Modeling Farmers' Adoption Potential to New Bioenergy Crops: An Agent-Based Approach

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Abstract The use of fossil fuels is the primary source of greenhouse gas emissions but there are alternatives to these especially in the form of biofuels, fuels derived from bioenergy crops. This paper aims to determine farmers' potential adoption rates of newly introduced bioenergy crops with a specific example of carinata in the state of Georgia. The determination is done using an agent-based modeling technique with two principal assumptions—farmers are profit maximizer and they are influenced by neighboring farmers. Two diffusion parameters (traditional and expansion) are followed along with two willingness (high and low) scenarios to switch at varying production economics to carinata and other prominent traditional field crops (cotton, peanuts, corn) in the study region. We find that a contract prices around \$9, \$8 and \$7 can be a viable option for encouraging farmers to adopt carinata in low, average, and high profit conditions, respectively. Expansion diffusion (that diffuses all over the geographical area), rather than centered to the few places like traditional diffusion at the early stage of adoption in conjunction with higher willingness conditions influences higher adoption rates in the short-term. As such, the model can be used to understand the behavioral economics of carinata in Georgia and beyond, as well as offering a potential tool to study similar bioenergy crops.

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1 Introduction

The uses of fossil fuels such as petroleum, natural gas, and coal is the primary source of greenhouse gas (GHG) emissions. Globally, about 65% of GHG emissions in 2010 occurred due to burning fossil fuels and currently, commercial aviation is responsible for 2.6% of annual global CO2 emissions [19]. Therefore, the mitigation strategies to combat climate change impacts are gaining attention from all sorts of transportation sectors, including that of the aviation industry. Utilizing biofuels can be the prime strategy in the goal to reduce GHG emissions. For example, it has been suggested that advanced biofuels produced from energy crops could reduce GHG emissions by as much as 50% when compared to fossil fuels [11]. In addition to this, bioenergy crops usually have high yield potentials; they can be grown productively on low-quality, fallow and marginal lands; they can increase soil carbon and reduce soil erosion (e.g., [35]), and are promising alternatives for rural economic development [29]. However, there is a great deal of economic, behavioral, and environmental challenges associated with adopting bioenergy crops, such as price and yield risks [24], lack of an established market [12], inexperience with new management practices, and cost of new crop-specific equipment [23]. For the last two decades several studies have tried to capture these challenges using several farm-scale modeling techniques ranging from agent-based models (e.g., [18]); choice experiment models (e.g., [23]); and mathematical programming models (e.g., [8]) to analyze different policy scenarios. Among those available modeling techniques, agent-based models have been argued to be an elegant tool for farm-scale modeling. The rationale for this is that farmers are heterogenous in their attitudes towards adopting bioenergy crops [30]. This heterogenous behavior is easily captured in such style of models [9], and it has been shown that agent-based modeling can capture farmers' heterogenous behaviors and their interaction with the biophysical environment and with other farmers [25]. These characteristics of agent-based models overcome some of the limitations of traditional econometric-based or theoretical microeconomic models which struggled incorporate heterogeneous behavior and spatial interactions [5]. It has also been argued that agent-based models can imitate the reality of farming and can be used more closely to understand the adoption pattern of a newly introduced bioenergy crops, where farmers' individual attitudes have large impact on overall adoption rates (e.g., [2, 20]).

