Supplementary Material

Increasing behavioral richness and managing structural uncertainty in social-ecological system agent-based models

Overview, Design Concepts, Details, and Decision-Making (ODD+D) Description

This document follows the ODD+D protocol to describe agent-based models with individual decision-making (Müller et al., 2013).

1. Overview

1.1. Purpose

The overall purpose of the model presented in this study is to create a scalable, agent-based framework that enables the simulation of multiple, heterogeneous, and cognitively plausible models of adaptation decision-making among agents in the same population. The modeling framework uses a 'building-block processes' (BBPs) approach to find the best combination among alternative objective functions and social network structures for each agent given their decision-making context. The specific application of the framework described here simulates adaptive farm management and associated land-use choices of producers throughout the state of Alabama. This model version is a generalized model of crop choice and irrigation decisions. The model is designed to explore the consequences of behavioral heterogeneity on farm security (food and financial), equity (e.g., distribution of farm loss versus consolidation), and sustainability of water resources use under scenarios of changing crop prices and/or precipitation patterns. Future model versions will explore additional adaptive decision-making, including shifting planting dates, introducing rotations with cover crops, and rotational grazing.

1.2. Entities, state variables, and scales

1.2.1. Agents

Producer Agents represent individual farmers and/or livestock producers. Producer agents have fixed geographic positions associated with specific land parcels. Producer agents interact unilaterally with the Credit Agent and their respective Extension Agent and other Producer Agents in their social neighborhood through variously structured social networks with strong and weak ties. Producer Agents choose specific crops and farm management techniques (e.g., irrigation) in response to perceived environmental and price changes, individual experience, and learned strategies from other agents. Producer Agents are considered 'active' (Burglund, 2015) agents given their ability to learn and select new behaviors in response to changing conditions.

One ***Extension Agent*** is represented per social neighborhood and recommends a specific crop and farm management technique for adoption to all Producer Agents in the social neighborhood. Extension Agents always represent weak ties in each Producer Agent's social network. Extension Agents are considered 'reactive' agents that have predetermined behavioral responses under varying conditions.

One ***Credit Agent*** is represented per social neighborhood and can issue Producer Agents loans to cover the transition costs to new farm management practices (e.g., irrigation). In the generalized version of this model, Credit Agents issue loans to Producer Agents if the potential revenue from the new crop and/or farm management practice is equal to or greater than estimated annual loan payments given interest rates. Future version of the model will consider differential or biased lending practices. Credit Agents are considered 'reactive' agents that have predetermined behavioral responses under varying conditions.

Table S1: Agent attributes.

Agent	Attribute	Description
Producer Agent	*FarmID*	Unique identification number corresponding to the parcel under direct management by the agent.
	Decision state	Integer between 1 and 4 indicating the decision-making state of the agent in the CONSUMAT framework.
	Demographic group	Integer indicating membership in a specific demographic group.
	Aspiration level	Level of farm income among social network connections against which each Producer Agent evaluates their satisfaction with their current crop choice and farm management.
	Needs	Minimum annual revenue needed to break even after fixed and variable costs of production.
	Satisfaction	Difference between actual and the greater of need or aspiration revenue levels; influences decision state.
	Uncertainty level	Proportion of other Producer and Extension Agents in each Producer Agent's social network producing/recommending the same crop and farm management technique as the given agent.
	Uncertainty threshold	Threshold of disagreement between the practices of a given agent and other agents as measured by *Uncertainty Level*; influences decision state.
	Salience Coefficient (γ)	'Local thinker' coefficient in salience-based risk perception (Bordalo et al., 2012). Default value is 0.5.
	Learning Rate (δ)	Coefficient used to weight recent and past information in Bayesian updating of risk information. Default value is 0.5.
	Perceived Risk	Dynamic, subjective perception of potential productivity loss for each crop and farm management practice. Bayesian updating using the *Learning rate*.
	BBP social network	Best performing social network structure model used in agent's decision-making model. Dynamically updated among social networks derived from only spatial proximity, spatial proximity and demographic group, or spatial proximity and crop choice.
	BBP objective function	Best performing objective function used in agent's decision-making model. Dynamically updated among random choice, satisficing (i.e., cost minimization), profit-maximization, risk aversion, and risk salience.
Extension Agent	*HubID*	Unique identification number assigned to the study area (Price et al., 2022).
Credit Agent	*HubID*	Unique identification number assigned to the study area (Price et al., 2022).
	Interest rate	Assumed to be 5%; used to set annual loan payments and adjust land prices.

Table S1.2: Environmental attributes

Entity	Attribute	Description
Parcel	*FarmID*	Unique identification number linking a parcel with geographic position to a specific Producer Agent.
	Acres	Area of parcel in production; derived from spatial intersection of parcel boundary and the Cropland Data Layer (CDL).
	Total acres	Total area of parcel.
	Soil quality	Class of soil based on suitability for agriculture derived from the SSURGO dataset.
	Surface water access	Binary indicator of parcel's riparian access to surface water body.
	Well depth	Average depth of wells interpolated from point data; used to estimate well digging costs.
	Pivot irrigation	Observed presence or absence of pivot irrigation infrastructure based on remote sensing analysis (Handyside, 2014)
	Market access	Travel time from parcel location to nearest city of 50,000 or more; sampled from Verburg et al. (2011).
	Parcel distance	Distance from any given parcel to every other parcel, used to identify strong social network ties based on spatial proximity.
	Production type	Dynamically updated production type (horticultural crop, row crop, pasture, or livestock) and method (rain-fed or irrigated).
	Total income	Net revenue after production costs from currently produced crop and farm management practice applied.
	Crop yields	Potential yields for each crop and farm management practice were estimated based on regional experimental yields for southern field peas and greens as representative horticultural crops and corn as the representative row crop, and modified given the parcel's soil quality characteristics.
	Land price	Per acre price for each parcel grounded in the value of the best and highest valued production methods and dynamically varying based on land market conditions (i.e., bid rent).
	Irrigation cost	Estimated installation and operating costs per acre for center pivot systems based on Alabama Cooperative Extension System (ACES) data[1] and assuming horticulture crops require twice the water as commodity row crops.
	Farm wage rate	Estimated per acre farm labor wage rate based on manual labor for horticultural crop (southern field peas and greens)[2], and average USDA ARMS hired labor rates from 2016-2020 for row crops (corn) and livestock (cow-calf) operations.

[1] https://www.aces.edu/blog/topics/crop-production/investment-costs-of-center-pivot-irrigation-in-alabama-three-scenarios/.
[2] https://www.aces.edu/wp-content/uploads/2020/02/Southern-Peas-Manual-Harvest.pdf.

	Operating costs	Estimated per acre variable costs based on 'break even' prices for horticultural crop (southern field peas and greens), row crops (corn)[3], and livestock (cow-calf) operations.
	Overhead costs	Estimated per acre fixed costs based on 'break even' prices for horticultural crop (southern field peas and greens), row crops (corn)[4], and livestock (cow-calf) operations.
	Transport costs	Estimated annual cost for transport to market assuming an average of 20-mile one-way trip, 32 weeks of growing season, and the federal mileage rate of $0.575/mile[5].
	Crop prices	Time-varying crop prices were specified using the U.S. Producer Price Index from 2000-2020 from FAOSTAT[6] (Figure S1).
	Precipitation	Time-varying precipitation increased/decreased baseline crop yields according to variations in the Standardized Precipitation Evapotranspiration Index (SPEI)[7] obtained from 2000-2020 for the region (Figure S1).
Social Hub	*HubID*	Unique identifier for each social neighborhood polygon produced by Theissen polygons around the centroid between Extension and farm co-operative locations.

