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Changing the World's Energy Future

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1 Introduction

Biofuels have the potential to limit fossil fuel use and offset environmental emissions particularly in the transportation sector [1]. The Energy Independence and Energy Security Act of 2007 established the Renewable Fuel Standard (RFS) and annual targets for biofuels from a variety of feedstocks. In its initial formulation, the RFS mandated 36 billion gallons of biofuel production by 2022, of which at least 16 billion gallons was to be produced from cellulosic sources. While the targets have been lowered on numerous occasions in the past, the goal of developing technologies for the sustainable and economically viable production of biofuels to encourage the creation of domestic business sectors and support for rural communities has sustained. Transportation biofuels, such as cellulosic ethanol, if produced from biomass grown on agriculturally marginal land or waste biomass can potentially increase biofuel supply and provide a range of environmental benefits [2, 3]. However, the commercial development of biofuels and bioproducts is incumbent on the availability of renewable biomass, that can be transformed into biofuels, while not directly competing with the production of food.

Lignocellulosic biomass sources, especially dedicated energy crops, are expected to play an important role in the development of supply chains for biofuels and bioproducts into the future [4-6]. Several studies have explored the potential for cultivating energy crops on lands under the Conservation Reserve Program (CRP) by investigating economic, environmental, and policy dimensions [7-9]. CRP is one of the most well-known voluntary conservation programs in the United States which enables changes to land use and cropping practices whereby farmers opt to enroll environmentally sensitive lands into a conservation program. While the perspectives of landowners and their motivations for enrolling land into CRP may vary, offering low-producing fields to the CRP is a way to minimize costs associated with cultivation of poor-quality lands [10]. However, the available spots in CRP are limited and many of the requests to enroll in the program go unfilled. In 2016 there were only 4,842 accepted requests, leaving over 81% of the requests unfilled, or 1.5 million acres (0.61 million ha)[11].

In addition to energy crop plantation on CRP lands, there are areas of high corn production which have the potential of supporting sustainable harvest of residue that should not be overlooked [12]. While a portion of the residue is required to remain on the field to maintain certain levels of soil organic carbon, excess residue potentially leads to increased Nitrogen supplementation and more intensive tillage practices [13, 14]. Both of these conditions lead to increased cost to the farmer and are potentially detrimental to the environment [13]. Under these conditions, the removal of crop residues can lead to reduction of operating costs and may serve as a motivator for farmers to provide corn stover as a biomass feedstock for an additional revenue stream. Roni et al. (2019) that crop removal in high corn production areas could reduce biomass access costs by 20% and increase biomass availabilities in Kansas, Nebraska and Colorado [15].

2 Literature Review

The opportunity for establishing energy crops or collecting agricultural residues exists, however, its fulfilment depends on farmer's willingness to participate. Surveys of farmer willingness to grow dedicated energy crops have been used to gain an understanding of the motivations of farmers [16-19]. These studies typically use the expected utility framework to evaluate farmer decisions and their willingness to produce bioenergy feedstocks under varying contexts including opportunity costs, contracts, risk, and individual or farm-level characteristics. Such approach assumes that farmers make purely rational decision, in which the farmer is acting in his or her own self-interest [20-22]. However, farmers considering entry into the bioenergy market are confronted with a range of uncertainties related to feedstock price, crop yields, market dynamics, policy contexts, etc. Their decision making process is rarely purely rational, but rather intuitively based on the needs at the time and guided by the information that they have access to [23, 24]. As a result, farmer behavior is difficult to model while taking into account a wide range of complex individual-level factors, socio-temporal dynamics, institutional settings, and their interactions [25].

Agent based models (ABMs) are well-suited for modeling a stochastic system, like farmer adoption behavior, that utilizes the interactions between agents and their environment to understand the behavior of complex systems [26]. ABMs provide a framework for incorporating economic and non-economic factors including environmental, spatial, and social influences into individual decision-making [27, 28]. These models are well suited to simulate a system in which the behavior of agents is not known with complete certainty and it is possible to incorporate stochastic decision-making based on underlying probability distributions. ABMs allow for decentralized decision-making, accounting for heterogeneity among individuals and enable an evaluation of broader system-level outcomes resulting from these interactions. As a result, ABMs have found wide application in agricultural research, and more specifically, in modeling of adoption practices pertaining to bioenergy. Since we are modeling a nascent industry and trying to understand how this market is likely to develop in the future, ABM provides a suitable tool for studying potential outcomes in scenarios.

Gan, Langeveld, and Smith (2014) [29] used an ABM to estimate the transboundary impacts between agents participating in the bioenergy value chain. They considered feedstock producers and conversion plant operators in their modeling framework to understand the beneficiaries of the economic values accruing to the different agents. While their analysis suggested that the value accrued to farmers may be minimal in the case of stover harvest, their estimates were sensitive to factors such as cost of harvest, stover price, and ethanol yield. Others have used a combination of mathematical programming and agent-based simulation model to model the decisions of farmers in Iowa, USA [30]. Their primary motivation was to explicitly include the impact of neighboring farmers on the decision of model agents. They found that raising the contract price for switchgrass was not an efficient way to promote its cultivation, whereas educational programs could provide more favorable outcomes for bioenergy adoption.

Although economic considerations are important, non-economic factors such as conservation motives and attitudes towards the environment can also influence farmer decisions. Combining insights from survey-based studies with ABMs has been used to evaluate adoption of bioenergy crops for different famer types and farming enterprises [31]. Zupko et al. (2016) [32] evaluated voluntary incentive programs wherein landowners received financial incentives for compliance with program guidelines. The mechanism provided additional financial incentives for neighbors to recruit others based on participation rates and concluded that such arrangements can result in better management of resources and produce more sustainable outcomes [32]. Furthermore, incorporating spatial attributes into the ABM framework can also provide valuable insights into farmer adoption decisions [33]. Jin, Mendis, and Sutherland (2018) [34] simulate the spatial diffusion of switchgrass in Indiana, USA under a range of biofuel market scenarios to find that high switchgrass productivity can increase adoption rates of farmers.

These studies, and many others, provide valuable contributions to the literature by investigating the propagation of bioenergy crop adoption from varied perspectives. Our research builds on earlier studies to examine farmer adoption of bioenergy feedstocks by estimating their participation and the proportion of land allocated for harvesting crop residues and energy crop cultivation. We focus on a combination of factors that have not been studied before to assess levers that can help establish bioenergy crops as feedstocks. First, we incorporate farmer characteristics including age, occupational life cycle, innovation propensity, and knowledge into the model framework. Second, we use spatial data to integrate county-level characteristics, farm attributes, and land quality into the model. This allows for a more realistic assessment of types of land use change that is likely to emanate from bioenergy crop adoption. Additionally, we account for market structure, social networks, and information dissemination pathways to study their influence on farmer adoption decisions. Our model can be adapted for a different geographic region and provides a framework that can be utilized to evaluate farmer behavior in alternate settings.

3 Study Region

The region of interest for this study includes 50 counties, encompassing three states: Nebraska, Kansas and Colorado (Fig. 1) as it constitutes a variety of land uses including pasture for hay production and corn cultivation. County characteristics such as crop land area, cropping pattern (% crop land in corn, winter wheat, soybeans, sorghum, etc.), irrigated pattern (% irrigated vs. non-irrigated), soil productivity (minimum, maximum, average) and farm size distribution are compiled from a variety of publicly available databases [35]. Within the 50-county study area, the eastern portion overlaps with some of the highest corn producing regions in the nation and has a great potential to supply crop residue. The central and western portions have the potential for cultivating energy crops and provides a suitable test-site for evaluating farmer adoption decisions within the United States.

