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Estimating Potential Economic Net Carbon Flux from U.S. Agriculture Using a High Resolution, Integrated, Socioeconomic-Biogeophysical Model

Chad M. Hellwinckel
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Chad M. Hellwinckel entitled "Estimating Potential Economic Net Carbon Flux from U.S. Agriculture Using a High Resolution, Integrated, Socioeconomic-Biogeophysical Model." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Geography.

Thomas L. Bell, Major Professor

We have read this dissertation and recommend its acceptance:

Carol P. Harden, Liem Tram, Daniel De La Torre Ugarte

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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A Dissertation
Presented for the
Doctor of Philosophy Degree
The University of Tennessee, Knoxville

Chad M. Hellwinckel
August 2008

DEDICATION

To Marty Bender—

Who formed questions with heart,

and relentlessly pursued their answers.

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ABSTRACT

Estimation of the carbon abatement potential of a national carbon market upon U.S. agricultural lands is needed by climate analysts, policymakers, and carbon market brokers. A high resolution, integrated, socioeconomic-biogeophysical model is developed in this research by linking the economics of land management with spatial data on soils and land use. The economic component of the model functions at the county level with biophysical data at the sub-county level of resolution.

The model is used to estimate changes in net carbon flux induced by incentives for conservation tillage on nine major crops. The *economic* potential reduction in net carbon flux at incentives of $500 per metric ton carbon (MtC) is estimated to be 18.92 million metric tons carbon (MMtC) below baseline, and 12.6 MMtC below baseline at an offered incentive of $125 per MtC.

Results indicate that the Northern Great Plains, northern Corn Belt, and Mississippi Delta have the greatest economic potential for carbon abatement. Regions with significant amounts of acreage in hay have the greatest potential for gains in net soil carbon. Application of incentives based on soil sequestration potential leads to “leakage” in some regions where land is reallocated from low input practices to higher input practices.

This analysis created an ideal opportunity to study the interactions of data resolution and analytical scale. When analyzing carbon abatement at the national scale, abatement

estimations were similar using either high or low resolution data. But, if regional estimation is a goal, the geographic resolution of data must match or surpass the geographic scale of analysis, otherwise estimation errors will be large. Although validation using field-level data indicates that model results are not appropriate for field-level estimation, it also indicates that the high resolution methodology developed here results in much smaller errors than lower resolution versions.

Results indicate that there are many challenges to implementation, but if policymakers decide to implement a carbon abatement program using conservation tillage, either through a market-based mechanism or through government ‘green payments’, the methodology developed here could help reduce uncertainty in estimating regional abatement quantities.

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CHAPTER I

INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) has reported that concentrations of greenhouse gases (GHG) in the atmosphere have risen at an increasing rate since 1861 and the beginning of the Industrial Revolution. Coincidentally, the Earth has warmed an average of 0.74°C over the last 100 years, with 11 of last 12 years being among the 12 warmest years on record (IPCC, 2007). IPCC also reports that GHG concentrations could double or even triple pre-industrial levels by the end of this century. Analysis of the 3.2 km Dome C ice core taken from Antarctica in December of 2004 revealed that current levels of CO_2 have not been surpassed in the past 800,000 years, and that the current rate of growth in atmospheric CO_2 is over 100 times faster than any increase found in the ice core data (BBC, 2006). In September of 2007, the National Snow and Ice Data Center reported that Arctic sea ice extent had reached a new record low, plummeting to only 39% of long term average ice cover (NSIDC, 2007).

Although there is still debate over the consequences of atmospheric CO_2 growth and warming, there is growing interest in taking action to curb GHG growth and even reduce their concentrations in the atmosphere. In 1998, 38 nations represented at the Kyoto Protocol (KP) of the United Nations Framework Convention on Climate Change (UNFCCC) agreed that industrialized countries should reduce GHG emissions by six to eight percent below 1990 emissions levels by 2012. Besides reducing carbon emissions directly, several methods of abating carbon emissions have been proposed, including bioenergy production, hydrologic dam construction, deep-ocean burial, terrestrial burial in geological formations, afforestation, reforestation, and soil sequestration. Within the KP, the Clean Development Mechanism[1] (CDM) was devised to evaluate, approve and oversee valid methods of abatement. The CDM has approved bio-energy production, dam construction, afforestation and reforestation as creditable sources of Certified Emission Reductions (Manguiat, 2005). Although carbon sequestration is creditable within KP (in the form of afforestation and reforestation), the CDM stopped short of including soil sequestration as a valid option for mitigation in the last round (2007), but stated that soil sequestration options should be investigated and reported for review of IPCC policy (Rosenbaum, 2004). Some studies have reported that sequestering carbon in agricultural soils through changes in land management have a low opportunity cost in the near future and may be the cheapest and most readily implemented of the sequestration strategies (McCarl and Schneider, 2001; Marland et al., 2001).

Currently within the US Congress there are several climate bills introduced that mention soil sequestration (S.2724; S.3698; S.4039; H.R.1590; S.1766; H.R.2069;S.1168; S.280; S.2191). In the recently introduced and highly touted America's Climate Security Act of 2007, soil carbon sequestration via conservation tillage is listed as an eligible offset mechanism (S.2191). If the US chooses to unilaterally initiate reductions in GHG emissions, it is likely that soil sequestration will be used as an offset mechanism under a larger GHG emission program.

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[1] The Clean Development Mechanism is an arrangement under the Kyoto Protocol allowing industrialized countries with a greenhouse gas reduction commitment (so-called Annex 1 countries) to invest in emission reducing projects in developing countries as an alternative to what is generally considered more costly emission reductions in their own countries.

Regardless of its status within the KP or the US government, carbon sequestration in US agricultural lands is moving from theoretical speculation into actual implementation. The Chicago Climate Exchange (CCX) is now paying farmers in some regions for their use of no-tillage practices that act to increase the level of carbon in their soils. Currently, 140,000 metric tons of carbon offsets are under contract on over 1,000,000 acres of US farmland per year. Carbon payments are low and the market is small, but if the US enters the Kyoto Protocol and soil carbon is accepted as a valid offset in the Clean Development Mechanism (CDM), or if the US decides to legislate emissions reductions unilaterally, incentives will likely increase.

In order for soil sequestration to gain credibility as a valid mechanism for abating emissions, it is essential to have accurate estimation of the carbon abatement potential of a national carbon market upon US agricultural lands. For example, in order for soil carbon sequestration to become an eligible offset mechanism under America's Climate Security Act of 2007, the legislation mandates that "research on soil carbon sequestration and other agricultural and forestry greenhouse gas management that has been carried out" needs to be reported to Congress within one year of the Bill's passage (S.2191). Knowing the achievable abatement quantities and their corresponding costs will influence policy choices, such as whether government agencies see it as worthwhile to subsidize market operation costs. Due to the spatial heterogeneity of soil properties, climate, and management practices, a high degree of geographic resolution, in both economic and soil data, is essential in accurate estimation and in moving the market toward implementation.

Several estimates of soil sequestration potential have been reported at highly aggregated levels of geographic resolution (Lal et al., 1998; Follett, 2001; McCarl and Schneider, 2001; Sperow et al., 2003; Lewandrowski et al., 2004). Nationally, *technical potential*[2] quantities of carbon sequestration (from afforestation, cropland to pasture conversion and conservation tillage) have been estimated at as high as 207 million metric tons carbon (MMtC) per year (Lal et al., 1998). Other studies, using integrated economic - biogeophysical models, have placed *economically feasible*[3] quantities far lower, in the range of 7 to 70 MMtC per year. This translates into US carbon emission offsets as great as 12% or as low as 0.5%. Model estimates have such a large range because of differences in model design and scale. Modeling differences in sequestration practices and payment structure has important implications upon outcomes. These studies acknowledge the great spatial heterogeneity involved in carbon sequestration, but aggregate soils and economic data to relatively large regions anyway (McCarl and Schneider, 2001; Lewendrowski et al., 2004). In evaluating the relative merits of spatial resolution, Antle et al. (2007) conclude that soil carbon research conducted using spatially explicit, disaggregated data may provide better estimates.

To date, national, integrated assessment models have undertaken analysis at low resolution levels in both economic and biophysical data. This has been shown to result in

[2] *Technical* potential sequestration is a common term in carbon sequestration literature to refer to the quantities of carbon that could be sequestered if all possible mitigating land-use changes were enacted.
[3] *Economic* potential sequestration refers to the quantities of carbon that could be reached with a given level of incentives for land managers to adopt alternative practices. Some technical potential quantities can never be reached because of their high cost. For this reason, economic potential is always less than technical potential.

aggregation error, where the distributional dynamics of both economic and environmental factors are not adequately estimated (Park and Garcia, 1994; Brown, 2000; Antle et al., 2007). The accuracy of integrated assessment models with national extent can be improved by a major refinement in the resolution of data representing both economic and environmental dynamics. If accurate estimates of the market potential of carbon sequestration are not available, policy makers may dismiss carbon sequestration policy as too risky of a venture due to unpredictable outcomes.

Objective

The objective of this dissertation is to improve the standard in integrated assessment modeling by building a high resolution economic-biogeophysical model using the most disaggregated data available *with national coverage*, with the intention of estimating *net carbon flux* from US agricultural lands from changes in management practices induced through carbon incentives. The economic decision-making component of the model will function at the county level of resolution. The model will be informed by higher resolution environmental data through the use of 30 x 30 meter resolution satellite data. Previous studies have identified conservation tillage as the most promising sequestration alternative (Antle and McCarl, 2001; Pautsch et al., 2001). I limited the scope of my research to the impacts of conversion of cropland to conservation tillage through an incentive mechanism. I analyzed the effects of conventional-tillage, reduced-tillage, and no-tillage of the eight major crops in the lower 48 states. Furthermore, the model developed in this analysis increases the temporal resolution by estimating net carbon flux annually for 20 years, allowing estimation of the market evolution during the important short-to-medium term.

In dealing with soils and their capabilities to sequester carbon, large variations exist within small geographic areas. Likewise, local economic differences in farming practices and potential yields can play significant roles in determining threshold levels where producers are induced into adopting carbon abating practices. Increasing the spatial resolution of economic potential carbon sequestration is intended to inform the international, national and regional policy process by giving the most precise estimates given current data and technology. Three primary results of my research will inform the policy process: 1) estimating the amount of net carbon flux from agriculture, nationally, that can be reduced through incentives on conservation tillage, 2) determining those regional areas of greatest potential to reduce net carbon flux, and 3) developing a methodology to use readily available data to improve the resolution in program implementation.

Additionally, this project presented an ideal opportunity to investigate the interaction of geographic resolution and scale of analysis. It is hoped that this analysis will greatly improve both the national and regional estimates of economic potential carbon abatement from incentive-induced changes in US agricultural management practices, and also demonstrate the roles of appropriate data resolution and analytic scale in modeling. The model and its results will be made available to climate modelers, policy makers, and market organizers.

My development of the model and simulations was guided by three working hypotheses:

1) In most regions the incentive will result in net abatement; yet in some regions, the incentive may act perversely and result in net emissions increases.

2) Higher resolution models are significantly better at replicating observed changes in soil carbon than lower resolution models.

3) If the scale of analysis is finer-grained than the spatial resolution of the model, then estimation errors will be great. Geographic scale of analysis must be equal to or coarser-grained than the model data resolution.

CHAPTER II:

BACKGROUND

To give a complete picture of the role of soil carbon in global climate dynamics, I first review the planetary carbon budget and soil carbon's role in the carbon cycle. Next I explain the dynamics that allow carbon to be sequestered in agricultural soils. Then I review previous studies and their estimates on potential quantities that can be sequestered in agricultural soils. Finally, I look at current views on the relationship between resolution and analytic scale in modeling highly variable dynamic spatial systems.

Soil carbon and the carbon reservoirs

Carbon cycles and accumulates in several different physical locations on the planet. The atmosphere is, by far, the smallest of the carbon reservoirs, but because it restricts long-wave radiation thereby warming the atmosphere, its importance to the dynamics controlling the other reservoirs and the temperature of the planet as a whole, far outweighs its relative scale. Table 1[4] lists the four major reservoirs of carbon and their total global quantities. Eight hundred ten giga tonnes[5] of carbon (GtC) are estimated to be in the atmosphere. The ocean reservoir is a largest and holds 38,000 GtC (Lal, 2003). Over 66 million GtC are stored in the geologic reservoir, which is made up of deposits such as limestone, dolomite, and chalk; but most of this carbon is out of the carbon cycle.

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[4] All Tables and Figures are located in Appendix C.

[5] All units in this document are in metric tons, which are commonly written in the literature as *tons* when the term *metric* proceeds it or as *tonnes*, if not proceeded by *metric*.

Table 1. Global carbon reservoirs.

Reservoir			Gigatons Carbon
Atmospheric			810
Terrestrial			3,060
	Soil Carbon		2,500
		organic	1,550
		inorganic	950
	Biotic		560
Oceanic			38,000
Geologic*			5,000
	Coal		4,000
	Oil		500
	Gas		500

Source: Lal, 2003
*carbonates in sedimentary rock not included

Fossil fuels are a part of the geologic reservoir, but only make up 4,000 GtC of the total (Lal, 2003). The terrestrial system holds 3,060 GtC; 560 GtC are held as current biotic forms of plants and animals, and 2,500 GtC are held in soil carbon. Soil carbon consists of 1,550 GT organic and 950 GT inorganic carbon (Eswaran et al., 1993; Batjes, 1996).

There is also an additional 970 GtC in the Arctic permafrost organic matter that, until recently, had been considered stable and outside of the carbon cycle (Zimov et al., 2006). Yedoma soils, consisting of frozen grass roots and animals bones, hold 500 GtC. Other permafrost soils hold an additional 400 GtC. As the Arctic warms and these soils thaw, carbon can be quickly released. Arctic peatlands hold 70 GtC, and are currently emitting methane, a potent greenhouse gas. As the Arctic warms, increasing amounts of peatland oxidize and emit stored carbon. In the future, these Arctic reservoirs of soil carbon will play an increasing role in the global carbon cycle (Smith et al., 2004).

The organic soil carbon reservoir holds twice as much carbon as current atmospheric levels and three times as much carbon as all living biota. The dynamics that occur within the soil carbon reservoir play a major role in impacting the atmospheric carbon level. If human land use and climate change act to release even a small percentage of soil carbon, the resulting (relative) increase in atmospheric carbon would be compounded. Alternatively, changes in human land use that increase the net absorption of carbon within soil could decrease atmospheric carbon by critical amounts.

Soil carbon and the carbon cycle

Scientists are independently determining the emissions of carbon from fossil fuels and land-use change, the quantities of carbon that the oceans absorb, the additional quantities being absorbed terrestrially through CO_2 fertilization and climate change, and the quantity of carbon increasing in the atmosphere. It is important to put these independent numbers together to see how close scientists are to balancing annual emissions of carbon with annual sinks of carbon.

The value of annual changes for some of the carbon reservoirs is more certain than for others. The level of atmospheric carbon is quite certain and can be easily measured. During the 1990s the average annual increase in atmospheric carbon was estimated to be 3.2 GtC (Prentice et al., 2001). Fossil fuel emission is the next most certain variable in the equation. Human burning of fossil fuels was estimated to emit an average of 6.5 GtC per year during the 1990s (Prentice et al., 2001). Oceanic uptake is less certain and was estimated to have been 2.2 GtC per year during the 1990s. Land-use change, the least certain due to complexities in its dynamics, was estimated to emit 1.6 GtC per year (Houghton, 2003). Table 2 lists these quantities along with the implied residual missing sink which is assigned to 'land' uptake. Subtracting oceanic uptake from total sources shows that there should be a 5.9 GtC per year increase in atmospheric carbon, but measurements indicate that the atmosphere only gained 3.2 GtC per year. This implies that 2.7 GtC per year accumulated in unmeasured locations. This is referred to as the 'missing sink' and is assumed by most climate scientists to reside in the land reservoir (Houghton, 2003).

Table 2 also shows the relative increases through time of the sources and sinks. The most recent data show an alarming increase in fossil fuel emissions and a simultaneous slow-down in the absorption of carbon by both ocean and land reservoirs. In their analysis of long-term trends in the carbon cycle, Canadell et al. (2007) hypothesize that land

Table 2. Average annual sources and sinks in the carbon cycle.

	Mean			
	1959-2006	**1970-1999**	**1990-1999**	**2000-2006**
Sources		**GtCy^{-1}**		
Fossil Fuel	5.3	5.6	6.5	7.6
Land Use Change	1.5	1.5	1.6	1.5
Total	6.8	7.1	8.1	9.1
Sinks				
Atmosphere	2.9	3.1	3.2	4.1
Ocean	1.9	2	2.2	2.2
	4.8	5.1	5.4	6.3
Residual Sink = Land Uptake	2	2	2.7	2.8

Source: Canadell, J.G. et al. 2007

resources have been absorbing less carbon due to increased drought (frequencies) during the current decade.

The Earth's soils (along with biota) have been playing an important role in absorbing 2.8 GtC of the 7.6 GtC of fossil fuel emissions. Soil's role in absorbing excess carbon is capable of expanding through changes in human land-use management. I will, next, discuss how the soil reservoir can be expanded though the promotion of soil carbon sequestration.

Soil carbon sequestration

Carbon can be sequestered in agricultural soils by changing land management to practices that increase soil organic matter. If the amount of carbon entering the soil can exceed amounts lost through soil respiration, then net gains can be made. Such practices include reducing tillage intensity, using perennial crops, using a winter cover crop, increasing rotation complexity, applying fertilizer efficiently, decreasing erosion, and reducing the amount of time fields lay fallow. In most cases, the reason agricultural soils can accumulate carbon is due to historic carbon losses caused by years of heavy cultivation. By changing management practices, some or all of the historically lost carbon can be regained over a few decades. It is estimated that historic global carbon losses from agricultural soils range from 40 to 60 GtC (Paustian et al., 1997). Yet not all of this carbon is likely to be regained, even through the most ambitious of land management plans. Lowland soils, such as Histosols, that retained much of their carbon by being water-saturated, have been drained and are not likely to be re-flooded. Therefore, the total likely peak potential for carbon sequestration has been estimated at one-half the total loss, or between 20 to 30 GtC. If accumulation of soil carbon occurs over a 100-year period and surplus agricultural lands revert to grassland or wetlands, then the annual potential global carbon sequestration in agricultural soils ranges from 0.2 to 0.4 GtC , or 6 to 12% of the estimated annual atmospheric carbon increase (Cole et al., 1996).

Some scientists suggest that sequestration potential above that which has been historically lost may be possible (Lehmann et al., 2003; Marris, 2006). Lehmann et al. (2003) propose that by amending soil with biochar, which is a bi-product of pyrolysis (low temperature gasification) of biomass for fuel production, soil quality can be improved while sequestering more carbon in a very stable molecular state. The idea of pyrolysis and biochar amendment came from studying the *Terra Preta* soils, or dark earths, of the Amazon, where intensive management of soil carbon was practiced historically by the indigenous populations. It is hypothesized that indigenous agriculturalists used a 'slash and smolder' form of agriculture where biomass was aggregated into charcoal (as opposed to temporary 'slash and burn', where most of the carbon is burned and released). The charcoal has remained in the fields for thousands of years, and its unique molecular structure aids in absorbing and storing vital micronutrients. Hence soil quality was improved as carbon was sequestered long term. Lehmann et al. (2003) estimate that if biochar schemes are used in conjunction with biofuel programs, they could offset upwards of 9.5 GtC per year, which is more than the current total annual global carbon emissions (Lehmann et. al., 2003; Marris, 2006).

Soil carbon dynamics

The original source of all carbon in soil organic matter is plant material photosynthesized from sunlight. The organic matter, consisting of carbon, oxygen and hydrogen, is returned to the soil through annual die-back of plant biomass, the eventual death of plants, or the return of manure or organic material from animals that ingested plant biomass (although animals may not return the organic material to the same locale). The newly fallen organic matter then interacts with the atmosphere and soil fauna through a decomposition process. Three primary reactions occur: 1) sugars, starches and amino acids are enzymatically oxidized and released as carbon dioxide, 2) proteins and lignin are decomposed slowly and release carbon dioxide, and 3) carbon compounds very resistant to decay are formed through microbial interactions. The soil fauna is composed of thousands of microorganisms that are uniquely evolved to feed upon specific molecules that emerge throughout the time-span of normal biomass decomposition. The first wave of microbes feeds upon the sugars, starches and amino acids, then another group of microbes flourishes as they break down proteins, cellulose and lignin. Depending on temperature and precipitation conditions, breakdown of cellulose and lignin could go on for decades, but eventually very little of the initial biomass exists. Yet some does remain by becoming *physically* protected from decay via encasement inside soil pores too tight for microbes to enter. Some also becomes *chemically* protected through microbial reactions which alter lignin into extremely resistant soil aggregates. At the end of the decomposition cycle, total soil organic carbon (SOC) increases slightly through the biomass residues being incorporated through decomposition into the soil (Brady and Weil, 1999).

Other variables affect the rapidness and completeness of decomposition. Soil microbes are most active when temperatures are warm and there is adequate moisture. The rate of decomposition increases with temperature and can be described by the power function, Q_{10}. Q_{10} is used in the Arrhenius equation, which figures the rate of chemical reactions as a function of temperature (and activation energy) (Davidson and Janssens, 2006). It is generally assumed that the rate of reaction, or decomposition, doubles for every 10°C rise in temperature (Davidson and Janssens, 2006). Optimal decomposition occurs when soil moisture is around 55-60% by weight. More moisture than this can limit oxygen availability and slow decomposition. Drier soils also slow decomposition (Paustian, 1997).

Because temperature and moisture are the two most important variables affecting speed of decomposition, sequestration ability varies with climate. In general, net primary productivity declines as the climate dries, making fewer residues available and resulting in a lower proportion of soil carbon. Also, as the climate changes from cooler to warmer, decomposition rates increase and soil carbon levels decrease. Sequestration in tropical climates does not hold the same carbon-retaining capabilities as soils in more temperate regions. In temperate soils, decomposition is slowed in winter months, therefore sequestering the carbon from release during those months. Additionally, plants in temperate climates distribute more of the biomass below the soil's surface for the purpose of over-wintering. As plants die, the below-ground biomass adds to soil carbon accumulation.

Effect of management on soil carbon

Conventional-tillage aerates the soil and breaks up organic residues into smaller particles that are more accessible to soil microbes. Cultivation can also increase soil temperatures by exposing darker energy-absorbing soil, and thus increasing the rate of decomposition. When virgin soils are tilled and brought into cultivation, SOC levels continue to drop until a new lower steady-state of SOC is reached. Switching to conservation tillage 1) reduces aeration compared to conventional-tillage, 2) allows organic residues to remain longer undisturbed and, therefore, less accessible to decomposition, and 3) allows soil temperatures to remain cooler due to surface residues. The combination of these processes allows conservation tillage to increase SOC levels (Lal et al., 1998).

Yet two recent studies have thrown doubt on whether conservation tillage results in a net reduction in SOC. Baker et al. (2007) point out that almost all the tillage experiments showing an increase in SOC under no-tillage only sampled to the 30-cm depth. The few studies that sample the deeper soil layers showed no significant difference in SOC between conventional-tillage and no-tillage. They hypothesize that, rather than tillage causing historical SOC losses, SOC may have been lost due to the change in ecosystems from perennial, deep-root plants to annual shallow-root plants. Additionally, Li et al. (2005) suggest that, by increasing SOC levels through no-tillage, nitrous oxide emissions may increase enough to offset the reduction in atmospheric carbon from the sequestered carbon, and resulting in a net increase in GHG's. This may occur through changing the carbon-nitrogen ratio. Raising carbon levels in carbon-deficient soils may raise the carbon-nitrogen ratio to benefit microbial growth, which, in turn, increases nitrous oxide emissions.

Rotations also have an effect upon soil carbon. Generally, rotations producing more annual residue lead to higher levels of SOC (Brady, 1999). For example, planting corn continuously would lead to higher SOC accumulations than a rotation of corn and soybeans. Exceptions involve rotations with crops that possess large root structures, which can add more biomass below the soil surface. Hay and alfalfa used in rotation with other crops act to increase SOC levels through the growth of deep roots which deposit carbon within the soil (Brady, 1999).

Nutrient amendments can have highly variable effects on SOC levels. They can either act to increase or decrease SOC. Nutrients can help increase net primary productivity; yet, at the same time, they can speed decomposition by feeding the microbes. Nitrogen is usually a limiting factor in decomposition where carbon is optimal. Soil microbes need about 25 parts of carbon for every part of nitrogen to grow; therefore, at carbon to nitrogen (C/N) ratios lower than 25:1, decomposition is slowed. If nitrogen is a limiting factor, and nitrogen is added, microbes can flourish and release more carbon to the atmosphere resulting in a lower level of SOC. Nitrogen amendments may also result in a net increase in atmospheric carbon due to the high rate of emissions associated with their industrial production (Schlesinger, 2000). On the other hand, limiting nitrogen to sequester more carbon is not a likely route either, due to decreased yield potential. The most beneficial use of nutrients to increase SOC levels is increasing the efficiency and timing of applications to assure that applied nutrients are mostly taken up by the growing biomass and not used to feed the soil fauna (Follett, 2001).

Effect of climate change on soil carbon

Recent studies indicate that there may be a synergistic effect between the use of no-tillage farming and increased levels of atmospheric CO_2, which may lead to a more rapid increase in SOC. In their study, Prior et al. (2005) compared plots of conventional and no-tillage crops grown under increased CO_2 levels. Soil carbon and residue accumulations were observed over a four-year period. Although all plots showed increases in residues and SOC, no-tillage residues increased by 30% above those of conventional-tillage.

Jain et al. (2005) estimated the amount of additional carbon sequestered under no-tillage in the US due to increased CO_2 levels. Using ISAM-2[6] simulation model and empirically based carbon management response curves for tillage practices, conversion of agricultural land to no-tillage was simulated over the period 1981 to 2000 under both steady CO_2 levels and historically higher levels. The study concluded that CO_2 fertilization sequestered an additional 42 MMtC over the time period, or 2.1 MMtC per year, under no-tillage. These studies indicate that conversion of cropland to conservation tillage has the potential to capture more carbon from CO_2 fertilization. This is in addition to increasing SOC through soil biophysical processes.

[6] The Integrated Science Assessment Model (ISAM-2) is a climate model developed by researchers at the University of Illinois that replicates terrestrial carbon and nitrogen cycles and their interaction with the atmosphere at the 0.5 degree latitude and longitude resolution level.

Other studies analyzing the effect of a warmer climate upon SOC levels show mixed conclusions. It is a long-held assumption that warming increases microbial activity, which causes SOC levels to decrease (Davidson and Janssens, 2006). Yet in their review of soil experiments, Thornley and Cannell (2001) found little empirical evidence that SOC levels decrease under warming. They hypothesized that, rather than assuming the temperature sensitivity of soil respiration to be overestimated (in current models), "warming may increase the rate of physico-chemical processes which transfer organic carbon to protected, more stable, soil carbon pools." They concluded that "if the rate of physico-chemical reactions have a 50% greater response than microbial reactions, then soil carbon would [actually] increase" under warming (Thornley and Cannell, 2001).

Melillo et al. (2002) studied net carbon flux and nitrogen mineralization in a ten-year study of forest plots comparing heated and unheated soil. While the heated plot did have a higher net flux of carbon out of soil, the spike in net flux was short-lived, due to limited amounts of carbon in the mid-latitude (Massachusetts) forest. They also found that warming increases nitrogen mineralization, which could potentially offset much of the lost carbon by stimulating additional plant growth (Melillo et al., 2002). The same dynamics could dominate in poorer-soil agricultural lands.

