Title: Evaluating the Incentive for Soil Organic Carbon Sequestration from Carinata Production in the Southeast United States

Abstract

Soil organic carbon (SOC) can be increased by cultivating bioenergy crops to produce low-carbon fuels, improving soil quality and agricultural productivity. This study evaluates the incentives for farmers to sequester SOC by adopting a bioenergy crop, carinata. Two agricultural management scenarios – business as usual (BaU) and a climate-smart (no-till) practice – were simulated using an agent-based modeling approach to account for farmers' carinata adoption rates within their context of traditional crop rotations, the associated profitability, influences of neighboring farmers, as well as their individual attitudes. Using the state of Georgia, US, as a case study, the results show that farmers allocated 1056×10^3 acres (23.8%; 2.47 acres is equivalent to 1 hectare) of farmlands by 2050 at a contract price of $6.5 per bushel of carinata seeds and with an incentive of $50 Mg^{-1} CO_2e SOC sequestered under the BaU scenario. In contrast, at the same contract price and SOC incentive rate, farmers allocated 1152×10^3 acres (25.9%) of land under the no-till scenario, while the SOC sequestration was 483.83×10^3 Mg CO_2e, which is nearly four times the amount under the BaU scenario. Thus, this study demonstrated combinations of seed prices and SOC incentives that encourage farmers to adopt carinata with climate-smart practices to attain higher SOC sequestration benefits.

Keywords: *Agent-based Model; Bioenergy; Climate-smart Agriculture; Soil Organic Carbon; Incentives, Sustainable Aviation Fuel*

1. Background

Soil Organic Carbon (SOC) is essential to maintain soil quality and agricultural productivity (Corning et al., 2016). Besides its role in soil health, SOC is important to address the issue of climate change (Lal, 2003; Paustian et al., 1997). It has been estimated that global soils contain the largest terrestrial pool of organic carbon (approximately 2126.44 Pg), which means that small changes in SOC stock could result in significant impacts on the atmospheric carbon concentration (Stockmann et al., 2013). On the one hand, releasing just 10% of the global SOC pool would be the equivalent of 30 years of anthropogenic greenhouse gas (GHG) emissions (Kirschbaum, 2000). On the other hand, increasing soil organic carbon by 0.4% per year in the top 1m of global agricultural soil would sequester 2-3 Pg C year^{-1}, effectively offsetting 20-35% of global anthropogenic GHG emissions (Minasny et al., 2017). Therefore, maintaining or increasing the global stock of SOC is a pressing need not only to ensure agricultural productivity and food security but also to combat climate change.

Energy crops can play a significant role in mitigating greenhouse gases by sequestering SOC and producing feedstock for low-carbon biofuels (Elless et al., 2023). However, bioenergy crops production must be carefully planned to balance these two objectives and minimize conflicts with land use for food crops, grassland, or forest land (Bonin & Lal, 2014; Qin et al., 2016). Carinata (*Brassica carinata* or Ethiopian Mustard) has been identified as a potential key feedstock for producing sustainable aviation fuel (SAF) in the Southeast United States (SE) because of its high yield, drought, and heat tolerance, suitability for winter production, and low rates of mature seed shattering (Christ et al., 2020; George et al., 2021). The oil content of carinata is 40%, while its close competitor, canola, has 43% oil content (George et al., 2021), but the potential yield of carinata is around 48% higher than canola in the physiographic context of the SE region. The high oil content of carinata can be converted to drop-in aviation fuels, with coproducts that include high protein meal for animal feed, as well as other oil and fiber products that can be used to produce valuable chemicals. In the context of the global debate about the land use change impacts of first-generation biofuels, carinata could also be valuable for its ecosystem services (George et al., 2021). As a winter crop, carinata provides cover crop benefits with little direct impacts on cropland use, and the plant residues after harvesting the seed would return significant amounts of carbon, nitrogen, and potassium to the soil.

There are ongoing efforts to understand the requirements for carinata adoption and enable a carinata-based SAF supply chain in the Southeast US. Ullah & Dwivedi (2022) used an agent-based model (ABM) to evaluate the role of farmers' profitability, neighborhood influences, and risk aversion attitudes on adoption rates of carinata as a winter crop in a Cotton-Cotton-Peanut rotation in a small-scale watershed study. That single neighborhood-based methodological framework was subsequently extended by Ullah & Crooks (2023) to the state of Georgia in an effort to simulate a greater geographical scale in the US South and consider a large number of neighborhood effects. However, the latter study did not determine the land allocation decisions of the farmers who were willing to adopt carinata. Furthermore, these two previous studies did not consider two important variables with respect to the production economics and environmental aspects of carinata: 1) the yield variation across geographical locations; 2) the net carbon sequestration effects of winter cultivation of carinata. The estimates of yield responses and SOC changes due to carinata cultivation as a winter crop are available across the counties in the three states of the Southeast United States, Alabama, Georgia, and Florida in Field, Zhang, Marx, et al. (2022). The study used an agroecosystem model, DayCent, based on biophysical information (e.g., soil quality, climate), which determined the net change in SOC of integrating carinata into traditional crop rotation against rotation without carinata. Their simulations include a business-as-usual (BaU) farm management scenario and two climate-smart agricultural management scenarios. However, the diffusion of carinata feedstock production across the larger geographic area of the US South was not explored.

Several studies have also examined the supply chain and techno-economic costs of SAF produced from carinata. Karami et al. (2022) estimated that a seed price of about \$485 Mg^{-1} or \$11 bu^{-1} (bushel= bu, 1 Mg = 44.1 bu) is necessary to reduce farmers' risk from crop rotation with carinata by 8%. Using this seed price, Ullah et al. (2023) estimated a price of about \$0.92 L^{-1} for SAF produced from carinata, which is about \$0.44 L^{-1} greater than the price of conventional aviation fuel (CAF). Given that the seed cost accounts for 80% of the total costs, therefore, the market competitiveness of SAF produced from carinata would require additional incentives for farmers to produce seeds. Alam et al. (2021) evaluated the potential role of carbon reduction on the breakeven cost of carinata-based SAF, estimating a breakeven price range of \$0.12 L^{-1} to \$0.66 L^{-1} only when both co-product and RIN credits (Renewable Identification Number under the US Renewable Fuel Standard program) are considered. However, the incentive for farmers, as the first point on the supply chain, to produce carinata using practices that sequester soil organic carbon at the farm level, assumed in these analyses, has not been examined.

Payments or incentives for SOC sequestration can encourage farmers to adopt bioenergy crops by complementing the revenue from the sale of feedstock to bioenergy facilities (Mishra et al., 2021). Such payments for ecosystem services (PES) could influence the competitiveness of farms through three outcomes (Piñeiro et al., 2020): – 1) productivity (e.g., yield/acre); 2) profitability (e.g., farms' income, production costs/acre); and 3) environmental sustainability (e.g., soil and water quality, climate change mitigation). Previous PES studies on bioenergy crops have primarily reflected the effects of soil and water quality improvement by reducing nitrogen loading in water (Woodbury et al., 2018), nutrient losses from soil (Wu et al., 2019), and application of nitrogen for farming (Li & Zipp, 2019), along with specific case studies, such as the impacts on marine ecosystem of nitrogen and other nutrients loading (Jager & Efroymson, 2018). However, only a handful of PES studies are available that focus on the SOC sequestration potential of bioenergy or other crops to mitigate climate change (Antle et al., 2001, 2007; Mishra et al., 2021). Only Mishra et al. (2021) conducted a spatially explicit study on PES for SOC sequestration due to perennial bioenergy crops. However, to the best of our knowledge, none of the studies considered – 1) the PES for adopting seasonal bioenergy crops, such as carinata, camelina, and canola; 2) the social and behavioral aspects of farmers which can affect the biophysical and economic outcomes of PES schemes and the dynamics of the adoption process.

This study uses a spatially explicit model constrained by social, economic, and behavioral factors to evaluate the SOC incentives for producing carinata in the US Southeast. The hypothesis is that valuing the SOC potential can improve farmers' competitiveness in producing carinata and increase SOC sequestration. Therefore, the current study significantly extends previous ABM studies of carinata adoption (Ullah & Crooks, 2023; Ullah & Dwivedi, 2022) by utilizing production economics of county-wise yields and SOC sequestration rates under the Business-as-Usual (BaU) and one climate-smart (no-till) scenarios estimated with the DayCent model (Field, Zhang, Marx, et al., 2022). We simulate the impact of different combinations of seed prices and SOC incentives under each of these scenarios to understand the effects on carinata adoption rates by farmers in Georgia and the associated changes in SOC. In the remainder of the paper we first present our methodology (Section 2) before presenting our results and a discussion of them in Section 3. Finally, Section 4 provides a conclusion to our paper and outlines areas of further work.

2. Methods

2.1. Study Area

Georgia is a state in the Southeastern region of the United States having an area of around 61.2 million acres. The major landcover types of the state are forest (58%), agriculture/pasture (20%), transportation (6%), and others (16%) such as urban areas, open water, and so on (USDA/NASS, 2019). With respect to agricultural lands, there are three major field crops, i.e., cotton, peanut and corn, which represents 98.5% of the cropland in Southern Georgia (Karami et al., 2022). The vast majority of agricultural land occupied by these crops remains fallow in the winter season, providing opportunities for alternative crops in the winter. For example, it is estimated that around 1.9 million acres of these fallow lands could be utilized for cultivating carinata (Alam & Dwivedi, 2019). Figure 1 shows the potential land area for winter carinata cultivation across the counties in Georgia estimated by Field, Zhang, Marx, et al. (2022). Georgia also hosts the Hartfield Jackson Atlanta Airport, which is reputedly the busiest airport in the world and an ideal end user of carinata-based SAF.

2.2. Data Description

2.2.1. Geospatial Data

For the spatial analysis part of this study, we used two geospatial datasets, specifically the Crop Data Layer (CDL) and a county shape file. The CDL is a remote sensing-based raster data set produced annually by the United States Department of Agriculture (USDA) at 30 or 56 meter spatial resolution (USDA/NASS, 2019) depending on the state or year. The raster data set contains 85 possible land cover categories, most of which represent agricultural landcovers (e.g., grassland/pasture, cotton, double crops) but also include other land use/cover types (e.g., forest, shrubland, wetland). We obtained the county shapefile from the US Census Bureau (2020).

