DISSERTATION

CLIMATE CHANGE, SOIL CARBON SEQUESTRATION, AND AGRICULTURAL TECHNOLOGY ADOPTION: THE CASE OF DEEPER ROOT SYSTEM CORN ADOPTION AND DIFFUSION IN THE U.S. CORN BELT

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ABSTRACT

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Traditional agricultural practices and land use changes have resulted in greenhouse gas emissions back into the atmosphere, which negatively contributes to climate change. Traditional practices also reduce soil organic matter including soil carbon which is essential for soil health, maintenance of soil biological processes, and environmental sustainability. Currently, a range of agricultural conservation practices has come to be recommended and incentivized for soil carbon sequestration by either increasing carbon inputs and/or reducing carbon losses. These include practices such as reduced tillage, cover cropping, and crop rotations. Although private carbon markets have taken the initiative to provide incentive payments for carbon sequestration in agriculture, the adoption of SCS practices can be hindered by different socioeconomic, farm operational, and environmental constraints. In addition to currently recommended soil management practices, new crop genetic innovations, including perennial grain crops and annual crops, such as corn, with larger root systems or deep root traits are emerging as additional examples of SCS frontier technologies. The first chapter of this dissertation utilizes a joint adoption model to hypothetically examine the impact of socioeconomic, environmental, and farm variables on the probability of adopting either or both of currently recommended SCS practices and these novel genetic innovations, such as deeper root corn varieties. Moreover, deeper root system traits are expected to maintain yields

under drought conditions. Deeper root system hybrids are also expected to be an effective agricultural technology for maintaining soil health as they can reduce soil erosion and increase soil organic matter. Existing drought tolerant (DT) corn varieties that have been commercially marketed for more than 10 years exhibit some of these same characteristics. Therefore, the adoption of existing DT hybrids is likely a good indication of the potential for the adoption of hybrids with further enhanced root systems. In the second chapter, we use state-level and field-level data for corn planted in the United States Corn Belt to examine the influence of climate change, soil characteristics, and production practices in the decision to adopt DT varieties. Seed industry data indicates that 44 percent of Corn Belt planted corn acres were allocated to a DT variety in 2021 and 58 percent were planted to DT in 2022. Results suggest that exposure to recent years' drought is a significant determinant of the adoption of DT corn. DT corn is more likely to be adopted in non-irrigated fields. We find that western Corn Belt states are more likely to increase the share of DT corn acres compared to eastern and central Corn Belt states, associated with lower precipitation values and higher drought severity. Thus, deeper root varieties are likely to be more attractive to farmers in western more arid regions of the Corn Belt, where associated soil carbon benefits of deeper root varieties are likely to be more limited. Anticipating that enhanced deeper root corn hybrids with public benefits may come to be treated as a conservation practice included under incentive payment programs, and understanding that soil carbon potential is heterogeneous, in the third chapter we consider the question of spatial targeting of payments. We develop three per acre payment scenarios under the benefit optimization approach to estimate and compare the metric tons of carbon inset under an optimal cropland acre enrolled in a carbon incentive program. The study uses cross section data for counties in the United States Corn Belt, a region with the largest number of productive cropland acres and higher potential carbon sequestration rates

compared to other regions across the United States. Results show that if the carbon incentive program is designed to target the adoption of SCS practices that result in high, medium, and low SCS rates respectively, then we can expect that about 32, 24, and 19 million metric tons of carbon can be sequestered in Corn Belt croplands annually.

Keywords: Soil carbon sequestration (SCS), agricultural technology adoption, conservation practices, carbon market, deeper root, corn, joint adoption decision, DT corn, drought severity, spatial targeting, benefit maximization, acreage maximization.

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INTRODUCTION

Climate change due to greenhouse gas (GHG) emissions, characterized by long-term shifts in the average temperature and increasing variation in the annual and seasonal precipitation, results in decreasing agricultural productivity, particularly due to water scarcity and drought risk (Ortiz-Bobea, Knippenberg and Chambers 2018; IPCC 2014). According to NASA (2023), carbon dioxide emissions have increased from 365 parts per million in 2002 to 420 parts per million in 2022. Agricultural activities such as crop cultivation and livestock account for 50.3 percent and 43.8 percent of the U.S. GHG emissions in 2021, respectively (U.S.EPA 2021). Consequently, the increased concentration of GHGs in the atmosphere resulted in the rise of global average temperature by 2.03 °F (1.13 ℃) and 3 °F (1.5 ℃) in 2022 and 2023, respectively (IPCC 2014; NASA 2023, NOAA 2023). Such changes can affect all forms of life including those involved in agriculture, and agricultural production practices which are expected to be highly variable with water availability, temperature levels, and soil health. Research shows that agricultural soils can play a significant role in carbon sequestration or carbon dioxide (CO_2) abatement, as well as reductions in other GHGs such as nitrous oxides (N_2O), if managed properly. According to FAO (2023), with the implementation of soil management practices that generate a 20 percent increase in soil carbon inputs, the resulting soil organic carbon sequestration rate ranges between 0.02 to 0.6 tons of carbon per hectare per year (at 0-30 cm soil depth) across the U.S. Corn Belt which are some of the highest rates of soil carbon sequestration in North America (see Figure 1). The sequestration rate can vary from field to field or county to county due to geographical, climatic, and environmental factors in addition to the type of agricultural production practices.

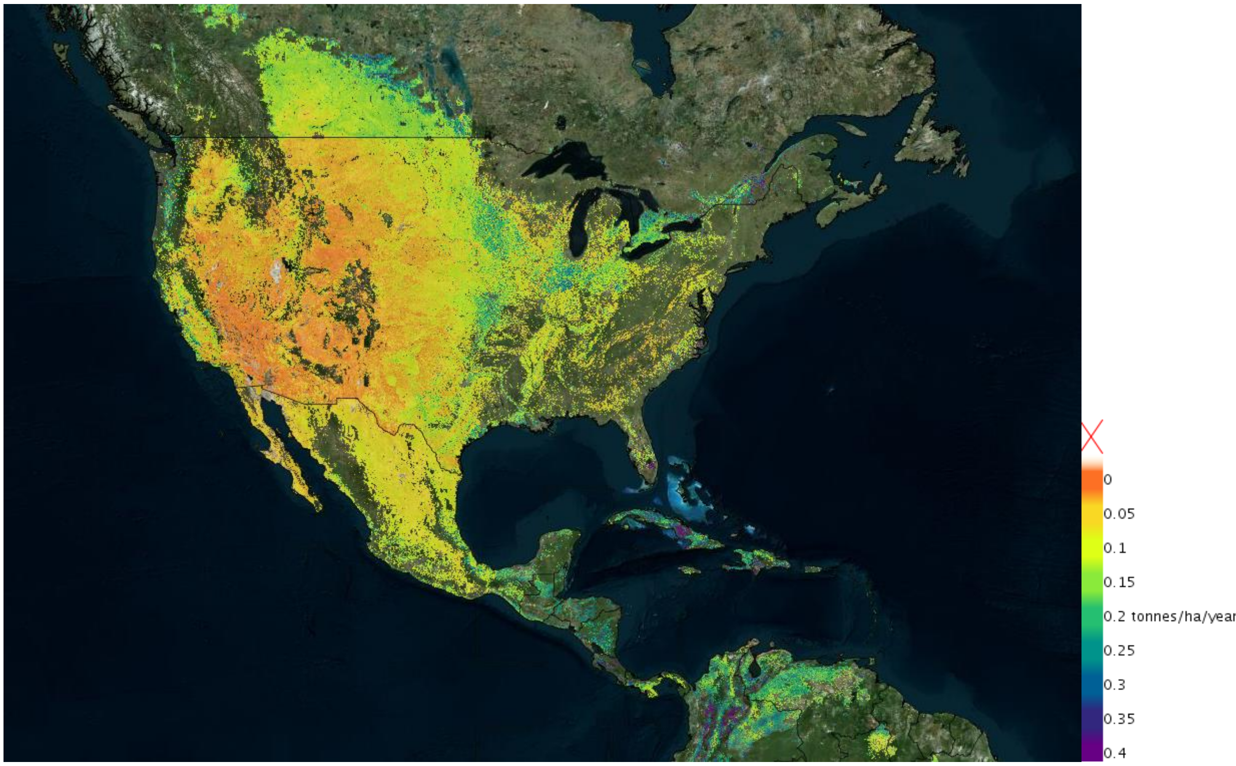

Figure 1: Soil organic carbon sequestration rate under soil management practices. Source: FAO. Global soil information system (GLOSIS), 2023. Note: The sequestration rates represent annual average soil carbon sequestration rates when implementing soil management practices that generate a 20% increase in carbon inputs at 0-30 soil depth and compared to business-as-usual management.

Research in plant breeding and genetic engineering has for decades led to the development of modified corn varieties that solve important production problems such as insect and weed pests and at the same time can help maintain soil health by reducing soil disturbance (i.e. enabling low or no-till). Recently there is a research effort to develop a new genetically improved corn varieties with deeper root system architecture and responsiveness to changes in the environment, including water, nitrogen, and other plant stressors (Lynch 2022; Raza et al. 2023; Zhe et al. 2023). The enhanced, larger and deeper root systems in future hybrids that we will refer to as deeper rooted corn varieties are considered a "frontier" technology since they are still in precommercial phases of research and development, and breeding programs (see Paustian et al. 2019). Yet they promise to sequester soil carbon, contribute to water conservation, improve nitrogen uptake, and help maintain yields under drought conditions. Such a frontier technology typically requires years of additional research and development (R&D), field testing, market placement, and provision of adoption incentives to convince farmers to adopt the technology.

Potentially, farmers can both gain private benefits and generate public benefits when adopting deeper root corn hybrids. Private benefits are the gains observed by farmers or landowners that consist of higher yields or at least reduced yield losses in the short term and improvements in soil quality, and thus the soil's holding capacity for water, which can increase or protect yields over the long term. Public or social welfare benefits are gained in the form of regional water and land quality enhancements and reductions in GHG emissions into the atmosphere, thus mitigating the impacts of climate change. Farmers generally weigh private benefits over public benefits when evaluating practice adoption decisions (Chouinard et al. 2008). Farmers are more likely to adopt deeper root corn if it turns out to be higher yielding and thereby economically profitable. However, realization of the public-good benefits depends upon the extent to which commercial farmers adopt these varieties. The shift to deeper rooted corn involves changes in the corn production function due to changes in the specific input requirements, compared to non-deep root system corn, including irrigation, fertilizer, pesticides, other chemicals, etc., which influence the adoption decision by corn growers. Thus, deeper root corn with genetic improvements that result in water use efficiencies, soil health improvements, and carbon sequestration will be proportional to the size of the acreage over which they are adopted, and that acreage potential is very large in corn.

Corn is a highly sensitive crop to high temperatures and severe drought (Roberts and Schlenker 2011; McFadden, Smith and Wallander 2022). From an economic perspective, corn is among the most important crops for the United States. Due to worldwide increasing demand for corn and soybean, there has been an observed increasing concentration of the U.S. principal crop acres in corn and soybean production, where the share of corn harvested acres from total U.S. crop harvest has increased from 22 percent in 1965 to reach 30 percent in 2021 (Zulauf et al., 2023). By 2022, the share of total corn planted acreage in the U.S. reached about 42 percent of total planted cropland area (USDA-NASS 2022). Additionally, the farm value of corn grain was about $91 billion in 2022 (USDA-ERS 2022) and it comes only after soybean in term of exported agricultural commodities, accounting for about 18.7 and 13 billion dollars in agricultural exports in 2022 and 2023, respectively (U.S. FAS 2023). All such economic contributions of corn production to gross domestic product (GDP) and corn growers indicates that the adoption of deeper root system varieties at large scale has significant potential to positively impact farmer welfare and environment.

It is essential to present planting characteristics and requirements of a corn variety and to design effective incentives as farmers make adoption decisions. Corn is planted primally in the Corn Belt in croplands that are generally characterized with high potential for soil carbon sequestration (SCS) (see Figure 1). The growing characteristics of corn in the Corn Belt has been described by Neild and Newman (1987). The corn growing season is May-September; however, actual planting times may differ from one geographic area to another. Planting occurs in late April, May, or early June. Silking[1] is achieved by July and maturity is achieved by September or October depending upon planting date and variety. Average maturity time for hybrid corn is 130-150 days. Moreover, corn requires at least 25 inches (60 cm) of water annually. Sufficient moisture is essential during the planting stage. Water requirements are met either from rainfall, water stored in soil, or by irrigation. Temperature requirement varies for corn growth with growth range limit from 41-95 °F (5-35 °C) while the survival range limit is 32-112 °F (0-45 °C). However, the

[1] Silking is the reproductive phase of ear formation and grain fill.

temperature range of 62-91 °F (17-33 °C) is the best for optimal corn growth. For the entire growing season, the average temperature should range from 68 °F to 73 °F (20-22 °C) to get fully mature corn with high yield. Such characteristics including temperature, water requirements, maturity per hybrid, and production practices are important information for farmers to decide on which corn variety to adopt.

Currently, the most common corn varieties on the market are single trait or multiple trait (stacked gene) genetically modified (GM) hybrids and conventional (non-GM) hybrids. Insect resident (Bt), herbicide tolerant (HT), and drought tolerant (DT) varieties are the most common and widely adopted corn varieties (see Figure 2 in chapter 2). A combination of two or more traits are called stacked genes (SG). Bt varieties can overcome pest problems and reduce the doses of toxic pesticides/insecticides released into the environment, which can kill beneficial insects such as honeybees. HT hybrid is used in combination with specific herbicides to control weeds and results in higher corn yield, reduces the number of sprays in the season, reduces soil compaction, reduces the use of other more toxic herbicides, and supports the use of no-tillage or reduced-tillage systems (Vencill et al. 2012). DT hybrid improves water use efficiency and can maintain yield under drought conditions. Commercially released DT varieties consist of both GM and non-GM hybrids. GM-DT hybrids such as Bayer's DroughtGuard express an inserted gene for cold shock protein that helps the corn plant to maintain normal physiology and protein production even during drought stress conditions (Bayer Crop Science, 2024). Non-GM DT hybrids, such as Pioneer's AQUAmax hybrids, incorporate a number of different traits, including improved root systems (Pioneer, 2024). DT corn was first adopted by U.S. corn growers in 2012, and the adoption level has increased steadily over time (see Figure 3 in chapter 2). However, future varieties such as enhanced deeper root corn may offer significant environmental public-good benefits, including water use efficiencies and soil carbon sequestration, and we do not expect all corn growers to respond to those public benefits (Chouinard et al, 2008). Therefore, the overarching research questions addressed in this dissertation are to what extent are farmers adopting enhanced corn varieties under private incentives and how can we improve the incentives for farmers to generate public goods that result from increasing soil carbon stocks and/or reducing greenhouse gasses (GHGs).

The first chapter answers the questions of how deeper root corn hybrids can be beneficial to farmers and environment, how farmers can be incentivized to support public goods, and what are the factors influencing farmers' decision to adopt either or both, accepted soil carbon sequestration (SCS) practices and enhanced deeper root corn hybrids. The chapter explores the potential interactions or trade-offs between more widely accepted SCS practices and what are still considered SCS frontier technologies (e.g. deeper root corn, biochar). It examines different types of carbon sequestration projects as well as current challenges to achieving implementation of those projects. This chapter contributes to the literature by developing conceptual framework to examine joint adoption decision of deeper root corn and other SCS practices, including a range of hypotheses about the marginal effects of changes in different farm, farmer, and environmental factors in the complementarity between deeper rooted hybrids and other SCS practices.

Because deeper root corn hybrids are still under development and are not yet commercially available, in the second chapter we analyze already commercialized DT corn varieties which have some common characteristics, to understand how farmers respond to those traits. The second chapter answers question about what factors influence farmers' decisions to adopt DT corn. First, we use state-level panel data for 2011 to 2022 to explore the diffusion of DT corn and to identify what factors are associated with the spread of DT corn in the states of the U.S. Corn Belt. Next, we use field-level production data for just the year 2022 to address the individual adoption decision and explore the influence of climate, soil, and other production factors on field-level adoption decision. Evaluating the historical and current adoption behaviour and emerging trends of DT corn can give an indication of how likely corn growers are to accept new enhancing deeper root system corn varieties with important public benefits.

Finally, anticipating that enhanced deeper root corn varieties with public benefits may come to be treated as a conservation practice included under incentive payment programs, and understanding that soil carbon potential is heterogeneous, we consider the question of spatial targeting of payments. What would be the highest benefit of soil carbon sequestration with a given county annual conservation budgets? In the third chapter, we utilize data from private carbon markets on soil carbon sequestration rates and carbon market prices to develop different payment scenarios under different targeting approaches.

1. General challenges for the potential widespread diffusion of SCS technology among U.S. corn growers

The adoption and diffusion of a newly emerging agricultural technology can be constrained by lack of incentives for environmental gains, low or uncertain profitability, lack of access to technical and financial support, and lack of familiarity and knowledge of how to implement the technology. The first constraint to the diffusion of a SCS technology is that the environmental outcomes are not measured or clearly observed by farmers. While farmers with social or conservation goals may be willing to adopt practices that could lower profitability, even such farmers need to observe the environmental benefits generated by the technology. Secondly, the long-time scale that is required to observe the benefits of carbon sequestered and yields improved can impact adoption. Implementation of practices can take many years to result in the ultimate or steady state of environmental benefit, such as reduced soil erosion, improved water and soil quality, and reduced GHG emissions.

However, the constraints to adoption caused by uncertainty about environmental impacts and the time scale needed to observe the effects can be overcome by farmers' participation in incentive programs and access to trials and technical assistance programs (Nowak 1992). Technical incentive programs and extension services can spread knowledge and awareness about practice implementation and outcomes. Also, regional trials of new technology help to reduce uncertainty about technology failures. Trails helps growers learn required skills for practice implementation, observe the outcomes, and avoid financial losses in case of failure or unexpected outcomes. An initial trail of technology on a small plot can influence farmers to then adopt on part or all of their fields, depending on trial results and farmer risk aversion. However, private trials can be costly and time-consuming, as farmers are required to purchase the new inputs and know the appropriate production practices. Thus, financial and technical support can increase the initial trial rate and reduce the risk of new technology failure.

Farmers are expected to be more willing to accept a new technology given the similarity of the technology to existing production practices. For example, in the case of biochar, farmers already use soil amendments to improve soil nutrients and crop growth, such as compost and manure, wood ash, leaf mulch, and poultry litter. And for example, in the case of enhanced deeper root corn, farmers are already adopting DT-corn hybrids, some of which include deeper root systems (such as Pioneer AQUAmax). About 44 percent of U.S. Corn Belt corn acres were planted with DT varieties in 2021 (see Figure 3 in chapter 2). Therefore, a decision to change corn varieties can be relatively easy to accept for farmers who already tried DT varieties.

In general, the diffusion of SCS technologies is expected to be highly influenced by the level of farmers' concern and interest in environmental quality. Growers can have individual goals ranging from only increasing farm profitability to also serving social interests by, for example, reducing land degradation and improving soil quality (Chouinard et al. 2008). But as we have noted, deeper root corn, with its complex portfolio of characteristics including soil carbon sequestration traits, drought tolerance traits, nitrogen use efficiency, and yield-enhancing benefits, can meet both private objectives of individual corn growers and public objectives for society. Thus, the questions of its adoption of deeper root system hybrids need to consider both.

2. Overview from literature of technology adoption in agriculture

The continuous advancement in agricultural innovation was a result of the growing demand for efficient utilization of scarce natural and capital resources to provide a healthy and safe food supply for the growing world population and to reduce the effects of environmental degradation and climate change. The introduction of agricultural technology requires a change in the production function either through increasing output level (e.g., quantity and or quality enhancement) while using the same input level or producing the same output level with fewer inputs (Just, Schmitz and Zilberman 1979). Agricultural technology refers to the modern equipment and materials, new production and management processes, and agricultural inputs that could positively impact agricultural productivity, farmer welfare, food security, and environmental sustainability (Ogundari and Bolarinwa 2018; Ruzzante, Labarta and Bilton 2021). Sunding and Zilberman (2001) provide examples for classifying agricultural technology, one is as embodied (e.g., new seed varieties) and non-embodied (e.g., irrigation techniques) technology into products. Another classification was according to the form of innovation which included mechanical innovations (e.g., new tractors), chemical innovations (e.g., new fertilizers), agronomic innovations (e.g., new production management practices), biological innovations (e.g., new seed varieties), or biotechnological innovations (e.g., computer technology). Also, modern agricultural technology and innovations can be categorized according to their impacts on the economy, farmers, consumers, and environments, such as yield maximizing, cost-minimizing, quality enhancing, risk-reducing, environmental protection, water use efficiency, and shelf-life enhancing (Zilberman et al. 2014). Ruzzante, Labarta and Bilton (2021) in their meat analysis study conclude that studies of the impact of adoption and diffusion of natural resource management and conservation practices, chemical inputs, improved crop varieties, material, and infrastructure; were the main agricultural innovations that receive significant consideration in the academic area.

Literature on technology and innovation progress categorizes technological changes into two main processes: innovation and diffusion of new technology. Theoretical and empirical adoption models attempt to identify the structure of technology adoption and spread of that technology, characterize adopter vs. nonadopter behavior, explain the role of distinct factors and characteristics in the adoption decision, rate and pattern of diffusion, and evaluate adoption behavior at static and dynamic settings.

Early studies on technology diffusion use epidemic spread models to address the adoption decision and how rapidly the innovation spread among firms. Epidemic or logistic models assume that the transfer of information and knowledge among the population will speed the diffusion of innovation (Griliches 1957; Mahajan and Peterson 1985; Mansfield 1961). Griliches (1957) uses a logistic trend function to model the diffusion rate of hybrid corn varieties among 31 states in the United States. He concludes that the adoption function is increasing with time and has an -S-shape. The S-shape curve shows the potential adopters and marginal diffusion rate over time. During the early stage of innovation, only a small rate of the population adopts the technology, over time, the adoption rate increases to reach a saturation point with the highest proportion of the population making adoption decisions, and as other modern technologies emerge the adoption rate declines. In addition, Mansfield (1961) model relies on information transfer to explain the process of technology imitation among four industries (coal, iron and steel, brewing, and railroad) using twelve innovations. He confirms that the adoption rate is S-shaped over time. However, such models were unsatisfactory in explaining the technology diffusion rate as they ignored the differences between adopters, assumed identical adoption behavior, and did not account for the possibility of not adopting given knowledge about the technology.

More recent models follow Just and Zilberman (1983) to account for the variation among adopters by including land size, credit availability, human capital, and risk aversion in adoption and diffusion models. Just and Zilberman (1983) assume that farmers will adopt the new technology with critical land size. They account for the decline in fixed and variable costs over time due to the learning-by-doing process, which reduces critical land size. The model results in a bell-shaped land size frequency distribution of adoption. Another model by Just and Zilberman (1988) address the effects of agricultural growth policies (e.g., credit funding enhancement, credit subsidies, input and output subsidies, and fixed cost subsidies) on income distribution. Such policies are found to encourage technology adoption and vary with farm size, risk preferences, and credit availability. Similarly, Feder and O'Mara (1981) confirm that farm size, credit availability, and working capital are important sources of heterogeneity in determining farmer adoption behavior of high-yield crop varieties.

Agricultural technology adoption decision includes two different decision stages: whether to adopt or not to adopt the new technology and then to decide the share of land allocated to the new technology. Empirically, individual adoption behavior has been modelled as a discrete choice, whether a farmer adopts the innovation or not at a certain time; or as a continuous choice to estimate the proportion of farmland share allocated to the new technology or to what extent the modern technology is used. For dichotomous or binary choice models (e.g., logit or probit), the literature assumes that a farmer's decision to adopt the technology is influenced by multiple factors, including financially driven desires to increase revenues and reduce costs. Conceptually, a farmer will choose to adopt if the utility of adopting the technology gives higher net farm income or profit (π) compared to the utility of not adopting, that is, $U_a^*(\pi) > U_{not}^*(\pi)$. While the payoff from adopting technology is unknown, i.e., $U_a^*(\pi)$ cannot be observed by the researcher, the adoption choice is observed and can be modeled using a binary choice model.

$$y_i = \begin{cases} 1, & if\ U_i = U_a^*(\pi) - U_{not}^*(\pi) \geq 0 \\ 0, & otherwise \end{cases}$$

Where, y_i is the observed adoption behavior of farmer i. Farmer utility function is unobserved, and it is assumed to be a linear function of variables (X), that influence technology adoption, $U_i = \beta X + \varepsilon_i$. For the choice analysis between a group of combined or interrelated technologies (technology package), Multinomial logit regressions were used to evaluate the adoption decision (e.g., Amankwah 2021; Fisher et al. 2015; Khonje et al. 2018).

Another approach to evaluate adoption behavior is through measuring the intensity of technology adoption. One example of such measures is to estimate the proportion of land planted with a high yielding variety of crop j, to the total land area allocated to crop j, in farm i.

$$intensity(y_{ij}) = \begin{cases} \delta U_{ij}, & if\ U > 0 \\ 0, & otherwise \end{cases}$$

Where, δ is a scaling term.

The intensity or extent of adoption represents the concept of the diffusion process. The spread or diffusion of agricultural technology is the aggregate adoption of the technology by producers in certain regions, and it can explain adoption behavior at the aggregated level. The dependent variable to represent the diffusion rate can be defined as the percentage of the population adopting the innovation in a certain area at time t, the land share in total land that adopts the technology at time t (e.g., Jelliffe et al. 2018; Gupta, Ponticelli and Tesei 2020), the duration in which modern technology has been adopted by farmers (e.g., Alcon, de Miguel and Burton 2011; Dadi, Burton and Ozanne 2004), or the extent and intensity of adoption (e.g., Shiferaw et al. 2015; Teklewold, Kassie and Shiferaw 2013).

Many of the adoption models were used to explain the impact of a group of farm and farm operator characteristics on the adoption decision (e.g., Daberkow and McBride 2003; Feder, Just and Zilberman 1985; Feder and Umali 1993). Socioeconomic factors (e.g., age, gender, education, experience, wealth or credit availability), human capital, access to information, social network, risk attitude, land tenure, land size, infrastructure, environmental attitude, geographical factors (e.g., land quality, drought, flood frequency, agroecological zone), and external factors (e.g., support programs membership) are an example of some factors that can explain the heterogeneity in the adoption behavior among the population. Findings suggest that farmers with higher education backgrounds in technology may benefit from adoption by reducing the cost of learning, and landowners may benefit more from adoption compared to farmers who rent the land because a rent increase can reduce farm net return (Sunding and Zilberman 2001).

Some researchers and policymakers on technology adoption focus on examining the different stages of adoption (e.g., Läpple and Van Rensburg 2011; Diederen e al. 2003; Lambrecht et al. 2014). They divide adopters as to in which stage of adoption are they: innovators, early adopters, followers, early and late majority, late adopters, and laggards; or as awareness, evaluation, or continued adoption stage. Other adoption models address adopter perception using models that describe farmer's perception toward technology adoption, by empirically evaluating the influence of knowledge, perception, and attitude toward environmental problems, chemical fertilizers, and resource conservation on adoption decisions (e.g., Sharifuddin, Mohammed and Terano 2016).

Recent studies give emphasis to the role of economic constraints on the adoption and diffusion of the technology (e.g., Balana and Oyeyemi 2020). Such models assume that farmers aim at profit maximization and input minimization in the decision and behavior of adoption. Such studies aimed to evaluate the influence of policy program intervention on agricultural technology diffusion. For example, the role of financial subsidy (e.g., input, output, and credit subsidies), and extension and technical support programs in speeding technology diffusion (e.g., Cremades, Wang and Morris 2015).

One side of previous research used optimization models to derive the optimal decision or choice of land allocation given the technology adoption decision. Lichtenberg (1989) looks at the interaction between land quality, cropping pattern, and irrigation technology choice. He utilizes optimization models to derive farmer decision problems, where the farmer aims at maximizing profit with crop and technology choices. He models the proportion of land of specific quality to be allocated to certain crops, assuming that better land should be allocated to the most profitable crop. He found that land allocated to different field crops varies significantly over land quality.

Another side of the literature on the adoption of biotechnology or genetically modified crops evaluate the impact of political factors on farmer acceptance to GM seed hybrids. Political variables include regulation on food safety and quality, and international trade regulation of biotechnology. The adoption rate of biogenetically enhanced crop hybrids has increased over the last twenty years. This is because farmers are highly motivated by economic incentives of adoption including higher yield with traits that better response to environmental factors (e.g., drought, weeds, pests and diseases). However, there were a slow acceptance rate of genetically modified crop varieties among some farmers around the world due to political factors including food safety and metric aspects of the genetically enhanced crops (Mabaya et al. 2015; Smyth et al. 2021). Thus, a group of farmers may decide to continue implementing organic farming practices in food production due to change in public concerns about environmental and food safety and quality of genetically modified crops (Merem et al. 2021). Therefore, due to the variation in the adoption decision of genetically modified crops and non-GM crops concerning the political factors, we expect to see variation in farmers' attitude toward the adoption of enhanced deeper root corn varieties and the reduction in agricultural carbon footprint.

Different studies in the field of agricultural technology adoption give an emphasis on the adoption behavior of corn hybrid varieties and suggest that the adoption behavior follows an S-shaped curve over time. Griliches (1957) uses state and agricultural district data for the share of hybrid corn grown in the U.S. in the early to mid-nineteen to fit a trend logistic function to the data. He estimates a measure for the variation of origin and other measures for the rate of acceptance of hybrid corn by farmers. He confirms that the central Corn Belt states were the first and fastest to adopt hybrid corn due to the availability of hybrid seeds to farmers in commercial quantities, given that commercial seed producers and experimental stations are concentrated in these states. Measures of acceptance have been approximated by the expected profitability. Market density or size, and the average size of sale are used as a measure of the profitability of entry, and results show that the acceptance of hybrid seed was higher in the Corn Belt given the earlier dates of origin of seeds and concentration of a higher number of hybrid seed producers.

CHAPTER 1/ AN EXPLORATION OF THE JOINT ADOPTION DECISION OF SOIL CARBON SEQUESTRATION PRACTICES AND GENETICALLY IMPROVED CORN VARIETIES

1. Introduction

Modern agriculture practices and changes in land use have been identified as essential factors that contribute to the acceleration of climate change. According to FAO statistics, agriculture contributes about 9.3 billion tons of CO2 equivalent emissions globally in 2018 (FAO 2018). Out of that, change in land use accounts for 4 billion tons of CO2 equivalent emission. A more recent statistic by the U.S. Environmental Protection Agency (EPA) shows that agriculture contributes about 11 percent of the U.S. greenhouse gas emissions in 2021 (EPA 2022). The increased CO2 emission is projected to increase the average surface temperature by 0.3 ℃ to 0.7 ℃ and decrease crop yield by more than 50 percent over the 21st century (IPCC 2014).

At the same time, agricultural practices that involve the intensive use of chemical pesticides, fertilizers, and other nutrient applications can result in the loss of soil health and fertility by releasing organic matter stored in soils back into the atmosphere (World Bank 2021). Soil organic carbon is essential for maintaining physical, chemical and biological processes in soil (Beillouin et al. 2022). Consequently, losing soil carbon from cropland can negatively impact soil health, and increase the concentration of carbon in the atmosphere thus accelerating climate change and global warming.

Globally, agricultural land has the potential to sequester 23.8 gigatons of CO2-equivalent per year (Bossio et. al. 2020). Cropland alone can sequester between 0.90 and 1.85 gigatons of carbon per year in the top 30 cm (Zomer et. al. 2017). Farmers and landholders can help increase soil carbon inputs and/or reduce carbon losses by switching from conventional production systems to soil carbon sequestration (SCS) practices. Conservation tillage, increased retention of crop residues, crop rotation, cover crops, nutrient management, manure and compost addition, grazing and forest management, land retirement or afforestation, water conservation, and irrigation management are all examples of SCS practices. The strategies of SCS can reduce soil disturbance, provide additional biomass inputs to soil, improve soil fertility and thus hold the potential for better yields over years of continuous use of recommended land management practices, which means additional revenue to farmers and/or higher land valuations over the long run. An equilibrium level of soil organic carbon is essential for the environment as it can enhance soil quality, maintain the holding capacity of water and nutrients, and provide soil materials that are required for soil micro-organisms (Lal 2004).

Another approach to enhancing carbon levels in agricultural soil is through the adoption of SCS “frontier” technologies including things like biochar applications, perennial grain crops, and annual crops with deeper and larger root systems (Paustian et al. 2019). The discovery of genes governing root system traits that then rely on breeding programs to develop crops with larger and deeper root systems can be complementary to other conservation practices that aim at enhancing agricultural soil quality and reducing carbon emissions. We thus expect that these adoption decisions are not made in isolation. This study focuses on understanding the adoption of genetically enhanced deeper root corn hybrids. These improved deeper root corn hybrids can potentially provide multiple co-benefits including improved ability to access soil moisture, greater accumulation of soil organic matter and thus soil carbon sequestration, and improved nitrogen use efficiency. This technology will be discussed in detail in the following sections.

This chapter answers the questions of how deeper root corn varieties are beneficial to farmers and environment, how farmers can be incentivized to support public goods, and what factors influencing farmers' decisions to adopt either or both currently recommended SCS practices and enhanced deeper root hybrids. We utilize evidence from the literature about the relative soil carbon sequestration rates by accepted SCS practices and estimated for deeper root corn varieties to support the hypothesis that the adoption of enhanced deeper root corn can contribute to SCS and reducing GHG emission. Second, we provide a detailed information about carbon market incentive payments to incentivize farmers to adopt SCS practices. This chapter contributes to the literature by developing a conceptual framework to examine joint adoption decision of a primary crop variety and associated in-field SCS practices. Moreover, we develop a set of hypotheses about the marginal effects of different farms, farmer and environmental factors on the adoption of (complementary) enhanced deeper root corn varieties and in-field SCS practices.

The chapter is organized as follows: The next section provides evidence from the literature on the potential SCS rates per different SCS practices. Then we list the barriers to the adoption of SCS practices in cropping systems. Section two presents some examples of private and public carbon incentive programs, challenges faced by carbon sellers and buyers, and lists different payment instruments to target SCS in agriculture. Section three introduces three examples of SCS frontier technologies, including deeper root corn hybrids, and compares the environmental benefits and adoption drawbacks of these different technologies. Finally, section four provides theoretical and empirical representations of a joint adoption model and marginal probabilities of adopting production technology bundles consisting of deeper root corn hybrids and/or SCS practices.

1.1. Quantifying soil carbon sequestration potential

Crop rotation practices, tillage conservation systems, and cover crops are the most widely used practices to improve soil quality and maintain soil organic matter. West and Post (2002) find that using conservation crop rotation practices can accumulate about 0.22 tons of carbon/hectare/year, on average. Studies on Australian soils conclude that using no-tillage practices in farming can sequester approximately 0.85 tons of carbon/hectare/year (Sanderman and Baldock 2010; Luo, Wang and Sun 2010). Another study by Antle et al. (2007) looking at regions in the central United States concludes that using increased conservation tillage in wheat and corn-soy rotations can produce up to 1.7 and 6.2 million metric tons of carbon per year. Conant et al. (2017) find that conversion to perennial grasses and legumes can accumulate 0.9 tons of carbon/hectare/year and improved grazing land management can store 0.28 tons of carbon/hectare/year in agricultural soils. Poeplau and Don (2015) conclude that improved crop rotation and cover crops can respectively sequester 0.32 tons of carbon/hectare/year and more than 1 ton of carbon/hectare/year. Tillage conservation practices can increase carbon by 0.25 tons of carbon/hectare/year on sandy soil and 0.29 ton of carbon/hectare/year on non-sandy soils (Ogle, Breidt and Paustian 2005). Such findings support the proposition that SCS practices can be an effective way to maintain carbon levels in soil and so improve soil fertility.

