Agricultural Carbon Sequestration

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Abstract

On-farm carbon sequestration offers a significant opportunity to mitigate global GHG emissions and meet IPCC and UN climate goals. Challenges in coordinating action among millions of decentralized agricultural producers may make widespread implementation difficult, however. This chapter explores the potential for addressing barriers to coordinated action by leveraging recent insights from plant and soil sciences to show how farmers' private economic incentives can be realigned with pro-carbon management practices like regenerative agriculture and organic farming that enhance soils' ability to store atmospheric carbon. Results show that a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields leads to increases in the adoption of organic management, agricultural carbon sequestration, and farmer welfare. In contrast, an organic subsidy leads to smaller increases in organic adoption and farmer welfare, and moreover does not substantially increase carbon sequestration.

Keywords: carbon sequestration; regenerative agriculture; organic farming; soil health
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1. Introduction

On-farm carbon sequestration offers a significant opportunity to mitigate global GHG emissions and meet IPCC and UN climate goals. Challenges in coordinating action among millions of decentralized agricultural producers may make widespread implementation difficult, however (Amundson and Biardeau, 2018). This chapter explores the potential for addressing barriers to coordinated action by leveraging recent insights from plant and soil sciences to show how farmers' private economic incentives can be realigned with pro-carbon management practices that enhance soils' ability to store atmospheric carbon, such as those found in regenerative agriculture (Chesapeake Bay Foundation, 2024; Natural Resources Defense Council, 2022) and organic farming.

Agricultural soils have the potential to sequester large amounts of atmospheric carbon. Studies report that implementing best practices may result in between 0.90 and 1.85 Pg C/year of additional carbon storage in global croplands alone, an amount representing up to 5% of the estimated GHG emissions from fossil fuels in 2023 (National Oceanic and Atmospheric Administration, 2023; Zomer et al., 2017). The soil sciences literature shows that soil microbes are a key driver of soils' ability to capture carbon (Bhattacharyya et al., 2022). Other researchers have found that such microbes can also improve crop yields by enhancing nutrient use and stress tolerance (Lo, 2010). These insights thus link social benefits from carbon sequestration with private economic returns. A parallel strand of research finds that synthetic pesticides and fertilizers harm beneficial soil microbes (Blundell et al., 2020; Hussain et al., 2009; Kalia and Gosal, 2011; Lo, 2010; Lori et al., 2017). Thus, while using such chemical inputs may initially improve crop yields, over time their use may negatively impact crop yields and soil carbon storage due to their effects on microbial communities. As a consequence, organic farming and other production regimes like regenerative agriculture that reduce dependence on chemical inputs may be beneficial for microbial health and, thus, soil carbon sequestration.

In this chapter we leverage findings from plant and soil sciences published since this Handbook's last edition to explore a promising avenue for aligning farmers' private incentives with soil carbon sequestration. In particular, programs and policies that facilitate adoption, or otherwise enhance the profitability, of regenerative agriculture (wherein less synthetic compounds are used) or organic management (wherein, with few exceptions, synthetic compounds are not used at all) will have the co-benefit of also enhancing soil carbon sequestration. One such example are information provision programs that improve farmers' understanding of the interaction between synthetic compounds, soil microbes, pest resistance, and crop yields. As better-informed farmers transition to organic management and re-optimize their input mix to improve yields through better use of soil microbes, they will generate larger quantities of the key public good of interest, carbon sequestration, via enhanced microbial activity. Likewise, policies such as agricultural carbon credits that incentivize carbon sequestration (and therefore diminished synthetic compound use) may also increase adoption of regenerative and organic practices.

We develop a dynamic bioeconomic model of a farmer's decisions regarding the use of synthetic pesticides and the transition from conventional to organic management that accounts for interactions between chemical inputs, soil health, crop yields, and soil carbon sequestration. We use the dynamic model to examine the effects of counterfactual scenarios on the adoption of organic management, agricultural carbon sequestration, and farmer welfare. In particular, we assess the following: (1) an organic subsidy, which can represent any of a number of policies (including agricultural carbon credits) that increase the effective organic price; and (2) a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields.

We find that the preferred policy is a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields, as such full information leads to reduced reliance on synthetic agrichemicals, as well as increases in the adoption of organic management, agricultural carbon sequestration, and farmer welfare. In contrast, an organic subsidy leads to smaller increases in organic adoption and farmer welfare, and moreover does not substantially increase carbon sequestration.

2. Social and Private Benefits of Agricultural Carbon Sequestration

Agricultural soils have the potential to sequester large amounts of atmospheric carbon, with implementation of best available management practices expected to generate between 0.90 and 1.85 Pg C/year of additional carbon storage in global croplands alone. Such an increase would amount to between 2.5% and 5% of the estimated GHG emissions from fossil fuels in 2023 (National Oceanic and Atmospheric Administration, 2023; Zomer et al., 2017).

While several factors are known to contribute towards soils' carbon sequestration potential, recent findings from the soil science and related literatures have demonstrated that soil microbes are a particularly important driver of soils' ability to store atmospheric carbon (Bhattacharyya et al., 2022). Khangura et al. (2023) find that microbial necromass can contribute more than 50% of total soil organic carbon in temperate agriculture topsoil, while living microbial biomass contributes another 5%, for a total contribution from soil microbes of over 55% of total soil organic carbon. These findings are corroborated by Mason et al. (2023), who find that microbial live biomass and necromass can account for between 50% and 80% of stable soil organic carbon. Liang, Schimel and Jastrow (2017) further discuss some of the mechanisms by which carbon storage is achieved. In addition to their direct contributions to soil organic carbon through biomass and necromass, soil microbes may also contribute to soil organic carbon through a number of indirect pathways. Many of these additional pathways involve supporting plant growth or resilience, and hence plants' ability to sequester carbon from the atmosphere. This plant carbon is at least partially incorporated into stable carbon pools in soils. As a consequence, the 50% to 80% range describing soil microbe's direct effect on soil carbon content is likely a conservative estimate of soil microbes' total (i.e. direct plus indirect) contributions to soil carbon content (Mason et al., 2023). Altogether, the literature on carbon sequestration by agricultural soil implies that management practices which promote microbial biomass are critical for realizing the agricultural sector's carbon sequestration potential.