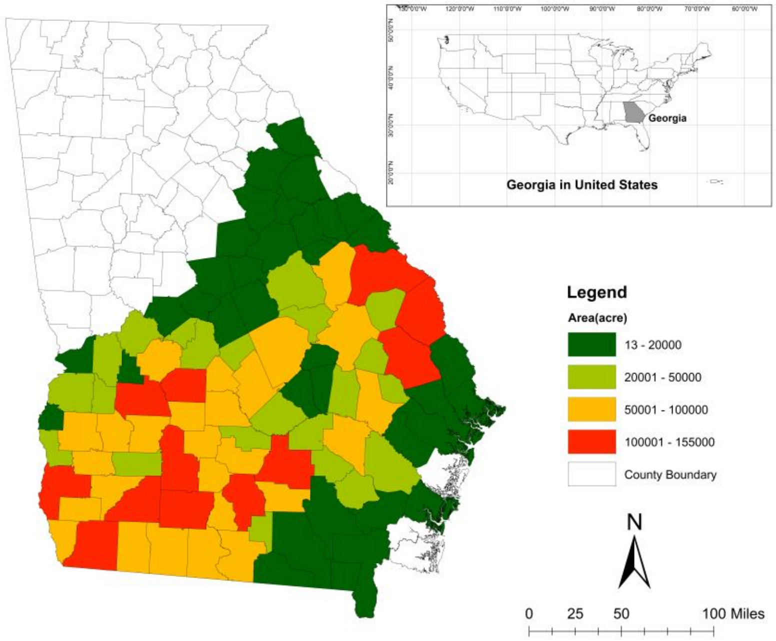

Figure 1: County-wise land availability for carinata production (adopted from Field et al., 2022)

2.2.2. Traditional Crop Production Economics

Table 1 shows the three key production economic variables, yields, prices, and production costs, used in this study for determining the profitability of three major crops based on data from the USDA Economic Research Service (2020) for 2009 through 2019, except 2012. The year 2012 was excluded from annual mean and standard deviation calculations due to extreme high prices for all the three crops in the this year, caused by a severe drought event. These annual datasets were collected for the Southern Seaboard agricultural region, which covers most of the part of Georgia including the counties that have potentials for producing carinata. Profits (i.e., net returns) for the crops are calculated as the difference between price and production costs, using yields to convert prices to per acre basis. The production costs are the operating costs for producing a crop, including seeds, fertilizer, irrigation, fuels, labor, taxes, insurances and other similar services. The fixed costs, such as machinery and equipment, are not subtracted from the net returns as those costs do not generally affect farmers' short-term planting decisions. The price and cost data were converted to real dollar values using the US producer price index (PPI) with the reference year of 2019. The Shapiro-Wilk normality test shows that all variables, except corn price, are normally distributed at a 5% significance level.

2.2.3. Carinata Production Economics and SOC

Candidate Georgia counties for carinata production were based on estimates of available land using the DayCent model (Field, Zhang, Marx, et al., 2022) (as shown in Figures 1 & 2). The spatially explicit DayCent model was previously calibrated to a depth of 20 cm for carinata grown in the Southeastern United States based on data from Nuseed (a commercial developer of carinata). In the DayCent simulations it was assumed that carinata is grown as a winter cover crop after the two cotton cash crops of a three-year cotton–cotton–peanut rotation, planting in mid-November, and harvesting in late May. This rotation was intended to avoid residual herbicide effects (Seepaul et al., 2019). The DayCent model simulations included three scenarios – one BaU scenario and two climate-smart (no-till and poultry litter) scenarios. In the BaU scenario, moderate-intensity field preparation was applied for cultivating all the crops in the rotation, including carinata. In the no-till scenario, carinata was cultivated with no-till and traditional crops with moderate-intensity field preparation. The estimated average yields of carinata and SOC sequestration due to the production of carinata seeds across the selected counties in Georgia under the BaU and no-till scenarios are used in this study (Figure 2). The yields for BaU scenarios are somewhat higher than for the no-till scenario in most counties. However, the SOC sequestration rates are considerably higher for no-till practices than for traditional farming (Field, Zhang, Marx, et al., 2022). Results for the poultry litter scenario is conservative in the DayCent model, hence, this study does not consider it (see Field, Zhang, Marx, et al., 2022 for detail).

Table 1: Variables affecting the profitability of major row crops and their normality test between 2009 to 2019. Source: USDA Economic Research Service (2020). (1 bu corn = 56 lb). *p-value for Shapiro-Wilk normality test. The production costs involve operating costs for producing a crop, which include costs of seeds, fertilizer, irrigation, fuels, labor, taxes, insurances and other similar services. Price and cost data were converted to reference dollar year of 2019 using the US Producers Price Index (PPI). Data for 2012 was excluded due to extreme high crop prices.

Return variables	Crop Name	Unit	Mean	Sd	p-value*
Yield	Corn	bu acre^{-1}	129.50	17.56	0.80
	Cotton	lb acre^{-1}	841.30	99.31	0.71
	Cottonseed	lb acre^{-1}	1361.00	160.81	0.70
	Peanut	lb acre^{-1}	4095.10	366.19	0.07
Price	Corn	\$ bu^{-1}	4.63	0.95	0.01
	Cotton	\$ lb^{-1}	0.75	0.11	0.25
	Cottonseed	\$ lb^{-1}	0.08	0.02	0.15
	Peanut	\$ lb^{-1}	0.21	0.04	0.18
Production cost	Corn	\$ acre^{-1}	427.60	60.94	0.92
	Cotton	\$ acre^{-1}	612.78	43.68	0.84
	Peanut	\$ acre^{-1}	586.95	47.00	0.41

There is no historical record of production costs for carinata in the study area. Several estimates have been made available from the experimental plots established under the Southeast Partnership for Advanced Renewables from Carinata (SPARC) (George et al., 2021; Seepaul et al., 2019). SPARC is a Coordinated Agricultural Project supported by the United States Department of Agriculture National Institute of Food and Agriculture. In light of SPARC's suggested cultivation guides, Karami et al. (2022) made a detail estimation of operational cost under the conventional tillage, which is \$286.32 acre^{-1}. This operating cost is used for our study assuming there is no variation in till versus no-till cultivation. This assumption is based on the management of till and no-till scenario specified in Field, Zhang, Marx, et al. (2022), that generated yield and SOC data for this study, and the possible costs specified in Karami et al. (2022). Field, Zhang, Marx, et al. (2022) suggests that the only variation in till versus no-till cultivation of carinata is in the field preparation, where 2 disk passes were applied for conventional tillage and herbicide burndown was applied for no-till cultivation. In the context of Georgia, the cost for land preparation of these two different managements are similar, which can vary from \$15-20 acre^{-1}. Besides, there is no additional equipment costs required for carinata as this crop can be cultivated with the equipment used for traditional field crops, e.g., cotton, corn and peanuts. Considering the maximum average yield in Georgia (53.26 bu acre^{-1} in the BaU scenario) and the estimated operating cost (\$286.32 acre^{-1}), the price of carinata should be at least around \$5.5 bu^{-1} to cover variable production costs. However, the variation in estimated yield levels, and likely production costs, across counties in Georgia mean that breakeven prices may vary significantly.

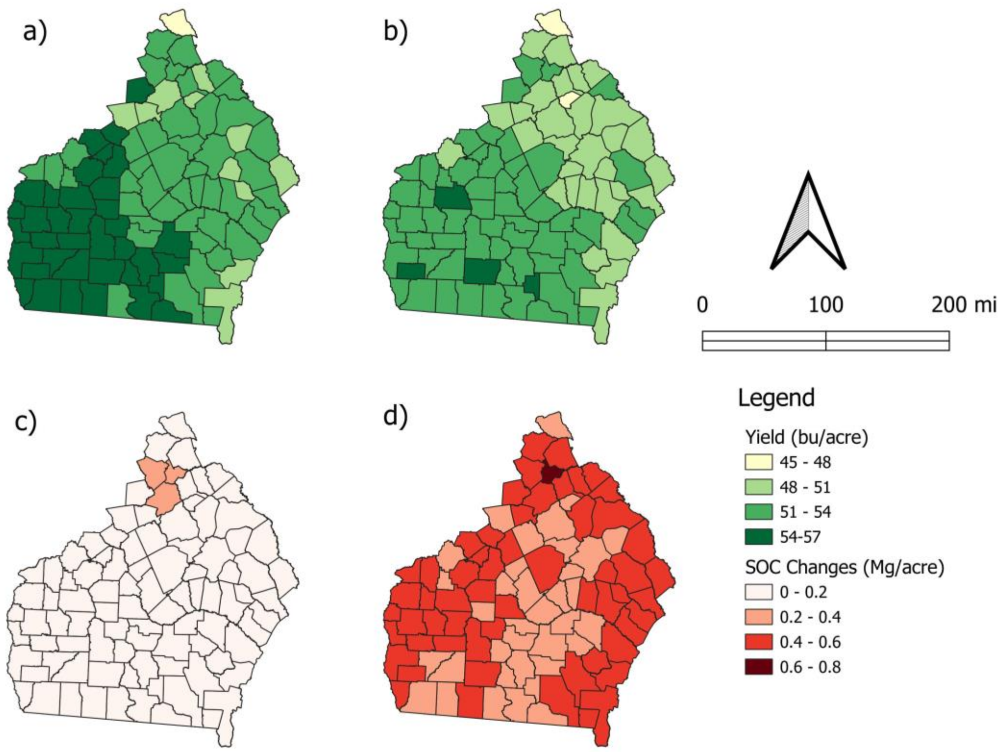

Figure 2: The Yield and changes of Soil Organic Carbon (SOC) for producing carinata in the counties of Georgia. Figure (a) & (b) are yields for BaU and no-till farming practices, respectively. Figure (c) & (d) are changes of SOC in the same order of farming practices. Source: Field, Zhang, Marx, et al. (2022).

2.3. Modelling Overview

The ABM used in this study builds on the version applied to a small-scale watershed in Ullah & Dwivedi (2022) which was subsequently extended by Ullah & Crooks (2023) to the state of Georgia. While both of those studies were useful to build an ABM framework in the first place, a more empirical model is necessary to understand how the profitability and diffusion of carinata adoption jointly determines the land allocation decisions of farmers under different farm management, yields conditions and given incentives for potential ecosystem services, such as SOC sequestration. Thus, in this study, farmer agents' adoption decisions of carinata, under the estimated yield and SOC response rates of two farm management scenarios (BaU and no-till), are reflected in three sub-models – profit modeling, diffusion modeling and land allocation modelling (Section 2.5 to 2.7) which was not the case in previous works.

The profit modeling evaluates farmers' profits of row crop rotations with and without carinata (Section 2.5). The diffusion modeling determines farmers' attitudes towards adopting carinata under neighborhood influences (Section 2.6). The land allocation modelling determines the proportion of lands that farmers will allocate for carinata cultivation integrated with cotton-cotton-peanuts (section 2.7). Farmers decide to adopt carinata for the current period only when they find their profit with carinata rotation is greater than without carinata rotation in the previous period, and the neighborhood influences from the same previous period provide a 'positive' outlook for adoption. For each farmer, the adoption behavior of the current period is updated and feeds into the next time step. Thus, the model works in a recursive manner until the end of the simulation period and the land allocation decisions determine farmers' expected utilities (profitability). Figure 3 shows the flow of farmers' decision-making framework across the three sub-models.