Soil carbon stocks are highly dependent on crop type, soil type and structure, weather conditions, farming system, and land use activities (Antle et al. 2003; Beillouin et al. 2022; Ogle et al. 2023; World Bank 2021). Previous studies that address changes in the level of soil carbon conclude that the carbon sequestration rate in dry soil and warm regions (such as a case study in the Central Highlands of Queensland) is about 0.001 to 0.11 tons of carbon/hectare/year with a cropping system under crop-rotation, zero tillage and nutrient management practices (Armstrong et al. 2003; Campbell et al. 2005) while in humid and cold regions the rate ranges from 0.11 to 0.88 tons of carbon/hectare/year with no-tillage, or other conservation practices and cropping systems (Campbell et al. 2005; Sa et al. 2001; Six et al. 2002; West and Post 2002**).**

Finally, increasing SCS can contribute to global food security. A study by Bauer and Black (1994) estimates the impact of soil organic matter (SOM) on soil productivity and finds that an addition of 1 ton per hectare of SOM increases wheat grain yields by 15.6 kg per hectare in the Northern Great Plains of the United States. Similar studies find an increase of 1 metric ton of soil organic carbon per hectare increases wheat yield by 40 kg per hectare in the semi-arid Argentinian pampas (Díaz-Zorita, Buschiazzo and Peinemann 1999; Díaz-Zorita, Duarte and Grove 2002). Despite the abovementioned evidence on the potential of conservation management practices to sequester soil carbon, there are barriers preventing the adoption of these practices.

1.2. Barriers to the adoption of SCS practices and heterogeneity in adoption

A range of factors influence a farmer's decision to adopt SCS practices, including social network or neighbor impacts, attitudes toward climate change and knowledge about causes of climate change, socio-demographic factors, willingness to increase long term farm sustainability and farmland value, and access to incentive payments (Barbato and Strong 2023; Kragt et al. 2016). Farmers with privately-held conservation goals may adopt SCS practices even if they do not increase or maintain farm profitability. Economic incentives by governmental and private sectors are other important drivers of SCS practice adoption. Nearly 74 percent of farmers surveyed by *Trust In Food and Field to Market* believe that farmers should receive incentive payments to adopt conservation practices that generate public goods (Filed to Market 2020).

Also, the adoption rate can differ across geographic areas or even within the same region due to variations in factors such as cropland size, soil type and structure, climate, base soil carbon level, and distance from market (Pannell, Pardey and Hurley 2020) which influences the selection of best practices to sequester carbon (Thamo and Pannell 2016). No-tillage or reduced-tillage practices are the most-commonly implemented practices around the world. For example, Australia has achieved about 90 percent adoption of no-tillage practices in cropland area, and about 40 percent of crop areas in the United State receives no-or reduced-tillage practices (Llewellyn, D'Emden and Kuehne 2012; Wade, Claassen and Wallander 2015).

Farmers can face different impediments which leave them unmotivated to implement or continue SCS practices. Kragt et al. (2016) argue that political uncertainty, inadequate information about carbon farming practices and economic incentive programs, and inability to access capital to cover investment and administrative costs are the main barriers to the adoption of SCS practices. Political uncertainty can be due to changes in carbon market policies, changes in carbon prices, and changes in incentive payments provided by carbon markets. Additionally, there is uncertainty related to yield and productivity of carbon farming, and input and output prices. Moreover, farmers who adopted SCS practices may not maintain SCS practices every year which can lead to the release of stored soil carbon back into the atmosphere during the years with no implementation. This could be due to high management and enforcement costs, low productivity, low yield, and so lower profit as well as long time lags between implementation and observing conservative benefits (including both economic and environmental benefits), and uncertainty about realizing the ultimate benefit due to spillover effects and other issues related to enforcement (i.e. leakage, permanence, and additionality) (Pannell, Pardey and Hurley 2020). Therefore, the coordination between farmers and providers of environmental benefit related payments are essential to understand farmers motivations to adopt SCS practices.

2. Carbon incentive programs, carbon markets, and challenges to participating in carbon projects

The two most common strategies to promote carbon sequestration activities are incentive payments by governments and the trade (sale and purchase) of verified carbon credits in voluntary carbon markets. The Conservation Reserve Program (CRP) and Environmental Quality Incentive Program (EQIP) are examples of governmental incentive programs in the United States that support the adoption of conservation practices in agriculture, including practices that sequester carbon. Such programs typically offer an incentive payment per conservation practice applied to each acre of land, regardless of the actual change in quantity of carbon stored in the soil.

In the private sector a variety of carbon programs take the initiative to create and sell offsets from carbon sequestration achieved in agriculture. These include carbon and ecosystem services market entities (e.g., ESMC eco-harvest, Soil and Water Outcomes Fund); carbon market entities (e.g., Indigo, Nori); input supply companies (e.g., Agoro Carbon Alliance, Bayer Carbon, Corteva, Nutrien); and data platforms (e.g., CIBO Impact, Gradable Carbon, TruCarbon) (Plastina and Wongpiyabovorn 2021). Such programs offer an annual incentive payment per verified carbon credits, based upon actually measured or estimated net GHG changes attained per acre in cropland that implements approved SCS practices.

Given the long-run nature of the contracts between farmers as sellers of carbon credits and the buyers of those credits, the contracts are typically bundled together and denominated within the industry as a “project”. Carbon sequestration projects define the rights and conditions for the carbon payment received by the participating farmers after measuring or estimating carbon benefits or other environmental outcomes. The project defines an agreement between farmers (sellers) who are supposed to supply carbon credits to carbon markets (buyers), with well-defined contract length, acres of land enrolled, monetary transactions involved, eligible crops, continued and new practices to implement, and other project implementation requirements. For example, a farmer may be required to participate with a determined number of acres on which they use specified conservation production practices to increase soil carbon stock. Then the farmer follows a protocol that involves measurement of change in carbon stock, reporting, and verification by a third party to make sure the contract has been fulfilled. Measurement, reporting, and verification (MRV) processes are time and resource-intensive, but they assure the quality of the carbon credits being marketed. For high quality credits, buyers need to be able to certify the practice is adopted and need to measure and quantify carbon level changes (the baseline, projected, and actual stocks), and a third party needs to verify the change in soil carbon stock. Finally, the farmer receives payment per practice, per verified carbon credits that are sequestered (or offset), or both.

Table 1 provides examples of both government and private carbon market payments for environmental benefits including soil carbon sequestration projects in agriculture. The Table shows that the carbon contract design is either per practice, per verified carbon credits (i.e. verified metric tons of CO_2 equivalents sequestered). Payment per practice is an example of per hectare or per acre contracts (Antle et al. 2001). Farmer receives a fixed annual payment per acre under practice implementation. For example, the EQIP program pays farmer per acre of land that implements no-tillage, cover crops, crop rotation, or reduced nutrient application, regardless of carbon stock within those acres. A per acre contract does not reflect the market value of carbon[2] and does not require the potentially large costs for measurement and validation of changes in the carbon stock, but the trade-off for a relatively low monitoring cost is an inability to ensure the full implementation of practices.

[2] Per acre per practice payment does not account for carbon sequestration outcome and so we can call it per non-verified carbon credits.

Payment per verified carbon credits for the metric tons of carbon (or equivalent tons of other GHGs) sequestered or removed from atmosphere is the payment instrument used by voluntary private carbon market. For example, by 2022, Indigo, Nori, and Corteva used estimated carbon base payment starting from \$20 and up to \$30 per verified carbon credit to pay farmers who engaged in carbon sequestration contracts. Per carbon credit payment reflects market value of carbon in which a carbon buyer with an active project can create and sell carbon credits. Moreover, it quantifies the environmental benefits generated through the implementation of carbon program. Measurement, monitoring, and verification costs are necessary to track changes in the soil carbon stock over time. Per carbon credit contracts are better than per acre contracts in assuring the actual soil carbon sequestration benefits generated by the practices.

Table 1: Different payment instruments for soil carbon sequestration in agriculture.

Payment type	**Description**	**Example**	**Measuring carbon level change and verification**	**Advantage**	**Disadvantage**
Payment per practice implemented	Payment per acre of land receiving soil management practices (e.g., no-or-reduced tillage, cover crops, crop rotation, mix cropping, nutrient management, water management…etc).	Environmental Quality Incentive Program (EQIP). And Natural Resource Conservation Service (NRCS) by USDA. 1-10 years contract length. Soil and Water Outcomes Fund (SWOF)-1 year contract with $25-$40 per acre per year for the environmental benefit.	Not required by EQIP and NRCS Measuring carbon level and verification is required by SWOF	Low monitoring cost to ensure the full implementation of the practice. Practice can lead to environmental benefits of improved soil health, reduced erosion, and increased soil moisture.	Environmental benefits from project implementation may not reflect actual soil carbon benefits. Equal payment per practice in the same geographical area regardless of soil type and slope, crop type, climate, and weather factors.
Payment based on agricultural land retirement	Annual per acre rental payment for land under retirement agreement. Examples: Cropland with very low productivity and poor quality for cropping system, highly erodible soil, cropland exposed to severe floods.	USAD land retirement programs, Conservation Reserve Program (CRP). Short-term contract, 1-10 years, or long-term contract, 10-15 years	Not required	Soil carbon in the retired cropland is not disordered by production practices. The farmer receives annual income for the period in which cropland is under retirement agreement.	Payment is based on an acre of land under retirement and may not reflect the environmental benefit of soil carbon sequestration. Farmers can use another area for crop production to compensate for the change in income which can offset the carbon stored in the retired cropland.

Payment per new practice implemented (payment based on performance ranking)	Annual Payment to maintain the existing practice, and additional payment to implement new practices. For example, corn growers who are using a no-tillage system can receive $'s per acre on field implementing no-tillage and additional payment when they plant cover crops on the same field.	Conservation Stewardship Program (CSP)- 5years contract Bayer Carbon, 10-20 years with up to $12-$36 per acre for approved practices (no-till/strip-till and/or cover crops)	Not required for CSP Verification is required by Bayer.	Low monitoring cost. Better soil health with the active implementation of old practices and additional conservation practices in the same acres under contract. Farmers receive additional payment per additional practices implemented.	Payment may not reflect the environmental benefit of soil carbon.
Payment per verified carbon credits sequestered or offset.	The farmer needs to do an in-field soil sampling test to determine the tons of carbon sequestered, and use carbon program or models (e.g., COMET-Farm model) to estimate how many carbon credits are sequestered or offset. Then a third party is required to verify the tons of equivalent CO_2 offset or inset. Finally, farmers sell the verified carbon credits to Indigo, Nori, or Corteva and get $ payments per credit per acre as agreed in the contract.	ESMC Market Launch Information-10-20 years contract. Nori-10-20 years contract. Indigo-5-10 years contract with a starting payment of $20-$30 per carbon credit[3]. Corteva -5-10 years contract with $20-$30 per carbon credit. Nutrien-1-3 years with $10-$20 per carbon offset.	Third-party verification of carbon inset or offset	Can reflect carbon market value and better estimation of carbon benefit. Farmers are motivated to participate in the project if the price per carbon credit is higher than the cost of practices implementation.	Farmers do not receive payments per practices used to increase soil carbon stock. Verification and soil test costs. Different farmers implementing the same practices in cropland of different soil structures, climate variability may observe different levels of change in carbon stock and get compensated with the same carbon market price. The farmer receives carbon payments after verifying carbon credits.

Sources: Bayer Carbon 2022; CIBO 2022; Corteva 2022; ESMC 2022; Indigo 2022; Nori 2022; Nutrien 2022; Soil and Water Outcomes Fund 2022; USDA 2022.

[3] One carbon credit equal one metric ton of carbon sequestered, or one ton of CO2 offset.

Primary issues that accounting protocols need to consider in GHG emissions mitigation projects are additionality, permanence, realness, and non-leakage (Broekhoff et al. 2019; Murray, Sohngen and Ross 2007; Wbcsd 2004; Wongpiyabovorn, Plastina and Crespi 2022). The principle of **additionally** states that a project developer (farmer) should receive incentive payments only for a new change in production practices or for an additional amount of sequestered carbon above and beyond that which would have occurred under normal business-as-usual production practices (Barbato and Strong 2023). **Permanence** refers to the extent to which when farmers change from conventional management practices to conservation practices, the new soil carbon stored during the contract period can remain in the ground or can be released back into the atmosphere. The release of such carbon is considered an impermanence of carbon mitigation benefits. Therefore, projects that target emission reduction should be designed to avoid the long-term release of soil carbon. **Realness** refers to the quantification of the actual quantity of carbon sequestered in soil as opposed to carbon expected to be sequestered based on modeling or the simple undertaking of SCS practices without measurements (Plastina and Wongpiyabovorn 2021). **Leakage** happens when the mitigated amount of carbon emission is attributed to another location outside a given emissions reduction project. Ensuring additionality, permanence, realness, and non-leakage conditions are met requires ongoing measurement, monitoring of carbon stock change, often using costly equipment such as sensors.

There are other challenges related to financial and technical support, given that changes in production practices can be costly to farmers. Farmers' awareness about carbon programs and uncertainties about how they will be paid and how they can meet the terms of their contracts are other barriers to participation in carbon incentive programs. In addition, there can be uncertainty about soil sampling test measures, or the different carbon model estimates by different carbon programs, such as the COMET-Farm model used by Nori and the Soil and Water Outcomes Fund versus the DNDC (DeNitrification-Decomposition) model used by ESMC's Eco-harvest versus the SALUS model used by CIBO Impact (Plastina and Wongpiyabovorn 2021). The economic, environmental, and political challenges of the continuous implementation of SCS practices can be partly overcome by contracts that offer incentive payments for farmers or landowners to cover adoptions' fixed expenses and transaction costs. Another alternative to SCS practices is the adoption of SCS frontier technologies which are discussed in detail in the next section.

3. SCS frontier technologies

Transaction costs spent on measurement, reporting, and verification of carbon credits, and the accurate monitoring of permanence, additionality, and non-leakage of stored carbon over the contract period are issues that need further research and consideration to ensure the benefits of carbon sequestration strategies. Time lags between practice adoption and desired benefit realization in terms of yield and productivity improvement (usually 10 to 20 years) are another challenge for the adoption of SCS practices (Pannell et al. 2020). Therefore, adoption of frontier technologies alongside the implementation of already established SCS practices may help to enhance soil carbon inputs and reduce GHG emissions into the atmosphere. In the field of soil carbon sequestration, a frontier technology is defined as an improved farming practice that can permanently store carbon and other organic matter in the soil (Paustian et al. 2019). Biochar applications, perennial grain crops, and annual crops bred with larger and deeper root systems are examples of frontier technologies that can contribute to soil carbon sequestration.

3.1. Biochar

3.1.1. Environmental benefits from biochar applications

Biochar is a substance like charcoal, produced from agricultural or other woody waste through a pyrolysis process. It contains about 70 percent carbon and has a high pH level (CTCN 2021). It provides some environmental benefits to cropland through increasing carbon level in soil, maintaining pH levels, and reducing the toxicity of some heavy metals (e.g., aluminium (Al)) (O'Neil, Miesel and Gould 2020). Moreover, biochar helps in water retention, increasing soil moisture, which can reduce the need for irrigation. Another role of biochar is nutrient retention, by holding nutrients in soil such as nitrogen (N), potassium (K) and phosphorous (P) (Biederman and Harpole 2013). Through increasing soil moisture and soil nutrients retention, biochar can improve soil health and fertility which is positively associated with yield and productivity enhancement.

Major et al. (2010) conduct four-year experiments in corn-soybean rotations and find that following a 20 ton per hectare biochar application, there was no change in yield in the first year, but subsequent yield of corn increased by 28 percent, 30 percent and 140 percent in the second, third and fourth years, respectively. A meta-analysis by Jeffery et al. (2011) finds that biochar increases crop productivity by 10 percent on average. Moreover, replacing crop residues and animal manure with biochar can reduce GHG emissions. Practices such as application of crop residue and animal manure are essential to enhance soil fertility and increase crop yield, however, they produce and releases N_2O and CH_2 gases to atmosphere (Chadwick et al. 2011). In addition, biochar applications have a comparative advantage on crop productions in terms of disease control, compared to other conservation practices (e.g., cover crop, crop residue or compost, manure addition). Iacomino et al. (2022) provide evidence that biochar applications under controlled experiments have suppression effects of 100 percent for oomycetes and viruses, 96 percent for bacteria, 86 percent for fungi, and 50 percent for nematodes. From an economic perspective, biochar can reduce fertilizer and irrigation applications as it increases soil nutrient and moisture retention. It is considered as a substitute for other soil management practices such as crop residue and cover crop. Biochar can persist in the soil for long time, but it requires higher first-time adoption costs compared to other practices such as crop residues or cover crops. While biochar addition can help to replace traditional soil amendments and reduce GHG emissions, it has few disadvantages in terms of cost of production and implementation and use efficiency under different climatic and geographical conditions.

3.1.2. Adoption drawbacks of Biochar applications

Biochar applications have disadvantages including the high cost of production and implementation on large scale cropland and the possibilities of disturbing the balance of nutrients in the soil and introducing undesired weeds (CTCN 2021). Biochar is made from different types of biomasses heated to different temperature levels with low to zero oxygen present, which can result in different physical and chemical properties of biochar. Therefore, biochar with different chemical compositions can behave differently in terms of intensity and time of impact. For example, biochar made from wood cuttings will have less impact of nutrient retention compared to biochar made from poultry manure (USBI 2023). Additionally, different soil types, in different geographic areas, and under different climate conditions react differently to biochar applications. Biochar in different soil texture, pH class level, latitude, biochar application rate, fertilizer coaddition (i.e. non, organic, inorganic), crop type, and biomass can result in different yield effects and might take more than a year to observe improved soil fertility and so enhance corn yield (Jeffery et al. 2011). Therefore, efficiency of biochar in carbon sequestration in relation to different environmental and geographical factors, might lower the adoption in some counties with poor soil quality.

3.2. Perennial grain crops

3.2.1. Environmental benefits of perennial grains

Root biomass traits in the form of perennial grain crops are another example of a frontier SCS technology. They can lead to co-benefits of carbon level in soil, thereby enhancing environment quality. Perennial cereal crops are grain crops such as wheatgrass, sorghum, and sunflowers that exhibit perennial growth, which means the crop can live and produce harvests for several years rather than being re-planted every season or annually. These crops tend to have a deeper and more extensive root system that can accumulate much more soil organic matter compared to annually grown crops (Chapman et al. 2022). Perennial crops can provide private benefits to farmers in term of reducing seasonal variable input cost (e.g., seed, labor, and less applied nutrients as it developed with larger roots to survive better in low nutrient environments) and reduce the need for intensive tillage system and thereby provide environmental benefits of reducing soil erosion and increasing soil carbon stock (Cox et al. 2006; Smaje 2015).

3.2.2. Adoption drawbacks of perennial grains

There are few drawbacks that might hinder or reduce the intensity of perennial grain crops adoption. Firstly, perennial grains can make seasonal or yearly crop rotation impossible on the same field. However, farmer growing perennial crops can undergo crop rotation after two-five years. Secondly, perennial growth habitat can reduce farmers' decision flexibility to change crop choice in respond for a change in market demand, output prices, and consumer preferences. Moreover, while the adoption of perennial grain crops can reduce the agricultural inputs used for planting, it can impact yield stability. Vico and Brunsell (2018) conduct a field experiment and grow perennial and annual crops in the same soil type and environment, and they conclude that perennial grain crops with larger roots requires less water but results in lower yield compared to annual grain crops. Factors such as crop-rotation, the need to change crop choice per field per season, and yield variation can decelerate the adoption rate and diffusion of perennial grain crops.

3.3. Enhanced larger and deeper root system crops

3.3.1. Environmental benefits of enhanced deeper root crops

Crops with larger and/or deeper root systems (bred or engineered with deep root genetic traits) have several potential benefits, including soil carbon sequestration, nutrient use efficiency, and drought tolerance. Crop varieties with enhanced root system trait have the potential to sequester more carbon stock in soil through root exudates, where the roots can provide 30-40 percent of total soil organic carbon inputs (Pett-Ridge, Nuccio and Mcfarlane 2018). Root systems with broader coverage are better able to reach and take up applied nutrients, such as nitrogen (Paez-Garcia et al. 2015). With deeper root systems, deeper root crops can access and absorb moisture from deeper layers of soil and potentially require less water application, which saves irrigation cost in irrigated corn fields and can work as insurance against drought for both irrigated and non-irrigated crop production systems.

These enhanced deeper root varieties can be considered a SCS technology that is effectively integrated into the genetics of the seed, and thus adopted by substituting one seed for the other. This offers strategic advantages compared to other SCS practices, through minimizing fixed transaction costs of adoption, and ensuring permanence, non-leakage, and additionality of stored soil carbon. Several experiments by teams of researchers and breeders aim at selecting the most appropriate root phenotypes for new maize seed varieties that become drought resistant, high yielding variety and can sequester soil carbon. A team from the plant breeding department at Penn

State University has chosen varieties with different root phenotypes or traits that have been grown in drought-condition environments in the USA, Nigeria, and Mexico (Iowa, Zaria, and Jalisco). For a total of six simulated environments, they find that the carbon level stored in the soil below 50 cm depth, has doubled with corn seed with "Steep, Cheap, and Deep" root phenotype in both dry and rainfall conditions, compared to other standard root phenotypes (Schaefer et al. 2022). The observed stock of carbon deposited below 50 cm after 42 days is over 0.9 grams of carbon in Jalisco, over 0.6 grams of carbon in Zaria, and below 0.5 grams of carbon in Iowa. The finding of this experiment can provide clear evidence of the application of deeper-rooted system crops in storing more soil carbon. However, the enhanced corn varieties with deeper root system are under development and experiment stage, which suggest uncertainty about cost of adoption and diffusion among the U.S. corn growers.

3.3.2. Adoption drawbacks of enhanced root system crops

As a new technology, the cost to the farmer of new seed varieties is often higher than other seed varieties already on the market. For example, during 2019 and 2020, average hybrid corn seed price was $288 per bag for non-drought tolerant varieties and about $305 per bag for drought tolerant varieties, representing the premium charged for one of the newest improved corn hybrids (Yost et al. 2022). However, with widespread diffusion over time, prices can converge to the prices of other corn varieties. Additionally, response of SCS and crop yield to different factors—drought, disease, pest, soil texture, irrigation system, tillage system, etc—can vary over years. For example, Schaefer et al. (2022) find that the carbon level stored in soil below 50 cm depth, doubles at different rates with deeper rooted corn in dry and rainfall conditions, across three different geographical environments (Iowa, Zaria, and Jalisco). These differences can raise concern about equity of incentive payments by carbon markets for farmers in different geographical location with different SCS rates per acre allocated to larger rooted crop varieties. Farmers who plan to participate in carbon sequestration projects may become less likely motivated to adopt deeper rooted crop varieties if climate and geographic conditions show low potential SCS effects.

In this study we focus on genetically improved corn hybrids with larger and deeper root systems as an important crop that can contribute to soil carbon sequestration in the United States. Corn is grown at a very large scale in the U.S. Corn Belt on cropland with high SCS potential (see Figure 1). Total corn planted acreage in the U.S. reaches about 42 percent of total planted crop acreage in 2022 (USDA-NASS 2022). And from an economic perspective, in 2022, the farm value of corn grain was about 91 billion dollars (USDA-ERS 2022) and came after just soybeans in term of value of exported agricultural commodities, accounting for about 18.7 billion dollars in agricultural exports (U.S. Census Bureau 2022).

Therefore, genetically improved deeper root corn with SCS benefits can be anticipated as a significant alternative or complementary SCS practice. We develop a joint adoption framework to address complementarity between in-field SCS practices and these novel corn varieties in order to assess the socioeconomic and farm factors affecting decisions to adopt either or both.

4. SCS adoption decisions: Conceptual framework

The enhanced deeper-rooted system (DR)[4] corn varieties may come to be treated as an acceptable and verifiable SCS practice that can be included under incentive payments or carbon markets alongside other SCS practices. Thus, we are interested in the factors affecting the adoption of in-field SCS practices and these novel corn varieties. Using a conceptual framework, we explore the farmers' joint adoption decision, if they consider deeper root corn as a substitute or complement to already-incentivized soil conservation or SCS practices. Under a verified carbon credit contract,

[4] We use the notation DR in the theoretical framework section to define the deeper root system corn in the equations.

a farmer may decide to adopt one or two SCS practices jointly with deeper root corn to increase carbon accumulation in the registered field. On the other hand, farmer may substitute SCS practices with deeper root corn to maintain an annual carbon flow into the soil at lower cost and effort.

The farmer can choose a hybrid corn seed variety that maximizes net return and has traits that respond better to field location characteristics, and anticipated environmental and climate conditions such as drought, insects, weeds, soil type, etc. However, farmers make the adoption decision of corn variety and SCS practices prior to the growing season. Farmers may already be engaged in conservation incentive program such as NRCS which follows 5-10 contract years and therefore, they may have only to make a seed variety choice each season, conditional on already predefined practices.

The opposite may also be true, where farmers may have an established seed purchase contract with an input supply company, and they need to make the decision of which SCS or other production practices to implement each season. Therefore, the estimation of conditional probability of adopting a practice given adoption decisions regarding other practices can provide insights for carbon incentive program in how socioeconomic characteristics, farm characteristics, and access to technical and financial incentives can impact the joint adoption.

This study builds on the literature by developing a joint adoption framework to assess the single and conditional adoption decisions of SCS practices and deeper root corn hybrids. We use a conceptual and empirical framework to examine corn growers' adoption decision of SCS practices and deeper root corn, and explore the influence of different farm, farmer, and environmental factors in the complementarity of adoption decision. Given that the prior implementation of SCS practices does not inform the utility or payoff function of the seed choice, a sequential adoption framework is not applied here (Khanna 2001). We focus on the adoption of SCS practices that are approved within the existing voluntary private carbon programs (e.g., Indigo, Nori, Corteva), including cover crops, no-tillage and reduced tillage systems.

Farmers can choose to adopt one or two SCS practices (for example, a cover crop and one improved tillage system) and can choose to adopt either DR corn or a non-DR corn hybrid. Suppose we have voluntary carbon markets that incentivized carbon credits for a menu or vector R consisting of n potential SCS practices or technologies $r = (1 \dots n)$, with a simple list of practices/technologies, for example, being:

$$R = \{covercrop\ (CV), reduced\ tillage(RT), deeper\ root\ (DR)\ corn\}.$$

Each n[th] decision equals to 1 if it is adopted as part of the corn growers' SCS plan, that is the n[th] element of R is $\mathrm{d}^{n} = \{0,1\}$. For example, if farmers decide to grow DR corn, then $\mathrm{d}^{DR} = 1$, but if they choose to plant other corn hybrid then $\mathrm{d}^{DR} = 0$. For a large sample that consist of I fields $i = 1,2 \dots I$, we may observe different SCS plans (r) or bundles. A grower is expected to make per field i one corn hybrid adoption choice, and can choose to not adopt any SCS practices, or can select two or more practices jointly. For example, with our group of n=3 potential SCS practices and for an individual corn field, we can list eight possible SCS plans.

No adoption decision:

1. $\mathrm{R} = (\mathrm{d}^{CV},\ \mathrm{d}^{RT}, \mathrm{d}^{DR}) = (0,0,0)$: No SCS practices, non-DR corn

Single adoption decision within the SCS plan:

2. $\mathrm{R} = (\mathrm{d}^{CV},\ \mathrm{d}^{RT}, \mathrm{d}^{DR}) = (0,0,1)$: DR corn
3. $\mathrm{R} = (\mathrm{d}^{CV},\ \mathrm{d}^{RT}, \mathrm{d}^{DR}) = (1,0,0)$: CV
4. $\mathrm{R} = (\mathrm{d}^{CV},\ \mathrm{d}^{RT}, \mathrm{d}^{DR}) = (0,1,0)$: RT

Two or more joint adoption decisions with in the SCS plan:

5. $R = (d^{CV},\ d^{RT}, d^{DR}) = (1,0,1)$: CV, DR corn
6. $R = (d^{CV},\ d^{RT}, d^{DR}) = (0,1,1)$: RT, DR corn
7. $R = (d^{CV},\ d^{RT}, d^{DR}) = (1,1,0)$: CV, RT
8. $R = (d^{CV},\ d^{RT}, d^{DR}) = (1,1,1)$: CV, RT, DR corn

We can observe that the above SCS plans or bundles (r) provide all possible combinations of adopting these SCS practices and DR corn varieties. We assume that corn growers can decide on the adoption of either SCS practices (e.g., each plan can have one soil practice or two) and separately on the adoption of DR corn hybrid. If a field is already committed to a given practice under a previous contract, that simply limits the farmers current choice set to those plans that include already contracted practice.

Following Gong, Bergtold and Yeager 2021, the farmer chooses the SCS plan that maximize the utility. let U_{ri} represents the farmer utility from choosing SCS plan r in field i. The expected U_{ri} from choosing SCS plan r is represented as:

$$U_{ri} = U\{E[\pi(X_i)]; Z_i; \beta_r\} \quad (1)$$

Where $E[\pi(X_i)]$ is the expected profit from the adoption of SCS plan r in field i. X_i is a vector of explanatory variables affecting the cost of adoption and profitability of SCS plan r in field i. $E[\pi(X_i)]$ in equation 1 suggests that each SCS plan is not equally costed due to variation in cost of adoption and expected yield. For example, we may observe cost variation due to variation in time of adoption, the cost for farmer who adopt zero till drill machine for the first time is different than farmer who already using the machine from three seasons. Z_i is a vector of other exogenous explanatory variables that impact the utility of selecting SCS plan r in field i, such as socio-demographic variables (e.g., age, sex, education, experience, employment, …etc) and farm and environmental characteristics (e.g., land productivity, soil type, the soil's native potential SCS rate, field size (acres), irrigation status, farm income, field location, land tenure, climate factors, …etc). β_r is a vector of unknown coefficients associated with the adoption of SCS plan r. Corn growers will adopt SCS plan r if:

$$r = ((\mathrm{d}^1 \dots \mathrm{d}^n) = 1 \; if \; U_r = \max(U_1 \dots U_R) \tag{2}$$

Which suggests that we may observe the adoption decision of SCS plan r =1 if it results in a larger net benefit to corn growers compared to other SCS plans.

Research can observe the SCS plan and not the utility U_{ri}. Therefore, we represent the utility in equation 1 as random utility function as follows:

$$U_{ri} = V_r\{E[\pi(X_i)]; Z_i; \beta_r\} + \mu_{ri} \tag{3}$$

V_r is the stochastic utility associated with SCS plan r in field i and μ_{ri} is the random error term.

Following the methods in Gong, Bergtold and Yeager (2021) and Wu and Babcock (1998), we use equation (3) to estimate the probability of adopting SCS plan r given a set of explanatory variables. If the μ_{ri} is identically and independently distributed then the probability of adopting SCS plan r can be represented as multinomial logit function (Gong, Bergtold and Yeager 2021; Huffman and Mercier 1991; Maddala 1983; Wu and Babcock 1998):

$$P_r = \Pr(d = r) = \frac{e^{V_r\{E[\pi(X_i)]; Z_i; \beta_r\}}}{\sum_{j=1}^{R} e^{V_j\{E[\pi(X_i)]; Z_i; \beta_j\}}} \tag{4}$$

Where $r = 1 \dots R$. The estimated probability (4) and coefficients from equation (3) can be used to derive the marginal effects. The marginal effects measure the impact of a change in explanatory variable on the probability of adopting SCS plan r. Marginal effect for explanatory variable Z_h is (Greene 1993; Wu and Babcock 1998):

$$\frac{\partial P_r}{\partial Z_h} = P_r \left[\beta_{r,h} - \sum_{j=1}^{R} P_j \beta_{j,h} \right] = P_r \beta_{r,h} - P_r \sum_{j=1}^{R} P_j \beta_{j,h} \tag{5}$$

To represents the marginal probability of adopting a single practice such as DR corn. Suppose DR corn is part of SCS plans 1 to R_1, then the probability that corn growers adopt DR corn is:

$$P^{DR} = \sum_{\substack{r=1 \\ r=1-R_1 \in \{d^{DR}=1\}}}^{R_1} P_r \tag{6}$$

Where d^{DR} is an indicator variable that equals to 1 if practice DR is included in a SCS plan r. Then we can derive the marginal effect equation that represents a derivative of equation 6 with respect to the explanatory variable, Z_h. Therefore, the marginal effect of a single probability adoption decision of DR is:

$$\frac{\partial P^{DR}}{\partial Z_h} = \sum_{\substack{r=1 \\ r=1-R_1 \in \{d^{DR}=1\}}}^{R_1} \frac{\partial P_r}{\partial Z_h} = \sum_{\substack{r=1 \\ r=1-R_1 \in \{d^{DR}=1\}}}^{R_1} P_r \beta_{r,h} - P^{DR} \sum_{j=1}^{R} P_j \beta_{j,h} \tag{7}$$

With the joint adoption model, we can derive the bivariate probabilities and conditional probability of adopting one practice given the adoption of another practice. For the joint probability of adopting two SCS practices/technology, let assume CV and DR are parts of SCS plans 1 to R_N:

$$P^{CV,DR} = \sum_{\substack{r=1 \\ r=1-R_N \in \{d^{CV}=1, d^{DR}=1\}}}^{R_N} P_r \tag{8}$$

And the marginal effect of a joint probability of adopting CV and DR corn is:

$$\frac{\partial P^{CV,DR}}{\partial Z_h} = \sum_{\substack{r=1 \\ r=1-R_N \in \{d^{CV}=1, d^{DR}=1\}}}^{R_N} \frac{\partial P_r}{\partial Z_h} = \sum_{\substack{r=1 \\ r=1-R_N \in \{d^{CV}=1, d^{DR}=1\}}}^{R_N} P_r \beta_{r,h} - P^{CV,DR} \sum_{j=1}^{R} P_j \beta_{j,h} \tag{9}$$

The third type of probabilities we can derive from joint adoption model is the conditional probability of adopting one practice given another practice adoption decision. Conditional probability is a measure of complementarity between two SCS practices (Gong, Bergtold and Yeager 2021). The conditional probability of adopting CV given the adopting decision of DR corn is derived by dividing equation 8 (joint probability function) by equation 6 (probability of a single adoption decision):

$$P^{CV|DR} = \frac{P^{CV,DR}}{P^{DR}} \tag{10}$$

Marginal effect for the conditional adoption of CV given DR adopted for a change in an explanatory variable Z_h is (Gong, Bergtold and Yeager 2021):

$$\frac{\partial P^{CV|DR}}{\partial Z_h} = \frac{\frac{\partial P^{CV,DR}}{\partial Z_h} * P^{DR} - P^{CV,DR} * \frac{\partial P^{DR}}{\partial Z_h}}{P^{DR^2}} \tag{11}$$

Conditional marginal effects explain how a change in one of socioeconomic or farm characteristics can impact the probability of adopting different practices or SCS plans. The above listed probabilities have different implications. First, marginal probabilities provide a tool to assist researcher explore what factors (i.e., monetary and non-monetary factors) can impact corn growers choice to select a bundle of SCS practices and technology or to intensify the adoption of different practices to increase soil carbon stock. This can help provide a recommendation of how to design an effective incentive mechanism and or extension and outreach strategies. Moreover, joint and conditional probabilities can be a good measure of complementarity between two SCS practices. For example, are farmers adopting two practices together to increase soil carbon stock or are they substitute one for the other to maintain annual soil carbon flow. The following section provides a selected factors that could possibly explain the probability of a single adoption decision vs. joint adoption decisions of SCS practices vs. DR corn or SCS frontier technology.

