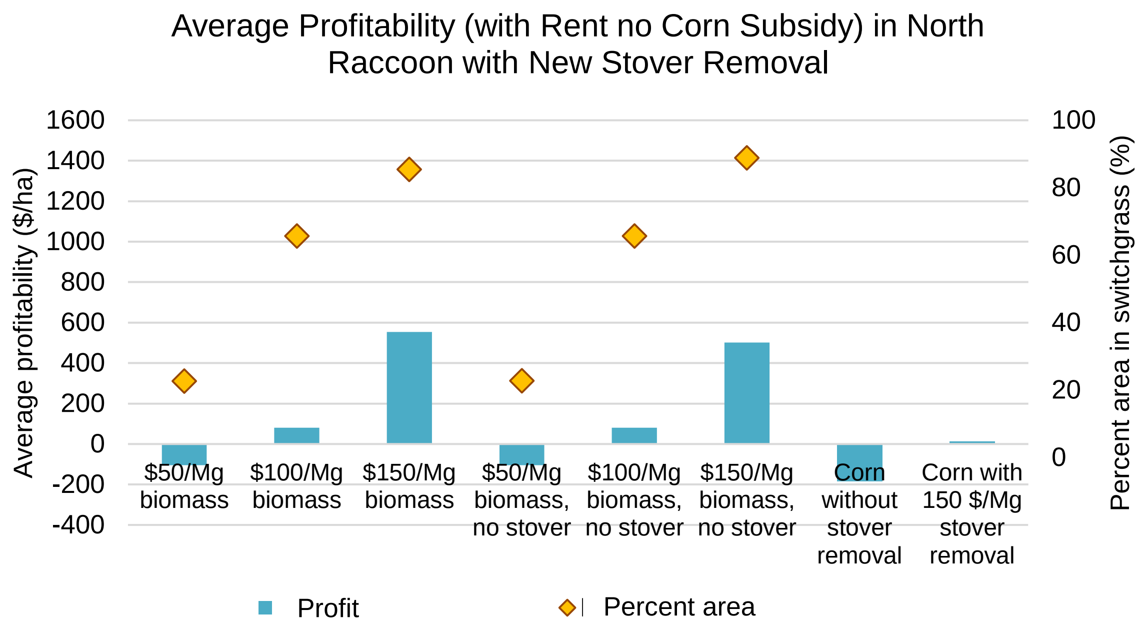


Figure **3-11**: Average profitability (2013-2018) in North Raccoon watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (4), with land rent included in the profitability estimation, and the corn grain subsidy not included.

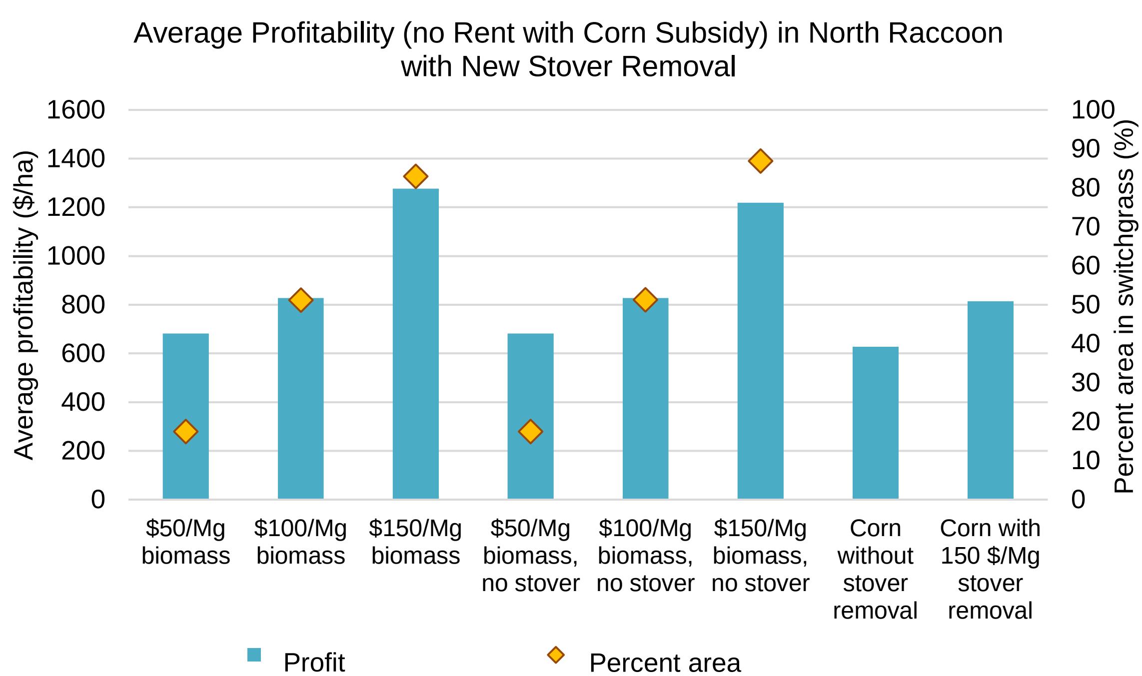


Figure **3-12**: Average profitability (2013-2018) in North Raccoon watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (4), with land rent not included in the profitability estimation, and the corn grain subsidy included.

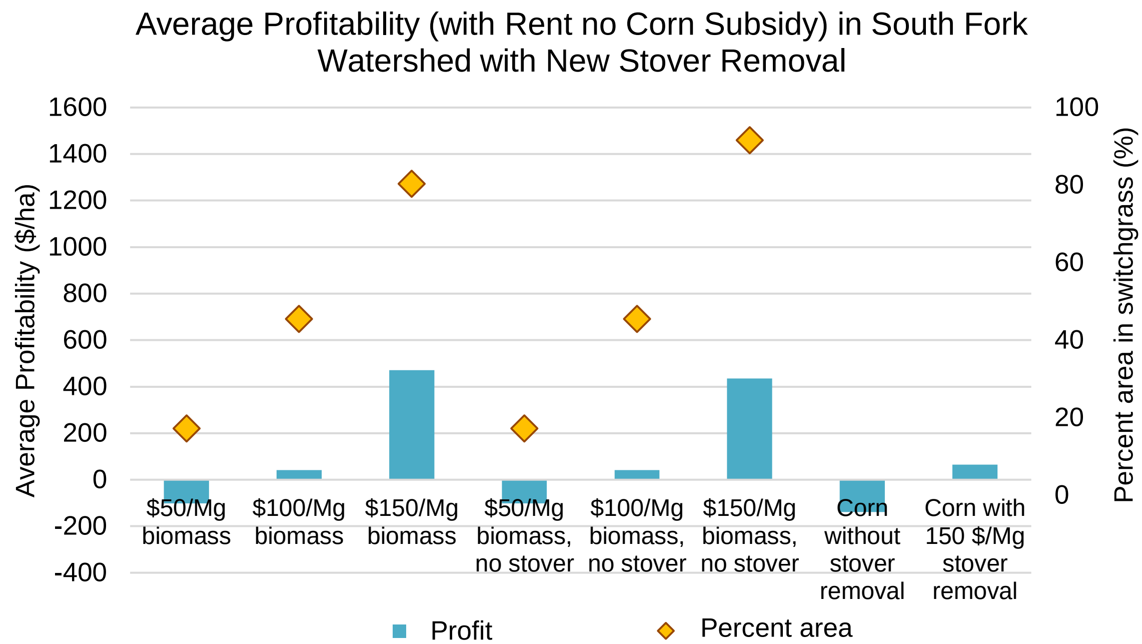


Figure **3-13**: Average profitability (2013-2018) in South Fork watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (4) with land rent included in the profitability estimation, and the corn grain subsidy not included.

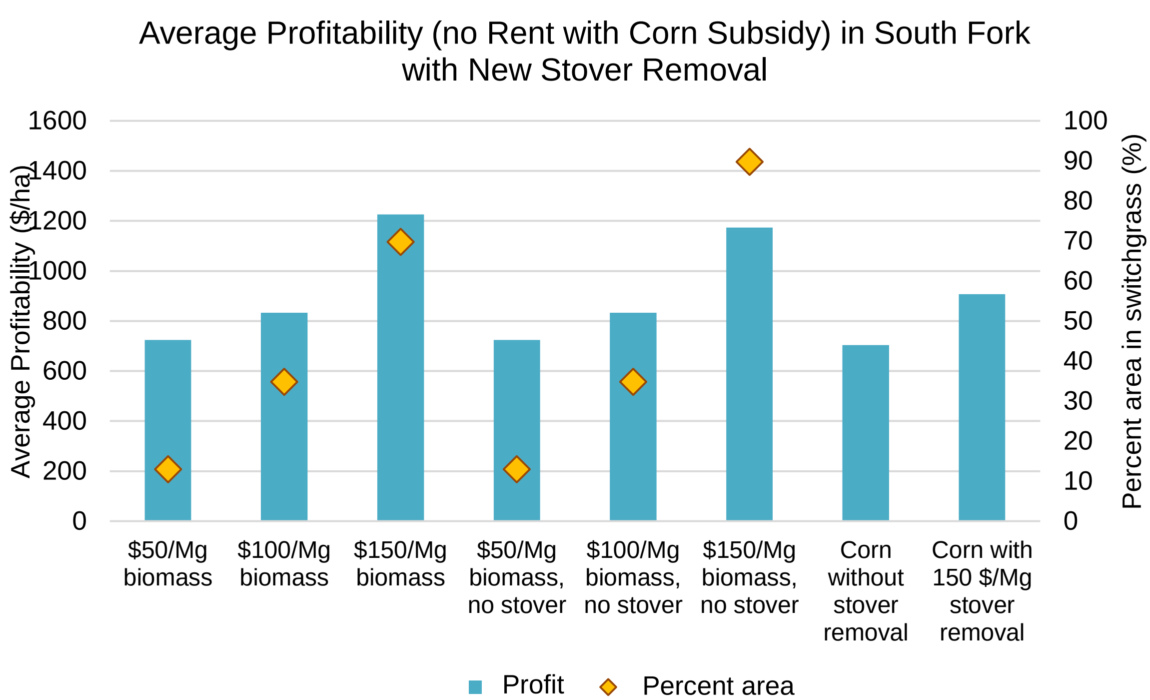


Figure **3-14**: Average profitability (2013-2018) in South Fork watershed given high switchgrass yield (10 Mg/ha) and corn stover yield calculation based on equation (4) with rent not included in the profitability estimation, and the corn grain subsidy included.

Similar scenarios were run assuming a low switchgrass yield (5 Mg/ha) with the original corn stover yield estimates. Such a scenario represents the yield that switchgrass could have on marginal land. The results suggest lower profit than the high switchgrass yield scenarios, especially for the $100/Mg and $150/Mg biomass price cases (Figures 3-15 to 3-18). Interestingly, across the scenarios, having a low switchgrass yield results in overall loss of average profitability, because the profit from biomass in the high-yielding switchgrass cases improved the average field profitability with or without corn stover harvest.

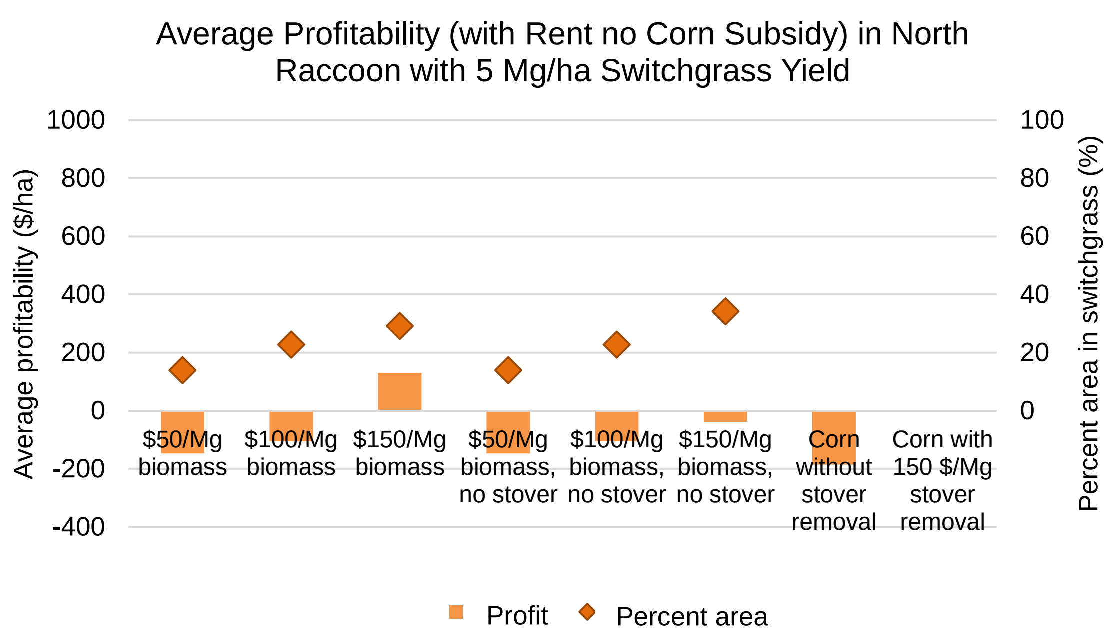


Figure **3-15**: Average profitability (2013-2018) in North Raccoon watershed given low switchgrass yield (5 Mg/ha) and corn stover yield calculation based on equation (3) with rent included in the profitability estimation, and the corn grain subsidy not included.

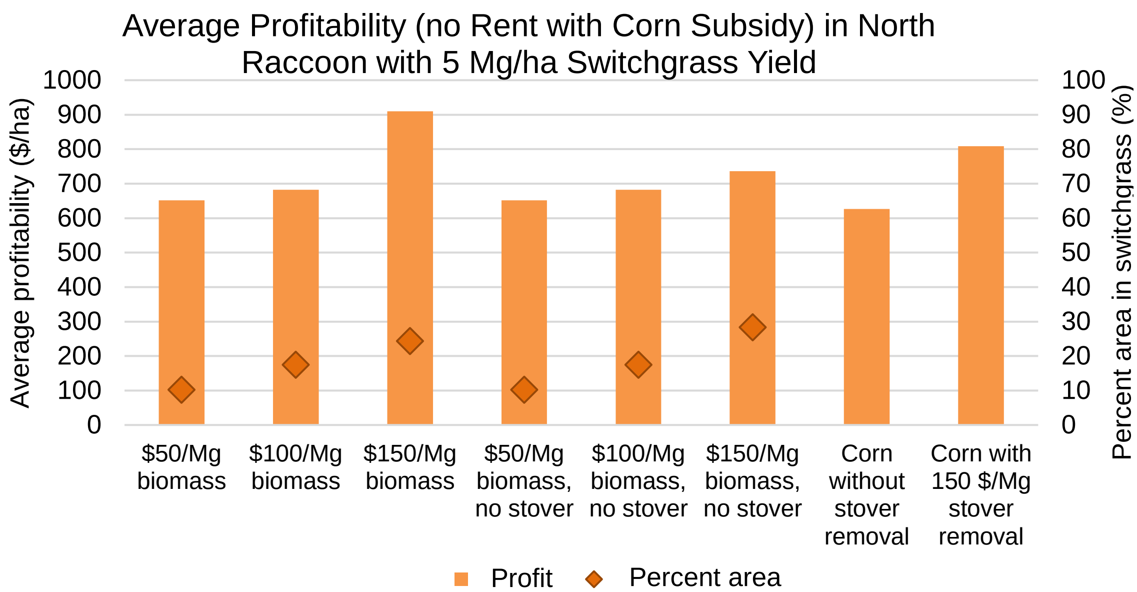


Figure **3-16**: Average profitability (2013-2018) in North Raccoon watershed given low switchgrass yield (5 Mg/ha) and corn stover yield calculation based on equation (3) with rent not included in the profitability estimation, and the corn grain subsidy included.

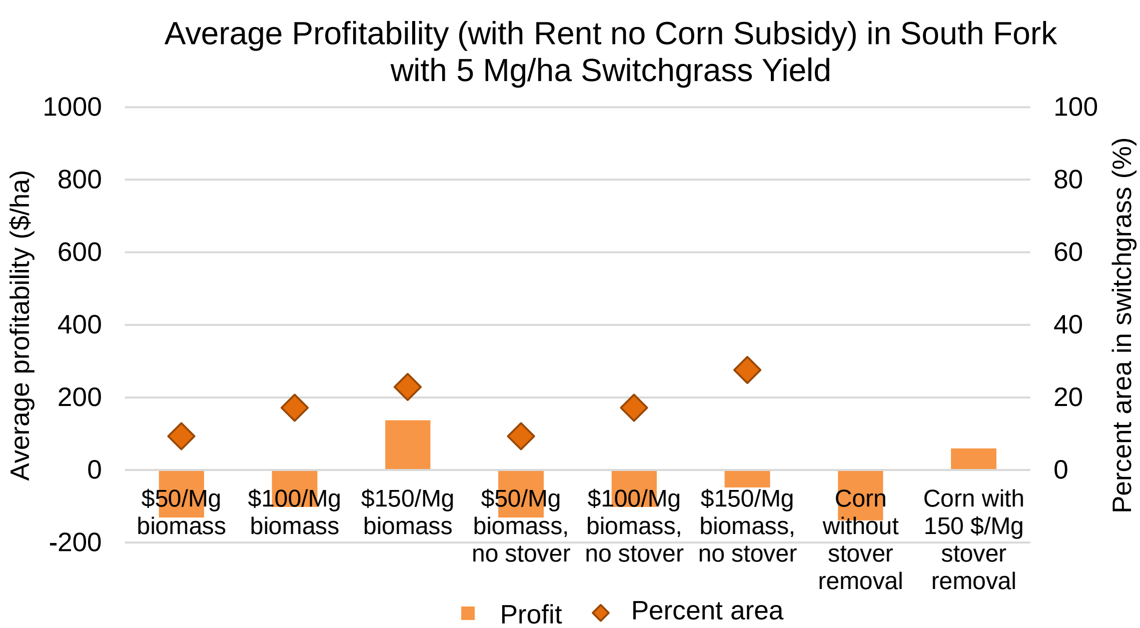


Figure **3-17**: Average profitability (2013-2018) in South Fork watershed given low switchgrass yield (5 Mg/ha) and corn stover yield calculation based on equation (3) with rent included in the profitability estimation, and the corn grain subsidy not included.

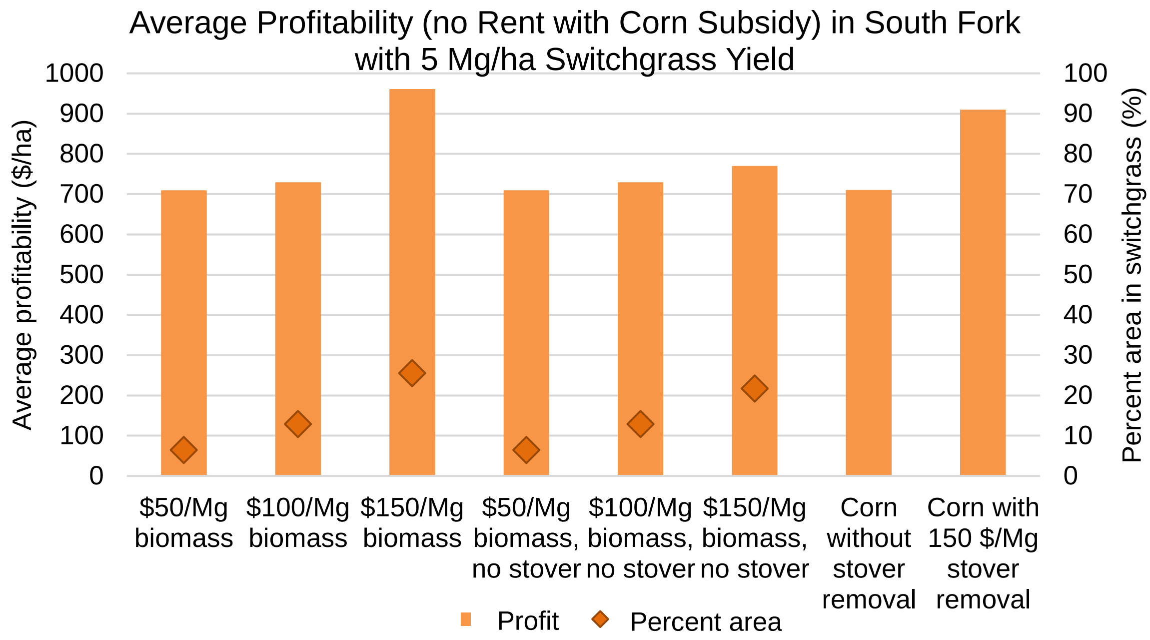


Figure **3-18**: Average profitability (2013-2018) in South Fork watershed given low switchgrass yield (5 Mg/ha) and corn stover yield calculation based on equation (3) with rent not included in the profitability estimation, and the corn grain subsidy included.

