Proceedings of the 2023 Winter Simulation Conference
C. G. Corlu, S. R. Hunter, H. Lam, B. S. Onggo, J. Shortle, and B. Biller, eds.

AN AGENT-BASED MODEL OF AGRICULTURAL LAND USE IN SUPPORT OF LOCAL FOOD SYSTEMS

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ABSTRACT

Local food systems, in which consumers source food from nearby farmers, offer a sustainable alternative to the modern industrial food supply system. However, scaling up local food production to meet consumer demand will require farmers to allocate more land to this purpose. This paper describes an agent-based model that represents commodity-producing Iowa farmers and their decisions about converting some of their acreage to specialty crop production for local consumption. Farmer agents' land-use decisions are informed by messages passed to them via their social connections with other farmers in their communities and messages from agricultural extension agents. Preliminary experimentation revealed that leveraging extension agents to increase the frequency and strength of messages to farmers in support of local food production has a modest positive impact on adoption. By itself, however, this intervention is unlikely to yield significant improvements to food system sustainability.

1 INTRODUCTION

Modern industrial food supply systems are capable of consistent and cost-efficient production of large volumes and varieties of food (Ohberg 2012). However, they are also responsible for toxic outputs to the environment, including greenhouse gases and pollution due to pesticide and nutrient run-off, as well as an unsustainable rate of energy and water consumption (Godfray et al. 2010). Industrial food systems have also severely impacted rural social sustainability, as independent farms have been increasingly consolidated and controlled by multi-national agricultural corporations (Lyson and Hinrichs 2007). These centrally controlled and vertically integrated food supply chains proved unable to respond to changes in distribution constraints at the height of the COVID-19, resulting in increase in prices and shortages (Hobbs 2020).

Localized food systems, in which food is sourced in geographic proximity to the consumer, offer a more sustainable alternative. They are characterized by short-distance transportation, seasonal and regional production, and few intermediaries between producers and consumers (Bloom and Hinrichs 2011). They can potentially reduce the environmental costs of long-distance transportation, redistribute value along the food supply chain, facilitate healthier diets, support rural development, and improve food system resilience (Todorovic et al. 2018; Mollenkopf et al. 2020; FAO 2020). Many consumers are motivated to purchase food from local sources, seeking fresh and nutritious food that supports their local economy with less environmental impact (Feldmann and Hamm 2015). Likewise, farmers may be encouraged by price premiums, as well as non-economic factors such as retaining their identity, continuing family traditions, connecting with community, and supporting local economy (Gasson 1973; Schoolman et al. 2021).

However, local food systems are not robust in most parts of the U.S., where 97% of food still travels through conventional food supply chains (Woods et al. 2013). Producing "specialty crops" (i.e., table food for human consumption) for local markets is often more challenging for farmers than large-scale commodity crop production (Selfa et al. 2008). High marketing, transportation, and distribution costs also tend to make local food more expensive (Miller et al. 2017; Ohberg 2012), and consumers have grown to expect cheap food that is abundant and available year-round (Bowman and Zilberman 2013).

As part of a larger project studying Iowa Urban Food-Energy-Water Systems (FEWS) to evaluate and model the potential effects increased local food production has on land use, energy consumption, and water quality, an agent-based model (ABM) was created to provide farmer agent decision-making inputs for biophysical systems models (Thompson et al. 2021). ABM simulations will explore the impact producer production decisions have on biophysical systems, for example, how increased local food production might affect urban heat island effects through increased green space from urban gardens. Research questions within the ABM include what factors might encourage farmers to allocate enough land to specialty crops sufficient to produce 50% of the food demand in the Des Moines Metropolitan Statistical Area (MSA).

Quantitative data in the form of commodity producer survey responses were used to inform the ABM's farmer agent parameters. Commodity producers from central Iowa were surveyed in early 2020 regarding their intentions toward specialty crop production. Cluster analysis of commodity producer intentions yielded three unique clusters of production intentions. These three intention clusters were further developed into unique producer personas (Traditional, Maybe, Supportive) using survey data measuring the theory of planned behavior constructs. Commodity farmers generally were hesitant to convert land to specialty crop production for local markets. However, some indicated that they would be willing to lease some of their land to farmers in their communities for this purpose. Through the use of agent-based modeling, this paper seeks to gain a greater understanding of how social influence among farmers can be leveraged to encourage greater production of specialty crops for local markets.