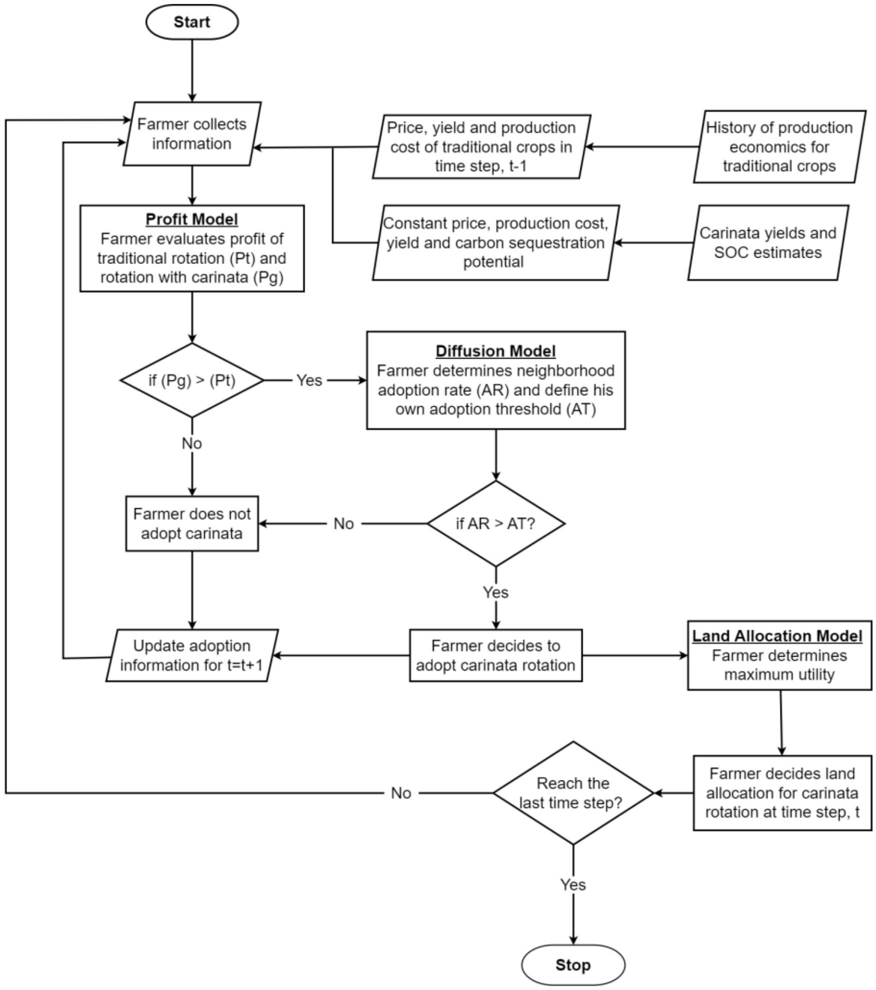

Figure 3: Process, overview and scheduling.

2.4. Model Initialization

The model is initialized at the farm, neighborhood and global levels using the associated variables and parameters across 93 counties out of 159 counties of Georgia. These 93 counties were selected as they have potential land availability for carinata production (Figure 1). The average farm area in Georgia is 247 acres and total farmland suitable for cultivating carinata across the 93 counties is 4,445,506 acres (USDA/NASS, 2019). By dividing the county-wise total farmlands with the average farm size we estimate about 17,998 farmers for Georgia. However, in this version of model, we create a farmer agent representing five farmers (1,235 acres) as a whole unit and at least three farmers (741 acres) where a whole unit is not possible. We chose this agent unit to reduce computational requirements and simplify the model. Two of the 93 counties with potential to grow carinata have less than three farmers based on the available land, and were excluded from the current study. A detailed discussion on how the model is initialized at the farm, neighborhood and global levels was given in Ullah & Crooks (2023), and the following paragraphs provide a brief overview.

Three categories of farmers are created at the farm level using the historical crop data layers (USDA/NASS, 2019) – 1) cotton-cotton-cotton farmers (53%); 2) cotton-cotton-peanut farmers (43%); and 3) cotton-cotton-corn farmers (4%). These three 3-year rotations are the major traditional crop rotations in the study area, which were utilized to estimate profits from the traditional crops without carinata. Carinata is integrated as Cotton-Cotton-Carinata-Peanut rotation for BaU and no-till scenarios based on – a) agronomic requirements (e.g., the herbicide effect for cultivating carinata after peanuts) (Seepaul et al., 2019); b) the analysis of most preferred and profitable three-year crop rotation in Georgia (see Ullah et al. (2022) for detail) . Thresholds of the farmers adoption of carinata rotation are set using two normal distributions, corresponding to high and low initial willingness scenarios (Section 2.6).

The neighborhood in this study is defined as a county and its immediate adjacent counties. Two neighborhood diffusion types are selected – 1) Traditional and 2) Expansion diffusion (Jordan-Bychkov, 1997) as shown in Figure 4. The rationale for exploring these different diffusion processes is to explore how carinata production might spread over the area under two policy options – one in which a pilot study is focused on a small geographical location, and one in which farmers are selected from across the state, i.e., Southern Georgia for this study. At the global level, parameters for crop production economics are set at the initialization of the model. Besides following the initialization framework of the previous ABM (Ullah & Crooks, 2023), two shapefiles provide county-wise yield and SOC changes of carinata for each of the BaU and no-till scenarios.

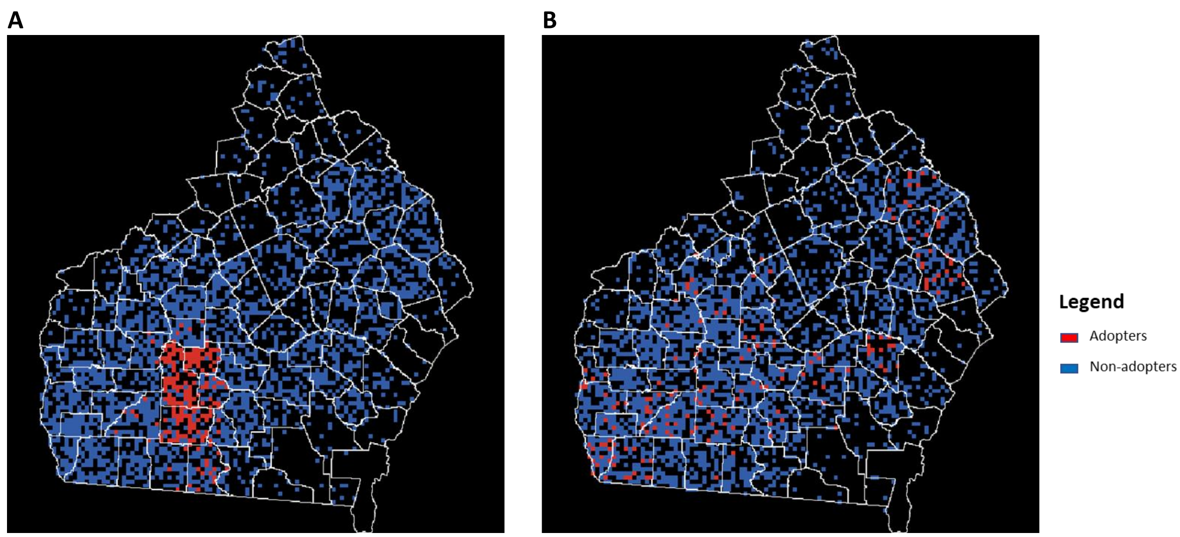

Figure 4: Adoption scenarios at early time steps where red agents (i.e., farmers) are the adopters: (**A)** traditional (**B**) expansion diffusion examples.

2.5. Profit Modeling

The expected profits during each three-year rotation of traditional row crops are based on the Net Present Value (NPV) of net returns calculated from yields, market prices, and cost of production for the previous period of rotation (Figure 3). Thus, the expected profit from traditional rotations without carinata for each farmer for period *t* is calculated using Eq. 1.

$$PF_t = \sum_{n,c} \left(Y_{t-1,n,c} * P_{t-1,n,c} - C_{t-1,n,c}\right) * \ NP_{t,n} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (1)$$

Where, t = 0, 1, 2, ….11 are each 3-year rotation periods, t = 0 is the base period. The n values are 1, 2, or 3 that represents the 1st, 2nd, and 3rd year of rotation period *t,* respectively, and c = 1, 2, 3 are crops, where 1 = corn, 2 = cotton, 3 = peanuts. The first term in the equation (*PF*) is the expected profit of a crop for a particular year calculated from yield (*Y*), price (*P*), and cost (*C*), which are stochastically generated for each rotation period based on Table 1. The third term, *NP,* is the multiplier to determine the NPV, where $NP_{t,n} = \frac{1}{(1+r)^{(3t+n)}}$, and *r* is the real discount rate (Godsey, 2008). All the production economics are calculated on a per acre basis.

The expected profit from a crop rotation for each farm with carinata (*PG*) is calculated using Eq. 2. The contract price, production cost, and SOC incentive for carinata is constant over the simulation period. However, the yields and SOC vary across the counties (Figure 2).

$$PG_t = PC_t * NP_{t,n=1} + PC_t * NP_{t,n=2} + (PA_t + SOC * Inc) * NP_{t,n=2} + PE_t * (1 - k) * NP_{t,n=3} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (2)$$

where,

PC_t = expected profit from cotton
PA_t = expected profit from carinata
SOC = Soil Organic Carbon sequestration rate (Mg CO2e acre^{-1})
Inc = Incentive for per Mg CO2e SOC sequestration, *s.t.* SOC > 0,
PE_t = expected profit from peanuts
k = yield loss of peanuts for late cultivation after carinata, ∀ k = 0.1
$NP_{t,(n=1,2,3)}$ = multiplier of NPV values in the 1st, 2nd, and 3rd year, respectively, for period t

The profits in Eq. 2 are calculated as a function of yield, price, and production cost, similar to the first term in the parenthesis of Eq. 1. In addition, an incentive is applied for the counties having positive SOC during the simulation to observe its impact on adoption behavior. Any county with negative or no change of SOC would receive no SOC incentive, but all the selected counties in Georgia have positive SOC. There could be some loss of peanuts yields due to planting after growing carinata between mid-November to end-May. We assigned an average loss of 10%, estimated from Drake et al. (2014).

2.6. Diffusion Modeling

Adopting carinata will be a new experience for farmers in the study area, and is analogous to new technology diffusion, which empirically follows an S-shaped curve (Alexander et al., 2013; Rogers, 2003). A number of approaches have been proposed for modeling technology diffusion processes (Alkemade & Castaldi, 2005), along with adopting new agricultural technologies in an agent-based modeling framework (Shang et al., 2021). In this study, we applied an adoption threshold approach proposed by Alexander et al. (2013), which was an extension of the work of Berger (2001). However, the novelty in our approach is in evaluating diffusion types, such as traditional and expansion diffusion (which are discussed below). The approach is based on two parameters: local adoption rate (AR) and individual adoption threshold (AT).

In the model, the current local AR is calculated from the net proportion of positive minus negative profit experiences from carinata among the farmers in the neighborhood from the previous time step. Each farmer is assigned an adoption threshold (AT) value that defines his degree of ‘resistance’ to change. If the AR value for a time step within the neighborhood is greater than the AT of an individual farmer, then the farmer shows a ‘positive’ attitude about adopting carinata due to neighborhood influence (see Figure 3). This diffusion process has been used in other agent-based models of adoption, for example on new technology adoption with respect to new irrigation suggested by Berger (2001). However, Berger (2001) applied a mathematical programming approach using experimental plot-level data to estimate crop production economics. We use farm production economics at the unit level by procuring secondary data (section 2.2.2). Furthermore, Berger’s (2001) study used extensive sample surveys and plot-level experimental data to represent the farm economics for the whole region. In this study we use remote sensing-based crop data layers, which are freely available, and estimate the crop economics over the cultivated farmlands. This allows the model to relate the profitability of farmers with direct spatial interactions, which influence the spatially explicit diffusion process as well. The use of readily available remote sensing data also allows us to instantiate and parameterize the model quickly compared to when more time-consuming field work is needed (Robinson et al., 2007).

