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

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Abstract

Agricultural soils represent one of the largest underutilized opportunities for climate mitigation through land-based carbon sequestration. This chapter analyzes how farmers make long-term decisions about adopting soil conservation practices, such as no-till and reduced tillage, when soil organic carbon (SOC) accumulation generates additional payments, while explicitly considering risk associated with SOC sequestration variability. Using an infinite-horizon dynamic optimization model, the study quantifies the carbon payment levels required to incentivize adoption across different soil types. Results show that the required payments vary widely, from \$8/ton C/year on well-drained soils to \$32/ton C/year on poorly drained soils, highlighting the need for spatially targeted carbon incentives. The analysis demonstrates that risk in the SOC sequestration amount affects farmer choices: higher uncertainty increases the payments needed and can lead farmers to prefer lower-risk, lower-reward practices. For farmers who value intertemporal consumption smoothing, compensation requirements rise with the elasticity of intertemporal substitution. These findings underscore the importance of accounting for soil heterogeneity, outcome variability, and intertemporal preferences when designing effective carbon payment programs to promote long-term soil carbon sequestration.

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

1 Introduction

Soil serves as a large carbon sink by absorbing carbon dioxide (CO_2) from the atmosphere and storing it as organic matter. However, traditional agriculture practices reverse this process. Currently, the agricultural sector contributes to roughly 11% of the greenhouse gas emissions in the United States (U.S. Department of Agriculture, 2024). Increasing conservation practices in land-use and land management has the potential to transform farmland from a carbon source to a sink, reducing emissions and strengthening the agricultural economy. The U.S. has close to 390 million acres of cropland and 660 million acres of grassland and pastures. A growing body of literature examines the potential of SOC through various mechanisms (Sperow, 2007; Stavins, 1999; Antle et al., 2001; Sperow, 2019). Research suggests adopting cover crops alone could sequester 16 million tons of carbon annually in the U.S. (Griscom et al., 2017).

Although soil carbon markets and public payment programs have expanded rapidly in recent years, farmer participation remains low due to uncertainties regarding sequestration potential, yield impacts, carbon markets, and compensation mechanisms (Pendell et al., 2006; Yao and Kong, 2018). Understandably, farmers are risk-averse (Chavas and Holt, 1996). Thus, risk is an important determinant in farmers' decisions to adopt a land management practice. Practices that result in more stable profits and yields over time are preferred over those that cause higher variability (Rejesus et al., 2025). 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.There is some evidence that practices like conservation tillage, growing cover crops, and crop rotation reduce crop yield variability (Anderson et al., 2020; Singh et al., 2021; Leuthold et al., 2021; Hristovska et al., 2013). Contrary to this, another study finds that organic farming and cover cropping lower maize yields and reduce yield stability and resistance (Li et al., 2019). Toliver et al. (2012) show that no till practices can either increase or decrease crop production risk depending on soil and climatic conditions. Beyond yield uncertainty, farmers who adopt conservation practices as a revenue source must also confront uncertainties in soil carbon outcomes. VandenBygaart et al. (2002) document substantial heterogeneity in soil carbon sequestration (SOC) sequestration responses to no till, conditioned by soil type and baseline carbon levels. Subsequent studies similarly report wide dispersion in SOC sequestration outcomes driven by soil properties and weather variability (Powlson et al., 2014; Cerri et al., 2004; Vicente-Vicente et al., 2016).

Spatial heterogeneity in sequestration outcomes and adoption costs has led to proposal for differentiated payment structures across agricultural landscapes (Antle et al., 2003; Baylis et al., 2022). Uniform per-hectare subsidies inadequately capture this heterogeneity, risking inefficient resource allocation and unintended incentives for farmers who would adopt practices even in the absence of additional compensation (Horowitz and Just, 2013). Conversely, narrowly targeted payments may unintentionally shift emissions elsewhere, thereby undermining broader climate objectives (Kim et al., 2014).

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 distorts incentive design, leaving the primary source of variation in farmer responses unaddressed. 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 apply a discount to credited carbon volumes in order to limit exposure to reversal or under-delivery risk (Kim and McCarl, 2009). This discounting, together with associated transactional costs, generates a wedge between the buyer's willingness to pay and the producer's reservation price for carbon (Liu et al., 2025). These dynamics provide the conceptual basis for payment schemes that explicitly incorporate environmental risk.

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. In addition, I examine optimal farmer decisions under a concave utility. Since conservation practices are associated with lower immediate rewards due to crop yield losses but higher future profits due to the accumulated SOC, farmers utilize capital in early periods to smooth their consumption across time. The minimum carbon payments increase with the increase in the elasticity of intertemporal substitution.

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 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 fluctuations that are central to realistic policy design.

Third, the analysis clearly identifies the economic thresholds required to induce farmer adoption. Optimal payment levels vary systematically with soil type, crop yield effects, baseline SOC stocks, and the magnitude of intertemporal elasticity. The results also identify upper payment bounds beyond which marginal increases in compensation generate negligible additional carbon sequestration. Together, these findings provide policymakers with concrete guidance for calibrating economically efficient carbon payment schemes.

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. The simulations reveal pronounced spatial heterogeneity in yield effects, with reduction ranging from 1.3% on sandy soils (hydrology group A) to more than 8% on silt loam soils (hydrology group B). These soil classes also exhibit marked differences in carbon sequestration outcomes. The results therefore underscore the need for differentiated payment schemes to achieve cost effective adoption of no till practices.

When variability in SOC outcomes under no till becomes substantial, farmers optimally shift to reduced tillage at intermediate SOC levels. Although this strategy yields lower average sequestration gains, it reduces income volatility associated with SOC linked payments. This response reflects production risk management: farmers trade higher expected sequestration for greater income stability. Once SOC approaches saturation, farmers revert to no till in order to maximize carbon accumulation.

Section 2 develops the theoretical dynamic economic model. Section 3 details the data sources, parameters, and assumptions underlying the economic framework. Section 4 presents the empirical policy simulation results. Finally, Section 5 concludes by examining the policy implications and deriving recommendations for the design of targeted and economically efficient carbon sequestration payment programs.

2 Theoretical Model

Absorption and release of carbon in soils are governed by complex geo- and bio-physical processes. Empirical studies show that SOC sequestration and release are inherently nonlinear processes (Georgiou et al., 2022; Gulde et al., 2008; Stewart et al., 2007). When soil carbon stocks are low, the marginal rate of SOC accumulation is relatively high. As SOC approaches its saturation level, denoted by C^*, the rate of accumulation declines. By contrast, carbon release occurs most rapidly at higher SOC levels and diminishes as stocks become depleted.

