MODELING CARBON DYNAMICS AND SOCIAL DRIVERS OF BIOENERGY AGROECOSYSTEMS

By

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Abstract

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Natalie D. Hunt

Under the supervision of Professors Stephen J. Ventura and Stith T. Gower
At the University of Wisconsin - Madison

Meeting society's energy needs through the production of bioenergy feedstocks presents a significant and urgent challenge, as it can provide a means to facilitate U.S. energy independence and mitigate climate change. With federal policy setting biofuel production standards to be met within the next decade, and with no broad commercial scale production or markets currently in place, there are many questions regarding the sustainability and social feasibility of bioenergy. Clarifying these uncertainties requires the incorporation of biogeochemical, biophysical, and socioeconomic modeling tools.

Chapter 2 validated the biogeochemical cycling model AGRO-BGC by comparing model estimates with empirical observations from corn (*Zea mays*) and perennial C_4 grass systems across Wisconsin and Illinois under varying management practices. AGRO-BGC, in its first application to an annual cropping system, was found to be a robust and competent model for simulating the carbon dynamics of an annual cropping system.

Chapter 3 investigated the long-term implications of bioenergy feedstock harvest on soil productivity and erosion in annual corn and perennial switchgrass agroecosystems using AGRO-BGC and the soil erosion model RUSLE2. Modeling environments included biophysical landscape characteristics and management practices of potential bioenergy feedstock production systems. This study found that intensifying aboveground residue harvest reduces soil organic carbon and nitrogen over time, and the magnitude of these losses is greater in corn than in switchgrass systems. Results of this study will aid in the design of sustainable bioenergy feedstock management practices.

Chapter 4 provided evidence that combining biophysical crop canopy characteristics with satellite-derived vegetation indices offers suitable estimates of crop canopy phenology for corn and soybean (*Glycine max*) crops in southwest Wisconsin farms. LANDSAT based vegetation indices, when combined with a light-use-efficiency (LUE) model, provide yield estimates in agreement with farmer reports, providing an efficient and accurate means of estimating crop yields from satellite data.

Incorporating a social component to the sustainability question brings the most important stakeholder to the bioenergy conversation, the farmer. Chapter 5 identified and measured the influence of bioenergy feedstock choice drivers using logistic regression choice models constructed from survey and geospatial data. The most influential choice drivers among farmers willing to participate in a proposed bioenergy feedstock production program included socioeconomic, biophysical, and environmental attitudes. Outcomes of this research will be useful in designing further bioenergy policy and economic incentives.

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Chapter 1. Introduction

1.1 Motivation

Approximately 80% of the United States' energy needs are met by the consumption of fossil fuels (US EIA, 2012). Burning fossil fuels releases CO_2 and other greenhouse gases into the atmosphere, contributing to climate change and generating imbalances in the carbon cycle. Agroecosystems are a significant component of the global carbon cycle as they comprise 24% of the world's land cover (Cassman & Wood, 2005), thus providing a significant linkage between atmospheric and terrestrial carbon stocks.

Growing bioenergy feedstocks provides a potentially viable contribution to reducing dependence on foreign oil and decreasing greenhouse gas emissions; however, major uncertainties about the sustainability of these bioenergy systems still exist. With a national population of 316 million and counting (https://www.census.gov/), meeting the demands for food, fiber, feed, and fuel in the U.S. will be a significant challenge to farmers in the twenty-first century.

Alternative energy sources considered for fossil fuel displacement should be carbon neutral or net carbon positive, be in sufficient quantity, deliver additional environmental benefits, and must be socially and economically competitive (Hill *et al.*, 2006). If managed properly, bioenergy feedstock systems have the potential to improve ecosystems through reducing carbon emissions, improving soil and water quality, and providing wildlife habitat (Ventura *et al.*, 2012). In addition, there is great potential in creating jobs with production, processing, transportation, and conversion steps of biofuel production (Wilhelm *et al.*, 2010).

Developing a bioenergy system is a complex undertaking, one that is driven by numerous economic, environmental, social, and political factors. Evaluating the potential for development in Wisconsin requires defining and measuring these drivers, including biophysical characteristics of crops and landscapes, landscape capability, existing policy and market structures that can potentially support or stifle development, and finally, the attitudes and perspectives of the landowners responsible for growing feedstocks on their land.

Because of the complex relationships among these drivers, there is a great deal of uncertainty around the willingness of farmers and landowners to adopt bioenergy feedstock management practices (Farber *et al.*, 2002). A means to navigate and clarify this uncertainty will require examination of the relationships among these drivers using a suite of ecosystem process, spatial, and econometric models. Fortunately, we have robust ecosystem process models that can estimate long-term effects of these processes, and extend the knowledge that is gained through short-term empirical studies. We also have ready access to large satellite datasets from which we can derive information about crop condition and quantity over broad spatial scales. And lastly, we have methods for surveying and interviewing members of the farming community to better understand their motivations and perspectives on bioenergy feedstock choice.

1.2 Research Objectives

This research follows an interdisciplinary framework for exploring sustainability that incorporates the biogeochemical, biophysical, and human aspects of managed agroecosystems. Sustainability is defined in this research as balancing production with maintenance or improvement of soil carbon, and maintaining social and economic feasibility. This research operates under the assumption that these processes are a function of existing environmental conditions and the human influences through land management. This dissertation emphasizes ecological sustainability and examines the feedback loops between human land use behaviors and the factors that drive them, with specific focus into the effects of land type and management practices on soil carbon and nitrogen dynamics. It provides a suite of methodologies for estimating the potential impacts of proposed bioenergy feedstock production systems, estimating crop productivity, and identifying the drivers behind farm management choices. The results of this research can inform farmers and policy makers as to the best way to manage feedstocks while minimizing environmental costs and maximizing environmental and agronomic benefits (Meehan *et al.*, 2013)

The two feedstocks of interest in this work include 1) harvesting the crop residues associated with corn (*Zea maize*) production, and 2) the production of a dedicated bioenergy feedstock crop switchgrass (*Panicum virgatum*). These two feedstocks are the focus of this research as they are the most viable candidates in the Midwest due to their compatibility with the climate, their low logistical barriers to accessing the agricultural infrastructure, and potential to deliver ecosystem service benefits (Ventura *et al.*, 2012).

Chapter 2 of this dissertation validates the ecosystem process model AGRO-BGC for corn agroecosystems in Wisconsin and Illinois to ensure accurate and consistent simulation of carbon and nitrogen dynamics for varying bioenergy feedstock management scenarios. It is the first application of AGRO-BGC in an annual cropping system, specifically for bioenergy feedstock production. Three field datasets in Wisconsin and Illinois were used to validate model performance at estimating leaf area index (LAI), soil organic carbon (SOC), and aboveground net primary productivity (ANPP). AGRO-BGC was also applied to examine the long-term implications of varying residue removal rates on soil productivity in corn agroecosystem and perennial C_4 grass ecosystems using a 47-year field SOC dataset for comparison.

Chapter 3 seeks to simulate the effects of residue removal on the soil carbon and nitrogen and soil erosion dynamics of corn and switchgrass agroecosystems through the use of AGRO-

BGC and soil erosion model, RUSLE2. The results of these simulations quantified the overall net carbon losses or gains for varying bioenergy feedstock management scenarios. With these estimates, we are able to identify which management scenarios maximize carbon storage and minimize carbon loss, with particular emphasis on the importance of carbon and nutrient replacement, and developing systems that maintain and improve the carbon and nutrient content of agricultural soils.

Chapter 4 aims to simulate canopy dynamics and estimate crop yields from satellite observations in corn and soybean agroecosystems in Wisconsin. The specific objectives of this research include accurate simulation of corn and soybean canopy characteristics using satellite derived vegetation indices and developing algorithms for linking empirical measurements with satellite data products for determining crop productivity on multiple spatial scales. Lastly, the algorithms were validated by comparing satellite-derived yields to farmer reports. The ability to estimate carbon and canopy dynamics across broad spatial scales is useful for estimating long-term sustainability of bioenergy feedstock production.

The foundation to every bioenergy system is laid by the farmer or landowner who makes the land management decision on whether or not to manage their land for bioenergy feedstocks. Chapter 5 examines the socioeconomic, biophysical, and spatial drivers of farmer choice around participation in a bioenergy feedstock production system. Through developing a logistical regression choice model, identification and measurement of farmer choice drivers was completed. The factors emerging from this chapter are at the intersection between social, biophysical, and economic spheres and will aid in generating land-type specific management recommendations, identifying places in the landscape where feedstock adoption likelihood is high, identifying linkages between energy and environmental policy, and recommendations for energy or environmental policy that are rooted in science.

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Chapter 2. Validation of an agroecosystem process model (AGRO-BGC) on annual and perennial bioenergy feedstocks

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Abstract

We validated the ecosystem process model AGRO-BGC by comparing model estimates with empirical observations from corn (*Zea mays*) and perennial C_4 grass systems across Wisconsin and Illinois under no-till, fertilized, and unfertilized management. Validation parameters included soil organic carbon (SOC), total soil nitrogen (N), aboveground net primary productivity (ANPP), net ecosystem productivity (NEP), and leaf area index (LAI). We parameterized the model to represent ecophysiological characteristics of corn agroecosystems and a perennial prairie grass system, and constructed scenarios to represent corresponding edaphic, climate, and management conditions. No-fertilizer estimates differed from field measurements by 7% for annual ANPP, 14% for SOC, and 29% for N, while fertilized simulations differed from field measurements by 7%, 19%, and 32 % for ANPP, SOC, and N, respectively.

We also examined the long-term implications of varying residue removal rates on soil productivity in the same agroecosystems. Model estimates compared to field data tested the hypothesis that long-term increased residue removal decreases SOC and productivity. Field observations showed 0.17 tC ha^{-1} yr^{-1} gain, 0.09 tC ha^{-1} yr^{-1} gain, and a 0.17 tC ha^{-1} yr^{-1} loss for the control, harvest, and bare grass residue removal treatments, respectively. Simulated SOC loss was greatest for the most intensive residue removal scenarios (0.48 and 0.68 tC ha^{-1} yr^{-1} loss for corn and grass, respectively), compared to no-harvest scenarios that increased SOC by 0.05 tC ha^{-1} yr^{-1} for both corn and grass. AGRO-BGC estimated a 0.07 tC ha^{-1} yr^{-1} loss under corn residue harvest, while estimating 0.09 tC ha^{-1} yr^{-1} loss for grass. These results suggest long-term increased corn and grass residue harvest (beyond grain) for biofuel feedstock will decrease SOC and soil productivity by approximately 15% in corn and 21% in grass systems over 47 years.

1. Introduction

Crop residues from agroecosystems are estimated to provide 350 million dry tons of bioenergy feedstock, 70% of which could come from corn stover or corncob biomass. Agricultural residues are proposed bioenergy feedstocks because of their ample supply, low cost, and widespread availability in the Upper Midwest (Perlack & Stokes, 2011). The 2007 Energy Independence and Security Act (EISA) set forth provisions to promote the use of renewable energy through the Renewable Fuels Standard (RFS). This mandate calls for the production of 36 billion gallons per year (BGY) of renewable fuels by 2022, 16 of which are to come from cellulosic biofuels and 14 BGY from advanced biofuels (Perlack & Stokes, 2011).

The amount of available crop residues is dependent upon crop production. The USDA estimates that crop yields will increase by 9.5% over the next ten years, providing a potential for increased amount of crop residues to be available for allocation to bioenergy production (Perlack & Stokes, 2011). While the production potential of crop residues is great, there is still great uncertainty around how much residue can be harvested to meet the bioenergy feedstock demands without decreasing long-term soil productivity (Mann *et al.*, 2002; Lal, 2005; Blanco-Canqui & Lal, 2007; Wilhelm *et al.*, 2007, 2010; Cruse & Herndl, 2009; Perlack & Stokes, 2011).

Land use change from a natural ecosystem to agriculture results in an initial, large loss of CO_2 from the vegetation and soil to the atmosphere. Continued cultivation results in chronic low-levels of CO_2 released to the atmosphere due to reduced inputs of plant detritus and increased decomposition rates when compared to pre-cultivation vegetation conditions (Jenkinson & Coleman, 1994; Schlesinger, 1997). There are competing uses for the agriculture residue including livestock bedding, manure-stover slurry, nutrient recycling, and wind or water erosion protection when residues are left on the field. These crop residues provide valuable carbon and nitrogen back to the soil, and some scientists speculate the long-term removal of the residues will create a nutrient deficiency unless nitrogen is replaced by alternative inputs (Wilhelm *et al.*, 2004; Lal, 2005). Another concern is that the removal of these residues will decrease soil organic matter (SOM) inputs to the system (Lal & Pimentel, 2007), which would result in decreased nutrient content, biological activity, and degraded soil structure. These soil functions affect productive capacity, filtering and buffering of contaminants, water and nutrient storage, and nutrient cycling, and all contribute to overall soil productivity (Perlack & Stokes, 2011). SOC is the product of a balance between organic C and N inputs through biomass production, fertilizer application, plant and animal residues, and losses of C and N through microbial decomposition, mineralization, and erosion.

The significance of SOC in crop productivity is attributed to its biological, physical, and chemical functions. Biologically, the quantity of SOC represents the soil's capacity to retain nutrients (e.g. nitrogen, phosphorus, potassium) for plant uptake. Physically, it provides structure through soil aggregation and tilth (Paustian *et al.*, 1998). Soil aggregates provide a structure that influences water infiltration, water holding capacity, aeration, and bulk density; all of which can determine soil quality and productivity. Chemically, SOC influences pH, nutrient availability and cycling, and capacity for ion exchange and buffering (Wilhelm *et al.*, 2004). The removal of crop residues can alter these processes by changing the energy balance and leaving the soil surface exposed to wind and water impacts. These can degrade the soil quality significantly and contribute to soil loss, which is detrimental to the agricultural and environmental community. The slow carbon loss from the soil to the atmosphere or through erosion as a result of continued cultivation is the focus of this study.

SOC content is dependent upon climate (e.g. temperature and moisture regimes) and edaphic characteristics (e.g. bedrock composition, soil structure, clay content, and cation-exchange capacity), both of which influence the amount of carbon that gets fixed through photosynthesis (Gregorich *et al.*, 1994). Fungal and microbial components of SOM also influence SOC cycling and are affected by management practices such as residue removal and tillage (Mann *et al.*, 2002). Carbon and nitrogen cycles are linked through the carbon to nitrogen (C:N) ratio of plant components (e.g. leaves, stalks, shoots, roots), which decompose and become part of the soil organic carbon pool. Soil organic C and N content is dependent upon the interactions between inputs via fertilizer application and decomposition of plant residues. Fertilization stimulates productivity and thus increases the amount of residue that left on the soil, which can increase soil organic carbon content (Brye *et al.*, 2002). Overall, these C and N dynamics are heavily influenced by crop management practices.

One of the major uncertainties surrounding bioenergy feedstock production is the long-term sustainability of soil fertility, and how much of these crop residues can be sustainably harvested to meet US bioenergy needs (Perlack & Stokes, 2011). Field studies provide useful insights on the short-term effects of different management practices on soil productivity, however soil carbon and nitrogen are slow to respond to external change (Jenkinson & Coleman, 1994) and empirical data on long-term residue manipulation studies for agroecosystems are rare. An alternative is to employ a long-term soil carbon dataset from a prairie as a proxy to explore the effects of residue manipulations in agroecosystems. Using ecosystem process modeling tools such as AGRO-BGC validated with empirical field data can help to elucidate the long-term implications of residue management policies (Peckham & Gower, 2011). We applied AGRO-BGC to this system to test and develop the model to describe the effects of residue manipulation over the long term. Balancing the needs of the agroecosystem over the long-term with the ability to provide biomass feedstock to generate a renewable energy source for our US energy needs will be a great challenge in the next few decades (Perlack & Stokes, 2011).

The application of ecosystem process models such as AGRO-BGC, BIOME-BGC, CENTURY and AGRO-IBIS (Parton *et al.*, 1987; Kucharik, 2003; Wang *et al.*, 2005; Di Vittorio *et al.*, 2010; Peckham & Gower, 2011) on natural and managed ecosystems improves our understanding of the functions and dynamics of complex ecosystems. They have been used to develop sound natural resource management policy by improving our understanding of the magnitude and variability of the effects of management practices over time scales that cannot be captured by existing empirical field research studies. Interactions among management practices, erosion, SOM, nutrients, and yield are complex, and the use of AGRO-BGC can assist in clarifying these interactions over the long-term.

Our ability to simulate the dynamics of an annual cropping system is constrained by our understanding of the underlying agroecosystem dynamics, access to accurate climate and edaphic information, and our ability to assign correct ecophysiological values to our vegetation abstraction. AGRO-BGC simulates carbon, nitrogen, and water cycles, and their interaction, and allows the user to simulate irrigation, annual seed planting, fertilizer application, and harvest (Di Vittorio *et al.*, 2010). The predecessor of AGRO-BGC, BIOME-BGC has been validated extensively against eddy covariance flux tower data (Turner *et al.*, 2005) and against long-term field empirical data sets across evergreen and deciduous forests (Turner *et al.*, 2002a; Peckham & Gower, 2011). Both models have been validated in perennial grass systems and BIOME-BGC has been validated in an annual corn cropping system in China (Wang *et al.*, 2005), but neither has been applied to annual corn cropping systems in the Upper Midwest under the context of bioenergy feedstock production.

The two objectives of this research are to i) validate AGRO-BGC by comparing simulated results with empirical observations from multiple field sites across the Wisconsin and Illinois, and ii) to use the model to explore the long-term implications of residue removal on soil productivity. Metrics of evaluation include comparing model estimates of state variables and magnitude of fluxes with field measurements. Because agroecosystems are highly modified through varying management practices and desired production outputs, a rigorous ecosystem process model ought to capture the effects of these practices on soil dynamics.

2. Methods & Materials

We modeled C and N dynamics for one agricultural system each in south central Wisconsin and in central Illinois, and for two restored prairie grass systems in Arlington and Madison, Wisconsin. Both farm validation sites were in an annual soybean (*Glycine max*) and corn (*Zea mays*) crop rotation, and the prairie site consists of mixed tallgrass perennial grass system. All AGRO-BGC simulations were continuous corn or perennial grass.

2.1 Study Site Descriptions

Validation field sites were selected to evaluate the model's performance in four specific areas: seasonal phenology (how well the model captures maxima, minima, and changes throughout the growing season), carbon allocation (how accurately the model distributes carbon to above ground plant pools), how well the model estimates carbon pools and fluxes, and how accurately the model captures the above soil and plant variable responses to repeated annual harvests (Table 1).

The pre-settlement dominant land cover type in Southern Wisconsin was a mixture of prairie and oak savannah (Cottam & Loucks, 1965). Following settlement, arable land was put into agriculture production for growing wheat, oats, tobacco, hops, and hay, or put into pasture for livestock or dairy. The late 1800s brought about production of annual row crops, particularly corn and soybeans (Schaefer, 1922). According to 1832 public land survey records, the site for the Arlington Agricultural Research station site consisted of mostly prairie with patches of timber groves (Wisconsin Public Land Survey Records, 2013). The site was put into agriculture production in the early 1900s until 1955, when the farmland was acquired by the research station. Since 1955, the land has been used as a field laboratory for agricultural research (Wisconsin Public Land Survey Records, 2013). The prairie site is situated in the Audubon Society's Goose Pond Sanctuary, less than 2.5 km from the Arlington agricultural research station. It was retired from agricultural use in June 1976 and restored to mesic tallgrass prairie.

The Arlington dataset provides a robust quantitative assessment of carbon stocks and fluxes in a corn agroecosystem and restored prairie system, particularly metrics for productivity including SOC, total soil nitrogen, and ANPP (Kucharik *et al.*, 2001; Brye *et al.*, 2002). It also provides a robust water budget to supplement the carbon simulations, including estimates of evapotranspiration (ET). These sites are situated in and around the University of Wisconsin-Madison's Arlington Agricultural Research Station in Arlington, WI (43°17'N, 89°22'W), where the soil is a Plano silt loam (fine-silty, mixed, superactive, mesic Typic Argiudoll) with a parent bedrock material of loess over glacial till (Brye *et al.*, 2002). The corn study includes test plots (four replicates of 9.1 x 12.2 m) of continuous corn, with an annual fall grain harvest and crop residues left on the field. The prairie study also includes test plots (four replicates of 7 x 7 m) established in the spring of 1995. Dominant vegetation includes big bluestem (*Andropogon* *gerardi* Vitman), Indiangrass (*Sorghastrum nutans*), switchgrass (*Panicum virgatum*), purple coneflower (*Echinacea purpurea*), goldenrod (*Solidago spp.*), and black-eyed Susan (*Rudbeckia hirta*) (Brye *et al.*, 2002). Data at both sites were collected during a carbon and nitrogen budget study from 1995 - 1999. Management practices included conservation (no-till) and conventional (chisel plow) tillage treatments. Nitrogen fertilizer treatments included N-fertilized (180 kgN ha^{-1} yr^{-1}, annual, post planting) and N-limited (no fertilizer application). Parameters measured in this study include annual SOC, ANPP, N, maximum annual LAI, daily ET, and daily LAI. At the prairie site, management included a burn approximately every three years since 1976. Prior to the carbon and water budget study (Brye *et al.* 2000), the prairie was burned in April 1998 (Day of year (DOY): 108). Biomass sampling and biophysical measurement methods are described in (Brye *et al.*, 2002).

The Bondville, IL research site has been in agriculture production for approximately 100 years, the last 30 of which have been in corn and soybean rotation. Before this, the farm was in small grain and hay production (J. Reifsteck, personal communication). This site is underlain by a combination of Flanagan silt loam and Drummer silty clay loam.

The Bondville, IL field site provides daily measurements of net ecosystem production, daily LAI, and daily leaf C (Meyers & Hollinger, 2004; Hollinger *et al.*, 2005). These site observations were used in order to assess the model's ability to simulate accurate carbon allocation within the plant (leaf carbon) and to test for its accurate estimation of seasonal CO_2 fluxes between the canopy and the atmosphere (Turner *et al.*, 2002b, 2005; Turner, 2003). The site consists of multiple agricultural fields in a no-till corn-soybean rotation stratified across 15 farms within a 25 km^2 study area, and research was established in 1996 (Meyers & Hollinger, 2004; Turner *et al.*, 2005). Validation data are from a carbon and nitrogen budget study using field measurements of leaf C and LAI representing mean averages for cornfields across the study area (Cover *et al.*, 1999; Turner *et al.*, 2005). Daily NEP flux tower data were collected for corn crops at one farm field within the study area (years 1997, 1999, 2001, 2003, and 2005) and aggregated over the growing season to determine whether the crop is a carbon source or carbon sink. Details on sampling and measurement methods are referenced in D.P. Turner *et al.* 2005 and Meyers and Hollinger, 2004.

According to 1834 public survey land records, the University of Wisconsin Madison Arboretum site land cover consisted of burr and black oak timber stands, and rolling hills of grass (Wisconsin Public Land Survey Records, 2013). The section of the arboretum where Curtis Prairie currently resides was then home to a private farm from unknown origin until 1932, when the land was acquired for the UW-Madison Arboretum. Prairie restoration of the site began between 1935 and 1940 (Nielsen & Hole, 1963). This site is underlain by a Wacousta silty clay loam.

The Curtis Prairie biomass and residue removal study provides measurements of prairie soil organic matter during a 47-year period (Nielsen & Hole, 1963; VanRooyen, 1973). Because empirical data on such long-term residue manipulation studies for agroecosystems are rare, we employed this dataset as a proxy to explore the effects of residue manipulations on corn and grass agroecosystems. Vegetation was established at the Curtis Prairie site in 1940, while residue manipulation treatment plots began in 1956. Initial prairie vegetation consisted of a mixture of big bluestem (*Andropogon gerardi*), Indian grass (*Sorghastrum nutans*), and switchgrass (*Panicum virgatum*), quack grass, dandelion, and bluegrass, among other prairie grass species. Three treatment plots were used: control (plot left undisturbed), harvested (vegetation cut and removed in fall), and bare (vegetation frequently cut and removed to minimize accumulation of above and belowground vegetation and residue). Data on soil carbon and bulk density to 10 cm were recorded in 1959, 1971, 1997, and 2006 (VanRooyen, 1973; Nadelhoffer *et al.* unpublished data).

2.2 AGRO-BGC Description

AGRO-BGC simulates carbon, nitrogen, and water fluxes and stocks on a daily time step. AGRO-BGC evolved from BIOME-BGC, with additional functions for simulating agricultural management practices such as annual seeding, fertilizer application, harvest, and irrigation (Di Vittorio *et al.*, 2010). Model estimates can be aggregated to a monthly or annual time step for analysis and interpretation. This study uses both daily and annual aggregations of the model estimates to correspond with the field validation datasets. Variables of interest to this study included total soil carbon (SOC) and nitrogen (N), net ecosystem productivity (NEP), net primary productivity (NPP), and leaf area index (LAI).

AGRO-BGC uses daily maximum and minimum temperature, total precipitation, average vapor pressure deficit, total solar radiation, and daylength for each study site to simulate carbon, water, and nitrogen fluxes. Climate data from 1980 - 2011 were cycled throughout the simulations over each study site (Di Vittorio *et al.*, 2010; Peckham & Gower, 2011), and were provided by DAYMET (http://www.daymet.org) through the National Center for Atmospheric Research (http://ncar.ucar.edu/). Growing degree-day (GDD) units for corn were included in the parameterization, specifically units for emergence, stem elongation, and flowering.

Model spinup was necessary to equilibrate the terrestrial C and N pools with the atmospheric C and N pools (Thornton & Rosenbloom, 2005). We accomplished this by recycling the annual climate data until steady state conditions were met, then following with managed agroecosystem simulations (Di Vittorio *et al.*, 2010; Peckham & Gower, 2011). Simulations for the four sites were constructed to mimic general land cover and land use patterns in the region.

We constructed validation test scenarios to mirror the conditions under which field observations were collected in terms of duration, management practices, and environmental conditions (Brye *et al.*, 2002; Turner *et al.*, 2005). Building the scenarios for the land use history of each site is based on the above records of each site's land cover and land use history. Following the steady-state spinup of an unmanaged C_4 grass system for the Arlington and Bondville sites, the model was run from the early 1900s to the 1990s to simulate a managed continuous corn agroecosystem converted from a mixed prairie grass system. For the perennial grass simulations, the model was run from the early 1900s to 1976 to simulate a managed continuous corn agroecosystem. Following 1976, the model was run to simulate a restored mesic tallgrass prairie system.

The UW Arboretum simulations also followed an unmanaged C_4 grass spinup scenario, followed by a 40-year simulation of continuous corn, followed by a C_4 grass simulation to mimic the conditions of a prairie restoration. Residue removal rates were simulated for fifty years to mirror the duration and conditions of the Arboretum residue removal trials. Planting and harvesting dates for these simulations were based on field planting and harvesting date estimates for each site. Both corn and perennial C_4 grass simulations were run at this site.

Atmospheric CO_2 concentrations were estimated for both pre and post-industrial periods using values from the Carbon Dioxide Information Analysis Center (http://cidac.ornl.gov). Nitrogen deposition estimates ranged from the pre-industrial values of 0.001 tons N ha^{-1} yr^{-1} to 1994 value of 0.005 tons N ha^{-1} yr^{-1} (National Atmospheric Deposition Program (http://nadp.sws.uiu.edu)). Edaphic characteristics including rooting depth, when not defined in the literature, were derived from the Soil Survey Geographic (SSURGO) Database (http://soildatamart.nrcs.usda.gov/) based on the site location (Peckham & Gower, 2011).

Ecophysiological parameters were assigned values from published literature (Bollero *et al.*, 1996; White *et al.*, 2000; Kucharik *et al.*, 2001; Ma & Dwyer, 2001; Brye *et al.*, 2002; Wang *et al.*, 2005; Di Vittorio *et al.*, 2010; Schulze *et al.*, 2011). For corn, mean values for C_4 grasses were used in the absence of species-specific values, and when these were unavailable, general ecophysiological values were employed (White *et al.*, 2000) (Table 2).

When specific parameter values could not be found in the literature, an Independent Variation Sensitivity analysis was conducted in order to minimize the percentage error between observed and simulated variables (White *et al.*, 2000; Xu *et al.*, 2008). This was done to test the effect of varying each parameter by a constant step throughout a known range, independently of all parameters. The simulated results were compared to observed field values and the percent error was calculated. Parameter values found in the literature were used in this analysis, and a mean, standard deviation, minimum, and maximum were included (White *et al.*, 2000; Xu *et al.*, 2008). Parameters included in the sensitivity analysis were grouped into biomass allocation (e.g. fine rootC:leafC), nutrient stoichiometry (e.g. leaf C:N, fine rootC:N), and general vegetation characteristics (e.g. rooting depth, flowering GDD, specific leaf area (SLA), fraction of leaf N in Rubisco (FLNR), fraction of leaf N in PEP Carboxylase (FLPEP), and maximum stomatal conductance (g_{smax})) (Table 3).

AGRO-BGC simulates photosynthesis based on the DePury and Farquhar two-leaf model. Each gross primary production calculation is done for both sunlit and shaded leaves, and the amount of C assimilated is summed at the end of the day. After accounting for metabolic demands estimated by vegetation specific allometric equations, the photosynthetically accumulated carbon is then allocated to the various plant (e.g. leaves, stem, and fine roots) and soil pools according to allocation parameters (White *et al.*, 2000; Di Vittorio *et al.*, 2010). Nitrogen concentrations of tissue pools are characterized by carbon to nitrogen ratios, and these drive new growth, plant respiration rates, photosynthetic capacity, and litter type. The calculation for NPP is the gross primary productivity (GPP) minus maintenance respiration and growth respiration, and a positive value reflects net biomass accumulation. Evapotranspiration is simulated in AGRO-BGC using a modified Penman-Monteith equation. This equation takes into account evaporated canopy intercepted water, photosynthetic transpiration, and soil evaporation (Di Vittorio *et al.*, 2010; Golinkoff, 2010).

NEP, or net ecosystem productivity, is the net quantity of carbon produced by the system, including C loss through autotrophic, growth, and heterotrophic respiration, erosion, and consumption by herbivory. In the model, NEP is calculated by subtracting heterotrophic respiration from NPP, as erosion is not accounted for in AGRO-BGC.

The disturbance function in AGRO-BGC is used to simulate agroecosystem management practices through prescribed addition, removal, or allocation of nitrogen and carbon to plant and soil pools. Practices such as grain and residue harvest, nitrogen fertilizer application, irrigation, and residue removal are simulated using this function. Crop management practices documented in the field studies were replicated in the AGRO-BGC simulations including the proportion of biomass to be removed from the system, frequency of residue removal, and the duration of the biomass removal (Di Vittorio *et al.*, 2010; Peckham & Gower, 2011). For this research, all annual cropping management practices are assumed to be no-till, as AGRO-BGC does not have the capacity to simulate tillage. Annual corn harvest was simulated by assuming 100% grain removal with all remaining residue (e.g. stem, leaf, and fine roots) transferred to the litter pool.

Fertilizer application was simulated by assigning the amount of fertilizer to be deposited into the available soil mineral nitrogen pool (Di Vittorio *et al.*, 2010) in specific quantities at a specific time. A nitrogen uptake efficiency of 40% (Cassman *et al.*, 2002) was assumed and the amount of applied nitrogen during the Arlington field study of 180 kgN ha^{-1} yr^{-1} that is taken up by the plant was calculated to be 72 kgN ha^{-1} yr^{-1}.

For the C_4 grass simulations at the Arboretum site, harvest was simulated by 100% removal of above ground biomass, but leaving the litter pool and fine roots on site, while the bare simulations removed the litter pool in addition to all above ground biomass. Control simulations of the grass systems experienced no disturbance.

2.3 Validation Parameters

Annual SOC and N were selected to evaluate AGRO-BGC's ability to simulate the long-term effects of residue management on soil productivity. LAI was selected because it allows us to evaluate AGRO-BGC's ability to capture annual plant phenology in a managed annual cropping system, and LAI is a primary determinant of productivity.

All aboveground biomass (e.g. leaves, stems, roots, fruit) was either harvested (i.e. removed from the system) or transferred to litter pools as the plant senesces and dies or residue is left on the soil after harvest. The litter pool fragments the detritus into different pools with differing recycling rates that are based on litter composition, temperature, and moisture content. Upon decomposition, the C and N in the "transient detritus" pools are transferred into the SOM pools, where the quantity of SOC and N can each be calculated.

LAI is a measure of the amount of leaf surface area exposed to light interception and attenuation, and it is a driver of photosynthesis in the plant canopy (Meyers & Hollinger, 2004).

LAI is calculated by multiplying the user-defined specific leaf area (SLA) by the quantity of modeled leaf C on a daily time step. In AGRO-BGC, LAI drives the absorption of photosynthetically active radiation, interception of precipitation, photosynthesis, and the amount and type of litter deposited into detritus pools (White *et al.*, 2000; Golinkoff, 2010).

2.4 AGRO-BGC Modeling Scenarios

Arlington, WI: We constructed two scenarios to simulate continuous corn under conservation tillage management and under two nitrogen fertilizer treatments from 1995-1999. Each harvest scenario experienced an annual fall grain harvest with residue left on the soil. The base scenario (NTNF0) consisted of an annual grain harvest, no-tillage, no fertilizer application, and the fertilizer scenario (NTF0) consists of the same practices but with an annual fertilizer application of 72 kgN ha^{-1} yr^{-1}. We constructed one scenario to simulate a perennial grass system restored from agriculture land use. The system experienced a burn disturbance every three years from 1976 to the beginning of the carbon budget study in 1995, then one additional burn in the spring of 1998.

Bondville, IL: We constructed one scenario to simulate a continuous corn system under conservation tillage management, with no fertilizer application for years 1999-2000 for comparison with daily leaf carbon and LAI measurements. We constructed an additional scenario to simulate a continuous corn system from 1997 - 2006 under conservation tillage management with no fertilizer treatment for comparison with FLUXNET tower measurements. Each harvest scenario experienced an annual fall grain harvest with residue left on the soil.

Madison, WI: We constructed six scenarios to simulate 1) an annual continuous corn and 2) a perennial C_4 grass system under conservation tillage management, no fertilizer application, and under three residue manipulations from 1956 - 2009. The "control" scenarios simulated both systems with no annual harvest or residue removal. The "harvest" scenarios simulated both systems with an annual fall removal of aboveground biomass and no additional residue removal. For the corn simulation, this meant a 100% grain removal with remaining plant residues left on the soil. For the C_4 grass simulation, this meant a 100% removal of above ground plant material. The "bare" scenarios simulated both systems with annual fall harvest and complete residue removal.

2.5 Evaluation Methods

We compared model outputs with field and eddy-covariance measurements from several carbon budget and biophysical studies to evaluate the model's ability to accurately simulate the ecosystem C and N dynamics. Each agroecosystem simulation was initiated at steady state carbon conditions, then run to parallel site history conditions, then again for the comparable number of years to the field study. Model outputs were compared to each site's respective field data, and relative error between simulated and observed values was calculated for annual pools. Annual NPP for the corn system was estimated from the annual above ground biomass accumulated and compared with field measurements of above ground biomass harvested in the fall. Using regression analysis, simulations of daily LAI were compared with both corn and prairie Arlington LAI measurements taken across the growing season for the duration of the study. AGRO-BGC requires a static planting date that is repeated yearly for the duration of the simulation, so it is unable to capture the variation in planting dates that farmers deal with every year. Model outputs were shifted to reflect actual planting dates for each simulated growing season, when available.

Total soil carbon and soil nitrogen estimates consisted of the summation all soil and nitrogen pool fractions at the end of the simulation year and were compared with field measurements to 1.2 m at the Arlington site, and to 10 cm at the Arboretum site. The Arlington soil C and N measurements were calculated as the average of the mean content for spring and fall. The Arboretum soil carbon estimates were estimated from the fall sampling period.

Simulated and measured SOC was compared for 1959, 1971, 1997, and 2006 to assess the model's ability to estimate response to residue manipulations at the Arboretum site. Total carbon loss under the varying residue manipulations was estimated as the difference between initial and final total carbon content.

To evaluate the model's ability to accurately simulate NEP, model estimates were compared to eddy-covariance flux tower measurements at the Bondville field. Carbon flux measurements during the growing season were summed to measure the carbon storage of the crop for corn years. Growing season was defined as the time period between planting and harvest.

3. Results

3.1 Sensitivity Analysis

Parameters included in the sensitivity analysis were grouped into biomass allocation (e.g. fine rootC:leafC), nutrient stoichiometry (e.g. leaf C:N, fine rootC:N), and general vegetation characteristics (e.g. rooting depth, flowering GDD, SLA, g_{smax}, FLNR, and FLPEP). The most sensitive parameters revealed through this analysis were SLA, g_{smax}, rooting depth, leaf C:N, FLPEP, and FLNR. These parameters represent the processes that drive leaf photosynthetic machinery, leaf infrastructure, and the biophysical dynamics of the crop canopy.

Maximum LAI was most sensitive to SLA showing an increase in overestimation in maximum LAI with an increase in SLA (Figure 1). While annual ANPP and annual total SOC were less sensitive to SLA than Maximum LAI, we observed a negative relationship between SLA and ANPP and SOC. White *et al.* (2000) found similar results in their sensitivity analysis across all biomes (deciduous broadleaf forest, evergreen needle leaf forest, grassland, shrubs), where an increase in SLA resulted in an increase in LAI, yet produced a decrease in NPP.

We also observed that maximum LAI, ANPP, and SOC were sensitive to g_{smax}, with SOC as the least sensitive of the three (Figure 2). We observe that as g_{smax} increased, ANPP and Maximum LAI decreased while SOC increased.

We observe that as rooting depth increased, SOC estimates tended to decrease, while Max LAI and ANPP tended to increase (Figure 3).

An increase in Leaf C:N increased ANPP, Max LAI, and SOC up to where Leaf C:N equals approximately 50 (Figure 4), and above this, all three parameters decreased.

Increasing the fraction of nitrogen investment in PEPCase up to 0.02 had a positive effect on Maximum LAI, SOC, and ANPP, but beyond this there was no effect on any of the parameters (Figure 5). ANPP, SOC, and Maximum LAI all increased with the amount of leaf nitrogen made available to Rubisco, with a decreasing rate of increase once FLNR exceeds 0.2 (Figure 6).

3.2 Validation Results

Estimated ANPP for corn NTNF0 and NTF0 treatments at Arlington averaged approximately 5 and 8 tC ha^{-1}yr^{-1} respectively over the 1995-1999 simulation. (Brye *et al.*, 2002) measured 5 and 9 tC ha^{-1}yr^{-1} for a continuous corn cropping system in Arlington, WI. AGRO-BGC overestimated ANPP on average by 7% for the no-fertilizer treatment and underestimated ANPP by 7% for the fertilized treatment (Table 4). Daily simulated evapotranspiration (ET) averaged 2.4 and 2.5 mm day^{-1} for no-till corn and prairie grasses respectively, across the 1995-1999 study period. Field estimates averaged 2.4 and 2.5 mm day^{-1} for no-till corn and prairie grasses, respectively, between 1996 and 1997 (Brye *et al.*, 2000).

The Bondville, IL flux tower measurements from years 1997, 1999, 2001, 2003, and 2005 are represented in Figure 7. AGRO-BGC captured the intra-annual variability of daily NEP, with maximum NEP occurring at full canopy closure during the growing season and negative NEP values outside the growing season (Figure 7). Model estimates of NEP averaged 3 tC ha^{-1}yr^{-1}, while flux tower measurements averaged at 5 tC ha^{-1}yr^{-1}, with a mean simulation underestimation of 47% across all corn years. (Hollinger *et al.*, 2005) measured a mean annual NEP of 6 tC ha^{-1} yr^{-1} from years 1997 - 2002 in a similar unfertilized corn agroecosystem in Illinois. (Wang *et al.*, 2005) also reported that BIOME-BGC underestimated NEP estimates for corn in China.

When model estimates were adjusted for variable planting dates, early season growth was captured by the model. AGRO-BGC captured the general phenology of corn LAI for both Arlington (Figure 8) and Bondville (Figure 10) field sites. In general, simulated and measured LAI increased during the early growing season, reached a maximum LAI on average around late August (DOY: 232- 234), then decreased as the corn canopy senesced. Measured and simulated LAI were positively correlated for the Arlington sites (R^2 of 0.85 for NTNF0 and R^2 of 0.83 for NTF0) (Figure 9). The NTNF0 simulation had a slope coefficient of 1.3 deviating significantly ($p < 0.05$) from zero, while NTF also deviated significantly ($p < 0.05$) from zero with a slope coefficient of 1.7. LAI estimates agreed with observations for lower LAI values, but the two estimates increased in deviance from observations for LAI values above 2.5 for NTNF0 and above 2.0 for NTF0.