Farmers that adopt carinata at the very beginning (first time step), considered risk takers in this study, are called innovative farmers. These innovative farmers will adopt carinata if only the profit conditions are met. Innovators will create the first net-positive AR. If the initial contract price of carinata is not as high enough to get positive return for any innovator, a new price is set in the model. The positive experience of innovators will influence other farmers. When other farmers find that the adoption rate due to adopting carinata by the innovators in the neighborhood is higher than their own AT, then those farmers cultivate carinata in the second time step. Sequentially, all the farmers including innovators and other farmers will update their experiences over each next time step in the simulation period. The AT values of individual farmers were assigned from normal distributions with a mean of 0.2 (Alexander et al., 2013; Jin et al., 2019), but with different standard deviations, depending on the initial willingness and diffusion types.

For expansion diffusion, two different distributions were used using standard deviations of 0.102 and 0.1216, to represent the low willingness and high willingness scenarios, respectively, thereby setting the innovator category at around 2.5% and 5% of total farmers (Ullah & Dwivedi, 2022). As the diffusion rate is slow in the early stage, only a small portion of farmers are willing to adopt carinata. In the low-willingness case, 2.5% of the farmers initially are willing to adopt new technology according to the theory of diffusion of innovations (Rogers, 2003). We selected 5% innovators to generate a less restrictive adoption rate and higher willingness to adopt a new crop in the initial stage. The AR was fixed at 0 for the base year. By using the selected distribution of AT, innovators had negative or zero AT values. Thus, setting an AR value of 0 at the initial stage fulfills the neighborhood requirement mathematically. That is to say, the innovators also adopt carinata if their AT values are equal or less than AR even though there are no experienced farmers in the community in the base year.

In the case of traditional diffusion, we select a single county in the Little River Watershed as a pilot site, which represents 2.5% of farmers in Georgia. Little River Watershed has been a prominent scientific experimental site for the agricultural extension in Georgia since 1967 (Bosch et al., 2007). We included three adjacent counties in the Little River Watershed as a pilot site to obtain 5% of farmers for the high willingness case. We assigned AT value 0 for these farmers for the same reason as in the expansion diffusion case, i.e., to make sure the AT value is equal or less than initial AR value. However, there remains the question of how to assign the AT values for the rest of the farmers, who do not exist in the pilot sites and are separated from the distribution of innovators? Even though we split the farmer population between innovators and non-innovators, the distribution of AT should be comparable with the non-partitioned distribution applied for expansion diffusion. To solve this problem, we applied a truncated normal distribution which is bounded between 2.5% and 100% for the low initial willingness scenario with the same mean and standard deviation value applied for the expansion diffusion. For the higher willingness scenario, the boundary was between 5% and 100%. Thus, we eliminate the innovators who are below the lower threshold and generate AT values for rest of the farmers using a truncated normal distribution as shown in Equation 3 (Botev & L'ecuyer, 2017):

$$AT = \Phi^{-1}\left(\Phi(\alpha) + U * \left(\Phi(\beta) - \Phi(\alpha)\right)\right)\sigma + \mu \dots\dots\dots\dots\dots\dots.. (3)$$

where,

Φ is the cumulative normal distribution function,

U is the uniform random number on (0,1)

μ,σ are the mean and standard deviation

α and β are the values to truncate the distribution range, e.g.,(.025,1) for low initial willingness scenario.

2.7. Land Allocation Modeling

The previous ABM of carinata adoption (Ullah & Dwivedi, 2022) applied the Mean-Variance (MV) modern portfolio optimization theory to determine farmers' land allocation decisions under their associated risk perceptions. However, this theoretical model could be misleading as integrating carinata in the traditional crop with a reasonable contract price will always bring additional profits for the farmers, while the land allocation rate could be either too low or too high in the MV method due to the volatility of production economics. This biased estimation could result from three shortcomings inherent to the classical MV portfolio optimization (see details in Kim et al., 2015): – 1) limitation of the use of variance for measuring risk, which represents both upside and downside deviations, whereas from investors point of view sometimes an upside deviation could mean less risk. 2) The input parameters of the model (e.g., means, variances and covariances) are difficult to estimate. Historical record could be helpful, but prediction of the future parameters is a difficult task, and for the case of carinata, there is no historical record of production economics as well. 3) The model is highly sensitive with respect to the resulting portfolio, as even a small deviation in the input values can have large effects on the portfolio and investment decisions.

Another approach to modeling land allocation to carinata is to use data on farmers' attitudes towards adopting oilseed crops (Embaye et al., 2018), which suggests that it is unlikely that farmers would allocate all of their farmland for cultivating carinata. A primary survey on farm and farmers' characteristics, such as in Embaye et al. (2018), could be helpful to understand the overall attitudes of different farmers. However, such perception-based information may not accurately reflect actual land allocations as farmers may change their mind when they evaluate their benefits during the actual implementation of an agricultural program (Park et al., 2022). Considering these unresolved issues in the previous literature and methodological approaches, we relied on the historical land allocation pattern from agricultural extension programs, such as conservation programs, to approximate farmers' land allocation decisions for carinata.

Conservation programs were implemented to improve soil, water and air quality associated with practices, such as cover cropping (Park et al., 2022). The USDA environmental quality incentives program (EQIP) and conservation stewardship program (CSP) are two of the largest conservation programs in terms of acreages and spending (Coppess & Gramig, 2018). Both programs give direct financial and technical assistance to farmers for conservation practices on land that remain in farming, therefore, they are considered 'working land' programs. CSP supports long term contracts (5 years) for the entire farm that need to meet a certain threshold of conservation over the years, whereas EQIP provides direct financial support for short term contracts (usually less than 3 years) to recover or share the cost of adding, maintaining, or improving conservation practices. EQIP is a target specific program and is more effective than CSP at the county level (Park et al., 2022) but the CSP imposes thresholds on farmers adding new conservation practices over the existing one. Since farmers make short-term (3 years) rotation decisions and there is no additivity other than integrating carinata into the cotton-cotton-peanuts rotation, we use data on EQIP adoption rates in Georgia to estimate the range of potential land allocation to carinata in this study as follows. The average land allocation rate per farming contract under the EQIP program between 2014 – 2022 in Georgia is 74.79 acres, which is around 30% of the average farm size in the state (USDA, 2022). However, to reflect greater flexibility in our simulation results, we use a uniform distribution of 20-50% to model the proportion of land allocated by farmers that choose to adopt carinata. Although lower than the average land enrollment rate for EQIP in Georgia, the lower bound of this range requires farmers to commit a significant portion of their farmland to carinata production after adoption. The upper bound of the range can be considered conservative since farmers may plant 100% of their land to carinata over the winter to increase profits.

2.8. Model simulation over the landscape of Georgia

As noted in Section 2.4, the landscape of the study includes 93 counties, which have potentials for carinata production. The model was simulated over 33 years (2018-2050) with a rotation of 3 years for each time step (t). The first 3-year rotation step (t=1) is 2018–2020, and the simulation was started with information on crop production economics between 2015 and 2017 (the base year, t=0) converted to real dollar values with the reference year of 2019. We captured the possible market, production, environmental, neighborhood, farmers' individual attitudes by setting the model's parameter values as highlighted below.

Table 2 shows the values of parameters used for simulating the profit sub-model as well as for sensitivity analysis of production economics under varying carinata contract prices and incentives for SOC sequestration. We set the initial farmgate contract price of carinata seed to \$5.5 bu^{-1} to represent a breakeven price based on assumptions about the average production cost and yield in Georgia (see section 2.2.3), and simulated prices (2019 dollars) of \$5.5 bu^{-1}, \$6 bu^{-1}, \$6.5 bu^{-1} and \$7 bu^{-1}. There were very little changes in adoption rates and land allocation after \$7 bu^{-1} as the adoption rates plateaued at this price. Assuming an average yield of 53.26 bu $acre^{-1}$ and SOC change of 0.12 Mg CO_2e $acre^{-1}$ due to carinata production in Georgia under the BaU scenario, an increase in contract price of \$0.5 bu^{-1} could be compensated by an incentive of \$222 Mg^{-1} CO_2e for the sequestered carbon. However, we set the ranges of SOC incentive between \$0-200 Mg^{-1} CO_2e (0 means no incentive) with \$50 increments to observe how different levels of incentives affect the adoption decisions of farmers across the state of Georgia.

In the profit modeling, the mean and standard deviation values of traditional crop yields, prices and production costs were used to capture the stochasticity of production economics (Table 2). However, the corn price was not normally distributed (Table 1). Therefore, a Poisson distribution with mean price (\$4.63 bu^{-1}) of corn were used as model inputs to capture the skewness in the distribution. The effect of time on returns from the various crop rotations was captured with an annual real discount rate of 6% (Upadhaya & Dwivedi, 2019), which was adopted for the investment decisions in agroforestry, in accordance with annual average stock market return with adjustment of inflation.

For the neighborhood effects, the model is designed to implement both the low and high willingness scenarios as well as traditional and expansion diffusions. The expansion diffusion appears to be a better option from the policy perspective because learning centers for the farmers are spread over a larger geographic region in this scenario. Thus, the maximum adoption rates occur earlier than the traditional diffusions cases (Ullah & Crooks, 2023). Even though there is no obvious case to determine the level of initial willingness to adopt carinata, low willingness is suggested by Rogers's classical theory of diffusion of innovations (Rogers, 2003). Therefore, to keep more focus on production economics and SOC incentives, maintain the brevity of the paper and minimize the run time of the program, we considered the low willingness and expansion diffusion scenario for the neighborhood sub-model in this study. For the land allocation sub-model, a uniform distribution of 20-50% is applied to model the proportion of land allocated by farmers who adopt carinata (see Section 2.7 for explanation).

To implement the simulation work, we preprocessed the agents' environment first, especially using geospatial techniques for estimating total land resources and the best rotation with carinata. Then, we built our profit, neighborhood, and land allocation models in the *NetLogo 6.3.0* environment (Wilensky, U. ,1999, see the Data Availability Statement section). Figure 5 shows an example output of a model run by 2050 with a SOC incentive of \$50 Mg^{-1} CO_2e at price \$6.5 for no-till farming practices. For each scenario, the model was run 20 times at first, then, it was run with 40 and 80 repetitions to observe the stochasticity with a more granular view. There were no visible changes from 40 runs to 80 runs, therefore, no further repetition was evaluated. The results in this paper are the average values of 40 runs.

Table 2: Variables and parameters of production economics. One bu corn = 56 lb. N(μ, ʊ²) represents the normal distribution, P(μ) represents Poisson distribution.