4.1. Factors influencing SCS plan adoption decision

We can use cross sectional data to estimate the marginal effects of change in socioeconomic and farm related factors on the single, joint, or conditional probabilities of adopting DR corn and

SCS practices. We advance a number of hypotheses that explore the impact of changes in explanatory variables on the probability of adopting various SCS plans.

4.1.1. No adoption decision

A farmer may decide to continue using other corn varieties, with no adoption of deeper root corn hybrids. This could be due to constraints that might restrict the adoption of deeper root corn, such as an input purchase contract with a seed company to purchase specific corn seed products. Farmers with self-motivated goals (e.g., to increase farm profitability) and with no social or environmental conservation goals (e.g., to reduce GHG emissions) may decide to stay with conventional production practices and current high-yielding corn varieties (other than deeper root corn) that the famer has greater certainty will incur lower production costs.

However, there are some factors that might impact the probability of adopting a single SCS practice or the conditional probability of adopting two practices. The following cases address the change in the probability of deeper root hybrid adoption along with SCS practices in response to changes in yield variance, risk aversion, climate variables, SCS rate, payment per acre and per metric tons of carbon sequestered, and land value and land tenure.

4.1.2. Complementarity and substitution between the adoption decisions

Hypothesis 1: *Corn growers may consider adopting more than one production practice, such as deeper root corn and low-cost SCS practices to increase soil carbon stock.* Complementarity of adoption suggests that using one practice or technology increases the marginal benefit of the other practice. Farmers may assign high adoption probability to both deeper root and tillage practices as they increase soil carbon, and less probability to combining the adoption of deeper root corn and conventional practices that may result in soil carbon emission. Farmer can also consider complementarity in adoption between SCS practices as alternative to corn genetic technology adoption by adopting soybean-corn-rotation, reduce-tillage, and cover crops to increase soil carbon sequestration and maintain nitrogen level in soil. This hypothesis can be tested by examine the impact of a change in SCS flow on the probability of the joint adoption decision. The testable hypothesis states that for a given change in SCS rates (or adoption costs) per field how likely farmer is to adopt two practices or more together to intensify soil carbon sequestration effort.

Hypothesis 2: *Farmers substitute one practices for another if using one practice or technology decreases the marginal benefit of the other practice, or when faced with low-vs. high adoption cost alternatives.* For example, corn growers may decide to adopt biochar applications to increase soil carbon and maintain nutrients level in soil as alternative to cover crop practices. Alternatively, farmer may increase the probability of adopting deeper root corn if it turns as a lower cost alternative to biochar applications given that both frontier technologies contribute to soil carbon sequestration. This hypothesis can be tested by estimating the impact of a change in SCS rate or implementation cost on the probability of joint adoption decision of SCS plans. The testable hypothesis states that for a given change in SCS rates (or adoption costs) per field how likely farmer is to change from one practice or bundle of practices to another bundle of practices.

4.1.3. Impact of change in yield variance and risk aversion

Hypothesis 3: *Loss aversion can increase the probability of adopting deeper root corn and decrease the probability of adopting SCS practices*. The main incentive for a farmer to adopt any corn variety is ensuring yield. Deeper root [5] corn with DT traits may increase payoff and yield from the first season. Therefore, it reduces yield variance in the current period, increase soil carbon, and soil fertility, and thus reduces yield variance in the future. However, SCS practices

[5] Deeper rooted system corn genotype can maintain yield under drought risk, increase soil carbon, and help corn efficiently uptake nitrogen from soil (Pett-Ridge, Nuccio and Mcfarlane 2018).

has a delayed effect where the use of SCS practices may take years of continuous implementation to result in a positive impact on soil fertility and maintaining average yield (e.g., cover cropping, and crop residue reduce yield variance or minimizing yield losses over years of continuous implementation)[6]. Therefore, farmers that are risk averse might consider the joint adoption decision of SCS practices and deeper root corn to increase soil carbon and to maintain yield variation. This hypothesis can be tested in chapter 2 for the impact of change in lagged yield variable on the adoption of DT corn varieties. Similarly, with per filed data availability of deeper root corn and SCS practices adoption, we can test this hypothesis by comparing the impact of change in yield due to the adoption of SCS practices vs. enhanced deeper root corn or any other SCS plan.

4.1.4. Impact of change in climate variables including drought and precipitation

Hypothesis 4: *Exposure to severe drought, low precipitation level in previous years and water shortage can either increase the probability of deeper root corn adoption[7] or the joint adoption of deeper root corn and SCS practices.* This can be observed in both irrigated and non-irrigated corn fields. By either a single adoption of SCS practice or deeper root corn, or the joint adoption in non-irrigated fields; farmer can observe a positive impact in the soil quality, water retention, and corn resistance to drought. With severe drought, farmer may decide to adopt deeper root corn to reduce irrigation applications. This hypothesis can be tested in chapter 2 for the impact of drought severity

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[6] Considering adoption decision from loss aversion preceptive differ if corn growers care about current year payoff or both current and future payoffs. Though, future periods' payoffs are discounted, farmers put more weight in the current period's payoff. Consequently, they are more likely to increase the adoption of deeper-root corn relative to SCS practices. Moreover, high yield variation and potential losses in profit could be reduced in the future periods if deeper-root corn adopted. Deeper-root corn hybrids have yield simulation effects as they could reduce yield variance or yield losses in the current or future periods of implementation. This is because deeper-root corn includes DT trait, soil carbon sequestration trait, reduce GHG emissions including nitrogen losses.

[7] Deeper root corn with larger root system works as a drought resistant corn variety.

and precipitation level on the probability of adopting drought tolerant corn varieties at field level as well as the intensity of adoption at aggregated state level.

4.1.5. Impact of change in SCS rate and annual carbon payment

Hypothesis 5: *High relative SCS rate can positively impact the probability of the joint adoption of deeper root corn and SCS practices.* Cron growers with fields characterized by high soil carbon accumulation rate are expected to be more likely to adopt deeper root corn and SCS practices. Soil quality and land productivity may determine which type of SCS practices or technology might be suitable to increase carbon inputs to that soil. The impact of change in SCS rate can highly influencing corn growers participating in carbon incentive programs. This hypothesis could be tested by evaluating the impact of change in SCS rates per different fields on the joint and conditional adoption decision of the enhanced deeper root corn and SCS practices.

Hypothesis 6: *Increased annual carbon payments per acre or per metric tons of carbon sequestered are expected to positively increase the probability of the joint adoption of deeper root corn and SCS practices*. Access to incentives, such as per acre or per carbon credit payments, seed company input support programs, or government subsidies and conservation programs can influence adoption decision of SCS practices and deeper root corn hybrids. Without incentives farmers may not be willing to adopt deeper root corn if they are already making profits with current non-deeper root corn hybrid. Therefore, farmers enrolled in a voluntary carbon market are more motivated to adopt deeper root corn and SCS practices to increase the annual accumulated tons of carbon, especially with increased carbon prices. This hypothesis could be tested by estimating the impact of a change in the per practices payment or per metric tons of carbon sequestered in field i on the probability of adopting SCS practices and/or deeper root corn. The impact of change in the potential SCS rates per field and incentive payment per practice will be addressed in chapter 3.

4.1.6. Impact of change in the share of GM corn

Hypothesis 7*: Farm fields that already grow GM corn, are expected to have higher adoption rate of deeper root corn*. For instance, corn growers with land already planted to DT corn are expected to positively respond to the improved corn varieties and therefore, adopt deeper root corn. This hypothesis can be tested in chapter 2 for the impact of change in the share of cornland allocated to GM corn on the probability and intensity of DT corn adoption.

4.1.7. Change in land value and land ownership

Farmers with social conservation goals care about future generations, at least in term of increasing the asset value of farmland through improving soil health and quality. The willingness of an operator to take actions or make investments that increase land value is highly dependent on land tenure (e.g., if land is owned, rented, or cost-shared). Considering the influence on adoption decisions from land tenure and land value perspectives also depend on farmers' discount rate when considering the future value of land assets.

Hypothesis 8: *Corn growers who own the cropland, or with multiperiod rent contract are more likely to adopt SCS practices and deeper root corn relative to farmers with one period rent contract.* Farmers who own the cropland in question are more likely to adopt deeper root corn and/or SCS practices to increase current and future land value. Alternatively, farmers who rent land for a season or one year contract are less likely to adopt deeper root corn or SCS practices as they care more about short run payoff rather than future land value. However, farmers renting cropland for multiple periods[8], do not care about the potential sale values of land but do care about that contracted land's soil quality, and its influence on current and future profitability. A cost-share lease is a contract where landowner and tenant farm operator share the expenses of production and

[8] We assume contract period of more than three seasons as multiple contract periods.

the returns from production. Therefore, it is harder to estimate the probability of adoption, as the production practices are highly influenced by the conditions agreed upon in the contract between landowner and tenant such as expense and profit split ratios, share of rented field acres, and contract length. This hypothesis could be tested by examine the impact of a change in land ownership or land value on probability of joint adoption decision of SCS plans.

4.1.8. Market access

Literature on the adoption of soil conservation practices in developing countries (e.g., Sub Saharan Africa) suggest that access to market, including distance to market and infrastructure quality, can highly impact the purchase of improved seeds and inputs required to implement soil conservation practices (Asfaw et al. 2011; Shiferaw et al. 2015). This might not be the case in the U.S. Corn Belt with a good quality hard infrastructure such as roads and railways transportation system. However, being in a county near the centre of corn production can increase the probability, or at least timing of deeper root corn adoption (Griliches 1957).

The adoption decision is highly influenced by profits earned by corn growers from deeper root corn vs. other corn hybrids with soil management practices. However, farmers may be motivated to adopt deeper root corn and SCS practices if they get a sufficient carbon incentive payment (e.g., per acre or per carbon credit) to cover adoption costs and to reduce farmers risk toward a decrease in productivity. However, there is a need to evaluate the environmental benefits, payment rates and budget allocation to target the adoption in the geographical areas where SCS practices and deeper root corn can result in a high environmental outcome, which will be discussed in chapter 3 in more details.

5. Conclusion

Soil carbon sequestration (SCS) practices and deeper root system corn varieties have the potential to provide multiple private and public co-benefits such as increasing soil moisture, increasing soil biomass inputs, soil carbon stock, and nitrogen use efficiency. This chapter has focused on a frontier technology of genetically improved corn hybrids with the potential to help maintain farmers' yield under drought conditions and mitigate climate change by reducing carbon and nitrogen emissions to the atmosphere. In this chapter we provided evidence from the literature on the potential SCS rates of different soil management practices under various climatic conditions and geographical variation. Additionally, we discussed the difference between "per acre" incentive payments (under public incentive programs such as NRCS) and "per ton" carbon credit payments (under private voluntary carbon markets such as offered by Nori, Indigo, Corteva). Per acre payments provides dollar incentives per field acre receiving SCS practices (e.g., reduced tillage, cover crops) while per carbon credit pay farmers for every ton of carbon dioxide equivalent of GHGs sequestered or abated annually at carbon market prices.

The adoption of deeper root corn alongside accepted SCS practices is expected to increase the largely public SCS benefits in corn. Therefore, we develop a simple joint adoption model to describe farmers' field level adoption decisions that addresses the complementarity between in-field SCS practices and the genetic innovation of deeper root corn varieties. The adoption decision of any SCS plan is determined by the expected profit and outcome that corn growers may earn. There are other factors that influence the probability of adopting either or both SCS practices and enhanced corn varieties. State specific factors that change over time can also impact the field level adoption decisions and thus intensity of adoption.

Because the corn varieties with genetically improved root systems are still under development and are not yet commercially available, in the next chapter we turn instead to analyse adoption of already-commercialized drought tolerant (DT) corn varieties, which have some common characteristics, to understand the diffusion of such hybrids at the state level and factors that influence adoption at the field level.

CHAPTER 2/ ADOPTION OF DROUGHT TOLERANT CORN VARIETIES IN THE U.S. CORN BELT: AN EXPLORATION IN THE ECONOMICS OF AGRICULTURAL TECHNOLOGY ADOPTION, SOIL HEALTH, AND CLIMATE CHANGE

1. Introduction

Soil can be considered a significant factor that could contribute to reducing GHG emissions and carbon sequestration through best soil management practices. Additionally, good soil quality and fertility can assist crops in withstanding drought, and fixing nitrogen and carbon levels in soil. Soil management practices under drought conditions can enhance crop yield (Richards 2006). One solution to improve soil fertility, reduce carbon emissions, and help corn growers increase yield under drought conditions is through the adoption of drought-tolerant (DT) corn varieties. Some DT corn traits come with larger root systems that may function as the enlarged root system or biomass root varieties in sequestering soil carbon. Corn Belt[9] can be the best region in the U.S. for the potential of high carbon sequestration rates.

Drought-tolerant corn varieties were developed by seed companies to help corn growers get better yields under drought conditions and to reduce irrigation costs. This chapter uses state-level data of corn acres allocated to DT together with field-level data of DT seed adoption by different corn growers in the U.S. Corn Belt region to evaluate the impact of different field operation practices, land and soil characteristics, and weather indicators in the adoption of DT varieties. The study uses recent seed industry data to approximate the DT corn diffusion curve in the U.S. Corn Belt, 2012-2022. The other contribution of this study is that the study uses discrete choice models to recommend the factors that can significantly influence the diffusion of DT corn at the aggregated

[9] See Figure 5 for the Corn Belt map.

level and the adoption of DT corn at the field level. Data analysis shows that about 44 and 58 percent of Corn Belt planted cornland was allocated to DT seed variety in 2021and 2022, respectively, with the highest share of DT corn acres in the western Corn Belt, where drought and irrigation applications are more dominant.

This chapter proceeds as follows: the next section provides a literature overview of DT corn development and adoption. Section three presents an overview of the diffusion of hybrid corn traits in the U.S. using state-level seed industry data. Then we present two empirical analyses and findings for DT corn adoption at the state level and at the field level in section four. Section five discusses the overall conclusion.

2. Literature review on drought tolerant corn development and adoption

In general, farmers adapted to climate variability through changing agricultural production practices; changing planting dates; crop rotation and diversification; soil and water conservation practices; use of crops and weather insurance, and the adoption of drought-tolerant, short-season, or early maturation seed varieties (Fisher et al. 2015; Fisher and Snapp 2014; Westengen and Brysting 2014). Bedeke et al. (2019) conclude that corn growers in Ethiopia combine more than one climate change adaptation strategy (including conservation tillage, DT corn adoption, mixed maize-legume cropping, mineral fertilizer, soil and water conservation practices) to increase or maintain corn productivity under climate change and low water stress. Enhanced seed varieties were a considerable farmer choice for adaptation to drought and to maintain yield and farm income. Crop breeding science has led to the development of seed varieties that are high-yielding, pest and disease-resistant, herbicide-tolerant, drought-tolerance, nutrient uptake efficiency, and varieties that adapt to soil moisture, and different soil structures. Drought-tolerant corn is one variety that provides corn growers with yield insurance against drought. There are two common methods for breeding DT corn varieties: Genetically modified (GM) and conventional or non-GM. GM-DT seed breeding is based on the manipulation of genes from corn or unrelated organisms such as soil bacterium and inserting them into plants. Conventional DT relies on the molecular breeding process which requires the selection of specific DNA sequences with the drought-tolerant trait. After field trials, in 2009, Monsanto input supply company submitted the petition of approval for the DroughtGrad corn variety which contains the bacterial cspB gene and has the ability to withstand only moderate drought levels (Gurian-Sherman 2012). The GM-DT corn seed received regulatory approval from USDA in 2011. Therefore, DT corn with non-genetically engineered or conventional DT corn was commercially introduced in 2011 and hybrid GM-DT corn was introduced to the market in 2012. By 2016 about 23 percent and 3 percent of the U.S. planted acres were conventionally bred DT corn and GM-DT corn, respectively (McFadden et al. 2019).

The adoption of different GM corn hybrids in the developing world, specifically sub-Saharan Africa (SSA) receives a significant emphasis by literature to evaluate the importance of technical, economic, and institutional factors in the adoption, diffusion, and farm profitability of hybrid corn technology (Heisey et al. 1998; Takahashi, Muraoka and Otsuka 2020). Drought and heat-tolerant varieties were the main varieties that received crucial support in Sub-Saharan African countries to assist farmers in adapting to climate change through the Drought Tolerant Maize for Africa (DTMA) project. Over 70,000 tons of DT corn varieties were produced in Sub-Saharan African countries and about 2.5 million hectares of corn land was allocated to DT varieties in 2016 (Cairns and Prasanna 2018).

The adoption of DT corn has a significant impact on corn productivity, farm income, consumption expenditure, reducing poverty levels, and enhancing food security (Awotide et al. 2016; Cooper et al. 2014; Khonje et al. 2015; Kostandini, La Rovere and Abdoulaye 2013; La

Rovere et al. 2014). La Rovere et al. (2014) conclude that the adoption of DT maize in SSA reduces yield variability, increases average corn yield by 532- 876 U.S. million dollars, and reduces the national poverty rate by 6-9.2 percent. Marteya, Etwirea and Kuwornuc (2020) use surveyed data for corn growers in northern Ghana to support the finding that the adoption of drought-tolerant corn in SSA increases corn yield, farmer's income, and intensity of maize commercialization by 193.4 percent (692kg/ha), 534percent, and 0.42 percent, respectively. Furthermore, Lunduka et al. (2019) find that farmers who adopted DT corn in southeastern Zimbabwe harvested 247 kg/acre more yield than those who adopted traditional corn varieties. Additionally, Cooper et al. (2014) provide an estimate for the long-term yield gain from DT corn hybrids that are experimented in different locations in the U.S. Corn Belt which has been developed by pioneer breeding effort. They track the yield potential of different DT corn hybrid with different agricultural drought conditions in the central and western regions of the U.S. Corn Belt, that undergo field experiments between 1990-2012 such as Pioneer 3394, drought-tolerant, and drought sensitive. They provide evidence for the yield gain potential in the long-term for the improved DT corn hybrids, which resulted in the development of Pioneer AQUAmax, that had been launched in 2012.

Exposure to drought, access to improved seed, access to extension service and financial support, access to market information, labor availability, distance to the local market, farm size, seed prices, perceived attributes of hybrid corn varieties, complementary inputs (water and fertilizers), risk and uncertainty, farmer preferences, expected yield, weather expectations, and household characteristics, are factors that influence the adoption of DT corn and farmer's choice of seed varieties (Fisher et al. 2015; Holden and Fisher 2015; Katengeza, Holden and Lunduka 2019; Marteya, Etwirea and Kuwornuc 2020; Simtowe et al. 2019). Simtowe et al. (2019) find that DT adoption rate was 14 percent in 2015 for Uganda farmers which was reduced by 8 percent, 16 percent, and 33 percent due to the lack of information, seed access constraints, and high seed prices, respectively. On the other hand, support of seed companies, agriculture extension, and farm input subsidy programs in SSA increase the intensity of DT corn adoption (Fisher et al. 2015). Katengeza, Holden and Lunduka (2019) address the impact of corn seed subsidized through farm input subsidy programs and conclude that exposure to the previous year's drought is more likely to increase the probability of DT corn seed adoption in Malawi by 3-5 percent with access to farm input subsidy program.

Exposure to drought and climate change has been found to be an important driver of DT corn adoption in the developing world mainly SSA (Holden and Quiggin 2017; Katengeza, Holden and Lunduka 2019). The impact of climate variables on the adoption decision of DT corn in the U.S. has been analyzed for the first time by McFadden, Smith and Wallander (2022) using ARMS field-level data in 2016. They construct a long-run drought indicator and short-term drought indicator to address the impact of drought risk in adoption decisions. They find that exposure to long-term drought is more likely to increase adoption level by 22 percentage points. While exposure to short-term drought in 2013 and 2014 did significantly influenced the corn grower's adoption decision in 2016. This study utilizes the model built by McFadden, Smith and Wallander (2022) to evaluate the recent adoption decision of corn growers in the U.S. Corn Belt using seed industry data. We expanded the McFadden, Smith and Wallander (2018) model and included soil management and production practices, and additional soil characteristics using a more recent DT corn filed level adoption data for the year 2022. This study also contributed to the literature by using seed industry data for state-level DT corn acres to approximate the DT diffusion curve and to statistically evaluate the factors that impact DT diffusion in the U.S.

3. Overview of the diffusion of DT hybrid corn trait in the United States

This section provides an overview of the percentage of corn acreage planted with different hybrid corn varieties by trait, state, and year in the U.S. from 2000-2022. R&D efforts by corn breeding companies in the early 1990s resulted in GM hybrid varieties primarily to help corn growers gain higher yields and overcome pest and weed problems. The most common GM corn varieties currently are insect-resistant (Bt), herbicide-tolerant (HT), drought tolerance (DT), and stacked gene. Then, beginning in the 2000s, leading corn breeding companies developed and launched corn varieties with DT traits. These included both conventionally bred hybrids as well as varieties that were genetically modified with a DT trait.

Corn and soybean are the most dominant crops in the Midwest U.S. or Corn Belt. In 2021 about 42 percent of total cropland in the U.S Corn Belt was allocated to corn production with the remaining 58 percent divided between other crop production and conservation programs (USDA-NASS 2022). Using historical data for corn seed varieties from USDA-NASS and private companies for DT variety adoption (FBN 2023; USDA-NASS 2022), we draw trends of the adoption of hybrid corn varieties among Corn Belt states. Figure 2 shows the trend in the proportion of hybrid corn varieties that are Bt, HT, and stacked with more than one seed trait, compared against conventional hybrid corn varieties in the U.S. from 2000 to 2022. The proportion of land allocated to staked gene varieties continuously increased over time, as farmers shifted from single trait varieties with Bt and HT, or conventional hybrids, to stacked gene variety. These trends reflect the farmers' perception and willingness to shift from single-trait varieties to stacked-trait varieties to gain benefits from different traits.

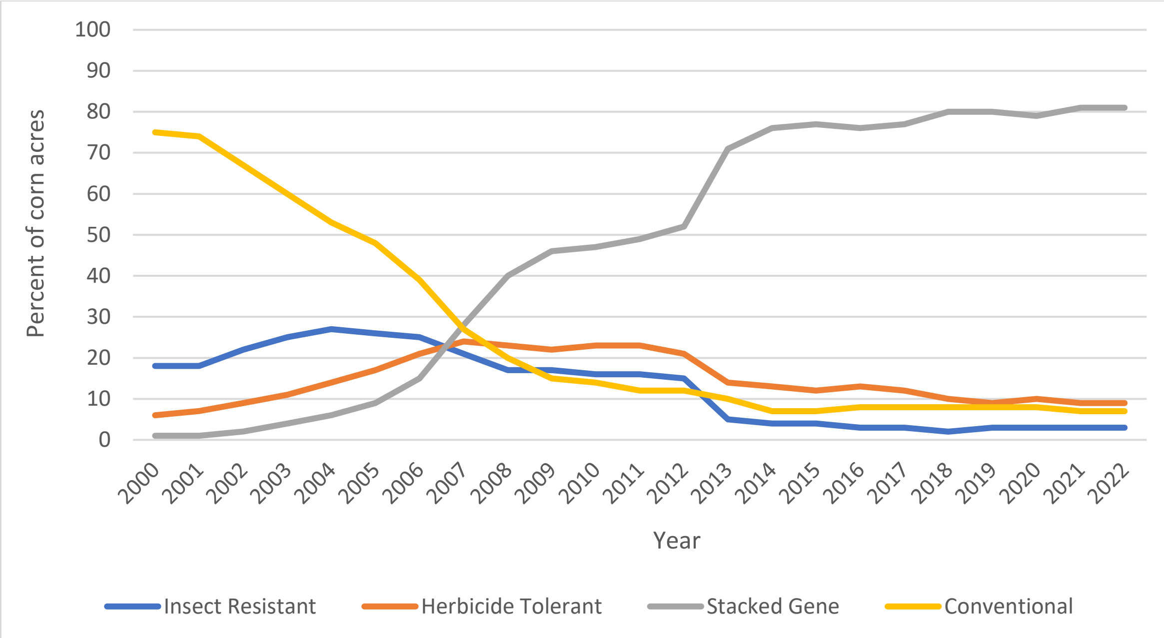

Figure 2: Percent of the U.S. corn acreage planted insect-resistant (Bt), herbicide-tolerant (HT), Conventional, and stacked genes corn seed varieties 2000-2022.
Data sources: Data are from USDA, ERS, 2022.

DT corn varieties have been marketed to U.S. corn growers starting in 2012, at which point farmers started to adopt these varieties as assurance against drought conditions. The adoption of DT varieties increased since first introduced in 2012 (2% of U.S. corn acreage) reaching 22% of total U.S. corn acreage planted in 2016 (McFadden et al. 2019). Using the Farmer Business Newark database to track corn acreages planted hybrid DT vs. non-DT, Figure 3 shows that the U.S. corn acres allocated to corn hybrid that includes DT genes are approaching the number of corn acres planted stacked hybrid with the non-DT trait, in 2021. On average, over 44 percent of Corn Belt planted cornland was allocated to DT seed variety in 2021. Using our field sample data to estimate the DT adoption rate in the U.S., about 58 percent of the Corn Belt cornland is allocated to DT corn. DT traits are stacked with other traits such as Bt and or HT traits, which make it a good choice for farmers to overcome more than one production obstacle such as weeds, insects, nutrient management, and drought risk.

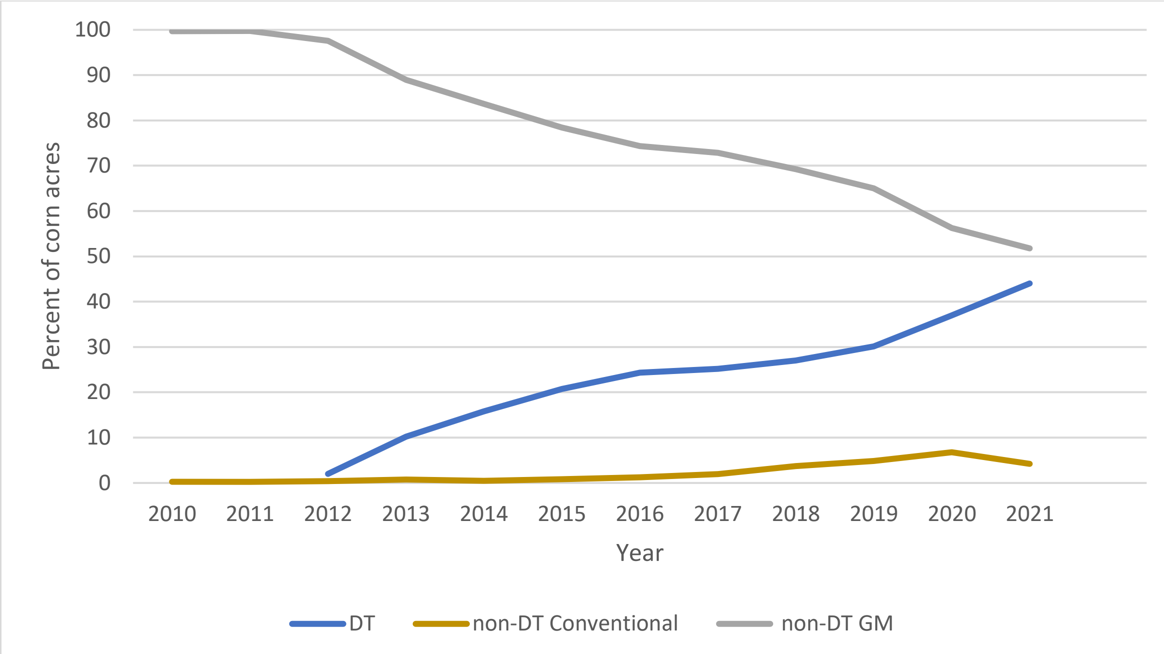

Figure 3: Percent of the U.S. corn acreage planted DT, non-DT conventional, and non-DT GM corn seed varieties 2010-2021.
Data Sources: FBN database used to calculate DT adoption rate 2012-2021.Note: non-DT GM includes corn seed with traits; Glyphosate Tolerance, Glufosinate Tolerance, Corn Borer Control, Rootworm Control, and 2,4-D Tolerance.

Figure 4 shows the proportion of corn acres planted with DT corn for selected states in the Corn Belt for years 2013-2021. The percentage of corn acres allocated to DT increased over time, with the highest adoption rate observed in the western part of the Corn Belt (Nebraska and Kansas) where drought is more common compared to central Corn Belt states. This broad trend suggests that farmers may respond to dry weather and seasonal water shortages by adopting DT corn varieties.

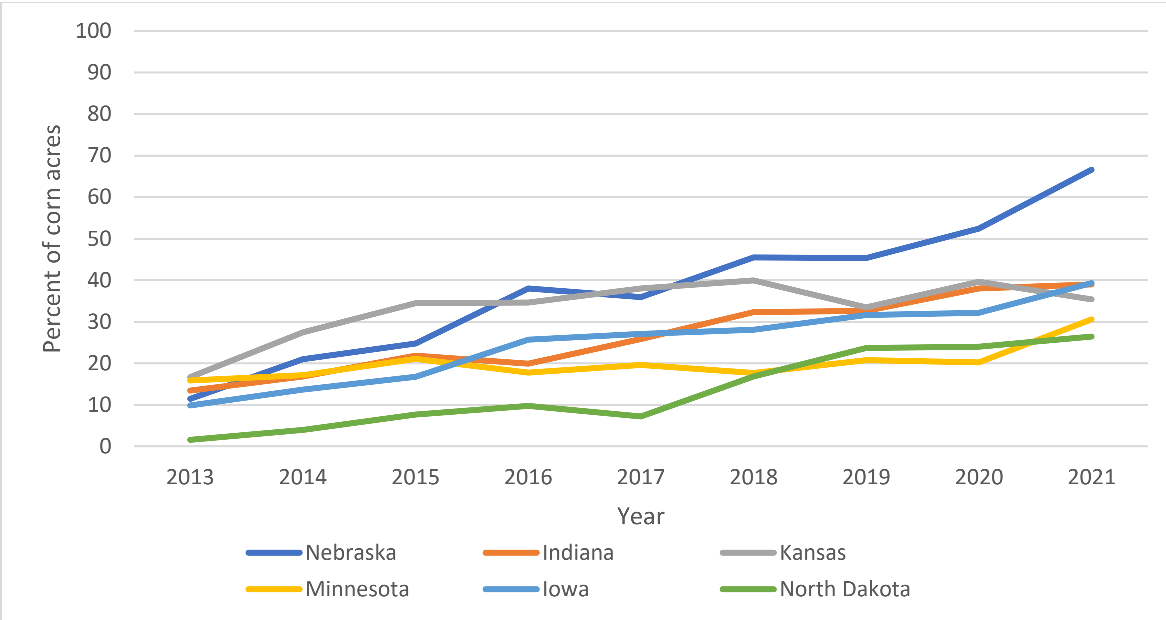

Figure 4: Percentage of corn planted acres with DT varieties.
Data sources: FBN (Farmer Business Network) database, 2023.

3.1. Corn Belt environmental and climate variability

The Corn Belt is located in the Midwest of the U.S. where the temperature has increasingly varied over the last twenty years and achieved the highest average temperature in 2012 and 2018, with an average temperature of over 70 °F for May-September (NOAA 2023). Moreover, about 93-96 percent of corn acres in the central Corn Belt (Iowa, Illinois, Wisconsin, Minnesota), are non-irrigated, while the western Corn Belt (Nebraska, eastern Colorado, and Kansas) depends on groundwater and surface water to irrigate about 39 percent of corn planted acres (USDA-ERS 2022) (See Figure 5 of Corn Belt map). Especially during severe and extreme drought years, corn growers can struggle to access sufficient water for irrigation. Conservation practices including reduced tillage systems, cover crops, crop rotations, and precision irrigation technology can assist farmers in increasing soil organic matter, improving soil moisture, and adapting to drought risk. Additionally, farmers can contribute to soil carbon sequestration, save irrigation costs, and maintain corn yield under drought conditions by adopting DT hybrids.

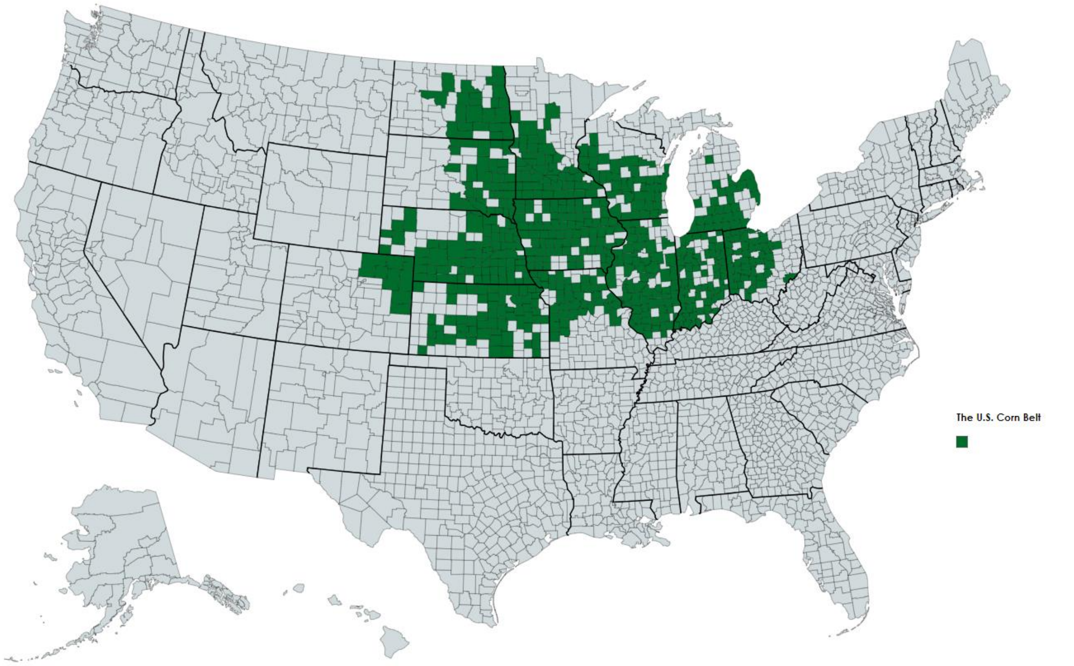

Figure 5: Study Region: The U.S. Corn Belt.
Source: Map is drown using U.S. counties Map chart by selecting counties included in our sample[10]: https://www.mapchart.net/usa-counties.html

Much of the Corn Belt depends on seasonal rainfall. However, there are interannual variations in the amount of annual and seasonal precipitation in the U.S. Corn Belt. Looking at Figure 6, May to September precipitation values ranged from 13 -24 inches for 2011-2022. The year 2012 experienced the lowest amount of annual precipitation while the year 2018 received the highest, during corn production season.

[10] We selected counties based on data availability.