Critically, soil microbes have also been found to benefit agricultural production owing to their capacity to improve crop yields by enhancing crop nutrient use, stress tolerance, and pest resistance (Lo, 2010; Singh et al., 2016; Lori et al., 2017; Yadav et al., 2017; Yibeltie and Sahile, 2018;

Blundell et al., 2020; Kalam et al., 2020; Verma et al., 2020; Righini et al., 2022; Thiebaut et al., 2022). These insights thus link social benefits from carbon sequestration with private economic returns. Producers' ability to capture this private benefit, however, is dependent on their management choices, since the use of synthetic agrichemicals has been found in many cases to harm plant-growth-promoting soil microbes (Blundell et al., 2020; Hussain et al., 2009; Kalia and Gosal, 2011; Lo, 2010; Lori et al., 2017). Thus, while using such chemical inputs can initially improve crop yields, over time their use may negatively impact both crop yields and soil carbon storage due to their effects on microbial communities. As a consequence, organic farming and other production regimes like regenerative agriculture that reduce dependence on chemical inputs may be beneficial for microbial health and, thus, soil carbon sequestration. Thus, reducing farmer reliance on synthetic agrichemicals has the potential to generate both public and private benefits.

3. Policy Implications

These insights from plant and soil sciences, which show that synthetic compounds may both harm soil microbes capable of improving agricultural yields and also lower soils' carbon sequestration potential, suggest a promising avenue for aligning farmers' private incentives with the public need for carbon sequestration. In particular, programs and policies that facilitate adoption of regenerative agriculture (wherein less synthetic compounds are used) or organic management (wherein, with few exceptions, synthetic compounds are not used at all) will have the co-benefit of also enhancing soil carbon sequestration.

One such example are information provision programs that improve farmers' understanding of the interaction between synthetic compounds, soil microbes, pest resistance, and crop yields, including the private benefits of soil microbes. Researchers have found that farmers can often lack a full understanding of soil microbes (Ploll et al., 2022) and their private benefits (Miller-Klugesherz and Sanderson, 2023). In our theoretical research in Meneses et al. (2025b), we show that not being informed about soil bacteria could change behavior in a way that leads farmers to adopt sub-optimal, and even detrimental management practices. Previous experimental analysis by Murphy et al. (2020) has shown that farmers in developing countries usually do not have sufficient information about their soil nutrient levels to make profit maximizing decisions about fertilizer usage; and that there can be potentially large net benefits to providing farmers with soil information. In our empirical research in Meneses et al. (2025a), we find that informing farmers about soil microbiomes decreases pesticide use, increases organic adoption, and increases mean farmer welfare in both the short and long run.

As better-informed farmers transition to organic management and re-optimize their input mix to improve yields through better use of soil microbes, they will generate larger quantities of the key public good of interest, carbon sequestration, via enhanced microbial activity. Likewise, policies such as agricultural carbon credits that incentivize carbon sequestration (and therefore diminished synthetic compound use) may also increase adoption of regenerative and organic practices.

4. Case Study: Rice Farmers in California

For our case study, we focus on rice farmers in California, a state with an estimated 40 million metric tons (MMT) of carbon stored in its cropland soils (California Air Resources Board, 2018). California is the second largest rice-producing state behind Arkansas, producing about $900 million in production value per year (Smith, 2023). Most California rice is medium-grain japonica rice, which is used in Asian and Mediterranean dishes such as sushi, paella, and risotto (Smith, 2023), and the majority of California rice is grown in the Sacramento Valley, where hot days, cool nights, and clay soil that retains moisture create ideal conditions for growing japonica rice (USA Rice, 2020).

Several pesticides commonly used to grow rice are known to harm plant-growth-promoting soil microbes, reducing their abundance and ability to sequester carbon from the atmosphere. In particular, according to data from the California Department of Pesticide Regulation's (CA DPR's) Pesticide Use Reporting (PUR) database, pesticides used in at least 88.8% of California farmer-field-years that grew rice between 1990 and 2019 are known to be harmful to soil bacteria (California Department of Pesticide Regulation [CA DPR], 2024).

Bensulfuron methyl, which was used at least once in 25.18% of PUR farmer-field-years growing rice between 1990 and 2019, has been found to reduce soil microbial biomass in a variety of settings (El-Ghamry et al., 2002; Gigliotti et al., 1998), including in waterlogged rice paddies and paddy soil (Saeki and Toyota, 2004; Xie et al., 2004; Xie et al., 2004).

Bispyribac sodium, which was used at least once in 13.81% of PUR farmer-field-years growing rice between 1990 and 2019, has been found to cause a significant decline in microbial biomass carbon in paddy soil (Kumar et al., 2020).

Lambda cyhalothrin, which was used at least once in 26.00% of PUR farmer-field-years growing rice between 1990 and 2019, has been found to lower bacterial and fungal count (Abubakar and Faizah, 2025) and harm nitrifying and denitrifying bacteria (Cycoń et al., 2006).

Molinate, which was used at least once in 27.19% of PUR farmer-field-years growing rice between 1990 and 2019, has been found to harm the nitrogen-fixing cyanobacteria *Anabaena cylindrica* (Galhano et al., 2009) and the cyanobacteria *Nostoc muscorum* (Galhano et al., 2010) in rice fields, and to reduce bacterial diversity (Saison et al., 2009).

Propanil, which was used at least once in 49.44% of PUR farmer-field-years growing rice between 1990 and 2019, has been found to cause a collapse in aerobic bacteria, including bacteria such as Streptomyces and Acinetobacter (Oanh and Duc, 2021) that promote plant growth (Olanrewaju and Babalola, 2019; Mujumdar et al., 2023).

Thiobencarb (a pre-emergence herbicide used to control grasses, sedge, and broadleaf weeds around rice crops), which was used at least once in 23.54% of PUR farmer-field-years growing rice between 1990 and 2019, harms nitrogen-fixing cyanobacteria that help maintain soil fertility and support crop yields (Dash et al., 2017).