Discussion and conclusions

Agricultural producers can financially benefit from installing switchgrass on parts of the fields where corn is less productive. The extent of that benefit depends on the price of biomass, corn production cost relative to corn price, and whether the land is rented or owned. The results suggest that high-value markets of $150/Mg (currently represented by an actual market for switchgrass used in erosion control socks) can make switchgrass competitive with annual crops on over 70% percent of the land in the two studied watersheds. Converting that land to switchgrass could increase average farm profitability in those counties by over $200/ha, suggesting that perennial grasses not only contribute to conservation efforts but also can improve the “bottom line”. If just 20% of land currently farmed as corn is converted to switchgrass as suggested by the CRP scenario or the lowest boundary of the $100/Mg assessment, with $200/ha increase in profit, that would result in additional $2.6 Million in the South Fork River Watershed, or $1.2 Million in the headwaters of the North Raccoon River watershed. Such increase in profit would support rural development, which was a high priority for producers as identified in the interviews in Chapter 2 “Producer Sustainability Perspectives”.

Biomass markets are still under development, which is why there is a risk that farmers might not be able to find buyers for their entire supply of perennial grasses immediately after planting. For that reason, a scenario was included where switchgrass is established as a CRP crop. Even in such a case, perennial grasses can out-compete corn and improve farm profitability on many acres. This is especially the case when the CRP subsidy covers the land rent, in which case CRP establishment can be a more profitable option than selling switchgrass for $50/Mg or even $100/Mg. While more stable, the income from CRP would depend on the change in policy and might be questioned by farmer’s goal for independence.

Frequently, the biomass price assumptions for bioenergy and biochemicals are $50/Mg-$80/Mg (Bioenergy KDF 2019). The analysis indicates that at these lower prices, switchgrass is only rarely competitive with the conventional crops, especially on rented land. The analysis indicates that to motivate the conversion towards more perennial grasses, higher value-added markets need to be encouraged, with a higher profit or some other grower payment mechanism for biomass, bioenergy and biochemicals. These findings are similar to the production cost analysis of Hansen et al. (2019), which estimated that switchgrass production costs can vary between $58/Mg and $74/Mg in integrated landscape designs.

The spatial distribution of the economic analysis at 10 m to 30 m scale indicates that corn profitability is variable not only between fields but also within fields, with many of the unprofitable areas along streams and in headlands. In the case of stream buffers, planting annual crops in floodplains can be challenging for not just the crops, but also the machinery to access the stream-side property in wet times of the year. Figure 3-19 presents a zoomed-in map of the profitability of fields and illustrates that the economic returns vary both among fields in a farm (for example, the highly profitable field in the bottom-right corner as compared to less profitable field in the center of the image), and within fields (for example, the low and high-profitability zones in the left corner of the image). This variability can be explained by topology, nutrient application rates, soil types, and other biophysical factors (Jin et al. 2019). Several studies use crop productivity prediction models to explain the variability in yield predictions. For example, Maestrini and Basso (2018) suggest that the variability could be linked to the topography–rain relationship, represented by the topographic wetness index. Similarly, Lobell and Azzari (2017) observe that yield variability is most likely caused by the soil and landscape differences, even more than field management. The goal of this study was not to understand the mechanisms that cause specific parts of the landscape to be marginal and thus suitable for switchgrass growth, but rather to evaluate whether switchgrass can be an economically feasible crop given the actual corn yields on Iowa landscapes. Nevertheless, understanding the causes for yield variability can help predict future marginal lands and suggest the long-term positioning of perennial crops.

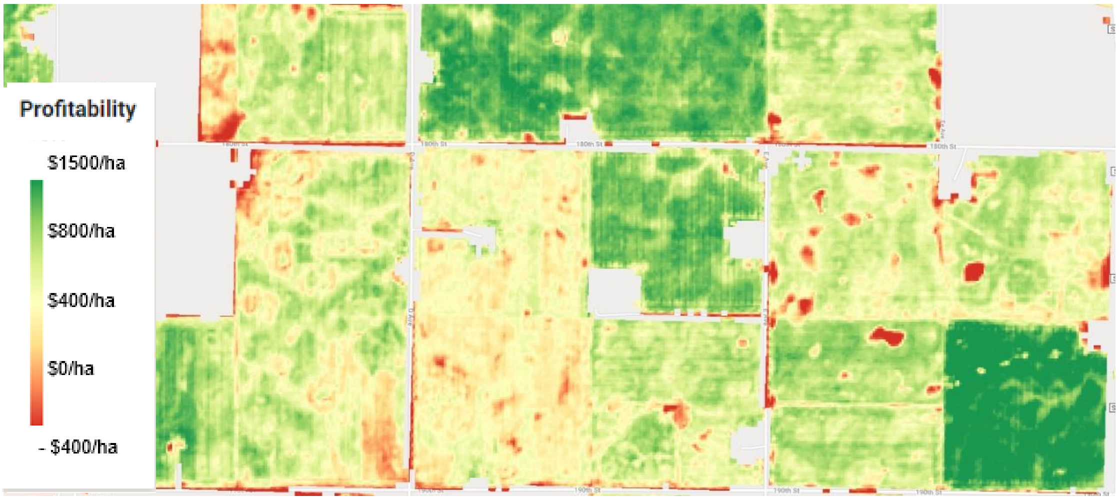


Figure **3-19**: Zoomed-in image of field profitability for 2013 (corn grain with corn stover harvest at $150/Mg price scenario, without adding switchgrass) of the Headwaters of the North Raccoon watershed, including both land rent and corn subsidy.

Subfield variability in yield, and the resulting "patchiness" of planting perennial grasses in small and awkward shapes, can be a problem for field operations. This is a problem that can be solved using optimization, examining opportunities for efficiency and synergies both in space and time. For example, if switchgrass is planted in the headland spaces, but that space is used for machinery turns to plant and harvest annual crops while the switchgrass is still growing and before it is harvested, the switchgrass biomass quality would be greatly reduced. Machine-induced soil compaction can be one of reasons for yield reduction in the headlands, and planting perennial grasses on the edge of the field could just shift that compaction deeper into the field over time if annual crop machinery is not allowed to drive over the grasses. To avoid this problem, the farmer could drive over the perennial grasses, but that would reduce biomass quality if the corn field harvest occurred before switchgrass harvest. On the other hand, harvesting switchgrass from the perimeter of the field before the corn harvest would avoid that problem, and could provide a more digestible grass biomass that may have higher value. A spatial and temporal optimization of the landscape design that includes considerations of the harvesting time could generate a possible solution, and represents one promising avenue for further research.

Because the placement of perennial grasses is an optimization problem not only in space, but also in time and can affect biomass quality, it would be useful to produce a farmer's guide that connects biomass quality (e.g. ash, moisture, carbon content), harvest timing and the markets that such biomass could suit. As discussed in the text above, different markets require different quality material, and differentiated quality characteristics could translate to different prices for the producer. For example, planting switchgrass that is later used for animal bedding might be appealing to one farmer as it might require lower quality, but higher volume. Another farmer, more interested in a smaller but higher-value biomass product, might consider producing pet bedding or biomass for pharmaceuticals. Such differentiation by quality and market will help this emerging industrial sector implement the "biorefinery" concept, which, similar to that of an oil refinery, directs different fractions of oil towards different purposes both because of the diverse quality of the material and also because of the diverse markets available.

Limitations of this study include the use of historical data, which is fixed over a particular period of time that is already past. In this analysis we evaluate the potential for switchgrass planting for the years 2013-2018. Even though there are some trends over these years, the time period is too short to be confident those trends reflect climate change. Yet many stakeholders would like to predict where the unprofitable areas will be in the future as a result of climate change. Further studies can evaluate how climate change will affect the definition of marginal lands, be that through flood, drought, or timing of weather events.

The results of this study suggest that a major part of Northcentral Iowa cropland can be economically converted to switchgrass. High-value functioning biomass markets can improve the adoption of perennial grasses, but they will also need to be high value to provide sufficient incentives to convert considerable areas of cropland. With biomass prices of $150/Mg, switchgrass could be economically viable on over 80% of the land in the two watersheds evaluated. Northcentral Iowa cropland is a high producing area for corn, so these results indicate that switchgrass can compete with corn on even high-quality soils. Similarly, switchgrass could make a compelling economic case that land with steeper slopes and poorer soil should also consider perennial grasses as an economic alternative to annual crops. Such conditions were estimated in the 5Mg/ha switchgrass yield scenario representing marginal land yields. By using subfield yield data derived from satellite imagery, and connecting those data with county-level estimates of crop yields, market prices and production costs, this study extends beyond prior research that used soil type-based yield and profitability estimates to make a case for perennial grasses.

Chapter 4

Multiple criteria spatial suitability analysis for sustainable crop allocation using stakeholder priorities

Abstract

Integrated landscape management designs that compare and reallocate annual and perennial crops to maximize utility offer a new way to both improve producer prosperity and reduce the negative environmental footprint of agricultural systems. Selecting the right design is a complex task because the decision problem is spatial and involves countless possible combinations of crop arrangements. Furthermore, many factors are considered in farm decision-making, each with different levels of priority, making the spatial decision problem also a multiple criteria optimization problem. This study demonstrates the use of stakeholder input for multiple criteria decision support by considering the real priorities that were found during producer interviews. By consulting with the stakeholders in advance about which decision variables are most relevant, having the stakeholders weight each of those variables, and using an algorithm to generate a new field cropping system design that is operable using agricultural machinery, the developed optimization framework proposes possible farm field designs that incorporate perennial grasses into the landscape. The framework allows producers to redesign agricultural landscapes to be valuable in ways that are most important to them. This study applies this framework to several demonstration cases based on different weighting functions of agricultural producer priorities. Using soil and other properties from a real field, the model optimized the design of that field for subfield layouts that include a corn-soybean rotation and switchgrass, with the designs based on spatial analysis of 15 weighted sustainability indicators that were identified

from producer interviews. This approach allows for modeling the most meaningful decision factors and including them in field-scale decision-making, even though some of those attributes are seldom modeled at a subfield level and are challenging to represent by a spatially explicit proxy. The decision support framework developed by this study offers a way to generate field layouts that maximize the total sustainability utility of the agricultural landscape, while making the layout operable for agricultural machinery. The distinct cases evaluated using the framework illustrate that for some combinations of producer values and priorities, the agricultural landscape would be transformed into a more perennial grass-dominated landscape.

Introduction

Agricultural decision-making is a complex task. Many factors influence the producer's decision-making process, which is specific to the location of the farm, available equipment and experience, local and national markets, and the planning time horizon. Decision support and spatial analysis techniques can assist in agricultural decision-making to propose farm landscape arrangements that satisfy producer priorities, and consider the impact of their decisions on surrounding communities and the environment. Such techniques are intended to help agricultural producers by leveraging both generalized and site-specific research findings, as well as the producer's farm- and field-specific knowledge. The resulting knowledge co-production (Bovaird 2007) can be leveraged by engaging the stakeholders in the decision support development from the onset of the project. As a result, the stakeholders not only verify and select a preferred scenario from the decision support system but participate in scenario generation. Designs, scenarios and solutions that arise through stakeholder collaboration initiated at the beginning of a project are more likely to be applicable and actually implemented than if proposed from the top down by researchers or policymakers (McGuinness and Slaughter 2019).

Stakeholder input has been solicited previously for decision support design. For example, Stillwell et al. (1983) compared various methods to elicit weights using a bank credit assignment as an example. They illustrated that different elicitation methods could lead to similar decision solutions, even when compared to equal weighting (setting the same weight on all priorities without stakeholder input). Even though equal weighting might have a similar outcome, involving stakeholders in determining which priorities are most relevant, and allowing them to set the corresponding weight of that priority, may increase stakeholder empowerment and increase the likelihood of implementation.

Effective involvement of stakeholders is a function of both the stakeholder engagement method and the modeling approach. Voinov and Bousquet (2010) review the different ways stakeholders can participate in modeling and report that multi-criteria optimization is one of the effective modeling methods for participatory decision analysis. Many of the existing land use decision tools recognize the complexity of stakeholder decisions and apply multi-criteria optimization techniques, including multi-objective or multi-attribute optimization. Such methods are designed to optimize a solution towards multiple goals, either illustrating the tradeoffs between each of the objectives or by normalizing a set of different indicators and weighting or ranking them to simplify the problem (Bartolini et al. 2007, Cao et al. 2011, Cisneros et al. 2011, Groot et al. 2018, Klein et al. 2013, Parish et al. 2012). Multiple criteria decision analysis can be used to compare a variety of alternative scenarios and, based on the weighting of the factors by the decision-maker, suggest which alternative is best (Huang et al. 2011). This ranking can be based on the sum of weighted utility values for each indicator, calculated as the outcomes of each scenario, essentially showing how much total benefit (or net benefit, if some functions are negative) the scenario will bring. This study uses a multi-criteria decision analysis framework because of the diversity of agricultural criteria (sustainability indicators) that stakeholders consider as priorities.

Utility functions can be used to interpret and evaluate how acceptable a level of decision variables is, or in this case – how acceptable the performance of sustainability indicators is. Using the utility approach has been described in a fundamental work by Bernoulli (1954) and has been widely used in multiple criteria decision analyses (Wallenius et al. 2008). The performance of decision variables can be expressed as a utility value where the weighted indicator values are all in common units. For example, profitability is calculated in USD and wildlife in diversity index values. Comparing or combining the two measures in a single objective function would be impossible without conversion factors that set the units to a consistent, normalized range (e.g. zero to one) within which these variables are calculated. Utility functions serve that role of normalizing the units of the different sustainability indicators, by assigning the upper and lower bounds of an indicator's "acceptable" levels and the type of behavior of the function between those levels. Weighting can be paired with such utility functions to prioritize some of the indicators' performance for the final decision. Because "acceptability" and utility are stakeholder-dependent, ideally utility functions should be defined by the user as should the underlying sustainability indicators (Stosch et al. 2019). While stakeholder-defined utility functions are possible in the model developed in this chapter, pre-set utility functions are also available to simplify the decision support process.

Design and decision-making about agricultural fields and cropping systems is a spatial problem, meaning that the decision solution has to be spatially explicit to account for variations in input and output variables at a subfield level. Spatial optimization problems have a large solution space – for example if a 5-acre field is split into a grid of 30x30 meters, that results in approximately 22 cells. If just two possible land use options are compared, there are 2^{22} = 4,194,304 possible arrangements of cells. If the size of each cell is 30x30 meters, the 100x100 grid would represent a field or farm of 900ha. On average, the corn stover harvesting producers interviewed for this study farmed over 1,200ha, so a useful spatial decision support tool needs to be able to process a very large number of possible solutions. For this study, raster spatial processing was selected as an efficient way to process subfield data, where “raster” is a way to represent spatial data as independent cells in a grid.

In addition to the large size of the decision space, spatial problems are inherently transdisciplinary and require multicriteria assessment techniques, with multiple utility values calculated for each cell. Ferretti and Pomarico (2013) have used the term, “multicriteria-spatial decision support systems” to discuss ecological land suitability analysis. Because of the complexity of spatial decisions, multicriteria spatial decision problems have been addressed using heuristic methods for spatial optimization (Fotakis et al. 2012, Li and Yeh 2005, Stewart and Jenssen 2014) or using site suitability analysis (Akinci et al. 2013, Ferretti and Pomarico 2013, Lovett et al. 2009, Pulighe et al. 2016). Site suitability analysis is the approach that is taken in this study.

The goal of this study is to develop a decision support framework that utilized stakeholder input to co-generate an agricultural decision that helps improve farm sustainability, where choices are made between installing a perennial grass (switchgrass) or rotation of annual crops (maize/soybean) in different parts of a field on highly productive farmland in the US Midwest. Such a decision framework can be applied to other spatial natural resource problems.

Methods

A producer decision support framework for crop allocation was developed to optimize weighted priorities applied to an agricultural field with defined priorities and market conditions. That framework consists of several key components such as stakeholder input, a model to evaluate the sustainability performance of a crop choice and the corresponding utility of such crop choice, and a spatial analysis algorithm that uses the sustainability evaluation to produce a crop suitability map that is further improved by “smoothing” the field, or making it less fragmented and more operable for agricultural machinery. Stakeholder engagement was carried out as a series of agricultural producer interviews and a gamified discussion on indicator priorities, targets and weighting functions by individual producers. To demonstrate the approach, an example field was divided into a grid of cells (represented by spatial raster files), and each cell was evaluated for the suitability of annual and perennial crops based on the utility value that the cell receives. These suitability results assigned crops to each cell based on a deterministic calculation of the utility scores were then adjusted to eliminate clusters of pixels below a minimum subfield size. A “smoothing” algorithm was run on these deterministic land suitability results, which produced field layouts that were efficiently operable with agricultural machinery.

Stakeholder priorities elicitation

Chapter 2 of this dissertation discussed in detail how indicators were selected and weighted during stakeholder interviews. This chapter provides a brief summary and details how the indicators and weights for indicators were quantified to optimize crop allocation across agricultural landscapes.

Modeling is a simplified representation of reality, which is why selecting the key decision variables is of prime importance to make sure the model characterizes the system it is trying to represent in ways that are relevant and meaningful to the users. The stakeholders were iteratively consulted (Figure 4-1) to determine the relevant sustainability indicators, thresholds, and weighting functions. In the first round of interviews 34 Iowa producers from across the state participated. These producers included participants who have established perennial crops as part of the Conservation Reserve Program, others who have planted miscanthus and/or switchgrass for power generation, and yet others who have harvested corn stover for a cellulosic ethanol plant. An initial list of indicators was generated based on those producer interviews. Participants were asked about their concerns in agriculture and what priorities they have for agriculture and farming. Based on the most frequent answers and a literature review of other stakeholder-based indicator selections, 18 indicators were selected that cover the social, environmental and economic dimensions of agriculture impacts, collectively referred to as sustainability indicators.

Sustainability indicators were verified, quantified and weighted during Phase 2 of the interviews. The producers were provided with cards illustrating the 18 priorities generated from the initial interviews, additional cards representing time and space boundaries that could be relevant to those priorities, and 100 poker chips to distribute among priorities to assign relative weights. Figure 4-2 provides several examples of how producers interacted with materials. Agricultural producers indicated which sustainability indicators were most relevant to them. When asked how they would measure those indicators, they matched each indicator with the most meaningful space-time boundaries, identified specific thresholds for which the indicator is at an acceptable level, and then weighted each of those personally relevant indicators.

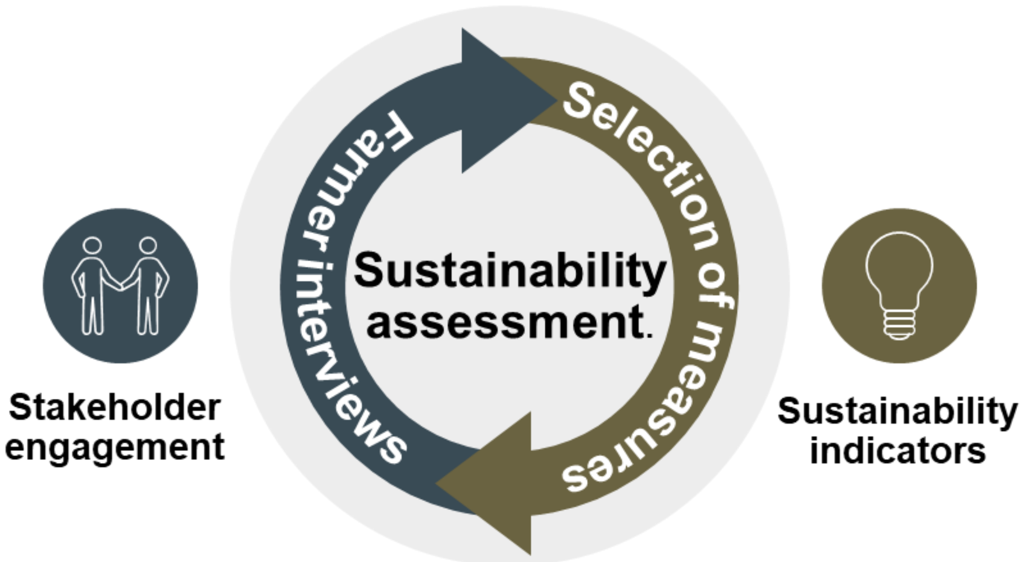


Figure **4-1**: Continued engagement of stakeholders to generate decision criteria and to verify the applicability of the indicators. Stakeholders were engaged iteratively in the study to verify the selected indicators.

