# Farmer Adoption and Payment Design Under Risk: Variability in Soil Carbon Sequestration Across Conservation Practices

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**Abstract**

This study develops a dynamic optimization framework to examine how variability in soil organic carbon (SOC) sequestration shapes farmers' adoption of conservation tillage practices and the carbon payments required to offset adoption risk. Using Environmental Policy Integrated Climate (EPIC) simulations for 70 fields in the U.S. Midwest, I quantify yield impacts, SOC accumulation, and their variabilities across reduced-till and no-till practices. Results show that while no-till delivers higher average SOC gains and lower yield losses, its greater sequestration variability raises adoption risk, leading farmers to prefer reduced tillage at moderate SOC levels despite its lower long-term potential. Near saturation, farmers switch back to no-till to maximize SOC gains. Increasing SOC variability systematically raises minimum payment thresholds, which range from \$10 to \$35 per ton per year depending on soil type. The findings highlight how risk considerations alter conservation adoption paths and provide targeted payment benchmarks for carbon market and policy design.

Keywords: soil carbon sequestration variability, agricultural risk management, farmer adoption decisions, carbon market incentives

# 1 Introduction

Global temperatures have risen approximately 1.1$^o$C above pre-industrial levels and are approaching the critical 1.5$^o$C threshold, beyond which irreversible climate impacts become increasingly likely.(Masson-Delmotte et al., 2021) Policymakers have responded by increasing investment in carbon capture and sequestration (CCS), yet current U.S. infrastructure captures only about 0.4% of annual carbon dioxide emissions, and even with planned expansions, capacity may reach only 3%. CCS costs vary considerably by industry. Capturing carbon dioxide in sectors such as natural gas processing, ethanol production, and ammonia manufacturing costs approximately $15 to $35 per ton, while heavier industries like cement, steel, and electricity generation incur costs between $50 and $120 per ton. Direct air capture technologies remain even more expensive, ranging from $135 to potentially exceeding $1,000 per ton.(Congressional Budget Office, 2023)

Agricultural soils emerge as an economically attractive and scalable alternative carbon sink, given their extensive coverage and responsiveness to specific conservation practices. Evidence suggests that land-based sequestration strategies could offset approximately 10 to 15 gigatons of carbon dioxide equivalents annually by 2050.(Griscom et al., 2017; Roe et al., 2021) Conservation practices such as reduced or no tillage, cover cropping, diversified rotations, and organic amendments enhance soil organic carbon (SOC) levels while also improving soil health and agricultural productivity.(Singh et al., 2023; Eagle et al., 2010) However, the agricultural carbon market remains nascent, in part because of uncertainty surrounding achievable SOC levels, incomplete knowledge of how management affects carbon dynamics, and the absence of well-designed payment mechanisms that account for production and environmental risk.(Capon et al., 2013; Buck and Palumbo-Compton, 2022; Pendell et al., 2006; Yao and Kong, 2018; Antle and McCarl, 2002) Another concern is the impermanence of land-based carbon sequestration, resulting in discounted carbon prices to account for this risk.Kim et al. (2008)

The Midwest United States is particularly well-suited for large-scale adoption of agricultural carbon sequestration policies. The region contributes over $152 billion annually to national agricultural production, representing more than 40% of total U.S. crop and livestock output.(AgAmerica, 2023) With a cultivated area exceeding 125 million acres, the Midwest has significant potential to achieve negative emissions through soil carbon sequestration.(Lal, 2004; Christopher et al., 2009) This potential creates opportunities for farmers to earn supplemental income through carbon sequestration services and for policymakers to advance national emissions reduction targets. Realizing these opportunities requires rigorous analysis that quantifies sequestration potential, farmer incentives, and program costs, while explicitly incorporating regional heterogeneity in soils, climate variability, and the joint management of yield and sequestration risk. These trade-offs are especially important when variability in sequestration outcomes influences farmer adoption decisions and the payments required to make conservation practices economically viable. Evidence from Karlan et al. (2014) illustrates that when risk-reducing instruments such as rainfall index insurance are paired with liquidity enhancements like cash grants, producers significantly increase investment in higher-return activities. This underscores how the combination of risk mitigation and liquidity can shift production portfolios, a dynamic directly relevant to understanding conservation under sequestration variability.

The primary objective of this research is to examine how increasing variability in soil carbon sequestration influences optimal farmer decisions between conservation and conventional practices, and to determine how this variability affects the minimum payment required for conservation adoption. By treating sequestration variability as a distinct form of production risk, the analysis aligns with the broader agricultural risk management literature. I develop a dynamic optimization model through which the impact of carbon sequestration variability in shaping the adoption decision is determined. In counterfactual simulations, I systematically increase SOC sequestration variability and evaluate its effect on both adoption choices and the payment thresholds that make conservation practices economically viable.

This study contributes to the literature in three substantive ways. First, it measures the risk associated with conservation adoption by explicitly distinguishing between yield variability and carbon sequestration variability, incorporating the latter into the optimization model. This distinction provides new insight into how specific sources of variability influence economic incentives and decision-making under uncertainty, extending earlier work that reported average sequestration costs without differentiated risk treatment (e.g., Antle et al. (2003); Murray et al. (2007); Feng et al. (2002); Raj Kunwar et al. (2025)). While previous works have explored farmers' behavioral response towards adopting risky strategies, this study estimates optimal response of a risk-neutral farmer to different levels of risk in SOC sequestration.(Guan et al., 2021; Block et al., 2024)

Second, this research advances existing work by combining empirical observations from long-term agricultural experiments (Blevins et al., 1983; Ismail et al., 1994; Blevins et al., 1977) with detailed simulations from the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1984). The EPIC model captures the interactions among soil properties, climatic factors, management practices, and yield outcomes, enabling precise quantification of SOC dynamics, and effectively accounting for the spatial and temporal variability critical to realistic policy design.

Third, my analysis clearly identifies economic thresholds necessary to incentivize farmer adoption. Optimal payment levels identified range from \$10 to \$35 per ton of carbon sequestered. The payments varying depending on the soil type, impact on crop yield, and initial SOC stocks. Moreover, this study reveals upper payment limits beyond which additional payments produce negligible increase in carbon sequestration. These findings offer policymakers with practical and targeted guidance for designing economically efficient carbon sequestration programs.

My model incorporates the nonlinear nature of carbon sequestration (and release) dynamics, emphasizing rapid accumulation during the initial years of conservation practice adoption followed by gradual saturation.(West and Six, 2007; Paustian et al., 2016; Stewart et al., 2007) The approach takes into account sequestration reversibility and recognizes that carbon release rates often surpass sequestration rates, factors previously underexplored in economic modeling literature.

Grounding the analysis in a framework that connects variability in ecosystem service outcomes to farmer adoption behavior, and positioning sequestration variability as a risk-management challenge, this research provides operational benchmarks for conservation payments and quantifies risk trade-offs across practices, enabling application in agricultural policy. By applying this dynamic optimization model to approximately 2.57 million acres of farmland in five representative Midwestern watersheds (Lower Maumee, Macoupin, Maple, Sugar, and Upper Fox), I estimate a carbon sequestration potential of approximately 9 million tons achievable by transitioning from conventional tillage to no-till practices. My simulations document substantial spatial heterogeneity in resulting yield reductions, ranging from only 1.3% on sandy soils (hydrology group A) to over 8% on silt loam soils (hydrology group B). These soil types also demonstrate significant carbon sequestration heterogeneity. The modeling results clearly demonstrate the necessity of targeted, differentiated payment schemes to cost-effectively incentivize widespread adoption of no-till practice. The simulation results reveal that when the SOC sequestration variability of the no-till practice becomes large, farmers switch to the reduced till practice at moderate SOC levels, accepting lower average sequestration gains but also lower risk. This shift reflects a form of production risk management, as farmers prioritize a steadier income stream from SOC-related payments despite lower yields. When the SOC levels of the field reach near saturation, farmers switch back to no till to maximize their fields' SOC.

In section 2, I review the existing literature on the impacts of various land management practices on SOC sequestration, emphasizing prior empirical and theoretical findings. Section 3 describes my theoretical dynamic economic model. Section 4 details the data sources, parameters, and assumptions used in my economic modeling and EPIC simulations. Section 5 presents results and policy simulation outcomes. Finally, Section 6 addresses the policy implications of this research, offering recommendations to policymakers aiming to design effective, targeted, and sustainable carbon sequestration payment programs.