In Meneses et al. (2025a), we empirically document that, for rice farmers in California, the use of pesticides increase contemporaneous yields, and also that, over time, not using pesticides increases yields. In Meneses et al. (2025a), we also find empirical evidence that rice farmers in California misperceive the crop yield benefits of soil microbes, and act as if the clean soil stock (our proxy for the state of the soil microbiome) has very little effect on rice crop yields, when in fact it increases yields.

5. Data

We use farmer-field-level pesticide use data from the California Department of Pesticide Regulation (DPR) Pesticide Use Reporting (PUR) database (California Department of Pesticide Regulation [CA DPR], 2024). This data includes information about whether pesticides, including those which are unapproved for use under the USDA Organic Program, were applied on a given farmer-field in a given year. Thus, in this chapter we use the terms “unapproved pesticide”, “synthetic pesticide”, and “pesticide” synonymously.

For crop yield data, we use county-level rice yield data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Quick Stats (U.S. Department of Agriculture [USDA], 2024).

For price data, we obtain data on conventional and organic rice prices from the USDA NASS Organic Production Survey (U.S. Department of Agriculture [USDA], 2007, 2012, 2017), the USDA NASS Certified Organic Survey (U.S. Department of Agriculture [USDA], 2023), the University of California Rice Research and Information Center (UC Rice Research and Information Center, 2023), and the University of California at Davis Cost and Return Studies (Espino et al., 2021). From these sources, we obtain annual data on conventional and organic rice prices for 10 years (2005, 2008-2012, 2014-2016, and 2019). We convert prices to real prices in 2010 USD using the consumer price index from the Federal Reserve Bank of Minneapolis (Federal Reserve Bank of Minneapolis, 2024).

We focus on farmer-fields in the CA DPR PUR data set that plant rice at least once during the 10 years for which we have conventional and organic rice price data. There are 17,695 such farmer-fields that plant rice, comprising 2,101 farmers and spanning 15 counties. These 15 counties are: Butte, Colusa, Fresno, Glenn, Lassen, Merced, Placer, Sacramento, San Joaquin, Solano, Stanislaus, Sutter, Tehama, Yolo, and Yuba. Over the 10 years for which we have conventional and organic rice prices (2005, 2008-2012, 2014-2016, and 2019), there are 67,230 farmer-field-year observations.

Following our work in Meneses et al. (2025a), we measure the clean soil stock by the number of previous consecutive years the farmer has not used any (unapproved) pesticide. In particular, the clean soil stock k_{it} is equal to 0 if the rice farmer used an unapproved synthetic pesticide the previous year, 1 if the rice farmer did not use an unapproved synthetic pesticide the previous year but used an unapproved synthetic pesticide two years ago, 2 if the rice farmer did not use an unapproved synthetic pesticide the previous two years but used an unapproved synthetic pesticide three years ago, and 3 if the rice farmer did not use an unapproved synthetic pesticide for the previous three years but used an unapproved synthetic pesticide four years ago, and so on.

More details about our data, including summary statistics and plots, are presented in Meneses et al. (2025a).

6. Methods

6.1. Dynamic Bioeconomic Model

We develop a dynamic bioeconomic model of a farmer's decisions regarding the use of synthetic pesticides and the transition from conventional to organic management that accounts for interactions between chemical inputs, soil health, crop yields, and soil carbon sequestration. Our dynamic bioeconomic model builds on the dynamic structural econometric model we develop and estimate in Meneses et al. (2025a).

Incorporating insights from soil science, the production function $q(c_{it}, k_{it})$ for rice yield is given by:

$$q(c_{it}, k_{it}) = \exp\left(\alpha_0 + \alpha_c c_{it} + \alpha_k k_{it}\right), \tag{1}$$

where c_{it} is a dummy variable for farmer-field i using an unapproved synthetic pesticide in year t, and k_{it} is the clean soil stock as measured by the number of previous consecutive years the farmer-field has not used any unapproved synthetic pesticide. In particular, the clean soil stock k_{it} is equal to 0 if the rice farmer-field used an unapproved synthetic pesticide the previous year, 1 if the rice farmer-field did not use an unapproved synthetic pesticide the previous year but used an unapproved synthetic pesticide two years ago, 2 if the rice farmer-field did not use an unapproved synthetic pesticide the previous two years but used an unapproved synthetic pesticide three years ago, and 3 if the rice farmer-field did not use an unapproved synthetic pesticide for the previous three years but used an unapproved synthetic pesticide four years ago, and so on.

For the production function parameters α, we use the parameter values we econometrically estimated in Meneses et al. (2025a), which show that, for rice farmers in California, the use of pesticides increase contemporaneous yields, and also that, over time, not using pesticides increases yields. In particular, following Meneses et al. (2025a), we use the following parameter estimates obtained from estimating a log-level production function when rice yield is in hundredweights (CWT), all of which are statistically significant at a 0.1% level: $\alpha_0 = 4.983$, $\alpha_c = 3.757$, and $\alpha_k = 0.400$. As we explain in more detail in Meneses et al. (2025a), α_c is significant and positive, which means that, in actuality, when accounting for soil microbes, the contemporaneous use of an unapproved synthetic pesticide has a positive effect on yield that year. In addition, consistent with recent insights from soil science that show the important of soil microbes and a clean soil stock, α_k is significant and positive, which means that yields are higher the more previous consecutive years the farmer-field has not used any unapproved synthetic pesticide.

While the true rice yield is given by the production function (1), it is possible that farmers may misperceive rice yield and its relationship with pesticide use c_{it} and clean soil stock k_{it}. The farmer's perceived yield (or quantity) $\breve{q}(a_{it}, s_{it})$ from planting rice is given by:

$$\breve{q}(a_{it}, s_{it}) = \exp\left(ln\, q(c_{it}, k_{it}) + \gamma_c c_{it} + \gamma_k k_{it}\right), \tag{2}$$

where $q(c_{it}, k_{it})$ is the true rice yield as given by the production function (1), and where the misperception parameters γ measure how the farmer misperceives the effects of pesticide use c_{it} and clean soil stock k_{it} on yield. For the misperception parameters γ, we use the parameter values we econometrically estimated in Meneses et al. (2025a), which show that rice farmers in California underestimate how the clean soil stock k_{it}, as measured by the number of previous consecutive years no unapproved synthetic pesticide was used, affects yield. In particular, we use the following parameter estimates we obtained in Meneses et al. (2025a) from estimating a dynamic structural econometric when the production function parameters in the true production function (1) are estimated using county averages that average over farmer-fields growing rice in a county-year, and a rice production cost function that includes terms that interact yield and yield squared with the dummy for pesticide use, both of which are statistically significant at a 0.1% level: $\gamma_c = -0.836$ and $\gamma_k = -0.285$.