National estimates of soil carbon sequestration potential

Potential quantities of carbon that can be sequestered by US agricultural soils fall into two groups: *technical* and *economic* potential. *Technical* potential measures the amount of carbon abatement if all proposed practices could be implemented in full, regardless of economic costs. *Economic* potential takes into consideration the costs of implementation versus potential payments received through incentives. Technical potential quantities are always higher than economic potential quantities.

In his analysis of technical potential, Follett (2001) estimated that, if conservation tillage were widely adopted, fallow periods were reduced, cover crops were more widely used, and production inputs were used more efficiently, then 30 to 105 MMtC per year could potentially be sequestered in US soils. Sperow et al. (2003) estimated that similar changes to crop management practices could sequester 60-70 MMtC. Lal et al. (1998) estimated 75-208 MMtC of potential soil storage in agricultural soils of the US.

Such potential quantities of carbon sequestration may not be realized due to economic constraints. Implementation of the new land management practices proposed in the above studies would result in some producers having to forgo more income than the new practices could earn. If incentives were offered, initial changes in land use might increase commodity prices and make further land-use changes prohibitably expensive. At low payment levels, some carbon sequestering practices may easily be put into practice, yet the cost per carbon storage unit would be expected to increase at an increasing rate as the marginal cost of conversion of remaining lands increases. For these reasons, several studies have analyzed the economic potential of carbon through the use of economic models. These models include the dynamic interactions of competition within crops for land use, along with the underlying demands from other sectors such as livestock, food and energy. While several economic studies have looked at carbon sequestration locally (Plantinga et al., 1999; Pautsch et al., 2001; Antle et al., 2007), only two have looked at the subject nationally (McCarl and Schneider, 2001; Lewandrowski et al., 2004).

McCarl and Schneider (2001) measured the economic potential of several mitigation strategies simultaneously, including soil sequestration, afforestation and biofuel offsets in their Agricultural Sector and Green House Gas Model (ASMGHG)[7]. They estimated that agricultural lands could sequester a maximum of 70 MMtC by changing management practices at carbon incentives at or below $500 per metric ton of carbon (MtC). McCarl and Schneider included conservation tillage, manure management and conversion of cropland to pasture within their defined category of land management. They did not consider transaction costs or discounting for impermanence, and only paid incentives to 'new adopters' (and also employed symmetric taxation on changes in management practices that result in higher emissions). Therefore, they considered their estimates as 'lower bound' costs. The study also accounted for changes in emissions from input use (e.g., fertilizers, pesticides, machinery fuel) in estimating net abatement quantities. The ASMGHG model disaggregates the nation into 63 regions and 22 commodities and is solved for market equilibrium in 10-year iterations. Soil carbon data are aggregated to the regional level and Erosion Productivity Impact Calculator (EPIC) biophysical model[8]

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[7] The ASMGHG model is a partial equilibrium economic market-clearing model developed at Texas A&M University by Bruce McCarl and Uwe Schneider specifically to analyze carbon sequestration in agriculture and forestry.
[8] The EPIC model is a biophysical model that simulates the dynamics of soil nutrient cycling at a high degree of resolution. It was developed in the 1980s at Texas A&M University.

was used to estimate sequestration quantities associated with crop and tillage types within the regions (McCarl and Schneider, 2001).

Lewandrowski et al. (2004) measured economic potential sequestration using the US Math Programming (USMP) model [9], which is a spatial and market equilibrium model similar to ASMGHG. They estimated 7-35 MMtC of potential economic sequestration in agricultural lands with offered carbon incentives at or below $125 per MT. The USMP model disaggregates the nation into 45 regions and 10 major crops. For estimating changes in SOC, Lewandrowski et al. (2004) used the IPCC methodology developed as a first-order approach to estimating soil carbon changes. Initial soil carbon levels were derived from weighting 1997 National Resources Inventory (NRI) data points to ten farm production regions. IPCC parameters for changing from conventional-tillage to no-tillage and from conventional-tillage to reduced-tillage were applied to the initial carbon levels to arrive at the net change in soil carbon. Lewandrowski et al. (2004) tested multiple incentive program designs through individual scenarios. The scenarios investigated farmer response to: a) rental payments versus full asset value (permanence assumption); b) payment of sequestration incentives versus additional taxes on carbon-emitting management practices; and c) government 'cost sharing' of a portion of the conversion costs to alternative practices versus requiring farmers to bear the full burden of conversion. In the scenario in which leakage [10] is controlled through symmetric

[9] USMP is a spatial and market equilibrium model designed for general-purpose economic and policy analysis of the U.S. agricultural sector developed at the US Economic Research Service in Washington, DC.

[10] Leakage is defined as the unintended *increase* in atmospheric carbon as a result of policies to *decrease* atmospheric carbon.

taxation, Lewandrowski et al. (2004) estimated that 27.6 MMtC can be abated annually at $125 per MtC.

Appropriate roles of resolution and scale

The geographic literature has long debated the proper role of resolution and analytic scale in capturing the real dynamics in both human and environmental systems[11] (Haggett, 1965; Harvey, 1968; Tobler, 1969). Recently, there have been many analyses of scale and resolution pertaining to climatic and geomorphological modeling (Easterling, et al., 2001; Mearns et al., 2001; Luoto and Hjort, 2006; Thoma et al., 2008). Yet few studies have rigorously assessed the roles of resolution and scale in integrated economic and environmental models (Adams et al., 2003). In modeling soil carbon policy, it is important to realize that heterogeneity in economic and environmental factors among deferring sites within a system boundary may lead to different thresholds of land-use adoption (Hochman and Zilberman, 1978; Openshaw and Taylor, 1979). When confronted with heterogeneity, modelers face many questions: What resolution of data do we use? Will different data resolutions affect the results? At what scale do you undertake an analysis? Are there appropriate and inappropriate scales for using a

[11] Because there is much confusion over the terms *scope, scale, extent*, and *resolution*, I will precisely define their use in this paper. *Resolution* will refer to the spatial level at which unique estimates of model variables are estimated. For example, soil carbon is estimated at the STATSGO regional resolution level. 'High' resolution refers to small spatial units of unique data, and 'low' resolution refers to large spatial units of unique data. *Scale* will refer to the spatial level at which the analysis results are reported. For example, although this study uses STATSGO resolution soil carbon data, the analysis is reported at the national scale. The terms *scope* and *extent* are also used within the literature to refer to the spatial level of analysis, but will be referred to as *scale* in this document for consistency. In this analysis, 'larger' scale analyses refer to larger spatial areas, whereas 'smaller' scale analyses refer to smaller spatial areas. Geographers often use the opposite meanings when referring to map scales, where 'large scale' means smaller more detailed areas, and 'small scale' means larger, less detailed areas. The use of 'scale' in level of analysis should not be confused with the common use of 'scale' in mapping

particular level of data resolution? While integrated models often confront issues of resolution and scale, few explicitly define their uses in practice (Meentemeyer, 1989).

Modeling, by definition, is a simplification of reality, but how we simplify can have major implications upon a model's results. There are tradeoffs in deciding at what resolution to model a system's behavior. As you bring the model to higher levels of resolution, the accuracy of the model may improve, yet the data collection costs, time investment and model complexity increase. So what is the appropriate relationship between resolution and scale in integrated economic biogeophysical modeling of soil carbon sequestration?

A growing body of scientific work has investigated the integration of economic and biogeophysical models at higher resolutions (Just and Antle, 1990; Goddard et al., 1996; Antle et al., 2001; Stoorvogel et al., 2004; Antle et al., 2007). Yet, in their evaluation of scale and resolution issues in integrated assessment modeling, Evans et al. (2002) concluded, "there is no consensus on how to deal with scale issues in the social sciences and by extension no evident answers in terms of integrated assessment modeling."

Although most integrated assessment modelers acknowledge heterogeneity, there is discrepancy over maintaining high resolution in scaled-up studies (Valdivia, 2006). Commonly, the unit of policy analysis is a large region, and models have often used aggregated data to arrive at the predicted effect upon the whole region (Antle et al., 2001). Yet it has not been clearly resolved whether smaller scale differences in outcomes that occur at finer resolutions will average out by aggregating to a larger scale (Antle and Wagenet, 1995; Dumanski et. al., 1998). In studying the effects of scale on carbon sequestration estimates for the central US, Antle et al. (2007) compared county-level econometric biophysical results with results from a larger regional level analysis where the mean carbon accumulation for the US central plains was used. They found that, for the region as a whole, results using aggregate mean carbon accumulation rates were within 10% of the results using the county-specific carbon accumulation rates.

Significantly greater errors may result from using low resolution data collected from a larger region to model dynamics on a smaller scale (Brown, 2000). Antle et al. (2007) also compared results from specific counties using both disaggregated county level soils data and aggregated regional level soils data. Their results indicate that estimates using aggregate mean carbon accumulation were very high compared to those using disaggregated data. They concluded that "the large errors in predictions for individual counties show that estimates of carbon rates do need to be matched to the spatial scale of analysis" (Antle et al., 2007).

Berger (2001) proposed a methodology for integrating GIS data into a disaggregated, agent-based land-use change model. He concluded that integrating economic and ecological models for policy analysis would be an ambitious undertaking, but, if accomplished, "…GIS-based integrated multi-agent models will become a powerful tool for policy analysis and natural resource management" (Berger, 2001). The intention of this study is to integrate satellite-derived biophysical data with other inventory data using

GIS that will allow land-use dynamics to be estimated at a higher resolution. These higher resolution data can then be used to test scale and resolution issues. Specifically, what is gained by higher resolution in the study of soil carbon sequestration?

CHAPTER III:

METHODOLOGY

Overview

The analytical tool used to conduct this analysis is an integrated socioeconomic-biogeophysical model. The integrated model uses economic and soil data at the highest degree of resolution feasible from currently available secondary sources with national coverage. The economic heart of the model is a modified version of POLYSYS, which is a partial equilibrium displacement model that iterates annually and simulates until the year 2025 (Ray et al. 1998a; De La Torre Ugarte et al., 1998; De La Torre Ugarte and Ray 2000). For this analysis, I have disaggregated POLYSYS to the county level, where, in each county, representation of cropping activities has been expanded to include conventional-tillage, reduced-tillage and no-tillage operations. Baseline acreage for each tillage type is derived from trends in Conservation Technology Information Center survey data (CTIC, 2004). Tillage yields are based upon National Agricultural Statistic Service county averages (NASS, 2007) and extrapolated to specific tillage yields by analyzing the results of regional tillage experiments. The model makes use of over 3,000 newly created unique regional crop budgets, which are based upon regional differences in crop production operations. Both direct and indirect use of energy and emissions of carbon have been tied to each input of the operation budgets, therefore the model can simulate changes in production emissions.

Carbon net flux is a result of changes in both SOC *and* changes in carbon emissions from agricultural inputs. Since some carbon-sequestering management operations have lower carbon emissions than others, there could be considerably greater potential amounts of net carbon reductions than if only accounting for SOC. The linear program design allows for accounting of domestic leakage in the agricultural carbon market. Leakage is defined as the unintended *increase* in atmospheric carbon as a result of policies to *decrease* atmospheric carbon.

Several layers of biogeophysical data were overlaid to create a model capable of simulating changes in SOC at the sub-county level. Regional carbon management response curves (West et al., 2003), STATSGO soils data (USDA, 1994) and Landsat land use cover data (Homer et al., 2007) were integrated to determine potential changes in SOC associated with each unique combination of soil type and crop type. The carbon management response curves give the percentage change in carbon per year of a particular management practice. STATSGO data give initial soil carbon at the MUID (soil map unit ID) level. And Landsat data are used to determine where the crop acres are located. Once the location of cropland is known, the overlay of STATSGO data gives the initial SOC of all cropland. The accuracy of carbon accumulation is greatly improved by this methodology. The overlay of these layers of data allows for estimation of the annual amounts of carbon that a particular crop in a particular county under a particular tillage-type can accumulate. A schematic of data layer integration is presented in Figure 1.

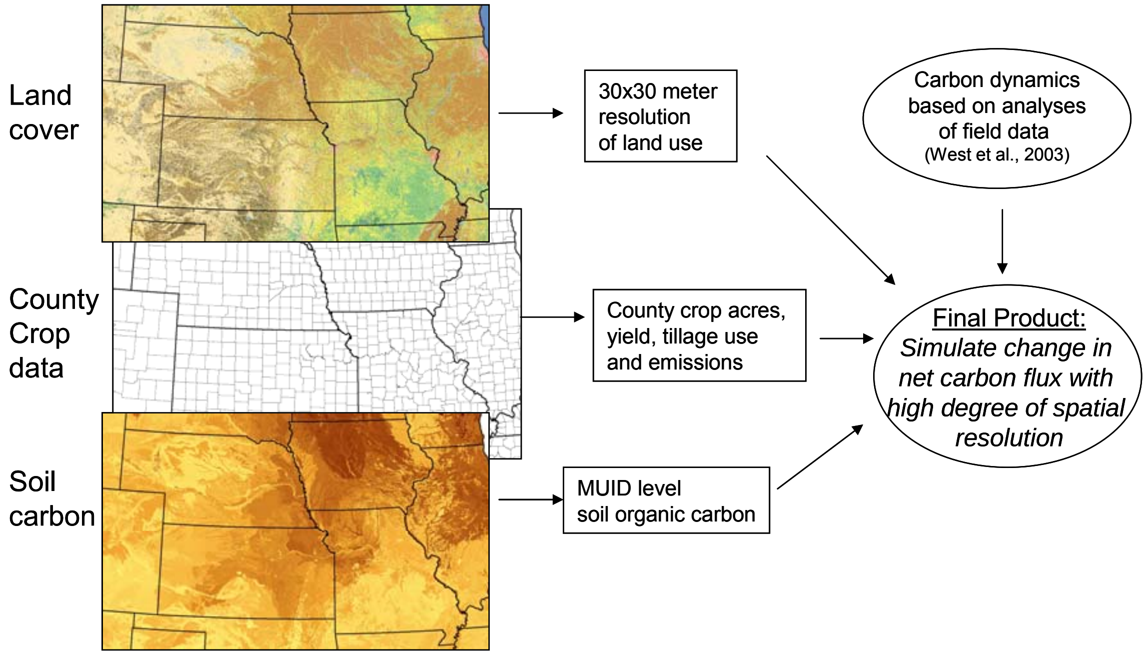

Figure 1. Schematic of layer integration and simulation. Although the data layers have national coverage, only a portion is shown here to depict the resolution.

The model uses secondary data from several different levels of resolution listed in Table 3. Resolution ranges from the highest resolution National Land Coverage Data (NLCD), which are at the 30 meter level, to lower resolution budget data, which are from the multi-county Agricultural Statistic Districts. In all instances, the model data are the highest resolution available from secondary sources with national coverage in each data category. Spatial information with the highest variability, such as SOC levels and cropland location are at very high levels of resolution, whereas information with less spatial variation, such as crop-operation schedules are at lower resolutions. The economic component of the model is used to solve scenarios at the county level, but soils information from higher resolutions informs the economic model. For this reason, the model can be considered sub-county in resolution.

Table 3. Spatial data source, resolution, and use in this research.

Data source	Spatial resolution	Use in this research
NASS	County	County Crop Acres
CTIC	County	Percentage of crops in conventional, reduced and no-tillage
STATSGO	MUID region	Weighted base soil carbon level underlying land use.
NLCD	30m x 30m	Placement of county crop acres upon base soils.
Field data on soil carbon change	Plot to field	Rate of change in base carbon by crop category.
Agricultural Budgeting System (ABS)	Agricultural Statistic District	Crop costs, operations and emissions

Core socio-economic model

The socioeconomic modeling component of this analysis is based on the University of Tennessee's Policy Analysis System model (Ray et al. 1998a; De La Torre Ugarte et al., 1998; De La Torre Ugarte and Ray 2000). POLYSYS is a rigorous model embedded in economic theory capable of estimating annual changes in land use and crop prices associated with exogenous changes in yield and management practices in the United States (De La Torre Ugarte et al. 1998, Ray et al. 1998b). The POLYSYS modeling framework can be conceptualized as a variant of an equilibrium displacement model (EDM). The general appeal of EDMs is in part due to the inherent ability to complete modeling exercises in a wide variety of market structures (Wohlgenant 1993, Piggot et al. 1995, Brown 1995, Kinnucan 1996).

The POLYSYS modeling framework has been previously developed to simulate changes in economic policy, agricultural management, and natural resource conditions, and to estimate the resulting impacts from these changes on the US agricultural sector (Ray et al. 1998b; Lin et al. 2000; De La Torre Ugarte and Ray, 2000). At its core, POLYSYS is structured as a system of interdependent modules simulating (a) crop supply for the continental US, which I have disaggregated into 3110 production regions; (b) national crop demands and prices; (c) national livestock supply and demand; and (d) agricultural income. Variables that drive the previously listed modules include planted and harvested area, production inputs, yield, exports, costs of production, demand by use, farm price, government program outlays, and net realized income. The POLYSYS modeling framework is capable of considering a wide variety of region-specific management practices. Crops currently considered in POLYSYS include corn, grain sorghum, oats, barley, wheat, soybeans, cotton, rice, and hay.

POLYSYS anchors its analyses to US Department of Agriculture (USDA) published baseline of projections for the agriculture sector. I have endogenously expanded the USDA ten-year baseline projection period through 2025 for this analysis.   Changes in agricultural land use, based on cropland allocation decisions made by individual farmers, are primarily driven by the expected productivity of the land, the cost of crop production, the expected economic return on the crop, and domestic and world market conditions. When provided with data for production inputs, changes in yields, and incentive levels that would accompany carbon management options, POLYSYS can be used to estimate potential changes in land use.

Changes in agricultural land use, based on cropland allocation decisions made by individual farmers, are primarily driven by the expected productivity of the land, the cost of crop production, the expected economic return on the crop, and domestic and world market conditions. By providing POLYSYS with data for production inputs, changes in yields, and incentive levels that would accompany carbon management options, we can estimate potential changes in land use. Using estimates of land-use change generated by POLYSYS in conjunction with the integrated biogeophysical data, a full carbon cycle, or net carbon flux, analysis for potential carbon management options is completed.

Previous economic modeling work on the role of agriculture as a carbon sink, by Lewandroski et al. (2004), McCarl et al. (2001) and Adams et al. (1992,1999) has approached the issue by analyzing long-term and intermediate-run outcomes, i.e., equilibrium situations, which occur in durations of ten or more years. Adjustment costs incurred in the short-run for implementing new technologies and/or policies are not considered by the models used in those studies (Schneider 2000). Additionally, such long-term modeling is incapable of assessing the near-term challenges of adoption. This is particularly important since changes in soil carbon resulting from changes in agricultural management are expected to occur, on average, within the first 15-60 years following the initial change depending on the particular management option (West and Post 2002, West et al. 2003).

The POLYSYS model has the unique ability to provide annual estimates of changes in land use, adoption of management practices, and changes in economic conditions as a result of policy changes in agriculture. Integrating terrestrial carbon dynamics with POLYSYS produces a framework capable of estimating future carbon sinks, sources, land-use change, and net greenhouse gas emissions that result from carbon management options and from economic incentives for carbon management options.

In making decisions, farmers take other factors besides net present value into consideration. For example, unique levels of risk aversion, lack of full knowledge of alternatives, local land characteristics, and landowners nearing retirement may all impact individual decisions. These factors, and many others, play a role in landowners not always choosing the management scheme with the highest net present value. While POLYSYS does not explicitly model these other factors, it does take them into account through the use of constraints within the linear programming models. These constraints act to limit the amounts of land that can switch to a particular management practice in a given time period. Based on historical studies evaluating the sudden emergence of dominant management practices, no more than a portion of the landmass is switched from one practice to another in one year (Dicks and Li, 1991). POLYSYS incorporates these historical constraints into the linear programming design. In this manner, other factors besides net present value are indirectly included into the land allocation decision.

Building the integrated model

In order to create a high-resolution model capable of simulating regional and national impacts of a carbon incentive program for conservation tillage, methods of collecting, scaling, and integrating biogeophysical data with POLYSYS economic model had to be created.

To create the integrated model these steps were taken:

1) Developed methodology to simulate SOC changes at the sub-county level of resolution.
    a. Estimated initial sub-county soil organic carbon levels by integrating:
        i. National Agricultural Statistics Service (NASS) county crop data that report acres of each crop in each county.

ii. Conservation Technology Information Center (CTIC) tillage data that report the percentage of each crop in each tillage type in each county.

iii. State Soil Geographic (STATSGO) database, which has data capable of estimating a weighted average of the soil components to arrive at one soil carbon estimate in units of metric tons per 0-30 cm depth, for each spatially delineated soil map unit (MUID).

iv. National Land Cover Data (NLCD) Landsat TM imagery that reports the land use at a 30x30 meter resolution in 2003.

b. Incorporated SOC response rates.

c. Adjusted response rate by initial soil carbon levels.

2) Developed methodology to simulate changes in emissions from the crop production process.

a. Developed unique conventional, reduced and no-tillage operation budgets for all major crops grown within the US, at the Agricultural Statistic District level.

b. Estimated carbon emissions (both direct and embodied) for all inputs to crop production and integrated them within the modeling framework to allow for the estimation of total emissions from crop practices.

3) Created a county-level decision-making linear programming supply module within POLYSYS.

4) Quantified the uncertainty of no-tillage due to yield changes over time within its net present value.

Each of these steps and their methodologies are explained in the following sections.

Soil carbon sequestration estimation

Accumulation of soil carbon is a function of crop and tillage combination and varies by county and crop depending upon soil quality and environmental conditions. The estimation of annual metric tons of soil carbon sequestration per acre is figured by:

$$Tacre_{i,j} = C_{i,j} * (\Delta_j * Adj_{Cij}) \qquad \text{(equation 1)}$$

Where,

$Tacre_{i,j}$ = MtC per acre in county i, for crop j.

$C_{i,j}$ = base (initial) carbon level in county i, for crop j (MtC per acre).

Δ_j = change in carbon level per year of crop j, under tillage t (%).

Adj_{Cij} = carbon response adjustment factor for Δ_j in soil $C_{i,j}$.

Estimation of base soil carbon ($C_{i,j}$) in metric tons per acre is disaggregated by crop and county (with higher resolution soils data more highly weighted to inform the county estimates). The base soil carbon is multiplied by the carbon response rate (Δ_j) of a particular crop under a particular tillage regime. The carbon response rate is adjusted by multiplying by the adjustment factor (Adj_{Cij}), which is dependent upon the regional soil carbon level. This results in an estimate of the real potential change in soil carbon per acre ($Tacre_{i,j}$) specific to each particular crop in each particular county under both reduced-tillage and no-tillage regimes.

Base soil carbon estimation

A major contribution of my research is estimating base soil carbon using sub-county resolution to create estimates specific to crop type and county. This was done by superimposing land-use data on regional soils data. First, I will review the methods of estimating regional soil carbon data; then, I will explain the layering of these data with land use data.

Geographically explicit base soil carbon quantities are weighted to the STATSGO MUID region and defined as per acre estimates of organic carbon to the 30 cm depth. Data on soil series base soil carbon were estimated and provided by Tristram West of Oak Ridge National Laboratory. The methodology of deriving soil carbon estimations at the 30 cm depth is described in West et al. (2007); the State Soil Geographic database (STATSGO, version 1.0; USDA, 1994), was used to obtain initial information for soil attributes. The STATSGO-delineated soil map units encompass between 1 and 26 soil components, representing phases of a soil series. Each soil series phase within a map unit is given a high and low value for each soil attribute (e.g., soil organic matter, bulk density, soil layer depth, soil texture). To generate a baseline soils map, West et al. averaged the high and low values for attributes of each soil series phase, converted soil organic matter content to soil organic carbon content, multiplied the carbon content by soil bulk density and by the depth of the respective soil layer, and corrected for the percentage of rock fragments in each soil layer. Soil carbon was estimated by 20 cm intervals to a 1 meter depth. A weighted average of soil carbon was calculated among soil series phases within each soil map unit, resulting in one soil carbon estimate for each spatially delineated soil map unit.

To weight regional soil carbon by crop type at the county level ($C_{i,j}$), I superimposed NLCD on the STATSGO-generated soil carbon data. The NLCD are derived from 2001 Landsat Thematic Mapper satellite data and have a spatial resolution of 30 m. The NLCD are available for the conterminous US and represent 21 land cover/use classes (Homer et al., 2007). For this analysis, all model crops are in the NLCD subclasses of row crops, small grains and pasture. Superimposing STATSGO MUID regions and NLCD allow one to determine the base soil carbon underlying agricultural crop areas. At this point, the base carbon level at the 30 cm depth is estimated from STATGO MUID regions underlying each 30x30 meter NLCD pixel. Once known at the 30 meter resolution, base soil carbon estimates are weighted to county level for each major land-use category by the relative area of each crop category.

This methodology yields more specific estimates of base soil carbon than simply weighting entire MUID regions within each county. Some counties contain large areas not in agriculture. These areas, and their soil carbon values, are not included in the estimation of base soil carbon using this methodology. Furthermore, base carbon estimates for ‘row crops’ are unique from those for ‘small grains’ and ‘pasture’ in each county.

A simplified example of the methodology is given in Figure 2 where there are row crops and small grains within the county. The overlay of NLCD and STATGO indicates that all small grain acres are grown on Soil B with a base soil carbon level of only 5 MtC per acre. The data also indicate that row crops are grown on both Soil A and B, with the majority in Soil B. Estimated base soil carbon for 'small grains' for this county would be 5 MtC per acre, but base soil carbon for 'row crops' would be the weighted average of areas in soil A (with 10 MtC per acre) and soil B (with 5 MtC per acre) which may be closer to 8 MtC per acre. An example of the actual overlays of county boundaries, soil regions and land use is depicted in Figure 3. In the sample county of Randolph County, Missouri, row crops are planted more often along stream and river drainages, so soils would be expected to have different qualities in these bottomlands than in the hillier areas. My methodology only includes row crop soils in its estimation of row crop base soil carbon for this region. The use of subcounty high resolution data inform the weighing of county-level base soil carbon estimates, and therefore integrates more accurate data on soil quality into the model.

Soil carbon response rate

There are two methods by which scientists can estimate carbon responses under changes in tillage practice. One is through the use of pool models, a class of computer models that simulate the turnover of photosynthesized plant material within plant–soil ecosystems. The other is through the use of directly observed experimental data of crop and tillage effects upon soil carbon. I use the second method.

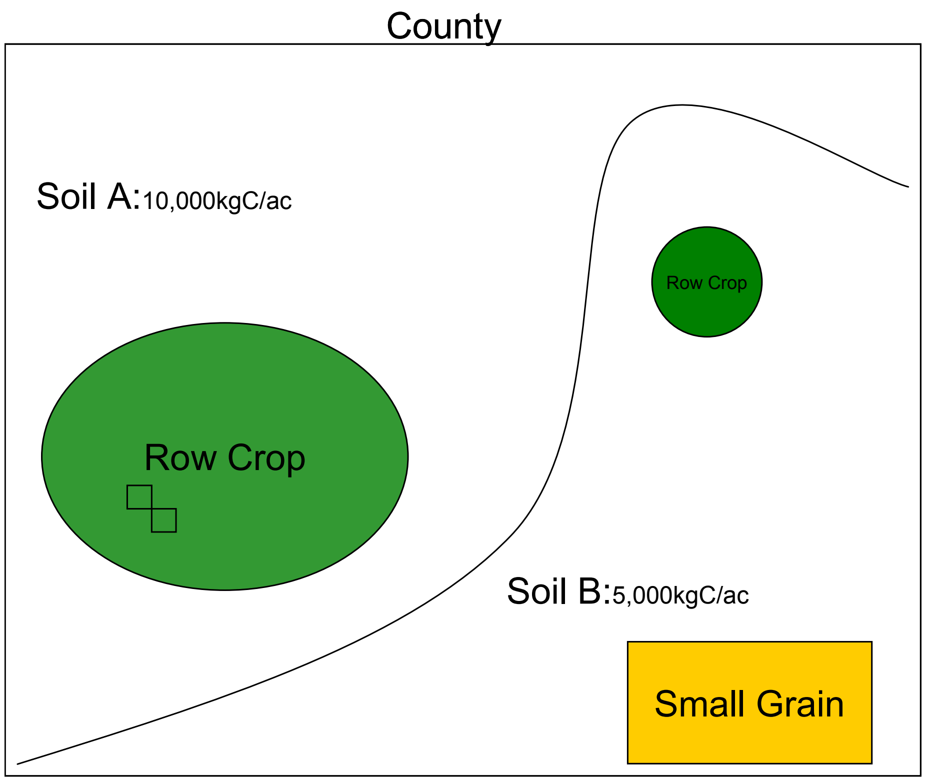

Figure 2. Locating county crop acres in soil type: A simplified example of two soil MUID regions (soil A and soil B) are overlaid on one county. NLCD landuse is also overlaid. Locations of row crop lands (green) and small grain lands (brown) are identified and the soils underlying them are known.

