Regional differences in water quality impacts from the Bioenergy Mandate: A scenario-based approach to quantifying the impacts from RFS2

by

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"The Road goes ever on and on
Down from the door where it began.
Now far ahead the Road has gone,
And I must follow, if I can,
Pursuing it with eager feet,
Until it joins some larger way
Where many paths and errands meet.
And whither then? I cannot say."

- J.R.R. Tolkien, The Fellowship of the Ring

To my family, for their unfailing encouragement, support and love on this winding road

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List of Abbreviations

CDL	Cropland Data Layer
DOE	Department of Energy
EPA	Environmental Protection Agency
HRU	Hydrological Response Unit
NS	Nash-Sutcliffe
PBIAS	Percent Bias
RFS2	Renewable Fuels Standard
SWAT	Soil and Water Assessment Tool
US	United States
USDA	United States Department of Agriculture

Abstract

The Renewable Fuels Standard (RFS2) under the Energy Independence and Security Act (EISA 2007) mandates the production of 36 billion gallons of biofuel by 2022 for use in the transportation sector. Although the mandate seeks to reduce greenhouse gas emissions by reducing our dependence on oil, there is concern that consequent land-use/cover (LULC) changes could result in significant unintended environmental impacts. The evaluation of water quality impacts from the mandate is challenging, especially for cellulosic and other advanced biofuels because the bioenergy supply chain is an emerging system with inherent uncertainties.

This research addresses several gaps in the literature on the water quality impacts of the mandate and is organized into three chapters. The first chapter addresses the regional differences in impacts to water quality from a similar land-use change for two watersheds in the Midwest (Upper Cedar) and Southeast (Lumber). The Soil and Water Assessment Tool, a hydrological model that is able to simulate crop growth and water and nutrient outputs is set up, calibrated and validated. The potential reduction in nitrogen loading per potential gallon of ethanol to surface waters, for a change from baseline corn/soy to switchgrass, is about 40% in the Midwest and around 80% in the Southeast. Although, the trend in reduction is similar in both watersheds, this study shows that results extrapolated from the Midwest, where a lot of the bioenergy literature is based, may not be representative of other bioenergy producing regions.

The second chapter investigates the impact of uncertainties in production costs of perennials on three objectives incentivizing different aspects of the biofuel industry – maximizing farmer profitability, surplus from feedstock production and ethanol production and land-use efficiency, using a Monte-Carlo Analysis. The study also investigates the impact of current farmer safety net for corn-soy production and bioenergy subsidies on the feedstock choice in each region. The analysis indicates that the three objectives result in different feedstock options in the two regions. Further, results indicate that the current incentive structure for perennial biomass is insufficient to encourage production on cropland, especially because the commodity crop alternative has better risk management.

The final chapter of the dissertation links the feedstock production and ethanol production stages of the bioenergy supply chain. A Mixed Integer Linear Programming (MILP) optimization is used to drive land-use change at the Hydrologic Response Unit (HRU) level for the three objectives investigated in the second chapter. Results indicate there are tradeoffs between profitability and water quality for the three objectives. When the location of the biorefinery was considered, the supply of biomass and changes to water quality were localized around it, and these changes were significant at the sub-watershed scale. Optimization of biorefineries is usually done at the county or other large administrative scales. Our results indicate that such a scale would miss the localization of impacts which could be especially sub-optimal for sensitive watersheds. Any optimization of the biofuel supply chain system for water quality will therefore have to be at a watershed or sub-watershed resolution. A limitation of this work is the use of a single water quality indicator to quantify water quality impacts. Optimizing the supply chain must also involve development of appropriate multi-metric indicators of water quality for the region under consideration.

Chapter 1 : Introduction

Increasing production of bioenergy has been a contentious issue, spanning economic, environmental and social dimensions. The present policy context for a bioenergy policy in the United States (US) arose out of concerns over energy security and independence following the oil crisis in the mid-70s. In 2007, the US Congress passed the Energy Independence and Security Act (EISA 2007) mandating the production of 36BGY of biofuels to be blended into transportation fuels, including 15BGY of corn ethanol and 21BGY of other advanced renewable fuels. The billion-ton annual supply report, commissioned by the US Department of Energy (DOE) and Department of Agriculture (USDA), predicted that the production of biofuels to meet the mandate will result in a land-use change of 40-60 million acres on agricultural and marginal land (Perlack et al., 2011). These changes include conversion of land protected under the Conservation Reserve Program (CRP) to energy crop cultivation, switching from traditional row crops grown for food and feed to corn and other energy crops, and changing crop rotations to continuous row crop production. A land-use change (LUC) of this scale would drive massive environmental changes in the country.

Although the mandate for corn-ethanol has been met, given the uncertainties in the economic and policy climate, as well as lack of sufficient advances in technology, the cellulosic ethanol industry in particular has been slow to develop. The Environmental Protection Agency (EPA) has waived or reduced the mandated requirement of cellulosic biofuels from 2010, due to the lack of infrastructure. So far, there are only 15 operating ethanol plants in the country with the combined capacity of 100 million gallons[1], as opposed to 4.25BGY, mandated by RFS2 for 2016. Further, processing costs for the cellulosic ethanol industry have not yet matured (Johnson, 2016; Kazi et al., 2010) adding to additional uncertainty in the availability and costs of ethanol and other

[1] Ethanol Producer Magazine. Updated Jan 23 2016.
<http://www.ethanolproducer.com/plants/listplants/US/Existing/Cellulosic>

advanced biofuels. As such, the cellulosic ethanol supply chain including feedstock production, logistics and location can be considered an emerging system.

The central objective of this dissertation is to contribute to the literature on how land-use change from bioenergy policy could impact water quality impacts in the US under system uncertainties in two different regions of the US. This study uses results from the Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2005), a physically based hydrologic model, to study the water quality impacts of land-use change from the baseline to cellulosic feedstock alternatives (Chapter 2). Then, it examines the barriers to cellulosic feedstock production from uncertainties in production economics through a Monte-Carlo analysis (Chapter 3) and uses a Mixed Integer Linear Programming (MILP) optimization method to generate plausible land-use scenarios and consequent water quality impacts (Chapter 4).

The bioenergy supply chain consists of upstream processes- feedstock production and feedstock logistics including storage and transportation of feedstock to ethanol processing plants, a midstream process- conversion of feedstock to ethanol and downstream distribution of ethanol to demand centers (Meyer et al., 2014). The impacts on water quality from biofuels are primarily driven by chemical inputs at the feedstock production stage. Consequently, a number of previous studies on the water quality impacts from the feedstock production have looked at impacts at the basin, watershed and farm-scale in isolation (Gramig et al., 2013; Love and Nejadhashemi, 2011; National Research Council Committee on Water Implications of Biofuels Production in the United States, 2007; Thomas et al., 2009; Thornton et al., 1998).

The nature and magnitude of water quality impacts from the bioenergy mandate depends on prior land-use, crop type, climatological, topological factors and management practices (Simpson et al., 2008; Thomas et al., 2009). For example, Thomas et al. (2009) modeled different corn-soy cropping systems in Indiana at the field scale and found that higher application rate of fertilizers had a non-linear relationship with nitrogen loading at the edge-of-field. Instead, nutrient runoff depended on soil type and slope characteristics. The results also suggested that a shift to continuous corn would significantly increase losses in nitrate-N and TP in surface runoff (Thomas et al., 2009).

While intensification of row crop agriculture for corn ethanol was found to impair water quality, impacts from biofuels need not be negative and can vary in the magnitude (Powers et al., 2011). For example, Wu and Liu (2012) simulated the removal of corn stover in Iowa and concluded that nitrate loading in the non-growing season decreases by up to 10% over traditional crop rotation systems (Wu and Liu, 2012). Likewise, it has been the general consensus that growing perennial grasses in the place of corn/ other row crops for cellulosic ethanol mitigates the water quality impacts and improves land quality (Fike et al., 2006; McLaughlin, Samuel B., Walsh, 1998; Randall et al., 1997; Sarkar et al., 2011). For example, replacing traditional row corn-soy rotation with miscanthus in Kansas has shown a 30% decrease (Ng et al., 2010) and replacing switchgrass on lands previously in cotton in South Carolina showed a 50% decrease in nitrogen loading from the baseline (Sarkar et al., 2011).

The effects of soil type on runoff volume and consequently nutrient loading is especially important in the context of using marginal lands and lands retired under the Conservation Reserve Program (CRP) to conserve highly erodible soils. Donner and Kucharik (2008) studied the expansion of corn by utilizing CRP land for grain based ethanol and removal of corn stover for cellulosic ethanol to meet 2022 mandate goals in the Upper Mississippi River Basin (Donner and Kucharik, 2008). They found that this would increase the dissolved inorganic nitrogen (DIN) input into the Mississippi river by 34%, more than double the national goal set by the Mississippi River/Gulf of Mexico Watershed Nutrient Task Force to reduce the “Dead Zone” in the Gulf of Mexico.

Many of the previous studies evaluating the water quality impact of corn ethanol and other biofuels are situated in the corn/soy dominant Mississippi River Basin (MRB) or the Corn Belt and many of them are in response to addressing future stressors exacerbating the Gulf of Mexico hypoxia (Costello et al., 2009; Donner and Kucharik, 2008; Powers et al., 2011; Dominguez-Faus, R. et al., 2006; Wu et al., 1997). However, perennials like switchgrass and miscanthus grow well in many regions other than the Midwest. A USDA study based on Agriculture Research Service (ARS) scientists’ research on biomass availability and energy yield in different regions found that more than 50% of biomass could come from the Southeastern states. There are few studies that look into the impacts of land-use change from bioenergy policy in watersheds in the southeast (Chamberlain et al., 2011; Lambert et al., 2016; Sarkar et al., 2011; Sharp and Miller, 2014; Yu et al., 2016). While the nature of land-use change impacts may be similar, there could be regional differences in impacts to water quality, which could be exploited to optimize the mandate from a water quality perspective.

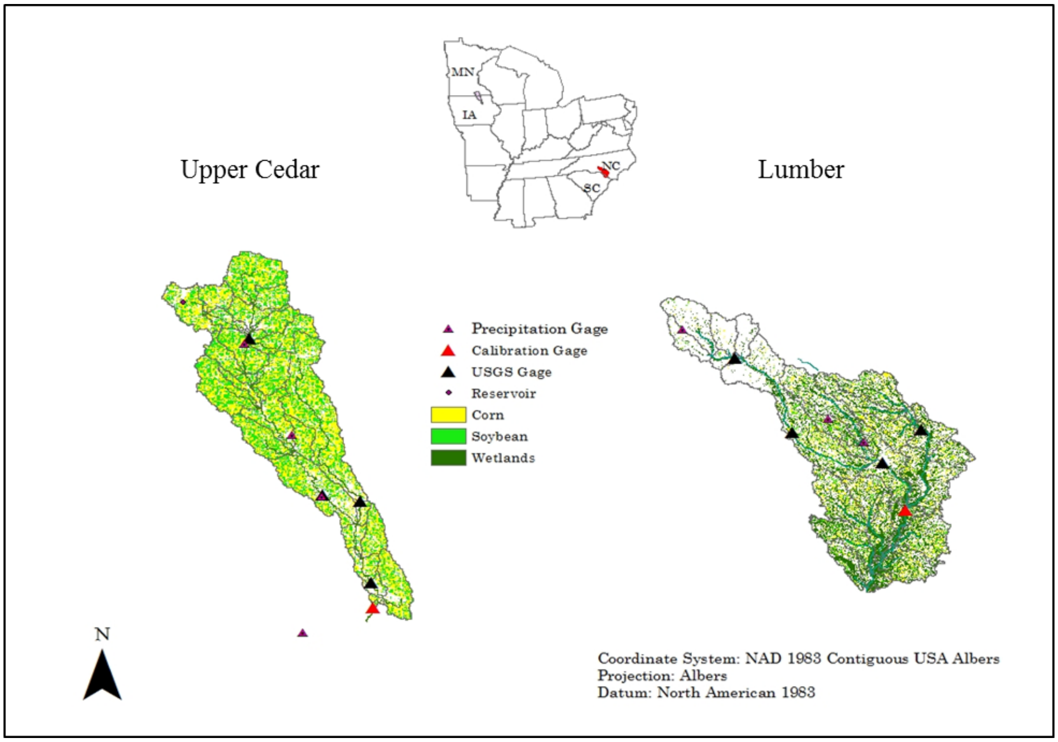

Figure 1-1: Map of the study watersheds – Upper Cedar in the Midwest and the Lumber watershed in the Southeast

Chapter 2 of my dissertation addresses this gap by studying watersheds from two regions – the tile-drained Upper Cedar watershed from the Midwest and the Lumber watershed from the Southeast that has a lot of riparian wetland vegetation (Figure 1-1). Using SWAT, I model, calibrate and validate the two watersheds for the baseline two-year corn-soy rotation. The SWAT model is a physically based basin-scale model that is very well suited to explore the soil and water quality impacts from land management practices (Arnold and Fohrer, 2005; Neitsch et al., 2005; Srinivasan et al., 2010). It is particularly useful in agriculture dominated watersheds, therefore the two watersheds chosen had agriculture as a dominant portion of its land-use – over 70% for the Upper Cedar and about 40% for the Lumber watershed. These watersheds are also representative of typical watersheds in the region in terms of land-use distribution. There were two objectives to this chapter: firstly, I wanted to explore if there were significant regional differences in water quality impacts from a similar land-use change (corn-soy to switchgrass in this case) and secondly, I wanted to understand land-use characteristics that may drive the impacts.

The results from the study show that tile drainage seems to exacerbate and riparian wetlands mitigate the water quality impacts from land management practices. Further, given the regional differences in corn and perennial productivity, there are differences in relative nitrogen loading between the two watersheds for a land-use change from corn-soy to switchgrass. This has significant implications on decisions optimizing feedstock sourcing depending on the decision maker, their objective and the scale of influence. While relative nitrogen differences between different regions are less important for planning at the watershed scale, they may be important for a system-wide policy analysis or optimization problems. I also use the baseline model developed in this chapter to simulate corn stover harvest and miscanthus production from cropland and switchgrass and miscanthus on pastureland in the two watersheds.

Quantifying and characterizing overall environmental impacts from the bioenergy mandate has been difficult because the bioenergy supply chain spans multiple decision makers across multiple scales (Cibin et al., 2015; Daystar et al., 2014; Gramig et al., 2013; Gutterson and Zhang, 2009; Stoof et al., 2015; You et al., 2012; Yue et al., 2014). Further, the drivers of decision making for each stakeholder, such as a federal or state-level policy maker, agricultural producer and ethanol producer, can be very different. In Chapter 3 of the dissertation, I explore the objectives of three federal agencies and their impact on the available crop mix in the two watersheds (Perlack et al., 2011; U.S. EPA, 2010; United States Department of Agriulture (USDA) and USDA, 2010).

The US-DOE Billion-Ton Report estimates the quantity of biomass at the county scale at different biomass prices using the Policy Analysis System (POLYSYS) model (Perlack et al., 2011). The model allocates feedstock based on maximizing the returns (profits) over the costs of feedstock production, assuming demands for food, feed and other markets are met. EPA's RFS2 Regulatory Impact Analysis optimizes the siting of biorefineries using a cost minimization algorithm to procure feedstock at the lowest price at the county-scale, to produce 16 BGY of biofuel by 2022 (U.S. EPA, 2010). The underlying model that estimates the quantity of biomass available in each county is the Forestry and Agriculture Sector Optimization Model (FASOM) which maximizes both producer and consumer welfare (returns over the costs for both agricultural producers and ethanol producers). USDA's Regional Roadmap to meet the mandate estimates the number of ethanol plants/biorefineries required to produce ethanol based on regional availability of feedstock (USDA , 2010). The regional availability of each feedstock was determined by experts at the ARS who made their calculations based on energy yield and other assumptions their estimates are based on are not clear. In Chapter 3, for the USDA objective I maximize the land-use efficiency or the energy produced per hectare for each watershed.

Using a Monte-Carlo Analysis (MCA) to characterize the uncertainty in production costs for the perennials (switchgrass and miscanthus) and variability in yields for the perennials, corn and stover harvest obtained from the SWAT simulation, Chapter 3 looks into how each objective impacts crop choice in each watershed. The optimal feedstock choice for bioenergy in the two regions was different when the different objectives were used. In the case of the Upper Cedar watershed, possibly due to very high productivity of corn-soy in the region, stover is the preferred feedstock. Miscanthus was preferred in the Lumber watershed. The change in the crop mix would impact the water quality differently. The analysis also finds that even with subsidies, there is a probability of negative returns for perennials under some cases while farm safety programs like crop insurance ensures that is not the case for commodity crops. This is a possible explanation to why there has not been an expansion in bioenergy production, especially on cropland, despite subsidies, as the economic risks of energy crops could be perceived to be higher.

There are several reviews of other studies optimizing of these various decision making objectives to overcome barriers to bioenergy production (Awudu and Zhang, 2012; Meyer et al., 2014; Scott et al., 2012). Awudu and Zhang (2012) identify decisions in the biofuel supply chain are of three primary types: (1) Strategic decisions that are long-term overarching decisions that cannot be changed often, such as the choice of technology for an ethanol plant or decisions ensuring sustainability of the system; (2) Tactical decisions are medium-term decisions that are geared towards achieving the goals of the long-term decisions, such as agricultural production decisions; and (3) Operational decisions are day-to-day operational decisions that ensure continuous operation of processes in the biofuel supply chain. These also identify the uncertainties that exist along each step of the biofuel supply chain and strategies that have been used to deal with them (Awudu and Zhang, 2012).

Scott et al. (2012) reviewed the methods used to address multi-criteria decision making in the context of the bioenergy system. They identify four categories of methods that have been used – optimization methods, predictive models to arrive at future scenarios, qualitative models based on survey and analysis of interviews or focus groups and miscellaneous methods like life cycle analysis or geospatial methods. About 72% of the studies they reviewed used optimization methods, however only 14% of the studies addressed sustainability objectives. Meyer et al. (2014) reviewed 71 studies between 1997 and 2012 that use MILP optimization scenarios to address the uncertainties in the bioenergy supply chain for these three decision types. Not surprisingly, a number of studies used the optimization on economic objectives such as minimizing overall costs or maximizing the net present value of the system (Shastri et al., 2011; Yue et al., 2014). Some studies also maximized net energy return or minimized greenhouse gas emissions (You et al., 2012). While water quality impacts from the mandate have been studied in isolation, until recently (Housh et al., 2015a, 2015b; Lambert et al., 2016), there have been few studies that look at the interdependencies between feedstock production and other processes downstream from production.

For example, Parish et al. (2012) use the Biomass Location for Optimal Sustainability Model (BLOSM) to improve sustainability across a watershed while simultaneously improving farmer profitability. They integrate data on biomass availability on a county scale from Policy Analysis Systems model (POLYSYS) with the environmental model SWAT (Parish et al., 2012). While their study showed improvement in both objectives through planned plantings of switchgrass across a watershed, they did not consider the location of biorefineries or the rest of the biofuel supply chain in their study.

Reconciling decisions on biorefinery locations that depend on demand and are made at larger scales and water quality impacts that are often local is especially difficult. Housh et al. (2015a) address this through a system of systems approach including feedstock production, logistics, biofuel production and distribution. The model makes land-use decisions at the downscaled land-parcel level (10 km x 10 km) from county-level yields. However, the SWAT model, which they use to determine water quality impacts, is spatially explicit at the sub-watershed level based on topographical characteristics. Therefore, they develop an equation to overlap the two spatial scales and determine the percentage of each land-parcel at the sub-watershed scale. This ensures that the interdependency of the supply and demand side is reflected in the water quality impacts as well. Their model seeks to maximize profitability for corn-soy producers (or their alternatives) as well as ethanol producers similar to the objective of the EPA Regulatory Impact Analysis, using an

MILP. They consider stover and miscanthus alternatives on cropland and find that cellulosic ethanol production could be considered a strategy for mitigating nitrogen pollution. However, the model fails to account for conversion from marginal, idle or pastureland. Studies have shown that it is likely that these lands are preferentially convert to cellulosic feedstock production in regions that have low corn productivity (Gelfand et al., 2013; Sharp and Miller, 2014).

Lambert et al. (2016) reconcile the interdependencies by integrating the Biofuels Facility Location Analysis Modeling Endeavor (BioFLAME) model (Wilson, 2009), a cost- minimizing site selection model with a hydrologic water quality model - Spatially Referenced Regressions on Watershed Attributes (SPARROW) - to predict land-use change and water quality impacts from RFS2 implementation in the Southeast (Lambert et al., 2016). The study first generates least-cost biorefineries based on level of RFS2 implementation and then predicts water quality impacts from the mandate. They find that water quality improvements in the region from perennials maybe overstated as marginal land is likely to be converted before cropland that is more intensively managed. However, Lambert et al. do not consider the optimization of the biorefinery locations for water quality.

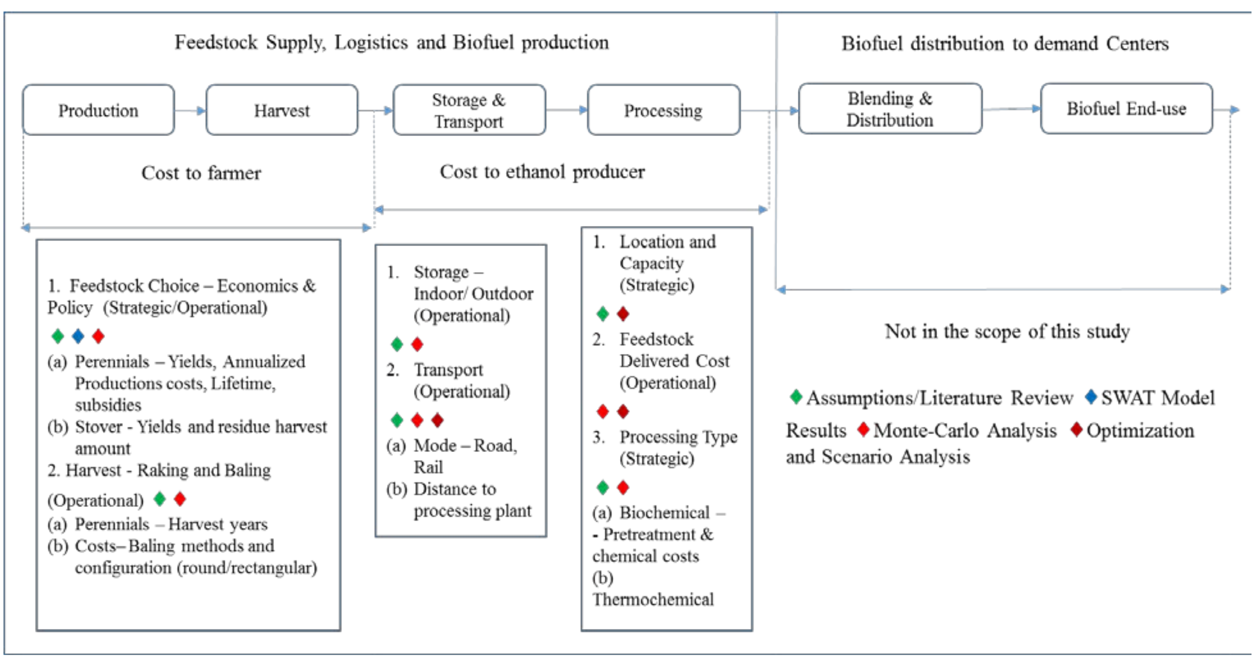

Figure 1-2: Scope of study and methods used to address uncertainty and variability in the biofuel supply chain

Although the two studies above are able to reconcile water quality impacts to the rest of the bioenergy supply chain, a question remains as to whether it is possible to further reduce the impacts from the mandate by including water quality metrics in the siting of biorefineries. If this could be accomplished, it is important to consider the tradeoffs with profitability to determine when such a process is necessary. In Chapter 4 of my dissertation, I consider a simplification of the upstream and midstream processes of the bioenergy supply chain and the uncertainties inherent in them (Figure 1 -2). Using Hydrologic Response Unit (HRU) level data generated by the SWAT model for yields and nitrogen output, I generate future land-use scenarios based on the three federal agency objectives explored under Chapter 3 for cropland and pastureland. I find that there are trade-offs between profitability and water quality for the three land-use scenarios generated by the optimization. Further, land-use change is "local" (Kim and Dale, 2015) to the location of the bio-refinery and consequently water quality impacts are often highly localized as well. Therefore, given that locations of biorefineries as well as sustainability are strategic, long-term decisions I argue that in sensitive watersheds, it may be necessary to include sustainability metrics in the siting of the bio-refinery at the sub-watershed scale rather than optimizing or planning plantings of cellulosic feedstock after a site has been established.

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Chapter 2 : Regional differences in impacts to water quality from the Bioenergy Mandate

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Abstract

The bioenergy mandate under Energy Independence and Security Act (EISA 2007) will result in large scale land-use changes in the US if it is ever fully realized. Energy crops such as switchgrass (Panicum virgatum) and miscanthus (Miscanthus X giganteus) can grow well throughout the continental United States; however, most studies on the water quality impacts of land-use change from bioenergy policy are based in the Midwest. Insufficient research has been conducted to determine whether the results from the Midwest are applicable to other regions in the United States. This study compares water quality impacts of converting from corn to switchgrass in the Midwest (Upper Cedar watershed) and Southeast (Lumber watershed) with nitrogen loading to surface water as a proxy metric for overall water quality impacts using the Soil and Water Assessment Tool (SWAT). The analysis shows that the fraction of nitrogen runoff compared to the fertilizer applied is 36% in Upper Cedar as compared to 6% in Lumber. Existing management practices like tile-drainage and land-cover like riparian wetlands contribute to this difference in the baseline nitrate export from each watershed. The potential reduction in nitrogen loading per potential gallon of ethanol to surface waters, which account for both nitrate export and productivities, from the baseline corn/soy to switchgrass is about 40% for the Upper Cedar watershed and around 80% for the Lumber watershed. Although, the trend in reduction is similar in both watersheds, this study shows that results extrapolated from the Midwest may not be representative of other bioenergy producing regions

1. Introduction

Following concerns over energy security and efforts to reduce greenhouse gas emissions to mitigate climate change, the US Energy Independence and Security Act (EISA 2007) mandated the production of 36 billion gallons of biofuel to be used in the transportation sector by 2022. This includes 15 BGY of corn ethanol and 21 BGY of cellulosic and other advanced biofuel. The updated Billion-Ton Annual Supply Report (BT2), commissioned by the US Department of Energy (DOE) and Department of Agriculture (USDA), predicted that the production of biofuels to meet the mandate would result in a land-use change of 40-60 million acres on agricultural and marginal land (Perlack et al., 2011). The BT2 analysis includes all states in contiguous US with significant quantities of feedstock coming from outside the Midwest. Such large scale land use change will significantly impact water resources, both in terms of quality and quantity.

The current knowledge about the impacts from the mandate comes from field studies (Nyakatawa et al., 2006; Sarkar et al., 2011; Thornton et al., 1998), modeling studies at the field, farm and watershed scales (Cibin et al., 2012; Love and Nejadhashemi, 2011; Thomas et al., 2009) and system-wide studies in the Mississippi River Basin in the context of the Gulf of Mexico hypoxia (Costello et al., 2009; Donner and Kucharik, 2008). The United States EPA (US Environmental Protection Agency, 2011), the National Research Council (National Research Council Committee, 2007) and the Government Accountability Office (US General Accountability Office, 2009) have extensively reviewed available literature on agricultural land-use change to evaluate the impacts of EISA 2007. These studies indicate that that the nature and magnitude of the impact of agricultural land-use change on water quality depends on the prior land-use, crop type, climatological, topological factors and management practices (Baskaran et al., 2010; Demissie et al., 2012; Wu et al., 2012). While intensification of row crop agriculture for bioenergy feedstock cultivation will undoubtedly impair water quality, not all impacts from biofuels are negative or equal in magnitude. Studies have shown that growing perennial grasses in the place of corn/ other row crops for cellulosic ethanol mitigates water quality impacts and improves soil quality (Ng et al., 2010; Randall et al., 1997; Sarkar et al., 2011).

The large scale studies that have evaluated the impacts of the mandate on water quality have been primarily in the context of the Gulf of Mexico hypoxia and therefore focus on land use change in the Mississippi River Basin (MRB). System-wide studies, which we define here as the studies that look at implementation of the 22 BGY EISA goal, have been generally assumed that all conventional and cellulosic ethanol in the US will be grown within the MRB. The challenge in conducting a large scale study is the uncertainty in predicting the future land-use in different parts of the US, therefore some system-wide studies address it in one of two ways; using deterministic models or physically based models coupled with agent based/economic models to model the future land use change (Donner and Kucharik, 2008) or employing scenario analysis to construct future landscapes (Costello et al., 2009; Demissie et al., 2012). Comparing these system wide studies show that the impacts from the mandate are scenario specific and goal-specific.

If all the production from EISA 2007 were to occur in the MRB, these studies indicate that the mandate may be unsustainable from a water and soil perspective. Perennials such as switchgrass and miscanthus have high, if not higher, productivity in the Southern and Southeastern parts of the United States (Behrman et al., 2013; McLaughlin and Kszos, 2005; Migue et al., 2012).There also has been recent interest in using marginal land in the Midwest and Northeast to grow alternative energy crops (Gelfand et al., 2013; Stoof et al., 2015). Therefore it is necessary to consider all major agricultural regions in the US to better understand how different land use changes in different regions will have different water quality impacts. Unfortunately, there are few studies that analyze the regions outside the Corn Belt and fewer still outside the MRB, either through modeling efforts or collection of field data and none that are at the system-wide scale to the best of our knowledge. Further, within the MRB there are far more modeled studies in the Corn Belt than other regions.

While the land-use change impacts, especially the conversion from a field crop to perennials, follow similar trends as in the Corn Belt, a comparison of relative differences between different regions has not yet been assessed. There are a number of field studies on small controlled plots (Garten et al., 2010; Nyakatawa et al., 2006; Thornton et al., 1998) but fewer modeling studies outside the MRB specifically looking at water quality impacts from bioenergy conversion (Parajuli, 2012; Sarkar et al., 2011; Sarkar and Miller, 2014). Of two recent studies looking at land-use change from cotton to switchgrass in the southeastern Coastal Plains in South Carolina and southern plains in Texas (Chen et al., 2015; Sarkar et al., 2011; Sarkar and Miller, 2014), only one looks at water quality impacts.

It is also more challenging to apply the methods used by the system-wide studies such as Donner and Kucharik (Donner and Kucharik, 2008) and Demissie et al. (Demissie et al., 2012) to areas outside the Mississippi River Basin using physically based hydrological models such as the Soil and Water Assessment Tool (SWAT). Most hydrological models, including SWAT, were developed specifically for watersheds dominated by agriculture (Neitsch et al., 2005; Srinivasan et al., 2010). Many of the agricultural regions outside the Corn Belt are characterized by heterogeneous landscapes that are more difficult to model and are data-scarce. SWAT requires more calibration from the defaults when applied to watersheds with poorly drained soils and mixed land-use, wetlands or forests, as is often the case in the watersheds in Southeastern Coastal Plain (Bosch et al., 2004; Golden et al., 2014; Wu et al., 1997). Nutrient monitoring data is less frequently available in these regions, making model calibration difficult. Despite these challenges, a comprehensive analysis of the biofuel mandate should incorporate regional differences in expected water quality impacts based on region-specific parameters.

Although there have been studies that have compared differences in water quality impacts from the mandate between watersheds (Cibin et al., 2015; Love and Nejadhashemi, 2011), this is the first study to our knowledge, that compares impacts between watersheds in two different regions. We demonstrate that there are significant regional differences in impacts to water quality for similar land-use transitions. The SWAT model was used to simulate the impacts of agricultural land management practices on nitrogen loading assuming a two-year corn-soy rotation replaced by switchgrass. The percentage difference in nitrogen loading per unit potential bioenergy produced between corn-soy rotation and switchgrass of an agriculture-dominated watershed in Iowa is compared to that of a more diverse watershed in North Carolina.

2. Data and Methods

2.1 Study Areas

The Upper Cedar River watershed in Iowa and the Lumber watershed in North Carolina were chosen to ensure that agriculture formed a significant portion of the land-use (Figure 2-1). From a simple statistical evaluation looking at the percentage of each land cover class, including agriculture, wetlands, forest, barren and water watersheds in the Midwest (387 watersheds) and southeastern region (432 watersheds), these watersheds appear to be fairly representative of the regions as represented by Figures 1 and 2 in Supporting Information (Appendix **A**).

The Upper Cedar Watershed (USGS HUC8 07080201, 1700 sq. mi.), located between 43° 45' 16.3" N, 93° 14' 47.1" W and 42° 43' 15.5" N, 92° 22' 1.8" W, is one of six sub-basins in of the Cedar River Basin, a well-studied region with more than 81% agriculture (IDNR, 2006). Within Upper Cedar Watershed, more than 70% of the total landcover is corn-soy rotation with extensive tile drainage (USDA CDL 2007), which is typical for the Midwest Corn Belt. The soils are primarily loamy derived from glacial till (Kocian et al., 2012) and are mostly poorly drained. The annual precipitation is between 800-900mm with the highest amount of precipitation occurring in the summer months (Iowa Flood Center, 2014).

The Lumber watershed (USGS 03040203, 1810 sq. mi.) in the Coastal Plain region of North Carolina and South Carolina, located between 35° 12' 39.81" N, 79° 38' 0.46" W and 34° 11' 26.51" N, 78° 44' 43.23" W is primarily wetland dominated (35%), with a large percentage of the land-use in forested land(26%) and agriculture (24%). The Coastal Plains are characterized by high annual precipitation (~1250mm/year), sandy-loamy soils and high evapotranspiration during the hotter months (Golden et al., 2014). The watershed is a part of the Coastal Plain and

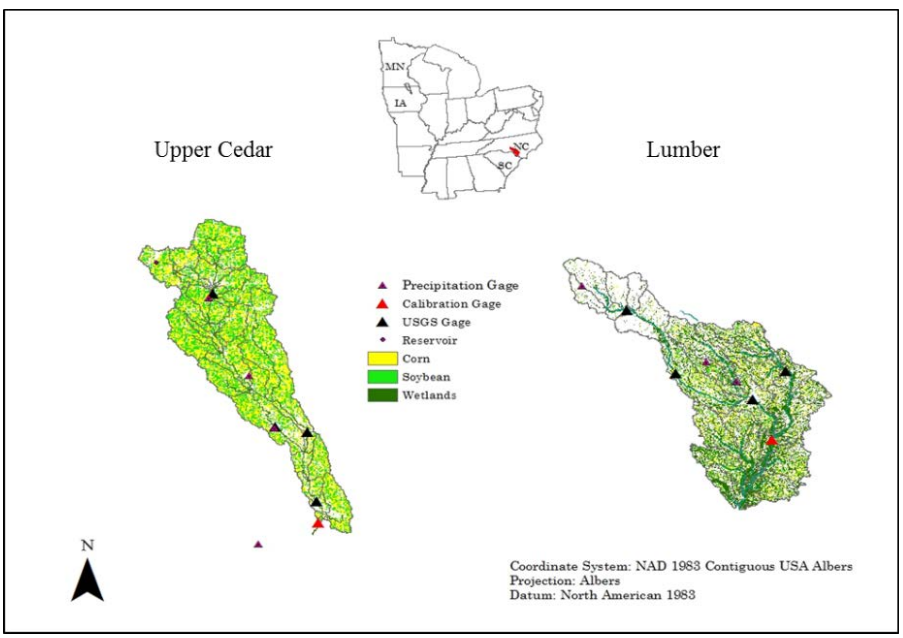


Figure 2-1: Map of the study watersheds – Upper Cedar in the Midwest and the Lumber watershed in the Southeast

groundwater discharge in wetlands contributes a significant portion of streamflow to riverine transport.