Following Ragot and Schubert (2008), the SOC dynamics are modeled using first-order kinetics, whereby the rate of change in carbon stocks is proportional to the deviation of the current stock from its long-run equilibrium level. The sequestration process can therefore be expressed as,

$$\frac{dC}{dt} = s(C^* - C) \tag{1}$$

Upon solving, the SOC sequestration process is given as,

$$C_{t+\Delta t} = C^* - (C^* - C_t)e^{(-s\Delta t)} + \sigma\varepsilon_t \tag{2}$$

Here, C^* is the maximum SOC storage potential under a given management practice. C^* also depends on soil type and climatic conditions (Wiesmeier et al., 2019). C_t represents the SOC at time t. The first two terms on the right hand side represent the deterministic component of SOC dynamics, hereafter represented by $\mu(t, \Delta t)$. The last term captures the stochasticity in SOC due to exogenous variables. Similarly, the SOC release rate is modeled as a first-order decay equation,

$$\frac{dC}{dt} = -s'(C - C_o) \tag{3}$$

This gives us the following time-trend of SOC during the release process,

$$C_{t+\Delta t} = C_o + (C_t - C_o)e^{-s'\Delta t} + \sigma\varepsilon_t \tag{4}$$

C_o denotes the minimum SOC level reached after prolonged conventional farming practices. The parameters s and s' are the sequestration and release rate constants, respectively.

2.1 Carbon Sequestration Process as an Infinite Horizon Model

Soil carbon sequestration draws criticism because of its impermanence: switching from conservation to conventional farming practices releases previously accumulated carbon back into the atmosphere. In addition, sequestration is a gradual process, with benefits accruing over extended periods that often span decades (Feng et al., 2002). Because SOC evolves slowly and remains vulnerable to future land-use decisions, current actions have long-lasting intertemporal consequences. These features imply that policy design must account for the entire dynamic path of soil carbon stocks rather than focusing on a finite planning window. For these reasons, framing the farmer's decision problem over an infinite time horizon appropriately characterizes the intertemporal incentives driving conservation practice adoption.

In the model, a farmer maximizes lifetime utility,

$$\max_{\theta_t, k_{t+1}} \sum_t \beta^t \, u(x_t) \tag{5}$$

where θ_t denotes the bundle of conservation or conventional practices adopted at time t, k_{t+1} is the capital stock at the beginning of time period *t+1*, $\beta \in (0,1)$ is the discount factor, and x_t is consumption in period t. Utility, *u(.)* is assumed to be isoelastic:

$$u(x) = \frac{x^{1-\gamma}}{1-\gamma} \tag{6}$$

Consumption in each time period is determined by the capital accumulation equation:

$$x_t + k_{t+1} = (1+r)k_t + \pi_t \tag{7}$$

Where r is the rate of return on capital, and π_t is the net farm profit in period t. Equation 7 implies that in each period the farmer chooses how much to consume and how much capital to carry forward. Farmer's profit function is specified as:

$$\pi_t = (C_t - C_o) \times m + P \times y_t - cost(\theta_t) \tag{8}$$

where C_t is the SOC stock at the end of period t; m is the carbon payment per unit of SOC above the baseline level C_o; P is the crop price; y_t is crop yield; and $cost(\theta_t)$ represent the cost of implementing the bundle of practice θ_t. Thus, farm profits depend on both carbon payments and crop production. Capital does not affect the profit function.

Crop yield is given by $y_t = y(C_t, \theta_t, H)$, where yield depends on the SOC C_t, management practices θ_t, and soil type H, which represents the soil hydrology group. Crop yield also depends on other exogenous factors, such as weather and additional soil characteristics that are not explicitly included in the functional form to maintain notational simplicity. The SOC sequestration process exhibits variability due to exogenous factors, including temperature, precipitation, field slope, and soil type (Campo and Merino, 2016; Lessmann et al., 2022). Carbon sequestration and release rates are functions of management practice and soil type, denoted as, $s(\theta_t, H)$ and $s'(\theta_t, H)$ respectively.

The carbon transition equation is given by:

$$C_{t+\Delta t} = \sum_{i=1}^{\nu} \left(\mu_i(t, \Delta t) + \sigma_i \varepsilon_{t,i}\right) \theta_{t,i}, \tag{9}$$

where $\theta_{t,i} \in \{0, 1\}$ indicates whether management bundle i is implemented in period t, and $\varepsilon_{t,i} \sim N(0, 1)$ represents an idiosyncratic shock to SOC dynamics. Because the farmer selects only one bundle in each period, the choice variables satisfy:

$$\sum_{i=1}^{\nu} \theta_{t,i} = 1 \tag{10}$$

In equation 9, $\mu_i(t, \Delta t)$ represents the deterministic component of next-period SOC implied by the first-order kinetics formulation in equation 2 or equation 4, depending on whether the selected practice induces sequestration or release. The stochastic term captures variability in SOC evolution arising from exogenous factors such as weather and soil conditions. The magnitude of this uncertainty is governed by the standard deviation parameter σ_i. This assumption of normally distributed shocks follows from the presence of multiple independent drivers of SOC dynamics, whose aggregate effect converges toward normality. Because SOC is bound between a minimum level C_o and a saturation level C^*, the transition equation is subject to the constraints: $C_{t+\Delta t} = min\{C^*, max\{C_o, C_{t+\Delta t}\}\}$. For consistency in notation, we choose $\Delta t = 1$.

2.1.1 Solving the Infinite Horizon Model

This optimization problem involves the following elements: **Decision Variables**: (a) The discrete bundles of practices θ_t available to the farmer in each period. (b) Capital in the next period k_{t+1}, which is determined by the consumption decision in the current period. **State Variables**: (a) Soil carbon stock, C_t and (b) available capital, k_t. The problem considers a farmer who chooses an optimal sequence of management practices and capital accumulation decisions over time, given constant carbon payments, crop prices, and implementation costs. Let $a_t = (\theta_t, k_{t+1})$ denote farmer's decision at time t. The state variables are collected in the state vector $S_t = (C_t, k_t)$. Given decision a_t, the state transitions to S_{t+1} according to the carbon and capital transition equations.

This transition is modeled as a Markov decision process (Sargent and Ljungqvist, 2000; Atashbar and Shi, 2022), such that the evolution of the state depends only on the current state and the current decision, and not on the full history of past states or decisions. The Markov structure assumes time-invariant parameters including crop prices, carbon payments, and costs. The farmer chooses actions to maximize lifetime utility, not merely current period returns.

Given the Markov property, the infinite horizon maximization problem admits a recursive representation in the form of a Bellman equation. The optimal value is characterized by the value function, *V(.)*, which gives the maximum attainable lifetime utility for any given state. In recursive form, the *V(.)* equals the maximnum of current-period utility and the discounted continuation value associated with the subsequent state (see equation 11).

Solving the Bellman equation yields both the value function and the optimal policy rules conditional on the current state. Under standard assumptions, the associated Bellman operator constitutes a contraction mapping, so repeated application converges to a unique fixed point corresponding to the true value function. The Bellman equation is solved numerically using value function iteration. Within this framework, the value function characterizes the farmer's maximum attainable lifetime utility at each state state. The associated policy function specifies the optimal action for every point in the state space. A fundamental result in dynamic programming establishes that, under standard regularity conditions for a Markov decision process, an optimal deterministic policy exists. The optimal policy therefore takes the form of a deterministic mapping from the state space to the action space.