2 LITERATURE REVIEW

A large body of literature describes the use of modeling and simulation to study farm-level decision-making and its collective impact on environmental sustainability measures. ABM can model social interactions between farmers and other food system stakeholders, as well as interactions between farmers and the environment. It is particularly useful for modeling individual farms as autonomous decision-makers that are nevertheless subject to social processes (e.g., variation in farmer reputations and persuasiveness) and non-monetary influences (e.g., variation in farmers' land ethics) (Matthews et al. 2007). Furthermore, ABM helps modelers capture heterogeneity, both between farms (i.e., different sizes, resources, knowledge, priorities) and within a given farm (i.e., multi-objective farmer decisions) (Berger and Troost 2014).

Recent literature reviews, including Reidsma et al. (2018); Kremmydas et al. (2018); Huber et al. (2018), indicate that nearly all farmer agent decisions in farm-level ABMs were related to land use. Furthermore, most of these models focused on crop choices and rotation decisions, emphasizing profit/yield maximization in which farmers were assumed to have perfect information. They found that most models incorporated some type of interaction between farmer agents, but most of these interactions involved land sales via bidding through a third-party intermediary (e.g., Happe et al. 2011). While most models included heterogeneous farmer agents, very few represented farmers as having diverse objectives (e.g., motivations regarding land stewardship) and decision-making processes. Risk and uncertainty were rarely represented in agent decision logic.

However, some models relax the assumption of strict profit maximization and instead assume that farmers will make decisions by imitating the strategies of successful (i.e., profitable) neighbors. Polhill et al. (2013) used ABM to study how different incentives impact farmers' land use decisions and regional biodiversity. Each farmer agent compares its annual profits to an aspirational threshold to determine whether it will convert land to a new purpose. They will then either experiment or ask neighbors' opinions about which to choose. Manson et al. (2016) modeled farmer agents' decisions about using rotational grazing practices, in which the agents imitate the behaviors that they perceive to be most profitable among their network of family, friends, extension agents, and other farmers. Coronese et al. (2023) describe farmer agents that seek to increase their profits through innovation and imitation of successful neighbor/partner farms. They can choose either conventional production practices, resulting in high short-term productivity but long-term soil nutrient depletion, or sustainable practices, which are less productive initially but preserve soil quality in the long run. Ding and Achten (2022) integrated life cycle analysis (LCA) with ABM to study the environmental impacts of farmer adoption of bioenergy crops, wherein farmers receive adoption subsidies, and "demonstration farms" are experimentally positioned to increase farmers' familiarity with these crops.

Several models employ the consumat approach (proposed by Jager et al. 1999) to define agent behavior, in which farmer agents rely on imitation, social comparison, deliberation, and repetition to make decisions. An agent's decision logic depends on the performance of its current strategy and the perceived uncertainty surrounding the decision. If performance is high and uncertainty is low, the agent will repeat the same strategy; otherwise, if uncertainty is high, it will imitate the strategy of the majoring. Alternatively, if performance is poor and uncertainty is low, the agent will optimize to the best of its ability; otherwise, if uncertainty is high, it will copy the most commonly used strategy of other similar agents. Janssen (2001) used the consumat approach to model farmer agent decisions about fertilizer application and the resulting pollution of a neighboring lake. Malawska and Topping (2016) assigned farmer agents heterogeneous priorities (i.e., profit-maximizing, yield-maximizing, environmentally oriented) and consumat logic to inform their decisions about crop selection and agrichemical inputs, thereby influencing environmental outcomes. Van Duinen et al. (2016) used the consumat approach to model farmer agents' decisions about adopting irrigation technology, wherein agents' social networks contain links of varying strength according to similarity and geographic proximity.