However, to date there has only been a handful agent-based models that have explored bioenergy crop adoption (e.g., [2, 10, 15, 18, 20]). More recent work by Ullah and Dwivedi [30] tried to address two gaps from previous studies. The first was the joint determination of farmers' profitability, neighborhood influences and risk preferences to build a case in the field of computational social and behavioral science to study the perspective of farmers' attitude toward bioenergy crop adoption. Secondly, their work moved away from a hypothetical grid space and created a realistic but simple environmental landscape utilizing actual biophysical information to build farmers' interaction with the environment. Furthermore, Ullah and Dwivedi's [30] study applied three sub-modeling techniques under three principal assumptions: —(1) farmers are profit maximizers [3], (2) farmers are influenced by their neighboring farmers [18], and (3) farmers are risk averse [24]. However, Ullah and Dwivedi's [30] study was limited to a small-scale watershed level (e.g., 650 farmer agents with 19,622 acre of farmland). Another major limitation in that study was how neighborhood influences where assigned. Their study represented only one neighborhood which was not connected to the surrounding neighborhoods. Thus, the adoption of the crop diffused over the simulation period monotonically by considering the previous adoption rates same for all the farmers over the study area. Therefore, in that study, farmers were influenced by only other neighboring farmers in the same community. Information sharing from other neighboring communities was missing, which is something that has been witnessed in reality (e.g., [4]). As a result, the diffusion of crop adoption could not be simulated to a greater geographical area. This paper significantly extends the work Ullah and Dwivedi [30] by incorporating a greater regional study area, making it geographically explicit and assigning neighborhood influences on the farmers within their communities along with the surrounding communities. Thus, this study aims to model the adoption potential of bioenergy crops, where the case study is adopting carinata (an oilseed crop) as a newly introduced energy crop in context of Georgia, United States (US). In what follows, we first present the methodology and rationale for choosing the study area (Sect. 2) before presenting the results of the model in Sect. 3 and finally in Sect. 4 we provide a summary of the paper and areas of further work.

2 Methodology

While we present our model in the following sections, we also provide a more detailed Overview, Design concepts and Details (ODD) protocol [14] along with the model and the data needed to run the model at https://www.comses.net/codebase-release/5c2c06f0-3f6d-4f8d-b198-ce24b55feb2f/. This additional material allows for a more in-depth description of the model, as well as facilitates the replication of results or extension of the model.

2.1 Study Area and Purpose

Brassica carinata, or simply carinata, is a promising annual oilseed crop for the commercial production of sustainable aviation fuel (SAF [28]). As a cover crop, carinata can provide several ecosystem services by reducing soil erosion, nutrient leaching, increasing soil organic matter, and retaining moisture [17]. In the Southeast (SE) US, carinata can be potentially cultivated on about 3.4 million acres of fallow agricultural land during the winter season [1]. The SE is also home to the world's busiest airport, the Hartsfield-Jackson Atlanta International Airport, located in Georgia which consumes around 3.9 million tons of conventional aviation fuel (CAF) per year, which is around 5.2% of the total CAF consumption in the US [31]. Therefore, the large supply of carinata feedstock could meet the immediate demand of SAF in Georgia and beyond. However, much of the contemporary research on promoting carinata in the US South has been done only at the experimental level [13]. The challenges in adopting carinata at a regional level is yet unknown. To address this challenge one of the first steps is to explore the farmers' attitudes towards adopting energy crops while still ensuring feedstock availability. Therefore, this study determines the potential adoption rates of carinata under different crop economics, behavioral and diffusion scenarios.

Building upon how Atlanta airport could utilize carinata for SAF, for a case study region we chose Georgia. Georgia is a state in the SE region of the US having an area of 95,635.24 sq. miles which agriculture/pasture make up 20% (US Department of Agriculture (USDA)/National Agricultural Statistics Service (NASS) [32]). With respect to agricultural lands, there are three major field crops: cotton, peanut and corn [22], however the vast majority of agricultural land occupied by these crops remains fallow in the winter season [1]. This provides 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 [1]. Figure 1 shows the county-wise potential land availability for producing carinata seeds [13] and the purpose of our study to understand how the diffusion of carinata adoption would take place. Our aim is to determine the future adoption rates of carinata as a newly introduced bioenergy crop in Georgia for producing SAF.

2.2 Entities, State Variables, and Scales

The agents in our model represent farmers. Each farmer is an agent who owns 247 acre of crop land, which is average farm size in Georgia [33] and follow either one of the three most popular three years crop rotations in Georgia: Cotton-Cotton-Cotton; Cotton-Cotton-Peanuts; Cotton-Cotton-Corn. These three rotations represent at least 95% of field crops in Georgia [22]. In each county, three types of farmer agents are randomly created according to their respective crop rotation’s ratio of total farmlands estimated from the total crop areas divided by the average area of crop land. We would argue that the creation of farmer agents in this manner is a good approximation for giving farmers aggregated information at county level, while at the same time preserving privacy of farmers which is often done in other agricultural agent-based models like AgriPoliS [16].