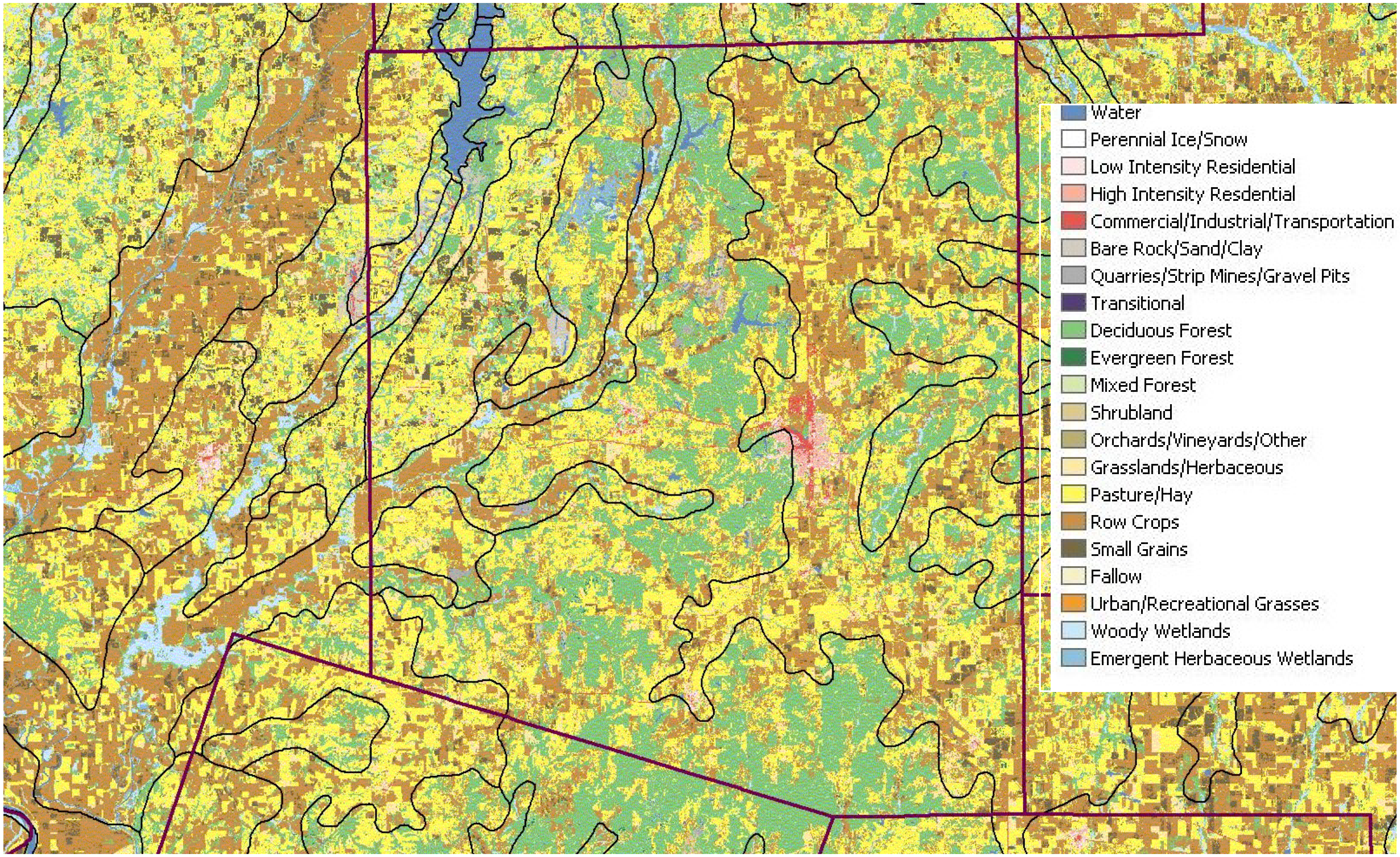

Figure 3. Example of actual high resolution overlay. Counties are outlined in purple, STATSGO soils regions are outlined in black, and NLCD data are displayed at the 30 meter resolution. This map of one county shows that land use and MUID regions are closely correlated. For example, the soil region along the creek running from north-central to southwest is used extensively for 'row crops'. Weighting base soil carbon by soil regions where particular crops are grown allows more precise estimation of sequestration ability of individual crop categories (Randloph County, MO).

West and Post analyzed results from 67 long-term tillage studies on different soils globally, consisting of 276 paired treatments (West and Post, 2002). They estimated Carbon Management Response (CMR) curves for every major crop and rotation within the US. West et al. (2003) mathematically illustrate changes in soil carbon stocks using Carbon Management Response (CMR) curves, which are regression functions that estimate sequestration rates over time (Figure 4). From a carbon accounting perspective, CMR curves are useful in their ability to be serially connected to represent changes in soil carbon following multiple changes in land use. Within this research, I assume that the total carbon accumulation estimated by CMR curves will occur linearly over a 20 year period. Linear approximations of CMR curves estimated by West and Post (2002) are applied to nine crop types (i.e., corn, soybean, wheat, sorghum, oats, barley, cotton, rice, and hay) to estimate the change in carbon level per year (Δ_j). The linear approximations used in this paper are listed in Table 4. No-tillage haylands can accumulate the largest increase in soil carbon, increasing soil carbon by 1.85% more than base soil carbon in one year. Cotton is the lowest carbon accumulator, increasing soil carbon 0.32% per year under no-tillage.

Adjustment of carbon response rate

The carbon accumulation rates listed above are estimated as a percentage or fraction of the initial soil carbon. The fraction (Δ_j) is adjusted as a function of the base soil carbon (Adj_{Cij}) and then multiplied by the base soil carbon content associated with respective cropping

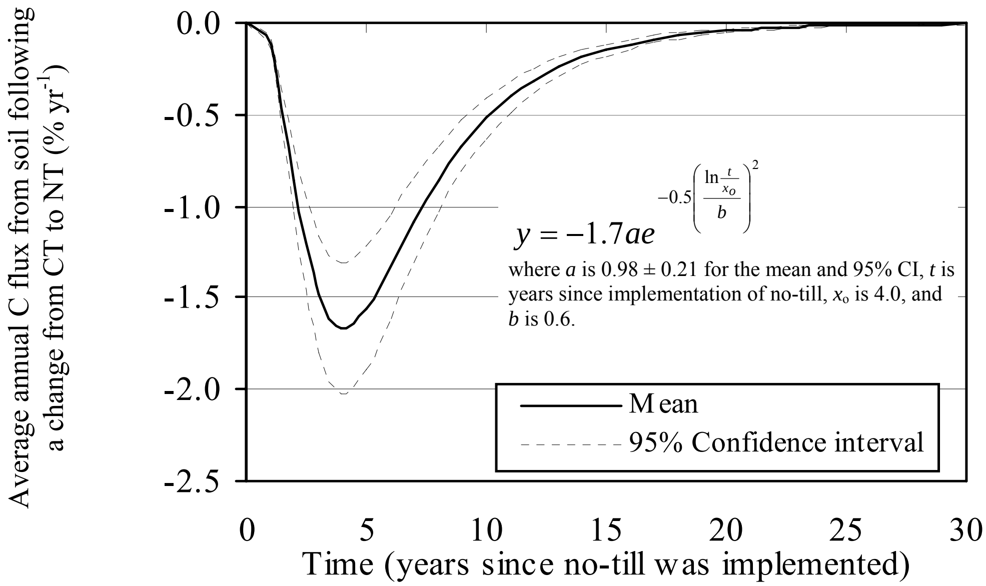

Figure 4. Example of a carbon management response curve: Estimated average annual carbon flux from soil to the atmosphere following a change from conventional-tillage (CT) to no-till (NT) on agricultural cropland (West et al., 2003).

Table 4. Estimated rates of soil carbon accumulation by tillage intensity.*

Land Use	Carbon accumulation following reduction in tillage intensity (% of initial soil carbon)			
	Annual Change		After 20 years	
	NT	RT	NT	RT
Corn	1.035	0.518	20.7	10.4
Soybeans	1.035	0.518	20.7	10.4
Sorghum	0.320	0.160	6.4	3.2
Cotton	0.320	0.160	6.4	3.2
Wheat	0.930	0.465	18.6	9.3
Barley	0.930	0.465	18.6	9.3
Rice	0.930	0.465	18.6	9.3
Oats	0.930	0.465	18.6	9.3
Hay	1.845	0.923	36.9	18.5

*This is the total carbon change following the change in tillage practice. Change is estimated to occur as 20 equal annual increments over a period of 20 years.
CT, RT and NT are conventional tillage, reduced tillage and no-till, respectively.
Sources: West and Post (2002), West et al. (2004), and Conant et al. (2001)

practices ($C_{i,j}$). Adjusting the rate of soil carbon accumulation is based on an analysis by Tan et al. (2006) that indicates increased sequestration rates occur on lower base carbon soils and reduced sequestration rates occur on higher base carbon soils. The adjustment factor equation is represented in Figure 5 as a function of base soil carbon level.

The real potential change in soil carbon is found by multiplying base carbon by the newly adjusted carbon response rate. Using this procedure, I calculated real potential change in soil carbon ($Tacre_{i,j}$) for all combinations of crop and tillage in every county. A sample of this data set is listed in Appendix A (counties in Tennessee). Change in total soil carbon is estimated at the county level by multiplying total acreage of each crop under each tillage by the real change in carbon per acre ($Tacre_{i,j}$) for each crop and tillage combination. The use of NLCD data allow for more specific selection of base soils underlying agricultural lands. This informs the weighting process at the county level, and, therefore, results in more precise estimation of changes in soil carbon. The relative strength of this method over more general aggregate methods will be tested in the validation section.

Emissions estimation

As cautioned by Schlesinger (2000), increases in soil carbon stocks do not necessarily equal a decrease in net emissions, because input emissions[12] may rise faster than soil carbon levels. A full carbon or greenhouse gas accounting should be completed to

[12] Input emissions include all carbon equivalent emissions from direct on-farm burning of fossil fuels and indirect emissions from the production of farm inputs, such as chemicals, fertilizers and seeds.

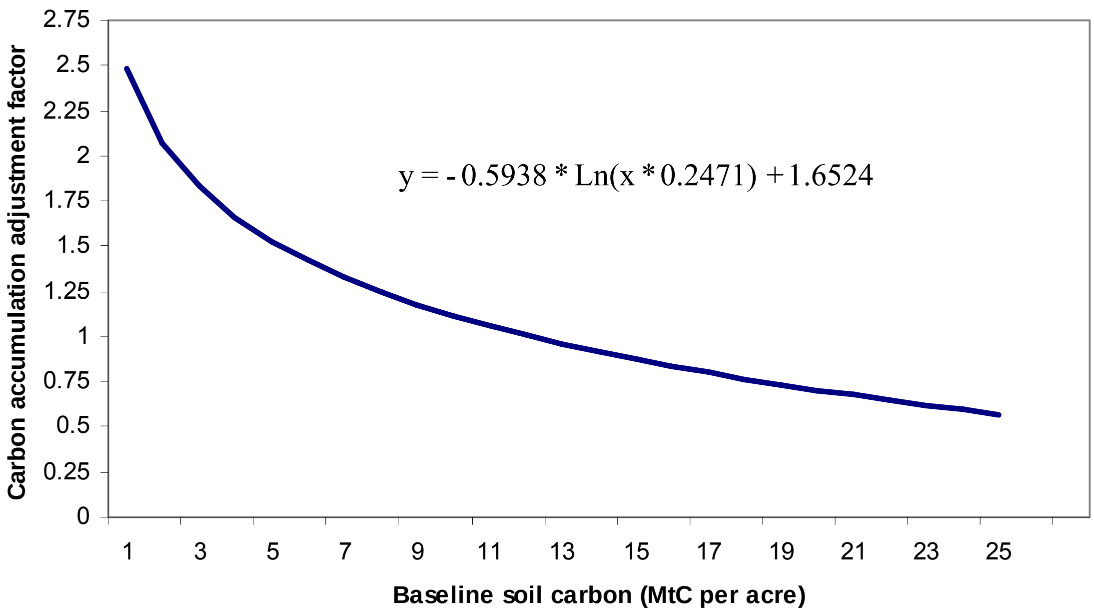

Figure 5. Carbon accumulation adjustment curve: carbon accumulation adjustment factor as a function of base soil carbon. The adjustment factor increases the rate of sequestration on lower carbon soils and decreases the rate of sequestration on higher carbon soils.

estimate net emissions reductions caused by carbon management options. Full carbon accounting must go beyond simply estimating changes in soil carbon. It must also take into account changes in production emissions. Net flux is then the net outcome of both soils carbon and production emissions changes between a baseline scenario and an alternative scenario.

Emissions from the use and production of farm inputs must be known in order to account for the change in net flux of atmospheric carbon caused by changes in farm management practices. Potential management options for cultivated agricultural lands include moving from conventional-tillage to either reduced-tillage or no-tillage. In this research, these management scenarios were applied to nine different crops (corn, wheat, soybean, sorghum, oats, barley, rice, cotton and hay). A major undertaking of my research was compiling management scenarios that represent the economic costs and material use associated with the carbon management options listed above. First, operation budgets were compiled for all crop and tillage combinations; then, emissions, both directly and indirectly associated with the material inputs of the production practices, were estimated.

Building operation budgets

Crop operation budgets are schedules of farm operations performed on an acre of land. They are commonly used by farmers and agricultural researchers to account for both physical quantities and costs of production. Accurate crop operation budgets are an integral part of modeling land-use change upon agricultural lands. In the past POLYSYS used only conventional-tillage budgets upon which to base its analyses. I have expanded the database of available budgets to include alternative management practices being used to produce the major crops in the US. The Agricultural Policy Analysis Center's Agricultural Budgeting System (ABS) has been expanded by this research to include over 3,500 conventional and alternative management practices of nine major crops in the 305 Agricultural Statistics Districts of the US The geographic resolution of the budgets corresponds to USDA-NRCS Agricultural Statistics Districts (ASD). Agricultural practices within each ASD are relatively homogeneous in production characteristics (Figure 6).

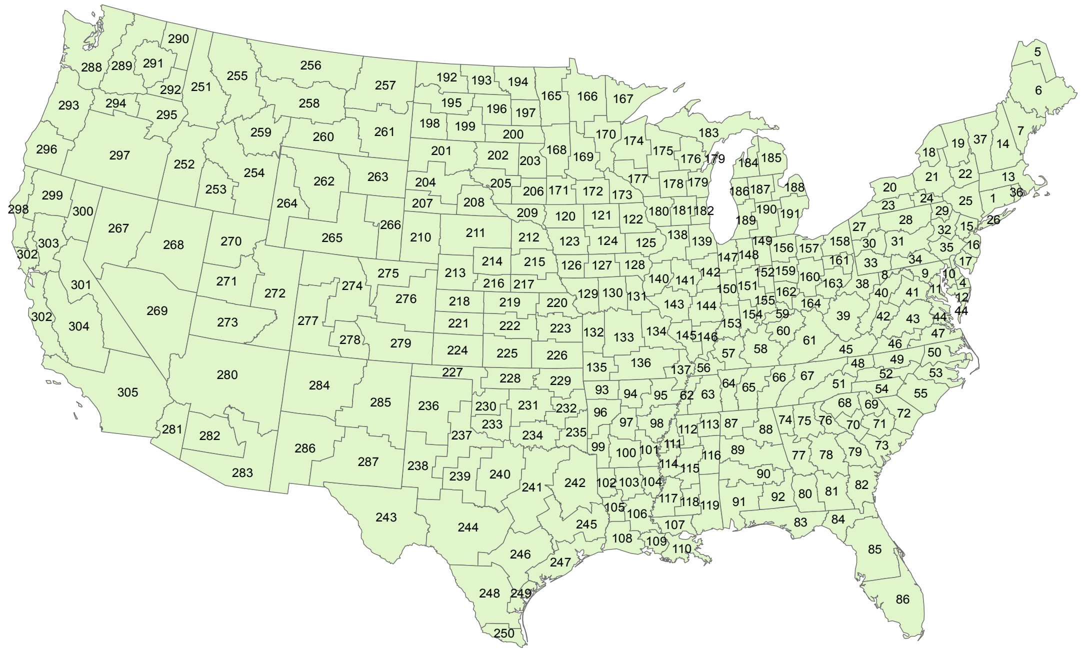

Figure 6. POLYSYS crop budget regions, corresponding to USDA-NRCS Statistics Districts (De La Torre Ugarte and Ray, 2000)

ABS budgets are expressed in both economic 'enterprise' format and specific operation format. Types of operations, machinery used, and input quantities associated with each management practice within ABS were built by consulting with regional extension service publications and personnel (APAC, 1996). In the ABS budgets, quantities of applied fertilizer and applied chemicals were taken from extension service sources but then standardized following established restrictions for herbicides and insecticide use (Meister, 2002A; Meister, 2002B). Traction and implement-equipment were obtained from regional extension sources, but equipment efficiencies for regions are standardized by data provided by the USDA Economic Research Service (ERS) database on regional level machinery efficiencies (ERS, 1997). Machinery time and fuel usage are figured by following American Society of Agricultural Engineering Standards estimation equations published in the American Agricultural Economics Association Costs and Returns Handbook (ASAE, 2004; AAEA, 2004). The ASAE equation for estimating length of time per acre of each operation is a function of equipment width, ERS equipment efficiency, and equipment speeds provided by the ASAE machinery database. ASAE methodology is then used to transform horse-power of each traction operation and machinery time into an estimate of fuel usage per operation.

Most regions in ABS, already had conventional budgets for all crops prior to the start of my research. In constructing the alternative reduced-tillage and no-tillage budgets, I began with the conventional budgets as the default. The same application rates of fertilizers and chemicals were used to construct the reduced-tillage budgets, but tillage operations were reduced to a maximum of two light tillage operations per year. The same application of fertilizers were used to construct the no-tillage budgets, but chemical applications were substituted for tillage operations. In place of spring tillage, glyphosate was applied two to four weeks prior to planting. Default quantities within ABS of glyphosate were used regionally. An example of a compiled no-tillage corn operation budget from Missouri is listed in Table 5. Fertilizer and chemical quantities are listed. Fuel quantities are figured from the type of machinery used and the time used.

Linking budgets with emissions

Carbon dioxide emissions from fossil fuels used in the production, transport, and application of agricultural inputs have been calculated by West and Marland (2002b) for cultivated lands. Emissions of N_2O resulting from the application of N fertilizer have recently been included in emissions analyses, as demonstrated by Marland et al. (2003). To quantify net carbon emissions resulting from carbon management options at the regional level, and hence be useful from a policy perspective, emissions estimates need to be applied to the newly disaggregated crop budgets.

As part of my research, both direct and indirect emissions are estimated and tied to each unique management practice in ABS. 'Direct carbon' includes emissions from the use of fuel on farms, lime decomposition in the soil, and carbon equivalent emissions from field decomposition of ammonia. Gallons of diesel per acre of each operation are determined by machinery horsepower and running time per acre following AAEA equations. Estimated gallons per acre are multiplied by the carbon content of diesel (6.75 lbs C/gal diesel) to estimate direct emissions from fuel usage. Lime applications act to release 0.06

Table 5. Operation budget example: no-tillage corn budget, central Missouri.

				Time*							Active	Seed		
Month	Day	Machinery	Power	Labor	Machine	Fertilizer	lbs	Chemical	Amount	Unit	Ingredient	Type	Rate	Unit
3	30	Dry Fert Spreader	Tractor 2wd 135 hp	0.0873	0.096	N	117		0				0	
3	30	Dry Fert Spreader	--	0	0	P2O5	54		0				0	
3	30	Dry Fert Spreader	--	0	0	K20	56		0				0	
5	1	7 Row No-till Planter	Tractor 2wd 135 hp	0.2001	0.2201		0		0			Corn Hybrid	22	thou
5	10	Chem Applicator GE30ft	Tractor 2wd 135 hp	0.0391	0.043		0	Lasso 4E (Alachlor)	3	QT	3		0	
5	10	Chem Applicator GE30ft	--	0	0		0	AAtrex 4L (Atrazine)	3.6	PT	1.8		0	
6	1	Chem Applicator GE30ft	Tractor 2wd 135 hp	0.0391	0.043		0	Dual 8E (Metolachlor)	1.92	PT	1.92		0	
6	1	Chem Applicator GE30ft	--	0	0		0	AAtrex 4L (Atrazine)	1.46	PT	0.73		0	
11	5	Combine w/ Row Header-2wd		0.1637	0.1801		0		0				0	
11	5	Single-axle Truck 2 ton (gas)		0.33	0.363		0		0				0	
11	5	Dry Fert Spreader	Tractor 2wd 135 hp	0.0873	0.096	Limestone	660		0				0	

* Units of labor and machine time in hours

Source: Agriultural Policy Analysis Center's Agricultural Budgeting System ton of carbon per ton of limestone applied. Carbon equivalent emissions of nitrous oxide from the use of nitrogen fertilizers are estimated by assuming 2.22 tons of carbon equivalent released per ton of nitrogen applied.

Indirect carbon, or embodied carbon, includes emissions from the processing, manufacturing and transportation of seeds, fertilizers, and chemicals applied to the field. I obtained per unit carbon emissions embodied in the production of inputs from the lifecycle literature (West and Post, 2002; Ogle et al., 2005). Quantities of seed, fertilizer and chemical inputs are linked in this research to these 'per unit' estimates to arrive at indirect carbon emissions. Indirect carbon emissions from 81 combinations of organic and inorganic fertilizers, and 403 chemical pesticides are linked to the operation budgets in this research.

Direct and indirect carbon emissions are summed to estimate total carbon equivalent emissions as a result of each unique regional management practice. Table 6 lists the national weighted average costs of production and emissions for all model crops and tillage practices. As expected, no-tillage generally emits less carbon than reduced-tillage, and reduced-tillage emits less carbon than conventional-tillage.

Building county level economic resolution

The smallest region with consistent national coverage of crop-acre data is the county level. To achieve a model capable of simulating regional land use dynamics at the highest resolution feasible, I expanded the linear programming model from 305 Agricultural

Table 6. Weighted average cost of production and emissions by crop and tillage.*

	Cost ($ per acre)			Emissions (MtC per acre)		
	CT	RT	NT	CT	RT	NT
Corn	132	121	131	0.100	0.083	0.083
Sorghum	79	69	77	0.063	0.055	0.052
Oats	66	63	59	0.049	0.047	0.035
Barley	73	78	75	0.044	0.044	0.043
Wheat	59	63	75	0.047	0.044	0.041
Soybeans	93	87	91	0.044	0.044	0.038
Cotton	185	227	336	0.107	0.123	0.098
Rice	247	256	233	0.151	0.134	0.120
Hay	212	na	240	0.090	na	0.091

CT, RT and NT correspond with conventional, reduced and no-till, respectively.
* These data are weighted averages across all regions in the U.S. In any particular region, budget costs and relative differences between the tillage regimes could be quite different.
Costs were estimated using 2006 input prices.
Emissions include both direct and indirect emissions.

Statistic Districts to 3,110 county level regions. Furthermore, the cropping activities in each of the counties were disaggregated to include conventional-tillage, reduced-tillage and no-tillage of all 12 model crops. The National Agricultural Statistics Service provides yearly crop acres for every county in the US and the Conservation Technology Information Center (CTIC, 2004) provides county level areas of each crop under conservation tillage. Baseline county acreages in each crop and tillage practice were collected from 2001 through 2004 and an average quantity of acres in each crop-tillage combination was used to create an index that disaggregates USDA national baseline acreage to the county level. In every simulation year, POLYSYS iterates through 3,110 counties, solving for the optimal linear programming solution in each county.

In the linear programming model, each crop and tillage type combination is a unique *activity*, with a corresponding net present value used for evaluating relative profitability. Twelve crops and three tillage operations sum to a possibility of 36 unique activities in each county. Acreage in each unique crop type is constrained by a maximum and minimum number of acres that can move from one tillage type to another within the same crop, and a maximum and minimum number of acres that can move between crops. The tabular representation of the model is presented in Appendix B. The following equations define the objective function and constraints within the county level linear programming models.

Objective Function:

$$\text{Maximize} \sum_{k=1}^{12}\sum_{t=1}^{3} Netpresentvalue_{kt} * planted_{kt} \qquad \text{(Equation 2)}$$

Subject To:

$$MaxTill_{kt} = planted_{kt_{-1}} + \sum_{t=1}^{3} planted_{kt_{-1}} * 0.1 \qquad \text{(Equation 3)}$$

$$MinTill_{kt} = planted_{kt_{-1}} - planted_{kt_{-1}} * 0.1 \qquad \text{(Equation 4)}$$

$$MaxCrop_{k} = \sum_{t=1}^{3} planted_{kt_{-1}} + \sum_{t=1}^{3} planted_{kt_{-1}} * 0.1 \qquad \text{(Equation 5)}$$

$$MinCrop_{k} = \sum_{t=1}^{3} planted_{kt_{-1}} - \sum_{t=1}^{3} planted_{kt_{-1}} * 0.1 \qquad \text{(Equation 6)}$$

Where,

$$netpresentvalue_{kt} = \sum_{i=1}^{20} netreturns_{kt_i} / (1 + drate)^{i} \qquad \text{(Equation 7)}$$

Where,

$$netreturns_{kt} = (price_{kt} * Yield_{kt}) - TotalCost_{kt} \qquad \text{(Equation 8)}$$

k=commodity,

t=tillage category,

i=year 1 to 20,

$Price$ = commodity expected price,

$Yield$ = commodity yield,

$TotalCosts$ = total variable costs of commodity production,

$drate$ = discount rate (6.25%)[13],

and,

$planted$ = planted acres.

First, net income returns are determined for the current year for each crop and tillage combination (eq. 8). Next, the net present value of each crop and tillage mix is determined for a 20 year time span (eq. 7). Within the linear programming model, the objective function is to maximize the next present value of all crop and tillage mixes subject to four constraints (eq. 2). Maximum planted acres of an individual crop-tillage mix are equal to last year's planted acres plus the sum of 10% of all tillage acres of that crop (eq. 3). Minimum planted acres of an individual crop-tillage mix is equal to last year's planted acres minus 10% of last year's planted acres of the same crop-tillage mix (eq. 4). Maximum planted acres within all tillage categories of an individual crop is equal to last year's planted acres of that crop plus 10% of last year's planted acres (eq. 5). Minimum planted acres within all tillage categories of an individual crop is equal to last year's planted acres minus 10% of last year's planted acres (eq. 6).

[13] Discount rate was determined by 5-year *certificate of deposit* rates in June of 2007.

