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

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Abstract

Responding to the challenges of societal transformation in the face of climate change, efforts to integrate behaviorally rich models of adaptation decision-making into large-scale macroeconomic and Earth system models are growing and agent-based models (ABMs) are an effective tool for doing so. However, behavioral richness in ABMs has been limited to implementations of single decision models for all agents in a simulated population. The main goals of this study were to: 1) implement the 'building-block processes' (BBPs) approach for decision model heterogeneity; 2) demonstrate the application of sensitivity and uncertainty analyses to quantify the scope of structural uncertainty produced by alternative decision models under variable price and climate conditions; and 3) apply the Observing System Simulation Experiment (OSSE) approach to validate such a behaviorally rich BBPs model at the level of individual agent decisions. Using an ABM of agricultural producers' decision-making, we demonstrated that uncertainty in crop and farm management decisions introduced by heterogeneous decision models was equal to and in some instances greater than that due to variable price or precipitation conditions. Unrealistically rapid or stagnant behavioral dynamics were evident in model versions implementing single decision models for all agents. Moreover, interactions among agents with diverse decision models in the same population produced consistently more accurate outcomes and realistic behavioral dynamics. The BBPs framework and accompanying sensitivity and uncertainty analyses demonstrated here offer a path forward for increasing behavioral richness in ABMs, which is key to understanding processes of adaptation central to societal responses to climate change.

Keywords

Model validation; sensitivity analysis; uncertainty analysis; adaptive decision-making.

Code availability

All supporting MATLAB code is available at https://github.com/nickmags13/SocioAgClim-ABM.

1. Introduction

There is growing recognition that an understanding of human agency, and the behavioral processes that underlie it, is critical for designing and implementing effective responses to large-scale societal challenges (Blythe et al., 2018; Brown et al., 2019; Irwin et al., 2018; Juhola et al., 2022; Niamir et al., 2020; Pindyck, 2013). The cumulative impacts of emergent, autonomous behavioral changes (i.e., adaptation) at the micro-level can have social-ecological system or economy-wide impacts (Beckage et al., 2018; Elsawah et al., 2020; Niamir et al., 2020). For

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example, in the context of natural hazards, heterogeneous adaptive behaviors can modify risks of future hazards, either mitigating or exacerbating them (Di Baldassarre et al., 2013; Magliocca et al., 2011; Viglione et al., 2014; Werner & McNamara, 2007), and can also create feedbacks that modify future risk perceptions and likelihoods of further adaptive behavior (Wens et al., 2019). Given the complexity of the social, ecological, and environmental systems involved, computational models are an important tool for understanding the dynamic feedbacks between human behavior and system-level change (Rounsevell et al., 2012; Verburg et al., 2019). However, our ability to explicitly account for human agency in computational models, particularly at scales compatible with the human and natural systems being managed, remains limited (An et al., 2021; Filatova et al., 2013; Robinson et al., 2022). Accordingly, there are growing numbers of efforts to integrate behaviorally-rich models that incorporate cognitive and/or social-psychological aspects of adaptation decision-making (e.g., risk aversion, social learning) into large-scale macroeconomic and physical models (e.g., Brown et al., 2019; Niamir et al., 2020; Rounsevell et al., 2014, 2021). However, behavioral richness has only been achieved at relatively small spatial extents, particularly in the context of adaptation, where micro-level processes such as social learning and subjective risk perception are so important and can be more feasibly measured (Brown et al., 2021).

Agent-based models (ABMs) are a popular and effective tool for simulating individual heterogeneity and decision-making processes (Taberna et al., 2023; Williams et al., 2022; Zagaria et al., 2021). Current approaches to integrating ABMs with large-scale models make simplifying assumptions to facilitate scaling at the cost of behavioral richness at the individual level (Brown et al., 2019, 2021; Groeneveld et al., 2017). Alternative approaches, such as inverse generative social science (iGSS) (Epstein, 2023) have suggested that multiple, heterogeneous decision-making models can be included in the same agent population, which would enable the emergence of autonomous, adaptive behavioral changes in response to both exogenous (e.g., climate disruptions) and endogenous (e.g., social cues) signals (e.g., Magliocca & Ellis, 2016). However, these approaches have been limited in scope, and the capacity to develop behaviorally-rich ABMs has outpaced modelers' abilities to calibrate and manage the resulting uncertainties in ABMs. ABM development, calibration, and validation with a single decision-making model is already challenging due to time-intensive and complex acquisition/solicitation of cognitive and social-psychological data (Elsawah et al., 2020; Filatova et al., 2013). Data collection to implement multiple, heterogeneous decision-making models, each varying in the goals and cognitive foundations, is often infeasible for localized studies and prohibitive at larger extents (Robinson et al., 2022).

Managing multiple sources of uncertainty, particularly model structural uncertainty, remains a core challenge in ABM research (An et al., 2021; Baustert & Benetto, 2017; McCulloch et al., 2022). Established uncertainty and sensitivity analysis methods, such as global sensitivity analysis (GSA) (Ligmann-Zielinska et al., 2020), can quantify the proportion of variance attributable to alternative decision parameters (e.g., Sanga et al., 2021), but have not yet been applied to assess structural uncertainty or model output sensitivity when multiple, heterogeneous decision models are simultaneously present and endogenously chosen in the same agent population.

Modeling more realistic adaptation decision-making for the purposes of explaining sources of observed maladaptation or investigating potential adaptation responses to behavioral interventions requires introducing levels of structural uncertainty that current ABM practices are not yet equipped to handle (Jakeman et al., 2024). Therefore, the overall purpose of the model presented in this study is to create a scalable, agent-based framework that enables the simulation of behaviorally-rich - i.e., multiple, heterogeneous, and cognitively plausible - models of adaptation decision-making among agents in the same population. To realize this purpose, this study addresses the following goals: 1) build on existing methods for implementing decision model heterogeneity; 2) demonstrate and quantify the scope of structural uncertainty produced by alternative decision models in response to exogenous price and climate variations; and 3) validate such a behaviorally-rich model in the absence of comparable empirical data, which is often case for large-scale ABM applications.

The remainder of the paper is structured as follows. The next section details the limitations of current large-scale ABM approaches that restrict the level of behavioral richness that can be incorporated. An ABM is then presented that uses the 'building-block processes' (BBPs) approach, which is an iGSS method through which agents endogenously learn and select among alternative decision model components (Magliocca & Ellis, 2016), for implementing multiple, heterogeneous decision models in the same agent population. The contributions of the alternative decision models to model output variability and uncertainty are then quantified using GSA and Bayesian Model Averaging (BMA) techniques (Madadgar and Moradkhani, 2015; Abbaszadeh et al., 2022). Finally, given the unlikelihood of obtaining individual decision-making level empirical data for large-scale ABM applications, a computational technique adapted from geosciences and remote sensing, known as Observing System Simulation Experiments (OSSE) (Moradkhani, 2008), is explored to assess the performance of the BBPs ABM to model irrigation adoption decisions.