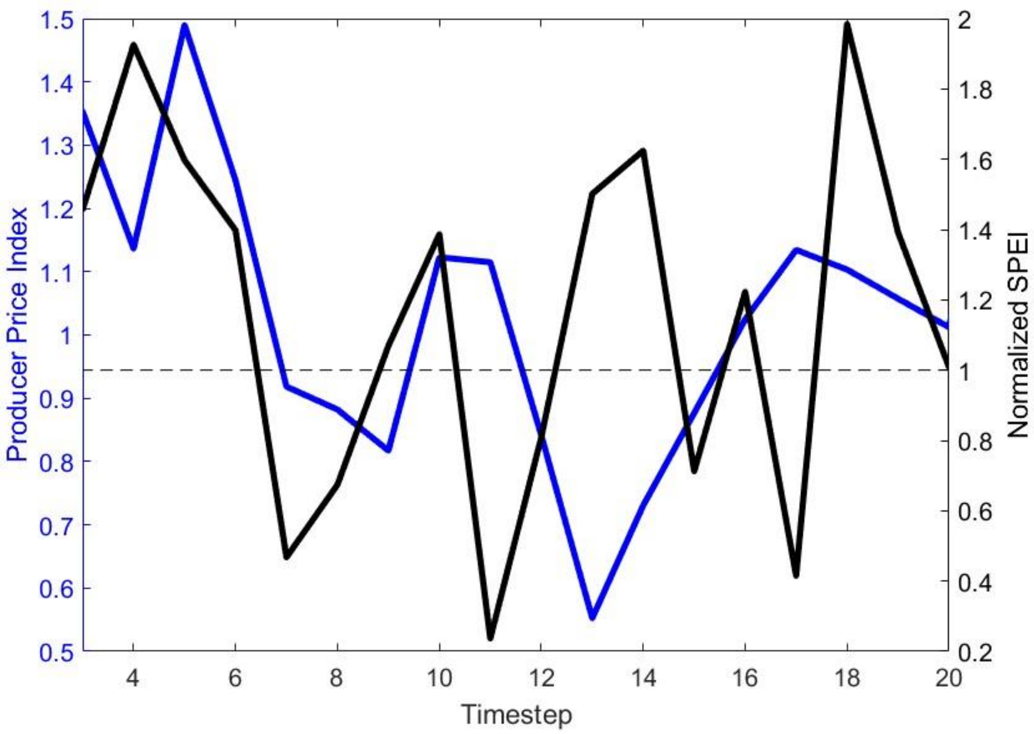

Figure S1. Time-varying indices for crop prices and yields based on the Producer Price Index and normalized Standardized Precipitation Evapotranspiration Index (SPEI), respectively.

[3] https://www.aces.edu/blog/topics/crop-production/alabama-row-crops-breakeven-prices/
[4] https://www.aces.edu/blog/topics/crop-production/alabama-row-crops-breakeven-prices/
[5] https://www.aces.edu/blog/topics/crop-production/determining-price-for-your-products/
[6] Producer Price Index (PPI): https://data.apps.fao.org/catalog/dataset/faostat-pp
[7] Standardized Precipitation Evapotranspiration Index (SPEI): https://spei.csic.es/spei_database/#map_name=spei01#map_position=1451

1.2.2. *By what attributes (i.e. state variables and parameters) are these entities characterized?*

Production types and farm management practices. Each producer chooses among eight possible production types and farm management practices: rain-fed or irrigated horticulture, commodity (row crop), or fodder, livestock production, or fallowing. Each option has varying requirements for variable costs (i.e., labor, water, fertilizer, and pesticides, if applicable) and fixed costs (i.e., operating and overhead costs). Irrigation infrastructure, water pumping, and other operating costs differed between horticulture and commodity crops and sources of surface or groundwater. Detailed parameterizations of each farm practice can be found in Section 3.3.1.

Alternative objective functions and social network structures. The objective function and social network structure implementations chosen as alternative building-block processes were selected for their generality. There are many cognitive and/or social-psychological decision models that can be included, but those selected for this model version attempt to implement a minimal set of models representing a set of factors most often cited as important in the social-ecological systems and climate adaptation contexts of ABM applications. Alternative objective functions represent different goals of production (e.g., cost-minimization vs. profit-maximization) and specify the basis for comparison and selection among production types and farm management practices. Generalizable factors of the decision model include labor/cost minimization, profit/utility maximization, risk aversion, and risk-taking. Alternative social network structures represent different processes through which social connections are made and information (e.g., farm management practices, aspirations) is diffused. Generalizable factors in social network structures included varying influence by location, homophily for demographic group, and shared activities. Together, these BBPs can either explicitly represent or approximate a wide variety of decision models. The Theory or Planned Behavior (TPB), for example, incorporates elements of risk via 'attitudes' and social influence via 'norms'. Additionally, many sophisticated decision models, e.g., TPB, have been formalized for empirical estimation and are thus probabilistic rather than mechanistic. Since one of the goals of the presented modeling framework is scalability and context-independence, the choice was made to develop a generalized mechanistic model that does not depend on estimation of empirical parameterization of decision model components. See Section 3.4.1 for more details about the implementation of each objective function and social network structure building-block process.

1.2.3. What are exogenous factors/drivers of the model?

Representative prices for field peas (Harbinson farm, interview data), corn (USDA), hay, and stocker cattle were used for horticulture, commodity, pasture, and livestock prices, respectively. Price fluctuations were simulated by multiplying per unit representative prices by the U.S. Producer Price Index (FAOSTAT) from 2000-2020. Variations in average crop yields for rain-fed horticultural, commodity, and pasture production were simulated in response to estimated precipitation and evapotranspiration trends based on the Standardized Precipitation Evapotranspiration Index (SPEI) for 2000-2020 (Vicente-Serrano, 2014).

1.2.3. How is space included in the model?

This modeling framework is spatially explicit and designed to ingest both raster and vector data inputs. Each Producer directly manages one or more parcels with georeferenced boundaries collected from tax assessor offices' records[8]. Strong social ties include other Producers within a user-specified spatial proximity. Biophysical and access variables are calculated using zonal statistics for each parcel from raster data layers. All geographic data use the WGS 1984 geographic coordinate system (WKID 4326), and areal-based calculations were conducted in the Albers Conical Equal Area projection and reprojected to the WGS 1984 UTM Zone 16N (WKID 32616) coordinate system.

1.2.4. What are the temporal and spatial resolutions and extents of the model?

The time step of the model is one year, which is assumed to capture all land use decisions over the course of spring and fall growing seasons. Producers update their perceived profit and risk of each production type and

[8] Parcel data purchased from Regrid (regrid.com) in 2019.

farm management combination on an annual basis. The model is initialized with input data drawn from multiple years but as close to 2009 (year of first CDL availability for Alabama) as possible.

The spatial extent of the simulated area is the state of Alabama. However, input data provided at the HUC 8 (watershed) level extended beyond the state's borders. Initially, each Producer makes crop choice and farm management decisions for at least one parcel. Producers can buy or rent parcels from other Producers and consequently manage multiple parcels.

1.3. Process overview and scheduling

The following provides a simplified version of the process overview and scheduling. For more detail regarding each process or agent attribute involved (*italics*), please see the Submodels section below. At initialization, parcel boundary data layers and suitability rasters (e.g., soil characteristics, average well depths, etc.) are imported as exogenous inputs. Producer agents are assigned one parcel each. Each Producer is also assigned to one of five farm type categories, a demographic group, membership in a spatial proximity-based social network (see *Collectives*), and the minimum cost crop or livestock production type (based on farm type category). Parcel-level yields and production costs are initialized for each production type and production methods based on user-specified average values and adjusted for the parcel's soil characteristics. Producer prices for horticultural and row crops, fodder, and livestock were initialized at regional average levels for the year 2000. Producer agents' price and yield prediction models are trained based on user-specified training data. Land prices are initialized as the maximum of each parcel's expected profits or production costs.