Parameters	Values for simulation	Reference
Corn yield	N (129.50 bu acre⁻¹, 17.56)	(USDA Economic Research Service, 2020)
Cotton yield	N (841 lb acre⁻¹, 99.31)	(USDA Economic Research Service, 2020)
Cottonseed yield	N (1361 lb acre⁻¹, 160.81)	(USDA Economic Research Service, 2020)
Peanut yield	N (4095.1 lb acre⁻¹, 366.19)	(USDA Economic Research Service, 2020)
Corn price	P (\$4.63 bu⁻¹)	(USDA Economic Research Service, 2020)
Cotton price	N (\$0.75 bu⁻¹, 0.11)	(USDA Economic Research Service, 2020)
Cottonseed price	N (\$0.08 bu⁻¹, 0.02)	(USDA Economic Research Service, 2020)
Peanut price	N (\$0.21 lb⁻¹, 0.04)	(USDA Economic Research Service, 2020)
Carinata contract price (\$ bu⁻¹)	\$5.5, \$6, \$6.5, \$7	
Corn production cost	N (\$427.60 acre⁻¹, 60.94)	(USDA Economic Research Service, 2020)
Cotton production cost	N (\$612.78 acre⁻¹, 43.68)	(USDA Economic Research Service, 2020)
Peanut production cost	N (\$586.95 acre⁻¹, 47.00)	(USDA Economic Research Service, 2020)
Carinata production cost	\$286.32 acre⁻¹	(Seepaul et al., 2019)
SOC incentives (\$Mg⁻¹ CO₂e)	\$0, \$50, \$100, \$150, \$200	
Annual discount rate	6%	(Upadhaya & Dwivedi, 2019)

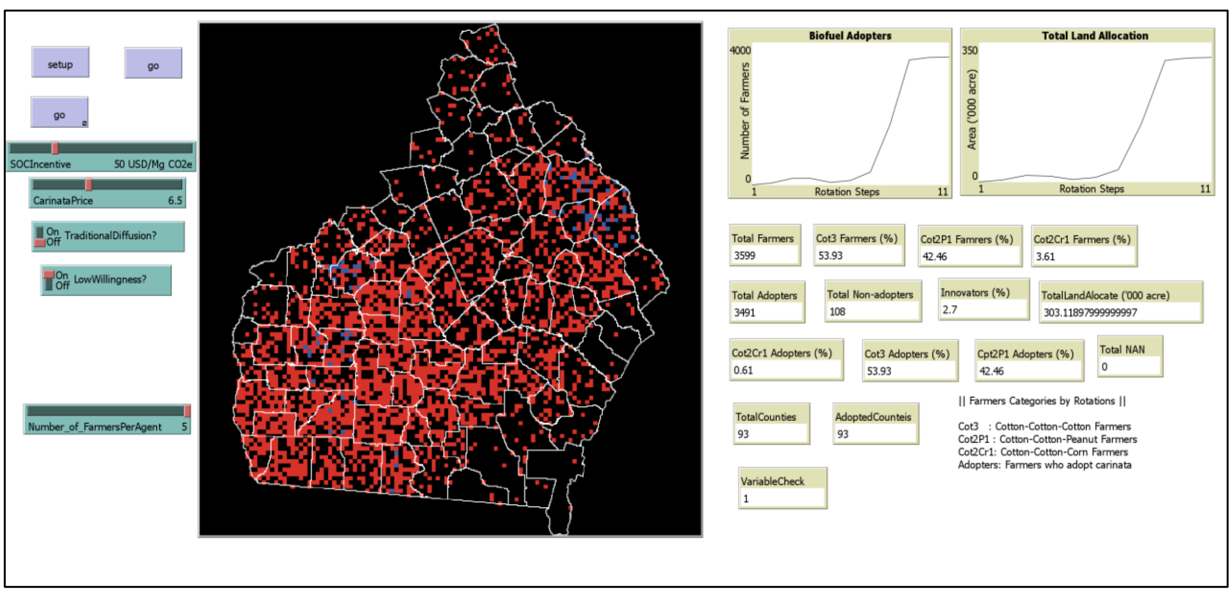

Figure 5: An example simulation output of a model run (SOC incentive = \$50 Mg^{-1} CO_2e, Carinata contract price = 6.5, Expanded diffusion, Low initial willingness scenario).

3. Results and Discussion

As can be seen in Figure 6, most of the farmers do not find carinata cultivation a profitable enterprise at a contact price of \$5.5 bu^{-1} with BaU farming. Only 15.3% of farmers find it profitable at this seed price in the long run under the high SOC incentive of \$200 Mg^{-1} CO_2e. However, a significantly higher number of farmers (60.6%) adopt carinata with the same price and a lower SOC incentive (\$150 Mg^{-1} CO_2e) for the no-till farming practice. It is also striking that the adoption rates for no-till scenario with a contract price of \$6.5 bu^{-1} and \$50 Mg^{-1} CO_2e SOC incentive are comparable with any scenario of BaU farming at higher prices, such as \$7 bu^{-1}. These findings follow from the much higher potential for SOC sequestration with carinata under no-till, relative to BaU farming, hence, farmers gain more profits with the incentives. For instance, the average SOC sequestration rate for Georgia, according to the DayCent result, is 0.12 Mg CO_2e $acre^{-1}$ for BaU farming (Field, Zhang, Marx, et al., 2022, Figure 2), but is around 3.5 times (0.42 Mg CO_2e $acre^{-1}$) that level for no-till farming. The effect of yield differences under the two farming practices are also distinguishable from Figures 2 and 6. For example, more farmers adopt carinata at prices of \$6-6.5 bu^{-1} with no SOC incentive (\$0 Mg^{-1} CO_2e) with BaU farming than with no-till farming. These results reflect the fact that the overall yield of carinata under BaU farming is slightly higher than with no-till farming; the average yields of carinata are 53.25 bu $acre^{-1}$ and 51.67 bu $acre^{-1}$ for BaU and no-till farming, respectively.

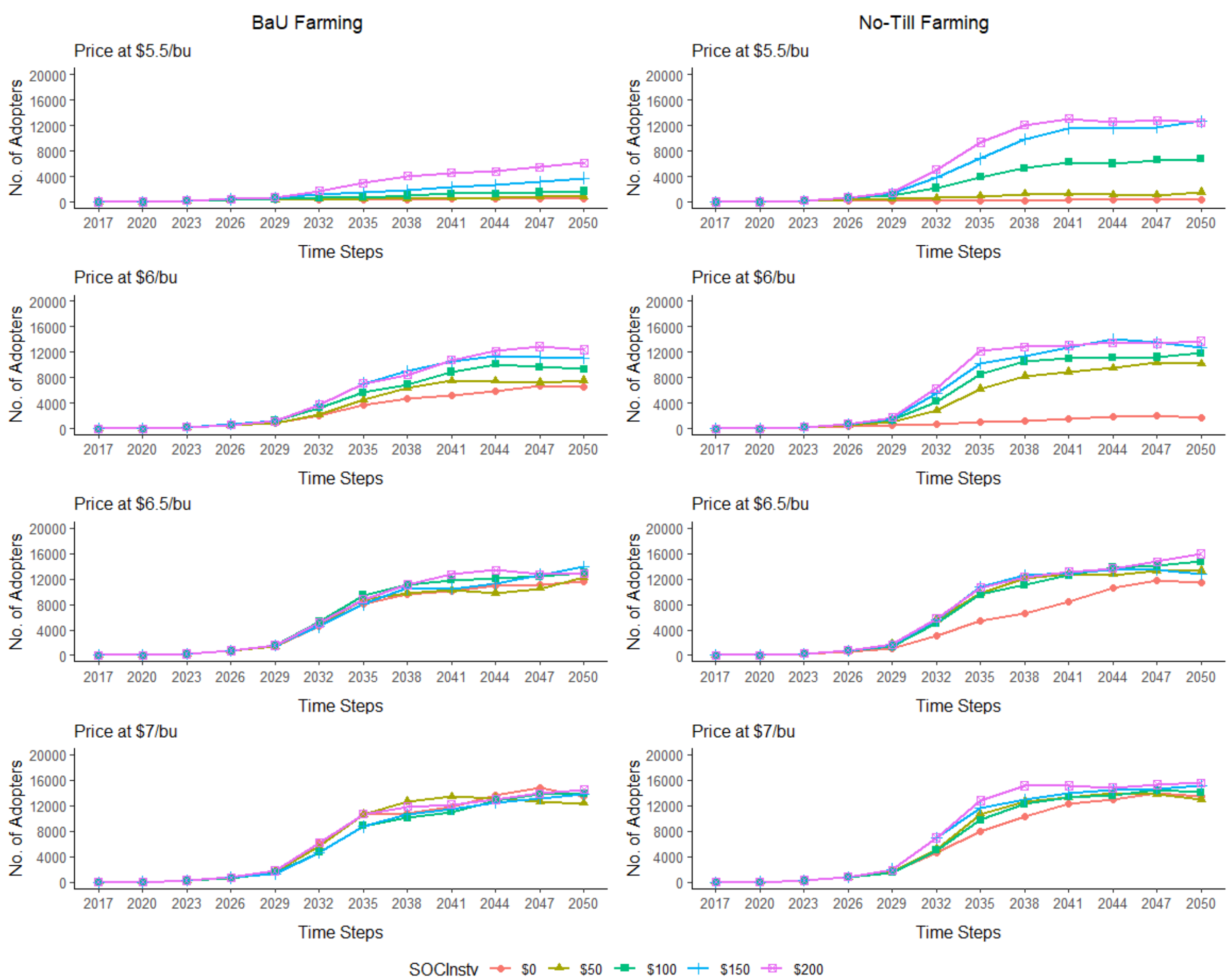

Figure 6: The total number of farmers who adopted carinata over the years for two farming scenarios at five levels of incentives for SOC sequestration and at the four price levels.

Determining the land allocation is the final objective in understanding the potential carinata seed supply and carbon sequestration, as well as ecological benefits across the region. Figure 7 shows the land allocation results have similar trend as in Figure 6. The similarity reflects the uniform distribution land allocation rates over a range of 20-50% in the model which would tend to the average value (i.e., 35%) for a large sample size. Since there is no established carbon market for bioenergy crops, this study evaluated different combinations of contract prices and SOC incentives. Existing carbon markets in the US and Canada, suggest that prices for carbon credits remain low, suggesting that high SOC incentives may not be feasible based on current policies and demand (Lokuge & Anders, 2022; Popkin, 2023). Figure 7, shows that under no-till cultivation an SOC incentive of \$50 Mg^{-1} CO_2e with a contract price of \$6.5 bu^{-1} and an SOC incentive of \$0 Mg^{-1} CO_2e with a contract price of \$7 bu^{-1} could attain the maximum land allocation area. Figure 8 further discusses the results of the \$6.5 bu^{-1} contract price scenarios.