## 2 Background

Given the variability in sequestration outcomes, spatially differentiated payment structures have been proposed to address differences in sequestration potential and farmer adoption costs across diverse agricultural contexts.(Antle et al., 2003; Baylis et al., 2022) Uniform per-hectare subsidies inadequately capture spatial heterogeneity, risking inefficient resource allocation and unintended incentives for farmers who would adopt practices without additional payments.(Horowitz and Just, 2013) Additionally, narrowly targeted payments may unintentionally shift emissions elsewhere, undermining broader climate objectives.(Kim et al., 2014) Recent empirical work demonstrates that farmer decisions are influenced not only by production and cost conditions but also by the interaction of reactive risk preferences and proactive social preferences. Fitzsimmons et al. (2025) show that these dimensions materially affect willingness-to-accept and policy responsiveness, underscoring the need to integrate risk management strategies and social preferences into conservation adoption models.

Hertel (2018); Engel and Muller (2016) argue that well-structured incentives balance environmental objectives with agricultural productivity. Designing incentives effectively requires understanding the factors influencing farmers' adoption decisions, including short-term costs (seed purchase, labor, termination), contractual flexibility, yield risks, and payment levels.(Gramig, 2012; Gramig and Widmar, 2018; Campbell et al., 2021; Bergtold et al., 2019; Blanco, 2023). Even if the sources of yield and carbon sequestration risks have been identified, quantifying the level of risk as well as the risk aversion coefficient of the agents is a challenging task.(McCarl and Bessler, 1989) Recognizing the limitations in government-run incentives, voluntary carbon markets offer complementary mechanisms to enhance SOC sequestration. However, these markets face distinct operational challenges in accurately measuring, verifying, and maintaining the permanence of stored carbon, and mitigating risks due to SOC variability.(Thamo et al., 2020; Wongpiyabovorn et al., 2023; Plastina, 2021)

Beyond the structural and cost factors that influence adoption, policy effectiveness is also shaped by how producers perceive and respond to risk. Balancing productivity gains with environmental objectives while ensuring payment schemes align with broader agricultural and economic goals requires recognizing that wealth effects and uncertainty can shift adoption outcomes away from those predicted under risk neutrality.(Hertel, 2018; Engel and Muller, 2016; Leathers and Quiggin, 1991) However, Just and Pope (2003) caution against attributing such outcomes solely to risk aversion, noting that technical constraints, imperfect capital markets, adjustment costs, or serial correlation in returns can produce similar responses under risk neutrality. Complementary evidence from Schoengold et al. (2015) demonstrates that ad hoc disaster and crop insurance programs can alter uptake of risk-reducing practices such as conservation tillage, revealing how risk management interventions can interact with production decisions in ways that influence the environmental effectiveness of agricultural policies. Misidentifying these drivers risks designing incentives that fail to address the actual sources of variability in farmer responses. Within this context, agricultural and environmental policy instruments interact at both intensive and extensive margins, producing different environmental outcomes depending on land quality, spatial heterogeneity, and input–production relationships.(Just and Antle, 2017) To account for uncertainty in carbon sequestration, purchasers may discount the reported quantity of sequestered carbon to mitigate potential liabilities from shortfalls.(Kim and McCarl, 2009) Due to this discounting and the associated transactional costs, there is a price gap between the buyer's and the producer's carbon price.(Liu et al., 2025) Together, these perspectives provide a conceptual foundation for carbon payment schemes that also address environmental risk.

To inform incentive design, integrated assessment models clarify interactions among agricultural practices, carbon sequestration, and climate feedbacks. For instance, Antle et al. (2001) show that economically incentivized conservation agriculture effectively mitigates climate impacts, an insight extended by Thomson et al. (2008) to global terrestrial ecosystems. Nevertheless, critical knowledge gaps remain. First, prior studies inadequately quantify how temporal SOC dynamics shape optimal incentive structures. Second, the integration of detailed, field-level biophysical modeling into economic analysis remains limited, constraining policymakers' ability to assess how spatial differentiation enhances cost-effectiveness. Third, while previous research recognizes spatial variability and additionality, it does not fully examine how increasing variability in carbon sequestration outcomes affects optimal farmer decisions or the minimum payments required for adoption of conservation practices over conventional practices.

This research addresses these gaps by comparing process-based EPIC simulations with empirical data from long-term agricultural experiments. I quantify the economic effects of nonlinear SOC dynamics, including rapid accumulation, saturation, and reversibility, and evaluate how increasing sequestration variability influences adoption decisions and payment thresholds. This approach produces field-specific economic thresholds that balance farmer incentives, yield changes, and sequestration permanence, providing actionable guidance for developing cost-effective and sustainable carbon sequestration programs.

# 3 Theoretical Model

Developing a theoretical model of carbon sequestration requires quantifying the effects of the complex geophysical processes governing soil carbon absorption rates. I develop a model that captures three key characteristics of Soil Organic Carbon (SOC) dynamics. First, each unit of land has a maximum absorption potential, denoted as $C^*$, associated with a given practice. This threshold is influenced by numerous factors, including soil type, climate conditions, and soil nutrients.(Wiesmeier et al., 2019)

Second, the model incorporates the reversibility of soil carbon sequestration.(Dynarski et al., 2020) This implies that land with high SOC will release the stored carbon back into the

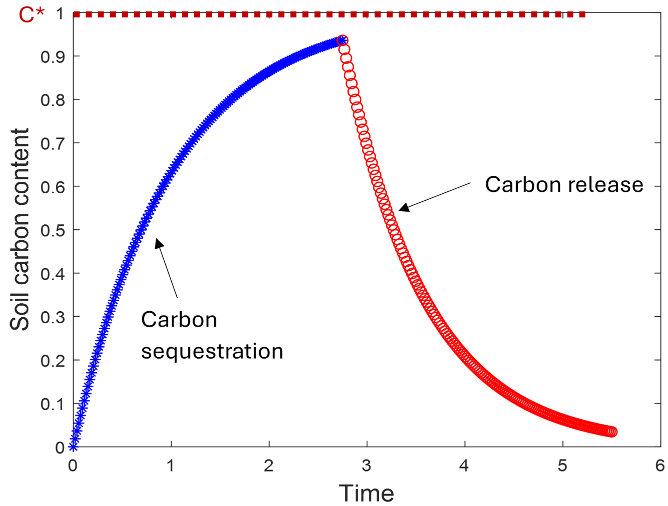


Figure 1: Dynamics of carbon sequestration and release processes.
$C^*$ represents maximum absorptive capacity of the soil. The rate of SOC accumulation is rapid when the soil is depleted of organic carbon but slows as it approaches the saturation limit. Conversely, the rate of carbon release is rapid when the SOC levels are high and decreases as the soil becomes depleted.

atmosphere if a conventional practice is followed. This impermanence of SOC casts doubt on its reliability as a long-term carbon reservoir. Generally, when a conservation practice is implemented on soils depleted of organic carbon, the rate of sequestration is initially high. The sequestration rate gradually decreases as the soil approaches its absorptive limit. Conversely, under a conventional practice, carbon is released at a rapid rate when SOC levels are high, but this rate decreases as the soil becomes depleted. These dynamics are represented by exponential functions (Ragot and Schubert, 2008). Following Ragot and Schubert (2008), the sequestration process is modeled as,

$$C(t) = C^* - (C^* - C_0)e^{(-st)} \tag{1}$$

where $C^*$ is the maximum amount of carbon that can be sequestered for a given practice; $C_0$ is the initial amount of soil carbon when the practice is adopted (t = 0); and $s$ is the parameter defining the rate of sequestration. From equation 1, the rate of carbon sequestration can be expressed as:

$$\frac{dC(t)}{dt} = (C^* - C_0)se^{(-st)} \tag{2}$$

The observation that soil carbon accumulation does not follow a linear trend when a conservation practice is implemented has been noted in prior studies (Georgiou et al. (2022); Gulde et al. (2008); Stewart et al. (2007)). Figure 1 illustrates carbon sequestration over time (blue line). Another key aspect is the release of stored carbon back to the atmosphere when a farmer adopts a conventional practice. The release process, depicted in Figure 1 (red line) is similarly modeled as an exponential function:

$$C(t) = C_o + (C_n - C_o)e^{-s't} \tag{3}$$

where $C_n$ is the initial amount of carbon in the soil when a conventional practice is adopted ($t = 0$). $s'$ is the parameter defining the rate of carbon release. $C_o$ denotes the minimum soil carbon content attained after prolonged conventional farming practices. From equation 3, the rate of carbon release is expressed as:

$$\frac{dC(t)}{dt} = -s'(C_n - C_o)e^{-s't} \tag{4}$$

The third key characteristic is that the rate of carbon release is faster than the rate of sequestration, meaning, $s' > s$. This relationship indicates that processes sequestering atmospheric carbon into soil inherently occur more slowly than processes releasing carbon back into the atmosphere (Ragot and Schubert, 2008).