The Bellman equation is given as:

$$V(S) = \max_a \{u(x_t) + \beta \sum_{S'} P_{SS'}{}^a V(S')\} \tag{11}$$

where *V(S)* denotes the value function for given the current state S; $u(x_t)$ is the utility when the farmer chooses action a, given state S; and ${P_{SS'}}^a$ is the transition probability from state S to *S'* when action a is taken (Sargent and Ljungqvist, 2000). In the recursive framework, the value function is decomposed into the immediate reward for an action a and the discounted value of the next state. The Bellman equation is solved iteratively. Starting with an initial guess, $V(S') = 0 \; \forall S'$, the value function is updated recursively until convergence. The optimal policy is determined by the action a that maximizes the value function.

Applying the Kuhn-Tucker conditions to this model yields the following Euler equation governing intertemporal consumption:

$$x_{t+1} = [\beta(1+r)]^{1/\gamma} x_t \tag{12}$$

Equation 12 only holds when $k > 0$ and θ is a constant, that is, the farmer does not switch between bundles.

2.1.2 Solving for a Risk Neutral Farmer

The baseline case considers the optimal decisions of a risk-neutral farmer. Risk neutrality corresponds to linear utility, which arises as $\gamma \to 0$ in the isoelastic utility function (equation 6). In this case, the utility function becomes $u(x) = x$, and the objective reduces to maximizing discounted lifetime profits. Under risk neutrality, we assume that all profits in each period are consumed, so there is no intertemporal saving or capital accumulation. As a result, the capital transition equation is eliminated, and the dynamic problem simplifies to:

$$\max_{\theta_t} \sum_{t=0}^{\infty} \beta^t \pi_t \tag{13}$$

subject to the carbon transition equation (equation 9).

3 Data

Solving the dynamic optimization model requires quantitative estimates of crop yields and carbon sequestration (or release) rates under alternative land management practices are required. Because soil carbon evolves gradually over time, accurate characterization of these processes demands data spanning extended time horizons. To meet this requirement, the analysis relies on simulated outputs from the Environmental Policy Integrated Climate (EPIC) model. The EPIC model integrates key biophysical components governing agricultural systems, including soil properties, weather conditions, site characteristics, topography, and land management practices. It simulates field-level physicochemical processes over long time horizons, accounting for interactions among climate, soil, and management decisions (Izaurralde et al., 2006; Lychuk et al., 2015, 2017). In particular, EPIC generates detailed time-series data on soil organic carbon (SOC) stocks and crop yields under alternative tillage and conservation practices across varying field conditions. These simulated outputs are used to parameterize the transition and profit functions in the optimization model. Specifically, EPIC-derived SOC trajectories inform the carbon transition equations, while simulated yield outcomes determine revenue components of farm profit. This integration enables the calculation of farmer payoffs under alternative management strategies and provides the quantitative foundation for identifying optimal practice selection over time.

To conduct the EPIC simulations, spatially explicit soil, weather, and field-level data are assembled from multiple publicly available sources. Soil property data are sourced from the Soil Survey Geographic Database (SSURGO), while daily climate inputs are drawn from the World Climate Research Programme Coupled Model Intercomparison Project Phase 6 (CMIP6). Field boundary and land-use information are obtained from datasets maintained by the United States Department of Agriculture.

The simulation inputs comprise geospatial characteristics such as latitude, longitude, slope, elevation, and aspect ratio, together with daily weather variables including precipitation, minimum and maximum temperature, solar radiation, humidity, and wind speed. Soil parameters in the model encompass albedo, hydrologic soil group, layer depth and bulk density, sand and silt fractions, pH, organic carbon content, calcium carbonate concentration, rock fragment content, and soil hydraulic conductivity.

Management practices are standardized across simulations to isolate the effects of tillage systems. Tillage operations (when applicable) are scheduled in late April, followed by corn planting in early May. Annual fertilizer applications are fixed at 185 kg/ha, 150 kg/ha, and 116 kg/ha. Irrigation responds endogenously through an automatic scheduling rule triggered by crop water stress thresholds. Harvest takes place in mid-September, followed by residue shredding. The analysis evaluates three tillage systems: no-till (NT), reduced tillage (RT), and conventional moldboard plow tillage (CT).

Soil carbon dynamics are closely linked to hydrologic characteristics, which influence water retention, runoff, and infiltration. Carbon absorptive capacity of a unit of land depends on soil and hydrologic properties that regulate water storage, infiltration, runoff, and retention within the soil profile. Runoff refers to water flowing over the soil surface, while infiltration measures the rate at which water enters the soil profile. Based on these properties, land is commonly classified into four hydrology soil groups (Auerswald and Gu, 2021). Group A soils (typically sandy) exhibit high infiltration and low runoff potential. Group B soils (silt loam or loam) display moderate infiltration rates. Group C soils (clay loam) have relatively low infiltration, while Group D soils (clay) are characterized by the lowest infiltration and highest runoff potential. These hydrologic distinctions have important implications for carbon sequestration. Clay-rich soils, due to their fine particle size and larger surface area, have greater capacity to bind and stabilize organic matter, thereby enhancing long-term carbon storage relative to coarser soils such as silt or sand.

The sample includes fields from five representative watershed in the Midwestern United States: Sugar, Lower Maumee, Maple, Macoupin, and Upper Fox. For each watershed, the analysis computes the distribution of hydrologic soil groups and sample fields in proportion to those distributions. This sampling strategy preserves soil heterogeneity while limiting computational complexity.

The final sample comprises seventy fields spanning watersheds and soil groups. Thirty-year simulations evaluate each field under NT, RT, and CT practices, generating long-run trajectories of soil organic carbon and crop yield. The resulting dataset captures cross-sectional variation in soil and climatic conditions and permits systematic comparison of tillage effects across heterogeneous environments.

4 Results

4.1 Environmental Policy Integrated Climate (EPIC) simulation Results

EPIC simulations are conducted for 70 fields belonging to five watersheds of the Midwest United States (Sugar, Lower Maumee, Maple, Macoupin, and Upper Fox). These watersheds in total cover 2.57 million acres of agricultural land of which 9.3%, 36.7%, 49.0%, and 5.0% belong to hydrology groups A, B, C, and D, respectively. The simulations study corn cultivation under different tillage practices. First, simulations are run for more than 200 years using conventional tillage (CT) to reach the minimum SOC level, denoted by C_o. Subsequently, simulations are performed under no-till (NT) and reduced tillage (RT, using a tandem disk) to determine the maximum attainable SOC levels under these practices, denoted by C^*. SOC saturation is reached after approximately 90-120 years. The carbon transition equation (Equation 2) is fitted to simulated SOC time paths to estimate sequestration rates s for NT and RT.