2. Current ABM limitations

ABMs are an established approach to study autonomous decisions and behaviors that produce macro-scale phenomena (An et al., 2021; Elsawah et al., 2020; Filatova et al., 2013). Moreover, a growing number of large-scale ABMs are being developed to study micro-level human agency in macroeconomic and climate systems for the purposes of replicating aggregate behavioral outcomes and experimenting with possible interventions (Brown et al., 2021; Robinson et al., 2022; Verburg et al., 2016, 2019). While important improvements have been made with current large-scale ABMs, such as including heterogeneous agent types with profit-maximizing versus pro-environmental behaviors (e.g., Brown et al., 2019; Niamir et al., 2020; Rounsevell et al., 2014, 2021), critical weaknesses remain stemming from the constraints imposed by large-scale modeling.

First, agents often represent aggregations of individual decision-making units (e.g., individuals, households, institutions). This model design choice can reduce computational burden when simulating over large geographic regions, which could contain millions of individual decision-makers. Typologies are the most common strategy for specifying aggregate agent representations, which simplify individual-level heterogeneity into more general patterns or pathways of change (Valbuena et al., 2008). In the agricultural sector, for example, typologies may focus on farmer and structural characteristics, such as demographics, farm assets, or relative power, to explain tendencies to certain farming decisions (Valbuena et al., 2008; Williams et al., 2023). Other typologies explain farming strategies by integrating psychological factors such as attitudes, perceptions, and values (Sanga et al., 2021). For example, the CRAFTY large-scale ABM framework (e.g., Brown et al., 2019; Guillem et al., 2015) implements agent functional types (AFTs) to describe combinations of agents' functional roles, preferences, decision-making strategies, and geographic niches (Arneth et al., 2014; Kaiser et al., 2020; Murray-Rust et al., 2014). AFTs have been successfully applied at large scales (e.g., European Union) to represent relevant aspects of agent heterogeneity leading to varying land-use intensities. However, agent representational and spatial simplifications are made, such as coarsening model resolution beyond what can be considered individual decision-making (e.g., ~ 20 km2 grid cells in CRAFTY-EU; Brown et al., 2019), to achieve computational tractability over large spatial extents and consistency with input data from macroeconomic and climate models. Group-level agent heterogeneity is still included at this aggregate scale, but behavioral richness at the micro-scale is lost.

Second, because of agent aggregation, agent interactions are reduced in complexity, often to be consistent with other large-scale modeling paradigms (e.g., equilibrium-based economic rationale; Brown et al., 2021). Such assumptions simplify model development and reduce structural uncertainties in model outcomes. However, resulting representations of agent interactions are inconsistent with the reality of heterogeneous decision-making styles and objectives and barely leverage rich knowledge and behavioral data from the social sciences (Elsawah et al., 2015, 2020; Niamir et al., 2020). Typically, if alternative behavioral theories are considered, they are implemented in separate scenarios in which all agents use an assigned behavioral theory (Janssen & Baggio, 2017; Sanga et al., 2021; Wens et al., 2020; Zagaria et al., 2021).This omits possible emergent outcomes arising from interactions among agents with different behavioral rules and objectives. Such interactions are particularly important when information transmitted through social networks, such as efficacy or risks of new farming practices, can influence agents' decision-making while also transcending geographic boundaries and spatially proximate interactions. Moreover, individual-level social learning or emergence of collective behaviors (e.g., cooperation) cannot be represented in this framework, but such social processes are critical to adaptation (Niamir et al., 2018, 2020). This is particularly problematic when studying mechanisms for transformative adaptation, which are adaptations that involve significant restructuring of the methods, goals, and/or governance of land-use practices away from the status quo, and which are often unprecedented and/or highly contested (Zagaria et al., 2021). 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).

2.1 Implementing simultaneous, heterogeneous decision-making models

One possible solution is to implemental multiple, heterogeneous decision-making models simultaneously within the same agent population. Decision-making models are defined here to be consistent with the Modeling Human Behavior, or MoHuB (Schlüter et al., 2017), framework in which human decision-making is dependent on interactions among an agent's perception and evaluation of the social and biophysical environment, internal state, and selection of perceived behavioral options to generate a behavior. This structure allows for heterogeneity in one or more of these aspects, reflecting the myriad of ways humans make decisions, which are influenced by diverse beliefs, values, and norms (Kuehne et al., 2017; Arbuckle et al., 2014). Moreover, individual decision-making is socially embedded such that adaptive behaviors are contingent on social, economic, and cultural influences and structures (Constantino et al., 2021; Davidson et al., 2024; Niesen et al., 2019; Sanga et al., 2021). Progress toward implementing such complexities in ABMs has been slow, however, due to challenges of selecting appropriate behavioral theories, lack of mathematical formalization from diverse behavioral theories, and specifying sufficiently generalizable input parameters (An, 2012; Balke & Gilbert, 2014; Groeneveld et al., 2017; Schulze et al., 2017). In addition, methods for quantifying and managing structural uncertainties associated with implementing multiple decision models simultaneously are not as well developed as for sources of input and stochastic uncertainty (Ligmann-Zielinska et al., 2020).

A promising approach to guide the implementation of multiple, heterogeneous decision models in the same agent population is that of inverse generative social science (iGSS). Generative social science has been a productive avenue for experimenting with alternative model structures and advancing the explanatory power of ABMs in multiple social simulation contexts (Axtell et al., 2002; Epstein, 2006). iGSS shares those goals, but rather than designing and parameterizing behaviorally realistic agents in an effort to collectively reproduce observed macro-scale phenomena, iGSS uses evolutionary programming to generate diverse combinations of behavioral building blocks, or 'primitive agent-rule constituents', that are capable of producing observed macro-scale phenomena (Epstein, 2023). The best explanation for observed phenomena is sought through abductive testing of alternative model structures. This is fully consistent with the 'building-block processes' (BBPs) approach (Ellis et al., 2018; Magliocca & Ellis, 2016), which is implemented here and described in detail in the Methods. The BBPs framework uses an abductive modeling approach in which each unique combination of BBPs represents an alternative hypothesis of how decisions are made given the agent's motivations, perceptions, experiences, and local context. However, full implementations of iGSS (see Epstein et al. (2023) for examples) and BBPs are similarly limited.

Sanga et al. (2021) provide perhaps the most advanced implementation of simultaneous, heterogeneous agent decision-making models in an empirical context. The authors developed an ABM called AG-ADAPT to simulate the adoption of one or more agricultural adaptation strategies in Norther India based on four decision-making rules - utility maximization, self-satisficing, social norms, and random choice. The distribution of these decision-making rules among the agent population was determined by assigning all agents one of the decision rules, executing 500 model runs each, and analyzing the proportion of adoption decisions that best fit the observed data (i.e., percent variance explained) on adoption counts for each strategy. Variance decomposition sensitivity analysis (SA) was also performed to quantify the influences of variability in five input parameters on adoption counts for each strategy. Ultimately, model fitting eliminated all but two decision models – utility-maximization, which is a standard assumption in most ABMs, and random choice, which is not grounded in any social-psychological decision-making theory. By selecting decision-making rules based on single decision model implementations and aggregate explained variance, the possible influence of social interactions among agents with different decision-making processes was lost. Building on this novel consideration of multiple possible behavioral models, further methodological innovations are needed to also allow the interactions among agents with diverse behavioral models to influence each agent's choice of behavioral model endogenously.