## 3.1 Carbon Sequestration Process: An Infinite Horizon Model

I model a farmer's decision-making process using an infinite horizon framework to capture the long-term dynamics of carbon sequestration and the decision of implementing agricultural practices. In this model, farmers are paid annually in proportion to the stock of SOC they maintain. Carbon sequestration is a gradual process, with benefits that accumulate over extended periods, often spanning decades (Feng et al., 2002). Since soil carbon storage can persist indefinitely if practices that release carbon back to the environment are not employed (Dynarski et al., 2020), an infinite time horizon is appropriate for this modeling.

Farmers adopting sustainable land management practices, such as no-till farming or cover cropping, seek to optimize both immediate returns and long-term soil productivity and health. The environmental and financial benefits, including improved yields and potential carbon credits, extend far beyond the short term. In the infinite horizon model, farmers make decisions in each period to optimize their lifetime utility, with discounted future benefits and costs.(Stokey and Lucas Jr, 1989).

Crop yield at time $t$ is modeled as: $y(C_t, \theta_t, N_t, H)$, where $C_t$ represents the soil carbon content at time $t$; $\theta_t$ is the indicator representing the bundle of conservation or conventional practices adopted at time $t$; $N_t$ denotes the nutrient content of the soil at time $t$; and $H$ reflects soil type, which is an exogenous variable. While the expected soil carbon content varies depending on the implemented practices, the carbon accumulation process exhibits variability driven by known exogenous factors, such as temperature, precipitation, and soil type (Campo and Merino, 2016; Lessmann et al., 2022). At each time interval (year), the farmer chooses an optimal practice, represented by $\theta_t$, considering the long-term implications for future SOC levels and profits. Soil nutrient content influences yield and impacts carbon levels by affecting microbial activity. Nutrient content of the soil can be controlled via application of fertilizers or manure.

Carbon absorptive capacity of a unit of land also depends on a variety of soil and hydrologic characteristics that determine the runoff, percolation, and retention rates of water. Runoff rate refers to the amount of water flowing over the soil surface, whereas infiltration rate indicates how much water enters the soil. Land can be classified into four hydrology groups based on soil porosity and root growth (which affect the water dynamics) (Auerswald and Gu, 2021): A (Sandy) exhibits low runoff and high infiltration rates; B (Silt loam or loam) displays moderate infiltration rates; C (Clay loam) has low infiltration rates; and D (Clay) demonstrates highest runoff and lowest filtration rate. For instance, clay and silt soils belong to different hydrology groups. Clay soil generally has greater potential to store carbon due to its significantly larger surface area from its fine particles, allowing more organic matter to bind to its surface and be retained effectively. Consequently, clay soil is more efficient at carbon sequestration than silt soil.

Carbon sequestration and release rates are functions of practice, nutrient content and soil type, denoted as, $s(\theta_t, N_t, H)$ and $s'(\theta_t, N_t, H)$ respectively. The maximum carbon sequestration capacity associated with a given practice is $C^*(\theta_t, N_t, H)$ and the cost of implementing a practice is $cost(\theta_t, \hat{N}_t)$ per year. $\hat{N}_t$ is the amount of nutrients added at time interval $t$. This model captures the dynamic interaction between carbon sequestration, agricultural practices, soil properties, and the costs associated with different practices, providing a comprehensive framework for evaluating both environmental and economic outcomes over time. The carbon transition equation is given by:

$$C_{t+\Delta t} = (\mu_c^{seq}(t, \Delta t) + \sigma_c^{seq} N(0,1))\theta_t + (\mu_c^{rel}(t, \Delta t) + \sigma_c^{rel} N(0,1))(1 - \theta_t) \tag{5}$$

with $C_{t+\Delta t} = min\{C_{t+\Delta t}, C^*\}$ and $C_{t+\Delta t} = max\{C_{t+\Delta t}, 0\}$.

where, $\mu_c^{seq} = C^* - (C^* - C_t)e^{-s\Delta t}$ (mean carbon sequestered from Equation 1) and $\mu_c^{rel} = C_t e^{-s'\Delta t}$ (mean carbon released from Equation 3). Stochasticity in carbon content is modeled by a normal distribution with a standard deviation of $\sigma_c^{seq}$ and $\sigma_c^{rel}$ for sequestration and release processes, respectively. This choice aligns with the Central Limit Theorem, which states that a variable influenced by several factors tends toward a normal distribution.

When considering multiple bundles of conventional and conservation practices, the carbon transition equation becomes:

$$C_{t+\Delta t} = \sum_{i=1}^{\nu_1} C_{seq,i}(t, \Delta t)\theta_{t,i} + \sum_{j=1}^{\nu_2} C_{rel,j}(t, \Delta t)\theta_{t,j} \tag{6}$$

where

$$C_{seq,i}(t,\Delta t) = \mu^{seq}_{c,i}(t,\Delta t) + \sigma^{seq}_{c,i} N(0,1) \tag{7}$$

$$C_{rel,j}(t,\Delta t) = \mu^{rel}_{c,j}(t,\Delta t) + \sigma^{rel}_{c,j} N(0,1) \tag{8}$$

with $C_{t+\Delta t} = min\{C_{t+\Delta t}, C^*\}$ and $C_{t+\Delta t} = max\{C_{t+\Delta t}, 0\}$, and where the subscripts $i$ and $j$ denote conservation and conventional practices, respectively. If the conservation practices are indexed $i = 1,\ 2,\ ..\ \nu_1$ and the conventional practices are indexed $j = 1,\ 2,\ ..\ \nu_2$ then the following constraint holds:

$$\sum_{i=1}^{\nu_1} \theta_{t,i} + \sum_{j=1}^{\nu_2} \theta_{t,j} = 1 \tag{9}$$

and

$$\theta_{t,i/j} \in 0, 1 \,\forall\, i, j \tag{10}$$

Equation 9 implies that only one bundle of practices is employed during each time-period. The following equation represents the nutrient balance equation:

$$N_{t+\Delta t} = N_t \times (1 - \gamma(H)(Prec + irr)) - \alpha y_t + \hat{N}_{t+\Delta t} \tag{11}$$

In equation 11, $Prec$ and $irr$ represent precipitation (in millimeters of rainfall) and irrigation amounts, respectively. The coefficient of nutrient runoff, $\gamma(H)$ depends on soil type $H$. $\alpha\gamma_t$ is the amount of nutrients used by the crops, and $y_t$ is the crop yield. It is important to note that farmers often maintain soil nutrients at roughly constant levels, resulting in $N_{t+\Delta t} = N_t$. In such cases, the nutrient balance equation can be excluded from the model. A farmer's expected profit in year $t$ is given by:

$$profit(C_t, \theta_t, \hat{N}_t) = (C_t - C_o) \times m + P \times y_t - cost(\theta_t) - P_f \times \hat{N}_t \tag{12}$$

Where $C_t$ is the SOC stock at the end of period $t$. $m$ is the compensation per unit of carbon stock. $P$ is the crop price, and $P_f$ is the fertilizer price. I consider the inflation adjusted $P$, $P_f$, and *cost*($\theta_t$) to be constant over time. The farmer's profit depends on the compensation $m$. In other words, farmers receive compensation for the total value of the services they provide through carbon sequestration. Additionally, profit includes the revenue earned from the crop yield, from which the variable costs associated with implementing a specific practice and using fertilizers are deducted.

A subtle but important point merits attention here. One can replace the SOC amount, *C(t)* in the profit equation 12 with $C(t) - C_o$. This substitution reduces the farmer's annual profit magnitude but does not affect decision-making, as farmers base their choices on trade-offs between SOC sequestration and crop yield. With a fixed $m$, the term $C_o \times m$ remains constant and thus drops out during optimization.