As an illustration, Figure 1 presents 30-year SOC trajectories for corn production under NT, RT, and CT for a field in the Sugar watershed in Indiana classified as hydrology group B. The figure shows that SOC increases most under NT, followed by RT, while remaining nearly constant under CT. Figure 2 shows the distribution of maximum SOC gains attainable under NT and RT across all 70 fields analyzed in the EPIC simulations. For every field,

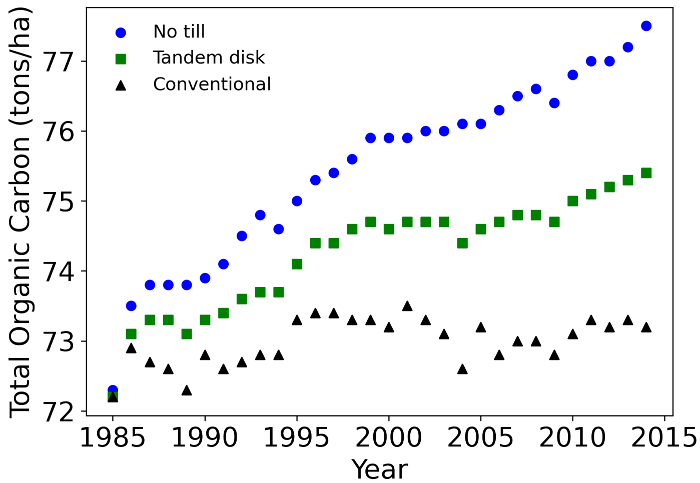

Figure 1: Time profiles of soil organic carbon (SOC) over 30-year EPIC simulations of corn production under no till, reduced tillage (tandem disk) and conventional tillage. Prior to initiating these simulations, EPIC is run under conventional tillage until SOC reaches its equilibrium value (C_o). SOC increases most rapidly under no till, followed by reduced tillage. The figure reports results for a field in the Sugar watershed classified as hydrology group B. Similar SOC trajectories arise across other fields and hydrology groups.

NT generates larger SOC gains than RT. The heterogeneity in SOC distribution reflects underlying differences in soil characteristics and climatic conditions.

Table 1 summarizes the EPIC results for average yield under CT, NT, and RT across hydrology groups, together with associated SOC gains and yield losses under NT and RT. Yield losses from conservation tillage (NT and RT) are smallest in hydrology group A; however this group also exhibits the lowest SOC gains. In contrast, hydrology group B achieves the largest average SOC gain, albeit with the greatest yield losses. Thus, fields in hydrology group A may be viewed as "low hanging fruit" where SOC increases can be achieved with relatively modest yield trade-offs. The EPIC simulations further indicate that, for the fields analyzed, RT results in larger yield losses and smaller SOC gains than NT. This suggests that, under the modeled conditions, RT is inferior to NT. However this conclusion may not generalize to other forms of reduced tillage, particularly those employing equipment other than a tandem disk.

Based on the carbon sequestration amounts reported in Table 1, approximately 9 million

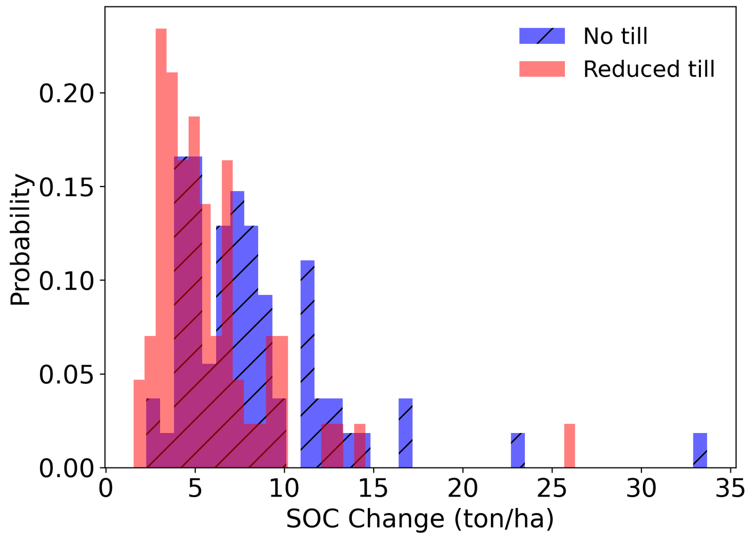

Figure 2: Distribution of SOC increases under no till and reduced tillage practices for corn cultivation across 70 fields. The shaded blue histograms correspond to no till, while the pink histograms represent reduced tillage. Purple regions indicate areas of overlap between the no-till and reduced tillage histograms. Overall, SOC increases are larger under no till than under reduced tillage.

tons of carbon could be sequestered by switching from CT to NT across the five watersheds, which together encompass 2.57 million acres of agricultural land. In comparison, approximately 6.3 million tons of carbon could be sequestered by switching from CT to RT, assuming that all fields within these watersheds currently employ CT. These figures therefore represent the maximum additional sequestration potential achievable under full adoption of NT or RT across all agricultural land in these watersheds.

4.2 Risk Neutral Farmer

This section presents the optimal decisions of a risk-neutral farmer, obtained from solving the Markov decision process described in Section 2. In the model, farmers receive annual payments proportional to the amount of SOC above the baseline level at a rate of m dollars per ton of carbon. In addition to carbon payments, farmers earn profits from crop production. In each period, they choose among CT, NT, and RT, balancing the yield-carbon trade-off to maximize discounted lifetime profits.

Table 1: Average corn yield and SOC outcomes under different tillage practices. Data are obtained from EPIC simulations. Yield loss and SOC gains are reported relative to the conventional tillage. Numbers in the parenthesis denote 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

Figure 3 illustrates optimal decisions for a representative field belonging to hydrology group D. The representative field is defined as the one with average yield, C_o, and C^* values. The figure depicts optimal practice choices as a function of SOC for different carbon payment levels, m. It is observed that for $m = \$15$/ton, the farmer chooses CT at all SOC levels. At such low payment rates, carbon revenues do not offset the associated crop yield losses from NT. For $m = \$20$/ton to \$30/ton, the farmer selects CT for low SOC levels and switches to NT at higher SOC levels [see Figure 3]. For $m \geq \$32$/ton, NT is optimal regardless of SOC. Thus, \$32/ton represents the minimum payment required to induce NT adoption for farmers in hydrology group D. RT is never selected because, under the modeled conditions, it remains inferior to NT.

The corresponding minimum payments required to induce NT adoption equal \$8/ton, \$25/ton, and \$30/ton for hydrology groups A, B, and C, respectively. In these estimates,