2.2 Structural uncertainty

Social-ecological systems are characterized by multiple, compounding uncertainties (Elsawah et al., 2020; Manson, 2007), a situation known as deep uncertainty (Lempert, 2002; Maier et al., 2016), which must be contended with when modeling such systems (Baustert & Benetto, 2017; Refsgaard et al., 2007; Srikrishnan et al., 2022; Walker et al., 2003). The most common source of model uncertainty stems from inherent variability of the study system and manifests as input uncertainty. According to Walker et al. (2003), input uncertainty is created by variability in the external forces that drive system change, system responses to such forces, and the magnitudes of each affecting outcomes of interest. Input uncertainty is further divided into aleatory and measurement uncertainty, with the former related to stochastic system variations in response to external forces and the latter originating in potential inaccuracies in observing and measuring dynamic systems and parameterizing models accordingly (Walker et al., 2003). An additional source of uncertainty is epistemic uncertainty "due to the imperfection of our knowledge, which may be reduced by more research and empirical efforts" (Walker et al., 2003: 13). Epistemic uncertainty poses a significant challenge in the context of modeling human decision-making, which is difficult to measure or observe directly (Elsawah et al., 2020; Filatova et al., 2013), and may also manifest as input uncertainty. Finally, structural uncertainty may exist when there are alternative explanations for how individual or system behaviors emerge and it is probable that none of the alternatives are entirely correct (Walker et al., 2003). When alternative explanations or model structures are integrated into the same model, existing aleatory and measurement uncertainties are compounded because each alternative may respond differently to the same sources of system variability, and those responses could accentuate or dampen endogenous system variability and may vary over time (Figure 1).

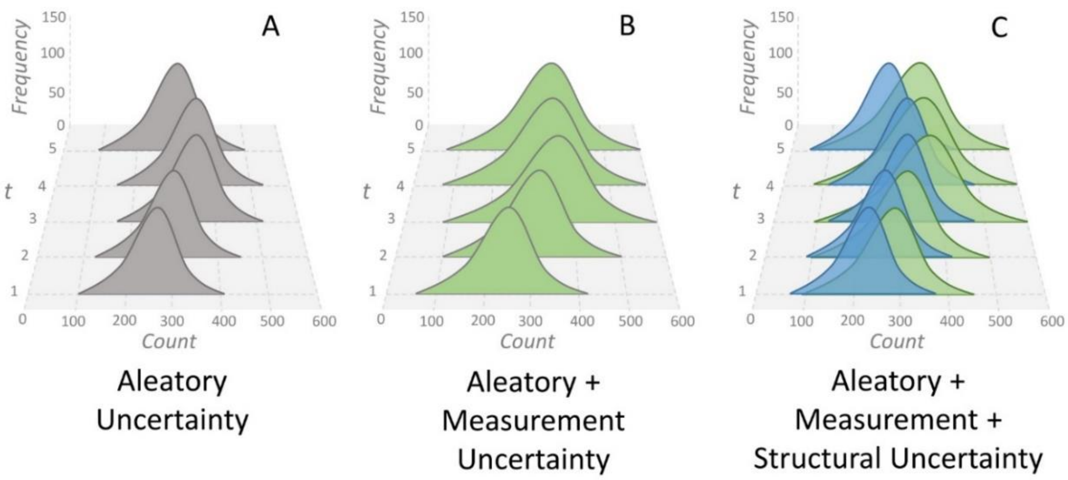

Figure 1: Stylized examples of evolving outcome distributions (e.g., count of agents; x-axis) over time (z-axis) across multiple model realizations (y-axis) illustrating how A) aleatory (i.e., stochastic) and B) measurement uncertainties can be compounded when C) alternative model structures are introduced.

Elsawah et al. (2020) identify the management of various types and sources of uncertainty as a priority and 'grand challenge' in social-ecological systems modeling. Implementing multiple, diverse behavioral models within an agent population increases model complexity substantially by incorporating all the aforementioned types of uncertainty. Model complexity begins to approach that of the real system, which makes interpretation of and tracing causality within model outcomes difficult (Sun et al., 2016). This challenge is exacerbated when multiple model types and/or sectors are integrated, such as human and Earth system models, due to the potential for compounding uncertainties, in which case model producers and users must decide what are acceptable sources and levels of uncertainty (Rounsevell et al., 2021). Thus, innovation is needed not only in implementation of more realistic, heterogeneous decision-making models, but also in supporting methods to characterize and quantify structural uncertainty beyond those developed for single behavioral models and/or external sources of system variability.

3. Rationale

Several tensions are thus apparent in the current state of knowledge. There is a clear need for better representation of human behavioral diversity in social-ecological system models to investigate adaptation decision-making and pathways. However, strategies for implementing multiple, heterogeneous decision-making models are underdeveloped, as are methods for identifying and managing the structural uncertainty that would result. Moreover, empirical data measuring decision-making processes and their outcomes at the individual level are rarely available, particularly when large-scale behavioral models are needed for integration with Earth system models. To navigate these tensions, we propose that a successful implementation of multiple, heterogeneous decision models to investigate adaptation dynamics would have to satisfy, at a minimum, the following three tests:

Test 1: A model structure implementing multiple, heterogeneous decision models should more accurately produce adaptive behaviors in 'out-of-equilibrium' system states than structurally homogeneous alternatives.

There is empirical evidence that many innovations emerge from 'fringe' ideas, are adopted first by those in the behavioral minority (i.e., 'pioneers'), and only after a critical mass of adopters does the innovation go mainstream (DellaPosta et al., 2017; Perello-Moragues et al., 2019; Schwarz & Ernst, 2009; Zagaria et al., 2021). Moreover, adaptative behavior is more likely to emerge under conditions of perceived crisis or perturbation (e.g., realignment of incentives under new policy or spatial planning following a natural disaster) when individual benefits of departing from current behavior may be higher than conforming (Arthur, 1999, 2006; DellaPosta et al., 2017; Orach et al., 2020). Thus, to satisfactorily pass this test heterogeneous behavioral models, which entail increased complexity and structural uncertainty, should perform better than simpler, structurally homogeneous models in times of stress, i.e., exogenous perturbations that significantly deviate from long-term norms/trends (i.e., remains realistic under extreme conditions, (Troost et al., 2023).

Test 2: A structurally valid model of autonomous adaptive decision-making should be able to reproduce emergent macro-scale outcomes better than alternative models with less realistic structures.

Structural validity is the ability of a simulation model to reproduce multiple empirical patterns at different levels of system organization simultaneously (i.e., pattern-oriented modeling (POM); Grimm et al., 2005; Magliocca & Ellis, 2013), which is a rigorous test of not only outcome accuracy but process accuracy requiring a realistic structure of agent-agent and agent-environment interactions. In principle, then, a model with structurally heterogeneous decision models would better reflect behavioral diversity and its effects on system-level outcomes (Latombe et al., 2011). However, much of the empirical data available against which to evaluate model outputs is aggregated in some way. Empirical data providing insights into behavioral mechanisms is difficult to obtain from survey data, which tend to describe respondent characteristics and patterns of decision outcomes (e.g., stated preference) rather than the social-psychological processes underlying the decision, including how those stated preferences may influence individual decision making under exogenous disturbances. Thus, the connections between individual social-psychological differences and aggregate outcomes cannot be traced (Niamir et al., 2020), and the effects of behavioral heterogeneity may be masked at aggregate measurement scales and/or in relatively stable exogeneous conditions. A *necessary* (although not *sufficient*) indicator of passing this test would then be the production of aggregate, distributional effects of heterogeneous adaptation that are consistent with empirical observations (e.g., levels of adaptation within a population).