Agents’ attitudes towards cultivation of certain row crops (e.g., corn, cotton, peanuts and carinata) on farmlands are defined by several profit maximizing variables and neighborhood influences’ parameters. The profit maximization variables (i.e., yield, production cost and price) determine the crop production economics at the discounted value to evaluate the profitability of integration of carinata into the major traditional crop rotations. While the production costs involve operating costs for producing a crop, including seeds, fertilizer, irrigation, fuels, and other similar

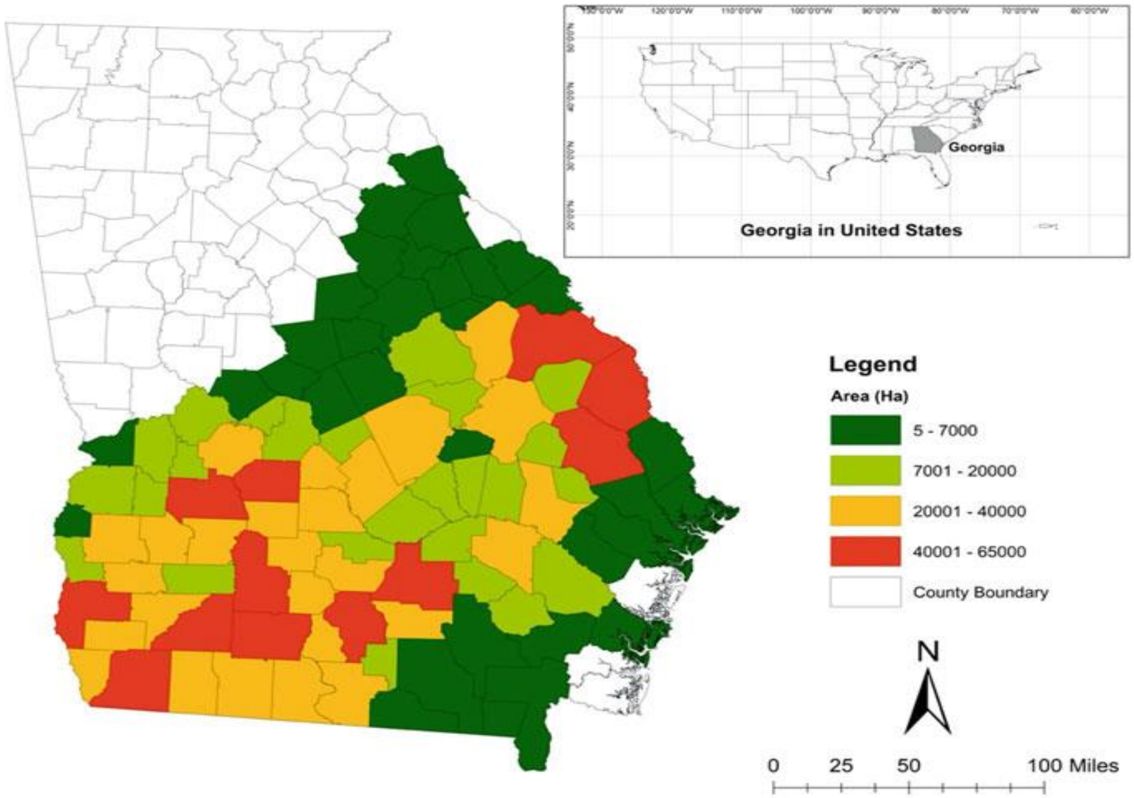


Fig. 1 County-wise land availability for carinata production (adopted from [13])

services. The allotted overhead costs, such as costs of labor, machinery and equipment, taxes, insurance, and other general farming overheads, are not included in net return estimations. As carinata is a row crop, it does not require any new machinery and equipment when being introduced into a new area. Therefore, considering only operating costs have no biasness for profit comparisons. Dedicated energy crops, which have no food value, are cultivated by the farmers as a cash crop in aspiration of making profit [23]. Therefore, without making profit farmers are not motivated for cultivating energy crops. The neighborhood influence parameters ascertain the adoption rate of rotations with carinata in the neighborhood that includes the county that a farmer belong and the surrounding adjacent counties. Each farmer has his own adoption threshold, which reflects how positive a farmer is for adopting carinata compared to the adoption rate [2, 4]. The adoption threshold parameters with different standard deviations shows whether the initial willingness on adopting carinata among the farmers are high or low.