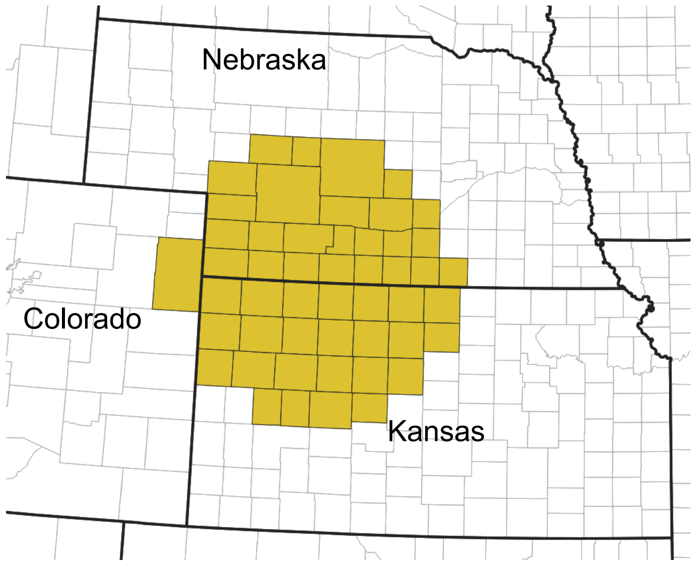

Figure 1: Study region for the analysis encompassing 50 counties in eastern CO, southwestern NE, and northwestern KS.

4 Model Overview

To model farm management, the decision analysis was done at the farm level. The model followed the Agent-Based Modelling principles and was constructed in the AnyLogic software, version 8.5 and has two main agent types: farmers and farms. The simulation in the model spans 50 years. There are 2,000 farmers in the model, which helps in limiting the computation time to approximately 30 minutes for each run on a personal desktop computer. The initialization mechanism to define the agents and farm characteristics ensures that they are representative of the region as the age distribution for the farmers and farm related variables such as size and soil quality are based on the distributions observed in the data for the region from USDA Census of Agriculture and National Commodity Crop Productivity Index (NCCPI) used by the Natural Resource Conservation Service At the beginning of the simulation, farmers are stochastically generated, with specific characteristics based on age, risk preferences and innovation propensity. Each farmer is randomly assigned to a farm in a randomly chosen county. The specifics of the farmer attributes are presented in the following section.

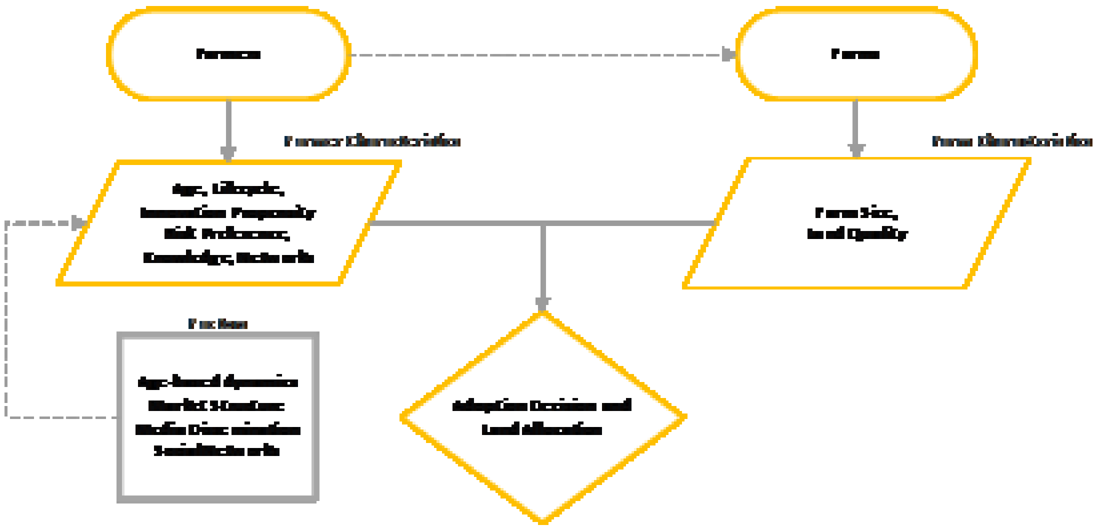

Figure 2: Simplified model overview diagram of farmer decision-making.

4.1 Farmer Characteristics and Decision Framework

4.1.1 Age

Survey-based studies have tried to identify the influence of farmer's age on farmer adoption decisions pertaining to bioenergy crops, however, the insights are somewhat ambiguous. For example, age may have important implications on the farmer's risk aversion and negatively influence adoption decisions for older farmers especially where modifications to farming practices require large capital investments or entail greater financial risk [36]. On the other hand, knowledge accumulation and experience with farming systems, often higher for older farmers, is likely to be positively related to technology adoption in farming practices [37, 38]. Similarly, some farmers could adopt perennial bioenergy crops because they are less demanding from a labor-input perspective [39].

Table 1: Farmer's age distribution [35]

Age group	% farmers
< 25	1%
25 – 34	7%
35 – 44	11%
45 – 54	18%
55 – 64	28%
65 – 74	22%
>=75	12%

In the model, farmer ages are initialized with the age distribution shown in Table 1, following from the Census of Agriculture conducted by USDA National Agriculture Statistics Service [35]. Farmer willingness to participate in bioenergy markets has been studied in several survey-based studies, in the mid-western United States, with willingness rates ranging between 26% and 46% [16-19, 39, 40]. Studies evaluating adoption of bioenergy crops, environmental best management practices, precision agriculture techniques and perennial crops for conservation were used to inform assumptions on the influence of age on farmer adoption decisions. The rates of change in adoption, both increases and decreases, are assumed at 2.5% across the age categories, which is reasonable based on the range of values estimated in the survey-based literature [17, 18, 40-42].

4.1.2 Occupational Life Cycle

Intergenerational succession is a critical aspect of farm management and sustenance of rural economies [43]. The USDA Census of Agriculture indicates an increasing average age of famers which points toward delayed retirement [44]. In some cases, surveys indicate that farmers do not intend to retire at all or only plan to semi-retire from farming [45]. A farmer's life cycle, implemented in this model, is delineated in in Fig. 2. A beginner becomes a mid-career farmer at age 35. At age 55, they become a senior farmer. At age 79, a farmer is ready to retire, and it takes them another year to arrange future ownership for their land, either by handing down to children/relatives or selling their land. Although the given cut-off ages are hypothetical and may vary, farmers working through their late-70s is not uncommon in the United States [46]. For this model, the cut-off ages help quantify the age structure of the farmer population at a given time.

Succession in farming is not a single event but a process that requires substantial effort and planning, usually occurring over a period of time [47, 48]. Previous studies highlight that in the United States, successors are identified in less than a third of the cases [45]. However, out of the land that is likely to be transferred, approximately 25% is estimated to be sold to a non-relative [49]. In our model, the "handover" transition of land is controlled by the variable "probabilityOfHavingHeirs" which is set at 0.75. In other words, 75% of retired farmers hand down their farms to their family. Meanwhile, 25% of the retirees sell their farms to a randomly selected neighbor. Once retired, that farmer is no longer tracked by the model.

4.1.3 Innovation propensity and Risk preferences

Openness to new practices or willingness to innovate is a key attribute for the initial establishment of a new practice. However, innovators are rare in any population. To mimic the relative tolerance of risk that is seen in the population in general, the agents were given an "innovation score". The purpose of the innovation score was to provide a numerical representation of an agent's propensity to learn about a new technology. Similarly, farmer attitudes towards risk also influence farmer willingness to participate in bioenergy markets where risk averse farmers are less willing to adopt bioenergy crops [16, 19].