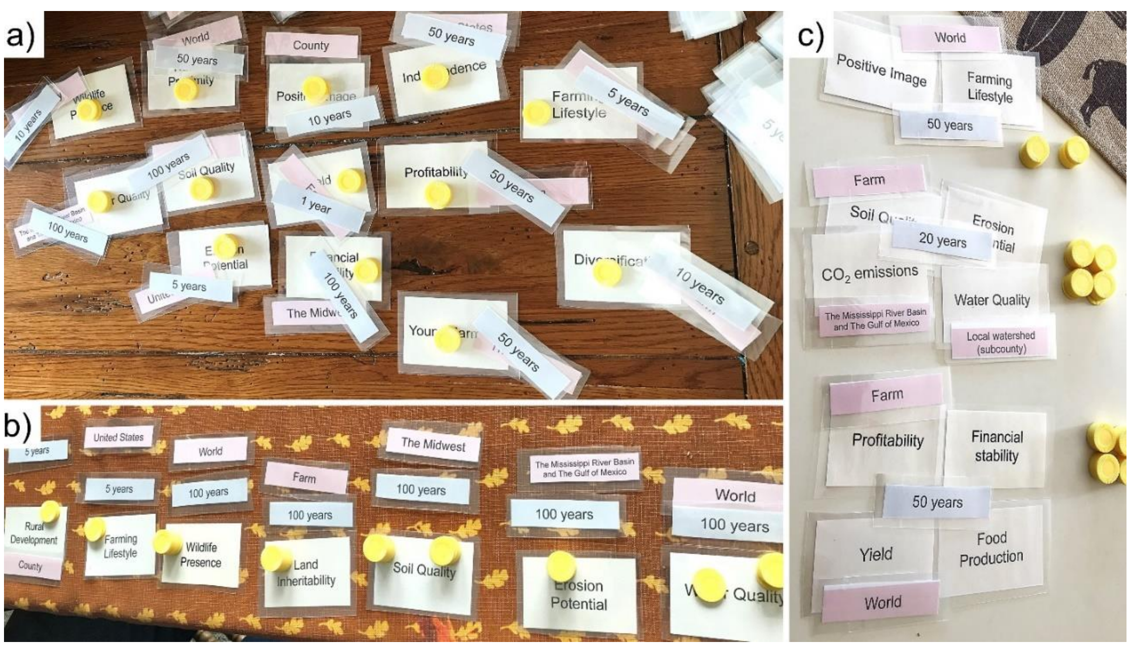


Figure **4-2**: Output of producer interaction with decision variables (cards with sustainability indicators), priority weights (poker chips) and space-time boundaries.

Stakeholder priorities

The indicators that were selected based on stakeholder interactions are presented in Table 4-1, together with the spatial measures for those indicators and the corresponding utility calculations. An initial list of 18 sustainability indicators was generated from the Phase 1 of the interviews (column 1 in Table 4-1). That list was refined during the second phase of the interviews, with the second column in Table 4-1 indicating those sustainability indicator categories that were modified after the interaction with producers. Some of the indicators were not clear to the participants or were not relevant as part of the discussion. Based on their feedback, the researcher reduced the indicator list to the 15 most relevant indicators. When asked whether any priority was missing, most of the producers replied that the list of indicators covered the most relevant concerns.

Many of the producers discussed how the indicators are connected and pointed out that it is challenging to separate and isolate priorities among them. That was especially the case with wildlife presence and nature proximity – usually wildlife was the perceived “Pristine Nature”, so those factors were merged into one category “Wildlife and Pristine nature”. Similarly, “Young Farmers” and “Land Inheritability” were connected in many of the producers’ minds, so these two factors were merged as “Young Farmers and Inheritability”. For most people, inheritability was related to whether young farmers would like to take over the production; young farmers staying in the area was in participants’ words connected to the amount of opportunity in the area and the profitability of the farm, which was also related to the inheritability of the farm.

Table **4-1**: Sustainability indicators included as decision variables and their measures in the decision support framework. The first column lists the 18 indicators initially selected through farmer interviews; the second column lists any changes in the indicators as a result of Phase 2 of the interviews; the third column explains the measurement approach for each of the indicators as based on farmer interview and literature; the fourth column describes the grain at which the input data were used.

Indicator identified after interviews (Phase 1)	**Indicator after interviews (Phase 2)**	**Measure**	**Spatial grain**
Independence	-same-	Ratio of profit from subsidies to the profit from competitive markets	Indicator by crop type
Equal opportunity	(excluded)		
Financial stability	-same-	Profit risks based on the variability of income due to markets, weather	Indicator by crop type
Profitability	-same-	Profitability based on yield and crop budgets	Subfield (10 m)
Yield	-same-	Annual crop yield. Calculated using Google Earth Engine imagery	Subfield (10 m)
Diversification	-same-	Number of markets based on the market assessment	Indicator by crop type
Water quality	-same-	Nitrate runoff. Based on the Sustainable Landscape Design team models	Subfield (by soil type, modeled)
Soil quality	-same-	Soil organic carbon (SOC). Based on Sustainable Landscape Design team models	Subfield (by soil type, modeled)
Nature proximity		Probability assumption based on literature by crop	Indicator by crop type
Wildlife presence	Wildlife and pristine nature		
CO_2 emissions	-same-	CO_2 equivalent emissions ($kgCO_2$-e). Emissions by crop based on the FEAT model (Camargo et al. 2013)	Indicator by crop type
Erosion potential	-same-	Erosion rate. Based on Sustainable Landscape Design team models	Subfield (by soil type, modeled)
Food production	-same-	Percent area under food production	Indicator by crop type
Rural development	-same-	Number of jobs assumption from the literature	Indicator by crop type

Positive image	-same-	Score assumption for consumer -approved practices	Indicator by crop type
Farming lifestyle	-same-	Score assumption for the ability to maintain a family operation	Indicator by crop type
Land inheritability	Inheritability and young farmers	Land value as a function of soil management and profit	Subfield (10 m)
Young farmers			

Sustainability indicators were not only connected between and among each other for many of the interview participants, but also did not need to be categorized into sustainability dimensions (e.g. environmental, economic, social) for producers to confidently assign priority. One producer categorized the indicators by what can be interpreted as the three dimensions of sustainability and then assigned weight to categories of indicators rather than individual priorities. All other participants assigned weight to stand-alone sustainability indicators, and while many discussed how the indicators can be correlated, that did not have the same importance. For example, yield and profitability are correlated, yet many producers specified that those indicators are not the same thing because of the different input costs. Because of the possible interrelation between the indicators, one has to be cautious of double-counting the factors that are closely linked. Nevertheless all factors that were relevant to the decision-makers were included in the tool to allow for cases when some stakeholders might chose assign weight "zero" to some of the indicators and others would not. As a result, the indicators that are included in the decision support are based not on the simplicity/complexity required to model them, but on the meaning they have to stakeholders.

The indicator "Equal Opportunity" was not an indicator that resonated with many interviewees. Even though it was described as, "having equal opportunity and access to markets and suppliers for smaller producers as for larger producers" and was placed on the list because of the multiple mentions by producers during Phase 1 interviews, in Phase 2 many understood it as referring to equal opportunity hiring for the people who work on their farm. Some producers also mentioned that equal opportunity in the marketplace is something they work to make happen but is not necessarily a factor they consider in their farm operations. A producer gave an example that this priority is becoming less of an issue over time. With increasing communication in the digital age and being in a network of producers in the Midwest, this participant stated that producers can now find the best access and best market deals for seeds, fertilizer and equipment through sharing with peers. Based on this stakeholder feedback and confusion about the multiple meanings associated with this term, this factor was removed from the decision support system.

Prior interviews showed that many stakeholders including agricultural producers are concerned about environmental quality, and these concerns were expressed in select sustainability indicators. Their environmental concerns can be summarized as “to prevent erosion, improve soil quality, improve and maintain water quality, provide habitat to wildlife and observe that wildlife, and reduce CO_2 emissions.” Table 4-1 summarizes the ways these environmental indicators were evaluated in this decision support model.

Social factors were one of the major concerns agricultural producers had. Many of these factors are difficult to measure, which is one reason they may have been left out from most previous agricultural sustainability studies in the literature. Nevertheless, because of the holistic definition of sustainability, sustainability assessment is often considered incomplete if social concerns are not addressed. Several social sustainability indicators are included in the current model. The social factors that were most relevant to the producers were rural business development, inheritability and opportunity for young farmers, growing healthy food, a positive image of agricultural practices, and farming lifestyle. Table 4-1 describes some ways these social factors can be measured in the utility assessment.

A farm's bottom line is what keeps the producer in business. Naturally, economic factors were important to the producers that were interviewed. The five economic priorities that were important during the interviews were: profitability, independence, production diversification, yield, and financial and market stability. Table 4-1 describes the ways these various economic sustainability indicators were estimated for this analysis.

Producers indicated that they found the interaction about their priorities engaging and found it interesting to use poker chips to place weight on priorities. Some participants suggested that such a hands-on method could be paired with an online tool that could output sample maps while still allowing the interactive work with cards and chips. Most participants said they would be ready to spend "a couple of hours" interacting with the decision-support, and offline hands-on game-like assignment of priorities with cards and poker chips allows for such flexibility because producers can assign their first weights, but then can reflect and come back to the cards and chips. Once these producer priorities and the sustainability indicators that best represent those priorities were weighted, the decision support framework could be used to calculate utility scores for the two cropping options on each part of a field.

Data processing and spatial analysis

The selected indicators and their measures are discussed in detail in Table 4-1 and 4-2. Input data included spatial indicators queried from raster or vector files, or as a constant for the entire farm when subfield data was not relevant or available. The latter included farm or county estimates of measures like the number of crop markets, species richness and CO_2 emissions. Raster files store spatial data information for every cell, which worked well for a field split into equally sized grid cells, while vector files store spatial data as shapes and lines based on underlying features like soil types. The output measures for sustainability indicators were generally spatially explicit and calculated based on spatial data inputs and the assumptions for non-subfield level indicators, and were converted into utility values using spatial data processing.

Table **4-2**: Spatial analysis inputs for the example cases run with the model, including the indicator measure units, upper and lower bounds of the indicator values and equations to calculate the utility of those indicators.

Indicator identified after interviews (Phase 1 and 2)	**Input details**	**Measure unit before utility calculation**	**Indicator value range in the example field**		**Utility calculation**
			Lower bound	**Upper bound**	
Independence	Assumption calculation based on subsidy calculations as in Chapter 3.	Unitless	\$100/ha subsidy to \$800/ha = 0.125	\$100/ha subsidy to \$400/ha = 0.25	$u_{ind} = 1 - Ratio\ of\ profit\ from\ subsidies$
Financial stability	Assumption calculation based on the profitability calculations.	\$/ha	\$1100/ha to \$2755/ha = 825\$/ha	\$800/ha to -\$400/ha = 1200\$/ha	$u_{fin} = 1 - \frac{Profit\ range}{Max\ Profit\ range}$
Profitability	Modeled results based on crop budget assumptions as in Chapter 3.	\$/ha	275	1100	$u_{prof} = \begin{cases} \frac{Cell\ Prof.}{Max\ Prof.}, & Prof > 0 \\ 0, & Prof < 0 \end{cases}$
Yield	Modeled results based on Google Earth Engine remote sensing data.	Mg/ha	0	14.7	$u_{yield} = \frac{Cell\ Yield}{Max\ Yield}$
Diversification	Assumption calculation based on the market assessment as in Chapter 3.	# (Unitless)	2	4	$u_{div} = \frac{Crop\ Markets}{Max\ Markets}$

Table **4-2 (continued)**: Spatial analysis inputs for the example cases run with the model, including the indicator measure units, upper and lower bounds of the indicator values and equations to calculate the utility of those indicators.

Indicator identified after interviews (Phase 1 and 2)	Input details	Measure unit before utility calculation	Indicator value range in the example field		Utility calculation
			Lower bound	Upper bound	
Water quality	Modeled results based on Sustainable Landscape Design team models (McNunn, 2018)	lbN/ac/yr	0	144.88	$u_{wat} = 1 - \frac{Runoff}{Max\ Runoff}$
Soil quality	Modeled results based on Sustainable Landscape Design team models (McNunn, 2018)	lbC/ac/yr	-1518	365.5	$u_{soil} = \frac{Cell\ SOC}{Max\ SOC}$
Wildlife and pristine nature	Assumption calculation based on Schulte et al. (2017) species diversity estimates	Unitless	0.33	1	$u_{wil} = Probability\ assumption$
CO_2 emissions	Modeled results based on the FEAT model (Camargo et al. 2003)	kgCO2-e/ha/yr	2293	2612	$u_{CO2} = 1 - \frac{Emissions}{Max\ Emissions}$
Erosion potential	Modeled results based on Sustainable Landscape Design team models (McNunn, 2018)	tn/ac/yr	0	50	$u_{CO2} = 1 - \frac{Erosion\ Rate}{Max\ Erosion}$
Food production	Assumption calculation based on the markets supplying the product	Unitless	0	0.5	$u_{food} = Percent\ assumption$
Rural development	Assumption calculation based on the possible number of rural jobs	# (Unitless)	4	6	$u_{rur} = \frac{Jobs}{Max\ Jobs}$
Positive image	Assumption	Unitless	0.4	0.8	$u_{img} = Score\ assumption$
Farming lifestyle	Assumption	Unitless	0.3	0.5	$u_{img} = Score\ assumption$
Inheritability and young farmers	Assumption calculation based on profit ($/ha) and soil quality modeling (lbC/ac/yr * 0.01)	Unitless	-11	13	$u_{inh} = \begin{cases} \frac{Cell\ Value}{Max\ Value}, & Prof > 0 \\ 0, & Prof < 0 \end{cases}$

Spatial data were processed using Python 3.6.9 language in Jupyter Notebook (https://jupyter.org/) with Geographic Information Systems (GIS) processing packages for spatial data processing: rasterio 1.0.21, pandas 0.25.3, geopandas 0.4.1, matplotlib 3.1.1., georasters 0.5.15 and numpy 1.17.4. To view the code used in the analysis, please see Appendix C. Most layers that were used in this project are raster layers, which means the layer is split in many rectangular cells of equal size, and each spatially referenced cell gets a value of the relevant data. Raster data are particularly useful for subfield land use decision-making because grid cells can be visualized and considered individually in decision-making about landscape designs. For that reason, vector input datasets were converted into raster datasets, which allowed for bit-wise calculation of utility and comparisons between alternative cropping system scenarios for each cell.

The subfield crop utility calculation was based on the weighted sum of each of the sustainability indicators as calculated using equation (1). The utility calculation for each sustainability indicator is listed in Table 4-2.

$$u_{sij} = \sum_{i=1}^{15} w_i \times Sustainability\ Indicator_i \tag{1}$$

Where w_m is the weight assigned to each sustainability indicator based on the user preferences. Sustainability objectives were subject to several constraints as listed in equations (2) and (3).

$$0 \leq w_m \leq 1 \tag{2}$$

$$\sum_{m=1}^{15} w_m = 1 \tag{3}$$

Two crop suitability maps were generated based on the utility calculations – one, based on a deterministic approach using bit-wise comparisons between the utility values of each raster cell, and the other, using a "smoothing" algorithm based on the bit-wise comparison to improve the operability of the field. Furthermore, small raster cell groupings were removed using a "sieving" procedure to resemble spatial feasibility constraints. Sieving conditions are listed in equations (4) and (5), such that if the grouping of the raster cells was smaller than 20 pixels for switchgrass plots or 150 pixels for annual crops, those small subfield areas were converted to the type of crop of the surrounding cells. Such sizes can be modified to fit the size of the field analyzed and the preference of the user. This spatial constraint was set to recognize and avoid excessively fractured landscapes. If a subfield under a crop type is very small, agricultural machinery will not be able to operate efficiently and production budget estimates used in the analysis would be incorrect.

$$A_{switchgrass} \geq 20\ pixels \tag{4}$$

$$A_{annual\ crops} \geq 150\ pixels \tag{5}$$

Where $A_{\text{switchgrass}}$ representing the area of each switchgrass subfield; $A_{\text{annual crops}}$ representing the area of each annual crop subfield.

To ensure that the resulting field layouts are operable, "smoothing" algorithms were applied to the field layouts. Several smoothing approaches were tested. These strategies are illustrated in Figure 4-3. One-pixel smoothing means that if two pixels that are one pixel apart and are of the same crop type, then the pixel between them is converted to the same crop type. Following the same logic, in the 2-pixel smoothing, if two pixels that are two pixels apart are of the same crop type, then the two pixels between them are converted to the same crop type. A similar pattern holds for 3-pixel and 4-pixel smoothing. Such approach connected the fragmented subfield sections.

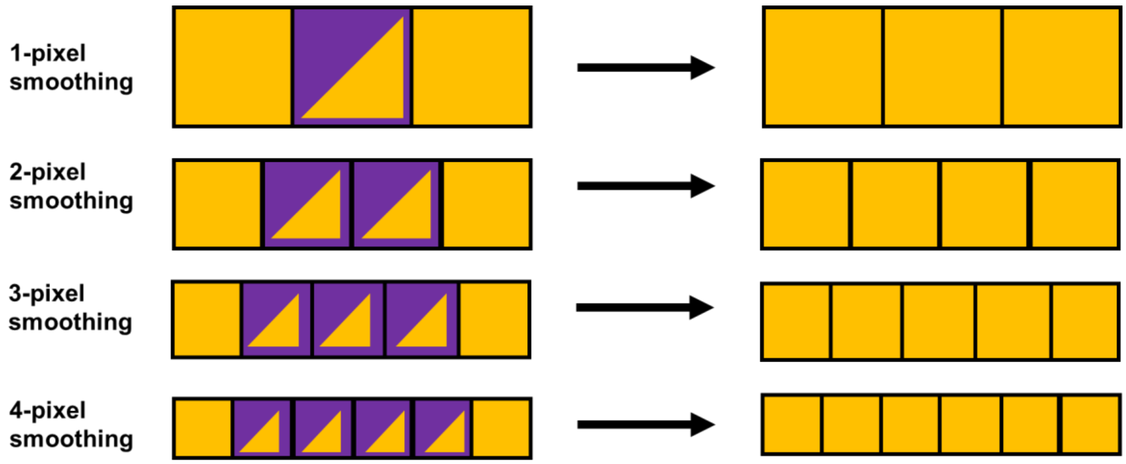
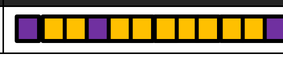


Figure **4-3**: Field smoothing approaches. Each raster file was smoothed using all four patterns both horizontally and vertically. 1-pixel smoothing means that if one pixel is found between pixels of the same crop type, it is automatically converted to the same crop types as the other two pixels. If the first and the last pixels are of different crop types, no change is applied. Similar approach is applied for 2, 3, and 4-pixel smoothing, but a larger number of pixels is automatically converted if they are between the same crop type.

The smoothing algorithm functions like moving window method (Hager-Zanker 2016), where instead of evaluating the entire area in the raster file, only a part is assessed for the given criteria. This approach drastically reduces computational processing time. In this study, the smoothing algorithm is applied first horizontally from left to right, and then vertically from top to bottom. Changing the order or direction in which pixels are considered can slightly impact the final layout. Table 4-3 lists the steps how the field layout is changed with each algorithm iteration for three smoothing approaches. The pattern in which crop types are initially arranged and the selected smoothing algorithm will impact the final layout of the row or the column in a cropland map.

Table **4-3**: Field layout change after applying the smoothing algorithm with each algorithm iteration for three smoothing approaches. Each step moves the area under algorithm consideration by one pixel from left to right.

Step	**1-pixel smoothing**	**2-pixel smoothing**	**3-pixel smoothing**
Initial layout			
Step 1			
Step 2			
Step 3			
Step 4			
Step 5			
Step 6			
Step 7			
Step 8			
Step 9			
Step 10			
Final layout			

The goal of the smoothing functions is to make the field more operable for agricultural machinery. To check this, the field designs were evaluated for how machinery operation efficiency would increase given the possible decrease in utility after smoothing. Field efficiency was calculated based on the equation found in Griffel et al. (2020) and is based on the perimeter-to-area ratio of the subfield with a given crop type as indicated in equation (6).

$$Field\ Efficiency = 0.179 - 0.145 \ln\left(\frac{Perimeter}{Area}\right) \tag{6}$$

To evaluate the loss of utility with the increase of efficiency, this study evaluates the efficiency elasticity – the percent change in efficiency given the percent change in utility.

Assessment case

The bit-wise spatial suitability assessment and the genetic algorithm crop suitability assessment were run on ten cases with stakeholder-informed weights to calculate pixel-by-pixel utility values for both switchgrass and the annual crop. Results from all ten cases are presented in an analysis of the smoothing algorithm for its impact on field efficiency and the elasticity of field efficiency with the calculated utility values. For five of those cases the weights used for each of the indicators are listed in Table 4-5 in the results section and presented in additional detail. These five cases were selected from producer interviews and based on how distinct the resulting landscape designs were as suggested by the decision support tool. Tables 4-1 and 4-2 describe the model inputs that were used to run the spatial analysis, including indicator measures, range of values for those measures, and equations for calculating the utility for each of the sustainability indicators. The case study where those measures were applied for spatial analysis was a field with 100 rows and 100 columns, each pixel's size being 10x10m. Thus, the size of the plot used in the spatial analysis is 100 ha.

The example field was an actual site located in Greene County, Iowa with the dominant soils of Nicollet loam, Webster clay loam, Clarion loam and Canisteo clay loam soil types (Soil Survey Staff 2020). The boundaries of this field were adjusted to focus the analysis on a square area of 100 ha. Profitability, calculated as the total income minus the crop expenses, was based on the remote sensing data from year 2018 used to estimate the subfield yield, maize price of $130/Mg (USDA 2019) and production cost of $1192/ha (ISU 2018). For that year, the sample field had an average maize yield of 12.6 Mg/ha (USDA 2019) and resulting average maize profit of $800/ha. Such values can be modified to fit the user's interest and specific location of that user's plot. Switchgrass yield was varied with an average of 10 Mg/ha (Wang et al. 2010) and profit was calculated based on $100/Mg biomass price. Both corn and switchgrass yields were allowed to vary from these averages using observed variations in corn yield from satellite data for this field, and then applying one third the observed subfield corn yield variation as a proxy for the switchgrass yield variation as described in Chapter 3. This spatial analysis example was for demonstration purposes only and was not used to advise a producer on crop allocation or landscape design for the specific example field that is visualized. For actual decision support, stakeholders would need to input their preferred weights and data for their actual farm field(s).