The presence of tile drainage in one watershed and riparian wetlands in the other makes the study of these two watersheds an exceptionally contrasting one. Tile drainage in the Midwest has steadily increased the proportion of baseflow in the watersheds. It has been found that the increasing nitrate export to surface waters in Iowa is correlated to the base flow (Schilling and Helmers, 2008; Schilling and Lutz, 2004). On the other hand, wetlands reduce nutrient export by settling nutrients, increasing their absorption into sediments, uptake through growth of biomass and presenting good conditions for denitrification (Acreman and Fisher, 2004). Therefore, the results of this study could also offer insight into the range of reduction in nitrogen export from LUC.

2.2 The SWAT Model

The Soil and Watershed Assessment Tool (SWAT) is a well validated, continuous time physically based hydrologic model that can simulate impacts of agricultural land management practices on sediment and nutrient loading (Arnold and Fohrer, 2005). The model has eight main sub-components including hydrology, soils, weather, sediment transport, plant growth, nutrients, pesticides and agricultural management (Arnold and Fohrer, 2005). SWAT delineates watersheds and the stream network based on the digital elevation model (DEM) input by the user or based on a pre-defined watershed. The watershed is further divided into sub-watersheds. All processes in SWAT are simulated at the Hydrologic Response Unit (HRU) level, that represent unique soil, slope and land-use characteristics within each sub-watershed. Flow, sediment yield and nutrient loading are simulated across all HRUs in a sub-watershed and are routed to the watershed outlet through the stream channels.

ArcSWAT 2012 was used to delineate the watershed using elevation data from the National Elevation Dataset at 30m resolution and SSURGO soil data layer, both downloaded from US Geospatial Data Gateway. HRU's were delineated by overlaying land use, soil and slope layers in the interface. Three slope classes were introduced to delineate the watersheds – 0 – 2%, 2-5% and greater than 5% to represent gentle, moderate and steep slopes. Further a threshold of 10% of subbasin area was used for land-use and soil type. The Upper Cedar watershed was delineated into

30 sub-basins with 2307 HRUs out of which 567 were in corn/soy rotation, 122 HRUs were deciduous forest, 1328 HRUs were either marginal lands (bermudagrass) or pasture and 46 HRUs were wetlands. Lumber watershed was delineated into 34 subbasins with 2487 HRUs out of which 378 HRUs were in corn/soy rotation, 35 HRUs were wheat, 10 HRUs 1006 HRUs were either marginal lands (bermudagrass) or pasture, 98 in rangeland, 462 HRUS in evergreen and deciduous forest cover and 195 HRUs in wetlands. The percentage of HRUs in each land-use speak to the difference in land cover between the two watersheds – with Midwestern landscape being fairly homogenous compared to the one in the Southeast. The climate and soils data used for the SWAT model for the two watersheds has been summarized in the Table 2-1.

Table 2-1: Data used for setting up the SWAT Model

Input Data	Upper Cedar Watershed	Lumber Watershed
Landuse[a]	CDL 2007/2006 IA/MN	CDL 2006 NC/SC
DEM[b]	NED 30 m	NED 30 m
Soils[c]	GSSURGO	GSSURGO
Weather Stations[d]	NCDC Weather Stations (USC00136492, USC00210355, USC00136305, USC00131402)	NCDC Weather Stations (USC00314464, USC00317165, USC00315177)
USGS Gage for Hydrologic Calibration (Multiple) – add the other gages	USGS 05457000 Cedar River near Austin, MN USGS 05458500 Cedar River at Janesville, IA	USGS 02133500 Downing Creek near Hoffman, NC USGS 02314500 Lumber River near Boardman, NC
USGS STORET Gage – Nutrient calibration	USGS 05458500 Cedar River at Janesville, IA	USGS 02314500 Lumber River near Boardman, NC

[a.] USDA Cropland Data Layer, [b] National Elevation Dataset, [c] Gridded Soil Survey Geographic (SSURGO) can be downloaded from NRCS GIS Data Gateway (https://gdg.sc.egov.usda.gov/); [d] National Climatic Data Center (http://www.ncdc.noaa.gov/)

2.2.1 Modeling tile drains in the Upper Cedar watershed

The presence of poorly drained soils in the watershed requires the installation of tile drains to avoid water-logging. Tile drainage was simulated based on the classification of drainage characteristics of the SSURGO soils for the Upper Cedar watershed. HRUs with soils that were classified as "somewhat poorly", "poorly" or "very poorly" drained and in row crop production were assumed to have tile drainage. About 64% of the corn-soy HRUs (50% of the total watershed area) were tile drained.

2.2.2 Modeling of wetlands in the Lumber watershed

Wetlands and forests have a major impact on the hydrology of the watershed. Although SWAT is able to model wetlands, there are relatively few applications of SWAT in literature that incorporate wetlands. Studies note that SWAT requires extensive calibration to model watersheds with a high percentage of wetlands and lakes (Wang et al., 2008; Wu and Johnston, 2008). However, the inclusion of wetlands within the model for such watersheds greatly improves model performance (Schmalz et al., 2008). SWAT allocates only one wetland/pond per subbasin and determining the fraction of water entering the wetland, so this study uses the aggregated Hydrological Equivalent Wetland (HEW) concept within SWAT (Wang et al., 2008) for the simulation of wetlands. From a literature review, parameters that are important for wetland calibration were obtained including wetland surface area and volume that drive storage, subbasin tributary length, Mannings coefficient of the channel, and hydraulic conductivity of the wetland channel that drive conveyance and retention in the wetland (Liu et al., 2008; Schmalz et al., 2008; Wang et al., 2008; Wu and Johnston, 2008).

Initial wetland parameters for the four most upstream subbasins from the hydrological calibration gage in the watershed are listed in Table 2-2. The maximum surface area were calculated by geospatial analysis. The depth parameter was manually calibrated to fit the streamflow data. The fraction of water entering the HRU was estimated to be between 0.85 – 1 as most sub-basins had riparian wetlands along their channel upon visual inspection of the Cropland Data Layer.

Table 2-2: Calculation of Wetland Parameters calculated using HEW concept by Wang et al. [40]

Sub-basin Number	Samax[a] (ha) (calculated)	Depth[b] (m)	Vmax[c] 10^4 cu. M	San/Samax	Sanormal[a] (ha)	Vn/Vmax	Vn[b]* 10^4 cu. m
9	5506.23	0.4	2202.50	0.6	3303.74	0.4	881.00
10	766.75	0.4	306.70	0.6	460.05	0.4	122.68
11	656.69	0.4	262.64	0.6	393.96	0.4	105.05
12	4576.24	0.4	1830.50	0.6	2745.75	0.4	732.20

[a.] Maximum surface area of wetland calculated from land cover, normal surface area assumed to be 60% of this area [b] Depth of ponding approximated to be 40 cm based on average maximum inundation tolerance of native species used in constructed wetlands, the normal volume is assumed to be 40% of maximum inundation volume

2.2.3 Modeling corn-soy rotation and switchgrass growth

A two-year corn-soy rotation was simulated from 1990-2004 using data from the Cropland Data Layer database in 2007 for Iowa and Minnesota and CDL 2006 for North Carolina (USDA CDL 2007). The land-use layers in 2007 and 2006 were selected because they capture the landscape characteristics prior to the impacts of EISA 2007. Data from the US Department of Agriculture National Agricultural Statistical Service (USDA NASS), including planting and harvesting dates (average 50% planting dates) and average fertilizer application over the period, was used to approximate management practices in the two regions, as well as recommendations from the state extension services (ISU University Extension, 2009). Tillage practices were adjusted according to Conservation Technology Information Center (CTIC) survey from 1990 – 2004. For Upper Cedar corn had reduced tillage practices from 1997 – 2004.

For the Upper Cedar watershed, this study also referred to management practices summarized by Hutchinson et al that used the SWAT model to simulate hydrology and water quality for the entire Cedar River Basin (Hutchinson and Christiansen, 2013). The study used average monthly nitrate loads for point sources from the National Pollutant Discharge Elimination System (NPDES) permitted facilities in the basin (https://www.epa.gov/npdes), estimated for the years 2007 – 2014 for the simulation years.

Once the baseline was established and the model calibrated, all the HRUs previously in corn-soybean rotation were converted to switchgrass. The calibrated parameter set was used at the basin and subbasin level, but HRU parameters for switchgrass were left at their default value except those pertaining to tile drainage. Different cultivars are likely to be chosen in the two regions according to biomass potential, lignocellulosic content and winter hardiness and both regions have a suite of cultivar choices (Lemus et al., 2002). Alamo and Shawnee switchgrass were chosen as representative of the lowland and upland types, as their plant growth parameters are documented in SWAT. For the Upper Cedar watershed, Shawnee switchgrass, that is an upland ecotype with superior biomass production potential in the region, was simulated based on the parameters developed by Trybula et al (Trybula et al., 2015). Alamo switchgrass was simulated for the Lumber watershed. The agricultural management practices for the two watersheds is summarized in Table 2-3. For both watersheds, the study assumed no nitrogen application in the establishment year to prevent invasive weeds and competition from other perennial grasses and a 12-year rotation with a one-cut harvest system and reestablishment on the switchgrass stand at the end of 12 years.

2.3 Calibration and validation of corn-soy rotation

Both watersheds were calibrated for hydrology and nitrate-nitrite nitrogen. The Upper Cedar watershed was calibrated for hydrology from 1997-2000 and validated from 2001-2004 at two USGS gages; upstream at 05457000 Cedar River near Austin, MN and at the watershed outlet at 05458500 Cedar River at Janesville, IA. The Lumber watershed was calibrated for hydrology at two outlets from1997-2000 and validated from 1993-1997; upstream at USGS 02134480 Downing Creek near Hoffman, NC and USGS 02314500 Lumber River near Boardman, NC. Multi-site calibration was carried out to counter the equifinality problem of having multiple optimal parameter sets [6].

Table 2-3: Crop Management Practices

	Date	Operation	Notes	Date	Operation	Notes
	Upper Cedar			Lumber		
Corn	1-April	Manure Application		4-April	Deep Spring Till with Ripper	Based on CTIC surveys and dig up hard pan
	15-April	Conservation Till	Based on CTIC* surveys	15-April	Fertilizer Application	DAP @300 kg/ha

	20 - April	Spring Fertilizer		20-April	Plant Corn	
	25-April	Plant Corn		15-July	Sidedress Fertilizer	32% UAN (N@112kg/ha)
	1-Jun	Fertilizer** Application	Anhy. NH3@112 kg/ha, P@70 kg/ha	15-Oct	Harvest and Kill	
	25-Oct	Harvest and Kill	-			
Soybean	20-April	Fertilizer Application	DAP@110 kg/ha	15-April	Deep Spring Till with Ripper	To dig up hard pan
	15-May	Plant Soybean		1-May	Fertilizer Application	DAP@115kg/ha
	1-Nov	Harvest and Kill		1-June	Plant Soybean	
	6-Nov	Reduced Till	Based on CTIC surveys	1-Sept	Fertlizer Application	
	10-Nov	Fertilizer Application	Anhy. NH3@50 kg/ha	11-Nov	Harvest and Kill	
Switchgrass	15-May	Plant Switchgrass	Shawnee	1-May	Plant Switchgrass	Alamo
	1-Jun	Fertilizer application	Anhy. NH3@85kg/ha[2], P@70 kg/ha	15-May	Fertilizer application	Anhy NH3@90 kg/ha[3],P@60 kg/ha
	25-Oct	Harvest Only/ Harvest and Kill	12 year rotation	1-Oct	Harvest Only/ Harvest and Kill	12 year rotation

*Conservation Technology Information Center Survey on Crop Residue Management (1990-2004); ** USDA National Agriculture Statistical Service data

Calibration for hydrology is especially important because nutrient data is not as readily available for most regions. Thus calibration, particularly with respect to partitioning between surface and base flows can reduce uncertainty in nutrient estimates (Feyereisen et al., 2007; Sarkar and Miller, 2014). Parameters for calibrating hydrology were chosen by a combination of literature review and sensitivity analysis (Feyereisen et al., 2007; Lemus et al., 2002; Sarkar and Miller, 2014).This study used the Nash-Sutcliffe efficiency and PBIAS to characterize model performance. Model simulation is considered satisfactory when NSE > 0.5 and PBIAS < +/-25% for streamflow and PBIAS < +/- 70% for nutrient calibration (Moriasi et al., 2007).

[2] M. Khanna, B. Dhungana, J. Clifton-Brown, Costs of producing miscanthus and switchgrass for bioenergy in Illinois, Biomass and Bioenergy. 32 (2008) 482–493. doi:10.1016/j.biombioe.2007.11.003.
[3] S. Sarkar, S.A. Miller, Water quality impacts of converting intensively-managed agricultural lands to switchgrass, Biomass and Bioenergy. 68 (2014) 32–43. doi:10.1016/j.biombioe.2014.05.026.

Approximate sensitivity of parameters were determined using the relative sensitivity to monthly total flow. The relative sensitivity is calculated using an equation (White and Chaubey, 2005):

$$Sr = x/y * \left((y2 - y1)/(x2 - x1)\right) \quad (1)$$

Where x is the initial value of the parameter prior to calibration, y is the initial value of the objective function, (monthly NSE for total flow). x2 and x1 are +/- 10% of initial parameter value and y2 and y1 are the objective function values at x2 and x1 respectively. The higher the relative sensitivity of a parameter, the more sensitive it is to streamflow calibration and consequently the parameters were ranked in the order of their sensitivity. These parameters were then adjusted manually to calibrate the flow at the gage.

A process adapted from Santhi et al. and Malago et al. was used to calibrate the watersheds (Malagò et al., 2014; Santhi et al., 2013). The streamflow was partitioned into baseflow and peakflow using the Baseflow Filter program (http://swat.tamu.edu/software/baseflow-filter-program/)(Arnold et al., 1995) to correctly calibrate the processes that control them. This separation is necessary to correctly predict the chemistry and transport of both sediments and nutrients (Feyereisen et al., 2007). In this study, hydrology monthly and daily total flow, base flow and peak flows were calibrated followed by calibration of nitrate by the modified NSE method.

For nitrogen calibration, only grab sample data were available for both watersheds from the STORET (STOrage and RETrieval data warehouse, http://www.epa.gov/storet/) and NWIS (National Water Information System, http://waterdata.usgs.gov/nwis). The Upper Cedar watershed was calibrated at the watershed outlet (Cedar River near Janesville) and the Lumber watershed was calibrated at the Boardman gage. Calibration parameters for nitrate calibration were chosen based on literature review (Boles, 2013; Bosch et al., 2004; Cibin et al., 2015; Demissie et al., 2012; Sarkar et al., 2011; Sarkar and Miller, 2014; Wang et al., 2008). A modified Nash-Sutcliffe goodness-of-fit method (Cibin et al., 2012) was used to determine the calibrated model performance. This method accounts for the temporal uncertainty in the management practices. For example, for North Carolina, the planting dates of corn were between April 20– June 1 in the year 1994 (National Agriculture Statistical Service dataset). Therefore, there is uncertainty in nutrient input and demand within a county and this scales up to the watershed level. Similar to Cibin et al, this study considers a time interval of +/- 15 days for each observation (Cibin et al., 2012). A modified NSE of 0.5 is considered satisfactory.

2.4 Calculation of nitrogen loading per unit area and per gallon of ethanol

The land-use change from corn-soy rotation to switchgrass will likely result in reduction of nitrate to surface waters. This study uses nitrate/nitrite-nitrogen as a water quality impact proxy metric because the runoff from the Upper Cedar watershed and the Lumber watershed flow to water bodies that are nitrogen limited for eutrophication; the Gulf of Mexico for the Upper Cedar watershed (Rabalais et al., 1994) and the Winyah Bay for the Lumber watershed (Ranhofer et al., 2009). Two quantities were calculated for both watersheds: (i) The difference in the nitrogen yield on an area basis (kg N/ha) between corn-soy rotation and switchgrass (ii) The difference in nitrogen yield per potential gallon of ethanol basis (kg N/ gal ethanol) between corn ethanol and cellulosic ethanol from switchgrass. Both metrics were calculated at the sub-basin level for nitrogen output and yields averaged over 1993 – 2004. The upstream sub-basins of each sub-basin outlet was determined by the Upstream Subbasins Utility program in SWAT CUP (Abbaspour et al., 2007). A bushel of corn was assumed to yield 2.84 gallons of ethanol (Wallace, R., Ibsen, K., McAloon, A. and Yee, 2005) while one dry ton of switchgrass was assumed to yield 79 gallons of cellulosic ethanol (Heaton et al., 2008).

The difference between nitrogen loading from corn-soy and switchgrass in the Upper Cedar watershed was then compared to that from the Lumber watershed. The metric evaluates the environmental cost/benefit of sourcing ethanol from a particular region as compared to another. The average nitrogen loading from an average of twelve simulated years (not including the warm-up years from the SWAT model) was calculated to account for the variation in nitrate in surface runoff in dry versus wet years as precipitation in each year strongly influences both the quantity of runoff and the nitrate in it (Hatfield et al., 2009).

Average annual nitrogen loading Ni (kg N/yr) of sub-basin *i* over simulation period for corn-soy and switchgrass for each subbasin was calculated using equation (2)

$$\mathrm{Ni} = 1/12 * (\sum_{1993}^{2004} \sum_{\mathrm{Jan1}}^{\mathrm{Dec\ 31}} (NO_3 + \mathrm{NO_2})_{\mathrm{out_{daily}}} \qquad (2)$$

Where the daily nitrate and nitrite was obtained from SWAT output to the reach level

For the first metric, this sub-basin level nitrogen was divided by the upstream area. For the second metric, the average annual productivity Pi (kg biomass/year) for corn/soy and switchgrass in each sub-basin *i* over the simulation period was calculated using equation (3)

$$\mathrm{Pi} \ = \ 1/12 * \sum_{1993}^{2004} \mathrm{YiAi} \qquad (3)$$

Where the Yi, yield (kg/ha) and Ai, area (ha) of corn/soy and switchgrass in each subbasin for each year was obtained from SWAT management output file

The metric M (kg N/ gallon) of ethanol was evaluated using the conversion efficiency for conversion for corn and switchgrass into ethanol with equation (4)

$$\mathrm{Mi} \ = \ \mathrm{Ni}/(\mathrm{Pi} * \mathrm{conversion\ eff}) \qquad (4)$$

3. Results

3.1 Calibration and Validation of the Upper Cedar model

The upstream gage at USGS 05457000 was calibrated first followed by USGS 05458500 at the watershed outlet. Snow processes that are calibrated at the basin level were especially important for calibration of the upstream gage at Cedar River near Austin Minnesota. The Hargreaves method was used for the estimation of Potential Evapotranspiration (PET) because it simulated baseflow better in this watershed. The daily curve number that controls infiltration of precipitation into the soil was calculated as a function of plant evapotranspiration. As expected, tile drainage processes were important at both gages. Although tile drainage is part of the return flow to the stream, it shows up in the hydrograph as a sustained peak over many days (Boles, 2013). Calibrating tile related parameters, especially DEP_IMP, the depth to the impervious layer, was important in improving the simulation as DEP_IMP controls the permeability of the soils (Boles et al., 2015).

Table 2-4: Calibrated Parameters in Upper Cedar (listed according to Sensitivity ranking)

Parameter		Process	Initial Value	Final Calibrated Value
CN2	.mgt	Surface Flow	Varies (31-77)	(-5% to -15%)**
ESCO	.hru	Lateral Flow	0.95	0.85
SOL_AWC	.sol	Lateral Flow	Varies(0.01 - 0.23)	(+20%)
OV_N	.hru		0.14	0.12
SLSUBBSN'	.hru		Varies 9.15 - 122	
SMFMX	.bsn	Snow (surface)	4.5	2.5
SMTMP	.bsn	Snow (surface)	1	-0.5
SLOPE	.hru		Varies 0.008 - 0.263	Not changed
CH_NI	.sub		0.014	0.065
CH_NII	.rte		0.014	0.065
SMFMN	.bsn	Snow (surface)	4.5	2.5
GWQMN	.gw	Base Flow	1000	0
ALPHA_BF	.gw	Base Flow	0.048	0.01
GW_DELAY	.gw	Base Flow	31	2
GW_REVAP	.gw	Base Flow	0.02	0.02
SFTMP	.bsn	Snow (surface)	1	1
SURLAG	.bsn	Surface Flow	4	8
DEP_IMP*	.hru	Tile Flow	6000	3850 for undrained 1200 for drained HRUs

Description of parameters: CN2 – SCS Curve Number; ESCO – Soil Evaporation Compensation Factor; SOL_AWC – Available Soil Water Capacity (mm H_2O mm^{-1} soil); OV_N – Manning's "n" value for overland flow; SLSUBBSN – Slope of the subbasin; SMFMX –Melt Factor for Snow on June 21 (mm H_2O °C^{-1} day^{-1}) ; SMTMP – Snow melt base temperature (°C) ; SLOPE – Slope of HRU; CH_N1- Manning's "n" for the channel; CH_N2 – Manning's "n" for the reach; SMFMN – Melt Factor for Snow on December 21 (mm H_2O °C^{-1} day^{-1}) ; GWQMN – Threshold depth of water in shallow aquifer for return flow (mm); ALPHA_BF – Baseflow recession factor (day^{-1}); GW_DELAY – Groundwater delay time (days); GW_REVAP – Groundwater Revap Coefficient; SFTMP – Snowfall temperature (°C) ; SURLAG – Surface Runoff Lag Coefficient; DEP_IMP – Depth to Impervious Layer (mm) *Suggested by Boles et al. (Boles, 2013). ** CN2 varied over a range, for HRUs upstream of USGS 05457000, CN decreased by 5% and the rest by 15%.

Accordingly, DEP_IMP was varied differently for HRUs that were drained and those that were not. Alpha_BF or the baseflow recession factor had to be increased from the value predicted by the Baseflow Recession Filter, to reflect faster drainage. The final calibration values of the adjusted parameters is summarized in Table 2-4. Calibration statistics at the daily and monthly timescales for total, peak and baseflow are listed in Table 2-6. The parameters for calibration of nitrogen were chosen based on Hutchinson et al (Hutchinson and Christiansen, 2013). The model was considered to be calibrated satisfactorily, with a modified NSE was 0.92 for calibration at the watershed outlet and for validation years it was 0.63. A visual inspection of the hydrograph

revealed that SWAT appeared to simulate high discharge periods better than low discharge periods (
Figure 2-2).

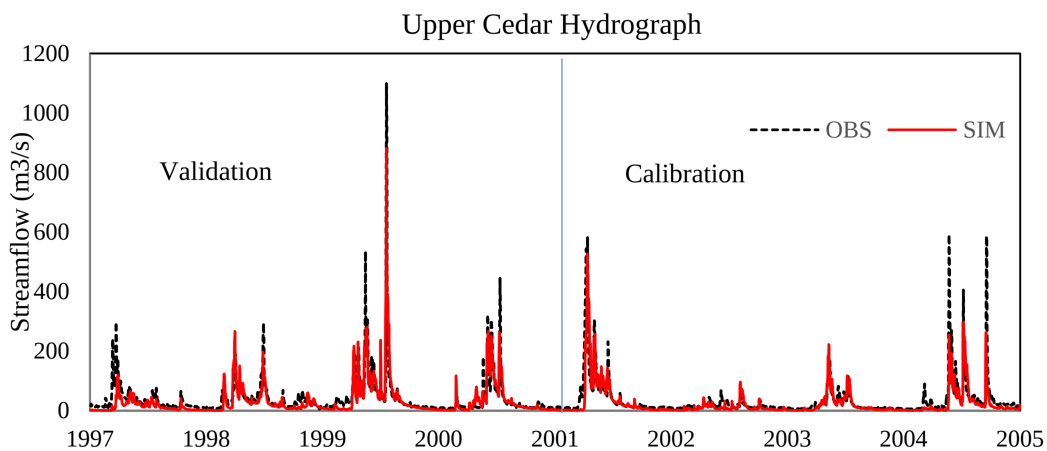


Figure 2-2: Observed (----) and Simulated (—) flow for the Upper Cedar watershed for Calibration (2001 – 2004) and Validation (1997 – 2000)

One challenge in this study was finding nutrient data to calibrate the model because only grab samples were available from the NWIS and STORET data. The calculated nutrient loads were therefore compared to other studies in the region. Using mass balance methods to calculate inputs and outputs of nutrients in Iowa, Libra et al. looked at the nitrogen budget for Iowa from 2000-2002. They estimated a stream load of 17.6 lb/acre/yr from the Upper Cedar watershed (Libra et al., 2004). The estimations from this study are within 8% of that value. Further, a study by the IDNR for Linn County modeled nutrient load to the Middle Cedar river using WASP (Water Quality Simulation Program), that is downstream of the Upper Cedar watershed, found that the watershed contributed an average of 13,679 tons NO3 – N/yr and 25.5 lb/acre/yr from 2000 – 2004 (IDNR, 2006). This study modeled the contribution at an average of 10200 tons NO3 – N/yr and 19 lb/acre for the same time period which is within 25% of the IDNR study.

3.2 Calibration and validation of the Lumber model

Similar to the Upper Cedar Watershed, a one-at-a time sensitivity analysis was performed based on parameters identified by SWAT literature in the Southeast (Bosch et al., 2004; Feyereisen et al., 2007; Sarkar and Miller, 2014). Sensitive parameters were manually calibrated for streamflow for both gages (USGS 02134500 at sub-basin 21 and USGS 02133500 at sub-basin 4). While this is not true multisite calibration, because the two sub-basins are nested, satisfactory Nash Sutcliffe coefficients in both are assumed to counter uncertainty in this deterministic stage of the calibration.

Table 2-5: Calibrated parameters for Lumber Watershed (according to sensitivity rankings)

Parameter		Process	Initial Value	Final Value
CN2 (CORN,SOYB)*	mgt	Surface flow	Varies	(-15%)
CH N1	sub		0.014	0.06
CN2(FRSE, FRSD)**	mgt	Surface flow	Varies	(-5%)
GWQMN	gw	Base flow	1000	0
WET_FR	pnd	Wetland	0.8 - 1.0	Unchanged
SOL_AWC	.sol	Lateral Flow	Varies	(-5%)
SLSUBBSN	hru		Varies	(+25%)
GW-DELAY	gw	Base flow	31	2
WET_VOL	pnd	Wetland	Varies	Unchanged
SFTMP	bsn	Snow (important in some years)	1	2
OV_N	hru		0.14	0.45
WET_SA	pnd	Wetland	Varies	Unchanged
TIMP	bsn	Snow (important in some years)	1	0.3
CH_N2	rte		0.014	0.06

WET_FR – Fraction of sub-basin that drains into a wetland; SOL_AWC – Available soil water capacity; WET_VOL –Initial volume of the wetlands (10^4 m^3 H_20); WET_SA – Surface area of the wetland at normal water level (ha);TIMP – Snow Pack Temperature Lag Factor_**SOYB - Soybean **FRSE – Evergreen Forest, FRSD – Deciduous Forest

Because of the presence of a large proportion of wetlands and forests in the watershed, wetland processes were important in calibrating the streamflow at both gages. The sub-basins upstream of subbasin 4 are dominated by forest land-use. Calibrating these subwatersheds separately greatly improved overall model calibration. Hargreaves method was used to simulate potential evapotranspiration and daily curve number was calculated as a function of the plant evapotransiration. Although some of wetland parameters were sensitive, we did not vary our initial assumptions; especially for WET_FR which was a high percentage as most channels appeared to have riparian wetlands from a visual inspection of the Cropland Data Layer for the Lumber watershed (Table 2-5). While the years from 1993 – 2000 were satisfactorily calibrated for the

Lumber watershed, 2001 – 2004 could not be satisfactorily calibrated for streamflow, therefore we present the calibration and validation statistics for 1993 – 2000 here (Figure 2-3).

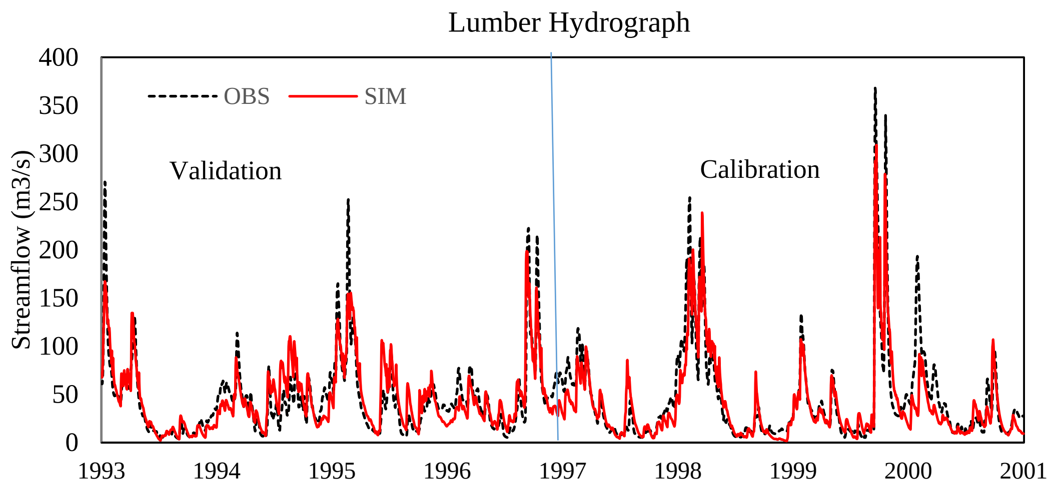


Figure 2-3: Observed (----) and Simulated (—) flow for the Lumber watershed for Calibration (1997 – 2000) and Validation (1993 – 1996)

Using manual calibration and SWAT CUP for hydrology, we achieved a satisfactory calibration for the watershed. The calibration statistics are summarized in Table 2-6. The parameters for calibration of nitrogen were chosen based on a sensitivity analysis. The modified NSE for calibration at the watershed outlet, USGS 02133500 was 0.53. Validation was not possible due to lack of nutrient data. However, comparing these results to EPA[4] estimates of nitrogen and phosphorus yields from each state from the SPARROW regression model (Preston et al., 2011), the model estimates that the nitrogen yield from the watershed is around 120 kg N /km^2-yr as compared to the estimate of 400 kg N/km^2-yr from the state of North Carolina that includes agricultural manure, fertilizer, manure and urban sources of nitrogen, which is of the same magnitude. The difference in the watershed nitrogen yield versus state average nitrogen yield could be because of the high proportion of wetlands and forest present in this watershed and because that estimate accounts for other sources of nitrogen.

[4] https://www.epa.gov/nutrient-policy-data/estimated-total-nitrogen-and-total-phosphorus-loads-and-yields-generated-within

Table 2-6: Calibration and Validation model performance given by the Nash Sutcliffe coefficient for Upper Cedar and Lumber watersheds

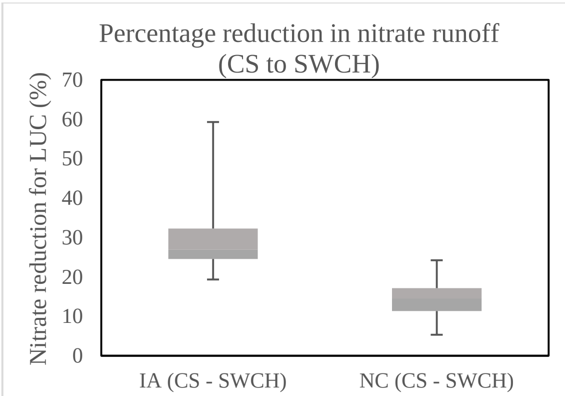
Station		Total Flow		Peak Flow		Base Flow	
		NS_{daily}	$NS_{monthly}$	NS_{daily}	$NS_{monthly}$	NS_{daily}	$NS_{monthly}$
Cedar River near Austin, MN	Calibration(2001-2004)	0.48	0.62	-	-	-	-
	Validation (1997-2000)	0.57	0.76				
Cedar River near Janesville, IA	Calibration(2001-2004)	0.73	0.88	0.65	0.88	0.82	0.83
	Validation (1997-2000)	0.73	0.82	0.68	0.89	0.65	0.64
Downing Creek near Hoffman, NC	Calibration (1997-2000)	0.61	0.78	-	-	-	-
	Validation (1993-1997)	0.49	0.76				
Lumber River near Boardman, NC	Calibration (1997-2000)	0.79	0.86	0.74	0.87	0.75	0.77
	Validation (1993-1997)	0.74	0.82	0.48	0.61	0.8	0.83

NS (Nash-Sutcliffe) coefficients for daily and monthly flows. NS > 0.5 is considered satisfactory model performance. Flow was partitioned into peak and baseflow and statistics are reported for the downstream gage in each watershed.

The availability of grab-sample data in both watersheds made it difficult to calibrate and validate nutrient runoff from the watershed. Because only one sample was available each month, a regression model such as LOADEST (Runkel et al., 2004) could not be used for monthly calibration. In addition, when samples are taken at taken at extreme high or low flow or after a precipitation event, it can bias the overall estimation of nutrients in the watershed. The modified NSE method has only limited applicability and cannot be used to validate yearly nutrient export. Therefore, in this study we used the soft data approach to verify the findings by (i) Using flow partitioning to calibrate hydrology to ensure appropriate partitioning (ii) Comparing predicted results with other studies using other models and approaches (iii) Verifying if annual yields were reasonable (Supporting information in Appendix **A**).

3.3 Impacts of land-use change from corn-soy rotation to switchgrass

As other studies have found, there was a reduction in the nitrogen loads (nitrate and nitrite -nitrogen) when agricultural lands were converted from corn-soybean rotations to switchgrass for both watersheds (Cibin et al., 2012; Nelson et al., 2006; Sarkar and Miller, 2014). The average annual nitrate-nitrogen export from corn-soy rotation in the Lumber watershed expressed as kg N/ha of nitrogen is more than 80% lower than that from a corn-soy rotation in the Upper Cedar watershed. The amount of nitrogen fertilizer applied in both the watersheds for corn is around 130 kg N/ha. Therefore, this difference could illustrate the influence of the riparian vegetation on nutrient removal in the Lumber watershed (Acreman and Fisher, 2004; Willems et al., 1997) as well as that of tile drainage in the Upper Cedar. Yearly nitrate-export from the corn-soy rotation also appears to be more highly sensitive to precipitation than the switchgrass rotation. For example, the maximum value of nitrogen export (55 kg N/ha) was in 1999 which had 40% more rainfall than the average between from 1990 – 2004. Figure 2-5 shows the nitrate-nitrogen export for Upper Cedar and Lumber watersheds for both corn-soy and switchgrass. Further, the percentage reduction in nitrogen exported at each subwatershed on conversion to switchgrass is therefore much higher in Upper Cedar than in the Lumber watershed. Figure 2-4 shows the percentage reduction in nitrate-nitrogen export for the LUC in both watersheds. There is greater variability in this reduction in the Upper Cedar because of the difference in export from tiled and non-tiled regions that will be discussed elsewhere in this document.