Other models explicitly include criteria beyond profitability in their farmer agents' decision logic. The ABM framework developed by Murray-Rust et al. (2014) and implemented by Guillem et al. (2015) allows non-economic factors, such as farmer well-being, social opinion, and perceived environmental impact, to influence farmer agents' decisions. Lan and Yao (2019) integrated LCA with ABM to evaluate the environmental impacts of farmers' crop choices, where agent decisions were motivated by profitability, environmental impacts, and familiarity. Agents' social interactions with their neighbors increased their familiarity with new crops, while educational interventions increased farmers' "environmental awareness." Similarly, Bayram et al. (2023) and Marvuglia et al. (2022) allowed for increases in farmer agents' "green consciousness" via social interactions with neighbors and other farmers who share their level of risk aversion, thereby influencing their decisions about production practices (i.e., conventional vs. organic) and crop types/rotations. Ambrosius et al. (2022) established social connections between farmer agents according to the similarity in their priorities (i.e., profitability, animal welfare, social opinion) and geographic proximity. They then modeled influence over farmers' decisions to adopt organic production practices according to social identity, in which agents with similar priorities acted as reference groups to other farmers, thereby establishing social norms. Xu et al. (2020) also used their model to explore how farmers' social identities influenced their decisions. Farmer agents may change their production practices if they believe that an alternative strategy (i.e., organic production) will give them greater satisfaction than their current strategy. In this case, agent satisfaction was based on the Theory of Reasoned Action (Ajzen and Fishbein 1980), such that farmer agents can increase their satisfaction by increasing their productivity and being viewed as a "good farmer" by members of their social networks.

While most sustainable farm-level ABMs described in the literature focus on decisions about crop types and production practices, other work has studied farm-level decisions about market channels. Specifically, Krejci et al. (2016) and Craven and Krejci (2017) used ABM to study farmers' decisions to sell their products for local markets via local food aggregators (i.e., food hubs).

3 MODEL DESCRIPTION

In this section an ABM representing Iowa farmers' social interactions and decisions about producing specialty crops for local markets is described in detail using Overview, Design Concepts and Details (ODD) protocol (Grimm et al. 2010). The model was built using NetLogo (Version 6.2.1).

3.1 Purpose

This model is part of the Iowa Urban FEWS project. The Iowa Urban FEWS project aims to conduct exploratory research to identify factors that may lead to a decrease in reliance on non-local food sources, reduce environmental impact, and improve sustainability. The objective of this model is to simulate the agricultural system of the six counties that constitute the Des Moines MSA to identify factors which may lead to an increase in local food production. This model will interact with other social, biophysical, and climatic models as a part of a co-simulation process.

3.2 Agents, State Variables, and Scale

The model is inhabited by the farmer agents that make land use decisions with respect to its acreage in each simulated time step (where one time step represents one year). The model contains 5,658 farmer agents, each representing an owner or tenant of farmland in one of the six counties that constitute the Des Moines MSA. Each farmer agent is characterized by location (i.e., county), acreage, and land use allocation based on the USDA 2017 Census of Agriculture (U.S. Census Bureau 2017). Farmer agents located within the same county are connected to one another via a random network through which information and influence can be transmitted. In each time step, each commodity farmer agent evaluates and chooses between two land-use alternatives: Alternative 1 (continue producing only commodity crops, i.e., the status quo) or Alternative 2 (allocate a portion of total acreage to produce specialty crops). Key parameters of each farmer agent that are held constant throughout the entire simulation run are:

- *county*: Each farmer agent belongs to one of the six Des Moines MSA counties, with 802, 924, 755, 986, 977, and 1214 farmer agents (total 5,658) assigned to Guthrie, Dallas, Polk, Jasper, Madison, and Warren counties, respectively, as per the USDA 2017 Census data (U.S. Census Bureau 2017).
- *farm-size*: Farmer agents within each county are then assigned to one of six farm-size categories (i.e., very small, small, medium small, medium big, big, and very big) according to the distribution obtained from USDA 2017 Census of Agriculture county data (U.S. Census Bureau 2017).
- *farm-acre*: Each farmer agent is assigned a specific acreage (farm-acre) based on its farm-size. The assignment of acres to a farm is random and follows a truncated normal distribution with the range of the farm's respective farm-size category. The mean and standard deviation values for each farm-size category were tuned until the total farmland acres per farm-size category and county in the model matched the real-world USDA Census values. It was assumed that acreage distribution is right-skewed for the "very big" farm-size category to account for extremely large farm sizes (e.g., 12,000 acres) that appeared in the survey data. It is assumed that the total land allocated to each farmer agent does not change; that is, the agents do not sell or buy additional land for farming.
- *cropland-acre and pastureland-acre*: A percentage of each farm's acreage is designated as being either for crop production (cropland-acre) or animal pasture (pastureland-acre). All other land use categories (e.g., woodland, buildings, sheds) are included in a single "Other" category and are assumed to be unavailable for food production.