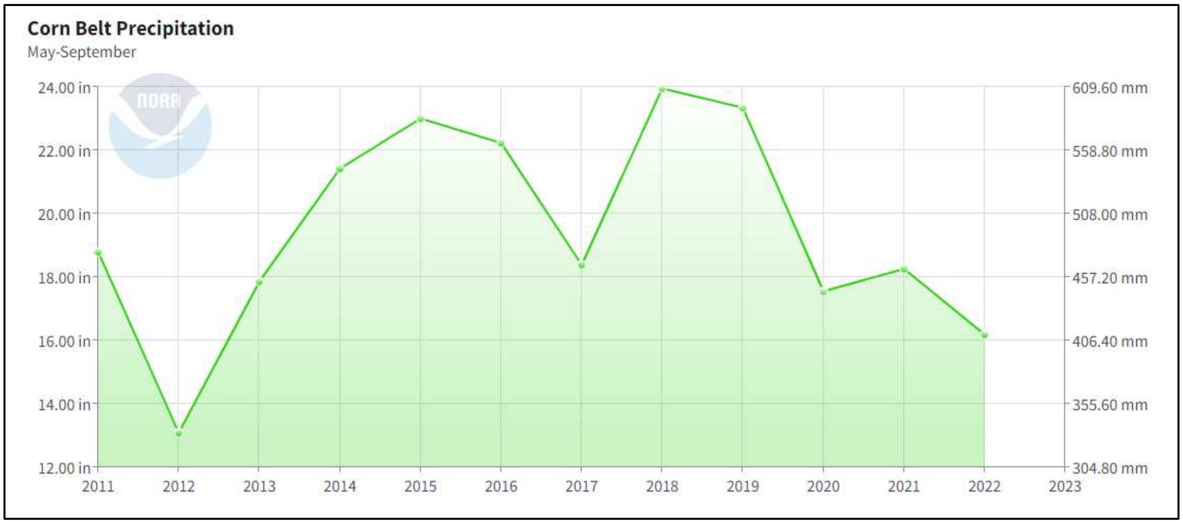

Figure 6: Precipitation value in the Corn Belt 2011-2022.
Source: National Center for Environmental Information of the National Oceanic and Atmospheric Administration (NOAA).

At the same period, the average seasonal temperature was the highest during 2012 and 2018 as shown in Figure 7. During 2022 western states of the Corn Belt and parts of Minnesota and Iowa experienced a severe drought (see Figure 8). In 2022, approximately 28 percent of corn production was within an area experiencing drought (U.S. Drought Monitor 2023). Drought severity increased in the 2023 corn production season, where about 70 percent of corn production was within an area experiencing drought by the end of June (see Figure 22 in the appendix). Therefore, it is expected that improved DT corn hybrids can result in yield stability in drought-prone regions. Such benefit can be particularly important in the western region of the U.S. Corn Belt, where there is more pressure on water resources and farmers need to pay for irrigation (Cooper et al. 2014).

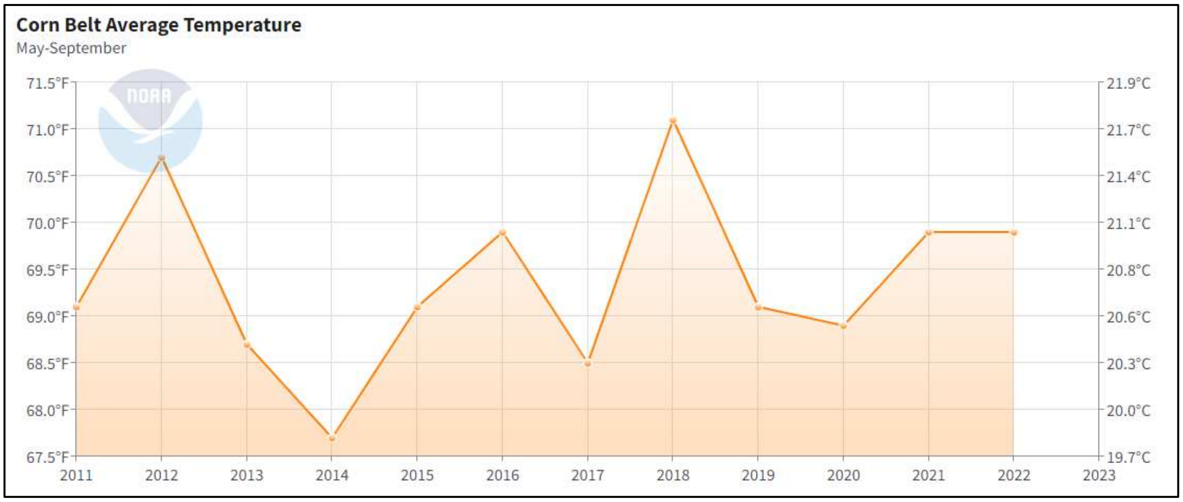

Figure 7: Average temperature in the Corn Belt 2011-2022.
Source: National Center for Environmental Information of the National Oceanic and Atmospheric Administration (NOAA).

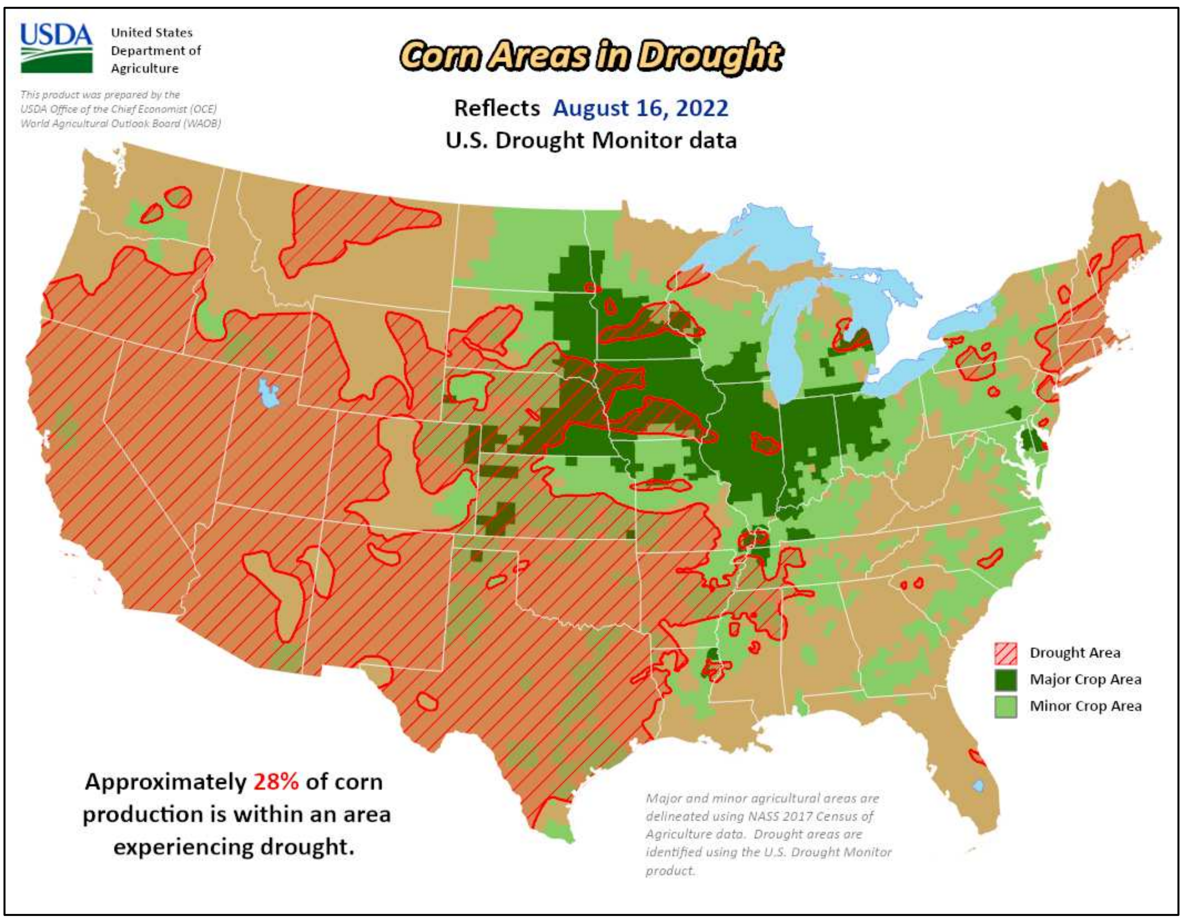

Figure 8: Corn planted areas in drought 2022.
Source: U.S. Drought Monitor database, 2023: https://agindrought.unl.edu/Maps.aspx?1

4. Methodology and Results

In This section, we use two different data sources; a state level data of corn acres allocated to DT together with field-level data of DT seed adoption by different corn growers in the U.S. Corn Belt to evaluate the impact of different field operation practices, soil characteristics, and weather indicators in the adoption decision of DT corn. The first section addresses the diffusion of DT corn in the U.S. Corn Belt while the second section evaluates the factors that impact the adoption of DT corn at individual field level.

4.1. Conceptual framework

Dichotomous models such as Logit, Probit and Tobit models have been widely used to address the relationship between the probability of adopting a specific practice and its determinants such as socioeconomic, institutional, and farm and environmental factors (Liu, Bruins and Heberling 2018). In this study, we use a Tobit regression to estimate the diffusion equation in which aggregated DT acres share across years is a function of climate, environmental, soil characteristics, and economic factors. In the second empirical analysis, we use a Probit regression to model DT corn individual adoption decision.

Corn growers aim at maximizing productivity when making corn variety and input selection decisions. The adoption decision of DT corn is constrained by factors including input prices, farm and farmer characteristics, access to technical and financial support, climate variables …etc. Thus, farmers are assumed to maximize their utility function ($\max_{DT\in(0,1)} U(\pi)$) subject to these constraints. Corn growers will choose to adopt DT corn varieties (DT=1) compared to not growing DT corn (DT=0) if the utility of adopting DT corn is greater than utility from non-adoption decision, that is

$Y_i^* = U_{DT=1}^*(\pi) - U_{DT=0}^*(\pi) > 0$. The utility is unobservable and expressed as a function of observed factors as the following[11]:

$$Y_i = \begin{cases} f(X_i\beta) & if\ Y_i^* = f(X_i\beta) + \varepsilon_i > 0 \\ 0 & otherwise \end{cases} \tag{1}$$

Where Y_i is an observed variable that represents either the adoption decision (adopt vs. not adopt), the probability of adopting DT corn, or the intensity of land used for DT corn. Y_i^* is a non-observable latent variable. β is a vector of parameters to be estimated, X_i is a vector of explanatory variables, and ε_i is a stochastic error term, $\varepsilon_i = Y_i - F(X_i\beta)$, $E(\varepsilon_i) = 0$, $var(\varepsilon_i) = \sigma_i^2$, and $\sigma_i^2 = F(X_i\beta)[1 - F(X_i\beta)]$, $F(X_i\beta)$ is the CDF of the standard normal distribution.

The first model examines the diffusion of DT corn in the U.S. Corn Belt using panel data, in which the dependent variable represents the share of corn land planted with DT corn. Therefore, we used the Tobit model to represent the relationship between the proportion of corn land allocated to DT in a state i and factors that influence the diffusion of DT.

We used a Tobit model to address the diffusion of DT corn in the Corn Belt in state i and year t.

$$DT_{it} = \begin{cases} DT_{it}^* = X_{it}\beta + \mu_{it} \quad if & DT_{it}^* > 0 \\ \\ 0 & otherwise \end{cases} \tag{2}$$

Where DT_{it}^* is the latent unobserved variables represent the difference between the utility of adopting and not adopting DT ($= U_{DT=1}^*(\pi) - U_{DT=0}^*(\pi)$), β is a vector of parameters to be estimated, X_{it} is a vector of explanatory variables such as drought indicators, precipitation level, soil quality, production practices, …etc in state i and year t. ε_i is a stochastic error term.

[11] The equation represents a probit model specification used to estimate the second adoption model for field level analysis.

The model is estimated using the maximum likelihood technique. The basic representation of the Likelihood function is the following (Greene, 2003):

$$\mathrm{L}(\beta,\sigma) = \prod_{t=1}^{T} \prod_{i=1}^{N} \left[\frac{1}{\sigma}\varphi\left(\frac{DT_{it} - X_{it}\beta}{\sigma}\right)\right]^{DT_{it}} \left[1 - \emptyset\left(\frac{X_{it}\beta - c}{\sigma}\right)\right]^{1-DT_{it}} \quad (3)$$

The resulting Log likelihood function is the following:

$$\log \mathrm{L}(\beta,\sigma) = \sum_{t=1}^{T}\sum_{i=1}^{N} DT_{it}\log\left[\frac{1}{\sigma}\varphi\left(\frac{DT_{it} - X_{it}\beta}{\sigma}\right)\right] + (1 - DT_{it}) \log \left[1 - \emptyset\left(\frac{DT_{it} - X_{it}\beta}{\sigma}\right)\right]$$

$$= \sum_{t=1}^{T}\sum_{DT_{it}^{*}>0} \log\left[\frac{1}{\sigma}\varphi\left(\frac{DT_{it} - X_{it}\beta}{\sigma}\right)\right] + \sum_{t=1}^{T}\sum_{DT_{it}^{*}=0} log\left[\emptyset(\frac{c - X_{it}\beta}{\sigma})\right] \quad (4)$$

Where: φ and $\emptyset$ are the standard normal probability density function and standard normal cumulative distribution function, respectively. $DT_{it}^{*} > 0$ represents the upper censored limit and $DT_{it}^{*} = 0$ represents the lower censored limit. Because the dependent variable in our model is a continuous dependent variable (land share allocated to DT corn), we use the Tobit regression to estimate the relationship between the continuous dependent variable and a group of independent variables. Tobit regression allows us to censor the regression around a threshold point, upper or lower limit. In our case, we use zero left censoring, where values that fall at or below zero are censored, given that we have zero adoption rate for the earlier years in some of our sampled states.

4.2. Factors that influence diffusion of DT corn hybrids in the U.S. Corn Belt: A state level analysis of factors and emerging trends

4.2.1. Data and variables

Data for this study consists of DT corn acres for 13 states[12] over 12 years (2011-2022), climate variables (precipitation and drought indicators), land quality measures, government and farm

[12] 13 states with a total of 572 aggregated to a state level.

subsidies, and other crops planted acres. The study region includes the Corn Belt states of Iowa, Indiana, Illinois, Nebraska, Minnesota, Wisconsin, South Dakota, Kansas, Missouri, Ohio, North Dakota, Michigan, and northeastern Colorado (states encompassing the counties shaded in Figure 5). For some variables, we used data for counties that produce corn and aggregated or averaged the data to represent state-level total or average, depending upon the variable.

The dependent variable is the share of DT corn planted acres in a specific state for a given year. Our data for each state's share of corn acres planted with DT corn seed is from the Farmers Business Network (FBN) database (FBN 2023). FBN is a farmer association that sells seed, other farm inputs, and technology to U.S. farmers. It provides farmers with financing to buy land, and equipment, and run farm operations. FBN also offers crop, livestock, and health insurance to farmers as well as farm data analysis to help farmers better make selection decisions regarding seed, machinery, and chemical inputs, as well as forming crop protection plans and marketing plans. We use DT corn seed acres reported in FBN[13] to get the total acres of DT planted per state per year. Data shows that the share of cornland allocated to DT corn increased over time and reached above 50 percent in 2022 for states such as Nebraska, Michigan, and Wisconsin. We use a set of independent variables to explore what drives the spread of DT corn in the Corn Belt over time. The estimated coefficients are important to suggest what constraints might influence the diffusion of new enhanced corn seed over time and accordingly target the adoption incentive programs to the geographical location with higher economic and environmental benefits attained from the adoption.

[13] Most of the FBN data are collected through electronic surveys distributed to FBN member farmers. DT corn acres data are provided for different seed company products, each with a list of traits, including conventional hybrids, Glyphosate Tolerance (Gly), Glufosinate Tolerance (Glu), Corn Borer Control (CB), Rootworm Control (RW), Drought Tolerance (DT), and 2, 4-D Tolerance (2,4-D)). Data is per state that grows corn per year. DT corn data are available from 2012 to 2022. DT traits are typically stacked with other traits. For example: DT genes in DEKALB and CHANNEL branded seed products (DroughtGard® VT Double PRO®) are stacked with Gly and CB and/or RW traits.

Precipitation level data at the county level are provided by the National Center for Environmental Information of the National Oceanic and Atmospheric Administration (NOAA 2023). DSCI data are provided by the U.S. Drought Monitor database. We collect winter and spring precipitation data from December of the previous year to March of the same year, given that farmers make seed selection decisions before the growing season[14]. Low precipitation level is expected to positively influence corn growers' decision to increase the share of corn acres allocated to DT corn, given the low level of soil moisture and available water quantity. We use August drought indices for 2010-2021, given that the drought variable in the model is a one-year lagged variable. DSCI values range from 0-500, where a value of 0 means none of the area in that county is under drought, while 500 means that the entire area in the county is under exceptional drought level (D4). Drought categories in terms of drought severity are none, D0=abnormally dry, D1=moderate, D2=severe, D3=extreme, D4=exceptional. County-level precipitation and drought indicators are aggregated for state-level analysis. We collect data for 572 corn-producing counties in the Corn Belt, and we compute a weighted sum of the percentages in D0 through D4 to get the DSCI value. County-level precipitation and DSCI values are averaged to get state-level variables. In the model, we lag the drought index by one year. Given that about 96-93 percent of corn acres in the central Corn Belt are non-irrigated or rainfed cropland, drought indices, and precipitation levels are important factors that can influence DT corn adoption decisions (USDA-ERS 2022), we assume that farmers may positively response to the exposure to severe drought in the previous year by increasing the share of corn land planted DT seed.

Acres planted with soybean, wheat, sorghum, and total cropland area are extracted from the USDA-NASS database at the state level. It is used to calculate the share of each crop in the state's

[14] The growing season is April-October.

total cropland area. All states in the sample grow soybeans except Colorado (eastern counties of Colorado), as soybeans are considered as a competing crop for land with corn and are used for crop rotation with corn to help maintain nitrogen levels in the soil. Furthermore, wheat is grown in all states included in the sample expect Iowa, and, in the model, it refers to other drought-tolerant crops. We expect that the share of land allocated to other crops can influence the share of cropland allocated to corn and so DT corn land share.

The share of corn area planted to all GM-non-DT corn seed varieties (insect-resistant, herbicides tolerance, and stacked genes corn varieties) are from FBN corn seed data. This variable can reflect farmers' knowledge and experience about bioengineered seed technology because farmers are assumed to make seed purchase decisions according to land and environment properties (e.g., weed, insects, soil moisture level, irrigation condition, drought severity…etc.). In addition, the share of corn acres received by GM corn can give an indication of farmers' acceptance of non-conventional seed varieties and willingness to take risks and try other varieties if required to overcome soil constraints and climate risks. Therefore, corn growers are assumed to increase the share of DT corn area if they previously grew other GM corn varieties.

Government payments and farm subsidy data are provided by the EWG farm subsidy database (EWG 2020). Total government farm payments include farm disaster payments with a trend highly correlated with the drought severity over time; therefore, we subtract farm disaster payment from government payment and call the resulting term "net government payments". Given that government payment includes conservation practices management, commodity subsidies, and crop insurance subsidies; we assume that net government payment to have an impact on the adoption of DT corn, as corn growers can apply for corn subsidy and corn insurance per acre of corn planted. Farm input subsidy program that financially supported the adoption of DT corn in SSA has increased the probability of DT corn seed adoption in Malawi by 3-5% (Katengeza, Holden and Lunduka 2019). Government payments are found to be highly correlated with cropland and corn total land, because states with large cropland acres are expected to have more acres registered in such programs (CRP, EQIP, commodity subsidies, crop insurance subsidies, …etc.). Therefore, we did not include corn land area in the model.

Land quality variables, such as the percentage of cropland with erosion risk and soil problems are provided by the USDA Natural Resource Conservation Services (NRCS) Soil Data series and by Web Soil Survey which are calculated from USDA-NRCS SSURGO data. The share of agricultural land with erosion risk and soil problems is assumed to influence the location of cropland allocated to a given crop. For example, highly erodible cropland can be assigned to sustainable management programs or CRP for years, which could reduce the share of land allocated to corn in that location, if corn is used to be grown in that cropland.

We included a control variable capturing the location in the Corn Belt to control for unobserved factors or variations within states that are not captured by the model. It includes three regions within the Corn Belt: western, central, and eastern as a reference group. The western Corn Belt includes Nebraska, Kansas, Colorado, North Dakota, and South Dakota; the central Corn Belt includes Iowa, Missouri, Illinois, Minnesota, and Wisconsin; and the eastern Corn Belt includes Indiana, Ohio, and Michigan. We expect that location within the Corn Belt can impact the share of DT corn land, given the geographical, environmental, and climate variation between the three regions. Summary statistics of the variables used in the state-level regression are presented in Table 8 in the appendix.

4.2.2. Econometric model

Moving from individual adoption decisions to aggregated adoption decisions requires a shift in the analysis from discrete adoption choices (e.g., adopt or not adopt) to the diffusion of the technology within a population. The diffusion equation is a function that relates the intensity of adoption and certain factors that influence the spread of technology within a group of adopters or expansion within farmland. The extent of land allocated to improved DT corn by the state i and year t is specified as a function of state-aggregated environmental, climate, and farm-related factors, that is:

$$\mathrm{DT}_{it} = \beta_0 + \beta_1\, D_{it-1} + \beta_2\ Pre_{it} + \beta_3 GM_{it-1} + \ \beta_4\, DRC_{it}\ + \beta_5 Irr_{it} + \beta_6\, NGP_{it} + \beta_7\, ers_{it} + \ \theta_i + \ \gamma_t + \varepsilon_i \qquad (5)$$

Where DT_{it} is the share of corn land planted with DT corn in the state $i = 1,..13$, and year $t = 2011,..2022$. D_{it-1} is the August Drought Severity and Coverage Index in the state i and year $t-1$[15]. Pre_{it} is the spring precipitation in the state i and year t, measured in inches. GM_{it-1} is the share of corn area planted to genetically engineered hybrid corn other than DT in a state i and year $t-1$. DRC_{it} is the share of wheat planted acres in the state i and year t, which represents the share of cropland allocated to either drought-resistant crops or for crop rotation purposes. Irr_{it} is the proportion of irrigated corn acres in the state i and year t. NGP_{it} is the net government payment (total government payment – disaster payment) to farms in the state i and year t. The variable ers_{it} refers to the proportion of cropland with erosion risk in a state i and year t. θ_i is a factor variable for state location within the Corn Belt (θ =1 if eastern, θ =2 if western, and θ =3 if

15 "Drought Severity and Coverage Index is an experimental method for converting drought levels from the U.S. Drought Monitor map to a single value for an area. It takes values from 0-500, where zero means that none of the areas is abnormally dry or in drought, and 500 means that all the area is in D4, exceptional drought" (U.S. Drought Monitor 2023).

central). $\gamma_t$is a time dummy variable to control for changes over time. ε_i is the error term $\varepsilon_i \sim N(0,1)$. The Tobit model is estimated using the maximum likelihood estimation technique and the estimated coefficients are presented in the following section.

4.2.3. Results and discussion

Table 2 shows the estimated coefficients and marginal effects[16] of Tobit regression. Among our sample, exposure to drought risk has a significant and positive relationship with the diffusion of DT corn. The estimated coefficient suggests that when a state is exposed to high and severe drought, farmers in that state are indeed more likely in the following years to grow more corn with DT traits. Marginal effects show that increased exposure to drought in the previous year by 1 unit, would increase the share of corn land allocated to DT in the Corn Belt by 0.7 percentage points. On the other hand, though insignificant, spring precipitation appears to have a negative effect on the diffusion of DT corn. A high spring precipitation level is a good sign for farmers to have moisturized soil for late April or early May planting decisions, which can negatively reduce the probability of picking DT seeds prior to the growing season. Our finding supports the finding by Katengeza, Holden and Lunduka (2019) in which drought and precipitation significantly influence the adoption decision and adoption intensity of DT corn. Katengeza, Holden and Lunduka (2019) conclude that exposure to the previous three years' drought is more likely to increase DT corn adoption in Malawi by 0.05 points while experiencing high precipitation levels in the past three years decreases DT adoption decision by 0.13 points.

16 Marginal effects represent a change in explanatory variable x_i on the dependent variable DT and is represented as: $\frac{\partial E(DT)}{\partial x_i} = F(\omega)\frac{\partial E(DT|DT>0)}{\partial x_i} + E(DT\,\big|DT > 0)\frac{\partial F(\omega)}{\partial x_i}$. Where $F(\omega)$ is the standard normal distribution function, $\omega = \frac{x\beta}{\sigma}$, $E(DT)$ is the unconditional expected value of DT, and $E(DT|DT > 0)$ is the condition expected value of DT for DT>0.

The estimated coefficients for the share of hybrid corn adopted by farmers and the share of wheat in cropland are statistically significant determinants of DT corn adoption. These suggest that states in the Corn Belt with larger acres of hybrid corn are more likely to increase the share of acres with DT corn varieties among the state's acres planted to corn. If farmers within a state already adopted other GM corn hybrids in the same year or previous years, then farmers in that state are more likely to adopt DT corn varieties in their cropland as they gain knowledge about the functions of different seed genetics. Among our sample, on average, for a one percent increase in the share of GM-non-DT corn in the Corn Belt cropland in the previous year is expected to increase the share of land allocated to DT corn by 74 percent. The share of wheat in the state's cropland area is also found to be significantly and negatively influencing the shares of land allocated to DT corn. DT corn share decreases in states with counties that have high shares of wheat. Wheat is a drought-resistant crop and can be a competing crop for cropland areas or a substitute crop for corn, in which farmers who are growing wheat in drought areas are more likely to grow DT corn, making the decision one of comparing net returns for wheat and DT corn. Among our sample, for a one percent increase in the share of land allocated to wheat in the Corn Belt, land allocated to DT corn is expected to decrease by 10 percent, on average.

The estimated coefficient of the irrigation variable confirms that the share of irrigation within a state increases the likelihood of DT adoption. Marginal effect results suggest that with a one percent increase in the irrigated corn area, the land allocated to DT corn would increase by 19 percent, on average. This can be the dominant case in the western Corn Belt. Because farmers in the western Corn Belt incur irrigation costs, they may decide to use DT to reduce the irrigation costs. Moreover, with deficit irrigation, farmers have water rights and may want to sell water to generate revenue. In such cases, the farmer is more incentivized to adopt DT to increase yield with reduced water amount.

Net farm government payment has a negative and significant impact on the adoption of DT corn varieties. The estimated coefficient suggests that corn growers in the Corn Belt are less likely to increase the share of corn land allocated to DT corn, with higher government payment. This can be attributed to the high crop insurance and commodity payments. Because if farmers receive sufficiently high payment, it will be as insurance against crop losses in case of severe or extreme drought and crop damage, thus, they will be less likely to adopt DT. The negative impact could be due to variations in government payment between states. For example, government payment is the highest to central and eastern Corn Belt states with more counties producing corn, compared to western Corn Belt states with higher adoption rates and lower number of corn-producing counties.

The state's location within the Corn Belt is an important indicator of the acreage share of the DT corn area. For example, corn growers in states located in the western Corn Belt (e.g., Nebraska and Kansas) are more likely to increase the share of DT corn area, relative to farmers in states of the eastern Corn Belt (e.g., Ohio and Michigan). Adversely, Griliches (1957) conclude that central Corn Belt states were the first and fastest to adopt hybrid corn varieties due to the influence of factors such as acceptance of hybrid seed, concentration of commercial seed producers and availability of hybrid seed in commercial quantities. However, the diffusion of DT corn is highly influenced by climate factors. States in the western Corn Belt have more exposure to severe drought (see Figure 8 and Figure 22) and corn growers highly depend on surface and groundwater to irrigate a large share of corn acres. Thus, adopting DT on a large scale can reduce the need for higher amounts of water as crops can withstand drought risk. On the other hand, though insignificant, corn growers in states located in the central Corn Belt (e.g., Iowa, Missouri, and

Illinois) are less likely to increase the share of DT corn area, relative to farmers in states of the eastern Corn Belt. This is likely due to higher precipitation levels and the fact that farmers do not incur irrigation costs.

Table 2: Tobit regression estimated coefficients and average marginal effects of state level analysis

Dependent variable: share of corn land planted with DT corn in the state i and year t		
Variables	**Model 1** **Estimated Coefficient**	**Model 1** **Average Marginal Effects**
Drought (DSCI)	0.005* (0.002)	0.007* (0.008)
Precipitation	-0.331 (0.256)	-0.736 (0.824)
Share GM corn hybrid	0.900* (0.352)	0.741* (0.825)
Share of cropland allocated to wheat	-0.401* (0.177)	-0.104* (0.300)
Share of irrigated corn area	0.303*** (0.058)	0.195*** (0.217)
Net government payment	-0.758*** (0.252)	-0.524*** (0.809)
Share of erodible cropland area	-2.919 (2.495)	-1.773 (1.019)
Western Corn Belt	13.387** (4.815)	9.426** (1.217)
Central Corn Belt	-1.807 (2.791)	-1.424 (0.159)
Intercept	-103.290 (4.984)	
Time dummy	Yes	
LogSigmaMu	0.801* (0.453)	
LogSigmaNu	1.931*** (0.064)	
Observations	156	
Log-Likelihood	-478.666	
Akaike Inf. Crit.	1003.333	
Bayesian Inf. Crit.	1073.479	
Wald F-statistics (X2) **Chi-squared test P(>X2)**	436.800*** (0.000)	

*Note: Standard errors are in parentheses. Significance is denoted as ***p<0.01, **p<0.05, *p<0.10.*

In addition to model 1 results, in Table 9 in the appendix, we run three different models to evaluate the effects of the share of soybean acres, past year of corn yield, and corn land area on DT diffusion. The model is estimated with eight variables included in the regression in addition to time dummies and region dummies, given the low sample observations (156), with additional variables to the model, the degree of freedom decreases, and we run off the power to estimate the model. We use the share of soybean and wheat acres in separate regressions given the high correlation between the two variables. The share of cropland allocated to soybeans is not significantly influencing the share of cropland allocated to DT corn in counties that produce corn in each state. Similarly, sorghum acres are highly correlated with soybean and wheat acres, and by including sorghum in the regression in Model 1 or 2, it results in non-significant estimated coefficient. In model 3, we run Tobit regression including total corn land area and dropping government payment variable, because corn land areas are highly correlated with government payment and share of soybean acres. Results suggest that the total cornland area is negatively influencing the diffusion of DT corn, which is not as expected. This could be due to changes in land use or a decrease in acres allocated to corn, compared to the fast diffusion of DT corn over 2012-2022. Moreover, there is a low adoption rate in states with large cornland areas (e.g., Illinois), and a high adoption rate in states with less cropland allocated to corn (e.g., Kansas). In Model 4 we included the lag yield variable which represents one year lag for the average corn yield of GM corn, and the estimated coefficient is insignificant.

This section examines the diffusion of DT corn in the U.S. Corn Belt using data on the share of corn acres planted DT varieties at the state level. The estimated coefficients suggest that diffusion of DT corn is highly impacted by exposure to drought risk in previous years, knowledge, and experience about GM hybrid corn, share of other crops in the cropland such as soybean and wheat, share of irrigated corn acres within the state, government payment, and state's location within Corn Belt. The next section investigates what drives the adoption of corn with DT traits at individual farm level.

4.3. A field level analysis of the Adoption pattern of drought tolerant corn seed in the U.S. Corn Belt.

4.3.1. Data and variables

The study uses a sample of 1,504 fields from 584 counties in the U.S. Corn Belt, that grow corn with and without the DT trait. Data is obtained directly from different seed companies[17]. Each sample observation represents the location of the grower, the seed variety, growing practices, and other characteristics such as soil type, tillage system, previous crops, and irrigation status. The study region is the U.S. Corn Belt and includes 584 counties from thirteen states: Iowa, Indiana, Illinois, Nebraska, Minnesota, Wisconsin, South Dakota, Kansas, Missouri, western Ohio, eastern North Dakota, southern Michigan, and eastern Colorado. Other variables included in the model are county-level variables including precipitation level, drought indices, and land quality measures.

Precipitation level data are provided by the National Center for Environmental Information, of the National Oceanic and Atmospheric Administration (NOAA 2023). We collected county-level precipitation data for the winter and spring before corn growing season, December 2021- March 2022. Precipitation level determines soil level moisture before planting season and the availability of ground and surface water for irrigation. Therefore, high precipitation levels may reduce the likelihood of DT adoption, given the moisturized soil and quantity of water available for irrigation.

[17] Corn seed brands and seed companies: Pioneer, DEKALB, and CHANNEL, Beck's Hybrids, NUTECH, Kruger, NK, and GOLDEN HARVEST. Data collected from Corteva and Bayer.

County-level drought indices are provided by the U.S. Drought Monitor. The drought data are reported as categories based on drought severity (none, D0: abnormally dry, D1: moderate, D2: severe, D3: extreme, D4: exceptional) and the data are in the form of percent of the area within the county exposing drought severity. In terms of the potential impact on crops, the drought indicators can represent: D0: short-term dryness, D1: less damage to crops, D2: farmers are likely to see crop losses, D3: farmers can observe major crop losses and D4: farmers can observe exceptional and widespread crop losses (McFadden, Smith and Wallander 2022). We used August drought indices for 2018-2021, given that July and August are the months when corn is in the reproductive growth phase, which requires a given amount of moisture for grain fill and ear formation (Neild and Newman 1990). For the year 2022, we used the March drought index to explore the influence of spring drought on DT adoption decisions. We then created a dummy variable for drought severity in a given county in August of the year t, which equals one if the county is exposed to moderate (D1), severe (D2), extreme (D3), or exceptional (D4) drought in time t, otherwise zero if none or just abnormally dry (D0).

County-level corn basis data are generated from different sources: USDA-AMS (2022); Iowa Department of Agriculture and Land Stewardship (2022); and Successful farming (2022). The corn basis variable is the difference between March corn cash prices and December future contracts. Corn cash prices and future contract prices can impact farmers' choice of seed varieties especially if farmers decide to participate in an input purchase contract with a seed company.

Land quality variables, percentage of cropland with erosion risk, soil problems, and wet cropland are provided by USDA Natural Resource Conservation Services (NRCS) Soil Data, and by Web Soil Survey which are calculated from USDA NRCS SSURGO data. Land quality is assumed to influence the choice of seed hybrid, for example, farmers in counties with lower share of wet cropland are more likely to adopt DT corn. Farmers in counties with poor soil quality were found to be more likely to adopt hybrid crops by 70 percent relative to farmers in counties with high soil quality (Matuschke and Qaim 2009). Table 10 in the appendix provides summary statistics of the variables included in the field-level analysis. Mean difference between fields allocated to DT corn vs. field allocated to non-DT corn are represented in Table 11 in the appendix.

The analysis of our sampled data for DT adoption vs. non-DT adoption for irrigated fields and for fields using strip tillage is shown in the following figures. Figure 9 compares the irrigated corn fields for DT corn and non-DT corn per state in 2022. It is clearly represented that higher and more significant rates of DT corn and non-DT corn fields in western Corn Belt states (Northeastern CO, NE, and KS) are irrigated, compared to other Corn Belt states. Our sample fields from SD, ND, and OH are one hundred percent non-irrigating DT corn fields. While IA, MN, and MO have lower rates of irrigated DT corn fields, compared to non-DT corn fields. Surprisingly, Ohio has zero irrigation ratio for both DT corn and non-DT sampled fields, this can be attributed to the high precipitation level (average value of 35.73 inches January-October 2022 (NOAA 2023)) and the low drought severity experienced in 2022 (see Figure 8 and Figure 22), in which farmers may totally shift DT corn acres to non-irrigation status.