In our dynamic bioeconomic model, each year t, each rice farmer-field i chooses an action $a_{it} \in A$. The possible actions for each rice farmer-field in each year are: (i) planting rice and using pesticide, (ii) planting rice and not using pesticide that year, ii) not planting rice that year and using pesticide that year, and (iv) not planting rice and not using pesticide that year.

The per-period payoff $u(\cdot)$ to a farmer-field from choosing action a_{it} at time t depends on the values of the state variables s_{it} at time t. The state variables s_{it} include the (discretized) conventional rice price $P_{con,t}$, the (discretized) organic rice price $P_{org,t}$, and the clean soil stock k_{it} as measured by the number of previous consecutive years the farmer-field has not used pesticide. For the discretized real conventional price P_{con} and the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$, we use the bins and empirical distributions described in Meneses et al. (2025a).

The per-period payoff $u(\cdot)$ to a farmer-field from choosing action a_{it} at time t also depends on the choice-specific shock $\epsilon_{it}(a_{it})$. There is a choice-specific shock $\epsilon_{it}(a_{it})$ associated with each possible action $a_{it} \in A$. The vector of choice-specific shocks $\epsilon_{it} \equiv \{\epsilon_{it}(a_{it}) | a_{it} \in A\}$ is observed by farmer-field i at time t, before farmer-field i makes his time-t action choice, but is never observed by the econometrician.

The per-period payoff to a farmer-field from choosing action a_{it} at time t is given by:

$$u(a_{it}, s_{it}, \epsilon_{it}) = u_0(a_{it}, s_{it}) + \epsilon_{it}(a_{it}), \tag{3}$$

where $u_0(\cdot)$ is the deterministic component of the per-period payoff.

A farmer-field i that plants rice in year t receives the following deterministic payoff in year t:

$$u_0(a_{it}, s_{it}) = P(a_{it}, s_{it}) \cdot \breve{q}(a_{it}, s_{it}) - c(a_{it}, s_{it}), \tag{4}$$

where $P(a_{it}, s_{it})$ is the relevant rice price, $\breve{q}(a_{it}, s_{it})$ is the farmers' perceived rice yield, and $c(\cdot)$ is the cost of planting rice. The relevant rice price $P(a_{it}, s_{it})$ is equal to the (discretized) organic rice price $P_{org,t}$ in year *t* plus any organic subsidy in year *t* if the farmer-field is organic, and the relevant rice price $P(a_{it}, s_{it})$ is equal to the (discretized) conventional rice price $P_{con,t}$ in year *t* if the farmer-field is conventional. Following the organic production and handling requirements of the National Organic Program in the United States, wherein the field or farm parcel must have had no prohibited substances applied to it for a period of 3 years immediately preceding harvest of the crop (USDA Agricultural Marketing Service, 2000), we define a farmer-field as being organic in year t if the farmer field does not use pesticide that year and the number of previous consecutive years the farmer-field has not used pesticide k_{it} is 3 or more.

The cost of planting rice is given by the following rice production cost function $c(a_{it}, s_{it})$:

$$\begin{aligned} c(a_{it}, s_{it}) = \kappa_c c_{it} + \kappa_l \breve{q}(a_{it}, s_{it}) + \kappa_{cq} c_{it} \breve{q}(a_{it}, s_{it}) + \\ \kappa_2 \breve{q}(a_{it}, s_{it})^2 + \ \kappa_{cq2} c_{it} \breve{q}(a_{it}, s_{it})^2, \end{aligned} \tag{5}$$

where $\breve{q}(a_{it}, s_{it})$ is the farmer's perceived rice yield (or quantity) as given by equation (2), and where κ are the cost parameters. For the cost parameters κ, we use the following parameter estimates we obtained in Meneses et al. (2025a) from estimating a dynamic structural econometric when the production function parameters in the true production function (1) are estimated using county averages that average over farmer-fields growing rice in a county-year, where perceived yield (or quantity) $\breve{q}(a_{it}, s_{it})$ is in units of 1 million pounds, and where costs are in units of ten thousand 2010 USD, all of which are statistically significant at a 0.1% level: $\kappa_c = -0.048$, $\kappa_1 = 0.063$, $\kappa_{cq} = 0.067$, $\kappa_2 = 0.08543$, and $\kappa_{cq2} = 0.08535$.

The deterministic payoff $u_0(\cdot)$ for a farmer-field who does not planting rice and uses pesticide is normalized to 0. To allow the per-period payoff to possibly differ when the farmer-field did not plant rice and also did not use pesticide, the deterministic per-period payoff for not planting rice that year and not using pesticide is set equal to a parameter ν. For the deterministic per-period payoff ν when a farmer-field does not plant rice and does not use pesticide that year (this is relative to a deterministic payoff of 0 when a farmer-field does not plant rice and uses pesticide), we use the following parameter estimate we obtained in Meneses et al. (2025a) from estimating a dynamic structural econometric when the production function parameters in the true production function (1) are estimated using county averages that average over farmer-fields growing rice in a county-year, where perceived yield (or quantity) $\breve{q}(a_{it}, s_{it})$ is in units of 1 million pounds, and where payoffs are in units of ten thousand 2010 USD, which is statistically significant at a 0.1% level: $\nu = -10.00$.

The farmers' value function, which gives the present discounted value of the grower's entire stream of per-period payoffs at the optimum, is given by the following infinite-horizon Bellman equation:

$$V(s_{it}, \epsilon_{it}) = \max_{a_{it} \in A} u_0(a_{it}, s_{it}) + \epsilon_{it}(a_{it}) + \beta V^c(s_{it}, a_{it}), \tag{6}$$

where $V^c(\cdot)$ is the continuation value, which is the expected value of the value function next period conditional on the state variables and action this period:

$$V^c(s_{it}, a_{it}) = E[V(s_{it}, \epsilon_{it}) | s_{it}, a_{it}]. \tag{7}$$

More details about our model, including how the parameters were estimated, are presented in Meneses et al. (2025a).