The following sequence of processes repeat every time step.

- **Producer states are updated**. Producer needs (i.e., production costs), aspirations, satisfaction, and uncertainty levels are updated given past information about productivity on managed parcels and from other Producers' parcels within their social network.

- **Crop and farm management choices**. Based on Producer states, and the theoretical Consumat decision-making framework (see *Theoretical and Empirical Background*), each Producer chooses a production type and acres in use following repetition, deliberative, social imitation, or social inquiry decision methods.

- **Credit application**. Conversion to irrigated production methods may require a loan to cover initial capital requirements. If a Producer's current income is not sufficient to cover the initial capital investment, but the expected profitability of the new production method is sufficient, the Credit Agent issues the Producer a loan and the monthly payment is added to the Producer's operating costs. Producers that do not meet these financial criteria revert to their previous production type.

- **Profit is observed**. Observed yields and prices are used to calculate each Producer's revenues net of production costs. Price and yield prediction models and willingness to accept and pay prices for land are updated.

- **Social network information is updated**. Production strategies and outcomes of other Producers in each Producer's social network are updated to inform production decisions in the next time step.

- **Fitness of building-block processes is updated**. Observed production and profit levels are compared to each Producer's aspirational levels, and all combinations of objective functions and social network structures are evaluated based on distance from their decisions' outcomes and each Producer's goals. The best performing combination of objective function and social network structure is selected for use in the next time step.

- **Land market dynamics**. Producers operating at a net loss enter the land sellers' pool, while Producers with net positive incomes and expansion aspirations become potential buyers. Market power is calculated and 'ask' and 'bid' prices are adjusted based on the relative number of buyers and sellers (see *Submodels*). The highest bidder (over the asking price) of each parcel enters into bilateral negotiations and transaction prices are determined. Producers that sell (or rent) their parcels exit from farming without the possibility of later re-entry. Buyers (or renters) add parcels to their management portfolios.

2. Design concepts

2.1. Theoretical and empirical background

2.1.1. Which general concepts, theories or hypotheses are underlying the model's design at the system level or at the level(s) of the submodel(s) (apart from the decision model)? What is the link to complexity and the purpose of the model?

An underlying concept guiding the model's development is that of transformational adaptation (Abson et al., 2017; Barrett et al., 2020; Blythe et al., 2018; Olsson et al., 2014; Scoones et al., 2020; Zagaria et al., 2021). Transformative adaptations in agriculture will involve significant restructuring of the methods, goals, and governance of farming to overcome various barriers that maintain the status quo, and such adaptations may be unprecedented and/or highly contested (Zagaria et al., 2021). From a behavioral perspective, transformational adaptation may entail attention to new information sources, restructuring of social interactions, re-prioritization of values, and/or behavioral paradigm shifts. Such significant structural and systemic changes are difficult to model with current approaches, which tend to represent human behavior with one or a simplified set of behavioral models (Brown et al., 2021; Sanga et al., 2021). Simplified behavioral models ignore the reality of heterogeneous decision-making styles and objectives, barely leveraging on rich knowledge from social science theories and behavioral data. This is particularly problematic when studying mechanisms for transformative adaptation. Such disruptive adaptations often originate from actors in the behavioral minority (i.e., 'pioneers' and 'early adopters'), and the diffusion of those adaptations can lead to regime shifts that are not captured by current large-scale ABMs (Verburg et al., 2016).

Guided by the need to represent behavioral diversity for transformational adaptation, this model implements a building-block processes (BBPs) approach (Ellis et al., 2018; Magliocca & Ellis, 2016). Each element of an agent's decision-making process can be represented as a 'building-block'. Multiple BBPs interact to produce coherent, dynamic behaviors (i.e., decision model). The types and diversity of BBPs represented depend on the decision-making context and may include several or all aspects of individual decision-making as described in the MoHub framework (Schlüter et al., 2017). Decision-making processes and structural elements leading to behavior include perception, evaluation, state (goals/needs, values, knowledge, assets), perceived behavioral options, and selection, and can include processes at either or both individual (e.g., objective function) and group or social interaction (e.g., social learning) scales. Variations of a given BBP are represented as 'levels', which range from the simplest (i.e., null hypothesis) to more sophisticated representations. The BBP framework uses an abductive modeling approach in which each unique combination of BBPs and their levels represents an alternative hypothesis of how decisions are made given the agent's motivations, perceptions, experiences, and local context. The goal of this model architecture is to find the most parsimonious configuration of BBPs needed to explain observed behavioral outcomes as the emergent result of agent-agent and agent-environment interactions, different mixes of individual and group BBPs, and variations in social and environmental pressures.

The selection of specific BBPs to represent in this model was informed by two main theoretical framings: environmental cognitions for land-use change (Meyfroidt, 2013) and innovation diffusion (Feder & Umali, 1993; Herrero et al., 2020; Schwarz & Ernst, 2009). The environmental cognitions concept provides guidance for representing more cognitively realistic agents in the context of land use choices. Environment, in the context of 'environmental cognitions', extends beyond ecological consideration to include changing social, political, and/or economic conditions in which the agent is embedded. Specifically, model design is guided by the proposition that "land use choices result from multiple decision-making processes and rely on various motives, influenced by social norms, emotions, beliefs, and values toward the environment" (Meyfroidt, 2013: 341). This guidance is implemented in two ways through a nested decision-making model structure. The BBPs approach provides decision model heterogeneity with alternative individual objective functions (i.e., goals and motivations; e.g., profit-maximizing) and alternative social network formation processes. (See Section 3.4.1).

The first level of decision-making implements the social network structure BBP in combination with the Consumat decision-making structure (Jager & Janssen, 2012). The Consumat decision-making framework is grounded in psychological research and provides a realistic meta-model of human cognition realism. Originally developed to model consumer behavior (Jager et al., 2000), four distinct 'modes' of decision-making are recognized based on a decision-maker's levels of uncertainty and satisfaction. The lowest cognitive burden decision-making mode is 'habitual' (i.e., repeat past behavior), which is used when satisfaction levels relative to aspirations are high and uncertainty in the decision-making context is low. If satisfaction remains high but uncertainty increases, a decision-maker imitates the choices of social connections in similar contexts. High uncertainty combined with low satisfaction leads to social inquiry, through which agent evaluate and select among the behavioral options observed in their social connections. Finally, if both satisfaction and uncertainty levels are low, reliable information can be obtained to undertake a deliberative decision-making process.

The second, nested layer of decision-making is activated for deliberative decisions. If a deliberative decision-making mode is chosen, the objective function BBP is used to evaluate and select the behavioral option that best achieves the agent's goals. (See section 3.4.1).

		Uncertainty	
		Low	High
Satisfaction	Low	Deliberative	Social Inquiry
	High	Habitual	Social Imitation

2.1.2. On what assumptions is/are the agents' decision model(s) based?

Producer agents are assumed to make decisions based on a combination of their own perceptions and experiences of their environment and information communicated through their social connections.

Agent are also assumed to follow cognitive tendencies related to habitual versus reflective decision-making modes as described by the Consumat framework, which determines the mode based on agents' levels of decision-making certainty and satisfaction relative to internal thresholds.