In our model, each farmer is randomly assigned an innovation score and a risk score, ranging between 0 and 1. A low risk score implies that the farmer has lower risk aversion and is more willing to take on additional risks. Furthermore, a low innovation score implies that the farmer is more willing to consider the new practice as it requires little innovation from the farmer. The risk and innovation scores were used to define the criteria necessary for an agent to consider adoption of a practice and adjust the age-based adoption percentages for the farmers.

A small population of innovators, based on their innovation scores, are triggered to adopt the new practice of residue harvest and to begin learning about energy crop cultivation. We assume that low innovation scores obviate need for knowledge through media or interactions with others in the social network that are practicing before adoption could occur. Farmers who have an innovative score of 0.025 or lower and a portion of their farmland with high yield practice harvesting crop residues. Meanwhile, farmers with an innovation score of 0.16 or less and having a portion of their farmland with low productivity are assigned to learn about energy crops. The decision rules based on the innovation scores were informed from the Roger's Diffusion of Innovation curve that delineate relative proportions of the population that fall into each innovation category [50, 51]. The calculation for the proportion of farm with high/low yield is described in the Farm agent sub-section. A farmer does not consider any of the aforementioned practices if they do not have a high yielding or a low yielding land.

4.1.4 Knowledge, Social Networks, and Learning

Initially, none of the farmers are aware of any new practices. As illustrated in Fig. 3, some farmers adopt crop residue harvest if their innovation score and land productivity based on the equations discussed below. Knowledge about new agricultural production practices is often passed through social connections and is an important aspect of diffusion of new practices and technologies in agriculture [52, 53]. In our model, farmers primarily learn about bioenergy practices though their social networks and media. Agents are assigned social connections randomly, with a contact rate of 10 farmers which translates to approximately 0.5% per year.

The adoption decisions of a farmer are calculated using equations 1 and 2. If a farmer is aware of bioenergy-related practices, they might be interested in adopting them based on their propensity to innovate. An innovation-based learning score, based on age-based adoption and the innovation score, is computed for each for each farmer using Equation 1:

(1)

The innovation-based learning score is updated by incorporating the farmer's age-based adoption rate and the likelihood of adoption based on their risk-taking propensity to arrive at a combined adoption rate as follows:

The learning process for crop residue does not have a time lag as it only involves baling of material and is assumed to be known by the agents. Meanwhile, once farmers adopt a practice, they tell members of their network about their adoption decision. Although individuals within a social network might become aware of bioenergy-related practices, only some of them are interested in pursuing this alternative owing to their propensity to learn, which is based on their innovation score as shown in Equation 1 and the whole cycle repeats.

To track each farmer's knowledge for crop residue, a "residue_knowledge_score" is assigned for each state. When farmers are aware of residue harvest, their score is 1. When they consider residue harvest, their score is 2. When they adopt, the score is 3. This score is handed down from one generation to another, meaning that if a farmer practices residue harvest, their children will also know how to implement it. Furthermore, when the land is sold to a neighbor, the farmer with a higher score will transfer knowledge to the farmer with a lower score. In this case, since crop residue is harvested at a farm, the buyer can easily learn about the practice and take over.

The modeling approach for the adoption of the energy crop is similar to crop residue but with some delays. Once the early learners are assigned by the model, farmers take three years to learn because establishing a perennial usually follows a similar timeframe. At the end of year 3, farmers decide if they want to adopt the new practice. The adoption rate is calculated by using Equation 2. Note that in this case the adoption rate based on age for Equations 1 and 2 are different because Equation 2 is applied 3 years after Equation 1 is calculated. Once farmers adopt, they will make other farmers in their social network aware of energy crop via word of mouth. In addition to talking to neighbors, other farmers can also learn about energy crop via the media. Their "want_to_learn" rate is calculated based on Equation 1. Energy crop knowledge score is tracked similarly to crop residue score, albeit on a 4-point scale, where 1, 2, 3 and 4 are assigned for being aware, learning, considering, and adopting energy crop. The same knowledge transfer (knowledge score) rules are applied when ownership is handed down to heirs or buyers.

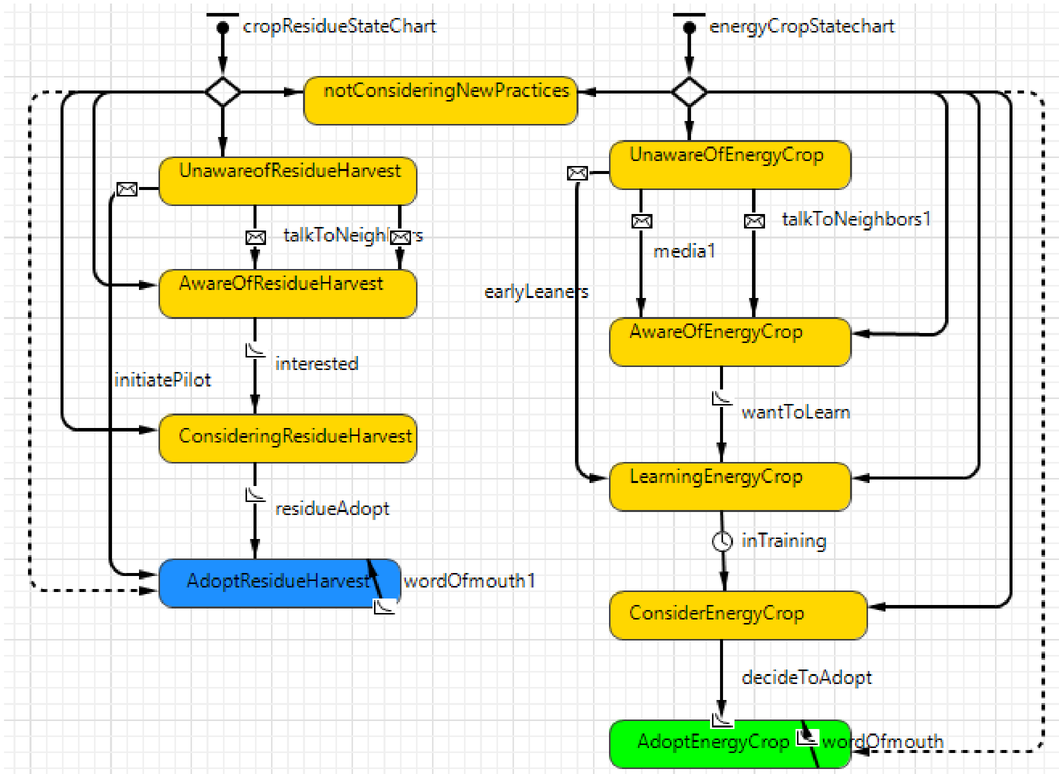

Figure 3: Farmer's learning state chart of crop residue and energy crop practices

4.2 Farm Characteristics

There were 2,000 farms in the model, equivalent to 1.05 million ha. of crop land. Each farm was randomly assigned to a county representing that county's soil profile, and the size of the farm was based on the distribution of land sizes for the specific county.

4.2.1 Farm Size

The size of the farm was based on the distribution of farm sizes for each country based on the Census of Agriculture [35]. The peak value was set to the midpoint of the minimum and maximum values for each county. There are 8 categories ranging from 40.47-56.64 ha, 56.65-72.83 ha, 72.84-89.02 ha, 89.03-105.20 ha, 105.21 – 202.33 ha, 202.34-404.68 ha, 404.69-809.36 ha and greater than 809.37 ha.