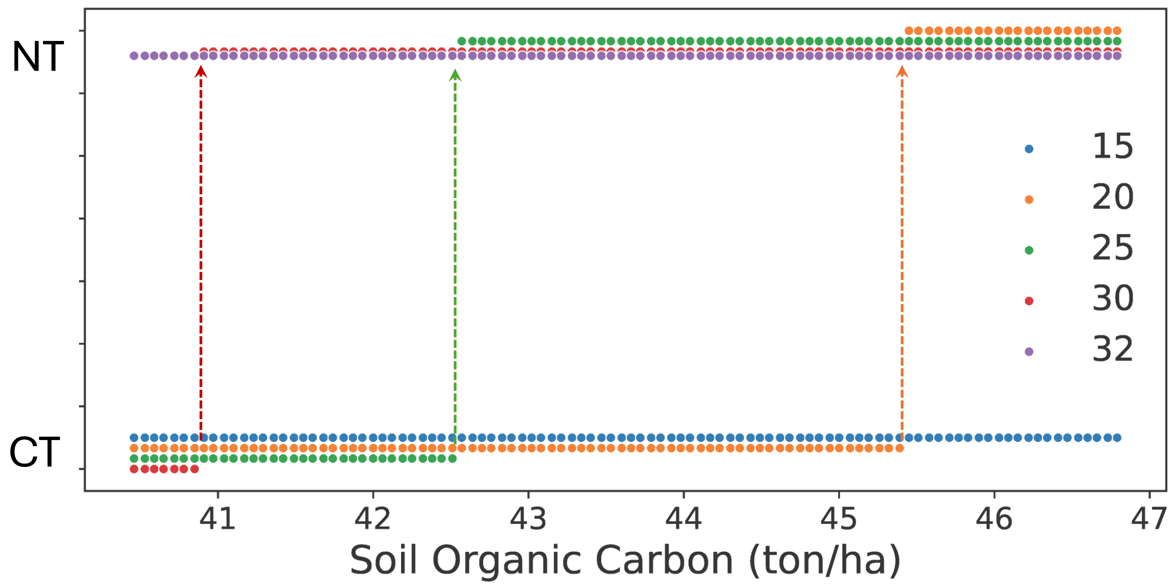

Figure 3: Optimal farmer decision for different carbon payment levels m for a representative field in hydrology group D. The legend reports the value of m in dollars per ton of carbon. Vertical arrows indicate transitions from conventional tillage (CT) to no till (NT). For low values of m, the farmer selects CT; for high values of m, the farmer chooses NT. For intermediate values, the optimal choice between CT and NT depends on the field's SOC level.

the standard deviation of SOC sequestration (and release), σ, is set to 0.2 tons/ha/year. These results suggest that policymakers could implement spatially targeted carbon payment thresholds that reflect soil characteristics. Identifying such thresholds provides guidance on the carbon price range necessary to incentivize conservation practices and to design efficient compensation schemes.

4.2.1 Quantifying the effect of SOC variability on farmer decisions

Even for a risk-neutral farmer, variability in SOC sequestration (and release) influences optimal decisions. Greater variability increases the dispersion of carbon payment outcomes: while higher-than-expected sequestration may yield larger rewards, lower-than-expected sequestration increases the likelihood of revenue shortfalls. This section examines how the minimum carbon payment required to induce adoption of conservation practices, m, varies with the degree of SOC variability. For this analysis, SOC variability is assumed to be identical across all tillage practices: conventional tillage (CT) using moldboard plow, reduced tillage (RT) using tandem disk, and no till (NT). Figure 4 shows that as SOC variability (measured by σ) increases, the required payment level m rises across all hydrology groups. Greater uncertainty in sequestration outcomes therefore requires higher carbon payments to compensate for increased variability in expected returns from conservation practices that entail yield losses.

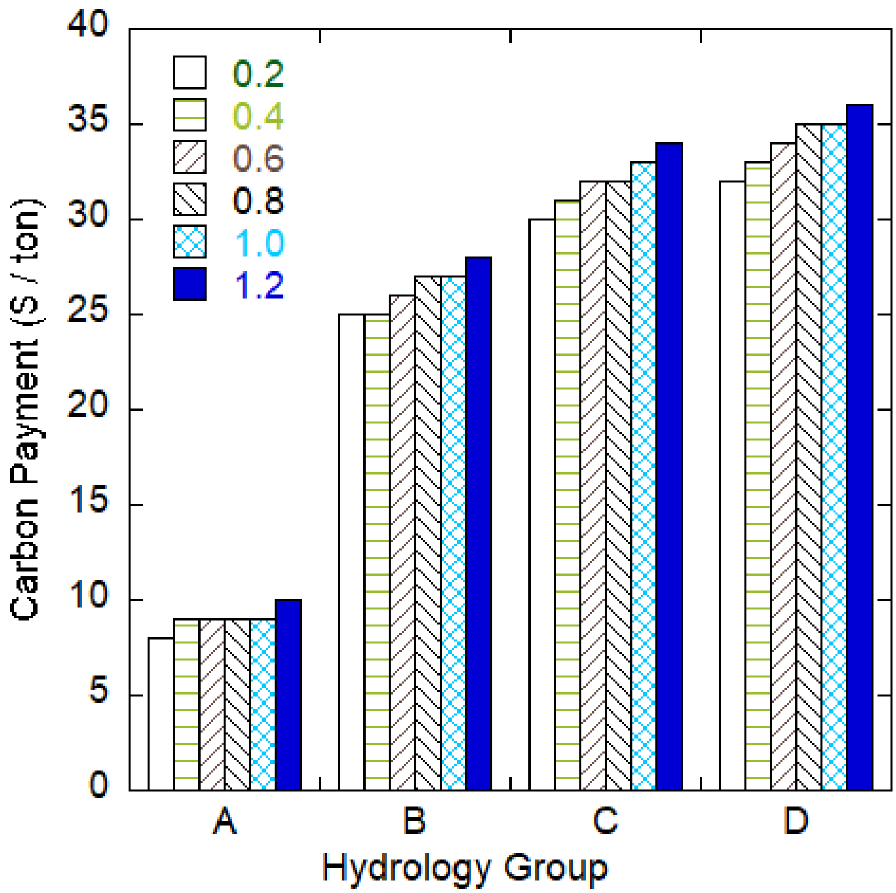

Figure 4: Minimum carbon payment, m, required for farmers to switch from conventional tillage (CT) to no till (NT) across hydrology groups as a function of SOC variability. In these calculations, SOC variability is assumed to be identical for all tillage practices. The required payment m increases with SOC variability.

The analysis next considers how optimal farmer decisions respond to differences in SOC variability across tillage practices. Here, SOC variability under CT is set at 0.1 tons/ha/year and under RT at 0.2 tons/ha/year. In a series of counterfactual simulations, the SOC variability of NT, σ increases up to 2.4 ton/ha/year.

Figure 5 presents optimal decisions for hydrology group D when the carbon payment is fixed at m = \$36/ton. At low SOC levels, farmers choose NT because it offers higher SOC gains and smaller yield losses. When the variability of NT is large, farmers switch from NT to reduced tillage (RT) at moderate SOC levels, even though RT entails larger yield losses and lower SOC gains. This shift occurs because in these simulations, RT is associated with lower variability in carbon sequestration outcomes. At intermediate SOC levels, farmers prefer a more predictable carbon trajectory, despite reduced crop profits. This figure also illustrates decisions when the NT σ=2.4 ton/ha/year is and m = \$79/ton. At higher payment levels, RT is chosen for a wider range of SOC values. As SOC approaches its saturation level, farmers opt for NT because the saturation level (C^*) under NT exceeds that under RT. Figure 6 illustrates the farmer's optimal management choices as a function of SOC variability under NT (σ), when carbon payments are relatively low (m = \$33/ton) for the hydrology group D. At low SOC levels, the farmer optimally selects CT. Under these conditions, carbon payments are insufficient to offset the yield losses associated with conservation practices. As SOC rises, NT becomes optimal. At intermediate SOC levels, the farmer switches to RT due to its lower variability relative to NT. For high SOC stocks, the farmer returns to NT because the carbon saturation level under NT exceeds that under RT.