On average, the model overestimated maximum LAI for the NTNF and NTF simulations by 54% and 125%, respectively (Table 4). Maximum LAI estimates averaged 5 and 8 for the NTF0 and NTF0 simulations, while Brye et al. (2002) reported maximum annual LAI values of 3 and 4, respectively (Table 4). However, for prairie grasses, measurements of maximum LAI in Goose Pond aligned with simulated average maximum LAI, each averaging at 4 (Brye *et al.* 2002). The model also overestimated LAI at the Bondville site. AGRO-BGC also overestimated daily leaf carbon in the AGRO site throughout the growing season at the Bondville site, as shown in figure 10.

3.3 Total Soil C and N

Simulated soil carbon content for the NTNF0 and NTF0 treatments averaged 170 and 195 tC ha^{-1} during the five year simulation, respectively, while Brye et al. (2002) reported soil carbon content at 151 and 166 tC ha^{-1}, respectively (Table 4). In the NTNF0 simulation, the model overestimated observed soil carbon by 14%, while NTF0 simulations overestimated soil carbon content by 19%.

AGRO-BGC overestimated total soil nitrogen for the NTNF0 and NTF0 treatment by 29% and 32%, respectively. Simulated total soil nitrogen for the NTNF0 and NTF0 treatments averaged approximately 17 and 19 tN ha^{-1}, respectively, while Brye *et al.* (2002) reported soil nitrogen content of 13 and 15 tN ha^{-1} (Table 4) in the top 1.5 meters of the soil profile.

3.4 Changes in SOC

The control field plots (Nadelhoffer *et al*. unpublished data, G. A. Nielsen & Hole, 1963; VanRooyen, 1973) accumulated 8 tC ha^{-1} SOC in the top 10 cm of the soil profile during the 47-year study period, or 0.2 tC ha^{-1} yr^{-1} gain. The harvested plots gained 4 tC ha^{-1}, while the bare plots lost 8 tC ha^{-1} over the 47-year study, averaging a 0.2 tC ha^{-1} yr^{-1} loss.

Similar treatment effects on SOC were observed for the corn ecosystem. SOC slightly increased (151 to 153 tC ha^{-1}) during the 47-year control simulation at a rate of 0.05 tC ha^{-1} yr^{-1}, but decreased slightly (151 to 148 tC ha^{-1}) for the harvest simulation at a rate of 0.07 tC ha^{-1} yr^{-1}. SOC in the bare simulation lost 22 tC ha^{-1} during the 47-year period, at a rate of 0.5 tC ha^{-1} yr^{-1} (Figure 11).

The results of the C_4 grass AGRO-BGC simulations showed an increase in soil carbon of 0.05 tC ha^{-1} yr^{-1} in the control (151 tC ha^{-1} to 154 tC ha^{-1}), a 0.09 tC ha^{-1} yr^{-1} loss in the harvest (151 tC ha^{-1} to 147 tC ha^{-1}), and a 21% loss in the bare scenario (151 tC ha^{-1} to 120 tC ha^{-1}) in the top 1.5 m soil profile (Figure 11). The greatest SOC rate loss was for the bare residue removal treatment, and averaged 0.49 and 0.68 tC ha^{-1} yr^{-1} loss for corn and grass simulations, respectively.

4. Discussion

When empirical field studies are unavailable at time scales necessary for understanding the long-term effects of farm management practices, ecosystem process models provide the best available tools. They provide a means for understanding the complex dynamics between the terrestrial, vegetation, and atmospheric components of open agroecosystems. They also provide the ability to make informed predictions about long-term effects of varying management practices; and when validated with long-term ecological data, their predictive power increases. No model is a perfect predictor of future outcomes and the performance of each model is limited by the user's understanding of agroecosystem dynamics. However, the ecosystem process model AGRO-BGC is driven by a series of empirically based equations and possesses a mechanical structure that allows for adaptation as understanding of agroecosystem processes improves.

Capturing all of the simultaneous processes of an open ecosystem within a single model is an impossible undertaking, particularly with agricultural systems that undergo frequent and significant disturbance. However, the above demonstration of AGRO-BGC's ability to approximate the carbon and nitrogen stocks and responses to bioenergy feedstock harvest is a significant contribution to the modeling community. Further application of AGRO-BGC can contribute to developing sound bioenergy feedstock management policy by improving our understanding of the magnitude and variability of the effects of management practices over time scales that cannot be captured by existing empirical field studies.

4.1 Sensitivity Analysis Discussion

Parameterizing a complex ecosystem process model such as AGRO-BGC presents several challenges. There are tradeoffs between simplicity and maintaining performance of the model and capturing the complexities of an agroecosystem. AGRO-BGC requires up to 54 vegetation parameters and 9 location and edaphic parameters (Di Vittorio *et al.*, 2010), so the results we found during this analysis were highly satisfactory. Some parameters represent ecosystem processes (e.g. fine root growth, a/symbiotic nitrogen fixation, turnover and mortality) that are not yet well documented in the literature. In other instances, the parameters represent dynamic processes during the growing season, but must remain static in the modeling environment for practical constraints (e.g. rooting depth, SLA). Testing the model's sensitivity to certain parameters revealed traits of the model's mechanics that perform well and others that require further development. The results of the independent sensitivity analysis reflect similar results found in White *et al*. (2000), and the most sensitive parameters that center around leaf photosynthesis physiology, leaf biochemistry, and crop canopy dynamics.

Some of the patterns observed in the sensitivity analysis were reflective of environmental conditions. For example, rooting depth can represent the environmental conditions of soil loss through poor soil management, or litter or leaf C:N can represent plant or leaf nutrition. By exploring the mechanics of AGRO-BGC through sensitivity analysis, we can also make predictions for the dynamics between the climate, edaphic conditions, and plant ecophysiological traits.

As SLA increases, maximum LAI also increases, due to the direct relationship between LAI, leaf carbon, and SLA. While ANPP and SOC are less sensitive, we did observe a negative relationship between SLA and ANPP and SLA and SOC. This feedback is attributed to increased water stress brought about by greater leaf surface area. There is a tradeoff between the amount of surface area available to absorb PAR to initiate photosynthesis and the amount of surface area subject to evapotranspiration. A high SLA means that the leaves are thinner and lighter and can be more susceptible to water and heat stress (White *et al.*, 2000) which can have adverse effects on ANPP. In turn, any remaining ANPP not removed by herbivory, harvest, or fire will eventually decompose and contribute to the SOC pool. As a result, we see a similar negative effect of increased SLA on the SOC pool. A reduction in ANPP means that there is less litter biomass to decompose and become assimilated into the soil microbial pools.

Mechanisms for CO_2 uptake and water loss are regulated by stomatal conductance. The greater the g_{smax}, the less resistance there is to stomatal closure, and the more readily the plant loses water via evapotranspiration. This increases its susceptibility to water stress, which can have adverse effects on ANPP.

When rooting depth increases, we observe an increase in maximum LAI and ANPP, which is what one would expect under normal plant growth conditions. The greater the rooting depth, the more soil volume is available for water and nutrient uptake, which contributes to greater productivity. When we look at this from an environmental process perspective, this pattern is what one would expect under conditions of decreasing soil depth as a result of soil loss through poor soil management, and we would expect to have less available organic matter to decompose and contribute to soil organic carbon pools (Wilhelm *et al.*, 2004).

Our results show that a 50:1 allocation of C:N in the leaves maximizes crop canopy construction, crop productivity, and SOC, revealing a sufficient carbon and nitrogen supply to the leaf for constructing the leaves and photosynthetic machinery. It is therefore not surprising that increased removal of residue containing valuable nutrients leads to a decrease in long-term productivity (Schlesinger, 1997; Lal, 2005; Blanco-Canqui & Lal, 2007; Peckham & Gower, 2011).

Plant nutrition is also reflected in the amount of nitrogen investment in the leaf biochemical components. The parameter for prescribing the amount of nitrogen investment in PEPCase is new to the AGRO-BGC enzyme driven C_4 photosynthesis routine, and is not present in BIOME-BGC. There is a maximum PEPCase carboxylation rate prescribed within the model that is based on the Michaeles Menten function (Di Vittorio *et al.*, 2010), and it accounts for different CO_2 and O_2 conductances through the mesophyll. This rate is adjusted to the actual PEPCase carboxylation rate, given actual mesophyll temperature and CO_2 concentrations. Increasing the amount of nitrogen investment in PEPCase up to 2% has a positive effect on max LAI, SOC, and ANPP, while any additional increase has no effect.

As FLNR increases, more nitrogen is available to the leaf photosynthetic machinery. It is currently set at 0.225 so less than 25% of the leaf nitrogen is made available to Rubisco. Rubisco is a significant plant pool in C_4 plants, as this enzyme is responsible for fixing atmospheric CO_2 in the bundle sheath cells during photosynthesis (Di Vittorio *et al.*, 2010). Rubisco activity is limited by the amount of N available for building the machinery as well as determining maximum potential rate of carboxylation, which is a significant control on canopy assimilation (White *et al.*, 2000).

4.2 Comparison of Model Simulations with Empirical Data

AGRO-BGC results demonstrate reasonable agreement between simulations and empirical data, with all predicted annual biomass and soil carbon pool falling within 7% and 12% of the empirical field data for the NTNF0 and NTF0 simulations, respectively. While AGRO-BGC overestimated LAI for the fertilized scenarios, it captured the seasonal minima and canopy phenology reasonably well in both the fertilized and non-fertilized scenarios. AGRO-

BGC simulations showed good agreement with field measurements of C_4 grass maximum LAI.

The capacity for bioenergy feedstocks to store carbon is demonstrated through the NEP. A feedstock that takes up more C than is released is considered a carbon sink, while a feedstock that releases more C than is taken up is considered a carbon source. When comparing the FLUXNET observations to model outputs, AGRO-BGC captures the growing season net storage of C and the net loss of C during the off season. As crops photosynthesize during the growing season, more carbon is stored than is being released through respiration. Before planting and after harvest, greater amounts of carbon are released through respiration than are stored, because there is no plant biomass photosynthesizing for approximately six months out of the year (Hollinger *et al.* 2005). The annual carbon totals run in AGRO-BGC are comparable with other validation studies such as (Wang *et al.*, 2005) who measured an average annual 4 tC $ha^{-1}yr^{-1}$ in an unfertilized corn agroecosystem in China. AGRO-BGC simulations averaged 3 tC $ha^{-1}yr^{-1}$ for 1997-2006. These results suggest that the model overestimates canopy respiration, because as shown at the Arlington site, the ANPP estimates are in good agreement of field measurements.

A feedstock that is C neutral is important to achieving goals of climate change mitigation while developing a new energy source. No-till agricultural management systems have long-term sequestration potential and can be effective at mitigating rising CO_2 concentrations (Hollinger *et al.*, 2005). In order to maximize SOC storage and minimize SOC loss through either oxidation or through erosion, one strategy is to maintain a vegetative cover on the soil surface and minimize tillage (Anderson-Teixeira *et al.*, 2009).

4.3 LAI and Crop Canopy Dynamics

While modeled LAI captured above 80% of the variation in field LAI observations and showed good agreement with observations during early and late season canopy dynamics, it still overestimated maximum LAI by a large amount under both NTNF0 (54%) and NTF0 (125%) simulations. Modeled LAI tended to increase in overestimation at observed LAI values of 2.0 or greater, indicating a larger contribution to leaf area at peak canopy closure. When this result is coupled with the accurate estimates of ANPP, it suggests that further exploration into the model's crop canopy model is warranted. The two layered model used in AGRO-BGC represents a canopy that has an increasing SLA with increased canopy depth, which requires assignment of different SLA for both sunlit and shaded canopy layers (White *et al.*, 2000). As the corn canopy grows, lower leaves are shaded by top leaves and by the leaves and stems of adjacent densely planted crop rows. In their sensitivity analysis, White *et al.* (2000) assigned a constant 2.0 for the shaded SLA: sunlit SLA (e.g. ENF, DBF, grasslands). The use of this static ratio in an agroecosystem may not accurately capture the morphological dynamics of a canopy where crops are densely planted in uniform rows and has possibly resulted in an imbalance of the biophysical canopy structure with the potential photosynthetic contribution of the shaded corn leaves.

Overall results of the sensitivity analysis and comparison of estimates with field observations suggest that AGRO-BGC is a competent and suitable modeling tool for estimating carbon and nitrogen dynamics in a corn agroecosystem. Further testing against empirical datasets will improve the model's performance and enhance our understanding of these dynamics over the long term.

4.4 Effects of Residue Removal on Soil C

The current level of complexity AGRO-BGC possesses for simulating the biogeophysical dynamics of residue is limited by its inability to incorporate more dynamic energy interactions with the litter and soil surfaces. The light and energy dynamics between the soil and plant canopy exclude the litter pool. That is, incoming solar radiation is either intercepted by the plant canopy or by the bare soil, and any surface energy fluxes including the litter pool are driven by soil temperature, which is calculated from air temperature. When there is no plant canopy and no matter allocated to the litter pool, there is no additional resistance for vapor transport to the soil surface (AGRO-BGC code). That is, there is no option for a residue barrier to alter the flow of vapor between the atmosphere and the soil surface, until the canopy starts to grow. Soil temperature is driven by an eleven-day running weighted average of the daily average air temperature (Di Vittorio *et al.*, 2010). Improving upon this would require the incorporation of the following routines to capture the biogeophysical complexity of the crop residue-soil surface dynamics: 1) variable changes in mass and reflectivity in the litter pool throughout the year. As the litter pool decomposes throughout the year its capacity to reflect, conduct, and conserve heat changes, in addition to its structural capacity as a physical buffer. 2) Input data including long and short wave radiation over finer temporal (e.g. hourly) resolution time step. This would facilitate improved surface energy balance understanding. 3) Inputs for parameterizing the architecture of the crop residue would affect the microclimate and surface energy fluxes. 4) Capacity for the litter to intercept excess precipitation not intercepted by the canopy, and the ability to adjust for different percentage cover.

Agricultural soils provide a significant stock of carbon to the terrestrial ecosystem, and when managed appropriately they can provide a sink for carbon and contribute to greater quality agricultural soils (Paustian *et al.*, 1998; Hollinger *et al.*, 2005). It is important to sustain and enhance soil organic carbon and soil nitrogen when managing agroecosystems, particularly as agricultural residues become more viable candidates for bioenergy feedstocks on a commercial scale (Anderson-Teixeira *et al.*, 2009).

Results of varying residue removal rates showed a slight increase in both corn and grass simulations under the control scenarios, while increasing residue removal rates decreased SOC over the duration of the study. This was also observed in the residue manipulation trials in the UW-Madison Arboretum studies (G. A. Nielsen & Hole, 1963; VanRooyen, 1973; Nadelhoffer *et al.* unpublished data). These results are similar to those reported in empirical field studies regarding land use change and SOC dynamics (Post & Kwon, 2000; Nave *et al.*, 2010; Powers *et al.*, 2011).

A meta-analysis conducted across multiple agroecosystems with differing land use histories and residue management regimes showed that SOC is typically depleted under harvest of corn residues (Anderson-Teixeira *et al.*, 2009). These results are applicable to any terrestrial ecosystem as the residue, the only pre-cursor for SOC, is removed. Similar results have been reported for forests (Peckham & Gower, 2011). This universal pattern suggests a first principle that cannot be ignored: increased residue removal will lead to long-term decline in soil organic matter. In corn systems, when land use shifts from a grain only to a grain and residue harvest regime, the system consistently loses SOC across treatments. Moreover, the removal of harvest residue renders the soil more vulnerable to wind and rain erosion.

In order to maintain and enhance soil carbon and nitrogen pools in a bioenergy cropping system, the above ground contribution to soil carbon and nitrogen provided by crop residues must be maintained by additional organic matter amendments, or by increasing application of nitrogen fertilizers to enhance productivity (Chivenge *et al.*, 2007). Our findings show an increase in SOC under the no-harvest scenario, showing that when the leaves, stems and stalks are left on the soil surface to decompose, there is an increased contribution to the SOC pool. Because SOC is the major driver of crop productivity, as the pool is depleted over time without replenishment through manure, synthetic fertilizer, or other nutrient amendments, we expect plant yields to decrease as well. Such an outcome of removing increased amounts of crop residue for bioenergy poses a contrast with USDA predicted yield increases into the future (Perlack & Stokes, 2011). Loss of SOC over the long term means that there is a decreasing pool of nutrients and environment in which the plant roots can uptake water and nutrients for photosynthesis and growth. If feedstocks such as crop residues are to be a substantial contributor to meeting US energy needs, it is important that corn systems are managed in such a way that minimizes SOC loss and maximizes SOC gain. Future bioenergy guidelines should recommend rates that do not lead to maximum soil C loss, or recommend other sources of bioenergy feedstock such as perennial grasses or short rotation woody crops.

The potential loss of SOC through oxidation or erosion is to be considered when thinking about converting lands not currently in production into production for row crops, or lands that are steeply sloped or have highly erodible soil. When land use is converted from natural prairie ecosystem to agriculture, there will be SOC loss due to tillage disturbing the microbial community and soil inversion. The increased carbon loss occurs from greater amounts of C released from the soil, from the reduced inputs of biomass from the crops over prairie grasses, and greater amounts of decomposition relative to inputs as the crop system gets established.

The findings of this study support the argument that crop residues are best left on the field for maintaining and improving soil productivity (Anderson-Teixeira *et al.*, 2009). Crop management practices for bioenergy should aim to minimize SOC loss. If the objectives of growing biomass for bioenergy include climate change mitigation, then it is important to ensure that when agroecosystems are managed for bioenergy, that there is not additional carbon being released back into the atmosphere. Agroecosystems have the potential to sequester significant amounts of carbon, only when all residues are left on site and wise conservation management practices such as no-till are implemented (Schimel *et al.*, 2001; Hollinger *et al.*, 2005).

In this study, we did not account for increased loss of SOC and N from erosion, which would increase with increased residue removal. Coupling AGRO-BGC with soil loss models (e.g. RUSLE2) can expand our understanding of the magnitude of carbon loss from the system, both from increased oxidation and from soil erosion. Long-term simulations of multiple crop management scenarios provide us the opportunity to evaluate the effects of different residue removal practices on soil C and N dynamics and their sustainability as the demand for bioenergy feedstocks from agroecosystems increases. The data generated from these model simulations can be used in identifying which residue removal scenarios would stabilize and enhance soil carbon content, and prevent loss in soil productivity under a bioenergy management plan.

Because cropping systems undergo frequent and intense disturbance through chemical inputs and residue manipulation, the potential for greater nitrogen and carbon loss is higher than for natural ecosystems. These findings suggest the importance of incorporating conservation practices such as no till, and conservative crop residue removal to maintain and improve the soil carbon and nitrogen content and productivity of cropping systems. Further research and validation of AGRO-BGC with long-term datasets will allow us to better estimate the capacity of Upper Midwestern farms to sustainably generate the necessary biomass to meet future energy demands.

This work lays the foundation to further exploration into estimating the quantities of SOC, productivity, and carbon budget changes across different management practices and on varying landscapes of varying biophysical characteristics.

Acknowledgements

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6. Figures

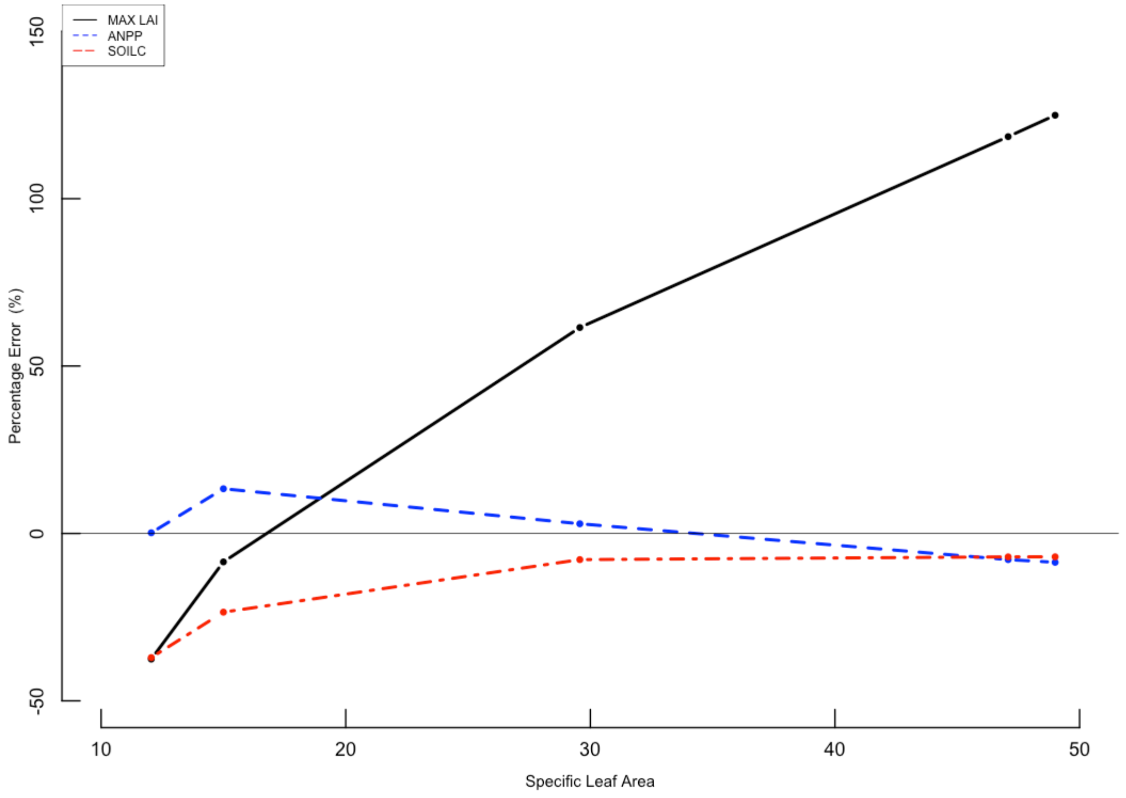


Figure 1. Sensitivity analysis results of specific leaf area (SLA) on maximum LAI, ANPP, and SOC

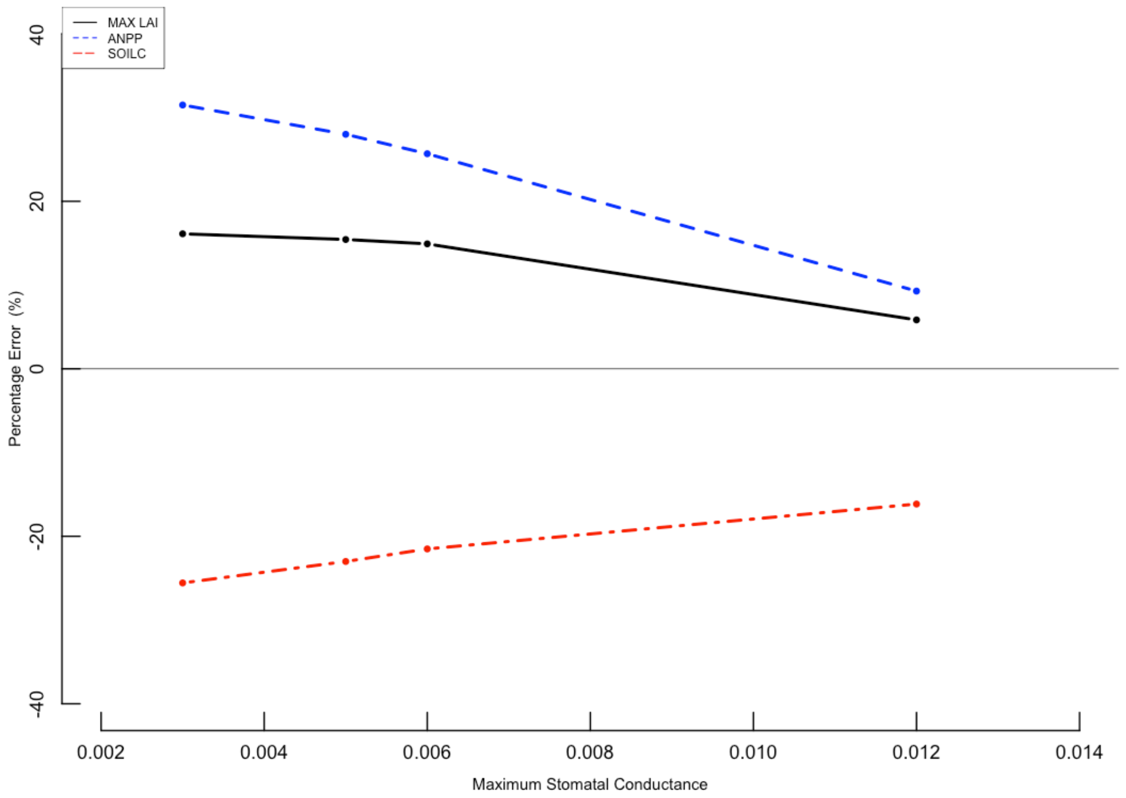


Figure 2. Sensitivity analysis results of maximum stomatal conductance (g_{smax}) on maximum LAI, ANPP, and SOC

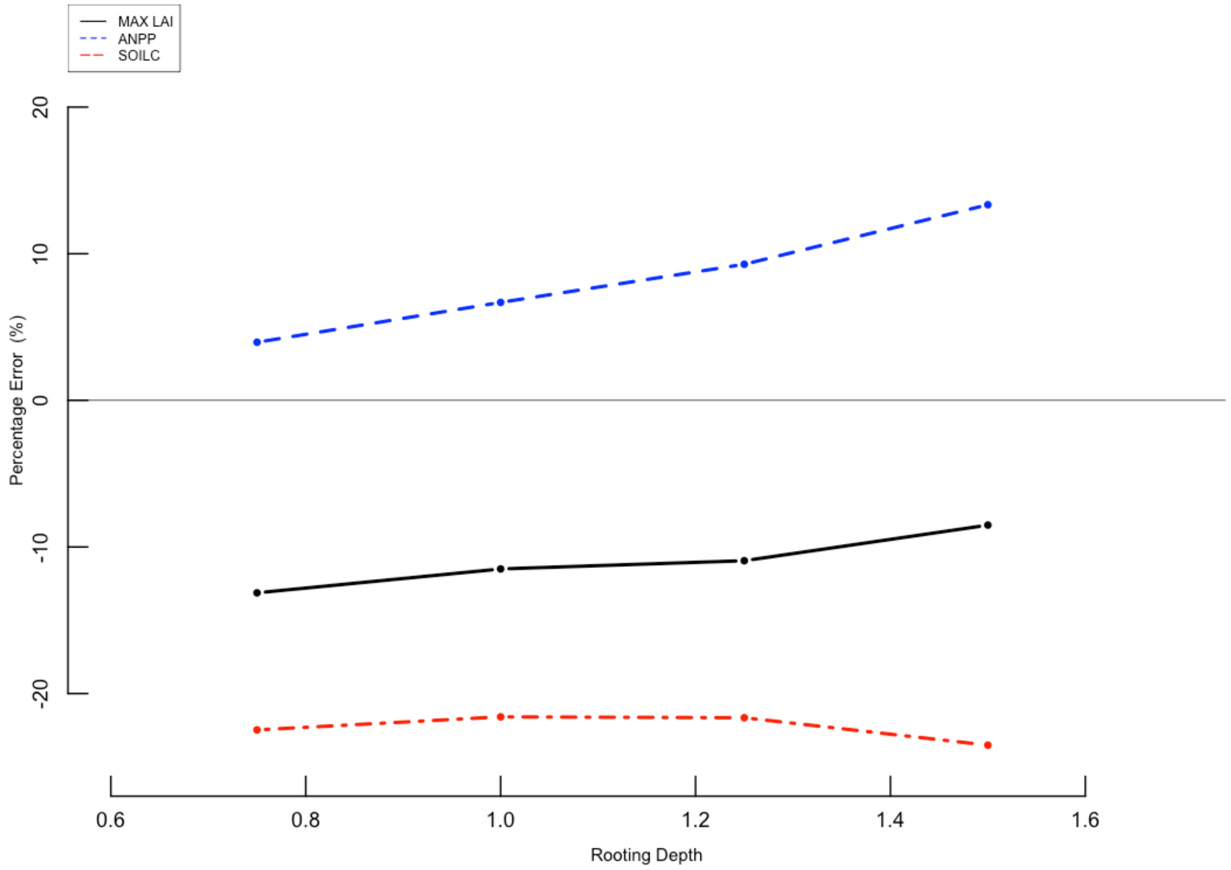


Figure 3. Sensitivity analysis results of rooting depth (meters) on maximum LAI, ANPP, and SOC

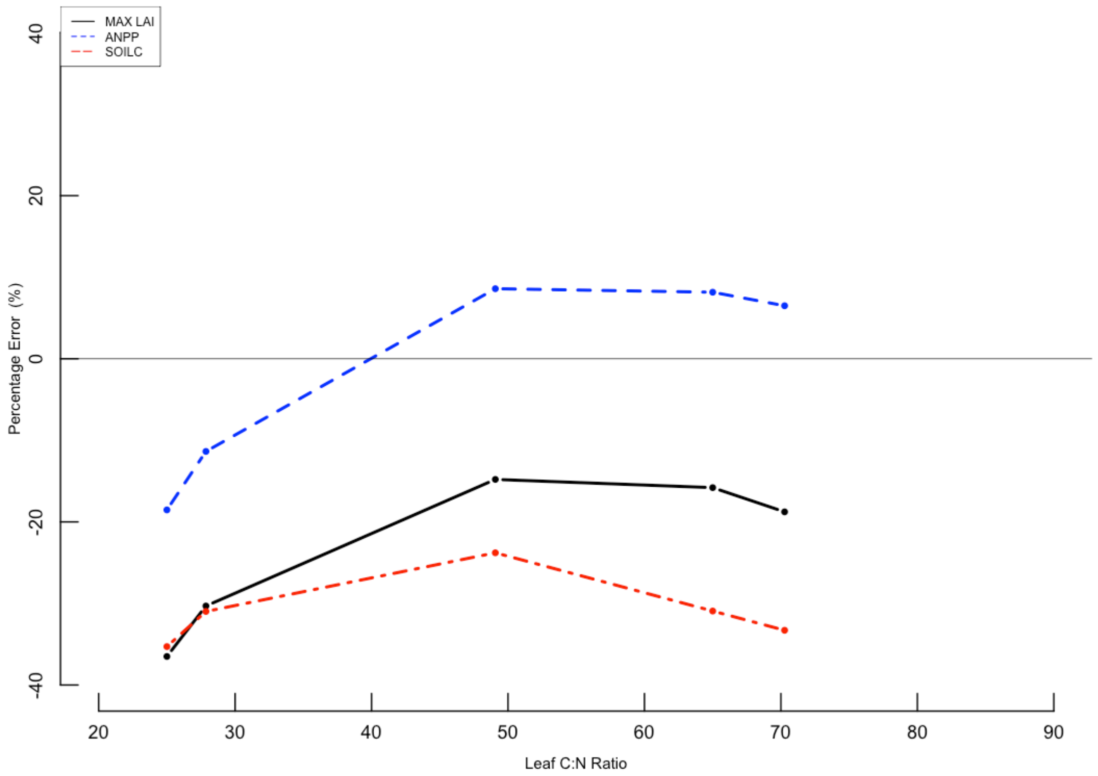


Figure 4. Sensitivity analysis results of Leaf C:N ratio on maximum LAI, ANPP, and SOC

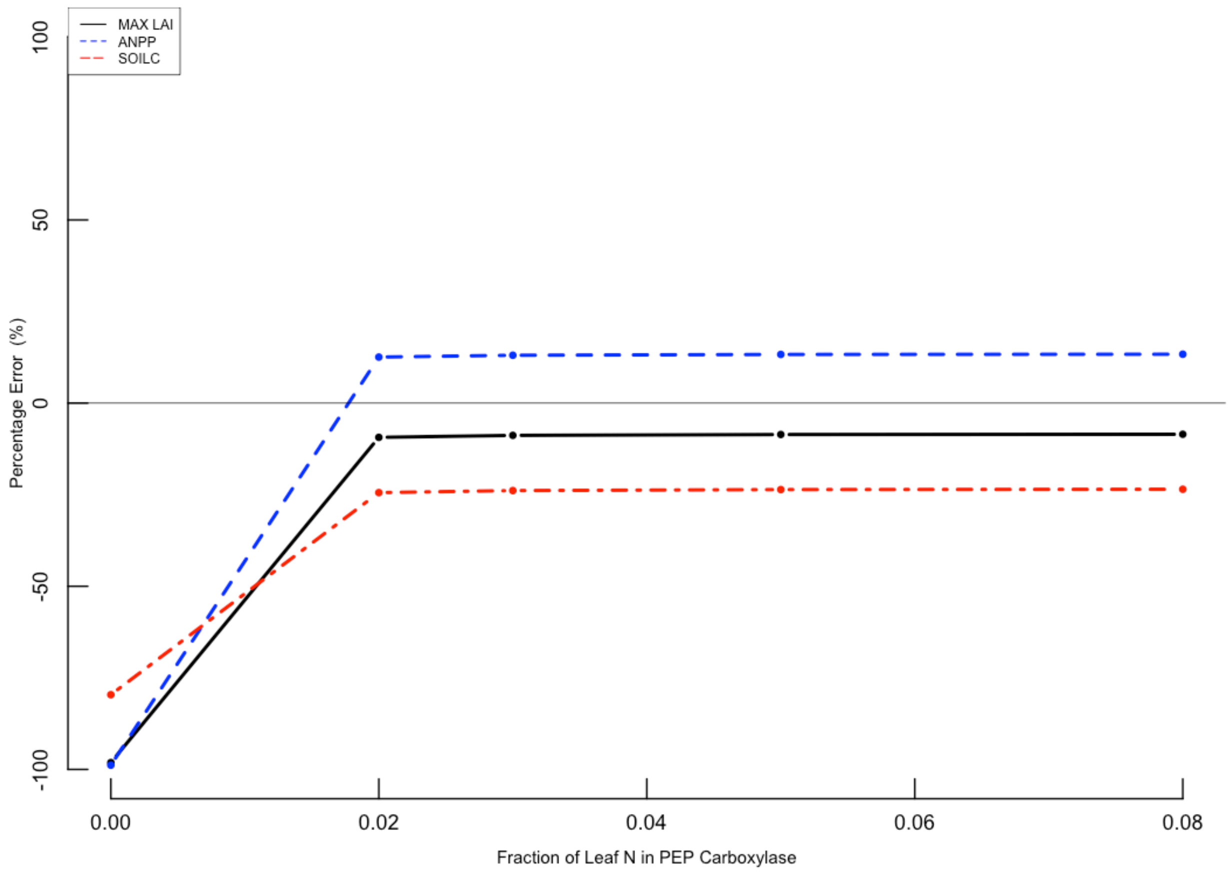


Figure 5. Sensitivity analysis results of Fraction of Leaf N in PEP Carboxylase on maximum LAI, ANPP, and SOC

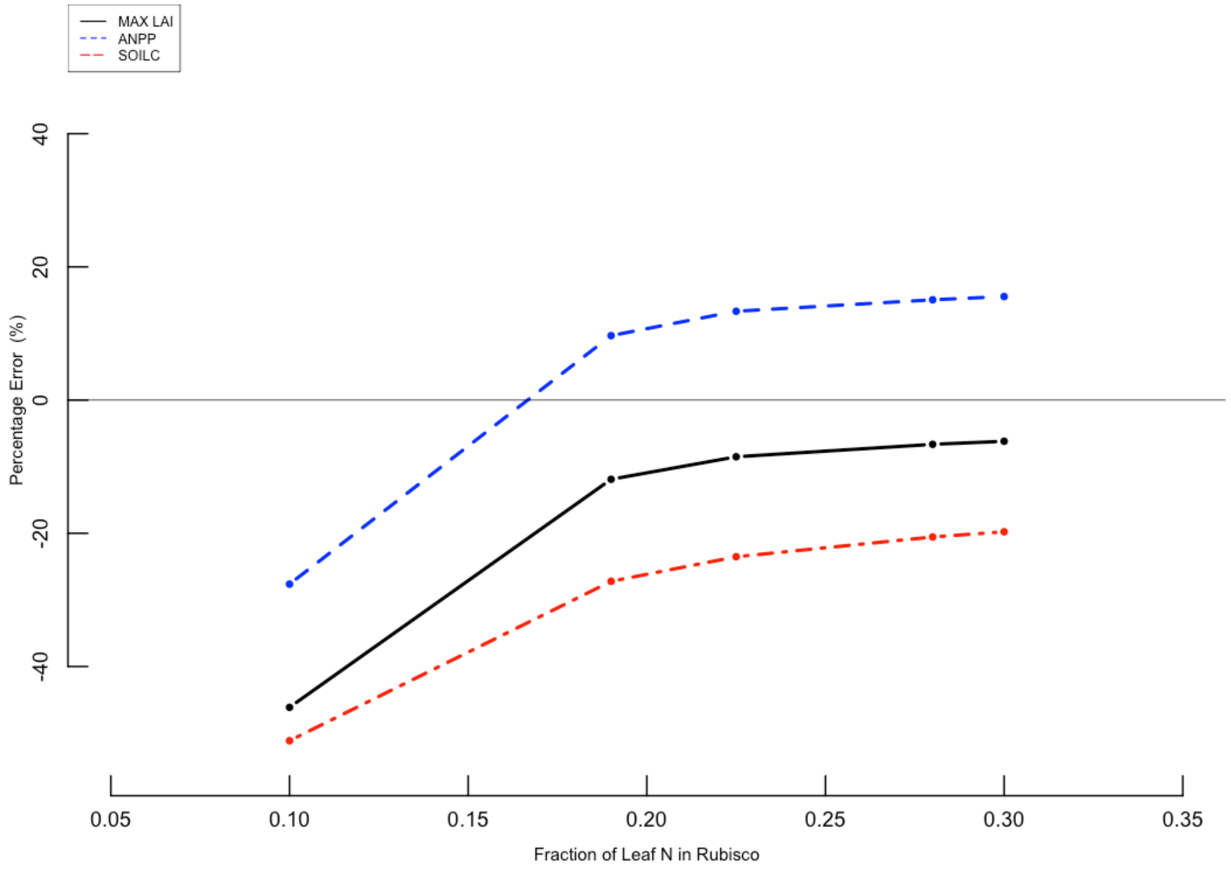


Figure 6. Sensitivity analysis results of Fraction of Leaf N in Rubisco on maximum LAI, ANPP, and SOC

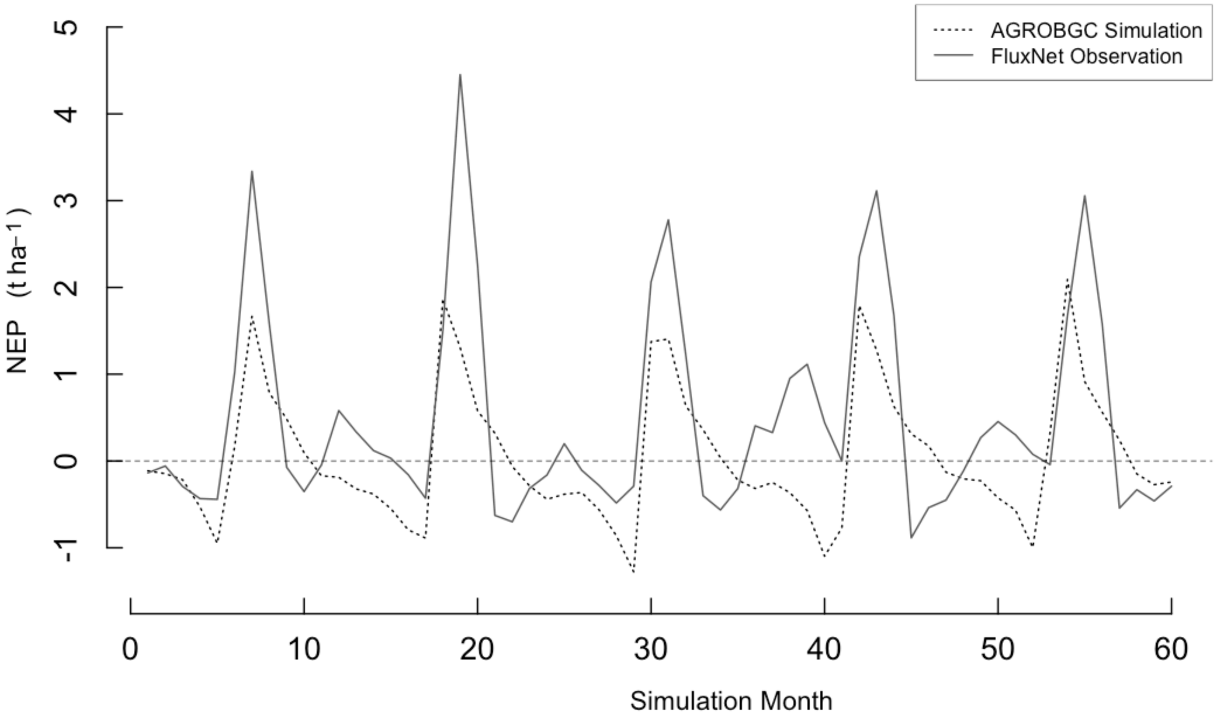


Figure 7. Monthly mean aggregated net ecosystem productivity (NEP) outputs for cornfields across the Bondville, IL study site, corn years only.