- *Persona*: Personas are detailed descriptions of fictional characters constructed from highly specified and well-understood data about real people (Pruitt and Grudin 2003). Three personas were derived from survey data to classify and characterize commodity farmer agents, and one persona – Specialty – was used to represent farmer agents that produce strictly specialty crops. The three commodity personas are named as per their interest in growing specialty crops: Traditional, Maybe, and Supportive. Traditional agents are quite satisfied with their current production practices (i.e., only commodity crop production) and are generally opposed to growing specialty crops. Maybe agents would be somewhat willing to consider growing specialty crops if major structural changes were to occur that made specialty crop production more attractive (e.g., better policy support and distribution channels). Supportive agents are also not particularly interested in growing specialty crops, but they would be willing to consider leasing land for specialty crop production to beginning farmers, especially members of their communities. The distribution of commodity farmers' personas for each county is shown in Table 1. While farmer agents might adjust their views on specialty crop production during a simulation run, it is assumed that they will not switch personas.

Table 1: Commodity farmer agent persona distribution.

	Guthrie	**Dallas**	**Polk**	**Jasper**	**Madison**	**Warren**
Traditional	46%	50%	57%	52%	57%	39%
Maybe	36%	35%	33%	32%	25%	30%
Supportive	18%	15%	10%	15%	18%	31%

- *link-weight*: Each link connection in a farmer agent's social network is assigned a link-weight. The value of link-weight ranges from 0 to 1 and represents the level of closeness, bonding, or influence between the two connected agents. Larger values of link-weight correspond to a greater probability of influence between the two linked agents.
- *Probability of communication (prob-com)*: Each link connection is assigned a prob-com value. The value of prob-com ranges from 0 to 1 and represents the likelihood of communication between two connected farmer agents regarding information about a land use alternative.
- *Communication interest (com-int)*: Each farmer agent is assigned a com-int value. Com-int indicates the farmer agent's unlikeliness in communicating a message regarding a land use alternative. The value of com-int ranges from 0 to 1 and represents the difference between the strength of the message received and the message that will be further communicated. Traditional agents are least interested in communicating about specialty crop production, thus their com-int value will be higher than other personas (between 0.5 and 0.9). Supportive agents are most open to the idea of producing specialty crops but are still hesitant to talk about it, thus their com-int value lie between 0.1 and 0.5. Some Maybe agent views are like the Traditional type, while others tend to think like the Supportive type, so their com-int values vary from 0.1 to 0.7. Com-int of Specialty agents varies between 0 and 0.3, representing the possibility of loss or change in information.

Key agent parameters that may change during each time step during the simulation run include:

- *commodity-acre, veg1-acre, veg2-acre, fruit1-acre, fruit2-acre, livestock-acre, grain-acre, oil-sugar-acre, idle-acre*: The acres belonging to each farmer agent are initially allocated to the production of one of eight different product types using the USDA Census data. These values may change based on the production decision made by the farmer agent during each time step. However, the total cropland-acre of each agent will remain the same throughout the simulation.
- *Utility of an alternative*: The agent's total utility ($U_{Total,i,j(k)}$) for each land use alternative i represents the total satisfaction that the agent j with persona k would experience if it chose this alternative. It is a weighted average of the perceived utilities associated with four attributes of each land use

alternative: profit and financial benefits – U_1, policies and regulations – U_2, efforts required in producing and selling the products – U_3, and social contribution and sustainability goals – U_4. These four attributes were identified as the most important factors in Iowa farmers' land-use decision process based on data from surveys, focus groups, and interviews. The weights are assigned based on the relative importance each persona places on each land-use attribute based on survey results and focus group discussions. Specialty persona agents are not assigned utility-weight values because they do not make production decisions in this model; their role is simply to convey information specific to specialty crop production (Alternative 2).

Table 2: Weights on land use attributes according to agent persona.

Utility Attribute	**Variable**	**Utility weight value**		
		Persona		
		Traditional	**Maybe**	**Supportive**
U_1 – Profit	$W_{1,j(k)}$	0.4	0.375	0.35
U_2 – Policies	$W_{2,j(k)}$	0.25	0.25	0.25
U_3 – Efforts	$W_{3,j(k)}$	0.25	0.225	0.2
U_4 – Social Contributions	$W_{4,j(k)}$	0.1	0.15	0.2