4.3 Intertemporal Preferences and Conservation Adoption

This section examines optimal management decisions under concave (CRRA) utility, allowing the farmer to value intertemporal consumption smoothing ($\gamma > 0$). In each period, the farmer chooses a bundle of management practices and a level of consumption, which determines the capital carried into the next period. To simplify the intertemporal allocation problem, the rate of return on capital (r) is set equal to $1/\beta - 1$. Under this condition, the Euler equation (equation 12) implies that in the absence of switching between management

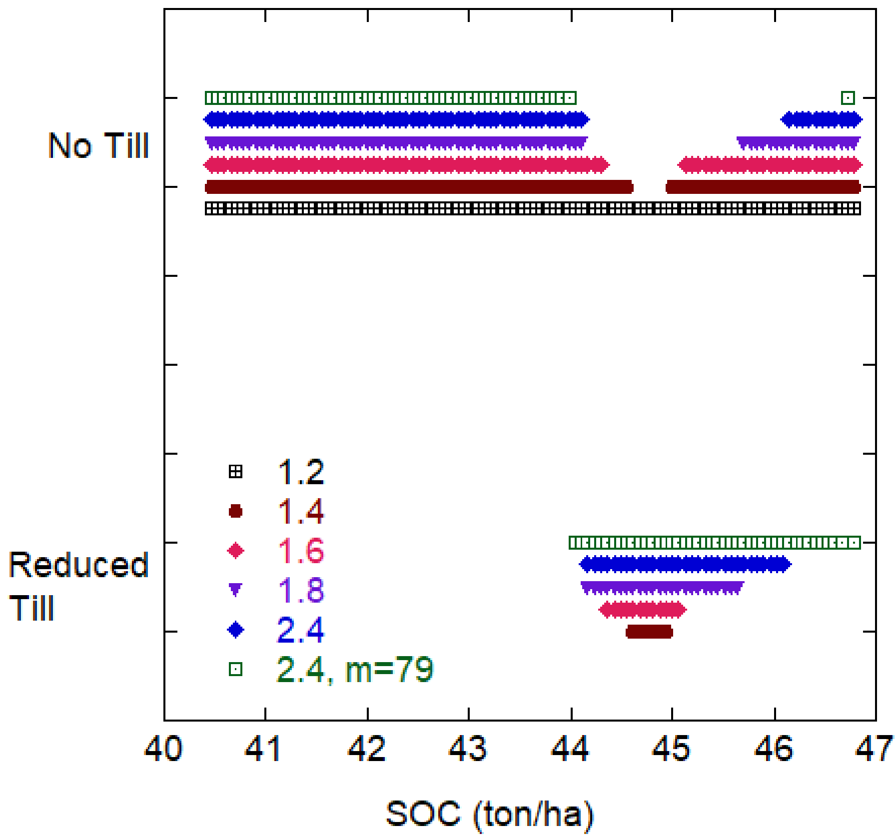

Figure 5: Optimal farmer behavior as a function of SOC variability σ under no till (NT) for hydrology group D with m = \$36/ton/y. As the SOC sequestration under NT becomes more variable, farmers switch to reduced tillage (RT) at intermediate SOC levels to limit the risk of carbon payment shortfalls. At higher SOC levels, farmers return to NT.

practices and when $k > 0$, consumption is smoothed over time.

With $\gamma > 0$, the value function becomes two-dimensional, depending on both soil carbon C_t and capital k_t. Solving for this value function is computationally intensive. To maintain tractability, this section abstracts from variability in crop yields and SOC realizations and solves the problem under deterministic transitions. The resulting Markov decision process is solved numerically using value function iteration for different values of the risk-aversion parameter γ. For each γ, carbon payment levels m vary in increments of \$5/ton to identify the minimum payment required to induce adoption of NT practice.

Figure 7 illustrates how the threshold carbon payment m required to incentivize NT varies with the degree of elasticity of intertemporal substitution, γ. For every hydrology

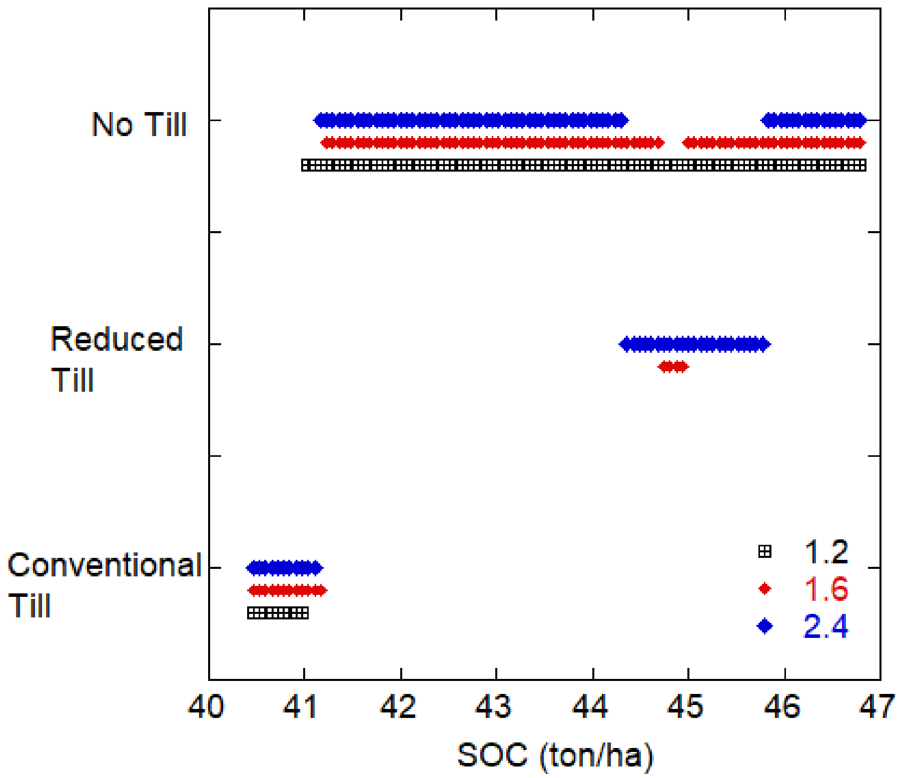

Figure 6: Optimal farmer behavior as a function of SOC variability σ under no till for the hydrology group D with $m = \$33$/ton/y. For low SOC levels, farmers opt for conventional tillage. For intermediate SOC values, farmers choose no till (NT). For higher SOC values, farmers switch to reduced tillage (RT) because of its lower variability. At highest SOC levels, farmers return to NT.

group, the required payment m increases with γ. A farmer with higher γ places greater weight on consumption smoothing over time. Because conservation practices reduce current income in exchange for future carbon benefits, higher compensation is necessary to induce adoption as the elasticity of intertemporal substitution increases.