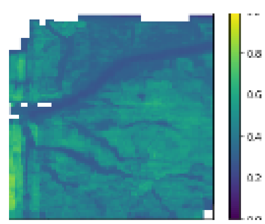
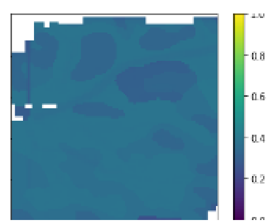
Results

Model inputs and literature-based assumptions were used as the basis for the spatial data processing. Table 4-1 lists how those data were spatially represented in the decision tool. Some of the factors, like profitability, erosion potential, or water quality, had subfield-specific inputs. Some other factors, like positive image, independence or wildlife and pristine nature had crop-specific assumptions or observations from prior literature as the inputs to the model. These spatial inputs were the foundation for both the crop suitability analysis and decision support for landscape layouts.

Ten example scenarios were run on the example field. The scenarios were defined by the sustainability indicator priorities, which were based on the priorities' weights from agricultural producer interviews. Even though the farm input files were the same for each scenario applied to this 100-ha field, the crop layouts were drastically different based on the farmer priorities.

The model results were highly dependent on the model inputs. Spatial inputs for the processing were two raster files – one with sustainability scores for annual crop rotation, and another – with similar scores for perennial grasses (Table 4-4). These simulations were based on 2018 corn profitability data, $100/Mg assumption for biomass price and environmental simulation data; and those specific inputs influenced the model outputs. In this example, the $100/Mg biomass price coupled with the cost of switchgrass production and harvest meant that switchgrass was an unprofitable crop and received zero utility. Similarly, at this biomass price no stover was profitable to harvest.

Table **4-4**: Example input fields for the annual corn and perennial switchgrass crops with the corresponding sustainability indicator values. Utility scores are the sum of individual scores for all 10,000 cells in this 100 x 100 pixel simulated 100 ha field. Each indicator can thus have a maximum score of 10,000.

	Corn annual crop utility layer	Switchgrass utility layer
Example spatial input for the crop type layer		
Utility scores:		
Soil quality	3305	7417
Profitability	2015	0
Independence	8806	7613
Financial stability	6785	5324
Yield	8122	6113
Diversification	3818	7637
Wildlife and pristine nature	3150	9546
CO_2	454	1620
Water quality	2174	4797
Erosion potential	7856	7692
Food production	4773	0
Rural development	6364	9546
Positive Image	3818	7637
Farming lifestyle	2864	4773
Inheritability and young farmers	2041	0

A simple pixel-by-pixel comparison between the two input files could generate a non-operable field layout even though the utility for each raster cell would be maximized. Note that the total utility of the spatial layout was defined as the sum of the utilities of each raster cell. That means the placement of each cell relative to each other did not affect the utility calculation even though crop arrangement changes the efficiency of the harvest and thus affects the cost of production and the final profit. As a way to represent such tradeoff in spatial decision-making, an optimization algorithm can be developed that calculates the total utility of the farm with farm-level indicators like field efficiency. As an alternative to such formal optimization, this study calculated the average field efficiency given the field layout and utilizes smoothing and sieving algorithms to produce a crop layout that is operable and has fewer subfields.

When selecting the smoothing method, all four smoothing algorithms were run for each of ten cases. The improvement in efficiency with each of the method was plotted in the Figures 4-4 and 4-5 below. For most of the examples, the improvement in field efficiency became marginal beyond 2-pixel smoothing. In the Figure 4-5 below, the efficiency elasticity is ratio between the percent change in field efficiency from no-smoothing to that smoothing scenario divided by the percent change in utility from no-smoothing to that smoothing scenario.

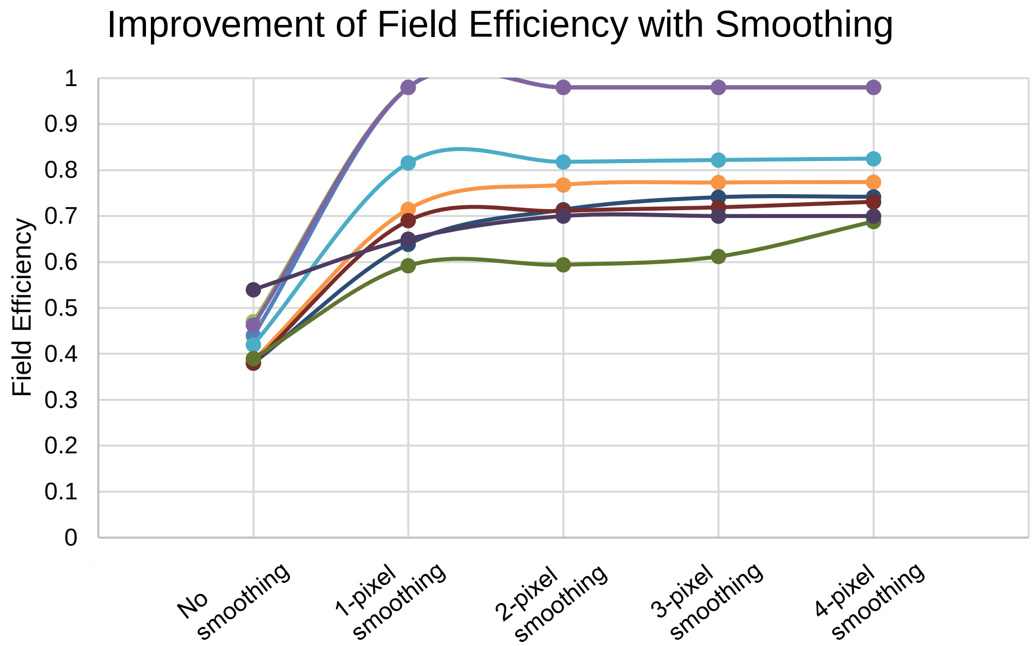


Figure **4-4**: Improvement in field efficiency for ten tested cases with four different strategies for field smoothing.

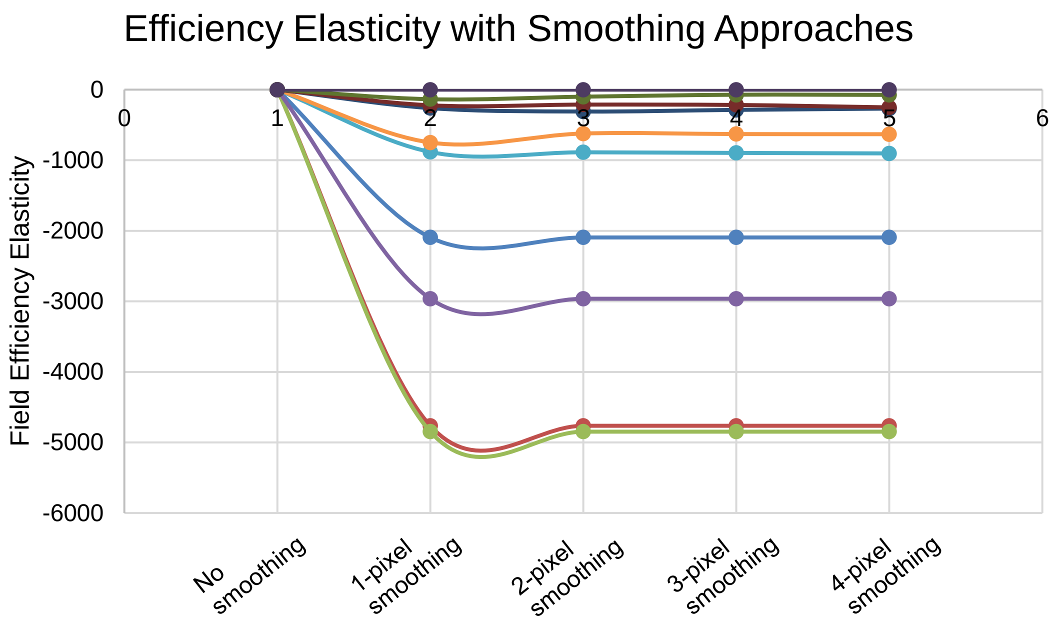
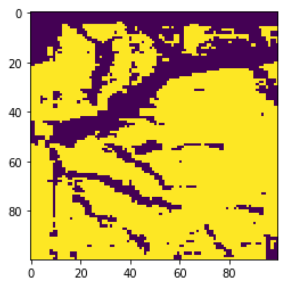
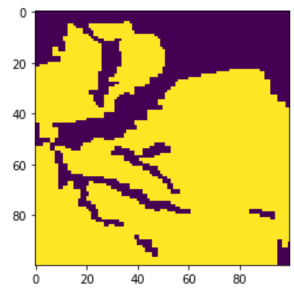
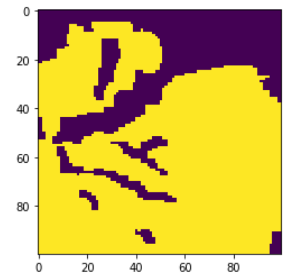
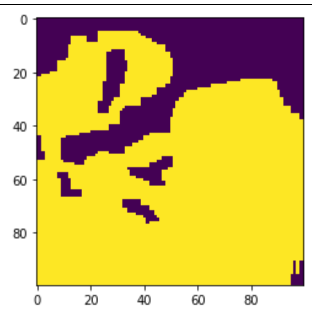
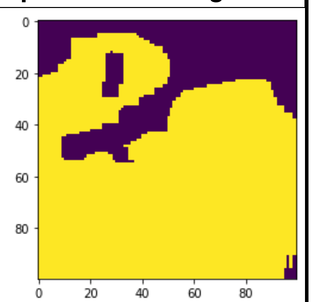


Figure **4-5**: Efficiency elasticity, or percent change in efficiency compared to the percent change in utility, with each of the smoothing approaches applied to field generated by ten utility function cases.

One case still saw an improvement between 3-pixel and 4-pixel smoothing. Table 4-5 illustrates the crop layouts and the corresponding field efficiency and utility for that case. The change between 3-pixel and 4-pixel efficiency can be explained by a high degree of complexity of the field. The improvement in efficiency in this example supports the necessity of using decision support and smoothing functions to ensure that while meeting producer needs, the generated field layouts have the most efficient arrangement even when they have complex subfield shapes.

Table **4-5**: Improvement of field efficiency in a complex field layout design with different smoothing operations.

	Pixel-by-pixel comparison	**1-pixel smoothing**	**2-pixel smoothing**
Layout			
Utility	4185	4169 (-0.38%)	4163 (-0.52%)
Number of subfields	90	9 (10 times)	9 (10 times)
Field Efficiency	39%	59.2% (+51.8%)	59.4% (+52.3%)

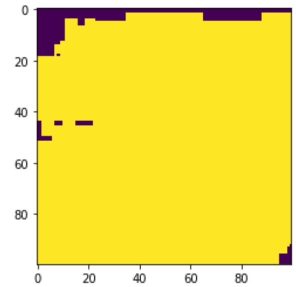
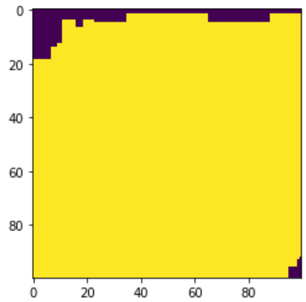
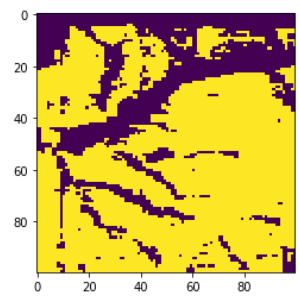
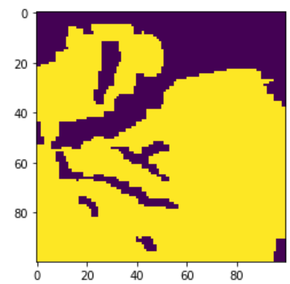
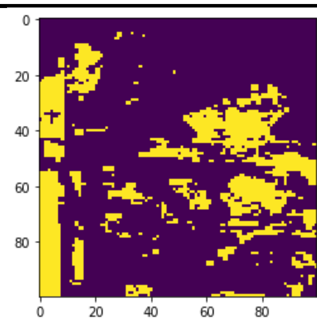
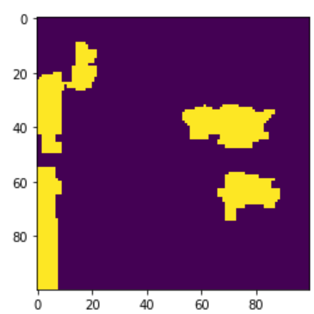
	3-pixel smoothing	**4-pixel smoothing**
Layout		
Utility	4152 (-0.79%)	4142 (-1.03%)
Number of subfields	8 (11.25 times)	4 (22.5 times)
Field Efficiency	61.2% (56.9%)	68.8% (76.4%)

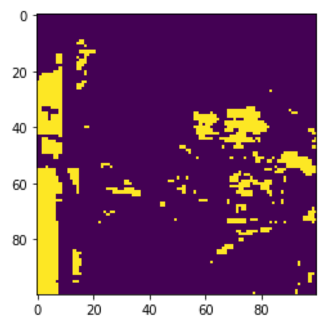
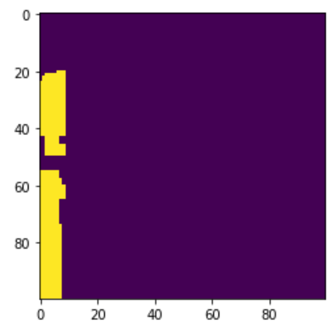
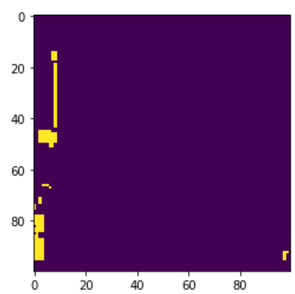
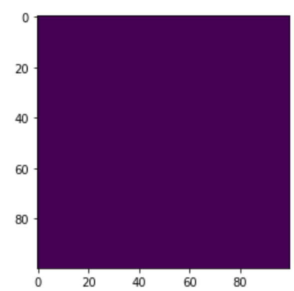
The sustainability assessment and crop layout decision support system were run for ten different cases. Each case represents an agricultural producer with their own set of priorities and weights for the sustainability indicators. Tables 4-6 and 4-7 below list the weights and the resulting field layouts of five most distinct scenarios that were run. Two maps are given in the results – one layout which is a result of a simple pixel-by-pixel comparison, and the second one after a smoothing algorithm (2-pixel), as the improvement of field efficiency leveled beyond the 2-pixel approach. Smoothing improved field efficiency by over 30% to 100% depending on the initial layout, with only a >1% reduction in the total utility.

Table **4-6**: Weights that were assigned to sustainability indicators for each of the decision cases based on agricultural producer interviews.

Agricultural producer	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Brief Description	Stover-harvesting farmer (economic factors-focused)	Bioenergy farmer – economic and yield-dominated	Stover-harvesting farmer with equal priority for profit and soil quality	Conservation farmer with diversified priorities	Bioenergy crop farmer (all factors are weighted equally)
Profitability	0.25	0.421	0.154	0.196	0.067
Independence			0.077		0.067
Financial stability	0.50		0.077	0.118	0.067
Yield	0.25	0.211	0.062	0.108	0.067
Diversification			0.108		0.067
Soil quality		0.105	0.154	0.118	0.067
Wildlife and pristine nature			0.046		0.067
CO_2				0.078	0.067
Water quality		0.053	0.077	0.137	0.067
Erosion potential		0.105	0.077	0.118	0.067
Food production			0.077		0.067
Rural development					0.067
Positive Image		0.053		0.049	0.067
Farming lifestyle				0.078	0.067
Inheritability and young farmers		0.053	0.092		0.067

Table **4-7**: Crop layouts as generated based on producer priorities with and without applying the smoothing algorithm. Yellow represents annual crop rotation and purple represents perennial grasses.

Agricultural producer	**Pixel-by-pixel comparison (no smoothing)**	**Smoothing and sieving of small subfields (2-pixel method)**
Case 1		
Utility	5676	5676 (0% change)
Number of subfields	7	3 (2.33 times)
Field Efficiency	0.54	0.70 (+29.6%)
Case 2		
Utility	4185	4163 (-0.52%)
Number of subfields	90	9 (10 times)
Field Efficiency	39%	59.4% (+52.3%)
Case 3		
Utility	4624	4605 (-0.41%)

Number of subfields	125	5 (25 times)
Field Efficiency	38%	71.1% (+87.1%)
Case 4		
Utility	4396	4389 (-0.16%)
Number of subfields	82	3 (27.3 times)
Field Efficiency	38.6%	76.8% (+99.0%)
Case 5		
Utility	5120	5117 (-0.06%)
Number of subfields	12	1 (12 times)
Field Efficiency	0.44	0.98 (+108.5%)

Discussion

Stakeholder engagement helped define the decision variables that were included in the spatial decision support. Similar to Kodikara et al. (2010), this study approached the participants asking to weight the decision priorities. Two important differences were that in the present study the list of priorities was generated by the producers themselves, and the weights were set using a visual pile of poker chips rather than a software interface. Furthermore, even though stakeholder-selected utility functions would have been useful for further modeling, not all producers agreed on the same measure for an indicator, and this would not allow for a consistent comparison of the utility function during the test and demonstration reported here. Some of these variables, like profitability, soil quality and water quality are frequently modeled in agricultural systems and were spatially explicit. Several of the other factors, like rural development, independence, and food production among others, are hardly ever included in farm-level decision modeling and were included in this model as decision variables set to a constant value for each cropping system. By recognizing the priorities of the stakeholder, the model moved beyond the typical factors that are currently commonly modeled in agriculture, into introducing the “nontangible” factors for landscape decision-making. Accounting for such factors is a challenge because they are not easily measured at the field, farm, or even community levels, even though they impact and inform field decisions according to producer participants.

Including the real preferences and measures to which stakeholders can relate comes with a tradeoff. While stakeholder engagement increases the relevance of the decision framework and provides a transparent set of indicators for modeling, some of the factors are challenging to represent quantitatively or consistently. This challenge was particularly problematic for factors like food production, rural development, or independence. While they need to be included as they are relevant to the decision-maker, these indicators have multiple meanings to different producers and are close to impossible to measure at a subfield level, so have to be represented by proxy. Further research into the spatial relationship between such social factors and the subfield-level decisions can help refine the decision support tool and provide a more robust output.

Spatial analysis using stakeholder-informed priorities helped identify possible crop arrangements that maximize landscape utility for the agricultural producer. Case 1 generated a suggested crop layout largely driven by a producer's economic priorities, as detailed by the priority weighting in Table 4-7. That set of weights generated a layout that is very similar to the fields that are currently found in the U.S. Midwest: dominated by an annual crop rotation, with only small portions of the land devoted to perennial grasses. As the priorities and the corresponding weight became more diversified in cases 2 through 5, increasing the amounts of perennial grasses are introduced into the landscape. Since in all the cases the weights reflected the actual priorities of agricultural producers that were previously interviewed, this study illustrates that accounting for longer-term and more diverse producer priorities could lead to a landscape transformation with more perennial grasses and biomass production plots.

Beyond sustainability indicator priorities, stakeholders conceptualized their impact differently in space and time. As has been discussed in the previous chapters, producer's spatial conceptualization of their priorities spanned from local and specific to their fields or farm to more global concerns about the entire planet. As with these spatial considerations, temporal considerations varied by person, and a meaningful and relevant decision support framework should accommodate a range of different time horizons for planning. Time considerations varied from relatively short terms of 6 month or one year, up to 50+ years and three generations. Future research could further develop the tool demonstrated in this chapter, illustrate the decision impact beyond a static spatial and temporal boundary, and allow stakeholders to select different boundaries for the indicators to reflect their interests and concerns. Such modeling could also incorporate uncertainty around the decisions, moving the spatial decision-making approach from being a function of deterministic utility calculations to more realistic stochastic results. Weather and market variables are particularly relevant in this regard.

Conclusion

Including stakeholders in the discussion in the early phases of model development can help inform the researcher and result in a more relevant and meaningful decision support model. In addition to providing input and feedback on possible outcomes of the developed decision support tool, producers suggested including sustainability indicators that were seldom used in agricultural and environmental decision-making, like positive image, independence, or inheritability of land. Inclusion of such factors can help reframe what are typically technocratic approaches to agricultural landscape designs and farming system objectives. Based on these stakeholder-derived priorities, this study developed and demonstrated a framework to assist in producer decision-making, starting from an early stakeholder interaction stage, through to data processing and layout design. The developed tool used spatial processing and smoothing algorithms to suggest a crop allocation layout that is operable with agricultural machinery. Using cases of real agricultural producer priorities, this study illustrated that landscape layouts would differ if stakeholder-specific priorities are included in the decision-making. Furthermore, the study illustrates that the more diversified priorities are, the more transformation was seen in the landscape towards perennial grasses compared to the status-quo of annual crop rotations. This study applied spatial decision analysis techniques to a new application – bioenergy agriculture planning, offering a new direction for feedstock supply and stakeholder engagement research. The framework can be extended beyond agricultural sustainability assessment through scenarios to agricultural sustainability planning, and can even be expanded beyond agricultural uses to other spatial stakeholder decision analysis problems.