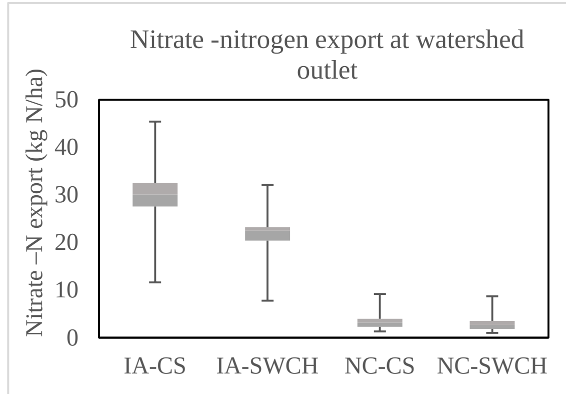


Figure 2-4: Variation in the annual nitrate-export (kg N/ ha-yr) at the watershed outlet between Upper Cedar corn-soy rotation land-use vs. switchgrass (IA-CS, IA-SWCH) and Lumber corn-soy rotation vs. switchgrass (NC –CS, NC-SWCH) over the simulation period from 1993 – 2004

Figure 2-5: Variation in the annual nitrate-export (kg N/ ha-yr) at the watershed outlet between Upper Cedar corn-soy rotation land-use vs. switchgrass (IA-CS, IA-SWCH) and Lumber corn-soy rotation vs. switchgrass (NC –CS, NC-SWCH) over the simulation period from 1993 – 2004

3.4 Influence of different rates of nitrogen fertilization for Alamo and Shawnee switchgrass

This study uses different rates of fertilization for Alamo and Shawnee switchgrass based on management practices recorded in the literature for the two different regions (Hutchinson and Christiansen, 2013; Sarkar and Miller, 2014). It is possible that these different rates of fertilization could account for some of the difference in nitrogen export in the two regions. However, a sensitivity analysis with different rates of fertilization (120 kg/ha, 100 kg/ha and 75 kg/ha of Anhydrous Ammonia) for both cultivars shows that the regional differences in nitrogen export are significant (Figure 2-6).

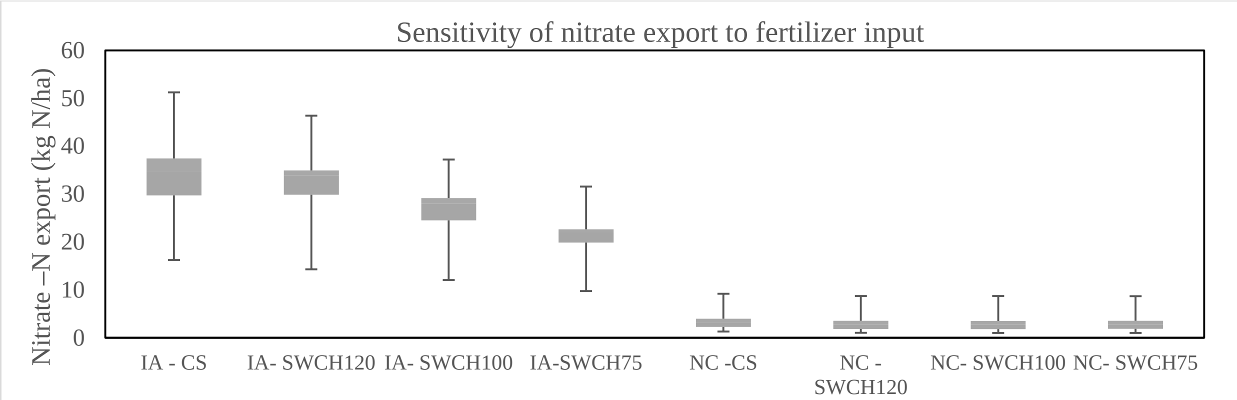


Figure 2-6: Variation in nitrate-nitrogen export for three different fertilizer treatments for switchgrass (120 kg/ha, 100 kg/ha and 75 kg/ha) in each watershed averaged over the period 1993 - 2004

3.5 Influence of tile drains

The presence of tile drains is likely responsible for some of the difference in the nitrate export (Figure 2-5). An HRU-level analysis of the annual average export of nitrate-nitrogen per unit area is greater in the case of HRUs with tile drains than those without (Figure 2-7). This may be because tile drains convey water faster to the reach without access to any biological processes such as those in riparian wetlands that reduce nutrient export to water (Randall et al., 1997). Research has shown that the presence of riparian buffers such as wetlands or riparian forests significantly reduce nutrient transport in the streamflow (Bosch et al., 2004). Figure 2-8 shows the nitrate export for switchgrass. There is substantial variation in the average nitrate export for switchgrass within the tile drained HRUs as in the corn-soy baseline although the overall trend is lower nitrate –nitrogen export. This result is also validated by field studies in Iowa that have found that prairie systems produce significantly lower concentration of nitrate-nitrogen regardless of fertilization as compared to corn-soy systems (Daigh et al., 2015).

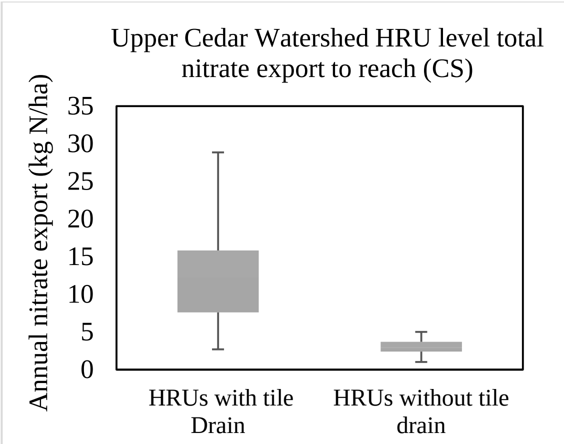


Figure 2-7: Comparison of the annual nitrate yield from corn-soy HRUs with tile drains to the reach compared to those without tile drains. The error bars represent the range of values for the 576 corn-soy HRUs in the Upper Cedar watershed averaged over 1993 - 2004

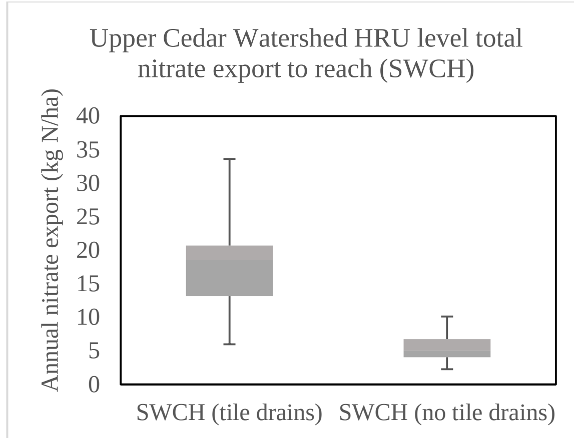


Figure 2-8: Comparison of the annual average nitrate N yield in switchgrass HRUs with tile drains to the reach compared to those without tile drains. The error bars represent the range of values for the 576 switchgrass HRUs averaged over 1993 – 2004

3.6 Influence of Riparian Wetlands

To understand the sensitivity of nitrate export to the presence of riparian wetlands, loss of riparian wetlands was simulated by decreasing the fraction of sub-basin water that enters wetlands by 10%, 30% and 50%. For each of the scenarios, the percentage change in nitrate export compared to the baseline corn-soy and switchgrass simulations was calculated (Figure 2-9). As expected, the nitrate export from the corn-soy rotation increased for a decrease in riparian cover but only beyond 10%. Nitrate export increased by 26% and 55% for a decrease in riparian cover of 30% and 50%. Although the nitrate export from switchgrass slightly increased by 18% for a 10% decrease in riparian cover, there was no increase in nitrate export for a further reduction. This could indicate the potential for minor water quality impact if switchgrass were to encroach upon riparian zones.

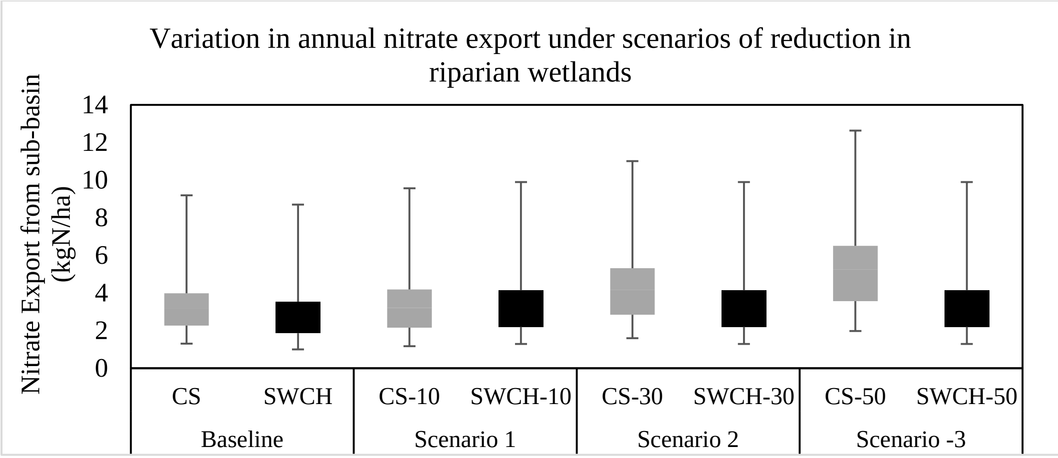


Figure 2-9: Annual average nitrate export for corn-soy (CS) and switchgrass (SWCH) under Scenario 1- 10% reduction, Scenario 2- 30% reduction and Scenario 3- 50% reduction in riparian wetlands compared to the baseline. The error bars represent the variation of nitrate export across subbasin outlets in the watershed

3.7 Accounting for productivity in the nitrogen loading metric

Another nitrate export metric with ethanol production potential as the basis was calculated for both crops in both watersheds (Figure 2-10). This metric takes into account the relative productivity of corn-soy and switchgrass within both watersheds and compares the advantage of sourcing cellulosic ethanol over corn ethanol from the same watershed. The change in nitrogen loading per gallon of potential ethanol when switchgrass is grown as compared to corn ethanol (referred to as N' kg N/gal) within the same region can be attributed to management practices and plant physiographical differences (Figure 2-11).

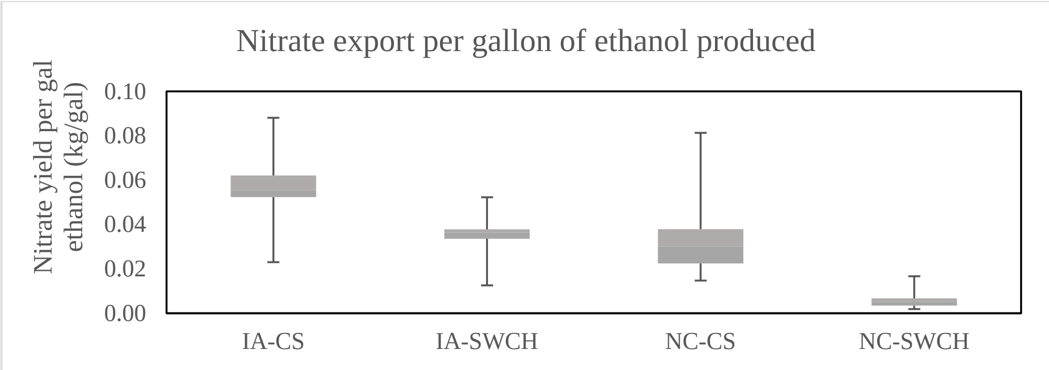


Figure 2-10: Comparison of the nitrate export per potential gallon of ethanol production from the two watersheds for corn-soy rotation (IA –CS, NC-CS) and switchgrass cultivation (IA-SWCH, NC-SWCH)

Although N’ was similar between the two watersheds, the percentage reduction in nitrate export per gallon of ethanol produced was significantly different for land-use change in Iowa as compared to North Carolina (Figure 2-11 and Figure 2-12). Levene’s test indicated that the variances of the two groups were not homogeneous, therefore an independent two-sample t-test for heteroscedastic data was carried out. The reduction from the corn-soy baseline in Lumber (mean reduction = 83%, S.D =1.9%) was significantly higher than the reduction in the Upper Cedar watershed (mean reduction = 38%, S.D. = 8.9%) $t(32) = 26.209$, $p < 0.001$. This is in contrast to the percentage reduction of the nitrate export from the watershed per unit area (kg N/ha) that showed that the overall percentage reduction in nitrogen export from the Upper Cedar watershed was higher than the Lumber watershed. This is probably because the Lumber watershed has a much lower productivity of corn compared to switchgrass so the gallons of ethanol that could be produced from switchgrass for the same area is higher than what could be produced with corn, as well as the low nitrate yield from the presence of riparian wetlands.

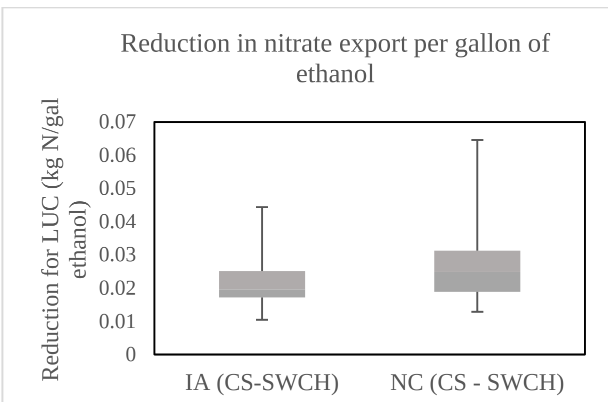


Figure 2-11: Plot compares the reduction of nitrate-nitrite N for corn-soy to switchgrass per gallon ethanol produced in Upper Cedar, IA(CS->SWCH) and Lumber, NC(CS->SWCH). Error bars represent the variation in annual average reduction among all the subbasins in the watershed.

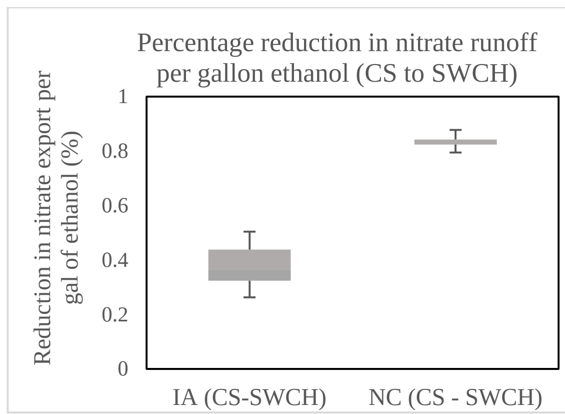


Figure 2-12: Plot compares the percentage difference in reduction of nitrate-nitrite N per gallon ethanol produced in Upper Cedar, IA(CS->SWCH) and Lumber, NC(CS->SWCH). Error bars represent the variation in annual average reduction among all the subbasins in the watershed.

The difference in the reduction in nitrate export between the two regions can be attributed to the impacts of each watershed’s hydrological processes as well as relative difference in crop productivities; the average productivity of corn-soy and switchgrass in Upper Cedar versus that in Lumber. N’ quantifies the relative advantage in producing one more gallon of ethanol from switchgrass as compared to that from corn within the same region. This demonstrates that some regions benefit more from a water quality perspective by switching to a cellulosic crop compared to the baseline for the same amount of ethanol procured.

4. Discussion

4.1 Implications

The difference in nitrogen loading between the watersheds is significant when assumptions of other system wide studies are considered. For example, Costello et al. use a constant 24% of fertilizer applied to be lost via surface runoff for corn-soy systems based on nitrogen fractionation factors developed by Miller et al. that is largely based in the Midwest (Costello et al., 2009; Miller et al., 2006). In our study, the average nitrate export as percentage of fertilizer applied was about 6% for the Lumber watershed and 35% for the Upper Cedar watershed. Although the trend in both watersheds is towards lower nitrogen export when switchgrass is grown, results indicates that simple fractionation factors may underestimate nitrate export from tile drained watersheds and overestimate nitrate export in regions with riparian or constructed wetlands such as the Lumber watershed. Nutrient behavior in these watersheds is generally different and provides further evidence that regional differences must be accounted for when estimating the impacts of bioenergy-related land use change.

The differences in relative nitrogen loading between the two watersheds for the land-use change also has significant implications on decisions optimizing feedstock sourcing depending on (1) the decision-maker (2) policy or purpose and (3) scale at which such decisions are to be undertaken. The relative nitrogen differences between different regions are less important for planning at the watershed scale. However, these results may be important for a system-wide policy analysis or optimization problems. Similar trends may be true for other cellulosic alternatives such as Miscanthus and crop residues in terms of improved water quality and productivity, as has been observed in the Midwest (Cibin et al., 2015; Demissie et al., 2012). However, since this study only looks at one specific land-use change, future work will have to evaluate other alternate energy crops and land-use changes in the region.

4.2 Context is necessary in evaluating regional water quality impacts

While our study looks at loading metrics, we have not evaluated the impacts of an additional kilogram of nitrogen avoided/ exported on the water quality health of the watershed. The annual average loading from the Upper Cedar watershed (10,300 tons/year) is much higher than that in the Lumber watershed (400 tons/year) owing both to the difference in their size and presence of cultivated land. Further, the Upper Cedar watershed is part of the MRB which has to reduce its nutrient export by 45% (based on 2005 levels) to contain the Gulf of Mexico hypoxia (Scavia et al., 2004). Therefore a kilogram of nitrogen could have a far larger impact on the overall water health of the watershed and the region when compared to the pristine Lumber watershed, as a contaminant of concern.

Further work is necessary if we are to generalize these results across the Midwest and the Southeast. While it has been established that the difference in land-cover, topography, management practices and climate do influence runoff, they are not the only explanatory variables (Daggupati et al., 2015; Malagò et al., 2014). Malago et al. introduced a concept of hydrologic similarity of sub-basins using the correlations between watershed and discharge characteristics that influence a watershed's hydrology (Malagò et al., 2014). "Similar" ungaged watersheds can be calibrated within SWAT, so it may be possible to begin to generalize model results from non-traditional watersheds to larger regions in order to improve estimates of the water quality impacts of the biofuels mandate.

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Chapter 3 : Different objectives for bioenergy production can lead to different land-use decisions under RFS2

Manuscript in Preparation for Applied Energy: Keerthi S and S Miller. Different objectives for bioenergy production can lead to different land-use decisions under RFS2.

Abstract

The Renewable Fuel Standard (RFS2) under the Energy Independence and Security Act (EISA 2007) contains the overall targets for the production of conventional, cellulosic and advanced biofuel. Federal agencies including the U.S. Department of Energy (DOE), the U.S. Department of Agriculture (USDA) and the U.S. Environmental Protection Agency (EPA), have developed spatially explicit feedstock production scenarios for the Renewable Fuel Standard (RFS2). The objectives guiding these scenarios are based on a common goal of incentivizing the bioenergy industry and meeting the RFS2 mandate. This study compares the optimal land-use decisions for growing four feedstock options according to three different objectives in representative Midwest and Southeast watersheds: maximizing farmer profitability, maximizing the economic welfare of both consumers and producers and maximizing production of ethanol per hectare under existing farmer risk management options and bioenergy subsidies. Land-use decisions regarding bioenergy crop production vary according to the objective used to meet the bioenergy mandate and the metric used to quantify the objective. For maximizing land owner profitability, stover production is favored in the Midwest as compared to the Southeast where miscanthus is the optimal choice. Maximizing economic welfare results in stover being optimal in both watersheds when measured returns per gallon of ethanol produced, but results in miscanthus when total returns are used. Despite the incentives for establishment, storage and harvest of switchgrass and miscanthus, there may not be a lot of land-use change to perennials from cropland in either watershed. We demonstrate that this is due to the uncertainty in production costs for perennials and better risk management available for corn-soy through the crop insurance program.

1. Introduction

The Energy Independence and Security Act of 2007 mandates the production of 36 billion gallons a year (BGY) of biofuel by the year 2022 under the Renewable Fuels Standard (RFS2). The mandate specifies three categories of biofuels: (i) Corn ethanol that is capped at 15BGY (ii) Cellulosic biofuel (16BGY) (iii) Other advanced biofuels (5BGY). The feedstock that can be used to produce the stated quantities of cellulosic and advanced biofuel are not specified (Perlack et al., 2011). This ambiguity in the sourcing of biofuel feedstock allows for flexibility in land-use decisions, yet poses a challenge in both land-use change (LUC) modelling and the evaluation of environmental impacts from the mandate. This study examines the optimal distribution of feedstock(s) within typical watersheds in the Midwest and the Southeast, informed by the scenarios developed in separate studies conducted by three federal agencies. These scenarios are based on incentivizing various stages of the biofuel production – from the feedstock production and logistics to the ethanol production, distribution and end-use. From an environmental policy perspective, it is important to determine how strategies to prioritize different objectives could lead to different land-use outcomes and consequently different environmental impacts. Studies have found that the metrics chosen to characterize objectives (the functional unit in life cycle assessments) could influence eventual environmental outcomes from bioenergy production (Cherubini et al., 2013; Choudhary et al., 2014).

A number of scenario-based studies have quantified the availability of biomass to meet the biofuel mandate (Department of Energy, 2011; U.S. EPA, 2010; USDA, 2010). Studies have compared modelling approaches by different agencies estimating the biomass available for RFS2 (Keeler et al., 2013; National Research Council, 2011). Keeler et al. (Keeler et al., 2013) compared the underlying assumptions and results from the modeling approaches among three federal agencies – the United States Department of Agriculture (USDA), the Environment Protection Agency (EPA) and the Department of Energy (DOE) and found that different objectives were used to derive the land and feedstock mix available for production. They also showed that each of these studies predicted different quantities of biofuel from residues and perennials, from different regions in the US.

Since results from these federal agencies have impacted policy and biofuel decisions, including federal loan guarantees for biorefineries and regions that receive funding for research (Keeler et al., 2013), it is important to understand both the impacts from objectives driving model results and the uncertainties inherent in them. Our study builds on Keeler et al.'s (Keeler et al., 2013) work in two ways: 1) Analyzes how different objectives applied to watersheds in the Midwestern and Southeastern regions affect the mixture of bioenergy crops in those watersheds 2) Incorporates uncertainty in production costs and variability in production. 3) Discusses the impacts of the existing farmer insurance programs and bioenergy subsidies in encouraging land-use change to dedicated energy crops.

The agency models are often large, complex models that take into account demand and supply side economics to allocate land-use to specific crops. In this study, we study land-use allocation on cropland, specifically on land that was in corn-soy rotation in 2006-2007 by simplifying drivers of land-use change and feedstock choice based on each agency's model assumptions to compare them. Three commonly cited studies are used as the basis to form the objectives used in this analysis. (1) The US-DOE Billion-Ton Report on biomass supply in the US estimates fuel volume and land-use trends based on feedstock availability using the Policy Analysis System (POLYSYS) model (Department of Energy, 2011). (2) The USDA's Regional Roadmap to meet the Biofuel Mandate. The Roadmap study estimates the number of biorefineries required to produce ethanol based on regional availability of feedstock (USDA , 2010). The regional availability of each feedstock was determined by experts at the Agricultural Research Service. (3) The EPA's RFS2 Regulatory Impact Analysis models availability of biomass using the Forest and Agriculture Sector Model (FASOM) that allocates land by maximizing economic welfare for the system , which is the sum of the consumer (ethanol producers) and producer (farmers) surpluses (Beach and McCarl, 2010). The EPA analysis also optimized the siting of biorefineries using a cost minimization algorithm to procure feedstock at the lowest price at the county-scale, to produce 16 BGY of biofuel by 2022 (U.S. EPA, 2010).

We use two watersheds, one in the Midwest and another in the southeast, in this study because the regional roadmap from USDA predicts that more than 90% of the biomass to meet RFS2 will come from the two regions (United States Department of Agriculture (USDA), 2010).The Soil and Watershed Tool (SWAT) (Neitsch et al., 2005) calibrated for the default corn-soy rotation (Keerthi and Miller, 2017 (Manuscript under Review)) is used to derive yields for corn stover from a corn-soy rotation, switchgrass (Panicum *virgatum L.*) and miscanthus (Miscanthus x *giganteus*) **–** feedstocks that have been well-studied as energy feedstock (Baskaran et al., 2010; Blanco-Canqui and Lal, 2007; Chamberlain and Miller, 2012; Christopher et al., 2015; Cibin et al., 2015, 2012; Cruse and Herndl, 2009; Gramig et al., 2013; Khanna et al., 2008; Nyakatawa et al., 2006; Powers et al., 2011; Sarkar and Miller, 2014; Thomas et al., 2011; Tyndall et al., 2011; Wilhelm J.M.F.; Karlen, D.L.; Lightle, D.T., 2007; Witzel and Finger, 2016). In the three existing commercial ethanol plants[5] currently operating in the US with a capacity of >20 million gallons a year, crop residues are the common feedstock of choice (Karlen et al., 2015). As such, it is the most commercially viable feedstock at the moment[6]. However, there have been concerns about the sustainable harvest of corn stover, particularly because of impacts on soil organic carbon (SOC), wind and water erosion (Wilhelm et al., 2007). Therefore, it is necessary to examine the profitability of alternatives to corn stover.

2. Methods

2.1 Overview

The study evaluates three objectives derived from federal agency reports to drive land-use change for a typical land parcel in corn-soy rotation in two watersheds. A Monte-Carlo analysis (MCA) is used to address the variability and uncertainty of the parameters in within the model, taking into account distributions of yield and production costs. The federal objectives used in this study are discussed in detail in this Section 2.3. The objectives require estimates of yields in both regions as well as an understanding of crop production economics, which is discussed in Section 2.4. To estimate the yields, we use the SWAT model to simulate the impacts of land-use change from corn-soy (without stover harvest) to corn-soy with stover harvest, switchgrass and miscanthus. The yields at the Hydrologic Response Unit (HRU) level were used to account for yield variability

[5]Ethanol Producer Magazine. Updated Jan 23 2016.
<http://www.ethanolproducer.com/plants/listplants/US/Existing/Cellulosic>
[6] Jeschke, M and A.Heggenstaller, "Sustainable Corn Stover Harvest for Biofuel Production". Dupont Pioneer Crop Insights. 22(5). 2012. Accessed on Jan 1 2016. Accessed at <http://www.dupont.com/content/dam/dupont/products-and-services/industrial-biotechnology/documents/IB-PDF-01_Pioneer_Crop_Insights.pdf>

across the watershed. While the HRUs are not spatially explicit, they represent aggregated units that have the same land-use, slope and soils.

2.2 Study Area

The Upper Cedar watershed in the Midwest and Lumber watershed in the Southeast were modeled using the SWAT model (Neitsch et al., 2005). The watersheds in both the Midwest and the Southeast were chosen to ensure that the land-use was representative of the region, agriculture formed a significant portion of the land-use and the watershed could potentially support similar alternative crops as the rest of the region. The calibrated baseline models for corn-soy and switchgrass have been described elsewhere (Keerthi and Miller, 2017 (Manuscript in Review)). Miscanthus and corn stover were modeled using the calibrated model for this study (agricultural practices detailed in Supporting Information in Appendix B).

2.3 Study objectives

2.3.1 Objective 1: Maximize Farmer profitability ($/ha)

The POLYSYS model allocates feedstock at a county-scale based on maximizing the returns (profits) over the costs of feedstock production, assuming demands for food, feed and other markets are met (Perlack et al., 2011). To echo this approach, the first objective tested by our study is to maximize farmer profits or profitability that drive land-use decisions. While positive returns over the total costs are preferable, for commodity crops with an established market, we expect at least a positive return over variable costs, to be a minimum condition to continue production of a crop.

For corn soy, returns are given by:

$$CS - \pi_{TC} = (P_{corn}Y_{corn} + P_{soy}Y_{soy} - TC_{CS})/2 \qquad \ldots\ldots \ (1)$$

$$CS - \pi_{VC} = (P_{corn}Y_{corn} + P_{soy}Y_{soy} - VC_{CS})/2 \qquad \ldots\ldots \ (2)$$

Where CS – π are the returns for corn-soy (\$/ha), P and Y are price (\$/bu) and yield (bu/ha), TC_{CS} and VC_{CS} are total and variable costs (\$/ha) of corn-soy production respectively. Production economics are discussed in section 2.4.

For stover production-

$$St - \pi_{TC} = [(P_{corn}Y_{corn} + P_{soy}Y_{soy} + P_{biomass}Y_{stover}) - (TC_{CS} + Stover\ costs)]/2 \quad \ldots\ldots (3)$$

$$St - \pi_{VC} = [(P_{corn}Y_{corn} + P_{soy}Y_{soy} + P_{biomass}Y_{stover}) - (VC_{CS} + Stover\ costs)]/2 \quad \ldots\ldots (4)$$

Where $St - \pi_{TC}$ are the returns for corn-soy production with stover harvest (\$/ha), P and Y are price (\$/bu) and yield (bu/ha), TC and VC are total and variable costs (\$/ha) of corn-soy production respectively. Equations 1 – 4 are divided by 2 to represent the assumption of a two-year rotation of corn-soy.

For the perennials, the land rental rate is used to estimate returns over total cost. The returns are given by:

$$Bio - \pi_{TC} = P_{biomass}Y_{perennial} - TC_{perennial} \quad \ldots\ldots (5)$$

$$Bio - \pi_{VC} = P_{biomass}Y_{perennial} - VC_{perennial} \quad \ldots\ldots (6)$$

Where $Bio - \pi$ is the returns of each perennial (switchgrass or miscanthus), $TC_{perennial}$ is the annualized variable cost of production for switchgrass or miscanthus ($VC_{perennial}$) plus the land rental rate of \$235/acre for Iowa[7] and \$60/acre for North Carolina[8] based on 2016 average cropland rental rates estimated by the state extension service.

2.3.2 Objective 2: Maximize Energy production per unit area (kJ/ha)

The second objective for our study is derived from the USDA study which assumes the highest proportion of bioenergy feedstock would come from the southeast because of the long growing

[7] Johanns, A. Iowa Farmland Rental Rates 1994-2016 (USDA).ISU Extension. March 2017. Accessed at < https://www.extension.iastate.edu/agdm/wholefarm/html/c2-09.html>

[8] Brown, B. North Carolina Farm Land Prices. NCSU Extension. April 2013. Accessed at <https://tobacco.ces.ncsu.edu/wp-content/uploads/2013/06/Farm-Land-Prices.pdf?fwd=no>

season and high yields, followed by the Midwest. Although the assumptions used in the study are not explicitly stated, it appears that similar results could be obtained via an objective to maximize the energy produced per hectare:

$$E_{feedstock} = Y_{feedstock} CE_{feedstock} * ED_{ethanol} \quad \text{……… (7)}$$

Where $E_{feedstock}$ is the energy production per unit area (kJ/ha), Y is the yield (ton/ha), CE is the conversion efficiency (gal/ton) and $ED_{ethanol}$ is the energy density of ethanol (kJ/gal). The energy density of ethanol is 84858 kJ/gal.

2.3.3 Objective 3: Maximize economic welfare of the system ($/gal)

The FASOM model used by the EPA to optimize the siting of biorefineries maximizes the consumer and producer surpluses of the system (U.S. EPA, 2010). This quantity depends on farmer profitability (Objective 1), storage and transport costs to an ethanol plant, the MESP for each feedstock (Gonzalez et al., 2012) and the wholesale price of ethanol. The storage costs are included in the farmer profitability calculation. The transportation costs for switchgrass, miscanthus and corn stover were obtained through a review of existing literature on production costs (Aravindhakshan et al., 2010; Khanna et al., 2008; Shastri et al., 2011; Witzel and Finger, 2016). We assume the median cost, as estimated by Shastri et al. 0.25 $/ton-km (Shastri et al., 2011) for this study. The higher cost for cellulosic ethanol may be due to size limitations in transporting of bales of perennials/residue as compared to grain. We assume a short transport distance for both corn and cellulosic feedstock to be 25 km for the purposes of this study, although the supply radius could be larger (Kim and Dale, 2015). The consumer and producer surplus for each feedstock is given by U:

$$U_{feedstock} = (WP_{eth} - MESP_{feedstock\ eth}) + (\pi_{VC,feedstock}/G_{feedstock}) \quad \text{…… (8)}$$

Where WP_{eth} is the whole sale price of ethanol ($/gal), MESP is the Minimum Ethanol Selling Price for ethanol ($/gal) and $\pi_{VC,feedstock}$ is the returns over variable costs for the feedstock. $G_{feedstock}$ is the volume of ethanol (gal) produced by each feedstock which depends on the conversion efficiency. The gallons of ethanol produced per hectare depends on the yield of the feedstock and the conversion efficiency to ethanol. MESP is given by the equation below:

$$MESP_{feedstock\ eth} = \ [(P_{feedstock}Y_{feedstock} + dC_tY_{feedstock})A + PE_{non-feedstock}\ ]/G_{feedstock} \ \ldots\ldots (9)$$

Where d is the distance from the plant (km), A is the area of the average HRU in the watershed (ha), C_t in \$/ton-km and $PE_{non\text{-}feedstock}$ is processing cost not associated with the feedstock (discussed further in section 2.4)

2.4 Production Economics

Objectives 1 and 3 need an examination of the production economics of alternative cropping choices because the relative profitability of dedicated energy crops compared to commodity crops is a major driving factors in farmer decision making. This includes costs primarily from: (i) production (ii) opportunity costs for dedicated energy arising from the profits foregone from commodity crops; and revenues from: (i) harvest (ii) subsidies and insurance payouts.

2.3.1 Corn-Soybean and stover production

For both corn-soy and stover production, this study uses the Iowa State University and the North Carolina State University estimates of total fixed and variable costs, assuming a 2 year corn-soybean rotation. The costs associated with corn stover in addition to corn-soybean production costs are nutrient replacement and harvesting costs, calculated according to actual residue removed, storage, and transportation (Thompson and Tyner, 2014).

The fixed and variable costs of production for corn-soybean and corn stover are discussed in the Supporting Information (Appendix B). The calculation of the metrics including farmer profits measured per hectare (\$/ha), consumer (ethanol plant) and farmer surplus/profit measured per gallon of ethanol (\$/gal) and land-use efficiency measured in the energy produced per hectare (kJ/ha) is discussed below in Section 2.4.

2.3.2 Switchgrass and Miscanthus Production

The costs of producing feedstock from perennials include (i) Costs of inputs including chemicals and seeds (ii) costs of the operating equipment for planting, maintenance and harvesting (iii) storage and transport costs (iv) opportunity costs for the land, assumed to be in corn-soy rotation

(Duffy, 2008; Khanna et al., 2008; Turhollow and Epplin, 2012; Yu et al., 2016). The average annualized costs of production were based on a literature review (Table 3-1 and Table 3-2).

The annualized production cost (C) for switchgrass and miscanthus ($/ha) is given by

$$C = [(EC + MY * (1 + r)^{.667} * (t - 1)) + (HSY * (t - 2))]/t + OC \qquad \ldots\ldots (10)$$

Where EC is the Establishment Cost ($/ha), MY is the yearly maintenance cost ($/ha-yr), r is the discount rate, t is the crop lifetime, HSY is the yearly harvest and storage costs ($/ ha-yr) and OC is the opportunity cost. The yearly maintenance cost interest is calculated over 8 months.

The opportunity cost is the returns above the total cost of production of commodity crop the perennial is replacing as in Jain et al. (Jain et al., 2010), in both watersheds, we consider a corn-soy rotation.

$$OC = [(P_{corn}Y_{corn} - (FC + VC)_{corn}) + (P_{soy}Y_{soy} - (FC + VC)_{soy})]/2 \qquad \ldots\ldots (11)$$

Where P, Y, FC and VC are price ($/bu), yield (bu/ha), fixed and variable costs ($/ha) respectively

2.3.3 Ethanol production from lignocellulosic feedstock

There are currently two primary pathways through which lignocellulosic biomass is converted to ethanol – (i) biochemical process that involves chemical/enzymatic hydrolysis or (ii) thermochemical that involves gasification. Both these processes are followed by microbial fermentation (Kazi et al., 2010). The costs included in estimating the MESP include cost of feedstock of procurement and handling (production costs and transport to ethanol plant), operating, processing and capital costs. The estimates for MESP from various studies from 2008 – 2013 are also included in the MCA discussed in the next section (Table 3-3).