Typically, it is suggested that carinata should be produced as double crop, once in every three years with two-years rotation gap [27]. To account for this in this model, the rotational period is three years for farm-scale modeling, which is extended up to 33 years (2018–2050) for long-term planning so that biorefinery investors can observe the feasibility of supply in the long run. Each tick or time step (t) of the model therefore represents three years (due to crop rotations). The model is spatially explicit in terms of aggregating individual agents' decisions to the county level. However, decisions are made at the farm level.

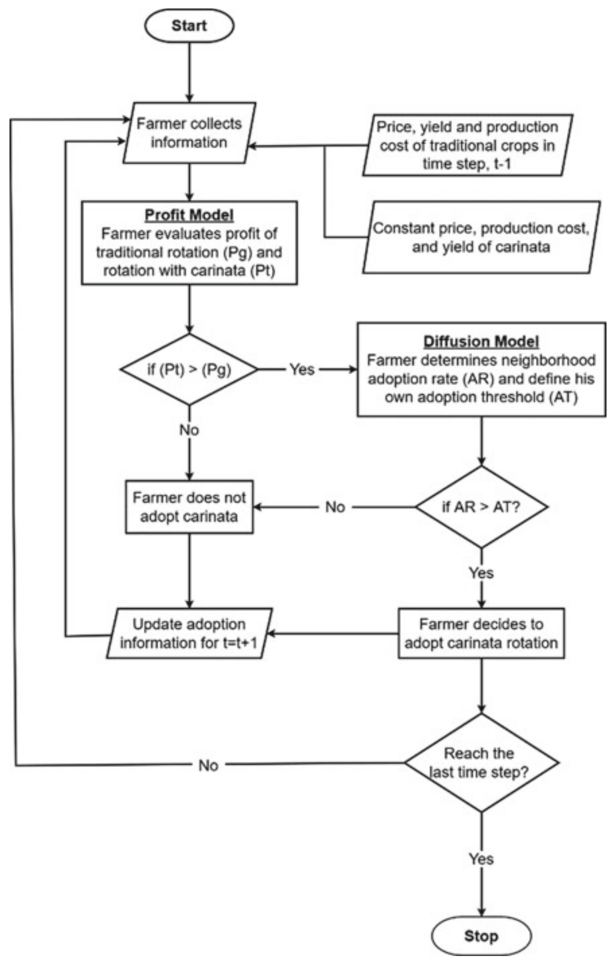
2.3 *Process Overview and Scheduling*

Farmer agents' adoption decisions of carinata are reflected in two sub-models of profit modeling, and diffusion modeling (see supplementary material at https://www.comses.net/codebase-release/5c2c06f0-3f6d-4f8d-b198-ce24b55feb2f for more details). The profit modeling evaluates farmers' profits of row crop rotations with and without carinata. While the diffusion modeling determines farmers' attitudes towards adopting carinata under neighborhood influences. 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 build 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. Figure 2 shows the flow of farmers' decision-making framework spread across two sub-models. How farmers decisions are reflected in both sub-models is discussed at detail in the supplementary material.