2.1.3. Why is/are certain decision model(s) chosen?

The Consumat decision-making framework was chosen because it integrates multiple cognitive aspects of decision-making, including needs, motivational processes, social comparison, social learning, and reasoned action, known to be important into a coherent model (Pacilly et al., 2019). The Consumat framework is a highly formalized model that enables the implementation of heterogeneous decision-making states and modes within the same agent population.

2.1.4. If the model/submodel (e.g. the decision model) is based on empirical data, where do the data come from?

The choice and design of decision-making models are qualitatively informed from surveys and field interviews conducted with producers from across the state of Alabama. Producer responses described their motivations, information sources for, experiences with, and perceived benefits/risks of a variety of farm management practices. The heterogeneity of these responses, which we not well explained by conventional factors, such as farm size or producer demographics, led to the design of multiple possible decision-making models independent of any farm or producer type.

2.1.5. At which level of aggregation were the data available?

See previous section.

2.2. Individual decision-making

2.2.1. What are the subjects and objects of the decision-making? On which level of aggregation is decision-making modeled? Are multiple levels of decision making included?

Producer agents make decisions about which crop and farm management practices to implement, how many acres for implementation, and whether to buy or sell land. All three decisions are based on expected production (yield and/or profit, depending on the objective function) relative to their aspiration levels. The results of these decisions are applied at the parcel level and a producer agent can operate multiple parcels.

2.2.2. What is the basic rationality behind agent decision-making in the model? Do agents pursue an explicit objective or have other success criteria?

A producer can pursue one of five different objectives at any given time step, and each objective has its own rationality (e.g., profit-maximization, risk averse, satisficing). See section 3.4.1 for more details about the BBPs submodel.

2.2.3. How do agents make their decisions?

Producer agents first consider their levels of decision-making uncertainty and satisfaction (e.g., income) relative to their aspirations. Following the Consumat framework, an agent repeats previous choices, seeks a new choice among social network connections, or undertakes deliberative decision making (see *Submodels*). If the latter, Producer agents calculate expected profits for each crop and farm management practice (e.g., irrigation) combination based on expected yields and prices net of production costs.

2.2.4. Do the agents adapt their behavior to changing endogenous and exogenous state variables? And if yes, how?

Agents adapt their behavior by choosing the combination of objective function and social networks (together constituting a 'decision model') performs the best given their specific location and production conditions. The best performing decision model is determined through a reinforcement learning algorithm based on error of predicted versus observed outcomes. For example, a profit-maximizing decision model may be the best performing when crop prices are high, but decreasing crop prices may favor a decision model with a risk aversion objective function.

2.2.5. Do social norms or cultural values play a role in the decision-making process?

Not in the version of the model presented here.

2.2.6. Do spatial aspects play a role in the decision process?

A Producer agent's location and proximity to other agents influence agent decision-making. Distance to market, approximated as travel time to cities of 50,000 or more, adds to transportation costs. Proximity to other agents can influence which 'neighbors' are included in an agent's social network based on the 'spatial neighborhood' social network structure.

2.2.7. Do temporal aspects play a role in the decision process?

Agents use past experiences to update perceptions of current conditions and form expectations of future conditions. All agents learn at specified rates by weighting current and past information by *Learning Rate*.

2.2.8 To which extent and how is uncertainty included in the agents' decision rules?

Uncertainty enters into Producer agents' decisions only by incomplete knowledge of other agents' actions and future prices, growing conditions, and crop yields.

2.3. Learning

2.3.1. Is individual learning included in the decision process? How do individuals change their decision rules over time as consequence of their experience?

Producer agents use reinforcement learning to select crops and farm management practices they believe to be most successful. When information about future crop prices and yields is limited, Producers form expectations based on individual and social network past experiences. Expected and observed outcomes are compared and the performance of decision models is updated. The objective function and social network structure combination (i.e., decision model) that performs best at each time step is selected for decision-making at the current time step. If exogenous conditions change and an alternative decision model's performance surpasses the current model, then the agent can switch decision models.

2.3.2. Is collective learning implemented in the model?

There is no explicit collective learning. However, successful farm management strategies are communicated through social networks, and social network connections are preferentially made among agents within similar groups.

2.4. Individual sensing

2.4.1. What endogenous and exogenous state variables are individuals assumed to sense and consider in their decisions? Is the sensing process erroneous?

Producer agents sense changing crop prices and yields and the actions of other agents in their social network. All agents have access to and perceive perfectly farm gate crop prices and observed crop yields. However, agents vary in their method and ability to predict future values based on their past experiences and predictive accuracies.

2.4.2. What state variables of other individuals can an individual perceive? Is the sensing process erroneous?

Producer agents can observe the crop choices and farm management practices of other Producer agents to which they are connected with strong ties in their social network. Producers can also make inquiries of their strong ties about their past yields of crop and farm management practices, which inform crop and farm management choices when prediction uncertainty levels are high.

2.4.3. What is the spatial scale of the sensing?

Sensing is based on social network structure, which can be geographically constrained to proximate neighbors, but can also extend over long distances when next work connections are based on similar crop and farm management types.

2.4.4. Are the mechanisms by which agents obtain information modeled explicitly, or are individuals simply assumed to know these variables?

Communication of productivity information is explicitly modeled among agents connected in a social network and varies with the assumed social network structure.

2.4.5. Are the costs for cognition and the costs for gathering information explicitly included in the model?

There are no explicit information acquisition costs.

2.5. Individual Prediction

2.5.1. Which data do the agents use to predict future conditions?

Agents use their knowledge of individual experiences and those communicated by other agents in their social network about past farm management strategies, profits, cost, and risk, in different places and times, to predict future conditions.

2.5.2. What internal models are agents assumed to use to estimate future conditions or consequences of their decisions?

Producers make crop choice decisions informed by expectations of future crop prices and yields. Adapted from price expectation models used in agent-based financial literature (e.g. Arthur, 1994, 2006; Axtell, 2005), Producer agents try to predict next period's price or yield based on current and past information. An agent is given a set of twenty prediction models. Each prediction model may use one of five different prediction methods, and there may be more than one model applying the same prediction method in the agent's set of twenty models. Some of these prediction methods map past and present price or yield information (I) into the next period using various extrapolation methods.

1. *Mean model*: predicts that *I(t+1)* will be the mean of the last *x* periods.

[1] $$I(t+1) = \frac{\sum_{i=t-x:t} I(t_i)}{x}$$

2. *Cycle model*: predicts that *I(t+1)* will be the same as *x* periods ago (cycle detector).

[2] $$I(t+1) = I(t-x)$$

3. *Projection model*: predicts that *I(t+1)* will be the least-squares, non-linear trend over the last *x* periods.

[3] $$I(t+1) = aI(t_x)^2 + bI(t_x) + c;$$

where t_s is the time span of *t-x* to *t*, and *a*, *b*, and *c* are coefficients of fit.

Other methods translate changes from only last period's information to next period's information.

4. *Mirror model*: predicts that *I(t+1)* will be a given fraction ξ of the difference in this period's information, I(t), from last period's information, I(t-1), from the mirror image around half of I(t).

[4] $$I(t+1) = 0.5I(t) + [0.5I(t) - (1-\xi)(I(t) - I(t-1))]$$

5. *Re-scale model*: predicts that *I(t+1)* will be a given factor ζ of this period's information bounded by [0,2].

[5] $$I(t+1) = \zeta I(t)$$

2.5.3. Might agents be erroneous in the prediction process, and how is it implemented?

All models in the agent's set of prediction models are used to predict the price or yield in the next time period (I*(t+1)*). In time *t*+1, the actual price or yield is known and the performance (i.e. error) of each model is determined by squaring the difference between the predicted and actual value. The prediction model with the least error is used to make the agent's decisions in the current period. This same process of prediction and evaluation is used every period so that the most successful prediction model is used every time. However, prediction model error is cumulative such that the most successful model may not continue to be used over time.