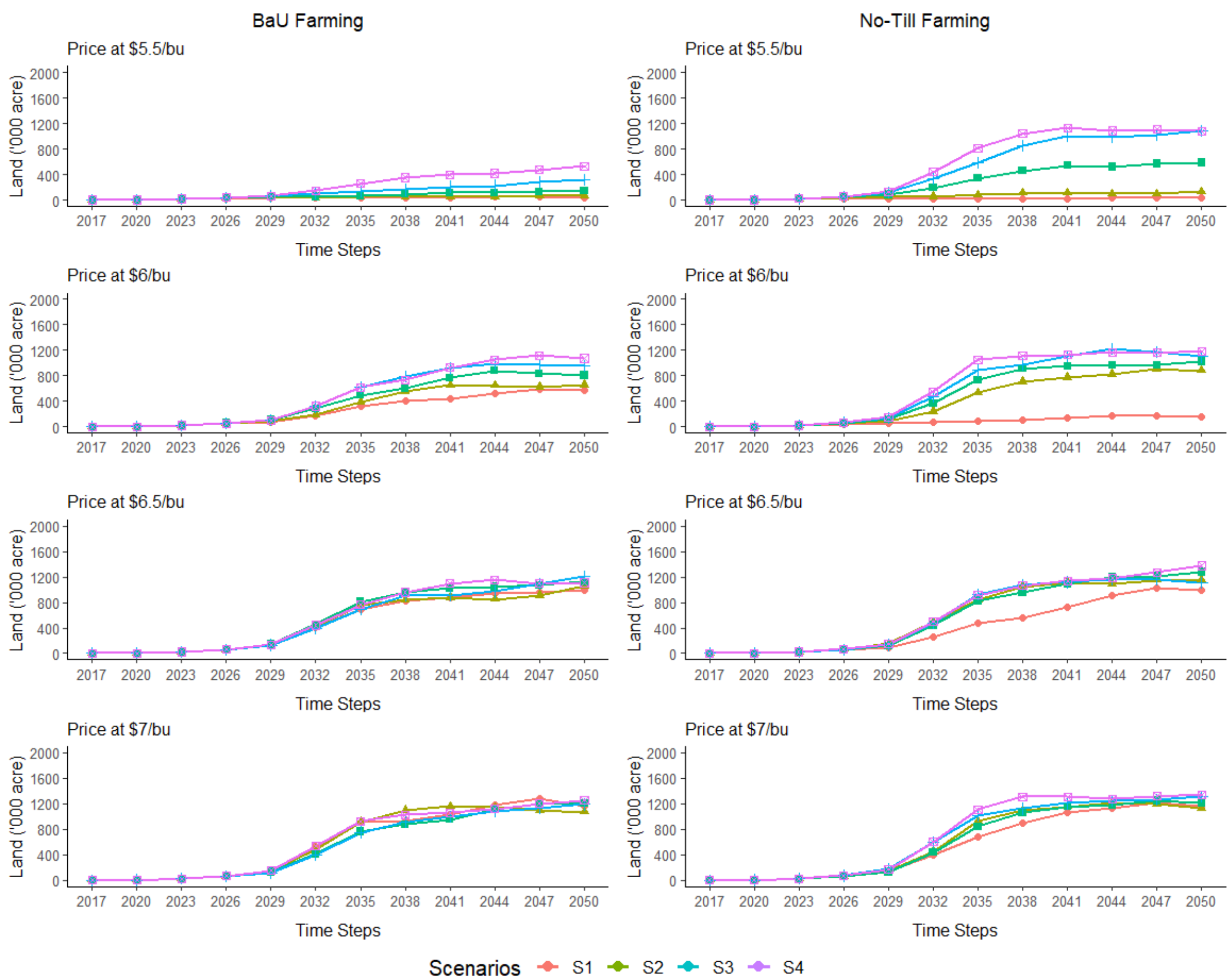

Figure 7: The total land allocated by the adopters over the years for two farming scenarios at five levels of incentives for SOC sequestration and at the four price levels.

According to Figure 8, at a price of \$6.5 bu^{-1} there is no significant difference between two BaU farming scenarios (S1 and S3) both in land allocation and SOC sequestration. The no-till farming with the same price but without SOC incentive (S2) attain almost the same land allocation as the two BaU scenarios in the long-run. However, the SOC sequestration is considerably higher for S2, compared to S1 and S3. This result means that an incentive for SOC sequestration would bring greater profits to farmers adopting no-till farming practices. This finding becomes more obvious for the S4 scenario. Land allocation for no-till farming (S4) scenario with a contract price of \$6.5 bu^{-1} and SOC incentive of \$50 Mg^{-1} CO_2e is consistently higher after 2029 than the BaU scenario (S3) with the same price and incentive. For instance, the total land allocations for S3 and S4 are around 1056 ×10^3 (23.8%) and 1152 ×10^3 (25.9%) acres by 2050, respectively. With these land allocation rates, the estimated seed supplies for S3 and S4 for the same year are 1275.1 x10^3 and 1349.7x10^3 Mg, respectively (1 Mg = 44.1 bu of carinata seed). The SOC sequestration amount for S4 is 483.83x10^3 $MgCO_2e$ by 2050, which is 3.82 times that for S3. These results are very interesting from a policy perspective. If there are no SOC incentives and market is free, farmers interested in cultivating carinata would do so under the BaU farming scenario because of the higher yield levels relative to the no-till farming, requiring a contract price of as high as \$6.5-\$7 bu^{-1} to achieve relatively high adoption rates (Figure 6 & 7). At a price of \$6.5 bu^{-1} and \$50 Mg^{-1} CO_2e incentive, farmers will receive a SOC payment of \$21 $acre^{-1}$ or \$0.41 bu^{-1} (or a total price of \$6.91 bu^{-1}) that achieve higher adoption rates. Such intervention would encourage the no-till farming scenario which increases SOC sequestration significantly. In contrast, even at a \$7 bu^{-1} price and without SOC incentives, farmers would allocate the similar number of acres but prefer BaU farming practices because of higher yields relative to no-till farming practices. Therefore, the net effect of investment for encouraging farmers toward carinata adoption could be the same without incentive and higher prices, but a trade-off between contract price and SOC incentive would be more effective for increasing SOC sequestration with similar or slightly higher investment.

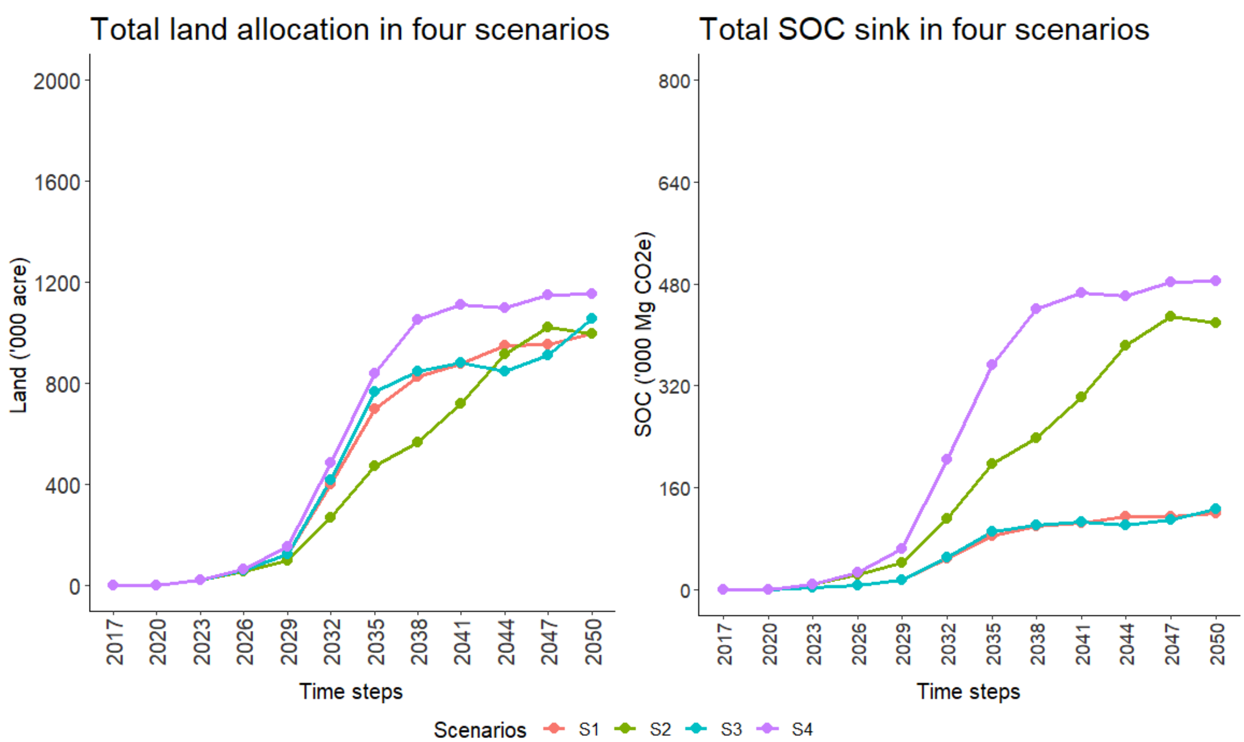

Figure 8: The total land allocated by the adopters over the years for four scenarios and their associated total SOC sequestrations. Scenario 1 (S1) = BaU farming, price \$6.5, SOC incentive \$0; Scenario 2 (S2) = No-till farming, price \$6.5, SOC incentive \$0; Scenario 3 (S3) = BaU farming, price \$6.5, SOC incentive \$50; Scenario 4 (S4) = no-till farming, price \$6.5, SOC incentive \$50.

Several additional factors, such as the stochasticity of traditional crops' economics, farmers' individual attitudes and associated neighborhood effects could affect the results presented above. How those factors affect carinata adoption and land allocation should be understood before implementation. Figure 9 shows the variations in the results for the four scenarios shown in Figure 8. Scenario 1 (S1) has overall higher land allocation numbers compared to S2 but has similar variations. For scenario 3 and 4 (S3 & S4), the variations in land allocation are highest between the rotation years, 2032 and 2038. In fact, this is the transition period, when majority of the farmers learn from early adopters. A significant proportion of farmers in the earlier part of the simulation period remain undecided, hence, widespread variations in adoption are obvious. Over time, a greater proportion of farmers become more positive about carinata adoption and region-wide more consistent decisions appear. This is because, with higher adoption rates, the distribution is close to that of an average level model where most of the farmers show a common attitude towards adopting carinata. Therefore, after 2038, the variances in adoption decisions decrease for S4. However, greater variations exist for S3 compared to S4 even in the long run. This happens because in that scenario farmers see lower carinata profitability and are affected more by the stochasticity of traditional crops' profitability. In addition, land allocation results for S4 have lower variance in the long run, which is also related to the distribution of yields under no-till farming. For no-till farming, the distribution of yield and SOC changes rates are N(51.67 bu acre^{-1}, 1.7) and N(0.42 Mg acre^{-1}, 0.04) across the counties, while for BaU farming the distributions are N(53.25 bu acre^{-1}, 2.0) and N(0.11 Mg acre^{-1}, 0.04). Thus, no-till farming has slightly lower but more consistent yield levels and higher SOC sequestration rates across the counties in Georgia. Still, the overall pattern of variations is not highly distinguishable across the scenarios for this contract price and time steps. Less variations will be expected with higher contract prices and longer time steps.