Test 3: Model structure with homogeneous behavioral assumptions should be more sensitive to the lack of disaggregate input data than model structures implementing heterogeneous behavioral models.

Related to the second premise, low process accuracy can become apparent when a model is applied to sufficiently diverse contexts beyond those in which the original model was developed. Large-scale ABM applications are confronted with this challenge due to the inherent spatial heterogeneity that must be simplified or abstracted. Moreover, aggregate data sources are most feasible when data acquisition becomes time and cost prohibitive at larger spatial extents, such as states, regions, or countries, which are the scales at which coupled model integration occurs and error propagation is a greater concern (Rounsevell et al., 2021). With a lack of disaggregated behavioral data, alternative model structures are not practically identifiable (i.e., variation in observational data cannot be directly explained by differences in model structures). However, evaluating the time path or dynamics of adaptive outcomes can mitigate this structural identification problem associated with equifinality (Troost et al., 2023). Sufficient structural validity, particularly of a model meant to provide insight into adaptive decision-making processes, can be successfully established by demonstrating lower uncertainties of decision-making outcomes over time.

4. Methods

An ABM of producer (i.e., both crop and livestock producers) decision-making has been developed to explain the timing and location of irrigation adoption as a climate change adaptation strategy. The overall purpose of this model was to create a scalable, agent-based framework, based on 'first principles' of goal-seeking and adaptation decisions, that enabled the simulation of multiple, heterogeneous decision-making models among agents in the same population. The modeling framework used BBPs approach to find the best combination among alternative objective functions and social network structures for explaining empirical patterns of production activities for each agent given their decision-making context. The specific application of the framework described here simulated adaptive farm management and associated land-use choices of producers throughout the state of Alabama. The model was 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. A full, detailed description of the model following the ODD+D protocol is provided in the Supplementary Material.

4.1 Agents and their attributes

Three types of agents were represented. Producer agents represented individual farmers and/or livestock producers. Producer agents had fixed geographic positions associated with specific land parcels. Initially, each Producer made crop choice and farm management decisions for at least one parcel. Producers could buy or rent parcels from other Producers and consequently some managed multiple parcels. Producer agents interacted unilaterally with the Credit and Extension agents and other Producer agents in their social networks. Producer agents chose specific crops and farm management techniques (e.g., irrigation) in response to perceived precipitation and price changes, individual experience, and learned strategies from other agents. Each Producer agent chose among eight possible production types and farm management practices: rain-fed or irrigated horticulture, commodity (row crop), or pasture, livestock production, or fallowing. Each option had unique 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 varied over space with availability of surface or groundwater sources. Producer agents were considered 'active' (Berglund, 2015; Magliocca, 2020) agents given their ability to learn and select new behaviors in response to changing conditions.

A representative Extension agent recommends a specific crop and farm management technique for adoption to all Producer agents in the social network. The Extension agent was considered a 'reactive' agent since it had predetermined behavioral responses to varying conditions. A representative Credit agent issues Producer agents loans to cover the transition costs to new farm management practices (e.g., irrigation). In the generalized version of this model, the Credit agent issued loans to Producer agents if the potential revenue from the new crop and/or farm management practice was equal to or greater than estimated annual loan payments given interest rates. Future versions of the model will consider differential or biased lending practices. The Credit agent was considered a 'reactive' agent since it had predetermined behavioral responses to varying conditions.

4.2 Environment

The model was initialized with input data drawn from multiple years and an assumed starting year of 2000 to have sufficient simulation time before the price volatility of 2007-2011. The spatial extent of the simulated area was the state of Alabama subdivided into 'social neighborhoods' centered around Extension offices and farmer co-op locations (Price et al., 2022). For the purposes of demonstrating the BBPs framework, structural uncertainty analyses, and individual-level validation, the ABM was applied to a single social neighborhood to minimize computation time and simplify model output analyses. The selected social neighborhood included parts of four counties (Monroe, Escambia, Conecuh, and Clarke) and three watersheds (Alabama River, Lower Conecuh River, and Big Escambia Creek). Individual georeferenced parcel boundaries within each social neighborhood were collated from county tax assessor offices and curated by Regrid[1] (Price et al., 2022). Only parcels that were larger than 3.6 ac (1.46 ha) and included pasture or cropland land uses as classified in the National Cropland Data Layer (NLCD) were retained for simulation (Price et al., 2022). Within the selected social neighborhood, 2,172 individual parcels were present and assigned to Producer agents (Figure 2a).

[1] Available at: https://regrid.com/

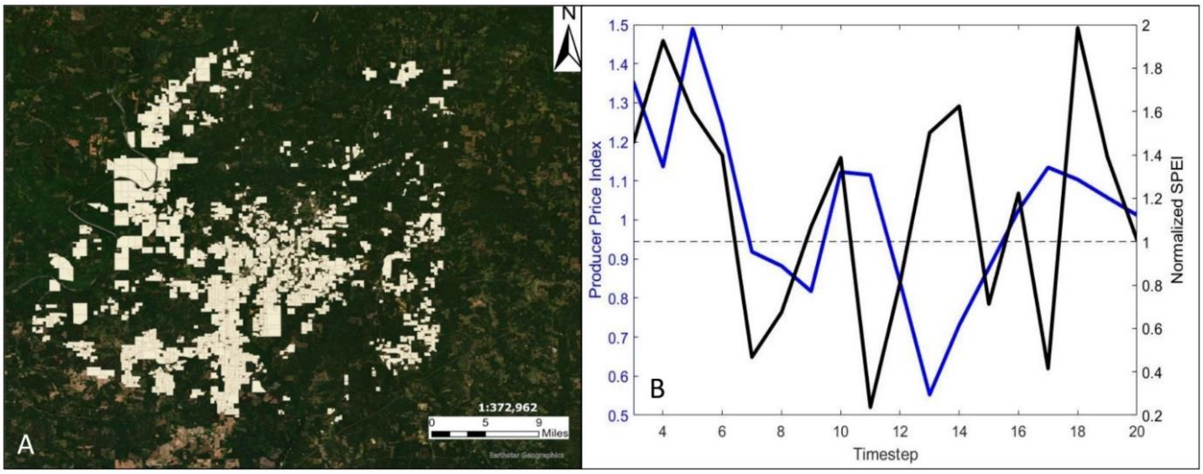

Figure 2: A) Simulated landscape in which each parcel was assigned to a Producer agent, and B) external sources of price and precipitation variability implemented during the simulation period.