Chapter 5

Conclusions and future work

Contributions and key findings

This dissertation describes a decision support framework that was developed to support agricultural producer decisions for designing farm landscapes. The decision framework suggests ways to reallocate land at the subfield level for either annual crops (maize or soybeans) or perennial crops (switchgrass) based on producers' priority indicators of economic, environmental and social sustainability. The framework was developed in partnership with agricultural producers who 1) identified key sustainability indicators towards which the landscape can be optimized, 2) verified whether the modeled indicators and their measures match the producer values and 3) weighted those indicators so that the model could produce a single crop layout based on producer priorities. Using this approach, stakeholder opinions were integrated in the framework from the onset through development and demonstration of this decision support tool. A combination of spatial environmental data, production economics and other factors are used to compute the subfield sustainability utility for different crops and suggest possible field crop arrangements that maximize those utility estimates. To support the decision support tool, several complementary studies were carried out and discussed in the individual dissertation chapters.

Chapter 2 describes two rounds of interview interactions with agricultural producers in Iowa. The goal of the initial interviews was to identify the key priorities of the stakeholders so that those priorities could later be used as sustainability indicators for decision-making. The second round of interviews were used to identify the spatial and temporal boundaries of indicators and weight those that mattered most to the producers. This study found that the three groups of potential bioenergy feedstock producers – agricultural producers who established perennial grasses for conservation, for biomass harvest, or who harvested corn stover for bioenergy – have a wide range of sustainability priorities. Such priorities include factors that are frequently modeled for decision-making, like profitability, financial stability and soil quality, but additional priorities that are less commonly found in agricultural sustainability modeling and assessment, such as independence, positive image and land inheritability. Furthermore, the study established that the diverse interview participants considered a wide range of space and time boundaries and that these boundary perspectives were largely unrelated to which of the three groups we classified them in, highlighting the complexity of producers' priorities and decision-making.

One of the top priorities of the stakeholders was farm profitability. In recognition of this priority, Chapter 3 investigated whether and where switchgrass might be economically competitive with the most prevalent annual crop in Iowa – maize. The study examined two example watersheds in high-yielding Hardin and Buena Vista counties in Iowa, both located near cellulosic bioenergy facilities, and found that for a range of possible biomass market prices of $50 to $150/Mg switchgrass can be more profitable on 10% to over 80% of the cropland when compared with maize even with stover harvest. These results are based on subfield maize yields estimated from remote sensing data as well as literature-based correlations for stover and switchgrass yield and crop production costs. The model indicated that maize profitability in recent years ranged from a loss of $400/ha to a profit of $1500/ha. This chapter's findings confirm the results from previous studies that switchgrass could be more profitable on parts of the land compared to maize. However, unlike the previous studies that relied on yield model predictions based on coarsely-grained maps of soil type, weather and other input variables, the fine-scale remote sensing data used in this study was at 30 x 30 meters or better, and the yield observations were from each year in a six year period.

Economic profitability was then integrated with 14 other indicators to develop a decision support framework for landscape crop allocation. As discussed in Chapter 4, the framework was tested using a spatial suitability assessment tool. The developed tool used spatial data processing to generate a crop layout based on sustainability utility values, and a smoothing algorithm to increase operability of the field layout. The framework successfully generated a field layout that maximized utility of the field, and the smoothing algorithm improved the operability as measured using field efficiency. Using the inputs from Chapter 2 of agricultural producer priorities, the developed framework illustrated that producers with different priorities would generate different crop layouts for the same field if they specify the sustainability indicator weights that reflect their values and are most relevant to them. The results show that the more diversified the producer priorities, the more the field landscape would be transformed into a mixture of perennial and annual crops to maximize that more diverse utility function. Overall, this dissertation demonstrated a decision support framework that can connect agricultural producer priorities to sustainability assessment, then uses such criteria to generate a possible farm field layout that integrates perennial grasses into a field with annual crops and maximizes the producer-defined sustainability of the field.

Recommendations for future research

The research for each of the chapters identified knowledge gaps that can be addressed in future research. The recommendations for future research related to each of the dissertation chapters are summarized below.

An understanding of the priorities of absentee landowners and of more conventional farmers can help design decision support tools that could meet the needs of a more diverse range agricultural producers. This study intentionally engaged producers that are innovative – those that have adopted new agricultural practices like planting perennial grasses for conservation or biomass production purposes, or harvested corn stover. The priorities of these innovative farmers could be different from producers who have not tried new agricultural practices. With over 50% of cropland in most agricultural regions rented by farm operators from absentee landowners, the values and motivations of absentee landowners have significant relevance as well.

A study on the priorities of absentee farmers or more conventional farmers could be paired with inquiring about the "connection" that the producers have to the land. Some of the interviewees hypothesized that other producers who do not have a strong connection to land might not have as high priority for soil, water quality, wildlife presence and other environmental factors. Being an absentee farmer could lessen the connection to land, and thus impact that group's priorities.

A longitudinal study on agricultural producer priorities and spatio-temporal boundaries of concern can shed the light on how these priorities change over time. This study highlighted the current priorities, but they do change over time as was mentioned by producers themselves. A long-term study on priorities could help prepare for the changes in the decision-making in agricultural fields as a function of experience, age, changing markets and a changing climate. Since perennial crops are costly to establish but have a production life of over 10 years, it is important to understand that such decisions are long-term, and also that the decision-maker might change their mind during the establishment and growth timeframe.

The economic assessment of the switchgrass opportunity in this study did not account for the risks related to the possible markets, weather and other impacts, yet resilience to such risks is considered a hallmark feature of switchgrass. While that resilience was to some extent accounted for by reducing the yield variability of switchgrass to one third the observed yield variability of corn, further quantifying such findings could help producers make more informed decisions about crop allocation.

The study findings suggest that a wide range of priorities and spatio-temporal boundaries matter to bioenergy decision-making. Further development is needed to develop decision support tools that work across scales and that can translate the implications of decisions across those scales. Because the stakeholders considered multiple spatial and temporal boundaries in defining their measures and priorities, the tools developed need to be flexible enough to address this variety. It will also be important to explore how a combination of models could avoid the complexity and computational intensity of multi-scalar decision modelling.

Using optimization methods could also include field efficiency in the profitability calculation, and thus create a feedback loop between the shape of the field and the final utility. Further development of optimization tools (heuristic and exact) can help find a solution that can be truly optimal as compared to the design that results from smoothing and reduces the total utility. An exact optimization technique could help find the global optimum of the landscape decision by considering every arrangement of the landscape plots, yet such technique would not be as computationally efficient as a heuristic method because of the large size of the problem. Possible techniques for addressing the optimization problem include applying graph theory to speed up the exact optimization processing of otherwise excessively large optimization problem.

Finally, it must be recognized that landscape decisions with perennial grasses require long-term planning and a long-term commitment to markets which are only beginning to emerge. This lack of experience with emerging biomass markets also implies that there is uncertainty around the implications of such decisions. Future work could incorporate risk and uncertainty of the possible impacts of converting subfields to switchgrass or annual crops. By transforming the decision from deterministic to stochastic, users would obtain more realistic information about the potential utility of their final landscape layout. Such detail could incorporate current risks and also project future risks due to climate change, which will likely increase the likelihood of flooding or droughts in the US Midwest. These impacts of climate change, which are happening now and will accelerate in coming decades, will also affect field profitability, and many of the other underlying economic, environmental and social sustainability assumptions necessary for a robust landscape design decision.

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Chapter 1

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Chapter 2

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Appendix A

Supplementary Data for Chapter 2

Researcher characteristics and possible bias

A researcher's conscious or unconscious bias can reduce the validity of the collected data. Eliminating personal input completely is impossible, which is why Noble and Smith (2015) suggest acknowledging and reflecting on personal biases in data collection and analysis. James & Vinnicombe (2002) suggest acknowledging the "person in the researcher", which has been done using the reflexivity approach, especially in feminist research (Pini 2004). To acknowledge the possible bias in analyzing the data, this section provides a brief overview of some of the researcher's possible biases.

The interviewer's biases are categorized in three ways: research background, personal background, and style of interaction. The researcher (Vazhnik) has been trained as an environmental scientist, with additional background in operations research and agricultural engineering. Furthermore, the researcher is part of a project that studies bioenergy and perennial grasses as alternatives to annual crops, because of the potential benefits to the environment and alternative profit for the growers. The researcher used the interviews to explore producer priorities in part to inform the decision support system that the project is developing. This particular research background could have encouraged producers to discuss their environmental or perennial grass-approving priorities compared to what could have been a conversation with a researcher from a different background. Coming from the standpoint of using sustainability indicators and sustainability pillars to understand producer priorities could also have affected how the interviews were coded.

Second, the researcher's personal background could have affected not just the topics that were brought up during the discussions but also the style in which producers interacted with the researcher. The interviewer is an environmentalist and could have provided approving non-verbal clues to interviewees when discussing water quality, soil quality and biodiversity priorities. The researcher comes from a city which could have strengthened the perception of being an outsider (but also recognizing that many of the interviewed producers assumed and addressed her as if she grew up on a farm). Most of the producers she interacted with were men, while the researcher was a young woman, which could have affected the language that the producers used in their interactions with her and what topics they chose to bring up.

Third, the style of interaction could have influenced the responses that the researcher received. Much of the information that was collected was intended to inform decision support models, which require quantifiable inputs. Yet, because the researcher interacted with the same group of producers both times and had developed relationships with them, she did not push for a hard answer when the producers seemed reluctant to reply or did not have a reply that easily came to mind. For example, when asking how the producers would measure whether their farm has improved in the future, and what time-frame they would be most concerned about when tracking progress, some of the participants did not have an answer or said that they don't know what that measure would be. In such a case, the researcher prioritized having a flowing conversation that was interesting to the producers and not pressuring them for an answer. However, moving on to the next question without further interrogation meant that not every datapoint was collected for every participant.

1. Phase 1 Producer Interaction Questions

The interviewer stated the following purpose of the interviews:

The purpose of this study is to understand the priorities that you have in designing their operations, and what space and time boundaries inform your opinion. You will hear questions about your priorities and concerns in agriculture and will be asked to answer them in detail. The interview will take approximately an hour. Confidentiality of your answers will be maintained and personal identifiable information will be removed from the data.

The interviewer later asked the participants the following questions:

- What issues in agriculture are currently most concerning to you?
- What are the major ways that agricultural systems affect you?
- What do you value in farming and agriculture? How would you measure that value?
- What or who have been the main sources of information influencing your views on agriculture?
- If you were to imagine a geographic map, where on the map do you think you influence people, nature, and agricultural systems by your farming operations? How would you describe that area?
- Looking at a similar map, where do you think that agricultural systems, people, and nature affect your farming operations?
- Thinking about time, what is the timespan in which your agricultural operations influence people, nature, and agricultural systems? How would you describe the time and duration of the effect?

- Reversely, what is the timespan that people, nature, and agricultural systems influence your agricultural operations? How would you describe the time and duration of the effect?
- Who do you think should be involved in improving agricultural practices?
- Who should be involved in promoting and enhancing potential positive impacts of agricultural management practices that do not harm water, soil and air quality?
- What is the (up to three) decision you would make to improve the current situation for agriculture?
- What would you measure or monitor to evaluate the improvements that resulted from your actions?
- How long would you monitor these changes? Where would you do the monitoring in space, and why?
- Would the indicators that you measure change the way you manage your farm?
- What [which indicators] would influence your decision around planning and managing your farm? (If you use conservation practices, what motivates you to do so?)
- In your view, can conservation crops/practices become a way of protecting farm income? If yes, how?
- Would you like to add any comments?

2. Phase 2 Producer Interaction Questions

The interviewer provided the following context:

The goal of this interview is to understand how you assign priorities when planning the landscape. In the previous interviews, I asked you about your concerns in agriculture, what motivates you to farm and put specific crops on the ground, but also how you understand sustainability. I took your input and among all the priorities you listed, I selected 18 core ones that can help inform the decision on the field. I have named them indicators of sustainability – how the farm can keep operating into the future. You can see these indicators in front of you. To make sure that the tool we are developing addresses your needs and interests, we will discuss these indicators.

The participants were presented with the cards that listed the different priorities, and also the cards with time and space boundaries. They were then asked the following questions:

(Table below was visible to the interviewer, but the participants could instead see cards with indicator names and poker chips to assign priorities.)

Table **A-1**: Table used by the interviewer to record producer sustainability indicator priorities.

Independence				Cat.	Water quality				Cat.	Food production				Cat.
time	space	min	max	weight	time	space	min	max	weight	time	space	min	max	weight
Equal opportunity				Cat.	Soil quality				Cat.	Rural development				Cat.
time	space	min	max	weight	time	space	min	max	weight	time	space	min	max	weight
Financial stability				Cat.	Nature proximity				Cat.	Positive image				Cat.
				weight					weight					weight
Profitability				Cat.	CO_2 emissions				Cat.	Farming lifestyle				Cat.
				weight					weight					weight
Yield				Cat.	Erosion potential				Cat.	Land inheritability				Cat.
				weight					weight					weight
Diversification				Cat.	Wildlife presence				Cat.	Young farmers				Cat.
				weight					weight					weight

- Which indicators would you include in your decision about which crop to put where on a field?
- How important is each indicator in the context of all indicators that you found relevant? Please, assign the appropriate number of poker chips and explain why.
- Is there a priority or an indicator that affects your decision that is not included on the list?
- For each indicator that you include in the decision-making, what is the time scale that is the most relevant to you? Please, place one of the 1, 5, 10, 20, 50, 100 year cards on the indicator. Is that the time scale at which you would commonly consider when making your decision in the landscape?
- For each indicator that you include in the decision-making, what is the geographic scale that is most relevant to you? Please, place one of the farm, local watershed (subcounty), county, state, Midwest, The Mississippi River Basin and Gulf of Mexico, U.S., world cards on the indicator. Is that the geographic area you would commonly consider when making your decision in the landscape?
- For indicators that you selected, what would you consider an excellent value or effect? What value is acceptable? Among the graphs below, which do you think represents that value better?
- To which category would you assign each of these indicators?

Tool output questions:

- What are your first thoughts when looking at the suggested map?
- On a scale from 0 to 10 how well does the suggested map meet your priorities?
- Which priorities are met most? Which priorities are met least?
- How would you like to change the map or the placement of crops?
- How you like to reset the importance among indicators to see if it meets your priorities better?
- (after the re-set) Which of these crop plans would you be more likely to adopt? What is the percent likelihood?
- How can the map be improved to increase the likelihood that you adopt the suggested plan?
- (Note the time that is takes to enter the new priorities when already familiar with the tool and its results)

Overall evaluation:

- What about the tool is difficult to understand? What guidance would be the most useful (text, service provider, video online…)?
- How much time would you be willing to spend working with the tool?
- What would you add or remove from the tool output?
- Overall, how satisfied are you with the experience using the tool? With its output?

Complete list of producer priorities as a result of Phase 1 interviews.

Table **A-2**: The complete list of producer priorities and the number of mentions per group as a result of Phase 1 interviews.

	Conservation producers (n=12)	Perennial biomass producers (n=16)	Corn stover harvesting producers (n=9)	All producers (n=37)
Profitability/cash flow	9	10	6	**25**
Freedom and independence (how independent is the decision of outside impacts)	8	8	5	**21**
Water quality	8	8	2	**18**
Erosion	6	9	1	**16**
Soil quality/Organic matter in soil/Soil health	7	5	4	**16**
Lifestyle/Type of work/Life and work with family	5	6	5	**16**
Stable markets and prices	5	6	3	**14**
Rural development	6	4	1	**11**
Young farmers and young families in farming	3	7	1	**11**
Developing a positive image of farmers among outsiders and city-dwellers	3	3	5	**11**
Diversified production and markets	1	7	2	**10**
Equal opportunity for small operations/Farms	5	4	1	**10**
Heritage/Tradition	4	4	1	**9**
Biodiversity/Presence of wildlife	6	2	-	**8**
Proximity to nature/Experience of pristine nature	2	4	2	**8**
“Feeding the world”	2	4	2	**8**
Yields	2	2	4	**8**

Table **A-2 (continued)**: The complete list of producer priorities and the number of mentions per group as a result of Phase 1 interviews.

	Conservation producers (n=12)	Perennial biomass producers (n=16)	Corn stover harvesting producers (n=9)	All producers (n=37)
Education opportunity/Informed decisions	3	3	-	**6**
Efficient use of labor	1	3	2	**6**
Opportunity for land ownership	1	3	2	**6**
Satisfaction with the work/Purposeful work/No guilt	1	1	3	**5**
Efficient use of inputs	2	3	-	**5**
Amount of wildlife habitat	1	3	-	**4**
Reduced risk/Uncertainty	1	1	2	**4**
Presence/Number of earthworms	2	1	-	**3**
Authority in price negotiation/Fair price for what they do	-	1	2	**3**
Supplier competition and free trade for bidding	1	2	-	**3**
Amount of forests	2	-	-	**2**
CO_2 emissions	1	1	-	**2**
Recreational value of clean water bodies	1	1	-	**2**
Opportunity to hunt	1	1	-	**2**
Comradery/Collaboration in the community	2	-	-	**2**
Data ownership	-	1	1	**2**
Making good investments	-	2	-	**2**
Seeding down marginal acres	-	1	1	**2**
Political and financial incentives	-	1	1	**2**
Weed resistance	-	-	1	**1**
Beauty/aesthetic value	1	-	-	**1**
Public health	-	1	-	**1**
Connection between landowners and land	-	1	-	**1**

Appendix B

Supplementary Data for Chapter 3

1. Google Earth Engine yield estimation code

The code below is provided for replicability and verifiability. It can be run using the Google Earth Engine.

```
var startCLU = ee.Date('2016-01-01');
var endCLU = ee.Date('2016-12-31');
var startImage = ee.Date('2016-06-15');
var endImage = ee.Date('2016-08-15');
var geometry: Table users/YourFolder
var coefficient = Value //coefficient to adjust for the average county yield
var corn_price = Value;
var corn_cost = Value;
var swt_prof = Value;
```

<table>
<tr><td>Sentinel</td><td>Landsat</td></tr>
<tr><td colspan="2">Crop out the parts of the field that have only corn (use CDL dataset from USDA)</td></tr>
<tr><td colspan="2"><pre>var dataset = ee.ImageCollection('USDA/NASS/CDL')
                  .filter(ee.Filter.date(startCLU, endCLU))
                  .filterBounds(geometry)
                  .select('cropland')
                  .first();

//Mask the image to leave only the "corn" (=1) plots
var crop_corn = dataset.updateMask(dataset.eq(1));

var corn = crop_corn.reduceToVectors({
    scale: 10,
    geometry: geometry,
    geometryType: 'polygon',
    maxPixels: 1e8

});
// A function to clip corn boundaries to the polygon shapefile
function clipper(image) {
  return image.clip(corn)
}</pre></td></tr>
<tr><td>Mask out the clouds and open the Sentinel maps</td><td>Open the Landsat maps (they already have clouds filtered out in the NDVI layers)</td></tr>
<tr><td><pre>// Function to mask clouds using the Sentinel-2 QA
band.
function maskS2clouds(image) {
  var qa = image.select('QA60')</pre></td><td><pre>var dataset =
ee.ImageCollection('LANDSAT/LC08/C01/T1_8D
AY_NDVI')
       .filterDate(startImage, endImage)</pre></td></tr>
</table>

```
  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = 1 << 10;
  var cirrusBitMask = 1 << 11;

  // Both flags should be set to zero, indicating clear
conditions.
var mask =  qa.bitwiseAnd(cloudBitMask).
                          eq(0).and(
                        qa.bitwiseAnd(cirrusBitMask).eq(0))

  // Return the masked and scaled data, without the
QA bands.
  return image.updateMask(mask).divide(10000)
      .select("B.*")
      .copyProperties(image, ["system:time_start"])
}

// Load Sentinel-2 TOA reflectance data.
var collection =
ee.ImageCollection('COPERNICUS/S2')
             .filterDate(startImage, endImage)
             .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCEN
             TAGE', 20))
    .map(clipper)
    .map(maskS2clouds)

// Map the function over one year of data and take
the median.
var composite = collection.median()
```

```
                    .filterBounds(table)
                    .map(clipper);
```

Calculate the NDVI from the layers	Access NDVI from the Landsat dataset

// Calculate NDVI = (NIR-RED)/(NIR+RED)
var ndvi =
composite.normalizedDifference(['B8','B4']);
	var colorized = dataset.select('NDVI');
	var ndvi = colorized.median()

Estimate corn yield	**Estimate corn yield**

```
// Corn yield calculation using indices
var corn_yield = ndvi.multiply(3.3525).exp().multiply(coefficient); //as in (Teal et al. 2006) in Mg/ha

var av_yield = corn_yield.reduceRegion({
  reducer: ee.Reducer.mean(),
  geometry: geometry,
  scale:30,
});

print('Average yield', av_yield);
```