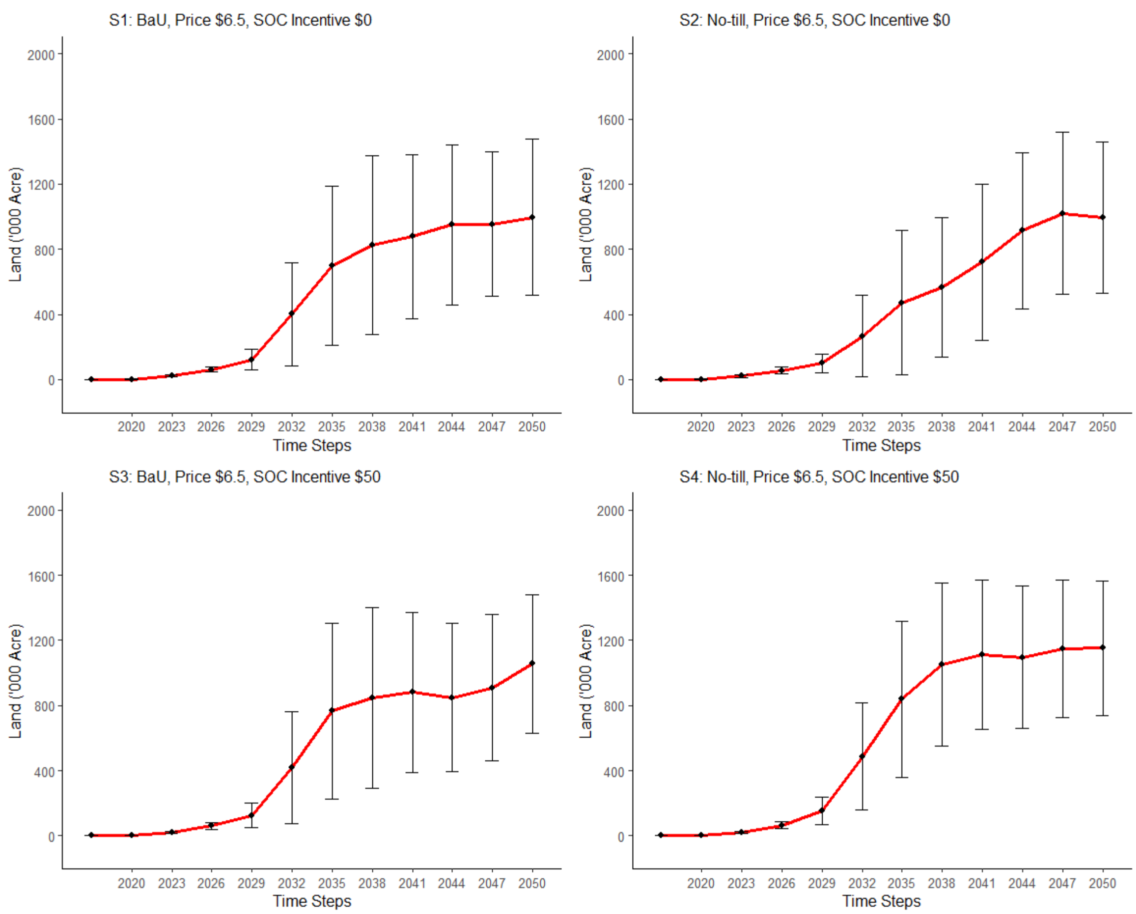

Figure 9: The mean land allocation area for four scenarios and their associated standard deviations (error bar).

4. Conclusion

Oilseed cover crops, such as carinata, camelina, and canola, have received significant attention for the production of SAF. This paper explored the potential benefits of incentives to sequester SOC on farmers' adoption of carinata, which has high yields and oil contents and can be produced as a winter crop with little to no impacts on cropland use. Results from our model suggest that a combination of carinata seeds' contract price at \$6.5 bushel^{-1} and incentive for SOC sequestration at \$50 Mg^{-1} CO_2e can persuade farmers to adopt carinata with no-till farming practices, which accelerates SOC accumulation. Similar to what one might observe in the real world (e.g., Rogers, 2003), the adoption rate for this newly introduced bioenergy crop was low at first but changing the dynamics of initial willingness can speed up the rate of adoption, especially under the expansion diffusion scenario. In addition to SOC sequestration, incentives would provide cover crop benefits and other ecosystem benefits (e.g., improving soil and water quality).

There are several existing conservation programs at the federal, state and local level of the United States aimed at incentivizing farmers to adopt cover crops with significant success (Wallander et al., 2021), leading to increases in adoption by 50% between 2012 and 2017. However, these cover crops are usually not harvested whereas bioenergy crops like carinata will be harvested for producing SAF, thereby, enabling full carbon mitigation benefits. Given the cover crop benefits, oilseed bioenergy crops may be alternatives or complements for existing cover crop programs. Therefore, a critical research question is whether SOC incentives for oilseed bioenergy crops should be fully provided by the carbon market? Currently, there are limited carbon markets in agriculture in the US and Canada (Lokuge & Anders, 2022), and so far there is no initiatives or studies with regards to carbon market for oilseed bioenergy crops. The prices in other carbon markets are on the lower end of the range of SOC incentives evaluated in this study. Therefore, carinata adoption for SAF production would benefit by receiving incentives from existing cover crop programs under no-till farming, which would lower the carbon price required to be profitable.

This study evaluated potential contract prices against variable costs to reflect short-term decisions by farmers, whereas market contract prices for SAF feedstock crops would be determined by many factors, including allocated fixed costs, demand for the SAF, government credit schemes, inflation, investors' return compared to other enterprises with same investments and so on. As such, the prices discussed in this study do not cover all the potential components of final contract prices that would be determined in actual markets. Also, our simulations are performed in 2019 dollars with data up to that year, and so do not capture recent high inflationary trends in the global economy. Existing SAF production mandates, such as the 2021 White House SAF target of 3 billion gallons by 2030 and 35 billion gallons by 2050, would increase the value of feedstock, such as carinata. The resulting higher contract seed prices could lower the required carbon payments necessary for farmers to adopt carinata.

A key assumption of the simulations in this study is that farmers' make short-term (3 years) carinata production decisions but keep the same traditional crop rotation over the next 33 years, since long-term commitment is essential to retaining the benefits of sequestered SOC. In reality farmers may be reluctant to sign long term contracts (Khanna et al., 2017), which has led to the slow growth of perennial crops adoption. Yet, changes in rotation and crop management practices over time can lead to the release of SOC to the atmosphere. Thus, our simulation scenarios can be interpreted as assuming that sequestered SOC could be preserved by providing incentives that ensure farmers profitability over the simulation period. Given the infancy of carbon credit markets, solutions to the permanence and additionality requirements for sequestered SOC are still being developed. Therefore, existing carbon credit markets vary widely in their approaches to these issues, including treating SOC accumulation as a side-effect of no-till or minimum-till practices with no active monitoring or reducing carbon payment to account for potential/natural loss of SOC over time (Sellars et al., 2021). In addition, our simulations evaluated the net SOC benefits of carinata adoption under no-till farming versus a baseline of conventional tillage for all agents. However, the adoption of no-till and cover crops has increased in the US in recent years (Wallander et al., 2021), but the majority of farmers in our region of study still do not use no-till farming and its use is often combined with minimum- or conventional-tillage within the rotation period. Although this means that the baseline for many farmers in Georgia would be no-till, a mix of no-till and conventional tillage, or other conservation practices rather than conventional tillage, the information necessary to characterize the baseline for individual farms/farmers is not publicly available. Therefore, the results in this study provide a starting point for understanding the role of SOC incentives for carinata adoption that would need to be complemented with data on specific farm baselines during the actual implementation of such a program.

In addition to the limitations of the assumptions discussed above, other follow-up areas of inquiry to this study include: 1) Considering the dynamic environmental factors, such as weather conditions that can affect the crop yield, as well as yield and SOC sequestration variations within the counties; 2) Considering the entire supply chain for carinata-based SAF; 3) Further examination of the land allocation approach used in this study and the assumption that these lands will remain in cotton-cotton-carinata-peanut rotation up to 2050. To address these gaps, our future modeling work will consider frost event frequencies; variations the yield and net soil organic carbon changes within the counties, including other Southeastern US states beyond Georgia; and integrate with spatially explicit supply chain model to help optimize the carbon footprint for carinata-based SAF. We will also further examine conditions and policies to promote long-term commitment to SOC sequestration practices. Even with these limitations and areas of further work, this paper offers a new way to explore the potential role of SOC incentives on the adoption of bioenergy crops. The provision of the source code and data allows others to extend or adapt the model for their own purposes towards climate-smart solutions that reduce greenhouse gas emissions.

Data Availability Statement

Data and detail codes are available in the https://github.com/KaziMaselUllah/Incentive_SOC_Carinata. Interested readers can run the model to observe other scenarios, such as, traditional diffusion and high initial willingness scenarios or extend the model as they see fit or just replicate what is presented in this paper.

References

Alam, A., & Dwivedi, P. (2019). Modeling site suitability and production potential of carinata-based sustainable jet fuel in the southeastern United States. *Journal of Cleaner Production*, *239*, 117817. https://doi.org/10.1016/j.jclepro.2019.117817

Alam, A., Masum, M. F. H., & Dwivedi, P. (2021). Break-even price and carbon emissions of carinata-based sustainable aviation fuel production in the Southeastern United States. *GCB Bioenergy*, *13*(11), 1800–1813. https://doi.org/10.1111/GCBB.12888

Alexander, P., Moran, D., Rounsevell, M. D. A., & Smith, P. (2013). Modelling the perennial energy crop market: the role of spatial diffusion. *Journal of The Royal Society Interface*, *10*(88), 20130656. https://doi.org/10.1098/rsif.2013.0656

Alkemade, F., & Castaldi, C. (2005). Strategies for the diffusion of innovations on social networks. *Computational Economics*, *25*(1–2), 3–23. https://doi.org/10.1007/s10614-005-6245-1

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*, *26*(2), 344–367. https://doi.org/10.22004/AG.ECON.31037

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*(1–2), 145–171. https://doi.org/10.1007/S10584-006-9176-5/METRICS

Berger, T. (2001). Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. *Agricultural Economics*, *25*(2–3), 245–260. https://doi.org/10.1111/J.1574-0862.2001.TB00205.X

Bosch, D. D., Sheridan, J. M., Lowrance, R. R., Hubbard, R. K., Strickland, T. C., Feyereisen, G. W., & Sullivan, D. G. (2007). Little River Experimental Watershed database. *Water Resources Research*, *43*(9). https://doi.org/10.1029/2006WR005844

Botev, Z., & L'ecuyer, P. (2017). Simulation from the Normal Distribution Truncated to an Interval in the Tail. *10th EAI International Conference on Performance Evaluation Methodologies and Tools*.