Two sources of external variability were also simulated (Figure 2B). Variations in crop prices were approximated using the U.S. Producer Price Index (PPI) from FAOSTAT[2] for the time period of 2000-2020 (Table S1.2). Variability in crop yields were also approximated with precipitation variations based on the Standardized Precipitation and Evapotranspiration Index (SPEI) (Vicente-Serrano, 2014) from 2000-2020 (Table S1.2). Precipitation variation only modified the average yield for rainfed horticultural and commodity crops and pasture, whereas yields from livestock and any irrigated land use were not affected.

4.3 Building-block processes (BBPs)

BBPs were initialized for all agents at their lowest levels (levels 0 and 1 for objective function and social network structure, respectively) so that agents had to adaptively choose a higher-level BBP (Table 1). This approach favored the most parsimonious combination of BBPs, all else equal. For more details about specific objective functions and social network formation algorithms, please see Supplementary Information Section 3.4.1.

Table 1: 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)	

4.4 Agent decision-making structure

Producer decision-making had a two-level, nested structure (Figure 3). The first level of decision-making implemented the social network structure BBP in combination with the Consumat decision-making structure (Jager & Janssen, 2012). 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 in a coherent model (Pacilly et al., 2019; van Duinen et al., 2016). The Consumat framework is a highly formalized model that enables each agent to endogenously select among multiple decision-making states and modes. The Consumat decision-making framework is grounded in psychological research and provides a realistic meta-model of human cognition realism. Originally developed to

[2] Available at: https://www.fao.org/faostat/en/#data/PP

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 agents 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.

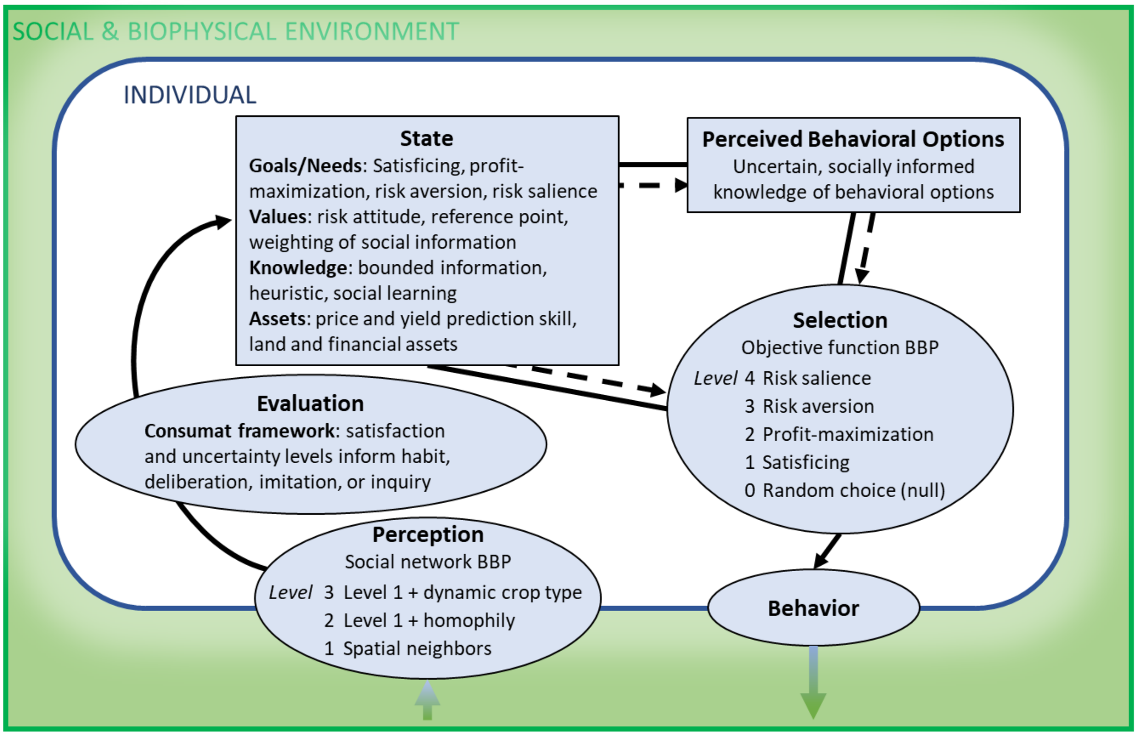

Figure 3: Description of the Producer agents' decision-making structure presented in the MoHuB framework.

4.5 Model execution

The time step of the model was one year, which was assumed to capture all land use decisions over the course of spring and fall growing seasons. Producers updated their perceived profit and risk of each production type and farm management combination on an annual basis. The model simulated over 30 time steps; the first 10 as spin-up and learning time and the subsequent 20 as simulation for comparison with empirical data available from 2000-2020. Model processes were executed in the following order at each 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, 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**. Each Producer compares observed production and profit levels to their aspirational levels, and all combinations of objective functions and social network structures are evaluated based on the difference between their outcomes and 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 SI section *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.

System-level outcomes, such as the number of acres planted, irrigated, and in each crop type (i.e., crop choice and farm management practice), were collected at each time step for evaluation against empirical data. In addition, other emergent metrics, such as water consumption and source, Gini coefficients for farm size and income, land prices and transactions, Producer agent decision states, as well as total and per acre incomes were recorded to investigate model output dynamics.

4.6 Model evaluation

4.6.1. Sensitivity analyses

Two different sensitivity analyses methods - dispersion indices and variance decomposition (Ligmann-Zielinska et al., 2020) - were conducted to quantify the effects of alternative decision models and variable external conditions on the final counts of Producers per crop type. Each BBP was executed for 30 model realizations paired with different combinations of the other type of BBP model. For example, sensitivity indices were calculated from all model executions with the random choice objective function BBP active and each of the three alternative social network structure BBPs. Simulations were also performed with static and time-varying crop prices and precipitation to understand their contributions to stochastic and deterministic uncertainties. Since input parameters were specified from empirically estimated values and repeated for each model realization, model stochasticity was only generated from model initialization routines, such as assignment of Producer agents to specific parcels and allocation of yield and price prediction models (see SI section 2.5). In total, 45 different experimental scenarios were implemented (five objective function BBPs, three social network BBPs, and three external conditions) and executed 30 times each for a total of 1,350 model runs.

The first sensitivity analysis calculated dispersion indices (i.e., variance-to-median ratio) to quantify the variance introduced by holding a BBP of one type constant while varying the BBPs of the other type for each exogenous condition. Variance-to-median ratios were calculated for each production option and the average taken across all options. This produced a summary index for each focal BBP under static or variable conditions. Second, variance decomposition was used to distinguish deterministic and stochastic output uncertainty using a one factor at a time (OFAT) approach (Ligmann-Zielinska et al., 2020; Magliocca et al., 2018). Stochastic uncertainty for each BBP was calculated as the model output variance produced by the 30 realizations for each BBPs configuration and exogenous conditions combination. First-order sensitivity indices were calculated as the proportion of total variance contributed by each BBP net of stochastic variance. Total-effect sensitivity indices for each BBP were calculated as the sum of variance for each objective function/social network BBP in combination with all other social network/objective function BBPs, respectively, net of stochastic and first-order variances. The outcome variable for each sensitivity analysis was the count of Producer agents per crop type at the end of each model run.