Calculate corn subfield profit

```
var profit = corn_yield.multiply(corn_price).subtract(corn_cost);

var av_profit = profit.reduceRegion({
  reducer: ee.Reducer.mean(),
  geometry: geometry,
```

```
  scale:30,
});

print('Average profit', av_profit);

// Calculate the amount of area that loses money
var loss = profit.updateMask(profit.lte(0));
var av_loss = loss.reduceRegion({
  reducer: ee.Reducer.mean().unweighted(),
  geometry: geometry,
  scale:30,
});
print('Average loss', av_loss);
var pixel_loss = loss.reduceRegion({
  reducer: ee.Reducer.count(),
  geometry: geometry,
  scale:30,
});
print('Number of pixels with losses', pixel_loss);

var pixelcount = profit.reduceRegion({
  reducer: ee.Reducer.count(),
  geometry: geometry,
  scale:30,
});
print('Total number of pixels', pixelcount);
```

Comparing corn profitability to the possible profitability from switchgrass

```
// Compare the 'profit' layer values to either 0 or switchgrass profitability. If the value is lower, replace with switchgrass

var compare = profit.where(profit.lte(swt_prof),swt_prof);

var av_profit2 = compare.reduceRegion({
  reducer: ee.Reducer.mean().unweighted(),
  geometry: geometry,
  scale:30,
});
print('Average profit (switchgrass comparison)', av_profit2);

var compare_loss = compare.updateMask(compare.lte(0));
var av_comp_loss = compare_loss.reduceRegion({
  reducer: ee.Reducer.mean().unweighted(),
  geometry: geometry,
  scale:30,
});
print('Average loss (switchgrass comparison)', av_comp_loss);

var pixel_comp_loss = compare_loss.reduceRegion({
  reducer: ee.Reducer.count(),
  geometry: geometry,
  scale:30,
});
print('Number of pixels with losses (switchgrass comparison)', pixel_comp_loss);
```

```
var swt = profit.updateMask(profit.lte(swt_prof));
var pixel_swt = swt.reduceRegion({
  reducer: ee.Reducer.count(),
  geometry: geometry,
  scale:30,
});
print('Number of pixels with switchgrass', pixel_swt);
```

Visualization

```
//Palettes for the imagery from https://github.com/gee-community/ee-palettes
var palettes = require('users/gena/packages:palettes');
var palette = palettes.colorbrewer.RdYlGn[7];
var visParams_profit = ({min: -400, max: 1500, palette: palette});
Map.addLayer(profit, visParams_profit, 'Profit');

// set position of panel
var legend = ui.Panel({
style: {
position: 'bottom-left',
padding: '8px 15px'
}
});

// Create legend title
var legendTitle = ui.Label({
value: 'Profitability',
style: {
fontWeight: 'bold',
fontSize: '18px',
margin: '0 0 4px 0',
padding: '0'
}
});

// Add the title to the panel
legend.add(legendTitle);

// create the legend image
var lon = ee.Image.pixelLonLat().select('latitude');
var gradient = lon.multiply((visParams_profit.max-visParams_profit.min)/100.0).add(visParams_profit.min);
var legendImage = gradient.visualize(visParams_profit);

// create text on top of legend
var panel = ui.Panel({
widgets: [
ui.Label(visParams_profit['max'])
],
});

legend.add(panel);

// create thumbnail from the image
var thumbnail = ui.Thumbnail({
```

```
image: legendImage,
params: {bbox:'0,0,10,100', dimensions:'10x200'},
style: {padding: '1px', position: 'bottom-center'}
});

// add the thumbnail to the legend
legend.add(thumbnail);

// create text on top of legend
var panel = ui.Panel({
widgets: [
ui.Label(visParams_profit['min'])
],
});

legend.add(panel);

Map.add(legend);
```

2. Switchgrass yield variability

Switchgrass yield variability was based on the findings from the study by Hao et al. (2016). In that experiment, the authors compared the yield of corn and switchgrass plots that were planted side-by-side in Southern Michigan. Because their switchgrass was planted on marginal land, Hao et al.’s switchgrass yields were 5 Mg/ha, which is lower than commonly discussed in the literature from other field trials. The study covered only two sites (Figure B-1 below) but still provided experimental data for yield variability between corn and switchgrass, which was approximately three times lower for switchgrass than for corn. That why this study used "three times less variation" in the switchgrass yield calculation using a similar equation as for corn grain yield calculation. That means the factor accounting for the subfield variability was divided by 3, while the average switchgrass yield was maintained either at 10 Mg/ha, which is more typical for the better soils in the Iowa watersheds that are the subject of the current study or 5 Mg/ha depending on the scenario.

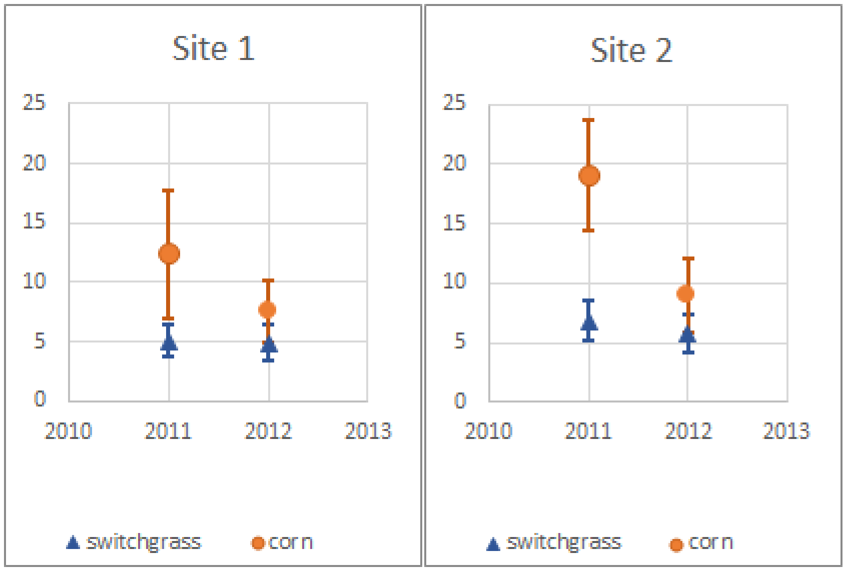


Figure **B-1**: Variability in yield for switchgrass and corn as in the study by Hao et al. (2016). Yield is given in Mg/ha for two years with averaged and standard deviations.

3. Economic assumptions and results

Table **B-1**: Cost assumptions for the Buena Vista County (North Raccoon River watershed) in constant 2018 USD values.

Buena Vista County (North Raccoon River watershed)	Unit	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Type of satellite data		Landsat	Landsat	Landsat	Sentinel	Sentinel	Sentinel
Producer Price Index (farming industry) (Bureau of Labor Statistics, 2020)		195.3	197.4	173.8	157.0	161.8	160.9
Corn grain yield (average county) (USDA, 2019)	Mg/ha	10.10	10.80	12.70	12.60	11.80	12.10
Land rent (Iowa Farm Bureau, 2019)	$/ha	864.22	902.96	693.47	604.97	564.14	591.00
Corn establishment and harvest cost excluding land rent (Duffy 2013 and 2014; Plastina 2015, 2016, 2017, and 2018)	$/ha	1773.41	1722.94	1535.19	1277.96	1174.94	1192.14
Corn grain price (USDA, 2019)	$/Mg	297.38	199.98	155.55	130.75	130.73	134.00
Corn stover harvesting cost (Thompson and Tyner 2014)	$/Mg	121.38	122.68	108.02	97.58	100.56	100.00
Switchgrass harvesting cost (Jacobs et al. 2016)	$/ha	569.27	575.39	506.6	457.63	471.62	469.00
Corn subsidy ($/ha) (Table B-2 values adjusted to 2018 USD values)	$/ha	139.22	53.00	247.14	94.06	79.74	32.40
Biomass price: $50/Mg*	$/Mg	60.69	61.34	54.01	48.79	50.28	50.00
Biomass price: $100/Mg*	$/Mg	121.38	122.68	108.02	97.58	100.56	100.00
Biomass price: $150/Mg*	$/Mg	182.07	184.03	162.03	146.36	150.84	150.00

*Note: Biomass price at the farm gate is the same for both switchgrass and corn stover.

Table **B-2**: Subsidy assumptions for Buena Vista county.

Buena Vista county corn subsidies (for North Raccoon River Watershed)	Unit	2013	2014	2015	2016	2017	2018
Total $ received (EWG, 2019)	$	8,213,849	3,014,779	15,373,089	6,630,557	5,341,158	2,142,565
Total area planted (USDA, 2019)	ac	177,000	172,500	166,000	170,000	166,500	164,000
	ha	**71,629**	**69,808**	**67,178**	**68,797**	**67,380**	**66,369**
Average subsidy	$/ac	46.4	17.5	92.6	39.0	32.1	13.1
	$/ha	**114.7**	**43.2**	**228.8**	**96.4**	**79.3**	**32.4**

Table **B-3**: Cost assumptions for Hardin County (South Fork Iowa River Watershed) in constant 2018 USD values.

Buena Vista County (North Raccoon River watershed)	Unit	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Type of satellite data		Landsat	Landsat	Landsat	Sentinel	Sentinel	Sentinel
Producer Price Index (farming industry) (Bureau of Labor Statistics, 2020)		195.3	197.4	173.8	157.0	161.8	160.9
Corn grain yield (average county) (USDA, 2019)	Mg/ha	9.80	10.40	12.50	13.10	13.40	13.60
Land rent (Iowa Farm Bureau, 2019)	$/ha	984.39	867.38	729.12	603.02	586.26	591.00
Corn establishment and harvest cost excluding land rent (Duffy 2013 and 2014; Plastina 2015, 2016, 2017, and 2018)	$/ha	1773.41	1722.94	1535.19	1277.96	1174.94	1192.14
Corn grain price (USDA, 2019)	$/Mg	297.38	199.98	155.55	130.75	130.73	134.00
Corn stover harvesting cost (Thompson and Tyner 2014)	$/Mg	121.38	122.68	108.02	97.58	100.56	100.00
Switchgrass harvesting cost (Jacobs et al. 2016)	$/ha	569.27	575.39	506.6	457.63	471.62	469.00
Corn subsidy ($/ha) (Table B-4 values adjusted to 2018 USD values)	$/ha	141.53	71.89	240.55	145.88	52.99	39.70
Biomass price: $50/Mg*	$/Mg	60.69	61.34	54.01	48.79	50.28	50.00
Biomass price: $100/Mg*	$/Mg	121.38	122.68	108.02	97.58	100.56	100.00
Biomass price: $150/Mg*	$/Mg	182.07	184.03	162.03	146.36	150.84	150.00

*Note: Biomass price at the farm gate is the same for both switchgrass and corn stover.

Table **B-4**: Subsidy assumptions for Hardin county.

Hardin county corn subsidies (for South Fork Iowa River)	Unit	2013	2014	2015	2016	2017	2018
Total $ received (EWG, 2019)	$	9,061,268	4,410,884	16,985,568	11,915,875	4,040,194	2,946,823
Total ac planted (USDA, 2019)	ac	192,000	186,000	188,500	197,000	189,500	183,500
	ha	**77,700**	**75,272**	**76,283**	**79,723**	**76,688**	**74,260**
Average subsidy	$/ac	47.2	23.7	90.1	60.5	21.3	16.1
	$/ha	**116.6**	**58.6**	**222.7**	**149.5**	**52.7**	**39.7**

Table **B-5**: Switchgrass production cost assumptions.

Cost category	Switchgrass (Jacobs et al. 2016)			
	Year 1	Year 2	Year 3+	**10-year average**
Seed ($/ac)	75.00	7.50		
Fertilizer ($/ac)	-	26.40	26.40	
Herbicide ($/ac)	13.12	6.40	6.40	
Pre-harvest machinery ($/ac)	31.15	28.60	12.55	
Harvest machinery ($/ac)	77.80	141.40	141.40	
Total ($/ac)	197.07	210.30	186.35	189.82
Metric Total ($/ha)				**469**

Table **B-6**: Profitability of fields in South Fork Iowa River Watershed.

Scenario	South Fork River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), Corn stover harvest based on Equation (1)	% Area in perennials with corn subsidy			69* *Note: The percent area in perennial grasses for “no rent” and “rented land” scenarios was the same number, which is why that value is provided only once.		35		13		14
	Average $/ha with corn subsidy	903	176	1229	502	833	107	725	-2	733
	% Area in perennials without corn subsidy			80		46		17		
	Average $/ha without corn subsidy	788	61	1162	473	768	41	626	-101	

Table **B-6 (continued)**: Profitability of fields in South Fork Iowa River Watershed.

Scenario	South Fork River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), Corn stover harvest based on Equation (2)	% Area in perennials with corn subsidy			70		35		13		
	Average $/ha with corn subsidy	907	180	1226	499	833	106	724	-3	
	% Area in perennials without corn subsidy			80		45		17		
	Average $/ha without corn subsidy	792	65	1198	471	768	41	625	-101	

Table **B-6 (continued)**: Profitability of fields in South Fork Iowa River Watershed.

Scenario	South Fork River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), No corn stover harvest	% Area in perennials with corn subsidy			90		35		13		
	Average $/ha with corn subsidy	704	-23	1174	447	833	107	725	-2	
	% Area in perennials without corn subsidy			92		46		17		
	Average $/ha without corn subsidy	588	-139	788	435	768	41	626	-101	

Table **B-6 (continued)**: Profitability of fields in South Fork Iowa River Watershed.

Scenario	South Fork River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
Low switchgrass yield (5 Mg/ha), Corn stover harvest based on Equation (1)	% Area in perennials with corn subsidy			26		13		6		14
	Average $/ha with corn subsidy	910	176	961	228	730	-3	710	-24	739
	% Area in perennials without corn subsidy			23		17		9		
	Average $/ha without corn subsidy	788	59	864	137	625	-102	596	-131	

Table **B-6 (continued)**: Profitability of fields in South Fork Iowa River Watershed.

Scenario	South Fork River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
Low switchgrass yield (5 Mg/ha), No corn stover harvest	% Area in perennials with corn subsidy			22		13		6		
	Average $/ha with corn subsidy	710	-23	770	37	730	-3	710	-24	
	% Area in perennials without corn subsidy			28		17		9		
	Average $/ha without corn subsidy	588	-139	678	-48	625	-101	596	-131	

Table **B-7**: Profitability of fields in the Headwaters of the North Raccoon River Watershed.

Scenario	North Raccoon River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), Corn stover harvest based on Equation (1)	% Area in perennials with corn subsidy			83 *Note: The percent area in perennial grasses for “no rent” and “rented land” scenarios was the same number, which is why that value is provided only once.		52		17		18
	Average $/ha with corn subsidy	809	105	1282	579	827	124	683	-20	694
	% Area in perennials without corn subsidy			85		66		22		
	Average $/ha without corn subsidy	701	-2	1259	556	783	79	599	-105	

Table **B-7 (continued)**: Profitability of fields in the Headwaters of the North Raccoon River Watershed.

Scenario	North Raccoon River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower: High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), Corn stover harvest based on Equation (2)	% Area in perennials with corn subsidy			83		51		17		
	Average $/ha with corn subsidy	814	111	1277	578	827	125	683	-21	
	% Area in perennials without corn subsidy			85		65		23		
	Average $/ha without corn subsidy	706	14	1254	554	782	80	598	-105	

Table **B-7 (continued)**: Profitability of fields in the Headwaters of the North Raccoon River Watershed.

Scenario	North Raccoon River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
High switchgrass yield (10 Mg/ha), No corn stover harvest	% Area in perennials with corn subsidy			87		52		17		
	Average $/ha with corn subsidy	626	-77	1221	518	827	124	683	-20	
	% Area in perennials without corn subsidy			89		66		22		
	Average $/ha without corn subsidy	519	-185	1203	499	783	79	599	-105	

Table **B-7 (continued)**: Profitability of fields in the Headwaters of the North Raccoon River Watershed.

Scenario	North Raccoon River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
Low switchgrass yield (5 Mg/ha), Corn stover harvest based on Equation (1)	% Area in perennials with corn subsidy			24		17		10		18
	Average $/ha with corn subsidy	809	105	910	206	683	-21	652	-52	694
	% Area in perennials without corn subsidy			29		23		14		
	Average $/ha without corn subsidy	701	-2	666	131	598	-105	556	-147	

Table **B-7 (continued)**: Profitability of fields in the Headwaters of the North Raccoon River Watershed.

Scenario	North Raccoon River Watershed	Base case (corn)		Convert only parts of land where profit is higher or loss is lower						
				High-price case for perennials (150 $/Mg)		Average-price case for perennials (100 $/Mg)		Low-price case for perennials (50 $/Mg)		Conservation plot
	Average for 2013-2018	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent	Rented land	No rent
Low switchgrass yield (5 Mg/ha), No corn stover harvest	% Area in perennials with corn subsidy			28		17		10		
	Average $/ha with corn subsidy	626	-77	736	33	683	-21	652	-52	
	% Area in perennials without corn subsidy			34		23		14		
	Average $/ha without corn subsidy	518	-185	666	-37	598	-105	556	-147	

4. Variations in grass production costs depending on the shape of the field

The assessment is based on the Science-based Trials of Rowcrops Integrated with Prairie Strips (STRIPS; IS, 2020) field geometries. The STRIPS project has established native prairie strips in Iowa cropland and has illustrated environmental benefits from such prairie strips (Schulte et al. 2017, S.T.R.I.P.S. Team 2019). Maps of fields that were used in the actual analysis are not presented to maintain the confidentiality of producers. The costs of growing native prairie and switchgrass differ because of the different harvesting efficiency, as discussed by Griffel et al. (2020).

Table **B-8**: Variation in switchgrass production cost due to different sizes of perennial grass fields as illustrated by STRIPS project perennial buffer strips.

	Farm 1	Farm 2	Farm 3	Farm 4	Farm 5
Farm landscape description	Two compact perennial strips	More than ten perennial strips of small area and complex shapes	More than ten perennial strips, some with complex geometry but most of large area	Ten perennial strips with large perimeter for small area	Five buffer strips, ranging from very small to extensive
Efficiency factor	69 %	58%	77%	62%	68%
Perennial crop % area	10% (2.29 ha or 5.65 ac.)	18% (5.51 ha or 13.61 ac.)	27% (51.36 ha or 126.91 ac.)	6% (3.88 ha or 9.59 ac.)	42% (6.73 ha 16.63 ac.)
Cost of switchgrass production with average rent	$1058/ha ($428/ac.)	$1132/ha ($458/ac.)	$1016/ha ($411/ac.)	$1100/ha ($445/ac.)	$1063/ha ($430/ac.)

Appendix C

Supplementary Data for Chapter 4

Decision support tool processing code

Utility calculation

In [214]:

```
# Import necessary packages for data inputs

import rasterio
import rasterio.features
import rasterio.warp
import pandas as pd
import geopandas as gpd
import numpy as np
import matplotlib.pyplot as plt
import georasters as gr
import os
from rasterio import features
import geopandas as gpd
from geopandas import GeoSeries, GeoDataFrame
```

Rasterization function

In [215]:

```
env = gpd.read_file("C:/Users/VAZHV/Desktop/Vector_input/Export_Output.shp")

def rasterize(gdf,out,in_layer,template,outDir):
    rst=rasterio.open(template)
    meta=rst.meta.copy()
    print(meta)
    #meta.update(nodata=-999)
    os.chdir(outDir)
    with rasterio.open(out,'w+',**meta) as out:
        out_arr=out.read(1)
```

```
      shapes=((geom,value)for geom,value in zip(gdf.geometry,in_layer))
      burned=features.rasterize(shapes=shapes,fill=0,out=out_arr,transform=out.transform)
      out.write_band(1,burned)
   return burned[:100, 100:200]
template = "C:/Users/VAZHV/Desktop/Raster_input/Profit_2018_cs_old.tif"
outDir = "C:/Users/VAZHV/Desktop/Raster_input"
```

Soil quality

Change in soil organic carbon as calculated by AgSolver. Ranges from -1518 lbC/ac/yr tto 365.5.