6.2. *Estimating Carbon Sequestration*

We make a back-of-the envelope carbon sequestration calculation as follows. First, we start with a figure for the total amount of carbon sequestered by cropland soils in the state of California. The California Air Resources Board (2018) estimates that approximately 40 MMT of carbon are stored in California's cropland soils. We then determine the share of the 40 MMT of carbon sequestered in CA cropland soils that can be attributed to soil microbes. Based on findings in Khangura et al. (2023) indicating that microbial necromass can contribute more than 50% of total soil organic carbon in temperate agriculture topsoil, and that living microbial biomass contributes another 5%, we assume soil microbes' overall contribution to CA cropland soil carbon to be 55%. Therefore, in 2018, 40 MMT x 0.55 = 22 MMT of carbon was sequestered by soil microbes in California's cropland soils.

We then want to find conventional and organic farming's contribution to this 22 MMT C. To estimate these values, we will make use of the following information. According to the 2017 Census of Agriculture (USDA, 2019), in 2017 there were 7,857,512 acres of harvested cropland (conventional and organic) in the state of California. In 2019 there were 438,395 acres of organic cropland in California (USDA, 2020). Assuming approximately no changes in acres farmed between 2017 and 2019 this implies that in 2018 we had approximately 7,857,512 - 438,395 ≈ 7,420,000 conventional acres and ~440,000 acres of organic cropland in California.

From the meta-analysis of the effects of organic management in Lori et al. (2017), we know that producing organically results in an average increase in microbial soil biomass of 41%. Thus, in our carbon sequestration calculation, we will assume that all organically certified crop producers have soil microbe biomass equal to 141% of the biomass that they would have had under conventional management. In particular, following the organic production and handling requirements of the National Organic Program in the United States, wherein the field or farm parcel must have had no prohibited substances applied to it for a period of 3 years immediately preceding harvest of the crop (USDA Agricultural Marketing Service, 2000), we assume that a farmer-field i has a soil microbe biomass 141% times that under conventional management in year t if farmer-field i does not use pesticide that year t and the number of previous consecutive years farmer-field i has not used pesticide k_{it} is 3 or more.

Using the information described above indicating an average increase in soil microbe content of 41% under organic management, we can calculate the number of metric tons of carbon sequestered by soil microbes per acre of conventionally and organically managed cropland, respectively, by solving the following system of equations describing the total carbon sequestered by soil microbes in California cropland in 2018, for $Cfactor_{con}$ and $Cfactor_{org}$:

$$acres_{con} \cdot Cfactor_{con} + acres_{org} \cdot Cfactor_{org} = Csequestered \tag{8}$$

$$Cfactor_{org} = 1.41 \cdot Cfactor_{con} \ , \tag{9}$$

where $acres_{con} = 7{,}420{,}000$ conventional cropland acres in California in 2018, $acres_{org} = 440{,}000$ acres of organic cropland in California in 2018, and $Csequestered = 22$ MMT carbon sequestered by soil microbes in California's cropland soils in 2018.

Solving the system of equations (8)-(9) for $Cfactor_{con}$ and $Cfactor_{org}$, we obtain $Cfactor_{con} = 2.736$ metric tons (MT) of C sequestered per conventionally managed acre, and $Cfactor_{org} = 3.858$ metric tons (MT) of C sequestered per organically managed acre. We can therefore approximate total carbon sequestered by conventionally managed fields by multiplying total conventional acres by the conversion factor 2.736 MT C per acre; and we can similarly approximate total carbon sequestered by organically managed fields by multiplying total organic acres by the conversion factor 3.858 MT C per acre. To get total carbon sequestered by all conventionally managed farmer-fields in a simulation, we add up the value calculated above over all farmer-fields.

When calculating carbon sequestration totals for organic and conventional rice farmer-fields over a simulated period of time, only the last year in which a farmer-field appears in the simulation will contribute towards the carbon sequestration total, so as to not double count carbon. For each farmer-field, carbon sequestration for that farmer-field is therefore calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation. Whether a farmer-field is organic in year t depends on its pesticide use in year t and its clean soil stock k_{it}. If a farmer-field is organic in the last year in which it appears in a simulation (i.e., if in the last year t in which it appears in the simulation, farmer-field i does not use pesticide in that year t and the number of previous consecutive years farmer-field i has not used pesticide k_{it} is 3 or more), then its sequestered carbon will count towards the organic total and not the conventional total. Similarly, if a farmer-field is conventional in the last year in which it appears in a simulation, then its sequestered carbon will count towards the conventional total and not the organic total.

6.3. Counterfactual Simulations

We use the dynamic bioeconomic model to simulate the effects of counterfactual scenarios on the adoption of organic management, agricultural carbon sequestration, and farmer welfare in both the short run and the long run. The "short run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to the final year of our data set, year 2019. The "long run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to 10 years past the final year of our data set (i.e., to year 2029). For each counterfactual scenario, we run 100 simulations and average over the 100 simulations.

Farmer welfare is measured by farmer-field net present value (NPV), which for each farmer-field i is the present discounted value (PDV) of the entire stream of per-period payoffs for that farmer-field i.

For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

7. Organic Subsidy

We first use our dynamic bioeconomic model to simulate the effects of a counterfactual organic subsidy on adoption of organic management, agricultural carbon sequestration, farmer welfare, and subsidy costs. An organic subsidy can represent any of a number of policies (including credits) that increase the effective organic price.

We consider three scenarios: No Intervention, Incremental Subsidy, and High Subsidy.

In the baseline "No Intervention" scenario, there is no organic subsidy. In this baseline scenario, the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ in any year is drawn from one 3 bins ("low", "medium", and "high") based on its empirical distribution in the data. We describe the bins and distribution in more detail in Meneses et al. (2025a).