Notably, the sensitivity of model output to each individual BBP could not be directly measured, because BBPs represent structural assumptions rather than continuous parameters whose range can be sampled as is typically implemented with variance decomposition and GSA (Ligmann-Zielinska et al., 2020). Rather, first-order interaction sensitivities could be calculated by the variance generated when one type of BBP was held constant (e.g., random choice objective function) while varying the other type of BBP (e.g., social network structures). Thus, variance decomposition was implemented in an unconventional way. The strength of influence (sensitivity) of each BBP on output variance can be inferred from the total-effect sensitivity index value, which was the sum of individual and interaction first-order indices.

4.6.2. Error measurement

Time-varying Bayes factor was calculated for each experimental BBP configuration described above and the all-BBPs model implementation. Bayes factor provides a ratio of the posterior probabilities of different models given empirical evidence as a means for model selection (Hartig et al., 2011; Hsu et al., 2009). Posterior probabilities were estimated for each combination of single BBP implementation (i.e., one objective function and social network structure for all agents) and the all-BBPs implementation based on empirical observations of total acres planted (i.e., rainfed or irrigated horticultural or row crops) obtained from the USDA Census of Agriculture 2017 for 2002, 2007, 2012, and 2017 (NASS, 2022). Bayes factor was selected over more direct measurements of model error (e.g., root mean squared error; see Section 4.6.3) because an empirical time series of planted acreage was not available for each time step and a Bayesian approach better accommodated the incomplete data (Hartig et al., 2011; Hsu et al., 2009). The implementation of the random choice objective function (level 0) and static, spatial neighborhood social network (level 1) was considered the null model against which posterior probabilities for all other BBP implementations were compared. Bayes factor values greater than 1 indicated that a given model had lower error compared to the null model. Interpreting the sensitivity analysis metrics and Bayes factor estimates in combination characterized the magnitude and direction of structural uncertainty introduced by each BBP in isolation and interaction with other BBPs, and the capability of the all-BBPs model version simultaneously to manage structural uncertainty and reduce output error.

4.6.3. Decision validation

Information describing the factors, timing, and/or outcomes of individual-level adaptive decisions cannot feasibly be acquired at large spatial scales. Thus, we could not directly validate the individual decisions simulated by the all-BBPs model implementation. We adapted the method of Observing System Simulation Experiment (OSSE) from geosciences (Moradkhani, 2008; Kumar et al., 2014; Yan et al., 2018) to overcome this challenge. OSSEs have been used in the context of hydrological model data assimilation to assess the sensitivity of model outcomes to variations in input data accuracy and spatial resolution (Moradkhani, 2008; Yan et al., 2018). Often an OSSE is conducted prior to obtaining true observational data, which might be computationally or financially expensive to acquire (e.g., high resolution satellite imagery), to analyze the suitability or performance of the data and/or model for end-user applications (Kumar et al., 2014).

In this context, an OSSE was designed to evaluate the ability of the all-BBPs implementation to simulate the location and timing of irrigation adoption decisions against an empirically derived, spatially explicit Irrigation Adoption Index (IAI) (Pathak et al., in review). The IAI was produced at 30-meter resolution for the entire state of Alabama. The IAI estimated a normalized index value between 0 and 1 expressing the likelihood for irrigation adoption based on spatially varying factors including: prevalence of USDA EQUIP funding, abundance of nearby agricultural land uses and irrigated acreage, slope, average well depth, market access, poverty rate, and drought intensity and frequency. The IAI was then used to extrapolate historical irrigated area available at the county-level for 2000, 2005, 2010, and 2015 to an annual county-level time series from 2000-2015 against which the ABM outcomes were compared. Within each county, pixels with the highest IAI values were selected for irrigation adoption until the annual irrigated acreage was met or exceeded. All agricultural pixels within a given parcel boundary that were contiguous to the pixel selected for irrigation adoption were switched to an irrigated state to approximate farm-level decisions. Thus, it was possible to exceed the interpolated, annual estimate of irrigated acreage due to this assumption. The resulting annual maps of likely irrigated areas enabled calculation of the root mean squared error of ABM versus simulated time series of irrigation acreage at each time step and Producer agent parcel.

5. Results

5.1 Structural uncertainties introduced by alternative decision models

The outcomes of Producer agents' crop and farm management choices varied substantially across model versions and were influenced similarly by exogenous price and precipitation variations and combinations of objective function and social network BBPs. For instance, the number of Producers exiting (i.e., discontinuing farming/and or selling land) ranged from zero in model versions with the satisficing objective function (independent of social network structure), to nearly 90% of Producers exiting in model versions with price volatility, risk salience objective functions, and spatial neighborhood social networks (Table 1). Generally, Producer agents' shifts to new crops and/or farm management practices responded to perturbations in annual prices and/or precipitation, and those shifts were reinforced and amplified through social networks (Figures 4 and 5). However, within these general trends there was substantial variability in the time paths of those shifts depending on the combination of BBPs implemented. For instance, the satisficing objective function produced rapid and persistent shifts to alternative crop and farm management strategies. Strategy adjustments occurred within the first two and eight time steps with the spatially-based and dynamic crop type social network structures, respectively. In the model versions with all producers using the profit-maximization objective function, the transitions between strategies were comparatively smoother but also became fixed after the first half of the simulation regardless of subsequent precipitation variations. In contrast, Producer strategies continued to adjust to precipitation variations throughout the simulation period in model versions implementing the risk salience objective function and were only minimally influenced by social network structure. Overall, the timing of crop and management choice adjustments differed under conditions of price volatility, but the relative differences in decision dynamics based on objective functions were qualitatively similar to those observed with precipitation variations.