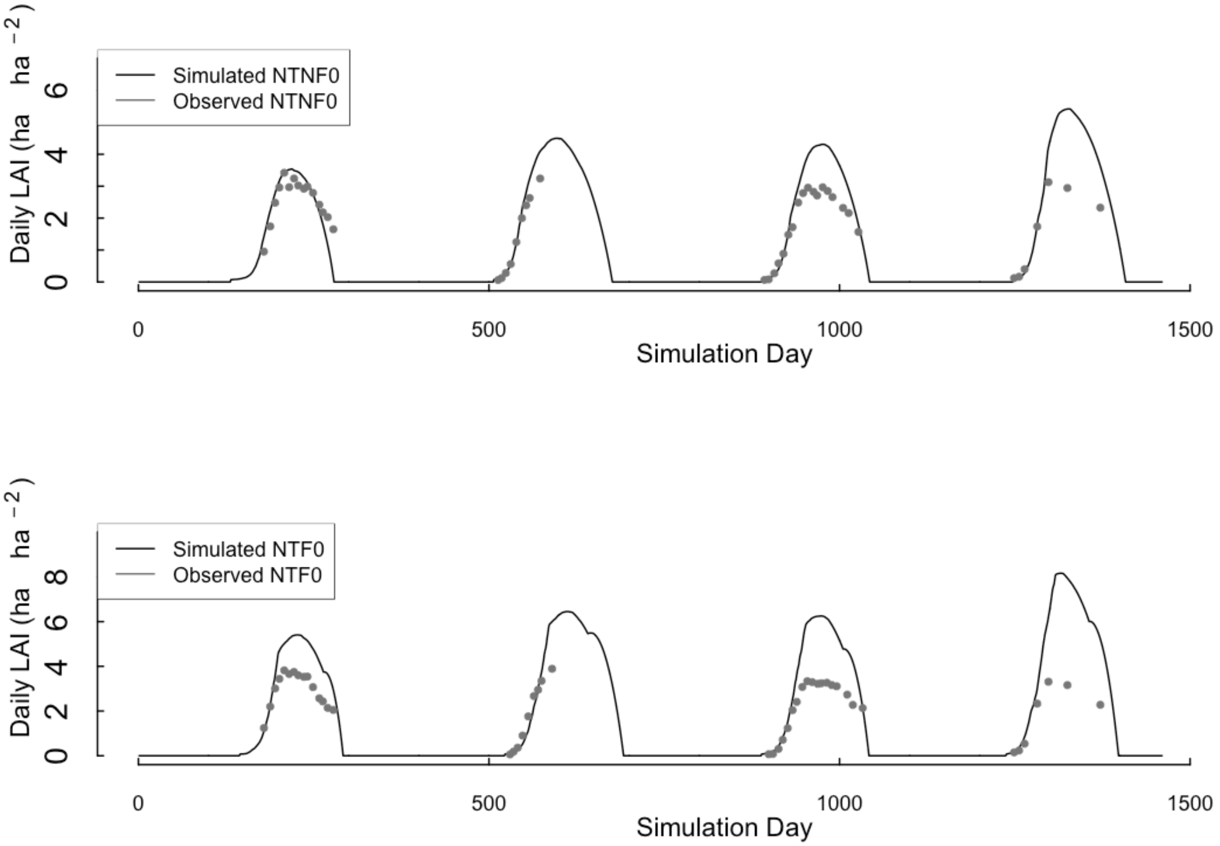
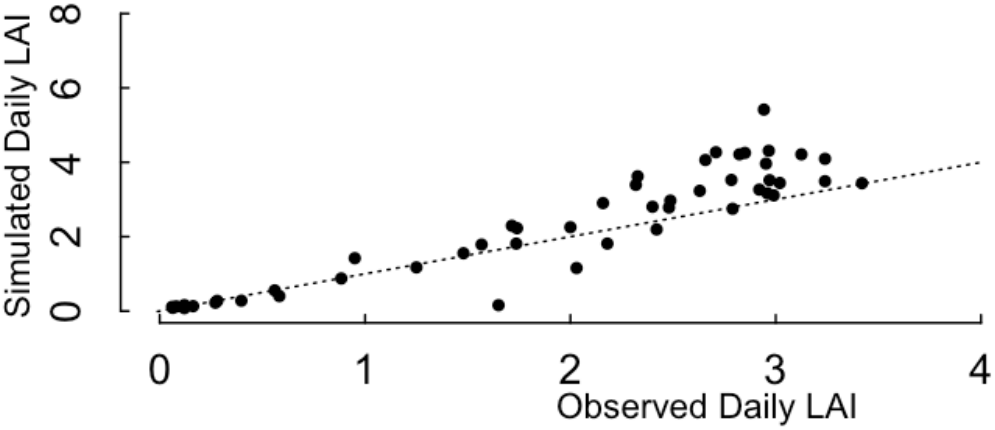


Figure 8. Daily leaf area index (LAI) model outputs compared with field observations for no-till, no fertilizer applied (NTNF0) scenario (top) and no-till, fertilizer applied (NTF0) scenario for Arlington field site (bottom).



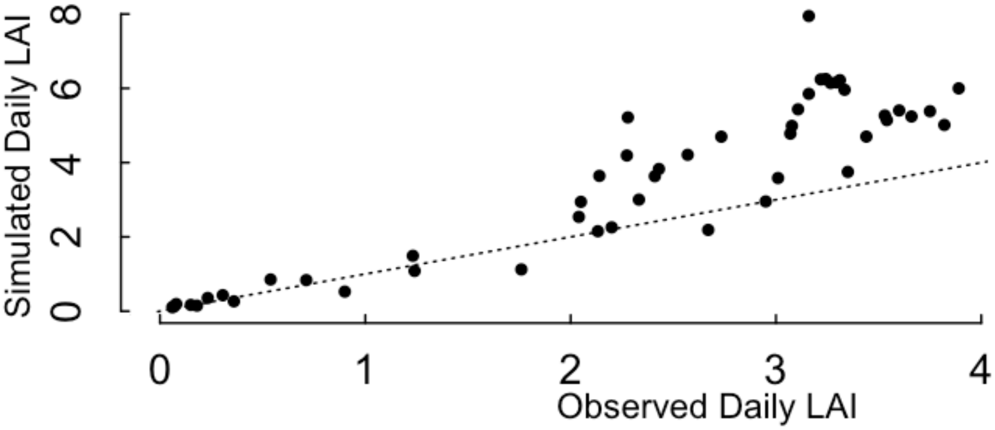


Figure 9. Plot of simulated versus observed daily LAI values for NTNF0 (top) and NTF0 (bottom) treatments for Arlington research site for 1995-1999. Dashed line represents the 1:1 relationship between simulated and observed LAI measurements.

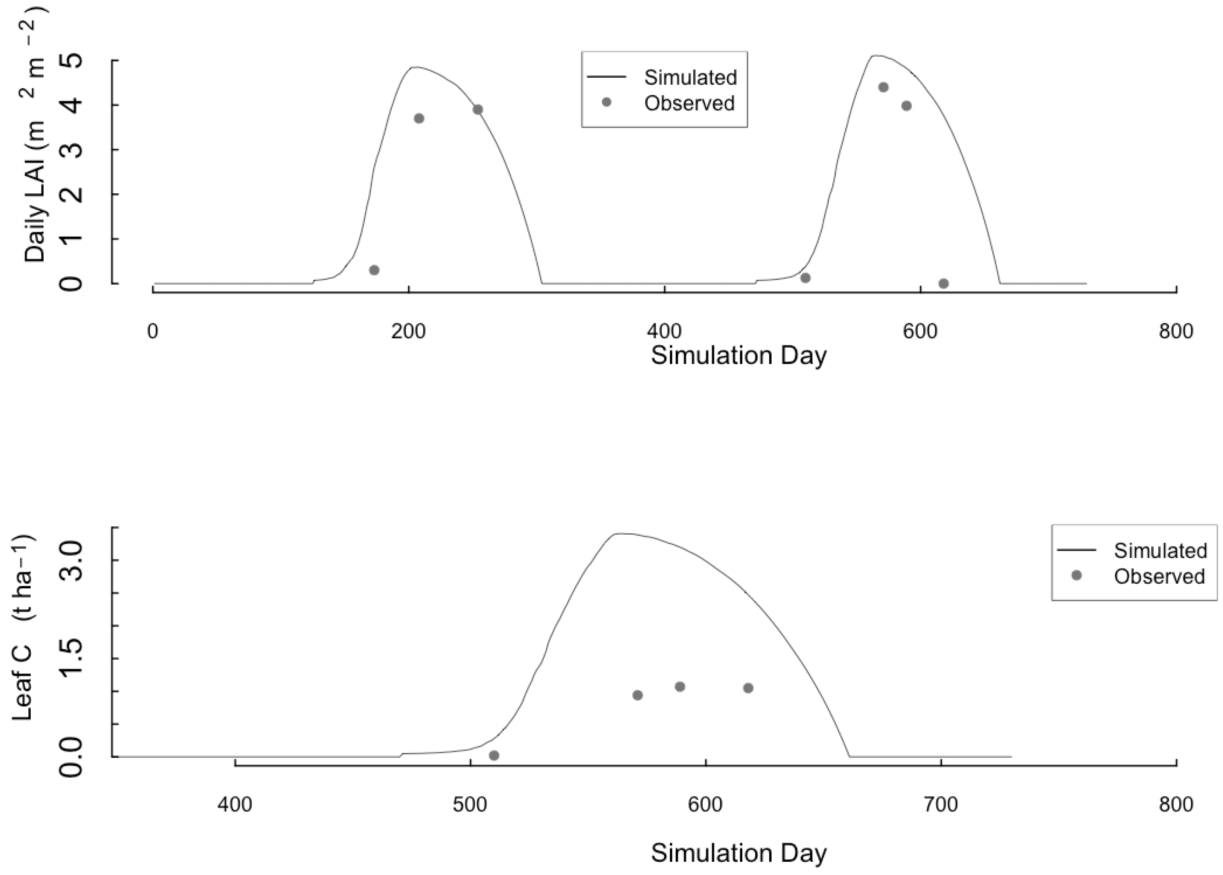
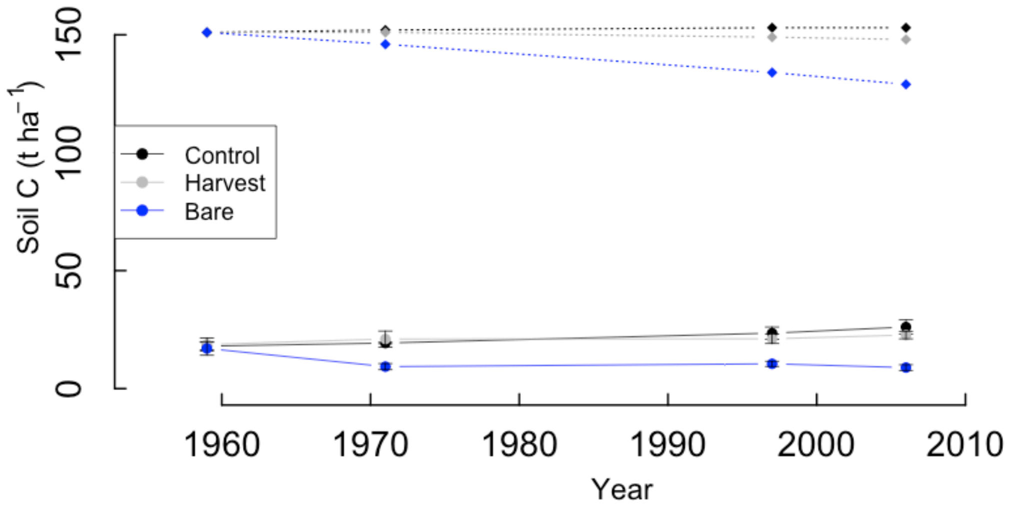


Figure 10. Daily leaf area index (LAI) model outputs compared with field observations for no-till, no fertilizer applied scenario (top), and daily leaf carbon content (bottom) compared with field observations for no-till no fertilizer applied scenario for Bondville, IL site



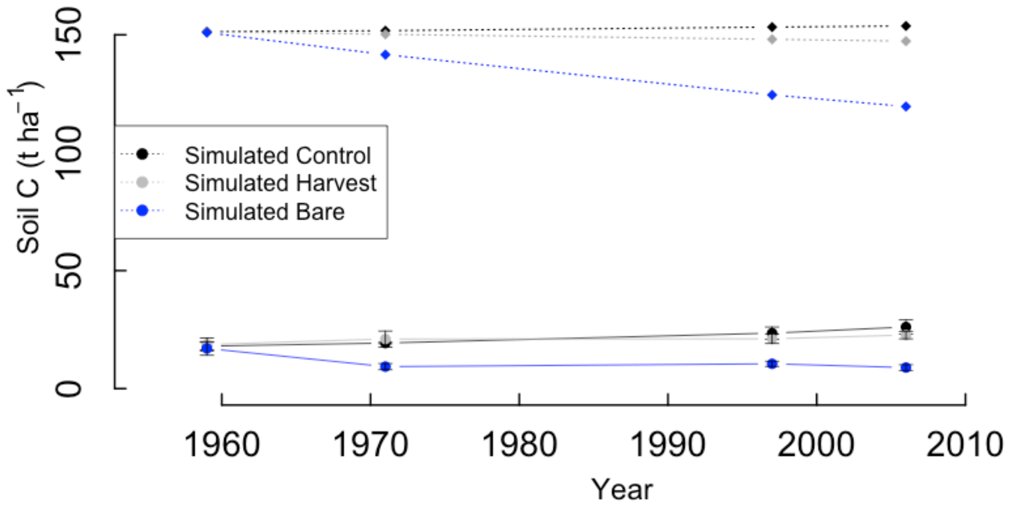


Figure 11. Simulated annual soil organic carbon content under varying residue removal rates from 1960 - 2006 for corn (top) and C_4 mixed grasses (bottom) compared to field observations at the UW Arboretum field site.

Table 1. Site location, average climate, and soil variables for validation field sites.

Site Name	MAT (ºC)	Vegetation	Location	PPT (cm)	Soil Type (% sand/silt/clay)	Elevation (m)
Arlington, WI	Max: 13.52 Min: 2.01	Continuous Corn, Mixed Prairie	Lat: 43.283, Lon: -89.366	94	16/59/25	305
Bondville, IL	Max: 17.01 Min: 5.57	Corn/Soybean	Lat: 40.006, Lon: -88.291	99	16/57/27	215
Madison, WI	Max: 13.70 Min: 2.08	Mixed Prairie	Lat: 43.038, Lon: -89.430	93	9/65/26	288

MAT, mean annual temperature, Lat, latitude; Lon, longitude, PPT, precipitation.

Table 2: Daily Climate Data Inputs for AGRO-BGC	Units
Maximum Daily Temperature	ºC
Minimum Daily Temperature	ºC
Mean Daily Temperature	ºC
Precipitation	cm
Vapor Pressure Deficit	Pa
Incoming Solar Radiation	Watts m^{-2}
Daylength	seconds

Edaphic Data Inputs for AGRO-BGC	Units
Effective Soil Depth	m
Sand Percentage by Volume	%
Silt Percentage by Volume	%
Clay Percentage by Volume	%
Site elevation	m
Site Latitude (- for Southern Hemisphere)	decimal degrees
Site Shortwave Albedo	-
Wet and Dry Atmospheric N Deposition	kgN m^{-2} yr^{-1}
Symbiotic and Asymbiotic N Fixation	kgN m^{-2} yr^{-1}

Corn Ecophysiological parameters for AGRO-BGC	
Allocation of Carbon and Nitrogen	
New fine root C: new leaf C	1.1[a]
New stem C: new leaf C	1.7[a]

C:N of leaves (kgC kgN^{-1})	49.0[a,b,d]
C:N of leaf litter (kgC kgN^{-1})	49.0[a,b,d]
C:N of fine roots (kgC kgN^{-1})	120.0[a]
Fruit C:N (kgC kgN^{-1})	33.0[c]
Leaf litter labile proportion	0.68[d]
Leaf litter cellulose proportion	0.23[d]
Leaf litter lignin proportion	0.09[d]
Fine root labile proportion	0.34[d]
Fine root cellulose proportion	0.44[d]
Fine root lignin proportion	0.22[d]
Biophysical Parameters	
Canopy water interception coefficient (1 LAI^{-1} day^{-1})	0.0225[d]
Canopy light extinction coefficient	0.48[d]
All-sided to projected leaf area ratio	2.0[d]
Canopy average specific leaf area (m^2 kgC^{-1})	15.0[e]
Ratio of shaded SLA:sunlit SLA	2.0[d]
Fraction of leaf N in Rubisco	0.225[d]
Fraction of leaf N in PEP Carboxylase	0.03[f]
Maximum stomatal conductance (m s^{-1})	0.012[g]
Cuticular conductance (m s^{-1})	0.00012[d]
Boundary layer conductance (m s^{-1})	0.04[d]
Leaf water potential: start of conductance reduction (MPa)	-0.73[a]
Leaf water potential: complete conductance reduction (MPa)	-2.7[a]

Vapor pressure deficit: start of conductance reduction (Pa)	930.0[d]
Vapor pressure deficit: complete conductance reduction (Pa)	4000.0[d]

Ecophysiological values are from the following studies: [a]Qinxue *et al.,* 2005, [b]Kucharik *et al.,* 2001, [c]Ma and Dwyer 2001, [d]White *et al.,* 2000, [e]Sensitivity Analysis Results, [f]Sugiharto *et al.,* 1990, [g]Schulze *et al.,* 1994

Table 3. Sensitivity analysis input ranges and steps.

Variable	Minimum	Mean	Maximum	Steps
Fine root C: leaf C	0.50	1.22	2.00	5
Leaf C:N	25.00	49.07	70.27	5
Fine root C:N	27.76	70.67	120	5
Rooting Depth	0.75	1.13	1.5	4
Flowering GDD	815	1075	1250	3
Specific Leaf Area	12.05	29.57	49	5
FLNR	0.1	0.23	0.3	5
FLPEP	0	0.05	0.08	5
Stomatal Conductance	0.003	0.007	0.012	4

Table 4. Annual summary of simulated and observed annual maximum leaf area index (LAI), aboveground net primary productivity (ANPP), total soil carbon, and total soil nitrogen for no-tilled non-fertilized (top) and fertilized (bottom) treatments for 1995-1999.

Year	Simulated [t ha^{-1}]				Observed [t ha^{-1}]				% Error			
	Max LAI	ANPP	SoilC	SoilN	Max LAI	ANPP	SoilC	SoilN	Max LAI	ANPP	SoilC	SoilN
1995	3.9	5	170	17	3.4	5	179	14	14.9	-5.8	-5.2	25.5
1996	4.9	5	170	17	3.2	5	160	13	52.9	5.7	6.2	26.3
1997	4.7	5	170	17	3	6	153	13	58.3	-16.3	11.0	27.3
1998	5.9	6	169	17	3.1	5	132	12	91.2	27.3	28.8	38.5
1999	-	5	170	-	-	4	131	-	-	24.9	29.3	-

Year	Simulated [t ha^{-1}]				Observed [t ha^{-1}]				% Error			
	Max LAI	ANPP	SoilC	SoilN	Max LAI	ANPP	SoilC	SoilN	Max LAI	ANPP	SoilC	SoilN
1995	6.6	7	194	-	3.8	7	179	-	74.1	2.0	8.3	-
1996	7.6	8	194	19	3.9	9	191	14	94.8	-6.2	2.0	41.4
1997	7.7	8	195	19	3.3	9	166	14	132.9	-16.3	17.4	38.6
1998	9.9	9	194	19	3.3	10	146	17	198.5	-4.0	33.6	15.4
1999	-	7	195	-	-	8	146	-	-	-8.1	33.6	-

Chapter 3. Simulating the long-term effects of bioenergy feedstock harvest on soil productivity in Wisconsin agroecosystems: Application of an ecosystem process model (AGRO-BGC) and a soil erosion model (RUSLE2)

Abstract

We used the ecosystem process model AGRO-BGC and the soil erosion model RUSLE2 to estimate the effects of bioenergy feedstock harvest, variable N application rates, and biophysical landscape characteristics on long-term soil carbon content (SOC), aboveground net primary production (ANPP), and erosion for corn residue and switchgrass crop harvest scenarios. We estimated these effects on a continuous, no-till corn ecosystem subject to varied annual residue removal rates, and a perennial switchgrass system with an annual aboveground harvest.

Model estimates of corn and switchgrass ANPP compared well ($R^2 > 0.8$) against field measurements. AGRO-BGC estimates of corn and switchgrass productivity both averaged between 5 and 7 t ha^{-1} yr^{-1}, and fertilizer application increased annual corn productivity by approximately 2.2 t ha^{-1}, and annual switchgrass productivity by less than 1 t ha^{-1}. Residue harvest decreased corn productivity by 3-5% when 25% or more was removed, and all rates of residue harvest decreased annual SOC during the 25-year simulation by 0.5-0.7 t ha^{-1} across all soil types and N application rates. All corn residue harvest simulations experienced soil erosion loss, with a 0.6 t ha^{-1} year increase in erosion rates as slopes increased from 0 - 7%.

In the switchgrass harvest scenarios, patterns of SOC loss, stabilization, and gain were all estimated. The greatest SOC gain (0.1 t ha^{-1} yr^{-1}) occurred under 112 kgN ha^{-1} application. Across all soil types, SOC loss decreased as nitrogen application rates increased, and at annual application rates of 112 kgN ha^{-1} or greater, we estimated stabilization and net gain of SOC. Simulated annual erosion loss ranged from 0 - 6.6, 0 - 11.8, and 0 - 5.3 t ha^{-1} yr^{-1} for sandy, silty, and clay loams, respectively, with maximum losses occurring on 12% slopes.

1. Introduction

Societies place great demand on agricultural soils to produce food, fiber, feed, and now to a greater extent, feedstock for biofuel. The U.S. renewable fuels standard (RFS) sets out requirements for maximum production of 56 billion liters of renewable fuels that can be sourced from corn grain by 2022. The remaining 80 billion liters must come from advanced biofuels, which are produced from cellulosic feedstocks including agricultural residues, municipal wastes, or dedicated perennial bioenergy crops such as switchgrass.

The most recent Billion Ton Study (Perlack & Stokes, 2011) estimated that 154 to 232 million metric tons of corn stover are potentially available for bioenergy feedstock, most of which will come from the Corn Belt and Northern Plains. They estimated that the total potential energy crop production could range from 136 to 345 million metric tons in the United States. Annual corn ecosystems currently provide the majority of bioenergy feedstock in the US, and in 2010 approximately 102 million metric tons of corn produced 50 billion liters of corn grain ethanol.

As the demand on agricultural soils increases through harvesting crop residues for dedicated energy crop production, designing management practices that are relevant to the landscape and that do not exacerbate existing degradation problems will be critical to a sustainable biofuel feedstock program. While there is great economic potential for bioenergy feedstock production, there is also great potential for long-term economic loss if soils are significantly degraded (Lal *et al.*, 1998). Soil erosion by wind and water, nutrient depletion, and reduction in soil organic matter through respiration or erosion all can decrease farm income by decreasing crop yields (Lal *et al.*, 1998). Sustaining agricultural soils requires stewardship that maintains environmental, social, and economic standards across multiple scales, does not harm other ecosystems, and continues to meet present and future societal needs (Hull *et al.*, 2011).

Crop residues provide many important ecological functions that may be adversely affected by residue removal. From a practical standpoint, this means that sustainable biofuel production must strike a balance between removing biomass from the system and sustaining the long-term soil productivity. Soil organic matter provides a multitude of biological, physical, and chemical properties to soils, all of which influence its capacity to maintain high plant productivity. Soil organic matter relies on the inputs of dead plant organic matter (detritus) and decomposition of that organic matter to produce nutrients and humus (Wilhelm *et al.*, 2007). The net balance between detritus input, organic matter deposition, and soil loss through erosion determine the long-term soil organic matter budget, and hence plant productivity. The removal of crop residues may decrease ecosystem services, such as economically viable food production, biodiversity, and water and air quality (Lal *et al.*, 1998).

In contrast to agriculture crops, switchgrass and other perennial grasses have extensive root networks that prevent erosion and replenish soil organic matter upon senescence and decomposition (Bonin & Lal, 2012). Aboveground productivity for corn and switchgrass are approximately 16 t ha^{-1} yr^{-1} and range between 9 and 26 t ha^{-1} yr^{-1}, respectively, while root: shoot ratios for fertilized corn and switchgrass range from 0.2 to 0.3 and between 1.8 and 6.1, respectively (Anderson-Teixeira *et al.*, 2009; Meehan *et al.*, 2013). This large difference in root-to-shoot ratios between corn and switchgrass translates into potentially significant different impacts of aboveground residue removal on long-term soil productivity. Soil carbon maintenance in corn agroecosystems relies heavily on organic matter inputs through surface residues, mulching, or cover crops, due to the low carbon allocation of roots relative to shoots.

Harvest timing is another important management consideration for optimizing maximum yields while minimizing nutrient export. Harvest after plants translocate nutrients belowground minimizes nutrient export and required fertilizer application the following year (Holou *et al.*, 2011).

The complete removal of corn stover has significant potential to reduce SOC, degrade physical soil properties, and reduce crop yields over time (Blanco-Canqui, 2010). In a twenty-year study comparing the rates of SOC storage under varying tillage regimes, those with reduced or no-till tillage practices stored 8.4 t ha^{-1} more SOC in the top 15 cm than the moldboard plow tillage regime (Wilhelm *et al.*, 2004). In a 2.5-year field study with varying rates of corn stover removal, increased stover harvest significantly decreased SOC concentrations (Blanco-Canqui & Lal, 2007). However, the magnitude of decrease was dependent upon soil texture, with greater depletion rates observed in silt loam soils than in clayey soils (Blanco-Canqui & Lal, 2007). Other soil characteristics such as soil drainage and slope also influence the magnitude of negative impacts from corn stover removal. Clayey soils have displayed resistance to SOC reduction in light of their lowered drainage capacity and high cohesiveness that can reduce the decomposition of organic matter (Blanco-Canqui & Lal, 2007).

However, some studies have found no significant difference in SOC between low residue removal rates (25%) and no corn stover removal, suggesting that a low level of corn stover removal scenario may not adversely impact agricultural soils (Blanco-Canqui & Lal, 2007). Determining amounts of stover that can be removed and still remain economically feasible for bioenergy feedstock is a challenge, because, as discussed above, it depends on a myriad of climate, management, and local edaphic characteristics.

Soil becomes vulnerable to wind and rain erosion when vegetative cover is removed (Lal & Pimentel, 2007), as the bare soil is exposed to the impact of raindrops or wind. Soil erosion decreases exponentially with increased residue retention rates (Lal & Pimentel, 2007). Erosion rates are suppressed in the short term by vegetation or residue cover that intercepts rainfall and protects the soil surface against the high-energy impact of raindrops. Exposed soil surface also increases CO_2 emissions from increased decomposition rates (Xue *et al.*, 2011). Interrill erosion removes the most biologically and chemically active, and thus most productive, component of agricultural fields, the topsoil. Over time these losses adversely affect the long-term productivity of the soil and the quality of adjacent aquatic ecosystems (Lal *et al.*, 1998).

The vulnerability of soil to erosion is affected by soil texture, structure, type and density of vegetative cover, and topography (Renard, 2013). Excess rainfall and significant storm events increase the volume and velocity of surface water transport, which dramatically increases erosion. As slope length increases, runoff volume and velocity increase. In general, erodibility is increased with silt and very fine sand content, and decreases as clay and organic matter content increase (Lal *et al.*, 1998). Clay acts as a bonding agent, thereby reducing soil particle detachment. Essentially, soils that are low in aggregation are the most susceptible to interrill erosion. Lands with significant topography features raise concern for the potential for removing corn stover, as these steep hillsides are already vulnerable to erosion.

Long-term datasets on soil organic carbon and its response to management are invaluable to understanding the complex processes of carbon fluxes and pools between soil, vegetation, and the atmosphere. These datasets complement the application of models to elucidate these complex processes, and models can extend our understanding of these processes into the future by making informed predictions of the impacts of varying management practices. While numerous long-term agricultural research programs have been in operation for many years (Paustian *et al.*, 1998), field trials specific to cellulosic biofuel feedstocks have emerged only within the last decade. These sites have initiated long-term experiments for dedicated bioenergy feedstock crops, short rotation woody crops, and management of annual crop residues. Among these are the Great Lakes Bioenergy Research Center (GLBRC) and the Energy Biosciences Institute (EBI), whose field trials were established in 2008 and 2007, respectively. In 2008, GLBRC established field trials in Wisconsin and Michigan that include experimental plots and integrated studies with operating farms (https://www.glbrc.org/). In 2007, EBI established an energy farm in Illinois, which also includes experimental plots (http://www.energybiosciencesinstitute.org/).

1.1 Research Objectives

In the absence of long-term empirical datasets, the extent of long-term soil impacts can be estimated through using models such as AGRO-BGC and the soil erosion loss model RUSLE2 (Perlack & Stokes, 2011). This research seeks to provide science and landscape based management recommendations that can be used by farmers and policy makers to optimize biomass feedstock production and long-term soil productivity. Current Wisconsin guidelines do not yet have specific recommendations that target a land condition or management practice beyond general indicators and relative recommendations that can lead to maximizing the delivery of particular ecosystem services (Hull *et al.*, 2011). This research will build a starting point for grounding these recommendations in science and place-based estimates of potential effects of varying bioenergy management practices through the application of validated models with supporting empirical data from ongoing field research.

The objective of this chapter is to model the effects of residue removal on the soil carbon and nitrogen and soil erosion dynamics of corn and switchgrass agroecosystems through the use of an ecosystem process model, AGRO-BGC, and erosion model, RUSLE2. I hypothesize that 1) increased aboveground residue removal rates will decrease soil organic carbon and nitrogen over the long-term, with greater loss occurring in the crop with a higher aboveground-to-belowground biomass allocation annual crop (e.g. corn) than with a perennial grass (e.g. switchgrass), 2) increased residue removal will decrease soil carbon and nitrogen content, which in turn will decrease aboveground net primary production (ANPP), 3) erosion losses, and hence SOC, will increase with slope, finer soil texture, and greater residue removal rate in corn and switchgrass ecosystems. I also hypothesize that within the gradient of modeling scenarios constructed for this study are a combination of biophysical land characteristics and management practices that represent a system whereby soil carbon loss through respiration and erosion is minimized for both corn and switchgrass bioenergy feedstocks.

2. Methods

2.1 Site and Model Descriptions

The Great Lakes Bioenergy Research Center has delineated regionally intensive modeling areas (RIMAs) across southern Wisconsin and Michigan to define common geographical boundaries for modeling efforts within the research center. RIMA2 is comprised of four counties in south central Wisconsin and includes Dane, Columbia, Sauk, and Iowa counties (Figure 1). We constructed two biofuel ecosystem scenarios in AGRO-BGC and RUSLE2 that represent an annual no-till, continuous corn ecosystem and a perennial switchgrass ecosystem. Variation in soil type, topography, and management practices were derived from bioenergy feedstock management and soil management guidelines (Schulte *et al.*, 2005; Hull *et al.*, 2011).

The extent of soil degradation can be assessed only relative to a baseline or reference state, and in this study, the reference state in corn systems is that in which only the grain is harvested and all crop residue is left in the field, and the field is on a 0% hillslope. In the switchgrass system, the baseline state has an already established stand, no harvest, no fertilizer application, and is situated on a 0% hillslope.

Carbon dynamics, without soil erosion, were simulated using AGRO-BGC (Di Vittorio *et al.*, 2010), while erosion was estimated using the Revised Universal Soil Loss Equation, or RUSLE2 (Perlack & Stokes, 2011). AGRO-BGC simulates carbon, nitrogen, and water fluxes and pools on a daily time step, and features agronomic functions including annual seeding, fertilizer application, harvest, and irrigation (Di Vittorio *et al.*, 2010). Climate data used in AGRO-BGC includes daily maximum and minimum temperature, total precipitation, average vapor pressure deficit, and total solar radiation.

RUSLE2 is a conservation management model used to calculate the predicted annual soil loss from an agroecosystem under a specified set of environmental and management conditions (Wilhelm et al., 2007). It estimates the effects of varying crop management practices on soil erosion, and is often used as a tool for conservation crop management planning. RUSLE2 produces average annual soil erosion estimates for site-specific crop management scenarios (Perlack & Stokes, 2011).

Modeling scenarios were constructed according to current crop management practices in the upper Midwest and recommended planting and harvesting guidelines for non-woody biomass (Hull *et al.*, 2011; Perlack & Stokes, 2011). These scenarios included fertilizer application, varying harvest dates, and residue removal rates based on current conventional crop management practices, climate and edaphic conditions in the Upper Midwest (Tables 1 and 2).

2.2 Modeling Scenario Construction and Model Parameterization

All modeling scenarios were based on information from the literature and bioenergy crop management guidelines (Hull *et al.* 2011). Characteristics for each scenario included crop-specific management practices (e.g. harvest, residue removal rates, fertilizer application), spatial characteristics of field sites (e.g. location, edaphic, and climate characteristics), and ecophysiological traits of each crop type. In AGRO-BGC, we parameterized switchgrass (*Panicum virgatum)* using ecophysiological characteristics documented in Di Vittorio et al. (2010), and corn was parameterized using ecophysiological characteristics documented in Chapter 2 of this dissertation.

Slopes of 0, 7, and 12% were selected to reflect some characteristics of NRCS Land Capability Classes I, II, and III, which describe the extent to which the underlying soil units can support certain agricultural practices (Klingebiel & Montgomery, 1961). Soils within each capability class are assumed to be uniform and possess the same management requirements and are considered to have similar productivity potential. Soils in capability class I have nearly level slopes, are responsive to fertilizer applications, and have few agronomic limitations. Soils in capability class II have gentle slopes and are subject to greater soil degradation in the absence of conservation practices. Soils in capability class III are more severely restricted in their agronomic potential due to their susceptibility to degradation by erosion. Some soils in this category have moderately steep slopes and require extensive conservation practices to maintain productivity. The modeling scenarios in this study do not reflect the full range of capability class soil characteristics, but rather present a qualitative grouping of optimal, intermediate, and marginal land characteristics. Sandy loam, clay loam, and silty loam soils were selected to represent a general range of soil textures that are present within the RIMA.

2.3 Data Sources

RUSLE2 is hybrid empirical process-based model that estimates rill and interrill erosion over a hypothetical land management scenario (http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm). RUSLES2 calculates interrill erosion and deposition along a single overland flow path, under the assumptions of Hortonian overland flow (Renard, 2013). Equations driving RUSLE2 are parameterized using the four major erosion drivers of climate, soil properties, topography, and land use. The functional form of RUSLE2 consists of three basic erosion processes, including soil particle detachment, transport, and deposition. Within the model they are integrated over time and distance, generating an average annual estimate for the basic modeling unit (Renard, 2013). The version of RUSLE2 (2.0.4.0) used in this analysis assumes that residue production occurs only during senescence or during harvest, which can result in an underestimation of vegetative cover and thus, an overestimation of soil erosion in perennial grass simulations (Dabney & Yoder, 2012).

Climate data incorporated into RUSLE2 includes erosivity, precipitation (for a 10-year 24 hour precipitation event), and temperature on a monthly time step. These data are provided by the USA-Natural Resources Conservation Service Water and climate Center, and were computed from measured weather data collected from the National Weather Service (Renard, 2013). All climate variables are disaggregated to a daily time step under the assumption that they vary linearly within each month. Average monthly values for precipitation and erosivity are generated by dividing the mean monthly value by the number of days in each month.

RUSLE2 management database represent characteristics of the crop management zone (CMZ) 04, which includes most states within the Corn Belt (Iowa, Minnesota, Nebraska, South Dakota, northern Illinois, Wisconsin, Michigan, and parts of Indiana and Ohio). CMZs were developed to capture more realistic cropping management scenarios across regions, specifically crop types, crop rotations, and supporting management practices. Information about common management practices and rotations for the CMZs were acquired through field and extension agents (Perlack & Stokes, 2011). The “K” factor represents the susceptibility of soil to erosion, a lower number represents less vulnerability to erosion (Varvel & Wilhelm, 2010) (Table 3). Annual yields are pre-set in the RUSLE2 core database and are considered sufficient for estimating current crop production and management practices (Renard, 2013). Yields set in this study were for a high production corn (12.3 t ha^{-1}) and for an establishing switchgrass stand (years 1-2 at 6.2 t $ha^{-1}yr^{-1}$ and for years 3 and beyond at 12 t $ha^{-1}yr^{-1}$).

2.4 Management Scenarios in RUSLE2

2.4.1 Corn Grain and Stover

In RUSLE2, corn grain was harvested by combine, which removes the corn grain and leaves all standing residue on the field for the baseline (no residue removal) scenarios. For the test simulations, all remaining residue was removed in controlled quantities (0, 25, 50 and 75%).

2.4.2 Switchgrass

In RUSLE2 switchgrass scenarios, the soil was disk tilled before planting, then switchgrass was seeded with a no-till air drill. New growth began in early April, and two annual harvest scenarios were followed, one during late August (date of year (DOY) 238- 240), and the other during late October (DOY 300 - 302). Under harvest, the switchgrass was mowed using a rotary mower. Ninety percent of the switchgrass residue was baled and removed from the field. This process requires flattening the standing residue, which is then transferred to the surface residue pool. Harvests are then made from the surface residue pool, including both standing and flattened residues (Renard, 2013).

2.5 Management Scenarios in AGROBGC

2.5.1 Corn grain and Stover

Annual corn harvest was simulated by assuming 100% grain removal with all remaining residue (e.g. stem, leaf, and fine roots) transferred to the litter pool. Harvest date was late October (DOY 300 - 302) and annual residue removal was simulated by removing grain, and increasing amounts from the litter pool (e.g. 0, 25, 50, and 75%). Fertilizer application was simulated by assigning the amount of fertilizer to be deposited into the available soil mineral nitrogen pool (Di Vittorio *et al.*, 2010) shortly after planting at specific rates of 0, 125, and 175 kgN ha^{-1} yr^{-1}.

2.5.2 Switchgrass

Nearly all the ecophysiological characteristics for the switchgrass vegetation type used in this study were derived from available field studies, and the rest were generated by a numerical optimization process outlined by Di Vittorio et al. (2010). Optimized characterized parameter values were those pertaining to carbon allocation to coarse roots, new leaves, and new stems (Di Vittorio *et al.*, 2010).

Control scenarios with no switchgrass harvest were built, and switchgrass harvest treatments were simulated by removing 90% of all live stem carbon content during late August (DOY 238- 240) or late October (DOY 300 - 302), with all remaining live material transferred to the litter pool. Fertilizer application was simulated by assigning the amount of fertilizer (0, 56, 112 kgN ha^{-1} yr^{-1}) added into the available soil mineral nitrogen pool shortly after planting (Di Vittorio *et al.*, 2010).

2.6 Analysis and Evaluation of Results

Model estimates were checked against field-collected data and published literature values when available to evaluate accuracy and consistency. Specifically, we compared annual above-ground net primary productivity (ANPP) and SOC measurements for corn and switchgrass systems against model estimates. Modeled ANPP and SOC for switchgrass were compared against a dataset that includes plot-level warm season grass yields and soil data collected from conservation reserve program (CRP) fields in southwest Wisconsin (Randy Jackson *et al.*, unpublished data). In this study, annual harvests of switchgrass were made in 2008 and 2009 across six working farms having CRP land in Grant County, WI (Miesel *et al.*, 2012). The Curtis Prairie biomass and residue removal study provided prairie soil organic matter data for a 47-year period (Nielsen & Hole, 1963; VanRooyen, 1973, Nadelhoffer *et al.*, unpublished data), and model estimates of SOC accumulation or loss rates were compared with it, and other studies.