I also expanded the net present value estimation to include an additional incentive variable. Its value is determined by the incentive level per MtC and also the county-wide average rate of carbon accumulation for each unique crop and tillage combination. For example, the satellite-derived land-use data may indicate that, historically, sorghum grows on carbon-poor lands with a low carbon accumulation rate, whereas corn in the county grows on carbon-rich lands with a high rate of carbon accumulation. The incentive is different for an acre of sorghum and an acre of corn, not only because they are different crops with different biomass growth rates, but also because high resolution land-use data reveal that they are historically grown on different quality soils.

Inclusion of yield change uncertainty

Research has shown that the mean net returns on reduced-tillage practices are equal to or greater than the return from conventional-tillage due to decreases in input costs, yet only 35% of agricultural lands have adopted conservation tillage practices (Sandretto 2001). One factor inhibiting the adoption of reduced-tillage is the additional risk of lesser yields perceived by farmers and the perceived effects of these risks on net returns (Nowak and Korsching 1985, Prato 1990, Larson et.al. 1998, Larson et.al. 2001). Lower no-tillage yields in the initial years after a switch from conventional-tillage may be a significant factor affecting estimates of incentive-induced carbon abatement. I quantify and include the uncertainty of low no-tillage yields in the initial years within the model methodology by valuing expected returns over future years.

No-tillage yields are lower in the initial years after switching from conventional-tillage. As soil conditions improve, yields increase to a new plateau after 20 years. The new plateau is usually higher than conventional-tillage yields. Because farmers value returns sooner rather than later, the model discounts returns over a 20-year planning period. The lower yields of no-tillage in the initial years carry more weight in the net present value calculation than the later higher yields. Discounting temporal yield trends in this manner influences the point at which farmers are willing to change practices, and therefore it affects net carbon flux estimation.

In a study comparing yield differences of 664 paired tillage experiments, Kunda (forthcoming) found that a non-linear, exponential functional form resulted in the highest r^2 value. Figure 7 shows the estimated equation and no-tillage yield change over time relative to mean conventional-tillage. In the initial period of 0 to 1 years, no-tillage experiences a 5.6% decrease in yields. By year two there is no significant difference in yield, and by year five, no-tillage yields increase to 2.5% above conventional-tillage.

Although average no-tillage yield over the entire 20-year period may be slightly higher than conventional-tillage, farmers value the returns closer to present. Uncertainty associated with promised yields increases as time increases. This uncertainty is quantified through discounting the net present value of a stream of revenue over the 20 year period. In the model, equation 9 is used to incorporate the yield differences through time.

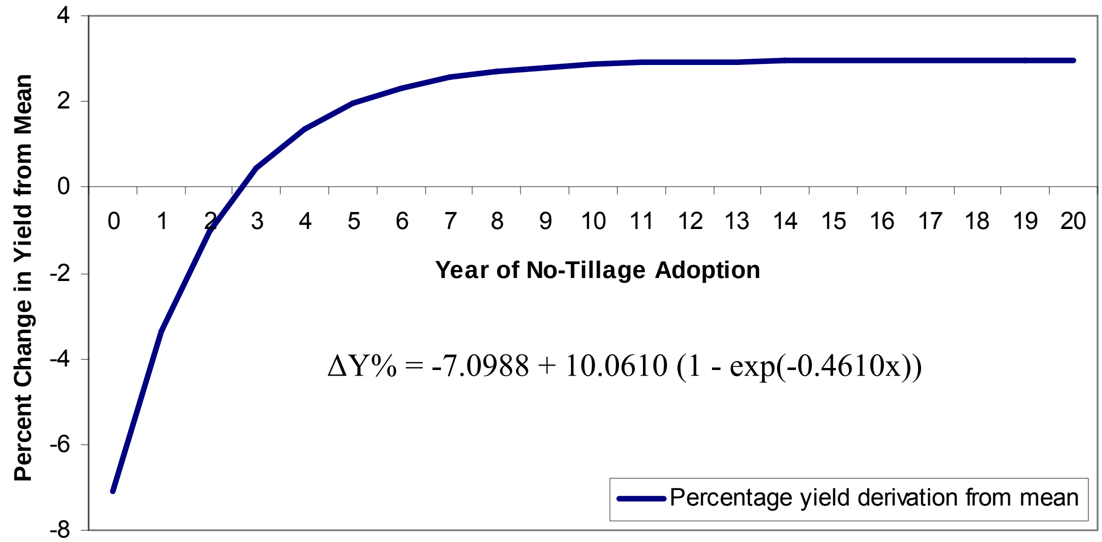

Figure 7. Change in no-tillage yield over time: percentage change in no-till yield from mean conventional-tillage yield over 20 years. Initially, no-till yields fall, but by year 2 no-till yields surpass conventional-tillage.

Net Present Value = $\sum$ (**Yield$_i$** * Price) / $(1+\text{drate})^i$, (equation 9)

Where,

Yield$_i$ = yield of no-tillage in year i,

Price = current expected price of commodity,

and,

Drate = discount rate (6.25%).

Methods of model application

Once the model was created and all economic and biogeophysical data were integrated into a framework that simulated at a high degree of resolution, I used the model to do the following:

1) Simulate 'baseline' net carbon fluxes to the atmosphere at the county level for US agricultural lands.

2) Develop a net carbon flux supply curve by simulating carbon incentive levels ($ per tonne), which estimated how much carbon can be abated both nationally and regionally at a given price of carbon.

3) Test the uncertainty of base soil carbon estimates and quantify their impact upon mean model outcomes.

4) Validate high resolution results as compared to low resolution results by comparing them to results of actual field level tillage trial experiments.

5) Analyze the interaction between model resolution and analytical scale.

Baseline simulation

As an initial step in simulation, I projected a baseline simulation to arrive at the *status quo* future outlook. The baseline simulation projects historic tillage trends forward in time. Current county-level crop acreages (2000-2004) and tillage mixes were used as an initial point of departure for projections. Data from the National Agricultural Statistics Service (NASS) (USDA, 2007) provided annual estimates of crop area per county for each major crop type. Data from the Conservation Technology Information Center (CTIC, 2004) provided information on the area of major crop types using different tillage practices including conventional-tillage, reduced-tillage, and conservation tillage. These three tillage practices are defined, respectively, as leaving less than 15% of the ground covered by crop residue, between 15-30% ground cover, and greater than 30% ground cover (CTIC, 2004). Conservation tillage encompasses tillage practices such as mulch tillage, ridge tillage, and no tillage. I combined mulch tillage and ridge tillage in the reduced-tillage category, and maintained no-tillage and conventional-tillage as separate categories.

Baseline simulation began in 2006. To estimate county level acreage as closely as possible to current allocations, I used the average county NASS acreages between 2003 and 2004 to cover any biannual changes in crop rotation. Individual county-level crop acres were divided into tillage type by applying CTIC data on the percentage of crop in a particular tillage. This method gave the initial year's quantity of acres in each tillage and crop type at the county level.

To project forward through 2025, additional methods were employed. At the national scale, the baseline simulation used USDA baseline through 2016, after which the model endogenously projected trends outward to 2025. Three exogenous assumptions were made for projection through 2025: population trends, export trends and yield trends were projected at 'historic' rates. In each year of baseline simulation, county crop acres were adjusted by both their initial weighted ratio of national acreage and by adjustments based on relative profitability. The relative share of crop acres in individual tillage types changed according to projected 'historical' trends. Analysis of tillage trends indicated a significant structural shift in tillage adoption occurred in 1996, after which the acres of reduced-tillage declined rapidly and then remained steady, and the rate of adoption of no-tillage decreased. I hypothesized that rapid conversion to no-tillage following the introduction of Round-up® (herbicide) was tailing off by 1996. Two opposing active dynamics will effect future no-tillage adoption. Herbicide-resistant weeds are making no-tillage less attractive to farmers. Contrary to this is the impact of increasing fuel costs, which farmers can alleviate by adopting less fuel-intense no-tillage. Analysts following no-tillage adoption believe that farmers will continue to adopt no-tillage but at one-quarter the historical rate (Tyler, 2007). In this analysis, trends from 1996 through 2004 are projected, at the state level, to the year 2025 at one-quarter the 'historic' rate (Figure 8).

The baseline simulation gives the *status quo* situation to which alternative policy scenarios will be compared. Baseline data include both regional and national acres in each crop and tillage, carbon emitted from production inputs, and carbon accumulation in soils from conservation tillage.

Simulation

The primary reason for undertaking the construction of the model is to analyze how much carbon can be abated and at what cost. To do this, a carbon abatement supply curve is

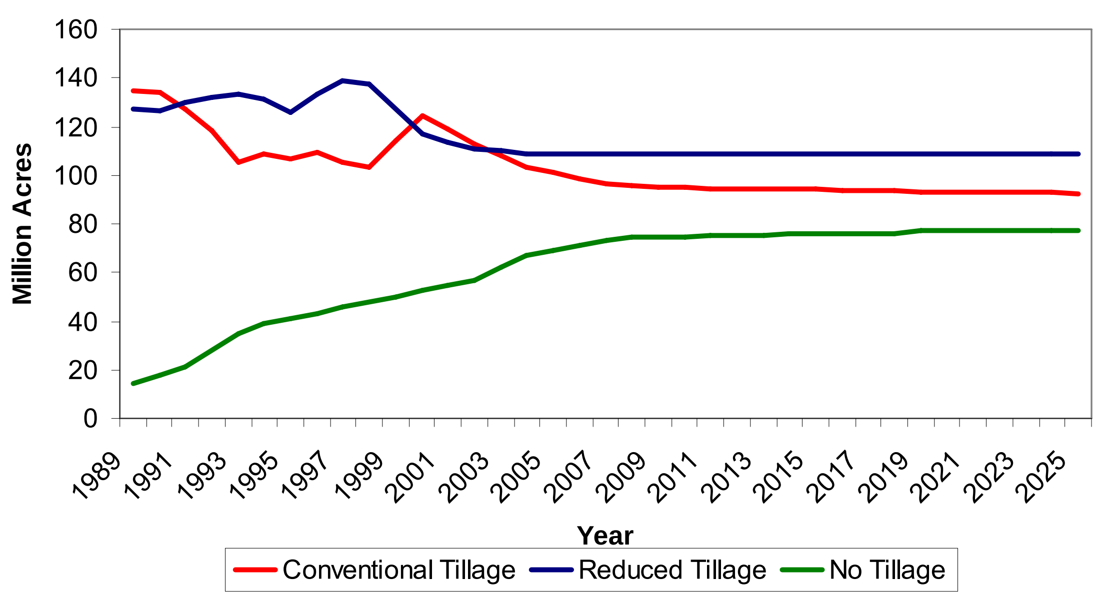

Figure 8. Tillage adoption: historical and baseline projected.

estimated by exogenously introducing incentive levels into the modeling framework, which act to trace the marginal supply curve. A particular carbon incentive level adds to the net present value of each unique crop, tillage and county combination depending upon each activity's estimated ability to sequester carbon. Once again, each activity's ability to sequester carbon depends upon: a) the type of crop; b) the type of tillage; and c) the quality of soils it is grown upon. The conversion of national 'per tonne' incentive to county and crop specific 'per acre' incentive can be written as:

$$Iacre_{i,j} = C_{i,j} * \Delta_j * Iton_{nat} \qquad \text{(equation 10)}$$

Where,

$Iacre_{i,j}$ = carbon incentive 'per acre' in county i, for crop j ($ per acre).

$C_{i,j}$ = base carbon level in county i, for crop j (tonnes per acre).

Δ_j = change in carbon level per year of crop j, under tillage t.

$Iton_{nat}$ = national incentive level 'per tonne' of carbon ($ per tonne).

In the simulations, the new net present value landscape changed the optimal solution within the linear programming models, and the incentives acted to change crop and tillage mix both regionally and nationally. The new incentive-induced crop and tillage mix sequesters more carbon than the 'baseline' case. Additionally, emissions increased in some regions, through the use of more energy intensive chemicals, and decreased in other regions, through the use of less tractor operations. I compared net flux of carbon to the baseline scenario to reveal the total reduction in atmospheric carbon at particular incentive levels.

In this analysis, my intention is to investigate carbon program implementation that is most similar in form to the emerging carbon trading markets, which is to pay 'all adopters' of tillage practices an incentive, and not only 'new adopters'. Furthermore, to arrive at an upper bound estimate of abatement potential, I assumed permanent sequestration and gave farmers the full asset value of carbon price (there is no discounting or transaction costs assumed). The regional incentive level is based upon 'sequestration' potential, or the ability of the soil to take up carbon from the atmosphere. The other option would be to apply the incentive to 'net flux' potential, which is the net amount of carbon reduction that occurs when both changes in soil uptake and emissions of carbon are totaled. Payments based on sequestration rather than net flux can cause leakage to occur through lands switching from conservation to conventional-tillage. Although I employ a sequestration based incentive, most of leakage is avoided due to payments going to 'all adopters'. Lands already in no-tillage do not switch to conventional-tillage. Unintended increases in emissions caused by incentives still occurs through conversion of land to higher emitting crops. But, by paying all adopters, a major source is avoided. Once again, this implementation of the model is to estimate the upper bound potential of carbon abatement of a carbon program most similar to those emerging.

There is wide variation in estimates of potential carbon price if the US were to begin regulating carbon emissions. Currently the US is not part of the Kyoto Protocol and polluters of CO_2 are under no obligation to reduce emissions. All carbon trading at the Chicago Climate Exchange (CCX) is completely voluntary. CCX carbon price is around $5 to $10 per MtC. In Europe, pre-Kyoto carbon prices have hovered in the range from $20 to $30 per MtC (Kyoto regulations take effect from 2008 to 2012). Canada's Tory (conservative) government estimated that it will take a carbon tax of $195 per MtC to compel Canada to meet its Kyoto obligations (Suzuki, 2007). Sweden instigated a $100 per MtC tax in 1991 and raised it to $150 per MtC in 1997 (Brannlund,1999). In testimony before the US House of Representatives Ways and Means Committee, Schneider and Mastrandrea stated that their research estimated a typical shadow price of $200 per MtC to keep atmospheric carbon concentrations from more than doubling (Schneider and Mastrandrea, 2005). If the US were to decide to reduce carbon emissions, carbon prices of $100 per MtC and higher are foreseeable. This analysis estimates abatement responses from carbon incentive levels ranging from a very low level of $12.5 per MtC up to a high estimate of $500 per MtC, with $125 being the analytical focal point.

Scenario analysis of base soil carbon uncertainty

Analysis of uncertainty in carbon estimates is performed by varying base soil carbon in separate scenarios. Galbraith et al. (2003) studied soil carbon estimation error from regional soil maps and found coefficients of variation associated with one standard deviation error ranged from 3% to 87%. This sensitivity analysis uses the mean coefficient of variation found in Galbraith et al. (2003). Two simulations are run by changing mean regional and commodity base soil carbon estimates by ±28% (mean coefficient of variation in Galbraith et al. (2003)), to estimate the range of error to approximately one standard deviational unit. The two additional simulations are compared to the mean estimate at the national level. These alternative scenarios yield the upper and lower carbon sequestration estimates at a given carbon price. The upper bound indicates carbon sequestration above the expected amount that is still significant. The lower bound indicates an amount of carbon sequestration below the expected amount that is still significant.

Validation of high resolution

The main purpose of this project is the development of a modeling methodology that is capable of accurately estimating carbon sequestration potential at the sub-county level, yet with national coverage. Sub-county estimation of carbon sequestration potential has been accomplished through the overlay of high-resolution satellite data. It is not guaranteed that, by increasing the resolution, the model will result in more accurate estimations at either the local, regional or national level. The model needs to be tested to verify any possible gains in accuracy over lower resolution methods.

To test whether the methodology is accurate at estimating site specific changes in soil carbon, the results of the high-resolution model are compared to empirical results of field trials measuring changes in soil carbon as a result of no-tillage adoption. Model estimates of MtC gains per acre per year are compared with empirical results from six experimental sites:

1) Dekalb County, AL – Corn under no-till from 1980-1990 (Edwards et al., 1992).

2) Johnson County, IL – corn/soybeans under no-till from 1989-1992 (Kitur et al., 1994).
3) Fayette County, KY – corn under no-till from 1975-1989 (Blevens et al., 1994).
4) Tate County, MS – cotton under no-till from 1980-1996 (Rhoton, 2000).
5) Cheyenne County, NE – wheat under no-till from 1978-1990 (Varvel, 1994).
6) Wood County, OH – corn/soybeans under no-till from 1980-1993 (Dick et al., 1997).

Because the high resolution estimates are derived from weighted initial soil carbon observations from the STATSGO database, it is not expected that the model will replicate precisely the observed changes in soil carbon. But it can be expected that estimates using the high-resolution model more accurately estimate observed changes than lower resolution versions. To test this expectation, empirical results are also compared to lower resolution (more aggregated) versions of the model. It is hypothesized that the high resolution estimates of carbon accumulation will be more similar to empirical estimates. Four model resolution versions are compared:

A) LANDSAT County Version –base soil carbon levels are weighted by STATSGO region for every LANDSAT crop-type at the county level. With LANDSAT data, there are weighted base soil carbon estimates for each crop type in each county. This is the high resolution method, to which the others are compared.
B) No LANDSAT County Version – base soil carbon level is weighted by the area of each STATSGO region within each county. Without the use of satellite imagery, only one weighted base soil carbon estimate can be derived for every county.

C) LANDSAT National Version –base soil carbon levels are weighted by STATSGO region and crop-type, but at the national level. With LANDSAT data, only soils with crops growing upon them are included in the weighted base soil carbon estimate.

D) No LANDSAT National Version – base soil carbon level is weighted by the area of each STATSGO region within the nation. Without the use of satellite imagery, there is only one base soil carbon estimate for the nation as a whole.

Scale comparisons

In addition to testing the model version results to empirical observation, the resolution versions are compared to each other in estimating total gains in soil carbon at differing scales of analysis. Estimated totals using the four resolution versions are compared at three different scales (levels of aggregation)–the national scale, the state scale and the county scale.

Simulations of each of the four versions are run at increasing carbon incentive levels to create individual supply curves indicating the amount of carbon that can be abated at increasing prices per MtC. Regionally, the results of the four versions are compared at the national, state, and county scales of aggregation. It is hypothesized that estimation of national carbon abatement will be similar for all model versions, but that regional differences in estimated carbon abatement will grow as the scale of analysis decreases from national to state and then to county.

Hypothesized differences in estimated carbon sequestration among the four resolution versions are due to the weighting of initial soil carbon. The highest resolution version weights initial soil carbon within a very small region. The lowest resolution version weights soil carbon for all soils within the nation. At the national scale of analysis, the aggregate totals of all resolution versions may be quite similar, but at the regional scale of analysis, differences in initial soil carbon (and therefore rate of accumulation) will affect the outcome in predicted sequestration through two mechanisms:

1) The offered incentive per acre reflects different potential carbon sequestration rates, resulting in different conservation tillage adoption rates.
2) Estimated total carbon accumulated results from different rates of accumulation.

The resolution of other model variables, such as crop budget costs, is kept at the county level. The purpose here is to test the impact of estimates of carbon accumulation alone. If too many variables change at once, the direction and weight of the individual variables may become lost. The primary innovation of this project is in bringing the resolution of carbon accumulation rates down to the sub-county level; therefore, this is the primary factor evaluated.

CHAPTER IV:

RESULTS

Baseline simulation

In the projected baseline case, 32% of US cropland is in reduced-tillage and 33% is in no-tillage by 2025 (up from 23% in 2004). Total uptake of carbon by US soils increases from the current level of 10.9 MMtC per year to 12.4 MMtC per year by 2025. The slight increase in soil uptake of 1.24 MMtC per year is offset by an equal increase in carbon emissions over the baseline period. In spite of conversion of lands to lesser emitting conservation-tillage regimes, total emissions from agriculture increase from 37.6 MMtC per year to 39.0 MMtC per year. The apparent discrepancy of increasing conservation tillage and increasing input emissions is due to changes in cropland allocation among different crops. Through the baseline period, ethanol demand increases, and with it corn production increases. Corn is a very input-intense crop, due to increased use of fertilizers, chemicals and seeds. So, even though more conservation tillage is being used by 2025, the expansion in corn acreage causes total input emissions to increase. The increase in annual soil carbon accumulation is exactly offset by increases in annual emissions from production inputs and, therefore, total net flux remains at 26.7 MMtC per year by 2025 (Table 7). All incentive-induced changes in atmospheric carbon reported in the results section are divergences from this calculated baseline.

Table 7. Baseline changes in atmospheric carbon through projection period as a result of agricultural soils and emissions (MMtC per year) from POLYSYS model, baseline simulation.

	2006	2025	Change
U.S. Agricultural Soils*	-10.94	-12.36	-1.42
Emissions			
Direct			
On-Farm Fuel	9.75	9.63	-0.11
N20 from Nitrogen	13.72	14.74	1.02
C02 from Lime	2.94	2.94	0.00
Total	26.41	27.31	0.90
Indirect			
Fertilizers	8.01	8.42	0.41
Chemicals	1.54	1.61	0.08
Seeds	1.64	1.68	0.04
Total	11.19	11.71	0.52
All Emissions	37.60	39.02	1.43
Total Net Flux	26.66	26.66	0.00

* Assuming all land in conservation tillage is still accumulating carbon

Note: Negative values correspond to reduction in C emissions to the atmosphere.
Positive values correspond to increase in C emissions to the atmosphere.

National carbon net flux supply curve

If all cropland could be switched to no-tillage, total *technical* potential carbon abatement reaches 33 million metric tons of carbon (MMtC) per year in 2025, which is 21.4 MMtC above baseline. To figure economic potential carbon abatement, incentives were increased to the upper bound of $500 per MtC. At 500 per MtC, abatement reaches 18.9 MMtC above baseline by 2025. Soil carbon uptake accounts for 16.5 MMtC, and reductions in emissions contribute another 2.5 MMtC to total carbon abatement. The estimated carbon abatement supply curve is shown in Figure 9. The brown curve indicates the additional soil carbon above baseline that would be sequestered at given incentive levels. The green curve indicates the total reduction of atmospheric carbon from both soil sequestration and changes in agricultural emissions. As expected, as the incentive level increases, carbon abatement increases. Also, as incentives increase, the distance between the soil carbon and total abatement curves increase due to changes from higher emitting tillage practices to lesser emitting practices.

The carbon supply curve indicates a rapid upward shift in marginal cost of abatement that occurs at around the $50 to $75 incentive level. This is caused by the convergence to two factors, (1) the marginal amount of acres switching out of conventional- and reduced-tillage and into no-tillage per dollar incentive begins to decrease after the $25 per ton level, and (2) the reduction in net flux per acre of newly switched land begins to drop after the $50 per MtC level (Table 8). At lower incentive levels, incentives can easily raise the profitability of no-tillage over conventional-tillage of some cropping activities. For example, in some regions, the cost of hay production under both conventional and

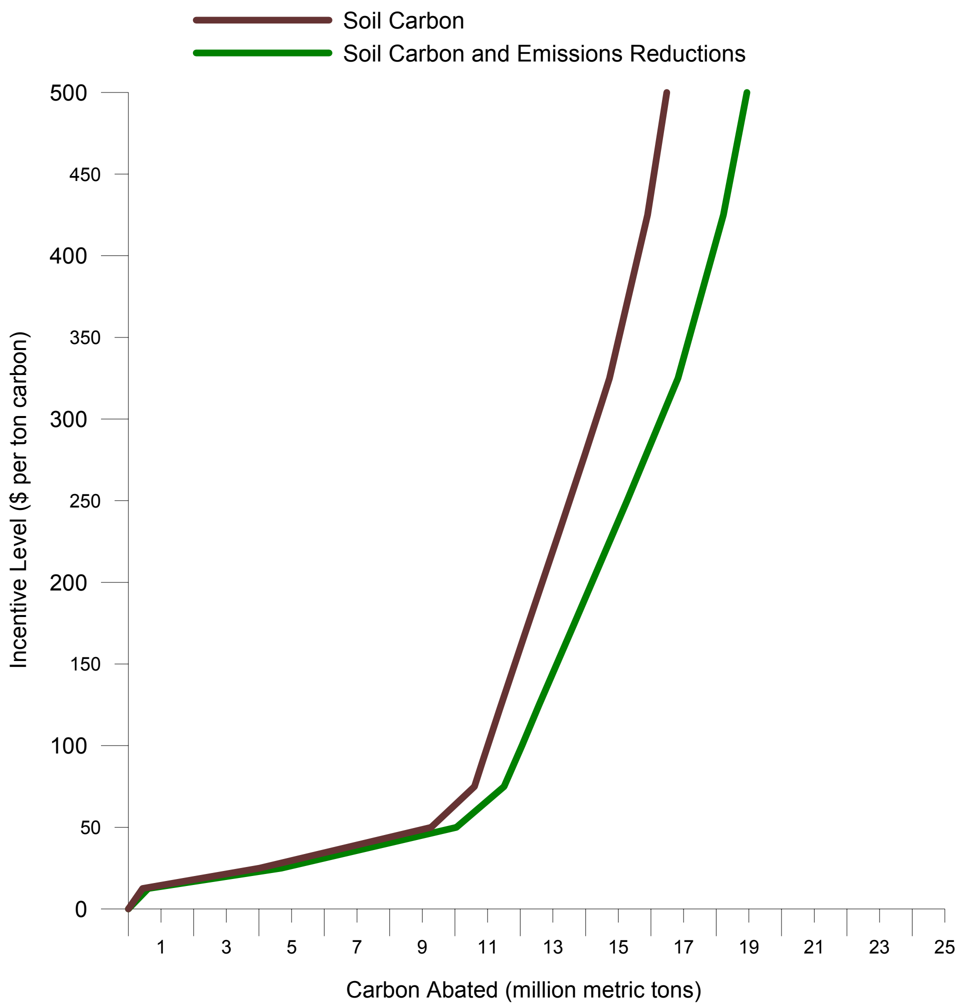

Figure 9. National carbon abatement supply curve with soil carbon changes and total carbon changes induced by carbon incentive by 2025.

Table 8. Marginal acreage change per dollar incentive, and marginal net flux per newly switched acre.

	Acreage change per $ incentive*			Net flux change per newly switched acre**
	Conventional	Reduced	No-till	
$12.5	-0.16	-0.36	0.52	-0.007
$25.0	-1.57	-0.27	1.84	-0.102
$50.0	-1.08	-0.15	1.24	-0.162
$75.0	-0.87	-0.12	0.99	-0.156
$125.0	-0.59	-0.08	0.67	-0.150
$250.0	-0.37	-0.07	0.44	-0.138
$500.0	-0.23	-0.07	0.30	-0.126

*This is the tillage acreage changes that each dollar of incentive stimulates.
At incentive levels above $25, the less acres switch per dollar of incentive.

** This is the change in net flux that as a result of each newly switched acre.
At incentive levels above $50, there is less of a drop in net flux per newly switched acre.

no-tillage are very similar. Hay lands have a high sequestration potential and therefore receive larger incentives. Slight increases in the net present value of no-tillage can induce its adoption. But as the incentive level is increased, less additional land is switching over because it either has a lower carbon potential, or the conservation tillage management practices are relatively more expensive than conventional-tillage practices. Additionally, as land with lower carbon potential does change practices, it sequesters marginally less, resulting in an even steeper upturn in marginal costs.

One major cause of the abrupt increase in marginal costs is due to the nearly complete switch-over of conventional haylands at the $50 incentive level. In the baseline case there are 57 million acres of haylands in conventional-tillage. At the $25 incentive level, 32 million of these acres are switched to no-tillage, and at the $50 incentive level, 44 million acres are switched to no-tillage. At $50 per MtC, only 13 million acres of haylands remain in conventional-tillage. Haylands usually have a larger sequestration potential than other crops due to two factors, (1) the root structure of hay deposits more carbon in the soil than other crops, and (2) a large portion of national hay acreage is located in northern areas, where soils can sequester more carbon due to cold conditions which act to slow microbial respiration.