4.2.2 Farm-land quality

A distribution of land quality for each farm was generated based on the National Commodity Crop Productivity Index (NCCPI). The NCCPI is an index used by the Natural Resource Conservation Service, to provide a standard way of comparing soil productivity on a national scale. For each farm, depending on the county, the minimum productivity is randomly selected between zero and the lowest county NCCPI. Average productivity is randomly determined within the range of county's minimum and average NCCPIs. Maximum values are set by selecting values between the county mean and maximum NCCPIs.

The distribution of NCCPI are utilized to identify the quantity of land that could be available for the production of perennial energy crops or for harvesting crop residues. The quantity of low producing land that could be made available for the production of perennial energy crops is determined by examining the percentage of land in each county that is offered into CRP. The percentage is then used to identify the cutoff value for the county. On the other hand, it was assumed that if the NCCPI value for an acre of land was within the top quartile of the specified values, crop residue harvest would be possible for an economic benefit. We posit that the harvesting of residues on high quality land will not adversely affect the soil health and removal of such residues will benefit ongoing cultivation practices.

Based on this distribution, percent of low yield and high yield of each farm are calculated as shown in Equations 3, 4a and 4b:

(4a)

Where: crp_{cutoff} is the cut-off productivity to determine low productivity land
$prod_{min,\ max,\ ave}$ are the minimum, maximum and average productivity of a farm
res_{cutoff} is the cut-off productivity to determine high productivity land suitable for crop residue, having a value of 0.75 for all counties.

Using the $\%low_{yield}$ values, actual low yield acreage for each farm was derived. Four types of crops were considered: corn, wheat, soybean, and sorghum. Irrigated and non-irrigated area of each crop were calculated based on each county's attributes, in which the non-irrigated area was subtracted from low productivity area. The model assumed that a farmer considers cultivating an energy crop only on low productivity area but might practice crop residue harvesting on both irrigated and non-irrigated corn areas. Therefore, the crop residue harvested area equals the $\%high_{yield}$ multiplied by the sum of irrigated and non-irrigated corn areas.

5 Scenarios

5.1 Base Case:

Age is an important characteristic that can influence propensity to try new agricultural practices and participation in new markets [36, 37]. To accommodate for the diversity in the literature, we formulate three separate cases for age-based adoption decisions for farmers wherein adoption 1) is negatively correlated with age indicating that older farmers are more risk averse, 2) positively correlated with age indicating that older farmers are less risk averse, and 3) follows a U-shaped curve representing a higher adoption rate at the younger and older segments of the age spectrum. Since younger farmers could be more willing to try out emerging technologies and participate in new markets based on their increased propensity to undertake risks and relatively longer time-horizons of engagement in farming practices, we assumed that farmers in the lowest age group (< 25 years) have a 50-50 likelihood of participating in harvesting crop residue or cultivating a dedicated bioenergy crop (switchgrass) on their farms.

Table 2: Farmer's adoption scenarios based on age

	Adoption decreases with age	**Adoption increases with age**	**U-shaped adoption curve**
Age group	% farmers		
< 25	50.0 %	50.0 %	50.0 %
25 – 34	48.8 %	51.3 %	48.8 %
35 – 44	47.5 %	52.5 %	47.5 %
45 – 54	46.3 %	53.8 %	48.7 %
55 – 64	45.2 %	55.2 %	49.9 %
65 – 74	44.1 %	56.6 %	51.2 %

The market for bioenergy is anticipated to grow in the future owing to government mandates and potential technological advancements. We posit that famers who have participated in the bioenergy market in their early years, will likely continue to participate as they gain more experience. As a result, we use the positive age-based adoption case as a point of comparison for the different scenarios evaluated in the remainder of this paper. We compare the differences between crop residue and energy crop adoption across these cases against the reference case to evaluate, the impact of the subsequent scenarios on farmer adoption.

5.2 Market Structure:

Given that the bioenergy industry is relatively nascent, uncertain prospects have inhibited farmer participation. Vertical integration as well as contracting are management strategies that have been implemented for risk-mitigation and encouraging greater farmer participation across various agricultural markets [54]. As farmer participation in crop residue or energy crops could be influenced by their perceived risk of entering this market, we mimic a vertically integrated supply chain wherein a biorefinery enters into purchase contracts directly with feedstock producers. Differences in market structure might result in market regimes that depict varying levels of demand volatility which in-turn could lead to varying risk exposure for feedstock producers. Since a vertically integrated market structure could mitigate risks faced by feedstock producers, it will provide them with an assured demand for their produce. In our model, when the market is vertically integrated the risk score of each farmer is reduced by 1% with every passing year. This risk reduction influences farmer adoption positively through Equation 2.

5.3 Influencer credibility

Social networks enable farmers to increase their knowledge, learn about technologies, and evaluate the usefulness of new practices [55]. In rural areas, information diffusion can also help reduce the uncertainty in the mind of potential users [52]. Meanwhile, studies have evaluated the effect of social networks on adoption decisions in agriculture by analyzing the relative strength of ties within a social network [53]. We hypothesize in our model that farmers with high credibility have a higher influence on other members within their social network. Farmer's credibility is assumed to increase with the size of their operation. We posit that a farmer might talk to various farmers but the one with the largest farm size will have the most impact. Their impact is implemented by an "influence_factor" serving as a multiplier to Equation 1 and 2. If an influencer has a farm size less than 404.68 ha (1000 acres), the "influence_factor" is 1, implying no influence. If his farm size is of 809.37 ha (2000 acres) or greater, the factor is 2, otherwise it is 1.5.

5.4 Media

This scenario considers other means of communication beyond the neighbor network. Farmers can learn about different practices via the radio, TV, internet or extension agents. These channels of information put more farmers into the "Aware" state, which makes them more likely to adopt bioenergy related practices. This scenario is distinct from the scenario in 4.3 because a farmer becomes aware of different practices by either talking to his neighbor or getting exposed to the media. Within this scenario, we introduce the farmers to bioenergy practices in the first year once the simulation starts.

5.5 Combining market structure, influencer credibility, and media

The scenarios described above are expected to influence adoption, however, combining the scenarios delineated above helps evaluate the interactions between the different scenarios and the combined effect on farmer adoption decisions.

Table 3: Set of scenarios and specific components

Scenario / Consideration	Base case	Market structure	Influencer credibility	Media (1 year)	Combined
Age-based	Yes	Yes	Yes	Yes	Yes

adoptions					
Vertical integration	No	Yes	No	No	Yes
Influencer credibility	No	No	Yes	No	Yes
Media effects	No	No	No	Yes	Yes

6 Results and Discussion

The model simulated the evolution of farmer decisions over a 50-year period; however, we present data from the first 30 years of the simulation to emphasize that model dynamics provide insights on agent behavior in the early years of the simulation. After year 30, the adoption curves flatten-out indicating slower growth rates in the outer years of the simulation. We utilized Monte Carlo simulations to ensure statistical robustness of the modeling results. The number of simulations were varied to ensure that replications encompass a 95% confidence interval around the mean estimates with 0.5% error. The lower bound on the replications was set at 10 whereas the upper bound was set at 100. The data analysis and comparisons were performed using the average of the runs under each scenario. Overall, the adoption rates for residue harvesting and energy crop adoption tend to exhibit some convergence in the latter part of the simulation. Thus, the figures included in the results section of the paper focus on the early years of the simulation to highlight the impact of the different factors on the bioenergy feedstock adoption pathways during the initial years.

6.1 Farmer Adoption

Figure 4 plots the simulation results for adoption of crop residues and energy crops following the three age-based adoption curves shown in Table 2 in which adoption is related positively, negatively, and u-shaped to the farmer's ages. The u-shaped adoption rule captures the phenomenon that mid-career farmers are least willing to adopt new technology and practices. As expected, the adoption of both crop residue harvest and energy crop cultivation is the highest when adoption tendency is positively related to age. Where adoption is negatively related to age, modeling results in the lowest adoption rates, and the results from the u-shaped adoption rule lie between these two scenarios. These results are also influenced by the overall age-demographic because nearly 62% of the farming community is over 55 years old.