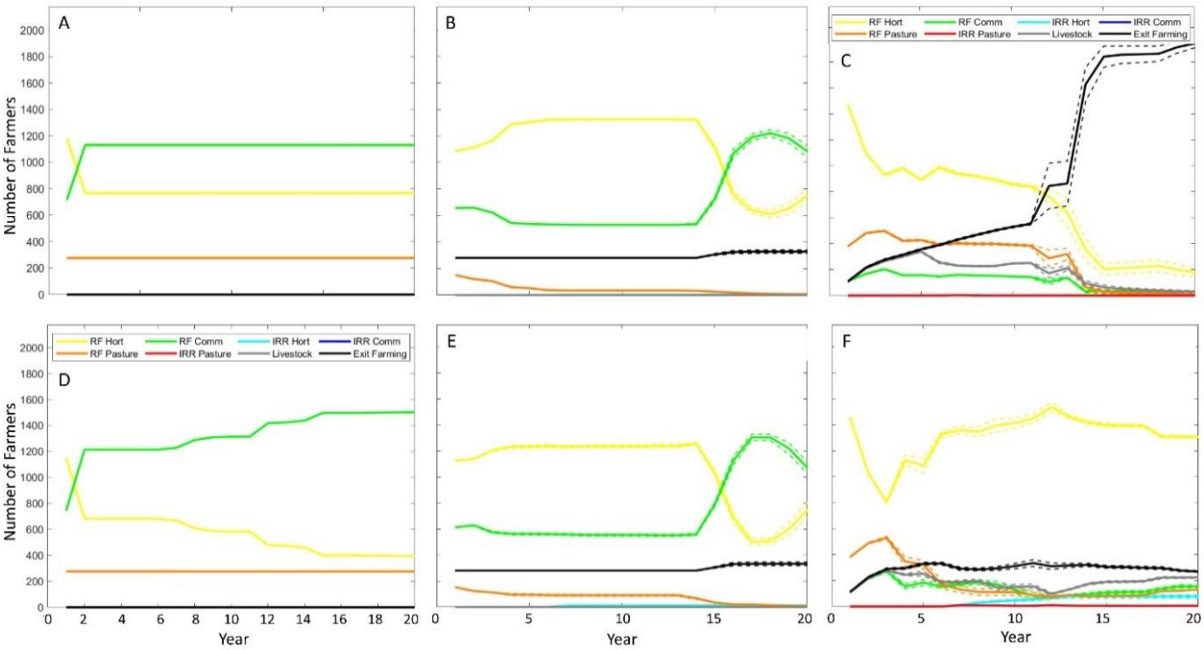

Figure 4: Time-varying model output of number of Producer agents under variable price conditions selecting each crop and farm management strategy using the spatial-only social network BBP with A) satisficing, B) profit-maximizing, and C) risk salience objective function BBPs; and the dynamic crop choice social network BBP with D) satisficing, E) profit-maximizing, and F) risk salience objective function. Producer choices included rainfed (RF) or irrigated (IRR) management, horticulture crops (Hort.), commodity row crops (Comm.), pasture, livestock production, and exit farming. Dashed lines represent 95% confidence intervals calcualted across 30 model realizations.

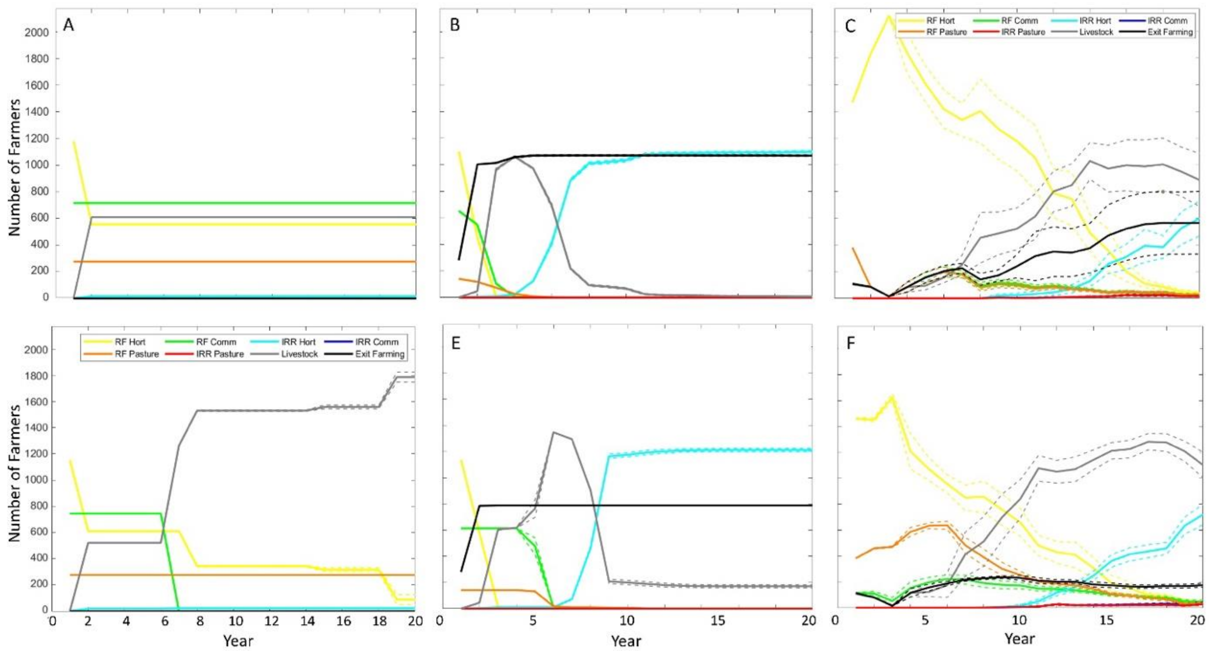

Figure 5: Time-varying model output of number of Producer agents under variable precipitation conditions selecting each crop and farm management strategy using the spatial-only social network BBP with A) satisficing, B) profit-maximizing, and C) risk salience objective function BBPs; and the dynamic crop choice social network BBP with D) satisficing, E) profit-maximizing, and F) risk salience objective function. Producer choices included rainfed (RF) or irrigated (IRR) management, horticulture crops (Hort.), commodity row crops (Comm.), pasture, livestock production, and exit farming. Dashed lines represent 95% confidence intervals calcualted across 30 model realizations.

Generally, differences in the objective function BBPs produced the largest variations in producer choices. When external price and precipitation conditions and specific objective function BBPs were constant, the maximum dispersion of Producer agents per crop type among model implementations with varying social network BBPs was about 31% (Table 2). In contrast, the maximum dispersion under static conditions with the same social network BBP but varying objective function BBPs was nearly 77%. Both risk-based objective function BBPs generated higher dispersions than the random choice objective function BBP. For the exception of the risk-based objective functions under variable price conditions (see below), variance among producer choices was relatively insensitive to different social network structures or variable external conditions. Notably, risk-based objective functions increased dispersion by roughly 30% over the profit-maximizing objective function with constant external conditions, but that difference was reduced to roughly 4% with variable precipitation.

The largest variances in Producer agent crop type choices of about 399% were observed for risk-based objective functions under conditions of price variability (Table 2). Dispersion of choices was small across alternative social network structures with random choice, satisficing, and profit-maximizing objective function, which indicated that the differences in information diffusion generated by different social network structures were amplified with risk-based objective functions and variable price conditions. This finding suggested that interactions between individual risk behaviors, localized social network structures (i.e., spatial neighborhood only or demographic group), and price variability created destabilizing, positive feedbacks influencing Producer agents' crop choices. In contrast, the dynamic crop type social network BBP acted as a stabilizing influence, all else being equal, that reduced variance in Producer agents' choices. This suggested that diffusion of production practices among social networks was a balancing feedback that scaled-up and reinforced successful production practices. In this case, risk-based objective function BBPs paired with alternative social network BBPs of spatial-only, demographic groups, and dynamic crop types reduced the average fraction of producers exiting to 89.5% (n=1,945), 47.0% (n=1,021), and 12.4% (n=269), respectively, while also increasing the number of producers engaged in rainfed horticultural production to 8.2% (n=178), 38.9% (n=844), and 60.2% (n=1,307).

Table 2: Average variance-to-median ratio (i.e., dispersion index) of production choices due to variations in external conditions (down columns) and BBPs (along rows).