3. Results

3.1 Corn Ecosystem: Stover Removal and N Fertilization

AGRO-BGC estimates for corn show good agreement ($R^2 = 0.87$) with field measurements obtained from a no-till corn carbon budget study that reported average ANPP between 4.3 - 6.1 t ha^{-1} yr^{-1} for no-fertilized treatment, and 7.2 - 9.70 t ha^{-1} yr^{-1} for the 180 kg N ha^{-1} fertilizer treatment (Figure 2) (Brye *et al.*, 2002). Based on AGRO-BGC predictions, ANPP averaged 6.2, 5.5, 5.2 t ha^{-1} yr^{-1} on silt loam, clay loam, and sandy loam, respectively (Figure 3). Residue removal decreased ANPP over the 25-year simulation, as hypothesized. However, the decrease was a modest 3 to 5%, or an average decrease of 0.2 t ha^{-1} yr^{-1} with increased residue removal treatments. Across all soils, fertilizer increased ANPP between 33 and 44%, with an average ANPP increase of 2.2 t ha^{-1} yr^{-1} as N fertilization rates increased from 0 - 175 kgN $ha^{-1}yr^{-1}$.

3.1.1 Total Soil Organic Carbon SOC)

Estimated total SOC ranged from 150 to 180 t ha^{-1} (simulation depth 1.5 meters) at the beginning of the residue removal scenarios. There is continuous SOC loss under all scenarios of harvest, regardless of N application, with greater SOC loss as residue removal rates increase (Table 4). Under scenarios with residue removal rates of 25% or less, SOC loss decreases with increased N application rates. However, when residue removal reached 50% or greater, SOC loss increases as N application increases**.** The greatest rates of SOC loss occurred when residue removal rate was 75% with no N fertilizer, and averaged 0.79, 0.83, and 0.96 t ha^{-1} yr^{-1} for sandy loam, clay loam, silt loam, respectively. This pattern is consistent across all soil types and N application, the greatest loss occurring with silty loams, followed by clay loam, then sandy loams, at an average 0.70, 0.60, 0.56 t ha^{-1} loss per year, respectively (Figure 4). We observe in the highest residue removal scenarios, even with the highest rates of N application, that there is a SOC loss rate that is approximately twice that of a scenario where no residue is removed at all.

Increased residue removal rates also decreased the effect of increased N application on litter or detritus carbon relative to the control (no-fertilizer) treatment (Figure 5). Litter carbon is the primary source of SOC in this system, and is supplied by plant detritus throughout the growing season. Under no-residue harvest scenarios, the high (175kgN ha^{-1}) application rates result in nearly 1 metric ton more litter carbon than the control scenario over the 25 year simulation, and the low (125 kgN ha^{-1}) application rates are 0.7 t ha^{-1} greater than the control. As residue removal rates increase to 75%, the average effect of N fertilizer diminishes to approximately 0.2 t ha^{-1} greater than the control.

3.1.2 Erosion Loss Effects

Minimum soil loss estimates occurred on level soil, with average soil losses of 0.02 t ha^{-1} yr^{-1} across all soil types. All scenarios predicted soil loss, but the greatest soil erosion loss was estimated for 75% residue removal on a 12% slope. The scenario predicting the least amount of soil loss at 0.01 t ha^{-1} yr^{-1}was that in which no residue was removed and slope was 0%. Slope increases from 0 - 7% and 7 - 12% increased soil erosion losses by 0.6 and 0.5 t ha^{-1} yr^{-1}, respectively, on average across all soil types. The silty loams experienced the greatest amount of soil erosion loss, at a rate of 2.9 t ha^{-1} yr^{-1} with a 12% slope (Figure 6). All scenarios, however, resulted in soil erosion losses that were less than the RUSLE2 Soil Loss Tolerance (T) value of 7.4 t ha^{-1} yr^{-1}.

3.2 Switchgrass Ecosystem ANPP

AGRO-BGC estimates for switchgrass show good agreement (R^2 = 0.88) with field measurements obtained from a switchgrass productivity study that reported average ANPP between 5.7 - 12.0 t ha^{-1} yr^{-1} for a Fall harvest treatment, and 4.8 - 11.5 t ha^{-1} yr^{-1} for a Spring harvest treatment (Figure 7) (Randy Jackson *et al.* data unpublished). Estimated switchgrass ANPP averaged 7.1, 6.1, and 5.8 t ha^{-1} yr^{-1} for silt loam, clay, and sandy loams, respectively (Figure 8). This pattern of productivity across soil types is consistent with the results from the corn stover system.

Average ANPP increased 0.72 and 0.74 t ha^{-1} yr^{-1} as N fertilization increased from 0 - 56 and 56 - 112 kgN ha^{-1} yr^{-1}, respectively, regardless of harvest timing. Across all N application rates and soil types, switchgrass ANPP was 0.5 t ha^{-1} yr^{-1} lower when feedstock was harvested at late summer than later in the fall (Figure 8). Simulated ANPP was always greater for all harvest treatments than the control scenario.

3.2.1 Total Soil Carbon

Under all control scenarios, SOC either remained stable or increased over the 25-year simulation. The greatest rates of SOC loss (0.2 t ha^{-1} yr^{-1}) occurred for the no-fertilizer treatment, regardless of harvest timing and soil type, and maximum gains (0.1 t ha^{-1} yr^{-1}) in soil carbon occurred in all soil types under harvest scenarios when 112 kgN ha^{-1} yr^{-1} was applied (Figure 9). Estimated total soil carbon pools ranged from 130 - 160 t ha^{-1} (simulation depth 1.5 meters) at the beginning of the residue removal scenarios. Across all soil types, SOC loss decreases as nitrogen application rates increase, and at annual application rates of 112 kgN ha^{-1}, there is a stabilization and net gain of SOC (Table 5).

3.2.2 Erosion Loss Effects

Soil erosion loss was lowest for no harvest and level ground (Figure 10). Simulated soil loss ranged from 0 - 6.6, 0 - 11.8, and 0 - 5.3 t ha^{-1} yr^{-1} for sandy, silty, and clay loams, with maximum losses occurring on 12% slopes. Harvesting switchgrass on silty loams of a 12% or greater slope resulted in soil erosion losses greater than the T- value of 7.4 t ha^{-1} yr^{-1}. In these systems, slope is the most influential biophysical landscape characteristic on total soil losses. Average soil erosion increased by 3.1 t ha^{-1} yr^{-1} as slopes increased from 0 - 7%, and increased by 3.4 t ha^{-1} yr^{-1} when slope increase from 7 - 12%, for all soil types (Figure 10). Soil erosion rates were greater for the summer than fall harvest for all soil types and percent slopes, though the difference between the two was 1.0 t ha^{-1} yr^{-1} or less.

4. Discussion

Ecosystem process models are used to explore the effects of different biofuel feedstock crops (Peckham & Gower, 2011; Surendran Nair *et al.*, 2012) in agroecosystems over longer time scales that cannot be captured by many current empirical field studies. The ability to estimate agroecosystem dynamics using these models is limited by our understanding of the underlying soil carbon and nitrogen processes, our access to existing empirical field data for validation, and our ability to accurately represent the vegetation type through its ecophysiological parameters. When we continue to validate such models against field datasets as they become available, the predictive power of these models increases. AGRO-BGC has been validated in perennial C_4 grass system (Di Vittorio *et al.*, 2010), and the previous chapter of this dissertation validates the model in an annual corn agroecosystem under a bioenergy feedstock management context. Simulations of an annual corn stover harvest and a perennial switchgrass harvest for bioenergy were successfully completed using the ecosystem process model AGRO-BGC and the erosion process model RUSLE2, and results are largely consistent with our hypotheses. Expected general patterns of carbon gain and loss under varying residue management scenarios were observed, and model estimates fell within the range of most reported field observations.

4.1 Corn ANPP and SOC Dynamics

AGRO-BGC estimates for corn show good agreement ($R^2 = 0.87$) with field measurements obtained from a no-till corn carbon budget study that reported average ANPP between 4.3 - 6.1 t ha^{-1} yr^{-1} for no-fertilized treatment, and 7.2 - 9.70 t ha^{-1} yr^{-1} for the 180 kg N ha^{-1} fertilizer treatment (Figure 2) (Brye *et al.*, 2002). When residue removal rates surpassed

25%, we observed an annual 0.2 t ha^{-1} reduction in corn ANPP. The starting range of estimated soil carbon pools (150 - 180 t ha^{-1}) compares reasonably well with total soil carbon observations for a corn residue carbon budget study (131 t ha^{-1}, measurement depth 1.2 meters) (Brye *et al.*, 2002).

Our simulations suggest long-term ANPP decreases as the percent of aboveground corn stover is harvested. Our findings are consistent with a Corn Belt study examining management practices in continuous corn rotations, where total SOC (up to 1 meter depth) decreased unless a winter cover crop was in the rotation (Mann *et al.*, 2002). Rates of SOC loss can be increased even further under a system where tillage is practiced, so our findings present a conservative estimate of potential carbon losses. Other continuous corn stover residue harvest experiments have shown that removal rates greater than 25% consistently reduced SOC, and removal rates above 50% resulted in a 1.5 t $ha^{-1}yr^{-1}$ loss in SOC in marginal Ohio soils (Blanco-Canqui & Lal, 2007). In these trials, SOC loss was more drastic in silt loams than in clay loams during the 2.5-year study, which is also consistent with our findings. However, the complex dynamics among climate, past and current land use practices, edaphic, chemical, physical, and biological soil characteristics of field studies present a wide range in results.

Supporting evidence of litter pool dynamics reveal the complex relationships between soil carbon and nitrogen in their various forms. Some studies have shown that productivity losses from harvest can be recouped by applying more fertilizer to increase crop productivity. However, our model simulations suggest that as more residues are harvested, increasing fertilizer rates does not prevent loss in productivity. Significant imbalances in nitrogen occur when fertilizer rates are in excess of what the crops can take up, and can deliver substantial environmental costs to agroecosystems over time. While examining the complexities of the nitrogen cycle is beyond the scope of this study, further exploration into synchronizing the timing of fertilizer application and crop uptake through applying AGRO-BGC can offer insights into how this nutrient imbalance can be minimized and nitrogen can be more efficiently applied in such an agroecosystem.

Further supporting the argument that soil productivity is jeopardized under management that consistently removes crop residues without replenishment is the estimated effects on the litter carbon pool. As more crop residues were harvested, we observed a shrinking litter carbon pool over time. This was accompanied by decreasing decomposition (heterotrophic respiration) rates. Such an effect is expected, as a smaller residue pool has less energy and available carbon substrate for microbial communities to decompose (Unger, 1994). This poses a disruption to the carbon cycle, as microbial communities provide a significant function to carbon pathways from vegetation to soil, which could lead to decreased productivity over time. Not only are they significant carbon pools, but litter pools also contribute to the surface energy balance, as they can buffer crops from extremes in temperature and moisture. Litter pools also provide a significant physical barrier to soil erosion loss. The depletion of litter and soil carbon pools can lead to significant soil degradation in the absence of intervention (Lal, 2005).

4.2 Corn Stover Erosion Dynamics

Crop residues and litter detritus increase surface roughness and interception of falling raindrops, and their removal can significantly increase erosion susceptibility (Lal *et al.*, 1998). RUSLE2 simulations reported greater soil loss as crop residue harvest rates increased. In addition, erosion accelerated as slopes increased, and the greatest amount of loss on silty loam soils, which are typically susceptible to water erosion (Lal *et al.*, 1998). Results from this study underscore the important physical role that crop residues provide in sustainable cropping systems. Under the most intensively harvested scenarios, each system lost from 2.5 to 4.6 times as much soil relative to the control, regardless of slope. At the most conservative residue removal rate (25%), the system still lost at least 1.3 times as much soil relative to the grain-only control scenario. Terrain was a strong driver in the amount of soil erosion, and as slope increased from 0 - 7%, the potential soil loss by erosion increased by 0.6 t ha^{-1} per year. The soil loss tolerance value, or T-value, describes an allowable amount of annual erosion loss that still enables economically sufficient crop productivity levels (Renard, 2013). While none of the corn stover removal scenarios exceeded their respective T-values, these findings provide sufficient evidence to strongly support recommendations that corn residues, particularly on erosion-prone soils on steep slopes, remain on the field.

4.3 Switchgrass Carbon Dynamics

The extensive root system and high productivity of switchgrass has been noted extensively in the literature for its capacity to increase soil carbon storage and it has been targeted as a viable bioenergy feedstock that can maintain and even increase underground carbon storage pools (Frank *et al.*, 2004; Thomason *et al.*, 2005). Our results support these claims, though AGRO-BGC estimates were on the lower end of measured switchgrass productivity. Our estimates of switchgrass productivity align well within ranges reported by empirical field studies (Jackson *et al.*, unpublished data, Garten Jr. *et al.*, 2010; Thomason *et al.*, 2005), and we observed an increase in these yields with an increase in fertilizer application rates. AGRO-BGC switchgrass productivity estimates align with measurements from an ongoing switchgrass productivity study in Southwest Wisconsin where average ANPP ranged between 4.8 and 12.0 t

ha^{-1} yr^{-1} were reported (Randy Jackson *et al.*, data unpublished). Yields from 7.2 to 9.7 t ha^{-1} yr^{-1} were reported from a four-year carbon budget study of a mixed C_4 grass prairie (Brye *et al.*, 2002). While our estimates of switchgrass productivity are low, they are within a reasonable range of field observations.

Fertilizer application rates were a strong driver of productivity across all scenarios, and nearly one metric ton of annual yield increase was observed from increasing fertilizer rates from 0 - 56 and 56-112 kgN ha^{-1} yr^{-1}. Patterns of soil texture influence on productivity were similar to those found in the corn stover simulations, with highest switchgrass productivity coming out of silty, clay, then sandy loams, respectively. There was little difference in switchgrass productivity across harvest dates, though we observed that a fall harvest typically produced 0.5 t $ha^{-1}yr^{-1}$ more than its summer harvest counterpart. In a field trial where switchgrass treatments were harvested in late fall or summer, an average of 8.4 and 8.1 t ha^{-1} yr^{-1} yields were observed, respectively (Randy Jackson *et al.* data unpublished). Delaying harvest allows nitrogen translocation from aboveground biomass to the rhizome and root stocks, which reduces the need for additional fertilizer applications during the following growing season. A field study in Tennessee switchgrass stand measured a 50% decline in leaf nitrogen concentration during leaf senescence from July to October, which was accompanied by a continued carbon accumulation in aboveground biomass pools during the same time (Garten Jr. *et al.*, 2010). While most aboveground production takes place early in the growing season (April to July), a net increase in root biomass production (e.g. rhizome, coarse and fine roots) was observed between July and October. Coupling our model estimates with these measurements provides supporting evidence for recommendations to delay harvest until after senescence.

All switchgrass scenarios resulted in less SOC loss than any of the corn stover harvest scenarios. Initial total soil carbon pools (130 - 160 t ha^{-1}) at the beginning of the residue removal simulation compared well with total soil carbon observations from a mixed C_4 grass prairie carbon budget study (121 t ha^{-1}, measurement depth 1.2 meters) (Brye *et al.*, 2002). Overall estimated trends in SOC loss and gain in this study are comparable to those reported in the literature. Estimated SOC losses approximate those reported in a 47-year long mixed C_4 prairie grass residue manipulation study (Nadelhoffer *et al.*, data unpublished), where a 0.17 t ha^{-1} yr^{-1} loss was observed for a plot with all residue removed. Our switchgrass harvest scenarios lost a maximum of 0.2 tC ha^{-1} per year with 90% above ground residue harvested. In situations where no fertilizer was applied, all harvest regimes across all soil types lost SOC over the 25-year simulation. As fertilizer was applied, SOC rates stabilized and we estimated net SOC gains approaching 0.4 t ha^{-1} per year. This supports arguments that switchgrass can be a net carbon sink and a sufficient provider of bioenergy feedstocks, as long as fertilizer is applied.

In AGRO-BGC, switchgrass roots are represented by coarse and fine root carbon pools (Di Vittorio *et al.*, 2010). The coarse root carbon pool is representative of the perennial rhizome of switchgrass and its turnover rates are uncertain due to the lack of widespread field root data. Upon coarse root mortality, carbon is sent to the coarse debris pool, which is incorporated into the total litter carbon pool. It is then subjected to prescribed harvest, respiration, and decomposition rates, and remaining carbon is incorporated into the soil carbon pools. There could be substantial live coarse and fine root contribution to SOC pools that is not accounted for in the current state of the model, which can lead to underestimates of SOC. These uncertainties could be improved by incorporating more empirical field data from long-term switchgrass studies as they become available, and developing more heterogeneous root carbon pools for allocation within AGRO-BGC.

4.4 Switchgrass Erosion Dynamics

Patterns of estimated soil erosion loss across soil types and hill slopes were consistent with our expectations. We observed the greatest erosion rates in silty loams over steep slopes and the lowest erosion rates across all soils overlaying flat slopes. The range of reported erosion loss 0 - 6.6, 0 - 11.8, 0 - 5.3 t ha^{-1} yr^{-1}for sand, silt, and clay loams, respectively) was consistent with estimates in other studies, falling within a range of 5.4 - 18.8 t ha^{-1} yr^{-1}, as was estimated for a southwest Wisconsin switchgrass study using RUSLE2 (Renz *et al.*, 2012). With the exception of harvesting switchgrass on silty loams of a 12% slope, all simulations resulted in erosion losses less than the 7.4 t ha^{-1} yr^{-1} T-value generated by RUSLE2. Across all scenarios, slope emerged as the most influential driver of erosion loss, generating an average 3 and 5 t ha^{-1} yr^{-1} increase when slopes increase from 0 - 7, and 8 - 12%, respectively. Such a dramatic increase in potential soil loss supports arguments for maximizing the amount of vegetative cover on these slopes, so as to reduce the erosive capacity of rainfall and runoff.

However, our estimates of soil loss under a switchgrass harvest system were greater than those reported from a corn stover harvest system. This is counter to our expectations and what is found in the literature. Because of the continuous residue cover and perennial root biomass that provides significant physical protection from erosion loss, these results are incongruent with expectations of greater loss from an annual corn cropping systems where crop soil is left bare and uncovered for significant portions of the year. This could be attributed to RUSLE2's assumptions about residue production throughout the year. The version used in this study

(RUSLE2 2.0.4.0) assumes no residue production during canopy growth, and only producing standing residue at the time of harvest. Such assumptions underestimate the amount of residue available throughout the growing season for erosion prevention (Dabney & Yoder, 2012), which results in overestimation of erosion in perennial grass systems. Recent additions to the RUSLE2 science version include a more robust routine for incorporating perennial grasses and a continuous residue production subroutine, which shows promise for improving model estimates in these systems. (Dabney & Yoder, 2012). However, the version of RUSLE2 used in this study did provide a sufficient modeling environment to represent the vegetation, landscape, and management characteristics of switchgrass systems, and provides a suitable tool for conservation management planning for bioenergy feedstocks.

Understanding the long-term impacts of proposed bioenergy feedstock management scenarios is of great importance as we look towards agroecosystems to produce sufficient biomass to meet the demands of a developing bioenergy economy. How producers manage their agricultural soil resources will determine how long these systems can sustain feedstock production and the extent to which local water and soil quality will be impacted. This study examined two distinct pathways for carbon loss in an agroecosystem; through harvest and respiration, and through total soil loss via erosion. The results of this study have supported our hypothesis that intensifying aboveground residue harvest reduces soil organic carbon and nitrogen over time, and the magnitude of these losses is greater in corn systems than in switchgrass systems.

For corn agroecosystems that rely heavily on aboveground biomass contribution to maintain SOC, our findings challenge the notion that applying additional fertilizer to a system will stimulate productivity enough to compensate for lost biomass through harvest. We found that if 50% or greater residue was harvested, the effect of fertilizer to increase productivity became diminished. This is useful information for farmers to incorporate into their management, as there are significant environmental and economic costs associated with excessive nitrogen inputs to the system.

The suitability of each feedstock to different landscape and management characteristics are largely attributed to the contrast in their above-to-below ground carbon allocation strategies. The abundant root biomass generated by switchgrass plants makes it a suitable feedstock candidate steeply sloped landscapes, especially those with highly erodible soils. These extensive root systems have the capacity to stabilize soil, facilitate water infiltration, both serving as a means to sequester soil carbon and prevent loss from erosion. This study showed that such a landscape would lead to significant SOC losses through respiration and erosion if managed for corn stover harvest, even under no-till management.

Land with gentle slopes and soils with low erodibility would make more appropriate sites for harvesting crop residues. Such landscapes present lower risk of SOC loss through erosion, however our results showed that any corn residue harvest will result in overall SOC loss. According to our estimates, the only way to approach SOC stabilization is to leave all crop residues on the field and to maximize N applications. In such a case, the introduction of mulch or cover crops may provide options for maximizing SOC gain. Our results show overlap in residue removal and N application rates for equal SOC loss, and it is within these spaces of overlap where a farmer will have to assess the tradeoffs between residue harvest and N application to minimize SOC loss.

Making such tradeoffs will be central to sustainable bioenergy feedstock production, and it will require an understanding of the complexities among land, management, and the farmer’s socioeconomic context. The continuous improvement and application of ecosystem process models like AGRO-BGC and erosion process models like RUSLE2 will aid in further examination into the effects of bioenergy crop management on long-term soil dynamics.

Acknowledgements

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6. Tables and Figures

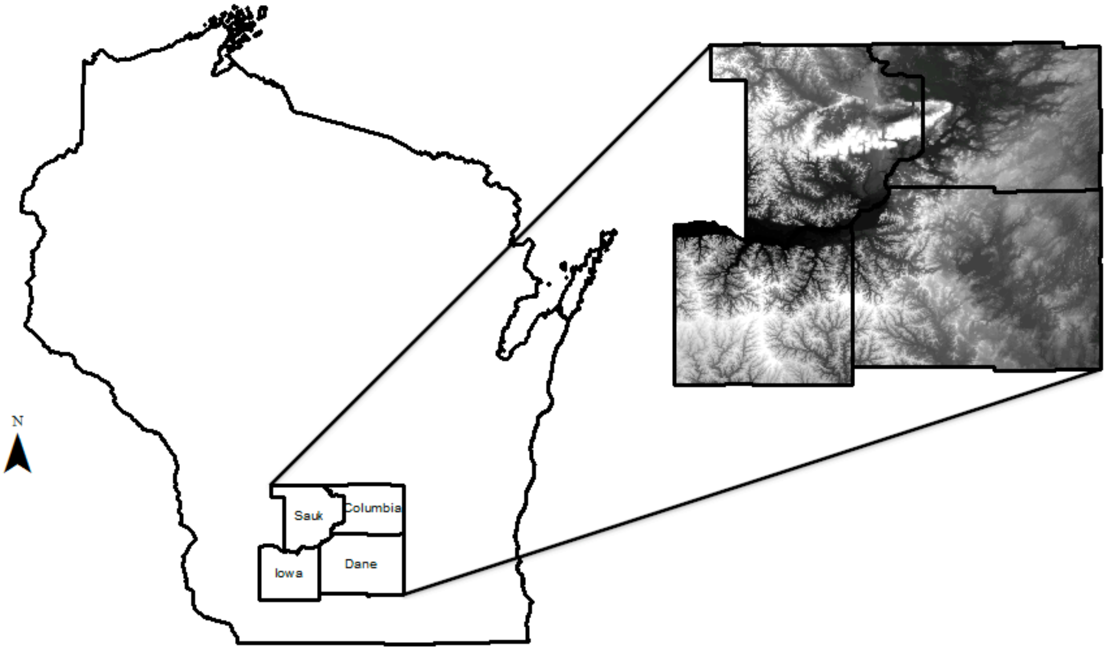

Figure 1. The Great Lakes Bioenergy Research Center southern Wisconsin RIMA extent and topography.

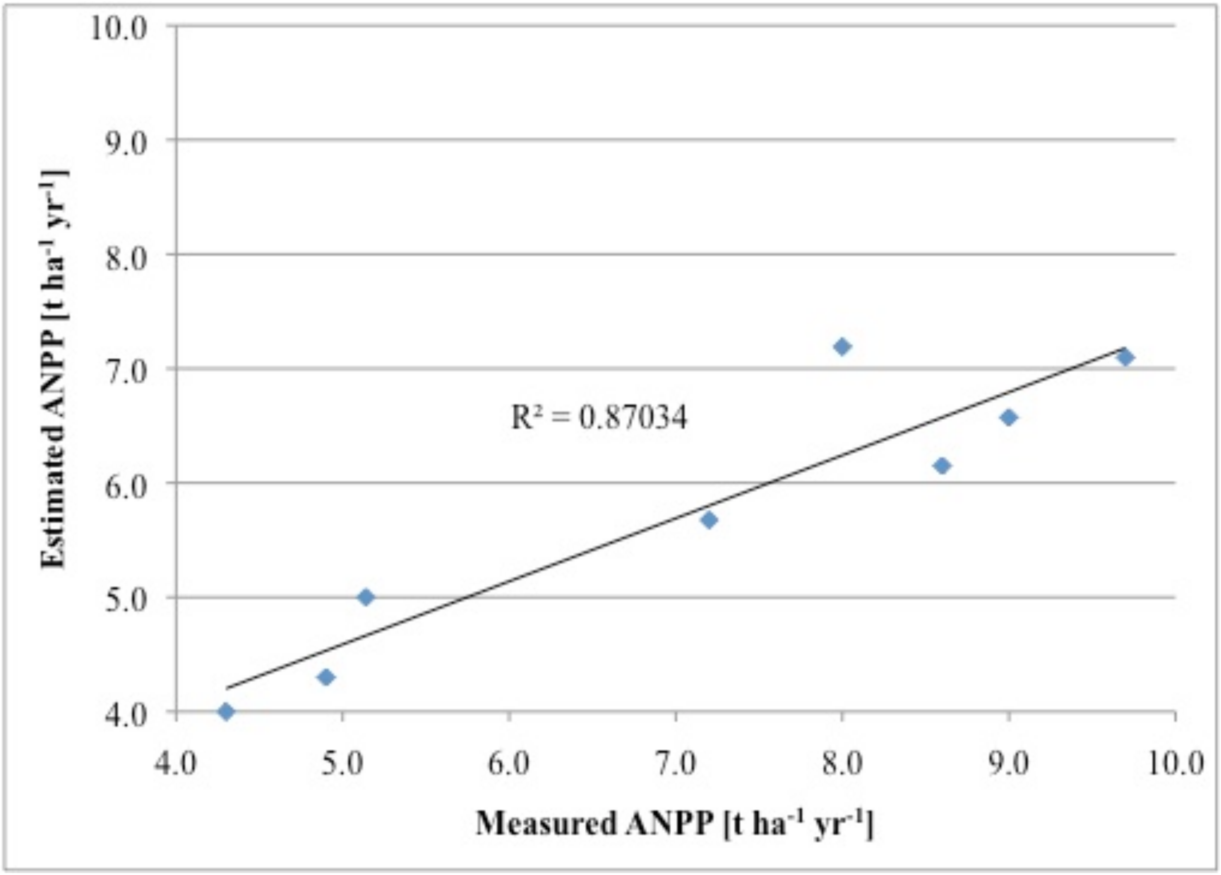

Figure 2. Estimated and observed ANPP values for no-till corn cropping system, with no residue removed, under fertilized and non-fertilized conditions (Brye *et al.*, 2002)

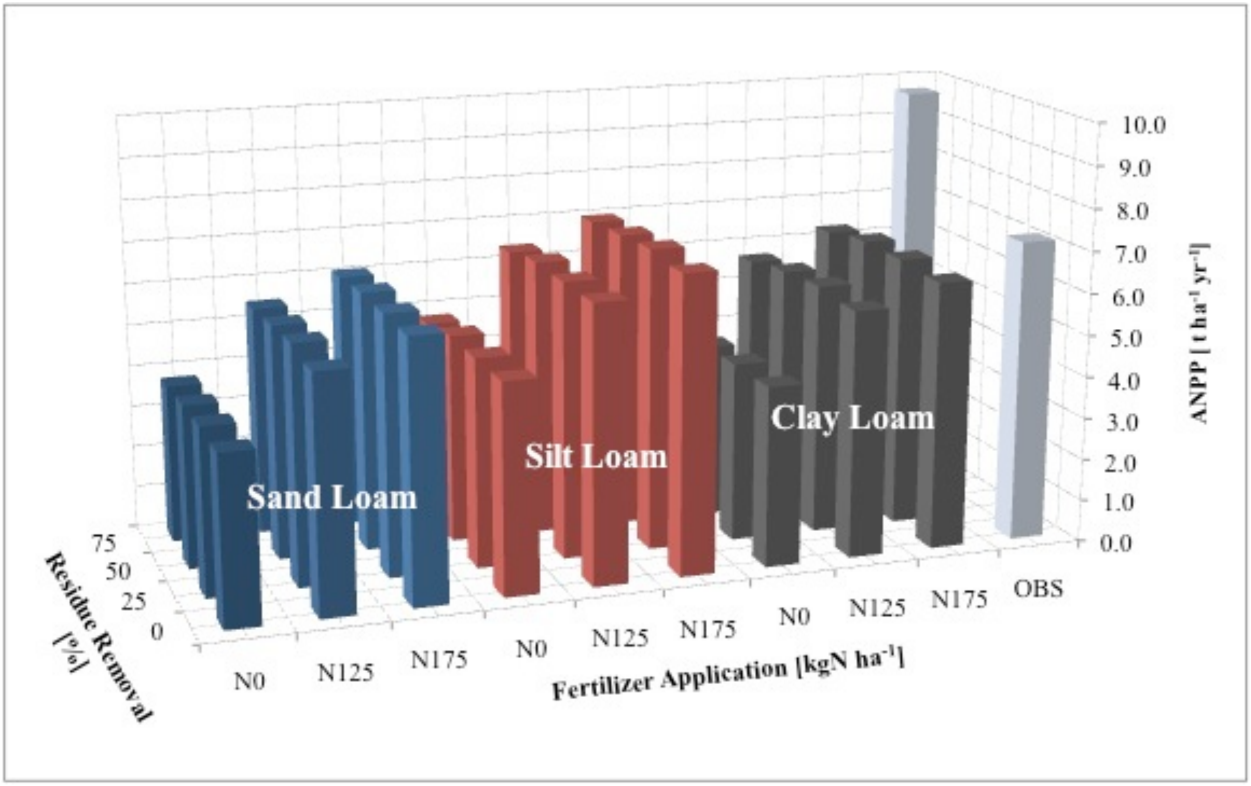

Figure 3. Average ANPP (t ha^{-1} yr^{-1}) estimates for corn stover harvest under varying residue removal and N application rates, and range of field corn ANPP observations from (Brye *et al.*, 2002).

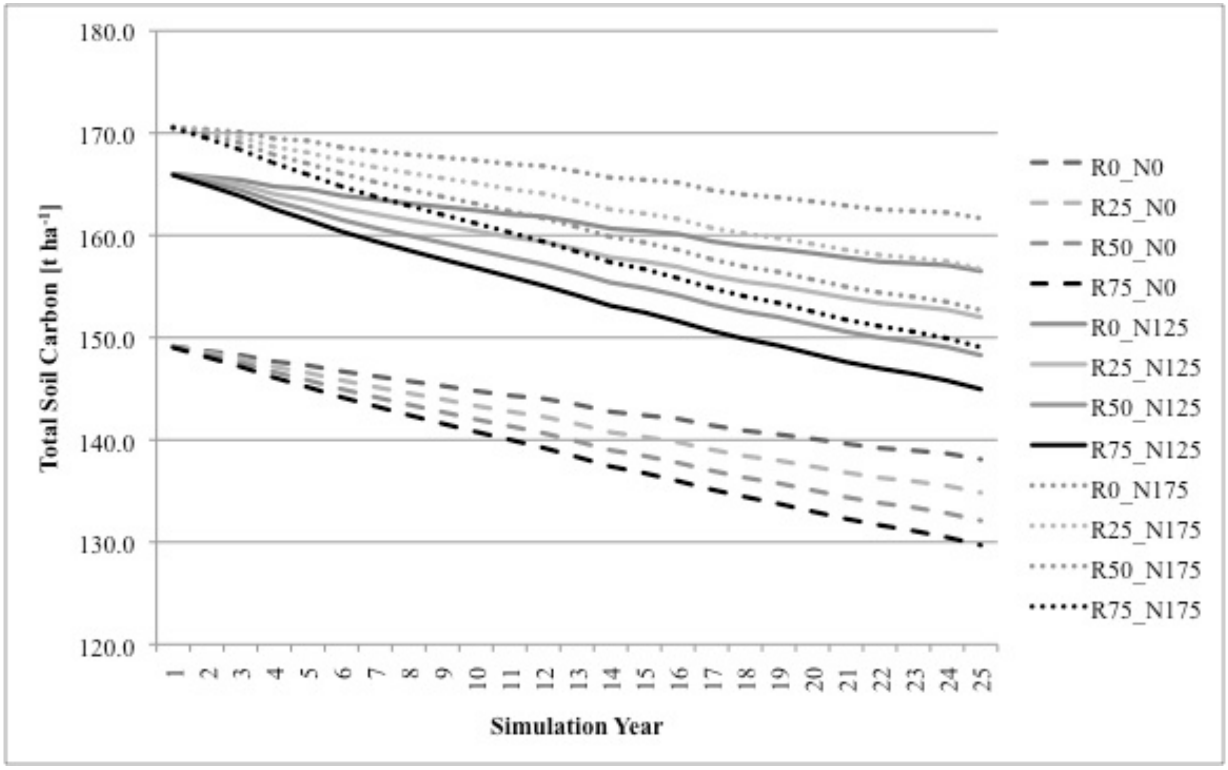

Figure 4. Changes in corn SOC in sandy loam soil over the 25-year simulation under varying residue removal and N application rates.

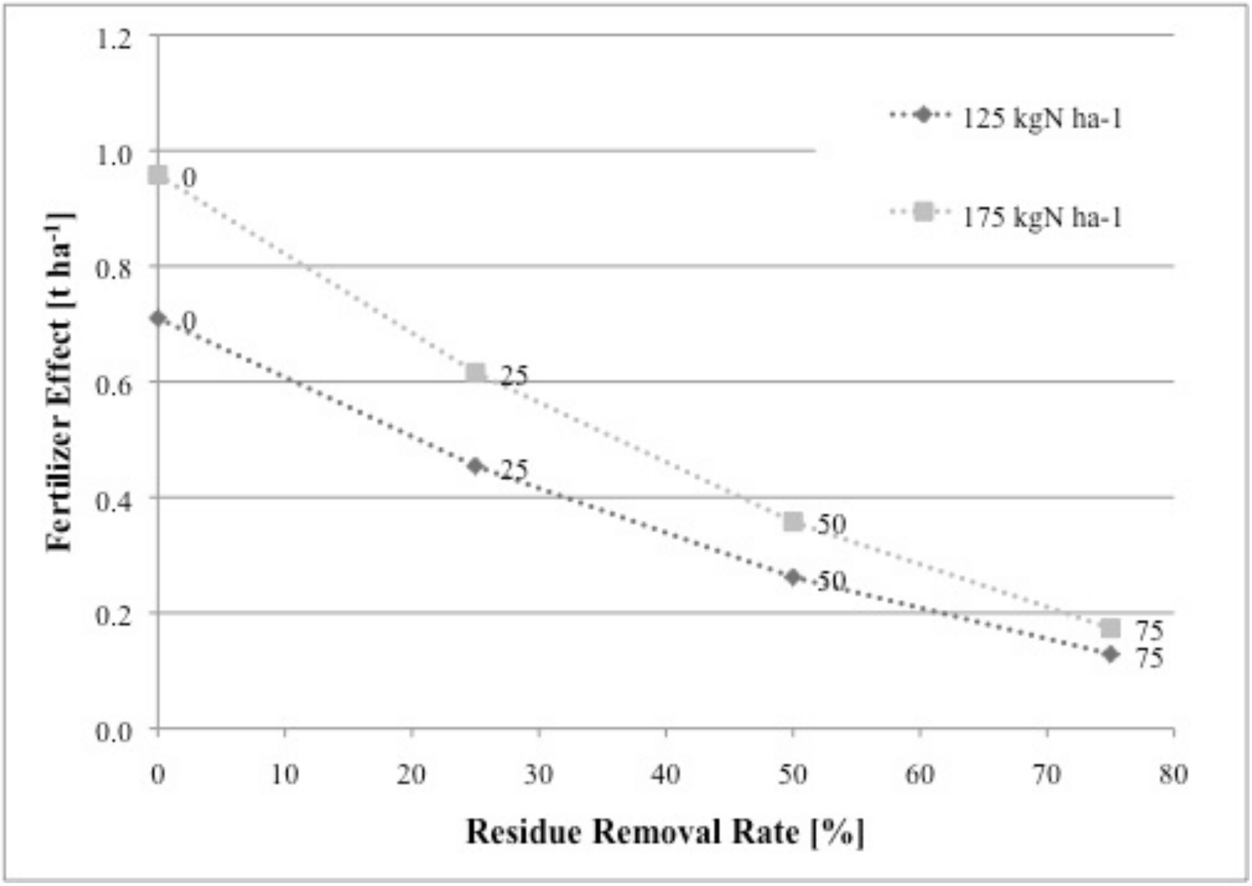

Figure 5. Effect of N application on litter pool carbon content across corn residue removal treatments and N application rates.

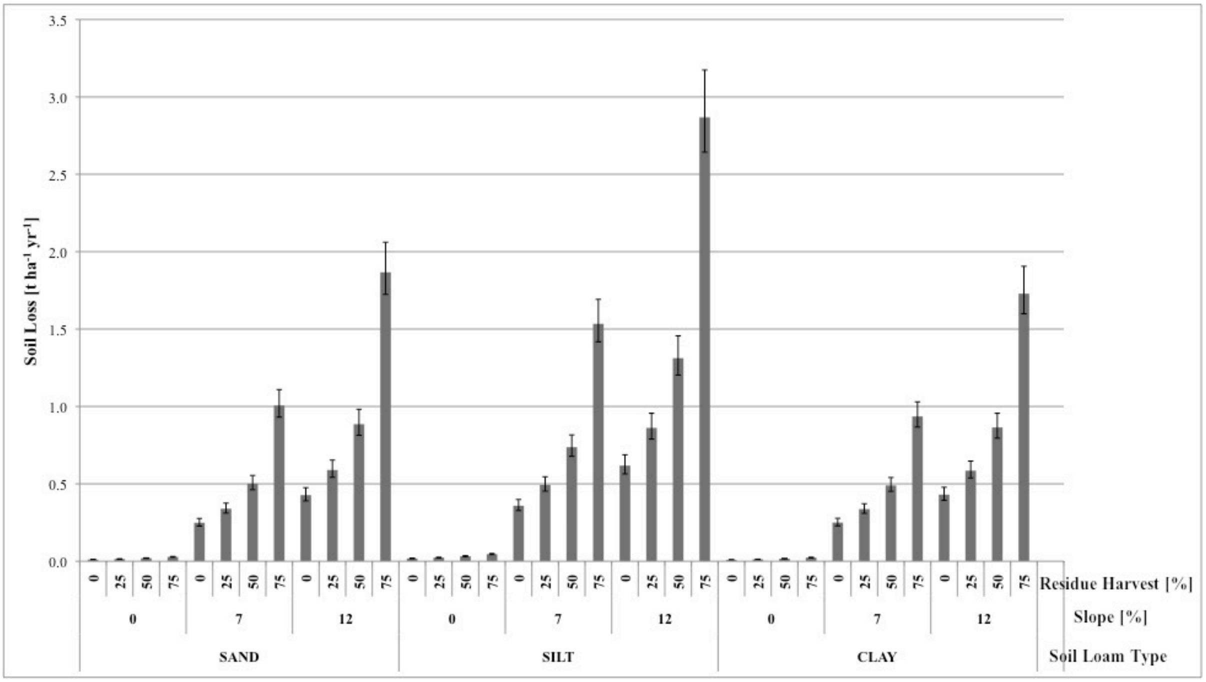

Figure 6. RUSLE2 estimated effects of residue harvest, soil type, and hillslope on soil erosion loss [t ha^{-1} yr^{-1}] in a corn stover harvest system. Error bars represent the range of soil loss across the four-county modeling unit.