It is informative to examine the farmer's optimal consumption decisions when adopting NT, since profits increase over time as the SOC accumulates. Consider the parameter values $\gamma = 1.45$, hydrology group A, and $m = \$40/ton$ with an initial capital of $k_o = \$1000$. For this parameter combination, the farmer optimally chooses NT (see Figure 7). Figure 8 shows that SOC increases over time, and Figure 9 illustrates the corresponding increase in profits. The results illustrate a clear intertemporal mechanism underlying the farmer's decision to adopt NT. Because carbon payments are tied to the SOC stock, NT generates a

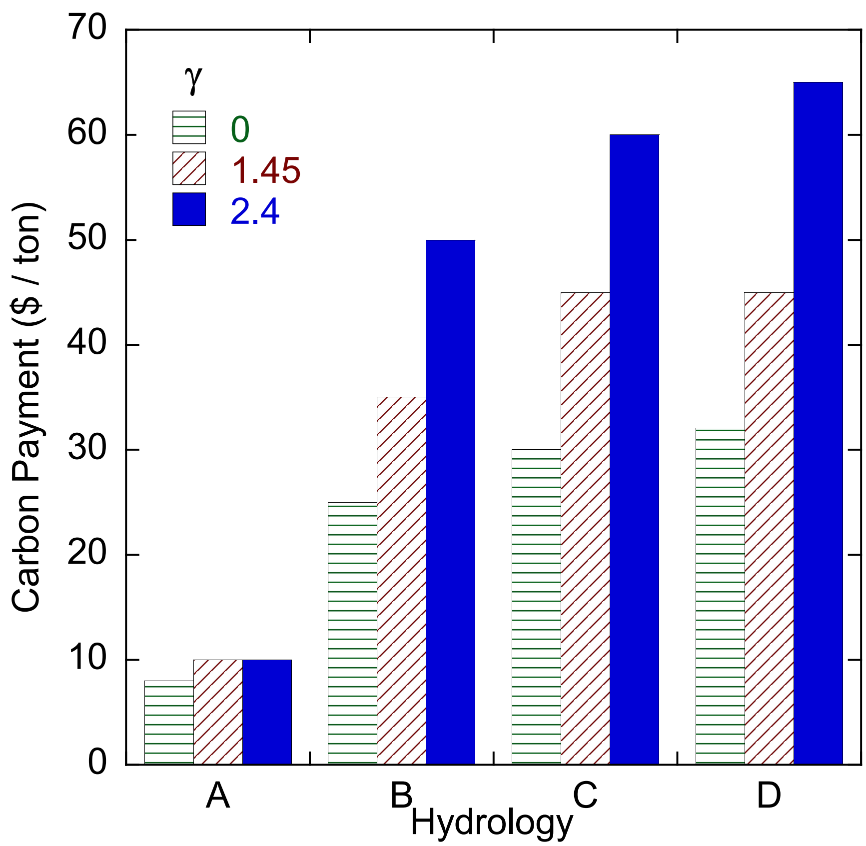

Figure 7: Minimum carbon payment m required to induce adoption of no till (NT) as function of intertemporal elasticity, γ, across hydrology groups. For every hydrology group, m increases with γ.

growing asset over time: as SOC accumulates, carbon revenues rise correspondingly. Thus, adoption shifts income toward the future, creating a dynamic income profile rather than an immediate gain. A forward-looking farmer internalizes this growth in future returns and smooths consumption accordingly, drawing down initial capital in the early years when profits are relatively low and anticipating higher income as SOC accumulates. In this sense, the SOC stock functions as an appreciating productive asset, and the farmer's behavior reflects standard intertemporal optimization: temporary reductions in current net returns are accepted in exchange for higher future income streams.

Figure 10 presents the time paths of capital, consumption, and profits for a representative farmer with the same parameters ($\gamma = 1.45$, $m = 40$, initial capital of $1000) but belonging to hydrology group B. The farmer optimally chooses NT in this case as well. However, initial

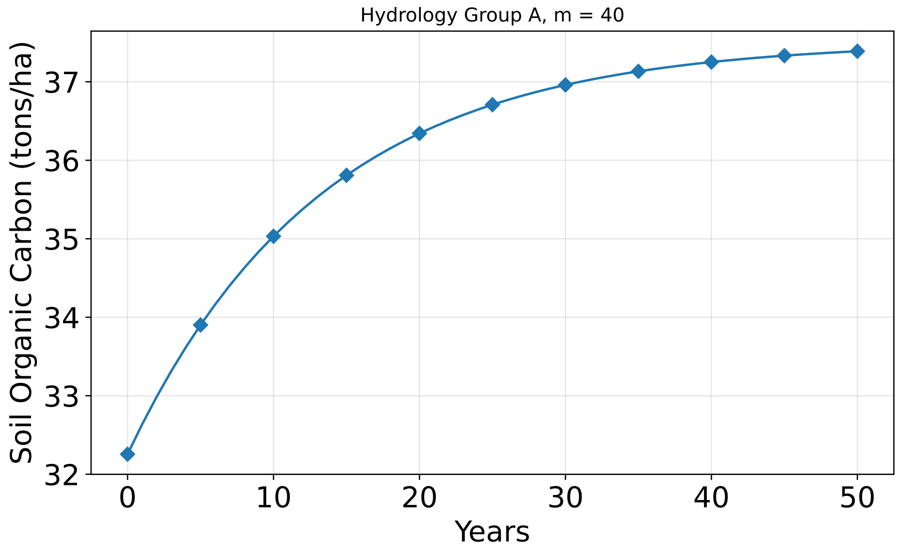

Figure 8: Time path of soil organic carbon (SOC) for a representative field in hydrology group A when the farmer selects no till (NT). SOC increases monotonically over time. Results are shown for $\gamma = 1.45$ and $m = 40$.

profits are lower than those for hydrology group A due to the larger yield losses associated with NT adoption (Table 1). Consequently, the farmer relies more heavily on available capital to smooth consumption, leading to faster capital depletion.

Lastly, Figure 11 shows the time paths of capital, consumption, and profits for a representative farmer with the same parameters ($\gamma = 1.45$, $m = 40$, initial capital of \$1000) but in hydrology group C. In this case, the farmer optimally chooses CT, so the SOC stock remains constant. Profits come solely from crop production and therefore remain steady over time. The farmer sustains high consumption in the early years by drawing on available capital. Once capital is partially depleted, the farmer smooths consumption by consuming only the interest on invested capital, maintaining a constant capital stock thereafter.