Figures 5-8 plot the comparison between the positive age-based adoption case and the scenarios described in section 4. In line with expectations, farmer adoption is indeed higher in the vertically integrated case for both residue harvesting and energy crop cultivation. The difference compared to the base case peaked in the 23rd year for crop residues (5.9 % higher) and the 21st year for energy crops (6.5 % higher), and subsequently tapered through to the end of the simulation period.

If large farmers are early adopters of residue harvesting practices or energy crop cultivation, their influence led to faster uptake of these practices by other farmers as well. In the case of crop residues, adoption under the influence of large farmer emerged almost immediately and persisted throughout the simulation timeframe. By the 6th year, the difference compared to the base case was over 22.4% in the case of crop residues. For energy crops, the difference between the two cases peaked in the 12th year and the magnitude was similar at 22.7%.

The effect of media influence reveals some interesting outcomes. For the crop residue case, the effect of media influence on percentage of farmers adopting residue harvesting practices was small, which could be attributed to no delay in learning the practice. On the other hand, information dissemination/media had a substantial influence on adoption of energy crops. Adoption was nearly 7.2% higher by the 9th year in the case with information dissemination as compared to the base case.

The combined effects of an integrated market structure, large farmers adopting bioenergy crops and practices, and 1 round of information dissemination with a positive age-based adoption scenario resulted in both faster adoption rates in the early years of the simulation and higher adoption rates at the end of the model timeframe. The difference compared to the base case peaked in the 6th year for crop residues (25.4 % higher) and the 11th year for energy crops (32.7 % higher)

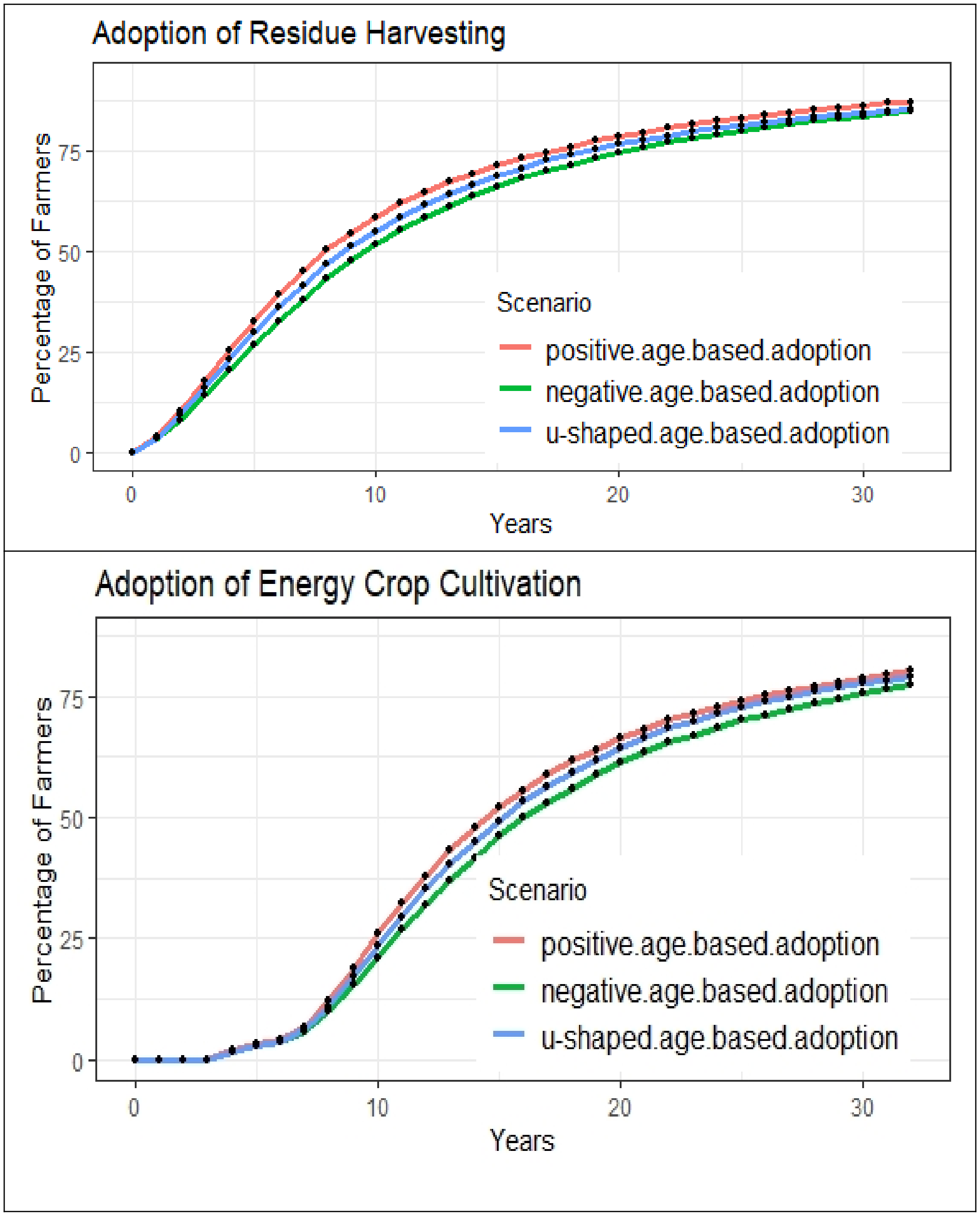

Figure 4: Comparison between adoption for residues(top) and energy crops (bottom) under multiple age-based adoption criteria.