In the "Incremental" organic subsidy scenario, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin: whenever the discretized real organic price premium is "low", the effective real organic price premium as a result of the subsidy is "medium"; and whenever the discretized real organic price premium is "medium", the effective real organic price premium as a result of the subsidy is "high". The maximum discretized real organic price premium is "high", or \$1.2326 (in 2010 USD per CWT), so whenever the discretized real organic price premium is "high", the effective real organic price premium as a result of the subsidy is "high".

In the "High" organic subsidy scenario, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). In other words, whenever the discretized real organic price premium is "low", the effective real organic price premium as a result of the subsidy is "high"; and whenever the discretized real organic price premium is "medium", the effective real organic price premium as a result of the subsidy is "high". The maximum discretized real organic price premium is "high", or \$1.2326 (in 2010 USD per CWT), so whenever the discretized real organic price premium is "high", the effective real organic price premium as a result of the subsidy is "high".

For each organic subsidy scenario, we calculate the present discounted value (PDV) of the entire stream of subsidy costs, where the relevant organic subsidy (in 2010 USD per CWT) is paid for each unit of rice yield (in CWT) produced in each farmer-field-year that is organic.

We also calculate the carbon sequestered by organic farmer-fields, the carbon sequestered by conventional farmer-fields, and the total carbon sequestered over all farmer-fields. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Tables 1a and 1b present the organic subsidy results over the short run and long run, respectively. There are several main results. First, in both the short and long run, both versions of the subsidy increase the frequency of organic adoption, as measured by the percent of farmer-field-years producing organically (i.e., the percent of farmer-field-years who have clean soil stock $k_{it} \geq 3$ and who choose not to use pesticide that year).

Second, in both the short and long run, although the "High" organic subsidy costs more than the "Incremental" subsidy, both versions of the organic subsidy lead to similar levels of organic adoption, carbon sequestration, and farmer welfare.

Third, neither version of the organic subsidy substantially increases total carbon sequestration in either the short or long run.

Fourth, even with an organic subsidy, organic adoption declines over time, with lower frequencies of organic adoption in the long run than in the short run, and very few farmer-fields producing organically in the final period of the long run simulation, leading to negligible amounts of carbon sequestration by organic farmer-fields in the last period of the long run simulation. This is because a farmer-field's choice probability for choosing to produce rice without using pesticides is very low, and declines as clean soil stock k_{it} (as measured by the number of previous consecutive years no unapproved synthetic pesticide was used) declines.

Fifth, both versions of the organic subsidy increase total farmer welfare (as measured by the total NPV over all farmer-fields) by more than the cost of the subsidy to the government (as measured by the PDV of the entire stream of subsidy costs).

Thus, while neither version of the organic subsidy substantially increase total carbon sequestration in either the short or long run, both increase organic adoption and both increase total farmer welfare by more than the cost of the subsidy to the government. The "Incremental" subsidy appears to be more cost-effective than the "High" subsidy, since it leads to similar levels of organic adoption, carbon sequestration, and farmer welfare as the "High" subsidy in both the short and long run, but at lower cost.

8. Farm Size

We also run our organic subsidy simulations by farm size to assess whether and how our results vary by farm size.

We use farmer-field acreage as our measure of farm size. We assign each farmer-field i into 3 bins -- small, medium, and large -- based on the median reported acreage for that farmer-field i over all years for which that farmer-field i planted rice. For the bin cutoffs, we use the 25th percentile and 75th percentile of acres over all farmer-field-years that plant rice, which are 39 acres and 115 acres, respectively. In particular, a farmer-field i is considered "large" if its median reported acreage over all years it planted rice is greater than or equal to 115 acres; "medium" if its median reported acreage over all years it planted rice is greater than or equal to 39 acres and less than 115 acres; and "small" if its median reported acreage over all years it planted rice is less than 39 acres. For this analysis, farmer-field-years for farmer-fields i that never reported acres during years they planted rice are omitted.

Tables 2a and 2b report the results by farm size in the short run and long run, respectively. There is very little difference in how small, medium, and large farmer-fields respond to the different levels of organic subsidy (No Intervention, Incremental Subsidy, High Subsidy) in either the short run or the long run. In terms of frequency of organic production, large acreage farmer-fields tend to adopt organic management the least frequently, while medium acreage farmer-fields tend to adopt organic management the most frequently, though the differences are small. For each given level of organic subsidy (No Intervention, Incremental Subsidy, High Subsidy) and time horizon (short run or long run), the frequency of organic production for medium farmer-fields is 0.01% higher than that for small farmer-fields, which in turn is 0.01% higher than that for large farmer-fields. On average, medium acreage farmer-fields have an NPV that is almost twice as high as that of small and large acreage farmer-fields.

9. Human Capital Improvement

Following Meneses et al. (2025a), we also use our dynamic bioeconomic model to simulate the effects of a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields on synthetic compound use, adoption of organic management, agricultural carbon sequestration, and farmer welfare.

To do so, we run a counterfactual "Full Information" simulation in which we set the misperception parameters γ_k and γ_c both to 0, and use our parameter estimates from Meneses et al. (2025a) for all the remaining parameters. We also simulate counterfactual scenarios that combine "Full Information" with each version of our organic subsidy (Incremental Subsidy and High Subsidy), respectively.

Tables 3a and 3b present the "Full Information" results over the short run and the long run, respectively. There are several main results.

First, "Full Information" alone (without any organic subsidy) leads to high organic adoption rates of 58.1 percent and 62.0 percent, respectively, in the short and long run. When farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields on synthetic compound use, adoption of organic management, agricultural carbon sequestration, and farmer welfare, the majority of farmer-field-years adopt organic management.

Second, when comparing the "Full Information" results under no organic subsidy with respective the baseline "No Intervention" results under status quo misperception in Tables 1a and 1b, "Full Information" results in an 11.0% increase in carbon sequestration in the short run, and a 14.6% increase in carbon sequestration in the long run.

Third, when comparing the "Full Information" results under no organic subsidy with respective the baseline "No Intervention" results under status quo misperception in Tables 1a and 1b, "Full Information" nearly doubles mean and total farmer welfare (as measured by the farmer-field NPV) in both the short and long run.