In [216]:

```
env = gpd.read_file("C:/Users/VAZHV/Desktop/Vector_input/Export_Output.shp")

####Annual####
soil_cs=rasterize(env, "soil_cs.tif", env.a_dsoc_cs, template, outDir)


####Switchgrass###
soil_swg=rasterize(env, "soil_swg.tif", env.a_dsoc_swg, template, outDir)
soil_swg = np.multiply(soil_swg, -1)

max_soil_swg = np.nanmax(soil_swg)
max_soil_cs = np.nanmax(soil_cs)
max_soil= max(max_soil_swg, max_soil_cs) # select the extreme value of that indicator

soil_util_c = (soil_cs/max_soil)
soil_util_c=np.where(soil_util_c<0, 0, soil_util_c) #Specify that if the values are negative - that is
zero utility


soil_util_s = (soil_swg/max_soil)
soil_util_s=np.where(soil_util_s<0, 0, soil_util_s) #Specify that if the values are negative - that is
zero utility
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs':
CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -
94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs':
CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -
94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

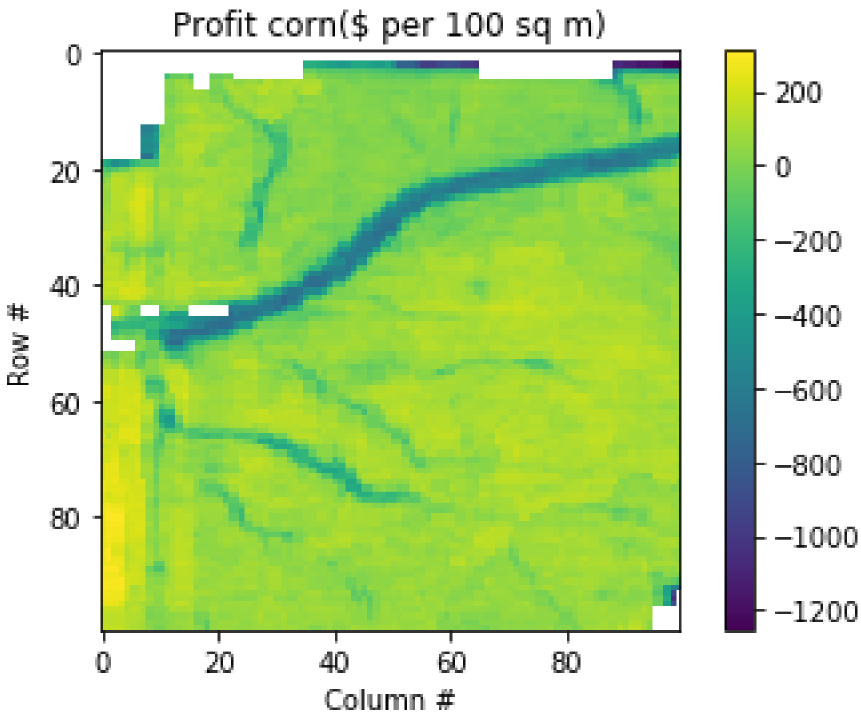
Profitability

Annual crop and switchgrass inputs are based on the profitability calculations from Google Earth Engine.

In [217]:

```
#####Annual crops####
profit_c = rasterio.open("C:/Users/VAZHV/Desktop/Raster_input/Profit_2018_cs_old.tif")
print(profit_c.bounds)

# Convert the raster into a numpy array so that further calculations can be carried out
ar_profit_c = profit_c.read(1)[:100, 100:200]

#Find maximum value of the numpy array,
max_prof_c = np.nanmax(ar_profit_c)


# Visualize the indicator
#plt.figure(figsize=(10,4))
plt.imshow(ar_profit_c)
plt.colorbar()
plt.title('Profit corn($ per 100 sq m)')
plt.xlabel('Column #')
plt.ylabel('Row #')
plt.show()

#####Switchgrass#####
profit_s=rasterio.open("C:/Users/VAZHV/Desktop/Raster_input/Profit_2018_swg_100.tif")
ar_profit_s = profit_s.read(1)[:100, 100:200]
max_prof_s = np.nanmax(ar_profit_s)

max_prof= max(max_prof_c, max_prof_s) # select the extreme value of that indicator

prof_norm_c = ar_profit_c/max_prof
prof_util_c=np.where(prof_norm_c<0, 0, prof_norm_c) # Specify that when unprofitable - zero utility

prof_norm_s = ar_profit_s/max_prof
prof_util_s = np.where(prof_norm_s<0, 0, prof_norm_s)
```

```
BoundingBox(left=-94.5902637980469, bottom=41.96479849764345, right=-94.5511870831877, top=41.99390391284892)
```



Independence

Assume average corn subsidy of 100/$ha\ given$ a 800/ha profit without subsidy - score of 0.125 Assume average switchgrass subsidy as 100/ha for 2 years of establishment averaged over 10 years of total growth with 8 years of harvest given a 400/ha profit without subsidy - score of 0.25. The best score is 0, the worst score is 1

In [218]:

```
### Annual ####

env['ind_cs'] = 0.125
ind_cs = rasterize(env, "ind_cs.tif", env.ind_cs, template, outDir)
ind_util_c = (1-ind_cs)

### Switchgrass ####

env['ind_swg'] = 0.25
ind_swg = rasterize(env, "ind_swg.tif", env.ind_swg, template, outDir)
ind_util_s = (1-ind_swg)
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

Financial stability

Based on the economic assessment, assume that corn profitability can vary between 25/ha to 850/ha with the score of 825 (assume that the profit is with subsidy, so crop subsidy mitigates some risk). Assume that switchgrass markets might not be functional, leading topaying the establishment cost but not getting the profit; thus the profit ranging from -400/ha to 400/ha to 800/ha in case of a good market with the score of 1200 Best score is 0, worst score is =(850/ha−(− 850/ha−(−1600/ha for corn establishment cost)) 2450

In [219]:

```
### Annual ####

env['fin_cs'] = 825
fin_cs = rasterize(env, "fin_cs.tif", env.fin_cs, template, outDir)
fin_util_c = (1-fin_cs/2450)

### Switchgrass ####

env['fin_swg'] = 1200
fin_swg = rasterize(env, "fin_swg.tif", env.fin_swg, template, outDir)
fin_util_s = (1-fin_swg/2450)
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

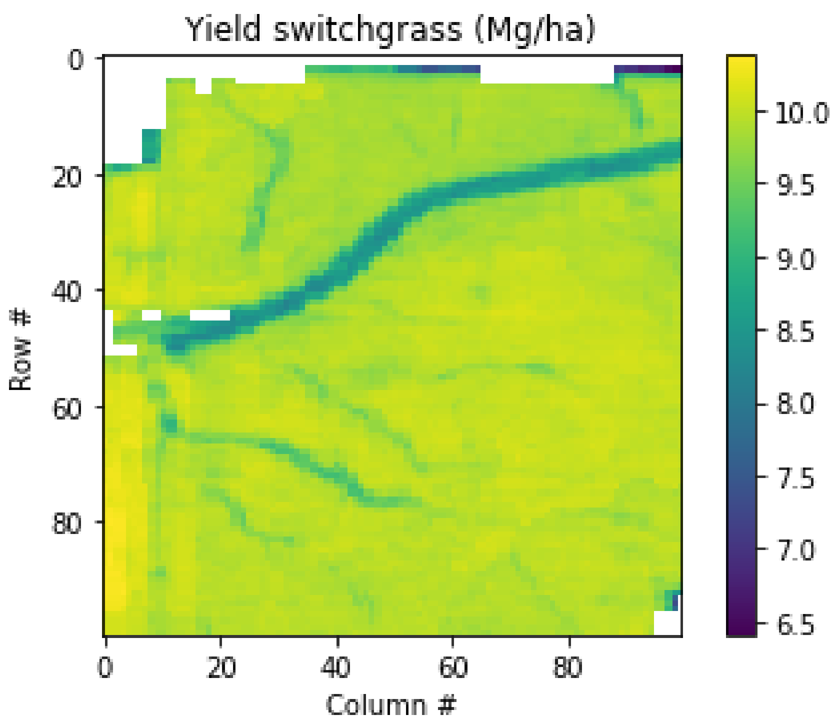
Yield

Both inputs are provided based on the Google Earth Engine estimates. Often, farmers implied corn or soybean yield when discussing this priority, so in other versions of the model, yield for the "switchgrass" layer can be set to zero.

In [220]:

```
#####Annual crops####
yield_c = rasterio.open("C:/Users/VAZHV/Desktop/Raster_input/Yield_2018_cs_old.tif")
# Convert the raster into a numpy array so that further calculations can be carried out
```

```
ar_yield_c = yield_c.read(1)[:100, 100:200]

#Find maximum value of the numpy array,
max_yield_c = np.nanmax(ar_yield_c)

####Switchgrass#####
yield_s=rasterio.open("C:/Users/VAZHV/Desktop/Raster_input/Yield_2018_swg_old.tif")
ar_yield_s = yield_s.read(1)[:100, 100:200]
max_yield_s = np.nanmax(ar_yield_s)

max_yield= max(max_yield_c, max_yield_s) # select the extreme value of that indicator

yie_util_c = ar_yield_c/max_yield
yie_util_s = ar_yield_s/max_yield

plt.imshow(ar_yield_s)
plt.colorbar()
plt.title('Yield switchgrass (Mg/ha)')
plt.xlabel('Column #')
plt.ylabel('Row #')
plt.show()
```



Diversification

Based on the market assessment, assume indicator value 2 for annual crops and indicator value 4 for switchgrass. Assume the worst value is 0, the best value is 5

In [221]:

```
### Annual ####

env['div_cs'] = 2
div_cs = rasterize(env, "div_cs.tif", env.div_cs, template, outDir)
div_util_c = (div_cs/5)

### Switchgrass ####

env['div_swg'] = 4
div_swg = rasterize(env, "div_swg.tif", env.div_swg, template, outDir)
div_util_s = (div_swg/5)
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

Water quality

Nitrate runoff is based on teh AgSolver analysis, ranges from 0 to 144.88 in teh specified example lbN/ac/yr, the greater - the worse

In [222]:

```
### Annual ####
wat_cs = rasterize(env, "wat_cs.tif", env.a_no3_sw_1, template, outDir)
max_wat_cs = np.nanmax(wat_cs)

### Switchgrass ####
wat_swg = rasterize(env, "wat_swg.tif", env.a_no3_swg, template, outDir)
max_wat_swg = np.nanmax(wat_swg)

max_wat = max(max_wat_swg, max_wat_cs)

wat_util_c = (1-wat_cs/max_wat)
wat_util_s = (1-wat_swg/max_wat)
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

Wildlife and pristine nature

Based on Schulte et al 2017 assume 1 for switchgrass and 0.33 (3 times less) for annual crops as based on species diversity estimates

In [223]:

```
### Annual ####

env['wil_cs'] = 0.33
wil_cs = rasterize(env, "wil_cs.tif", env.wil_cs, template, outDir)
wil_util_c = wil_cs

### Switchgrass ####

env['wil_swg'] = 1
wil_swg = rasterize(env, "wil_swg.tif", env.wil_swg, template, outDir)
wil_util_s = wil_swg
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

CO2 emissions

Based on the FEAT model, assume annual crop emissions are 2612 kgCo2e/yr/ha and 2293 kgCO2e/yr with 0 being the best value, 2612 - the worst

In [224]:

```
### Annual ####

env['co2_cs'] = 2612
```

```
co2_cs = rasterize(env, "co2_cs.tif", env.co2_cs, template, outDir)
co2_util_c = (1-co2_cs/2612)

### Switchgrass ####

env['co2_swg'] = 2293
co2_swg = rasterize(env, "co2_swg.tif", env.co2_swg, template, outDir)
co2_util_s = (1-co2_swg/2612)
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

Erosion potential

Water erosion rate as calculated by AgSolver, ranges from 0 to 50 tn/ac/yr.

In [225]:

```
### Annual ####
ero_cs = rasterize(env, "ero_cs.tif", env.watero_cs, template, outDir)
max_ero_cs = np.nanmax(ero_cs)

### Switchgrass ####
ero_swg = rasterize(env, "ero_swg.tif", env.watero_swg, template, outDir)
max_ero_swg = np.nanmax(ero_swg)

max_ero = max(max_ero_swg, max_ero_cs)

ero_util_c = (1-ero_cs/max_ero)
ero_util_s = (1-ero_swg/max_ero)
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

Food production

The amount of land for food production. Assume 0 for switchgrass and 0.5 for annual crops.

In [226]:

```
### Annual ####

env['food_cs'] = 0.5
food_cs = rasterize(env, "food_cs.tif", env.food_cs, template, outDir)
food_util_c = food_cs

### Switchgrass ####

env['food_swg'] = 0
food_swg = rasterize(env, "food_swg.tif", env.food_swg, template, outDir)
food_util_s = food_swg
```

```
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
       0.0, -8.983152841195215e-05, 41.99390391284892)}
```

Rural Development

The number of rural jobs. Assume that for corn: machine operator+ fertilizer/seed seller + co-op rep + farm manager/landowner = 4; for switchgrass: machine operator + seed seller + market 1 + market 2 + depot operator + farm manager/landowner = 6. The worst is 0 the best is 6

In [227]:

```
### Annual ####

env['rur_cs'] = 4
rur_cs = rasterize(env, "rur_cs.tif", env.rur_cs, template, outDir)
rur_util_c = rur_cs/6

### Switchgrass ####

env['rur_swg'] = 6
rur_swg = rasterize(env, "food_swg.tif", env.rur_swg, template, outDir)
rur_util_s = rur_swg/6
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

Positive image

Consumer-approved practices. Assume 0.8 for switchgrass, 0.4 for corn

In [228]:

```
### Annual ####

env['img_cs'] = 0.4
img_cs = rasterize(env, "img_cs.tif", env.img_cs, template, outDir)
img_util_c = img_cs

### Switchgrass ####

env['img_swg'] = 0.8
img_swg = rasterize(env, "img_swg.tif", env.img_swg, template, outDir)
img_util_s = img_swg
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
0.0, -8.983152841195215e-05, 41.99390391284892)}

Farming lifestyle

Ability to maintain a family operation. Assumption: 0.5 for switchgrass and 0.3 for corn

In [229]:

```
### Annual ####

env['lif_cs'] = 0.3
lif_cs = rasterize(env, "lif_cs.tif", env.lif_cs, template, outDir)
lif_util_c = lif_cs
```

```
### Switchgrass ####

env['lif_swg'] = 0.5
lif_swg = rasterize(env, "lif_swg.tif", env.lif_swg, template, outDir)
lif_util_s = lif_swg
```

{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
    0.0, -8.983152841195215e-05, 41.99390391284892)}
{'driver': 'GTiff', 'dtype': 'float64', 'nodata': None, 'width': 435, 'height': 324, 'count': 1, 'crs': CRS.from_dict(init='epsg:4326'), 'transform': Affine(8.983152841195215e-05, 0.0, -94.5902637980469,
    0.0, -8.983152841195215e-05, 41.99390391284892)}

Inheritability and young farmers

Land value as function of profit and management. Use as a sum of profit and soil organic carbon multiplied by 0.01 as a factor for improved land quality

In [230]:

```
#####Annual crops####
factor_cs = soil_cs*0.01
inh_cs = np.add(ar_profit_c, factor_cs)

max_inh_c = np.nanmax(inh_cs)



factor_swg = soil_swg*0.01
inh_swg = np.add(ar_profit_s, factor_swg)
max_inh_s = np.nanmax(inh_swg)



max_inh = max(max_inh_c, max_inh_s)




inh_norm_c = inh_cs/max_inh
inh_util_c=np.where(inh_norm_c<0, 0, inh_norm_c) # Specify that when unprofitable - zero utility

inh_norm_s = inh_swg/max_inh
inh_util_s = np.where(inh_norm_s<0, 0, inh_norm_s)
```

Utility evaluation

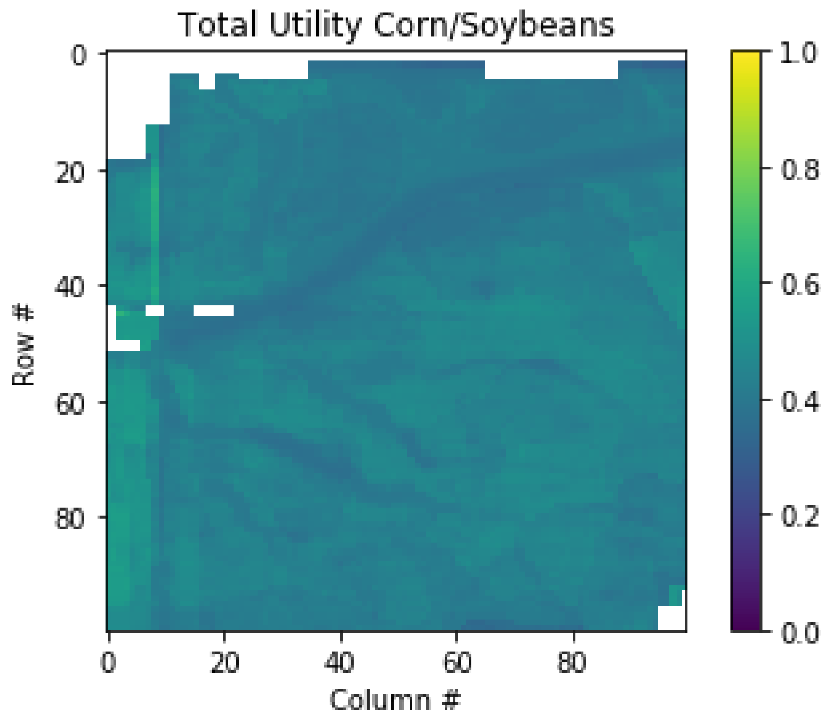
Annual crop only

In [231]:

```
# Total utility
weight_soil_c = soil_util_c*0.1
weight_prof_c = prof_util_c*0.133
weight_ind_c = ind_util_c*0
weight_fin_c = fin_util_c*0.133
weight_yie_c = yie_util_c*0.133
weight_div_c = div_util_c*0
weight_wil_c = wil_util_c*0
weight_co2_c = co2_util_c*0.1
weight_wat_c = wat_util_c*0.1
weight_ero_c = ero_util_c*0.1
weight_food_c = food_util_c*0
weight_rur_c = rur_util_c*0
weight_img_c = img_util_c*0.1
weight_lif_c = lif_util_c*0.1
weight_inh_c = inh_util_c*0


tot_util_c=weight_soil_c+weight_prof_c+weight_ind_c+weight_fin_c+weight_yie_c+weight_div_c
+weight_wil_c+weight_co2_c+weight_wat_c+weight_ero_c+weight_food_c+weight_rur_c+weight
_img_c+weight_lif_c+weight_inh_c

plt.imshow(tot_util_c)
print('Total utility all corn/soybeans',np.nansum(tot_util_c))
plt.colorbar()
plt.title('Total Utility Corn/Soybeans')
plt.xlabel('Column #')
plt.ylabel('Row #')
plt.clim(0,1)
plt.show()

print('Soil quality utility for corn/soybeans', np.nansum(soil_util_c))
print('Profitability utility for corn/soybeans', np.nansum(prof_util_c))
print('Independence utility for corn/soybeans', np.nansum(ind_util_c))
print('Financial stability utility for corn/soybeans', np.nansum(fin_util_c))
```

```
print('Yield utility for corn/soybeans', np.nansum(yie_util_c))
print('Diversification utility for corn/soybeans', np.nansum(div_util_c))
print('Wildlife and pristine nature utility for corn/soybeans', np.nansum(wil_util_c))
print('CO2 utility for corn/soybeans', np.nansum(co2_util_c))
print('Water quality utility for corn/soybeans', np.nansum(wat_util_c))
print('Erosion potential utility for corn/soybeans', np.nansum(ero_util_c))
print('Food production utility for corn/soybeans', np.nansum(food_util_c))
print('Rural development utility for corn/soybeans', np.nansum(rur_util_c))
print('Positive image utility for corn/soybeans', np.nansum(img_util_c))
print('Farming lifestyle utility for corn/soybeans', np.nansum(lif_util_c))
print('Inheritability and young farmers utility for corn/soybeans', np.nansum(inh_util_c))

# Output table with values for every cell (for Roni's exact optimization)
# Convert the raster into a numpy array so that further calculations can be carried out
ar_profit_c = profit_c.read(1)

row_num = ar_profit_c.shape[0]
col_num = ar_profit_c.shape[1]

points=[]

#for row in range (0,row_num-1):
#for col in range (0,col_num-1):
#		px,py=profit_c.xy(row,col)
#		#Use append as a way of creating a list of lists in "points"
#		points.append([px,py,ar_profit_c[row,col], soil_cs[row, col], ind_cs[row, col], fin_cs[row, col], yield_c[row, col], div_cs[row, col], wil_cs[row, col], co2_cs[row, col], wat_cs[row,col], ero_cs[row, col], food_cs[row, col], rur_cs[row, col], img_cs[row, col], lif_cs[row, col], inh_cs[row, col]])
#		col+=1
#	row+=1
#out_coord="C:/Users/VAZHV/Desktop/Raster_input/Coordinates_sustainability_indicators_corn.csv"
#df=pd.DataFrame.from_records(points)
#df.columns=['x','y','profit cs','soil quality cs', 'independence cs', 'financial stability cs', 'yield cs', 'diversification cs', 'wildlife cs', 'co2 cs', 'water quality cs', 'erosion cs', 'food production cs', 'rural development cs', 'positive image cs', 'lifestyle cs', 'inheritability cs']
#print(points[0])
#print(df.head())
#df.to_csv(out_coord,index=False)
```

Total utility all corn/soybeans 4080.404733038932



Soil quality utility for corn/soybeans 3305.5532170039896
Profitability utility for corn/soybeans 2015.773785371442
Independence utility for corn/soybeans 8806.75
Financial stability utility for corn/soybeans 6785.530612244899
Yield utility for corn/soybeans 8122.183063344403
Diversification utility for corn/soybeans 3818.4000000000005
Wildlife and pristine nature utility for corn/soybeans 3150.1800000000003
CO2 utility for corn/soybeans 454.0
Water quality utility for corn/soybeans 2174.0320913202668
Erosion potential utility for corn/soybeans 7856.643336529241
Food production utility for corn/soybeans 4773.0
Rural development utility for corn/soybeans 6363.999999999999
Positive image utility for corn/soybeans 3818.4000000000005
Farming lifestyle utility for corn/soybeans 2863.7999999999993
Inheritability and young farmers utility for corn/soybeans 2040.9074908659904