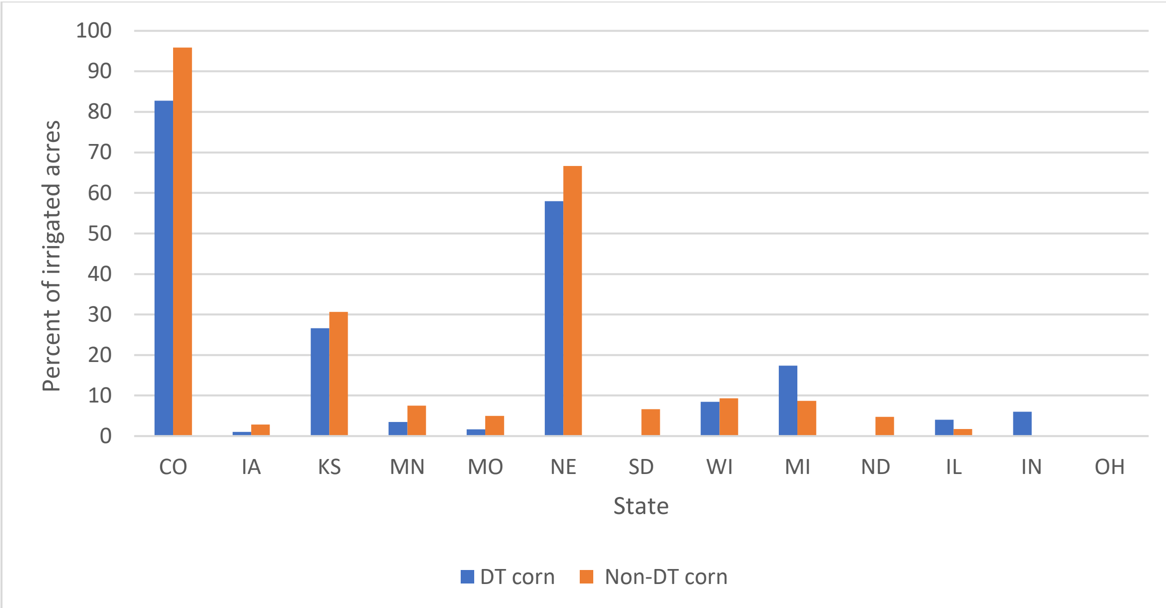

Figure 9: Percent of acres that are irrigated, for acres planted to DT corn vs. for acres planted to non-DT corn, state, 2022.

Our sampled observations show that about 24, 18, and 58 percent of the DT corn fields are using no-tillage, strip-tillage, and conventional or other soil management practices systems, respectively. Figure 10 compares the share of DT corn planted with strip tillage vs. non-DT corn planted with strip tillage system. Across our sample, all states except IA and WI are using a strip-tillage system in non-DT corn fields at a higher rate compared to DT corn fields in 2022. Moreover, no-tillage systems are more observed in counties with states that have high DT adoption rates including KS, NE, IN, and OH (see Figure 23 in the appendix). Corn Growers' choice of tillage system can be attributed to the impact of tillage system on soil fertility and health which can reduce the need for high applications of chemical fertilizers. Moreover, different seed companies recommend a group of appropriate production practices with certain seed hybrids, for instance, "DEKALB corn seed with trait: DroughtGard™ Hybrids and VT Double PRO® corn seed by Bayer company" is an excellent drought tolerant seed, performs well in dryland and limited irrigation systems, and a good fit for early planting and reduced tillage systems. The tillage system can impact soil fertility, as no-tillage and strip tillage are found to have a significant impact on corn nitrogen (N) uptake and nitrate (NO_3) movement through the soil profile. Al-Kaisi and Licht (2004) conducted field-level experiments in Iowa from 2001-2002 to evaluate corn response to nitrogen uptake and soil nitrate movement, and the experiment shows that no-tillage and strip tillage result in lower residual soil nitrate buildup in 0-1.2m soil depth, compared to other tillage systems.

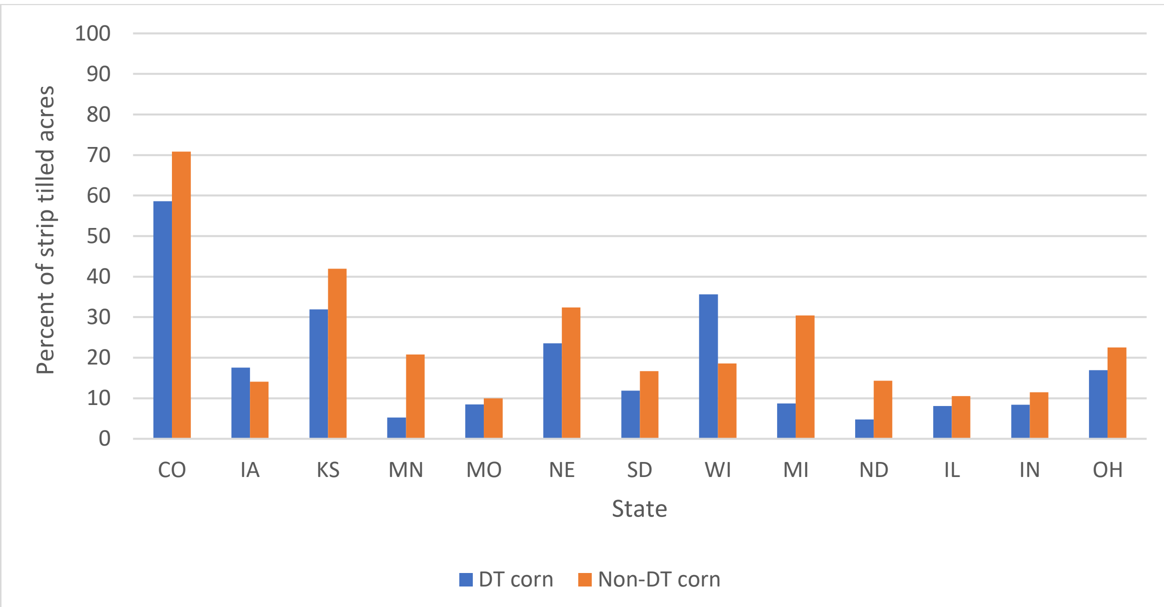

Figure 10: Of acres planted with DT corn, the percent treated with Strip tillage, vs of acres planted with non-DT corn the percent treated with Strip tillage, per state in 2022.

Among our sampled data, the highest DT corn acres are grown in clay loam soil compared to silt loam and sandy loam soil, with 41 percent of our sampled fields growing DT corn in clay loam soil. For the majority of the Corn Belt states, the share of DT corn in clay loam soil is higher than the share of non-DT corn planted in the same soil type (see Figure 11). However, those rates might not be representative, given that the distribution of clay loam, silt loam, sandy loam soil, and other soil types varies from state to state. Therefore, the proportion of DT and non-DT corn in clay loam soil should be compared to the actual proportion of clay loam soil in the state.

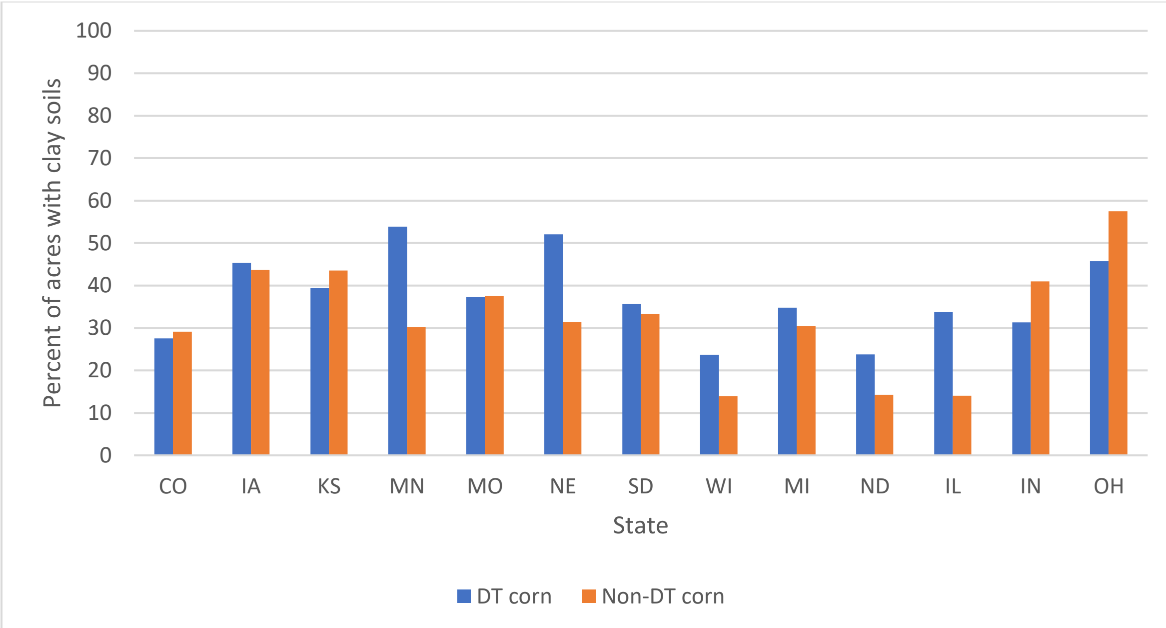

Figure 11: Of acres planted with DT corn, the percent that are clay loam soil vs. of acres planted with non-DT corn, the percent that are clay loam soil, per state in 2022.

4.3.2. Empirical specification

We expand McFadden, Smith and Wallander (2018) DT adoption model and include soil management practices as well as soil characteristics. We also included the spring drought of 2022 to evaluate the impact of exposure to drought risk and low precipitation immediately before the growing season on the DT corn adoption decision. Following is the DT corn seed adoption on a cornfield i in year 2022:

$$DT_i = \beta_0 + \sum_{d=1}^{4} \sum_{t=2018}^{2022} \beta_1 DI_t + \beta_2 Pre_i + \beta_3 Irr_i + \beta_4 clay_i + \beta_5 ST_i + \beta_6 NT_i + \beta_7 CR_i + \beta_8 CB_i$$

$$+ \beta_9\, Ers_i + \beta_{10}\, SP_i + \beta_{11}\, Wet_i + \theta_i + \mu_i \qquad (7)$$

DT_i is a dummy variable of DT corn seed adoption in the field i , $DT_i = 1$ if field adopts DT corn, zero otherwise. DI_t is an indicator of drought severity in a given county in August of the year $t = 2018 - 2021$, and March of the year 2022. We run two regressions, one including individual drought indicators per year: moderate (D1), severe (D2), extreme (D3), and exceptional (D4), and the other regression includes one drought indicator per year represented by $DI = 1$ if the county is exposed to moderate (D1), severe (D2), extreme (D3), or exceptional (D4) drought in time t, $DI = 0$ otherwise, None or abnormally dry (D0). Pre_i is the precipitation level from December 2021 to March 2022 (inch). Irr_i is a dummy variable for the field-level irrigation state, $Irr_i = 1$ if field i is irrigated, zero otherwise. $clay_i$ refers to soil texture in the field i $clay_i = 1$ if the seed is grown in a filed i with clay loam soil type, zero otherwise. ST_i is a dummy variable for the strip tillage conservation system, $ST_i = 1$ if field i uses strip tillage system, zero otherwise. NT_i is a dummy variable of a no-tillage conservation system, NT_i =1 if field i uses no-tillage system, zero otherwise. CR_i is an indicator of the field-level crop rotation system, $CR_i = 1$ if farmer in field i rotate corn with other crops, $CR_i = 0$ otherwise. CB_i refers to the county-level corn basis (dollar/bushel).[18] Ers_i, SP_i, and Wet_i represent the county-level proportion of cropland with erosion risk, soil problems, and wetlands, respectively. θ_i are state-fixed effects included to capture unobserved factors or variations within states that are not included in the model. μ_i is the error term, $\mu_i \sim N(0,1)$. Variables included in equation 7 are physical variables that impact soil quality and variety's average yield. However, cost and net return related variables are not included in the model. We assume that the population of farmers in the U.S. is homogenous as they are well capitalized given the access to commodities, crop insurance, and conservation incentives. In addition, we assume that there is no big variation in seed prices between different corn hybrids, where the average price can range between $200 and $400 per bag. For example, the average hybrid corn seed price was $288 per bag for non-drought tolerant varieties and about $305 per bag for drought tolerant varieties during 2019 and 2020 (Yost et al. 2022). Therefore, we assume that the prices and input costs are not a big constraint to the U.S. corn growers, as farmers care more

[18] Corn price basis equals cash prices minus futures prices.

about yield effects when adopting a specific corn hybrid. Thus, adding cost variables per variety to the model may not improve the variation within our sample. Because the model is a discrete choice model and the dependent variable is yes vs. no decision choice (adopt DT vs. not adopt), we use a probit regression to estimate the relationship between the dependent variable and a group of independent variables.

4.3.3. Results and discussion

Table 3 presents the estimated coefficients for the exposure to yearly drought risk. Based on our sample data, results show that the recent year's drought is significantly related to the adoption of DT corn seed in the U.S. Corn Belt. We find that exposure to the year 2021 drought did significantly influence the adoption of DT corn in 2022 in the U.S. Corn Belt. Drought severity in 2021 seemed to negatively influence DT corn adoption in 2022, in which fields that were exposed to 2021 drought are 8 percentage points less likely to adopt DT. According to the U.S. drought monitor, about 37 percent of corn production is within an area experiencing drought in August 2021 (see Figure 22). The negative impact could be due to non-exposure to drought risk during the 2021 corn production season by states with major corn production areas including Indiana, Illinois, Ohio, Michigan, Missouri, Kansas, and parts of Iowa, Nebraska, and Minnesota. In contrast, exposure to early spring drought has a positive impact on the adoption of DT corn in 2022. For exposure to spring 2022 drought; relative to no drought, adoption would be expected to increase by about 6 percentage points after exposure to drought in March year 2022. This suggests that exposure to immediate drought risk during months before the growing season can influence farmer’s decision to adopt DT corn variety. Though not significant in these regressions, spring precipitation levels observed prior to the growing season appear to negatively influence the adoption of DT corn. It is reasonable that if precipitation is higher before the corn growing season, farmers are less likely to adopt DT corn.

We find that irrigation and strip-tillage systems have a significant and negative impact on DT corn adoption, which suggest that DT corn tends to be adopted more in non-irrigated corn fields and in fields that use no-tillage systems or conservation systems other than strip tillage. Average marginal effects for irrigation variables show that farmers in irrigated corn fields are less likely to adopt DT corn seed by 13 percentage points relative to non-irrigated corn fields. It could be due to the water access and availability in these fields, in which farmers with irrigated fields can access sufficient quantity of water to irrigate corn fields and so less likely to adopt DT corn. Deep strip tillage and conventional tillage systems were found to reduce soil penetration resistance and have no significant impact on root growth (de Lima et al. 2022). Moreover, a no-tillage system can be a best practice with DT seed varieties as it is more efficient in water retention and increasing soil moisture up to 60 cm soil depth during corn growing season, compared to strip tillage or intensive tillage system (Blevins et al. 1971). Estimated coefficients of soil texture suggest that farmers with fields of clay loam soil are more likely to adopt DT corn varieties relative to farmers with fields of silt loam or sandy loam soil.

Also, estimated coefficients of crop rotation are insignificant and with positive effects on the adoption of DT corn. The impact of previous crops on the adoption of DT variety can be explained in terms of the contribution of previous crops to soil productivity (i.e. Beans contribute to soil fertility and maintain nitrogen levels in soil). Also, growing crops by other crops per season can reduce some insects, or weeds, so farmers can change from Bt and HT varieties to adopt DT varieties.

Though insignificant, DT corn is less likely to be adopted in wet cropland. On the other hand, it is more likely to be adopted in cropland that is susceptible to erosion problems, given that root length and biomass may assist in reducing erosion damage. Also, it is more likely to be adopted in cropland with soil problems such as low moisture holding capacity, low soil fertility, and shallowness of the rooting zone.

Table 3: Probit regression estimated coefficients and marginal effects with yearly drought indices.

Dependent variable: DT corn seed adoption in field *i*				
Exogenous variable	**Model 1 Estimated Coefficients**	**Model 1 Average Marginal Effects**	**Model 2 Estimated Coefficients**	**Model 2 Average Marginal Effects**
Drought 2018	-0.140 (0.085)	-0.055 (0.033)		
Drought 2019	0.007 (0.096)	0.003 (0.037)		
Drought 2020	-0.077 (0.094)	-0.030 (0.035)		
Drought 2021	-0.187** (0.097)	-0.080** (0.037)	-0.162** (0.092)	-0.057** (0.035)
Drought Spring 2022	0.180* (0.093)	0.069* (0.036)	0.181* (0.091)	0.068* (0.035)
Precipitation	-0.010 (0.016)	-0.004 (0.006)		
Irrigation	-0.321*** (0.128)	-0.127*** (0.051)	-0.324*** (0.124)	-0.126*** (0.049)
Clay loam	0.126* (0.072)	0.049* (0.028)	0.125* (0.072)	0.052* (0.028)
Strip-Till system	-0.210** (0.096)	-0.083** (0.038)	-0.216** (0.088)	-0.083** (0.035)
No-Till system	0.036 (0.097)	0.014 (0.037)		
Crop Rotation	0.028 (0.095)	0.011 (0.037)		
Corn basis	0.194 (0.169)	0.075 (0.066)		
Proportion of cropland with erosion risk	0.001 (0.003)	0.0004 (0.001)		
Proportion of cropland with soil problems	0.001 (0.005)	0.0004 (0.002)		
Proportion of wet cropland	-0.003 (0.003)	-0.001 (0.001)		

Constant	-0.742** (0.460)	-1.035*** (0.283)
State dummy	Yes	Yes
Observations	1504	1504
McFadden PseudoR2	0.051	0.049
Wald F-statistics (X2)	131.700	124.500
Chi-squared test P(>X2)	(0.000)	(0.000)
log-likelihood	-970.797	-972.917
Akaike Inf. Crit.	1999.594	1985.833

*Note 1: Estimates are for the population of 2022 U.S. Corn Belt fields. Standard errors are in parentheses. Significance is denoted as ***p<0.01, **p<0.05, *p<0.10.*

Table 4 presents probit regression estimated coefficients and marginal effects for field-level adoption decisions of DT corn with drought severity indicators (moderate, severe, extreme, and exceptional drought). Exposure to severe drought levels in 2018 has a negative and significant impact on the adoption of DT corn in 2022. During 2018, the Corn Belt received high precipitation levels with a total average value of 22 inches (NOAA 2023)) and low drought, where only 3- 10 percent of major corn production areas are within areas experiencing drought during corn production season (see Figure 22 in the appendix). Exposure to severe drought in 2020 has a positive and significant influence on the adoption of DT corn in 2022. Marginal effects suggest that exposure to severe drought in 2020, increased the adoption of DT corn in 2022 by about 10 percent, relative to exposure to moderate, extreme, and exceptional drought. By early May 2020, the Corn Belt area was under a non-dry or abnormally dry index and exposed to moderate drought by the end of July, however, by August-December 2020, more than 30 percent of the corn production area was within the areas experiencing drought, a period in which corn is in the silking, reproductive and maturity phase (U.S. Drought Monitor 2023). The severe drought experienced by corn growers may create a learning process to adopt DT corn so that if drought is to happen after the planting phase, corn grower is already growing DT as insurance against severe drought and major crop losses.

Exposure to a moderate drought during winter or early spring before the growing season has a positive and significant impact on the adoption of DT corn during the corn production season. Results suggest that corn growers positively respond to drought severity of current and past two years by adopting DT seeds, relative to more than three previous years.

Similar to the estimated coefficients in Table 3, irrigation and the use of strip tillage system estimated coefficients are significantly and negatively associated with DT adoption, while fields with clay loam are positively and significantly related to the adoption of DT corn.

Table 4: Probit regression estimated coefficients and marginal effects with drought severity indices.

Dependent variable: DT corn seed adoption in field *i*				
Exogenous variable	**Model 1 Estimated Coefficients**	**Model 1 Average Marginal Effects**	**Model 2 Estimated Coefficients**	**Model 2 Average Marginal Effects**
Moderate Drought 2018	0.089 (0.112)	0.036 (0.043)		
Severe Drought 2018	-0.314* (0.163)	-0.128* (0.064)	-0.259* (0.144)	-0.102* (0.057)
Extreme Drought 2018	0.200 (0.205)	0.078 (0.075)		
Moderate Drought 2019	0.125 (0.166)	0.047 (0.063)		
Moderate Drought 2020	-0.048 (0.100)	-0.021 (0.039)		
Severe Drought 2020	0.316* (0.162)	0.118* (0.058)	0.254* (0.138)	0.096* (0.051)
Extreme Drought 2020	-0.077 (0.225)	-0.035 (0.089)		
Moderate Drought 2021	-0.053 (0.096)	-0.021 (0.038)		
Severe Drought 2021	0.173 (0.128)	0.066 (0.049)		
Extreme Drought 2021	0.048 (0.148)	0.019 (0.057)		
Moderate Drought Spring2022	0.094 (0.145)	0.036 (0.058)		
Severe Drought Spring2022	0.200** (0.094)	0.077** (0.037)	0.188** (0.092)	0.073** (0.035)
Precipitation	-0.010 (0.016)	-0.004 (0.003)		

Irrigation	-0.369*** (0.133)	-0.148*** (0.053)	-0.363*** (0.126)	-0.143*** (0.049)
Clay loam	0.130* (0.072)	0.052* (0.028)	0.140** (0.071)	0.054** (0.027)
Strip-Till system	-0.198** (0.096)	-0.078** (0.038)	-0.212** (0.089)	-0.083** (0.035)
No-Till system	0.033 (0.097)	0.013 (0.037)		
Crop Rotation	0.020 (0.095)	0.008 (0.037)		
Corn Basis	0.156 (0.171)	0.061 (0.067)		
Proportion of cropland with erosion risk	0.001 (0.003)	0.0004 (0.001)		
Proportion of cropland with soil problems	0.001 (0.005)	0.0003 (0.002)		
Proportion of wet cropland	-0.003 (0.003)	-0.001 (0.001)		
Constant	-1.360*** (0.507)		-1.443*** (0.316)	
State dummy	Yes		Yes	
Observations	1504		1504	
McFadden PseudoR2	0.054		0.050	
Wald F-statistics (X2) Chi-squared test P(>X2)	136.700 (0.000)		56.000 (0.000)	
log-likelihood	-967.973		-971.763	
Akaike Inf. Crit	2007.945		1983.526	

*Note 2: Estimates are for the population of 2022 U.S. Corn Belt fields. Standard errors are in parentheses. Significance is denoted as ***p<0.01, **p<0.05, *p<0.10.*

4.4. Aggregated state level vs. field level results

For the exposure to previous year's drought severity, we conclude that exposure to previous year's drought positively and significantly increases the diffusion of DT in the U.S. Corn Belt by 0.7 percent. While exposure to previous year's drought severity decreases the individual field level adoption rate by 5 percent. Results suggests that exposure to previous year's drought leads to the increasing diffusion of DT corn while individual exposure to short-term drought may not lead to immediate field level adoption decision. However, exposure to persistent effects of drought severity over long term, might positively influence individual farmers adoption decision of DT corn. The second justification for the negative impact of the field level adoption decision is that within our sample, fields with high adoption rate might not be exposed to sever drought in 2021, especially in fields located in the central and eastern U.S. Corn Belt.

Although insignificant, precipitation level estimated impacts are consistent across the two parts of analysis. Which suggests that exposure to high level of spring and winter precipitation decreases the adoption and diffusion of DT corn.

The estimated coefficients and marginal effects of irrigation variables result in different direction of effects across the two parts of analysis. For the aggregated adoption analysis, results suggest that for a one percent increase in the share of irrigated cornland, the land allocated to DT corn would increase by 19 percent, on average. While for field level adoption analysis, results suggest that farmers with irrigated corn fields are less likely to adopt DT corn by 13 percent, on average. For the diffusion of DT corn, we assume that farmers in states with high share of irrigated corn areas, will be more likely to adopt DT to reduced cost of irrigation, specifically the western Corn Belt with larger share of cropland exposed to severe drought and high dependency in ground and surface water for irrigation. In contrast, farmers with irrigated corn fields are less likely to adopt DT corn if they can access enough water for irrigation, while farmers with non-irrigated corn fields are more likely to adopt DT corn to adapt to drought risk.

There are other factors that may highly influence farmer seed choice such as market contracts. Farmers can make a technology purchase contract with a seed or agricultural market company for an agreed number of seasons and prices. Therefore, farmers are bound to fulfill the contract and, in such cases, farmers' decision to use seed hybrid is only determined by the seed purchase contract or future corn sale contract. Another factor that can influence the diffusion of DT corn seed is the network or information spread among farmers. Farmers can be influenced by other farmers' decisions in the same counties (e.g., maybe farmers share information, know about the impact of new varieties from extension programs, farmers' cooperations …etc). Farmers can be early adopters if they already planted one trait or more than one trait GM-corn, and can be followers, in which they wait to see the result of adoption by others and then adopt slowly in the next season. This can lead to increasing adoption over time but at a slow rate. However, once a new variety comes to the market, the adoption level will start to decrease for an older variety (following the technology adoption curve).

5. Conclusion

DT corn seed with deeper and larger root system traits can maintain yield under severe drought conditions and can function as soil carbon sequestration practices, given the ability of roots to reduce soil erosion and provide soil with soil carbon inputs. Using state-level and field level analysis of DT corn adoption decision. DT varieties are already commercialized corn seed, thus looking at the factors that might drive or increase the adoption rate can give a conclusion of how likely corn growers are to accept new seed varieties that might function as DT corn and as soil carbon sequestration technology.

Our analysis suggests that the adoption and diffusion of DT corn are responsive to the previous year's drought conditions. Farmers can base their adoption decisions to increase the extent of cropland with DT corn hybrids on drought and precipitation expectations. If previous years' experience high precipitation, farmers lower their expectations of drought in the current year and have a low adoption rate. Counties with a high share of areas under drought and with a low level of annual precipitation are expected to have a high adoption rate and adoption is assumed to increase over time, which is the case in the western part of the Corn Belt and southern part of the U.S.

The impact of different environmental and climate factors on increasing the share of corn acres planted with DT depends highly on the location of the state. In the central Corn Belt, farmers' adoption decision is highly influenced by expectations about drought, prices, and losses due to natural factors, such that even if the central Corn Belt area receives a moderate level of precipitation during the growing season, farmers there will adopt DT seed as insurance against drought and to avoid profit losses during the fall season or reproductive phase. But for the western Corn Belt, including Nebraska, Kansas, and Colorado; precipitation level is lower than other Corn Belt areas, and drought level is higher, but farmers have crop insurance. However, a specific percentage of corn grown in Nebraska, Colorado and Kansa is irrigated through ground water or surface water (river), and farmers use water rights to get access to water which incur an irrigation cost, and/or irrigation technology cost, so farmers are more likely to adopt DT to avoid such costs and as insurance against drought.

Looking at the influence of environmental and climate conditions on the share of land allocated to DT corn variety, the magnitude of the impact can be an important indicator to suggest the counties or states with higher or lower impact and so, counties that experience severe, or extreme drought condition can optimize land use by devoting higher share of corn land to DT seed. State-level analysis of DT corn diffusion can overestimate or underestimate the impact of climate and geographical factors on DT corn adoption, however, with data availability for DT corn adoption at the county level, the diffusion of DT seed technology can be better explained given the large variation in decisions regarding seed prices, distance to market, distribution of corn acres, average farm expenses and farm income, and the availability of seed technology or hybrid in a county.

A deeper root system corn hybrid can function as a DT hybrid with larger root traits in terms of extracting water and nutrients deeper in the soil and withstanding severe drought. Therefore, changes in the adoption and diffusion of DT corn over time can provide some insights into how likely corn growers are to accept and adopt other corn hybrids with large or intensive root biomass in the future. However, there is a need to evaluate how the adoption rate could change with drought shock by increasing exposure to drought and lower precipitation levels. This can be a helpful tool to suggest where to target carbon market incentives to support the adoption of soil carbon frontier technology, by targeting the best counties in terms of higher potential for soil carbon sequestration.

CHAPTER 3/ DESIGN OF AN INCENTIVE PAYMENT TARGETING SOIL CARBON SEQUESTRATION

1. Introduction

Agricultural production practices in the thirteen states[19] that encompass the U.S. Corn Belt contributed an average of 25 MMTCO2 equivalent to Greenhouse Gas (GHG) emission[20] in 2021 (see Figure 12). Of this, crop cultivation contributed an average GHG emission of 15 MMTCO2 equivalent (EPA 2023). This rate could be mitigated over time given that the agricultural sector has the potential to sequester soil carbon using soil carbon sequestration (SCS) practices.

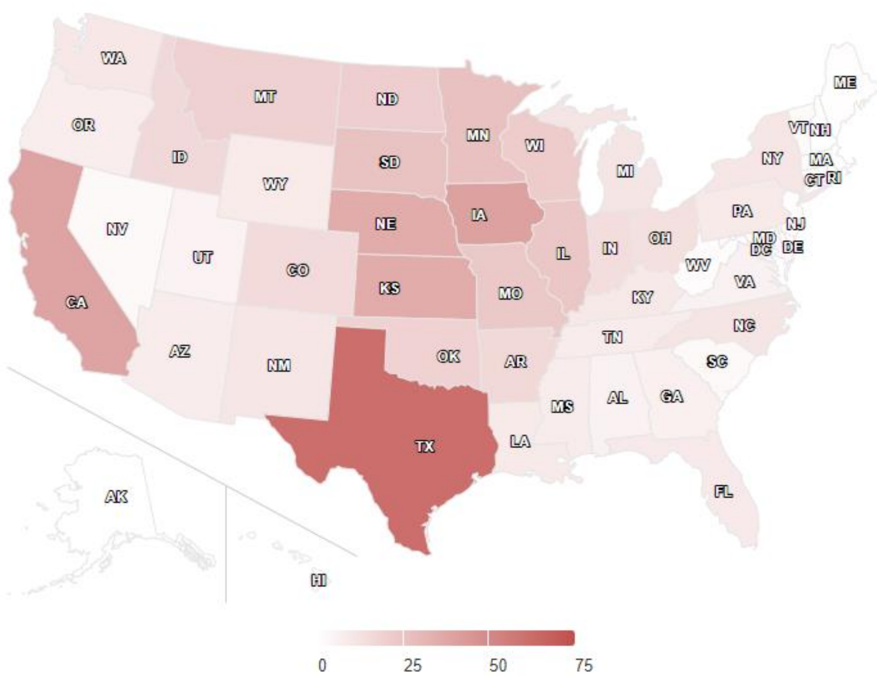

Figure 12: U.S. GHG Emissions from the Agriculture Sector by State, 2021 (Million metric tons of carbon dioxide equivalent).
Source, EPA, 2023: https://cfpub.epa.gov/ghgdata/inventoryexplorer/

[19] CO, IA, KS, MN, MO, NE, SD, WI, MI, ND, IL, IN, OH.

[20] The rate of GHG emissions includes emissions in the form of carbon dioxide, fluorinated gases, methane, and nitrous oxide.

Figure 1 of the FAO (2023) map shows that U.S. Corn Belt soils can sequester significantly higher rate of soil carbon if managed carefully and continually with the appropriate practices for a long time (e.g., over 20 years). The U.S. Corn Belt crop lands are used primarily to produce corn, soybean, and wheat. Croplands can do a good job in soil carbon sequestration if treated properly with appropriate soil management and crop production practices. The adoption of SCS practices is influenced by different factors, as discussed in Chapter 1. Farmers may confront a single adoption decision regarding a generally accepted SCS practice, such as reduced tillage or cover cropping. Or they might consider adopting a so-called "frontier" technology, for which SCS potential is still being evaluated. Farmers more realistically often face a joint adoption decision. As presented in Chapter 1, the probabilities of single, joint and conditional adoption decisions can be influenced by a range of different factors. Moreover, farmers may be more likely to jointly adopt frontier technology along with SCS practices to increase SCS rate and earn higher payment per carbon credits when participating in private carbon markets.

Access to conservation incentive payment can be an essential driver for the adoption of SCS practices. However, the allocation of conservation incentive payments toward environmental benefits highly depends on the budget limitation, participants' selection criteria, and degree of environmental damage or benefit (Cattaneo et al. 2005). Previous studies on the payments for ecosystem services emphasize on environmental benefits resulting from such things as changes in land use, adoption of soil conservation practices, environmental benefits per pastureland vs. forest land, improving wildlife habitat, and reducing the impact of wind and water erosion (Antle and Just 1991; Babcock et al. 1996 and 1997; Bulte, et al. 2008; Claassen, Cattaneo and Johansson 2008; de Souza, Dupas and da Silva 2021; Feather and Hellerstein 1997; Guo et al. 2020).

However, only a few studies address the spatial targeting in payments for soil carbon sequestration services, such as Kim and Cho 2019; Skidmore, Santos and Leimona 2014; Wünscher, Engel and Wunder 2008. The idea of a spatial targeting approach is to identify the priority land area to target with an incentive payment for environmental amenities. The rational for spatial targeting is rooted in the fact that the potential for environmental benefits—in this case the potential for soil carbon sequestration—is heterogenous across land. Some areas will yield significantly greater environmental benefits than others, or conversely some areas will yield a given level of environmental benefit at lower costs. The main objective is to attain as much of the desired environmental benefit as possible for the cost.

Three common approaches to spatially target payments for ecosystem services are benefit targeting, cost targeting, and benefit-cost ratio targeting (Babcock et al. 1996; Wang and Swallow 2016; Wu et al. 2000; Wünschera, Engelb and Wunderc 2008). Babcock et al. (1997) evaluate these different approaches within the context of CRP programs to target lands with water erosion, wind erosion, and water vulnerability to pesticides. The benefit approach is benefit-maximizing payment scheme but is cost-ineffective as it targets the highest environmental benefit (Babcock et al. 1997; Fooks and Messer 2013; Fooks and Messer 2012; Wang and Swallow 2016; Wu, Zilberman and Babcock 2001; Wünschera, Engelb and Wunderc 2008). The cost approach targets the largest possible number of acres at the lowest possible per acre cost regardless of the environmental benefit achieved per acre, until the available budget is exhausted (Babcock et al. 1996; Duke et al. 2014; Wang and Swallow 2016; Wang, Yang and Zhang 2016). The benefit-cost ratio approach selects locations to incentivize according to the environmental benefit per dollar spent subject to budget constraints (Babcock et al. 1996; Duke et al. 2014; Guo et al. 2020; Wang and Swallow 2016).

This chapter uses the benefit maximization approach to develop three different payment scenarios for three different levels of SCS practices with different potential ranges (high, medium, and low) of carbon sequestration rates. We used cross section data for the year 2022 of county level conservation budgets from the USDA, available working cropland, and estimated potential metric tons of carbon sequestration per type of SCS practice. By implementing these three scenarios, we compare the resulting benefits in terms of soil carbon accumulation across counties of the U.S. Corn Belt. Therefore, this chapter begins to explore the question of how to get an optimal benefit of soil carbon sequestration by targeting cropland acres, even with the constraint of available county conservation budgets as currently allocated.