2.6. Interactions

2.6.1. Are interactions among agents and entities assumed as direct or indirect?

Agents interact directly through sharing of information in their social networks. In particular, agents can inquire about other agents' farm management practices, and each agent's aspirations are informed by performance of other agents in their social network.

2.6.2. On what do the interactions depend?

Interactions depend on the structure of two-way linkages among agents in their social network. Agents can be connected by either 'strong' or 'weak' ties in the social networks. Strong ties are agents that meet the criteria for direct connections in the social network, which varies based on the social network structure BBP implemented (see Section 3.4.2.1), while weak ties form between all other agents. Communicated information is weighed differently between 'strong' and 'weak' linkages in the social network. Full weight (w=1) is given to strong ties and weak ties are initialized with a baseline value (w=0.5), including the Extension agent. If the dynamic social network structure is implemented, weighting of weak ties that remain weak ties are updated each time step with a network decay factor of 10%.

Social network information informs an individual agent's decision-making through the following procedure. First, the average weak tie weighting factor, S_{wfac}, is calculated as:

[6] $$S_{wfac} = \frac{\sum_{n=1}^{N_{weak}} S_n}{N_{weak}}$$

where N_{weak} is the number of weak ties in a given agent's network and S_n is the weight assigned to that social network connection. Agent *n*'s aspiration level, $A_{n,t}$, for comparison at time *t* is then calculated with the following combination of annual incomes between strong and weak ties:

[7] $$A_{n,t} = \frac{1}{1+S_{wfac}} \hat{I}_{strong} + \frac{S_{wfac}}{1+S_{wfac}} \hat{I}_{weak}$$

where $\hat{I}_{strong}$ and $\hat{I}_{weak}$ are the median annual incomes of strong and weak ties, respectively.

2.6.3. If the interactions involve communication, how are such communications represented?

Inquiry about farm management practices among connected agents is done among strong network times, whereas communication of productivity information is passive among all agents connected in a social network.

2.6.4. If a coordination network exists, how does it affect the agent behavior? Is the structure of the network imposed or emergent?

The social network structure provides productivity information among agents for comparison, and farm management options among strong social ties. The structure of the social network is imposed for social network BBPs based on spatial proximity and demographic group. A third social network BBP is dynamic in which strong ties emerge based on similarity in farm management practices. See section 3.4.2.1 for more details.

2.7. Collectives

2.7.1. Do the individuals form or belong to aggregations that affect and are affected by the individuals? Are these aggregations imposed by the modeler or do they emerge during the simulation?

Individual Producers belong to a single social network either imposed or emergent depending on the social network BBP being implemented (see section 2.6.4).

2.7.2. How are collectives represented?

Social networks are represented by member Producers.

2.8. Heterogeneity

2.8.1. Are the agents heterogeneous? If yes, which state variables and/or processes differ between the agents?

Producer agents are heterogeneous in all individual and environmental attributes listed in Table S1 and S2. Individual attributes related to behaviors are assigned randomly at model initialization and can be updated/modified during model execution in response to environmental changes and/or interactions with other agents. Environmental attributes are empirically parameterized and vary by location.

2.8.2. Are the agents heterogeneous in their decision-making? If yes, which decision models or decision objects differ between the agents?

Producer agents are heterogeneous in the objective function and social network BBPs they select, as well as their individual prediction models (Section 2.5.2), and dynamically updated decision states related to the four modes of decision-making specified by the Consumat framework (section 2.1.1).

2.9. Stochasticity

2.9.1. What processes (including initialization) are modeled by assuming they are random or partly random?

Individual agent attributes (Table S1) are randomly created at initialization. However, using the Matlab default random number generator ('twisted'), individual attributes and network structure were held constant across all model executions with the same random number seed. The model was executed 30 times for each unique parameterization to account for the effects of stochasticity in individual attributes.

2.10. Observation

2.10.1. What data are collected from the ABM for testing, understanding and analyzing it, and how and when are they collected?

System-level outcomes, such as the number of acres planted, irrigated, and in each crop type, are collected at each time step.

2.10.2. What key results, outputs or characteristics of the model are emerging from the individuals? (Emergence)

In addition to the data described in 2.10.1, other emergent metrics, such as water consumption and source, Gini coefficients for farm size and income, land prices and transactions, Producer agent decision states, and total and per acre incomes are also recorded.

3. Details

3.1. Implementation details

3.1.1. How has the model been implemented?

The current version is implemented in Matlab, compatible at least up to version 2021a.

3.1.2. Is the model accessible, and if so where?

Model code and documentation is available at Github, https://github.com/nickmags13/SocioAgClim-ABM.

3.2. Initialization

3.2.1. What is the initial state of the model world, i.e. at time t = 0 of a simulation run?

At initialization, parcel boundaries, productivities and costs for each land use, and prices are imported as exogenous inputs. Producer agents are assigned to individual parcels and social network connections implemented (see *Interactions*) based on the social network BBP implemented (section 3.4.1). Producer agents train their prediction models with simulated production and price data until root mean square prediction error (RMSE) stabilizes below 10% for all agents.

3.2.2. Is the initialization always the same, or is it allowed to vary among simulations?

Matlab's random number generator can be seeded to reproduce identical results. Initializations are thus identical across different BBP scenarios with the same random number seed, but are allowed to vary for each of the 30 realizations for each BBP scenario.

3.2.3. Are the initial values chosen arbitrarily or based on data?

Individual attributes are assigned based on normal distributions around likely values informed by qualitative insights from field interviews. Environmental attributes are assigned based on empirical parcel and landscape data.

3.3. Input data

3.3.1. Does the model use input from external sources such as data files or other models to represent processes that change over time?

See Section 1 for description and sources of external input data for model parameterization. Cost tables from Alabama Cooperative Extension System (ACES) and USDA are provided below.

Irrigation installation and operating costs, per acre. Surface and well water estimates based on 111- and 134-acre demonstration farms, respectively.

	Surface	Well
Installation costs	1162.33	62.50
Operating costs	1276.14	35.00

Sources: data from ACES[9].

Estimated farm labor wage rates, per acre. Irrigation is assumed to add 20% to operator labor.

	Horticulture	Row crop	Pasture	Livestock
Rain-fed	840	12	13	95
Irrigated	988	31	15	-

Sources: ACES budget for field greens[10] and southern cow peas[11]; pasture and livestock estimates from USDA ARMS data extract[12].

Estimated farm operating (i.e., variable) costs, per acre.

	Horticulture	Row crop	Pasture	Livestock
Rain-fed	1229	451	309	1442
Irrigated	1520	929	641	-

Sources: ACES breakeven prices for southern cow peas[3] and row crops[13]; pasture and livestock estimates from USDA ARMS data extract[4].

Estimated overhead (i.e., fixed) costs, per acre.

	Horticulture	Row crop	Pasture	Livestock

[9] https://www.aces.edu/blog/topics/crop-production/investment-costs-of-center-pivot-irrigation-in-alabama-three-scenarios/.
[10] https://www.aces.edu/wp-content/uploads/2021/07/Greens2021-JB.pdf
[11] https://www.aces.edu/wp-content/uploads/2020/02/Southern-Peas-Manual-Harvest.pdf
[12] https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/
[13] https://www.aces.edu/blog/topics/crop-production/alabama-row-crops-breakeven-prices/

Rain-fed	291	79	113	53
Irrigated	324	239	342	-

Sources: ACES breakeven prices for southern cow peas[3] and row crops[5]; pasture and livestock estimates from USDA ARMS data extract[4].