2.4 Monte Carlo Analysis (MCA)

MCA is a tool used to quantify uncertainty using probability distributions for the independent variables to derive the probability distribution for the dependent variable. Because these are emerging systems, we find that there is both uncertainty and variability in the estimates for production of miscanthus and switchgrass arising from the lifetime assumed for the perennials, discount rate assumed for operating costs, fixed costs, and variable costs. Further, the yield of all crops (commodity – grain and residues and dedicated energy crops) also vary across the watershed following a normal distribution. The probability distributions for all costs, lifetime and discount rate was assumed to be triangular as that we had around 8-9 estimates for switchgrass and miscanthus costs (Table 3-1 and Table 3-2), and 6 estimates for the cellulosic ethanol plant costs from a review of techno-economic studies (Table 3-3). Lifetime and discount rates were also assumed to have an integer value. The ranges and most likely values of each parameter is included in the Supporting Information (Appendix B).

The analysis therefore captures both the uncertainty in cost parameters and the variability in yields for the watershed. Additionally, for the calculation of the second objective (under Section 2.3.2), the process used to produce ethanol results in both variability, for example, different pretreatment methods used in the production) (Kazi et al., 2010) as well as uncertainty in costs for enzymes, other process costs and allowances for technological learning in an industry that is not yet mature (Kazi et al., 2010; Sendich et al., 2008).

Table 3-1: Literature review of production costs for Miscanthus used in Monte Carlo Analysis

Cost Category	Dolginow et al. (2014)[a]		Khanna et al. (2008)[b]		James et al. (2010)[c] - High Cost		James et al. (2010)[c] – Low Cost	
($/ha)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)
Establishment (Non-yield)	2802.17		440.06		18000		500	
Maintenance (Non-yield)	610.17	87.32	186.58	53.73	139.2	139.2	139.2	139.2
Maintenance (yield)* Y								
Harvest (Non-yield)			40.52	40.52				
Harvest (Yield)	0.0404	0.0404	0.056	0.056				
Storage (Yield)			0.008	0.008				
Discount Rate	6	6		4		5		5
Operating interest period (months)	8	8			10			
Lifetime	15	15		20		10		10

Cost Category	Jain et al. (2010)[d]		Hoque, Artz and Hart (2014)[e]		Shastri et al. (2011)[f]		Aravindhakshan (2010)[g] -	
($/ha)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)	Years (1-2) ($/ha)	Years 3 - lifetime ($/ha/yr)
Establishment (Non-yield)	3097		1874.730		3750		556.4	
Maintenance (Non-yield)	222.24	111.16	782.175	175.247			64.3	64.3
Maintenance (yield)* Y					0.05	0.05		
Harvest (Non-yield)	46.2	46.2	65.455	65.455			35	36
Harvest (Yield)	0.005	0.005	0.019	0.019			0.026	0.026
Storage (Yield)	0.006	0.006	0.005	0.005	0.0065	0.0065		
Discount Rate		4		5		4		7
Operating interest period (months)				8				
Lifetime		15		20		15		10

References: a. (Dolginow et al., 2014), b. (Khanna et al., 2008), c. (James et al., 2010), d. (Jain et al., 2010), e. (Hoque et al., 2014), f. (Shastri et al., 2011), g. (Aravindhakshan et al., 2010)

Table 3-2: Literature review of production costs for Switchgrass used in Monte Carlo Analysis

Cost Category	**Duffy et al. (2008)[a]**		**Madhu Khanna et al. (2008)[b]**		**Dolginow et al. (2014)[c]**		**Mooney (2009)[d] - TN (low seeding rate, low fert)**		**Mooney (2009)[d] - TN (high seeding rate, high fert)**		**Perrin et al. (2008)[e]**		**Jain et al. (2010)[f] - Low Cost**		**Jain et al. (2010)[f] - High Cost**		**Aravindhakshan (2010)[g]**	
($/ha)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)	Years ($/ha) (1)	Years 2 - lifetime ($/ha/yr)
Establishment (Non-yield)	138.94		133.34		146.62		123.48		617.40		151.05		113.13		270.8		150.6	
Maintenance (Non-yield)	224.86	87.32	183.72	52.59	351.88	111.99	248.25	114.87	139.64	244.34	197.70	35.96	129.42	159.53	346.27	355.13	148.6	66.1
Maintenance (yield)* Y																		
Harvest (Non-yield)	70.51	39.64	67.67	17.65									39.27	46.21	23.1	46.21	35	35
Harvest (Yield)	0.0313	0.0313	0.0374	0.0374		0.047		0.028		0.029		0.003	0.019	0.018	0.03	0.03	0.026	0.026
Storage (Yield)	0.004	0.004	0.004	0.004		0.003						0.013	0.004	0.004	0.008	0.008		
Discount Rate	8	8		4		10		6		6		5		4		4		7
Operating interest period (months)	8	8			10*							8						
Lifetime	11	11		10		12		10		10		10		10		10		10

References: a. (Duffy, 2008), b. (Khanna et al., 2008), c. (Dolginow et al., 2014), d. (Mooney et al., 2009), e. (Perrin et al., 2008), f. (Jain et al., 2010), g. (Aravindhakshan et al., 2010)

Table 3-3: Literature review of processing costs for cellulosic ethanol used in Monte Carlo Analysis

Assumptions	**Sendlich et al. (2008)** [a]	**Sendlich et al. (2008)**[a]	**Aden and Foust (2009)**[b]	**Humbird et al. (2011)**[c]	**R. Gonzalez, J. Daystar, M. Jett et al. (2012)**[d]	**Chovau, Degrauwe and Van der Bruggen (2013)**[e]
Capacity (MT/year)	771550	771550	700500	700833	453597	700500
Process	Biochemical (SSCF*)	Biochemical (CBP**)	Biochemical	Biochemical	Thermochemical	Biochemical (Ammonia Pretreatment)
Feedstock	Corn Stover	Corn Stover	Corn Stover	Corn Stover	Loblolly Pine	Corn Stover
Conversion (gal/dry-ton)	68.9	77.8	89.8	79	118.61	74.88
Cost Category ($/gal)						
Biomass	0.6	0.4	0.505	1.00	0.62	0.93
Depreciation	0.15	0.19	0.57	0.28	0.55	0.65
Overhead	0.05	0.05	0.05	0.05	0.21	0.00
Maintenance					0.17	
Labor	0.12	0.15			0.05	
Chemical	0.1	0.08	0.2	0.52	0.07	0.71
Other FC			0.09	0.22	0.09	0.17
Cost converted ($/dry-ton)						
Biomass	41.34	31.12	45.35	79.00	73.54	70.00
Depreciation	10.335	14.782	51.19	22.00	65.24	48.64
Overhead	3.445	3.89	4.49	4.00	24.91	0.00
Maintenance	0	0	0.00		20.16	0.00
Labor	8.268	11.67	0.00		5.93	0.00
Chemical	6.89	6.224	17.96	41.10	8.30	52.83
Other FC	0	0	8.08	17.50	10.68	12.73
MESP ($/gal)	1.02	0.87	1.42	2.07	1.76	2.46
Feedstock cost/MESP (%)	**59%**	**46%**	**36%**	**48%**	**35%**	**38%**
[MESP - Feedstock Cost ($/dry-ton)]	28.94	36.57	81.72	84.60	135.22	114.21
MESP - Feedstock Cost ($/gal)	**0.42**	**0.47**	**0.91**	**1.07**	**1.14**	**1.53**

A MATLAB® code was written to generate the MCA with 10,000 trials, sampling the yields (distribution for the yield is obtained from the SWAT simulation at the HRU level) for all four feedstock options and soybean and the cost parameters (establishment costs, yearly maintenance costs, storage and harvest costs, lifetime and discount rate) for the energy crops in each trial. This code is included in the Supporting Information (Appendix B).

Table 3-4: Assumptions for constants for calculating objectives

Parameter	Value	Unit	Reference and Comments
Conversion Efficiency (corn to ethanol)	2.84	gal/bu	(Wallace, R., Ibsen, K., McAloon, A. and Yee, 2005)
Conversion Efficiency (cellulosic biomass to ethanol)	79.0	gal/dry-ton	(Humbird et al., 2011) , National Renewable Energy Laboratory study ranges from 42 – 106 gal/ton
Corn Price	4.37	$/bu	Average 2012 – 2016 prices paid to Iowa farmers[9]
Soybean Price	9.79	$/bu	Average 2012 – 2016 prices paid to Iowa farmers[5]
Biomass Price	60.0	$/dry-ton	Assumption
Wholesale ethanol price	2.00	$/gal	Average 2012 – 2016 trading prices[10]

2.5 Crop Insurance as a revenue supplement to corn-soy production

We include crop insurance as a component of production economics for the corn-soy rotation. Crop Insurance for corn and soybean production is an important risk management and revenue supplementing measure. There are two primary forms of farm support for commodity crops like corn and soybean under the current Farm Bill: the traditional Federal Crop Insurance program that includes yield or revenue-based guarantees and Farm Commodity Programs that includes the Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC), authorized by the 2014 Farm Bill (Shields, 2014). Farmers can choose to purchase federal insurance and enroll in one of the two commodity programs.

In 2015, more than 96% of soybean farmers and 91% of corn farmers opted for the ARC program instead of PLC (Shields, 2015), so we chose to simulate supplemented revenue from ARC. Under the Federal Crop Insurance program, while Revenue Protection insurance is more common, in a study based on the years 2015 and 2016 in Iowa, Schnitkey (Schnitkey, 2016a) found that farmers

[9] Johanns, A. Iowa Cash Corn and Soybean Prices. ISU Extension Ag Decision Maker. March 2017. Accessed at <https://www.extension.iastate.edu/agdm/crops/pdf/a2-11.pdf>
[10] Trading Economics, Ethanol 2005 – 2016 Historical Data, Accessed at <http://www.tradingeconomics.com/commodity/ethanol>, Accessed on Dec 20, 2016

could move towards using Yield Protection (YP) insurance in combination with ARC enrollment for risk management to reduce their premiums (Schnitkey, 2016a, 2016b). This study analyses the impacts of these two programs as risk management on optimal land-use in terms of returns to farmers. The details on the calculation of payouts from two programs – the ARC-CO and Yield Protection Insurance is included in the Supporting Information (Appendix B).

2.6 Impact of the Biomass Crop Assistance Program

The BCAP was established under the Food, Conservation, and Energy Act in 2008, reauthorized by Farm Bill 2014, to overcome barriers to energy crop establishment[11]. This study models the different kinds of support that BCAP provides, as additions to revenue, thereby increasing farmer profitability for perennials. There are three forms of subsidy that we consider: (i) Establishment costs subsidy. (ii) Payment to cover years with no revenue and (iii) Subsidies for harvest, storage and transport. Additional information on the calculation of the details are presented in the Supporting Information (Appendix B).

3. Results and Discussion

This section presents the results for the three objectives considered from the MCA simulation. For the first objective on farm profitability, we consider two scenarios: (1) Profitability without revenue supplements from federal risk management programs for corn-soy production and bioenergy subsidies for perennials (2) With crop insurance and bioenergy subsidies. This is done to evaluate how the impact of these programs on relative affordability between the options.

3.1 Maximizing the farmer profitability ($/ha)

3.1.1 Farm profitability (returns) without crop insurance and bioenergy subsidies

Farm profitability is a major driver of land-use decisions. We consider both variable and total costs because the revenue generated should at the very least cover the variable costs to be feasible. High returns on total costs indicates the overall economic sustainability of the operation. Figures 3-1 to

[11] USDA Factsheet. Biomass Crop Assistance Program. USDA Farm Service Agency (2010). Accessed at <https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2016/BCAP_Fact_Sheet.pdf> Accessed from 2 November 2016

3-4 show the net returns over variable and total costs for the four alternative land-use options in the two watersheds. Since the first objective is to maximize the farm profitability, the land-use option that has high net returns and a high probability of the high returns among the options is the most competitive option.

Figure 3-1 and Figure 3-2 show the probability distribution of farm profitability for the four alternatives over variable costs for IA and NC. Figure 3-1 shows that even without any revenue supplements from commodity or bioenergy programs, corn-soy production has comparable returns to corn stover production in Upper Cedar (IA, Midwest), but stover is likely to be the most competitive option. Switchgrass does not break-even in any of the scenarios. Miscanthus breaks even less than half the time without subsidies and in a small number of cases has higher returns than stover. Since this analysis includes both yield variability and uncertainty in production costs, this could be the case in a minority of cases predicting lower corn and stover yields and low miscanthus costs. Figure 3-2 shows that when incentives are not considered, like in IA, stover is more competitive than the other land-use options in NC. Miscanthus breaks even more than half of the scenarios and the likelihood of miscanthus having higher returns than stover is greater than in IA. Switchgrass breaks even in a small number of cases but is still not competitive with the other options.

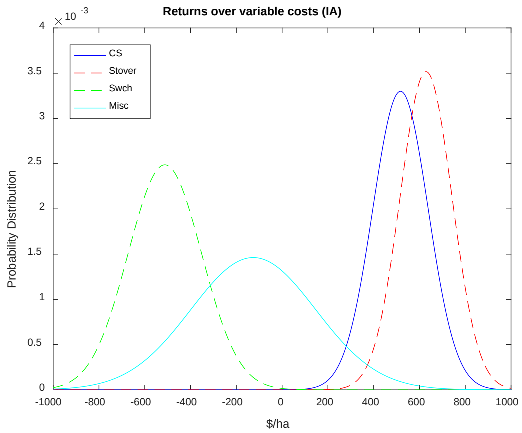


Figure 3-1: Probability distribution for the profitability/returns to the farmer per hectare over variable costs for the four crops in IA capturing uncertainty in production costs and yield variation

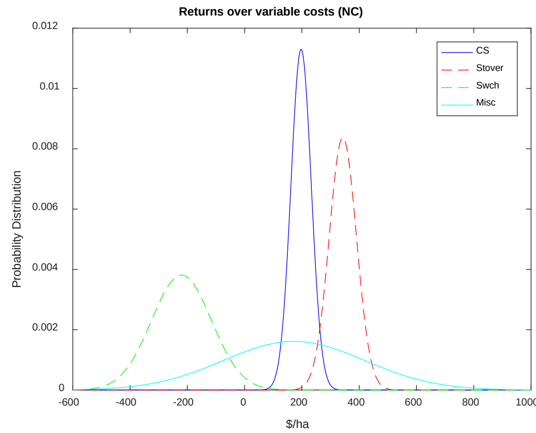


Figure 3-2: Probability distribution for the profitability/returns to the farmer per hectare over variable costs for the four crops in NC capturing uncertainty in production costs and yield variation

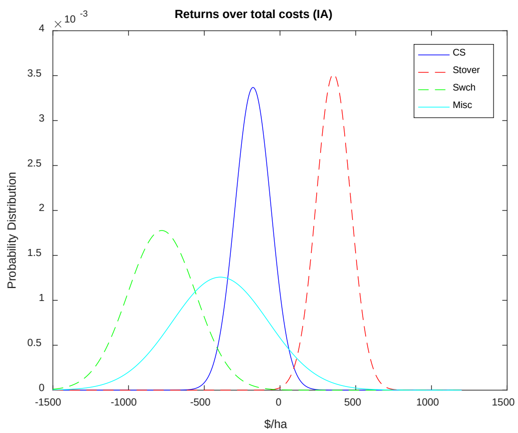


Figure 3-3: Probability distribution for the profitability/returns to the farmer per hectare over total costs for the four crops in IA capturing uncertainty in production costs and yield variation

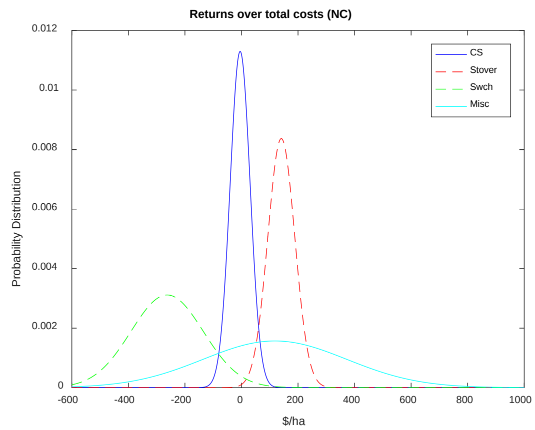


Figure 3-4: Probability distribution for the profitability/returns to the farmer per hectare over total costs for the four crops in NC capturing uncertainty in production costs and yield variation

Figure 3-3 and Figure 3-4 look at return over total costs production without a farm safety net. In this scenario, the opportunity cost for switchgrass and miscanthus production is also calculated over the total costs of corn and soybean production. If the total cost of corn-soy production is negative, it is assumed that enrolling in land retirement programs such as the Conservation Reserve Program (CRP) is the next best option. Using the average CRP rental rates in Iowa and North Carolina from the Farm Service Agency (USDA FSA) over the last five years, this cost was approximated to be $105/acre in IA and $67/acre in NC[12]. The analysis shows that for the Midwest, stover remains the most competitive option, although some in some cases (perhaps marginal cropland with low yields), miscanthus is preferred over corn-soy. In the southeast however, miscanthus is more competitive than corn-soy in 70% of the simulations and is preferred over stover in 40% of the simulations.

Our analysis also shows a negative return about half the time in NC and more than half of the simulations in IA for corn-soy production without stover harvest without the crop insurance program, at current production costs and corn-soy prices considered. This speaks to the long-term economic sustainability of row-crop production and perhaps a need to control production costs. Switchgrass remains uncompetitive in both watersheds.

3.1.2 Impacts of using the farm safety net and bioenergy subsidies for returns over variable costs

The ARC-CO payments and YP insurance was used as a revenue supplement for corn-soybean production. The conditions for the payments to be triggered are included in the Supporting Information (Appendix B). Biomass subsidies under BCAP were used for switchgrass and miscanthus as discussed under Section 2.6. Figure 3-5 and Figure 3-6 show the distribution of farm profitability over variable costs in IA and NC respectively. The combination of the ARC-CO and YP insurance programs ensure that commodity crop production remains profitable. The inclusion of the BCAP subsidies for miscanthus and switchgrass makes miscanthus slightly more competitive with corn-soybean production in IA, as compared to the no subsidies scenario as seen in Figure 3-5. However, stover remains the best land-use option in IA. In NC, miscanthus appears to be more profitable than corn-soy production more than half the time and more profitable than stover about half the time. Considering the "spread" of miscanthus profitability however (Figure 3-6), although high yielding miscanthus on low productivity soil could generate more profit for the farmer than stover with subsidies, stover harvest could be perceived as an option with less risk.

[12] USDA. "Conservation Reserve Program Statistics". Accessed at <https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index>

The results of our analysis are qualitatively validated by results from previous studies. For example, Dolginow et al. (Dolginow et al., 2014) found that miscanthus performs better than other perennial options in Missouri. Skevas et al. (Skevas et al., 2016) conducted a similar analysis in the Great Lakes region for marginally productive soils. Their results revealed that corn stover was more profitable and less risky investment compared to perennials across a wide range of farmer risk preferences. Based on DAYCENT model predictions yield for four regions (Midwest, Great Plains, Southeast and Northeast), Miao and Khanna (Miao and Khanna, 2014) find that switchgrass and miscanthus have the lowest breakeven price in the southeast, given the low yields of corn and high yield of perennials.

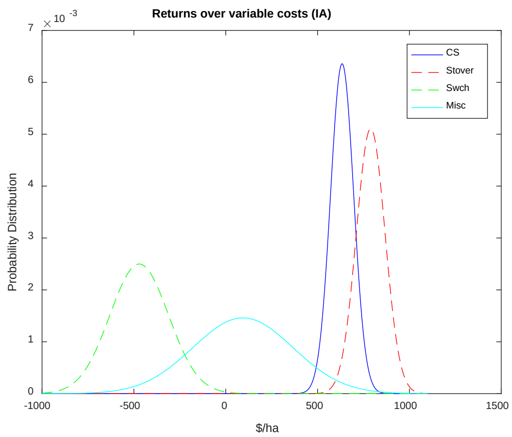


Figure 3-5: Probability distribution for the profitability/returns to the farmer per hectare over variable costs for the four crops in IA. Corn-soy area enrolled in the ARC-CO program and carrying YP insurance. Switchgrass and Miscanthus receive subsidies through BCAP.

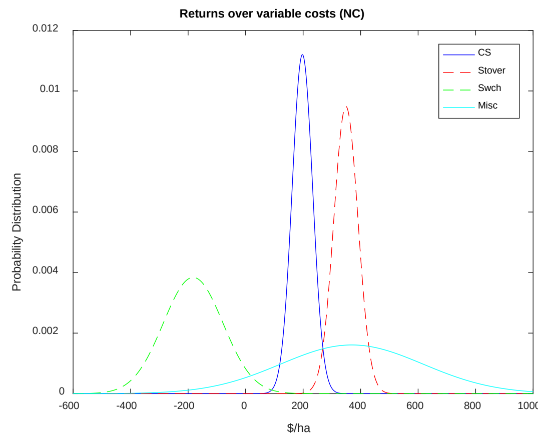


Figure 3-6: Probability distribution for the profitability/returns to the farmer per hectare over variable costs for the four crops in IA. Corn-soy area enrolled in the ARC-CO program and carrying YP insurance. Switchgrass and Miscanthus receive subsidies through BCAP.

3.2 Maximize Energy production per unit area (kJ/ha)

Figure 3-7 and Figure 3-8 look at total potential ethanol produced assuming all corn goes into ethanol production in IA and NC respectively. Figure 3-9 and Figure 3-10 allocate only 40% of the total corn production for ethanol production. Miscanthus is a higher yielding crop than switchgrass and corn, and therefore is the optimum feedstock choice for both the Midwest and the Southeast in all scenarios that seek to maximize ethanol production per hectare. Corn stover production in Iowa, if all corn ethanol were to go into energy production is the second-best option while switchgrass is a better option in NC. This is because we expect lower stover availability given the lower productivity of corn in the southeast. Lower residue availability also means less of it can be sustainably harvested per hectare (Wilhelm et al., 2007). Therefore harvesting stover does not yield as much energy in NC as in IA.

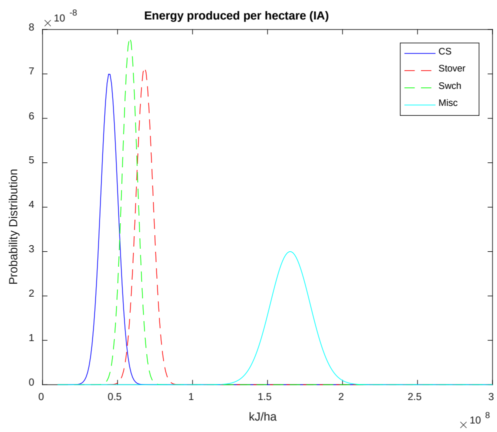


Figure 3-7: Probability distribution for the energy produced per hectare for the four crops in IA. All the corn grain in stover land-use option also goes into energy production

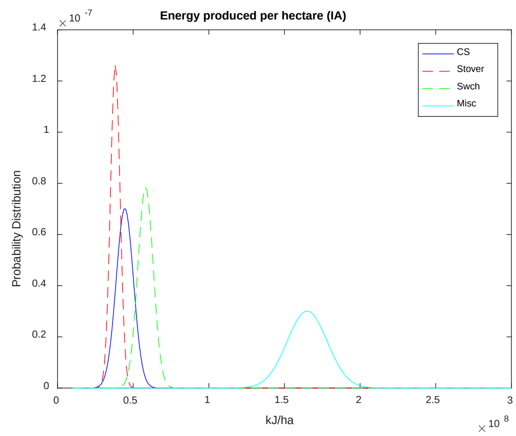


Figure 3-8: Probability distribution for the energy produced per hectare for the four crops in IA. 40% of the corn grain in stover land-use option also goes into energy production

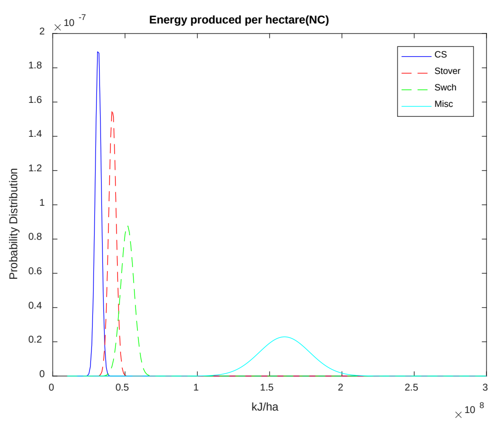


Figure 3-9: Probability distribution for the energy produced per hectare for the four crops in NC. All the corn grain in stover land-use option also goes into energy production

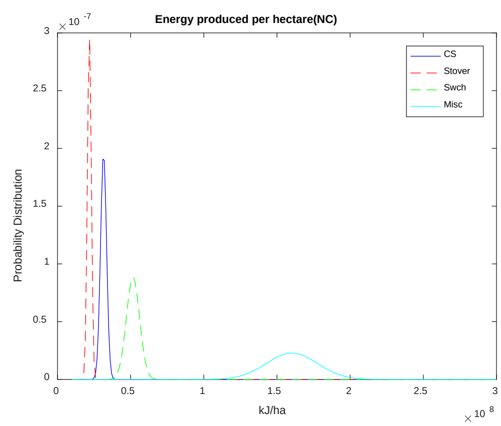
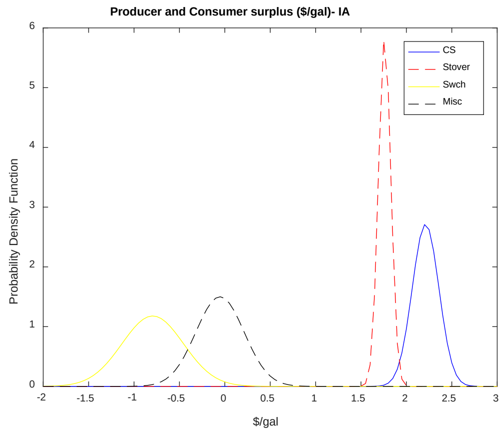


Figure 3-10: Cumulative distribution for the energy produced per hectare for the four crops in NC. 40% of the corn grain in stover land-use option also goes into energy production

3.3 Maximize economic welfare of the system ($/gal)

Figure 3-11 and Figure 3-12 are the probability distributions for consumer and producer surpluses (overall economic welfare of the system) in IA and NC respectively. This objective combines the farm profitability and the profits from the ethanol producer. Corn-soy production is the best option under this objective in IA. This is because (i) grain is cheaper to transport than residues/grass (ii) the technology for corn ethanol production is mature (Kazi et al., 2010; Lynd et al., 2005), so the overall production costs per gallon are lower. In NC, both corn stover and corn could be optimal options, but the uncertainty in the surplus value is greater for stover. The reason for this difference between the regions is that the difference in returns over variable costs (farm profitability) of corn stover to corn-soy production without stover harvest is greater in NC as compared to IA. However, it should be noted that the actual surplus produced ($) could result in a different land-use option, as miscanthus produces higher amounts of ethanol than that of corn or stover, especially in NC.

Figure 3-13 and Figure 3-14 show the cumulative distribution of the MESP ($/gal) of ethanol produced from each feedstock. As expected corn has the lowest MESP of all the feedstocks. Because we assume the same conversion efficiency and the same biomass price, the delivered costs (biomass price and storage and transportation costs) for stover, switchgrass and miscanthus are the same. Therefore they have the same MESP for similar technology. The cost of production of corn ethanol from a dry-mill plant (Irwin, 2016) was around $1.50/gal in 2015. The predicted cost here is slightly lower than the literature value. This is because a simplification has been made equating delivered feedstock cost to 70% of the total production cost for a mature technology (Lynd et al., 2005). The cost of production of cellulosic ethanol for feedstock sourced at $60/dry-ton (Johnson, 2016) in an enzymatic hydrolysis plant was estimated to be between $2.78 - $2.36/gal depending on the location of the plant producing cellulose for the process. The MESP in this study ranges between $1.50 and $3/gal. The assumed transportation distance of 25 km in this study is likely to be an underestimation.



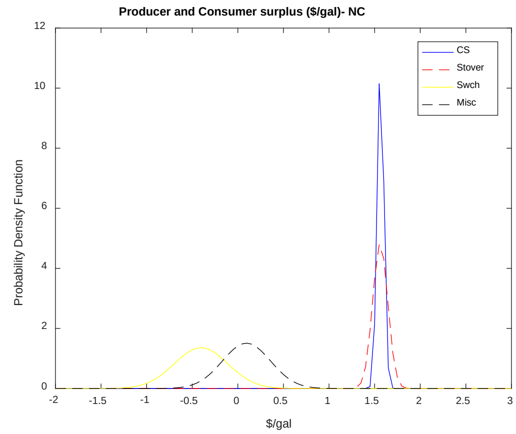
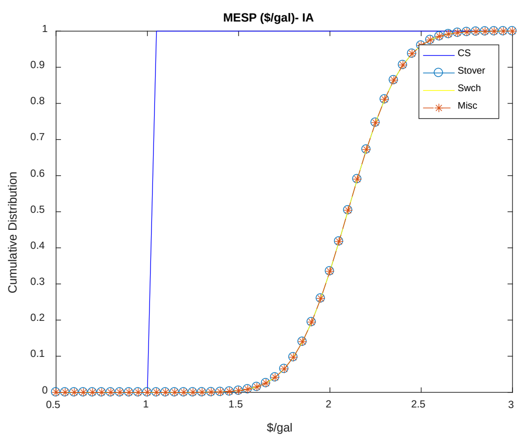


Figure 3-11: Probability density function for the producer and consumer surplus in $/gal for the four crops in IA. The quantity is a sum of farm profitability and ethanol producer profits

Figure 3-12: Probability density function for the producer and consumer surplus in $/gal for the four crops in IA. The quantity is a sum of farm profitability and ethanol producer profits



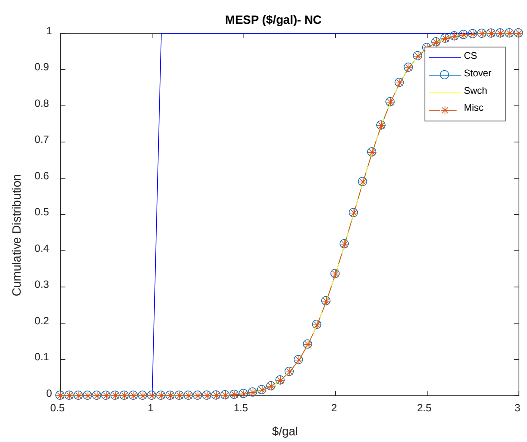


Figure 3-13: Cumulative distribution of the minimum ethanol selling price (MESP) per gallon of ethanol produced from each feedstock in IA. Lower MESP would result in higher overall profits for the ethanol producer

Figure 3-14: Cumulative distribution of the minimum ethanol selling price (MESP) per gallon of ethanol produced from each feedstock in NC. Lower MESP would result in higher overall profits for the ethanol producer

3.4 Sensitivity Analysis of Biomass and Corn Prices

The analysis presented above considered a single price for corn and biomass. We conduct a sensitivity analysis to understand the impacts of biomass and corn prices on (1) total farmer profitability over the farmed area ($) (2) the total consumer and producer surplus ($). The analysis indicates that the land-use options under the two objectives are price sensitive and often do not align.

In Iowa, at very low biomass prices (Figure 3-15), corn-soy production is the most competitive option for farm profitability (Objective 1). However, low biomass prices means lower delivered costs for stover, miscanthus and switchgrass. So they perform better on overall economic welfare (Objective 2). As biomass becomes more expensive (holding corn-soy prices constant at the default), profitability increases for cellulosic feedstock but delivered costs also increase. At a biomass price of $60/ dry-ton both objectives seem to align and stover is the preferred objective. Any further increase in biomass price makes miscanthus more profitable. In NC, at low biomass prices, the objectives lead to the same options as Iowa. As biomass becomes more expensive (holding corn-soy prices constant at the default), at $60/ dry-ton both objectives seem to align and miscanthus is the preferred objective. Any further increase results in corn-soy being favored for the second objective due to lower delivered costs to the ethanol processing plant.

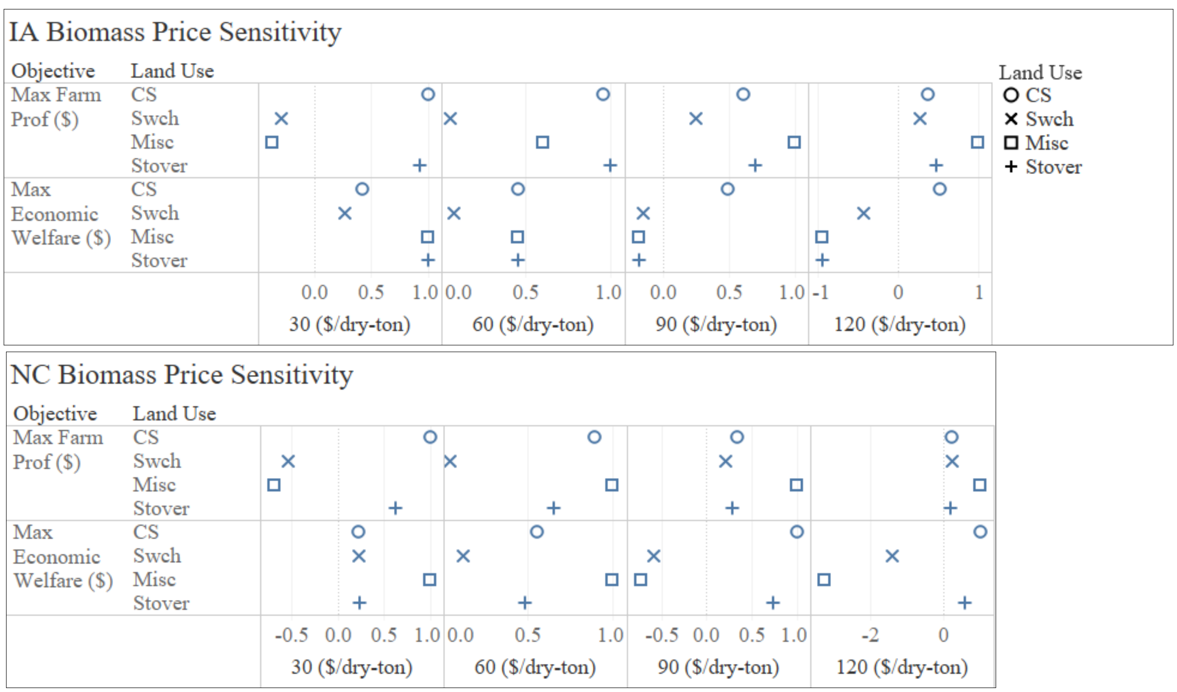


Figure 3-15: Sensitivity of optimal feedstock options to different biomass prices for objectives 1 and 2. Each land-use is represented by a different shape and objective values are indexed to the maximum value in each scenario. Optimum land-use option is the right-most shape for each biomass price scenario

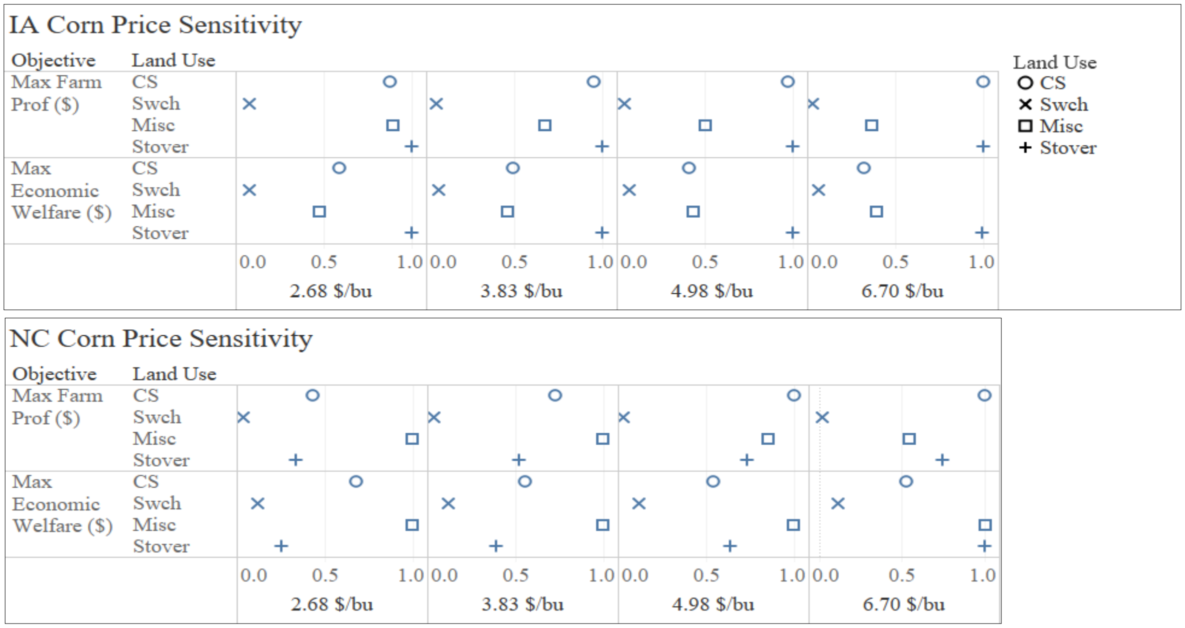


Figure 3-16: Sensitivity of optimal feedstock options to different corn prices for objectives 1 and 2. Each land-use is represented by a different shape and objective values are indexed to the maximum value in each scenario. Optimum land-use option is the right-most shape for each corn price scenario

Holding the biomass price constant at $60/dry-ton, Figure 3-16 shows that stover is the most competitive option for both objectives in IA for all but the most expensive corn scenario. In NC, miscanthus is the most competitive option when corn is at a low price for both objectives. At high corn prices, corn replaces miscanthus as the most profitable option. Miscanthus remains the optimum option for maximizing the economic welfare ($). This appears contradictory to Figure 3-12. However, given that miscanthus yields are more than double the corn yields in the region, even though the surplus per gallon is smaller, the high volume of ethanol produced makes this the optimum option in this sensitivity analysis. Therefore the metric used to quantify the objective also changes the outcome (Choudhary et al., 2014). The analysis indicates that the two objectives are sensitive to biomass and corn prices and result in very different land-use change configurations depending on the objective prioritized.