We develop three payment scenarios and account for metric tons of soil carbon gained when adopting low, medium, and highly intensity SCS practices. These scenarios follow the benefit maximization approach as we assign different payment rates to practices with different potential SCS rates. In the benefit maximization approach, conservation incentive programs would generally aim at maximizing the sequestered carbon by assigning higher payment to SCS practices with high sequestration rates and lower payments to practices with lower sequestration rates, until the budget is exhausted (Babcock et al. 1997; Fooks and Messer 2013; Fooks and Messer 2012; Wang and Swallow 2016; Wu, Zilberman and Babcock 2001; Wünschera, Engelb and Wunderc 2008). Secondly, we use the acreage maximization approach to estimate the lowest average payment to deplete the full county budget, and the resulting average metric tons of carbon sequestered. In the acreage maximization approach, the conservation incentive program aims at increasing the number of enrolled cropland acres under the carbon program by targeting the cheapest acres with the lowest per acre payment (Babcock et al. 1996). We used linear optimization method to solve for the optimal metric tons of carbon sequestered accounting for county cropland acres and conservation budget. We conclude that higher payment scenarios for highly intensive SCS practices result in a higher carbon sequestration rate, but fewer acres assigned to those carbon incentive efforts, compared to lower payment rate scenarios.

The structure of the chapter is as follows: the next section provides an overview of public incentive programs and private carbon markets. Section three provides an overview of the general requirements to consider for the design of the environmental incentive program. Section four presents methodology including data sources, and the design of payment scenarios. Section five presents the results aggregated at the state level and discussion of the resulting metric tons of carbon sequestered under different payment scenarios.

2. Targeting incentive payment programs: public incentive programs and private carbon markets

Since 1935, following the enormous environmental impacts of the "Dust Bowl", the U.S. has implemented Natural Resource Conservation Service (NRCS) programs to reduce environmental damage, improve soil quality, and to reduce soil erosion resulting from increasing agricultural production and intensive pressure on natural resources (USDA-NRCS 2023). Land conservation programs such as the Conservation Reserve Program (CRP), the Environmental Quality Incentives Program (EQIP), and the Conservation Stewardship Program (CSP) are public incentive payment programs that target environmental concerns such as water quality, soil health, water and soil erosion, wildlife habitat, etc. CRP seeks to overcome resource degradation by converting working land to non-working land (land retirement) for a 10-15-year contract period (Stubbs 2014). Farmers receive an annual payment as farm income compensation for what they would have earned from crop production. The land is eligible for CRP if it is highly erodible, is exposed to water erosion and contamination, or provides wildlife habitat. In 2020 about 22 million acres were enrolled under the CRP program in the U.S. with a total payment of 1795 million dollars and an average payment of 81.88 dollars per acre (USDA 2023). Under EQIP, farmers are incentivized with a payment per acre to adopt for the first-time conservation practices such as zero or reduced tillage system, nutrient management, cover crop on working cropland and maintain them for a 1–10-year contract period. EQIP payment rates were based on average bid rate and average cost share rate until 2001(Stubbs 2010). Since 2002, the EQIP payment rate changed to a fixed 50 percent cost-shared rate (Claassen, Cattaneo and Johansson 2008). However, the CRP payment rate is determined based on the maximum bid approved by the local cash rental rate, cropland productivity, and farm annual income. The conservation stewardship program (CSP) pays farmers for continuously adopted conservation practices to encourage farmers to keep using the conservation practice after the end of the EQIP contract.

Current public programs (EQIP, CRP, CSP) pay per acre per practices adopted or per acre of land retired to improve environmental amenities. They do not directly pay per environmental outcomes such as verified tons of carbon insets or offsets. This suggests that there is a need for public incentive programs that target carbon outcomes. In this study we develop a set of hypothetical scenarios to inform the design of such a carbon incentive program.

Private carbon market programs that target carbon sequestration in U.S. agriculture have emerged more recently with verified carbon credit payments. Farmers, by participating in contracts with a private carbon program, are expected to adopt approved qualifying practices that maintain soil carbon level or result in soil carbon accumulation. The major approved SCS practices are cover crops, no-tillage, reduced tillage, diversifying crop rotation, nitrogen management, residue management, and shifting from annual to perennial crops. Farmers get paid per metric ton of carbon insets after third party verification. Carbon by Indigo, Nori, Bayer Carbon Program, Corteva, ESMC Eco-Harvest, Soil and Water Outcomes Fund, Agoro Carbon Alliance, Nutrien, CIBO Impact, Gradable Carbon, TruCarbon, and Cargill's RegenConnect are all examples of carbon programs offered by private carbon market players (Plastina 2021). Current applied carbon payment rates range between 15 dollars per metric ton (e.g., ESMC Eco-Harvest) and 35 dollars per metric ton (e.g., Cargill's RegenConnect). The following table provides geographical coverage, approved practices, contract lengths, minimum acres, and payment structures of the various soil carbon incentive programs offered by Corteva, Indigo, Bayer, and Nori.

Table 5: Private market carbon incentive programs

Carbon Market program	Corteva Carbon Program	Carbon By Indigo	Bayer Carbon Program	Nori Removal Tonnes (NRTs)
Geographical coverage	Cropland field located in the U.S.	30 qualifying US states: Alabama, Arkansas, Colorado, Delaware, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Maryland, Michigan, Minnesota, Mississippi, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Vermont, Virginia, Wisconsin	Alabama, Arkansas, Iowa, Illinois, Indiana, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Missouri, Mississippi, Nebraska, Ohio, Tennessee, Wisconsin	Cropland field located in the U.S.
Approved practices	Reduced, no-tillage, cover crops, improved nitrogen efficiency	Reduced tillage, no-tillage, cover crops, crop rotation	No-till/strip-till and/or cover crops	No-till, strip-till, cover crop, crop rotation
Eligible crops	Corn and soybeans	Up to 22 types of crops including field crops; corn and soybeans	Corn and soybeans (could adopt crop rotation with wheat)	Field crops including corn and soybeans
Minimum contract length	10 years	5 years	10 years	At least 10 years

Minimum acreage enrollment	None	At least 150 acres per field	At least 10 acres per field	None
Payment rate	\$20-\$30 per carbon credit	\$20, \$30 per carbon credit	\$6-\$36 per acre and carbon stock verification is required.	Farmers can set a "floor price" for NRT and farmers are required to sell >15% of NRTs via the Nori marketplace and sell other credits in any other carbon markets.
Website information	Corteva carbon program. https://www.corteva.us/products-and-solutions/digital-solutions/carbon.html	Carbon by Indigo. https://www.indigoag.com/carbon	Bayer Carbon. https://www.bayer.com/en/agriculture/carbon-program-united-states	Nori. https://nori.com/suppliers/farmers/requirements

3. Design of an environmental incentive program: general requirements

Public programs incentivize environmental benefits through annual practice based-payments (or per-acre payments) while voluntary private market incentivize SCS benefit through a payment of per metric ton of carbon insets or offsets. This study designs the payment scenarios on the relevance of public incentive programs to set varied per acre payment per the intensity of SCS rate per practice. We assume that the designed public carbon incentive program pays per qualifying practices that are demonstrated and approved to maintain or increase SCS rates in cropland.

In general, the design of the environmental incentive program involves a full plan of eligibility, an enrollment screen, payment incentives, and budget (Cattaneo et al. 2005). The eligibility of participants depends on the degree of land and resource degradation, farm location, past practices vs. new practices to adopt, and the cropland's potential for carbon sequestration. The enrollment screen determines the selection of participants to enroll in the program. For example, CRP uses an Environmental Benefits Index (EBI) to select participants across different geographic locations

(Claassen, Cattaneo and Johansson 2008; Kirwan, Lubowski and Roberts 2005). Then, payment incentives can vary depending on the conservation program objectives (e.g., per metric ton of carbon inset, per acre), or the payment can be bid-based which depends on farmers' willingness to accept a minimum payment offered by the conservation program (e.g., CRP) (Stubbs 2014). Conservation budgets can limit the number of participants. Thus, environmental incentive programs aim at maximizing environmental benefits subject to budget constraints (Babcock et al. 1997).

There is significant variation in the total conservation budgets allocated to counties depending on acres of agricultural land, resource degradation, and other variables. The decision on the total acres receiving conservation efforts, within a county, depends on the program budget, as once the annual budget is fully allocated additional applications get rejected. Participants are selected based on criteria, such as the degree of resource degradation in their land, and expected environmental benefit they offer, and the maximum bid accepted by the farmer (Cattaneo et al., 2005). Farmers rejected in the current year may be discouraged from applying in following years, which can reduce the number of participants in the future. Such limitation of funds and minimum acreage limitation per participant can change the objective of the conservation program to be based on the cost-effective distribution of the annual conservation budget rather than maximizing environmental benefits.

Payment rate, number of recipients, and budget allocation of conservation programs (including EQIP, CRP, CSP, WRP, ACEP[21]) can differ from year to year. For example, in Iowa with more than 97,000 farms and an average farm size of 300-400 acres, the state NRCS program allocated in 2016 a total budget of 372 million dollars to 54,451 recipients while in 2021 a budget of 381

[21] WRP refers to Wetland Reserve Program and ACEP refers to Agricultural Conservation Easement Program.

million dollars was distributed among 51,727 farmers (EWG 2022, USDA-NASS 2023). In Colorado with more than 39,000 farms and an average farm size of 500-800 acres, the NRCS program allocated in 2016 a total budget of 66.1 million dollars to 6,454 farmers, while in 2021, it allocated a budget of 49.9 million dollars to 5,086 farmers (EWG 2022, USDA-NASS 2023). These differences in numbers of recipients over time with the variation in an annual budget reflect changes in payment rates per practice or per environmental benefit as well as changes in enrollment criteria.

For our scenarios, we use the county conservation budgets as allocated for 2022 by those USDA programs that target soil conservation efforts, land use change efforts, and payments for ecosystem services, including EQIP, CRP, and CSP, as an approximation of a reasonable upper limit for each county's budget that could be directed towards public carbon incentive programs (at least in the short to medium run).

These conservation programs pay farmers for the adoption of practices such as tillage systems, cover crops, crop rotation, etc, which all can have a positive impact on soil carbon sequestration. We assume that this designed carbon program aims at maximizing soil carbon sequestration benefits generated per different incentive payment rates, within this given county conservation budget.

4. Methodology

In this study we evaluate the potential soil carbon sequestered in the Corn Belt cropland when applying different payment rates per acre, accounting for the SCS rates generally attained under different practices in different geographical locations (at the county level). We use an optimization model with designed payment scenarios to solve for the metric tons of carbon sequestered, given county conservation budgets, and indices of low, medium, and highly intensive SCS rates. Then we compare the benefit generated per different scenarios to decide on the best approach to get the highest level of soil carbon sequestration.

4.1. Theoretical framework

4.1.1. Benefit maximization

We assume that within a given plot of cropland, a farmer could sequester soil carbon through the adoption of SCS practices (e.g., cover crop, no- or reduced-tillage, crop-rotation, nutrient management, crop residue, manure and compost addition, shifting from annual to perennial crops, etc.) or through the adoption of frontier technology (e.g., deeper root system crops, perennial cereal crops, biochar, etc.). The decision maker aims at maximizing soil carbon sequestration rates ($\sum_{i=1}^{I} X_i V_i$) subject to a given county budget constraints and available working cropland. At the same time, farmers by participation in carbon incentive programs aim at maximizing per acre annual net return ($X_i p_i$). Following Babcock et al. (1996), Duke et al. (2014), Wange and Swallow (2016), and Wünschera, Engelb and Wunderc (2008) the optimization problem at the county level can be represented as

$$max \sum_{i=1}^{I} X_i V_i \qquad s.t.\ X_i p_i \leq B_i \ and \ X_i \ \leq A_i \tag{1}$$

where i is an index for counties ($i = 1, \dots \dots . I$). X_i is the number of cropland acres enrolled in the carbon incentive program in county i. V_i is the environmental benefit in the form of average metric tons of carbon sequestered per acre in county i. $X_i V_i$ represents the metric tons of carbon sequestered in county i, and p_i is the average incentive payment per acre in county i (dollar/acre). B_i is the total available conservation budget in county i. A_i refers to the total available working cropland acres in county i. The resulting Lagrange function is the following:

$$L = \sum_{i=1}^{I} X_i V_i + \lambda(B_i - X_i p_i) + \omega(A_i - X_i) \quad (2)$$

Taking the F.O.Cs. to solve for optimal solutions $X_i{}'$, λ', and ω':

$$\frac{\partial L}{\partial X_i} = V_i I + \lambda(B_i - p_i) - \omega = 0$$

$$\frac{\partial L}{\partial \lambda} = B_i - X_i p_i = 0$$

$$\frac{\partial L}{\partial \omega} = A_i - X_i = 0$$

Where λ is the shadow price of the budget constraints and the optimal solution value represents the SCS benefit and ω is the shadow price of the cropland in county i. We used a linear optimization method to solve for metric tons of carbon stored $\sum_{i=1}^{I} X_i V_i$ and the corresponding $\sum_{i=1}^{I} X_i$.

4.1.2. Acreage maximization

We use acreage maximization approach to solve for the lowest average payment rate required per county to get the county's budget fully exhausted. Under this approach, we assume policy makers tend to maximize acres enrolled or participation rate in carbon incentive programs in order to optimize the environmental benefit in a situation of constrained conservation budget. Then, if the objective is to maximize the largest number of county cropland acres enrolled in carbon incentive program subject to budget constraints, then the design maker should target acres with the lowest per-acre participation costs until county budget is depleted. The optimization problem is the following (Babcock et al. 1996):

$$\max_{X_i} \sum_{i=1}^{I} X_i \ \ s.t. X_i p_i \leq B_i \ and \ X_i \ \leq A_i \quad (3)$$

The resulting Lagrange function is the following:

$$L = \sum_{i=1}^{I} X_i + \gamma(B_i - X_i p_i) + \omega(A_i - X_i) \tag{4}$$

And the F.O.Cs. is the following:

$$\frac{\partial L}{\partial X_i} = I + \gamma(B_i - p_i) - \omega = 0$$

$$\frac{\partial L}{\partial \gamma} = B_i - X_i p_i = 0$$

$$\frac{\partial L}{\partial \omega} = A_i - X_i = 0$$

Where γ is the shadow price of the budget constraints. The optimal solutions are X_i', γ', ω'. We assume here that the decision maker will target the least expensive cropland acres until the total county budget is exhausted. In our optimization analysis, we used county level data to get the optimal number of acres ($\sum_{i=1}^{I} X_i$) to be enrolled in carbon incentive program with the lowest per acre payment.

The third targeting approach to prioritize enrollment of cropland under conservation programs is benefit cost ratio maximization. This approach will not be included in the analysis of our scenarios, because it is more commonly used to decide on prioritizing enrollment of individual farms in a specific geographical area based on the highest benefit to cost ratio (V_i/p_i) given allocation of a fixed budget (see equation (1)).

4.2. Data

We use county cross sectional data for the year 2022 for the available budgets, working cropland areas, and average SCS rates by county. We run our optimization analysis at the county level to determine the optimal metric tons of carbon sequestered and optimal number of county cropland acres to be enrolled given the fixed county budget, available working cropland acres, and potential average county SCS rates under each of three payment scenarios. The study sample consists of 788 counties from 13 states that make up the Corn Belt (see Figure 13) in which cropland is used mainly to grow field crops such as corn, soybeans, and wheat.

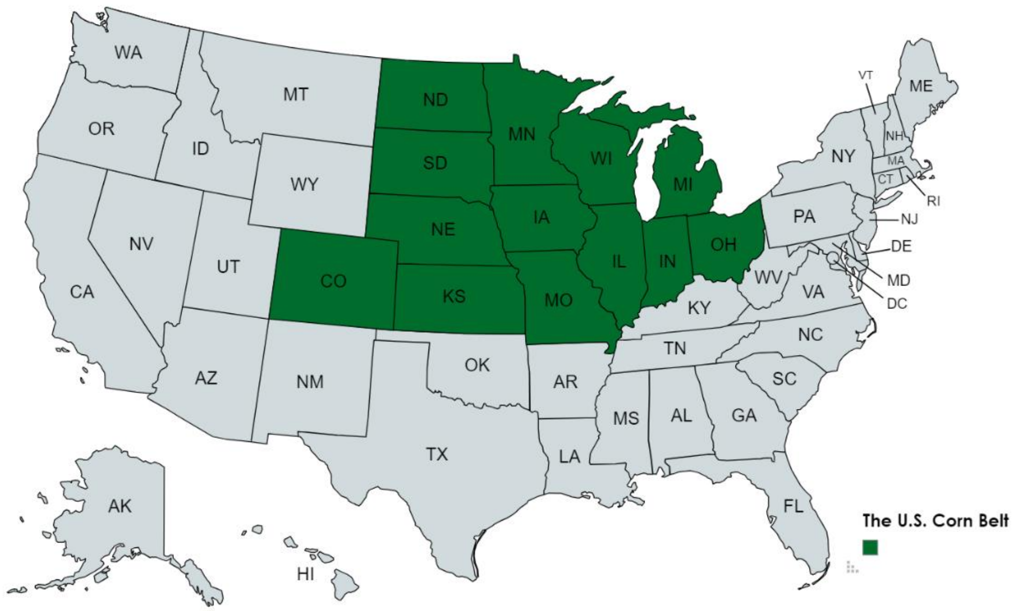

Figure 13: Study Area: The U.S. Corn Belt.

County-level data of average potential SCS rates are extracted from the carbon payment calculator by the Indigo carbon program and Corteva carbon program[22]. These platforms provide per county an approximation of lower to higher potential SCS rates in the county and the corresponding average payment prices. Farmers are expected to implement no tillage, reduced tillage, strip tillage, single or multi species cover crops, crop rotation, nitrogen management or

[22] Carbon Programs by Indigo and Corteva provide an online carbon calculator estimates to allow farmers to make decisions before they decide if to participate in the carbon program and which practices to implement. The carbon calculator provides an estimate of how much farmers can earn with carbon farming. The program shows the potential carbon sequestration rate in each county, and payment rate, and farmers can enter the number of acres to register and get the estimated payments over five years.

other practices that result in higher annual SCS rates. Average SCS rates represent the environmental benefit that we aim to maximize through our thought experiment. Data on the working cropland acres per county are collected from USDA-NASS census of agriculture (2023). We collate county-level conservation budgets from farm subsidy data (EWG 2022). We assume that practices implemented through these conservation programs result in positive environmental impacts including soil quality, reduced GHG emissions, and soil carbon accumulation.

Table 6 presents summary statistics of the variables used to estimate equations (1) and (3). At minimum, land in the U.S. Corn Belt could participate with 0.01 metric tons[23] of carbon stored per acre per year in the carbon market. Across the Corn Belt, between 0.46 and 0.95 metric tons of carbon per acre per year can be potentially sequestered if highly intensive SCS practices are adopted on high quality cropland. We assume here that the carbon incentive program accounts for the geographical and environmental variation in each county such as land quality, and climatic factors, when providing estimated SCS rates per different SCS practices. Among our sampled counties, in 2022, the largest working cropland area is 1,081,042 acres in Cass County, ND while the smallest working cropland area is 22,450 acres in Monroe County, IN. Our county sample conservation budgets range from 2,054 dollars in Marinette County, WI, to 10,585,439 dollars in Ringgold County, IA.

[23] one metric ton of carbon equals one carbon credit or one metric ton equals 1.1 tons.

Table 6: Summary statistics

Variable	Min	Max	Mean	S.D.	Source
Low potential SCS rates (metric tons)	0.01	0.43	0.22	0.08	Carbon by Indigo and Corteva Carbon program
Medium potential SCS rates (metric tons)	0.26	0.66	0.46	0.07	Our estimates using LSCS and HSCS values
High potential SCS rates (metric tons)	0.46	0.95	0.71	0.08	Carbon by Indigo and Corteva carbon program
Cropland (1000 acres)	22.45	1081.04	260.49	147.27	USDA-NASS census of agriculture data
Conservation Budget (1000 dollars)	2.05	10585.44	1487.46	1625.75	EWG farm subsidy data
N=788 counties					

To illustrate the data on available cropland and conservation budgets, we aggregate the counties' data to the state level. Figure 14 shows the aggregate conservation budgets per state. Much of the conservation budget is allocated to counties in Iowa, Illinois, and Minnesota, while the least are allocated to conservation programs in counties in Michigan, Wisconsin, and Colorado, which correspondingly have the lowest acreages of working cropland.

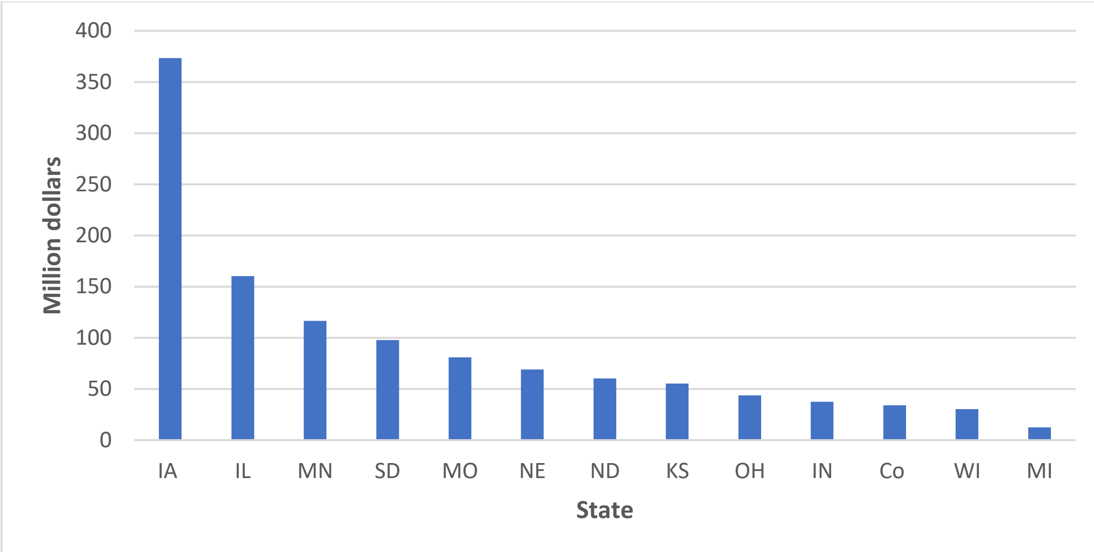

Figure 14: 2022 conservation budget (million dollars)

Figure 15 shows the number of working cropland acres for our sample counties, again aggregated to a state level. The aggregated data might not represent the actual size of working cropland per state because here we aggregate only across the selected sample counties that represent Corn Belt cropping patterns, not all counties within the state. The aggregated sample data show that Iowa and Illinois have the largest number of working cropland acres in 2022, about 26 and 23 million acres, respectively. Colorado and Michigan have the least in 2022, among our sample states, with about 7 and 6 million acres planted, respectively.

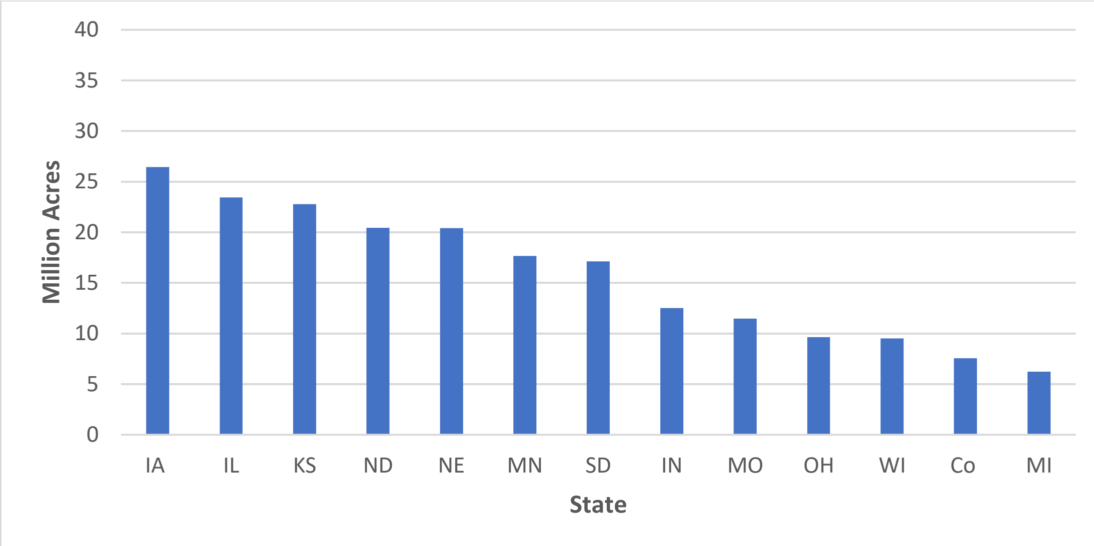

Figure 15: Working cropland acres in the sample, 2022.

4.3. Design of payment scenarios.

We utilize county level data for the average SCS benefits, conservation budget and cropland acres to develop a though experiment which assumes that decision makers with a given county budget will enroll acres with lowest to highest potential SCS benefit using different payment rates. We assume that prices are allowed to change between participants within the county but are averaged to a county level. Therefore, for our analysis, we used the average county price per acre. We develop three payment scenarios that assume the implementation of different SCS practices and frontier technologies result in different sequestration potentials. Scenarios are structured as follows:

Scenario 1: Low potential SCS practice per acre payment (LSCS).

Through this scenario we assume that the policy maker aims at maximizing SCS benefits given county budgets and cropland available by targeting the adoption of low intensive SCS practices that generate low average metric tons of carbon inset (0.01-0.43 metric tons per acre). For example, if farmers in Adams County, IA, change from conventional tillage to reduced tillage they could sequester an average of 0.12 metric tons/acre/year (Corteva carbon program 2023). These can be thought of as the average sequestration rate improvements feasible in low-quality croplands. According to the low range of SCS rates we assume lower payment rates of 10-15 dollars per acre.

Scenario 2: Medium potential SCS practices per acre payment (MSCS).

Under MSCS scenario, given county conservation budgets and available cropland acres, we assume that policy makers seek to maximize SCS benefit by imposing an average payment of 16-25 dollars per acre for the adoption of medium intensive SCS practices that could generate a range of 0.26 to 0.66 metric tons of carbon per acre per year. For example, farmers in Adams County, IA that change from reduced tillage and no cover crops to no-tillage and a single species cover crop could sequester an average of 0.30 metric tons of carbon per acre/year (Corteva carbon program 2023).

Scenario 3: High potential SCS practices per acre payment (HSCS).

Under scenario 3, we assume that policy makers seek to maximize SCS benefits given county budgets and cropland constraints by offering an average payment of 26-30 dollars per acre for the adoption of highly intensive SCS practices that could generate a range of 0.46-0.95 metric ton of carbon insets per acre per year. For example, in Adams County, IA, if farmers change from conventional tillage and no cover crops to no tillage and multi-species cover crops, they could sequester an average of 0.67 metric tons of carbon per acre/year (Corteva carbon program 2023). Croplands with highest SCS rates are generally the highest-quality croplands.

The above designed payments are offered in per acre contracts (from public incentive program) for the adoption of practices that have the potential to increase soil carbon accumulation in cropland. The payments range from 10-30 dollars per acre. We assume these practice-per-acre payment rates could approximate the payments for verified tons of carbon given that private carbon markets (e.g., Indigo, Corteva, Nori, ESMC eco-harvest) generally offer a payment rate of 15-30 dollars per metric ton of carbon inset.

Finally, we use the acreage maximization approach (equation 3) to maximize the number of county cropland acres receiving carbon incentive payments subject to a given county conservation budget and working cropland available. Under this approach we constrain the utilized budget to be equal to the given county budget to target the largest acres of county cropland and estimate the lowest per acre average payment rate, regardless of metric tons of carbon sequestered. After deriving the optimal number of acres under the estimated lowest payment rate, we used average per county LSCS and MSCS rates to derive the corresponding potential metric tons of carbon sequestered.

5. Results and discussion

This section presents the optimization results for the designed payment scenarios including optimal metric tons of carbon stored ($\sum_{i=1}^{I} X_i V_i$), optimal cropland allocation decisions ($\sum_{i=1}^{I} X_i$), and total budget utilized to allocate county acres under carbon incentive efforts ($\sum_{i=1}^{I} X_i p_i$).

5.1. Benefit maximization approach results

Figure 16 presents the resulting carbon insets in metric tons under the three payment scenarios, aggregated at the state level. Under the three designed carbon incentive programs targeting the adoption of SCS practices that result in HSCS, MSCS, and LSCS rates within our sample counties, we calculate that, respectively, about 32, 24, and 19 million metric tons of carbon can be sequestered in the Corn Belt croplands annually. Across the three scenarios, Iowa cropland has the highest sequestration benefit with about 10, 8, and 5 million metric tons of carbon stored under scenario HSCS, MSCS, and LSCS, respectively. This could be because of the highest number of cropland acres and thus lower budget limitations. Michigan cropland results in the lowest annual metric tons of carbon sequestered with about 311, 243, and 206 thousand metric tons of carbon stored under scenario HSCS, MSCS, and LSCS, respectively, given the lower number of working cropland acres and budget limitations for the Michigan counties included in the sample. Comparing the average SCS benefits for the sample data, the average high SCS rate is 0.75 and 0.65 metric tons of carbon per acre for IA and MI, respectively.

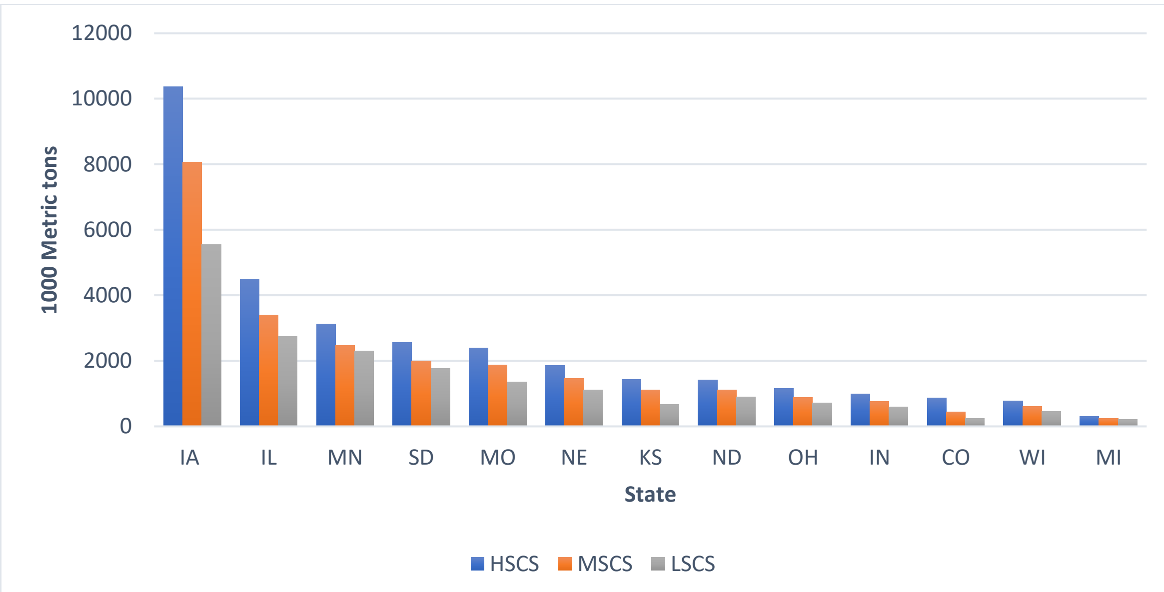

Figure 16: Maximum annual metric tons of carbon sequestered under the designed payment scenarios HSCS, MSCS, and LSCS, aggregated at the state level.

Figure 17 represents the optimal share of state working cropland enrolled under the incentive program under each scenario. The bar chart shows that when the decision maker increases per acre payment rate to target the adoption of more intensive SCS practices, the number of acres receiving incentive payments decreases. Among our sample counties, if the carbon incentive program targets the adoption of LSCS practices with a payment rate of 10-15 dollars per acre, then it is expected to result in about 83 million acres of the U.S. Corn Belt cropland enrolled in the incentive program. However, if the carbon incentive program targets the adoption of HSCS practices with payment rate of 26-30 dollars per acre, this results in more carbon sequestered with fewer cropland acres, about 39 million of the U.S. Corn Belt croplands, registered in carbon incentive program. The midline scenario targeting MSCS practices with averaged payment rates of 16-25 dollars per acre results in about 47 million acres of the U.S. Corn Belt cropland enrolled in incentive program. Comparing our aggregated results, Iowa has the highest share of acres enrolled under incentive program with about 76, 54, 46 percent of working cropland acres receive per acre payment according to payment scenario LSCS, MSCS, and HSCS, respectively. While among our sample data, North Dakota, Kansas and Michigan have the lowest share of cropland acres enrolled under incentive program with about 23, 20 and 17 percent of working cropland receive incentive payment under scenario 1 (LSCS), respectively. The number of cropland acres enrolled per state are included in Table 14 in the appendix.

Results suggest that with payment scenarios aiming at increasing the payment rate to target the adoption of HSCS practices, can result in more metric tons of carbon stored per acre, but a lower number of acres covered under the carbon incentive program for a fixed budget level. Within the county, the third scenario (HSCS) may be preferred more by landowners with lands of high SCS potential, and by environmentalists; because high land quality owners gain higher returns and environmentalists achieve greater environmental benefits with more carbon insets. However, farmers in low-quality land with low carbon sequestration rates are better off under scenario 1 (LSCS) and 2 (MSCS) registering larger number of acres albeit at lower payment rates.

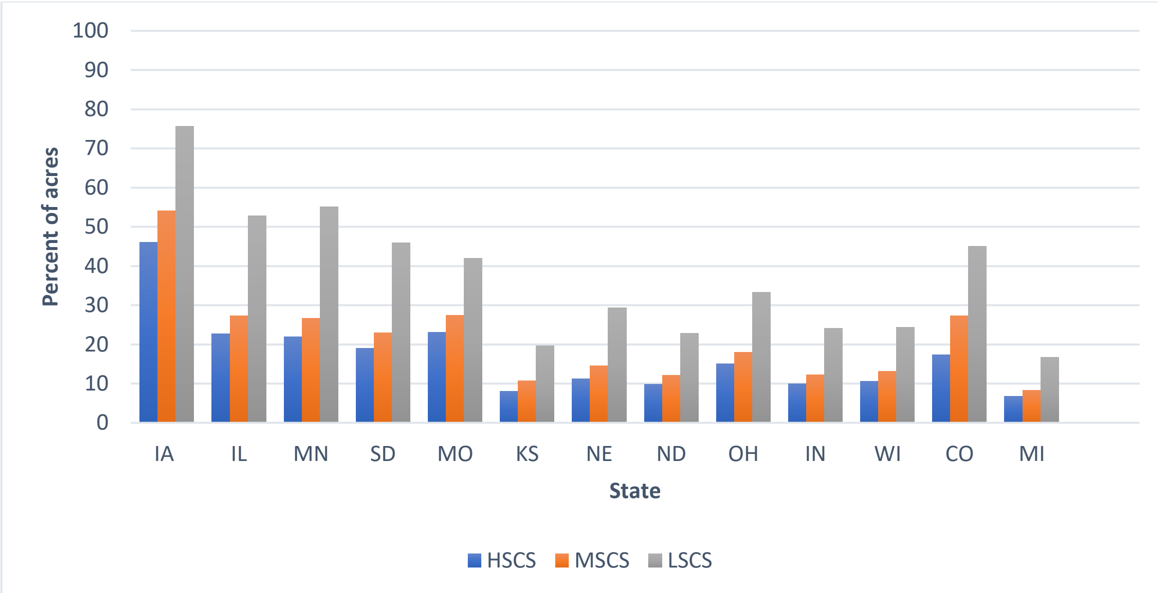

Figure 17: Share of cropland acres allocation targeting adoption of low, average, and highly intensive SCS practices by different payment rates per acre.