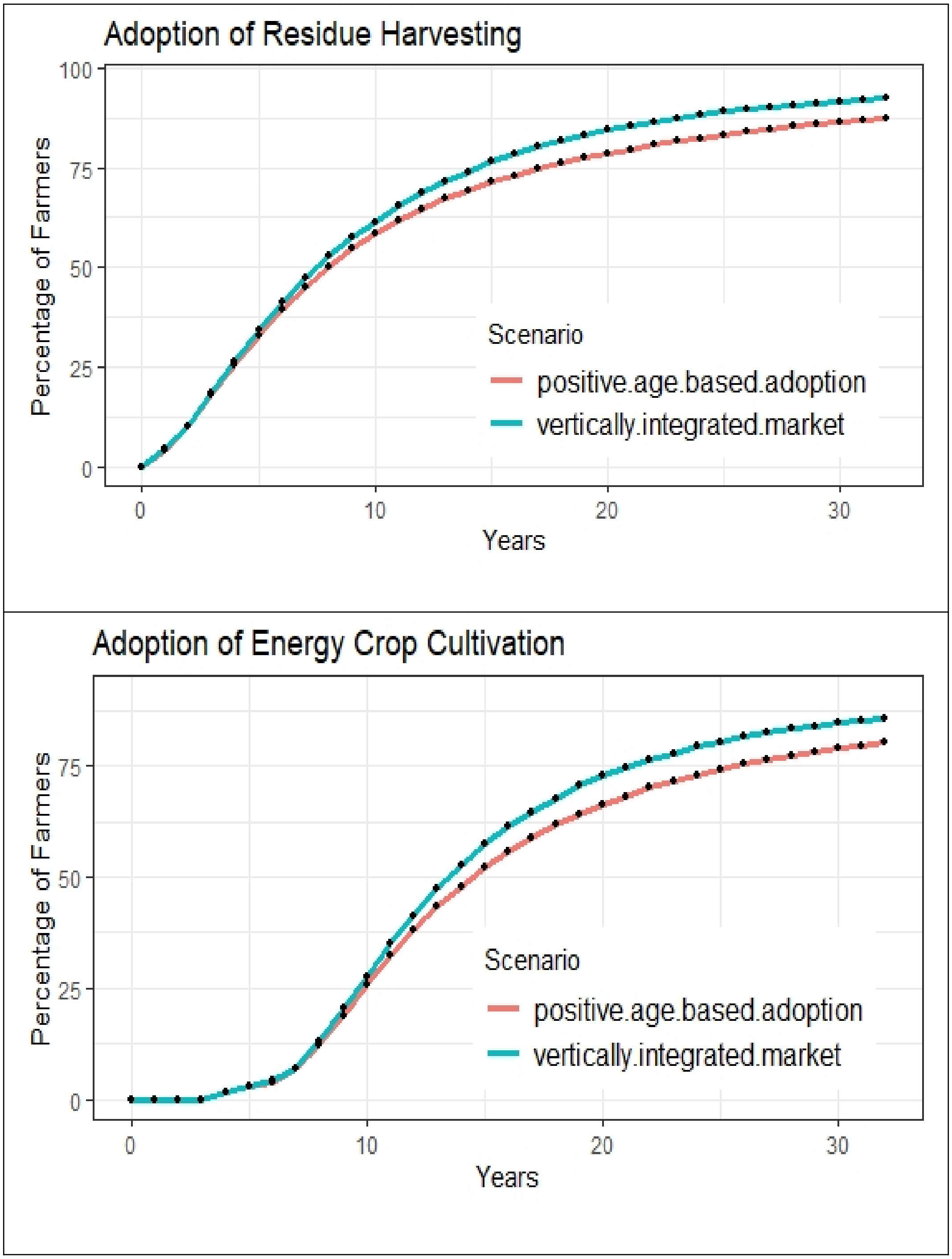

Figure5: Comparison between adoption for residues (top) and energy crops (bottom) under the vertically integrated and non-vertically integrates market structures.

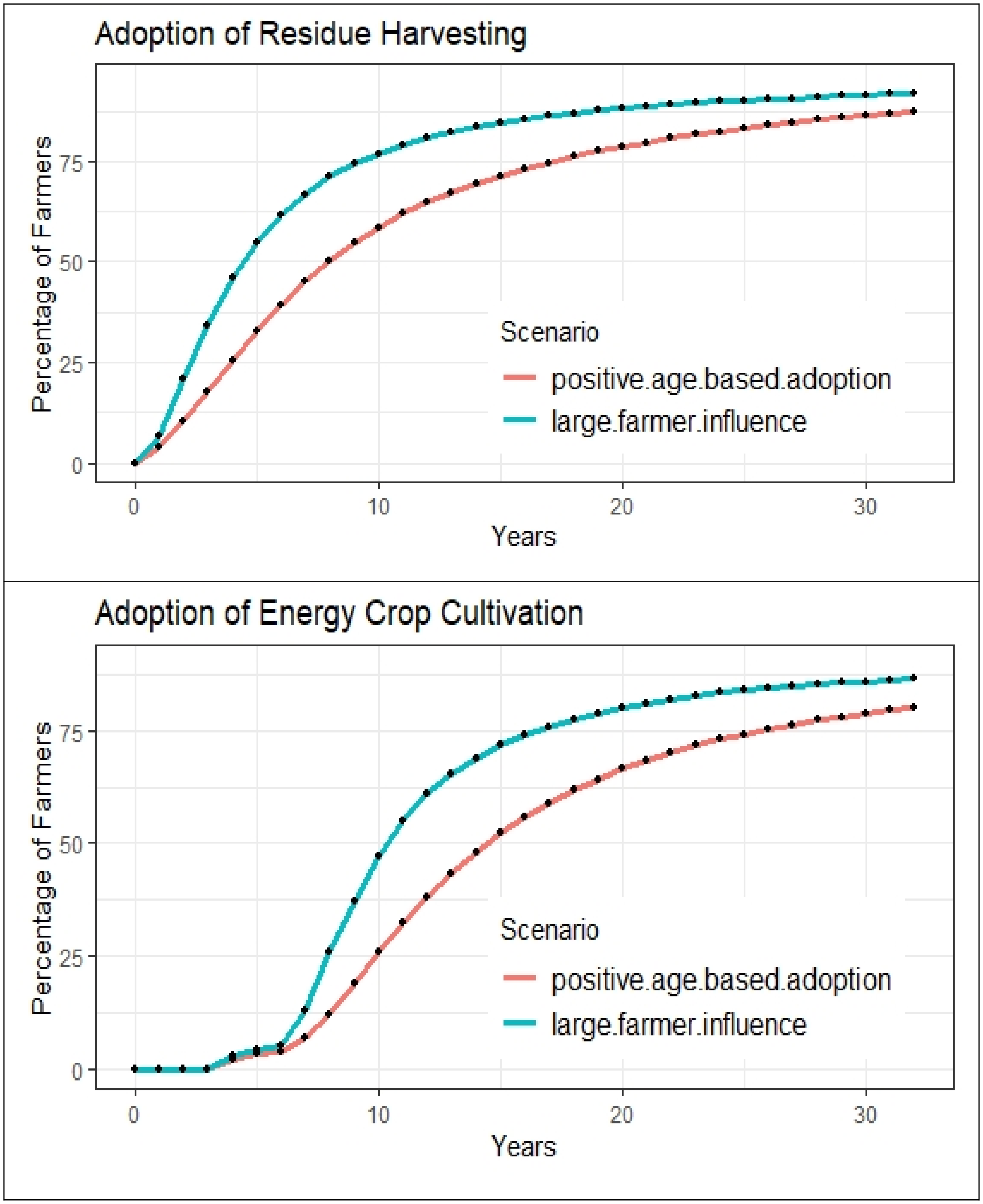

Figure 6: Comparison between adoption for residues (top) and energy crops (bottom) accounting for influence of large farmers.