Fourth, under full information, combining full information with an organic subsidy increases organic adoption and carbon sequestration relative to full information alone, and the "High" organic subsidy weakly increases organic adoption and carbon sequestration more than the "Incremental" organic subsidy. Nevertheless, these increases in organic adoption and carbon sequestration from combining full information with an organic subsidy are marginal compared to the large increases in organic adoption and carbon sequestration resulting induced by full information alone.

Fifth, unlike the respective results in Tables 1a and 1b under status quo misperception, when farmers are fully informed about soil microbes, organic adoption increases over time.

Sixth, under full information, for both versions of the subsidy, the cost of the subsidy to the government (as measured by the PDV of the entire stream of subsidy costs) is two orders of magnitude higher than it was when the subsidy was not combined with full information (Tables 1a and 1b). This is owing primarily to the large increase in organic adoption induced by full information, since the increase in organic adoption induced by combining an organic subsidy with full information is more marginal. Thus, much of the large cost of the subsidy under full information is being paid to inframarginal organic rice production that would still have occurred under full information alone without the addition of the costly organic subsidy.

Seventh, under full information, both versions of the organic subsidy increase total farmer welfare (as measured by the total NPV over all farmer-fields), but this time by an amount slightly less than the cost of the subsidy to the government (as measured by the PDV of the entire stream of subsidy costs).

Thus, "Full Information" substantially increases organic adoption, carbon sequestration, and farmer welfare, and much more than either version of the organic subsidy. Relative to "Full Information" alone, combining "Full Information" with an organic subsidy leads to marginal increases in organic adoption, carbon sequestration, and farmer welfare, but at a substantial cost to the government.

10. Discussion and Conclusions

On-farm carbon sequestration offers a significant opportunity to mitigate global GHG emissions and meet IPCC and UN climate goals. Challenges in coordinating action among millions of decentralized agricultural producers may make widespread implementation difficult, however. This chapter explores the potential for addressing barriers to coordinated action by leveraging recent insights from plant and soil sciences to show how farmers' private economic incentives can be realigned with pro-carbon management practices like regenerative agriculture and organic farming that enhance soils' ability to store atmospheric carbon.

We develop a dynamic bioeconomic model of a farmer's decisions regarding the use of synthetic pesticides and the transition from conventional to organic management that accounts for interactions between chemical inputs, soil health, crop yields, and soil carbon sequestration. We use the dynamic model to examine the effects of counterfactual scenarios on synthetic pesticide use, adoption of organic management, agricultural carbon sequestration, and farmer welfare. In particular, we assess the following: (1) an organic subsidy, which can represent any of a number of policies (including agricultural carbon credits) that increase the effective organic price; and (2) a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields.

Results of our organic subsidy simulations show that, while neither version of the organic subsidy substantially increase total carbon sequestration in either the short or long run, both increase organic adoption and both increase total farmer welfare by more than the cost of the subsidy to the government. The "Incremental" subsidy appears to be more cost-effective than the "High" subsidy, since it leads to similar levels of organic adoption, carbon sequestration, and farmer welfare as the "High" subsidy in both the short and long run, but at lower cost.

Results of our simulations of a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields show that "Full Information" substantially increases organic adoption, carbon sequestration, and farmer welfare, and much more than either version of the organic subsidy. Relative to "Full Information" alone, combining "Full Information" with an organic subsidy leads to marginal increases in organic adoption, carbon sequestration, and farmer welfare, but at a substantial cost to the government.

We find that, of the policies we analyze, the preferred policy is a human capital improvement wherein farmers are fully informed about the interactions between chemical inputs, soil health, and crop yields, as such full information leads to increases in the adoption of organic management, agricultural carbon sequestration, and farmer welfare. In contrast, an organic subsidy leads to smaller increases in organic adoption and farmer welfare, and moreover does not substantially increase carbon sequestration.

Programs and policies that facilitate the adoption of regenerative agriculture (wherein less synthetic compounds are used) or organic management (wherein, with few exceptions, synthetic compounds are not used at all) may have the co-benefit of also enhancing soil carbon sequestration. In particular, human capital improvement programs (such as educational programs, information provision programs, and/or extension programs) that improve farmers' understanding of the interactions between chemical inputs, soil health, and crop yields may help address barriers to coordinated action by aligning farmers' private economic incentives with pro-carbon management practices like regenerative agriculture and organic farming that enhance soils' ability to store atmospheric carbon.

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Table 1a. Organic Subsidy Results: Short Run

	No Intervention	Incremental Subsidy	High Subsidy
Organic production (% farmer-field-years)	0.06	0.08	0.08
Carbon Sequestration			
Organic farmer-fields (MMT)	0.008	0.010	0.010
Conventional farmer-fields (MMT)	5.538	5.537	5.537
Total carbon sequestered (MMT)	5.547	5.547	5.547
Net Present Value (NPV)			
Mean over farmer-fields (million 2010 USD)	0.51	0.51	0.51
Total over all farmer-fields (billion 2010 USD)	12.8	13.0	13.0
Subsidy Costs (billion 2010 USD)	0	0.036	0.043

Notes: Table presents averages over 100 simulations. The "Short Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to the final year of our data set, year 2019. In the baseline "No Intervention" scenario, there is no organic subsidy. In the "Incremental" subsidy scenario, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. In the "High" organic subsidy scenario, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Table 1b. Organic Subsidy Results: Long Run

	No Intervention	Incremental Subsidy	High Subsidy
Organic production (% farmer-field-years)	0.04	0.05	0.05
Carbon Sequestration			
Organic farmer-fields (MMT)	0.000	0.000	0.000
Conventional farmer-fields (MMT)	5.544	5.544	5.544
Total carbon sequestered (MMT)	5.544	5.544	5.544
Net Present Value (NPV)			
Mean over farmer-fields (million 2010 USD)	0.70	0.71	0.71
Total over all farmer-fields (billion 2010 USD)	17.8	17.9	17.9
Subsidy Costs (billion 2010 USD)	0	0.036	0.044

Notes: Table presents averages over 100 simulations. The "Long Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to 10 years past the final year of our data set (i.e., to year 2029). In the baseline "No Intervention" scenario, there is no organic subsidy. In the "Incremental" subsidy scenario, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. In the "High" organic subsidy scenario, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Table 2a. Organic Subsidy Results by Farm Size: Short Run