Initially, the utility values associated with Alternatives 1 and 2 are assigned based on the farmer agent's persona, although the values may update over time as the agent communicates with other agents and its perception of an alternative changes. The utility values for all four attributes are defined on a scale of 0 to 1. Commodity agents' utility values for Alternative 1 (status quo) are 0.7, 0.85, 0.8, and 0.2 for U_1, U_2, U_3, and U_4 respectively. These values are allotted based on the evidence that commodity crops are relatively profitable, have very favorable policies and regulations, require very little effort to produce when compared with specialty crops, but they do not add much value toward community or social aspects. Specialty agents are not assigned any utility values for Alternative 1 because it is not an option for them. Commodity agents' initial values for U_1, U_2, U_3, and U_4 for Alternative 2 (convert some land to specialty crop production) are 0.8, 0.2, 0.3, and 0.4, respectively. These values are assigned based on the assumption that specialty crops are likely very profitable, are unsupported by government policies and may be strictly regulated, require significantly more efforts to produce, store and distribute, but their production can contribute significantly to the community. Specialty agents have comparatively higher Alternative 2 utility values due to their experience with specialty crop production and are assigned 0.85, 0.3, 0.4, and 0.6 for U_1, U_2, U_3, and U_4 respectively.

The total utility of agent j with persona type k for each alternative i is calculated as:

$$U_{Total,i,j(k)} = U_{1,i,j(k)} * W_{1,j(k)} + U_{2,i,j(k)} * W_{2,j(k)} + U_{3,i,j(k)} * W_{3,j(k)} + U_{4,i,j(k)} * W_{4,j(k)}$$

- *Message number (msg-num)*: During each time step, farmer agents producing specialty crops may generate a positive message about adopting specialty crop production and pass the message along the social network. Each message can impact the agent's perception of only one attribute of an alternative; thus, msg-num takes discrete values 1-4, representing the four attributes U_1, U_2, U_3, and U_4 respectively.
- *Message received (msg-rec)*: The value of msg-rec ranges from 0 to 1 and represents the strength of the message received by the agent, where larger values have a stronger potential impact on the change in the agent's perception of an alternative's utility.
- *Message send (msg-send)*: The value of msg-send ranges from 0 to 1 and represents the strength of the message that the agent will communicate to its social network. The value of this variable

depends on the value of the message received and the value of communication interest and is calculated as *msg-send* = *msg-rec* − *com-int*.

Key global parameters to be determined before the start of simulation run include:

- *max-friends-links*: This parameter assigns the maximum number of friendship network links generated per agent. For example, if max-friends-links is set to 3, the number of friends links an agent may have can be 1, 2, or 3.
- *Number of farmer agent interactions with friends (yearly-interaction-friends)*: This parameter determines the number of times an agent will interact with a linked agent during each time step.
- *Extension agent participation status (ext-agent-active?)*: This is a binary parameter that activates/deactivates extension agents according to the experimental scenario being run. Extension agents only provide information and do not participate in the decision-making process.
- *Extension agent target strategy (ext-agent-type)*: Depending on the experimental scenario being run, this parameter can be assigned one of two different values: random-select or focus-select. "random-select" enables the extension agent to target all three commodity persona agents, whereas "focus-select" enables the extension agent to target only Maybe and Supportive persona agents.
- *Number of extension agent interventions (ext-agent-intervention)*: This parameter determines the number of times an extension agent will communicate with the farmer agents in each time step.

3.3 ABM Overview

The ABM consists of five submodels, which are described below.

Initialization: At the beginning of the simulation, the model contains 5,658 farmer agents, which are initialized on a 2D grid that represents the agricultural landscape of Des Moines MSA. Each farmer agent is assigned a county, and based on the county, each agent is assigned x and y coordinates on this grid to facilitate experimentation; however, these coordinates do not represent actual farm locations in the real-world system. The farmer agents are initialized with values of farm-size, farm-acres, cropland-acres and pastureland-acres according to USDA Census data. Each farmer agent is designated as one of the four personas (Specialty, Traditional, Maybe, Supportive). The Specialty persona is assigned to farmer agents that produce only fruits, vegetables, or livestock products and no commodity products. The remaining farmer agents are assigned one of the three commodity personas based on the distribution obtained from the survey data. Once the farmer agents' attribute values have been initialized, they are connected to other farmer agents via links, which represent the farmer agents' friendship social network. A random network was deemed appropriate since little data is available regarding Iowa farmers' social network structure (Daloğlu et al. 2014). Each link connection is assigned a link-weight, prob-com, and com-int. Each farmer agent is assigned weights for each of the four utility values based on its persona. Finally, each farmer agent is assigned initial perceived utility values for each alternative for all attributes according to its persona.