3.5 Implications from the analysis

The optimal feedstock choice for bioenergy in the two regions is different when different objectives are used, as in the scenarios in Sections 3.1 – 3.3. While stover is the best option for the first and third objective in the Midwest, miscanthus is more profitable in the southeast. Depending on the metric used to measure the economic welfare of consumers and producers ($ or $/gal), different feedstocks are optimum in the southeast. For both watersheds, miscanthus maximizes land-use efficiency because it is the highest yielding feedstock.

It may not be possible to rank these objectives in order of importance as they incentivize different facets of the development of the bioenergy industry, if we were to meet the objectives of RFS2 (Department of Energy, 2011; U.S. EPA, 2010). But, it is clear from the analysis that there are some cases where miscanthus is competitive for all objectives. Because this MCA looks at both variability in yield and uncertainty in cost parameters, we speculate these opportunities could be the result of all or some of the following: (i) lower costs of production for miscanthus, for example availability of low cost rhizomes for planting (ii) low productivity of corn-soy, for example on marginal cropland (iii) high productivity of miscanthus on cropland. However the cost of production of cellulosic ethanol at a plant is significantly higher than corn ethanol as discussed under Section 3.2. With improvements in technology, technology-learning and increase in volume, these costs could be lowered, making cellulosic ethanol more competitive as in other bioenergy technologies (Junginger et al., 2006). While the differing objectives of maximizing energy production per hectare and maximizing returns appear contradictory, these results indicate that there is potential for simultaneous optimization of the different feedstock by location, especially in the southeast.

Additionally, as demonstrated in Figure 3-5 and Figure 3-6, although the presence of farm safety net makes growing commodity crops more profitable, the BCAP subsidies make miscanthus more competitive with corn stover in comparison to the absence of subsidies. We did not consider Revenue-Protection insurance (RP) that is more commonly purchased in both regions (Schnitkey, 2016a). Further, because we use actual statistics for YP insurance premiums, given the lower enrollments in this program, the premiums are unusually high in the southeast. Therefore there may be some overestimation of miscanthus competitiveness, although the trend should hold. Further, even with subsidies, there is a probability of negative return for switchgrass and miscanthus under some cases, unlike the impact of crop insurance for commodity crops. This could explain why there has not been an expansion in bioenergy production despite subsidies, as the risks of energy crops could be perceived to be higher. We also find that switchgrass in uncompetitive in every scenario for these two watersheds. A review of field trials in the US has indicated average yields between 10 - 12 ton/ha (Heaton et al., 2004) as compared to the 7 – 9 ton/ha simulated in the two watersheds in this study. In some field trials in the southeast, yields of up to 16 ton/ha were obtained (Fike et al., 2006). So it is likely that we are underestimating the competitiveness of switchgrass in the southeast.

4. Conclusion

This study determines the preferred cellulosic feedstock between stover and two perennials (switchgrass and miscanthus) for three federal agency objectives – maximizing farm profitability, minimizing the cost of procurement of ethanol or maximizing the economic welfare of both the farm and ethanol producers and maximizing land-use efficiency. We use a Monte-Carlo Analysis to consider the impacts of uncertainty in production costs for the perennials, incentives to grow biomass, risk management through federal crop insurance programs and the variability in yields across the watersheds on crop choice. We find that (i) Feedstock choice in the two watersheds depends on the different federal agency objective used to drive land-use change, as well as the metric that is used to quantify the objective. This is a significant result because these studies inform policy (Keeler et al., 2013) and form inputs for planning and environmental studies (Parish et al., 2012; Yue et al., 2014). Uncertainty in feedstock choice would result in uncertain environmental impacts. (ii) Despite the incentives for establishment, storage and harvest of switchgrass and miscanthus through BCAP, there is not a lot of land-use change to perennials. This could be due to greater risk perception for perennials and better risk management being available for corn-soy through the crop insurance program (Skevas et al., 2016). If the RFS2 mandate has to be fulfilled, better risk management for energy crops and other potential streams of revenue such as payments for environmental stewardship and ecosystems services will have to be used to drive land use change. The current subsidies and commodity crop insurance result in the use of mostly residue harvest for cellulosic ethanol production in both regions, which could be a sub-optimal option under other objectives.

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Chapter 4 : Trade-offs between profitability and water quality under different federal agency objectives for sourcing cellulosic feedstock

Manuscript in Preparation for Biomass and Bioenergy: Keerthi S and S Miller. Trade-offs between profitability and water quality under different federal agency objectives for sourcing cellulosic feedstock.

ABSTRACT

Large-scale agricultural land-use change from the Renewable Fuels Standard (RFS2) mandate can have significant water quality impacts. For cellulosic ethanol, there is uncertainty in the kind and location of feedstock that will be available. Consequently the impacts on land use and water quality are highly uncertain. The sourcing of lignocellulosic biomass to fulfil the requirements of RFS2 has often been studied as a biofuel supply chain model, including the optimization of locations for costs and sustainability. These models are often optimized at the county or larger scales, while water quality impacts are apparent on a watershed or sub-watershed scale. Here, we consider objectives used by three federal agency studies to determine the availability of biomass from different regions in the United States to develop land-use change scenarios for two watersheds. Considering switchgrass, miscanthus and corn stover as alternative options on cropland and marginal pastureland, we find that the crop mix obtained from each of these objectives are different and result in different predominant options in the two watersheds. Given the relative profitability of the options on cropland and pastureland, conversion from pastureland to switchgrass or miscanthus is more prevalent than cropland. While conversion from cropland to any of the alternatives generally improves water quality from a nitrogen perspective, the impacts from pasture conversion are highly uncertain. There are tradeoffs between profitability and water quality for each scenario. When the optimal location of the biorefinery was considered, the supply of biomass and changes to water quality were localized around biorefinery location, and these changes were significant at the sub-watershed scale. Any optimization of the biofuel supply chain system for water quality will therefore have to be at this resolution.

1. Introduction

The Renewable Fuels Standard (RFS2) under the Energy Independence and Security Act (EISA 2007) mandated the production of 36 billion gallons of biofuel by the year 2022. Federal agencies including the US Department of Energy (DOE), Department of Agriculture (USDA) and the Environmental Protection Agency (EPA) have conducted studies to understand the impacts from the mandate, catalogue the availability of biomass (Perlack et al., 2011; USDA, 2010) and optimize the siting of bio-refineries (U.S. EPA, 2010). This study evaluates tradeoffs between water quality and profitability resulting from land-use change on cropland and pastureland, driven by different objectives in two watersheds – the Upper Cedar watershed in the Midwest and the Lumber watershed in the southeast.

There has been a long history of studies looking into environmental impacts from RFS2, particularly, greenhouse gas emissions from direct and indirect land-use change (Feyereisen et al., 2007; Cherubini et al., 2009; US General Accountability Office, 2009; Smith and Searchinger, 2012) and impacts to water scarcity and quality (Dale et al., 2010; Yeh et al., 2011; Powers et al., 2011; Wu et al., 2012; Wu and Liu, 2012; Gramig et al., 2013; Sarkar and Miller, 2014). These studies are at various scales and find trade-offs between different objectives of environmental sustainability.

RFS2 specifies two separate categories of biofuel – the conventional corn grain based ethanol and biofuels from other sources including lignocellulosic biomass, algal and other advanced biofuels (Perlack et al., 2011). However, the actual feedstock for the other categories of biofuel have not been specified. Therefore there is uncertainty regarding where and what kind of land-use change is likely to take place, how much feedstock will be available and at what cost. Further, the cellulosic ethanol industry has also been slow to develop due to both technological challenges and policy uncertainties, as the Environmental Protection Agency (EPA) has waived or reduced the mandated requirement of cellulosic biofuels from 2010, due to the lack of infrastructure. As of January 2016, there were 15 operating ethanol plants in the country with the combined capacity of 100 million gallons[13], as opposed to the mandated 4.25 billion gallons a year. Further processing

[13] Ethanol Producer Magazine. Updated Jan 23 2016.
<http://www.ethanolproducer.com/plants/listplants/US/Existing/Cellulosic>

costs for the cellulosic ethanol industry have not yet matured (Johnson, 2016; Kazi et al., 2010) adding to additional uncertainty in the availability and costs of ethanol and other advanced biofuels.

The optimization of biofuel systems and large-scale study of environmental impacts are complicated by two factors. First, there are numerous stakeholders in the system who have varying levels of influence at multiple scales, from feedstock producers (farmers) to policy-makers at the federal level. Second, the variability and uncertainty associated with ethanol production is high, particularly with respect to land-use change and socio-economic drivers in the current policy environment. These key challenges and uncertainties inherent in the development of bioenergy supply chain are summarized by Yue et al. (Yue et al., 2014) as two key types – strategic and operational. Strategic uncertainties include climate, farmer decision making, incentives and policy, and technological advances. Operational uncertainties include process yields, production costs, and supply and demand fluctuations. The integration of these uncertainties across multiple scales is a challenge, especially in the study of sustainability, where impacts on land and water quality may be experienced at a different scale than, say, greenhouse gas emissions or water scarcity.

Among the methods available to address these uncertainties are stochastic modeling and scenario analyses. A number of studies use scenario analyses to address uncertainty in future land-use, in particular. A review of the literature on land-use change due to bioenergy suggests different approaches to designing land-use change scenarios to evaluate environmental impacts. While there are a few studies that involve the development of a narrative that may include participatory assessment from stakeholders (qualitative scenario analyses (Swart et al., 2004)) to evaluate the environmental impacts of land-use change from bioenergy, quantitative analyses have been more frequently used. Three approaches are particularly prominent. First, land-use change is modeled as a fraction of existing land-use change to exploring a range of scenarios (Kim et al., 2009). While this method is certainly useful in evaluating best and worst case scenarios, application to real world scenarios is difficult. The second approach relies on inputs from socio-economic and policy models. These scenarios are richer, often involve narratives from qualitative scenario analysis, and are more grounded in the real world (Beach and McCarl, 2010; Perlack et al., 2011). However, the large-scale and complexity of these models are also a disadvantage in evaluating environmental impacts like water quality and scarcity that can be localized, and it is computationally difficult to apply these models at a high resolution. The last approach is a combined approach, targeting land-use change at a high resolution using optimization of objectives or goals identified. These objectives can also involve assumptions from socio-economic models and policy, and can be used to evaluate impacts of normative scenarios (Baskaran et al., 2010; Cibin et al., 2015, 2012; Gramig et al., 2013; Parish et al., 2012; Wu et al., 2012).

A number of studies have looked into the optimal siting of biorefineries optimizing the locations nationally using average availability of biomass feedstock, usually at the county scale (Daystar et al., 2014; Egbendewe-Mondzozo et al., 2011; Kim and Dale, 2015; Lambert et al., 2016; Shastri et al., 2011; Tan et al., 2009; You et al., 2012; Yue et al., 2014; Zamboni et al., 2009). Often, these are multi-objective studies establishing a Pareto-optimum between conflicting objectives of supply chain costs, farmer profitability and environmental goals. For example, You et al. (2012) integrated a life-cycle analysis of greenhouse gas (GHG) emissions with a multi-objective optimization for a bioenergy supply chain (feedstock production, logistics and supply using county-level data in Illinois to minimize annualized cost of the system as well as GHG emissions. Their analysis revealed a tradeoff between ethanol supply chain cost ($/gal of ethanol) and GHG emissions, particularly because the costs were determined by capital costs and economies of scale for the biorefinery. Larger biorefineries would require trucking from distant locations increasing the GHG emissions. By locating the large bio-refineries closer to demand centers (like Chicago), GHG emissions could be reduced on a system-wide basis (You et al., 2012). However, for localized effects like water quality, a county-scale analysis may prove insufficient. The literature around farmer decision making suggests also that they are likely to convert smaller plots of land for energy crop production (John Graham, Joan Nassauer, Personal Comm) (Graham, 2016). Therefore, discussion of water quality impacts lends itself to consideration of higher resolution data than at county-scale.

Egbendewe-Mondzozo et al. (2011) combined a spatially explicit EPIC model to acquire yield potentials in southwest Michigan for alternative biomass resources at a higher resolution (HUC10 level) than county scale and an optimization model to maximize farmer returns. Their model indicated that increasing biomass prices relative to other crops, initially made more crop residues available increasing GHG emissions (CO_2 and N_2O) and negatively impacting water quality due to increased nutrient loss. As biomass prices increased, more perennial biomass became available and resulted in better environmental outcomes and higher farm returns. High subsidies for establishment from Biomass Crop Assistance Program (BCAP) were needed to ensure production (Egbendewe-Mondzozo et al., 2011). However, their model does not consider the impact of biomass prices on the rest of the biofuel supply chain and consequently their environmental incomes.

Parish et al. in the Biomass Location for Optimal Sustainability Model (BLOSM) attempt to improve sustainability metrics, including water quality, across a watershed while improving farmer profitability by integrating economic data on biomass availability on a county scale from Policy Analysis Systems model (POLYSYS) with the environmental Soil and Water Assessment Tool (Parish et al., 2012). Their study showed that simultaneous improvement in both objectives could be possible by planned plantings of switchgrass across a watershed. However, the study also did not consider other alternatives to switchgrass in the watershed, and the rest of the biofuel supply chain to determine overall impacts from the mandate.

A recent study by Lambert et al. integrated the Biofuels Facility Location Analysis Modeling Endeavor (BioFLAME) model (Wilson, 2009), which is cost- minimizing site selection model with the Spatially Referenced Regressions on Watershed Attributes (SPARROW) hydrologic water quality model to predict the land-use change and water quality impacts at various levels of RFS2 implementation in the Southeast (Lambert et al., 2016). This study looks at cellulosic ethanol from switchgrass at the basin-scale and finds that water quality improvements in the region from perennials may be overstated as marginal land is likely to be converted before cropland that is more intensively managed.

The actual local impacts of the land-use change, however, depend on the local configuration of land-use. We demonstrate that uncertainty in production economics for switchgrass and miscanthus contributes to uncertainty in land-use change among two land-use categories – cropland and pastureland. Our study adapts some aspects from the Lambert et al. study to determine a range of impacts from the bioenergy mandate at a higher resolution. We use a simplified siting method to represent optimization similar to those used in the BioFLAME model and EPA's siting model to drive one land-use change scenario in the model. By also studying the major driver for land-use change, farm profitability, this study is able to compare the land-use configurations under different objectives. Further, by looking at other potential locations for the ethanol plant, we examine the local effects of biorefinery locations on land use change. We make the case that impacts to water quality can be better managed as a strategic decision during the siting of the model, given the localization of impacts.

We use Hydrologic Response Unit (HRU) level results from the Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2005; Srinivasan et al., 2010) to optimize the biofuel supply chain system under three different objectives in two watersheds in different regions of the US. We use Mixed-Integer Linear Programming (MILP) to (i) Maximize farmer profitability which drives land-use change; (ii) Minimize the cost of procurement of ethanol or the Minimum Ethanol Selling Price (MESP); and (iii) Maximize land-use efficiency, objectives that are simplified proxies for some federal agency models (discussion in Keerthi and Miller, 2017b – Chapter 3) (Perlack et al., 2011; U.S. EPA, 2010; USDA, 2010). We also model a scenario that minimizes nitrate-nitrogen to assess the tradeoffs between other objectives and water quality. In our previous work (Keerthi and Miller, 2017b (Under review)), we stochastically modeled production and processing costs for switchgrass and miscanthus using a Monte-Carlo Analysis to understand how existing policy incentives for row crops and lignocellulosic biomass would drive the crop mix available for the production of biofuel. To our knowledge, none of the siting models examine the impacts of the crop insurance program (post Farm Bill 2014) on the incentives to grow biomass resulting in an overestimation of land-use change in each region. The mean expected values from the stochastic model from the analysis are included here in the estimation of relative profitability of three cellulosic ethanol feedstock – corn stover, switchgrass and miscanthus.

2. Method

2.1 Study approach

The two watersheds in this study are the Upper Cedar watershed located in the midwest (Iowa and Minnesota) and the Lumber watershed located in the southeast (North/South Carolina). They were chosen to represent different land-use configuration (agriculture dominated versus mixed-use and wetland dominated), climate (different length of growing season) and management practices (tile drained versus no tile drains) to understand the range of impacts from RFS2. The two watersheds were modeled, calibrated and validated using the SWAT model (Keerthi and Miller, 2017 (In Review)) for a baseline two year corn-soy rotation. The SWAT model is a watershed-scale, physically based model that groups units with the same land-use, soil and elevation into computationally efficient HRUs (Gassman et al., 2007; Neitsch et al., 2005). The model is able to simulate yields, sediment, nitrogen and phosphorus outputs at the HRU level. Three alternatives to corn-soy rotation without stover harvest were simulated – corn-soy with stover harvest, switchgrass and miscanthus. HRU-level yields and nitrogen outputs for each land-use change were obtained from the model. Similarly pasture management was replaced with switchgrass or miscanthus to get HRU-level outputs.

We use Mixed Integer Linear Programming optimization to generate three scenarios of land-use change from different federal agency objectives. The trade-offs between the objectives and impact to water quality in each case is examined. Decision making by the farmer is assumed to be primarily driven by production economics between corn-soy rotation without stover harvest and three alternative sources of cellulosic biomass – corn-soy rotation with stover harvest, switchgrass and miscanthus and the baseline corn-soy rotation on cropland and baseline pasture management on pastureland. The Soil and Water Assessment Tool (SWAT) is used to generate a look-up table of yields and nitrogen output to surface water (kg/ha) for the corn-soy baseline and the alternatives at the Hydrologic Response Unit (HRU) level.

There are a number of studies that estimate the production costs for switchgrass and miscanthus that do not have an established market at present. We conducted a Monte-Carlo Analysis to determine the probability distribution for the annualized costs based on the estimations (Keerthi and Miller, 2017b). Production costs for perennials ($/ha) here are estimated from the mean expected values for parameters for the annualized costs from the MCA, taken to be their median value (From Keerthi and Miller, 2017b (In Review) – Chapter 3). For the second objective, we also develop a simplified biofuel supply chain that includes feedstock production, logistics and ethanol processing discussed in Section 2.2, to estimate delivered costs of feedstock. Figure 4-1 shows a simplified schematic of the bioenergy supply chain, inherent uncertainties and variability and their treatment in this study.

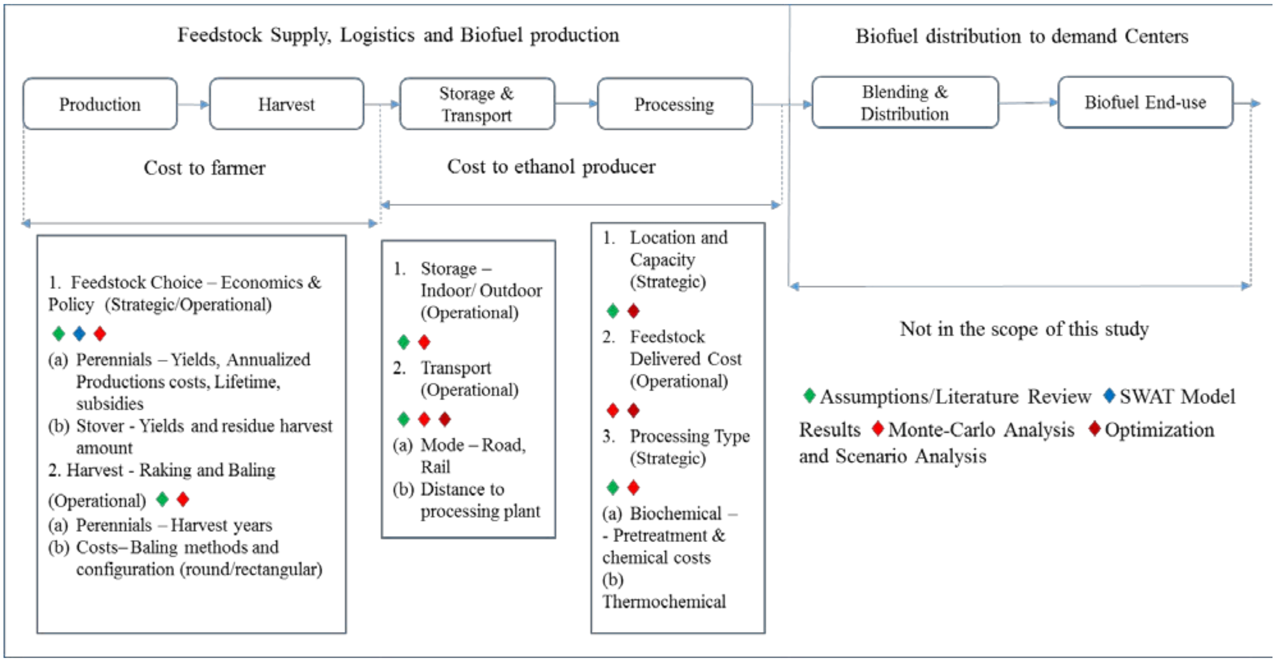


Figure 4-1: System boundary for the biofuel supply chain and methods used to address uncertainty and variability in the biofuel supply chain. The type of decisions and uncertainty – strategic or operational - is indicated in parenthesis. The cost of production of ethanol is partitioned to the farmer and the ethanol producer as required for the optimization

2.2 System boundary for the biofuel supply chain

The simplified biofuel supply chain incorporated in this study looks at feedstock supply, logistics and processing and not the demand side of the equation including the transport to a blending facility.

2.2.1 Feedstock Production

We assume three alternatives available for cropland– Corn-soy with stover harvest, switchgrass and miscanthus. To represent marginal land, we consider only the Cropland Data Layer 2007 classification of pasture in this analysis, and two cellulosic alternatives for pasture – switchgrass and miscanthus. Pasture management, switchgrass and miscanthus management practices and production economics are described in the Supporting Information (Appendix B and Appendix C).

2.2.2 Feedstock logistics

Storage costs are included in the production costs for both corn-soy and cellulosic feedstock in Keerthi and Miller (In Review, 2017). The estimates for transportation by truck per ton of corn/cellulosic feedstock to the nearest wet-milling corn/dry-milling ethanol plant or cellulosic ethanol plant transported are obtained from a review of available literature. Corn transportation costs to nearby corn ethanol plants (< 300 miles) by truck per mile per load are estimated from the Grain Transport Quarterly Updates between 2010 and 2016[14]. Assuming each truck load is around 25 ton or 980bu of corn (Iowa Department of Transportation - http://www.iowadot.gov/compare.pdf), the cost of transport per ton per km is calculated to be 0.102 $/ton-km. A map of the existing corn ethanol plants was obtained from the US Energy Information Administration (https://www.eia.gov/maps/layer_info-m.php), representing ethanol plants online as on January 1, 2015. Because HRUs are not spatially explicit, the distance from the centroid of the subbasin to the closest corn ethanol plant is considered to be the transportation distance.

The transportation costs for switchgrass, miscanthus and corn stover were obtained through a review of existing literature on production costs (Aravindhakshan et al., 2010; Khanna et al., 2008; Shastri et al., 2011; Witzel and Finger, 2016). We assume the median cost, as estimated by Shastri et al. 0.25 $/ton-km (Shastri et al., 2011) for this study. The higher cost for cellulosic ethanol may be due to size limitations in transporting of bales of perennials/residue as compared to grain. For cellulosic ethanol, as of January 2016, there are only 15 commercial plants operational. For this study, we consider the centroid of each county intersecting the watershed to be a potential location for a biorefinery (Figure 4-2). The distance from the centroid of each sub-basin to each potential location was determined for transportation distances for lignocellulosic feedstock in each subbasin. One of the objectives (discussed under Section 2.3) was specifically optimized to solve for the optimal location for a biorefinery in the watershed.

[14] Grain, Truck and Ocean Rate Advisory, https://www.ams.usda.gov/services/transportation-analysis/gtor. Accessed on 15 Jan 2017

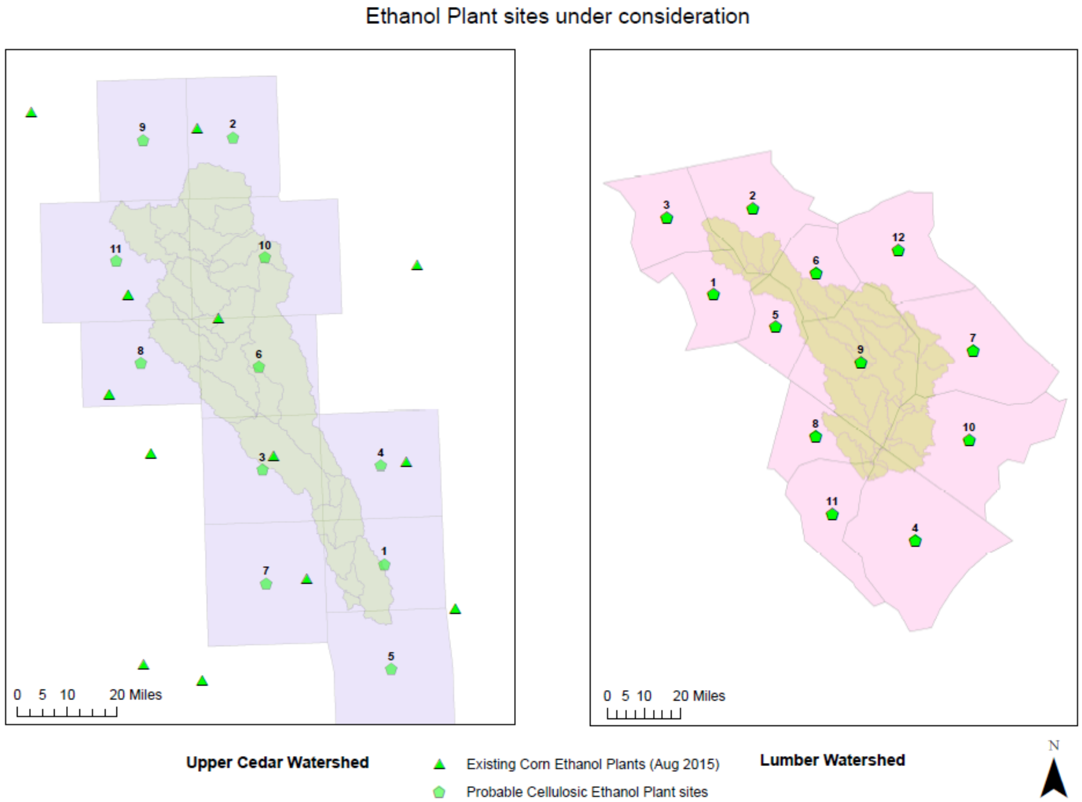


Figure 4-2: Potential cellulosic ethanol plants under consideration in the Upper Cedar and Lumber watersheds approximated to be the centroid of counties intersecting the watershed. Existing corn ethanol plants in Iowa from US EIA data (see text)

2.3 Mixed Integer Linear Programming Optimization

A Mixed Integer Linear Programming (MILP) model was built and implemented using the MATLAB® 2015a INTLINPROG solver and look-up tables developed through the SWAT model. A sample code is available in the Supporting Information (Appendix C). The MILP selects the land-use configuration for the optimization of three objectives that were also used in some federal agency models for biomass availability. The decision variables, objectives and constraints are discussed below.

2.3.1 Decision variables

For Upper Cedar, the study considered 567 Corn-Soy Baseline HRUs with three alternative management options (switchgrass, miscanthus and stover harvest) and 229 Pasture baseline HRUs with two alternative management options (switchgrass and miscanthus), for a total of 2955 binary decision variables. For Lumber, the study considered 378 Corn-Soy Baseline HRUs and 51 Pasture baseline HRUs with the same alternative options as the Upper Cedar watershed, for a total of 1287 decision variables. Each individual HRU was considered, for this study's purpose, to be an individual farm.

2.3.2 Objective functions

2.3.2.1 Maximizing Farm Profitability

The first objective is simplified from the POLYSYS model used by the US-DOE for the Billion-ton study (Perlack et al., 2011), maximizing farm profitability over the watershed. For each watershed, farm profits ($\pi_{watershed}$) were a function of revenue calculated and production costs, which are in turn functions of HRU productivity and area (See SI for discussion) for each land-use option. The study includes the impacts of crop insurance on corn-soy profitability and the Biomass Crop Assistance Program (BCAP) incentives for switchgrass and miscanthus.

$$max\ \pi_{watershed} = \sum_{n=1}^{CS-HRU} \sum_{LU=1}^{4} [r_{LU,n} - c_{LU,n}] x_{LU,n} + \sum_{m=1}^{Past-HRU} \sum_{LU=1}^{3} [r_{LU,m} - c_{LU,m}] x_{LU,m} \quad \ldots\ldots (1)$$

Where $r_{LU,n}$ and $c_{LU,n}$ ($) are the annual revenue and production costs for a single land-use (LU) for the nth HRU with the corn-soy baseline. $r_{LU,m}$ and $c_{LU,m}$ are the annual revenue and production costs for the mth HRU with the pasture baseline. $x_{LU,n}$ and $x_{LU,m}$ are the binary decision variables to select a land-use option for each HRU.

2.3.1.2 Maximizing Economic Welfare (Consumer and producer surplus)

The second objective was derived from EPA's RFS2 Regulatory Impact Analysis. The analysis used the Forest and Agriculture Sector Model (FASOM) model that estimates biomass available by allocating land so as to maximizing economic welfare for both producers and consumers in both sectors (Beach and McCarl, 2010). It also optimized the locations of biorefineries using a cost minimization algorithm to procure feedstock at the lowest price at the county-scale (U.S. EPA, 2010).

This study maximizes the sum of the consumer and producer surpluses ($U_{watershed}$) where surplus is the difference between revenue generated and cost of production per gallon of ethanol produced. This quantity depends on farmer profitability (Objective 1), storage and transport costs to an ethanol plant, the Minimum Ethanol Selling Price (MESP) for each feedstock (Gonzalez et al., 2012) and the wholesale price of ethanol[15].

$$max\ U_{watershed,i} = \sum_{n=1}^{CS-HRU} \sum_{LU=1}^{4} (P_{eth} - MESP_{LU,n}) x_{LU,n} G_{LU,n} + \sum_{n=1}^{CS-HRU} \sum_{LU=1}^{4} [r_{LU,n} - c_{LU,n}] x_{LU,n}$$
$$+ \sum_{m=1}^{Past-HRU} \sum_{LU=2}^{3} (P_{eth} - MESP_{LU,m}) x_{LU,m} G_{LU,m} + \sum_{m=1}^{Past-HRU} \sum_{LU=1}^{3} [r_{LU,m} - c_{LU,m}] x_{LU,m} \quad \ldots\ldots (2)$$

Where P_{eth} is the whole sale price of ethanol ($/gal), $MESP_{LU,m/n}$ is the Minimum Ethanol Selling Price for ethanol ($/gal) produced from land-use in the n^{th} or m^{th} HRU. $G_{LU,n}$ and $G_{LU,m}$ are the volume of ethanol (gal) produced by n^{th} or m^{th} HRU for a particular land-use. We assume no ethanol production from pasture land-use and assume that the consumer surplus is zero. MESP is given by the equation below:

$$MESP_{LU,m/n} = [r_{LU,m/n} + d_{m/n}(i) CtY_{LU,m/n} A_{m/n} + PE_{LU}] / G_{LU,m/n} \ldots \ldots (3)$$

Where C_t is the transportation cost (for grain or lignocellulosic feedstock in $/ton-km), $d_{m/n}(i)$ are the distances from corn-soy or pasture baseline HRUs to the potential ethanol plant i, $Y_{LU,m/n}$ is the yield (kg/ha) from a particular land-use in the n^{th} or m^{th} HRU, $A_{m/n}$ is the area (ha) of the n^{th} or m^{th} HRU and PE_{LU} is the processing costs in the ethanol plant excluding feedstock production and handling costs (see Discussion in SI). The i^{th} biorefinery location with the largest $U_{watershed}$ is assumed to be the optimal biorefinery.

2.3.1.3 Maximizing Land-use efficiency

The third objective for optimization is derived from USDA's Regional Roadmap to meet the Biofuel Mandate (USDA, 2010). In the study, the regional availability of each feedstock was

[15] The MESP ($/gal) is the minimum price at which ethanol is sold, so as to guarantee a specific rate of return (assumed to be 12% here) on the cost of production that includes feedstock, processing, operating and capital costs (Kazi et al., 2010).

determined by the Agricultural Research Service. The assumptions used in the study are not explicitly stated but it appears that similar results could be obtained via an objective to maximize the energy produced per hectare or the land-use efficiency, which is used as our third objective.

$$\max E_{watershed} = \left(\sum_{n=1}^{CS-HRU} \sum_{LU=1}^{4} [Y_{LU,n} Eff_{LU} A_n] x_{LU,n} + \sum_{m=1}^{Past-HRU} \sum_{LU=2}^{3} [Y_{LU,m} Eff_{LU} A_m] x_{LU,m} \right) \Big/ (A_n + A_m) \dots\dots (4)$$

Where $E_{watershed}$ is a measure of land-use efficiency (kJ/ha), $Y_{LU,n/m}$ is the yield (kg/ha) from a particular land-use in the n^{th} or m^{th} HRU, $A_{m/n}$ is the area (ha) of the n^{th} or m^{th} HRU and Eff_{LU} is the conversion efficiency (kJ/kg) for ethanol produced from a particular land-use option.