The infinite horizon optimization problem is:

$$max_{\theta_t, \hat{N}_t} \sum_t \beta^t \, \mathbb{E}(profit_t) \tag{13}$$

This optimization problem involves the following: **Decision Variables**: (a) The discrete bundles of practices $\theta$. I assume discrete conservation practice bundles because there are a finite number of bundles for the farmer to choose from. An example of a bundle would be (no-till, cover crops, leaving no residue upon harvesting). In principle, the bundles can be a continuous function, for instance, tillage depth, or fertilizer amount, etc., but practically farmers would seldom adjust tillage depth or fertilizer amount in small increments. Researchers are currently studying innovations enabling micro-dosing of fertilizers and other inputs, but I exclude these practices from the present work. The amount of fertilizer to be added, $\hat{N}_t$, will also be treated as a discrete variable, classified as low, medium, or high. While this theoretical classification enhances model flexibility, I do not explicitly incorporate time-dependent fertilizer amounts in the numerical analyses due to lack of experimental studies where fertilizer amounts were varied systematically over time along with measurements of change in the nutrient content of the soil. I focus on comparing the effect of different tillage practices at standard fertilizer application rates. **State Variables**: (a) The carbon content, $C_t$ and (b) the nutrient content of the soil $N_t$ are the state variables. The model incorporates several additional assumptions. Farmers receive compensation in each period proportional to their carbon stock during that period. The model assumes complete information, implying farmers possess full knowledge of their current carbon stock and understand how different practices influence its dynamics. Farmers also recognize the variability linked to carbon accumulation and release caused by environmental conditions, although they lack precise knowledge of future weather conditions. Lastly, the model assumes risk neutrality, with farmers maximizing lifetime profits.

### 3.1.1 Solving the Infinite Horizon Model

The problem considers a farmer deciding on an optimal sequence of conventional or conservation practices and nutrient applications over time, given constant payment levels, crop prices, soil carbon sequestration, and nutrient evolution. In mathematical terms, $a_t =$ farmer decision of $(\theta, \hat{N})$ at time $t$. At any time $t$, the state variables are $S_t$. Based on the farmer's decision of $(\theta, \hat{N}_t)$, the state variables evolve to $S_{t+1}$. The transition of the state variables from $S_t$ to $S_{t+1}$ is history-independent, implying that the time-evolution of a field can be thought of as a Markov decision process (Sargent and Ljungqvist, 2000; Atashbar and Shi, 2022), that is, a Markov process wherein the transition between the states is governed by a decision taken in each state. It should be noted that a farmer's decision of $(\theta, \hat{N})$ is not directed towards optimizing the current state, but the entire lifetime profits.

Because of the Markovian property, the infinite horizon maximization problem can be converted into a recursive Bellman equation. The optimal value of the infinite horizon problem is called value function, *V()*. In the recursive form, *V()* can be constructed as the optimum value of profit in the first period plus the discounted *V()* for the remaining time periods (as shown in equation 14). An intuitive way to understand Bellman equation is to recognize that at any time $t$, there are infinite number of time-periods in the future, and so will be the case at time *t+1*.

The state variables are defined as: (a) carbon content, $C_t$, where $C_t \in [C_0, C^*]$, and (b) nutrient content of the soil, $N_t$, where $N_t \in [0, N_{max}]$. The state of the soil is expressed as $S_t = (C_t, N_t)$, which can be approximated as a finite number of discrete states. Thus, the farmer makes decisions based on the carbon and nutrient content of the soil. Both carbon and nutrient content are bounded. This characterization allows for a finite number of states.

An essential element of a Markov decision process is the policy. A policy specifies the action, $a$ that an agent will undertake based on the current state. For a deterministic policy, the probability of taking a specific action in the current state is either 0 or 1.

**Policy**: $\pi(a|S) = \mathbb{P}[a|S_t = s]$

**Deterministic policy**: $\mathbb{P}[a|S_t = S] \in \{0, 1\}$

Policies are stationary, meaning that they are time independent. The farmer's decisions, therefore, are not influenced by time but are solely determined by the current state. I solve the Bellman equation numerically by value function iteration. This approach allows me to compute the value function, which represents the optimal value of the objective function given the current state. In this context, the value function captures the farmer's maximum profit from optimal decisions in each state. A useful theorem states that for any Markov decision process, there exists an optimal deterministic policy that outperforms all other policies. This implies that the optimal policy can be identified as deterministic mapping from states to actions.

To find the optimum deterministic policy, I formulate and solve the Bellman equation below:

$$V_\pi(S) = \sum_a \pi(a|S)(\mathbb{E}(Profit_S{}^a) + \beta \sum_{S'} P_{SS'}{}^a V_\pi(S')) \tag{14}$$

where:

- $V_\pi(s)$ denotes the value function for policy $\pi$ given the current state $S$.

- $Profit_S{}^a$ is the expected profit when the farmer chooses action $a$, given state $S$.

- $P_{SS'}{}^a$ is the transition probability from state $S$ to $S$' when action $a$ is taken.

The action, denoted as $a$ encompasses implementing either conventional or conservation practices or adding nutrients to the soil. The current state $S$ is defined by the carbon and nutrient content in the soil. To account for variability in carbon accumulation due to changing environmental conditions, I utilize the transition probability $P_{SS'}{}^a$, which is the probability of transitioning from state $S$ to state $S$'. In the recursive framework, the value function is decomposed into the expected immediate reward and the discounted value of the next state (Sargent and Ljungqvist (2000)). To solve the Bellman equation, I employ value function iteration. Starting with an initial guess, $V_\pi(S') = 0$, the value function is iteratively updated until convergence. The optimal policy is determined by the action $a$ that maximizes the value function.

$$V_\pi(S) = argmax_a(\mathbb{E}(Profit_S{}^a) + \beta \sum_{S'} P_{SS'}{}^a V_\pi(S')) \tag{15}$$

Assuming that the stochastic variation in the state space variables *(C, N)* vary normally around their expected values, the value function is then given by:

$$V_\pi(S) = \textstyle\sum_a \pi(a|S)\left(\mathbb{E}(Profit_S{}^a) + \beta\left[\int_{-\infty}^{\infty} \frac{e^{-(C'-\mathbb{E}(C'))^2/(2\sigma_c^2(a))}}{\sqrt{2\pi}\sigma_c(a)} \int_{-\infty}^{\infty} \frac{e^{-(N'-\mathbb{E}(N'))^2/(2\sigma_N^2)}}{\sqrt{2\pi}\sigma_N} V_\pi(C', N')dC'dN'\right]\right) \tag{16}$$

If a farmer maintains a constant nutrient content of the soil and the stochastic variation exists only in the carbon content, the equation 16 simplifies to:

$$V_\pi(S) = \sum_a \pi(a|S)\left(\mathbb{E}(Profit_S{}^a) + \beta\left[\int_{-\infty}^{\infty} \frac{e^{-(C'-\mathbb{E}(C'))^2/(2\sigma_c^2(a))}}{\sqrt{2\pi}\sigma_c(a)} V_\pi(C')dC'\right]\right) \tag{17}$$

Since carbon content of the soil, $C \in (C_0, C^a_{max})$, the integral in the equation 17 is modified as follows:

$$
\begin{aligned}
V_\pi(S) = \sum_a \pi(a|S)\Bigg(\mathbb{E}(Profit_S{}^a) + \beta\Bigg[\int_{-\infty}^{C_o} \phi_a(C')\, V_\pi(C_o)\, dC' \\
+ \int_{C_o}^{C^a_{\max}} \phi_a(C')\, V_\pi(C')\, dC' \\
+ \int_{C^a_{\max}}^{\infty} \phi_a(C')\, V_\pi(C^a_{\max})\, dC'\Bigg]\Bigg)
\end{aligned}
\tag{18}
$$

where $\quad \phi_a(C') = \frac{\exp\left(-\frac{(C'-\mathbb{E}(C'))^2}{2\sigma_c^2(a)}\right)}{\sqrt{2\pi}\,\sigma_c(a)}$.

The variability in the amount of soil carbon sequestration associated with the practice $a$ is given by $\sigma_c(a)$, which quantifies the risk associated with the practice. There is variability in crop yield as well. However, it is a random variable, whose value depends on weather, soil, and field conditions. Only the expected value of crop yield appears in the profit equation when one is solving for optimal farmer decisions.

# 4 Data

I utilize simulated data from EPIC to parameterize and then solve the theoretical model. To check the reliability of EPIC results, I also parameterize and solve the theoretical model using data from long timescale field experiments. The EPIC model integrates essential components required for simulating biophysical processes, including soil characteristics, weather conditions, site characteristics, and diverse land management practices. It generates detailed spatial data and simulates the physicochemical processes occurring on homogeneous fields, farms, or small watersheds, considering factors such as climate, soil, land use, and topography (Izaurralde et al., 2006; Lychuk et al., 2015, 2017). EPIC simulations produce SOC levels and crop yields under various tillage practices and field conditions. These simulated outputs are used to parameterize input parameters in the optimization model, enabling calculation of farmer payoffs under alternative management scenarios and thus informing optimal practice selection.