Agent interaction and utility value update: During the simulation, agents send messages to other agents who are a part of their social network. Social propagation is inspired by the two-stage diffusion model and the change process in farm decision-making (Valente 1996; Huet et al. 2018). The strength of the message ranges from 0 to 1 and depends on the persuasiveness of the sender (msg-send) and the receptiveness of the receiver (msg-rec). At the start of each time step, between 1 to 10 Specialty persona agents generate a positive message/information (msg-num) about producing specialty crops with respect to one of the four utility values. The number of Specialty agents that generate a message in each time step is experimentally varied. The strength of the original message from Specialty agents is assumed to be 1. The Specialty agents pass the message generated to members of their social network, and agents who receive the message may pass it to their social networks. Each farmer agent communicates with other farmer agents in their social network multiple times (yearly-interaction-friends) in each time step. Every time an agent with a message communicates with linked agents, it assesses whether to pass the message based on the prob-com. If the agent decides to pass the message, the strength of the message (msg-send) that the agent will send will be less than the strength of the message received (msg-rec), and the variable com-int dictates this difference in strength. The value of com-int ranges from 0 to 1 and depends on the sender's persona. If the com-int of an agent is higher than msg-rec, the agent will not communicate the message further along its social network. The message's propagation logic is built on the premise that the message's strength reduces as it travels via social networks, as well as the message's modification based on the farmer agent's own opinions.

At the end of every interaction, the farmer agent evaluates the impact of the received message to update its perceived utility associated with the specialty cropland use alternative (i.e., Alternative 2). The increase in utility corresponding to the msg-num is product of the strength of the message received (msg-rec), the link-weight of the connection, and the respective utility value of the agent sending the message.

However, for all farmer agents, it is assumed that the individual utility values associated with Alternative 2 cannot exceed predetermined upper bounds, regardless of the amount/strength of information they receive from other agents ($U_{1\text{-}max}$ = 0.85, $U_{2\text{-}max}$ = 0.5, $U_{3\text{-}max}$ = 0.5, $U_{4\text{-}max}$ = 0.75). These limits reflect the reality of specialty crop production in the Des Moines MSA; for example, governmental support for this type of production in this region is virtually nonexistent, and it is not easy to find adequate labor for specialty crop production in this region, making the farm's required effort relatively high.

Extension agent intervention: If the parameter ext-agent-active? is set to "on", then this submodel is executed. In each time step, extension agents randomly target between 0 and 10 commodity farmer agents from each county and provide them with positive information regarding specialty crop production (Alternative 2 utility values). If the ext-agent-type is set to "random-select", the extension agent will target all three commodity farmer personas (i.e., Traditional, Maybe, Supportive). When ext-agent-type is set to "focus-select", the extension agent will only target Maybe and Supportive personas. Messages received directly from an extension agent increase the recipient's utility value corresponding to the msg-num. The increase in utility value will be 0.025, 0.05, 0.075, or 0.1, depending on whether ext-agent-intervention is set to 1, 2, 3, or 4, respectively. The upper bounds of each utility value for messages received directly from extension agents ($U_{1\text{-}max}$ = 0.9, $U_{2\text{-}max}$ = 0.6, $U_{3\text{-}max}$ = 0.6, $U_{4\text{-}max}$ = 0.8) differs compared to messages received through social network interaction as extension agents can not only provide information but can also help commodity agents with finding favorable insurance, capital access via government programs, labor, access to various markets, and community outreach.

Production decision-making: At the end of each time step, all farmer agents with commodity personas will calculate and compare their total utility for each alternative to make land use decisions for the next time step. In this version of the model, it is assumed that Specialty farmer agents do not change their production plans; their role in the model is to share specialty crop production specific information via the social network. Agents with a higher utility value for Alternative 1 will not make any changes in crop production. Interviews and focus group discussions revealed that farmers are likely to limit land conversion to specialty crop production to no more than two acres. Thus, agents with a higher utility for Alternative 2 will convert 0.5,1, or 2 acres of their land to produce one of the specialty crop product types (fruit1, fruit2, veg1, veg2, grain, or livestock products). Product types and acreage for specialty crop production are randomly assigned according to a uniform distribution. Agents with idle acres will produce specialty crops on idle acres, whereas agents with limited or no idle acres will convert commodity acres for specialty crop production. The adoption of specialty crop production is assumed to be in an absorbing state (i.e., once an agent adopts Alternative 2, it cannot return to Alternative 1).