2.3.1.4 Minimize Nitrogen output from watershed

To assess the tradeoff between water quality and the other objectives, the minimum nitrogen runoff from the watershed was determined, while meeting the other constraints. A HRU look-up table for both corn-soy and pasture baselines and their alternatives was generated for the two watersheds for the surface nitrogen produced (kg) at the HRU level, going into the sub-basin reach/stream. The sum of the nitrogen output of these HRUs is a proxy for watershed level nitrogen runoff.

$$\min N_{watershed} = \left(\sum_{n=1}^{CS-HRU} \sum_{LU=1}^{4} [N_{LU,n} A_n] x_{LU,n} + \sum_{m=1}^{Past-HRU} \sum_{LU=1}^{3} [N_{LU,m} A_m] x_{LU,m} \right)$$

Where $N_{Lu,n}$ is the surface nitrogen (kg/ha) from the n/m^{th} HRU in land-use, LU, $A_{n/m}$ is the area of the n^{th} or m^{th} HRU.

2.3.3 Constraints

2.3.3.1 Decision variable constraints

For each HRU, a single land-use can be chosen, the decision variable therefore is non-zero and binary. The constraints are represented as follows:

$$\sum_{LU} x_{LU,n/m} = 1 \qquad \forall\, n/m \dots\dots (5)$$

Where n represents all corn-soy baseline HRUs and m represents all pasture baseline HRUs and LU are the land-use decisions.

2.3.3.2 Capacity constraints

Stover, switchgrass and miscanthus, all have non-zero costs of production, so it is economically efficient for the supply to meet the demand from biorefinery. Therefore, we assume that the sum of all the lignocellulosic biomass feedstock in each watershed cannot exceed the capacity of the single bio-refinery in the watershed. From a literature review, the average capacity of a cellulosic ethanol plant was about 2000 Mg/day and the plant operates about 8410h a year (Gonzalez et al., 2012; Humbird et al., 2011; Johnson, 2016; Kazi et al., 2010), amounting to between 700,500 – 700,833 Mg/year of biomass. This biomass availability constraint is expressed as follows:

$$\sum_{n=1}^{CS-HRU}\sum_{LU=2}^{4}[Y_{LU,n}A_n]x_{LU,n}+\sum_{m=1}^{Past-HRU}\sum_{LU=2}^{3}[Y_{LU,m}A_m]x_{LU,m}>700{,}500 \qquad \ldots\ldots(6)$$

$$\sum_{n=1}^{CS-HRU}\sum_{LU=2}^{4}[Y_{LU,n}A_n]x_{LU,n}+\sum_{m=1}^{Past-HRU}\sum_{LU=2}^{3}[Y_{LU,m}A_m]x_{LU,m}<700{,}833 \qquad \ldots\ldots(7)$$

$Y_{LU,n/m}$ are the yields (Mg/ha) for stover harvest, switchgrass and miscanthus land-use selections in the n^{th} and m^{th} HRUs.

2.3.3.3 Land-use change constraints

About 40% of the corn produced in the country goes into ethanol production, at present[16]. Assuming that there is 60% of corn in food and feed production, the maximum land-use change allowable from the baseline is 40%. However, we assume that increasing cellulosic production could offset some, but not all of the corn ethanol use in the future. Corn-soy with stover harvest could supply grain and cellulosic ethanol and switchgrass and miscanthus have higher productivities than corn, especially in the southeast. Therefore they require less land for the same amount of ethanol produced. Further, allowing for future corn expansion to meet increasing

[16] U.S. Bioenergy Statistics, Accessed from https://www.ers.usda.gov/data-products/us-bioenergy-statistics/us-bioenergy-statistics/#Feedstocks. Accessed on 16 Feb 2017

food-feed demand, for this study, we assume that the land-use in corn-soy production cannot decrease to less than 75% of the original corn-soy area to avoid food-fuel conflicts. This is given by:

$$\sum_{n=1}^{CS-HRU} x_{CS,n} A_n \geq 0.75 \sum_{n=1}^{CS-HRU} A_n \dots\dots (8)$$

Where $x_{CS,n}$ is the corn-soy binary decision variable and A_n is the area (ha) of the n^{th} HRU with a corn-soy baseline.

2.4 Sensitivity analysis

A MATLAB® program was written to generate 1000 switchgrass and miscanthus annualized cost estimates. An MCA for the optimization of the first objective was run over these 1000 estimates to determine the impact of uncertainty in switchgrass and miscanthus production costs on the optimization of farm profitability on the crop mix and water quality. For each run, the overall farm profitability and total nitrate-nitrogen from the HRUs were recorded.

To understand system sensitivity, the annualized costs for switchgrass and miscanthus, input into the MCA were divided into four quartiles. The estimates lower than the first quartile of all cost estimates for each perennial were considered to be "low" cost scenarios and estimates greater than the third quartile for cost estimates were considered to be "high" cost scenarios. The results for change in profitability and water quality from the baseline were than analyzed under four quadrants- 1) Low switchgrass and miscanthus costs 2) Low switchgrass and high miscanthus costs 3) High switchgrass and low miscanthus costs and 4) High switchgrass and high miscanthus costs.

3. Results and Discussion

3.1 MILP optimization results: Crop mix and water quality impacts

For both watersheds, the results for the optimization indicate that the each federal objective results in a different crop-mix and consequently, different water quality impacts. Limiting land-use change from corn-soy production, stover is predominantly favored as lignocellulosic feedstock over other crop alternatives in the Upper Cedar watershed for all objectives except Obj 3 which is maximizing the land-use efficiency (Figure 4-3). The optimum solution for economic welfare of the system (Obj 2) selects more ethanol from the corn-soy with stover harvest system as both grain and stover for ethanol can be harvested. The overall MESP for corn tends to be lower, as the technology is assumed to be mature. This results in less land-use conversion from pasture as compared to the scenario maximizing profitability (Obj 1). (Figure 4-3)

Miscanthus is the preferred feedstock for the Lumber watershed for all objectives. Switchgrass was not as competitive as stover harvest on cropland and miscanthus on pastureland (Figure 3b). Similar to the Upper Cedar watershed, maximizing land-use efficiency resulted in the least land-use change from cropland (Figure 4-4). The actual crop mix from each of the feedstock in each sub-watershed is also different, as indicated by the maps in Figure 4-7. This contributes to the difference in the water quality impact.

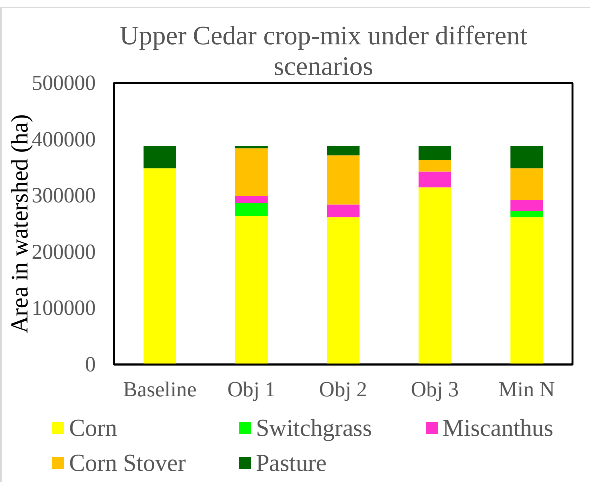


Figure 4-3: MILP optimization results for the four objectives show different crop-mix between objectives. Stover is predominantly available over other lignocellulosic options in the Upper Cedar watershed.

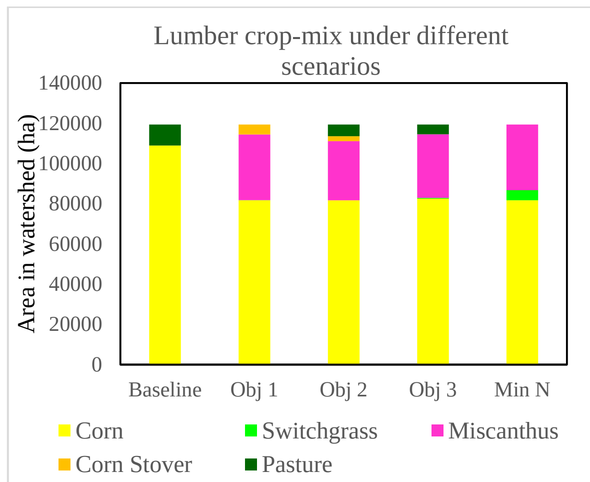


Figure 4-4: MILP optimization results for the four objectives show different crop-mix between objectives. Miscanthus is predominantly available over other lignocellulosic options in the Lumber watershed

Figure 4-5 and Figure 4-6 indicate that there is a clear tradeoff between farm profitability and the impact to water quality. In general, there is a decrease in nitrogen runoff into surface water when there is land-use change from cropland without stover harvest to switchgrass, miscanthus and stover harvest in both watersheds. The extent of this improvement depends on the HRU characteristics. For example, we find that in the Upper Cedar watershed, the average nitrogen runoff for the different feedstock options obtained from the SWAT model (Supporting Information-Appendix C) are significantly different ranging from about 21 kg N/ ha for Corn-Soy, followed by corn stover and switchgrass that are comparable at 14.44 kg N/ha and 13.7kg N/ha and 7 kg N/ha for Miscanthus (Keerthi and Miller, 2017a (Manuscript under Review)).

However, land-use change from pasture to switchgrass or miscanthus can deteriorate water quality or improve it, depending on the characteristics of the watershed and the intensity of pasture management. For example, while maximizing overall economic welfare (Obj 2) of the system decreases overall farm profitability for both watersheds, the effect on water quality is different. Pasture conversion to perennials appears to deteriorate water quality in the Upper Cedar watershed while improving it in the Lumber watershed. It should be noted that the magnitude of nitrogen runoff in each watershed is different due to the exacerbating presence of tile drains in the Upper Cedar watershed, increasing nitrogen runoff into surface streams and the mitigating presence of riparian wetlands in Lumber watershed (Keerthi and Miller,2017a (In Review)). The percentages expressed indicate small absolute differences in the Lumber watershed but significantly large differences in the Upper Cedar watershed.

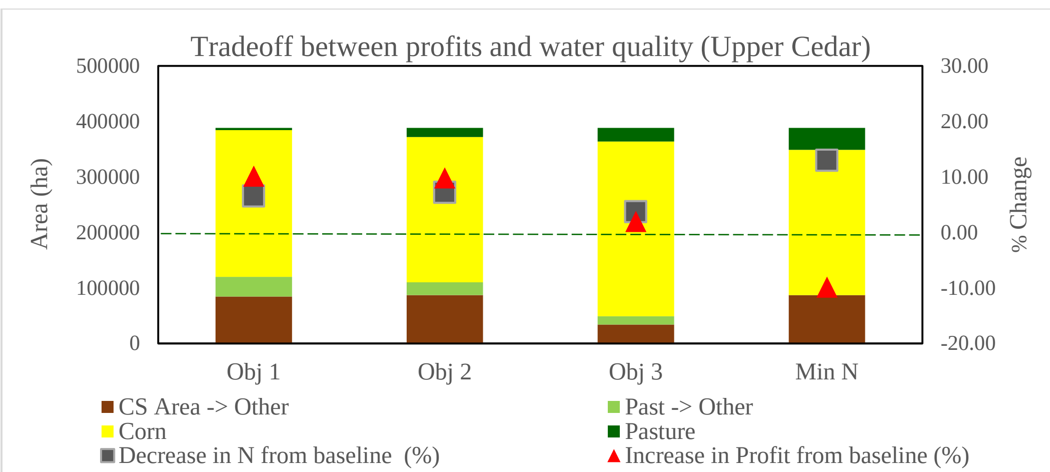


Figure 4-5: The primary axis shows the land-use change from cropland (Corn) into alternatives (switchgrass, miscanthus and stover) and pastureland into alternatives (switchgrass and miscanthus) in the Upper Cedar watershed. The secondary axis indicates tradeoffs between change in water quality in water quality and change in profit from the baseline for different objectives. The optimization for minimum nitrogen is included for comparison.

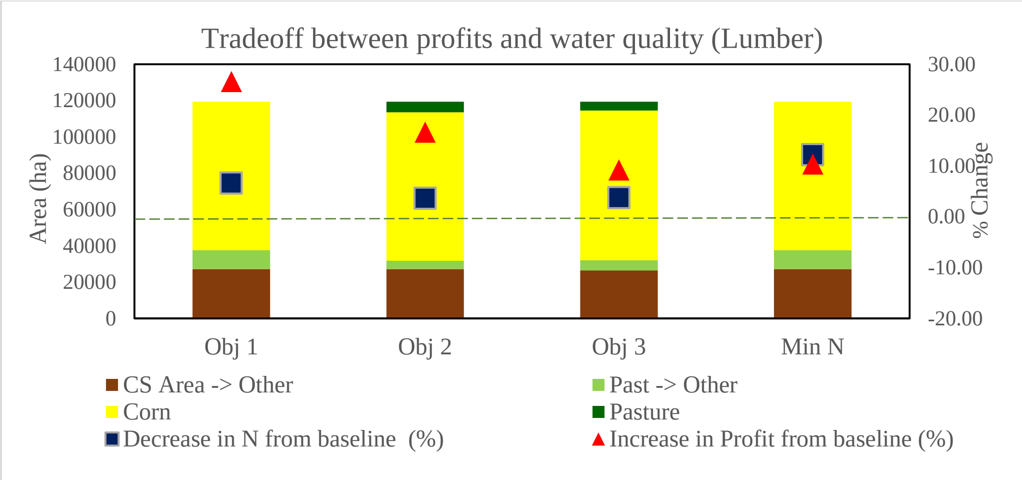


Figure 4-6: The primary axis shows the land-use change from cropland (Corn) into alternatives (switchgrass, miscanthus and stover) and pastureland into alternatives (switchgrass and miscanthus) in the Lumber watershed. The secondary axis indicates tradeoffs between an improvement in water quality and increase in profit from the baseline for different objectives. The optimization for minimum nitrogen is included for comparison.

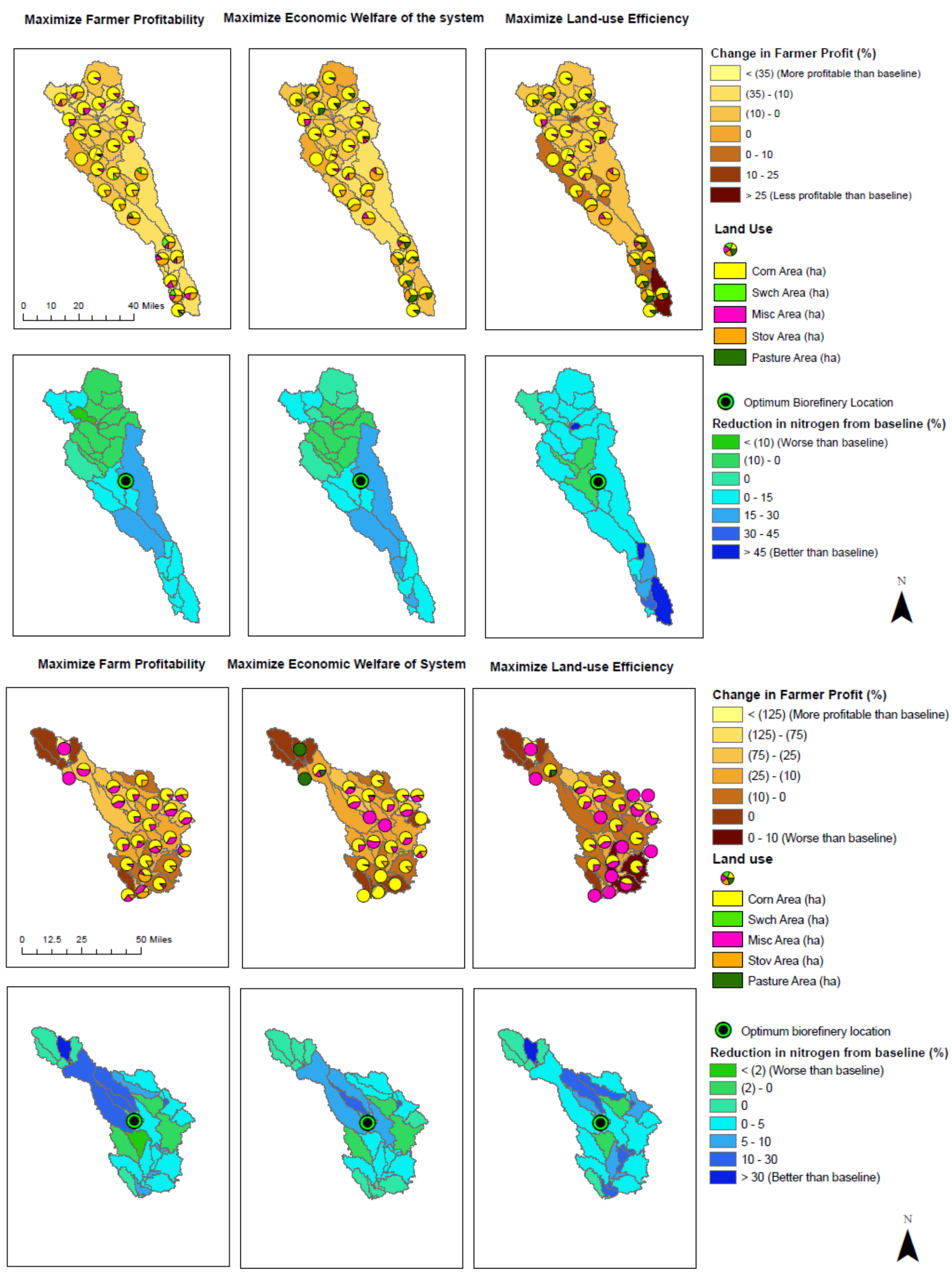


Figure 4-7: Relative changes in Farm Profitability and Surface nitrogen runoff from the baseline (Corn-soy and Pasture) for Upper Cedar watershed (top) and Lumber watershed (bottom) for the three scenarios. The result for the maximizing economic welfare for the system also selects an optimum location for 2000 Mg/day biorefinery.

In the Lumber watershed, the profitability of the minimum nitrogen scenario is higher than that of the baseline. This could be because of the lower productivity of corn in the southeast, and high productivity of switchgrass and miscanthus. Maximizing land-use efficiency (Obj 3) converts most of pastureland to miscanthus or switchgrass and results in the least land-use change from cropland. This is expected because miscanthus and switchgrass yields on pastureland are higher than stover harvest on cropland. Further, because baseline pastureland produced no ethanol but cropland does, the optimization selects out pastureland first to maximize land-use efficiency (Figure 4-6).

Results from the optimization also indicate that the land-use configuration, i.e., the biomass that is available from each sub-watershed, for each objective is different (Figure 4-8). The different land-use configurations within the watershed result in widely different water quality impacts within different sub-basins. This localization of water quality impacts is further examined below.

3.2 Localized water quality impact near biorefineries

Figure *4-8* shows the land-use configuration and water quality impacts of three different locations of biorefineries in the two watersheds. It is observed that the sourced biomass is “local” or close to where the biorefinery is located, most likely due to significant transport costs for biomass from the farm and storage locations (Kim and Dale, 2015). For example, in the Upper Cedar watershed, in the optimum location in the center of the watershed, there is almost no conversion of cropland or pastureland from the northern sub-basins. We see that in the next best biorefinery location, that there is significant change in the biomass sourced from the sub-basins. Similarly, for the Lumber watershed, while there is no conversion from pastureland in the northern sub-basins for the optimum location, there is a significant amount of miscanthus from those same sub-basins for the next-best optimum locations. The conversion of pastureland in this case appears to significantly improve the local water quality.

However, in areas that are highly sensitive to nitrogen runoff, for example, sub-basins with streams that exceed or are close to exceeding Total Maximum Daily Load limits, this effect is of concern. Since most siting studies look at biomass availability on a county level (Tan et al., 2009; You et al., 2012; Yue et al., 2014) and optimize the system at this scale, an opportunity to improve water quality in these areas and more importantly, avoid further deterioration may be missed.

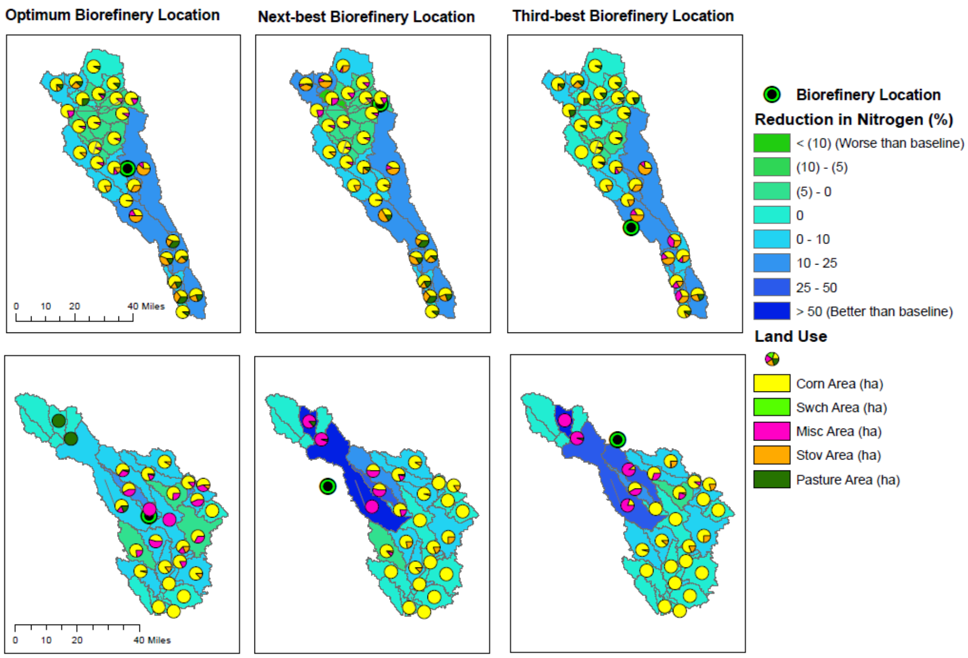
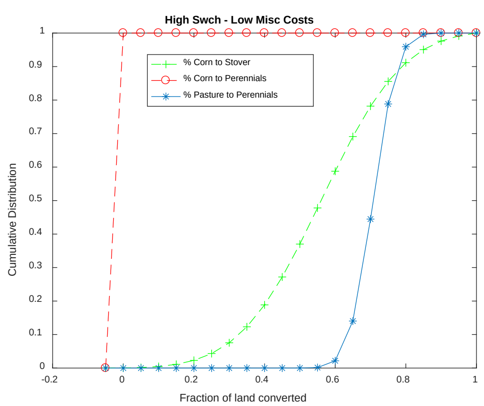
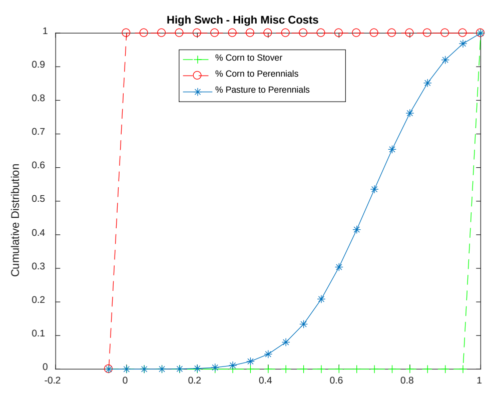


Figure 4-8: Localized water quality impacts around bio-refinery location in the Upper Cedar (top row) and Lumber (bottom row) watersheds. The pie charts indicate the proportion of baseline corn-soy rotation and pasture area. Local effects are both the change in crop mix and reduction (or increase in nitrogen). For example, for the Upper Cedar, there is little conversion coming from the northern sub-watersheds for the third best biorefinery location in the south, resulting in better local water quality in the north-east as compared to the case for the next-best biorefinery location.

3.3 Impacts of uncertainty of switchgrass and miscanthus production costs on land-use change and environmental impacts





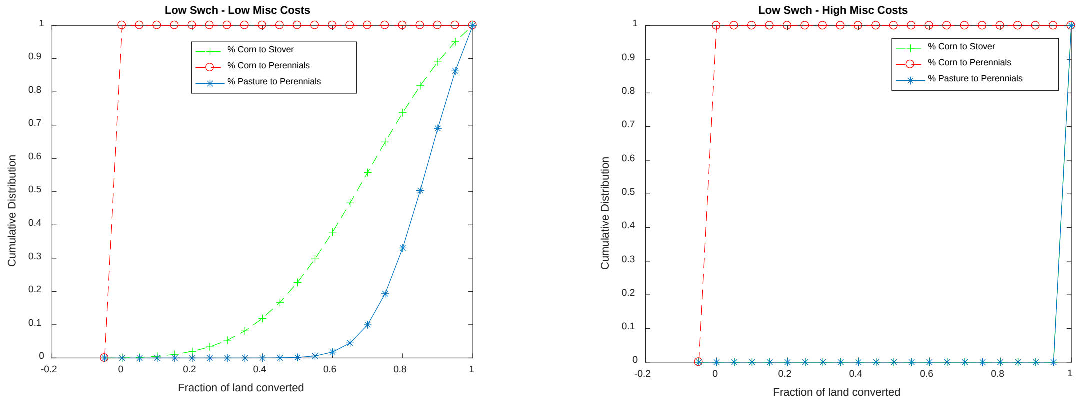


Figure 4-9: Cumulative Distribution of the conversion of cropland and pastureland under uncertain production costs of switchgrass and miscanthus on crop-mix in the Upper Cedar watershed for maximizing farm profitability. MCA results on switchgrass and miscanthus costs in the lower and upper quartiles (low, high scenarios) were used in the optimization. Values were truncated to fall between 0-100% of land converted.

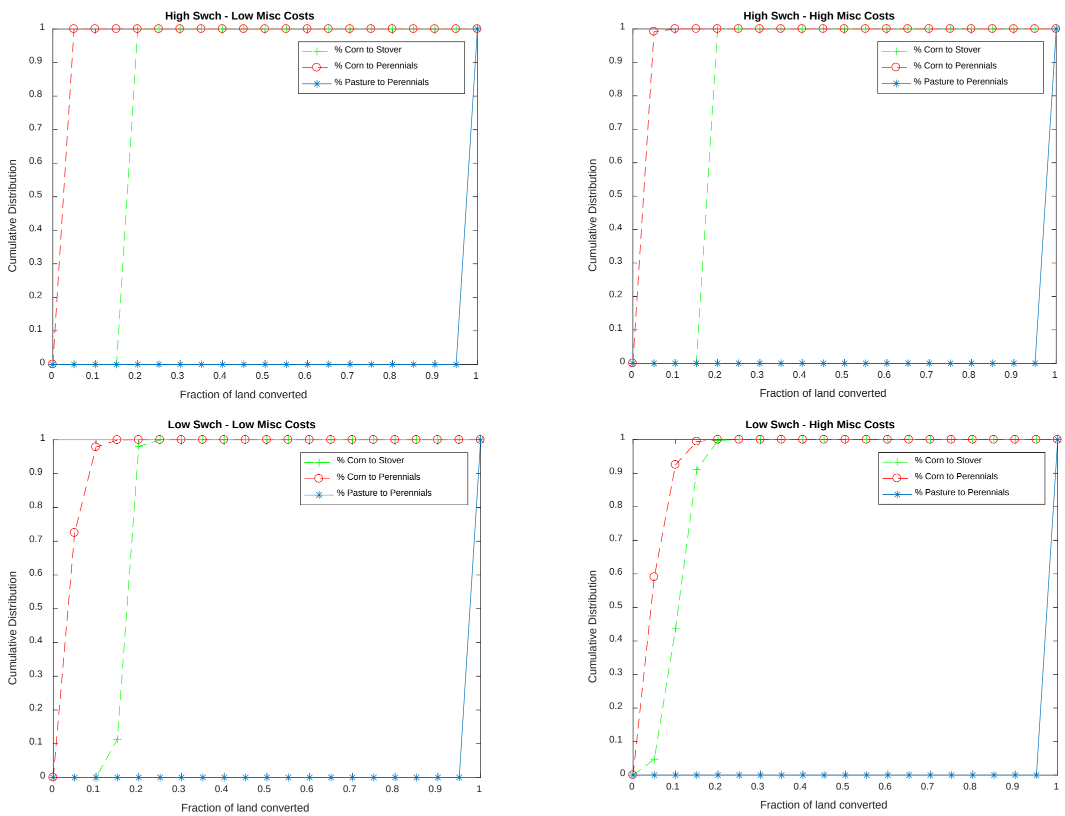


Figure 4-10: Cumulative Distribution of the conversion of cropland and pastureland under uncertain production costs of switchgrass and miscanthus on crop-mix in the Lumber watershed for maximizing farm profitability. MCA results on switchgrass and miscanthus costs in the lower and upper quartiles (low, high scenarios) were used in the optimization. Values were truncated to fall between 0-100% of land converted.

Figure 4-9 and Figure 4-10 are the cumulative distribution of the results from an MCA for the optimization of farm profitability under uncertainty in production costs for switchgrass and miscanthus. The production costs are divided into low and high cost scenarios for switchgrass and miscanthus as detailed in Section 2.4.

For the Upper Cedar watershed (Figure 4-9), regardless of the production costs of switchgrass and miscanthus, cropland (corn to perennials) does not convert to perennials and stover is the predominant biomass of choice. At low costs of switchgrass and miscanthus, we see some uncertainty in the amount of pastureland and cropland conversion to perennials and stover respectively. This is because of the variation in the yields of miscanthus and switchgrass that causes different amounts of land to satisfy the constraint limiting the amount of biomass sourced from the watershed. At high costs of miscanthus and low costs of switchgrass, pastureland preferentially converts to switchgrass. At high costs of switchgrass and low costs of miscanthus, pasture is preferentially converted to miscanthus. Miscanthus, being high-yielding requires less land to supply the same amount of biomass. At high costs of switchgrass and miscanthus, corn converts to corn with stover harvest to the maximum allowable extent. Pastureland conversion is uncertain under high costs of switchgrass and miscanthus. Lower percentage of conversions indicate miscanthus is pre-dominantly sourced. It should be noted that pastureland conversion was not constrained in these scenarios. Constraining pastureland conversion may have resulted in other land-use configurations.

For the Lumber watershed (Figure 4-10), maintenance of pastureland was found to be more expensive than in Upper Cedar using data from the NCSU and ISU extension services. Consequently, given the lower productivity of corn and stover, all of the pastureland converted to perennials in all scenarios. A similar result on the preferential conversion of pastureland before cropland, especially at lower biomass prices, was also found in the study by Sharp and Miller, (Sharp and Miller, 2014). At the high cost scenario for both switchgrass and miscanthus, a small amount of cropland is converted to include stover harvest. At low switchgrass and miscanthus cost scenario, there is some uncertainty in the amount of cropland conversion, depending on whether switchgrass or miscanthus is chosen during the simulation. At low switchgrass prices however, there is some conversion of cropland to perennials. Switchgrass is cheaper to establish and given the lower productivity of corn and stover in the region, switchgrass production could be more profitable than stover harvest.

The uncertainty in conversion of cropland or pastureland to stover production and perennials is also significant from a water quality perspective (Figure 4-11 and Figure 4-12).

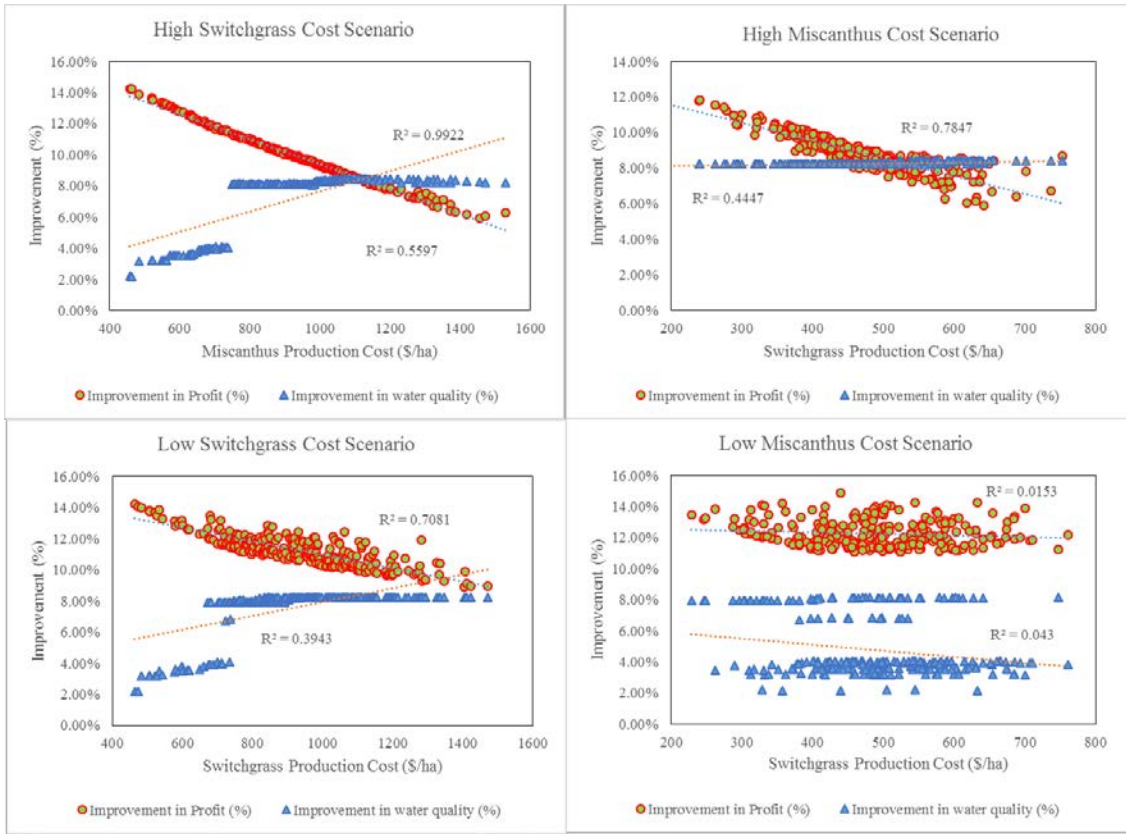


Figure 4-11: Impacts from uncertain production costs of switchgrass and miscanthus in the Upper Cedar watershed on farm profitability and water quality. MCA results on switchgrass and miscanthus costs in the lower and upper quartiles (low, high scenarios) were used in the optimization.