Christ, B., Bartels, W. L., Broughton, D., Seepaul, R., & Geller, D. (2020). In pursuit of a homegrown biofuel: Navigating systems of partnership, stakeholder knowledge, and adoption of Brassica carinata in the Southeast United States. *Energy Research & Social Science*, *70*, 101665. https://doi.org/10.1016/J.ERSS.2020.101665

Coppess, J., & Gramig, B. (2018). Reviewing Directions in Conservation Policy: CSP and EQIP in the House Farm Bill. *Farmdoc Daily*, *8*(104). https://farmdocdaily.illinois.edu/2018/06/reviewing-directions-in-conservation-policy-html.html

Corning, E., Sadeghpour, A., Ketterings, Q., & Czymmek, K. (2016). *The Carbon Cycle and Soil Organic Carbon Agronomy*. http://nmsp.cals.cornell.edu

Drake, W. L., Jordan, D. L., Johnson, P. D., Shew, B. B., Brandenburg, R. L., & Corbett, T. (2014). Peanut response to planting date, tillage, and cultivar in North Carolina. *Agronomy Journal*, *106*(2), 486–490. https://doi.org/10.2134/agronj2013.0340

Elless, M. P., Levy, C., & Otwell, A. (2023). *Bioenergy's Role in Soil Carbon Storage Decarbonizing Transportation, Agriculture, and Industrial Sectors*. https://www.energy.gov/eere/bioenergy/events/workshop-bioenergys-role-soil-carbon-

Embaye, W. T., Bergtold, J. S., Archer, D., Flora, C., Andrango, G. C., Odening, M., & Buysse, J. (2018). Examining farmers' willingness to grow and allocate land for oilseed crops for biofuel production. *Energy Economics*, *71*, 311–320. https://doi.org/10.1016/J.ENECO.2018.03.005

Field, J. L., Zhang, Y., Marx, E., Boote, K. J., Easter, M., George, S., Hoghooghi, N., Johnston, G., Masum, F. H., Mulvaney, M. J., Paustian, K., Seepaul, R., Swan, A., Williams, S., Wright, D., & Dwivedi, P. (2022). Modeling Yield, Biogenic Emissions, and Carbon Sequestration in Southeastern Cropping Systems With Winter Carinata. *Frontiers in Energy Research*, *10*(April), 1–14. https://doi.org/10.3389/fenrg.2022.837883

George, S., Seepaul, R., Geller, D., Dwivedi, P., DiLorenzo, N., Altman, R., Coppola, E., Miller, S. A., Bennett, R., Johnston, G., Streit, L., Csonka, S., Field, J., Marois, J., Wright, D., Small, I. M., & Philippidis, G. P. (2021). A regional inter-disciplinary partnership focusing on the development of a carinata-centered bioeconomy. *GCB Bioenergy*, *13*(7), 1018–1029. https://doi.org/10.1111/gcbb.12828

Godsey, L. D. (2008). *Economic Budgeting for Agroforestry Practices*.

Jager, H. I., & Efroymson, R. A. (2018). Can upstream biofuel production increase the flow of downstream ecosystem goods and services? *Biomass and Bioenergy*, *114*, 125–131. https://doi.org/10.1016/J.BIOMBIOE.2017.08.027

Jin, E., Mendis, G. P., & Sutherland, J. W. (2019). Spatial agent-based modeling for dedicated energy crop adoption and cellulosic biofuel commercialization. *Biofuels, Bioproducts and Biorefining*, *13*(3), 618–634. https://doi.org/10.1002/bbb.1973

Jordan-Bychkov, T. G. (1997). *The human mosaic : a thematic introduction to cultural geography*. Longman.

Karami, O., Dwivedi, P., Lamb, M., & Field, J. L. (2022). Economics of Crop Rotations With and Without Carinata for Sustainable Aviation Fuel Production in the SE United States. *Frontiers in Energy Research*, *10*, 461. https://doi.org/10.3389/FENRG.2022.830227/BIBTEX

Khanna, M., Louviere, J., & Yang, X. (2017). Motivations to grow energy crops: the role of crop and contract attributes. *Agricultural Economics*, *48*(3), 263–277. https://doi.org/10.1111/AGEC.12332

Kim, W. C., Kim, J. H., & Fabozzi, F. J. (2015). Shortcomings of Mean-Variance Analysis. In *Robust Equity Portfolio Management* (pp. 22–38). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118797358.CH3

Kirschbaum, M. U. F. (2000). Will changes in soil organic carbon act as a positive or negative feedback on global

warming? *Biogeochemistry*, *48*(1), 21–51. https://doi.org/10.1023/A:1006238902976/METRICS
Lal, R. (2003). Global Potential of Soil Carbon Sequestration to Mitigate the Greenhouse Effect. *Https://Doi.Org/10.1080/713610854*, *22*(2), 151–184. https://doi.org/10.1080/713610854
Li, X., & Zipp, K. Y. (2019). Dynamics and Uncertainty in Land Use Conversion for Perennial Energy Crop Production: Exploring Effects of Payments for Ecosystem Services Policies. *Agricultural and Resource Economics Review*, *48*(2), 328–358. https://doi.org/10.1017/AGE.2019.3
Lokuge, N., & Anders, S. (2022). *CARBON-CREDIT SYSTEMS IN AGRICULTURE: A REVIEW OF LITERATURE* (Vol. 15).
Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z. S., Cheng, K., Das, B. S., Field, D. J., Gimona, A., Hedley, C. B., Hong, S. Y., Mandal, B., Marchant, B. P., Martin, M., McConkey, B. G., Mulder, V. L., … Winowiecki, L. (2017). Soil carbon 4 per mille. *Geoderma*, *292*, 59–86. https://doi.org/10.1016/j.geoderma.2017.01.002
Mishra, S. K., Gautam, S., Mishra, U., & Scown, C. D. (2021). Performance-Based Payments for Soil Carbon Sequestration Can Enable a Low-Carbon Bioeconomy. *Environ. Sci. Technol*, *55*, 5188. https://doi.org/10.1021/acs.est.0c06452
Park, B., Rejesus, R. M., Aglasan, S., Che, Y., Hagen, S. C., & Salas, W. (2022). Payments from agricultural conservation programs and cover crop adoption. *Applied Economic Perspectives and Policy*. https://doi.org/10.1002/AEPP.13248
Paustian, K., Andrén, O., Janzen, H. H., Lal, R., Smith, P., Tian, G., Tiessen, H., Van Noordwijk, M., & Woomer, P. L. (1997). Agricultural soils as a sink to mitigate CO2 emissions. *Soil Use and Management*, *13*(4 SUPPL.), 230–244. https://doi.org/10.1111/J.1475-2743.1997.TB00594.X
Piñeiro, V., Arias, J., Dürr, J., Elverdin, P., Ibáñez, A. M., Kinengyere, A., Opazo, C. M., Owoo, N., Page, J. R., Prager, S. D., & Torero, M. (2020). A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. *Nature Sustainability 2020 3:10*, *3*(10), 809–820. https://doi.org/10.1038/s41893-020-00617-y
Popkin, G. (2023). Shaky Ground: A company called Indigo is paying farmers to trap carbon in their soils. Some researchers say the climate benefits are dubious. *Science*, *381*(6656). https://doi.org/10.1126/science.adj9318
Robinson, D. T., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. A., Huigen, M., Wittmer, H., Gotts, N., Promburom, P., Irwin, E., Berger, T., Gatzweiler, F., & Barnaud, C. (2007). Comparison of empirical methods for building agent-based models in land use science. *Http://Dx.Doi.Org/10.1080/17474230701201349*, *2*(1), 31–55. https://doi.org/10.1080/17474230701201349
Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
Seepaul, R., Small, I. M., Mulvaney, M. J., George, S., Leon, R. G., Paula-Moraes, S. V, Geller, D., Marois, J. J., & Wright, D. L. (2019). *Carinata, the Sustainable Crop for a Bio-based Economy: 2018-2019 Production Recommendations for the Southeastern United States 1*.
Sellars, S., Schnitkey, G., Swanson, K., Paulson, N., & Zulauf, C. (2021). Weekly Farm Economics: What Questions Should Farmers Ask about Selling Carbon Credits? *FarmdocDaily*, *11*(59), 1–7. https://farmdocdaily.illinois.edu/wp-content/uploads/2021/04/fdd130421.pdf
Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies - integrating farm-level evidence and system interaction. *Agricultural Systems*, *190*, 103074. https://doi.org/10.1016/J.AGSY.2021.103074
Stockmann, U., Adams, M. A., Crawford, J. W., Field, D. J., Henakaarchchi, N., Jenkins, M., Minasny, B., McBratney, A. B., Courcelles, V. de R. de, Singh, K., Wheeler, I., Abbott, L., Angers, D. A., Baldock, J., Bird, M., Brookes, P. C., Chenu, C., Jastrow, J. D., Lal, R., … Zimmermann, M. (2013). The knowns, known unknowns and unknowns of sequestration of soil organic carbon. *Agriculture, Ecosystems & Environment*, *164*, 80–99. https://doi.org/10.1016/j.agee.2012.10.001
U.S. Census Bureau. (2020). *TIGER/LINE shapefiles*.
Ullah, K., Crooks, A. (2023). Modeling Farmers' Adoption Potential to New Bioenergy Crops: An Agent-Based Approach. In: Yang, Z., Núñez-Corrales, S. (eds) Proceedings of the 2022 Conference of The Computational Social Science Society of the Americas. CSSSA 2022. Springer Proceedings in Complexity. Springer, Cham. https://doi.org/10.1007/978-3-031-37553-8_5
Ullah, K. M., & Dwivedi, P. (2022). Ascertaining land allocation decisions of farmers about the adoption of carinata as a potential crop for sustainable aviation fuel production in the Southern United States. *GCB Bioenergy*,

14(7), 824–839. https://doi.org/10.1111/GCBB.12945
Ullah, K. M., Masum, F. H., Field, J., & Dwivedi, P. (2023). Designing a GIS-Based Supply Chain for Producing Carinata-Based Sustainable Aviation Fuel in Georgia. *Biofuels, Bioproducts and Biorefining*. https://doi.org/10.1002/bbb.2483
Upadhaya, S., & Dwivedi, P. (2019). The role and potential of blueberry in increasing deforestation in southern Georgia, United States. *Agricultural Systems*, *173*, 39–48. https://doi.org/10.1016/J.AGSY.2019.01.002
USDA/NASS. (2019). *Cropland Data Layer*.
USDA. (2022). *NRCS Financial Assistance Program Data*. https://www.farmers.gov/data/financial-assistance-download
USDA Economic Research Service. (2020). *Comodity Costs and Returns*.
Wallander, S., Smith, D., Bowman, M., & Claassen, R. (2021). *Cover Crop Trends, Programs, and Practices in the United States*. www.ers.usda.gov
Wilensky, U. (1999). NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
Woodbury, P. B., Kemanian, A. R., Jacobson, M., & Langholtz, M. (2018). Improving water quality in the Chesapeake Bay using payments for ecosystem services for perennial biomass for bioenergy and biofuel production. *Biomass and Bioenergy*, *114*, 132–142. https://doi.org/10.1016/J.BIOMBIOE.2017.01.024
Wu, M., Xu, H., Ha, M., Xu, H., Wu, M., & Ha, M. (2019). Recognizing economic value in multifunctional buffers in the lower Mississippi river basin. *Biofuels, Bioproducts and Biorefining*, *13*(1), 55–73. https://doi.org/10.1002/BBB.1930