5 Conclusions

This chapter investigates how farmers make long-term decisions about adopting soil conservation practices, such as no-till (NT) and reduced tillage (RT), under a framework

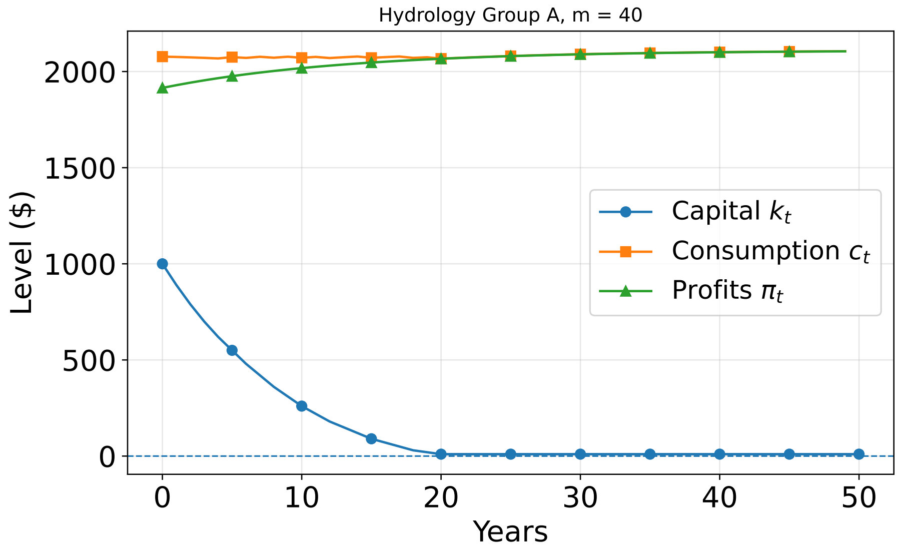

Figure 9: Time paths of capital, consumption, and profits of a representative farmer with $\gamma = 1.45$, hydrology group A, $m = 40$, starting with an initial capital of \$1000. Profits are initially low due to low SOC levels but increase over time as SOC rises. The farmer smooths consumption over time by drawing on available capital during the early years.

where soil organic carbon (SOC) accumulation generates additional payments. Using an infinite-horizon dynamic optimization model, the study quantifies the carbon payment levels required to incentivize adoption of conservation practices across different soil types.

Results indicate that the minimum carbon payments needed to encourage adoption vary widely by soil drainage characteristics, ranging from \$8/ton C/year for well-drained soils (hydrology group A) to \$32/ton C/year for poorly drained soils (hydrology group D). This finding highlights the importance of spatially targeted carbon payment schemes to efficiently promote soil carbon sequestration.

The study conducts counterfactual simulations showing that variability in SOC accumulation influences farmer decisions, even under risk-neutrality. As the uncertainty in SOC sequestration increases, higher carbon payments become necessary to offset the risk of lower-than-expected returns. When variability under NT exceeds that under RT, farmers may prefer RT for fields with intermediate SOC levels, despite its lower expected yield and SOC gains. This occurs because, under the modeled conditions, RT delivers more predictable carbon payment. These findings demonstrate that outcome variability alone, independent

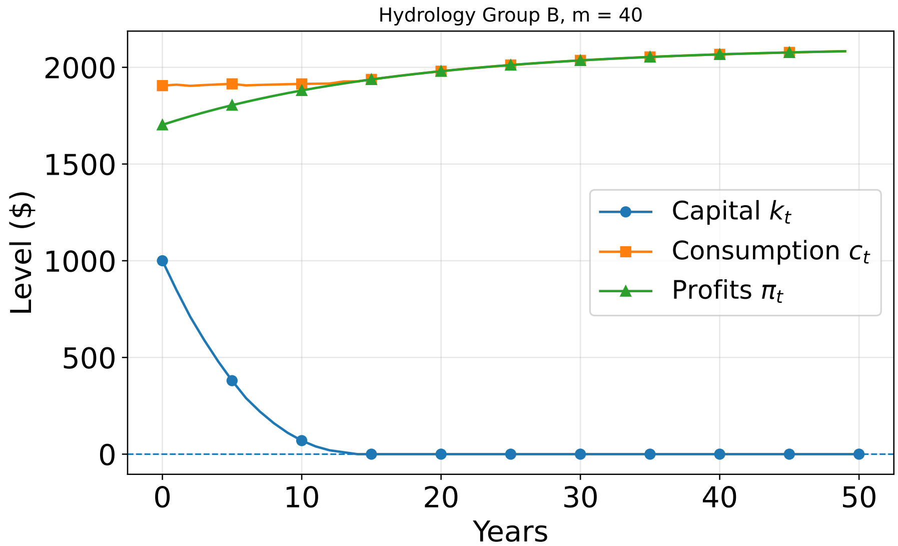

Figure 10: Time paths of capital, consumption, and profits of a representative farmer with $\gamma = 1.45$, hydrology group B, $m = 40$, starting with a capital of \$1000. Profits are initially low due to low SOC levels but increase over time as SOC rises. The farmer smooths consumption over time by drawing on available capital during the early years.

of risk aversion, can alter optimal management practices.

For farmers with concave (isoelastic) utility, the carbon payments required to induce conservation adoption increase with the degree of intertemporal elasticity of consumption. Farmers who prioritize consumption smoothing over time demand higher compensation to offset short-term income reductions associated with conservation practices. In these cases, farmers draw on available capital to sustain consumption in the early years when SOC stocks and associated carbon revenues are remain low.

Overall, the chapter shows that both the spatial heterogeneity and variability in carbon sequestration outcomes shape optimal adoption of conservation practices. These results have direct implications for the design of payment-for-ecosystem-services programs, suggesting that spatially targeted, risk-adjusted carbon payments can promote adoption and enhance long-term soil carbon sequestration.

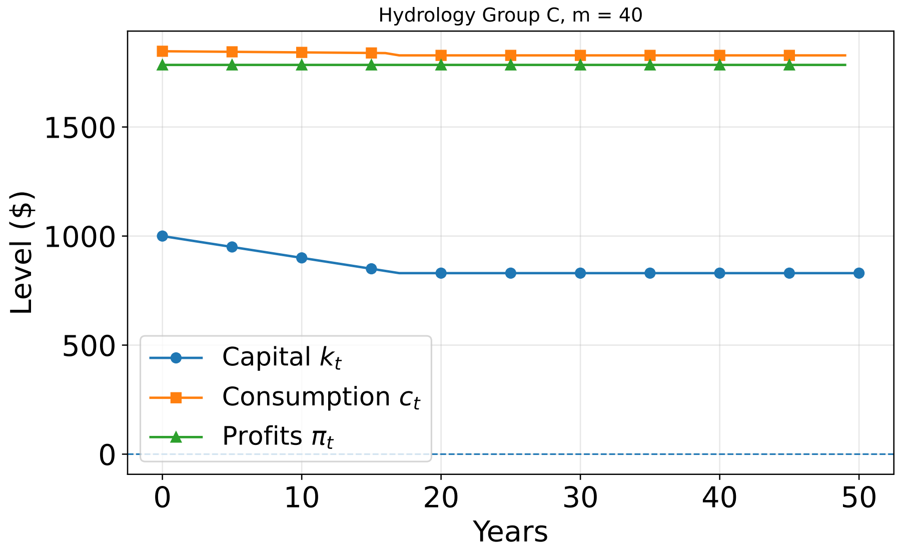

Figure 11: Time paths of capital, consumption, and profits of a representative farmer with $\gamma = 1.45$, hydrology group C, $m = 40$, starting with a capital of \$1000. Profits remain constant over time as the farmer adopts conventional tillage and therefore the carbon stock does not change. The farmer draws from available capital during the early years.

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