2.4 Initialization

At the farm level, three categories of farmer agents are created in each county with specific crop rotations:—(1) cotton-cotton-cotton farmers; (2) cotton-cotton-peanut farmers; and (3) cotton-cotton-corn farmers. The number of farmer agent in each category under a particular county was created according to the ratio of those three major crop rotations among the total field crop area of the county for the year of 2015–2017. The total farmland and the ratios of major rotations of each county were captured from the Crop Data Layer (CDL) [32]. The creation of farmer agents from actual crop rotation histories enabled us to build a more spatially and temporarily informed agent-based model compared to existing models in the context of energy crop adoption (e.g., [7, 20, 26]). By utilizing this temporally and spatially explicit crop distribution attribute, we can more realistically estimate farmers' profits and the potential integration of carinata into traditional rotations according to the agronomic conditions (e.g., the herbicide effect for cultivating carinata after peanuts) [27]. The adoption thresholds of the farmers are set using two normal distributions, which ultimately create a high and a low initial willingness scenario. Initial adoption rate (AR) is assigned zero at the start of the simulation period. The AR value is a neighborhood level value (which is discussed further below), however, all the farmers

Fig. 2 Process, overview and scheduling



in their respective neighborhoods are equally informed about that value, hence, the parameter is assigned as a farmers' attribute for simulation purposes.

At the global level, crop yields, prices, and farming costs are set at the initialization of the model. The crop economics data is acquired from USDA, Economic Research Service at the Southern Seaboard regional level [34]. The initial contract price of carinata is fixed by analyzing historical crop rotations and by comparing with the best profitable scenarios of traditional crop rotations in previous three years period from base year (see [30] for more details).

Two diffusion types are selected—(1) Traditional and (2) Expansion diffusion [21] as shown in Fig. 3. The rationale for exploring these different diffusion processes is to explore how carinata might defuse over the area. These could be considered as two different 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., the entire Georgia for this study). Traditional diffusion, which can also be

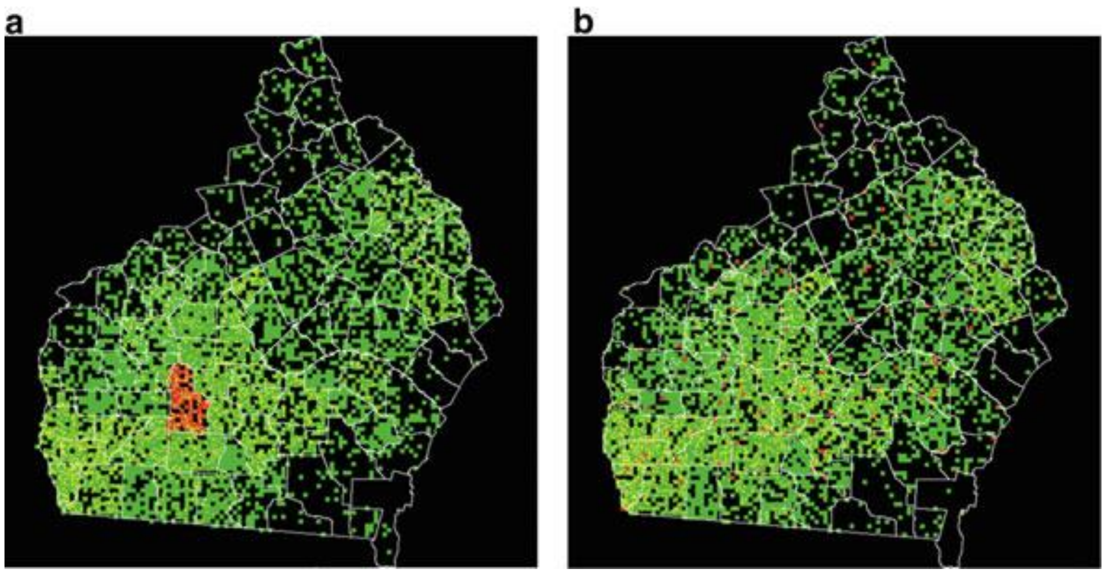


Fig. 3 Adoption scenarios at time step 1 where Red agents (i.e., farmers) are the early adopters: a traditional b expansion diffusion exam

considered as contiguous diffusion, (e.g., [21]) starts from pilot site in a single or few adjacent counties located at Experimental Little River Watershed, which contains around 2.5–5% farmers of the whole Georgia. This part of Little River Watershed is the most prominent place in Georgia for doing experimental and field research led by universities and relevant agricultural extension departments [6]. Starting at this watershed, the adoption behavior is diffused from early adopters to the neighboring farmers and subsequently, it spreads all over Georgia throughout the simulation period. In case of expansion diffusion, the early adopters are spread all over Georgia at the initial stage rather than located within a single small geographical area; and then, other neighboring farmers learn from their experiences, thus, the adoption behavior is diffused over the study area.