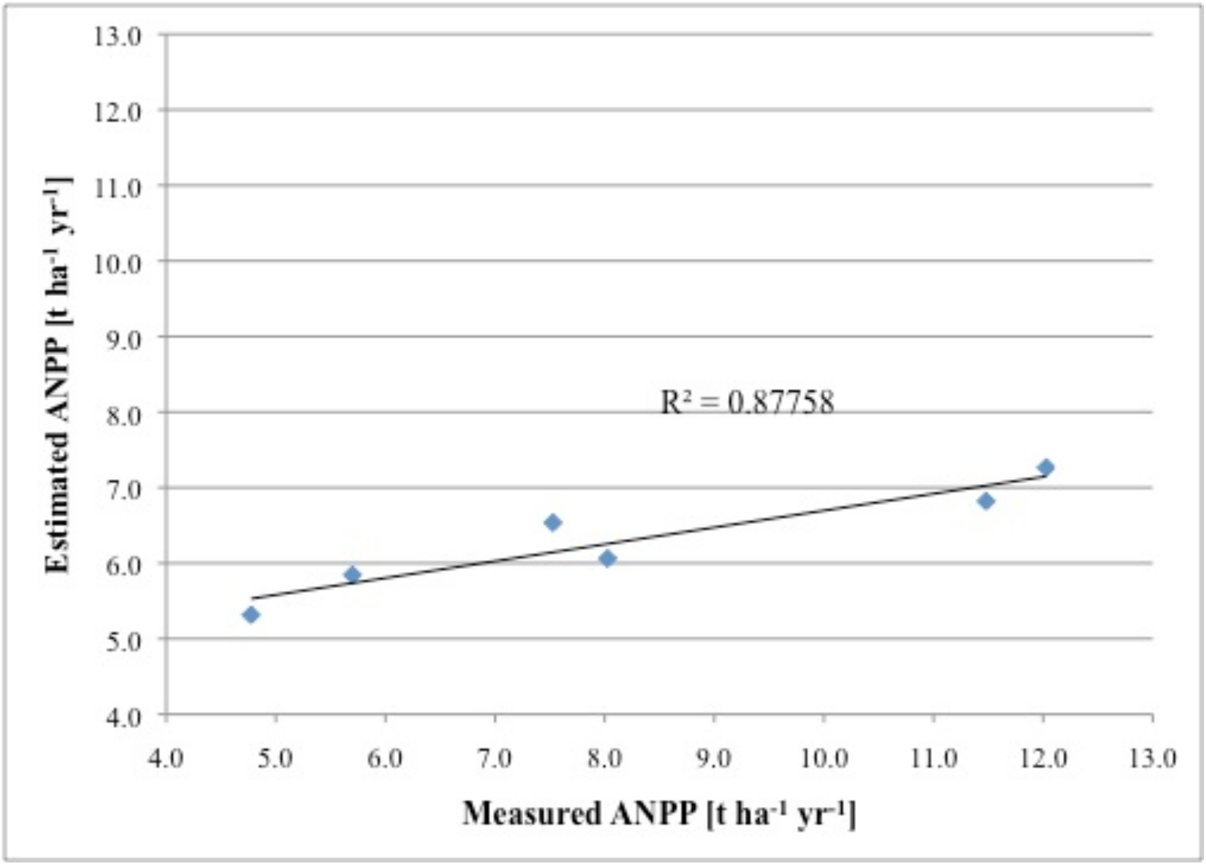

Figure 7. Estimated and observed ANPP values for switchgrass field study, under fertilized and unfertilized conditions (Randy Jackson *et al.* unpublished data)

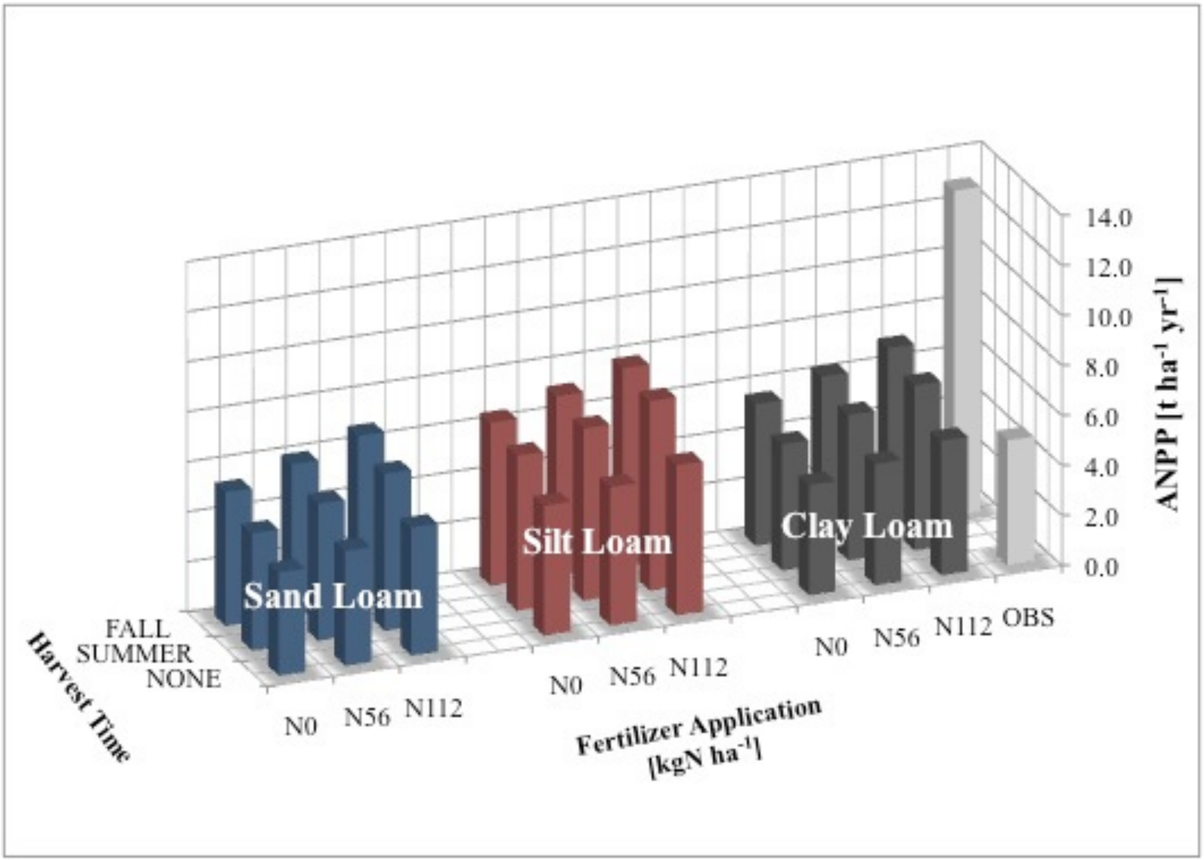

Figure 8. Average ANPP (t ha^{-1} yr^{-1}) estimates for switchgrass with varying N fertilizer application rates and variable harvest time, and range of field C_4 grass ANPP observations from Brye *et al.* 2002.

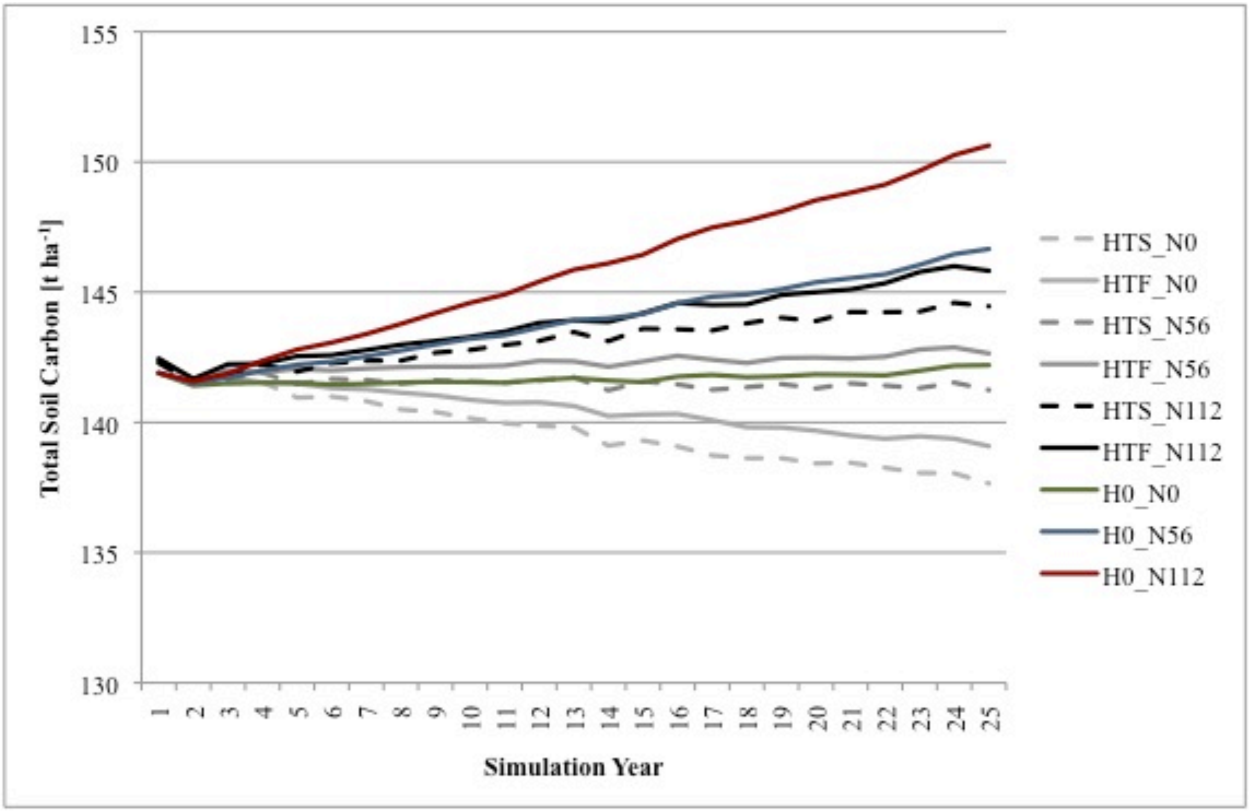

Figure 9. Changes in switchgrass SOC in sandy loam soil over the 25-year simulation under varying fertilizer application rates and harvest times.

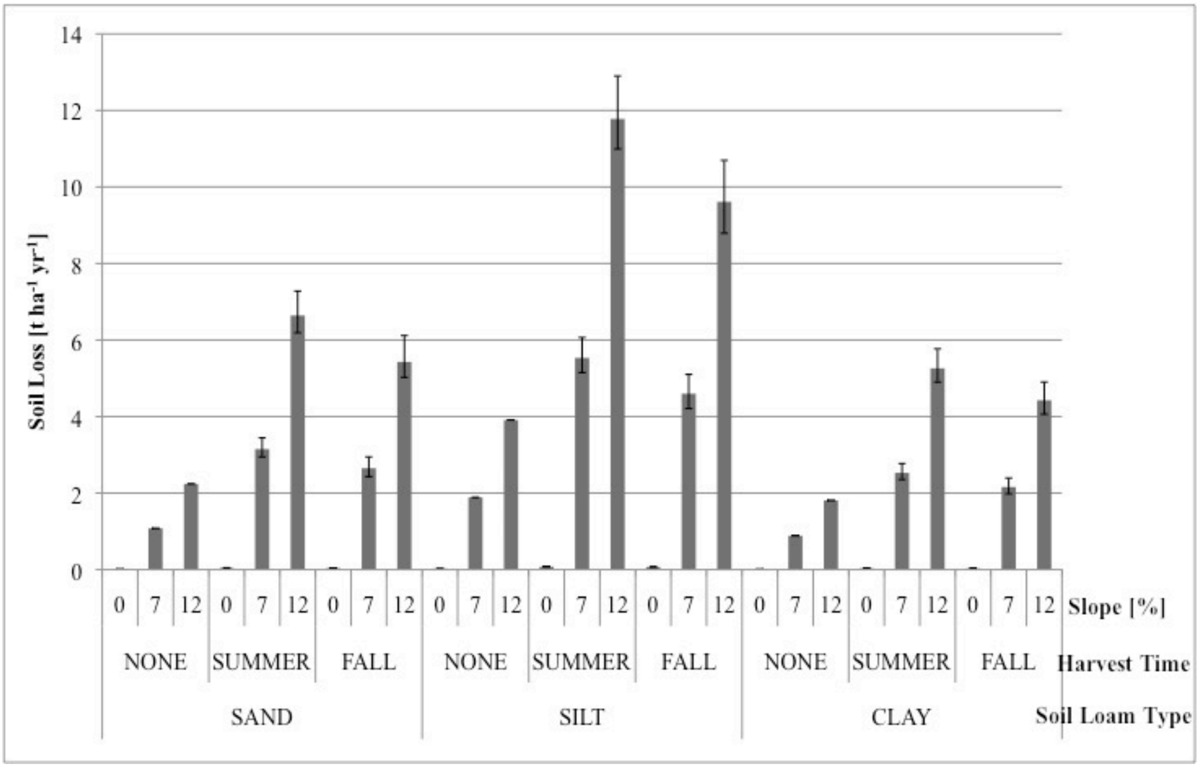

Figure 10. RUSLE2 estimated effects of harvest time, soil type, and hillslope on soil erosion loss [t ha^{-1} yr^{-1}] in a switchgrass system. Error bars represent the range of soil loss across the four-county modeling unit.

Table 1. Modeling scenarios for AGROBGC

Crop	*Harvest Date*	*Harvest Rates*	*Nitrogen Application [kgN ha^{-1} yr^{-2}]*	*Dominant Soil Types*
Corn	Late October (305-306)	Grain only, 25%, 50%, 75% residue	0, 125, 175	Sand loam, silt loam, clay loam
Switchgrass	Fall (305 - 306) Summer (234 - 235)	0%, 90%	0, 56, 112	Sand loam, silt loam, clay loam

Table 2. Modeling scenarios for RUSLE2

Crop	*Harvest Date*	*Harvest Rates*	*Slope [%]*	*Dominant Soil Types*
Corn	Late October (305-306)	Grain only, 25%, 50%, 75% residue	0, 7, 12	Sand loam, silt loam, clay loam
Switchgrass	Fall (305 - 306) Summer (234 - 235)	0%, 90%	0, 7, 12	Sand loam, silt loam, clay loam

Table 3. Edaphic Site Characteristics for RUSLE2

Soil Texture	*RUSLE2 Nomograph Erodibility 'K' Factor*	*Composition [% Clay, Silt, Sand]*
Silt Loam	0.48	20, 60, 20
Sandy Loam	0.28	10, 25, 65
Clay Loam	0.23	34, 33, 33

Table 4. Average annual rates of SOC change [t ha^{-1} yr^{-1}] over the 25-year simulation for corn stover harvest with varying N fertilizer application rates and variable residue removal rates

N Application [kgN ha^{-1}]	*0% Residue Removal*	*25% Residue Removal*	*50% Residue Removal*	*75% Residue Removal*
Sand Loam				
0	-0.39	-0.51	-0.61	-0.70
125	-0.33	-0.50	-0.64	-0.77
175	-0.30	-0.49	-0.65	-0.79
Silt Loam				
0	-0.51	-0.65	-0.77	-0.88
125	-0.45	-0.64	-0.80	-0.94
175	-0.42	-0.63	-0.81	-0.96
Clay Loam				
0	-0.43	-0.55	-0.65	-0.75
125	-0.37	-0.54	-0.68	-0.81
175	-0.34	-0.54	-0.69	-0.83

Table 5. Average rates of SOC change [t ha^{-1} yr^{-1}] over the 25-year simulation for switchgrass with varying N fertilizer application rates and variable harvest time. Values in bold show scenarios with net SOC gain.

	Sand Loam			*Silt Loam*			*Clay Loam*		
N Application [kgN ha^{-1} yr^{-1}]	*None*	*Summer*	*Fall*	*None*	*Summer*	*Fall*	*None*	*Summer*	*Fall*
0	0.0	-0.2	-0.1	0.0	-0.2	-0.2	0.0	-0.2	-0.2
56	**0.2**	0.0	0.0	**0.2**	-0.1	-0.1	**0.2**	-0.1	0.0
112	**0.4**	**0.1**	**0.1**	**0.3**	0.0	**0.1**	**0.4**	**0.1**	**0.1**

Chapter 4: Estimating crop productivity using remotely sensed data products

Abstract

This study provided evidence that combining biophysical crop canopy characteristics with satellite-derived vegetation indices offers suitable estimates of crop canopy phenology for both corn (*Zea mays L.*) and soybean (*Glycine max*) in southwest Wisconsin farms. Combining the fraction of photosynthetically active radiation (f_{APAR}) with LANDSAT-derived vegetation indices offers accurate estimates of green up, maturity, and senescence. Normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and green chlorophyll index (CI_{GREEN}), when combined with a light-use-efficiency (LUE) model, can also provide crop yield estimates in agreement with farmer reported yields, providing an efficient and accurate means of estimating crop yields from satellite data.

CI_{GREEN}, NDVI, then EVI, had a relative error from mean reported corn yields of 15, 17, and 20%, respectively. Mean reported corn yields from one site were extremely low in 2011, so when removed from the pool of results, the relative error of CI_{GREEN}, NDVI, and EVI is 8, 9, and 14%, respectively. Ranking the VI soybean yield estimates in order of lowest to greatest relative error was CI_{GREEN}, EVI, and NDVI with a mean relative error of 12, 13, and 14%, respectively. All three vegetation indices overestimated and underestimated corn and soybean yields with equal frequency over all sites. While the predictions can be improved by having more spatially explicit validation data and more complete interpolation over of early season VI data, this method that involves a model based entirely on satellite data is still robust in estimating crop yields.

1. Introduction

Agroecosystems are a significant component of the global carbon cycle, as they comprise 24% of the world's land cover (Cassman & Wood, 2005). Agricultural fields are also sites for generating the world's food, fiber, animal feed, and increasingly, fuel for heating and transportation. They play a significant role in the carbon cycle, and in turn, have a role in climate change (Gitelson *et al.*, 2012).

During the growing season crop canopies reflect light that can be measured by satellite sensors. Therefore we can use remote sensing datasets to estimate the magnitude of crop productivity over broad areas and over time. Cropping characteristics that generate the spectral signal captured by satellite sensors are a function of plant species and cultivar, crop maturity and condition, climate, soil type and soil moisture, and management practices (Liu *et al.*, 2010). This variation can be captured through the use of numerical modeling. Applications of remote sensing technology in agricultural systems have included crop type classification, crop condition monitoring, and crop yield predictions (Doraiswamy *et al.*, 2003; Gitelson *et al.*, 2012).

The ability to generate yield maps in a timely and accurate fashion is an effective and powerful tool for yield assessment following a growing season with extreme weather conditions, for farmers trading on futures markets, or for carbon budget researchers, among others (Alganci *et al.*, 2014; Johnson, 2014). The challenge of generating such maps lies in the accurate estimation of these yields across broad spatial extents. Variation in edaphic and climate conditions influence crop yields on scales that cannot be captured by a global scale model, and obtaining field-level crop yield data is often limited by landowner permission. Fine spatial and temporal resolution satellite datasets across extensive areas are now available in near-real time from online databases, so the potential to calculate yield data via remote sensing is significant.

In such highly modified systems as agroecosystems, the ability to capture these effects using spatial and ecosystem process tools is important for estimating bioenergy feedstock supplies across extensive areas.

Satellites such as LANDSAT Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+), NOAA Advanced Very High Resolution Radiometer (AVHRR), and Earth Observing System's Moderate Resolution Imaging Spectro-Radiometer (MODIS) are engineered so that their sensors measure surface reflectance in discrete sections of the visible and infrared light spectrum (Schlesinger, 1997; Turner *et al.*, 2002a; Lillesand *et al.*, 2004). MODIS offers 8-day composite coverage of the Earth's surface at spatial resolutions from 250 - 1000 meters, while TM and ETM+ provide 15 - 30 meter resolution at 16-day intervals. By mathematically combining bands across the electromagnetic spectrum into vegetation indices, we can infer much about the status of the crop canopy throughout the growing season and estimate crop yields (Turner *et al.*, 2002a, 2005; Lillesand *et al.*, 2004; Liu *et al.*, 2010).

Biophysical descriptors such as fraction of absorbed photosynthetically active radiation (f_{APAR}), Leaf Area Index (LAI), and vegetation indices including Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI) and Green Chlorophyll Index (CI_{GREEN}) are indicative of the crop's photosynthetic capacity (Liu *et al.*, 2010) and can be derived from remotely sensed observations (Lobell *et al.*, 2002). These three VI are the most widely used in agricultural studies (Table 1), and their accessibility and ease-of-use make them suitable candidates for assessing performance in predicting crop yields. Monitoring these descriptors throughout the growing season tells us much about the biophysical dynamics of the crop canopy and about the end-of-season productivity yields. f_{APAR} based yield calculations have been successfully applied in the past for general agriculture (Los *et al.*, 2000), corn and cotton

(Alganci *et al.*, 2014), corn and wheat (Lobell *et al.*, 2002), and corn and soybeans (Fang *et al.*, 2011; Gitelson *et al.*, 2012).

1.1 Vegetation Indices

Vegetation indices are combinations of surface reflectance values across multiple spectral bands used as proxies for biophysical vegetation characteristics. They incorporate bands with the greatest contrast in response to vegetation, soil, and water, as the strong contrast allows for detection and measurement of vegetation growth over time. This relationship between reflectance and absorption across bands provides the foundation for detection and crop productivity estimates (Gitelson *et al.*, 2012). The greatest contrast in vegetative surface reflectance lies between the Red (600 - 700 nm) and Near Infrared (700 - 1300 nm) wavelengths on the electromagnetic spectrum. Healthy green vegetation absorbs red very strongly while strongly reflecting in the NIR (Gitelson, 2004). The incorporation of the Blue (450 - 520 nm) band is used in accounting for atmospheric effects (Huete *et al.*, 2002).

The normalized difference vegetation index (NDVI) is a ratio of the difference between spectral reflectance in the red and near infrared bands. However this relationship is influenced by background signals by soil or bare earth, which can contaminate the vegetative signal. In addition, NDVI's sensitivity to chlorophyll content can lead to signal saturation at high biomass levels, particularly in late season corn and soybean fields (Chen <i>et al.</i>, 2006). Further VIs built upon NDVI's simple calculation to account for more complex surface, vegetation, and atmospheric dynamics.

Huete et al. (2002) developed the Enhanced Vegetation Index (EVI), which improves upon NDVI by correcting for distortions introduced by atmospheric scattering. It incorporates a blue band that maintains the vegetative spectral signal under varying atmospheric conditions (Kaufman & Tanr, 1992). It also adds a canopy adjustment factor that minimizes background factors such as soil and bare earth, and accounts for the dense vegetation saturation sensitivity often observed in maize canopies. This canopy adjustment factor also accounts for greater variation in canopy characteristics, including leaf area index, canopy type, and canopy architecture through incorporating canopy adjustment coefficients (Viña *et al.*, 2011).

Chlorophyll content is related to a plant's nutritional status, level of stress, and degree of senescence. The green chlorophyll index (CI_{GREEN}) is an estimate of the amount of leaf chlorophyll content, which is also a determinant of biomass productivity (Gitelson *et al.*, 2003). It incorporates the near infrared and green bands and was developed for use in maize canopies, where we observe a loss in NDVI sensitivity during late season (tasseling) growth phases due to increased reflectance in the red band. CI_{GREEN} overcomes this limitation by substituting the red band with the green band (Gitelson, 2003).

LANDSAT derived vegetation indices are related to f_{APAR} and have a well-documented history of providing accurate estimates of biomass productivity across multiple crop types (Wiegand *et al.*, 1991; Liu *et al.*, 2010; Gitelson *et al.*, 2012). However, each VI possesses its own strengths and limitations that vary across crop type, temporal availability, spatial resolution, and efficiency of processing. While the simplicity of the NDVI equation makes it a more efficient index for estimating greenness over global scales, it fails to capture the complex surface and vegetative dynamics of an annual cropping system. EVI accounts for the canopy structure and atmospheric scattering, however it is more computationally complex for making broad scale spatial productivity estimates. CI_{GREEN}, while highly sensitive to changes in chlorophyll content, is influenced by potential atmospheric effects, in the absence of correction (Viña *et al.*, 2011).

All three VI used in this study are available from LANDSAT and MODIS sensor platforms, and are considered to be equally suitable for the spatial and temporal resolution of this study. Relating these vegetation indices with f_{APAR}, then combining those results with a light use efficiency (LUE) model allows for estimating crop dynamics and productivity (NPP) over broad spatial scale.

1.2 Light Use Efficiency Model

The light use efficiency model by Monteith (1972) describes the positive relationship between photosynthetically active radiation (PAR) interception and leaf canopy architecture to predict biomass production. This component of the spectrum falls between 400 and 700 nm, and it is within this range that the chlorophyll molecules are excited by the incoming photons, initiating photosynthesis (Federer & Tanner, 1966). The amount of PAR intercepted by crops is measured by the fraction of PAR (f_{APAR}) assimilated by the developing crop canopy. By integrating this value over the growing season, then applying a light use efficiency constant, ε_N, we can estimate net primary productivity (Lobell *et al.*, 2002; Doraiswamy *et al.*, 2005). Values of ε_N vary across the literature in terms of spatial scale (Los *et al.*, 2000), ecosystem type (Ruimy *et al.*, 1994; Bradford *et al.*, 2005), vegetation type (Sinclair & Muchow, 1999; Turner *et al.*, 2002b), and crop type within agricultural systems (Gower *et al.*, 1999; Bradford *et al.*, 2005; Lindquist *et al.*, 2005; Singer *et al.*, 2011) due to physiological differences in photosynthetic pathways (Turner *et al.*, 2002b).

The distinction between crop productivity and crop yield is that productivity is a function of the biophysical plant canopy characteristics, and crop yield is a function of management. Biological productivity is the measured or modeled amount of above ground biomass, and is a product of the amount of light intercepted and the ecophysiological conditions of the crop canopy. Crop yields are a function of crop cultivar, equipment (cut height), economics, environment, plant age and condition, moisture content, and harvest index (Serbin *et al.*, 2009), and can vary across geographic and economic regions. Advances in biotechnology through crop breeding have led to increased carbon allocation from vegetative (shoots, leaves, roots) to reproductive (grain) crop components, resulting in increased Harvest Index (HI) values (Prince *et al.*, 2001). HI represents the ratio of harvested grain mass to total green biomass, and in this study, corn and soybean were assigned a harvest index value of 0.55 and 0.4, respectively (Prince *et al.*, 2001; Lobell *et al.*, 2002). The distinction between productivity and yield is important because this study uses the best approximation for crop productivity; farmer reported yields, to validate the satellite-derived productivity estimates.

The objective of this study is to model canopy dynamics and estimate crop yields from satellite observations in corn and soybean agroecosystems in Wisconsin. The specific objectives of this research include to 1) accurately estimate biophysical canopy characteristics of corn and soybean fields using satellite derived vegetation indices, 2) develop algorithms for linking empirical measurements with satellite data products for determining crop yields on multiple spatial scales, and 3) validate the accuracy of these algorithms by comparing derived yield values to farmer reported yields.

I hypothesize that f_{APAR} derived from NDVI, EVI, $CI_{GREEN,}$ can accurately predict canopy phenology of corn and soybean agroecosystems in Wisconsin, when derived from LANDSAT remotely sensed data. I hypothesize that, when coupled with a local LUE model, aggregated f_{APAR} can accurately estimate crop productivity in corn and soybean fields in Wisconsin. Methods of estimating crop dynamics and crop productivity can be validated through comparison of the VI temporal profiles with field sensor f_{APAR} observations, and by comparing VI-derived yields with farmer reported yields.

2. Methods

2.1 Study Area

The Driftless region of Wisconsin is characterized by rolling hills, steep slopes and deep valleys, and a heterogeneous mix of farms, forests, and high quality habitat for game and fish species. Annual precipitation ranges from approximately 2.5 to 11.8 cm month^{-1} throughout the year, with annual average temperatures of 44° F ± 2° (http://www.aos.wisc.edu/). Three corn and three soybean fields were selected in Dane and Iowa Counties in southwest Wisconsin for the 2010 and 2011 studies. Fields of sufficient size were required so as to contain multiple LANDSAT 30m pixels within their boundaries. One field in Grant County adjacent to the Grant-Iowa County border was included in 2010 due to its availability and landowner cooperation. Fields across a gradient of soil types and topography were selected (Table 2) based on availability and access permission. All fields were corn or soybean crops in an annual corn-soybean rotation, and ranged in size from 60 to 170 acres.

2.2 f_{APAR} Field Measurements

Light sensors were deployed from mid to late April until late September (DOY 147 - 260 in 2010, DOY 136 - 280 in 2011) in order to measure f_{APAR} intercepted by the canopy. Shortly after crops were planted and before plant emergence occurred, four Li-Cor LI-191SA Line Quantum Sensors were installed in each field, where continuous measurement of light within the PAR spectrum falling on the sensor was aggregated on an hourly time step throughout the growing season (photon density m^{-2} s^{-1}). Three sensors were situated on the ground perpendicular to crop rows and one was perched atop a tower approximately four meters off the ground and was oriented in the same direction as the sensors. Continuous hourly measurements of incoming PAR, soil temperature, and soil moisture were recorded to the internal memory of a Campbell Scientific CR23X data logger. Soil temperature was measured using a thermocouple soil temperature probe while soil moisture was recorded using a Theta soil moisture probe.

To minimize random experimental error, field sites were visited on a weekly basis to check the condition of the sensors and equipment (e.g. to ensure the sensors are intact, cables are not chewed through, tower is upright), and observations were recorded in a field journal. Observations of canopy height and crop condition, and photographs of crop canopy greenness were also recorded and were later checked against the sensor data to flag and correct erroneous values in the dataset. The data recording system remained in place until the crop canopy senesced prior to harvest, after which time the towers were disassembled and sensors removed (Serbin *et al.*, 2009). The growing season was defined as the time between crop emergence and when the crop canopy is mostly senesced.

2.3 Field Data Processing and Analysis

Fraction of intercepted PAR (f_{IPAR}) was calculated using both the ground and tower measurements of incoming PAR. Because of the dense and homogeneous nature of corn and soybean canopies, f_{IPAR} is assumed to be a reasonable approximation of fraction of absorbed PAR (f_{APAR}) and it will be referred to as f_{APAR} throughout this study (Daughtry *et al.*, 1992; Gower *et al.*, 1999). Data analysis began with cleaning and processing the data by removing measurements taken at night and those that met the following criteria (Serbin et al., 2009):

i. $PAR_{above} < PAR_{below}$

ii. $PAR_{below} < 0$

Dropped values within the growing season were linearly interpolated, however continuous missing data points did not exceed five consecutive days. Daily f_{APAR} was then calculated for each field over the course of the growing season using the following equation:

iii. $f_{APAR} = (PAR_{above} - PAR_{below})/PAR_{above}$

where PAR_{above} is the incident downward PAR above the canopy, and PAR_{below} is the incident downward PAR below the canopy. All data were processed and analyzed using R statistical software.

2.4 Remote Sensing Data Processing and Analysis

The multispectral and multi-temporal remote sensing dataset included 2010 - 2011 LANDSAT 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) images covering the same spatial and temporal extent as the study fields. Both TM and ETM+ images were used to maximize the number of cloud-free scenes over the study fields. These images underwent level 1G systematic radiometric and geometric correction prior to acquisition, and atmospheric correction using the Landsat Ecosystem Disturbance Adaptive Processing System algorithm (LEDAPS) (Alganci *et al.*, 2014).

TM and ETM+ data are available at a minimum 16-day temporal frequency, and some images were omitted due to cloud cover or line drops over the field site locations. LANDSAT images taken at or near time of planting and before the onset of senescence were also collected. Images with significant cloud contamination were omitted, and all grassy waterway and non-productive land pixels were excluded from the analysis to prevent the contribution of non-crop pixels to the yield estimates. ArcGIS was used to delineate the field boundaries and ENVI was used to calculate the VI values within a subset of those boundaries. A sample rectangle area was constructed within the field boundaries where the field sensors were deployed and pixels of interest were extracted from these areas. Reflectance values for each site were calculated by averaging all the per-pixel values within the polygon and paired with the f_{APAR} observation of the same location and day-of-year. In total, 27 images were compiled for the cornfields and 29 images were compiled for the soybean fields.

Best-fit linear and non-linear models between the vegetation indices and field f_{APAR} observations were calculated. Each crop-specific equation of the regression model was applied to VI observations within the extracted field boundaries to calculate daily f_{APAR}. This step is the most significant of the calculations as it provides the linkage between satellite and field measurements.

2.5 Light Use Efficiency Model

The Epsilon LUE model for calculating crop productivity incorporates the following equation (Daughtry *et al.*, 1992):

$$\text{iv. } NPP = (\sum APAR) * \varepsilon_N$$

Where NPP is the net primary productivity, or amount of carbon produced over the course of the growing season [gC m^{-2}], ε_N is the crop dependent light use efficiency constant [gC MJ^{-1} PAR], or the mass of carbon fixed per unit of PAR absorbed. ∑APAR is the cumulative absorbed PAR over the course of the growing season [W m^{-2}]. Methods for calculating APAR are described in (Daughtry *et al.*, 1992; Gower *et al.*, 1999).

Crop-specific ε_N coefficients used in this study were derived from field studies across the upper Midwest (Gower *et al.*, 1999; Sinclair & Muchow, 1999; Turner *et al.*, 2002b; Bradford *et al.*, 2005; Lindquist *et al.*, 2005; Singer *et al.*, 2011). ε_N estimates for soybean and corn crops were assigned values of 1.6 and 3.8, respectively, and were multiplied by ∑APAR to calculate seasonal NPP. Fields in this study were not irrigated but were fertilized with nitrogen two times during the growing season (Farmers, personal communication), so fields were not considered to be nitrogen or water limited during the 2010 - 2011 growing season.

Estimating crop yields incorporates the amount of harvestable grain through the harvest index (HI), moisture content of crops at harvest (MC), and allocation of above and belowground biomass (AL). Farmers provided at-harvest moisture contents for each crop along with their yield reports, and AL values were provided by compilations of field measurements in the literature (Xin et al., 2013). The model then applied HI to the estimated NPP to calculate crop yields (Alganci *et al.*, 2014):

$$\text{v. Crop Yield} = \text{NPP} * \text{HI} * \text{MC} * \text{AL}$$

This yield model was applied to both empirical f_{APAR} data and VI-derived f_{APAR} for all six sites for both growing seasons. Estimated yields were then compared against farmer reports to estimate the accuracy of this model. Two of the farms provided spatially explicit yield maps, and yield values were extracted from the locations of the sensor clusters. They served as validation points for testing the relationship between field f_{APAR} and crop yields.

3. Results

3.1 Estimates of Canopy Characteristics

Both NDVI and f_{APAR} captured the seasonal patterns of corn and soybean canopies by simulating canopy emergence, leaf expansion, and canopy closure (Figure 1). In the soybean profile, we observe canopy senescence through the decreasing values after approximately DOY 250. Over all soybean canopies, f_{APAR} reaches a maximum 0.99 around days 205 - 210, while NDVI reaches a maximum 0.95 near day 220. In corn canopies, f_{APAR} peaks at 0.99 near day 200, while NDVI peaks at 0.94 near day 193. Full canopy is represented by both NDVI and f_{APAR} as they approach 1.0. f_{APAR} decreases as the canopy senesces in both crops, however the decrease is more pronounced in the soybean canopy than in corn, where we observe a drastic decrease in greenness in parallel with a decrease in light interception. In the corn canopy we observe a late season separation of f_{APAR} and NDVI as the canopy senesces.

Both EVI and f_{APAR} captured the seasonal patterns of corn and soybean canopies by simulating the increase in light interception during canopy emergence, leaf expansion, and canopy closure (Figure 2). Over all soybean canopies, EVI reaches a maximum 0.95 near day 241. In corn canopies, EVI peaks at 0.87 near day 193. Full canopy is represented by both EVI and f_{APAR}, as they approach 1.0.

When taking the natural log of CI_{GREEN}, we observe that it displays the same temporal patterns of canopy growth as f_{APAR} (Figure 3). CI_{GREEN} and f_{APAR} captured the seasonal patterns of corn and soybean canopies during canopy emergence, leaf expansion, and canopy closure. Over all soybean canopies, $\ln(CI_{GREEN})$ reaches a maximum 2.97 near day 232. In corn canopies, $\ln(CI_{GREEN})$ peaks at 2.73 near day 193. Full canopy is represented by both $\ln(CI_{GREEN})$ and f_{APAR}, as they approach 3.0 and 1.0, respectively.

NDVI and EVI displayed a late season separation between the VI and f_{APAR} in corn canopies, but not in soybean canopies. In soybean canopies we observed a tandem decrease in both VI and f_{APAR} values during the late season.

3.2 Algorithm Development

Because of their distinct photosynthetic pathways and variation in crop management, the relationships between f_{APAR} and VI for corn and soybean crops were estimated using separate equations. These equations were determined for all field observations pooled by crop type.

Figures 4 and 5 display f_{APAR} field observations plotted against NDVI values obtained from TM and ETM+ data. Linear relationships between both observations are significant ($p < 0.05$) and show good agreement, with coefficients of correlation (R^2) greater than 0.8 for both crops. Patterns of scatter for both crops are similar in that they are more heavily weighted towards late season NDVI. However, the scatter patterns vary slightly with soybean having more observations present during mid-season than corn crops.

Figures 6 and 7 display f_{APAR} field observations plotted against TM and ETM+ derived EVI values, with a linear relationship demonstrating the best fit between them. Linear relationships between both observations are significant ($p < 0.05$) and show good agreement, with $R^2 > 0.85$ for both crops. Qualitatively, patterns of scatter for both crops are similar in that there are more EVI observations at higher values, which occurred mid to late season before senescence.

f_{APAR} field observations plotted against CI_{GREEN} values obtained from TM and ETM+ data are displayed in figures 8 and 9. Non-linear relationships between both observations are significant ($p < 0.05$) and show good agreement, with coefficients of correlation (R^2) of 0.8 and 0.6 for corn and soybean, respectively. The patterns of scatter for both crops are similar and we observe a good spread of observations across the growing season.

When regressing satellite derived vegetation indices against field f_{APAR} measurements, significant correlations were observed (Table 3). EVI and NDVI are both related linearly to f_{APAR} observations, while CI_{GREEN} displayed a logarithmic relationship with empirical observations. Performance of each algorithm by crop type was evaluated by their fit to field data (coefficient of determination, R^2) and root mean squared error (RMSE). Equations for estimating corn f_{APAR} from EVI, NDVI, and CI_{GREEN} accounted for 86, 85, and 80 percent of variability, and these model predictions reported RMSE of 0.11, 0.07, and 0.13, respectively. Similar patterns of explaining variability were observed in soybean f_{APAR} data with EVI, NDVI, and CI_{GREEN} explaining 91, 84, and 61 percent of the soybean f_{APAR} variability. Predicted variables had RMSE of 0.08, 0.08, and 0.17, for EVI, NDVI, and CI_{GREEN}, respectively. Overall, EVI and NDVI performed equally well in predicting corn f_{APAR} values, while EVI emerged as the best predictor of soybean $f_{APAR.}$ CI_{GREEN} ranked last for both crops in terms of best fit to field data.

3.3 Yield Estimates

Across all corn sites, NDVI generated the highest crop estimates, followed by CI_{GREEN}, then EVI (Figure 10). Across all soybean sites with the exception of 4.11, NDVI generated the highest crop estimates, followed by CI_{GREEN}, then EVI (Figure 11). The range of variation across VI methods was less for soybeans than that for corn, and all estimate variation was less than that of the reported yields. Variance for NDVI corn estimates was 0.9 t ha^{-1}, 3.0 t ha^{-1} for EVI, and 0.9 t ha^{-1} for CI_{GREEN}. Variance for NDVI, EVI, and CI_{GREEN} estimates were all 0.1 t ha^{-1}. Variance of reported corn and bean yields were 3.7 and 0.2 t ha^{-1}, respectively.

All estimated yields fall within the reported range of yields for all corn sites (Table 4). Ranking the VI estimates in order of lowest to greatest relative error was CI_{GREEN}, NDVI, then EVI, with a reported relative error from mean of 15, 17, and 20, respectively. All three VI overestimated and underestimated yields with equal frequency over all sites. Mean reported yields from site 6.11 were extremely low in 2011, so when removed from the pool of results, the relative error of CI_{GREEN}, NDVI, and EVI is 8, 9, and 14, respectively.

All estimated yields fall within the range of farmer reported yields for all soybean sites as well (Table 5). Ranking the VI estimates in order of lowest to greatest relative error was CI_{GREEN}, EVI, and NDVI with a reported mean relative error of 12, 13, and 14, respectively. All three VI indices overestimated and underestimated yields with the same frequency over all sites.

3.4 Sensor PAR and Reported Yield Map Yields

Supporting evidence for the relationship between f_{APAR} yields and farmer reported yields is shown by figures 12 and 13, where two farmer-reported soybean yield maps were compared against sensor-estimated yields. There is good correlation between estimated and observed yields for both fields, with estimates explaining approximately 90% of the variability. When comparing yield map observations with VI estimates, all VI underestimated reported yields by 22% or less. These few reported yields were extracted from the only available spatially explicit yield maps provided by the farmers.