The temporal resolution of the model is at the annual level; therefore, the changes in carbon abatement induced by a given incentive level can be tracked annually through the important short to medium-term period. Figure 10 shows annual reduction in atmospheric carbon induced at the $125 per MtC incentive level. The initial years result in the greatest annual decrease in atmospheric carbon. By 2009, marginal reduction in atmospheric carbon is decreasing annually. Eighty-five percent of total carbon reductions occur halfway through the simulation period (2015). By 2025, when 12.58 MMtC are abated annually, the marginal reduction is near zero, and all acres capable of switching management practice have done so. After 2025, it can be expected that carbon abatement will decrease even though no-tillage remains in practice. Conservation tillage can only increase soil carbon levels for about 20 years, after which SOC remains steady. By 2025, the initial acres that switched into conservation tillage will have reached the 20-year mark, no further gains in SOC can be made, and total annual abatement would decline.

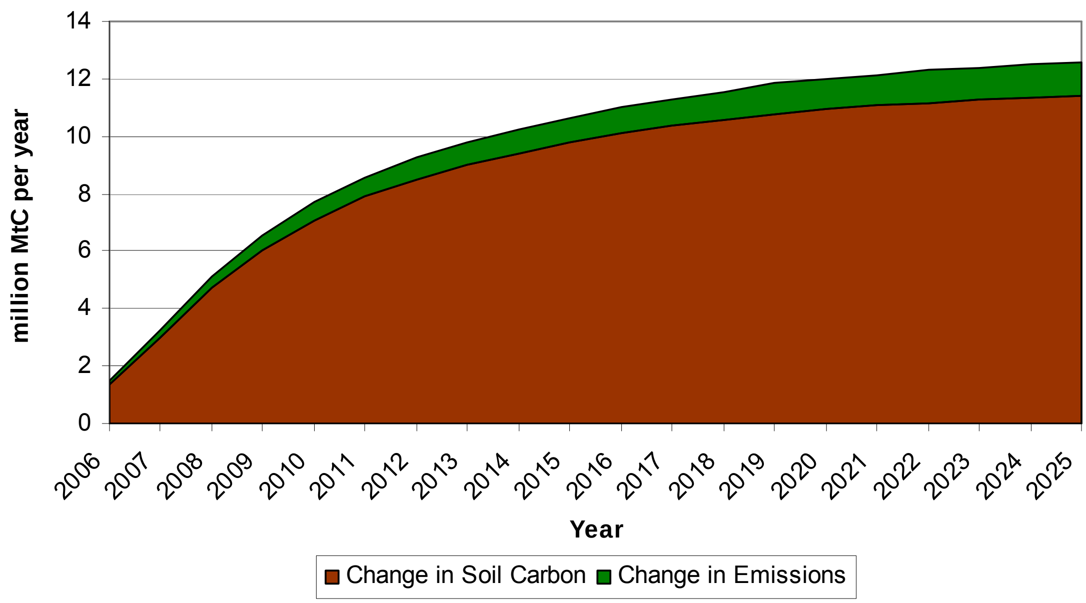

Figure 10. National reduction in atmospheric carbon through 2025 at $125 per MtC.
Source: POLYSYS simulation.

Carbon changes

Table 9 lists the impacts to atmospheric carbon levels as a result of annual emissions and soil carbon uptake. It also lists the total net flux that results from the net effect of agricultural emissions and soil uptake. As incentives increase, both direct and indirect emissions decrease and soil carbon uptake increases. At $500 per MtC, emissions total 36.6 MMtC per year, and soil uptake reduces atmospheric carbon by 28.8 MMtC. Although incentives have acted to reduce total net flux by 18.9 MMtC below the baseline case, in total, agriculture is still a net contributor to atmospheric carbon, with an annual net flux of 7.7 MMtC to the atmosphere per year.

Table 10 lists the same information but in terms of changes from the initial baseline. An incentive of $50 per MtC is estimated to increase soil uptake by 9.3 MMtC above baseline. The same incentive acts to decrease total emissions by 0.8 MMtC below baseline. This results in a total net flux reduction of 10.1 MMtC below baseline (Table 10). As incentives increase, and more land is put into conservation tillage, direct on-farm emissions from tractor operations decline. Indirect chemical emissions increase slightly due to higher chemical usage in no-tillage operations, but total indirect emissions decline due to less fertilizer use with no-tillage. Reduced fertilizer use also reduces direct emissions from nitrogen and lime decomposition in the soil. At the upper bound scenario of $500 per MtC, conversion of cropland to conservation tillage results in a total reduction of 18.9 MMtC per year from the atmosphere below baseline projections.

Table 9. Modeled impacts to atmospheric carbon from annual emissions and soil carbon uptake under increasing soil carbon incentive levels, 2025 (MMtC).

Incentive $ per tonne	Direct Emissions* On-farm Fuel	N_20 from Nitrogen	$C0_2$ from Lime	Total	Indirect Emissions** Fertilizers	Chemicals	Seeds	Total	All Emissions	Soil Carbon***	Net Flux†	Change in Net Flux‡
Baseline	9.63	14.74	2.94	27.31	8.42	1.61	1.68	11.71	39.02	-12.36	26.66	0.00
$12.5	9.53	14.71	2.93	27.17	8.40	1.61	1.67	11.68	38.85	-12.80	26.05	-0.61
$25	9.32	14.51	2.94	26.77	8.31	1.61	1.66	11.59	38.36	-16.38	21.98	-4.68
$50	9.25	14.49	2.93	26.67	8.30	1.62	1.66	11.59	38.25	-21.64	16.61	-10.05
$75	9.17	14.45	2.92	26.54	8.29	1.63	1.66	11.58	38.12	-22.96	15.16	-11.50
$125	9.07	14.36	2.90	26.32	8.24	1.65	1.65	11.54	37.86	-23.78	14.08	-12.58
$250	8.79	14.16	2.83	25.79	8.13	1.71	1.65	11.48	37.27	-25.88	11.39	-15.27
$500	8.36	13.93	2.82	25.11	8.02	1.80	1.64	11.46	36.57	-28.85	7.72	-18.94

Incentives are paid to reduced and no-till practices.

*Direct emissions represent all on farm carbon equivalent emissions.

**Indirect emissions include all emissions embodied in the production of these inputs.

***Negative numbers represent an uptake of carbon from the atmosphere and into the soil.

†Net flux is the net result of emissions from production and carbon uptake by soils due to soil conservation management practices.

‡Change in Net Flux represents changes from the Baseline level.

Table 10. Modeled change in impacts from baseline to atmospheric carbon from annual emissions and soil carbon uptake under increasing soil carbon incentive levels, 2025 (MMtC).

	Direct Emissions*				Indirect Emissions**				All	Soil	Net
Incentive $ per tonne	On-farm Fuel	N_20 from Nitrogen	$C0_2$ from Lime	Total	Fertilizers	Chemicals	Seeds	Total	Emissions	Carbon***	Flux[†]
$0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$12.5	-0.11	-0.04	0.00	-0.14	-0.02	-0.01	0.00	-0.03	-0.17	-0.44	-0.61
$25	-0.31	-0.23	0.00	-0.54	-0.11	0.00	-0.02	-0.13	-0.67	-4.02	-4.68
$50	-0.39	-0.25	-0.01	-0.64	-0.12	0.01	-0.02	-0.13	-0.77	-9.27	-10.05
$75	-0.47	-0.29	-0.01	-0.77	-0.14	0.02	-0.02	-0.14	-0.91	-10.60	-11.50
$125	-0.57	-0.39	-0.03	-0.99	-0.18	0.04	-0.02	-0.17	-1.16	-11.42	-12.58
$250	-0.84	-0.58	-0.10	-1.52	-0.30	0.09	-0.03	-0.24	-1.76	-13.51	-15.27
$500	-1.27	-0.81	-0.11	-2.20	-0.41	0.19	-0.04	-0.25	-2.46	-16.49	-18.94

Incentives are paid to reduced and no-till practices.

*Direct emissions represent all on farm carbon equivalent emissions.

**Indirect emissions include all emissions embodied in the production of these inputs.

***Negative numbers represent an uptake of carbon from the atmosphere and into the soil.

[†]Net flux is the net result of emissions from production and carbon uptake by soils due to soil conservation management practices.

Average costs of abatement

Conservation tillage only sequesters additional carbon for about 20 years, after which no further gains in SOC can be made (Schlesinger, 2000). In analyzing the costs of implementing a program, it is important only to credit conservation tillage acres on which carbon is still accumulating. In this analysis, I have simulated the implementation of a carbon program that pays all adopters of conservation tillage and not only new adopters. This will raise implementation costs above paying only new adopters. This scenario was chosen to simulate carbon payment programs most similar to those already emerging, such as the CCX.

Table 11 reports total costs of national implementation of incentives and the average costs under two separate assumptions. The "baseline plus additional" category reports the average cost if all conservation tillage lands are assumed to still be accumulating additional carbon annually. The "only additional" category reports the average cost if it is assumed that only newly converted lands are counted as abated carbon. Total program costs at $125 per MtC are estimated at $2.97 billion, which equates to an average cost of $119 per MtC of net carbon flux reduction under the "baseline plus additional" assumption. The costs per MtC are slightly lower than the incentive levels due to the additional savings generated by net reductions in emissions.

If we only count additional carbon abatement, above quantities which would have been abated in the absence of incentives, then all baseline carbon abatement cannot be included in the computation of average cost. In this case, land in conservation tillage will

Table 11. Costs of atmospheric carbon abatement as a result of incentives targeting agricultural soil carbon sequestration in 2025. Annual program costs under two different accounting assumptions, (1) all carbon changes counted as abated, and (2) only additional carbon counted as abated.

Incentive ($ per MT)	Total mil $	Baseline plus additional carbon (MMT)	Cost per MT*	Only additional carbon (MMT)	Cost per MT**	Cost increase above incentive level
Baseline	-	12.36	$0	0.00	$0	0%
$12.5	160	12.97	$12	0.61	$263	2003%
$25	410	17.05	$24	4.68	$87	250%
$50	1,082	22.41	$48	10.05	$108	115%
$75	1,722	23.87	$72	11.50	$150	100%
$125	2,973	24.94	$119	12.58	$236	89%
$250	6,469	27.63	$234	15.27	$424	69%
$500	14,425	31.31	$461	18.94	$762	52%

Simulated incentive program pays ALL adopters, not only new adopters for total estimated soil sequestration.

*Cost assumes the incentive program counts all carbon changes, even baseline, as abated carbon.

**Cost assumes the incentive program counts only new carbon above baseline as abated carbon.

be receiving payments regardless of whether they are still accumulating soil carbon or not. The payments going to non-additional carbon will raise average costs significantly. At $125 per MtC, ‘additional’ carbon abatement costs are estimated at $236 per MtC.

Acreage changes

In the baseline case, by 2025, 34% of total acreage in the eight major crops is in conventional-tillage, 32% in reduced-tillage and 33% in no-tillage. At an offered incentive of $125 per MtC, no-tillage practices are estimated to increase by 84 million acres to account for 52% of total acreage (Table 12). At $500 per MtC, 150 million acres are estimated to switch to no-tillage to account for 74% of total acreage. Although reduced-tillage also receives incentives based in sequestration ability, the higher incentives received by no-tillage pulls acreage away from reduced-tillage. Reduced-

Table 12. Acreage changes induced by carbon incentive (mil acres) by 2025.

Incentive $ per ton	Conventional tillage	Change	% of Total	Reduced tillage	Change	% of Total	No-tillage	Change	% of Total
0	131	0	43%	99	0	32%	76	0	25%
$12.5	129	-2	42%	94	-4	31%	82	7	27%
$25	92	-39	30%	92	-7	30%	122	46	40%
$50	77	-54	25%	91	-8	30%	137	62	45%
$75	66	-65	22%	90	-9	29%	150	74	49%
$125	58	-74	19%	88	-10	29%	160	84	52%
$250	39	-92	13%	80	-19	26%	187	111	61%
$500	16	-116	5%	64	-35	21%	226	150	74%

Incentives are paid to reduced and no-till practices

tillage declines from 32% of total acreage in the baseline case to only 21% at the $500 per MtC incentive level.

The relative amount of cropland in each crop does not vary by much (Table 13). Nationally, there are slight movements of land out of corn, sorghum, cotton and hay, and into wheat and soybeans. While crop acreage changes at the national level are small, regional changes in acreages could be quite significant.

Price changes

Prices change in response to incentive-induced changes in total crop production. In most regions and crops, reduced-tillage has the highest yield, followed by conventional-tillage and then no-tillage. As acres switch out of conventional and reduced-tillage and into no-tillage, total production declines and prices rise. Table 14 reports the price changes of the four major commodities through the simulation period at $125 per MtC. Most price increases are no greater than three percent. New virgin lands do not come into production for several reasons.

Table 13. Cropland changes under incentive levels: percentage of total model cropland.

Incentive	Corn	Sorghum	Wheat	Soybeans	Cotton	Hay	Total*
$0	29.2%	1.8%	19.2%	21.8%	4.8%	19.8%	97%
$12.5	29.5%	1.8%	19.3%	21.7%	4.6%	19.7%	97%
$25	29.4%	1.8%	19.2%	21.8%	4.6%	19.8%	97%
$50	29.4%	1.8%	19.1%	21.8%	4.6%	19.9%	97%
$75	29.4%	1.8%	19.2%	21.8%	4.6%	19.9%	97%
$125	29.4%	1.7%	19.2%	21.8%	4.6%	19.9%	97%
$250	29.3%	1.7%	19.4%	22.0%	4.4%	19.7%	97%
$500	29.1%	1.5%	19.9%	22.4%	4.4%	19.3%	97%

*Other 3% of total model cropland is in sorghum, oats, barley, cotton and rice.

Table 14. Commodity price changes through simulation period at $125 per MtC.

		2010	2015	2020	2025
Corn					
	Baseline	3.55	3.35	3.37	3.19
	Simulation	3.57	3.40	3.44	3.28
	% Change	0.6%	1.5%	2.1%	2.8%
Soybeans					
	Baseline	7.00	6.75	6.69	6.46
	Simulation	6.88	6.70	6.69	6.49
	% Change	-1.7%	-0.7%	0.0%	0.5%
Wheat					
	Baseline	4.35	4.55	4.43	4.3
	Simulation	4.34	4.6	4.48	4.37
	% Change	-0.2%	1.1%	1.1%	1.6%
Cotton					
	Baseline	0.570	0.560	0.616	0.621
	Simulation	0.576	0.568	0.627	0.633
	% Change	1.1%	1.4%	1.8%	1.9%

First, we are using 2007 USDA baseline projections, which already assume that over 10 million acres of idled cropland comes into production to meet increased ethanol demand. Therefore, most of the readily convertible idle cropland is already in baseline production. Second, since converted pastureland would not be accumulating soil carbon (by tilling, it would be emitting stored soil carbon), it is assumed that converted pastureland does not receive incentives. And third, without incentives, the relatively small price rises listed in Table 14 are not significant enough to bring other lands into production.

Regional estimates

Figure 11 shows changes in average soil carbon level per acre from baseline in 2025 at the $125 per MtC incentive level. The greatest gains in carbon per acre are estimated to be in regions where a large portion of total switched acres are from haylands. Deep penetration of soil by hay root structures lead to greater soil carbon gains on haylands over other crops. Areas such as the northern plains, the northeast, Missouri and eastern Kansas have a high portion of total cropland in hay, therefore Figure 11 indicates that these areas gain the most per acre.

Figure 12 depicts total soil carbon change at the county level. In general, it mirrors the average change per acre shown in Figure 11, but the total carbon map also shows that intensive agricultural areas such as the Mississippi Delta and the Corn Belt of Iowa and Illinois sequester significant amounts of carbon. Mapping total change at the county level can be somewhat misleading due to different land areas within the counties. For example, Figure 12 indicates that large western counties sequester large amounts of carbon, yet the carbon sequestration occurs over vast areas. Figure 12 also shows that

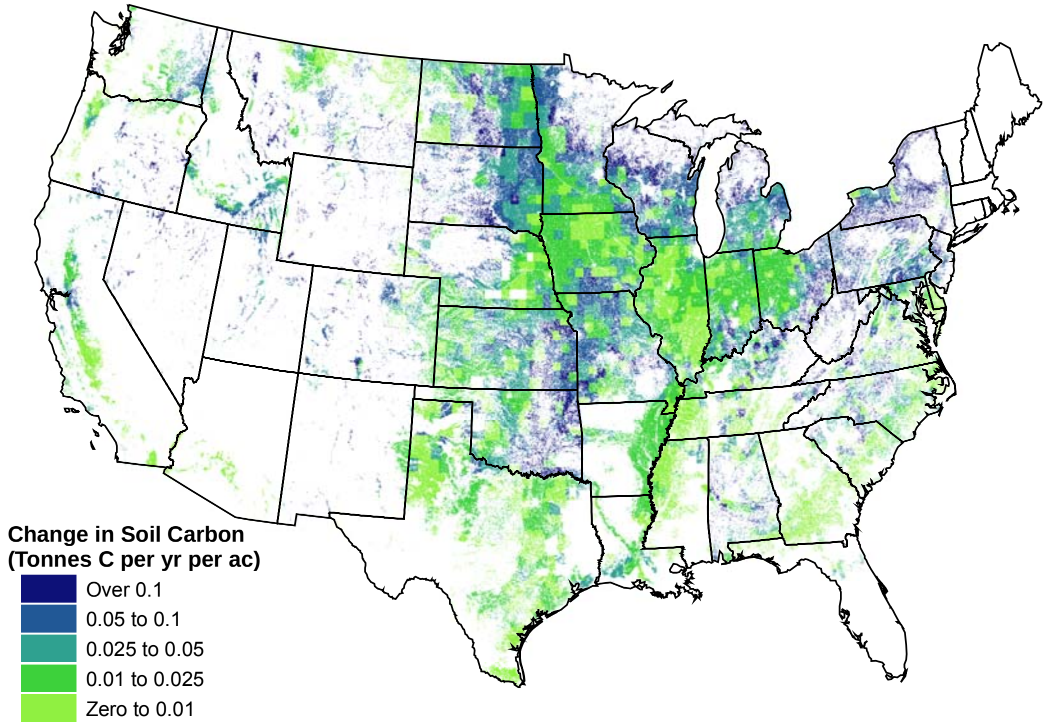

Figure 11. Regional changes in soil carbon from baseline case at $125 per MtC: average per acre in 2025.

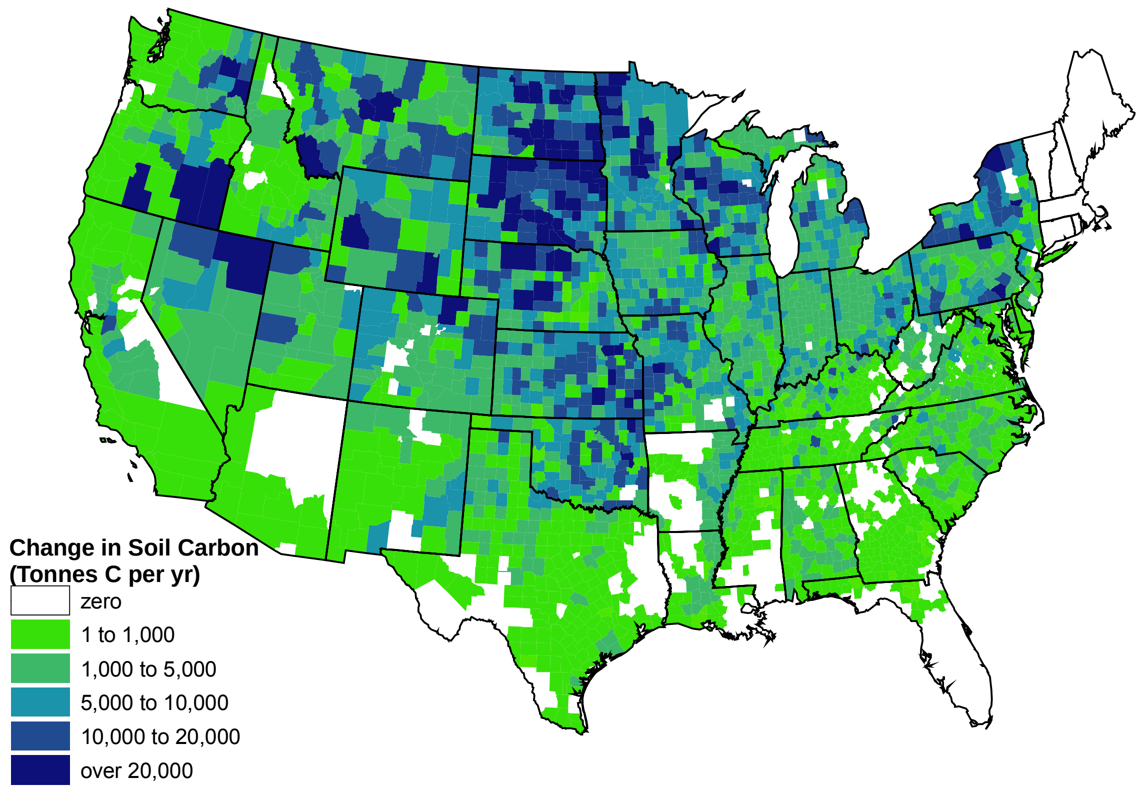

Figure 12. Regional changes in soil carbon from baseline case at $125 per MtC: regional totals in 2025.

smaller and more dispersed gains in soil carbon occur in all agricultural regions of the US Net production emissions changes per acre, depicted in Figure 13, show that incentives based on soil sequestration potential can cause emissions to increase in some regions. Agricultural operations and application of inputs causes emissions of carbon, and incentive-induced changes in crop and tillage types can lead to net changes emissions from the baseline case. In the majority of regions, such as the Red River Valley, Mississippi Delta and Ohio, increased conservation tillage leads to net decreases in emissions (shaded in blue in Figure 13). Yet in other regions, such as parts of North Dakota and eastern Kentucky, the incentives cause net production emissions to increase (shaded in pink in Figure 13). No-tillage operations emit less directly, due to fewer tillage operations, but emit more indirectly due to increased chemical usage. In general, the net outcome is a drop in emissions when switching to no-tillage. But the mix of cropland is not static. Incentives to higher-sequestering management practices act to pull land out of some crops and into others. For example, in North Dakota, there are significant amounts of reduced-tillage wheat acreage switching to no-tillage hay. Hay sequesters more carbon than wheat, but the process of growing hay can cause much larger emissions of carbon than wheat production. As a result, net emissions per acre in some regions actually increase. In eastern Kentucky, significant amounts of land moves from reduced-tillage soybeans to no-tillage corn. Although no-tillage corn can sequester more carbon, it also emits more in the production process. Also, eastern Kentucky is a hilly region that has already converted a significant portion of cropland to no-tillage in the baseline case, therefore, less additional abatement can occur. Figure 14 shows the regional total changes in emissions in 2025.

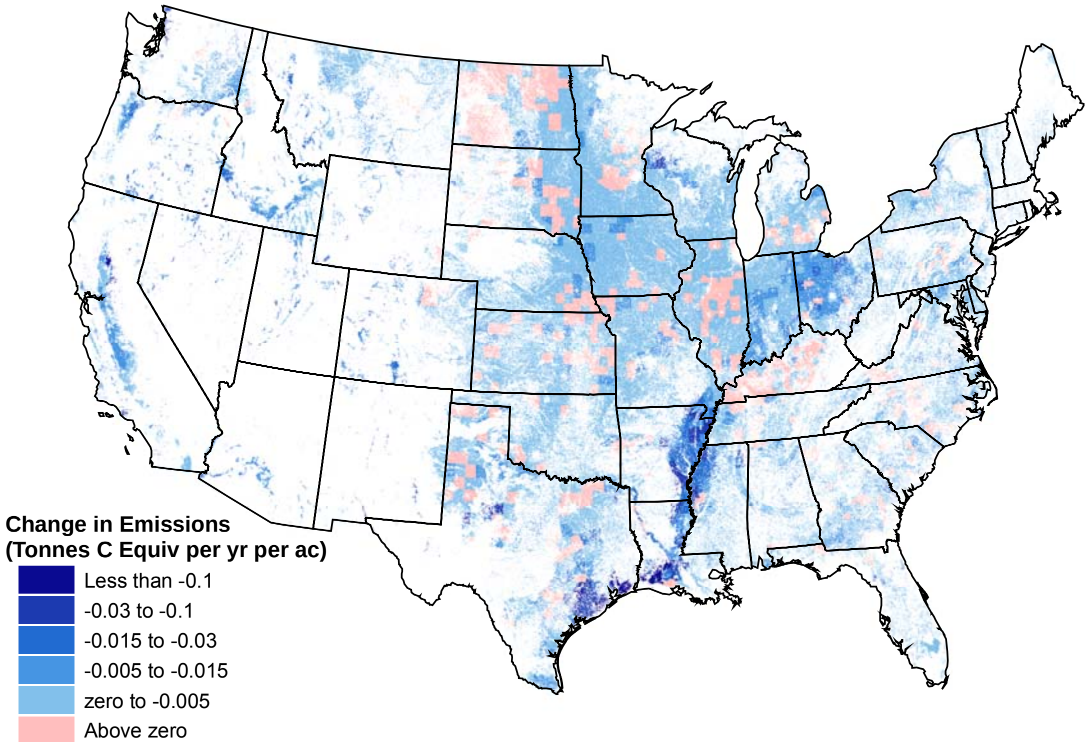

Figure 13. Regional changes in emissions from baseline case at $125 per MtC: average per acre in 2025.

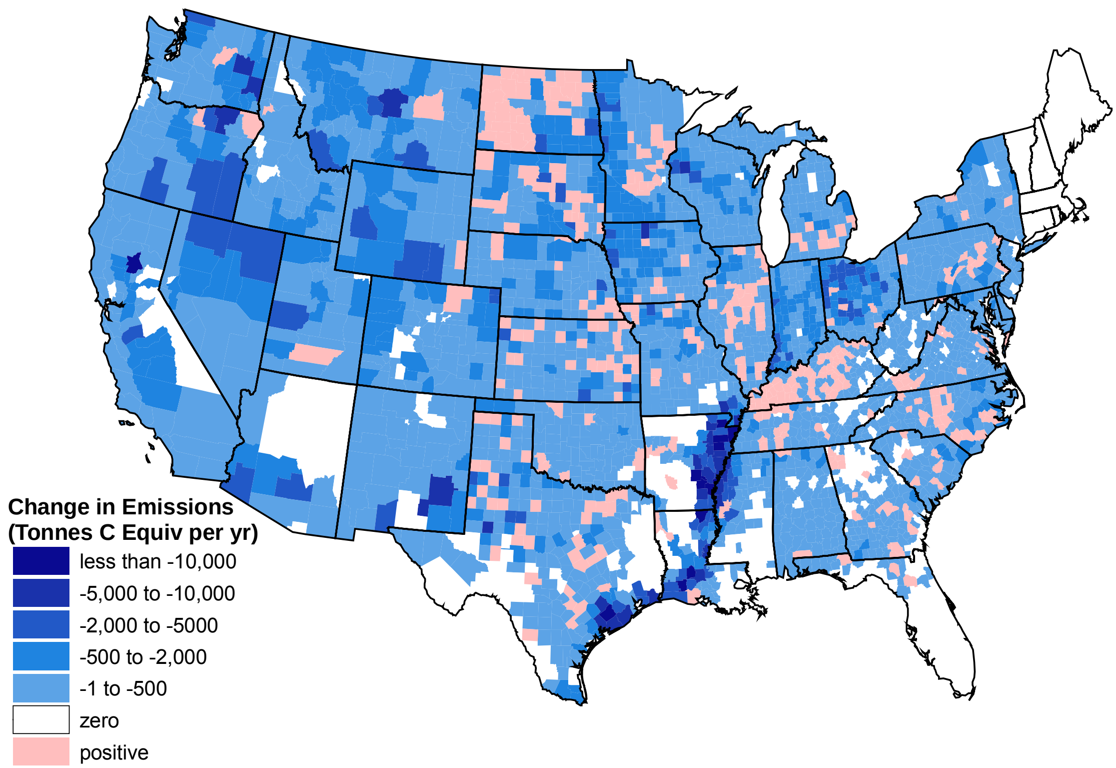

Figure 14. Regional changes in emissions from baseline case at $125 per MtC: regional totals in 2025.