3 Results

Before presenting the results of the model, we applied several verification processes to ensure that the model matches its design. We achieved model verification using iterative design review (i.e., code walkthroughs), visual debugging and parameter testing via sensitivity analysis. Once we were satisfied the model was verified, we then moved onto scenarios exploration. The model is simulated under three profits (low, average, high), two diffusions and two willingness scenarios on adoption with the contract prices of carinata at $7, $8, $9 and $ 10. The low profit scenario is defined with lowest yield (40 bu/acre) and highest production cost ($280/acre) of carinata. The average profit is determined with average yield (50 bu/acre) and production cost ($270/acre). The high profit is calculated using highest yield (60 bu/acre) and lowest production cost ($260). Each scenario of the model is run for 10 times and the average results are presented in this paper.

According to Fig. 4, there is virtually no profit outcomes at price, $7, hence, there are very low adoption rates in the long run (e.g., only 3.3% by 2050 on average, and less than 5% for any scenarios). Adoption rates go considerably higher from $8 to $9 and $10. For instances, 7,408 (41.2%), 16,585 (92.2%), and 17,232 (95.8%) farmers adopted carinata by 2032 at a price of $8, $9 and $10, respectively under traditional and low initial willingness scenario (Fig. 4a). However, the adoption rates fluctuate at the price of $9 and $10, and there is no significant difference between them for long term adoptions. For example, in 2044, the adoption rate under expansion diffusion and high willingness scenario was 80% at a price of $10 and that adoption rate under the similar scenario was 94.5% at the price of $9 (Fig. 4d). By 2050, the adoption rate at $10 was higher than that of $9. From investors perspective, they would rather offer a contract price of $9 to the farmers rather than fixing it more than that, because investors will get almost equal adoption rates at this price. The overall adoption rates in the long run remain almost similar for all the scenarios, but adoption rates are higher at the year of 2026 for high initial willingness scenarios, and for expansion diffusion with high willingness scenarios, that figure is highest at any given contract price.

Carinata could be a profitable enterprise even at a price of $7 in an average yield and production cost as shown in Fig. 5. A high adoption rate appeared at $7 under any condition of average profit scenarios. However, the adoption rates get more stable at $8. Therefore, investors may look for getting carinata seeds at that contract price. Similar to Figs. 4 and 5 also shows the higher adoption rates (e.g., 60.7% and 65.6% at price $8) in short term (before 2026) in higher initial willingness scenarios (Fig. 5b, d) and highest in case of expansion diffusion (Fig. 5d). The same findings are also reflected with Fig. 6 in the high profit scenarios. However, in high profit scenarios, a contract price of $7 can be enough to maintain the desirable adoption rates in the