4. Discussion

This study provided evidence that NDVI, EVI, and CI_{GREEN} all provided suitable estimates of the crop canopy growth patterns and distinct growth phases of green up, maturity, and senescence when compared with the temporal profiles of field f_{APAR} observations. The present analysis provided VI-derived yield estimates that all fell within the range of farmer reported yields, providing a suitably accurate means of estimating crop yields. However it did not consistently track crop minima and maxima across the VI predictions. The source of the discrepancy between estimates and reported yields is twofold: the accuracy of this method is limited by the availability of spatially explicit yield reports from farmers for more precise validation, and the underlying model assumes a constant light use efficiency constant across the growing season and across crop cultivars.

Distinguishing photosynthetically active plant matter from plant matter that is senesced is critical to making yield estimates. Inclusion of non-photosynthetically active plant matter can lead to yield overestimates, and it is a challenge to determine the end date of the growing season using f_{APAR} alone. We observed that late season f_{APAR} values do not make a distinction between green and senesced plant matter, however vegetation indices provide us with the distinction in certain canopy types (Wiegand *et al.*, 1991). We observed a late season separation between VI estimates and f_{APAR} observations in the corn canopies, but not in soybean canopies. This can be attributed to the differences in crop leaf architecture between the two crops. As a corn plant senesces, the amount of chlorophyll in the leaves decreases, but the robust stem and leaf matter continue to intercept PAR. This contributes to sustained closed canopy f_{APAR} values while the greenness signals captured by satellite imagery decrease, which can lead to contribution of non-photosynthetic measurements to the overall yield estimates. We do not observe this separation in soybeans because leaves not only lose chlorophyll rapidly as the crop senesces, but the less robust stems and leaves drop, allowing PAR to penetrate the crop canopy. These differences in crop canopy architecture are revealed in the temporal patterns of VI, and can contribute to crop type identification when conducting broad scale agricultural productivity analyses.

A limitation to acquiring more usable LANDSAT imagery during the early growing season is the frequent cloudy conditions over the field sites. Of the 53 available LANDSAT images over the study sites, 7 were omitted due to interference by thick cloud cover, even with the use of atmospheric correction. These temporal omissions can be improved by employing appropriate interpolation methods to the available image set. This study applied linear interpolation methods to estimate daily-derived f_{APAR} values. However, this method could be improved by applying the piecewise logistic growth function as reported by Zhang *et al.*(2003) to early season canopy values, so that growth phases of green up to maturity can be more accurately captured. The distinctions among vegetation index derived yields can be better described when we have more behavior to observe during the early growing season, particularly the variation in spectral interaction with ground surface characteristics. The spectral reflectances of soils are distinct from those having vegetative cover, particularly in the blue, red, and near-infrared bands.

4.1 *Relationships Between Field f_{APAR} and VI Observations*

Linking equations between satellite data and crop canopy conditions are central to extracting information about crop yields and canopy characteristics. The linear and non-linear relationships observed between VI and f_{APAR} measurements provided strong supporting evidence for the use of VIs as a suitable medium for deriving f_{APAR}. EVI and NDVI are related linearly to f_{APAR} observations, while CI_{GREEN} displayed a logarithmic relationship with empirical observations. Equations for estimating corn f_{APAR} from EVI, NDVI, and CI_{GREEN} accounted for 86, 85, and 80 percent of variability in f_{APAR}, which is suitable for our purposes. The linear relationships between EVI and f_{APAR} and NDVI and f_{APAR} lend themselves to a more computationally efficient process for supporting the use of VI based yield predictions. We have congruity in time scales between f_{APAR} and satellite-derived f_{APAR}, and all equations displayed low RMSE for both crops.

As crop canopies enter the reproductive phase, vegetation allocation decreases and photosynthate is allocated towards the reproductive plant components. In this study, observations following a peak VI value were not included in the calculations to ensure that all observations included were those capturing canopy photosynthesis. In addition, VI observations too early in the season (pre-planting) and too late into senescence were omitted from analysis, as they do not reflect the crop canopy’s photosynthetic characteristics.

A potential source of error can be attributed to the lack of evenly spaced acquisition of VI data across the growing season. For all VIs, more usable images were incorporated later in the growing season. Images without significant thick cloud cover were difficult to extract for the study region, resulting in an undersampling of VI values early in the growing season. Further exploration into the performance of each VI can be further examined by incorporating sensor specific yield reports against which VI derived yields can be compared, and error can be measured.

4.2 Light Use Efficiency Model Performance

Because of changing climate, environmental, and phenological factors over the growing season, a crop's LUE will change. In addition to improvements such as nitrogen use efficiency, pest resistance, and enhanced crop productivity, advances in biotechnology have also increased light use efficiency of many crop cultivars. In order to maintain accurate yield estimates into the future, it will be necessary to update light use efficiency models to keep up with crop cultivar productivity characteristics used by farmers in their operations. Many methods of estimating crop yields using a fixed LUE constant fail to capture this complexity, and this can result in errors because of the dynamic effects fertilizer, irrigation, and other management practices have on crop yields (Doraiswamy *et al.*, 2005). Incorporating environmental limitations such as temperature and soil moisture will further improve these LUE estimates.

Another source of error between reported and estimated yields is the use of varying crop cultivars within crop species types and variation in cultural management. Management practices such as planting density, time and magnitude of fertilizer and pesticide application, or irrigation influence crop productivity, which can, in turn, influence the spectral response of the canopy. Cultural practices (planting density, fertilizer application), canopy architecture (leaf angle, canopy openness, and height), are all contributors to variation in spectral response of crops that are incorporated into the reflectance signal. However, when conducting broad scale crop yield assessments (e.g., statewide or multi-state), the acquisition of such field-specific data is infeasible.

4.3 VI Estimated Yields

There were not large differences among NDVI, EVI, and CI_{GREEN} estimated yields. The difference in relative error across the three methods was 5% for corn and 2% for soybeans. The lack of significant difference across the methods of predictions could be accounted for in part by the lack of more explicit and less variable crop yield reports. However, when we compared estimated yields against yield maps from two soybean sites, we did observe that all VIs underestimated yields, with NDVI having smallest relative error (7%) followed by CI_{GREEN} (8%), then EVI (21%).

There was less variation across soybean yield predictions than there was for corn yield predictions. This could be attributed to more accurate capture of the soybean canopy dynamics within the predictive algorithm. Because of the separation between f_{APAR} and VI pixel values late in the soybean growing season, it was easier to distinguish between the days in which the canopy was photosynthesizing and when the canopy entered senescence. This resulted in an algorithm that included values only when the canopy was photosynthesizing.

Because all three VI methods do a suitable job of estimating the crop canopy growth phase patterns, it is important to ensure that the early season characteristics are captured. In order to get more precise VI estimates, we will need to obtain more early-season imagery to capture the variation in how the ground surface interacts with the spectral characteristics of each vegetation index.

While the predictions can be improved by having more spatially explicit validation data and more complete interpolation of early season VI data, this method that involves a model based entirely on satellite data is still robust in estimating crop yields. This study confirms that LANDSAT derived VI can serve as reliable means of predicting crop yields for corn and soybean fields in Wisconsin. Because the original VI - f_{APAR} relationship is highly local, there are limitations to the spatial extent to which we can apply these f_{APAR} equations to crop fields. However, this method can be extended by comparing model estimates against additional field-level yield reports and county-level statistics. In addition, replication of this study against fields across a larger spectrum of edaphic, climate, and management conditions could further explore the application of this model to a more broad spatial extent. The performance of these VI derived f_{APAR} values in predicting crop canopy dynamics and crop yields is encouraging, and further research will do well to examine these relationships in greater detail. Continued exploration and application of the yield prediction models along with their strengths and weaknesses can improve our crop yield predictions and further our understanding of variability in crop dynamics.

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6. Tables and Figures

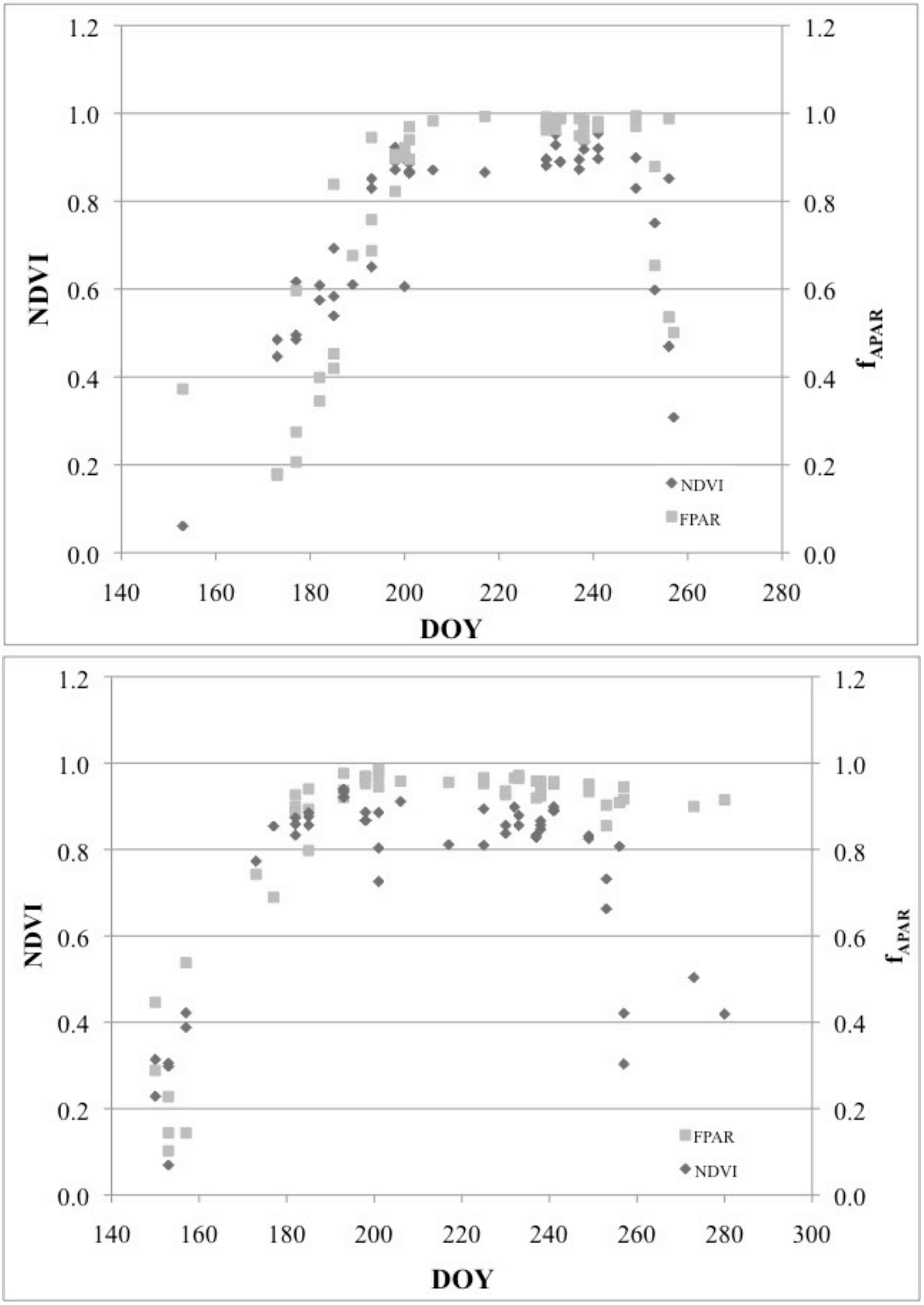

Figure 1. NDVI and f_{APAR} temporal profiles of soybean (top) and corn canopies (bottom) for all sites and both years.

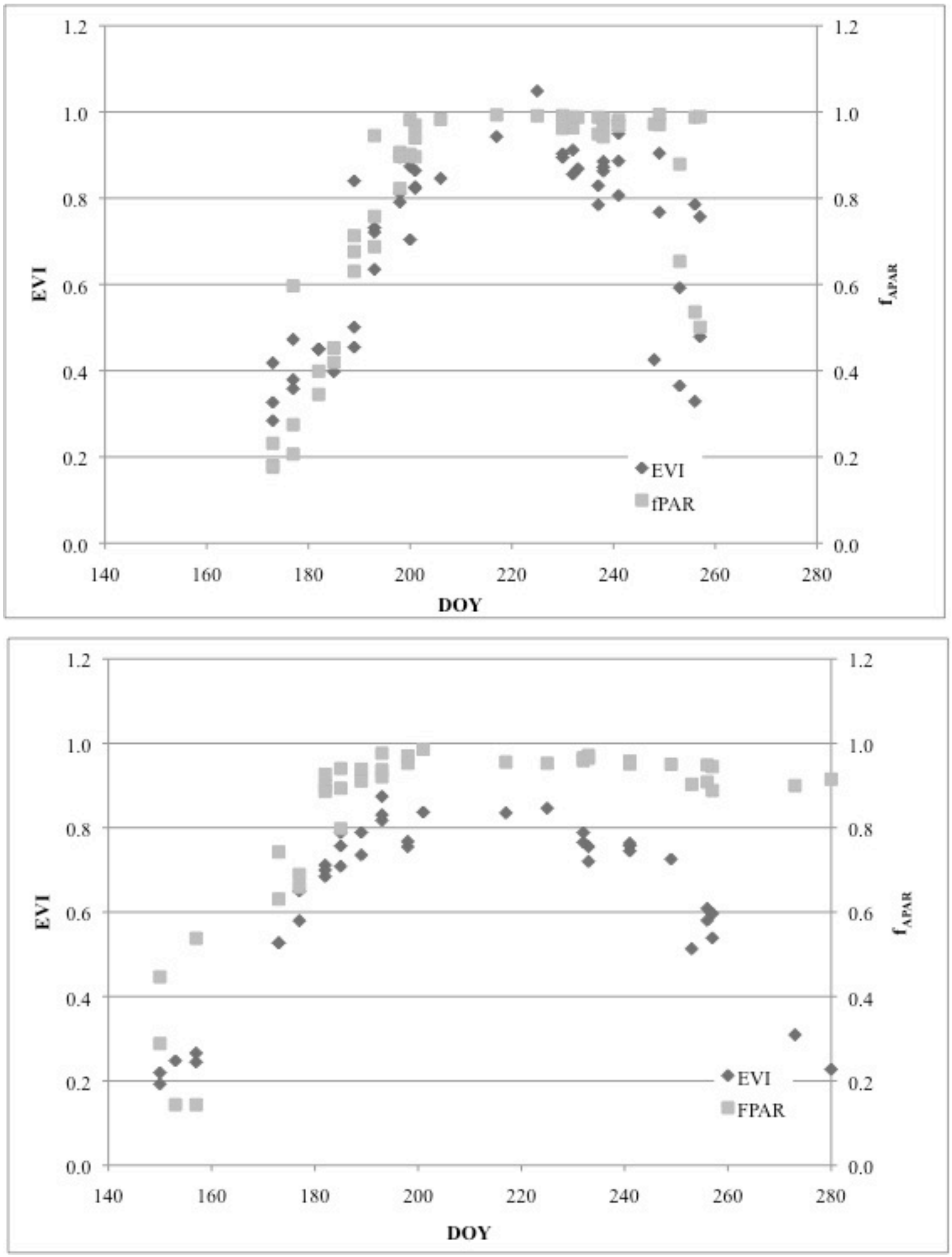

Figure 2. EVI and f_{APAR} temporal profiles of soybean (top) and corn canopies (bottom) for all sites and both years.

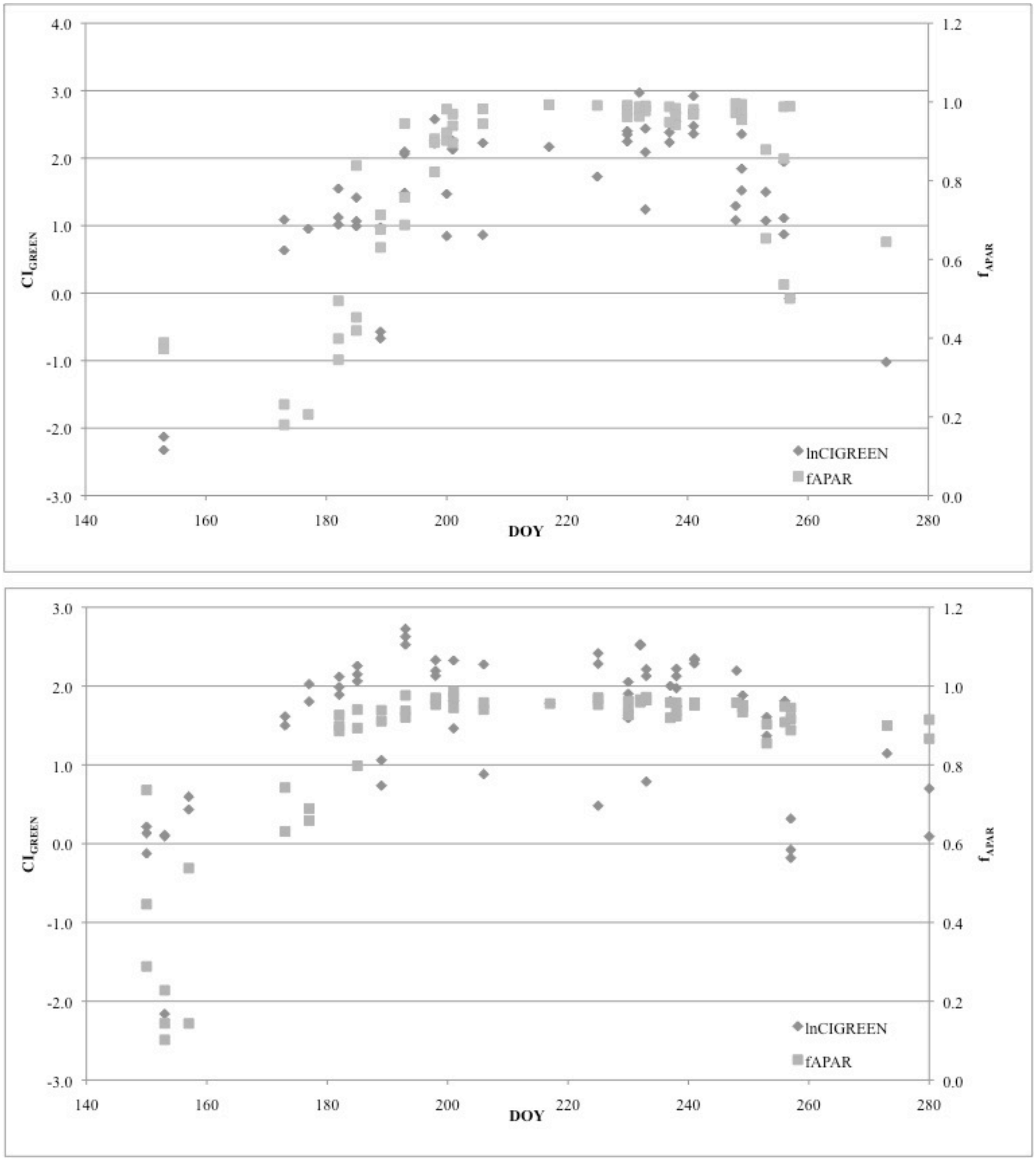

Figure 3. CI_{GREEN} and f_{APAR} temporal profiles of soybean (top) and corn canopies (bottom) for all sites and both years.

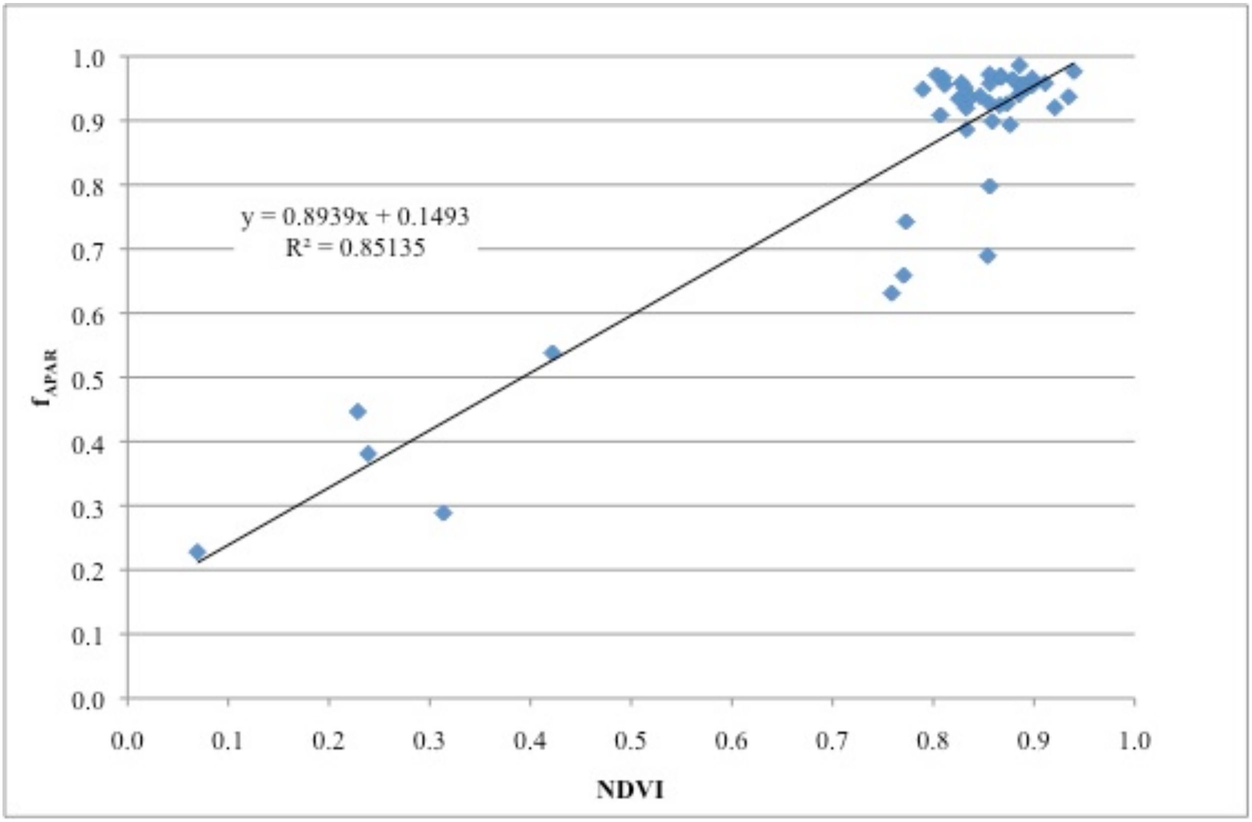

Figure 4. Linear relationship between NDVI and f_{APAR} in corn

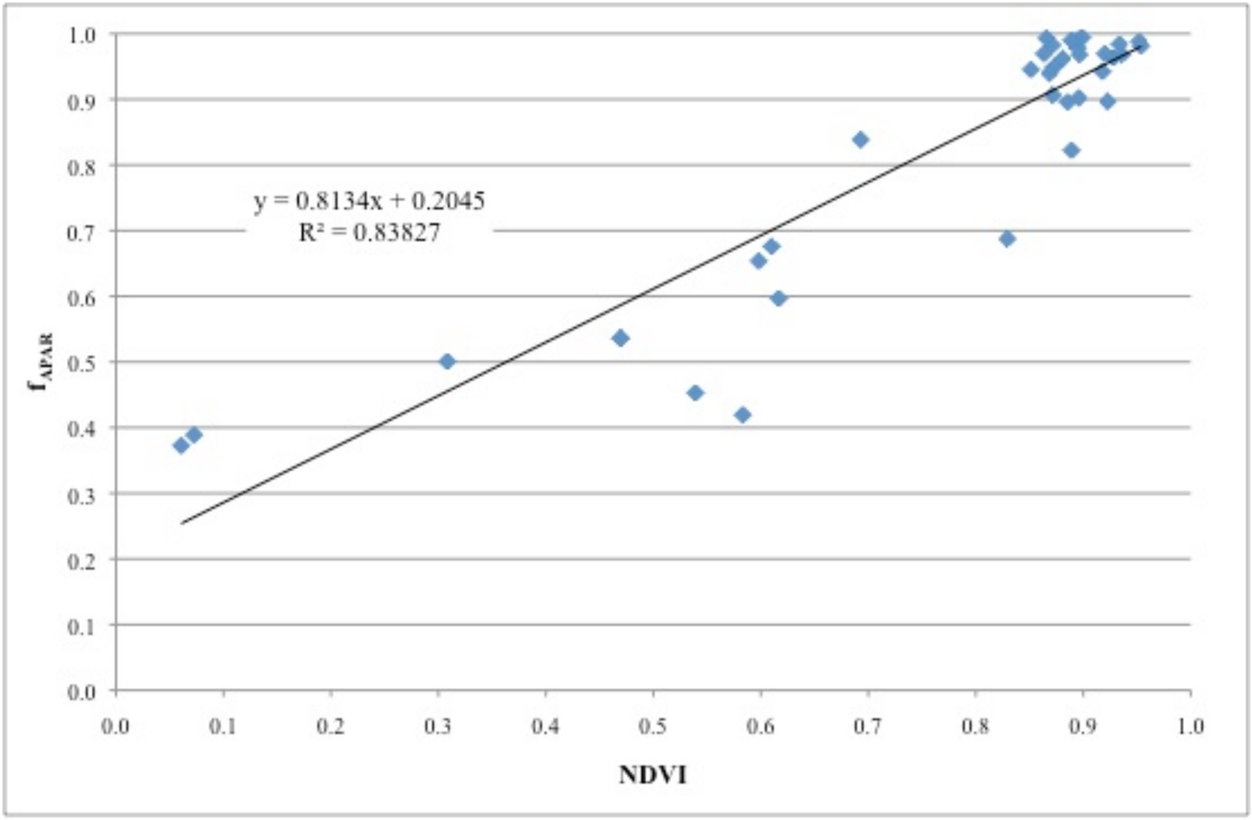

Figure 5. Linear relationship between NDVI and f_{APAR} in soybeans

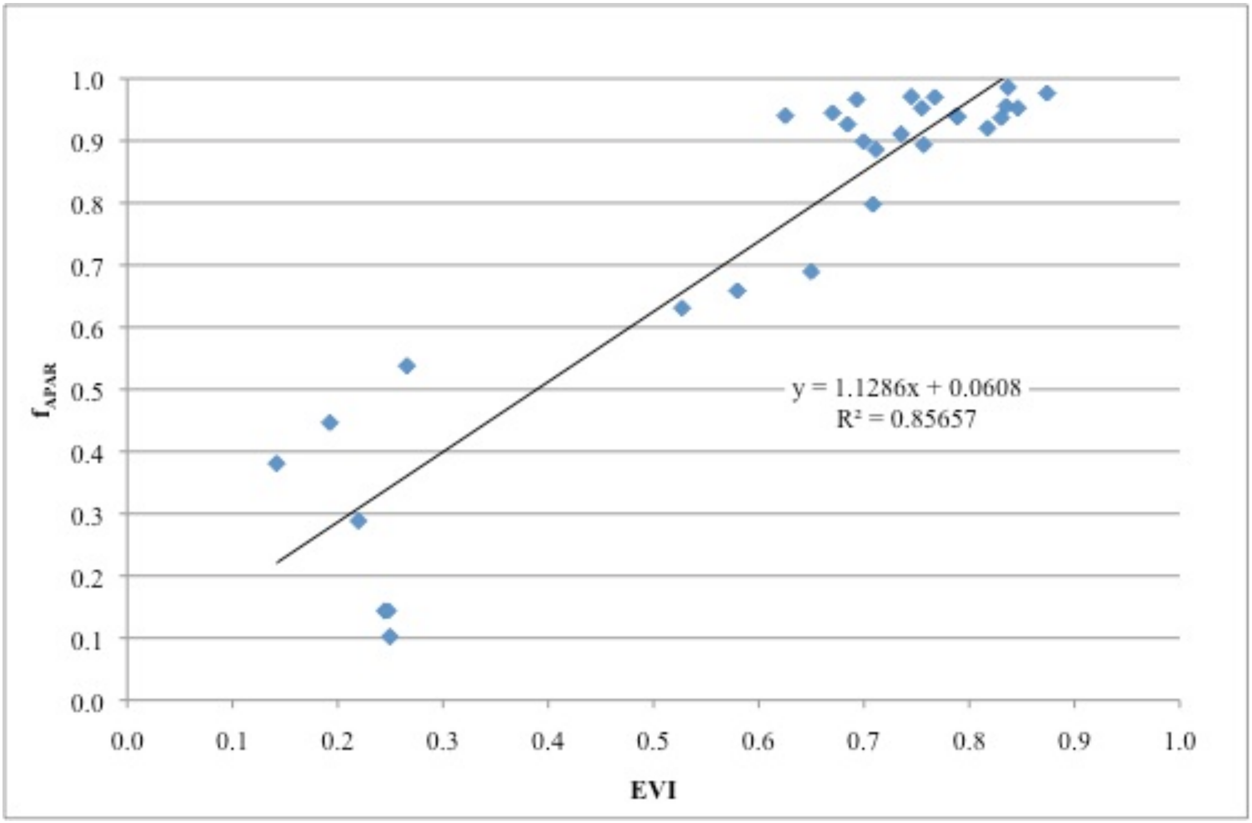

Figure 6. Linear relationship between EVI and f_{APAR} in corn

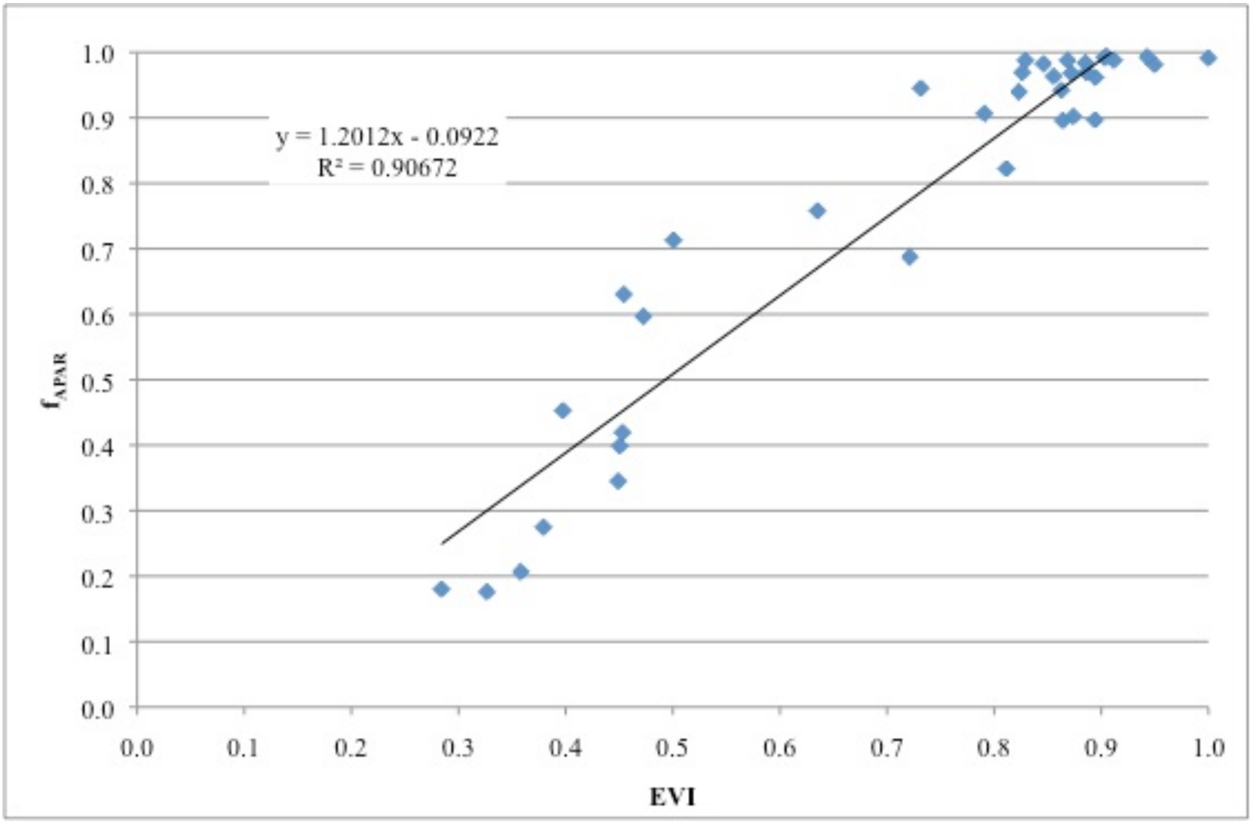

Figure 7. Linear relationship between EVI and f_{APAR} in soybeans

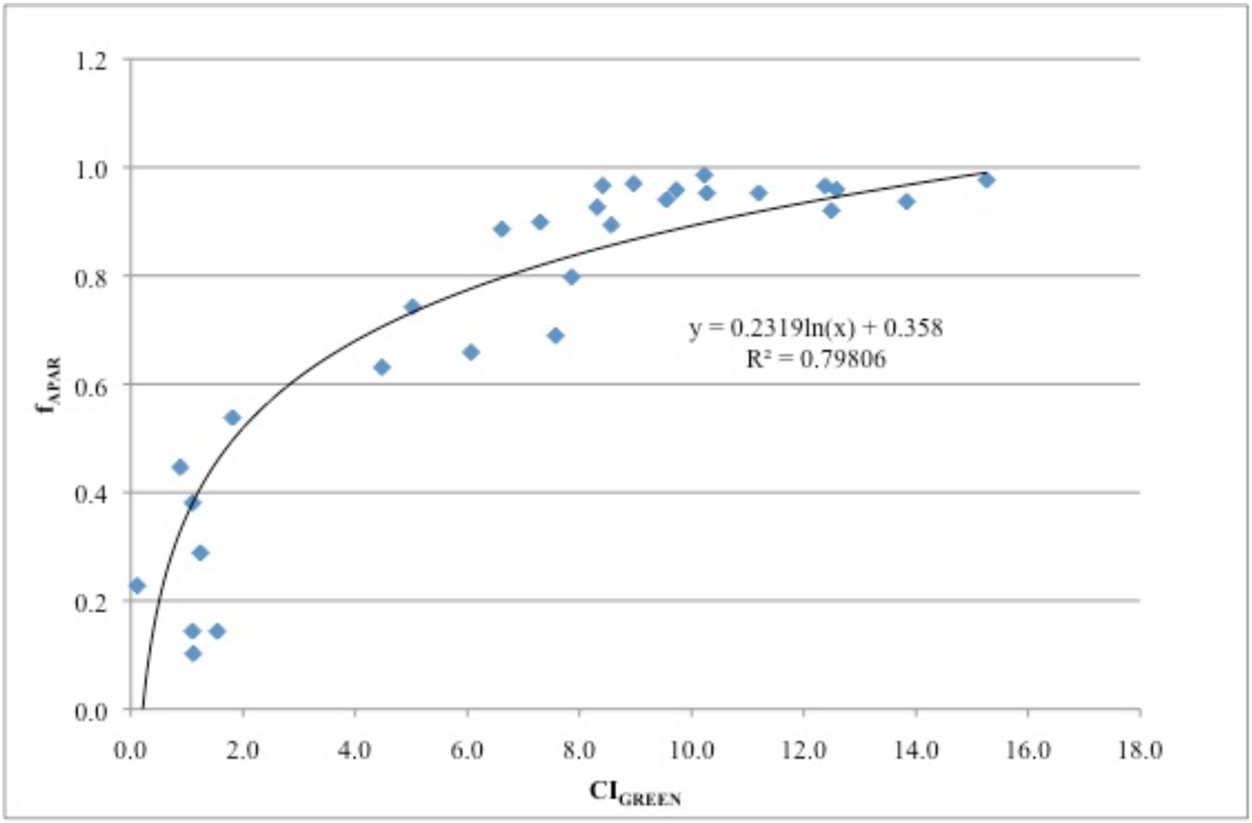

Figure 8. Non-linear relationship between CI_{GREEN} and f_{APAR} in corn

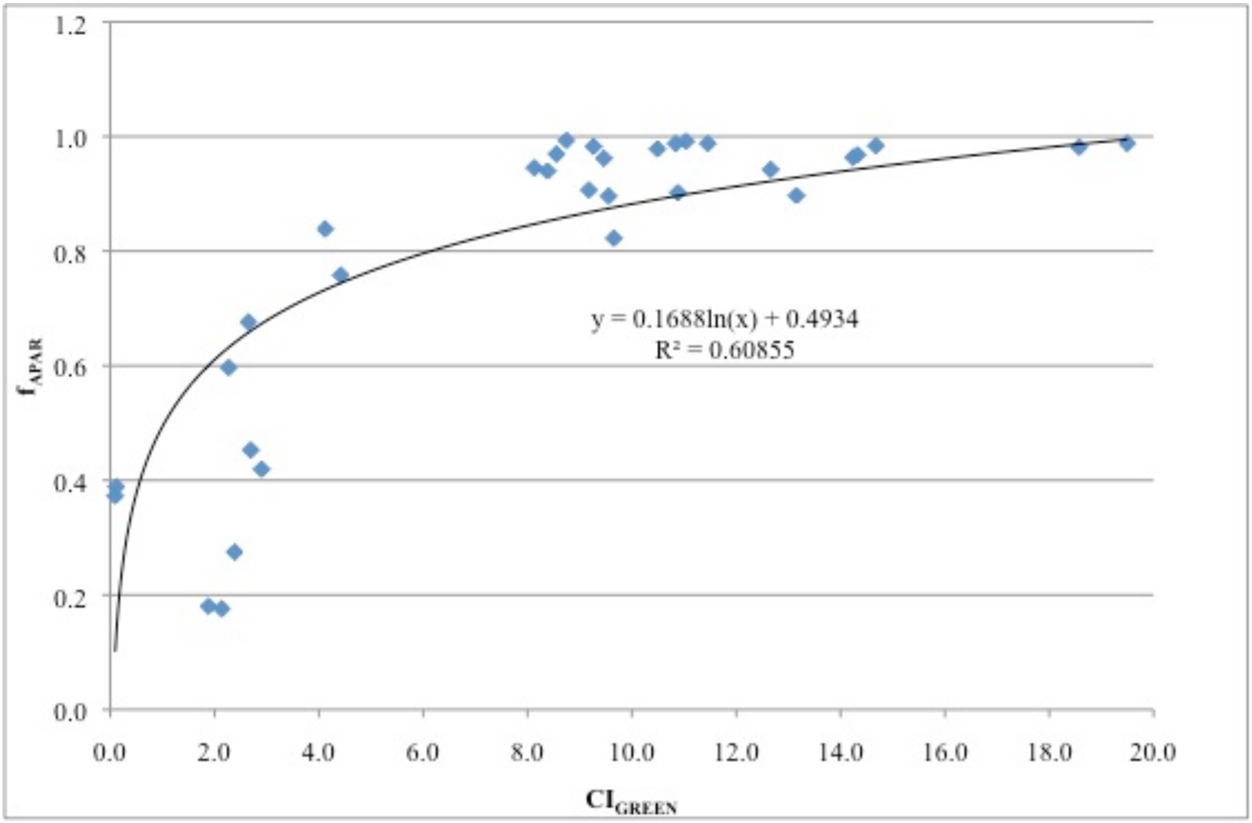

Figure 9. Non-linear relationship between CI_{GREEN} and f_{APAR} in soybean

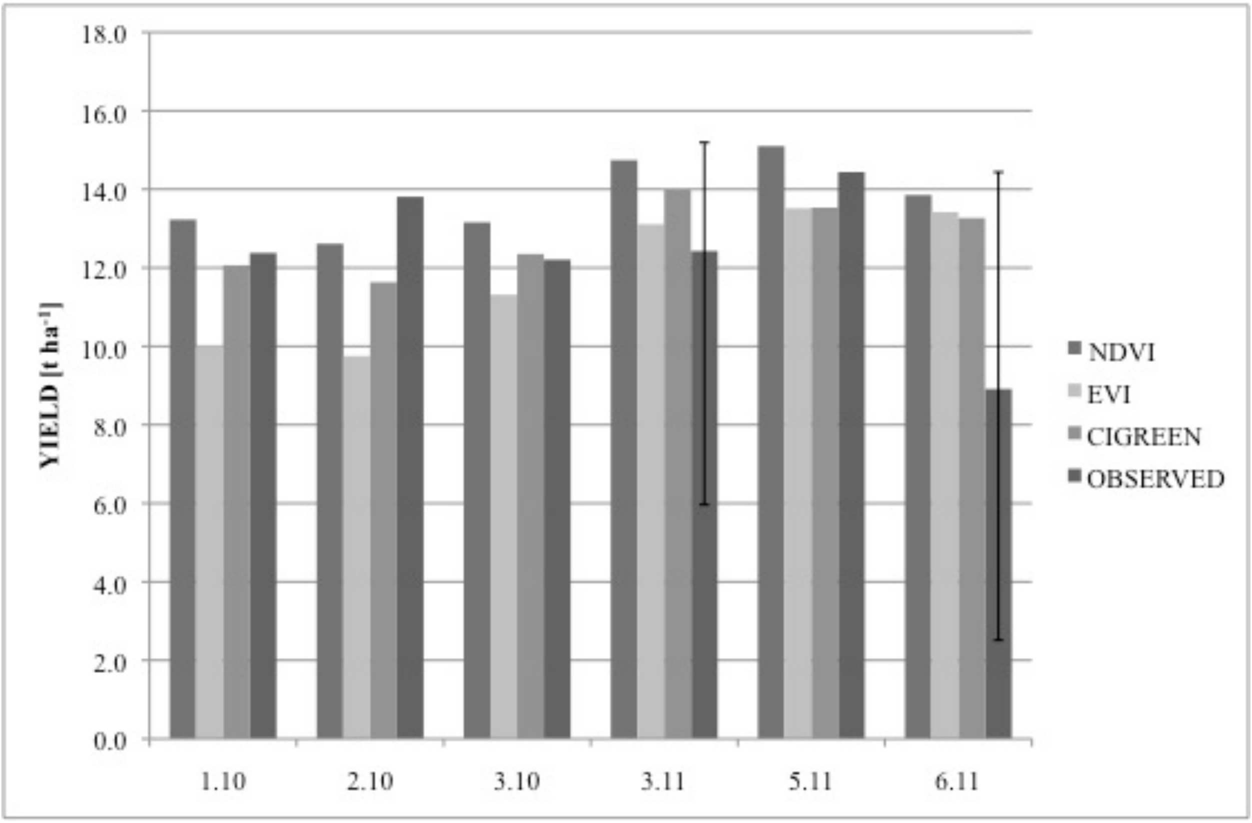

Figure 10. All corn yields as estimated by NDVI, EVI, and CI_{GREEN}, compared with observed yields for each field site. Bars represent range of farmer reported yields.