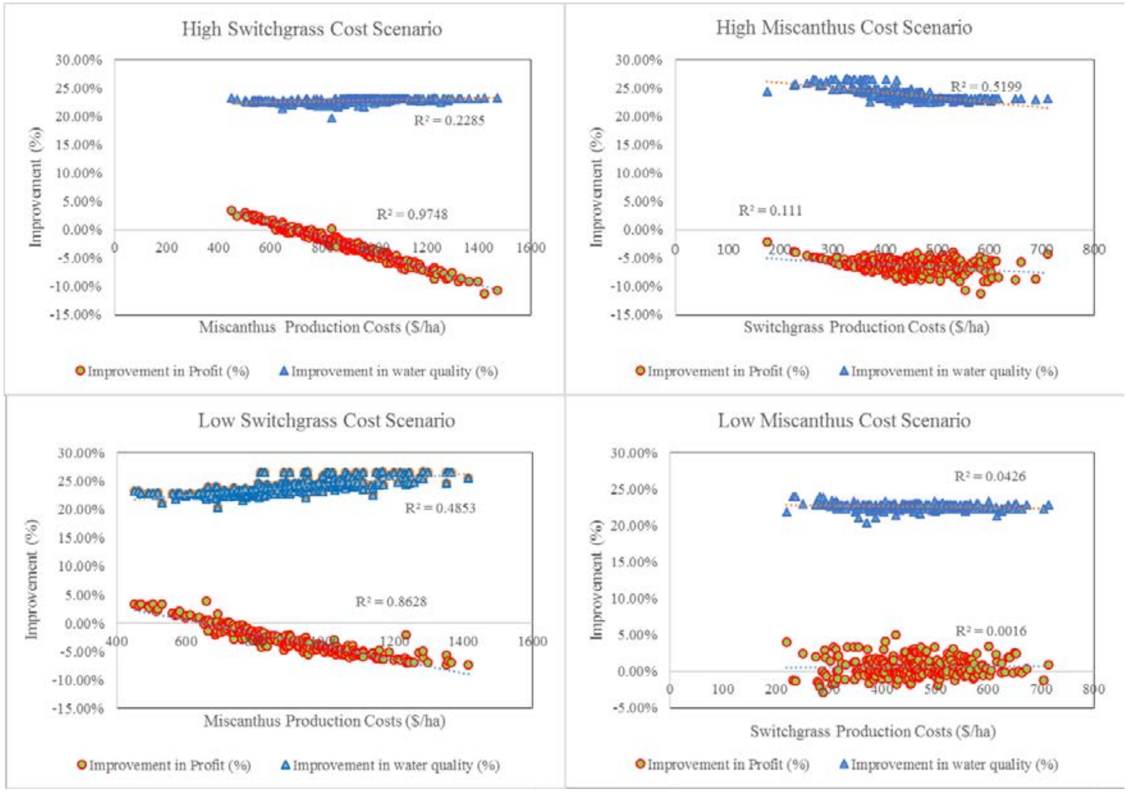


Figure 4-12: Impacts from uncertain production costs of switchgrass and miscanthus in the Lumber watershed on farm profitability and water quality. MCA results on switchgrass and miscanthus costs in the lower and upper quartiles (low, high scenarios) were used in the optimization.

For the Upper Cedar watershed (Figure 4-11), high switchgrass or miscanthus costs result in an overall decrease in farm profitability in the watershed. In general, water quality impacts are more uncertain for most scenarios, as indicated by the low R^2 for nitrogen runoff. The MCA analysis found that at low miscanthus costs, an increase in switchgrass costs is not likely to impact profitability, because miscanthus is the preferential option over switchgrass, especially for pastureland. However, the impact on water quality is highly uncertain. This could be due to different land-use configurations that result with this combination (Figure 4-9), as pastureland conversion to perennials and cropland conversion to stover harvest become competitive.

For the Lumber watershed (Figure 4-12), profitability decreases with an increase in miscanthus cost for both high and low switchgrass costs. As seen from Figure 4-4 for the original crop mix for the mean, miscanthus at average costs is probably more profitable than switchgrass. At very high costs of miscanthus, pasture converts to switchgrass but lowers the overall profitability in the watershed. At low miscanthus costs, there is a small improvement in profitability and water quality for higher switchgrass production costs, possibly due to higher conversion from corn to stover. The water quality impacts from miscanthus costs are more uncertain than a change in the projection of switchgrass costs, probably because miscanthus is the dominant crop of choice in most scenarios.

The main take-away from this analysis is that environmental impacts from land-use change are sensitive to uncertainty in production economics. This is especially true in watersheds where stover harvest is a less attractive option, like the Lumber watershed. Further, at the price for biomass considered ($60/dry-ton), it is more likely that there is land-use change from pasture to perennials, resulting in highly uncertain impacts to water quality.

4. Conclusion

This study looks at three scenarios of land-use change for bioenergy based on the simplified objectives used in three federal agency studies. The land-use scenarios from these objectives result in different crop mixes in each watershed as well as different tradeoffs from water quality and profitability. The main driver for land-use change from a land-owner's perspective is profitability. Although for nitrogen, conversion from cropland to stover, switchgrass or miscanthus is likely to improve water quality, we see that there is a tradeoff between water quality and profitability in both watersheds because pastureland is converted before cropland. Under current crop risk management under the federal crop insurance program and the biomass incentives under the Biomass Crop Assistance Program (BCAP), in regions with high corn productivity, there is not sufficient incentive for cropland conversion to perennials. Constraining land-use change and enrollment in land-retirement programs may change overall results, but is left as an exercise for future work.

While there have been other studies looking into the supply chain, including studies that attempt to include sustainability in a multi-objective optimization (You et al., 2012; Yue et al., 2014), these studies often derive data at a county scale. We find that the optimization for water quality is best conducted keeping in mind that impacts can be localized within a watershed. While the impacts on water quality can be minimized once a refinery is already located, for some sensitive regions, it is important to consider local impacts to water quality before siting an ethanol plant. One of the limitations of our study is that we consider only surface inorganic nitrate - nitrogen as an indicator of sustainability. There are tradeoffs between different indicators of environmental impact such as water-use, nitrogen, phosphorus and sediment for each of the alternative feedstock and appropriate programs will have to be determined at state or local scale, to address the indicator of concern. For example, Demeisse et al. found that stover harvest on cropland in the Upper Mississippi River Basin increased the total annual sediment and phosphorus by 12% and 45% but decreased nitrogen by 3% (Demissie et al., 2012). Therefore, a multi-metric approach should be included for multi-objective optimization of biorefinery sites. Studies that have looked at the watershed-scale water quality impacts from the bioenergy previously (Demissie et al., 2012; Parish et al., 2012; Wu et al., 2012) do not considered the impact of the location of biorefineries, which could be an important component for future studies. Instituting a nitrogen damage cost (Singh, 2015), for example could reconcile different federal agency objectives while improving water quality.

The scale of nitrogen output from different regions is very different, owing to land-use characteristics, as seen in the tile-drained Upper Cedar watershed and the riparian wetland-dominated Lumber watershed (Keerthi and Miller, 2017a (In Review)). On a system scale, it may be important to consider marginal impacts of nitrogen reduction or deterioration. For example, recent studies have attempted to estimate the marginal social costs of nitrogen on a county scale, which could indicate sensitive regions for water quality (Keeler et al., 2016; Polasky, 2014). Finally, the overall environmental impacts from the bioenergy mandate are highly sensitive to perennial production costs. Accounting for these uncertainties while designing the biofuel supply chain can improve the overall sustainability of the bioenergy mandate.

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Chapter 5: Conclusion

My dissertation addresses gaps in the literature on water quality impacts from bioenergy policy in two different regions of the US. Water quality impacts from RFS2, in particular from corn ethanol, has drawn significant attention from researchers (Costello et al., 2009; Donner and Kucharik, 2008). While there are a number of studies that look into impacts from cellulosic ethanol at the farm, watershed and basin scales, most are based on stover production in the Midwest (Cibin et al., 2012; Gramig et al., 2013; Karlen et al., 2015; Tan et al., 2012; Thomas et al., 2011; Thompson and Tyner, 2014). Although there are some studies from the south, southeast and northeastern parts of the US (Chen et al., 2015; Gelfand et al., 2013; Lambert et al., 2016; Sarkar et al., 2011; Sarkar and Miller, 2014), a comparative study assessing the relative merits of sourcing biomass from different regions in the US has not been conducted.

To address this, Chapter 2 of my dissertation compares the difference in water quality impacts from land-use change from corn-soy to switchgrass between two watersheds – the Upper Cedar watershed in the Midwest and the Lumber watershed in the Southeast using the SWAT model. Key lessons from the study are (1) Tile drains exacerbate negative water quality impacts while riparian watersheds mitigate water quality impacts. Consequently, the baseline nitrogen loading from corn-soy rotation in the Upper Cedar watershed is much higher than the Lumber watershed. (2) Potential reduction in nitrate-nitrogen loading per potential gallon of ethanol to surface waters, which accounts for relative productivities of corn and switchgrass in the watershed, is about 40% for the Upper Cedar watershed and around 80% for the Lumber watershed. The relative reduction could offer opportunities to optimize the water quality impacts from the mandate by incentivizing production in one region over others.

Further, most studies on impacts from lignocellulosic/perennial alternatives like switchgrass and miscanthus do not consider the inherent economic risk and uncertainty in their production that drives land-use change from cropland and marginal land (Cibin et al., 2015; Parajuli, 2012; Parish et al., 2012; Sarkar et al., 2011; Sarkar and Miller, 2014; Wu and Liu, 2012). This includes federal agency studies that use different models to estimate the biomass available regionally as well as those that optimize the siting of biorefineries based on the availability of biomass (Perlack et al., 2011; U.S. EPA, 2010; USDA, 2010).

Chapter 3 of my dissertation looks at typical cropland in each watershed to determine the preferred cellulosic feedstock between stover and two perennials (switchgrass and miscanthus) for three federal agency objectives – maximizing farm profitability, minimizing the cost of procurement of ethanol or maximizing the economic welfare of both the farm and ethanol producers and maximizing land-use efficiency. The study uses a Monte-Carlo Analysis to consider the impacts of uncertainty in production costs for the perennials, incentives to grow biomass, risk management through federal crop insurance programs and the variability in yields across the watersheds on crop choice. Key takeaways include (1) Feedstock choice in the two watersheds is different when different objectives are used. Stover is predominantly preferred in the Upper Cedar watershed while miscanthus is preferred in the Lumber watershed. (2) Despite the incentives for establishment, storage and harvest of switchgrass and miscanthus, there is not a lot of land-use change to perennials. This could be due to greater risk perception for them and better risk management option for corn-soy through the crop insurance program.

Lastly, until recently there has not been a significant effort to link impacts from feedstock production to the larger biofuel supply chain in the context of water quality (Housh et al., 2015; Lambert et al., 2016). The studies that use multi-objective optimization for the biofuel supply chain are often at county-scale while water quality impacts are significant at the watershed or sub-watershed scale (You et al., 2012; Yu et al., 2016; Yue et al., 2014). Chapter 4 of my dissertation uses the three federal agency objectives to drive land-use change from the mandate and determine an optimum location for a biorefinery. Hydrologic Response Unit (HRU) level results from the SWAT model for yields and nitrate-nitrogen output to surface waters are used in the MILP optimization of the objectives on cropland and pastureland. Key takeaways include (1) Land-use configuration or crop-mix obtained from each of these objectives are different and result in different predominant options in the two watersheds. (2) Considering the relative profitability of the options on cropland and pastureland, conversion from pastureland to switchgrass or miscanthus is more prevalent than cropland. (3) The supply of biomass and changes to water quality are localized around biorefinery location and significant at the sub-watershed scale. (4) Uncertainty in production costs for perennials results in uncertainty in land-use change consequent water quality impacts. (3) and (4) indicate that optimization of the biofuel supply chain system for water quality will have to be at a higher resolution than county-scale and water quality considerations should be included when looking at sensitive sub-watersheds.

Limitations and future work

This dissertation identifies and addresses several gaps in the current understanding of impacts from the mandate. However, there are several limitations that can be addressed by future work. First, my dissertation considers nitrogen and not phosphorus or sediments as an indicator for water quality. The trade-offs between these different indicators could be significant (Demissie et al., 2012) and have to be considered for any true optimization of water quality. Secondly, the HRUs used in the study are not spatially explicit. The assimilation of nitrogen through sub-watershed streams are not considered. Since streams may have different assimilative capacities based on the length and background concentration of nutrients, this could be significant for spatial optimization for water quality impacts. Finally, given the regional differences in water quality impacts, there may be potential for optimization from a water quality perspective on a system scale. However, some regions may be more sensitive in terms of water quality than others. For example, the Upper Cedar watershed is part of the Mississippi River Basin. The MRB has a nutrient reduction goal of 45% (based on 2002 levels) to contain the Gulf of Mexico hypoxia (Scavia et al., 2004). A marginal social cost for nitrogen or phosphorus (Keeler et al., 2016) could be used in future studies for a multi-objective optimization for siting biorefineries.

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Appendix A

Supporting Information for Chapter 2

I. Selection of watersheds

The Midwest and Southeast regions were defined to be similar to that used by the Oak Ridge National Laboratory[17] to define the approximate geographic regions for dedicated biomass crops[18]. The watersheds in both the Midwest and the Southeast were chosen to ensure (i) Agriculture forms a significant portion of the land-use (ii) Land-use was representative of the region (iii) Potentially support similar alternative energy crops as rest of the region.

The National Land Cover Dataset (NLCD 2006)[19] was used to conduct a simple statistical evaluation of the land-cover of watersheds in the Midwest (387 watersheds) and southeastern region (432 watersheds). The analysis calculated the percentage of each watershed under seven major land-cover categories including Agriculture, Forests, Wetlands, Barren (Bare Rock/Sand), Grassland/Shrubs, Urban and Water. Representative watersheds were those that had median land-cover percentages for each land-cover category. The Lumber & Upper Cedar watershed appear to be fairly representative of the regions (Fig. A - 1).

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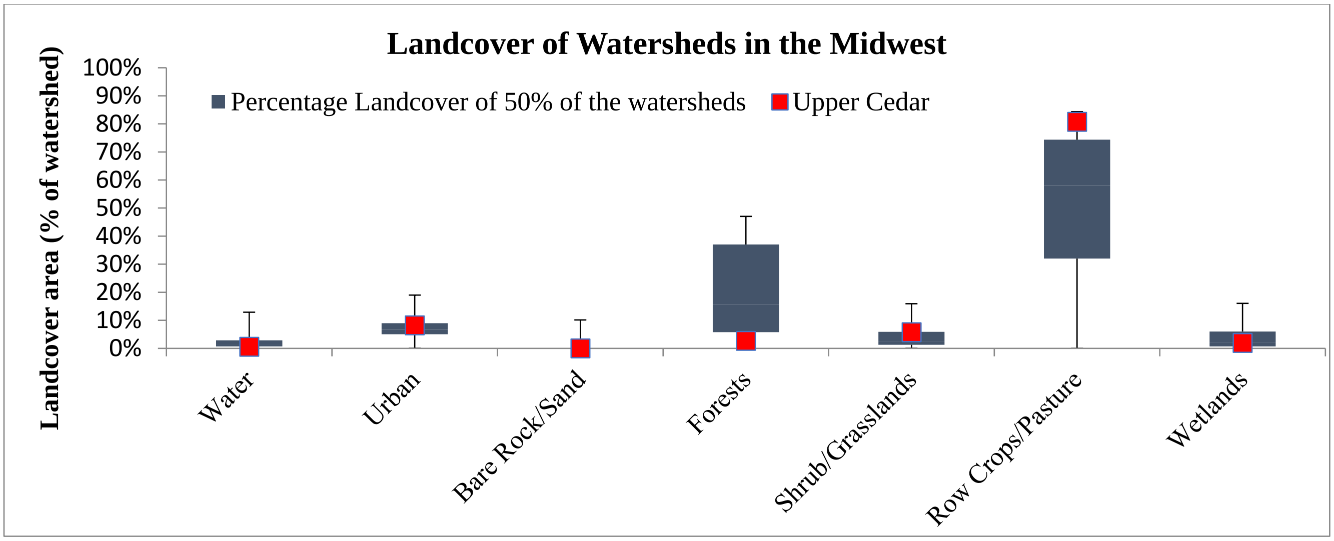
[17] Approximate Geographic Distribution of Potential Dedicated Biomass Crops**,** Adapted from ORNL. Last Accessed on 5 May 2016. Accessed from<
https://public.ornl.gov/site/gallery/detail.cfm?id=138&topic=53&citation=&general=&restsection=>

[18] U.S. DOE. 2006. *Breaking the Biological Barriers to Cellulosic Ethanol: A Joint Research Agenda*, DOE/SC/EE-0095, U.S. Department of Energy Office of Science and Office of Energy Efficiency and Renewable Energy. (p. 61) (website)

[19] Fry, J., Xian, G., Jin, S., Dewitz, J., Homer, C., Yang, L., Barnes, C., Herold, N., and Wickham, J., 2011. Completion of the 2006 National Land Cover Database for the Conterminous United States, *PE&RS*, Vol. 77(9):858-864.



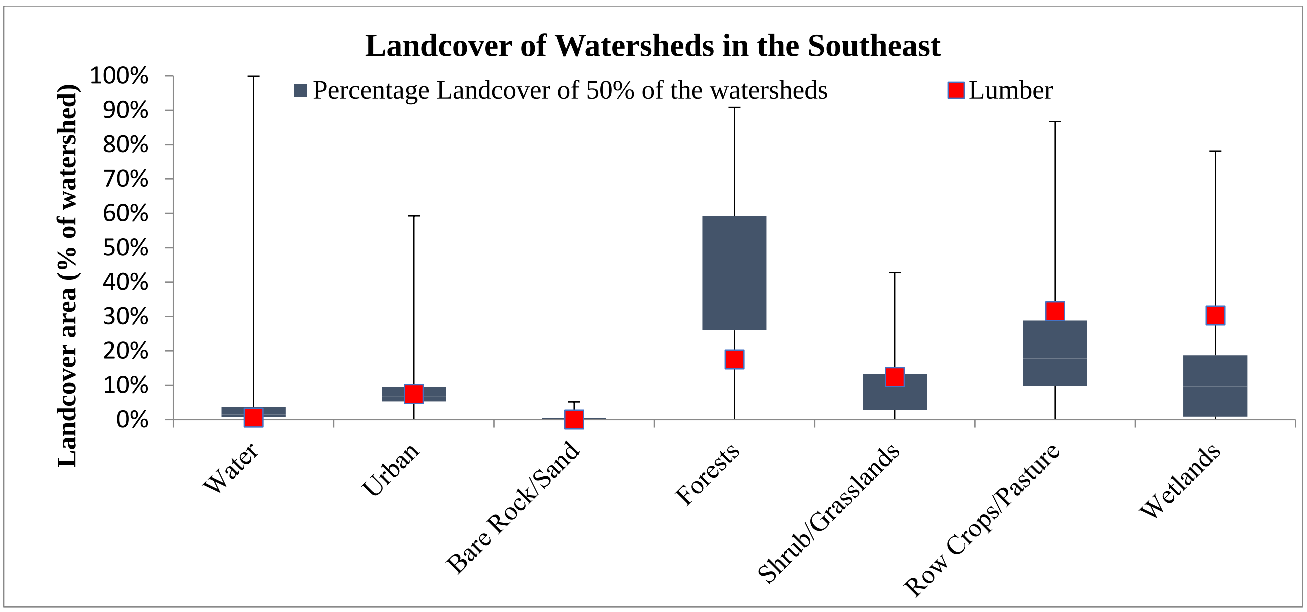


Figure A-1: Variation of each land-cover as a percentage of total watershed area for the Midwest and South-East region. Error bars represent the range of land-cover percentages across the region

II. Use of soft-data to calibrate SWAT model: Observed versus Simulated yields

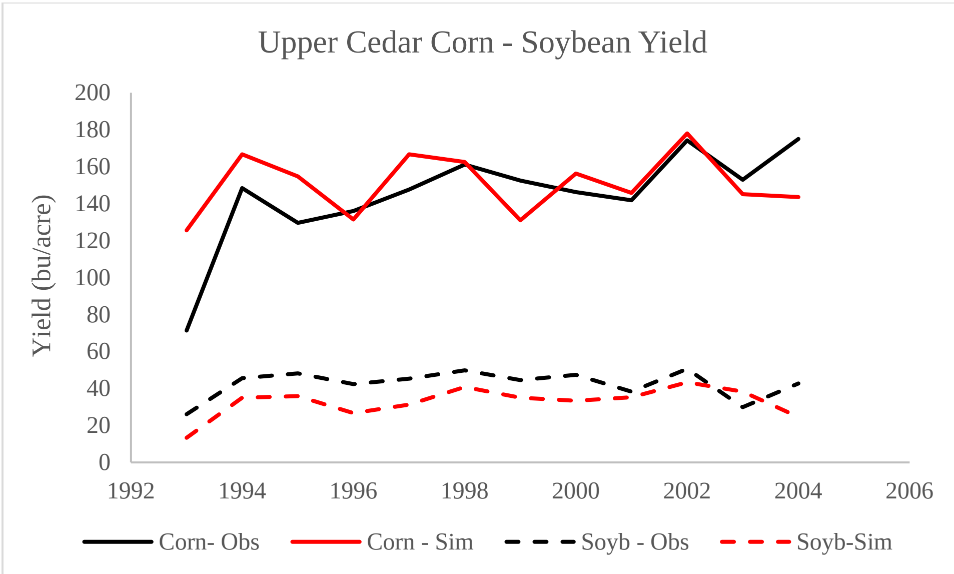
County level data from the National Agriculture Statistical Service from 1990 – 2004 was used to estimate if simulated yields were reasonable. Percentage Bias (PBIAS) was used as a model evaluation statistic to determine if yields were under- or over-estimated. The PBIAS calculates the tendency of the simulated data to be larger or smaller than the observed data[20] and is given by:

$$\text{PBIAS} = \sum \frac{\text{Yiobs} - \text{Yisim}}{\sum \text{Yiobs}} * 100 \tag{1}$$

Where Y_i^{obs} is the yield estimated from NASS data and Y_i^{sim} is the simulated yields averaged over the watershed from SWAT. 11% for corn and -38% for soybean over the simulation years indicating that corn yield is underestimated and soybean yield is vastly over estimated. For both corn and soy, the year 2002 has the worst simulation. Since the period 2001 – 2004 could not be well calibrated for this watershed, we speculate that there may have been changes to the watershed that our model could not capture. The graphs below show satisfactory model performance for yield simulation.

The PBIAS for corn and soy in the Upper Cedar watershed is -4% and 23% respectively which indicates that corn yield is overestimated and soybean is underestimated. For Lumber PBIAS was

[20] Moriasi, Daniel N., et al. "Model evaluation guidelines for systematic quantification of accuracy in watershed simulations." *Transactions of the ASABE* 50.3 (2007): 885-900.



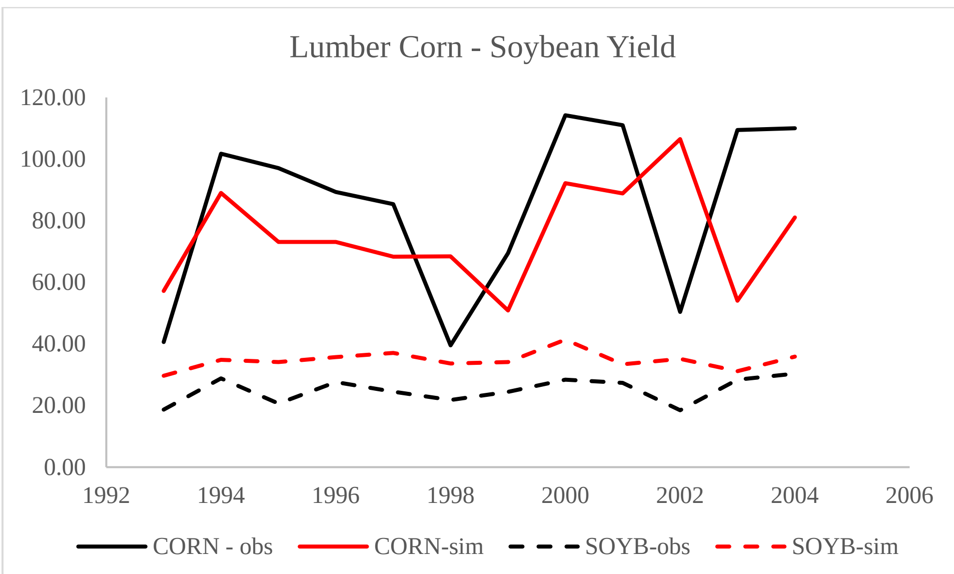


Figure A-2: Observed and Simulated Corn and Soybean yields. Observed yields from county-level NASS data

Appendix B

Supporting Information for Chapter 3

I. Modeling Miscanthus and Corn Stover in SWAT

Miscanthus Management

The NRCS currently recommends a nutrient management approach to adjust the fertility of the site to the amount of dry – matter that is removed as suggested by Heaton et al [1,2]. From field trials (Heaton et al. 2008), the average yield of Miscanthus in the Midwest is between 20 – 34 dry - tons/ha. On the other hand, field trials at a coastal plain site in North Carolina yielded a Miscanthus yield of 20 tons/ha (harvested)[3]. Accordingly, Miscanthus was fertilized at 120 kg N/ha, 25 kg P/ha in the Midwest and 80 kg N/ha, 20 kg P/ha in the Southeast to account for differences in the yield. The updated plant parameters from Trybula et al. were used in the SWAT model [4]. However as these parameters are site specific, we expect that the yields may be overestimated in the case of North Carolina.

Corn Stover Management

In a literature review of over 49 studies mostly based in the Midwest and including a study from the Southeast at the PeeDee station in Florence, SC, Johnson et al. found that the average minimum residue needed to sustain Soil Organic Carbon levels was 5.74 ± 2.4 Mg ha^{-1} yr^{-1} [5]. However, it should be noted that the rate of stover harvest always depends on the baseline soil carbon, tillage practices and land characteristics such as slope and climate that control erosion processes as well as stover price [6]. Johnson et al. also note that corn stover may not be the ideal choice for the Southeast when compared to other sources of cellulosic energy. For Iowa, since the yields are over 160 bu/acre or 10 Mg/ha, we used a residue harvest of 52.5% from each HRU.

Shabaz and Li found that in North Carolina the sustainable rate of stover harvest was about 35%. The average yields in North Carolina are smaller, closer to 110 bu/acre or 7 Mg/ha, which also points towards a lower sustainable harvest of residues.

Accordingly, the nitrogen and phosphorus management practices were varied for the two regions based on the nutrient content of the stover removed[21]. For Iowa this meant that for stover removal greater than 5 Mg/ha, an additional 30 kg N/ha and 11.3 kg P/ha was required. For North Carolina, a stover removal of about 1.25 Mg/ha, an additional 7.5 kg N/ha and 3 kg P/ha was assumed to be required.

II. Production Economics for corn-soy rotation

Given that we are comparing annual crops with perennials with significant establishment costs, annualized costs was calculated for each crop based on a review of existing literature. Corn and corn stover are expected to have no upfront capital investment.

Corn – Soybean

Corn-Soybean production costs for a 2-year rotation was calculated using estimates from the ISU and NCSU Extension (Table 1). The additional revenue stream of insurance is addressed in the main text under the variability studied with a Monte-Carlo analysis.

Stover Harvest

The costs associated with corn stover in addition to corn-soybean costs are nutrient replacement, calculated according to actual residue removed, harvesting, that also depends on the amount of residue removed, storage, and transportation[7]. Transportation costs have been estimated as a function of plant distance in this study to calculate overall delivered cost of feedstock for ethanol production. The overall profitability or present value is assumed to be the revenue from corn/ stover above the costs. A credit has been assumed to account for the yield increase from stover

[21] Jeschke, M and A. Heggenstaller. “Sustainable Corn Stover Harvest for Biofuel Production”. Crop Insights. DuPont Pioneer https://www.pioneer.com/home/site/us/agronomy/library/corn-stover-biofuel/ - 10 – 15 lb N/ton stover removed, 3 – 7 lb P/ton

harvest in some studies[8] but average HRU values are used from SWAT directly in this study. The costs are summarized in Table B - 1.

Table B- 2: Corn - Soy Production Costs

	Corn after Soybean				Soybean after Corn			
	Iowa		North Carolina		Iowa		North Carolina	
Costs	Fixed ($/acre)	Variable ($/acre)	Fixed ($/acre)	Variable ($/acre)	Fixed ($/acre)	Variable ($/acre)	Fixed ($/acre)	Variable ($/acre)
Pre-harvest machinery	20.10	16.80	21.98	15.04	21.10	17.40	21.52	14.46
Seeds		111.20		81.2		53.60		46.2
Nitrogen		52.04		(Included)				
Phosphorus		30.60		111.2		18.00		8.96
Potash		18.90		12.5		26.00		10.94
Lime (annual cost)		8.80		13.2		8.80		13.2
Herbicide		38.10		27.64		32.20		35.83
Crop insurance		12.20		12.2		7.80		7.80
Miscellaneous		10.00				10.00		14.3
Interest on preharvest variable costs		10.27		9.38		5.97		5.21
length of period (months)		8.00		8		8.00		8
interest rate		0.05		6.50%		0.05		6.50%
Total pre-harvest	20.10	308.91	21.98	282.36	21.10	179.77	21.52	156.90
Harvest machinery								
Combine	15.90	6.80		57	15.90	6.80		48.79
Grain Cart	6.20	2.70		(Included)	6.20	2.70		(Included)
Haul	0.04Y	0.03Y	Drying	0.2Y	0.04Y	0.03Y	Drying	0.2Y
Handling	0.02Y	0.02Y	Haul	0.26Y	0.02Y	0.02Y	Haul	0.25Y
Labor		29.25		9.8		29.25		9.8
Land Rent	233		60		233		60	
Total	**275.20 + 0.06Y**	**347.65 + 0.05Y**	**81.98**	**349.16 + 0.46Y**	**276.20 + 0.06Y**	**218.52 + 0.05Y**	**81.52**	**215.49 + 0.46Y**
Y	Yield (bu/acre)				Yield (bu/acre)			

III. Calculation of ARC Coverage and Yield Protection pay-outs

Calculation of the revenue supplement from Agriculture Risk Coverage (ARC – CO)

The revenue from enrollment in the ARC-CO (ARC County) is estimated using the average county yields, and is triggered if the farm crop revenue is less than what is guaranteed by the program[22]. The ARC benchmark revenue is calculated as follows:

$ARC\text{-}R = MYA_{C\text{-}Yield} * MYA_{P\text{-}Yield}$ ………………………….. (11)

Where MYA is the Multi Year Average or a 5 year Olympic average (3-year average in the last five years, excluding the highest and lowest values) of county yield and national market price of the preceding years. The guaranteed revenue is 86% of this benchmark. If crop revenue is less than the guaranteed ARC-CO revenue, actual total farm revenue is calculated on 85% of the acreage that is covered by the program. For corn, this is given by:

$ARC\text{-}CO\ payout = (0.86ARC\text{-}R - Y_{crop}P_{crop})*0.85A_{farm\ acres}$ ………………….. (1)

Where Y and P are actual yield from the farm, represented here by the HRU yield and actual price and $A_{farm\ acres}$ is the enrolled farm acres, simplified in this analysis to be the HRU area. The ARC-CO payout is capped at 10% of ARC – R. In this study, we use the years 1990 – 2004 for yield simulation through the SWAT model. From USDA-NASS data, the MYA yield based on the years 1996 – 2000 was 142 bu/acre for corn and 45 bu/acre for soybean for Iowa. For North Carolina the MYA yield was 88 bu/acre for corn and 30 bu/acre for soybean. We use current corn and soybean prices for the simulation. Therefore, the MYA for price was estimated based on the years 2011 – 2015 obtained from ISU extension[23]. For corn, MYA price is \$4.8/bu and for soybean, \$11.9/bu.

Calculation of revenue supplement from YP guarantee

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[22] Olson, Kent. "Choosing between ARC and PLC". University of Minnesota Agricultural Extension. Nov 2014. Accessed at <http://www.extension.umn.edu/agriculture/business/farm-bill/plc-and-arc/>

[23] https://www.extension.iastate.edu/agdm/crops/pdf/a2-11.pdf

For YP insurance, the calculation of premiums depends on the risk calculated for the crop and county, coverage levels and total number of acres covered, therefore, these are very different for Iowa and North Carolina. We use statistics from USDA and the Federal Crop Insurance Commission (FCIC) for the years 2014 – 2016 to estimate premiums (Table B - 2).

The yield for the calculation of guarantee is calculated using the Actual Production History (APH) for the farm between 4 – 10 years. The indemnity payout for YP is triggered if the actual yield is lesser than the APH. In this study we use the average of all HRU yields for the calculation of the APH and the payout is triggered if the yield sampled by the Monte Carlo Analysis is lesser than the APH. The indemnity payout (YP-R) for an 85% coverage level is calculated by:

$$YP\text{-}R = 0.85(APH - Y_{crop})*P_{crop}*A_{farm\ acres} \text{ ………………… } (2)$$

Table B - 2: Estimates of corn-soy premiums and federal subsidies for Yield Protection insurance from FCIC data (2014 - 2016)

	YP - $/acre[24]		
Corn	Premium Costs	Federal subsidies	Prem. Cost to producer
IA	18.98	7.81	11.17
NC	48.71	25.66	23.04
Soybean			
IA	15.57	6.41	9.16
NC	44.73	23.56	21.17

IV. Calculation of Bioenergy Subsidies

Establishment costs subsidy

The BCAP payments can cover 50% of establishment costs up to $1235/ha ($500/acre). This subsidy on costs was included in the calculation of the Annualized costs of production of switchgrass and miscanthus. The establishment costs (E_C) are sampled by the MCA. The annualized subsidy is calculated

[24] http://prodwebnlb.rma.usda.gov/apps/SummaryofBusiness/ReportGenerator

$BCAP_{Est} = 0.5 * E_C / L$ if $E_C < \$2470/ha$ or

$= 1235/L$ if $E_C > \$2470/ha$ ……………………. (3)

Where L is the lifetime sampled by the MCA.

Payment to cover revenue-less years

These are annual payments to cover the period before revenue is generated by harvest, for up to 5 years. We model this as a payment for two years in the case of miscanthus, which has no revenue in the first year and half the expected mature yield in the second. For switchgrass, we assume half the mature yield in the first year. Therefore the annualized BCAP subsidy is calculated as:

$BCAP_{R\text{-}Misc} = Y_{misc} * P_{bio} * 1.5 / L$ ……………………………. (4)

$BCAP_{R\text{-}Swch} = Y_{swch} * P_{bio} * 0.5 / L$ …………………………… (5)

Where Y, L is the yield and lifetimes sampled by the MCA for switchgrass and miscanthus.

Subsidies for harvest, storage and transportation

These are payments that mitigate harvest and transportation costs at a \$1 match per \$1 spent up to \$20/dry-ton for two years. The annualized subsidy is calculated as follows:

$BCAP_{HST} = Y * HST_{energy\ crop} * 0.5 * 2 / L$ if $Y < 20$ dry-ton/ha

$= 20 * HST_{energy\ crop} * 0.5 * 2 / L$ if $Y > 20$ dry-ton/ha

Where HST, Y and L are the harvest and storage costs, yields and lifetimes sampled by the MCA.