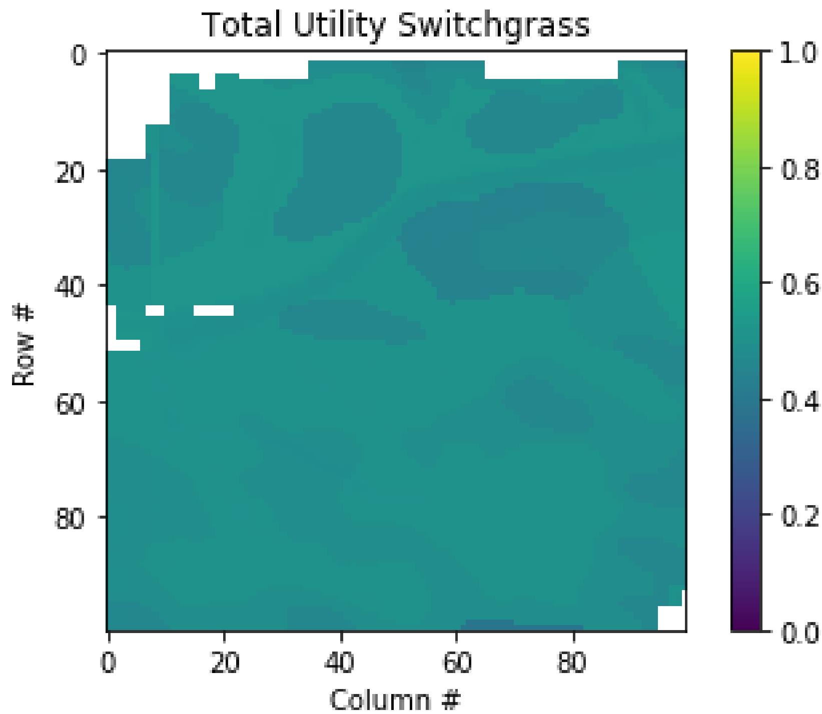
Switchgrass only

In [232]:

```
# Total utility
weight_soil_s = soil_util_s*0.1
weight_prof_s = prof_util_s*0.133
```

```
weight_ind_s = ind_util_s*0
weight_fin_s = fin_util_s*0.133
weight_yie_s = yie_util_s*0.133
weight_div_s = div_util_s*0
weight_wil_s = wil_util_s*0
weight_co2_s = co2_util_s*0.1
weight_wat_s = wat_util_s*0.1
weight_ero_s = ero_util_s*0.1
weight_food_s = food_util_s*0
weight_rur_s = rur_util_s*0
weight_img_s = img_util_s*0.1
weight_lif_s = lif_util_s*0.1
weight_inh_s = inh_util_s*0


tot_util_s=weight_soil_s+weight_prof_s+weight_ind_s+weight_fin_s+weight_yie_s+weight_div_s
+weight_wil_s+weight_co2_s+weight_wat_s+weight_ero_s+weight_food_s+weight_rur_s+weight
_img_s+weight_lif_s+weight_inh_s

plt.imshow(tot_util_s)
print('Total utility all switchgrass' ,np.nansum(tot_util_s) )
plt.colorbar()
plt.title('Total Utility Switchgrass')
plt.xlabel('Column #')
plt.ylabel('Row #')
plt.clim(0,1)
plt.show()

print('Soil quality utility for switchgrass', np.nansum(soil_util_s))
print('Profitability utility for switchgrass', np.nansum(prof_util_s))
print('Independence utility for switchgrass', np.nansum(ind_util_s))
print('Financial stability utility for switchgrass', np.nansum(fin_util_s))
print('Yield utility for switchgrass', np.nansum(yie_util_s))
print('Diversification utility for switchgrass', np.nansum(div_util_s))
print('Wildlife and pristine nature utility for switchgrass', np.nansum(wil_util_s))
print('CO2 utility for switchgrass', np.nansum(co2_util_s))
print('Water quality utility for switchgrass', np.nansum(wat_util_s))
print('Erosion potential utility for switchgrass', np.nansum(ero_util_s))
print('Food production utility for switchgrass', np.nansum(food_util_s))
print('Rural development utility for switchgrass', np.nansum(rur_util_s))
print('Positive image utility for switchgrass', np.nansum(img_util_s))
print('Farming lifestyle utility for switchgrass', np.nansum(lif_util_s))
print('Inheritability and young farmers utility for switchgrass', np.nansum(inh_util_s))
```

```
# Output table with values for every cell (for Roni's exact optimization)
# Convert the raster into a numpy array so that further calculations can be carried out
ar_profit_c = profit_c.read(1)

row_num = ar_profit_c.shape[0]
col_num = ar_profit_c.shape[1]

points=[]

#for row in range (0,row_num-1):
#       for col in range (0,col_num-1):
#           px,py=profit_c.xy(row,col)
#           #Use append as a way of creating a list of lists in "points"
#           points.append([px,py,swg_prof[row,col], soil_swg[row, col], ind_swg[row, col],
fin_swg[row, col], yie_swg[row, col], div_swg[row, col], wil_swg[row, col], co2_swg[row, col],
wat_swg[row,col], ero_swg[row, col], food_swg[row, col], rur_swg[row, col], img_swg[row, col],
lif_swg[row, col], inh_swg[row, col]])
#           col+=1
#       row+=1
#out_coord="C:/Users/VAZHV/Desktop/Raster_input/Coordinates_sustainability_indicators_switc
hgrass.csv"
#df=pd.DataFrame.from_records(points)
#df.columns=['x','y','profit swg','soil quality swg', 'independence swg', 'financial stability swg', 'yield
swg', 'diversification swg', 'wildlife swg', 'co2 swg', 'water quality swg', 'erosion swg', 'food
production swg', 'rural development swg', 'positive image swg', 'lifestyle swg', 'inheritability swg']
#print(points[0])
#print(df.head())
#df.to_csv(out_coord,index=False)
Total utility all switchgrass 4671.815531592435
```



Soil quality utility for switchgrass 7417.768630234208
Profitability utility for switchgrass 0.0
Independence utility for switchgrass 7613.5
Financial stability utility for switchgrass 5324.408163265308
Yield utility for switchgrass 6113.0137260663705
Diversification utility for switchgrass 7636.800000000001
Wildlife and pristine nature utility for switchgrass 9546.0
CO2 utility for switchgrass 1619.839969372128
Water quality utility for switchgrass 4797.324574628474
Erosion potential utility for switchgrass 7692.300095877277
Food production utility for switchgrass 0.0
Rural development utility for switchgrass 9546.0
Positive image utility for switchgrass 7636.800000000001
Farming lifestyle utility for switchgrass 4773.0
Inheritability and young farmers utility for switchgrass 0.0

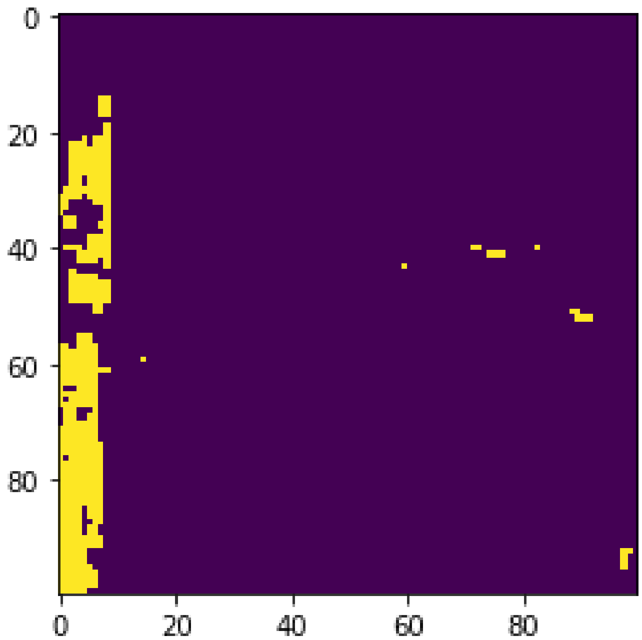
Maximized pixel values

In [233]:

```
max_util = np.greater(tot_util_c, tot_util_s)
plt.imshow(max_util)
```

Out[233]:

<matplotlib.image.AxesImage at 0x139213d4f28>



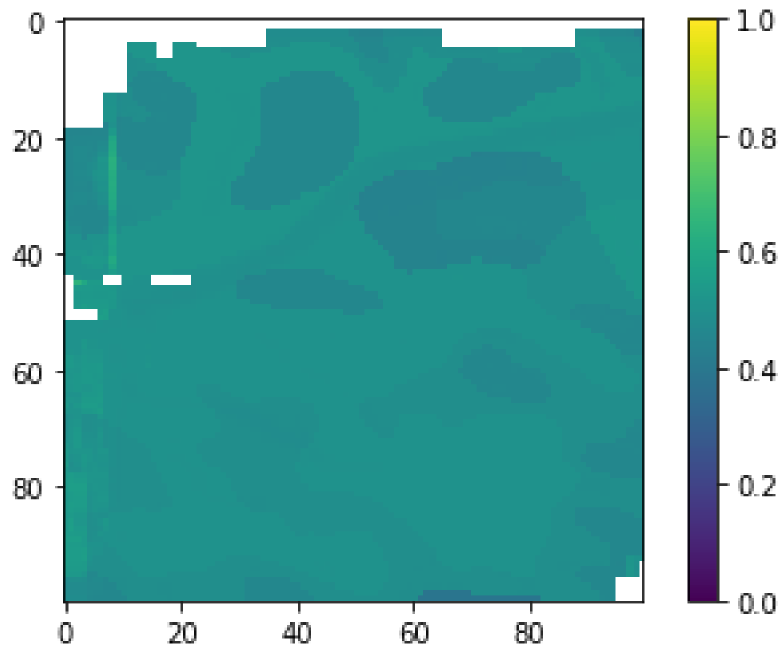
In [234]:

```
#Calculate the total utility given the crop plan - to be maximized
import numpy.ma as ma

cornsoy = ma.masked_where(max_util==0, tot_util_c)
switchgrass = ma.masked_where(max_util==1, tot_util_s)
field = ma.filled(cornsoy, switchgrass)
plt.imshow(field)
plt.colorbar()
plt.clim(0,1)
util = np.nansum(field)
print('Total field utility:', util)

#Calculate the total utility given the crop plan - to be maximized
import numpy.ma as ma
switchgrass=ma.masked_where(tot_util_s<tot_util_c, tot_util_s)
cornsoy=ma.masked_where(tot_util_s>tot_util_c, tot_util_c)
field=ma.filled(cornsoy, switchgrass)
fin_utility=np.nansum(field)
print('Total field utility:', fin_utility)

cornsoy = ma.masked_where(max_util==0, soil_util_c)
switchgrass = ma.masked_where(max_util==1, soil_util_s)
field = ma.filled(switchgrass, cornsoy)
```

```
util = np.nansum(field)
print('Total soil quality utility', util)

cornsoy = ma.masked_where(max_util==0, prof_util_c)
switchgrass = ma.masked_where(max_util==1, prof_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total profitability utility', util)

cornsoy = ma.masked_where(max_util==0, ind_util_c)
switchgrass = ma.masked_where(max_util==1, ind_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total independence utility', util)

cornsoy = ma.masked_where(max_util==0, fin_util_c)
switchgrass = ma.masked_where(max_util==1, fin_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total financial stability utility', util)

cornsoy = ma.masked_where(max_util==0, yie_util_c)
switchgrass = ma.masked_where(max_util==1, yie_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total yield utility', util)

cornsoy = ma.masked_where(max_util==0, div_util_c)
switchgrass = ma.masked_where(max_util==1, div_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total diversification utility', util)

cornsoy = ma.masked_where(max_util==0, wil_util_c)
switchgrass = ma.masked_where(max_util==1, wil_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total wildlife and pristine nature utility', util)

cornsoy = ma.masked_where(max_util==0, co2_util_c)
switchgrass = ma.masked_where(max_util==1, co2_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
```

```
print('Total CO2 utility', util)

cornsoy = ma.masked_where(max_util==0, wat_util_c)
switchgrass = ma.masked_where(max_util==1, wat_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total water quality utility', util)

cornsoy = ma.masked_where(max_util==0, ero_util_c)
switchgrass = ma.masked_where(max_util==1, ero_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total erosion potential utility', util)

cornsoy = ma.masked_where(max_util==0, food_util_c)
switchgrass = ma.masked_where(max_util==1, food_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total food production utility', util)

cornsoy = ma.masked_where(max_util==0, rur_util_c)
switchgrass = ma.masked_where(max_util==1, rur_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total rural development utility', util)

cornsoy = ma.masked_where(max_util==0, img_util_c)
switchgrass = ma.masked_where(max_util==1, img_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total positive image utility', util)

cornsoy = ma.masked_where(max_util==0, lif_util_c)
switchgrass = ma.masked_where(max_util==1, lif_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total farming lifestyle utility', util)

cornsoy = ma.masked_where(max_util==0, inh_util_c)
switchgrass = ma.masked_where(max_util==1, inh_util_s)
field = ma.filled(switchgrass, cornsoy)
util = np.nansum(field)
print('Total inheritability and young farmers utility', util)
```

```
#Need to convert from float 64 format to int 32 to be able to process further
max_util = np.int32(max_util)

from rasterio.features import sieve, shapes
from shapely.geometry import Polygon, shape

#Print the number of shapes in the source raster
print("Number of subfields: %d" % len(list(shapes(max_util))))

#shapes= shapes(max_util, connectivity=4)
#gdf = gpd.GeoDataFrame(shapes)
#gdf.columns=['geometry', 'value']
#gdf['perimeter'] = gdf['geometry'].length
#gdf['area']= gdf['geometry'].area
#print(gdf)

#print(perimeter)

# Detailed utility by indicator
Total field utility: 4683.793569778185
Total field utility: 4683.793569778185
Total soil quality utility 7248.066444776192
Total profitability utility 274.3042957500676
Total independence utility 7664.25
Total financial stability utility 5386.551020408164
Total yield utility 6238.40806233531
Total diversification utility 7474.4000000000015
Total wildlife and pristine nature utility 9273.98
Total CO2 utility 1570.25574272588
Total water quality utility 4787.088304975232
Total erosion potential utility 7670.9539789069995
Total food production utility 203.0
Total rural development utility 9410.666666666666
Total positive image utility 7474.4000000000015
Total farming lifestyle utility 4691.8
Total inheritability and young farmers utility 274.8863457119887
Number of subfields: 20
```



Smoothing heuristic + sieving

In [235]:

```
row_num = max_util.shape[0]
col_num = max_util.shape[1]
smoothed_util = max_util

#2 pixels over
for row in range (0, row_num-3):
    for col in range (0, col_num-1):
        if max_util[row, col] == max_util[row+3, col]:
            smoothed_util[row+1:row+2, col] = max_util[row, col]

for row in range (0, row_num-1):
    for col in range (0, col_num-3):
        if max_util[row, col] ==max_util[row, col+3]:
            smoothed_util[row, col+1:col+2]=max_util[row, col]

plt.imshow(smoothed_util)

cornsoy = ma.masked_where(smoothed_util==0, tot_util_c)
switchgrass = ma.masked_where(smoothed_util==1, tot_util_s)
field = ma.filled(switchgrass, cornsoy)
```

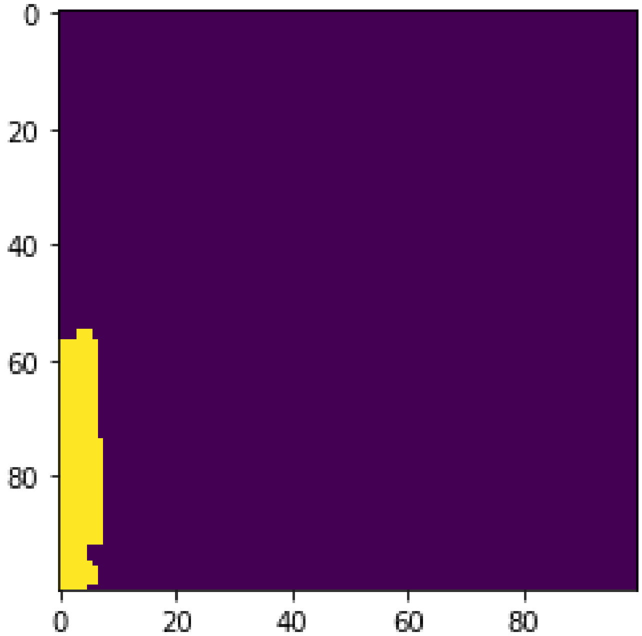
```
util = np.nansum(field)

print('Total utility', util)

from rasterio.features import sieve, shapes
import matplotlib.patches as mpatches

#Need to convert from float 64 format to int 32 to be able to process further
smoothed_util = np.int32(smoothed_util)

#Print the number of shapes in the source raster
print("Number of subfields: %d" % len(list(shapes(smoothed_util))))

#Create masks for corn and switchgrass to sieve out the subfields - small for switchgrass, large
for corn
sieve20 = sieve(smoothed_util, 20, connectivity=4)
mask_s2=ma.masked_where(sieve20==[True],sieve20)

sieve150 = sieve(smoothed_util, 150, connectivity=4)
mask_c2 = ma.masked_where(sieve150==[False], sieve150)

sieved_field=ma.filled(mask_s2, mask_c2)

non_sieved2=len(list(shapes(mask_s2)))
print("Sieved switchgrass shapes: %d" % non_sieved2)
sieved2=len(list(shapes(mask_c2)))#
print("Sieved corn shapes: %d" % sieved2)

sieved_switchgrass=ma.masked_where(sieved_field==0,tot_util_c)
sieved_cornsoy=ma.masked_where(sieved_field==1,tot_util_s)
sieved_util=ma.filled(sieved_cornsoy, sieved_switchgrass)

sieved_tot=len(list(shapes(sieved_field)))
print("Sieved total shapes: %d" % sieved_tot)
print("Sieved utility:", np.nansum(sieved_util))

plt.imshow(sieved_field)
print(sieved_field)

from rasterio.features import sieve, shapes
from shapely.geometry import Polygon,shape

shapes= shapes(sieved_field, connectivity=4)
```

```
gdf = gpd.GeoDataFrame(shapes)
gdf.columns = ['geometry', 'value']
for index,row in gdf.iterrows():
    gdf.loc[index,'geometry']=shape(gdf.loc[index,'geometry'])
gdf['perimeter']=(gdf['geometry'].length)*10
gdf['area']=(gdf['geometry'].area)*100
gdf['FE'] =0.179-0.145*np.log(gdf['perimeter']/gdf['area'])
print ('Average field efficiency:', gdf["FE"].mean())
gdf
```

```
Total utility 4682.448356095204
Number of subfields: 5
Sieved switchgrass shapes: 1
Sieved corn shapes: 1
Sieved total shapes: 2
Sieved utility: 4679.349876399971
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [1 1 1 ... 0 0 0]
 [1 1 1 ... 0 0 0]
 [1 1 1 ... 0 0 0]]
Average field efficiency: 0.8179277374061036
```

Out[235]:

	geometry	value	perimeter	area	FE
0	POLYGON ((3 55, 3 57, 2 57, 0 57, 0 100, 5 100...	1.0	1100.0	31600.0	0.665888
1	POLYGON ((0 0, 0 57, 3 57, 3 55, 6 55, 6 57, 7...	0.0	4140.0	968400.0	0.969968


0
20
40
60
80
0
20
40
60
80

VITA

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Education

Ph.D. **The Pennsylvania State University**, USA. *2016-2020*(exp)
BioRenewable Systems Major; Operations Research Minor

B.Sc. **Albert-Ludwigs Universitaet Freiburg**, Germany. *2012-2016*
Liberal Arts and Sciences with major in Earth and Environmental Sciences

Exchange Year. **Hong Kong University**. *2014-2015*
Civil and Environmental Engineering curriculum

Work Experience

Idaho National Laboratory. Graduate Fellow. 2019-current
Research bioenergy farm decision-making and feedstock logistics as part of the Bioenergy Analysis group.

The Pennsylvania State University. Graduate Research Assistant. 2016-2019
Research biomass supply for bioenergy, the possible bioenergy markets and the decision-making necessary to supply biomass.

Institute of Microsystems Engineering (University of Freiburg). Research Assistant. 2015-2016
Research on Microbial Electrolysis Cells to improve reactor performance by adding granular activated carbon to the anode.

Community Engagement

American Society for Agricultural and Biological Engineers (**ASABE)**, Ad-hoc committee related to diversity and inclusion. 2019-now. *Member*

The Pennsylvania State University, Stewarding Our Planet's Resources Strategic Planning. 2018-now. *Steering committee member*

ASABE Young Professionals Committee. 2018-now. *Graduate Student Representative*

ASABE ASE-16 Committee Engineering for Sustainability. 2018-now. *Secretary*. Joined the committee in 2017 as an observing member