	No Intervention			*Incremental Subsidy*			*High Subsidy*		
	Small	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Organic production (% farmer-field-years)	0.06	0.07	0.05	0.07	0.09	0.06	0.08	0.09	0.06
Carbon Sequestration									
Organic farmer-fields (MMT)	0.000	0.004	0.003	0.000	0.005	0.004	0.000	0.005	0.005
Conventional farmer-fields (MMT)	0.397	2.335	2.807	0.396	2.335	2.806	0.396	2.335	2.806
Total carbon sequestered (MMT)	0.397	2.340	2.810	0.397	2.340	2.810	0.397	2.340	2.810
Net Present Value (NPV)									
Mean over farmer-fields (million 2010 USD)	0.13	0.25	0.13	0.13	0.25	0.13	0.13	0.25	0.13
Total over all farmer-fields (billion 2010 USD)	3.2	6.2	3.4	3.3	6.3	3.4	3.3	6.4	3.4
Subsidy Costs (billion 2010 USD)	0	0	0	0.007	0.019	0.008	0.009	0.023	0.010

Notes: Table presents averages over 100 simulations. A farmer-field i is considered "large" if its median reported acreage over all years it planted rice is greater than or equal to 115 acres; "medium" if its median reported acreage over all years it planted rice is greater than or equal to 39 acres and less than 115 acres; and "small" if its median reported acreage over all years it planted rice is less than 39 acres. For this analysis, farmer-field-years for farmer-fields i that never reported acres during years they planted rice are omitted. The "Short Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to the final year of our data set, year 2019. In the baseline "No Intervention" scenario, there is no organic subsidy. In the "Incremental" subsidy scenario, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. In the "High" organic subsidy scenario, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Table 2b. Organic Subsidy Results by Farm Size: Long Run

	No Intervention			*Incremental Subsidy*			*High Subsidy*		
	Small	**Medium**	**Large**	**Small**	**Medium**	**Large**	**Small**	**Medium**	**Large**
Organic production (% farmer-field-years)	0.04	0.05	0.03	0.05	0.06	0.04	0.05	0.06	0.04
Carbon Sequestration									
Organic farmer-fields (MMT)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Conventional farmer-fields (MMT)	0.397	2.338	2.809	0.397	2.338	2.809	0.397	2.338	2.809
Total carbon sequestered (MMT)	0.397	2.338	2.809	0.397	2.338	2.809	0.397	2.338	2.809
Net Present Value (NPV)									
Mean over farmer-fields (million 2010 USD)	0.18	0.34	0.18	0.18	0.34	0.18	0.18	0.35	0.18
Total over all farmer-fields (billion 2010 USD)	4.5	8.7	4.6	4.5	8.7	4.7	4.5	8.8	4.7
Subsidy Costs (billion 2010 USD)	0	0	0	0.007	0.019	0.008	0.009	0.023	0.010

Notes: Table presents averages over 100 simulations. A farmer-field i is considered "large" if its median reported acreage over all years it planted rice is greater than or equal to 115 acres; "medium" if its median reported acreage over all years it planted rice is greater than or equal to 39 acres and less than 115 acres; and "small" if its median reported acreage over all years it planted rice is less than 39 acres. For this analysis, farmer-field-years for farmer-fields i that never reported acres during years they planted rice are omitted. The "Long Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to 10 years past the final year of our data set (i.e., to year 2029). In the baseline "No Intervention" scenario, there is no organic subsidy. In the "Incremental" subsidy scenario, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. In the "High" organic subsidy scenario, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Table 3a. Full Information: Short Run

	Full Information	Full Information + Incremental Organic Subsidy	Full Information + High Organic Subsidy
Organic production (% farmer-field-years)	58.1	58.3	58.3
Carbon Sequestration			
Organic farmer-fields (MMT)	2.369	2.384	2.390
Conventional farmer-fields (MMT)	3.865	3.853	3.849
Total carbon sequestered (MMT)	6.233	6.238	6.239
Net Present Value (NPV)			
Mean over farmer-fields (million 2010 USD)	1.36	1.52	1.56
Total over all farmer-fields (billion 2010 USD)	34.4	38.4	39.6
Subsidy Costs (billion 2010 USD)	0	4.19	5.35

Notes: Table presents averages over 100 simulations. The "Full Information" scenario is a counterfactual simulation in which we set the misperception parameters γ_k and γ_c both to 0, and use our parameter estimates from Meneses et al. (2025a) for all the remaining parameters. The "Short Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to the final year of our data set, year 2019. Under the "Incremental" organic subsidy, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. Under the "High" organic subsidy, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.

Table 3b. Full Information: Long Run

	Full Information	Full Information + Incremental Organic Subsidy	Full Information + High Organic Subsidy
Organic production (% farmer-field-years)	62.0	62.3	62.4
Carbon Sequestration			
Organic farmer-fields (MMT)	3.258	3.310	3.328
Conventional farmer-fields (MMT)	3.234	3.197	3.184
Total carbon sequestered (MMT)	6.492	6.507	6.512
Net Present Value (NPV)			
Mean over farmer-fields (million 2010 USD)	2.47	2.71	2.78
Total over all farmer-fields (billion 2010 USD)	62.7	68.6	70.3
Subsidy Costs (billion 2010 USD)	0	6.06	7.76

Notes: Table presents averages over 100 simulations. The "Full Information" scenario is a counterfactual simulation in which we set the misperception parameters γ_k and γ_c both to 0, and use our parameter estimates from Meneses et al. (2025a) for all the remaining parameters. The "Long Run" simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to 10 years past the final year of our data set (i.e., to year 2029). Under the "Incremental" organic subsidy, the organic price subsidy increments the discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ by one bin. Under the "High" organic subsidy, the organic price subsidy makes the effective discretized real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ as a result of the subsidy "high", or \$1.2326 (in 2010 USD per CWT). "Net Present Value (NPV)" is the present discounted value (PDV) of the entire stream of per-period payoffs, which is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year, which is normalized to 0. "Subsidy Costs" is the present discounted value (PDV) of the entire stream of subsidy costs. For each farmer-field, carbon sequestration for that farmer-field is calculated based on the farmer-field's acreage and whether the farmer-field is organic or conventional in the last year of the simulation.