3.4. Submodels

3.4.1. Building-Block Processes for objective function and social network structures

The BBPs approach was first described in Magliocca et al. (2016) and provides an abductive approach to exploring alternative decision-making structures. Based on qualitative insights gathered during field interviews and surveys of Alabama producers, BBPs for individual production motivations (i.e., objective functions) and social network structures were implemented to capture these main sources of heterogeneity among producers. Five and three alternative levels were implemented for objective functions and social network structure BBPs. The lowest level of each BBP is the simplest representation, and the sophistication (i.e., number of dependencies and information sources, decision factors) increases with higher levels (Table S3).

Table S3. Building-block processes (BBPs) for objective functions and social network structure ranging from the simplest (null model) at level 0 to the most sophisticated at level 4.

	Building-Block Process (BBP)	
Level	Objective Function	Social Network Structure
4	*Level 3* + Risk Salience	
3	*Level 2* + Risk Aversion	*Level 1* + Dynamic, Production Type
2	Profit-Maximization	*Level 1* + Static, Homophilly
1	Satisficing	Static, Spatial Proximity (Neighborhood)
0	Random choice (null model)	

BBPs are initialized for all agents at their lowest levels (levels 0 and 1 for objective function and social network structure, respectively) so that agents must actively choose a higher-level BBP. This approach favors the most parsimonious combination of BBPs, all else being equal.

3.4.1.1. Objective function BBPs

All objective functions are calculated on the basis of expected revenues and costs from each potential production strategy (e.g., different crops, rain-fed versus irrigated). Expected revenues, $R_{f,u,t}$, for farm *f* consisting of parcels *p*, land use *u*, and at time *t* are calculated as:

[8] $$R_{f,u,t} = a_p \cdot Y^{expt}_{p,u,t} \cdot P^{expt}_{p,u,t};$$

where a_p is the cumulative area of parcels comprising farm f (acres) and $Y^{expt}_{p,u,t}$ and $P^{expt}_{p,u,t}$ are the expected yield and price per unit of production, respectively.

Total productions costs, $C^{tot}_{f,t}$, for farm *f* at time *t* are the combination of fixed and operating costs. See section 3.3 for cost values.

[9] $$C^{tot}_{f,u,t} = C^{fixed}_{f} + C^{op}_{f,u,t};$$

Fixed costs, C^{fixed}_{f}, vary by the location of farm *f* and are independent of farm size and land use:

[10] $$C^{fixed}_{f} = C^{irr}_{f} + C^{trans}_{f};$$

where C_f^{irr} are one-time costs for irrigation infrastructure and C_f^{trans} are travel costs to the nearest market that varies with farm location (calculated from the centroid of all farm parcels).

Operating costs, $C_{f,u,t}^{op}$, increase with the size of the farm and are calculated as:

[11] $$C_{f,u,t}^{op} = a_p\left(W_u + C_u^{input} + SW \cdot C_u^{irrop}\right);$$

where W_u is the wage labor rate for each land use *u*; C_u^{input} are costs associated with production inputs (e.g., seed, fuel, fertilizer, pesticides); *SW* is a binary variable indicating the presence or absence of surface water access, which influences irrigation operating costs, C_u^{irrop}, that vary based on the source of irrigation water (e.g., pumping costs for groundwater).

3.4.1.1. Satisficing

The level 1 satisficing model recognizes the time and cognitive burdens of identifying the optimal farm production strategy among many possible options under conditions of uncertainty, and instead identifies the first strategy that is expected to satisfy the agent's goals and/or needs (Schuelter et al., 2017). In this implementation, the Producer agent chooses the expected payoff, $\pi_{f,u,t}$, and land use *u* that minimizes costs relative to expected returns:

[12] $$\pi_{f,u,t} = max\left(\frac{\left(R_{f,u,t} - C_{f,t}^{tot}\right)}{C_{f,t}^{tot}}\right)$$

3.4.1.2. Profit-maximizing

The level 2 profit-maximizing model follows standard assumptions of economically rationale actors maximizing the difference between revenues and costs:

[13] $$\pi_{f,u,t} = max\left(R_{f,u,t} - C_{f,t}^{tot}\right)$$

3.4.1.3. Risk aversion

Risk aversion, in the form of avoidance of losses, is based on Prospect Theory (Kahneman and Tversky, 2013), which assess potential payoffs relative to a reference point and overweighs potential losses. A formalization of Prospect Theory by Ligmann-Zielinska (2009) is adapted to the study context. Risk aversion is taken into account using the mean prediction error, σ, associated with the most successful price and productivity prediction models for each land use (see Agent Prediction). Based on this prediction error, expected returns are bracketed by high ($R_{f,u,t}^{high}$) and low ($R_{f,u,t}^{low}$) estimates for land use *u* in farm *f* at time *t*:

[14] $$R_{f,u,t}^{high} = \sigma_{t-1} + R_{f,u,t} - C_{f,t}^{tot};$$

[15] $$R_{f,u,t}^{low} = R_{f,u,t} - \sigma_{t-1} - C_{f,t}^{tot};$$

[16] $$R_{f,u^*,t}^{curr} = R_{f,u^*,t} - C_{f,t}^{tot}$$

High and low estimates of expected returns are then considered in a risk-aversion framework modified from Ligmann-Zielinska (2009) to conform to Prospect Theory. Potential gains (potgain) and losses (potloss) are calculated relative to a reference point of changes in potential payoffs relative to the current land use, $R_{f,u^*,t}^{curr}$.

[16] $$\text{potgain}(f,u,t) = \begin{cases} R_{f,u,t}^{high} - R_{f,u^*,t}^{curr}, & \text{if } R_{f,u,t}^{high} - R_{f,u^*,t}^{curr} > 0 \\ 0, & \text{if } R_{f,u,t}^{high} - R_{f,u^*,t}^{curr} \leq 0 \\ \text{potgain}(f,u) + R_{f,u,t}^{low} - R_{f,u^*,t}^{curr}, & \text{if } R_{f,u,t}^{low} - R_{f,u^*,t}^{curr} \geq 0 \end{cases}$$

$$\text{potloss}(f,u,t) = \begin{cases} \left(\dfrac{R_{f,u,t}^{high} - R_{f,u^*,t}^{curr}}{\omega_{loss}}\right)^{\frac{1}{\omega_{loss}}}, \text{if } R_{f,u,t}^{high} - R_{f,u^*,t}^{curr} \leq 0 \\ \text{potloss}(f,u) + \left(\dfrac{R_{f,u,t}^{low} - R_{f,u^*,t}^{curr}}{\omega_{loss}}\right)^{\frac{1}{\omega_{loss}}}, \text{if } R_{f,u,t}^{low} - R_{f,u^*,t}^{curr} < 0 \\ 0, \qquad \text{if } R_{f,u,t}^{low} - R_{f,u^*,t}^{curr} \geq 0 \end{cases}$$

where ω_{loss} = 2.5 is a skewedness factor modified from Ligmann-Zielinska (2009). Expected payoffs from each land use are then calculated as:

[17] $$\pi_{f,u,t} = \frac{\text{potgain}(f,u,t)}{\text{potgain}(f,u,t)+\text{potloss}(f,u,t)}$$

Land uses are ranked from highest to lowest expected payoffs excluding those with negative expected payoffs. The land use with the highest expected payoff is chosen.

3.4.1.3. Risk salience

Decision-making under risk is typically characterized by some type of bias, such as loss aversion, which results in decision outcomes that may be different than if the decision-maker had full information about risks. Loss aversion is often formalized as an over-valuing of potential losses versus equal potential gains relative to a given reference point – implemented by 'probability weighting' – which over-weights low probability, high impact outcomes (e.g., Barseghyan et al., 2014; Kőszegi and Rabin, 2007; Sydnor, 2010).