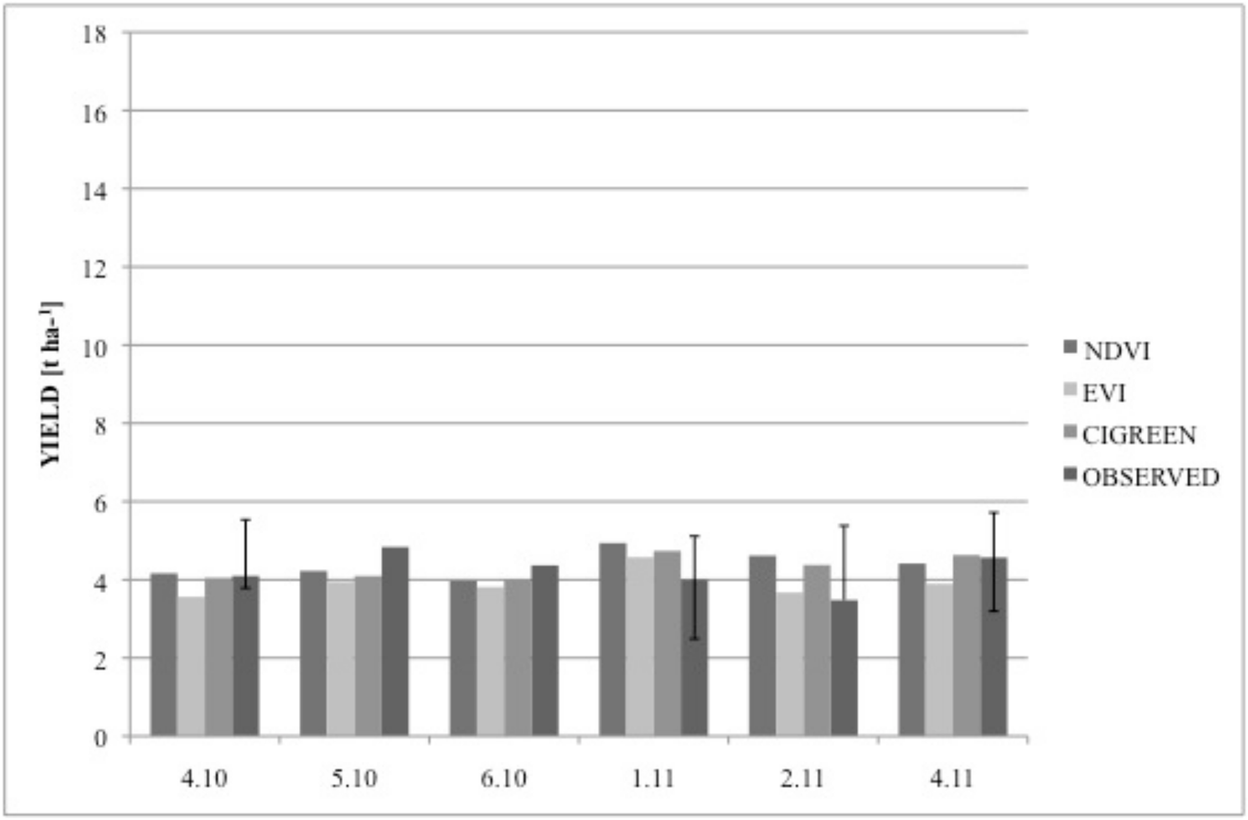

Figure 11. All bean yields as estimated by NDVI, EVI, and CI_{GREEN}, compared with observed yields for each field site. Bars represent range of farmer reported yields.

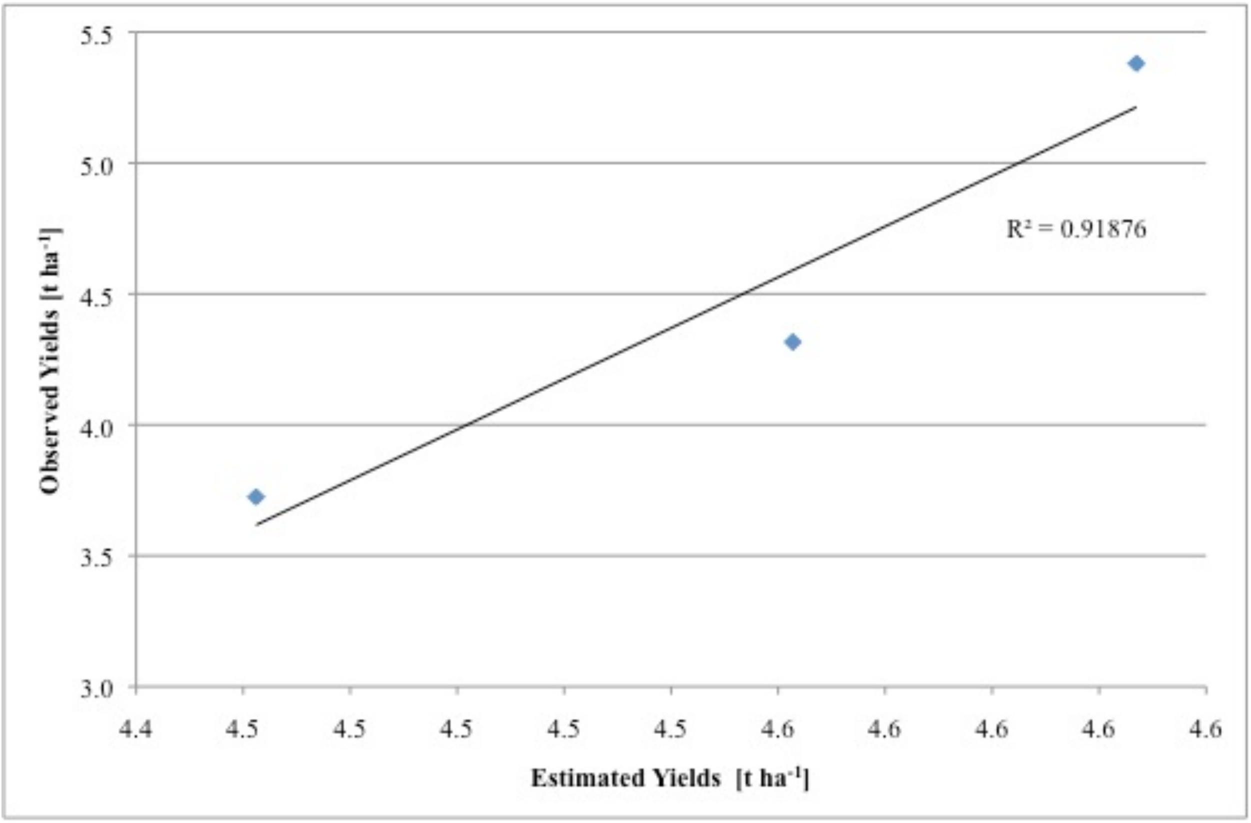

Figure 12. Comparison of f_{APAR} sensor derived yield estimates with farmer reported yields for soybean field site 2.11

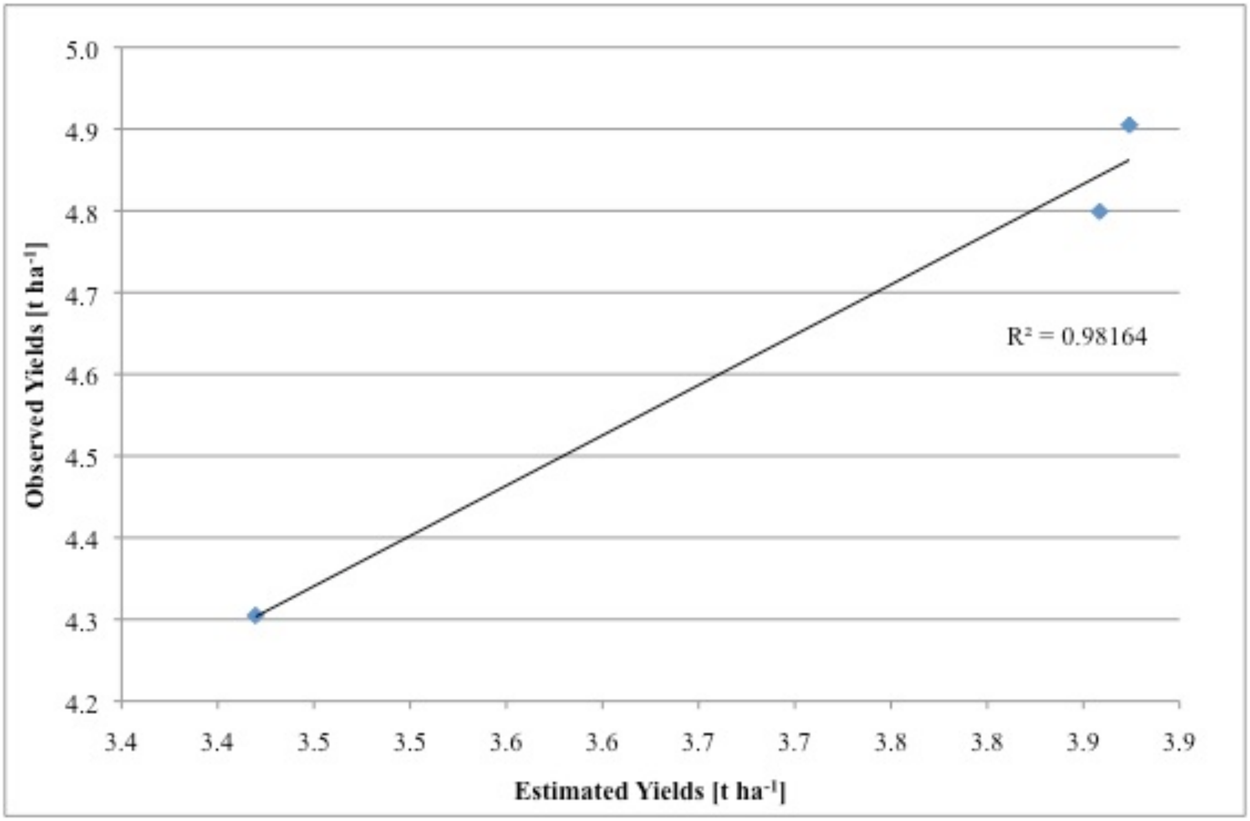

Figure 13. Comparison of f_{APAR} sensor derived yield estimates with farmer reported yields for soybean field site 4.10.

Table 1. Vegetation Indices derived from TM and ETM+ data and used in this study

Vegetation Index	Formula	Reference
Normalized Difference Vegetation Index (NDVI)	$(\rho_{NIR} - \rho_{RED})/(\rho_{NIR} + \rho_{RED})$	(Gitelson *et al.*, 2012)
Enhanced Vegetation Index (EVI)	$G\{(\rho_{NIR} - \rho_{RED})/[\rho_{NIR} + C_1(\rho_{RED}) - C_2(\rho_{BLUE}) + L]\}$	(Huete *et al.*, 2002)
Green Chlorophyll Index (CI_{GREEN})	$(\rho_{NIR} / \rho_{GREEN}) - 1$	(Gitelson *et al.*, 2012)

Where ρ represents atmospherically corrected surface reflectance, G represents the gain factor of 2.5, C_1 and C_2 are the coefficients for the aerosol resistance term 6.0 and 7.5 respectively, and L represents the canopy adjustment coefficient of 1.0.

Table 2. Location and Conditions of 2010 - 2011 Field Sites

Site Name	**Crop Type**	**Elevation (m)**	**Dominant Soil Type**
1.10	Corn	344	Dodgeville Silt Loam
2.10	Corn	329	Dubuque Silt Loam
3.10	Corn	326	Plano Silt Loam
4.10	Soybean	345	Tama Silt Loam
5.10	Soybean	342	Dodgeville/Tama Silt Loam
6.10	Soybean	245	Dickinson Sandy Loam/Spinks and Plainfield Loamy Sands
1.11	Soybean	344	Dodgeville Silt Loam
2.11	Soybean	329	Dubuque Silt Loam
3.11	Corn	326	Plano Silt Loam
4.11	Soybean	356	Tama Silt Loam
5.11	Corn	344	Dodgeville/Tama Silt Loam
6.11	Corn	245	Dickinson Sandy Loam/Spinks and Plainfield Loamy Sands

Table 3. Regression Relationship of VI and f_{APAR} field measurements

Crop Type	NDVI Regression Equation	R square	RMSE
Corn	$y = 0.894x + 0.149$	0.851, $p < 0.05$	0.0743
Soybean:	$y = 0.813x + 0.205$	0.838, $p < 0.05$	0.0820

Crop Type	EVI Regression Equation	R square	RMSE
Corn	$y = 1.129x + 0.0608$	0.857, $p < 0.05$	0.107
Soybean:	$y = 1.201x - 0.0922$	0.907, $p < 0.05$	0.0835

Crop Type	CI_{GREEN} Regression Equation	R square	RMSE
Corn	$y = 0.232*\ln(x) + 0.358$	0.798, $p < 0.05$	0.133
Soybean:	$y = 0.169*\ln(x) + 0.493$	0.609, $p < 0.05$	0.166

Table 4. VI derived estimated yields compared with farmer reported corn yields.

CORN	Estimated Yield [t ha^{-1}]			Observed Yield [t ha^{-1}]			Relative Error [%]		
SITE	NDVI	EVI	CI_{GREEN}	Mean	Min	Max	NDVI	EVI	CI_{GREEN}
1.10	13.2	10.0	12.4	12.4			6.9	19.2	2.5
2.10	12.6	9.8	11.6	13.8			8.7	29.0	15.8
3.10	13.2	11.3	12.3	12.2			7.8	7.4	1.2
3.11	14.7	13.1	14.0	12.4	6.0	15.2	18.6	5.5	12.5
5.11	15.1	13.5	13.5	14.4			4.6	6.5	6.3
6.11	13.9	13.4	13.3	8.9	2.5	14.4	55.4	50.5	48.8

Table 5. VI derived estimated yields compared with farmer reported soybean yields

SOYBEAN	Estimated Yield [t ha^{-1}]			Observed Yield [t ha^{-1}]			Relative Error [%]		
SITE	NDVI	EVI	CI_{GREEN}	Mean	Min	Max	NDVI	EVI	CI_{GREEN}
4.10	4.2	3.6	4.0	4.1	3.8	5.5	1.6	13.1	1.3
5.10	4.2	3.9	4.1	4.8			12.6	18.4	15.3
6.10	4.0	3.1	4.0	4.4			9.1	12.7	8.0
1.11	4.9	4.2	4.7	4.0	2.5	5.1	23.2	14.2	18.2
2.11	4.6	4.2	4.8	3.5		5.4	32.7	5.5	25.8
4.11	4.4	4.9	5.2	4.6	3.2	5.7	3.4	14.7	1.4

Chapter 5. Determining the biophysical and socioeconomic drivers of cellulosic bioenergy feedstock choice

Abstract

This research shows connections among the facets of land and operation characteristics, management practices and attitudes that farmers apply in their land use decisions around bioenergy. Two discrete logistic regression choice models were constructed to identify the socioeconomic and biophysical drivers of bioenergy feedstock choice. Results from mail surveys to farmers in Southwest Wisconsin revealed that there is predominant lack of interest to proposed corn stover or switchgrass feedstock programs, with 65% of farmers stating that they would not enroll in any of the proposed bioenergy feedstock programs. Among those who are willing to participate in a proposed corn stover management program, significant ($p < 0.10$) drivers of bioenergy feedstock choice included age, amount of open acreage, percentage of operational acres that are moderate to steeply sloped, having a history of water quality management on farm, and expressing a willingness to make tradeoffs in economic certainty for environmental benefit. Among those who are willing to participate in a proposed switchgrass management program, significant ($p < 0.10$) drivers included raising dairy cattle, age, having an income of $100,000 or greater, percentage of operational acres with marginal characteristics, history of soil quality management on farm, familiarity with switchgrass as a bioenergy feedstock, and an expressed willingness to make tradeoffs in economic certainty for environmental benefits. This research showed significant linkages between land characteristics and the choices the farmers make, and these relationships could be examined in further detail by obtaining more spatially resolved biophysical data at the farm level.

1. Introduction

Heavy reliance on fossil fuels for energy production and transportation fuel has resulted in great social, economic, and environmental costs (Hill *et al.*, 2006; Tilman *et al.*, 2009; Perlack & Stokes, 2011). Alternative energy sources including cellulosic bioenergy have been identified as a means to alleviate these costs. As a result, policy emphasizing the importance of alternative energy sources that reduce greenhouse gas emissions, stimulate rural economies, and reduce reliance on foreign energy sources through the production of cellulosic bioenergy feedstocks has been developed. Because of its long history of agriculture and land stewardship, Wisconsin has emerged as a potential candidate for generating sustainable energy through the production of bioenergy feedstocks.

The Renewable Fuels Standard (RFS) set forth in the 2007 Energy Independence and Security Act (EISA) calls for accelerated production of biofuels (36 billion gallons per year by 2022, 16 of which to come from cellulosic feedstock) with a simultaneous stabilization of conventional biofuels production (15 BGY by 2022). Despite this federal policy, there has been limited commercial production and development of large-scale feedstock markets to meet these fuel standards (Carriquiry *et al.*, 2011). As a result, the production of cellulosic bioenergy feedstocks has yet to live up to its promise. The reasons for this are numerous, including the perceived risk of changing management practices, the lack of economically viable conversion technology, the uncertainty that is accompanied by a lack of widespread established feedstock markets (Swinton *et al.*, 2011), incompatibility with existing land management, aversion to allocating arable acres to non-food agriculture, and substantial decline in the cost of natural gas. Wisconsin farmers are not unique in facing these challenges; however the landscape of

Wisconsin offers promise in its vast and varied biophysical and environmental character, and long history of agricultural land stewardship.

Southwest Wisconsin in particular is highly productive and biophysically diverse, characterized by unglaciated terrain, steep slopes, and dendritic drainage patterns. The region's agricultural activity includes dairy, livestock, short rotation and long rotation mixed crop production. Most farms are integrated, consisting of more than one of these operations on site. With existing row crop agriculture production already in place, counties in this part of the state have the capacity to produce more than 50,000 Mg yr^{-1} of dry corn stover (Roos *et al.*, 1999).

Marginal lands are being considered as a source for growing bioenergy feedstocks due to their potential to address the above concerns, including acreage availability (Campbell *et al.*, 2008), potential for minimizing negative environmental impacts, increasing delivery of ecosystem services, and potential economic viability (Hill *et al.*, 2006; Tilman *et al.*, 2009; Blanco-Canqui, 2010). In this study, marginal land includes privately owned acres that are currently arable but possess marginal characteristics such as poor drainage, highly erodible soils, shallow depth to bedrock or water table, or significant presence of rocks. They also include non-cropped acres that are potentially available for bioenergy production, including fallowed, shrubby, or open land.

A study conducted by Ventura and Garcia found that there are 1.5 million acres of marginal land that would be appropriate for bioenergy feedstock production in southwest Wisconsin. This includes one million acres of marginal cropland (currently arable land that possesses highly erodible soil characteristics) and 500 thousand acres of marginal non-cropped land (land that is potentially available for bioenergy production, including fallow, shrub, or open acres) (Mooney *et al.*, 2013).

The biophysical and technical capacity of privately owned marginal land to produce bioenergy feedstocks has been thoroughly researched (Perlack & Stokes, 2011; Ventura *et al.*, 2012; Gelfand *et al.*, 2013). Findings show that low input perennial grasses such as switchgrass grown on marginal land could provide sufficient feedstock supplies, deliver ecosystem services, and could be economically viable without competing with land for food crops (Tilman et al., 2009, Blanco-Canqui, 2010). Although corn stover provides an abundant supply and has fewer logistical requirements than establishing switchgrass, the annual cropping cycle (e.g., tillage, application of synthetic inputs) and harvest of these crop residues can result in deleterious environmental and agronomic effects (Varvel *et al.*, 2008)

Developing a renewable energy system is a complex undertaking, one that is driven by numerous economic, environmental, social, political, and practical drivers. Evaluating the potential for development in Wisconsin requires defining and balancing these drivers, including biophysical factors, landscape capability, existing policy and market structures that can potentially support or stifle development, and finally, the attitudes and perspectives of the landowners who will be growing the biomass on their land. Because of the complex relationships among these drivers, there is a great deal of uncertainty around the willingness of farmers and landowners to change land management practices for bioenergy. A means to navigate and clarify this uncertainty will be to adapt a conceptual framework for evaluating, assessing, and acting upon these various factors (Roos *et al.*, 1999).

1.1 Potential Bioenergy Feedstocks

Cellulosic bioenergy feedstocks include crop residues (stalk, leaves, corn cobs, and husks left on the field following grain harvest), forage grasses, or dedicated bioenergy crops such as switchgrass or miscanthus. Each feedstock has its own advantages and limitations, in terms of technical and biophysical capacity and in terms of farmer preference.

Many distinct technical, agronomic, economic, environmental, and biophysical tradeoffs are associated with managing farmland for corn stover or switchgrass production. Logistically, barriers are fewer for corn stover than for switchgrass including an ample supply, the fact that farmers typically possess corn harvesting equipment, corn is already in production for grain, and there are already familiar markets for selling crop residues (Song *et al.*, 2011a). However, the challenges associated with the harvest of corn stover include competing uses for bedding in dairy farms, corn residues in silage production, and a desire to leave crop residues on site for soil health. The environmental costs to harvesting corn stover are numerous, including increasing the soil's vulnerability to loss by water or wind erosion, depleting nutrients and organic matter from the soil, degradation of soil structure, and increased potential for nutrient runoff to water bodies, in the absence of prudent corn stover management. The literature gives numerous reasons to be cautious about harvesting corn stover for bioenergy feedstock (Jensen *et al.*, 2007; Paulrud & Laitila, 2010; Tyndall *et al.*, 2011).

Switchgrass attributes, while having numerous potential environmental benefits and fewer chemical input requirements, include greater agronomic barriers than harvesting corn stover. These include few widespread markets for commercial sale and a one to two year viable harvest delay while the switchgrass stand establishes, thus delaying potential net income (Perlack & Stokes, 2011).

1.2 Ecosystem Service Attributes of Bioenergy Feedstocks

In addition to producing bioenergy, dedicated bioenergy feedstocks can deliver environmental benefits to the land including improved soil and water quality or delivery of wildlife habitat improvements. Perennial grass production systems have the potential to mitigate soil loss to erosion, increase soil carbon, reduce greenhouse gas emissions through management practices, and to provide habitat for wildlife (Carriquiry *et al.*, 2011). In addition, these systems possess low water and nutrient inputs compared to corn and other agronomic crops, which alleviates potential soil and water quality issues and reduce management and labor costs borne by the farmer.

In order for bioenergy feedstock programs to be sustainable, management of these crops must not exacerbate existing environmental or productivity issues on farm, and should provide opportunities to halt or even improve upon these environmental issues on farm (e.g. reduce soil erosion and nutrient runoff, improve biodiversity, increase soil carbon storage and sequestration). Farm operations with non-cropped marginal acres would make strong candidates for growing perennial grasses such as switchgrass (Carriquiry *et al.*, 2011).

1.3 Bioenergy Feedstocks

Feasibility of cellulosic bioenergy feedstock programs will depend upon the capacity and willingness of farmers to grow those feedstocks on the land being targeted for production. Recent research shows that willingness to convert land management towards corn stover or dedicated bioenergy crop production is not widespread (Jensen *et al.*, 2007; Paulrud & Laitila, 2010; Tyndall *et al.*, 2011). A challenge with bioenergy feedstock production on marginal lands is that in order to incorporate bioenergy feedstocks into a farmer's management portfolio, the practice must be compatible with their existing operations. Song et al. (2011b) point out the challenges associated with growing dedicated bioenergy crops on marginal land including reluctance of farmers to produce a crop for which there is no familiar market and few proven production practices. This is especially challenging, as in the absence of any existing large-scale bioenergy markets, it is impossible to measure farmers' willingness to grow such feedstocks.

1.4 Farmer Feedstock Choice

Within farmer choice literature, potential choice drivers include demographic information (age, total income, education level of operator, contribution of family labor to the farm), physical land characteristics (presence of marginal or steeply sloped land, soil characteristics), operation characteristics (number and type of farming activities, farm size, land owned or rented), and farmer attributes (knowledge of bioenergy feedstocks, perceived relative risk of bioenergy feedstocks, attitudes about bioenergy in general, willingness to make tradeoffs, price points of proposed feedstocks). This information is often collected through surveys, focus groups, and interviews (Jensen *et al.*, 2007; Wossink & Swinton, 2007; Paulrud & Laitila, 2010; Tyndall *et al.*, 2011).

At the same time, remotely sensed data for large extents of land area are becoming readily available. These high spatial and temporal resolution datasets are necessary to assess biophysical landscape characteristics such as soil and water quality and can be used to identify areas of the landscape that are poor in agricultural productivity or environmentally sensitive. These datasets tell us a great deal about the landscape in which farmers and landowners make management decisions, and about the effects of those management decisions through monitoring changes in land cover or land management. The integration of such geospatially based biophysical data into an econometric choice model can increase its predictive power.

Farmer decisions involve the management of land, water, labor, and energy (Lal & Pimentel, 2007), and the outcomes of those decisions can have both positive benefits and negative social, economic, and environmental costs. In turn, the biophysical and economic contexts in which these farmers and rural landowners live and operate also influence the management decisions they make (Wossink & Swinton, 2007). Atwell *et al.* (2009) found that linking the biophysical and social landscapes when exploring perspectives and attitudes around ecosystem services resonated positively with rural community members in a Corn Belt study. In order for a farmer to incorporate bioenergy feedstock there must be compatibility of the proposed feedstock with both the existing farm enterprise and the existing landscape (Sheikh *et al.*, 2003; Knowler & Bradshaw, 2007). The decision to grow these crops will be a function of the landscape in which the farmer is operating (e.g. topography, soil type), equipment and infrastructure for growing and transporting feedstocks, beliefs about mitigating risk and future income choice, and the farmer's attitude and perspectives about growing bioenergy feedstock crops (Graham *et al.*, 1996).

Management behaviors are driven by not only an inclination to maximize utility, but are also informed by a constellation of attitudes, values, and norms that are shaped by the landowner's cultural, biophysical, and social contexts (Atwell *et al.*, 2009; Brady & Irwin, 2011). Among these are economic and policy drivers that describe current market and policy forces. They include existing policy (federal, state, and local levels), prices for biomass, existence of biomass markets, and financial assistance programs including ecosystem services payment programs (federal or otherwise). These also include farmer or rural landowner's knowledge of existing policies that support bioenergy development (e.g., through research and development, subsidies, information dissemination), policies that regulate existing markets, or those that may be in competition with bioenergy feedstocks.

Additional landowner considerations include general perceptions of bioenergy, attitudes of their surrounding community, support of local policy makers and neighbors, willingness to participate in payment programs, level of understanding bioenergy systems (Roos *et al.*, 1999; Ma *et al.*, 2012), and a reluctance to deviate from their current management. Several landowner-focused bioenergy studies have focused on willingness-to-pay or willingness-to-participate in various proposed bioenergy feedstock payment programs (Jensen *et al.*, 2007; Wossink & Swinton, 2007). They find that farmers' and rural landowners' willingness to participate in bioenergy programs is also positively influenced by perceptions of risk, household income, and potential of ecosystem services delivery in addition to feedstock production. Level of understanding of ecosystem services programs and ecosystem service delivery, and previous participation with an ecosystem services program all positively influence their willingness to participate (Ma *et al.*, 2012). In addition, farmers are more likely to participate in ecosystem service provision programs when the management is similar to what they currently practice. This is due to perceived lower risk and lower costs of changing practices. Lastly, when farmers perceive that their production practices can support ecosystem services delivery, they are more likely to enroll in an ecosystem services program (Ma *et al.*, 2012).

1.5 Conceptual Framework

This study draws together the realms of biophysical landscape characteristics and the attitudes, perspectives, and farm operation requirements of the farmers who manage that land. It combines qualitative and quantitative research that relies on the use of remotely sensed data, Geographic Information Systems (GIS) data, and survey methodologies to examine the intersection of physical and human aspects of a developing bioenergy system. It builds upon literature that explores those decision-making factors in addition to maximizing the landowner's utility and seeks to describe the enterprise and landscape characteristics that can shape the farmer's attitude and perspective on participating in a bioenergy system. The farmer is assumed to be a rational individual who makes decisions based on maximizing utility or satisfaction (Penson Jr. *et al.*, 2002). My assumption is that these drivers shape the understanding, the attitudes, and willingness to participate, and will ultimately compel the action taken by the farmer.

This research aims to identify the socioeconomic, biophysical, and spatial drivers of bioenergy feedstock choice of corn stover and switchgrass in Southwest Wisconsin. The working hypothesis is that biophysical land characteristics are a significant and measureable influence on farmers' potential to participate in bioenergy feedstock production. This research will examine these potential choice drivers through the lens of the steady-state typical biophysical environment in which those land use decisions are made. I hypothesize that farmer survey results will reveal relationships between the biophysical landscape characteristics and farmers' willingness to participate in a hypothetical bioenergy feedstock production system. These biophysical land context drivers of choice cannot be examined in the absence of other known choice variables without introducing bias into the model. This analysis will emphasize these factors and examine the patterns in which they emerge across the farmer sample.

2. Methods

2.1 Survey Implementation

In April of 2011, surveys were deployed to farmer landowners in four counties in Southwest Wisconsin (Iowa, Sauk, Richland, and LaCrosse Counties) in order to assess their level of knowledge of bioenergy issues and constraints using a modified Dillman (Dillman, 1991) approach. Sampling was stratified to ensure than an adequate number of farmers with the appropriate land cover types were included in the sample pool. Within the stratified sample frame, survey takers were randomly selected then mailed surveys along with consent forms to share their identity and property location with the researchers. A reminder postcard and two follow-up mailings were sent out in May and June.

Survey questions focused on potential economic returns to the landowner for growing bioenergy feedstocks, assessing owner's willingness to participate in a bioenergy system, and identifying the social and economic signals that generate land management behaviors. Survey questions also included perspectives on environmental impacts of management practices, potential economic returns of bioenergy feedstocks, change in management practices, uncertainty, policy, and delivery of ecosystem services. Some questions focused on the potential of delivery of ecosystem services in bioenergy cropping systems while others focused exclusively on prices and incentive program participation. All procedures surrounding the implementation and analyses of landowner surveys and interviews followed human subject requirements of the UW-Madison Institutional Review Board.

2.2 Clustered, Stratified Random Sample Design

Potential survey participants included all agricultural producers in La Crosse, Richland, Iowa, and Sauk counties who manage crops or raise cattle and who possess sufficient rural acreage having the desired land cover characteristics. These counties were selected based on availability of farm-level GIS and remote sensing data. Farmers were selected from lists maintained by USDA Farm Services Agency (FSA). FSA made initial contacts and maintained anonymity for respondents. Between six and nine townships in each county were selected for participation in the survey based on the following characteristics.

2.3 Biophysical Characteristics Stratification

The survey sample frame was stratified on the biophysical landscape characteristics, land tenure type, and local infrastructure using spatial analysis. Biophysical characteristics of the target population included privately owned acreage of appropriate land cover, specifically forested, cropped and non-cropped marginal (e.g. having highly erodible, wet, or droughty soils and steeply sloped terrain) land, cropland on non-marginal land, and land enrolled in conservation programs (CRP). Land enrolled in CRP was in the sample frame strata, as enrollment in this program requires having land with marginal characteristics. These include privately owned acres that are prone to erosion or adjacent to streams or other surface water bodies. Townships within these four counties were selected based on presence and distribution of these biophysical characteristics, which were determined by spatial analysis of satellite-derived land cover data.

The four major classes of land cover included in this analysis were CRP, forested, highly erodible land (open land, currently in row crop production, with steep, droughty, or wet soils), and marginal land (open land, not currently in row crop production with same characteristics as HEL).

2.4 Operation Characteristics Stratification

Farmers of interest to this study were those with any combination of field and forage crops, livestock, or dairy cattle. Only privately owned land of four acres or more was included in the analysis. Suitable land use types included agricultural land, acres enrolled in a managed forest program, undeveloped land, and agricultural forest. Landowner data and land use classification data were acquired through tax parcel data from each of the four county land offices. The number of surveys deployed is representative of the land type and land sizes across the sampling area within each county (Table 1).

2.5 Model Specification

Decision choice variables gleaned from survey responses were selected based on their literature presence and were clustered into conceptual blocks for predicting bioenergy feedstock choice on the individual level, including think, have, do. A general model was constructed based on general farmer characteristics, including socioeconomic, land, and attitudes data. These variables were selected from the literature and were based on contextual, theoretical, and statistical relevance. Preliminary tests for covariance among the predictor variables were run and indices were constructed to account for highly correlated variables among the predictor dataset. Variables with a significant correlation with feedstock choice (at the $\alpha = 0.10$ level) were included into the large initial model.

2.5.1 What Farmers Think

Farmers' decisions are informed by their level of education, attitudes about policy issues that affect their livelihood or operation, and perceptions of and willingness to mitigate risk (Knowler & Bradshaw, 2007). A tradeoff index was created that described willingness to accept income uncertainty in the interest of ecosystem services delivery. This was expressed as the number of ecosystem services a farmer is willing to trade uncertainty in income for, including improved local soil and water quality, improved local wildlife populations, decreased greenhouse gas emissions, and a reduction in labor and/or management requirements. Questions also examined their previous knowledge of corn stover or switchgrass as potential bioenergy feedstocks. The predictors in this category are all are survey-derived, and describe the farmer's stated preference.

2.5.2 Who Are the Farmers

There is much literature on the significance of operator characteristics to making land management decisions (Sheikh *et al.*, 2003; Knowler & Bradshaw, 2007; Useche *et al.*, 2009). Variables in this category describe the household and operator characteristics of the farmer sample set and include age, possession of a college degree or greater, and whether their total household income exceeds $100,000 US, and were all drawn from the survey responses.

2.5.3 What Farmers Have

Perceptions of risk and potential profitability through changing management practices are highly variable. These perceptions are informed in part by the biophysical landscape in which the operator is making decisions (Knowler & Bradshaw, 2007). This category refers to the land characteristics on which the farmer operates and describes the environment in which the land use decisions are made. These include the type and size of the operation, the presence and extent of marginal or sloped land characteristics, and the extent of open land.

Biophysical landscape characteristics including acres operated, land slope, soil texture, soil drainage capacity, highly erodible land, and fallow holdings have been found to significantly influence farmer adoption of conservation agriculture practices (Knowler & Bradshaw, 2007). The survey used in this study asked farmers to describe the presence and extent of particular marginal characteristics, including operational acres subject to seasonal flooding, poor drainage, excessive stoniness, shallow depth to bedrock or water table, highly erodible soils, or sandy soils. The heterogeneity in biophysical land characteristics may render certain sections of their land unsuitable for conventional row crop agriculture, and may be subjecting these environmentally vulnerable pieces of land to exacerbated productivity issues.

Akin to land having marginal characteristics, farms with slopes of 6% or greater may also be uniquely susceptible to problems with productivity under management practices that are not compatible with the landscape. Steeply sloped lands are more vulnerable to soil and nutrient loss by erosion or surface water runoff. Although 12% is commonly used as a metric for steeply sloped lands, slope information common to both field and rotational mixed crops was limited to 6% or less. Our analyses clustered survey responses on both cropland types.

2.5.4 What Farmers Do

This category refers to farmer reported management practices and operation history and includes the specific practices that can improve water quality, soil quality, or biodiversity. Conservation practices for soil quality improvement include terracing, contour strip cropping, contour tillage, or cover cropping. Water quality practices included stream protection, buffer strips, and installing grassy waterways. Biodiversity quality practices include wildlife management, habitat restoration, and the practice of integrated pest management. The number of reported management practices under each category was included in the model.

2.6 Model Description

The survey included a section with a hypothetical bioenergy feedstock program in which the farmer was presented with two non-woody bioenergy feedstock market programs and a short rotation woody crop feedstock program, which was not included in this analysis. Descriptions of each feedstock production system were provided, and farmers had the option of selecting any combination from none to all three. For the corn stover program, an annual contract to supply corn stover was described. Three versions of the survey presented three price points per dry ton of corn stover offered to the survey taker (Table 2). Each survey taker was offered an initial market-approximated price point. Depending on their response, survey takers were further questioned on higher or lower prices. Each price was calculated based on current corn bushel and milk market prices at the time of survey deployment ($5.00/bushel and $16.00/cwt, respectively). For the switchgrass program the farmer was offered a multi-year contract to supply switchgrass. There were also three price points per dry ton of switchgrass supplied offered to the survey taker, again each based on current corn bushel and milk market prices at the time of the survey deployment (Table 2).

A general logistical choice model was specified to include explanatory variables from across the four aforementioned categories and the price level of the bioenergy feedstock (e.g. low, medium, high). Two models were generated to estimate the choice drivers for both corn stover and switchgrass because the two feedstocks differ significantly in their operational requirements and land constraints. Feedstocks of interest in this research are identified as corn stover (CS) and switchgrass (SG).

Whether or not a farmer selects to participate in a proposed bioenergy feedstock program is a discrete choice that was modeled using a multiple regression logit model. Stated acceptance of the proposed bioenergy feedstock program was designated with a binary response (Yes = 1, No = 0). The underlying assumption is that the farmer makes a rational choice to maximize their utility. Formally stated, if U_{i1} is the utility derived from selecting a feedstock and U_{i2} is the utility derived from not selecting a feedstock, a farmer either adopts a particular feedstock if $U_{i1} > U_{i2}$, or abstains from selecting a feedstock if $U_{i1} < U_{i2}$. The qualitative choice descriptor, y_i, is equal to 1 if a farmer does select a feedstock, and equal to 0 if the farmer does not.

Feedstock choices are not mutually exclusive, as a number of farmers chose one, two, or none of the proposed non-woody bioenergy feedstocks. We can estimate model parameter values by taking the natural logarithm of both sides of the following equation:

$$\text{i. } P_i = P(y_i = 1) = P(U_{i1} > U_{i2})$$

$$\text{ii. } \ln[P_i/(1-P_i)] = \ln[\beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots. + \beta_i x_i],$$

where P is the probability of a farming choosing a feedstock program, β_i terms represent the regression coefficients to be estimated, x_i is the value of the independent variable, and i represents the number of independent predictor variables. Initial models were specified that included more independent variables than are reported in the results. Several iterations of the model selection were conducted, including and excluding variables checked against statistical and theoretical criteria.