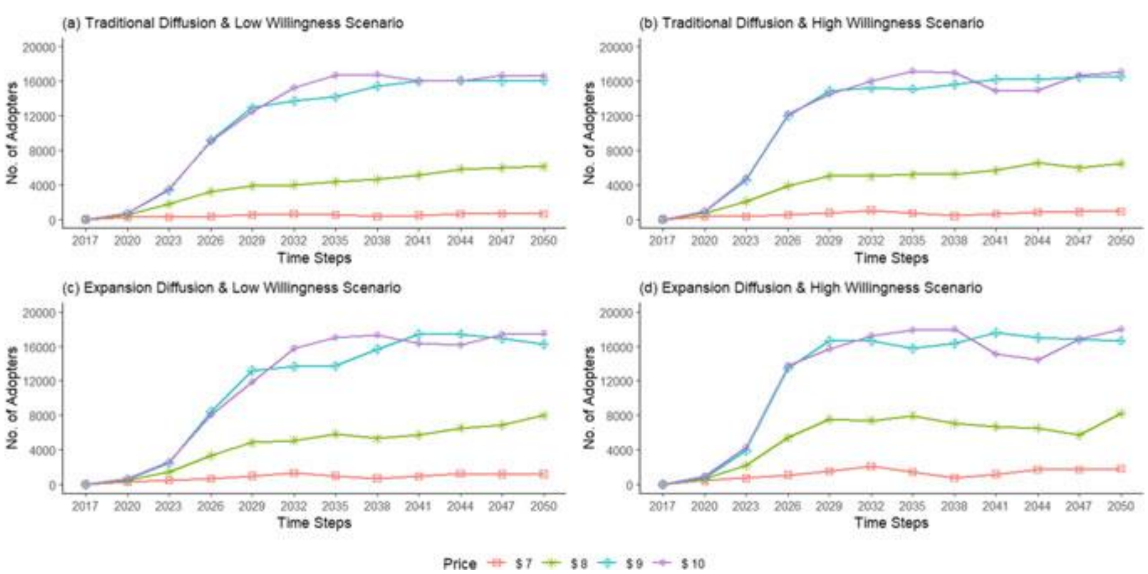


Fig. 4 Number of farmers who adopt carinata in specific rotation years with low profit condition (carinata yield = 40 bu/acre, carinata production cost = $280/acre)

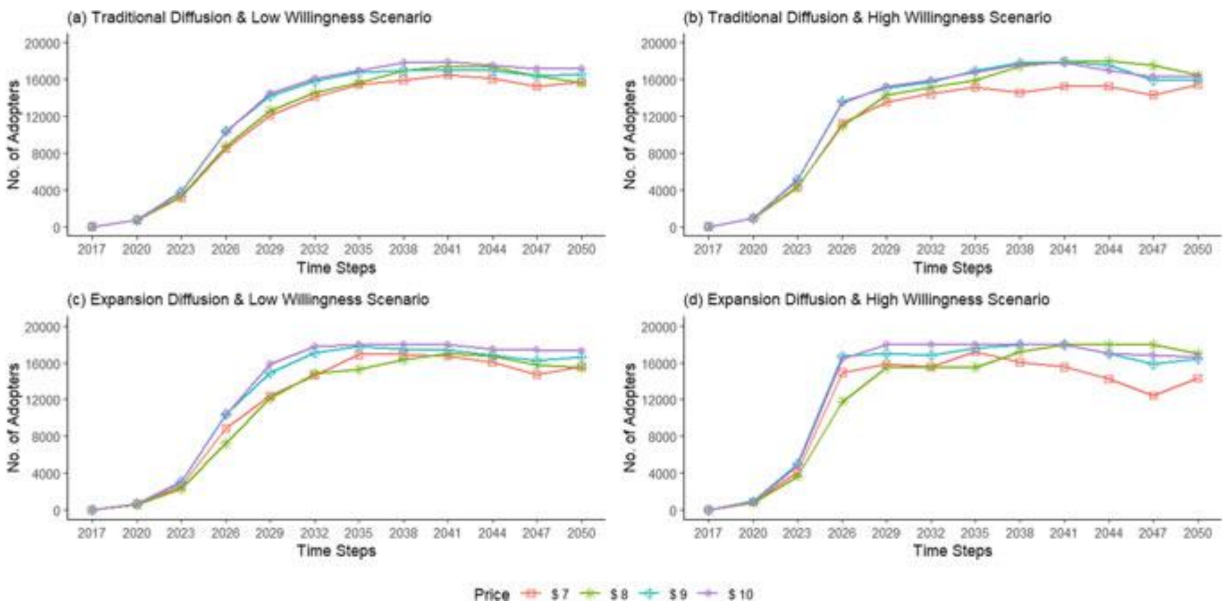


Fig. 5 Number of farmers who adopt carinata in the rotation years with average profit condition (carinata yield = 50 bu/acre, carinata production cost = $270/acre)