4 EXPERIMENTATION AND RESULTS

To understand the impact of social interactions and educational interventions on the adoption of specialty crops by commodity farmer agents, the ABM was used to conduct a set of preliminary experiments. The experiments (summarized in Table 4) focused on the inclusion of an extension agent, the targeting strategy used by this agent for messaging (i.e., whether or not to target the Maybe and Supporting farmer agents, who are more receptive to adoption), and the number of times per year that the extension agent reached out to farmer agents. The purpose of these experiments was to evaluate the relative impact of putting resources (i.e., agricultural extension agents' time) toward favorable messaging on specialty crop production for local markets without making any structural changes (e.g., new policies, distribution channels). It is assumed that each time an extension agent interacts with a farmer agent, the message that it shares only contains information about one of the four land-use attributes (i.e., Profit, Policies, Efforts, Social Contributions).

For each scenario, the model was run for 30 time steps (years), per the requirements of the Iowa Urban FEWS project, which seeks to understand the impacts of farmers' decisions over a 30-year timespan. Over the 30-year run length, it is assumed that farmers do not age or disappear, nor are any new agents added to the system. The following output metrics are captured at the end of each time step: total specialty acres (summation of fruit1-acre, fruit2-acre, veg1-acre, veg2-acre, grain-acre, livestock-acre, and oil-sugar-acre) and the total number of Supportive, Maybe, and Traditional agents that adopted specialty crops. Given the low variation of output metrics between replications, ten replications were found to be sufficient.

Table 3: Experimental scenarios.

ext-agent-active?	**ext-agent-type**	**ext-agent-intervention**
no	NA	NA
yes	"random-select" (RS) or "focus-select" (FS)	1, 2, 3, or 4 times per year

The experimental results are represented in the figures below as "(AT, EAI)", where "AT" is the extension-agent-type (random-select or focus-select) and "EAI" is the number of extension agent interventions per year. Figure 1 shows the average increase in acreage of total system-wide specialty crop production (specialty-acres) from year 1 to year 30 for all replications as a result of the adoption of specialty crops by commodity farm agents. Results indicate that scheduling one extension agent intervention per year does not significantly increase the number of acres in specialty crops, even when the extension agent targets Maybe and Supportive farmer agents (FS, 1). However, the adoption rate picks up when the number of interventions by extension agents is greater than or equal to two per year. Comparing the two extension agent target selections (ext-agent-type) demonstrates modest increases in specialty crop acreage due to the "focus-select" for three or four interventions per year. These results suggest that extension agents should reach out to farmers at least three times per year but focus their efforts on convincing Supportive and Maybe farmers (rather than wasting time trying to persuade the intractable Traditional farmers).

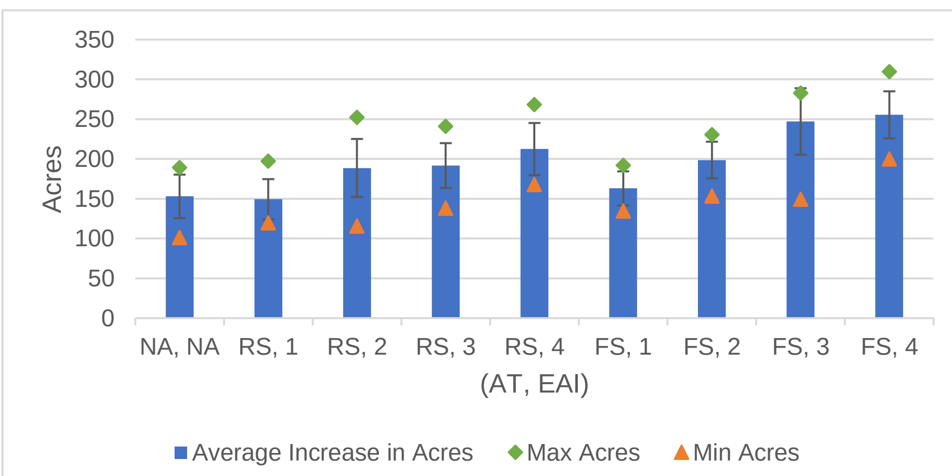

Figure 1: Average Increase in Acres due adoption of specialty crops.