Significant drops in emissions occurred in Ohio and the Mississippi Delta. In Ohio, the baseline scenario indicates very little acreage in no-tillage. Incentives act to switch most of the corn and wheat acreage to no-tillage. The regional budgets of no-tillage use fewer inputs and therefore total emissions decline. In the case of the Mississippi Delta, incentives act to move land out of input-intensive cotton production and into less input intensive crops such as no-tillage corn or soybeans.

Net carbon flux is defined as the net amount of carbon emitted by farming an area of land when both soil carbon sequestration and input emissions are accounted for. Because total agricultural emissions far outweigh total soil sequestration, the beneficial effect of a carbon incentive is to reduce the net flux of carbon. Regional changes per acre in net carbon flux as a result of an incentive of $125 per MtC are shown in Figure 15. Here, we

see that, in most regions, increases in soil carbon are enough to outweigh any increases in net emissions. The result in most regions is, therefore, a net reduction in carbon flux to the atmosphere. Yet, in a few scattered regions, such as western Kentucky, and parts of Texas and Nebraska, the increase in emissions is greater than the countering increase in soil carbon. In these instances, the incentive program acts in a perverse manner and actually causes an increase in net flux of carbon to the atmosphere. This is an unintended leakage caused by the incentive program targeting soil sequestration ability. Nationally, at $125 per MtC, there is 0.108 MMtC of gross leakage.

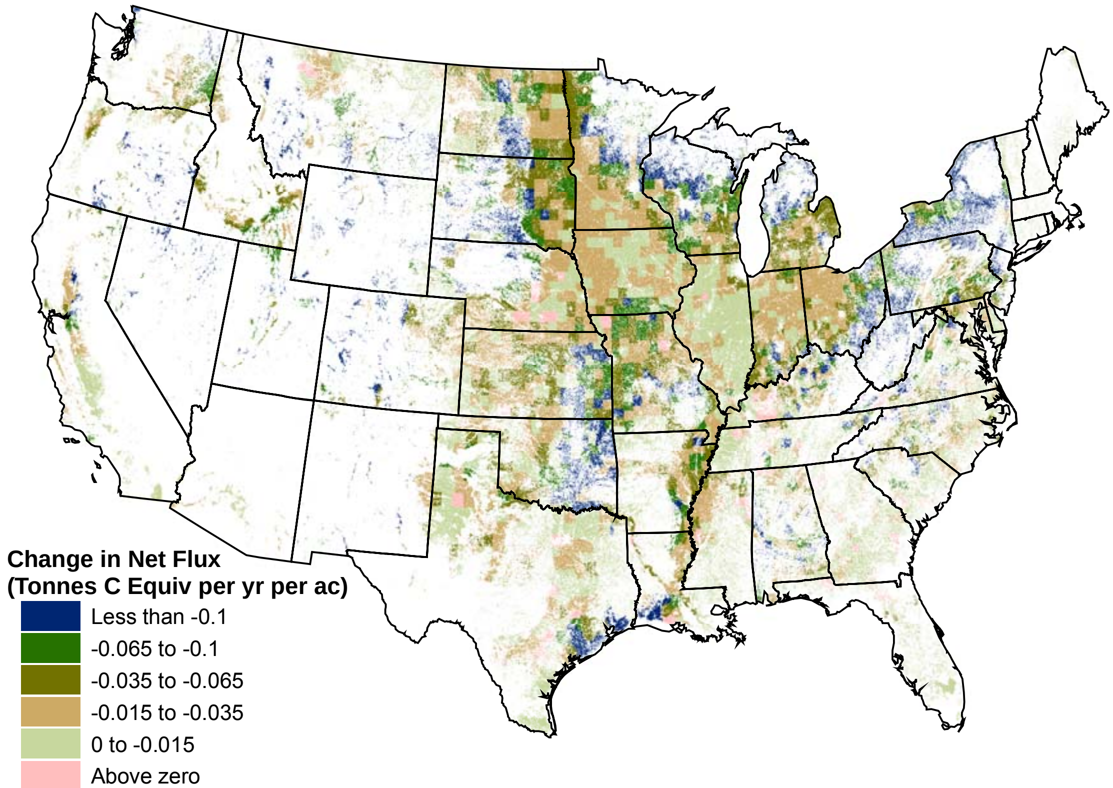

Figure 15. Regional changes in net carbon flux from baseline case at $125 per metric ton: averages per acre in 2025.

Figure 16 shows total change in net flux at the county level. Some counties reduced net carbon flux by over 30 thousand MtC per year. Results indicate that regions currently producing hay under conventional-tillage have the greatest potential to reduce net carbon flux. Such regions include the northern perimeter of the Corn Belt, eastern Kansas, Missouri, and New England. Also, intensive agricultural areas such as the Red River Valley, Mississippi Delta, and northern Corn-Belt have the high potential to reduce net flux. Although North Dakota had significant increases in emissions from production, the deficit was rapidly made up by the amount of carbon that new no-tillage haylands accumulate. This is not the case in eastern Kentucky, where, in some regions, the increases in soil carbon accumulation is not enough to correct the simultaneous increases in emissions from production. In this region of Kentucky, the baseline case already had significant amounts of land in no-tillage (hilly countryside). Many of the acreage shifts were from reduced-tillage soybeans to no tillage corn. Because reduced-tillage soybeans were already sequestering carbon, the land shifts did not sequester significantly more. Therefore, emissions increases were not completely offset by soil carbon accumulation.

Uncertainty

Changes in soil carbon as a result of conservation tillage are dependent upon initial estimates of base soil carbon. I have used empirical observations from STATSGO to derive the weighted mean soil carbon content at the STATSGO soils region level. To test the uncertainty of the estimated carbon abatement curve presented in Figure 9, two alternative scenarios were run with initial base soil carbon adjusted by ±28% in every region based on the mean standard deviations of STATGO data found by Galbraith et al.

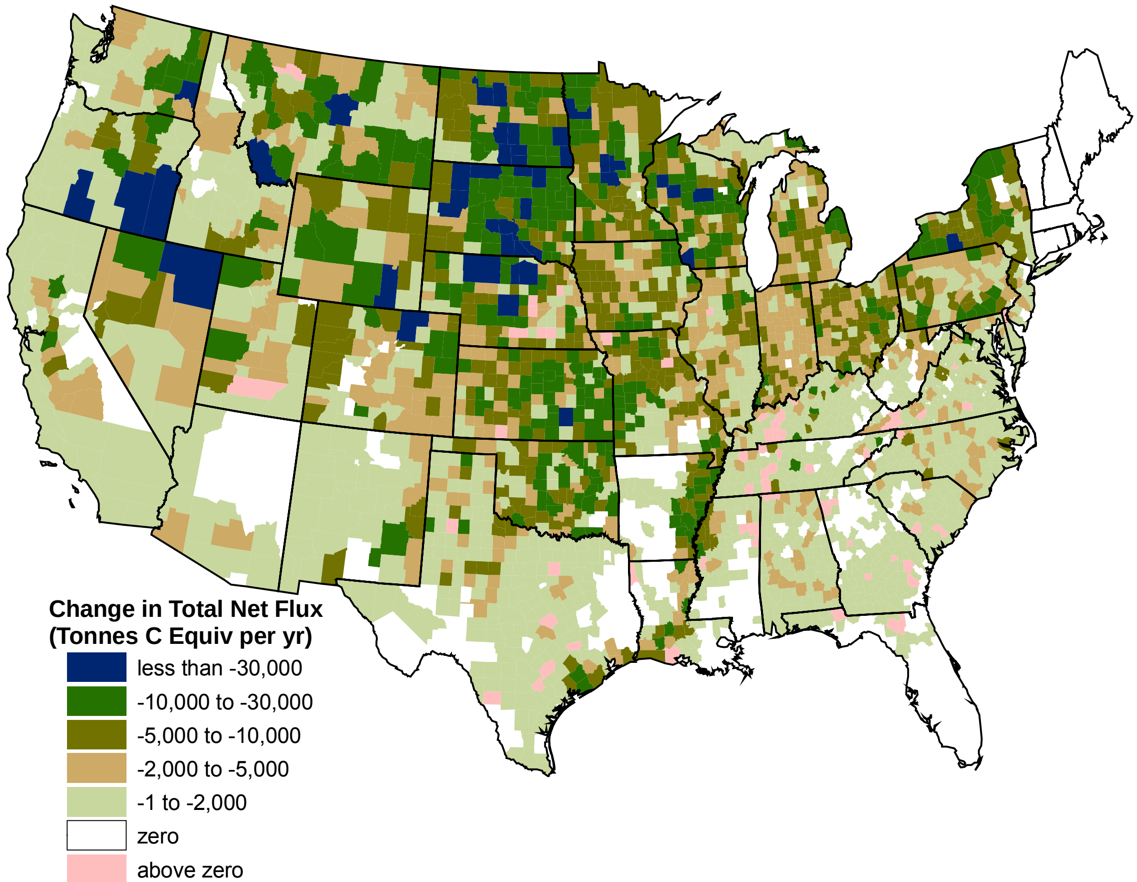

Figure 16. Regional changes in net carbon flux from baseline case at $125 per MtC: Regional totals in 2025.

(2003). This gives an upper and lower bound estimate of uncertainty. The first scenario assumes that initial soil carbon in all regions is 28% less than estimated, and the second scenario assumes that initial soil carbon is 28% more than estimated. In reality, initial carbon in some regions is likely underestimated, and overestimated in other regions. So, the uncertainty would lie somewhere between these two extremes.

Figure 17 gives the results of the two alternative scenarios around the original mean carbon abatement curve. The decline (rise) in estimated abatement is considerably less than the applied decline (rise) in initial soil carbon. At $125 incentive level, the lower estimate is 2.02 MMtC less than mean level, or 16% less. The upper estimate is 1.49 MMtC greater than mean level, or 12% more. Percentage changes in carbon abatement from the mean level are less than the 28% change in initial soil carbon. In the model, this is due to the effect of the carbon rate adjustment factor. This factor acts to bring down the rate of change in carbon on higher carbon soils and bring up the rate of adjustment on lower carbon soils, which corresponds to soil dynamics. Empirical tests show that even though higher carbon soils may be able to accumulate more total carbon per acre, the relative rate of change is lower. Higher carbon soils cannot increase proportionally to the same extent as lower carbon soils. In lower carbon soils, the rate of accumulation is larger than the mean. The carbon rate adjustment factor considers these dynamics and adjusts the rate of change in soil carbon by the initial base soil carbon level. In testing for uncertainty, we lowered initial soil carbon estimates in the first simulation. For higher carbon soils, this acted to decrease the adjustment factor so that the relative change in accumulated carbon was not as drastic as the applied change in initial soil carbon

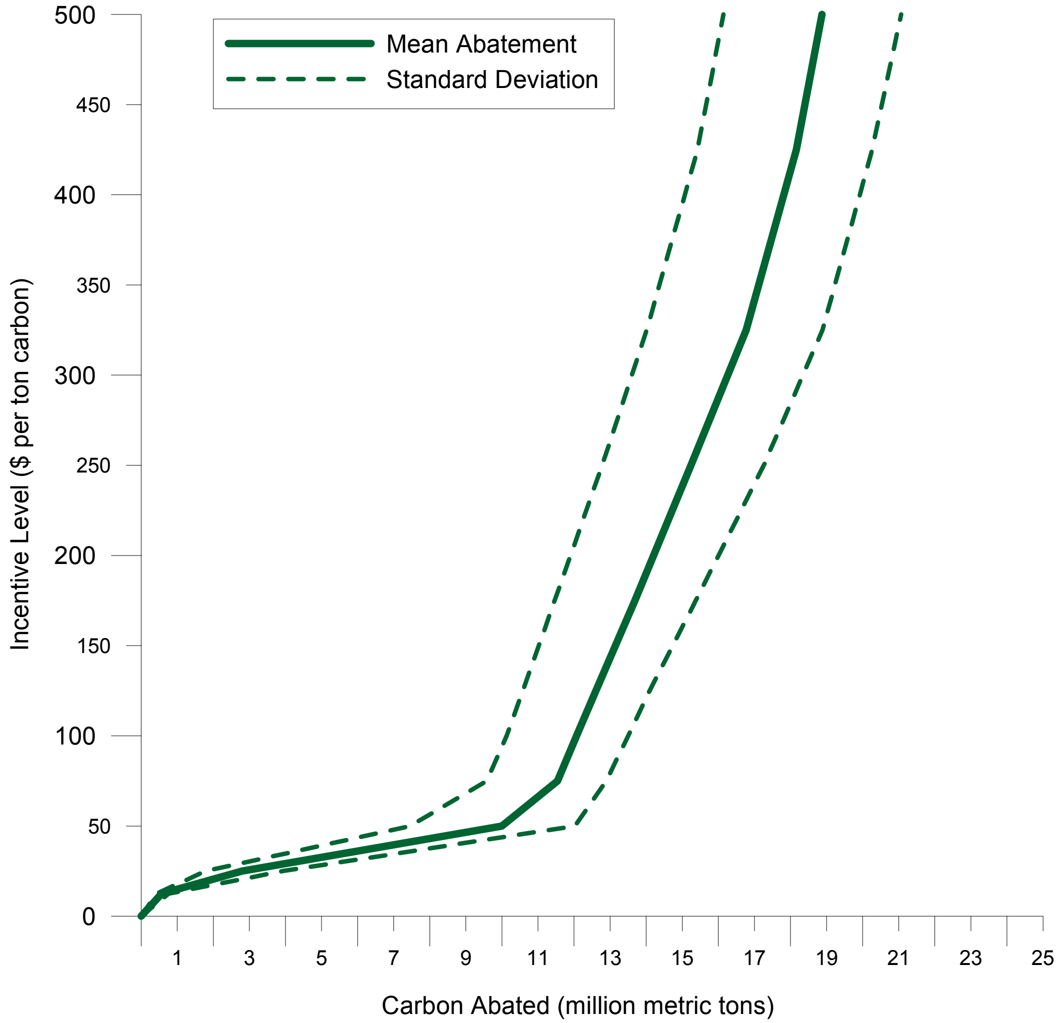

Figure 17. Uncertainty around national mean carbon abatement curve: Mean net carbon abatement curve and range of error to one standard deviation. Uncertainty in initial estimates of soil carbon can lead to errors in estimating soil carbon accumulation. Galbraith et al. (2003) found that the mean standard deviation of soil carbon in STATSGO data are ±28%. The model was run under two alternative scenarios with initial soil carbon at ±28% of STATSGO estimations.

estimates. For lower carbon soils, the lower initial soil carbon estimates acted to raise the adjustment factor so that the lower estimate was closer to the original mean level. In effect, the adjustment factor acts to smooth the estimates of quantities of soil carbon change across different estimates of initial soil carbon. The net result is that the estimated changes in carbon abatement shown in Figure 17 are less, proportionally, than the changes in initial soil carbon applied.

Validation of high resolution

The high-resolution methodology developed in this analysis for estimating changes in soil carbon is still based upon aggregation of soil conditions in individual fields. To test the high resolution methodology and its ability to estimate field-level changes in soil carbon, empirical results from specific tillage experiments were compared to modeled estimates. Six tillage experiments located in Alabama, Illinois, Kentucky, Mississippi, Nebraska and Ohio tested the effects of no-tillage adoption on soil carbon accumulation. The experiments ranged in number of years tested from three to 25 years. The average rates of change in soil carbon are reported in Table 15. The Table also lists the estimated rate of change using the high resolution, 'LANDSAT-county', version of the model. Percentage error is reported in italics below the actual rate of change figures. The errors are considerable, ranging from only a 3% error in the Mississippi cotton experiment to a -73% error in the Kentucky experiment. The median absolute error was 25% for all the experimental locations combined. Although the error seems quite large, it must be remembered that the high-resolution model estimates of carbon change are figured through the use of a weighted initial soil carbon estimate. The initial soil carbon estimate is weighted by all soil in each specific land use category (row crops, small grains, or pasture). Each experiment is located on only one of these soils, therefore it can be expected that modeled results will vary from field trial results. This is justification for not using the model results to estimate soil carbon changes at the field level. Rather, the high-resolution model is designed for county-level estimates where changes in tillage on all soils within the county are considered. Unfortunately empirical estimates of soil carbon are not available at the county level.

The empirical results can be useful in testing the estimation abilities of the high resolution over lower resolution versions of the model. In Table 15, lower resolution

Table 15. Average annual rates of change of soil carbon in empirical experiments and comparisons with estimated rates using four different model resolution versions.

		Estimated Rate of Change of Soil Carbon and *% Error in Replicating Emprical Rate*			
Experiment Site	Empirical Rate of Change MT Ac^{-1} Yr^{-1}	LANDSAT County*	Non-LANDSAT County**	LANDSAT National†	Non-LANDSAT National‡
Dekalb County, AL	0.073	0.066	0.038	0.107	0.091
(corn)		*-10%*	*-49%*	*46%*	*23%*
Johnson County, IL	0.200	0.134	0.053	0.107	0.091
(corn/soybeans)		*-33%*	*-74%*	*-47%*	*-55%*
Fayette County, KY	0.247	0.066	0.109	0.107	0.091
(corn)		*-73%*	*-56%*	*-57%*	*-63%*
Tate County, MS	0.073	0.076	0.015	0.033	0.028
(cotton)		*3%*	*-80%*	*-55%*	*-62%*
Cheyenne County, NE	0.058	0.042	0.059	0.096	0.081
(wheat)		*-26%*	*2%*	*67%*	*41%*
Wood County, OH	0.102	0.127	0.127	0.107	0.091
(corn/soybeans)		*24%*	*24%*	*5%*	*-11%*
	Median Absolute Error	*25%*	*52%*	*51%*	*48%*

Source of estimated changes in soil carbon of resolution versions: POLYSYS simulation.
*LANDSAT-county refers to the highest resolution scale developed in this project
**Non-LANDSAT county refers to initial soil carbon weighted by all soil regions at the county level.
† LANDSAT national refers to initial soil carbon weighted by only cropland at the national level.
‡Non-LANDSAT national refers to initial soil carbon weighted by all soil regions at the national level.

versions of the model are also compared to empirical observations. The 'Non-LANDSAT' county version does not use satellite data to weight the initial soil carbon. In Non-LANDSAT-county, all STATSGO initial soil carbon estimates are weighted by all areas within the county. 'LANDSAT-national' version uses satellite data, but unlike the county version, they are weighted as the national level, and not the county level. 'Non-LANDSAT-national' version does not use satellite data and weights initial soil carbon by area of all STATSGO regions at the national level. When comparing the estimated rate of soil carbon change in these lower resolution models to empirical observations at the six sites, they have about a 50% median absolute error in estimation. This is double the error observed in the high resolution model. Errors had a wide spectrum, ranging from as high as -80%, in the case of the cotton experiment in Mississippi, and as low as 2%, in the case of wheat rotation in Nebraska.

Although the model was not designed to replicate individual field-level changes in soil carbon, there is justification for comparing the results to empirical observations for validation of the relative scale of error in the model resolution versions. It was hypothesized that the higher resolution model would have better predictive capabilities than a lower resolution version. In the case of the six experiments compared, the high resolution version came the closest to replicating the observed rate of increase in three cases. In the other three experiments, it placed second, third and forth in replication error. At some individual sites, the high-resolution version may not have had the best replication ability, but in the majority of cases, it was the best version for replicating the empirical rate of change in soil carbon. Although the number of site observations is too few to analyze the results statistically, overall, the median absolute error for the high-resolution version was half that of the other resolution versions. For these reasons, we can be reasonably confident that the high resolution is doing a better job at estimating soil carbon changes at the county level than other lower resolution methodologies.

Resolution and scale

To study the interactions of resolution and scale and determine whether there is significant improvement occurs from using one resolution version over another in undertaking an analysis at a particular scale, the results of the four resolution versions were compared at three different scales of analysis. Each resolution version of the model was run with an offered incentive of $125 per MtC soil sequestration to every region in the lower 48 states. The resolution versions have different estimates of potential carbon sequestration due to the inherent nature of weighting the same initial soil carbon data at different resolutions. All other geographic variables, such as yield or crop budgets, stayed at the same resolution in all versions in order to test the effects of resolution and scale *ceteris paribus*. Analyses of estimates are compared at the national, state, and county scales.

At the national scale of analysis, Figure 18 shows that all resolution versions are fairly close in their estimates of incentive-induced reductions in net carbon flux (or carbon abated). When comparing all other resolution versions to the highest resolution version (LANDSAT-county), they are all within ±15% at all incentive levels. The carbon

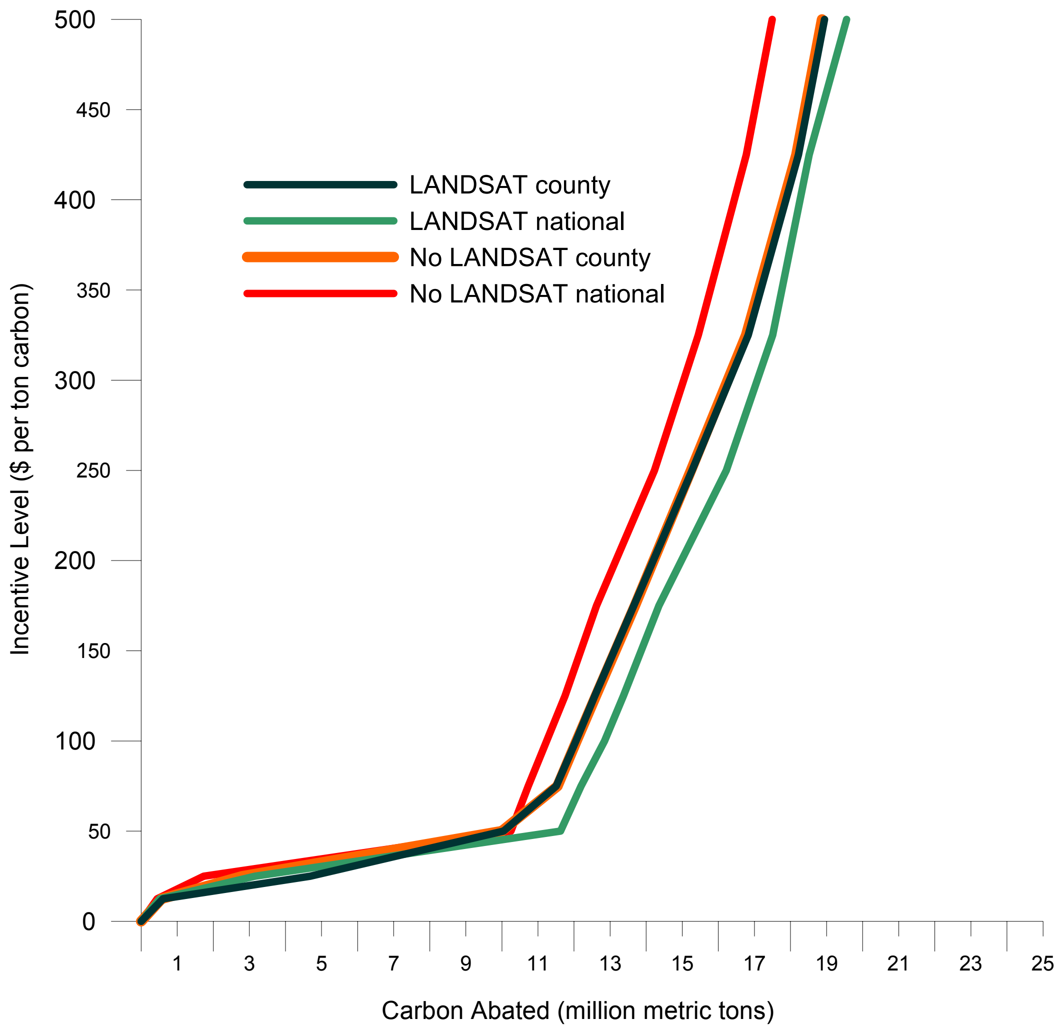

Figure 18. Carbon abatement curves of using differing resolutions in figuring initial soil carbon quantities. *LANDSAT county* resolution uses satellite data to weight initial soil carbon quantities by crop-specific soils at the county level. *No LANDSAT county* resolution weights initial soil carbon quantities by area of each unique soil region at the county level regardless of land-use. *LANDSAT national* resolution and *No LANDSAT national* resolution use these two methodologies but weighted at the national level. Source: POLYSYS simulations.

abatement supply curves shown in Figure 18 display the results of the four resolution versions at the national scale of analysis.

Table 16 reports the results of the resolution versions at all three scales of analysis. Results following the regions of the empirical field trial locations are listed also, but the reported mean absolute differences are for all regions and not only these sample locations. Because the high-resolution version was shown to best replicate field level data, it will be used as the standard by which the other versions are compared. As the scope of analysis decreases from national to state and then to county, there is an increasing level of disparity between the resolution estimates. Table 16 lists MtC increases in soil carbon for each particular geographic boundary and also the percentage divergence of the resolution version from the highest resolution version (LANDSAT-county). At the national scale, the NO LANDSAT-county estimation differs by only -4% from the highest resolution version. LANDSAT-national and NO LANDSAT-national differ by 5% and -13% respectively at the $125 per MtC incentive level. National-scale results followed expectations, as the estimates using only soils upon which crops are grown is expected to come closer to high resolution results than estimates using all soils in the nation.

At the state scale, the estimates diverge further. The 48-state mean absolute difference in estimated soil carbon for the NO-LANDSAT-county resolution is only 5% more than the highest resolution version. But, when using the nationally weighted versions, mean absolute difference increases by 20% and 24% for LANDSAT-national and NON-

Table 16. Scale comparisons: comparison of soil carbon sequestration estimates of high resolution version to other resolution versions at the national, state and county scale of analysis. Example states and counties correspond to locations of empirical tests listed in Table 15, but mean absolute differences are for all states and counties.