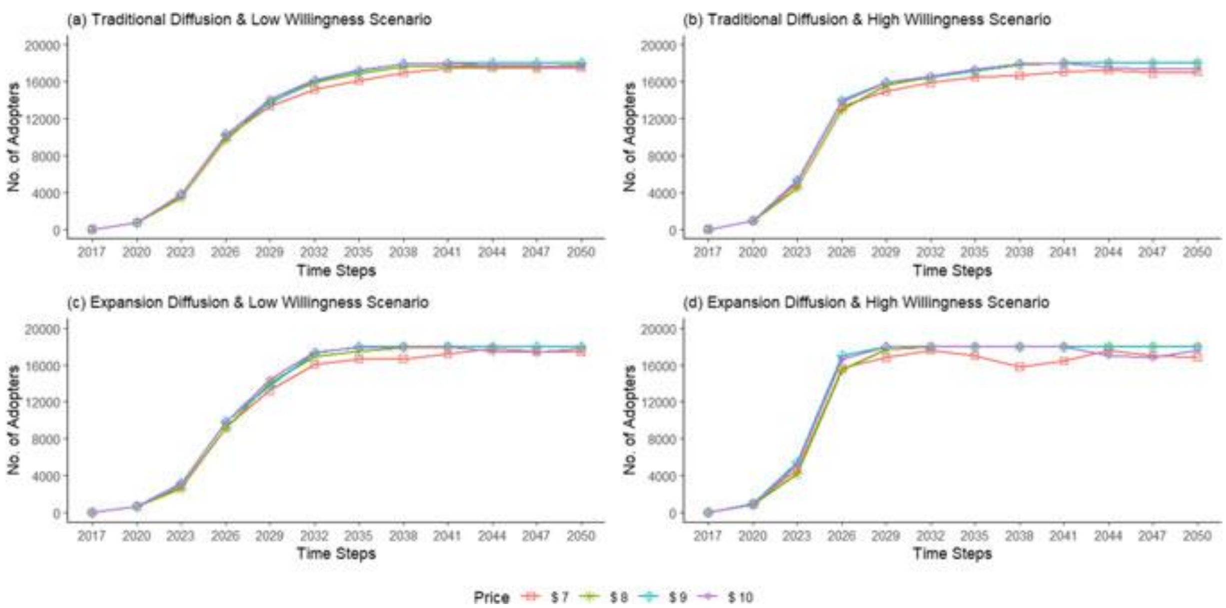


Fig. 6 Number of farmers who adopt carinata in the rotation years with high profit condition (carinata yield = 60 bu/acre, carinata production cost = $260/acre)

long run, such as the adoption rates ranged between 93.2 and 97.3% by 2050 for all the scenarios at that price.

4 Summary

The aim of this paper was to explore how farmers might adopt bioenergy crops across a large geographical area. Results from our model suggest that a viable contract price made by investors can persuade farmers to adopt carinata. Similar to what one might observe in the real world (e.g., [4]), the adoption rate for this newly introduced crop remains low at first but changing the dynamics of initial willingness on adoption can speed up the rate of this new bioenergy crop, especially under the expansion diffusion scenario. Therefore, it could be suggested that if there was a campaign to promote the adoption of this bioenergy crop, policymakers should consider its initial dispersion of pilot sites over a large geographical region and provide a reasonably high contract price.

Looking towards future work, all models have their limitations, and this model is no different. One such area is that of the farmers' risk aversion, which is currently not accounted for in this model, but it might impact their land allocation decisions (e.g., [2]). Therefore, one might want to explore the usefulness of risk portfolio estimation methods (e.g., mean–variance optimization, statistical dominance analysis), which could be embedded within the farmers individual decision making. In addition to this, the current model does not consider dynamic environmental factors such as weather conditions that can affect crop yield or how yield variations across the counties due to different soil conditions and the environmental benefits or loss that can accrue for cultivating bioenergy crops. To fulfill this gap, our future modeling work will consider frost event frequencies based on past events along with potential yield variations and net soil organic carbon stocks which can be estimated from other models such as the DayCent model [13]. Even with these limitations and areas of further work this paper offers a new way to explore how farmers might adopt bioenergy fuels and through the provision of the source code and data allows others to extend or adapt the model to their own biomass and bioenergy study fields which could be used as a tool to reduce greenhouse gas emissions from fossil fuels.

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