Figure 2 shows the average number of specialty crop production adopters per commodity persona type. Supportive persona dominates the adoption rates, whereas the Maybe persona shows a steady increase in adoption rate with respect to the number of extension agent interventions. Adoption of specialty crops by Traditional persona is only seen for random-select type target selection with three or four interventions by extension agents. This indicates that Traditional persona will require a lot of convincing for them to adopt specialty crops. It is interesting to note that the average increase in adoption rate for the Maybe persona is higher compared to the Supportive persona when the ext-agent-type is set to "focus-select".

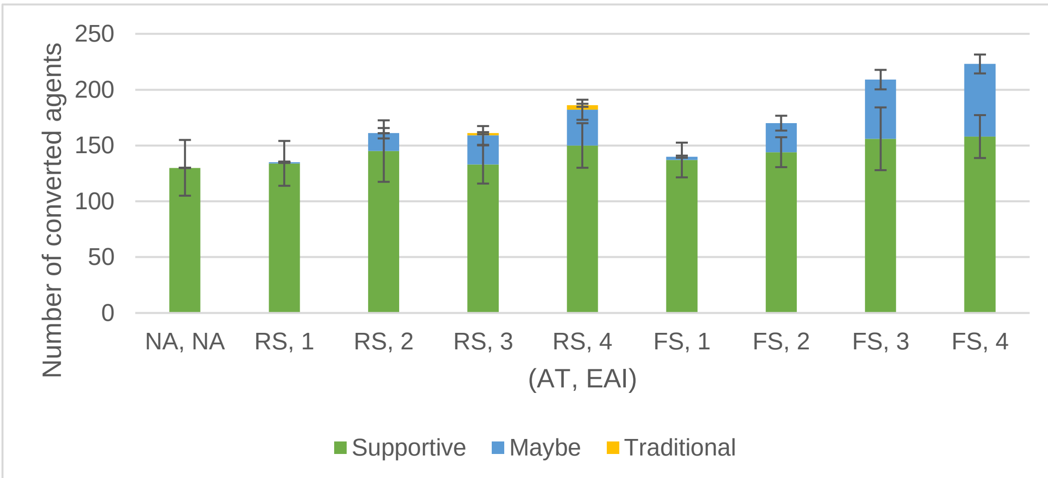

Figure 2: Average number of specialty crops adopters.

One of the objectives of the Iowa Urban FEWS project is to determine which factors might encourage farmers in the Des Moines MSA to allocate sufficient land for specialty crop production to satisfy 50% of the dietary requirements for the MSA population solely using local crop production. LCA outputs reveal that approximately 10% of total cropland in the Des Moines MSA should be producing specialty crops to fulfill that requirement (Brighenti et al. 2022). However, the results of the ABM experiments presented here indicate that extension agent intervention by itself yields at best an average increase of 250 acres of specialty crop production, which is merely 1.36% of total cropland acres in the MSA (an increase of only 0.4%). Based on survey data, focus groups, and interviews with Des Moines MSA farmers, these results could very likely be accurate. Without significant changes to current agricultural policy (which favors commodity production over specialty crop production for local markets) and major improvements to local food system setup (especially labor, marketing, and distribution), it will be very difficult to make substantial inroads in converting commodity farmland in Iowa to specialty crop production for Des Moines consumers.

5 CONCLUSION

This paper described an agent-based model of Iowa commodity farmers' land-use decisions to study the impact of farmer social interactions and extension agent interventions on the adoption of specialty crop production for local markets. Results from these preliminary experiments indicate that multiple focused interventions can somewhat improve adoption rates. While the model is grounded in empirical data, it has not yet been validated, and it is currently limited by a set of simplifying assumptions. For example, the social network is currently random (rather than geographically informed) and assumes a fixed number of links, agent interactions, and extension interventions in each time step. Each message regarding specialty crop production is assumed to focus on only one attribute (i.e., profitability), which is likely unrealistic. The model also does not consider farmers' age or the addition of new farmers and the resulting potential changes in persona distribution; for example, data suggests that farmers near retirement may become more open to leasing out land for specialty crop production. Ongoing development of the model will include modifications to the farmers' social networks, the inclusion of a more complex farmer utility function (including farmer learning based on their experiences), and more alternatives from which agents can choose. The ABM will also experiment with different policies in an effort to determine what it would take to fulfill 50% of Des Moines consumers' dietary requirements via local production.

ACKNOWLEDGMENTS

This work was supported by the National Science Foundation Research grant (Award #1855902).

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