The corresponding distribution of utilized conservation budget for cropland allocation to incentive program under the three designed scenarios is presented in Figure 18. As the bar charts show that with our designed payment scenarios, the available conservation budgets are fully expended under all three scenarios for states: CO, KS, NE, MN, and MI. However, we find that there are a remining of a conservation budget that has not been utilized under the three scenarios for states IA, MO, OH. If carbon incentive programs pay less per acre to cover more acres in counties with lower SCS rates and high enough budget, then we may observe 100 percent enrollment of cropland with a budget remaining. It is recommended that the remaining unutilized budgets be reallocated to counties with the highest SCS sequestration potential when making the budget allocation decision at state level. However, with benefit maximization approach, to get full utilization of the budget in counties with high enough conservation budget and lower number of cropland acres, per acre payment rate need to be high enough to target the acres with the highest SCS rates until expanding the full budget.

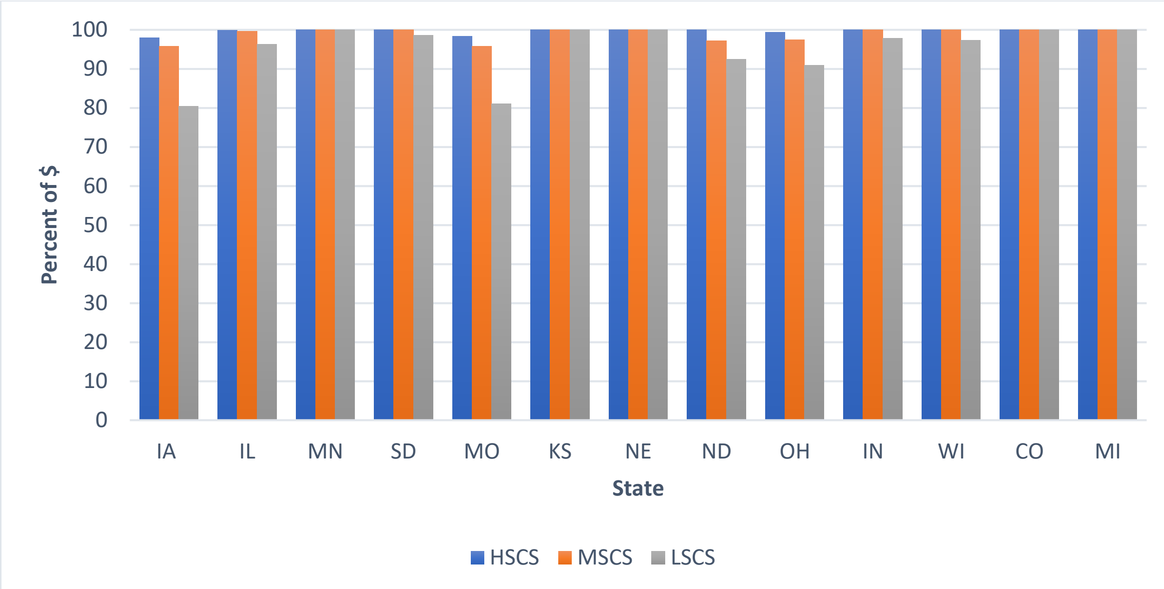

Figure 18: Share of available budget allocation targeting adoption of low, average, and highly intensive SCS practices by different payment rates per carbon sequestration benefit.

5.2. Acreage maximization approach results

We can see that using payment scenarios 1, 2, and 3, we did not exhaust the full budget to get the maximum environmental benefits for some of the states in Figure 18. Therefore, alternatively, we use acreage maximization approach to estimate the lowest average per acre payment rate to offer to get the full conservation budget expended under the incentive program. Results of the lowest possible per-acre payment rate are presented in Table 7. We can observe that the lowest average price estimates for states including IA, MO, OH, and IL are higher than the highest price in scenario 3, given that we have a large enough budget to target a larger number of cropland acres than are available in the counties of these states. The difference between lowest per acre payments to increase the number of acres under conservation program, implies that the conservation budget is positively correlated with size of cropland in the county. However, when the targeting approach considers the maximization of higher soil carbon sequestration per acre, then the current allocation could suggest a potential misallocation of budget. Higher budget is recommended to be reallocated to counties with high quality land and SCS rates relative to counties with low potential SCS.

Table 7: Lowest possible per acre payment per state to get the full available budget exhausted under the carbon incentive program.

State	Lowest per acre payment rate that depletes the full county budget ($/acre)
IA	39.45
MO	34.20
OH	31.80
IL	31.40
ND	28.00
MN	22.30
WI	17.70
IN	17.00
SD	15.70
NE	13.50
MI	11.77
KS	8.30
CO	8.10

Figure 19 shows the resulting metric tons of carbon inset under the acreage maximization approach to target the largest number of cropland acres with the lowest average per acre payment rate while utilizing the full county conservation budget. Under the acreage maximization approach and the estimated lowest average payment rates within our sample counties, we calculate that, about 22 million metric tons of carbon can be sequestered in the Corn Belt croplands annually. We can notice that the value of metric tons of carbon sequestered under low average payment rate of the acreage maximization approach is lower than the benefit maximization approach in scenario 3 (HSCS) for all states and it is higher than the estimated metric tons of carbon stored in scenario 1 (LSCS) for all states except NE and SD. Therefore, the estimated metric tons of carbon sequestered in the acreage maximization approach (Figure 19) range between the observed metric tons of carbon sequestered under scenarios 1 and 3 of the benefit maximization approach.

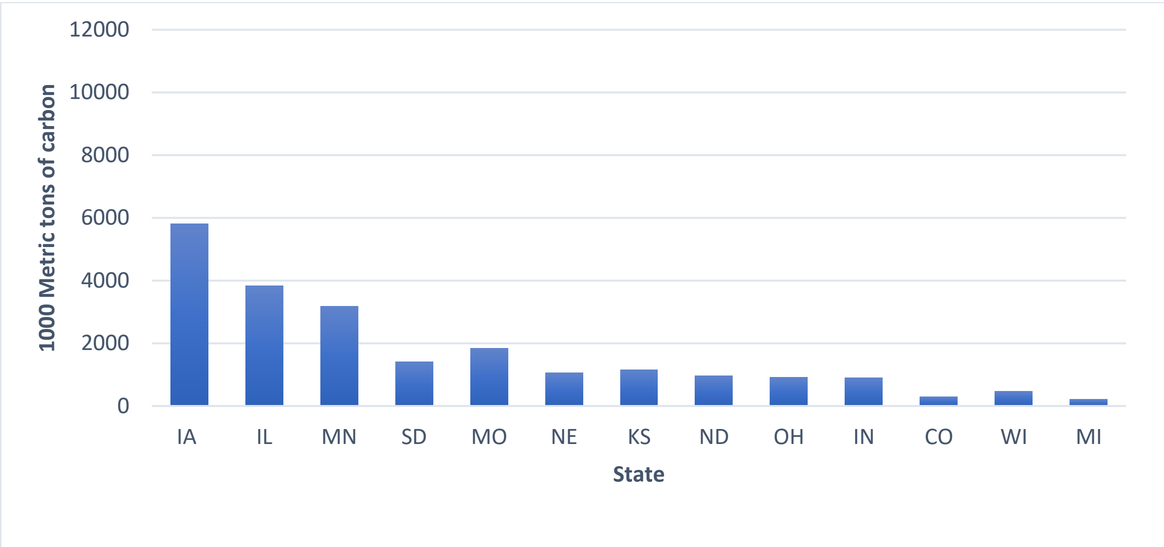

Figure 19: Metric tons of carbon sequestered under the lowest payment rate to utilize the full county conservation budget, aggregated at the state level.

With the lowest average possible payment rate, about 62 million acres of the U.S. Corn Belt cropland are enrolled in the incentive program, which is higher than the total cropland acres under scenario 2 (MSCS) and scenario 3 (HSCS) (see Figure 17 and Figure 20). Comparing our aggregated results, due to lower payment rates, Colorado, Indiana, and Kansas results show that 55.6, 36.3, and 33.1 percent of working cropland acres enrolled under incentive program with the lowest payment rate, which are higher than the proportion of acres under scenario 1 (LSCS), respectively. The number of acres enrolled are presented in Table 14 in the appendix. In the other side Iowa and North Dakota show a lower proportion of acres enrolled under the conservation program compared to all three scenarios, given the high payment rate used to exhaust the full budget.

These results suggest that acreage maximization approach is not the appropriate measure to target carbon sequestration benefit as it does not necessarily result in a higher proportion of high-quality cropland acres successfully participating in the incentive program compared to a higher payment rate scenario of the benefit maximization approach. Also, the acreage maximization approach does not account for the environmental benefit of metric tons of carbon sequestered. The acreage approach however might be a good approach for conservation incentive programs with low conservation budget levels in counties with large acres of cropland.

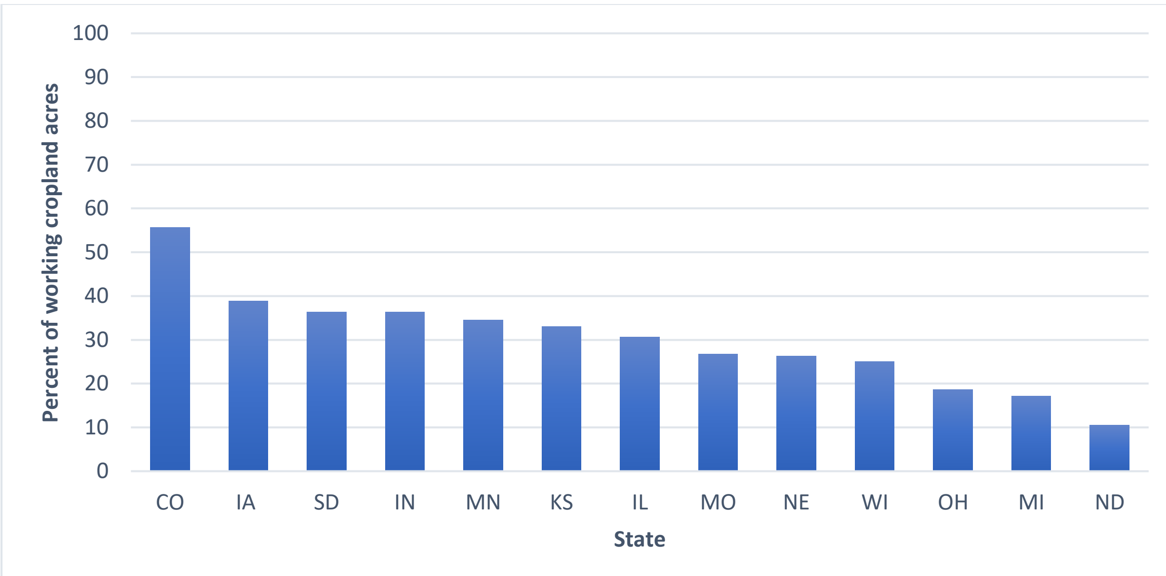

Figure 20: Optimal acres allocated to carbon incentive program with the lowest per acre payment rate to deplete the full county conservation budget.

6. Conclusion

Cropland has the potential to sequester carbon and reduce GHG emissions if treated properly with appropriate SCS practices. Farmers can be incentivized to implement SCS practices and technologies if they are offered a sufficient payment incentive. However, the allocation of conservation payments toward environmental benefits highly depends on budget limitation, participants' selection criteria, data availability, and degree of environmental damage (or potential environmental benefit). The objective of this chapter is to recommend an appropriate approach to allocate a county's allocated annual conservation budget to get optimal benefits of soil carbon sequestration. Different approaches might benefit different parties in different ways. For example:

landowners with higher quality cropland participating in carbon incentive programs may gain higher returns per cropland acres from approaches that target high SCS per acre outcomes.

We use a linear programming optimization model to determine the optimal number of cropland acres to enroll in the carbon incentive program under three per acre payment scenarios: low, medium and high intensity SCS practices. These scenarios work according to the concept of benefit maximization in which decision maker aims at maximizing the SCS benefit by targeting highly intensive SCS practices with higher pricing per acre. High payment rates to target the adoption of highly intensive SCS practices result in more metric tons of carbon sequestered but a lower share of county croplands participating in the carbon incentive program. Targeting the adoption of highly intensive SCS practices can be preferred more by environmentalists and landowners of high-quality croplands. Environmentalists support the higher soil carbon sequestration outcomes, while owners of high-quality land with high potential SCS rates can earn higher returns when participating in carbon incentive program that targets the benefits maximization with higher payments made for higher intensity practices.

The cost approach uses the limited conservation budgets to target the largest possible number of cropland acres under the carbon incentive program with the lowest possible per-acre payment rate, regardless of metric tons of carbon sequestered. The payment rates per county depend on the budget limit and cropland availability. For example, farmers in counties with large budgets and fewer cropland acres might receive higher per acre payments if participated in a carbon incentive program functioning under this cost targeting approach. On the other hand, farmers in low-budget counties with more cropland acres would receive lower payments per acre.

The benefit-cost approach, not explored in this chapter, can be used to target the selection of individual participants with the highest sequestration benefit per dollar spent. It is preferred by carbon buyers with a limited budget who aim at gaining higher metric tons of carbon sequestered annually per dollar spent on cropland that receives a change in SCS practices. We did not use the benefit-cost ratio approach, as our optimization model targets the number of acres to be enrolled by county based on county averages rather than selecting individual plots.

Due to unavailability of farm-level data, our selection decision represents the optimal benefit generated by targeting cropland allocation in the carbon incentive program at the county level. However, with field-level data on SCS rates and payment rates per practice or per ton of carbon, the binary selection decision can explain the sequence of the enrollment process in a carbon incentive program with budget limitations, as some farms may get rejected due to very low potential sequestration rate under a benefit maximization or benefit-cost ratio approach.

APPENDIX

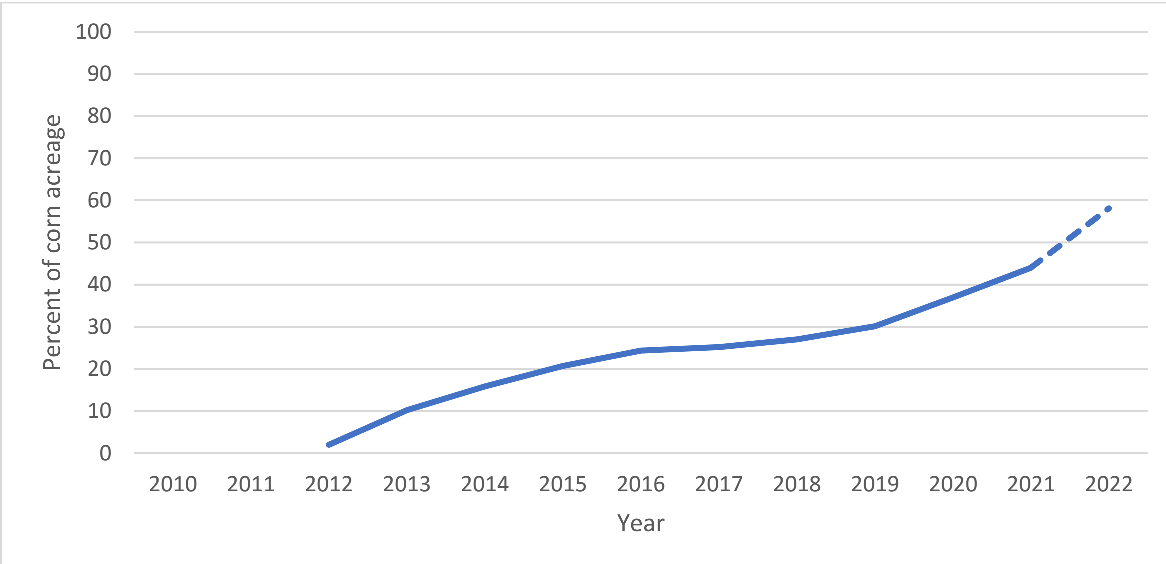

Figure 21: Percent of the U.S. corn acreage planted drought tolerant corn seed varieties 2012-2022.
Data Sources: FBN database used to calculate DT adoption rate 2012-2021, 2022 adoption rate is estimated using our filed sample data.

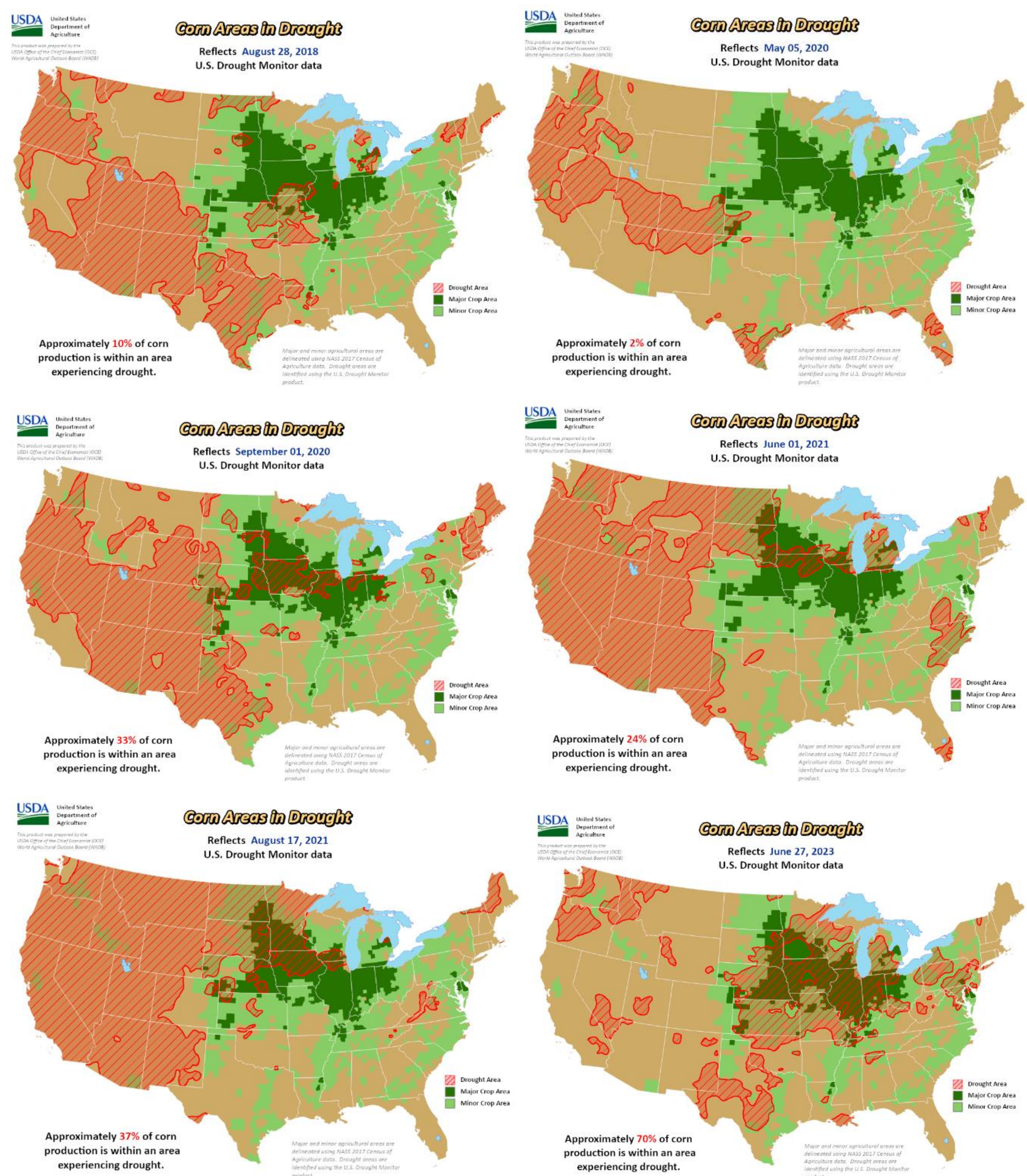

Figure 22: Corn Areas in Drought
Source: U.S. Drought Monitor database, 2023. https://agindrought.unl.edu/Maps.aspx?1

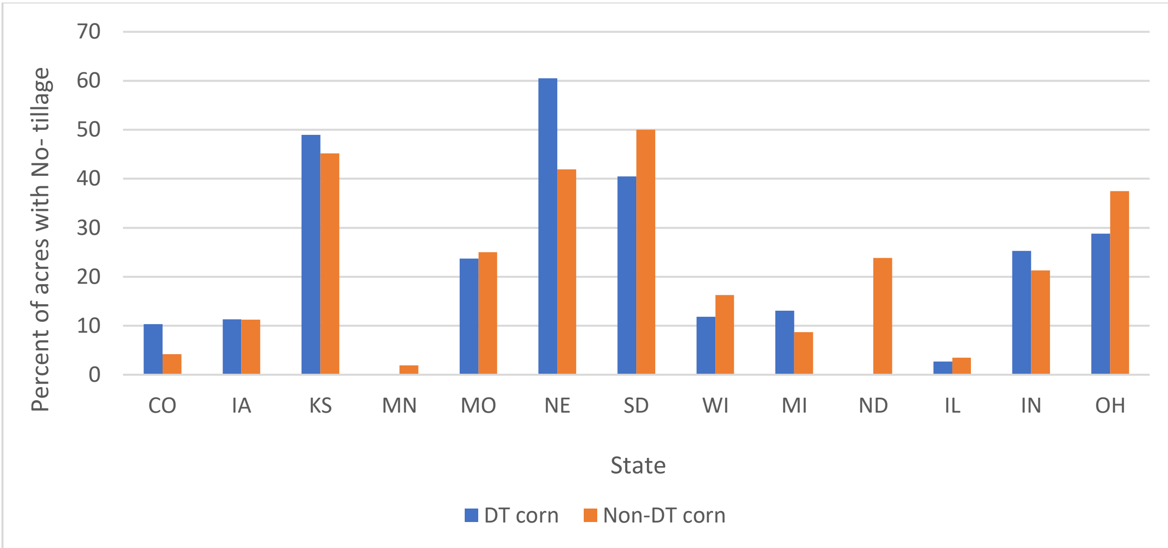

Figure 23: Of acres planted with DT corn, the percent treated with No tillage, vs of acres planted with non-DT corn the percent treated with No tillage, per state in 2022.

Table 8: Summary Statistic of state level DT corn diffusion.

Variables	Min	Max	SD	Overall Mean	Unit
Outcome variable					
DT land share	0	0.666	0.161	0.231	Percent (0-1)
DT land share	0	66.620	16.071	23.120	Percent (0-100)
Explanatory variables					
Year	2011	2022	-	2016	Factor
Drought (DSCI)	0	453	106.008	75.370	Number
Precipitation	2.980	25.290	5.182	12.220	inch
Share GM corn hybrid	0.257	0.970	0.155	0.680	Percent (0-1)
Share of land allocated to wheat	0	35.845	7.473	4.953	Percent
Share of land allocated to soybean	0	49.020	12.366	22.920	Percent
Share of irrigated corn area	0	89	25.830	19.101	Percent
Net government payment	0.989	23.402	4.440	7.911	Billion dollars
Corn land	1.100	14.200	3.618	5.946	Million acres
% erodible cropland area	0.290	0.642	0.110	0.443	Percent (0-1)
Location in Corn Belt	1	3	-	-	Factor 1 eastern CB 2 Western CB 3 Central CB

Table 9: Tobit regression estimated coefficients and marginal effects.

Variables	Model 2 Estimated Coefficient	Average Marginal Effects (2)	Model 3 Estimated Coefficient	Average Marginal Effects (3)	Model 4 Estimated Coefficient	Average Marginal Effects (4)
Drought (DSCI)	0.002* (0.008)	0.006* (0.007)	0.003* (0.008)	0.007* (0.007)	0.004* (0.008)	0.007* (0.008)
Precipitation	-0.032 (0.255)	-0.015 (0.006)	-0.169 (0.258)	-0.188 (0.209)	-0.118 (0.246)	-0.307 (0.292)
Share GM corn hybrid	0.958*** (0.353)	0.915*** (0.109)	0.809* (0.359)	0.731* (0.814)	0.932*** (0.359)	0.758*** (0.845)
Share of cropland allocated to wheat			-0.414* (0.212)	-0.275* (0.306)	-0.404** (0.175)	-0.278** (0.310)
Share of irrigated corn area	0.278*** (0.063)	0.018*** (0.204)	0.362*** (0.067)	0.243*** (0.270)	0.308*** (0.059)	0.301*** (0.224)
Net government payment	-0.762*** (0.273)	-0.594*** (0.661)			-0.979*** (0.277)	-0.685*** (0.762)
share erodible cropland area	-1.064 (2.722)	-0.300 (0.342)	-2.917 (2.738)	-2.001 (2.227)	-2.887 (2.464)	-1.811 (2.018)
Lag yield					-0.017 (0.041)	-0.018 (0.201)
Share of cropland allocated to soybean	-0.002 (0.121)	-0.002 (0.181)				
Corn land area			-1.002** (0.378)	-3.765** (0.819)		
Western C.B.	16.025*** (5.412)	1.103*** (1.261)	17.763** (5.485)	1.311** (2.431)	14.290*** (5.242)	1.024*** (1.171)
Central C.B.	-2.609 (3.404)	-2.170 (2.441)	-1.945 (3.287)	-1.240 (1.772)	-1.941 (2.770)	-1.563 (1.755)
Intercept	-114.250 (5.696)		-95.712 (5.157)		-103.078 (3.696)	
Time dummy	Yes		Yes		Yes	
LogSigmaMu	1.130*** (0.319)		1.069** (0.329)		0.763 (0.485)	
LogSigmaNu	1.927*** (0.063)		1.939*** (0.063)		1.933*** (0.064)	
Observations	156	156	156	156	156	156
Log-Likelihood	-480.827		-481.976		-478.579	
Akaike Inf. Crit.	1007.654		1009.952		1005.157	
Bayesian Inf. Crit.	1077.801		1080.098		1078.354	
Wald F-statistics (X2)	1018.7***		1090.4***		381.3***	
Chi-squared test P(>X2)	0.000		0.000		0.000	

Table 10: Summary statistics for field level analysis

Variable	Min	Max	SD	Mean	Units
2022 DT corn seed adoption	0	1	0.494	0.581	Indicator
Irrigation	0	1	0.379	0.174	Indicator
Conventional	0	1	0.497	0.557	Indicator
No Tillage conservation	0	1	0.428	0.241	Indicator
Strip Tillage conservation	0	1	0.401	0.201	Indicator
Clay loam	0	1	0.488	0.389	Indicator
Silt loam	0	1	0.494	0.423	Indicator
Sandy loam	0	1	0.390	0.187	Indicator
Crop Rotation	0	1	0.381	0.824	Indicator
% of cropland with erosion risk	0.252	90.401	18.486	42.690	Percent
% of cropland with soil problems	0.000	47.100	8.049	5.593	Percent
% of wet cropland	0.000	96.60	20.099	26.080	Percent
Corn Basis	-2.223	-0.010	0.414	-0.529	Continuous
Drought Indicator Aug2018	0	1	0.499	0.477	Indicator
Drought Indicator Aug2019	0	1	0.460	0.304	Indicator
Drought Indicator Aug2020	0	1	0.499	0.525	Indicator
Drought Indicator Aug2021	0	1	0.476	0.652	Indicator
Drought March 2022	0	1	0.499	0.527	Indicator
Abnormally dry Aug2018	0	1	0.475	0.343	Indicator
Moderate Drought Aug2018	0	1	0.388	0.184	Indicator
Severe Drought Aug2018	0	1	0.314	0.111	Indicator
Extreme Drought Aug2018	0	1	0.288	0.091	Indicator
Exceptional drought Aug2018	0	1	0.219	0.051	Indicator
Abnormally dry Aug2019	0	1	0.459	0.302	Indicator
Moderate Drought Aug2019	0	1	0.226	0.054	Indicator
Severe Drought Aug2019	0	1	0.036	0.001	Indicator
Extreme Drought Aug2019	0	0	0	0.000	Indicator
Exceptional drought Aug 2019	0	0	0	0.000	Indicator
Abnormally dry Aug 2020	0	1	0.495	0.429	Indicator
Moderate Drought Aug2020	0	1	0.441	0.265	Indicator
Severe Drought Aug2020	0	1	0.330	0.124	Indicator
Extreme Drought Aug2020	0	1	0.203	0.0432	Indicator
Exceptional drought Aug 2020	0	0	0	0.000	Indicator
Abnormally dry Aug 2021	0	1	0.494	0.425	Indicator
Moderate Drought Aug2021	0	1	0.460	0.304	Indicator
Severe Drought Aug2021	0	1	0.426	0.239	Indicator
Extreme Drought Aug2021	0	1	0.346	0.139	Indicator
Exceptional drought Aug 2021	0	1	0.112	0.013	Indicator
Abnormally dry March 2022	0	1	0.455	0.293	Indicator
Moderate Drought March2022	0	1	0.459	0.301	Indicator
Severe Drought March2022	0	1	0.408	0.211	Indicator
Extreme Drought March 2022	0	1	0.169	0.029	Indicator
Exceptional drought March2022	0	1	0.026	0.001	Indicator

Table 11: Summary statistics and mean difference for field level analysis

	Full sample (n=1504)		Adopter (n=873)		Non-Adopter (n=631)		Mean difference =Adopt-non-adopt
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
2022 DT corn seed adoption	0.580	0.494	1	0	0	0	1
Irrigation	0.174	0.379	0.163	0.369	0.190	0.393	-0.027
Conventional	0.557	0.497	0.578	0.494	0.528	0.499	0.0507
No Tillage conservation	0.241	0.428	0.243	0.429	0.239	0.427	0.003
Strip Tillage conservation	0.202	0.401	0.179	0.383	0.233	0.423	-0.054
Clay loam	0.389	0.488	0.411	0.492	0.358	0.479	0.053
Silt loam	0.423	0.494	0.413	0.493	0.437	0.496	-0.024
Sandy loam	0.187	0.390	0.175	0.380	0.204	0.404	-0.029
Crop Rotation	0.824	0.381	0.832	0.374	0.813	0.390	0.019
% of cropland with erosion risk	42.693	18.486	42.704	18.580	42.678	18.367	0.026
% of cropland with soil problems	5.593	8.049	5.502	7.884	5.718	8.277	-0.215
% of wet cropland	26.076	20.099	26.319	19.731	25.739	20.600	0.580
Corn Basis	-0.529	0.414	-0.518	0.396	-0.543	0.437	0.025
Precipitation	8.980	5.514	9.043	5.649	8.893	5.325	0.150
Drought Indicator Aug2018	0.477	0.499	0.460	0.499	0.499	0.500	-0.039
Drought Indicator Aug2019	0.304	0.460	0.300	0.459	0.309	0.462	-0.009
Drought Indicator Aug2020	0.525	0.499	0.508	0.500	0.547	0.498	-0.038
Drought Indicator Aug2021	0.652	0.476	0.648	0.478	0.658	0.475	-0.009
Drought March 2022	0.527	0.499	0.528	0.499	0.525	0.499	0.003
Abnormally dry Aug2018	0.343	0.474	0.326	0.469	0.366	0.482	-0.039
Moderate Drought Aug2018	0.184	0.388	0.176	0.381	0.195	0.396	-0.018
Severe Drought Aug2018	0.111	0.314	0.104	0.306	0.120	0.326	-0.016
Extreme Drought Aug2018	0.091	0.288	0.095	0.293	0.086	0.280	0.009
Exceptional drought Aug2018	0.050	0.219	0.057	0.232	0.041	0.199	0.016

Abnormally dry Aug2019	0.302	0.459	0.298	0.458	0.307	0.462	-0.009
Moderate Drought Aug2019	0.054	0.226	0.055	0.228	0.052	0.223	0.003
Severe Drought Aug2019	0.001	0.036	0.001	0.034	0.002	0.039	-0.001
Extreme Drought Aug2019	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Exceptional drought Aug 2019	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Abnormally dry Aug 2020	0.4295	0.495	0.409	0.492	0.458	0.499	-0.049
Moderate Drought Aug2020	0.265	0.441	0.255	0.436	0.277	0.448	-0.022
Severe Drought Aug2020	0.124	0.330	0.127	0.333	0.120	0.326	0.007
Extreme Drought Aug2020	0.043	0.203	0.412	0.493	0.044	0.206	-0.002
Exceptional drought Aug 2020	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Abnormally dry Aug 2021	0.425	0.494	0.417	0.493	0.436	0.496	-0.019
Moderate Drought Aug2021	0.304	0.460	0.307	0.461	0.299	0.458	0.007
Severe Drought Aug2021	0.239	0.426	0.258	0.438	0.212	0.409	0.045
Extreme Drought Aug2021	0.139	0.346	0.147	0.354	0.128	0.335	0.018
Exceptional drought Aug 2021	0.013	0.112	0.007	0.083	0.021	0.142	-0.014
Abnormally dry March 2022	0.293	0.455	0.305	0.460	0.2773	0.448	0.027
Moderate Drought March2022	0.301	0.459	0.307	0.461	0.293	0.456	0.014
Severe Drought March2022	0.211	0.408	0.206	0.405	0.219	0.414	-0.012
Extreme Drought March 2022	0.029	0.169	0.024	0.153	0.036	0.188	-0.012
Exceptional drought March2022	0.001	0.026	0.001	0.034	0.000	0.000	0.001

Table 12: Correlation matrix for state level DT corn diffusion.

	DTshare	Drought	Precipitation	GM corn	Wheat acres	Soybean acres	Irrigation	GP	erosion	Cornland	lagYield
DTshare	1	0.054	-0.024	0.256	-0.012	-0.036	0.298	-0.018	-0.151	-0.061	-0.302
Drought	0.054	1	-0.064	0.072	0.178	-0.162	0.195	0.102	-0.013	0.004	-0.153
Precipitation	-0.024	-0.064	1	-0.472	-0.287	0.454	-0.361	-0.028	-0.540	0.078	0.296
GM corn	0.256	0.072	-0.472	1	-0.086	-0.132	0.335	0.402	0.433	0.235	0.074
Wheat acres	-0.012	0.178	-0.287	-0.086	1	-0.641	0.558	-0.357	-0.299	-0.439	-0.371
Soybean acres	-0.036	-0.162	0.454	-0.132	-0.641	1	-0.512	0.375	-0.022	0.673	0.634
Irrigation	0.298	0.195	-0.361	0.335	0.558	-0.512	1	0.002	0.131	-0.044	-0.253
GP	-0.018	0.102	-0.028	0.402	-0.357	0.375	0.002	1	0.189	0.635	0.254
erosion	-0.151	-0.013	-0.540	0.433	-0.299	-0.022	0.131	0.189	1	0.032	-0.095
Cornland	-0.061	0.004	0.078	0.235	-0.439	0.673	-0.044	0.635	0.032	1	0.504
lagYield	-0.302	-0.153	0.296	0.074	-0.371	0.634	-0.253	0.254	-0.095	0.504	1

Table 13: Correlation Matrix for field level DT corn adoption.