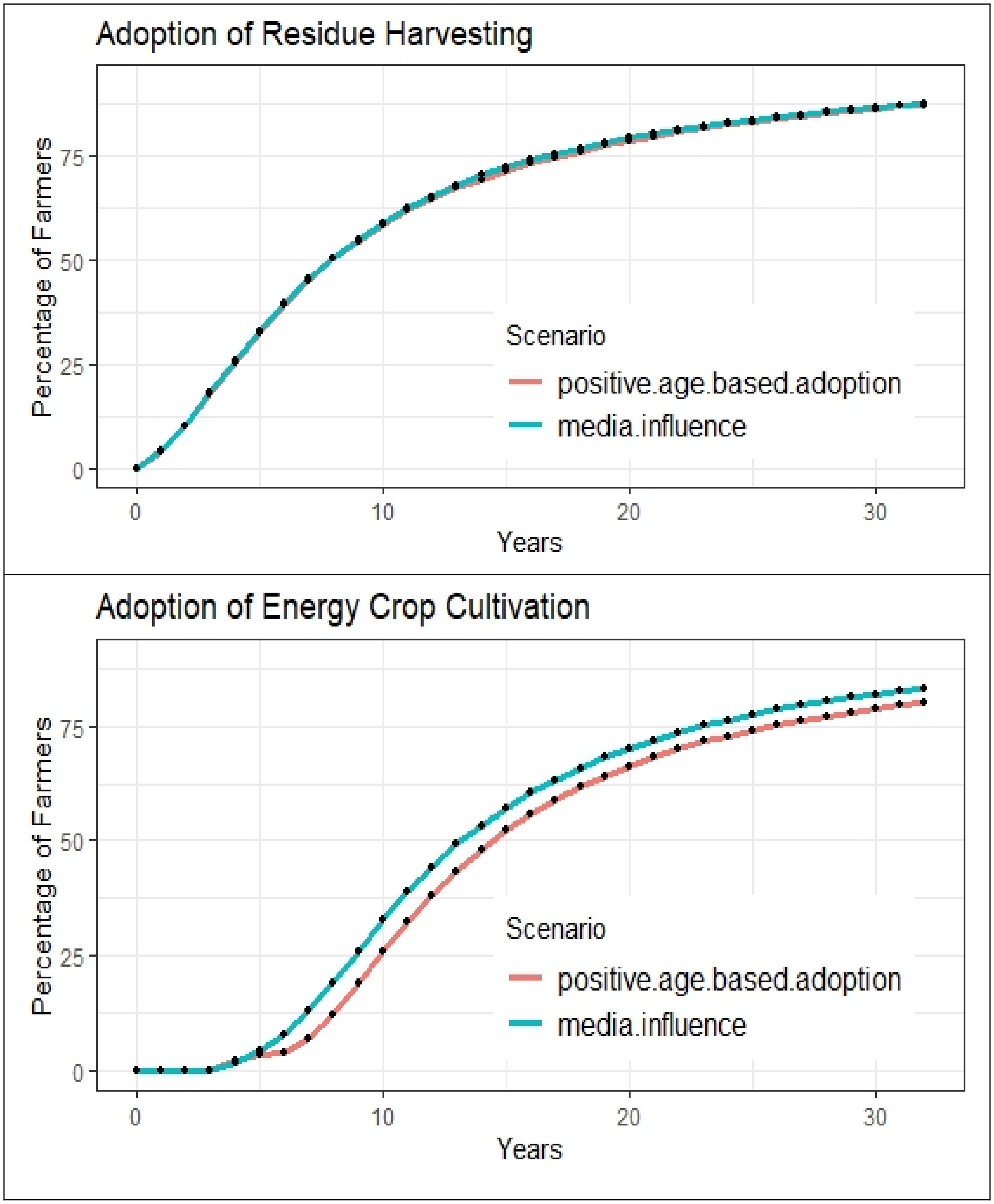

Figure 7: Comparison between adoption for residues (top) and energy crops (bottom) with information dissemination in year 1

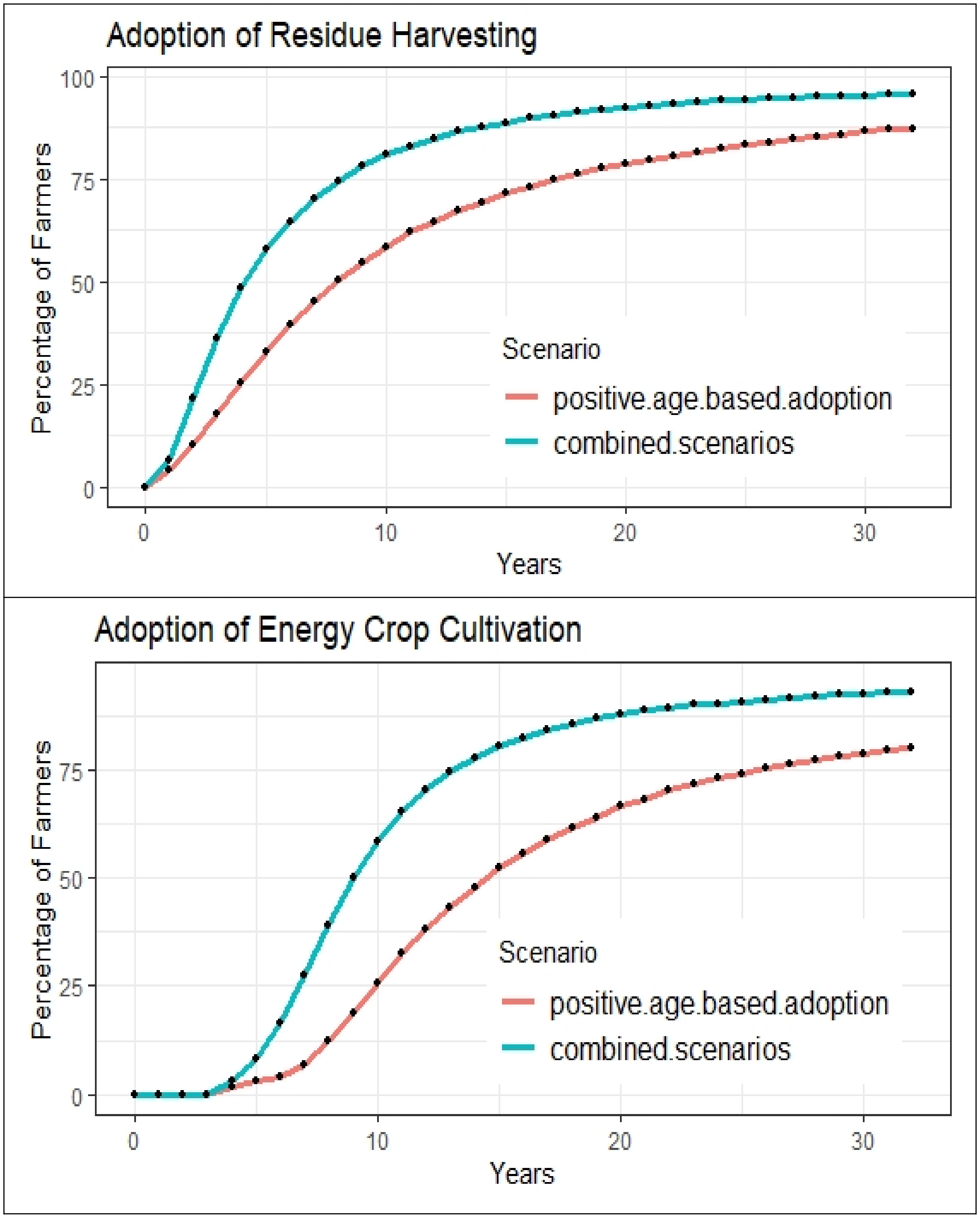

Figure 8: Comparison between adoption for residues (top) and energy crops (bottom) for the combined scenario with one round of information dissemination in year 1.

The analysis focuses on estimating bioenergy feedstock adoption by farmers to evaluate their likelihood of participation. We consider only high-productivity cropland under corn and low productivity land for energy crops and, as a result, our model implies that bioenergy feedstock-related decisions are considered only on lands where such activities are likely to be economically viable. We do not explicitly consider market drivers, demand constraints, biorefineries in the region, transportation networks and production costs etc. Placing such constraints could also limit the number of contracts available, resulting in slower adoption rates. Moreover, with limited use for corn stover, it farmers would be more likely to remove the material from the field unless the excess material was significantly impacting their operations. Yet, the analysis provides valuable insights on adoption rates among farmers based on a variety of micro and macro factors.

6.2 Land Conversion

At the beginning of each Monte Carlo run, the farmers were randomly assigned to farms. As a result, the initial allocation of farm sizes changes across each simulation run. While the farmer decisions pertaining to crop residue harvest and energy crop cultivation are influenced by the different scenarios, the computations for land conversion are subject to the initial assignment. Therefore, instead of evaluating these results as point estimates we analyze the range of values observed, which covers the 95% confidence interval for each scenario.

Figure 9 shows a boxplot and a density plot for the land allocated for residue harvest (top panel) and energy crop cultivation (bottom panel). The visualization shows the first and third quartiles as well as the median and outliers in the boxplot, while the density plot provides a representation of the frequency and range of values. This analysis highlights that as additional conditions are added to the base scenario, the results exhibit higher variation in outcomes underscoring the role of initial land allocation, influences of individual scenario-based decision rules, and interaction effects in the combined scenario.