Field data from experiments report measured crop yields, SOC, and details of operations performed. The model parameterized using these data serves as a robustness check of the results obtained from biophysical simulations.

For EPIC simulations, I obtain soil data from the Soil Survey Geographic Database (SSURGO), and daily weather data from the World Climate Research Program (WCRP) Coupled Model Intercomparison Project (CMIP)-6, the most up-to-date weather model. I source site (field-level) data from the Cropland Sequence Boundaries dataset provided by the United States Department of Agriculture. I use the following data: location of the field (latitude/longitude), field slope, field elevation, field aspect ratio, daily precipitation, maximum and minimum daily temperatures, solar radiation, humidity, and daily wind speed.

Soil characteristics considered in the simulations include soil albedo, hydrology group, layer depths and densities, sand content, silt content, soil pH, organic carbon concentration, calcium carbonate content, rock content, and soil conductivity. In these simulations, tillage (if applicable) is performed on April 25 each year with corn planting on May 2. Fertilizers are added in the amounts 185 Kg/ha, 150 Kg/ha, and 116 Kg/ha each year. Automatic irrigation schedule is used, that is, field is irrigated when the water stress on the crops reaches a certain threshold. Corn is harvested on September 14, and then shredded. Three different tillage practices are studied: NT, reduced till (RT), and CT (moldboard plow). Within the Midwest region, I selected fields from five different watersheds: Sugar, Lower Maumee, Maple, Macoupin, and Upper Fox. For each watershed, I calculated the proportion of areas belonging to different hydrology groups and then randomly selected fields from each hydrology group based on these proportions. In total, I selected 70 fields covering all hydrology groups and the watersheds. I performed 30-year simulations with NT, RT, and CT practices to compare changes in SOC and crop yield. In total, I conducted EPIC simulations for the selected 70 fields providing a comparative analysis of tillage effects on SOC and yield across different hydrology groups within the selected watersheds. I chose to study 70 fields so that I am able to capture the heterogeneity in soil and weather conditions in yield and SOC, and also keep the computational costs reasonable.

# 5 Results

## 5.1 Baseline Results

Before examining the role of SOC variability on farmer decisions and optimal carbon payments, it is helpful to discuss the results when the SOC variability associated with different tillage practices is set to be the same, equal to 0.2 ton/ha/y. First, I will discuss the SOC and yield distributions of the fields that have only been tilled with CT. Figure 2 shows the distributions of SOC and yield obtained with CT for corn in fields belonging to different hydrology groups. These SOC distributions represent stable SOC levels after the fields have been tilled with CT for an extended period. Hydrology group A has the smallest average SOC, whereas group C has the largest average SOC. Hydrology group B shows the greatest range of stable SOC values. The corn yield distributions for CT is relatively constant across the different hydrology groups, although the average yield is slightly higher for the fields in hydrology group $A$.

EPIC simulations reveal that no till (NT) and reduced till (RT), using a tandem disk, result in an increase in SOC. As an illustration, Figure 3 shows the time-trends of SOC over 30-year simulations of corn growth with NT, RT, and CT for a field in the Sugar watershed in Indiana belonging to hydrology group $B$. The graph shows that SOC increases the most with NT, followed by RT. SOC remains almost constant with CT. By performing EPIC simulations for longer periods, I ascertain the maximum SOC increase that is achievable with NT and RT conservation practices for corn cultivation. Figure 4 shows the distribution of the maximum SOC increase achievable using NT and RT across all 70 fields analyzed in the EPIC simulations. Overall, more SOC is gained using NT compared to RT for all fields. The heterogeneity in the SOC distribution is due to different soil characteristics and weather

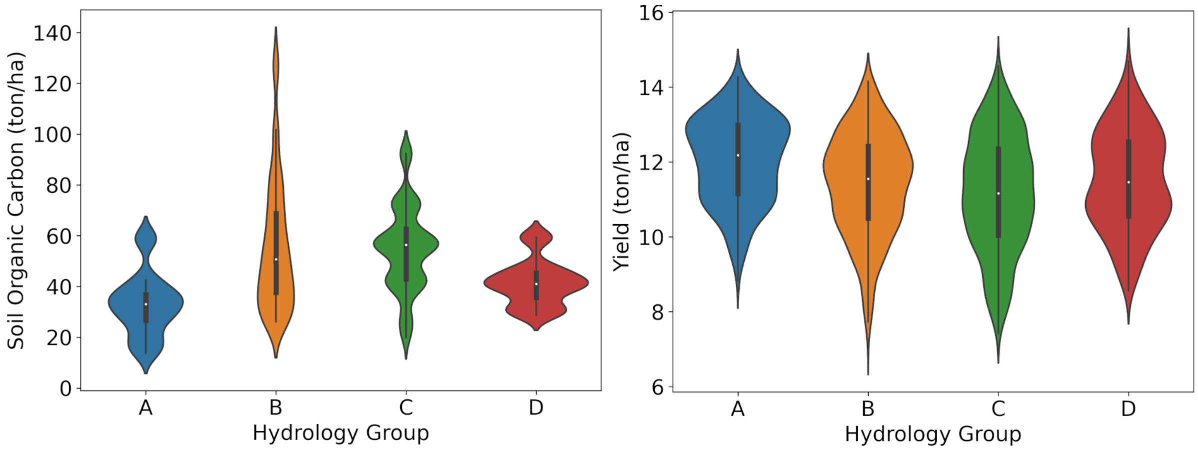


Figure 2: Distributions of SOC levels (left) and corn yield (right) across different fields under conventional tillage from EPIC simulations.
Hydrology group B exhibits the highest SOC and the lowest yields. Hydrology group D has the lowest SOC levels but displays a bimodal distribution. Yields in hydrology group D are relatively high and show significant variability. SOC levels in hydrology group A also exhibit a bimodal distribution.

conditions.

To ascertain the role of soil characteristics, Figure 5 shows the distribution of SOC increase and yield loss associated with NT and RT practices. It is observed that the yield loss is smallest in hydrology group A when conservation tillage is employed, but it is also associated with smallest SOC gain. Hydrology group *B* shows largest average SOC gain but also the largest yield loss. Therefore, fields in hydrology group *A* can be considered the "low hanging fruit" where SOC increase is attained with minimal yield loss. Interestingly, EPIC simulations reveal that for the fields studied, RT results in larger yield loss but smaller SOC gain compared to NT, implying that RT is an inferior practice to both NT and CT and will not be preferred. However, this result may not hold for other RT practices, such as those using equipment other than tandem disk, as literature evidence suggests.

Table 1 summarizes the EPIC results for average yield for CT, NT, and RT for different hydrology groups, as well as SOC gain, and yield loss with NT and RT. Therefore, there is a trade-off between yield and SOC: while NT and RT practices increase SOC, they cause yield loss.

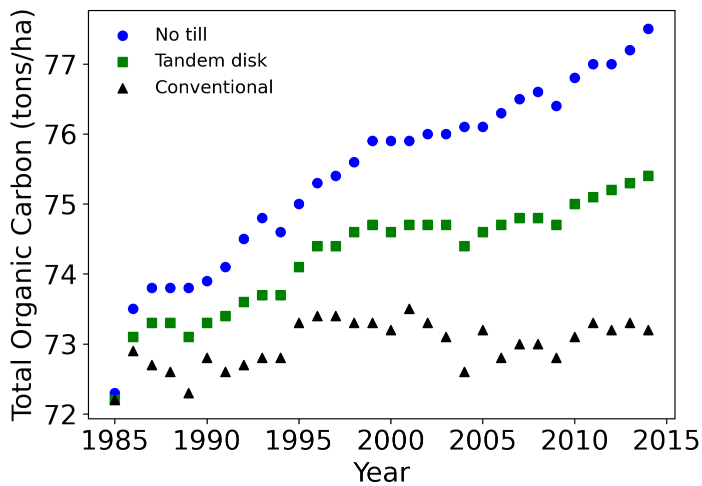


Figure 3: Time profiles of SOC from 30-year simulations in EPIC for corn growth under no till, reduced tillage (tandem disk) and conventional tillage.
SOC increases most rapidly under no till followed by reduced till. This data represents a field in the Sugar watershed with hydrology group B. Similar time profiles of SOC are obtained for other fields and those belonging to different hydrology groups.