Geographic Scale and Boundary		LANDSAT County*	Non-LANDSAT County**	LANDSAT National[†]	Non-LANDSAT National[‡]
			Resolution Versions[ξ]		
		($MtC\ yr^{-1}$)	($MtC\ yr^{-1}$ and % Δ from LANDSAT County scenario)		
National Level					
Nation		11,416,133	10,944,722	12,075,931	10,079,927
			-4%	*5%*	*-13%*
State Level	(select states)				
Alabama		71,730	69,811	107,231	91,047
			-3%	*33%*	*21%*
Illinois		270,848	270,402	272,718	224,557
			0%	*1%*	*-21%*
Kentucky		162,866	164,018	189,941	156,946
			1%	*14%*	*-4%*
Mississippi		26,000	29,112	32,698	29,112
			11%	*20%*	*11%*
Nebraska		662,264	646,765	768,272	646,765
			-2%	*14%*	*-2%*
Ohio		372,566	328,045	393,473	328,045
			-14%	*5%*	*-14%*
	Lower 48 State Weighted Mean Absolute Difference from LANDSAT County Scenario		*5%*	*20%*	*24%*
County Level	(select counties)				
Dekalb County, AL		969	951	1582	1338
			-2%	*39%*	*28%*
Johnson County, IL		861	889	1029	869
			3%	*16%*	*1%*
Fayette County, KY		329	329	374	316
			0%	*12%*	*-4%*
Tate County, MS		330	337	285	391
			2%	*-16%*	*15%*
Cheyenne County, NE		1133	1148	1625	1368
			1%	*30%*	*17%*
Wood County, OH		4108	4099	3257	2612
			0%	*-26%*	*-57%*
	All U.S. Counties Weighted Mean Absolute Difference from LANDSAT County Scenario		*22%*	*35%*	*40%*

[ξ] Percentage differences of each scenario from the high resolution 'LANDSAT County' scenario are listed below metric tons soil carbon sequestration per year estimates.
All scenarios are compared at the $125 per MtC incentive level.
*LANDSAT sub-county refers to the highest resolution scale developed in this project
**Non-LANDSAT county refers to initial soil carbon weighted by all soil regions at the county level.
[†] LANDSAT national refers to initial soil carbon weighted by only cropland at the national level.
[‡]Non-LANDSAT national refers to initial soil carbon wieghted by all soil regions at the national level.

LANDSAT-national respectively. Just as at the national scale, the NON-LANDSAT-national has the greatest divergence in estimation from the high resolution at the state scale as well. Table 16 also gives individual states results from the six sample states (where empirical experiments were located). At the individual state level, the order of divergence does not always follow the national trend. For example, in the case of Ohio, the LANDSAT-national estimate best replicated the high-resolution estimate. But in five of the six sample states, the NON-LANDSAT-county version best replicated the high-resolution estimates. These results follow expected behavior. Estimates based on using weighted initial soil carbon only from soils within each state are closer in estimation than using weighted initial soil carbon from soils nationally.

At the county scale, Table 16 shows that the divergence in estimations grow even larger with mean absolute divergence of NON-LANDSAT-county growing to 22%, LANDSAT-national rising to 35%, and NON-LANDSAT-county increasing the most to 40%. Of the six individual county cases listed in Table 16, the range of divergence is quite great. In the case of Fayette County, KY and Wood County, OH, the NON-LANDSAT-county version estimated the same change in soil carbon at the high-resolution version. In all sample cases listed, the NON LANDSAT-county version did very well at replicating the high resolution results. The national resolution versions show very large errors at replicating the county scale high-resolution results, with Wood County, OH showing a -57% difference using NON LANDSAT-national, and Dekalb County, AL showing a 39% difference using LANDSAT-national.

The low-resolution nationally-weighted versions tend to have large errors at the regional scale; but, at the national scale, these errors (positive and negative) balance out to give national estimates that are closer to high resolution estimates. This follows expected results. In the national resolution versions, one weighted-average initial soil carbon value is applied to all regions, so expectedly, about half the regional estimations will be under-estimated and half overestimated. This can be seen in Figure 19, which shows the difference in estimated changes in soil carbon between the No LANDSAT-national version and the LANDSAT-county version at the $125 per MtC incentive level. Here, the national resolution model tends to overestimate the gains in soil carbon in the Western and Southeastern regions of the county. Whereas the same version underestimates soil carbon gains of Midwestern and Northeastern regions compared to the high-resolution county version. The pattern of initial soil carbon is very apparent in Figure 19. Soils with a lower initial soil carbon level than the national weighted average are in green, and soils with a higher initial soil carbon level than the national average are in blue. The national resolution model overestimates on low carbon soils and underestimates on high carbon soils. The map is essentially showing the carbon-poor soils in green and the carbon-rich soils in blue.

As the scale of analysis expands to larger regions, the differences in estimations using the different resolution versions may decrease. This is shown in Figure 20 where the scale is expanded to the state level. Here, the pattern of differences is similar to Figure 19, but the magnitude of differences is somewhat lessened in many states. For example, in the case of North Carolina, Figure 19 shows wide county-level differences in estimated

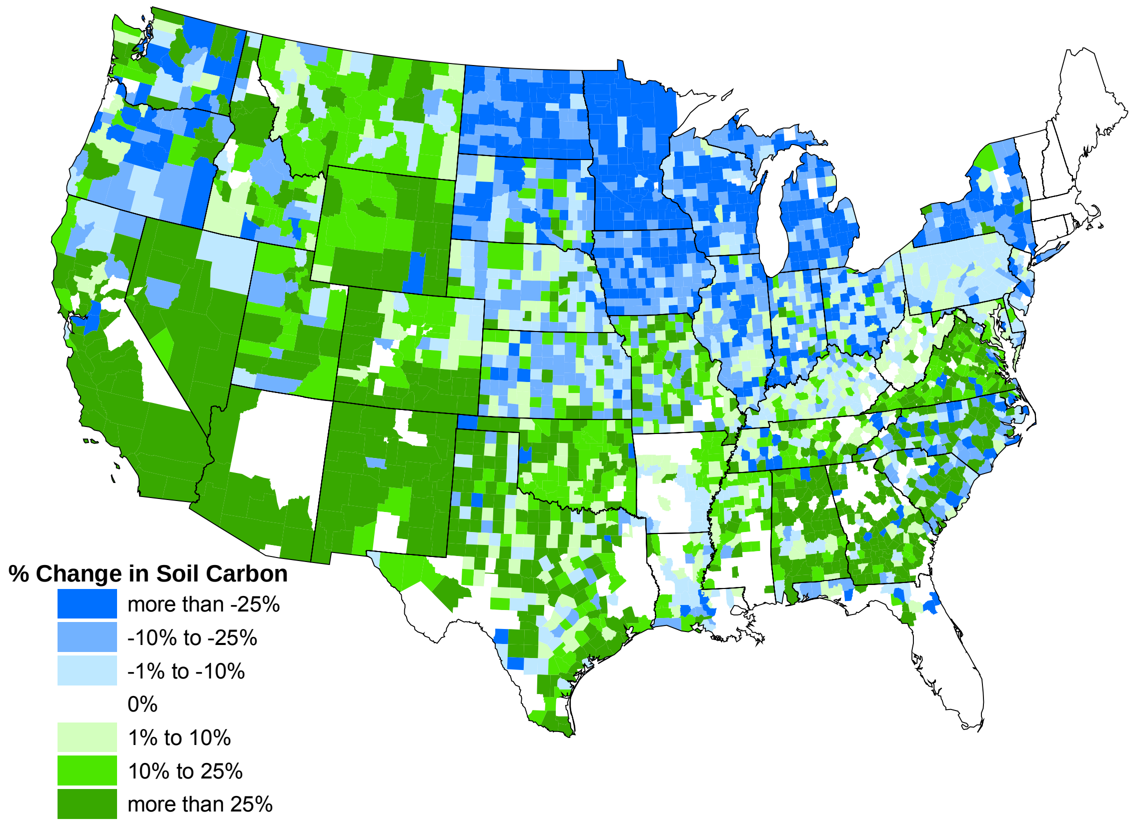

Figure 19. Regional differences in estimation using differing resolutions: This map shows differences in regional estimates of changes in soil carbon when using low resolution compared to high resolution in estimating initial soil carbon. In comparing the No LANDSAT-national version to the LANDSAT-county version, the No LANDSAT-national version over-estimates changes in soil carbon in the poorer soils of the western and southeastern US and underestimates in the richer soils of the upper Midwest. Nationally, the estimates are similar, but estimates widely diverge at the regional level.

carbon, but these differences cancel each other out in Figure 20 at the state level. Interestingly, in some states with soils consistently at the extremes of national sequestration ability, either low or high, increasing the scale does little to lessen estimation divergence. For example, in Minnesota, soils are consistently estimated to sequester more using the high-resolution county version than using the low-resolution national version. Figure 20 shows that Minnesota still has estimation differences greater than 25%, even at the state scale.

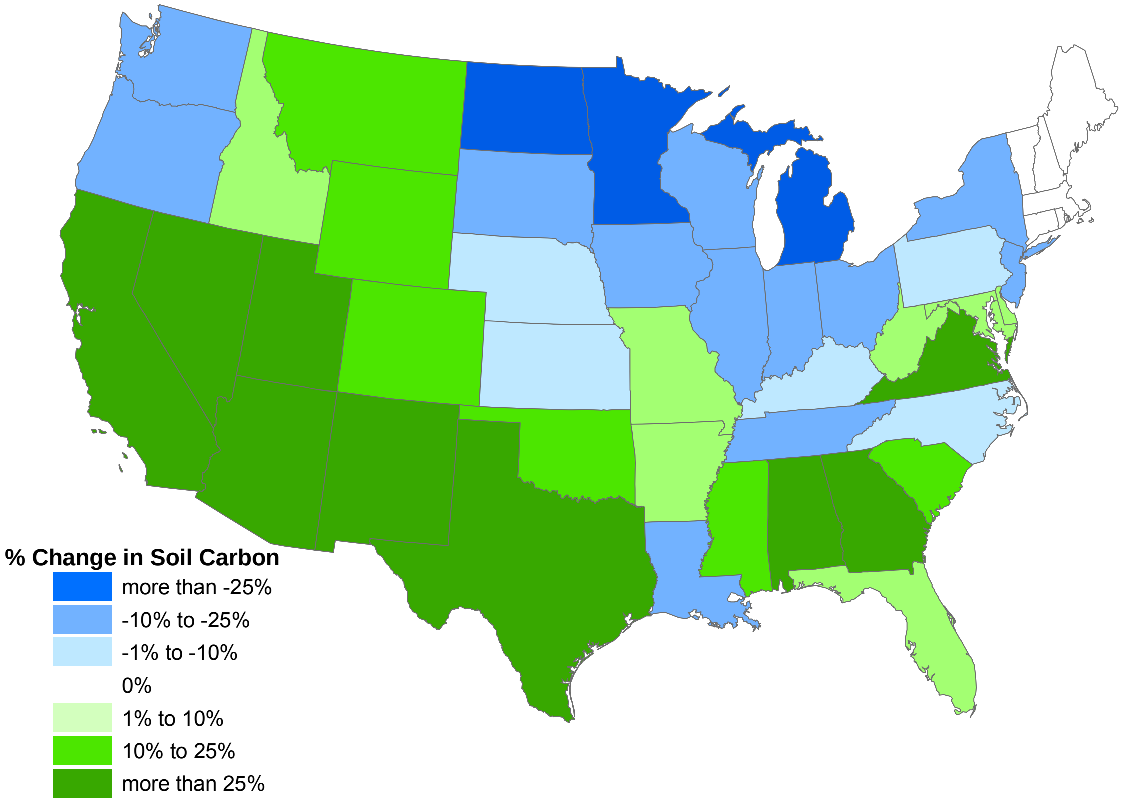

Figure 20. State scale differences in estimation using differing resolutions: This map shows differences in state estimates of changes in soil carbon when using low resolution (LANDSAT-county) compared to high resolution (No LANDSAT-national) in estimating initial soil carbon. The pattern of differences is similar to Figure 19, but at aggregation to the state level somewhat lessens extreme divergences in estimations (those greater than ±25%).

CHAPTER V:

DISCUSSION

Overall implications

The results of the analysis indicate a maximum technical potential abatement of 21.4 MMtC above baseline by 2025. Economic potential abatement reaches 18.9 MMtC per year above baseline at incentives of $500 per MtC. At this maximum level, a national program to sequester carbon in agricultural soils through adoption of conservation tillage would abate less than 1% of projected US annual carbon emissions. At $125 per MtC, which is a price carbon may likely reach, and if the nation pursues rigorous reductions in GHG's, 12.6 MMtC can be abated per year by 2025. At these quantities, conservation tillage will not be a major solution to solving the atmospheric carbon problem. At best, it can fill one small wedge of the GHG stabilization triangle (Pacala and Socolow, 2004) in the short to medium term. Regardless of the small total offset potential, the inclusion of conservation tillage within a national carbon mitigation program may be attractive if it can be implemented at low cost and with minimal uncertainty in abatement quantities.

Regional analysis using the high-resolution model indicates that the greatest abatement can occur in regions where hay is a dominant crop. The Dakotas, eastern Kansas, and the northeast are intensive hay regions where potential abatement is high. Conversion of haylands to conservation tillage offers the 'lowest hanging fruit' in terms of carbon abatement per dollar incentive. The Mississippi Delta was also determined to be a significant region in terms of reduction in net carbon flux. Unlike regions with high concentrations of haylands, the reduction in net carbon flux in the Mississippi Delta does not come mainly from increases in soil carbon, but from decreases in production emissions. Incentives act to move land out of input-intensive cotton production and into less input-intensive crops. High-resolution results also indicate that, in some regions, such as eastern Kentucky, incentives may act in a perverse manner and cause net increases in carbon emissions.

Besides the relatively small economic benefits of carbon sequestration by altering tillage practices, there are other challenges to soil carbon sequestration: 1) the duration of significant annual abatement is only 20 to 30 years; 2) payment to all adopters increases program costs significantly; 3) assuring permanence in offsets would also increase costs significantly; and 4) unintended leakage of carbon could occur through incentive-induced land-use changes. I will discuss each of these challenges to implementation below.

Duration

Biophysical constraints restrict soil sequestration to a short to medium-term option. Historic tillage of US soils has depleted SOC below naturally occurring levels. Changing to conservation tillage cropping systems will allow SOC levels to increase once again. But the increases will only continue until a new steady state is reached. Beyond this point, continuation of conservation tillage will keep SOC levels steady, but they will not increase further. It is estimated that a new steady state of SOC will be reached 20 years after the initial change in tillage is made. Figure 21 shows that, after 20 years, annual reductions in atmospheric carbon begin to decrease just as rapidly as they increased. If an incentive program were initiated today, soil carbon sequestration on agricultural lands would drop to near zero by the 2040s. Only the small net reductions in input use continue to accrue annually thereafter. In the long term, reductions in GHG levels will need to come from either direct reductions in emissions or other sequestration technologies. Policy makers and market organizers should consider the relatively small duration of benefits from a sequestration program using conservation tillage. Yet, of the many sequestration options proposed, such as geological sequestration or deep sea sequestration, soil carbon sequestration may be the most viable in the short to medium term, due to the fact that no technological hurtles need to be overcome before implementation.

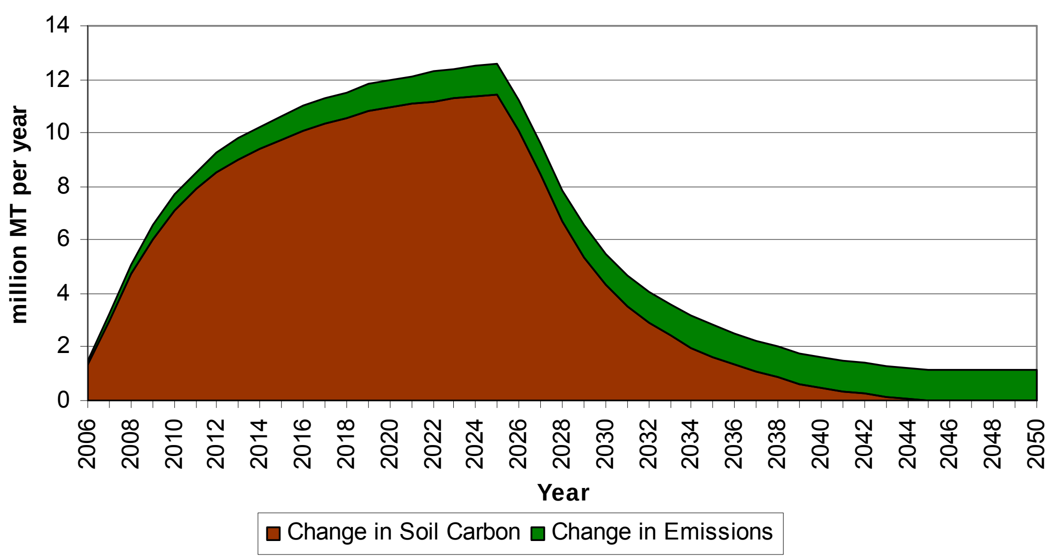

Figure 21. Changes in abatement over a 50 year period. At \$125 per MtC, incentives switch land to no-tillage and soils gain in carbon content annually until reaching the soil's potential maximum level of carbon content, which is thought to occur about 20 years after conversion. After 20 years, soil carbon no longer increases and total abatement declines just as rapidly as it increased. By 2045, there is no longer abatement through soil carbon, yet the decrease in emissions from lands switched to conservation tillage remain.

Additionality

It is import to make the distinction between total carbon sequestration and additional carbon sequestration. Currently, there are over 175 million acres in conservation tillage, most of which are still making gains in soil carbon every year. If a sequestration program were started today, the carbon sequestered in today's conservation tillage acres will do nothing to abate atmospheric carbon below projected estimates of CO_2 increases. They are creating no 'additional' carbon abatement. Additionality commonly refers to the measurement of atmospheric carbon reductions above that which would have been achieved in the absence of abatement actions. Truly additional abatement quantities only come from acres that would be induced into conservation tillage through the incentive program.

Additionality becomes a large problem in program design. Ideally, a program would only pay the new adopters of conservation tillage which add additional acres above the baseline case. If incentives are paid only to new adopters, then earlier adopters will be placed into a 'moral hazard' of switching out of no-tillage, releasing carbon, and then switching back into no-tillage to gain the incentive. This is a form of leakage, where an incentive program targeting only new adopters gives a perverse incentive to release carbon. Lewandrowski et al. (2004) estimated that the leakage in an incentive program paying all adopters could reduce total net carbon abatement by 90%! One alternative to this situation is to simultaneously tax land movements out of conservation tillage along with incentives for land movements into conservation tillage. This is called symmetric incentives and would have the effect of stopping the perverse incentive to release stored carbon. Farmers switching out of no-tillage would be taxed, or fined, by an amount equal to what no-adopters are being paid. Theoretically, symmetric incentives are a sound solution, but implementation of such a tax would face high obstacles, both technically and politically.

In this analysis, I chose to investigate carbon program implementation that is most similar in form to the emerging carbon trading markets—to pay 'all adopters' of tillage practices an incentive, and not only 'new adopters'. Currently the Chicago Climate Exchange is paying farmers for their use of no-tillage. Yet, most CCX program farmers were using no-tillage before payments began, or would have switched to no-tillage without the extra incentive. In effect, the current CCX is contributing very little additional carbon abatement above which would have been done in its absence. As in the CCX program, this analysis paid incentives to all adopters of conservation tillage; yet, unlike the CCX program, only additional carbon above baseline was accounted for as net carbon abatement gains. This avoids the moral hazard issue by eliminating the need for farmers to switch out of conservation tillage in order to qualify for the incentive. But it also increases total program costs significantly. Table 11 shows that, by paying all adopters at the $125 incentive level, per unit costs increase from $119 per MtC to $236 per MtC. The program is, in effect, paying all 'good actors', which adds inefficiencies to the program's implementation.

The intention of any new carbon program would be to abate additional carbon beyond what would occur without the program. It would seem most efficient to only pay new adopters of conservation tillage, but this may not be the best option due to the perverse incentive to emit stored soil carbon. Symmetric taxation and incentives could solve the moral hazard, but may be hindered by both monitoring costs and political unwillingness. Technically, the carbon program would have to monitor not only program participants, but all agricultural land practices. The tillage practice of every parcel would need to be accounted for annually. Currently, the monitoring costs may exclude this option. If the costs of such a monitoring program could be estimated, they should be compared to the cost of paying all adopters outright (as done in this analysis). Table 11 shows that the cost of paying all adopters at the $125 incentive level increases by 89% to $236 per MtC. If a symmetric incentive program that pays only new adopters is to be implemented, the estimated costs need to be less than this amount. With improvements in satellite-based techniques, it is a future possibility that monitoring could be achieved at a fairly low cost. Yet politically, the fight would be much harder. The combined political power of agricultural regions and the cultural context of land rights make a tax on soil emissions unlikely at best. For these reasons, paying all adopters, yet only counting net abatement above baseline, seems the most likely route to program implementation. Such a program would increase abatement costs significantly and should be considered by policymakers.

Permanence

The ultimate goal of carbon mitigation strategies is to permanently remove carbon from entering the atmosphere. Reductions in emissions, such as those estimated from switching from conventional to no-tillage, are permanent; one year's reduction in emissions will not be released in future years. Unfortunately this is not necessarily the case with increases in SOC. One year's increase in SOC can be released in future years if the soil is tilled. For this reason, the issue of permanence is vitally important to implementation of any soil carbon program. How can a program assure that the carbon is permanently removed from entering the atmosphere? If we can't assure permanence, can we still use agriculture in the short term to store carbon? How would a program pay for this service? Historical trends indicate that once farmers switch to no-tillage and realize the benefits of increased long-term yields, they will remain in no-tillage. If this is assumed, then permanent storage is assured. Farmers could receive the full asset value for the duration of soil carbon gains, after which incentives would end. Yet there is a risk that farmers will till their soil after incentives end, and emit soil carbon.

Risk of carbon release can be approached by viewing farmers as providing a storage service through which a carbon program will lease or rent the storage right of soil carbon for a particular contract period. Through a lease program, the farmer only receives the market value of annual storage of carbon and not the 'full asset' value of abating the carbon permanently. Lease contracts can be implemented for the duration that carbon is accumulating (20 years), or for longer periods after soils have reached their maximum carbon levels. In both cases, incentives will be less than the market value of carbon. Under contracts that only pay farmers for 20 years while carbon is accumulating, incentives would be equal to the discounted net present value transformed into yearly annuity payments. Due to discounting, farmers would receive only 38% of the market value of carbon (McCarl et al., 2001). After the 20 years, the farmer would be free to till and release the carbon. The market entity that promised to permanently abate the carbon must either find other means of reducing atmospheric carbon elsewhere, or continue to pay the farmer for not releasing the carbon. Under a longer-term contract, say 100 years, farmers would agree not to till their soils even after maximum soil carbon has been reached. In this case, farmers would receive 56% of market carbon value. By reducing the farmer incentives below the carbon market value, abatement quantities per dollar are decreasing, or put another way, abatement costs per unit increase. Policymakers should consider the additional costs necessary to reduce the risk of future release.

Leakage

Another challenge facing agricultural soil carbon sequestration policy is the issue of leakage. Leakage is the unintended increase in carbon emissions that occur when incentives are given to decrease carbon emissions. Leakage can occur through several different mechanisms, such as farmers using more inputs, idle or virgin land being cleared, plowed and planted, or crop production increasing in other countries.

This analysis observed leakage occurring in some regions as incentives caused farmers to emit more carbon from increased production input use. This analysis employed incentives based upon potential soil sequestration gains. Yet in some instances, when farmers changed from a low input crop, such as oats, to a high input crop, such as corn, emissions increased. Figure 14 shows the regions where the model estimated net emissions gains caused by the incentives. Table 17 shows that there was leakage through emissions increases in 374 counties totaling 108 thousand MtC, but in the vast majority of counties there were emission decreases as a result of incentives, totaling 1,267

Table 17: Leakage through production input increases as a result of incentives at $125 per MtC.

	Number of Counties	Emissions Changes at $125 per MtC
Sum of All Regions with Emissions Increases	374	108,015
Sum of All Regions with Emissions Decrease	2,265	(1,267,902)
National Net Emissions Change	3,110	(1,159,886)

( ) indicates negative values

thousand MtC. At the national scale, regional leakage is overcome by the 'free' reductions in emissions, and there is a net decrease in total emissions. Therefore emissions leakage may be an issue at the county level, but it is not an issue at the national level.

In counties where leakage is present, in most cases the increase in emissions is not enough to offset the increase in soil carbon and there is still a net gain in abatement. But because total abatement is lessened, the marginal cost of abatement has increased, and incentives are not abating as much as intended. In some cases (65 counties), the increase in emissions does overtake the increase in soil carbon and there is actually a net increase in atmospheric carbon (total of 42 thousand MtC). In designing a carbon program, it should be recognized that there may be perverse incentives at the regional level. Scaling the program's geographic area of accounting to larger regions will balance out regional leakage.

One proposed solution to this form of leakage is to pay the incentive on decreases in net flux, and not simply soil carbon sequestration potential. While this would surely stop this form of leakage, it would require estimation of the emissions, both direct and embodied in the cropping system forgone and the new one adopted. I have compiled and used emissions estimations on a regional level in this analysis, but using it on an individual farmer level would be an inappropriate use for three reasons: First, there is some variability in farm equipment and operations even within a small region. Second, it may hamper innovation by tying a fixed estimation of emissions to a particular crop and tillage mix. For example, a farmer of conventional-tillage cotton may be able to employ biological pest controls at a far lower input rate, yet the program is giving disincentives based on the older estimation of cotton emissions. Third, it has been argued that emissions associated with input use should not be accounted for at the user level because emissions from production management input are already accounted for in the industrial sector (Penman et al., 2003).

Leakage could also occur if the program gave incentives for management practices that reduced production and increased market prices. The higher prices would spur idle or virgin lands to be planted either domestically or abroad. In this analysis, no-tillage did not reduce production significantly, and prices increased slightly (Table 14). The price gains were not enough to bring more domestic cropland into production. Therefore this form of leakage was avoided.

Although outside the geographic scale of the model used in this analysis, price rises can affect plantings in other nations. The US is a major price setter for agricultural commodities (Ray et al., 2003). Farmers in Brazil, Australia or the Ukraine will respond to price rises in the US and plant more crops. This would lead to unintended increases in emissions and possible reductions in soil carbon as a result of US policy. In the case of incentives of tillage adoption tested in this analysis, the price rises are too small to significantly increase production abroad. But this form of leakage should be considered in potential expansion of incentives for planting perennial grasses for carbon sequestration or biofuel offsets on US cropland. In those cases, the potential for commodity price increases is large and may spur crop production upon new land both domestically and abroad (Searchinger et al., 2008).

Discussion of resolution and scale

This analysis is the first test of a model designed to yield geographically precise estimates of carbon sequestration, emissions and net flux. It is still valid to ask whether the increased complexity in geographic precision has really led to an actual gain in estimation accuracy. By comparing the high resolution results to actual field level trial data, we see that the errors are highly variable, with a mean error of all six trials of 24%. This indicates that the methodology developed here is not appropriate for estimating carbon changes at the field level. Although the methodology uses high resolution disaggregated data, it is still aggregated from individual sites and estimates are drawn from sample data.

But in comparing the field level trial data to the lower resolution versions of the model, significantly larger errors than the high resolution version were observed, with a median error across all locations greater than 48% for all three lower resolution versions. These errors are twice the magnitude of the high-resolution version. Given these differences, it can be concluded that the high-resolution methodology is an improvement over other lower resolution methodologies in estimating changes in soil carbon.

In investigating the use of the resolution versions at different scales of analysis, several conclusions became apparent. At the national scale, estimates from all resolutions are fairly similar. Yet, as the geographic scope of analysis became smaller, divergence in estimations increased. At the state scale, the national resolution version errors increased dramatically over the county resolution versions. At the county scale, the national resolution version estimates diverged even more. There was also a large divergence between the two county-level resolution models. This is due to further differences in resolution. The LANDSAT-county version only considers soils upon which crops are grown, whereas the NON LANDSAT-county version considers all soils within the county for use in estimating changes in soil carbon. Just as the analysis of field level data showed that it may not be appropriate to use the high-resolution model at the field scale, it may not be appropriate to use the national resolution model at any scale less than the national scale. Weighting data at one level of resolution and using that model to estimate at a scale lower than that level will carry error with it. The data weighted at the larger geographic unit are essentially carrying information on soils from outside the smaller unit of analysis. This follows expected results, as regional estimations are being based upon data from outside the region.