Salience Theory (ST; Bordalo et al., 2012) formalizes probability weights as a function of payoffs. Rather than specifying outcomes relative to a reference point, each outcome is valued based on the relative salience of its payoffs (i.e., magnitude of change relative to one another), and perceived probabilities of each outcome are thus increased (decreased) for more (less) salient outcomes.

ST frames decisions under risk as a choice problem between payoffs from two or more 'lotteries'. In this context, lotteries are analogous to different behavioral options for each current or potential land uses. Potential losses are calculated identically as in Eq. 16, but potential gains are weighted differently:

[18] $$\text{potgain}(f,u,t) = \begin{cases} \left(\dfrac{R_{f,u,t}^{high} - R_{f,u^*,t}^{curr}}{\omega_{gain}}\right)^{\frac{1}{\omega_{gain}}}, & \text{if } R_{f,u,t}^{high} - R_{f,u^*,t}^{curr} > 0 \\ 0, & \text{if } R_{f,u,t}^{high} - R_{f,u^*,t}^{curr} \leq 0 \\ \text{potgain}(f,u) + \left(\dfrac{R_{f,u,t}^{low} - R_{f,u^*,t}^{curr}}{\omega_{gain}}\right)^{\frac{1}{\omega_{gain}}}, & \text{if } R_{f,u,t}^{low} - R_{f,u^*,t}^{curr} \geq 0 \end{cases}$$

where ω_{gain} = 3 is a skewedness factor modified from Ligmann-Zielinska (2009) to weight gains higher than losses. Expected payoffs from each land use are calculated the same as in Eq. 17.

3.4.1.4. Social network structure BBPs

Three alternative social network structures are represented as building-blocks (Table S3).

The first BBP level and simplest structure is based on proximity. All Producer agents within the 50th percentile of all distances from a given Producer agent to all other Producer agents are considered strong ties (w=1), while others further away are assigned as weak ties (w=0.5). Weights on all social network connections remain constant throughout the simulation (Section 2.6.2).

The second BBP level social network structure includes the spatial neighborhood network of level 1 and additionally creates strong ties with other Producer agents of the same demographic group. All other agents are considered weak ties. In the current model version, demographic group is randomly assigned at the model's initialization. However, insights from field interviews and community engagement events reinforce the importance of these homophilic social network ties, and the model is designed to incorporate demographic data if available. Consistent with level 1, weights on all social network connections remain constant throughout the simulation (Section 2.6.2).

The third BBP level social network structure includes the spatial neighborhood network of level 1 and additionally creates strong ties with other Producer agents practicing the same land use and farm management strategy (e.g., irrigation). All other agents are considered weak ties. This network structure was also informed by field experiences and existing community-based producer organizations' structures, which tend to emerge around similar production practices and/or ethics (e.g., Alabama Sustainable Agriculture Network). Distinct from the first two levels, land use and farm management strategy is selected each year, and thus social network connections in this BBP are dynamically updated to reflect changing land use practices.

3.4.2. Land market

Land transactions occur following the bilateral land market structure developed in Parker & Filatova (2008) and Magliocca et al. (2011). Potential buyers (F^{buy}) and sellers (F^{sell}) among Producer agents are determined, respectively, as those that are using the profit-maximizing BBP and have positive total income, and those that have negative total income. These Producer agents enter the buyer and seller pools, respectively. Agents in the buyer pool are then screened to determine whether their budget (B) is positive:

[19] $$B_t^{F^{buy}} = I_t^{F^{buy}} - C_{F^{buy},u^*,t}^{tot};$$

where $I_t^{F^{buy}}$ is the income of each Producer agent in the buyer pool at time t, and $C_{F^{buy},u^*,t}^{tot}$ are the total production costs for each Producer agent in the buyer pool given their current land use u^*. Producer agents whose budgets are less than zero are removed from the buyer pool.

3.4.2.2. Formation of buyers' willingness to pay (WTP)

Buyers calculate a maximum price they would be willing to pay for each farm available on the market. WTP is based on their expected profit from their current land use adjusted by differences between total production costs on their farm and each available farm *f* for their current land use *u**. This WTP price is constrained by the buyer's budget and represents a breakeven point given current prices and production levels. Production costs vary by farm location given differences in water availability, soil, and proximity to markets. WTP is calculated as:

[20] $$WTP_{f,t}^{F^{buy}} = min\left(\pi_{f,u*,t} + \left(C_{F^{buy},u,t}^{tot} - C_{f,u,t}^{tot}\right), B_t^{F^{buy}}\right)$$

3.4.2.3. Formation of seller's willingness to accept (WTA)

Sellers calculate the minimum price they would be willing to accept for their farm below which it would be more beneficial to continue farming. WTA is determined as the maximum of the expected payoff or total production costs of from least productive land use that generates non-negative revenue. This ensures that the seller is paid at least the costs of production, otherwise it would be more beneficial to continue farming. The WTA is given by Eq. 21:

[21] $$WTA_t^{F^{sell}} = max\left(\pi_{F^{sell},u^{min},t}, C_{F^{sell},u^{min},t}^{tot}\right), \pi_{F^{sell},u^{min},t} > 0$$

3.4.2.4. Bargaining power in the land market

Bilateral negotiations in land markets reflect the relative bargaining power of buyer and sellers, which depend on the relationship between land supply and demand. Bargaining power in the land market, ε, is adapted from Parker and Filatova (2008) and captures differences in total buyers' demand for, and total sellers' supply of, land:

[22] $$\varepsilon = 0.5\frac{A_{F^{buy}} - A_{F^{sell}}}{A_{F^{buy}} + A_{F^{sell}}}$$

where $A_{F^{buy}}$ is the acreage demanded by buyers and $A_{F^{sell}}$ is the acreage supplied by sellers. If buyers demand more land than sellers supply, ε is positive and sellers ask a price above their WTA. If sellers supply more land than is demanded by buyers, ε is negative and buyers will bid below the initial WTP.

3.4.2.5. Formation of bid and asking prices

Given market conditions and bargaining power, buyers and sellers for bid and asking prices, respectively. Buyers calculate their bid prices ($P_{f,t}^{bid}$) for every farm on the market, subject to a budget constraint, as:

[23] $$P_{f,t}^{bid} = min\left((1+\varepsilon)WTP_{f,t}^{F^{buy}}, B_t^{F^{buy}}\right);$$

Similarly, sellers modify their WTA to form an asking price ($P_{F^{sell},t}^{ask}$) greater than or equal to the current land price ($P_t^{F^{sell}}$):

[24] $$P_{F^{sell},t}^{ask} = max\left((1+\varepsilon)WTA_t^{F^{sell}}, P_t^{F^{sell}}\right);$$

The maximum bid and associated buyer for each farm in the sellers' pool is identified. Farms that do not receive any bids greater than their asking price are removed from the sellers' pool, and the new land price for that farm is updated to the discounted asking price based on the interest rate (Table S1).

For all farms receiving bids higher than their asking prices, potential transaction prices ($P_{F^{sell},t}^{trans}$) are calculated as the mean of $P_{f,t}^{bid}$ and $P_{F^{sell},t}^{ask}$. Each buyer then calculates the potential return on the purchase of each farm at the potential transaction price:

[25] $$Ret_{F^{sell},u*,t} = \pi_{F^{sell},u^*,t} - P_{F^{sell},t}^{trans};$$

Beginning with the buyer with the highest overall bid, the farm that would generate the highest return at the transaction price is selected, ownership updated to the buyer and the seller removed from the sellers' pool, and future land prices updated to the transaction price. Land transactions continue with the next highest overall bidder iteratively and bilaterally until no more transactions are possible. If the seller owned only the farm that was sold, that agent is removed from the simulation; otherwise, they remain and can participate in the land market at future time steps as either a buyer or seller.