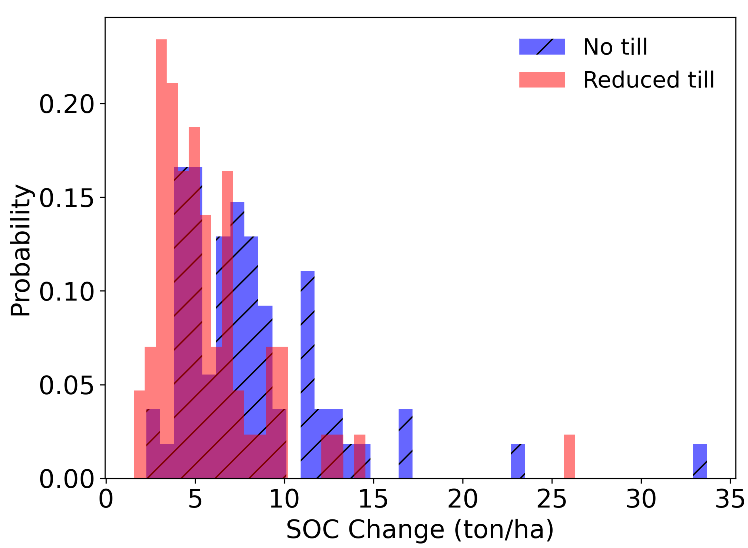


Figure 4: Distribution of increase in SOC under no till and reduced till practices for corn cultivation from EPIC simulations.
The shaded blue histograms represent no till, while the pink histograms represent reduced till. Purple regions indicate overlapping areas between the no-till and reduced-till histograms. Overall, greater SOC increase is observed under no till compared to reduced till.

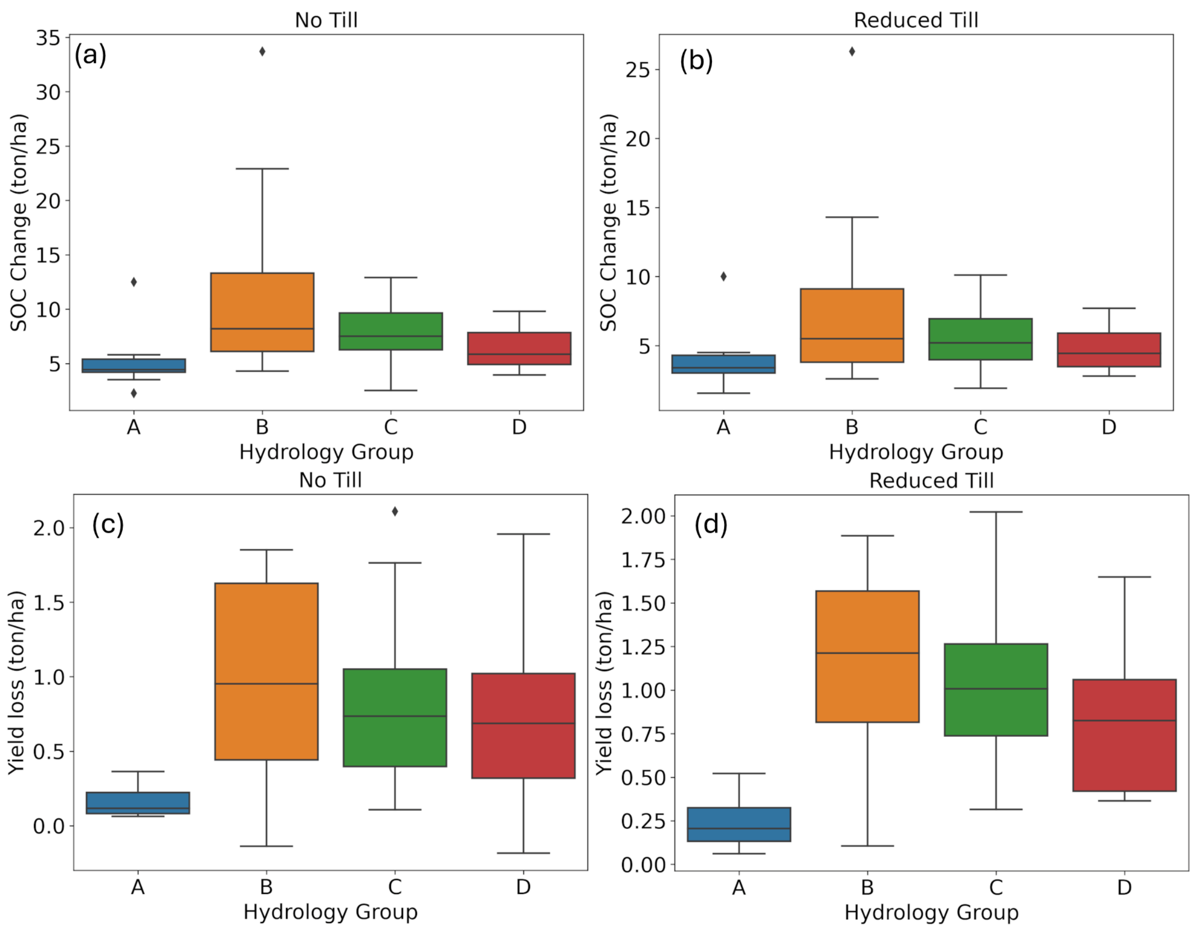


Figure 5: Distribution of increase in SOC for fields in different hydrology groups under (a) no-till and (b) reduced till practices from EPIC simulations.

Hydrology group A exhibits the smallest SOC increase and the smallest yield loss. Hydrology group B shows the largest SOC increase as well as the largest yield loss.

The five watersheds of the Midwest United States that I studied (Sugar, Lower Maumee, Maple, Macoupin, and Upper Fox) cover 2.57 million acres of agricultural land of which 9.3%, 36.7%, 49.0%, and 5.0% belong to hydrology groups of $A$, $B$, $C$, and $D$, respectively. Given this distribution and based on the rates summarized in Table 1, it is estimated that a total of 9 million tons of carbon can be sequestered by switching from CT to NT, whereas 6.3 million tons of carbon can be sequestered by switching from CT to RT, assuming all fields within these watersheds currently employ conventional tillage (CT). Thus, these figures represent the maximum additional sequestration capacity achievable through full adoption of NT or RT across all agricultural land within these watersheds.

Table 1: Average yield and SOC data of corn grown with different tillage practices. Data obtained from EPIC simulations. Yield loss and SOC gain values are relative to the baseline of conventional tillage. The numbers in the parenthesis are the sample standard deviation.

| **Hydrology** | **Variable** | **Conventional till** | **No till** | **Reduced till** |
|---|---|---|---|---|
| A | Yield (ton/ha) | 12.04 (0.87) | 11.87 (0.84) | 11.79 (0.96) |
| | Yield loss (ton/ha) | | $0.16^{**}$ (0.10) | $0.25^{**}$ (0.16) |
| | SOC gain (ton/ha) | | $5.26^{**}$ (2.91) | $4.05^{**}$ (2.40) |
| | Count | 9 | 9 | 9 |
| B | Yield (ton/ha) | 11.41 (1.11) | 10.49 (1.00) | 10.28 (1.11) |
| | Yield loss (ton/ha) | | $0.92^{**}$ (0.63) | $1.13^{**}$ (0.48) |
| | SOC gain (ton/ha) | | $10.70^{**}$ (7.20) | $7.54^{**}$ (5.50) |
| | Count | 21 | 21 | 21 |
| C | Yield (ton/ha) | 11.15 (1.30) | 10.33 (1.38) | 10.14 (1.49) |
| | Yield loss (ton/ha) | | $0.83^{**}$ (0.54) | $1.02^{**}$ (0.45) |
| | SOC gain (ton/ha) | | $8.00^{**}$ (2.52) | $5.52^{**}$ (1.99) |
| | Count | 31 | 31 | 31 |
| D | Yield (ton/ha) | 11.50 (1.14) | 10.78 (1.38) | 10.67 (1.33) |
| | Yield loss (ton/ha) | | $0.72^{**}$ (0.68) | $0.83^{**}$ (0.44) |
| | SOC gain (ton/ha) | | $6.33^{**}$ (2.11) | $4.79^{**}$ (1.79) |
| | Count | 8 | 8 | 8 |

$^{**}$ 95% significance

Next, I determine optimal farmer decisions by solving the Markov decision process, as described in the section 3. Farmers are paid for their current SOC stock each year. Based on their SOC stock, farmers decide whether to choose CT, NT, or RT. Farmer decisions are based on maximizing their value function.