Given these results, the following conclusions regarding resolution and scale can be drawn:

1) With highly variable data, the geographic scale of analysis should be equal to or larger than the geographic unit of data resolution.
2) With highly variable data, if the geographic scale of analysis is smaller than the geographic unit of data resolution, large errors in estimation will occur.
3) Differences between high-and low-resolution estimates are relatively small at broader geographic scales of analysis.

The broader analysis presented here presented an ideal opportunity to study the effects of data resolution and scale of analysis. In particular, the estimation of initial soil carbon level allowed the study of a geophysical variable with high spatial variability to be analyzed. The conclusions above are for variables with high spatial variability. For variables with low spatial variability, exceptions to what was observed in this analysis can be imagined. For example, another variable in this analysis, crop production costs, are fairly stable. Crop production cost estimates at the multi-county level (Agricultural Statistic District) could conceivably be used in scale analyses smaller than their multi-county level and not result in large errors. This would refute conclusion (3). In this case, crop production cost data estimated at larger units of aggregation are adequately representative of smaller units within. Further studies could evaluate the point at which a variable estimated at a lower resolution (larger area) not represent what actually occurs at a smaller scale (smaller area) of analysis.

Value of this analysis to implementation

The increase in model resolution will aid in the implementation of a functioning carbon market by reducing the uncertainty between estimated abatement and actual abatement. Under the current CCX market, regional farmers 'pool' their carbon potential to sell as a block (CCX, 2008a). If purchasers of the block want to be assured that the potential carbon abatement meets actual abatement, the finer resolution of the methodology developed here would be more useful than lower resolution models. If farmers in a five-county area wanted to pool their potential abatement, it would be more appropriate to pool the county resolution estimations up to the larger region. Whereas the analysis of resolution and scale showed that large errors could exist in scaling down lower resolution data to the five-county area. Currently, the CCX uses very low resolution data. CCX assumes that large estimation errors in one region will be balanced by equally large errors in another region. Yet, if there is a disproportionate amount of total acreage entering the program from one region over another, then actual sequestration will be skewed from predicted sequestration and result in net estimation error. Because the market is currently voluntary, there is little oversight, but if the soil carbon market became a creditable offset under national or international legislation, oversight and accountability would increase.

Exact precision in estimation is impossible. Even with detailed meter-by-meter soils data, unpredictable climate variability would change the net primary productivity and, therefore, alter the actual abatement from the estimated abatement. A carbon program would have to acknowledge some level of error between actual and estimated carbon. The errors could be balanced over larger geographic areas or discounted from the estimated abatement. The CCX currently lessens uncertainty by requiring that 20% of contract potential abatement be placed in a reserve pool (CCX, 2008b). The high-resolution methodology developed here is a cost-efficient compromise between collecting detailed soils data on one hand, and using lower resolution estimations on the other. With the high-resolution methodology, uncertainty in estimated abatement quantities can be reduced at little additional cost, therefore increasing the efficiency of the program as a whole.

Alternative program design

If implementation problems surrounding leakage, additionality, permanence and 'measuring, monitoring, and verification' are seen as insurmountable, a market using conservation tillage may not be included as a valid offset mechanism in forthcoming legislation. If this occurs, potential carbon abatement of agriculture may still be realized through an alternative government program which offers 'green payments'. Instead of tying farmer payments to the amount of carbon per acre that a particular farmer can sequester, 'green payments' can target conversion of cropland to conservation tillage practices. Conservation tillage has many other non-market environmental benefits besides abating atmospheric carbon. Conservation tillage also decreases erosion, decreases stream and river sedimentation which results in cleaner water, increases soil fertility (insuring future productivity), increases wildlife habitat, and reduces chemical and fertilizer runoff. 'Green payments' can be made on a per acre basis for the many non-market environmental services that conversion of cropland to conservation tillage offers society. The Conservation Reserve Program (CRP) is a type of 'green payment' program that has worked to transfer 35 million acres of cropland into perennial grasses, resulting in many environmental benefits.

Like the CRP, conservation tillage 'green payments' could vary by region in order to reach target levels of cropland conversion. In regions where the known potential to sequester carbon is high, payments could be offered at a higher level than in regions with lower potential. There is not the urgency to measure actual quantities of soil carbon if payments are not specifically for carbon abatement. Problems of additionality and the moral hazard of paying only new adopters would be avoided because all farmers who agree to keep their land in conservation tillage would receive payments.

Some farmer groups fear that if a 'green payments' design were implemented, they might lose out on higher payments from the market (Kiely, 2008). But, if a market program truly accounted for permanence, additionality, leakage and uncertainty, payments might, in fact, be lower than those in a program that targets the multiple societal benefits of conservation tillage. ‘Green payments’ could target the 10 MMtC that can be abated at low marginal costs (below $50 per MtC in Figure 9). By using a CRP-type program, 10 MMtC may be abated annually at a cost near one billion dollars per year. Future simulations using the model developed in this research could be used to analyze the outcome of ‘green payment’ program design in more detail.

Results compared to earlier studies

Nationally, the carbon abatement results of my analysis are considerably less than previous estimates (McCarl and Schneider, 2001; Lewandrowski et.al., 2004). Although previous studies used much lower resolution data, my analysis of resolution and scale indicates that the differences at the national scale of analysis should be fairly minor. There are several other reasons for the lower estimate: There are differences in key parameters, such as 'base carbon' or 'rate of carbon growth'. The other analyses include other management options besides conservation tillage. There are differences in estimated regional budgets of the management options. Other analyses included additional carbon that this analysis excluded due to baseline projection of tillage trends. And finally, other analyses used long-term equilibrium solutions that solve once every 25 to 30 years, whereas this analysis solved annually and considered annual constraints on movement of acreage to new practices.

CHAPTER VI:

CONCLUSIONS

In this analysis, I have expanded the POLYSYS model to be capable of analyzing land changes and carbon fluxes at a high degree of resolution. The regional budgets were expanded to include over 3,000 unique crop management practices. The linear programming model now functions at the county level. Carbon emissions were tied to all crop management operations and soil carbon accumulation rates were linked to cropping practices. Using this model, I was able to track county-level net carbon flux from croplands as a result of carbon incentives. This is the first analysis, with national coverage, to account for leakage at the regional scale. My first hypothesis stated that, in most regions, the incentives will result in net reductions in carbon emissions to the atmosphere, but that in some regions, net emissions may actually increase. The model results indicate that this hypothesis is correct. In most regions, the incentives act as intended and net emissions decrease. Yet, in a few regions, the incentives act perversely, and cause emissions to increase.

My second hypothesis stated that high-resolution models are significantly more accurate than low-resolution models. My results indicate that this may not be true at all scales of analysis. At the national scale, lower resolution versions did very well at replicating the results of the high-resolution version. Yet at more fine-grained scales of analysis (e.g., state or county level), my results indicate that the higher resolution versions are significantly better at estimating net carbon flux.

This is the first net carbon flux analysis to study the interactions of data resolution and analytical scale with national coverage. My third hypothesis stated that if the scale of analysis is finer-grained than the spatial resolution of the model, then estimation errors will be great. My results indicate that this is true. If a low-resolution model (e.g., national), is used to estimate changes in net carbon flux at a more fine-grained geographic scale (e.g., county or state), then the errors will be large. At the national scale, the improvements might not be that significant over lower resolution results, but if regional estimation is a goal, the geographic resolution of data (e.g., county) must match or be finer than the spatial scale of the analysis (e.g., nation). Otherwise, estimation errors will be large.

This study found that nationally, a soil sequestration program through conservation tillage could abate an economic maximum of 18.9 MMtC per year. This maximum would be reached after 20 years and then begin to fall. Given that this is only 1% of current annual US fossil fuel emissions, conservation tillage will not play a major role in alleviating the problem of increasing GHG's in the atmosphere. Because there are no major technical hurtles to overcome in implementing conservation tillage, it could play a minor role in the short-to-medium term, giving time for other more effective solutions to emerge. If legislation is passed that allows for conservation tillage as an abatement option, the high-resolution methodology developed here can improve regional estimation over other low-resolution methods, and therefore reduce estimation uncertainty.

If the US does pass carbon reduction legislation to seriously reduce carbon emissions, this may act to further expand the already emerging soil carbon trading markets. The high-resolution model was used to simulate national implementation of a carbon market that is simple in design, and similar to the newly emerging regional carbon markets. Due to many complications and program costs discussed in the literature of soil carbon sequestration (Paustian et al., 1997, Pautsch, et al., 2001), implementation of a national carbon program may have to be done in a simple manner of paying 'all adopters' on carbon sequestration ability. Paying all adopters on sequestration ability is simple, but has one major drawback: a significant amount of land in conservation tillage would have been in conservation tillage regardless of incentives. The program would be paying these farmers for practices that are adding no additional abatement, and therefore increasing costs per MtC by a factor of 1.0 to 4.5. These costs need to be weighed against the extra costs, both monetarily and politically, of the alternative policy design, such as only paying new adopters and penalizing conversion of conservation tillage to conventional-tillage.

A national program of carbon abatement through incentives for conservation tillage faces other challenges, such as a limited duration of abatement, the potential for future releases of stored soil carbon, and the potential for perverse incentives to cause carbon leakage elsewhere. Policy makers should consider all costs before initiating a national program. Alternatively, a market for carbon sequestration could be forgone in favor of a government program similar to the successful CRP design. 'Green payments' could target soil sequestration quantities that can be accomplished at fairly low marginal costs while simultaneously rewarding the other environmental benefits of conservation tillage.

Future research directions

The same high-resolution methodology should be used to evaluate other GHG abatement policy choices which impact soil carbon levels. In December of 2007, the Energy Independence and Security Act of 2007 was signed into law. It mandates that 36 billion gallons of fuel be produced from alternative (primarily plant derived) sources. This legislation will promote the use of corn grain in the production of ethanol, which will increase prices and give farmers more incentive to grow corn. Additionally, the new legislation requires 16 billion gallons to be produced from cellulosic sources, such as switchgrass. Farmers will have an incentive to plant cropland to permanent grasses. These changes will affect both the regional sequestration of carbon in the soil and also the emissions from cropland production. The legislation may likely result in more production emissions as farmers move to more emissions-intensive crops like corn, yet soil carbon may increase as more perennial grasses are planted. The high-resolution model developed for this analysis could be used to evaluate the net result.

In some climate change mitigation legislation, there is the potential for biofuel offsets to be tied to the production of feedstocks for ethanol. Farmers could receive payments based on the net fossil carbon displaced by feedstocks grown upon their land for biofuel production. Incorporating bioenergy dedicated crops and their effects upon soil carbon levels into the framework developed here will also allow for the analysis of biofuels offsets.

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APPENDICES

Appendix A

Soil Sequestration Potential by County and Crop:
Estimated metric tons soil carbon gain per year of conversion of land from conventional-tillage to no-tillage.

Tennessee counties listed.
Dataset of all counties archived at
Agricultural Policy Analysis Center, University of Tennessee.

STATE	COUNTY	FIPS	Corn	Sorgh	Oats	Barley	Wheat	Soy	Cotton	Rice	Hay
TN	Crockett	47033	0.0716	0.0221	0.0636	0.0636	0.0636	0.0716	0.0221	0.0636	0.1273
TN	Cumberland	47035	0.0818	0.0253	0.0735	0.0735	0.0735	0.0818	0.0253	0.0735	0.1458
TN	Davidson	47037	0.0880	0.0272	0.0779	0.0779	0.0779	0.0880	0.0272	0.0779	0.1522
TN	Decatur	47039	0.0805	0.0249	0.0727	0.0727	0.0727	0.0805	0.0249	0.0727	0.1451
TN	De Kalb	47041	0.0847	0.0262	0.0756	0.0756	0.0756	0.0847	0.0262	0.0756	0.1492
TN	Dickson	47043	0.0894	0.0276	0.0803	0.0803	0.0803	0.0894	0.0276	0.0803	0.1590
TN	Dyer	47045	0.0780	0.0241	0.0783	0.0783	0.0783	0.0780	0.0241	0.0783	0.1306
TN	Fayette	47047	0.0723	0.0223	0.0646	0.0646	0.0646	0.0723	0.0223	0.0646	0.1274
TN	Fentress	47049	0.0786	0.0243	0.0715	0.0715	0.0715	0.0786	0.0243	0.0715	0.1434
TN	Franklin	47051	0.0908	0.0281	0.0814	0.0814	0.0814	0.0908	0.0281	0.0814	0.1612
TN	Gibson	47053	0.0716	0.0221	0.0603	0.0603	0.0603	0.0716	0.0221	0.0603	0.1272
TN	Giles	47055	0.0794	0.0245	0.0714	0.0714	0.0714	0.0794	0.0245	0.0714	0.1416
TN	Grainger	47057	0.0617	0.0191	0.0563	0.0563	0.0563	0.0617	0.0191	0.0563	0.1133
TN	Greene	47059	0.0690	0.0213	0.0617	0.0617	0.0617	0.0690	0.0213	0.0617	0.1217
TN	Grundy	47061	0.0864	0.0267	0.0758	0.0758	0.0758	0.0864	0.0267	0.0758	0.1467
TN	Hamblen	47063	0.0640	0.0198	0.0576	0.0576	0.0576	0.0640	0.0198	0.0576	0.1146
TN	Hamilton	47065	0.0647	0.0200	0.0586	0.0586	0.0586	0.0647	0.0200	0.0586	0.1172
TN	Hancock	47067	0.0670	0.0207	0.0593	0.0593	0.0593	0.0670	0.0207	0.0593	0.1159
TN	Hardeman	47069	0.0679	0.0210	0.0737	0.0737	0.0737	0.0679	0.0210	0.0737	0.1211
TN	Hardin	47071	0.0826	0.0255	0.0734	0.0734	0.0734	0.0826	0.0255	0.0734	0.1441
TN	Hawkins	47073	0.0664	0.0205	0.0604	0.0604	0.0604	0.0664	0.0205	0.0604	0.1213
TN	Haywood	47075	0.0719	0.0222	0.0644	0.0644	0.0644	0.0719	0.0222	0.0644	0.1274
TN	Henderson	47077	0.0702	0.0217	0.0605	0.0605	0.0605	0.0702	0.0217	0.0605	0.1262
TN	Henry	47079	0.0698	0.0216	0.0628	0.0628	0.0628	0.0698	0.0216	0.0628	0.1246
TN	Hickman	47081	0.0825	0.0255	0.0742	0.0742	0.0742	0.0825	0.0255	0.0742	0.1473
TN	Houston	47083	0.0914	0.0283	0.0822	0.0822	0.0822	0.0914	0.0283	0.0822	0.1632
TN	Humphreys	47085	0.0872	0.0270	0.0787	0.0787	0.0787	0.0872	0.0270	0.0787	0.1568
TN	Jackson	47087	0.0882	0.0273	0.0779	0.0779	0.0779	0.0882	0.0273	0.0779	0.1520
TN	Jefferson	47089	0.0693	0.0214	0.0624	0.0624	0.0624	0.0693	0.0214	0.0624	0.1239
TN	Johnson	47091	0.0871	0.0269	0.0754	0.0754	0.0754	0.0871	0.0269	0.0754	0.1437
TN	Knox	47093	0.0666	0.0206	0.0598	0.0598	0.0598	0.0666	0.0206	0.0598	0.1187
TN	Lake	47095	0.0913	0.0282	0.0876	0.0876	0.0876	0.0913	0.0282	0.0876	0.1738
TN	Lauderdale	47097	0.0775	0.0240	0.0755	0.0755	0.0755	0.0775	0.0240	0.0755	0.1316
TN	Lawrence	47099	0.0830	0.0256	0.0734	0.0734	0.0734	0.0830	0.0256	0.0734	0.1433
TN	Lewis	47101	0.0814	0.0252	0.0727	0.0727	0.0727	0.0814	0.0252	0.0727	0.1433
TN	Lincoln	47103	0.0835	0.0258	0.0749	0.0749	0.0749	0.0835	0.0258	0.0749	0.1483
TN	Loudon	47105	0.0681	0.0210	0.0604	0.0604	0.0604	0.0681	0.0210	0.0604	0.1185
TN	Mcminn	47107	0.0691	0.0214	0.0616	0.0616	0.0616	0.0691	0.0214	0.0616	0.1212
TN	Mcnairy	47109	0.0771	0.0238	0.0689	0.0689	0.0689	0.0771	0.0238	0.0689	0.1358
TN	Macon	47111	0.0840	0.0260	0.0753	0.0753	0.0753	0.0840	0.0260	0.0753	0.1488
TN	Madison	47113	0.0710	0.0220	0.0653	0.0653	0.0653	0.0710	0.0220	0.0653	0.1279
TN	Marion	47115	0.0820	0.0253	0.0745	0.0745	0.0745	0.0820	0.0253	0.0745	0.1495
TN	Marshall	47117	0.0779	0.0241	0.0711	0.0711	0.0711	0.0779	0.0241	0.0711	0.1432
TN	Maury	47119	0.0915	0.0283	0.0822	0.0822	0.0822	0.0915	0.0283	0.0822	0.1632
TN	Meigs	47121	0.0703	0.0217	0.0640	0.0640	0.0640	0.0703	0.0217	0.0640	0.1286
TN	Monroe	47123	0.0706	0.0218	0.0627	0.0627	0.0627	0.0706	0.0218	0.0627	0.1228
TN	Montgomery	47125	0.0931	0.0288	0.0835	0.0835	0.0835	0.0931	0.0288	0.0835	0.1655
TN	Moore	47127	0.0780	0.0241	0.0707	0.0707	0.0707	0.0780	0.0241	0.0707	0.1416
TN	Morgan	47129	0.0854	0.0264	0.0755	0.0755	0.0755	0.0854	0.0264	0.0755	0.1472
TN	Obion	47131	0.0745	0.0230	0.0768	0.0768	0.0768	0.0745	0.0230	0.0768	0.1317
TN	Overton	47133	0.0911	0.0282	0.0816	0.0816	0.0816	0.0911	0.0282	0.0816	0.1614
TN	Perry	47135	0.0883	0.0273	0.0795	0.0795	0.0795	0.0883	0.0273	0.0795	0.1580
TN	Pickett	47137	0.0907	0.0280	0.0814	0.0814	0.0814	0.0907	0.0280	0.0814	0.1613
TN	Polk	47139	0.0729	0.0225	0.0660	0.0660	0.0660	0.0729	0.0225	0.0660	0.1318
TN	Putnam	47141	0.0895	0.0277	0.0799	0.0799	0.0799	0.0895	0.0277	0.0799	0.1573
TN	Rhea	47143	0.0654	0.0202	0.0593	0.0593	0.0593	0.0654	0.0202	0.0593	0.1188
TN	Roane	47145	0.0692	0.0214	0.0618	0.0618	0.0618	0.0692	0.0214	0.0618	0.1221
TN	Robertson	47147	0.0918	0.0284	0.0823	0.0823	0.0823	0.0918	0.0284	0.0823	0.1630
TN	Rutherford	47149	0.0815	0.0252	0.0732	0.0732	0.0732	0.0815	0.0252	0.0732	0.1453
TN	Scott	47151	0.0796	0.0246	0.0717	0.0717	0.0717	0.0796	0.0246	0.0717	0.1426
TN	Sequatchie	47153	0.0910	0.0281	0.0798	0.0798	0.0798	0.0910	0.0281	0.0798	0.1544
TN	Sevier	47155	0.0712	0.0220	0.0642	0.0642	0.0642	0.0712	0.0220	0.0642	0.1277
TN	Shelby	47157	0.0763	0.0236	0.0793	0.0793	0.0793	0.0763	0.0236	0.0793	0.1311
TN	Smith	47159	0.0842	0.0260	0.0759	0.0759	0.0759	0.0842	0.0260	0.0759	0.1511
TN	Stewart	47161	0.0837	0.0259	0.0766	0.0766	0.0766	0.0837	0.0259	0.0766	0.1548

Appendix B

Tabular form of county level linear programming models.

			Net Present Value																
		Acres	CornCT NPV	SorghumCT NPV	OatsCT NPV	BarleyCT NPV	WheatCT NPV	SoybeansCT NPV	CottonCT NPV	RiceCT NPV	undefined NPV	undefined NPV	undefined NPV	HayCT NPV	CornRT NPV	SorghumR NPV	OatsRT NPV	BarleyRT NPV	WheatRT NPV
	Total	ACRES	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MAX	Corn	ACRES	1																
	Sorghum	ACRES		1															
OF	Oats	ACRES			1														
	Barley	ACRES				1													
CT	Wheat	ACRES					1												
	Soybeans	ACRES						1											
	Cotton	ACRES							1										
	Rice	ACRES								1									
	undefined	ACRES									1								
	undefined	ACRES										1							
	undefined	ACRES											1						
	Hay	ACRES												1					
MAX	Corn	ACRES													1				
	Sorghum	ACRES														1			
OF	Oats	ACRES															1		
	Barley	ACRES																1	
RT	Wheat	ACRES																	1
	Soybeans	ACRES																	
	Cotton	ACRES																	
	Rice	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	Hay	ACRES																	
MAX	Corn	ACRES																	
	Sorghum	ACRES																	
OF	Oats	ACRES																	
	Barley	ACRES																	
NT	Wheat	ACRES																	
	Soybeans	ACRES																	
	Cotton	ACRES																	
	Rice	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	Hay	ACRES																	
MAX	Corn	ACRES	1												1				
OF	Sorghum	ACRES		1												1			
ALL	Oats	ACRES			1												1		
TILLAGE	Barley	ACRES				1												1	
OF	Wheat	ACRES					1												1
CROP	Soybeans	ACRES						1											
	Cotton	ACRES							1										
	Rice	ACRES								1									
	undefined	ACRES									1								
	undefined	ACRES										1							
	undefined	ACRES											1						
	Hay	ACRES												1					
MIN	Corn	ACRES	1																
	Sorghum	ACRES		1															
OF	Oats	ACRES			1														
	Barley	ACRES				1													

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		SoybeansRT NPV	CottonRT NPV	RiceRT NPV	undefined NPV	undefined NPV	undefined NPV	HayRT NPV	CornNT NPV	SorghumN NPV	OatsNT NPV	BarleyNT NPV	WheatNT NPV	SoybeansNT NPV	CottonNT NPV	RiceNT NPV	undefined NPV	undefined NPV	undefined NPV	HayNT NPV
	Total	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MAX	Corn																			
	Sorghum																			
OF	Oats																			
	Barley																			
CT	Wheat																			
	Soybeans																			
	Cotton																			
	Rice																			
	undefined																			
	undefined																			
	undefined																			
	Hay																			
MAX	Corn																			
	Sorghum																			
OF	Oats																			
	Barley																			
RT	Wheat																			
	Soybeans	1																		
	Cotton		1																	
	Rice			1																
	undefined				1															
	undefined					1														
	undefined						1													
	Hay							1												
MAX	Corn								1											
	Sorghum									1										
OF	Oats										1									
	Barley											1								
NT	Wheat												1							
	Soybeans													1						
	Cotton														1					
	Rice															1				
	undefined																1			
	undefined																	1		
	undefined																		1	
	Hay																			1
MAX	Corn								1											
OF	Sorghum									1										
ALL	Oats										1									
TILLAGE	Barley											1								
OF	Wheat												1							
CROP	Soybeans	1												1						
	Cotton		1												1					
	Rice			1												1				
	undefined				1												1			
	undefined					1												1		
	undefined						1												1	
	Hay							1												1
MIN	Corn																			
	Sorghum																			
OF	Oats																			
	Barley																			

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Continued on page 138

Continued on page 135

Continued on page 138

			Net Present Value																		
		Acres	CornCT NPV	SorghumCT NPV	OatsCT NPV	BarleyCT NPV	WheatCT NPV	SoybeansCT NPV	CottonCT NPV	RiceCT NPV	undefined NPV	undefined NPV	undefined NPV	HayCT NPV	CornRT NPV	SorghumR NPV	OatsRT NPV	BarleyRT NPV	WheatRT NPV
CT	Wheat	ACRES					1												
	Soybeans	ACRES						1											
	Cotton	ACRES							1										
	Rice	ACRES								1									
	undefined	ACRES									1								
	undefined	ACRES										1							
	undefined	ACRES											1						
	Hay	ACRES												1					
MIN	Corn	ACRES													1				
	Sorghum	ACRES														1			
OF	Oats	ACRES															1		
	Barley	ACRES																1	
RT	Wheat	ACRES																	1
	Soybeans	ACRES																	
	Cotton	ACRES																	
	Rice	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	Hay	ACRES																	
MIN	Corn	ACRES																	
	Sorghum	ACRES																	
OF	Oats	ACRES																	
	Barley	ACRES																	
NT	Wheat	ACRES																	
	Soybeans	ACRES																	
	Cotton	ACRES																	
	Rice	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	undefined	ACRES																	
	Hay	ACRES																	
MIN	Corn	ACRES	1												1				
OF	Sorghum	ACRES		1												1			
ALL	Oats	ACRES			1												1		
TILLAGE	Barley	ACRES				1												1	
OF	Wheat	ACRES					1												1
CROP	Soybeans	ACRES						1											
	Cotton	ACRES							1										
	Rice	ACRES								1									
	undefined	ACRES									1								
	undefined	ACRES										1							
	undefined	ACRES											1						
	Hay	ACRES												1					

		SoybeansRT NPV	CottonRT NPV	RiceRT NPV	undefined NPV	undefined NPV	undefined NPV	HayRT NPV	CornNT NPV	SorghumNT NPV	OatsNT NPV	BarleyNT NPV	WheatNT NPV	SoybeansNT NPV	CottonNT NPV	RiceNT NPV	undefined NPV	undefined NPV	undefined NPV	HayNT NPV
CT	Wheat																			
	Soybeans																			
	Cotton																			
	Rice																			
	undefined																			
	undefined																			
	undefined																			
	Hay																			
MIN	Corn																			
	Sorghum																			
OF	Oats																			
	Barley																			
RT	Wheat																			
	Soybeans	1																		
	Cotton		1																	
	Rice			1																
	undefined				1															
	undefined					1														
	undefined						1													
	Hay							1												
MIN	Corn								1											
	Sorghum									1										
OF	Oats										1									
	Barley											1								
NT	Wheat												1							
	Soybeans													1						
	Cotton														1					
	Rice															1				
	undefined																1			
	undefined																	1		
	undefined																		1	
	Hay																			1
MIN	Corn								1											
OF	Sorghum									1										
ALL	Oats										1									
TILLAGE	Barley											1								
OF	Wheat												1							
CROP	Soybeans	1												1						
	Cotton		1												1					
	Rice			1												1				
	undefined				1												1			
	undefined					1												1		
	undefined						1												1	
	Hay							1												1

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VITA

Chad Matthew Hellwinckel was born in Hutchinson, Minnesota, and grew up in Olathe, Kansas. He attended St. Olaf College in Northfield, Minnesota and graduated with majors in Economics and Urban Studies in 1991. After college, he was fortunate enough to spend several years working and learning at the Land Institute in Salina, Kansas. There, he was introduced to the ideas of Wes Jackson, Wendell Berry, John Todd, Bill Mollison and others. These years shaped his moral base and set his internal compass toward working on the problems of agriculture and human livelihood. After completing a Masters Degree in Agricultural Economics from the University of Tennessee in 1996, Chad spent several years walking back roads, living in fire towers, and building trails in our national forests. He also served as a Peace Corps volunteer in Panama. In 2001 he returned to Knoxville to begin working, once again, for the Agricultural Policy Analysis Center. In August of 2008, Chad completed his academic training by fulfilling the requirements for the Ph.D. in Geography from the University of Tennessee, Knoxville. He is currently forming a Permaculture Guild in Knoxville, whose purpose is to share and implement intelligent urban agricultural and dwelling design strategies that produce plentiful food while reducing material needs and wastes.