V. Sample Code for Monte-Carlo Analysis simulations

The MATLAB code for the Monte-Carlo simulation is included here. The example provided here is for the Upper Cedar watershed in Iowa.

```
% Metrics with MCA for Iowa

%Base_Case with average area of an HRU – Initializing constants
CornP = 4.27 ; BioP = 60; SoyP = 9.79; A = 615;

%Yield - IA - normal distribution for all feedstock

Corn_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/Corn_yield_IA.csv');
mu = mean(Corn_IA);
sigma = std(Corn_IA);
Ydistcorn = makedist('normal','mu',mu,'sigma',sigma);
Ycorn = random(Ydistcorn,10000,1);

Soy_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/Soy_yield_IA.csv');
mu = mean(Soy_IA);
sigma = std(Soy_IA);
Ydistsoy = makedist('normal','mu',mu,'sigma',sigma);
Ysoy = random(Ydistsoy,10000,1);

Swch_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/Swch_yield_IA.csv');
mu = mean(Swch_IA);
sigma = std(Swch_IA);
Ydistswch = makedist('normal','mu',mu,'sigma',sigma);
Yswch = random(Ydistswch,10000,1);

Mis_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/Mis_yield_IA.csv');
mu = mean(Mis_IA);
sigma = std(Mis_IA);
Ydistmisc = makedist('normal','mu',mu,'sigma',sigma);
Ymisc = random(Ydistmisc,10000,1);

C1_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/C1_yield_IA.csv');
mu = mean(C1_IA);
sigma = std(C1_IA);
Ydistc1 = makedist('normal','mu',mu,'sigma',sigma);
YC1 = random(Ydistc1,10000,1);

S1_IA = csvread('C:\Users\skeerthi\Documents\Journal Paper 2/S1_yield_IA.csv');
mu = mean(S1_IA);
sigma = std(S1_IA);
Ydists1 = makedist('normal','mu',mu,'sigma',sigma);
YS1 = random(Ydists1,10000,1);

%calculation of farm safety net numbers
ARC_IAC = 586.2 ; %$/acre for 86% of ARC benchmark revenue for corn
ARC_IAS = 460.53 ; %$/acre for 86% of ARC benchmark revenue for soybean
Prem_C = 11.17 ; %$/acre for 85% coverage levels
Prem_S = 9.16 ; %$/acre for 85% coverage levels
AHP_C = mean(Corn_IA);
AHP_S = mean(Soy_IA);

% Corn Soy for OC costs and to calculate metrics
for i = 1: 10000
```

```
CSCost(i) = ((347.65 + 0.05*Ycorn(i)*0.89/56)+  (218.52 +
0.05*Ysoy(i)*0.89/60))*A*2.47/2 + (Prem_C + Prem_S)*A*2.47/2;%including Insurance
premiums
CSFCost(i)= ((275.20 + 0.06*Ycorn(i)*0.89/56 + 347.65 + 0.05*Ycorn(i)*0.89/56)+
(276.20 + 0.11*Ysoy(i)*0.89/60 + 218.52))*A*2.47/2 + (Prem_C + Prem_S)*A*2.47/2;
CSRev(i)= (CornP*Ycorn(i)*0.89/56 + SoyP*Ysoy(i)*0.89/60)*A*2.47/2;
CSProfit(i)= CSRev(i) - CSCost(i); % this has to be calculated before insurance for OC
for switchgrass and miscanthus
OC(i) = CSProfit(i)/(A); %also returns over unit area without fixed costs
OC1(i) = CSFProfit(i)/A; % returns over unit area with fixed and variable costs
%additional revenue from ARC for corn and soybean
CornRev = CornP*Ycorn(i)*0.89/56;
SoyRev = SoyP*Ysoy(i)*0.89/60;
if CornRev < ARC_IAC
    ARC_IACP = (ARC_IAC - Ycorn(i)*CornP*0.89/56)*0.85*A*2.47 ;
    if ARC_IACP > 58.62*A*2.47
        ARC_IACP = 58.62*A*2.47;
    end
elseif CornRev >= ARC_IAC
    ARC_IACP = 0;
end
if SoyRev < ARC_IAS
    ARC_IASP = (ARC_IAS - Ysoy(i)*SoyP*0.89/60)*0.85*A*2.47 ;
    if ARC_IASP > 46.05*A*2.47
        ARC_IASP = 46.05*A*2.47;
    end
elseif SoyRev >= ARC_IAS
    ARC_IASP = 0;
end
% additional revenue from YP insurance for corn and soybean
if Ycorn(i)< AHP_C
    YP_RC = 0.85*(AHP_C*0.89/56 - Ycorn(i)*0.89/56)*CornP*A*2.47 ;
else
    YP_RC = 0;
end
if Ysoy(i)< AHP_S
    YP_RS = 0.85*(AHP_S*0.89/60 - Ysoy(i)*0.89/60)*SoyP*A*2.47 ;
else
    YP_RS = 0;
end
CSRev(i)= CSRev(i) + (ARC_IACP + ARC_IASP + YP_RC + YP_RS)/2;
CSProfit(i) = CSRev(i) - CSCost(i);
CSobj1(i) = CSProfit(i)/A;
CSFProfit(i)= CSRev(i) - CSFCost(i);
CSgal(i) = (2.84*Ycorn(i)*0.89/56*A*2.47/2);
CSobj3(i)= CSgal(i)/CSRev(i);
CSobj4(i) = CSRev(i)/A;
CSobj5(i) = (CSgal(i)*84858)/A;
%%% Corn Stover
StovCost(i) = A*2.47*((347.65 + 0.05*YC1(i)*0.89/56)+  (218.52 +
0.05*YS1(i)*0.89/60))/2+ (11.04 +8.04/1000*YC1(i)*0.52)*A/2;
StovFCost(i) = ((275.20 + 0.06*YC1(i)*0.89/56 + 347.65 + 0.05*YC1(i)*0.89/56)/2 +
(276.20 + 0.11*YS1(i)*0.89/60 + 218.52))*A*2.47/2 + (11.04
+8.04/1000*YC1(i)*0.52)*A/2;
StovRev(i) = (YC1(i)*0.892/56*CornP + YS1(i)*0.892/60*SoyP)*A*2.47/2 +
YC1(i)*0.52*BioP/2000*A;
%additional revenue from ARC for corn and soybean
if CornP*YC1(i)*0.89/56 < ARC_IAC
    ARC_IACP = (ARC_IAC - YC1(i)*CornP*0.89/56)*0.85*A*2.47 ;
    if ARC_IACP > 58.62*A*2.47
        ARC_IACP = 58.62*A*2.47;
    end
elseif CornP*YC1(i)*0.89/56 >= ARC_IAC
```

```
    ARC_IACP = 0;
end
if SoyP*YS1(i)*0.89/60 < ARC_IAS
    ARC_IASP = (ARC_IAS - YS1(i)*SoyP*0.89/60)*0.85*A*2.47 ;
    if ARC_IASP > 45.03*A*2.47
        ARC_IASP = 45.03*A*2.47;
    end
elseif SoyP*YS1(i)*0.89/60 >= ARC_IAS
    ARC_IASP = 0;
end
% additional revenue from YP insurance for corn and soybean
if YC1(i)< AHP_C
    YP_RC = 0.85*(AHP_C*0.89/56 - YC1(i)*0.89/56)*CornP*A*2.47 ;
else
    YP_RC = 0;
end
if YS1(i)< AHP_S
    YP_RS = 0.85*(AHP_S*0.89/60 - YS1(i)*0.89/60)*SoyP*A*2.47 ;
else
    YP_RS = 0;
end
StovCost(i) = StovCost(i)+ (Prem_C + Prem_S)*A*2.47/2;
StovRev(i)= StovRev(i) + (ARC_IACP + ARC_IASP + YP_RC + YP_RS)/2;
StovProfit(i) = StovRev(i) - StovCost(i);
StovFProfit(i)= StovRev(i) - StovFCost(i);
Stovobj1(i)= StovProfit(i)/A;
Stovobj2(i)= StovFProfit(i)/A;
StovGgal(i) = (2.84*YC1(i)*0.892/56*A*2.47)/2;
Stovgal(i) = (YC1(i)*0.52/1000*A*79/2);
Stovobj3(i)= (StovGgal(i) + Stovgal(i))/StovRev(i);
Stovobj4(i) = StovRev(i)/A;
Stovobj5(i) = ((StovGgal(i)*0.4+Stovgal(i))*84858)/A;
end

%Switchgrass costs

%Establishment Costs - Triangular Distribution
Est = [138.94,133.34,146.62,123.48,151.05,113.13,270.8,139.55,150.6, 617.40,270.8];
lower = min(Est);
mpv = median(Est);
upper = max(Est);
Estd2=makedist('triangular','a',lower,'b',mpv,'c',upper);
r = random(Estd2,10000,1);

% Maintenance Costs - Non-Yield (1-2)- MNY1, and MNY3 Triangular
% distribution
MNY1 = [224.86,183.72,351.88,248.25,139.64,197.70,129.42,346.27,148.6];
MNY3 = [87.32,52.59,111.99,114.87,35.96,159.53,66.1,244.34,355.13];
lower = min(MNY1);
mpv = median(MNY1);
upper = max(MNY1);
MNY1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
MNY1 = random(MNY1dist,10000,1);
lower = min(MNY3);
mpv = median(MNY3);
upper = max(MNY3);
MNY3dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
MNY3 = random(MNY3dist,10000,1);

%Harvest Non-yield HY1, HY3 - Triangular Distribution
HY1 = [0,0,0,70.51,67.67,39.27,23.1,35];
HY3 = [0,0,39.64,67.67,17.65,39.27,46.21,23.1,46.21,35,35];
lower = min(HY1);
```

```
mpv = median(HY1);
upper = max(HY1);
HY1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
HY1 = random(HY1dist,10000,1);
lower = min(HY3);
mpv = median(HY3);
upper = max(HY3);
HY3dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
HY3 = random(HY3dist,10000,1);

% Harvest - yield dependent - Triangular distribution
H1 = [0.0313,0.0374,0.047,0.028,0.029,0.003,0.018,0.03,0.026];
lower = min(H1);
mpv = median(H1);
upper = max(H1);
H1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
H1 = random(H1dist,10000,1);
%Storage - Yield dependent
S1 = [0.004,0.004,0.003,0.013,0.004,0.008];
lower = min(S1);
mpv = median(S1);
upper = max(S1);
S1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
S1 = random(S1dist,10000,1);

%Lifetime - Triangular
L = [11,11,10,12,10,10,10,10,10,10];
lower = min(L);
mpv = median(L);
upper = max(L);
Ldist=makedist('triangular','a',lower,'b',mpv,'c',upper);
L = random(Ldist,10000,1);

%discount rate - Triangular
d = [8,4,10,6,6,5,4,4,5,7];
lower = min(d);
mpv = median(d);
upper = max(d);
ddist=makedist('triangular','a',lower,'b',mpv,'c',upper);
d = random(ddist,10000,1);
% To ensure that lifetime and discount rates are integers
for i = 1:10000
    L(i) = round(L(i));
    d(i) = round(d(i))/100;
end

%Actual simulation
for i = 1:10000
AnnualizedSwchCostIA(i) = (r(i)+ MNY1(i)*(1+d(i))^0.667 + HY1(i)+
H1(i)*Yswch(i)*1000/2 + S1(i)*Yswch(i)*1000/2)/ L(i)+ (MNY3(i)*(1+d(i))^0.667 +
HY3(i)+ Yswch(i)*1000*(H1(i)+S1(i)))*(L(i)-1)/L(i);
% assumed for optimization
AssumedSWCHIA(i) = 292.79 + 31.92*Yswch(i);
%Establishment Costs
if r(i)<= 2470
    AnnualizedSwchCostIA(i)= AnnualizedSwchCostIA(i)-(r(i)/2)/L(i);
else
    AnnualizedSwchCostIA(i) = AnnualizedSwchCostIA(i) - 1235/L(i);
end
% To cover loss of revenue during establishment - for upto 5 years (2 years
% establishment period for Miscanthus)
AnnualizedSwchCostIA(i)= AnnualizedSwchCostIA(i)-(Yswch(i)*BioP*(0.5))/(L(i));
% % to cover harvest and storage costs for two years
```

```
if Yswch(i)< 20
AnnualizedSwchCostIA(i)= AnnualizedSwchCostIA(i)- (Yswch(i)*2/L(i));
else
AnnualizedSwchCostIA(i)= AnnualizedSwchCostIA(i)- (20*2/L(i));
end
SwchRev(i)= Yswch(i)*BioP*A;
SwchProfit(i)= Yswch(i)*BioP*A - AnnualizedSwchCostIA(i)*A - OC(i)*A ;
if OC1(i)< 0
    SwchFProfit(i) = Yswch(i)*BioP*A - AnnualizedSwchCostIA(i)*A - 105*2.47*A -
235*2.47*A ; % enrollment in CRP
else
SwchFProfit(i) = Yswch(i)*BioP*A - AnnualizedSwchCostIA(i)*A - OC1(i)*A ;
end
SwchProfit1(i)= Yswch(i)*BioP*A - AssumedSWCHIA(i)*A ;
Swchobj1(i)= SwchProfit(i)/A;
Swchobj1a(i)= (SwchProfit(i)+ CSProfit(i))/A;
Swchobj1b(i)= (SwchProfit1(i))/A;
Swchobj2(i)= SwchFProfit(i)/A;
Swchobj2a(i)= (SwchProfit(i)+ CSFProfit(i))/A;
Swchgal(i) = 79*Yswch(i)*A;
Swchobj3(i)= Swchgal(i)/SwchRev(i);
Swchobj4(i) = SwchRev(i)/A;
Swchobj5(i) = (Swchgal(i)*84858)/A;
end

%%%Miscanthus
%Establishment Costs - Triangular Distribution - Miscanthus
Est = [2802.17,440.06,500,3097,1874.730,3750,556.4];
lower = min(Est);
mpv = median(Est);
upper = max(Est);
Estd2=makedist('triangular','a',lower,'b',mpv,'c',upper);
r = random(Estd2,10000,1);

% Maintenance Costs - Non-Yield (1-2)- MNY1, and MNY3 Triangular
% distribution Miscan
MNY1 = [610.17,186.58,222.24,782.175,64.3];
MNY3 = [87.32,53.73,111.16,175.247,64.3];
lower = min(MNY1);
mpv = median(MNY1);
upper = max(MNY1);
MNY1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
MNY1 = random(MNY1dist,10000,1);
lower = min(MNY3);
mpv = median(MNY3);
upper = max(MNY3);
MNY3dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
MNY3 = random(MNY3dist,10000,1);

%Harvest Non-yield HY1, HY3 - Triangular Distribution Miscanthus
HY1 = [0,40.52,46.2,65.455,35];
HY3 = [40.52,46.2,65.455,36];
lower = min(HY1);
mpv = median(HY1);
upper = max(HY1);
HY1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
HY1 = random(HY1dist,10000,1);
lower = min(HY3);
mpv = median(HY3);
upper = max(HY3);
HY3dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
HY3 = random(HY3dist,10000,1);
```

```
% Harvest - yield dependent - Triangular distribution Miscanthus
H1 = [0.0404,0.056,0.005,0.019,0.026];
lower = min(H1);
mpv = median(H1);
upper = max(H1);
H1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
H1 = random(H1dist,10000,1);
%Storage - Yield dependent
S1 = [0.008,0.006,0.005,0.0065];
lower = min(S1);
mpv = median(S1);
upper = max(S1);
S1dist=makedist('triangular','a',lower,'b',mpv,'c',upper);
S1 = random(S1dist,10000,1);

%Lifetime - Triangular Misc
L = [15,20,10,15,15,20,15,10];
lower = min(L);
mpv = median(L);
upper = max(L);
Ldist=makedist('triangular','a',lower,'b',mpv,'c',upper);
L = random(Ldist,10000,1);

%discount rate - Triangular Misc
d = [6,4,5,4,4,5,4,7];
lower = min(d);
mpv = median(d);
upper = max(d);
ddist=makedist('triangular','a',lower,'b',mpv,'c',upper);
d = random(ddist,10000,1);
% To ensure that lifetime and discount rates are integers
for i = 1:10000
    L(i) = round(L(i));
    d(i) = round(d(i))/100;
end

%Actual simulation Misc
for i = 1:10000
AnnualizedMiscCostIA(i) = (r(i)+ MNY1(i)*(1+d(i))^(0.667)+ HY1(i)+ H1(i)*
Ymisc(i)*1000/2 + S1(i)*Ymisc(i)*1000/2)/ L(i) + ((L(i)-2)*MNY3(i)*(1+d(i))^(0.667)+
...
   + HY3(i)*(L(i)-2)+ H1(i)*Ymisc(i)*1000*(L(i)-2)+ S1(i)*Ymisc(i)*1000*(L(i)-
2))/L(i);
%Establishment Costs
if r(i)<= 2470
    AnnualizedMiscCostIA(i)= AnnualizedMiscCostIA(i)-(r(i)/2)/L(i);
else
    AnnualizedMiscCostIA(i) = AnnualizedMiscCostIA(i) - 1235/L(i);
end
% To cover loss of revenue during establishment - for upto 5 years (2 years
% establishment period for Miscanthus)
AnnualizedMiscCostIA(i)= AnnualizedMiscCostIA(i)-(Ymisc(i)*BioP*(1.5))/(L(i));
% % to cover harvest and storage costs for two years
if Ymisc(i)< 20
AnnualizedMiscCostIA(i)= AnnualizedMiscCostIA(i)- (Ymisc(i)*2/L(i));
else
AnnualizedMiscCostIA(i)= AnnualizedMiscCostIA(i)- (20*2/L(i));
end
% assumed for optimization
AssumedMISCIA(i) = 915.24+8.75*Ymisc(i);
MiscRev(i)= Ymisc(i)*BioP*A;
MiscProfit(i)= Ymisc(i)*BioP*A - AnnualizedMiscCostIA(i)*A - OC(i)*A ;
if OC1(i)< 0
```

```
    MiscFProfit(i) = Ymisc(i)*BioP*A - AnnualizedMiscCostIA(i)*A - 105*2.47*A -
235*2.47*A ;
else
MiscFProfit(i) = Ymisc(i)*BioP*A - AnnualizedMiscCostIA(i)*A - OC1(i)*A ;
end
MiscProfit1(i)= Ymisc(i)*BioP*A - AssumedMISCIA(i)*A ;
Miscobj1(i)= MiscProfit(i)/A;
Miscobj1a(i)= (MiscProfit(i)+ CSProfit(i))/A;
Miscobj1b(i)= (MiscProfit1(i))/A;
Miscobj2(i)= MiscFProfit(i)/A;
if CSFProfit(i)< 0
  Miscobj2a(i)= (MiscProfit(i)+ 230)/A ;
else
 Miscobj2a(i)= (MiscProfit(i)+ CSFProfit(i))/A;
end

Miscgal(i) = 79*Ymisc(i)*A;
Miscobj3(i)= Miscgal(i)/MiscRev(i);
Miscobj4(i) = MiscRev(i)/A;
Miscobj5(i) = (Miscgal(i)*84858)/A;
end

%%Pdfs for each metric
% Objective 1 : DOE - returns over VC
%CS
% mu = mean(OC);
% sigma = std(OC);
mu = mean(CSobj1);
sigma = std(CSobj1);
CSobj1_IA = makedist('normal','mu',mu,'sigma',sigma);
%Stover
mu = mean(Stovobj1);
sigma = std(Stovobj1);
Stovobj1_IA = makedist('normal','mu',mu,'sigma',sigma);
%Switchgrass
mu = mean(Swchobj1);
sigma = std(Swchobj1);
Swchobj1_IA = makedist('normal','mu',mu,'sigma',sigma);
%Miscanthus
mu = mean(Miscobj1);
sigma = std(Miscobj1);
Miscobj1_IA = makedist('normal','mu',mu,'sigma',sigma);
figure(1);
x = -400: 0.5 : 1500;
y = pdf(CSobj1_IA,x);
y1 = pdf(Stovobj1_IA,x);
y2 = pdf(Swchobj1_IA,x);
y3 = pdf(Miscobj1_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('$/ha');
ylabel('Probability Distribution')
title('Returns over variable costs');

%without OC
%Switchgrass
mu = mean(Swchobj1a);
sigma = std(Swchobj1a);
Swchobj1a_IA = makedist('normal','mu',mu,'sigma',sigma);
%Miscanthus
mu = mean(Miscobj1a);
sigma = std(Miscobj1a);
Miscobj1a_IA = makedist('normal','mu',mu,'sigma',sigma);
```

```
figure(2);
x = -300: 0.5 : 1000;
y = pdf(CSobj1_IA,x);
y1 = pdf(Stovobj1_IA,x);
y2 = pdf(Swchobj1a_IA,x);
y3 = pdf(Miscobj1a_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('$/ha');
ylabel('Probability Distribution')
title('Returns over variable costs without an opportunity cost');
%
% % with only yield variability, no OC
mu = mean(Swchobj1b);
sigma = std(Swchobj1b);
Swchobj1b_IA = makedist('normal','mu',mu,'sigma',sigma);
%Miscanthus
mu = mean(Miscobj1b);
sigma = std(Miscobj1b);
Miscobj1b_IA = makedist('normal','mu',mu,'sigma',sigma);
figure(3);
x = -300: 0.5 : 1000;
y = pdf(CSobj1_IA,x);
y1 = pdf(Stovobj1_IA,x);
y2 = pdf(Swchobj1b_IA,x);
y3 = pdf(Miscobj1b_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('$/ha');
ylabel('Probability Distribution');
title('Returns over variable costs without an opportunity cost (only yield
variability)');

%USDA - Objective 2 : Maximize ethanol production
mu1 = mean(CSobj5);
sigma1 = std(CSobj5);
CSobj5_IA = makedist('normal','mu',mu1,'sigma',sigma1);
%Stover
mu2 = mean(Stovobj5);
sigma2 = std(Stovobj5);
Stovobj5_IA = makedist('normal','mu',mu2,'sigma',sigma2);
%Switchgrass
mu3 = mean(Swchobj5);
sigma3 = std(Swchobj5);
Swchobj5_IA = makedist('normal','mu',mu3,'sigma',sigma3);
%Miscanthus
mu4 = mean(Miscobj5);
sigma4 = std(Miscobj5);
Miscobj5_IA = makedist('normal','mu',mu4,'sigma',sigma4);
figure(4);
x = 10^7:10^6:3*10^8;
y = pdf(CSobj5_IA,x);
y1 = pdf(Stovobj5_IA,x);
y2 = pdf(Swchobj5_IA,x);
y3 = pdf(Miscobj5_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('kJ/ha');
ylabel('Probability Distribution')
title('Energy produced per hectare');

%EPA - Cost of procurement/gal
mu1 = mean(CSobj3);
```

```
sigma1 = std(CSobj3);
CSobj3_IA = makedist('normal','mu',mu1,'sigma',sigma1);
%Stover
mu2 = mean(Stovobj3);
sigma2 = std(Stovobj3);
Stovobj3_IA = makedist('normal','mu',mu2,'sigma',sigma2);
%Switchgrass
mu3 = mean(Swchobj3);
sigma3 = std(Swchobj3);
Swchobj3_IA = makedist('normal','mu',mu3,'sigma',sigma3);
%Miscanthus
mu4 = mean(Miscobj3);
sigma4 = std(Miscobj3);
Miscobj3_IA = makedist('normal','mu',mu4,'sigma',sigma4);
figure(5);
x = 0:0.05:3;
y = pdf(CSobj3_IA,x);
y1 = pdf(Stovobj3_IA,x);
y2 = pdf(Swchobj3_IA,x);
y3 = pdf(Miscobj3_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'y',x,y3,'--k');
legend('CS','Stover','Swch','Misc');
xlabel('gal/$');
ylabel('Probability Distribution')
title('Ethanol procured per dollar spent');

%DOE - Returns over Total cost
mu = mean(OC1);
sigma = std(OC1);
CSobj2_IA = makedist('normal','mu',mu,'sigma',sigma);
%Stover
mu = mean(Stovobj2);
sigma = std(Stovobj2);
Stovobj2_IA = makedist('normal','mu',mu,'sigma',sigma);
%Switchgrass
mu = mean(Swchobj2);
sigma = std(Swchobj2);
Swchobj2_IA = makedist('normal','mu',mu,'sigma',sigma);
%Miscanthus
mu = mean(Miscobj2);
sigma = std(Miscobj2);
Miscobj2_IA = makedist('normal','mu',mu,'sigma',sigma);
figure(6);
x = -1500: 0.5 : 1200;
y = pdf(CSobj2_IA,x);
y1 = pdf(Stovobj2_IA,x);
y2 = pdf(Swchobj2_IA,x);
y3 = pdf(Miscobj2_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('$/ha');
ylabel('Probability Distribution')
title('Returns over total costs');

%without OC
%Switchgrass
mu = mean(Swchobj2a);
sigma = std(Swchobj2a);
Swchobj2a_IA = makedist('normal','mu',mu,'sigma',sigma);
%Miscanthus
mu = mean(Miscobj2a);
sigma = std(Miscobj2a);
Miscobj2a_IA = makedist('normal','mu',mu,'sigma',sigma);
```

```
figure(7);
x = -500: 0.5 : 1000;
y = pdf(CSobj1_IA,x);
y1 = pdf(Stovobj1_IA,x);
y2 = pdf(Swchobj2a_IA,x);
y3 = pdf(Miscobj2a_IA,x);
plot(x,y,'b',x,y1,'--r',x,y2,'--g',x,y3,'c');
legend('CS','Stover','Swch','Misc');
xlabel('$/ha');
ylabel('Probability Distribution')
title('Returns over total costs without an opportunity cost');
```

Appendix C

Supporting Information for Chapter 4

I. Pasture management:

This study followed the supporting information provided by Cibin et al. (2016). Rotational grazing and hay cut with a Tall Fescue (cool season grass) crop was considered as pasture in the Upper Cedar watershed. For the Lumber watershed, Bermudagrass (warm season grass) with a hay cut was considered to be pasture crop, based on data available from the North Carolina State University extension.

The data for the average number of cattle heads in each county was obtained from USDA NASS Census 2007. The pastureland in each county was calculated from the Cropland Data Layer 2006/2007. SWAT requires inputs of the biomass consumed, trampled and manure deposited per day. We assume that the biomass consumed and trampled per day per cow are the same, 3% of their average body weight of 500 kg and 60% of biomass consumed is deposited back.

To simulate rotational grazing, all pasture HRUs were randomly assigned 25% of the grazing period (being divided into 4 groups), grazing 14 days in each of the group and resting them 75% of the time, completing a cycle of rotation in two months.

II. Production economics for Pasture

The annual cost of pasture maintenance is given in Table C -1. The revenue from pasture maintenance was assumed to be from the yield of hay growing on the HRU that could be sold as feed.

Table C- 2: Annual Cost of Pasture Maintenance in IA and NC

	IA[25]	NC[26]
	Annual Cost of Pasture maintenance ($/acre)	
Machinery	27	27
Fert, herbicide	28.17	100
Labor	12	9.73
Land	40	21
Annualized Initial Establishment Cost	23.14	25.54
Total cost/acre	113.88	183.27

[25] Barnhart, Duffy and Smith. "Estimated Costs of Hay and Pasture Production".ISU Extension. 2000. Accessed at < http://www2.econ.iastate.edu/faculty/duffy/Pages/pastureandhay.pdf>
[26] NCSU Extension Service. "Bermudagrass production in North Carolina". NCSU Extension. Accessed at < https://duplin.ces.ncsu.edu/wp-content/uploads/2014/05/AgBermudagrassAG-493.pdf?fwd=no>

III. SWAT results for conversion of cropland and pastureland to alternatives

1) Pastureland conversion

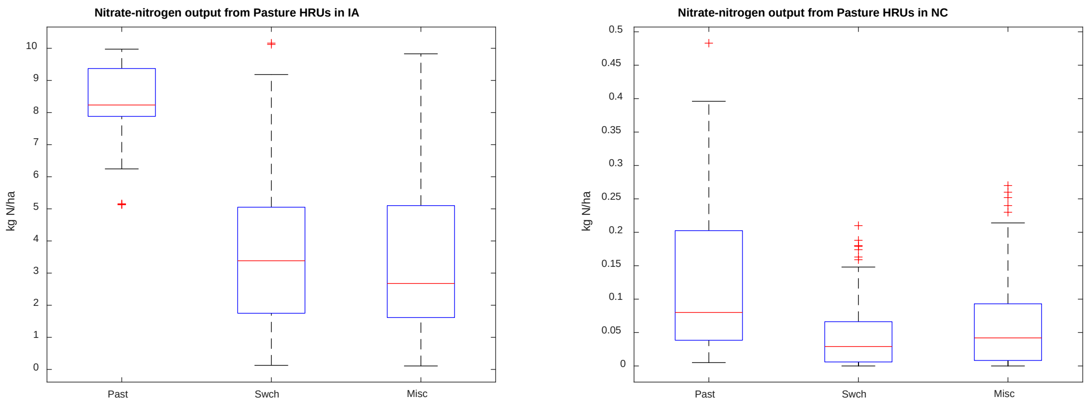

Figure C – 1: Box plots show the variation in nitrate-nitrogen output from Pasture HRUs in IA and NC under different land-use options

2) Cropland Conversion

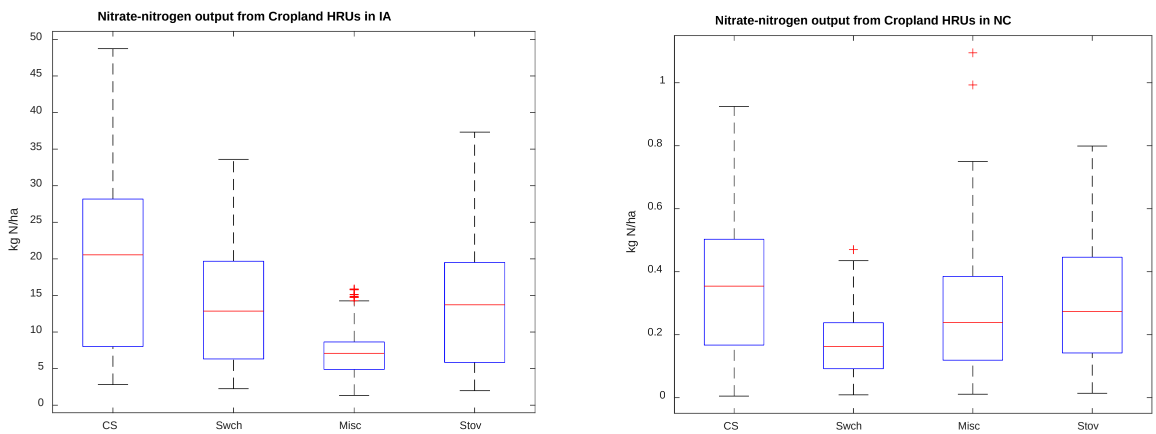

Figure C- 2: Box plots show the variation in nitrate-nitrogen output from Pasture HRUs in IA and NC under different land-use options

IV. MILP Optimization Sample Code

The sample code provided here uses a HRU-look up table of profitability to maximize the overall farm profitability. The output is a land-use table with the land-use decision for each HRU.

```
%% To find the best performing biorefinery for North Carolina to maximize farmer
profitability

%Declaring Land-use matrix for the 11 options
OptLU = zeros(378,4);
OptLU1 = zeros(51,3);
% Reading OF and constraint coefficients for maximizing farmer
% profitability
% for the system - Obj1_NC

Lfin = zeros(1665,1);
Nfin = zeros (1665,1);
Prodfin = zeros(1665,1);
Afin = zeros(1665,1);

Obj1Val = zeros(1,2);
P = xlsread('C:\Users\skeerthi\Documents\Journal Paper 3\Obj1_NC.xls');
P1 = xlsread('C:\Users\skeerthi\Documents\Journal Paper 3\Obj1Past_NC.xls');
Area = csvread('C:\Users\skeerthi\Documents\Journal Paper 2\Area_NC.csv');
AreaP = csvread('C:\Users\skeerthi\Documents\Journal Paper 3\AreaPast_NC.csv');
N = csvread('C:\Users\skeerthi\Documents\Journal Paper 2\Nit_NC.csv');
N1 = csvread('C:\Users\skeerthi\Documents\Journal Paper 3\NitPast_NC.csv');
Productivity = csvread('C:\Users\skeerthi\Documents\Journal Paper 2\Prod_NC.csv'); %
in Mg
ProductPast = csvread('C:\Users\skeerthi\Documents\Journal Paper 3\ProdPast_NC.csv');
% in Mg

Areshaped=reshape(Area,[1512,1]);
APreshaped = reshape(AreaP,[153,1]);
Prodre = reshape(Productivity,[1512,1]);
ProdPre = reshape(ProductPast,[153,1]);
Nin = reshape(N,[1512,1]); %coefficients for the Nitrogen Coefficient
N1in = reshape(N1,[153,1]);

L = -1*P; %conversion to maximization function (all intlinprog does min)
f = reshape(L,[1512,1]); %OF vector

L1 = -1*P1; %pasture max
f1 = reshape(L1,[153,1]);

for i = 1:1512
    Lfin(i,1)= f(i,1);
end
for i = 1:153
    Lfin(i+1512,1) = f1(i,1);
end

for i = 1:1512
    Afin(i,1)= Areshaped(i,1);
end
for i = 1:153
    Afin(i+1512,1) = APreshaped(i,1);
end

for i = 1:1512
    Nfin(i,1)= Nin(i,1);
end
```

```
for i = 1:153
    Nfin(i+1512,1) = N1in(i,1);
end

for i = 1:1512
    Prodfin(i,1)= Prodre(i,1);
end
for i = 1:153
    Prodfin(i+1512,1) = ProdPre(i,1);
end

    %%specifying that all decision variables are intergers
    E = 1:1:1665;
    intcon = 1:1665;
    lb = zeros(1665,1);

    %Constraint 1 : Upper bound for all dec variables = 1
    C = zeros(1665,1);
    for i = 1:1665
        C(i,1)= 1;
    end
    ub = C;

    % Constraint 2 that one one of CS,SWCH,MISC,STOVER chosen for each parcel
    Aeq = zeros(429,1665);
    for i = 1:378
        for j = 1:1512
            if(j==i)||(j==i+378)||(j==i+378*2)||(j==i+378*3)
                Aeq(i,j)=1;
            end
        end
    end
        for i = 1:51
        for j = 1:153
            if(j==i)||(j==i+51)||(j==i+51*2)
                Aeq(i+378,j+1512)=1;
            end
        end
    end
    beq = zeros(429,1);
    for i = 1:429
        beq(i,1)=1;
    end

    % Constraint 3
    % Scenario #1 - Sum of all CS and STOVERare not less than 75% of original (control
    % LUC)

    %Constraint 4&5 - Total production ~= 700,500 Mg/year

    % Constraint 6 - Pasture - less than 50% LUC from Pasture

   % A1 = zeros(4,1665);

    A1 = zeros(3,1665);
     for i = 1:378
        A1(1,i)= -1*Areshaped(i,1);
%       A1(1,i+1701) = -1*Areshaped(i,1);
        A1(2,i+378)= 1*Prodre(i+378,1);
        A1(2,i+378*2)= 1*Prodre(i+378*2,1);
        A1(2,i+378*3)= 1*Prodre(i+378*3,1);
        A1(3,i+378)= -1*Prodre(i+378,1);
        A1(3,i+378*2)= -1*Prodre(i+378*2,1);
```

```
        A1(3,i+378*3)= -1*Prodre(i+378*3,1);
     end

        for i = 1: 51
        A1(2,i+1512+51) = ProdPre(i+51,1);
        A1(2,i+1512 + 51*2)= ProdPre(i+51*2,1);
        A1(3,i+1512+51) = -1*ProdPre(i+51,1);
        A1(3,i+1512 + 51*2)= -1*ProdPre(i+51*2,1);
        end

%          for i = 1:51
%          A1(4,i+1512)= -1*APreshaped(i,1);
%          end
    % B1 = [-817.161,700833, -700500,52];
      B1 = [-817.161,700833, -700500];

    % Constraint 4 - Constraint limiting the amount of stover, miscanthus
    % and switchgrass that can be used by a biorefinery (700,500 Mg/year)

[x1,fval1,exitflag1,output1] = intlinprog(Lfin,intcon,A1,B1,Aeq,beq,lb,ub); %Solver
selection for MILP

for i = 1: 1665
    Obj1Val(1,1) = Obj1Val(1,1) + x1(i)* (-Lfin(i));
    Obj1Val(1,2) = Obj1Val(1,2) + x1(i)* (Nfin(i));
end


for i = 1: 378
    OptLU(i,1)= x1(i);
    OptLU(i,2) = x1(i+378);
    OptLU(i,3) = x1(i + 378*2);
    OptLU(i,4) = x1(i + 378*3);
end

for i = 1:51
    OptLU1(i,1) = x1(1512+i);
    OptLU1(i,2) = x1(i+1512+51);
    OptLU1(i,3) = x1(i+1512+51*2);
end

xlswrite('Obj1LU_NC.xls',OptLU);
xlswrite('Obj1LUPast_NC.xls',OptLU1);
```