Figure 6 shows the farmers' decisions as a function of their SOC amount for different carbon payment levels. For this calculation, I consider average yield and SOC values obtained from all the fields belonging to a hydrology group. For the hydrology group A, a carbon payment of \$7/ton of carbon results in farmers switching from CT to NT when their SOC is greater than 33 tons/ha (Figure 6A). When SOC is high, the SOC payments more than compensate for the yield loss. A payment of \$10/ton of carbon is sufficient to make farmers adopt NT irrespective of their SOC level for hydrology group A. For the hydrology group B, the yield loss is larger when switching from CT to NT (Table 1). Hence, farmers switch from CT to NT for payments of \$15-20/ton (Figure 6B). For payments of \$25/ton, farmers adopt NT irrespective of the SOC levels. Similarly, for hydrology groups C and D, payments of \$30/ton and \$35/ton are required for farmers to select NT for all SOC levels.

The switch from CT to NT does not depend on the absolute amount of the SOC stored but on the increase in SOC that results from the switch, as well as the concomitant yield loss. In these simulations, farmers never opt for RT for the fields studied because RT is an inferior practice to NT, resulting in larger yield loss but smaller SOC gain. These findings indicate that policymakers should implement spatially targeted payment thresholds that account for soil characteristics and economic conditions. Identifying these thresholds enables policymakers to define a clear range of potential carbon payments necessary to effectively incentivize conservation practices, guiding the development of efficient compensation schedules.

## 5.2 Quantifying the effect of SOC risk

First, I examine how the minimum carbon payments needed to incentivize the adoption of conservation practices, $m$, change as a function of SOC variability. For this calculation, the SOC variability is kept the same for all the tillage practices (conventional tillage using moldboard plow, reduced tillage using tandemdisk, and no till). It is observed that as the SOC variability or risk increases, the $m$ increases across all hydrology groups (Figure 7). In

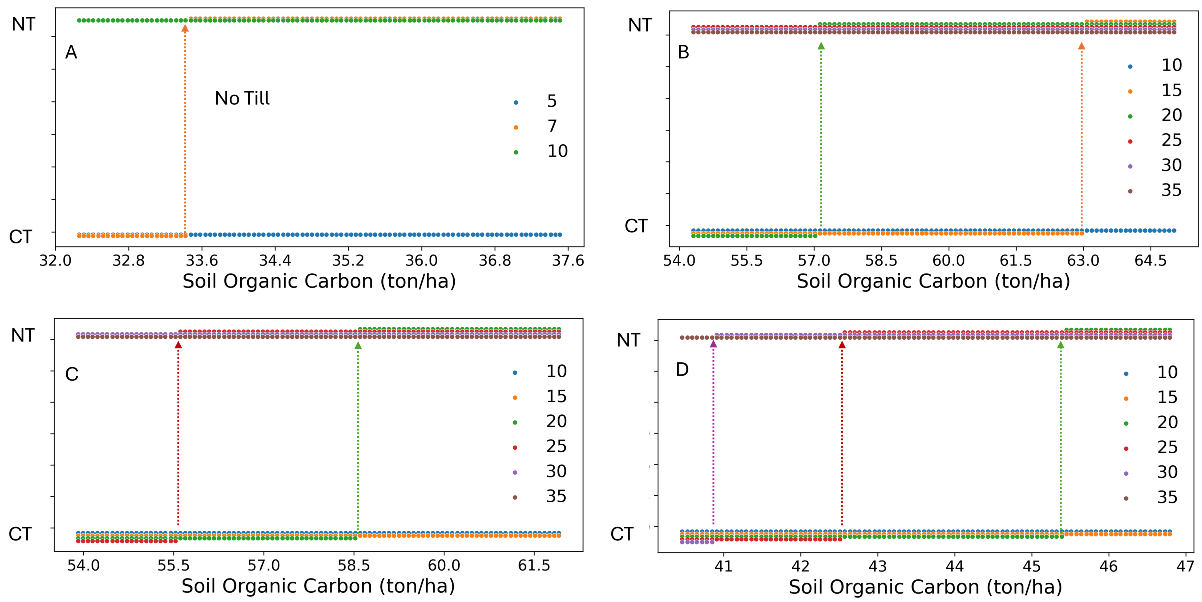


Figure 6: Results from solving the Markov decision process to determine the optimal policies adopted by farmers for fields in different hydrology groups (A, B, C, and D). The legend indicates payment amounts for carbon sequestration in dollars per ton of carbon. The panels are labeled according to the hydrology group that they represent. Vertical arrows show the transition from CT to NT.

all cases, the farmers adopt no till over reduced till because of its lower yield loss and higher SOC gain. This result shows that when farmers perceive a higher risk or variability in SOC, they would require higher carbon payments to adopt conservation tillage that would result in yield losses because the gains from carbon sequestration are more uncertain.

Next, I examine how optimal farmer decisions are impacted by different levels of SOC risk associated with different tillage practices. For this calculation, I set the SOC variability of conventional tillage to 0.1 tons/ha/y and that of reduced tillage to 0.2 ton/ha/y. In a series of counterfactual simulations, I change the SOC variability, $\sigma$ of no till up to 2.4 ton/ha/y. Figure 8 shows optimal farmer decisions when $m$ is \$36/ton/y for the hydrology group $D$. For small SOC values, the farmers choose no till as that is associated with lower crop yield loss and higher SOC gain. However, as the $\sigma$ increases, farmers start opting for reduced tillage for moderate levels of SOC even though reduced till is associated with higher crop yield losses. This is because reduced till is associated with smaller variability or risk.

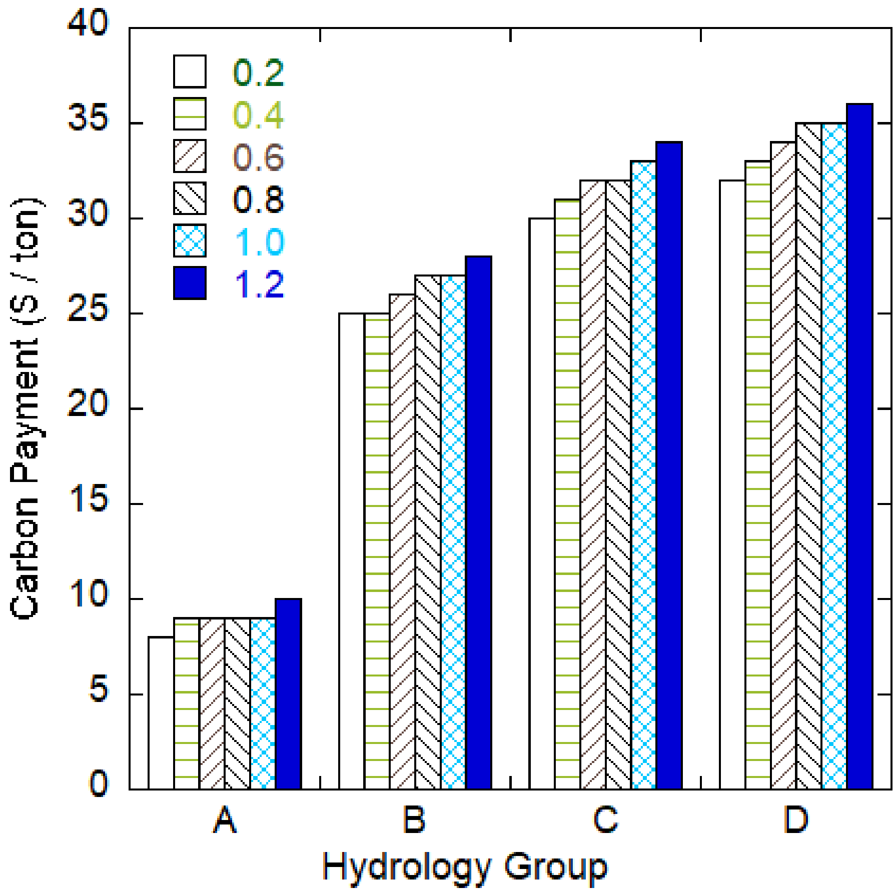

Figure 7: Minimum carbon payments, $m$, needed for the farmers to switch from switch from conventional tillage (CT) to no till (NT) for different hydrology groups as a function of SOC variability. In these calculations, the SOC variability is chosen to be the same for all tillage practices. The $m$ increases with SOC variability.