	DT	SD 18	SD 20	SD 22	Precipitation	Irrigation	clay	NoTill	StripTill	CR	CB
DT	1	-0.026	0.009	0.014	-0.014	-0.033	0.052	0.003	-0.064	0.021	0.030
SD 18	-0.026	1	-0.120	-0.020	0.059	-0.101	0.039	0.167	0.018	0.069	-0.257
SD 20	0.009	-0.120	1	0.205	-0.406	0.316	0.046	0.032	0.142	-0.169	-0.129
SD 22	0.014	-0.020	0.205	1	-0.498	0.252	-0.075	0.070	0.151	-0.198	-0.133
Precipitation	-0.014	0.059	-0.406	-0.498	1	-0.408	0.041	-0.083	-0.212	0.230	0.074
Irrigation	-0.033	-0.101	0.316	0.252	-0.408	1	-0.118	-0.005	0.298	-0.261	-0.224
clay	0.052	0.039	0.046	-0.075	0.041	-0.118	1	0.054	-0.078	0.093	0.020
NoTill	0.003	0.167	0.032	0.070	-0.083	-0.005	0.054	1	-0.283	0.130	-0.146
StripTill	-0.064	0.018	0.142	0.151	-0.212	0.298	-0.078	-0.283	1	-0.155	-0.184
CR	0.021	0.069	-0.169	-0.198	0.230	-0.261	0.093	0.130	-0.155	1	0.060
CB	0.030	-0.257	-0.129	-0.133	0.074	-0.224	0.020	-0.146	-0.184	0.060	1

Table 14: Maximum number of state cropland enrolled under conservation program with designated scenarios (Million acres).

	Scenario 1 LSCS	Scenario 2 MSCS	Scenario 3 HSCS	Lowest price to deplete the full budget
IA	20.022	14.326	12.185	10.275
IL	12.391	6.401	5.343	7.181
MN	9.737	4.709	3.885	6.089
SD	7.862	3.934	3.256	6.223
NE	5.987	2.976	2.304	5.359
MO	4.8297	3.153	2.653	3.080
ND	4.656	2.487	2.015	2.159
KS	4.468	2.452	1.844	7.533
CO	3.399	2.059	1.307	4.197
OH	3.215	1.734	1.453	1.800
IN	3.016	1.542	1.251	4.551
WI	2.3160	1.2530	1.0095	2.3756
MI	1.0471	0.5197	0.4199	1.0702

REFERENCES

Alcon, F., de Miguel, M. D., & Burton, M. (2011). Duration analysis of adoption of drip irrigation technology in southeastern Spain. *Technological Forecasting and Social Change*, *78*(6), 991-1001.

Al-Kaisi, M., & Licht, M. A. (2004). Effect of strip tillage on corn nitrogen uptake and residual soil nitrate accumulation compared with no-tillage and chisel plow. *Agronomy Journal*, *96*(4), 1164-1171.

Amankwah, A. (2021). Adoption of Multiple Agricultural Technologies and Impact on Productivity in Rural Nigeria–a Plot-Level Analysis.

Antle, J. M., & Just, R. E. (1991). Effects of commodity program structure on resource use and the environment. In *Commodity and resource policies in agricultural systems* (pp. 97-128). Berlin, Heidelberg: Springer Berlin Heidelberg.

Antle, J. M., Capalbo, S. M., Mooney, S., Elliott, E. T., & Paustian, K. H. (2001). Economic analysis of agricultural soil carbon sequestration: an integrated assessment approach. *Journal of agricultural and resource economics*, 344-367.

Antle, J. M., Capalbo, S. M., Paustian, K., & Ali, M. K. (2007). Estimating the economic potential for agricultural soil carbon sequestration in the Central United States using an aggregate econometric-process simulation model. *Climatic change*, *80*(1), 145-171.

Antle, J., Capalbo, S., Mooney, S., Elliott, E., & Paustian, K. (2003). Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture. *Journal of environmental economics and management*, *46*(2), 231-250.

Armstrong, R. D., Millar, G., Halpin, N. V., Reid, D. J., & Standley, J. (2003). Using zero tillage, fertilisers and legume rotations to maintain productivity and soil fertility in opportunity cropping systems on a shallow Vertosol. *Australian Journal of Experimental Agriculture*, *43*(2), 141-153.

Asfaw, S., Shiferaw, B., Simtowe, F., & Haile, M. (2011). Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. *Journal of Development and Agricultural Economics*, *3*(9), 436-477.

Awotide, B. A., Abdoulaye, T., Alene, A., & Manyong, V. M. (2016). Adoption of drought tolerance maize varieties for Africa, productivity, food security and welfare in Nigeria: An Ex-Post Impact Assessment. *Unpublished PhD Thesis, University of Ibadan, Nigeria*.

Babcock, B. A., Lakshminarayan, P. G., Wu, J., & Zilberman, D. (1996). The economics of a public fund for environmental amenities: a study of CRP contracts. *American journal of agricultural economics*, *78*(4), 961-971.

Babcock, B. A., Lakshminarayan, P. G., Wu, J., & Zilberman, D. (1997). Targeting tools for the purchase of environmental amenities. *Land economics*, 325-339.

Balana, B., & Oyeyemi, M. (2020). *Credit constraints and agricultural technology adoption: Evidence from Nigeria* (Vol. 64). Intl Food Policy Res Inst.

Barbato, C. T., & Strong, A. L. (2023). Farmer perspectives on carbon markets incentivizing agricultural soil carbon sequestration. *npj Climate Action*, *2*(1), 26.

Bauer, A., & Black, A. L. (1994). Quantification of the effect of soil organic matter content on soil productivity. *Soil Science Society of America Journal*, *58*(1), 185-193.

Bayer Carbon, 2022. https://www.bayer.com/en/agriculture/carbon-program-united-states.

Bayer Carbon. https://www.bayer.com/en/agriculture/carbon-program-united-states

Bayer Crop Science, 2024. https://www.cropscience.bayer.us/traits/corn/droughtgard-hybrids

Bedeke, S., Vanhove, W., Gezahegn, M., Natarajan, K., & Van Damme, P. (2019). Adoption of climate change adaptation strategies by maize-dependent smallholders in Ethiopia. *NJAS-Wageningen Journal of Life Sciences*, 88, 96-104.

Beillouin, D., Demenois, J., Cardinael, R., Berre, D., Corbeels, M., Fallot, A., ... & Feder, F. (2022). A global database of land management, land-use change and climate change effects on soil organic carbon. *Scientific Data*, *9*(1), 228.

Biederman, L. A., & Harpole, W. S. (2013). Biochar and its effects on plant productivity and nutrient cycling: a meta-analysis. GCB bioenergy, 5(2), 202-214.

Blevins, R. L., Cook, D., Phillips, S. H., & Phillips, R. E. (1971). Influence of No-tillage on Soil Moisture 1. *Agronomy Journal*, *63*(4), 593-596.

Bossio, D. A., Cook-Patton, S. C., Ellis, P. W., Fargione, J., Sanderman, J., Smith, P., ... & Griscom, B. W. (2020). The role of soil carbon in natural climate solutions. *Nature Sustainability*, *3*(5), 391-398.

Broekhoff, D., Gillenwater, M., Colbert-Sangree, T., & Cage, P. (2019). Securing climate benefit: a guide to using carbon offsets. *Stockholm Environment Institute & Greenhouse Gas Management Institute*, *60*.

Bulte, E. H., Lipper, L., Stringer, R., & Zilberman, D. (2008). Payments for ecosystem services and poverty reduction: concepts, issues, and empirical perspectives. *Environment and Development Economics*, *13*(3), 245-254.

Cairns, J. E., & Prasanna, B. M. (2018). Developing and deploying climate-resilient maize varieties in the developing world. *Current Opinion in Plant Biology*, *45*, 226-230.

Campbell, C. A., Janzen, H. H., Paustian, K., Gregorich, E. G., Sherrod, L., Liang, B. C., & Zentner, R. P. (2005). Carbon storage in soils of the North American Great Plains: Effect of cropping frequency. *Agronomy Journal*, *97*(2), 349-363.

Carbon by Indigo: https://www.indigoag.com/carbon , And:https://app.indigoag.com/programs/how-much-can-i-earn-carbon-farming?utm_medium=paid&utm_source=semgb&utm_campaign=us-pql-carbon_farmer-ad-search_brand-q4.2023&utm_term=indigo+carbon&_bt=641939540055&_bm=e&_bn=g&gad_source=1&gclid=EAIaIQobChMIvJDh4IDnggMVYyutBh2erALvEAAYASABEgJ7IfD_BwE

Cattaneo, A., Claassen, R., Johansson, R., & Weinberg, M. (2005). Flexible Conservation Measures on Working Land. *Agricultural Economics Report*, 58.

Chadwick, D., Sommer, S., Thorman, R., Fangueiro, D., Cardenas, L., Amon, B., & Misselbrook, T. (2011). Manure management: Implications for greenhouse gas emissions. *Animal Feed Science and Technology*, *166*, 514-531.

Chambers, R. G., & Quiggin, J. (2000). Uncertainty, production, choice, and agency: the state-contingent approach. Cambridge University Press.

Chapman, E. A., Thomsen, H. C., Tulloch, S., Correia, P. M., Luo, G., Najafi, J., ... & Palmgren, M. (2022). Perennials as future grain crops: opportunities and challenges. *Frontiers in Plant Science*, *13*, 898769.

Chouinard, H. H., Paterson, T., Wandschneider, P. R., & Ohler, A. M. (2008). Will farmers trade profits for stewardship? Heterogeneous motivations for farm practice selection. Land Economics, 84(1), 66-82.

CIBO (2022). https://www.cibotechnologies.com/.

Claassen, R., Cattaneo, A., & Johansson, R. (2008). Cost-effective design of agri-environmental payment programs: US experience in theory and practice. *Ecological economics*, *65*(4), 737-752.

Conant, R. T., Cerri, C. E., Osborne, B. B., & Paustian, K. (2017). Grassland management impacts on soil carbon stocks: a new synthesis. Ecological Applications, 27(2), 662-668.

Cooper, M., Gho, C., Leafgren, R., Tang, T., & Messina, C. (2014). Breeding drought-tolerant maize hybrids for the US corn-belt: discovery to product. *Journal of Experimental Botany*, *65*(21), 6191-6204.

Corteva (2022). https://www.corteva.us/products-and-solutions/digital-solutions/carbon.html.

Corteva carbon program 2023. https://www.corteva.us/products-and-solutions/digital-solutions/carbon.html

Cox, T. S., Glover, J. D., Van Tassel, D. L., Cox, C. M., & DeHaan, L. R. (2006). Prospects for developing perennial grain crops. *Bioscience*, *56*(8), 649-659.

Cremades, R., Wang, J., & Morris, J. (2015). Policies, economic incentives and the adoption of modern irrigation technology in China. *Earth System Dynamics*, *6*(2), 399-410.

CTCN, 2021. UN Climate Technology Center & Network. UNFCCC Technology Mechanism. Biochar. The Climate Technology Centre and Network (CTCN), UN City, Marmorvej 51, 2100 Copenhagen, Denmark, https://www.ctc-n.org/technologies/biochar.

Daberkow, S. G., & McBride, W. D. (2003). Farm and operator characteristics affecting the awareness and adoption of precision agriculture technologies in the US. *Precision agriculture*, *4*(2), 163-177.

Dadi, L., Burton, M., & Ozanne, A. (2004). Duration analysis of technological adoption in Ethiopian agriculture. *Journal of Agricultural Economics*, *55*(3), 613-631.

de Lima, C. C., De Maria, I. C., da Silva Guimarães Júnnyor, W., Figueiredo, G. C., Dechen, S. C. F., & Bolonhezi, D. (2022). ROOT parameters of sugarcane and soil compaction indicators under deep strip tillage and conventional tillage. *Scientific Reports*, *12*(1), 18537.

de Souza, A. R., Dupas, F. A., & da Silva, I. A. (2021). Spatial targeting approach for a payment for ecosystem services scheme in a peri-urban wellhead area in southeastern Brazil. *Environmental Challenges*, *5*, 100206.

Díaz-Zorita, M., Buschiazzo, D. E., & Peinemann, N. (1999). Soil organic matter and wheat productivity in the semiarid Argentine Pampas. *Agronomy Journal*, *91*(2), 276-279.

Díaz-Zorita, M., Duarte, G. A., & Grove, J. H. (2002). A review of no-till systems and soil management for sustainable crop production in the subhumid and semiarid Pampas of Argentina. *Soil and Tillage Research*, *65*(1), 1-18.

Diederen, P., Van Meijl, H., Wolters, A., & Bijak, K. (2003). Innovation adoption in agriculture: innovators, early adopters, and laggards. *Cahiers d'Economie et de Sociologie Rurales*, *67*, 29-50.

Duke, J. M., Dundas, S. J., Johnston, R. J., & Messer, K. D. (2014). Prioritizing payment for environmental services: Using nonmarket benefits and costs for optimal selection. *Ecological Economics*, *105*, 319-329.

EPA (2020). United States Environmental Protection Agency. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

EPA, 2023. https://cfpub.epa.gov/ghgdata/inventoryexplorer/.

ESMC (2022). Ecosystems Services Market Consortium. https://ecosystemservicesmarket.org/.

EWG (2020). EWG's Farm Subsidy Database. https://farm.ewg.org/.

EWG, 2022.EWG's Farm Subsidy Database. https://farm.ewg.org/.

FAO 2023. Global soil information system. https://www.fao.org/global-soil-partnership/areas-of-work/soil-information-and-data/en/

FAO (2018). Emissions due to agriculture. Global, regional and country trends 2000–2018. Food and Agricultural organization for the United Nation. FAOSTAT Analytical Brief 18.

FBN (2023). https://www.fbn.com/.

Feather, P., & Hellerstein, D. (1997). Calibrating benefit function transfer to assess the conservation reserve program. *American journal of agricultural economics*, *79*(1), 151-162.

Feder, G., & O'Mara, G. T. (1981). Farm size and the diffusion of green revolution technology. *Economic Development and cultural change*, *30*(1), 59-76.

Feder, G., & Umali, D. L. (1993). The adoption of agricultural innovations: a review. *Technological forecasting and social change*, *43*(3-4), 215-239.

Feder, G., Just, R. E., & Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic development and cultural change*, *33*(2), 255-298.

Filed to Market 2020. https://fieldtomarket.org/new-report-highlights-farmers-perception-of-sustainability-and-extent-of-conservation-adoption/

Fisher, M., & Snapp, S. (2014). Smallholder Farmers' Perceptions of Drought Risk and Adoption of Modern Maize in Southern Malawi. *Experimental Agriculture*, *50*(4), 533-548.

Fisher, M., Abate, T., Lunduka, R. W., Asnake, W., Alemayehu, Y., & Madulu, R. B. (2015). Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa. *Climatic Change*, *133*(2), 283-299.

Fooks, J. R., & Messer, K. D. (2012). Maximizing conservation and in-kind cost share: Applying Goal Programming to forest protection. *Journal of forest economics*, *18*(3), 207-217.

Fooks, J. R., & Messer, K. D. (2013). Mathematical programming applications to land conservation and environmental quality. *Computational intelligent data analysis for sustainable development*, 159-178.

Gong, S., Bergtold, J. S., & Yeager, E. (2021). Assessing the joint adoption and complementarity between in-field conservation practices of Kansas farmers. *Agricultural and Food Economics*, *9*, 1-24.

Greene, W. (1993). Econometric analysis New York: Mcmillan.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica, Journal of the Econometric Society*, 501-522.

Guo, Y., Zheng, H., Wu, T., Wu, J., & Robinson, B. E. (2020). A review of spatial targeting methods of payment for ecosystem services. *Geography and Sustainability*, *1*(2), 132-140.

Gupta, A., Ponticelli, J., & Tesei, A. (2020). *Information, technology adoption and productivity: The role of mobile phones in agriculture* (No. w27192). National Bureau of Economic Research.

Gurian-Sherman, D. (2012). Why genetic engineering is not solving agriculture's drought problem in a thirsty world. *Report. Cambridge, MA*.

Heisey, P. W., Morris, M. L., Byerlee, D., & Lopez-Pereira, M. A. (1998). Economics of hybrid maize adoption. *Maize seed industries in developing countries.*, 143-158.

Holden, S. T., & Fisher, M. (2015). Subsidies promote use of drought tolerant maize varieties despite variable yield performance under smallholder environments in Malawi. *Food Security*, *7*, 1225-1238.

Holden, S. T., & Quiggin, J. (2017). Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences. *European Review of Agricultural Economics*, *44*(2), 285-308.

Huffman, W. E., & Mercier, S. (1991). Joint adoption of microcomputer technologies: An analysis of farmers' decisions. *The Review of Economics and Statistics*, 541-546.

Iacomino, G., Idbella, M., Laudonia, S., Vinale, F., & Bonanomi, G. (2022). The Suppressive Effects of Biochar on Above-and Belowground Plant Pathogens and Pests: A Review. Plants, 11(22), 3144.

Indigo (2022). https://www.indigoag.com/.

Iowa Department of Agriculture and Land Stewardship 2022. https://iowaagriculture.gov/agricultural-diversification-market-development-bureau/month-end-grain-price-reports.

IPCC (2014): *Climate Change 2014: Synthesis Report*. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Jeffery, S., Verheijen, F. G., van der Velde, M., & Bastos, A. C. (2011). A quantitative review of the effects of biochar application to soils on crop productivity using meta-analysis. *Agriculture, ecosystems & environment*, *144*(1), 175-187.

Jelliffe, J. L., Bravo-Ureta, B. E., Deom, C. M., & Okello, D. K. (2018). Adoption of high-yielding groundnut varieties: The sustainability of a farmer-led multiplication-dissemination program in Eastern Uganda. *Sustainability*, *10*(5), 1597.

Just, R. E., & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. *Oxford Economic Papers*, *35*(2), 307-328.

Just, R. E., & Zilberman, D. (1988). The effects of agricultural development policies on income distribution and technological change in agriculture. *Journal of Development Economics*, *28*(2), 193-216.

Just, R. E., Schmitz, A., & Zilberman, D. (1979). Technological Change in Agriculture: The sources, diffusion, and social imports of technological change in agriculture are examined. Science, 206(4424), 1277-1280.

Katengeza, S. P., Holden, S. T., & Lunduka, R. W. (2019). Adoption of drought tolerant maize varieties under rainfall stress in Malawi. *Journal of Agricultural Economics*, *70*(1), 198-214.

Khanna, M. (2001). Sequential adoption of site-specific technologies and its implications for nitrogen productivity: A double selectivity model. *American journal of agricultural economics*, *83*(1), 35-51.

Khonje, M. G., Manda, J., Mkandawire, P., Tufa, A. H., & Alene, A. D. (2018). Adoption and welfare impact of multiple agricultural technologies: evidence from eastern Zambia. *Agricultural Economics*, *49*(5), 599-609.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. *World development*, *66*, 695-706.

Kim, Y., & Cho, S. H. (2019). How spatial targeting of incentive payments for forest carbon storage can be adjusted for competing land uses. *Regional Environmental Change*, *19*, 441-450.

Kirwan, B., Lubowski, R. N., & Roberts, M. J. (2005). How cost-effective are land retirement auctions? Estimating the difference between payments and willingness to accept in the conservation reserve program. *American journal of agricultural economics*, *87*(5), 1239-1247.

Kostandini, G., La Rovere, R., & Abdoulaye, T. (2013). Potential impacts of increasing average yields and reducing maize yield variability in Africa. *Food Policy*, *43*, 213-226.

Kragt, M. E., Gibson, F. L., Maseyk, F., & Wilson, K. A. (2016). Public willingness to pay for carbon farming and its co-benefits. *Ecological Economics*, *126*, 125-131.

La Rovere, R., Abdoulaye, T., Kostandini, G., Guo, Z., Mwangi, W., MacRobert, J., & Dixon, J. (2014). Economic, production, and poverty impacts of investing in maize tolerant to drought in Africa: an ex-ante assessment. *The Journal of Developing Areas*, 199-225.

Lal, R. (2004). Soil carbon sequestration impacts on global climate change and food security. *science*, *304*(5677), 1623-1627.

Lambrecht, I., Vanlauwe, B., Merckx, R., & Maertens, M. (2014). Understanding the process of agricultural technology adoption: mineral fertilizer in eastern DR Congo. *World development*, *59*, 132-146.

Läpple, D., & Van Rensburg, T. (2011). Adoption of organic farming: Are there differences between early and late adoption?. *Ecological economics*, *70*(7), 1406-1414.

Lichtenberg, E. (1989). Land quality, irrigation development, and cropping patterns in the northern high plains. *American Journal of Agricultural Economics*, *71*(1), 187-194.

Liu, T., R. Bruins, and M. Heberling. (2018). Factors influencing farmers' adoption of best management practices: Areview and synthesis. Sustainability 10(2):432.

Llewellyn, R. S., D'Emden, F. H., & Kuehne, G. (2012). Extensive use of no-tillage in grain growing regions of Australia. *Field Crops Research*, *132*, 204-212.

Lunduka, R. W., Mateva, K. I., Magorokosho, C., & Manjeru, P. (2019). Impact of adoption of drought-tolerant maize varieties on total maize production in south Eastern Zimbabwe. *Climate and development*, *11*(1), 35-46.

Luo, Z., Wang, E., & Sun, O. J. (2010). Soil carbon change and its responses to agricultural practices in Australian agro-ecosystems: a review and synthesis. *Geoderma*, *155*(3-4), 211-223.

Lynch, J. P. (2022). Harnessing root architecture to address global challenges. *The Plant Journal*, *109*(2), 415-431.

Mabaya, E., Fulton, J., Simiyu-Wafukho, S., & Nang'ayo, F. (2015). Factors influencing adoption of genetically modified crops in Africa. *Development Southern Africa*, *32*(5), 577-591.

Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics* (No. 3). Cambridge university press.

Mahajan, V., & Peterson, R. A. (1985). *Models for innovation diffusion* (No. 48). Sage.

Major, J., Rondon, M., Molina, D., Riha, S. J., & Lehmann, J. (2010). Maize yield and nutrition during 4 years after biochar application to a Colombian savanna oxisol. *Plant and soil*, *333*, 117-128.

Mansfield, E. (1961). Technical change and the rate of imitation. *Econometrica: Journal of the Econometric Society*, 741-766.

Martey, E., Etwire, P. M., & Kuwornu, J. K. (2020). Economic impacts of smallholder farmers' adoption of drought-tolerant maize varieties. *Land use policy*, *94*, 104524.

Matuschke, I., & Qaim, M. (2009). The impact of social networks on hybrid seed adoption in India. *Agricultural Economics*, *40*(5), 493-505.

McFadden, J. R., Smith, D. J., & Wallander, S. (2022). Weather, Climate, and Technology Adoption: An Application to Drought-Tolerant Corn in the United States (No. w30121). National Bureau of Economic Research.

McFadden, J., Smith, D. J., & Wallander, S. (2018). Adoption of drought-tolerant corn in the US: A field-level analysis of adoption patterns and emerging trends.

McFadden, J., Smith, D., Wechsler, S., & Wallander, S. (2019). *Development, adoption, and management of drought-tolerant corn in the United States* (No. 1476-2019-1675).

Merem, E. C., Twumasi, Y. A., Wesley, J., Olagbegi, D., Crisler, M., Romorno, C., ... & Leggett, S. (2021). Analyzing the Use of Genetic Modified Organisms (GMOs) in Agriculture in the US Midwest Region. *Food and Public Health*, *11*(1), 1-17.

Murray, B. C., Sohngen, B., & Ross, M. T. (2007). Economic consequences of consideration of permanence, leakage and additionality for soil carbon sequestration projects. *Climatic change*, *80*(1), 127-143.

NASA (2023). Global Climate Change, Vital Signs of the Planet. https://climate.nasa.gov/vital-signs/carbon-dioxide/.

Neild, R. E., & Newman, J. E. (1987). Growing season characteristics and requirements in the Corn Belt. Cooperative Extension Service, Iowa State University.

NOAA (2023). National Centers for environmental information, National Oceanic and Atmospheric Administration. https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/county/mapping.

Nori (2022). Own, Track, and Showcase Verified Carbon Removal. https://nori.com/.

Nori. https://nori.com/suppliers/farmers/requirements

Nowak, P. (1992). Why farmers adopt production technology: Overcoming impediments to adoption of crop residue management techniques will be crucial to implementation of conservation compliance plans. Journal of soil and water conservation, 47(1), 14-16.

Nutrien (2022). https://www.nutrien.com/sustainability/strategy/carbon-program.

Ogle, S. M., Breidt, F. J., & Paustian, K. (2005). Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. *Biogeochemistry*, *72*, 87-121.

Ogle, S. M., Breidt, F. J., Del Grosso, S., Gurung, R., Marx, E., Spencer, S., ... & Manning, D. (2023). Counterfactual scenarios reveal historical impact of cropland management on soil organic carbon stocks in the United States. *Scientific Reports*, *13*(1), 14564.

Ogundari, K., & Bolarinwa, O. D. (2018). Impact of agricultural innovation adoption: a meta-analysis. *Australian Journal of Agricultural and Resource Economics*, *62*(2), 217-236.

O'Neil, C., Miesel, j., & Gould, M. C., (2020). Biochar: An emerging soil amendment. Michigan State University Extension - June 17, 2020.

Ortiz-Bobea, A., Knippenberg, E., & Chambers, R. G. (2018). Growing climatic sensitivity of US agriculture linked to technological change and regional specialization. *Science advances*, *4*(12), eaat4343.

Paez-Garcia, A., Motes, C. M., Scheible, W. R., Chen, R., Blancaflor, E. B., & Monteros, M. J. (2015). Root traits and phenotyping strategies for plant improvement. *Plants*, *4*(2), 334-355.

Pannell, D. J., Pardey, P. G., & Hurley, T. M. (2020). *Private Incentives for Sustainable Agriculture: Principals and Evidence for Sustainable Agricultural Change* (No. 1784-2020-650).

Pannell, D. J., Pardey, P. G., Thamo, T., & Hurley, T. M. (2020). *Private Incentives for Sustainable Agriculture: Synthesis* (No. 1784-2020-654).

Paustian, K., Larson, E., Kent, J., Marx, E., & Swan, A. (2019). Soil C sequestration as a biological negative emission strategy. *Frontiers in Climate*, 8.

Pett-Ridge, J., Nuccio, E., & Mcfarlane, K. (2018). *Deeply Rooted: Evaluating Plant Rooting Depth as a Means for Enhanced Soil Carbon Sequestration* (No. LLNL-CONF-750320). Lawrence Livermore National Lab. (LLNL), Livermore, CA (United States).

Pioneer, 2024. https://www.pioneer.com/us/products/corn/traits-technologies/aquamax.html

Plastina, A. (2021). How to Grow and Sell Carbon Credits in US Agriculture. Ag Decision Maker. *Extension Bulletin*, (A1-76).

Plastina, A., & Wongpiyabovorn, O. (2021). How to grow and sell carbon credits in US agriculture. *Ag Decision Maker File A1–76. extension. iastate. edu/agdm*.

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops–A meta-analysis. *Agriculture, Ecosystems & Environment*, *200*, 33-41.

Raza, A., Mubarik, M. S., Sharif, R., Habib, M., Jabeen, W., Zhang, C., ... & Varshney, R. K. (2023). Developing drought-smart, ready-to-grow future crops. *The Plant Genome*, *16*(1), e20279.

Richards, R. A. (2006). Physiological traits used in the breeding of new cultivars for water-scarce environments. *Agricultural water management*, *80*(1-3), 197-211.

Roberts, M. J., & Schlenker, W. (2011). The evolution of heat tolerance of corn: implications for climate change. In *The economics of climate change: adaptations past and present* (pp. 225-251). University of Chicago Press.

Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: a meta-analysis of the empirical literature. *World Development*, *146*, 105599.

Sá, de M., J. C., Cerri, C. C., Dick, W. A., Lal, R., Filho, S. P. V., Piccolo, M. C., & Feigl, B. E. (2001). Organic matter dynamics and carbon sequestration rates for a tillage chronosequence in a Brazilian Oxisol. *Soil Science Society of America Journal*, *65*(5), 1486-1499.

Sanderman, J., & Baldock, J. A. (2010). Accounting for soil carbon sequestration in national inventories: a soil scientist's perspective. *Environmental Research Letters*, *5*(3), 034003.

Schaefer, E., Ajmera, I., Farcot, E., Owen, M., Band, L., & Lynch, J. (2022). In silico evidence for the utility of parsimonious root phenotypes for improved vegetative growth and carbon sequestration under drought. *bioRxiv*.

Sharifuddin, J., Mohammed, Z. A., & Terano, R. (2016). Rice farmers' perception and attitude toward organic farming adoption. *Jurnal Agro Ekonomi*, *34*(1), 35-46.

Shiferaw, B., Kebede, T., Kassie, M., & Fisher, M. (2015). Market imperfections, access to information and technology adoption in Uganda: Challenges of overcoming multiple constraints. *Agricultural economics*, *46*(4), 475-488.

Simtowe, F., Marenya, P., Amondo, E., Worku, M., Rahut, D. B., & Erenstein, O. (2019). Heterogeneous seed access and information exposure: implications for the adoption of drought-tolerant maize varieties in Uganda. *Agricultural and Food Economics*, *7*(1), 1-23.

Six, J., Feller, C., Denef, K., Ogle, S., de Moraes Sa, J. C., & Albrecht, A. (2002). Soil organic matter, biota and aggregation in temperate and tropical soils-Effects of no-tillage. *Agronomie*, *22*(7-8), 755-775.

Skidmore, S., Santos, P., & Leimona, B. (2014). Targeting REDD+: an empirical analysis of carbon sequestration in Indonesia. *World Development*, *64*, 781-790.

Smaje, C. (2015). The strong perennial vision: A critical review. *Agroecology and Sustainable Food Systems*, *39*(5), 471-499.

Smyth, S. J., McHughen, A., Entine, J., Kershen, D., Ramage, C., & Parrott, W. (2021). Removing politics from innovations that improve food security. *Transgenic research*, *30*, 601-612.

Soil and Water Outcomes Fund (2022). https://www.theoutcomesfund.com/.

Stubbs, M. (2010). *Environmental quality incentives program (EQIP): status and issues*. Congressional Research Service.

Stubbs, M. (2014). Conservation Reserve Program (CRP): status and issues. Washington, DC, USA: Library of Congress, Congressional Research Service.

Successful farming 2022. Commodity Prices. https://www.agriculture.com/markets/commodity-prices

Sunding, D., & Zilberman, D. (2001). The agricultural innovation process: research and technology adoption in a changing agricultural sector. *Handbook of agricultural economics*, *1*, 207-261.

Takahashi, K., Muraoka, R., & Otsuka, K. (2020). Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agricultural Economics*, *51*(1), 31-45.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. *Journal of agricultural economics*, *64*(3), 597-623.

Thamo, T., & Pannell, D. J. (2016). Challenges in developing effective policy for soil carbon sequestration: perspectives on additionality, leakage, and permanence. *Climate Policy*, *16*(8), 973-992.

USBI (2023). Biochar Enhances Crop Yield, Enriches Soil & Protects Water. https://biochar-us.org/soil-water-benefits-biochar

U.S. Census Bureau (2022). https://www.census.gov/foreign-trade/data/index.html

US Drought Monitor (2023). https://droughtmonitor.unl.edu/DmData/DataTables.aspx

U.S.EPA (2021). United States Environmental Protection Agency's Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990-2021. https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2021

U.S. FAS (2023). https://apps.fas.usda.gov/gats/default.aspx

USDA (2022). Conservation Practice Standards Information. https://www.nrcs.usda.gov/getting-assistance/conservation-practices

USDA (2023). Conservation Reserve Program Statistics. https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index

USDA-AMS 2022. https://www.ams.usda.gov/market-news/custom-reports

USDA-ERS (2022). https://www.ers.usda.gov/topics/farm-practices-management/irrigation-water-use/

USDA-NASS (2023). https://www.nass.usda.gov/

USDA-NASS (2022). https://quickstats.nass.usda.gov/

USDA-NASS census of agriculture (2023). https://www.nass.usda.gov/Publications/AgCensus/2022/index.php

USDA-NRCS 2023. A brief History of NRCS. https://www.nrcs.usda.gov/about/history/brief-history-nrcs

Vencill, W. K., Nichols, R. L., Webster, T. M., Soteres, J. K., Mallory-Smith, C., Burgos, N. R., ... & McClelland, M. R. (2012). Herbicide resistance: toward an understanding of resistance development and the impact of herbicide-resistant crops. *Weed Science*, *60*(SP1), 2-30.

Vico, G., & Brunsell, N. A. (2018). Tradeoffs between water requirements and yield stability in annual vs. perennial crops. *Advances in water resources*, *112*, 189-202.

Wade, T., Claassen, R., & Wallander, S. (2015). *Conservation-practice adoption rates vary widely by crop and region* (No. 1476-2017-3877).

Wang, C., Yang, Y., & Zhang, Y. (2016). Cost-effective targeting soil and water conservation: A case study of Changting County in Southeast China. *Land Degradation & Development*, *27*(2), 387-394.

Wang, H., & Swallow, B. M. (2016). Optimizing expenditures for agricultural land conservation: Spatially-explicit estimation of benefits, budgets, costs and targets. *Land Use Policy*, *59*, 272-283.

Wbcsd, W. R. I. (2004). The greenhouse gas protocol. *A corporate accounting and reporting standard, Rev. ed. Washington, DC, Conches-Geneva*.

West, T. O., & Post, W. M. (2002). Soil organic carbon sequestration rates by tillage and crop rotation: a global data analysis. *Soil Science Society of America Journal*, *66*(6), 1930-1946.

Westengen, O. T., & Brysting, A. K. (2014). Crop adaptation to climate change in the semi-arid zone in Tanzania: the role of genetic resources and seed systems. *Agriculture & Food Security*, *3*, 1-12.

Wongpiyabovorn, O., Plastina, A., & Crespi, J. M. (2022). Challenges to voluntary Ag carbon markets. *Applied Economic Perspectives and Policy*.

World Bank (2021). *Soil Organic Carbon MRV Sourcebook for Agricultural Landscapes*. World Bank.

Wu, J., & Babcock, B. A. (1998). The choice of tillage, rotation, and soil testing practices: Economic and environmental implications. *American Journal of Agricultural Economics*, *80*(3), 494-511.

Wu, J., Adams, R. M., Zilberman, D., & Babcock, B. (2000). Targeting resource conservation expenditures. *Choices*, *15*(2), 33-38.

Wu, J., Zilberman, D., & Babcock, B. A. (2001). Environmental and distributional impacts of conservation targeting strategies. *Journal of Environmental Economics and Management*, *41*(3), 333-350.

Wünscher, T., Engel, S., & Wunder, S. (2008). Spatial targeting of payments for environmental services: a tool for boosting conservation benefits. *Ecological economics*, *65*(4), 822-833.

Yost, M., Sullivan, T., Boren, D., Johnson, L., Mills, M., Creech, E., ... & Violett, R. (2022). Guide to Drought Tolerance of Utah Field Crops.

Zhe, C. H. E. N., Wei, R. E. N., Xia, Y. I., Qiang, L. I., Cai, H. G., Farhan, A. L. I., ... & Chen, F. J. (2023). Local nitrogen application increases maize post-silking nitrogen uptake of responsive genotypes via enhanced deep root growth. *Journal of Integrative Agriculture*, *22*(1), 235-250.

Zilberman, D., Khanna, M., Kaplan, S., & Kim, E. (2014). Technology adoption and land use. *The Oxford Handbook of Land Economics*, 52.

Zomer, R. J., Bossio, D. A., Sommer, R., & Verchot, L. V. (2017). Global sequestration potential of increased organic carbon in cropland soils. *Scientific Reports*, *7*(1), 1-8.

Zulauf, C., J. Colussi, G. Schnitkey and N. Paulson. "Concentration of US Principal Crop Acres in Corn and Soybeans." *farmdoc daily* (13):166, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, September 13, 2023.