For predicted probabilities of 0.5 or greater, the farmer selected the proposed feedstock. For probabilities less than 0.5, the farmer did not select the proposed feedstock. Parameters were estimated using the maximum likelihood criteria within the R statistical program. The β_I coefficients were then interpreted using their sign and magnitude of effect on the response variable. Goodness of fit, correct classification of outcomes, and the significance of attributes at 0.10 and 0.05 levels were all used in selecting the final set of predictor variables for the model.

2.7 Data Analysis

The survey data were stratified and described according to presence of non-optimal land characteristics (e.g. having marginal and/or land that is sloped at 6% or more) and optimal land characteristics, the breakdown of which is represented in Figure 1. Because the term "marginal" is not universally defined, we refer to acres that possess marginal characteristics, are sloped at 6% or greater as "Non-optimal" agricultural land, while the farms that possess none of these characteristics are considered "optimal" agricultural land.

3. Results

3.1 Descriptive Characteristics

Out of the 1,543 farms included in the final sample, 783 survey responses were returned. Among the returned were those rendered ineligible due to current inactive farming status, incompatible operation type, and participation declines. Of the 27 female and 267 male farmers, the mean age was 57. The average farm has been in family operation for 45 years, and approximately one-quarter of all farmers hold a college degree or greater. Among these farms in the four-county study area, the family provided a reported average of 87% of farm labor, while income from farming provides approximately a third (33%) of the household income. 78% of farmers report an annual income of $99,000 or less. The most common operation type is one of an integrated (more than one activity) field crop, livestock, and forage operation. 22% of surveyed farms are of an exclusive type (dairy, livestock, field crops, or forage only), while nearly 78% of the farms reported having integrated farming operations, of at least two farm activities taking place.

On average, farmers operate 130 acres of cropland (including field crops and rotational mixed crops). Most farms (64%) reported having "non-optimal" land characteristics, including marginal (e.g. shallow soils, highly erodible or sandy soils, poor drainage, seasonal flooding, or excessive stoniness) or sloped (6% or greater) land, while the remaining 36% of farms reported having none of these characteristics (Table 3). On average, 50 operated acres were subject to marginal characteristics. Farmers having unfarmed open space constituted 20% of the population, which includes acres in private easement programs, shrubland, or fallow land.

None of the survey respondents currently grow crops for bioenergy. However, 21% of respondents report having used biofuels or other renewable energy technologies on their farming operation. Of those who use renewable energy on farm, they reported use of biodiesel, E85 gasoline, solar panels, wind turbines, biofuels, firewood, waste oil, ethanol, and soy diesel. 70% of farmers are already familiar with corn stover as a bioenergy feedstock, and 78% report having previous knowledge of switchgrass as a bioenergy feedstock. The majority of farmers perceive both corn stover and switchgrass to be more risky than their more conventional counterparts of harvesting corn grain and hay, at 73% and 80%, respectively.

Nearly three-fourths of the survey respondents agree that the government should do more to promote bioenergy, while more than half agree that meeting renewable energy goals is the key to growing our rural economy (Table 4). More than three-quarters (77%) agreed that meeting renewable energy goals is key to reducing our independence on foreign energy sources. However, less than half the respondents agree that meeting renewable energy goals will be key to slowing climate change, and few (13%) have confidence that we will meet the Renewable Fuels Standard by 2022.

Table 5 describes attitudes about the following policy goals as stratified by land type. There is little variation in attitudes about these bioenergy issues across land type, although more farmers with non-optimal land characteristics than not tend to agree with the aforementioned statements about meeting policy goals.

Overall, farmers express a desire for greater government promotion, but express little confidence in the capacity to meet current RFS goals. There is stronger support for bioenergy's capacity to grow rural economies and for reducing dependence on foreign energy sources. However there is little support for bioenergy's role in slowing climate change.

Farmers reported the presence and extent of marginal characteristics to which the field crop and rotational mixed crop acres were subject (Table 6). The picture of marginality in the study area includes excessive stoniness, poor drainage, and seasonal flooding in terms of frequency and extent. Additional marginal landscape characteristics reported included sandy soils and highly erodible soils. Averaged sloped land per farm (6% or greater) is higher than average acreage subject to marginal land characteristics.

3.2 Farmer Choice

Mean choice probabilities for participating in the corn stover or switchgrass feedstock programs were 0.23 and 0.36, respectively. Overall, the probability of any farmer choosing either feedstock is less than half, revealing a population of farmers who are not enthused about bioenergy (Table 7). Among farmers with optimal land, those who choose corn stover constitute approximately half of the sub-population. There was little variation across land characteristics among farmers who chose switchgrass.

3.3 Results From Logit Models

Full candidate logistical choice models for corn stover and switchgrass included potential choice variables of socioeconomic, land, and attitudes survey data (Table 8). Of the original pool of candidate predictor variables, those selected for use in the final corn stover and switchgrass models were selected through the stepwise process of estimating contextual and statistical ($p < 0.1$) significance of each predictor variable to feedstock selection choice, and estimating overall model stability and consistency.

Results produced from the final reduced corn stover logit model are given in Table 9. Coefficients are the maximum likelihood estimators for the dataset, and they represent the best estimate of each model parameter. As the value of each explanatory variable increases by one unit, the odds of a farmer selecting corn stover changes in the direction and value of that coefficient.

Classification of predicted model results against observations of choice show that the model correctly predicts more non-adoption outcomes with greater frequency than adoption outcomes (Table 10). Overall, the model performs well, with an average overall 78% correct classification.

3.3.1 Corn Stover Model Coefficients

Of all the proposed model variables, the significant choice drivers were those that pertain to what farmers think and what they do on their farmland. Among the significant drivers of feedstock choice, the implementation of water quality practices and an increased willingness to make tradeoffs in the interests of ecosystem services delivery had the greatest effect on feedstock choice (Table 9).

Farmers willing to make more tradeoffs in economic returns in the interests of ecosystem service delivery are more likely to become corn stover adopters. Farmers reported their willingness to accept uncertainty in net returns if one or more of the following ecosystem or social services were delivered:

-if labor and/or management requirements decrease
-if local wildlife populations increase
-if soil quality on my farm increases
-if water quality improves in nearby streams or lakes
-if greenhouse gas emissions decrease

Those who agreed with one or two of those statements have nearly four times the odds of selecting corn stover over those who did not agree with any of those statements. Among those who agreed with more than two of those statements, the odds of choosing corn stover is 4.5 times greater than those who did not agree with any of those statements. Farmers having a greater number of water quality management practices in place are more inclined to choose corn stover feedstock. For every additional water quality practice implemented on farm, the odds of selecting corn stover increase by nearly twofold. Among these water quality practices are stream protection, buffer strips, and grassy waterways. The remaining significant (at the 5% level) choice drivers included acreages of open land and farmer age, though their individual effects on odds approximated zero (Table 9). The amount of open acreage in the form of shrubland, fallow pasture, or conservation easement land has a significant but weakly positive influence on corn stover choice. Age and proclivity for corn stover are inversely related.

Percentage of operated acres with a 6% slope or greater was significant at the 10% level. Insignificant drivers at the 10% level included operation type and possession of a college degree or greater. These factors remain in the model because of their known effect on farmer management choice, and omitting them would introduce bias (Knowler & Bradshaw, 2007). Throughout the stepwise model selection process, candidate choice variables were removed due to their lack of predictive power, contextual relevance, or contribution to overall model stability. These variables included feedstock price point, having an income of $100,000 or greater, acres of operated agland, percentage of operated acres subject to marginal characteristics, number of soil and biodiversity quality management practices, and previous knowledge of corn stover or switchgrass.

3.3.2 Switchgrass Model Coefficients

Like the corn stover model, classification of predicted model results against observations of choice show that the model correctly predicts more non-adoption outcomes with greater frequency than adoption outcomes. Overall, the model performs well, with an overall 74% correct classification (Table 12).

Of all the proposed model variables, the significant choice drivers were those that pertain to what farmers think, what they know, the type of land they have, and what they do on their farmland. Among the significant drivers of switchgrass choice, having a dairy farm, knowledge of switchgrass as a bioenergy feedstock, the implementation of soil quality practices, having an income of $100,000 or greater, and an increased willingness to make tradeoffs in the interests of ecosystem services delivery had the greatest influence (Table 11).

Dairy operators were 16 times less likely to adopt switchgrass on their operations than those who were grain or livestock operators, at the 1% significance level. Those who agreed with one or more of the tradeoff statements listed above increase their odds of selecting switchgrass nearly three times over those who did not agree with any of those statements. There is a significant and positive relationship between the number of soil quality management practices in place and a farmer's likelihood of choosing a switchgrass feedstock program. For every additional soil quality practice implemented on farm, the odds of selecting switchgrass increase by 1.5. Among these soil quality practices are terracing, contour tillage, contour strip cropping, and cover crops. Farmers having a total household income of $100,000 or greater were more inclined to select switchgrass over those who do not; their odds of selecting switchgrass are nearly 2.5 times greater. Previous knowledge of switchgrass as a bioenergy feedstock was a strong and significant driver of positive switchgrass choice. The odds of selecting switchgrass are three times greater among farmers familiar with the feedstock than those who are not.

The remaining significant choice drivers included percentage of operated acres with marginal characteristics and farmer age, though their individual effects on odds approximated zero (Table 11). The percentage of acres in operation having poor drainage, shallow soils, seasonal flooding, highly erodible or sandy soils, or stoniness has a significant but weakly positive effect on switchgrass choice. As in the corn stover scenarios, age is a significant but weakly negative predictor of corn stover feedstock adoption.

Drivers that were not significant at the 5% level but still included in the model were grain and livestock operation type and amount of acres operated. These factors remain in the model because of their known effect on farmer management choice, and omitting them would introduce bias (Knowler & Bradshaw, 2007). Throughout the stepwise model selection process, candidate choice variables were removed due to their lack of predictive power, contextual relevance, or contribution to overall model stability. These variables included feedstock price point, having a college degree or greater, acreage of owned unfarmed open land, percentage of sloped operated acres, number of water quality and biodiversity management practices, and previous knowledge of corn stover as a bioenergy feedstock.

4. Discussion

Significant variables on choice feedstock that emerged from this study were classified under the categories of farmer attitudes, farmer behavior (experience and current farm management practices), farmer characteristics (age, education level, knowledge), and farmland characteristics (economic and biophysical). Overall response to feedstock price point was insignificant for both corn stover and switchgrass, and was thus not included in the final reduced model. However, willingness to make economic tradeoffs in the interests of ecosystem service delivery emerged among the strongest drivers of choice in both feedstock choice models, though the effect was not as strong in the switchgrass model. Age also emerged as a significant though weakly negative predictor of either feedstock choice.

Farmers who are willing to make tradeoffs in economic returns in the interests of ecosystem service delivery are more likely to become adopters of both feedstocks. The strong effect across both models suggests that there is a willingness to accept uncertainty in net returns for the possible improvement in soil and water quality, habitat improvement, reduced labor and management requirements, or greenhouse gas emission reduction. Farmers are typically more willing to accept lower economic returns if ecosystem services are jointly produced with the agricultural products (Wossink & Swinton, 2007). Our findings reflect a perceived value of these deliverables that is greater than the perceived risks of uncertain net returns. Each ecosystem service described in this survey is not explicitly linked to direct economic returns to the individual (e.g. reduced labor and management requirements, increased on-farm soil quality), but rather represent services that deliver returns to the general public (e.g. improved water quality in nearby water bodies, reduction in greenhouse gas emissions). Among this pool of farmers with low confidence and willingness to adopt either bioenergy feedstock program, the strong signal of willingness to make tradeoffs suggests that the low participation comes not from a lack of economic motivation but a lack of external supporting factors, including bioenergy infrastructure and established widespread markets (Jensen *et al.*, 2007; Kelsey & Franke, 2009).

As farmer age increases, the odds of selecting either feedstock program decreases. Age is a significant but weakly negative predictor of feedstock adoption. It is known that younger farmers tend to be less risk averse and thus, more likely candidates for adoption of a bioenergy feedstock or new technologies (Useche *et al.*, 2009). In this example however, we do not observe a strong effect in either direction.

Because the management requirements of corn stover and switchgrass are distinct, the following choice drivers will be broken out by feedstock choice.

4.1 Corn Stover Choice Drivers

For existing corn farmers, adoption of corn stover feedstock program would not be a significant shift in farm management. While the logistical and economic hurdles for managing corn stover as a bioenergy feedstock are low, the potential environmental losses are great. Crop residues deliver numerous biological, physical, chemical services to overall soil productivity, and serve as protection from wind and water erosion. Harvesting these residues in quantities that are not sustainable or on land that is already vulnerable to soil loss would be a constraint to producing bioenergy feedstock in a sustainable manner (Wilhelm *et al.*, 2007). However, on land that is highly productive and not susceptible to erosion, the harvesting of crop residues could deliver the dual benefits of a bioenergy feedstock and alleviating planting issues with land having dense residue cover (Mann *et al.*, 2002). We observe that fewer farmers with optimum land characteristics are selecting corn stover.

Farmers having a greater number of water quality management practices in place are more inclined to choose corn stover. This suggests that the farmer perceives compatibility of corn stover management with their current operation management. This is also counterintuitive, as the removal of corn stover from farm fields has the potential to reduce local water quality over the long term in the absence of sufficient erosion prevention measures (Mann *et al.*, 2002). This could suggest that farmers already taking precautions for water quality practices perceive the removal of crop residues to be less risky due to those water quality precautions already in place. The water quality precautions they already incorporate into their management would be sufficient in mitigating any potential risk brought about by removing corn stover.

The amount of open acreage in the form of shrubland, fallow pasture, or conservation easement land has a significant but weakly positive influence on corn stover choice. The presence of such acreage on a farm could indicate that a farmer has more land on which to try out a feedstock management program, and such farmers would make good candidates for any bioenergy feedstock pilot programs. In addition, having greater diversity in land tenure or management portfolio reduces the risk that changed management practices will significantly reduce their farm income. In addition, there is the caveat that the open acreage could provide extra land for crop expansion, should corn stover become profitable.

4.2 Switchgrass Choice Drivers

Research involving landowner surveys has shown that livestock ownership has a negative effect on the farmer's willingness to adopt bioenergy crop management practices, due to the opportunity costs involved with converting existing hay or pasture land into bioenergy crops (Jensen *et al.*, 2007). For example, dairy farmers have their land allocated to livestock, and their feed and bedding needs are already met. If additional acreage on their farm is not contributing to dairy operations, therein lies potential acreage for allocation to bioenergy crop production. Additionally, if a dairy farmer sources their bedding and feed from existing markets, it is possible that they would not support bioenergy activities, due to the potential for demand competition, which could result in bedding and feed price increases (Penson Jr. *et al.*, 2002).

Grain farmers already have widespread market and policy support for selling their products. While national policy for growing switchgrass and other dedicated bioenergy feedstock crops is driven by the Energy Independence and Security Act and the 2008 Farm Bill, there still lacks a widespread market or subsidies for buying and selling. For the grain farmer, grain and stover prices will be a primary determinant in whether or not a farmer would harvest the stover for bioenergy. For the farmer seeking to maximize their utility, or income, and minimize their risk, it is unlikely that they would partake in any activities where there is little security in selling their product. If bioenergy feedstock prices increase to more than what a farmer could receive for their traditional crops, then the likelihood tips in favor of growing bioenergy feedstocks. In the absence of strong policy and financial support, the disincentives for participation outweigh the incentives (Roos *et al.*, 1999).

Familiarity with switchgrass as a bioenergy feedstock was a significant and strong positive driver of switchgrass choice. This result is compatible with previous research findings that knowing the requirements and benefits of managing such a feedstock makes farmers more likely to adopt a management practice (Ma *et al.*, 2012).

The significant and positive relationship between the number of soil quality management practices in place and a farmer's likelihood of choosing a switchgrass feedstock program communicates a signal of conservation mindedness. Farmers already in the habit of implementing soil quality practices may see an opportunity to continue or expand their soil conservation goals through establishment of a switchgrass feedstock program. The establishment of perennial grasses such as switchgrass is well known to provide numerous soil quality benefits (Varvel & Wilhelm, 2010; Meehan *et al.*, 2013). The more soil quality practices in place reflects a concern on behalf of the farmer to maintain or improve these ecosystem services on their land (Jensen *et al.*, 2007).

For farmers with land of marginal productive quality, growing switchgrass could provide both an economic and ecosystem benefits (Meehan *et al.*, 2013), particularly when targeting lands that are significantly degraded. Specific types of marginal landscape characteristics can limit on-farm production options. For example, lands subject to excessive stoniness present a challenge with crops that require tillage. Lands with steep slopes are not conducive to field crop rotations that require multiple equipment passes for management. Such landscape characteristics both constrain and offer opportunities for management, and could influence a farmer's choice to incorporate bioenergy feedstock crops. For example, a farmer having land with steep slopes and highly erodible soils may benefit from planting a perennial grass, due to its lower input requirements and capacity to maintain or improve soil structure.

The percentage of marginal acres was a significant though weak positive driver of switchgrass choice, which suggests a linkage between the land that a farmer has and the types of management decisions they will make. Counter to my hypothesis, having a greater amount of marginal land characteristics does not strongly suggest that a farmer will be more likely to select switchgrass. However, if linked with the appropriate incentive mechanisms, farmers with marginal land may take those acres out of annual row crop production and dedicate them to perennial grass production, as suggested by the positive relationship with ecosystem services. Farms with greater amounts of marginal characteristics will require more conservation practices to maintain productivity, so non-optimal lands have more to gain by implementing conservation practices on farm (Soule *et al.*, 2000).

Greater economic resources may be required to adopt new management practices (Knowler & Bradshaw, 2007) for new equipment provision, and to minimize economic risk brought about by the first years of switchgrass establishment. Larger income farmers are more likely to adopt a new management program when they have the economic safety net, so it is unsurprising that having a total household income of $100,000 or greater is a strong positive driver of switchgrass choice. Such a high income level may also indicate that a farmer is well established and has the capacity to expand their crop management portfolio.

While there is overall support for bioenergy's capacity to meet larger societal goals of growing rural economies and reducing dependence on foreign energy sources, there is little confidence in our ability to meet current policy goals. In addition, we observed an overall low expressed willingness to participate in proposed bioenergy feedstock production programs among Southwest Wisconsin farmers. Considering these research outcomes, we can conclude that meeting RFS goals by 2022 will continue to be a great challenge in the absence of rapid bioenergy feedstock market development or infrastructure building. Meeting RFS goals will require meeting both farmer and sustainability requirements, which will call for policy and economic mechanisms that incorporate economic, environmental attitudes, and landscape factors.

The factors emerging from this research lie at intersections between social, biophysical, and economic spheres, and they provide a foundation for further research to examine in greater detail the biophysical and spatial aspects of bioenergy feedstock decision-making. The results of this research can be used in targeting farmers thorough developing incentive programs that target farmers with environmentally vulnerable land, and designing policies that resonate with the environmental attitudes and operational characteristics of Wisconsin farmers.

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6. Tables and Figures

Table 1. Summary of Farmer Bioenergy Survey Mailings.

		Questionnaires		Invalid Returns (reason)			
County	**Sample**	**Mailed**	**Returned**	**Inactive**[a]	**Not Eligible**[b]	**Refused**[c]	**Valid Returns**
Iowa	Random	298	135	31	7	22	75
	CRP	150	92	44	11	17	20
LaCrosse	Random	126	59	26	1	4	28
	CRP	123	70	30	6	9	25
Richland	Random	287	136	61	3	21	51
	CRP	110	59	22	7	10	20
Sauk	Random	322	152	55	8	27	62
	CRP	127	80	33	13	11	23
All	Random	1033	482	173	19	74	216
	CRP	510	301	129	37	47	88
Total		1543	783	302	56	121	304

[a] Farm landowner does not actively farm (e.g. is retired or rents out all farmland), [b] Farm landowner is ineligible to complete survey (e.g. does not grow grain/forage crops or raise livestock), [c] Farm landowner declined to complete survey (e.g. returned the questionnaire blank or otherwise refused). (D. Mooney, *in prep*).

Table 2. Price points for the bioenergy feedstock programs in US dollars [$/dry ton]

Survey Version	**Corn Stover**			**Switchgrass**		
	Low	**Medium**	**High**	**Low**	**Medium**	**High**
Low	20	50	80	35	65	95
Medium	30	60	90	45	75	105
High	45	75	105	60	90	120

Table 3. Types of farm operations against biophysical land quality

	MSL	***OPT***
Grain/Pasture	42	16
Dairy	56	8
Livestock	97	61
Total (NA’s)	195	85 (24)

Table 4. Attitudes around Bioenergy Feedstocks

Statement	***Agree***	***Disagree***	***% Agree***
The government should do more to promote bioenergy	213	91	**70.0**
Meeting our renewable energy goals is key to growing the rural economy	192	112	**63.1**
Meeting our renewable energy goals is key to slowing climate change	144	160	47.4
Meeting our renewable energy goals is key to reducing our dependence on foreign energy sources	234	70	**77.0**
We will meet the Renewable Fuels Standard by 2022	39	265	12.8

Table 5. Attitudes about bioenergy aiding in meeting policy goals stratified by land type

Land Type	*Climate Change*	*Independence*	*Rural Economy*	*Gov’t Promotion*	*Meet RFS*
MSL (N = 195)	47	81	67	75	15
OPT (N = 109)	48	71	56	61	8

MSL refers to having marginal or sloped land, OPT refers to having none of those characteristics

Table 6. Non-optimal Land Characteristics

MSL (N = 195)	**Average**	**Maximum**
Marginal Farms	130	-
Sloped Farms	176	-
Marginal Acreage (mean)	50	1010
Sloped Acreage (mean)	80	1250
Field Crops Marginal Land Acreage		
Poor Drainage	16	150
Seasonal Flooding	11	200
Excessive Stoniness	14	500
Shallow	2	47
Other	4	170
Rotational/Mixed Crops Marginal Land Acreage		
Poor Drainage	4	60
Seasonal Flooding	2	40
Excessive Stoniness	32	1010
Shallow	4	100
Other	4	200

Table 7. Breakdown of Feedstock Choice by Biophysical Landscape Characteristics

	% Corn Stover Choice	*% Switchgrass Choice*
MSL	23	37
OPT	12	35
GEN	19	36

Table 8. Candidate variables for the full farmer logit feedstock choice models.

Variable Name	*Variable Type*
Survey Price Point	Categorical (Low, Medium, High)
Operation Type	Categorical (Grain/Pasture, Dairy, Livestock)
Operator Age	Continuous [years]
Farmer possesses college degree or greater	Binary [0/1]
Annual income greater than $100,000	Binary [0/1]
Acres of ag land in operation	Continuous [acres]
Acreage of unfarmed open land	Continuous [acres of shrubland, conservation easements, fallow pasture]
Percent of operational acres subject to marginal characteristics	Continuous [%]
Percent of operational acres with slopes of 6% or greater	Continuous [%]
Soil, Water, Biodiversity Quality Practices	Continuous [count]
Willingness to make economic tradeoff for environmental benefits	Categorical [0/1/2]
Prior knowledge of switchgrass, corn stover as bioenergy feedstocks	Binary [0/1]

Table 9. Odds-ratio Coefficients for Corn Stover Choice Model

Coefficient	*Exp(β)*	*Confidence Interval (low)*	*Confidence Interval (high)*
Grain Operation	0.24	0.02	2.34
Dairy Operation	0.22	0.02	1.79
Livestock Operation	0.17	0.02	1.40
Age **	0.96	0.93	0.99
College (Yes)	1.85	0.81	4.22
Open Acres Owned **	1.03	1.00	1.06
Percentage Sloped *	1.01	0.99	1.02
Water Quality Practices ***	1.84	1.22	2.84
Tradeoff Scale 1 **	3.90	1.24	14.02
Tradeoff Scale 2 ***	4.56	1.57	15.82

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

N = 204
logLik = -90 (df = 10)
AIC = 200

Table 10. Classification of the logit model predictions versus observations of corn stover choice

	Observed Non-Adoption (0)	*Observed Adoption (1)*	*Percentage Correct (%)*	
Predicted Non-Adoption (0)	149	36	Non-Adoption	81
Predicted Adoption (1)	8	11	Adoption	58
			Overall	**78**

Table 11. Odds-ratio Coefficients for Switchgrass Choice Model

Coefficient	*Exp(β)*	*Confidence Interval (low)*	*Confidence Interval (high)*
Grain Operation	0.36	0.04	2.98
Dairy Operation ***	0.06	0.01	0.48
Livestock Operation	0.23	0.03	1.61
Age **	0.97	0.94	1.00
Income > $100,000 **	2.45	1.11	5.53
Agland Acres Operated	1.00	0.99	1.00
Percentage Marginal *	1.01	1.00	1.02
Soil Q Practices **	1.54	1.08	2.22
Tradeoff Scale 1 **	3.07	1.13	8.80
Tradeoff Scale 2 **	3.11	1.31	7.85
Previous Switchgrass Knowledge **	3.11	1.19	9.14

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

N = 202
logLik = -107 (df = 11)
AIC = 235

Table 12. Classification of the logit model predictions versus observations of switchgrass choice

	Observed Non-Adoption (0)	*Observed Adoption (1)*	*Percentage Correct (%)*	
Predicted Non-Adoption (0)	117	36	Non-Adoption	87
Predicted Adoption (1)	17	32	Adoption	47
			Overall	**74**

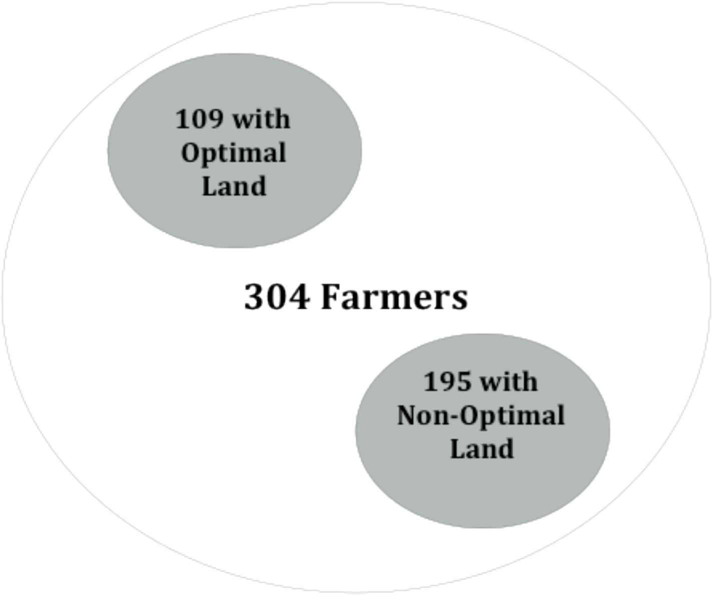

Figure 1. Land characteristics breakdown of the farmer sample pool.

Appendix I: Farmer Survey Excerpt

Section C: What is Your Attitude Toward Bioenergy? (C1-C6)

C1. Prior to this survey, had you heard about the following feedstocks used for bioenergy purposes?

(*check one for each feedstock*)

a. Corn stover?	☐ Yes	☐ No	c. Hybrid poplar?	☐ Yes	☐ No
b. Switchgrass?	☐ Yes	☐ No	d. Woody biomass?	☐ Yes	☐ No

C2.What factor did you consider most when making decisions whether or not to participate in the bioenergy feedstock programs in Section B? (*check one factor per column*)

	a. Corn Stover (*check one*)	b. Switch-grass (*check one*)	c. Hybrid poplar (*check one*)	d. Woody biomass (*check one*)
Economic returns	☐	☐	☐	☐
Impact on the environment/natural resources	☐	☐	☐	☐
Compatibility of feedstock with existing land uses	☐	☐	☐	☐
Level of risk or uncertainty associated with the bioenergy feedstock program	☐	☐	☐	☐
Other (*specify*):__________________	☐	☐	☐	☐

C3. Do you agree or disagree with the following statements: (*check one for each statement*)

	Agree	*Disagree*	*Don't know*
a. "Government should do more to promote bioenergy."	☐	☐	☐
b. "Developing bioenergy is key to growing Wisconsin's rural economy."	☐	☐	☐
c. "Developing bioenergy is key to slowing global climate change."	☐	☐	☐
d. "Developing bioenergy goals is key to reducing our national dependence on foreign oil."	☐	☐	☐
e. "Government should allow regular harvesting of CRP lands for bioenergy purposes."	☐	☐	☐

f. “Government should allow regular harvesting of land enrolled in public forestry programs (e.g. MFL) for bioenergy purposes.”	☐	☐	☐
g. “I favor using more bioenergy to produce heat, electricity and transportation fuels.”	☐	☐	☐
h. “Agricultural crops should be used for bioenergy feedstocks.”	☐	☐	☐
i. “Wisconsin should prioritize bioenergy more than solar and wind.”	☐	☐	☐
j. “Dedicated bioenergy crops should <u>not</u> be grown on land currently used for food crops”	☐	☐	☐

C4. In 2010, did you use biofuels or other renewable energy sources on your property (e.g. biodiesel, E85 gasoline, E10, solar panels, wind turbine)? (*check one*)

☐ No ☐ Yes ☞ *If yes, which ones?* #1: ___________ #2:____________

C5. If identical bioenergy programs were offered by the following entities, which would you prefer to join? (*check one*)

☐ Federal program ☐ Private business ☐ Ag cooperative
☐ State program ☐ Non-profit ☐ Energy cooperative ☐ It does not

C6. Would you be more willing to grow bioenergy feedstocks if they were used locally to produce energy? (*check one*)

☐ Yes ☐ No ☐ It does not matter ☐ Don’t know

D5. Do you agree or disagree with the following statements: (*check one for each statement*)

	Strongly agree	*Somewhat agree*	*Somewhat disagree*	*Strongly disagree*	*Don’t know*
a. “I would accept lower economic returns from my land <u>if wildlife populations increased</u>.”	☐	☐	☐	☐	☐
b. “I would accept lower economic returns from my land <u>if soil quality on my land improved</u>.”	☐	☐	☐	☐	☐
c. “I would accept lower economic returns from my land <u>if water quality in nearby streams/lakes improved</u>.”	☐	☐	☐	☐	☐
d. “I would accept lower economic returns from my land <u>if greenhouse gas emissions decreased</u>.”	☐	☐	☐	☐	☐

Chapter 6. Conclusions

6.1 Overview

Humans place significant demands on agricultural systems for provision of food, feed, fiber, and fuel. With a national population of 316 million and counting (https://www.census.gov/), meeting these demands in the United States will be a significant challenge to farmers in the twenty-first century, especially under the context of a changing global climate. As fossil fuel reserves decrease, and access to what remains becomes more politically volatile and environmentally damaging, we look to agricultural systems to produce bioenergy feedstocks to displace fossil fuels and to improve upon the environmental impacts of their production (Perlack & Stokes, 2011). In addition to provision of feedstock, these systems have potential to deliver ecosystem services including climate change regulation, water and soil quality improvement, and biodiversity enhancement. If done carefully and with foresight, these bioenergy landscapes can provide significant environmental and economic benefits. If done poorly and without consideration of the needs of the agroecosystem, these landscapes can have significant adverse effects on our agricultural and environmental systems (Hill *et al.*, 2006; Tilman *et al.*, 2009; Dale *et al.*, 2010; Liska *et al.*, 2014).

To ensure the long-term production of these bioenergy landscapes, the coupling of agriculture and energy systems must be sustainable. Sustainable systems are those that, among other attributes, maintain or improve upon current ecosystem functions (Davis *et al.*, 2013). In this dissertation I focused on the sustainable management of agricultural soil organic carbon, as it provides the foundation for not only feedstock production, but also for climate change regulation. I looked at this from both broad and specific biophysical perspectives and from the perspectives of factors potentially influencing farmer adoption of bioenergy feedstocks.

6.2 Summary

The interdisciplinary framework of this research provided a means to bridge gaps between disciplines of relevance in the sustainable bioenergy conversation, which include agronomy, ecology, agricultural economics, soil science, and environmental science. This framework also allowed for the implementation of robust spatial and process modeling tools to answer significant questions about bioenergy sustainability. Specific focus was placed on simulating the effects of managing farms for bioenergy feedstock production, determining the quantity of potential bioenergy feedstocks using satellite data, and identifying factors that drive farmers' willingness to incorporate bioenergy feedstocks into their operations.

The validation and application of AGRO-BGC in this research contributes to a growing body of modeling that extends beyond estimating potential crop yields to incorporate the system carbon dynamics between terrestrial and atmospheric pools (Di Vittorio *et al.*, 2010; Surendran Nair *et al.*, 2012). This approach facilitates development and design of future bioenergy systems and crop management plans that will minimize carbon fluxes to the atmosphere and maximize carbon storage in terrestrial soils. This study validated the ecosystem process model, AGRO-BGC using multiple soil carbon and productivity field datasets for comparison. We demonstrated the model's capacity to accurately simulate the carbon dynamics of an annual corn cropping system under conventional cropping conditions and under a scenario of bioenergy feedstock harvest. This study produced the first application of AGRO-BGC on an annual bioenergy feedstock cropping system. Using this carbon-focused ecosystem process model allows us to provide solutions to the most central questions around the potential of bioenergy feedstock production to not only meet renewable energy production goals, but to also serve as a mitigating force to the effects of climate change.

This research then applied the model in Chapter 3 to estimate potential impacts on soil productivity of harvesting corn and switchgrass for bioenergy feedstock in Wisconsin. This study also saw the application of a soil erosion model, RUSLE2, to these same bioenergy feedstock production scenarios, and estimated the effects of management on potential soil erosion losses. This research joins a wealth of studies that also strongly support the argument that crop residues are best left on the field to deliver their biological, chemical, and physical benefits to agricultural soils, particularly in steeply sloped fields with highly erodible soils (Blanco-Canqui & Lal, 2009; Powers *et al.*, 2011; Liska *et al.*, 2014). Our results also show support for the potential for switchgrass to sequester soil carbon over the long term while producing sufficient bioenergy feedstock. This study extends our understanding of the interactions between biophysical landscape characteristics, management practices, and the long-term effects of the management decisions on the landscape, and provides additional evidence for developing landscape-specific bioenergy feedstock management guidelines.

The fourth chapter of this dissertation explored a methodology for using vegetation indices derived from remotely sensed datasets to simulate crop canopy dynamics and predict crop yields using a light use efficiency model (Doraiswamy *et al.*, 2005; Alganci *et al.*, 2014). There is great predictive power in the ability to accurately estimate large spatial extents of cropland, and this research sets a foundation for further examination into improving means of capturing the spatial heterogeneity of crop productivity. This study also highlights the importance of having spatially explicit ground truth data, against which our models and satellite estimates can be validated. Continued exploration and application of the algorithms developed in this research will further our understanding of variability in crop dynamics, and allow us to better estimate the productive potential of our agricultural landscapes.

Incorporating a social component to the question of sustainability brings the most important stakeholder to the bioenergy conversation, the farmer. At present, there are no expansive markets for cellulosic bioenergy feedstocks, nor do we see large bioenergy farms in the landscape in the upper Midwest (Perlack & Stokes, 2011). Yet there are federal policies that set out cellulosic biofuel production standards to be met within the next decade. By communicating with farmers through surveys, we were able to identify the perspectives, attitudes, biophysical landscape characteristics and behavior drivers that can act as obstacles to bioenergy feedstock choice. Like a growing body of literature that examines drivers behind farmer management decisions, this research showed significant linkages between the land, farmers environmental attitudes, and the choices farmers make (Jensen *et al.*, 2007; Atwell *et al.*, 2009; Ma *et al.*, 2012). Outcomes of this research have potential management and policy implications through developing feedstock production incentives or policies that target farmers with environmentally vulnerable farmland.

6.3 Synthesis

The two major potential bioenergy feedstocks of interest in the Upper Midwest are corn stover and switchgrass. Each feedstock presents its own suite of adoption challenges and strengths, and the management of each presents two distinct sustainability futures. Integrating the research findings of this dissertation elucidates some of the uncertainties around sustainable futures of corn stover and switchgrass feedstocks.

Coupling the potential significant negative effects to soil productivity over the long term with a lack of willingness to adopt, the results of this research strongly suggest that corn stover harvest on fragile landscapes no longer be considered a viable sustainable bioenergy feedstock, particularly where it is already in use on extant farming systems. While logistical and managerial barriers to harvesting corn stover for bioenergy are lower than those of switchgrass, the potential soil carbon losses as a result of their harvest are too great to consider this feedstock as a sustainable replacement for fossil fuels. This research showed that continued harvest of corn stover over the long term not only drains the system of the means to replenish soil productivity, but it also fails to appeal to the potential pool of Wisconsin farmers as a practical management option for their current operations. This research points to the greater potential in switchgrass for delivery of ecosystem services while producing sufficient bioenergy feedstock, as long term model predictions project great potential for soil carbon storage and retention of agricultural soils on marginal lands. The challenge will lie in minimizing logistical and economic barriers for farmer adoption of this new crop in order to generate sufficient feedstock supply.

6.4 Research Contributions and Future Directions

Finding solutions to environmental problems requires a variety of disciplinary methodologies, tools, and datasets to extend research into the dynamics between humans and the environment. This research is the first to validate and apply the ecosystem process model, AGRO-BGC into an annual cropping system in an area of the United States that has great potential to become a hotspot for bioenergy feedstock production. In complement to AGRO-BGC, the erosion process model RUSLE2 applied to bioenergy feedstock production scenarios provided estimates to the potential soil carbon loss pathways through erosion. Having a suite of robust ecosystem and erosion process modeling tools at the hands of researchers is highly valuable in estimating the long term soil productivity impacts of bioenergy feedstocks, and can aid in developing policy recommendations for best management practices, or bioenergy feedstock management practices that minimize environmental harm and maximize ecosystem services delivery.

Further avenues for exploration into AGRO-BGC's application in intensively managed agricultural systems should include continued validation of the model across multiple bioenergy feedstock systems, deeper examination into the model mechanics for improvement of crop dynamics simulation, and improvement of the model's ability to simulate crop management practices on an annual basis. Improvement of allocation parameters to maize crop components across phenological stages would include comparing model estimates of corn grain, stem and leaf biomass to field measurements when available to improve the model's capacity to capture the phenological transitions across an annual growing season. Further exploration into simulated field management practices such as irrigation, nitrogen application, and annual crop rotations would improve our ability to apply AGRO-BGC in answering further carbon research questions in sustainable agriculture.

The application of AGRO-BGC and RUSLE2 to examine the pathways of potential carbon loss and gain from agroecosystems is significant to answering long-term questions about bioenergy sustainability. Improvements would include incorporation of updated model versions that incorporate bioenergy crop management-specific modeling parameters, and have improved residue creation functions.

The performance of vegetation index-derived f_{APAR} values in predicting crop canopy dynamics and crop yields is encouraging, and further research will do well to examine these relationships in greater detail. It will be important to pay specific attention to maintaining the most up-to-date light use efficiency coefficients that are in step with the crop cultivars used by farmers, as biotechnology continues to improve the efficiency with which crops photosynthesize.

Incorporation of environmental stress factors such as soil moisture and temperature into these models will also be of importance, particularly as climate change continues to strongly impact agricultural systems with extreme weather events.

While yield predictions can be improved by having more spatially explicit validation data and more complete interpolation of early season vegetation index (VI) data, this method employing a model based entirely on satellite data is still robust in estimating crop yields. This study confirms that LANDSAT derived VI can serve as reliable means of predicting crop yields for corn and soybean fields in Wisconsin. Because the original VI - f_{APAR} relationship is highly local, there are limitations to the spatial extent to which we can apply these f_{APAR} equations to crop fields. However, this method can be extended by testing the predictions against more field-level yield reports and county-level statistics. In addition, replication of this study against fields across a larger spectrum of edaphic, climate, and management conditions could further the application of this model to a broader spatial extents.

Because agricultural systems are dominated by human influence, the external environmental effects of agriculture are tightly coupled with farmer and rural landowner land use decisions. Designing effective and sustainable bioenergy policy will require consideration of not only the economic drivers, but also the environmental attitudes and biophysical landscape characteristics drivers of land use decisions. Although economic viability is critical to farmer adoption, this research revealed that potential for environmental benefit is also a strong driver of bioenergy feedstock adoption. Future research questions should continue to combine biophysical and socioeconomic datasets into logistic modeling to further examine the drivers behind farmer land use decisions. In particular, as more geospatial datasets become widely available, incorporating spatially explicit features of farmers and their operations to decision modeling will provide useful insight into the links between humans and their land use decisions. Generating probability maps derived from farm-level spatial information would aid identifying potential “hotspots” for sustainable bioenergy development.

Integrating the outcomes of the logistic choice models into building bioenergy feedstock scenarios will aid in further understanding of the impacts of different management approaches on long-term soil productivity. Combining socioeconomic and biophysical choice drivers into numerical modeling scenarios will provide researchers with an integrated picture of future bioenergy landscapes under varying farmer perspectives.

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