Therefore, at moderate SOC levels, farmers prefer to maintain their SOC stock with higher certainty and are willing to take a larger hit on their crop yield. Figure 8 also shows farmer decisions for $\sigma$=2.4 ton/ha/y for no till and $m$ = \$79/ton/y. For larger SOC payments, farmers will opt for reduced till for a larger range of SOC values. Interestingly, when the SOC levels reach near saturation, the farmers switch back to no till as the SOC saturation limit of no till is higher than reduced till. In the Figure 9, optimal farmer decisions are shown as a function of SOC variability associated with no till, $\sigma$ when the carbon payments are lower ($m$ = \$33/ton/y) for the hydrology group $D$. When the SOC levels are small, the farmers prefer to practice conventional tillage as the carbon payments do not compensate

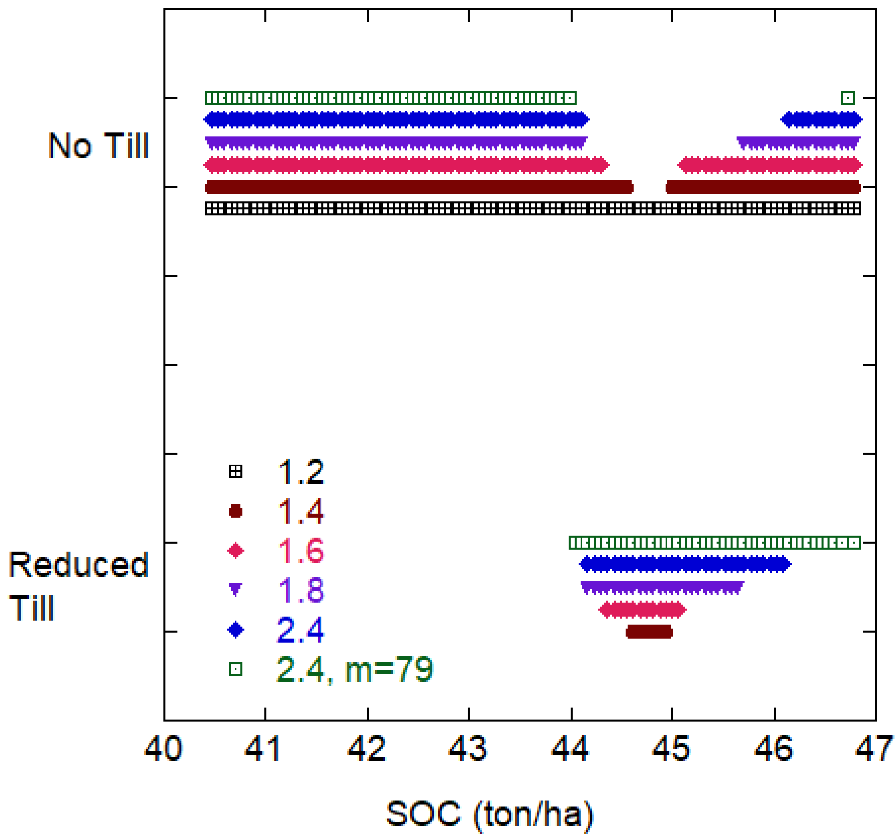


Figure 8: Optimal farmer behavior as a function of SOC variability, $\sigma$ of no till for the hydrology group $D$ with $m$ = \$36/ton/y. As the SOC sequestration becomes more risky with no till, farmers switch to reduced till for moderate SOC values to ensure that their carbon stock payments do not decrease because of this variability. At higher SOC levels, farmers switch back to no till.

completely for the associated yield losses. Again, one observes that the farmers switch to reduced tillage for moderate levels of SOC and back to no till when high SOC levels are reached.

# 6 Conclusion

This study estimates the payment levels required to incentivize farmers to adopt conservation practices. Through EPIC simulations, I assess the SOC storage potential of agricultural lands across five watersheds in the Midwest U.S., covering 2.57 million acres. Assuming corn as the primary crop, the results suggest that transitioning from conventional tillage (CT)

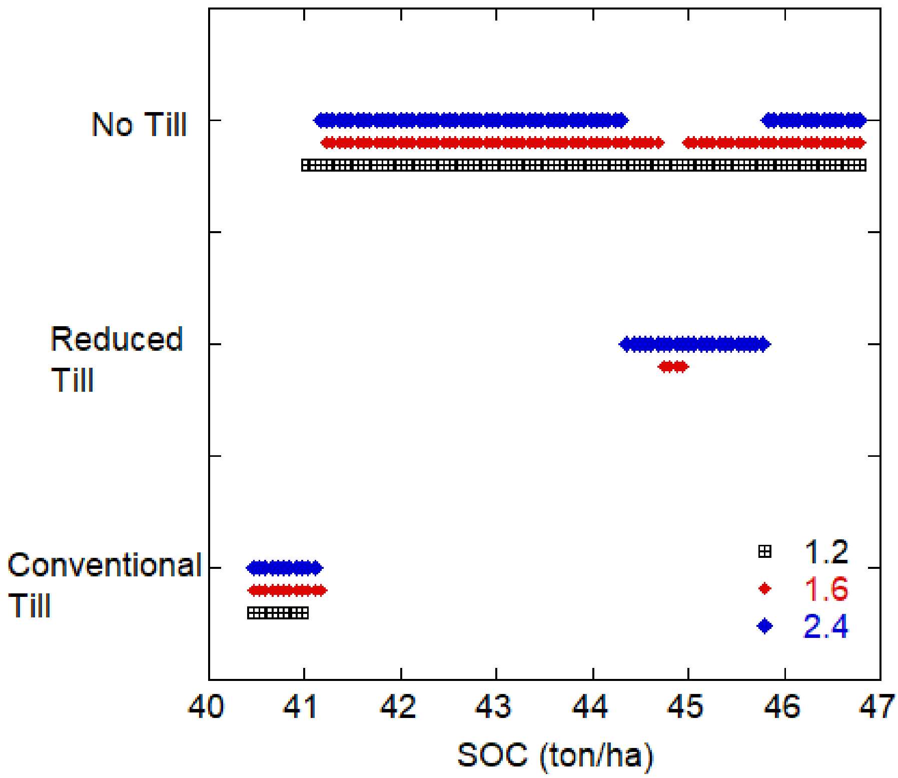


Figure 9: Optimal farmer behavior as a function of SOC variability, $\sigma$ of no till for the hydrology group $D$ with $m = \$33/\text{ton/y}$. For small SOC levels, farmers opt for conventional tillage. As the SOC sequestration becomes more risky with no till, farmers switch to reduced till for moderate SOC values to ensure that their carbon stock payments do not decrease because of this variability. At higher SOC levels, farmers switch back to no till.

to no-till (NT) could sequester an additional 9.0 million tons of carbon, while shifting from conventional tillage to reduced tillage could store an additional 6.3 million tons.

Required carbon payments vary significantly across hydrology groups, which are classified by soil drainage capacity. Fields in hydrology group $A$ experience the smallest yield loss when transitioning from CT to NT. Therefore, for such fields, a payment of \$10/ton of carbon is sufficient to encourage farmers to shift to NT irrespective of the SOC level. On the other hand, fields in hydrology group $D$ require the highest payment of \$35/ton of carbon to incentivize the transition from CT to NT.

The study quantifies how increasing SOC sequestration variability raises required carbon payments for fields in different hydrological groups. As the SOC variability increases from

0.2 tons/ha/y to 1.2 tons/ha/y, the carbon payments increase by \$2/ton/y (hydrology group $A$) and \$4/ton/y (hydrology groups $C$ and $D$). When SOC variability differs substantially between tillage practices, important patterns in farmer decision making emerge. When the SOC variability is much higher for no-till as compared to reduced till, farmers switch to reduced till when their fields have moderate SOC levels, even though reduced till is associated with lower yields and SOC levels than no till. This happens because the lower SOC variability of reduced till ensures that farmers can more reliably maintain their incomes from SOC stocks. Interestingly, when the SOC levels reach close to saturation, farmers switch back to no till to maximize SOC gains.

While there is a significant focus on how farmers with different risk-profiles behave, this study shows that the optimal behavior of a risk-neutral farmer can also result in switching from high risk, high reward no till to low risk but low reward reduced till under certain conditions. This highlights that variability in sequestration outcomes, not just farmer risk preferences, can drive shifts between practices, with direct implications for the design of payment-for-ecosystem-services programs.

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