References

Abson, D. J., Fischer, J., Leventon, J., Newig, J., Schomerus, T., Vilsmaier, U., von Wehrden, H., Abernethy, P., Ives, C. D., Jager, N. W., & Lang, D. J. (2017). Leverage points for sustainability transformation. Ambio, 46(1), 30–39. https://doi.org/10.1007/s13280-016-0800-y.

Arthur, W. B. (1999). Complexity and the Economy. Science, 284(5411), 107–109. https://doi.org/10.1126/science.284.5411.107

Arthur, W. B. (2006). Chapter 32 Out-of-Equilibrium Economics and Agent-Based Modeling. In L. Tesfatsion & K. L. Judd (Eds.), Handbook of Computational Economics (Vol. 2, pp. 1551–1564). Elsevier. https://doi.org/10.1016/S1574-0021(05)02032-0

Axtell, R. L., Epstein, J. M., Dean, J. S., Gumerman, G. J., Swedlund, A. C., Harburger, J., Chakravarty, S., Hammond, R., Parker, J., & Parker, M. (2002). Population growth and collapse in a multiagent model of the Kayenta Anasazi in Long House Valley. Proceedings of the National Academy of Sciences of the United States of America, 99 Suppl 3(suppl 3), 7275–7279. https://doi.org/10.1073/pnas.092080799

Barrett, C. B., Benton, T. G., Cooper, K. A., Fanzo, J., Gandhi, R., Herrero, M., James, S., Kahn, M., Mason-D'Croz, D., Mathys, A., Nelson, R. J., Shen, J., Thornton, P., Bageant, E., Fan, S., Mude, A. G., Sibanda, L. M., & Wood, S. (2020). Bundling innovations to transform agri-food systems. Nature Sustainability 2020 3:12, 3(12), 974–976. https://doi.org/10.1038/s41893-020-00661-8

Blythe, J., Silver, J., Evans, L., Armitage, D., Bennett, N. J., Moore, M. L., Morrison, T. H., & Brown, K. (2018). The Dark Side of Transformation: Latent Risks in Contemporary Sustainability Discourse. Antipode, 50(5), 1206–1223. https://doi.org/10.1111/ANTI.12405

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience Theory of Choice Under Risk. The Quarterly Journal of Economics, 127(3), 1243–1285. https://doi.org/10.1093/qje/qjs018

Brown, C., Holman, I., & Rounsevell, M. (2021). How modelling paradigms affect simulated future land use change. Earth System Dynamics, 12(1), 211–231. https://doi.org/10.5194/ESD-12-211-2021

Ellis, E. C., Magliocca, N. R., Stevens, C. J., & Fuller, D. Q. (2018). Evolving the Anthropocene: linking multi-level selection with long-term social–ecological change. Sustainability Science, 13(1). https://doi.org/10.1007/s11625-017-0513-6

Feder, G., & Umali, D. L. (1993). The adoption of agricultural innovations. A review. In Technological Forecasting and Social Change (Vol. 43, Issues 3–4, pp. 215–239). North-Holland. https://doi.org/10.1016/0040-1625(93)90053-A

Handyside, C. (2014). Development of agricultural and irrigation water demand. Final report, Alabama Department of Water Resources, Montgomery, AL.

Herrero, M., Thornton, P. K., Mason-D'Croz, D., Palmer, J., Benton, T. G., Bodirsky, B. L., Bogard, J. R., Hall, A., Lee, B., Nyborg, K., Pradhan, P., Bonnett, G. D., Bryan, B. A., Campbell, B. M., Christensen, S., Clark, M., Cook, M. T., de Boer, I. J. M., Downs, C., … West, P. C. (2020). Innovation can accelerate the transition towards a sustainable food system. Nature Food 2020 1:5, 1(5), 266–272. https://doi.org/10.1038/s43016-020-0074-1

Jager, W., & Janssen, M. (2012). An updated conceptual framework for integrated modeling of human decision making: The Consumat II. Workshop Complexity in the Real World @ ECCS 2012 - from Policy Intelligence to Intelligent Policy.

Magliocca, N. R., & Ellis, E. C. (2016). Evolving human landscapes: a virtual laboratory approach. Journal of Land Use Science, 11(6). https://doi.org/10.1080/1747423X.2016.1241314

Meyfroidt, P. (2013). Environmental cognitions, land change, and social–ecological feedbacks: an overview. Http://Dx.Doi.Org/10.1080/1747423X.2012.667452, 8(3), 341–367. https://doi.org/10.1080/1747423X.2012.667452

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., & Schwarz, N. (2013). Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. Environmental Modelling & Software, 48, 37–48. https://doi.org/10.1016/J.ENVSOFT.2013.06.003

Olsson, P., Galaz, V., & Boonstra, W. J. (2014). Sustainability transformations: a resilience perspective. Ecology and Society, Published Online: Oct 14, 2014 | Doi:10.5751/ES-06799-190401, 19(4), 1. .

Pacilly, F. C. A., Hofstede, G. J., Lammerts van Bueren, E. T., & Groot, J. C. J. (2019). Analysing social-ecological interactions in disease control: An agent-based model on farmers' decision making and potato late blight dynamics. Environmental Modelling & Software, 119, 354–373. https://doi.org/10.1016/j.envsoft.2019.06.016

Sanga, U., Park, H., Wagner, C. H., Shah, S. H., & Ligmann-Zielinska, A. (2021). How do farmers adapt to agricultural risks in northern India? An agent-based exploration of alternate theories of decision-making. Journal of Environmental Management, 298, 113353. https://doi.org/10.1016/J.JENVMAN.2021.113353

Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M. A., McAllister, R. R. J., Müller, B., Orach, K., Schwarz, N., & Wijermans, N. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. Ecological Economics, 131, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008

Schwarz, N., & Ernst, A. (2009). Agent-based modeling of the diffusion of environmental innovations — An empirical approach. Technological Forecasting and Social Change, 76(4), 497–511. https://doi.org/10.1016/J.TECHFORE.2008.03.024

Scoones, I., Stirling, A., Abrol, D., Atela, J., Charli-Joseph, L., Eakin, H., Ely, A., Olsson, P., Pereira, L., Priya, R., van Zwanenberg, P., & Yang, L. (2020). Transformations to sustainability: combining structural, systemic and enabling approaches. Current Opinion in Environmental Sustainability, 42, 65–75. https://doi.org/10.1016/J.COSUST.2019.12.004

Verburg, P. H., Dearing, J. A., Dyke, J. G., Leeuw, S. van der, Seitzinger, S., Steffen, W., & Syvitski, J. (2016). Methods and approaches to modelling the Anthropocene. Global Environmental Change, 39, 328–340. https://doi.org/10.1016/J.GLOENVCHA.2015.08.007

Vicente-Serrano, S. (2014). Standardized Precipitation Evapotranspiration Index (SPEI). NCAR Climate Data. Available at: https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-evapotranspiration-index-spei. Last accessed June 12, 2023.

Zagaria, C., Schulp, C. J. E., Zavalloni, M., Viaggi, D., & Verburg, P. H. (2021). Modelling transformational adaptation to climate change among crop farming systems in Romagna, Italy. Agricultural Systems, 188, 103024. https://doi.org/10.1016/j.agsy.2020.103024