6.2.1 Crop Residues

On average, under the base case, there were 375,409 (min: 359,355; max: 388,811) ha under corn cultivation. Land conversion rates for crop residues ranged between 22.7% and 32.7% resulting in an estimated 85,482 – 123,116 ha of crop land on which residues were harvested. Under the various scenarios evaluated within the modeling framework, the model estimated a large spread in acres for residue harvest owing to inherent model uncertainty and interaction between scenario parameters. At the other end of the spectrum, i.e. the combined scenario, the 95% confidence interval for estimated acres on which residues are harvested ranged between 64,440 ha and 140,511 ha.

6.2.2 Energy Crops

Under the base case, the average acres of low yield land were estimated at 156,121 (min:150,058; max: 164,172) ha. Estimates for land converted to energy crops ranged between 87.2% and 92.8% for energy crops resulting in an estimated 134,302-148,421 ha of crop land on which residues were harvested. Meanwhile, under the combined scenario, the land brought under energy crop cultivation ranged between 89.6% and 93.9% for an estimated acreage ranging between 133,783 ha and 151,942 ha.

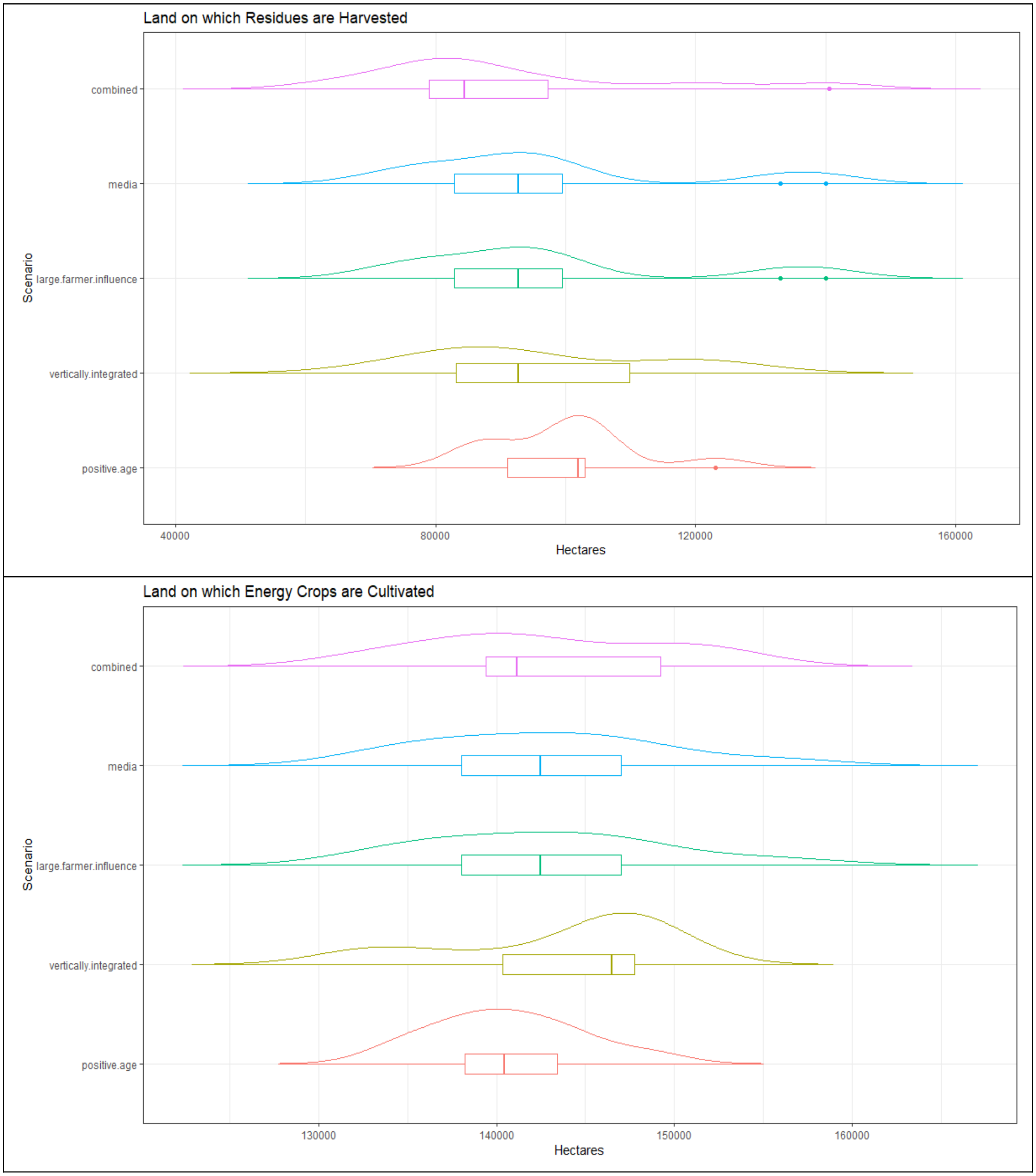

Figure 9: Comparison between residue harvests on cropland (top) and land converted for energy crop cultivation (bottom) under different scenarios.

7 Conclusions

The adoption of innovative practices or participation in a relatively nascent industry is often uncertain. However, the future of the bioenergy sector hinges on farmer participation and their willingness to supply feedstocks that will enable the economic viability of feed-to-fuel conversion operations. This research used an agent-based model to simulate the evolution of farmer participation in crop residue harvesting and energy crop cultivation under multiple scenarios. The model is not intended to provide a unique solution to a problem but identify patterns that provide insight into agent behavior. Since the decision-making process is not completely understood, agent-based models are useful in determining the conditions under which farmer participation is higher and enables identification of levers that result in adoption at faster and higher rates. Farmer credibility emerges as a dominant factor influencing adoption for both feedstocks. This dynamic provides valuable information for a policymaker or an industry player to target their initial interventions to larger farmers. However, in other cases, information dissemination might be more effective in increasing adoption vis-à-vis a vertical integration strategy. Moreover, incentives that reduce the risk for the farmer are likely to increase participation, albeit the magnitude of the influence might vary based on the design of the incentive.

The results illustrate that farmers' credibility has the greatest impact on adoption of crop residue harvest. By the end of the simulation, nearly 95% of the farmers adopt to harvest crop residues. The rate of adoption is considerably higher than the base case with over 50% farmers adopting between the 4^{th} and 5^{th} year compared to nearly 8 years under the base case. Additionally, the type of market structure – specifically vertically integrated markets – tends to positively impact farmer adoption. Meanwhile, media influence tends to have the least impact on crop residue harvesting. The low impact of information dissemination could emanate from existing practices related to crop residue removal as farmers might be already aware of its hinderance on continuing agricultural practices.

In contrast to the corn stover case, for energy crops, farmer credibility and media have substantial impacts on farmer adoption. Given the relatively higher risk associated with energy crops, access to information and examples of other farmers adopting the practice has a positive influence on adoption. While market structure also has a positive influence on farmer adoption, the magnitude is the smallest among the different scenarios considered in our model. The influence of combined effects of the scenarios evaluated in this analysis, indicates accelerated farmer adoption for both crop residue harvesting and energy crop adoption, which could lead to a substantially higher supply for feedstocks within a decade. This indicates potential synergies between two or more scenarios that can be utilized to boost adoption rates to support faster growth within the bioenergy industry. Future research could examine the interactions between the farmers and other market agents to explore the dynamic relationship between producer and consumer.

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