	Objective Function					Social Network Structure		
	Rnd.	Sats.	Profit.	Risk Adv.	Risk Sal.	Sptl.	Dem.	Dyn.
Static	26.28	6.74	1.00	30.80	31.35	63.69	76.80	37.53
Price	11.39	3.40	6.43	399.2	399.0	171.4	115.3	130.4
Prod.	16.31	17.45	16.84	20.72	21.02	282.1	299.6	164.0

Variance decomposition of the final counts of Producers choosing horticulture crops, commodity row crops, or livestock production further illustrated divergent decision outcomes produced by different BBPs and static/variable price and precipitation conditions. Stochastic variance was minimal across objective function BBPs and absent from social network BBPs in experiments with price variations, which illustrated how strong an influence price was on agent decision-making (Figure 6). Specifically, the relative effects of alternative social network BBPs were polarized between entirely first-order variance for localized BBPs (i.e., spatial neighborhood, demographic group) versus total-effect variance for dynamic crop type social networks. Risk-based objective functions and the dynamic crop type social network structure BBPs were most sensitive to stochastic variations across model executions. This was an intuitive result since these BBPs all provided some capacity for nonlinear responses by disproportionately weighting large losses (risk aversion), losses and gains (risk salience), or positive feedbacks in adopting particular farming practices/crop choices (social network based on dynamic farm type). Effects of the dynamic crop type social network structure were consistent across crop types (Figure 6a, b, c), but varied depending on price or production perturbations. Notably, model outcomes were generally more sensitive to social network BBP interactions with variations in objective function BBPs than vice versa, which suggested the amplification effects of social network structures on different objective function assumptions. There was no adoption of commodity row cropping in the static scenario because the baseline price was not high enough to motivate shifts away from relatively lower input horticultural or livestock production.

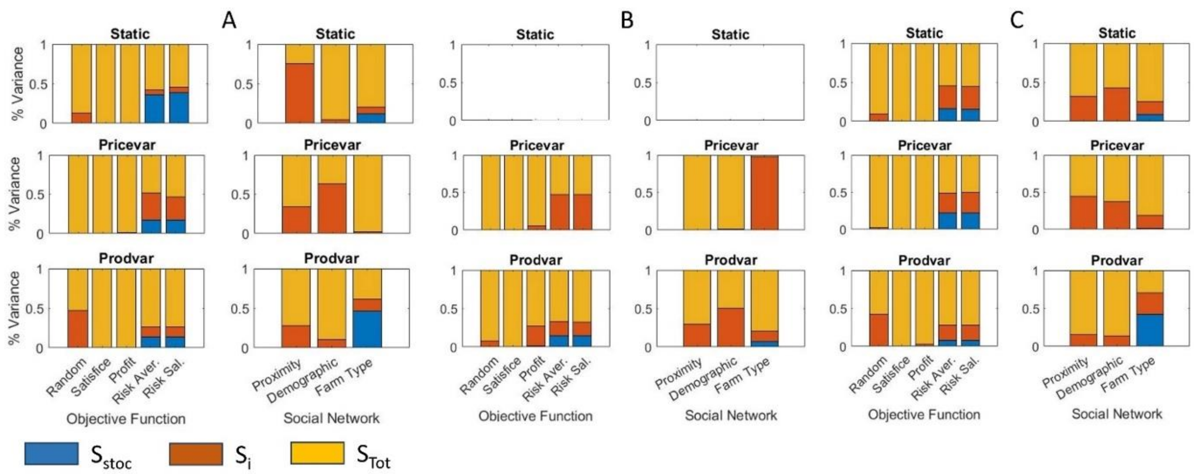

Figure 6: Sensitivity indices for stochastic (Sstoc), first-order (Si), and total-effect (STot) variance calculated from single BBP model executions holding one type of BBP constant (e.g., objective function) and varying the other (e.g., social network structure) for A) horticultural crops, B) row crops, and C) livestock production options.

5.2 Implementation of the all-BBPs model version

Additional model executions were conducted with variable price and precipitation conditions for every combination of objective function and social network BBPs and a version in which all BBPs were available for Producer agents to endogenously choose. Time-varying Bayes Factor was calculated by comparing simulated to observed total planted acres for the time steps that overlapped with 18-year period of available data (Figure 7). The all-BBPs model version was consistently among the best performing model versions. Among the model versions implementing only one combination of BBPs for all agents, those with the satisficing objective function BBP performed best initially; but as price and/or precipitation decreases impacted production decisions over time model versions with profit-maximizing and risk-based objective function BBPs showed better agreement with observed planted acreage. Moreover, model performance was primarily dependent on the objective function BBP in use as little variation was evident due to social network BBPs.

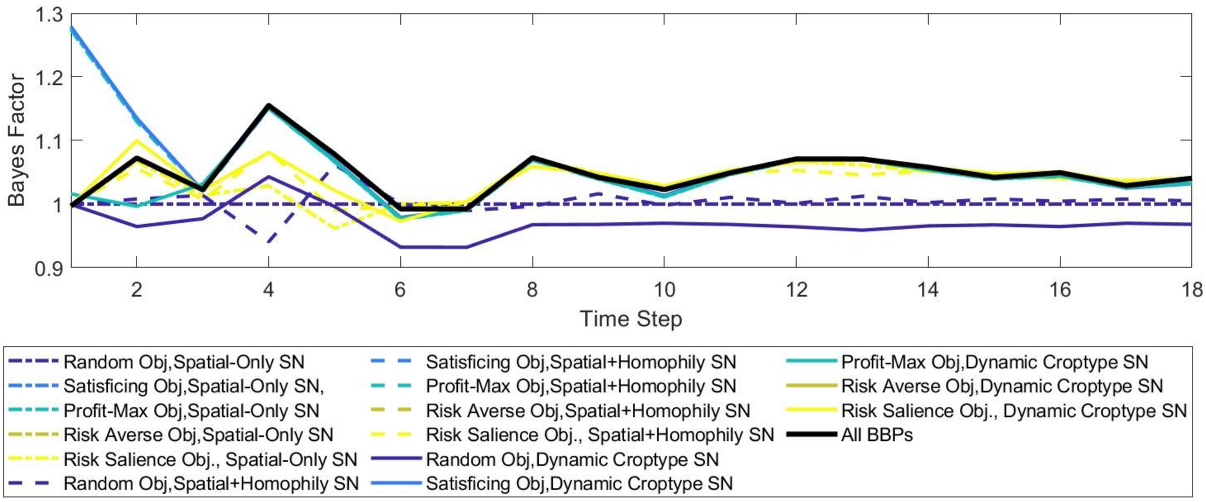

Figure 7: Time-varying Bayes Factor based on acreage planted for single and all-BBPs implementations under variable price and precipitation conditions.

5.3 Implementation of all-BBPs with the OSSE irrigation data

The all-BBPs implementation demonstrated an overall more balanced performance compared to the model versions implementing only one combination of BBPs for all agents under variable price and precipitation conditions. Overall, the all-BBPs implementation did not produce the lowest RMSE in predicted irrigated acres (satisficing), but it produced the most accurate time series and spatial configuration of irrigation adoption decisions overall (Figure 8 and 9, respectively). Early in the simulation period, the RMSE matched the lowest across all implementations similar to the implementations with risk-based objective function BBPs, and after the first major decline in precipitation RMSE only increased moderately. This contrasted with the profit-maximizing and risk-based objective function BBPs whose RMSE increased rapidly during the same period.

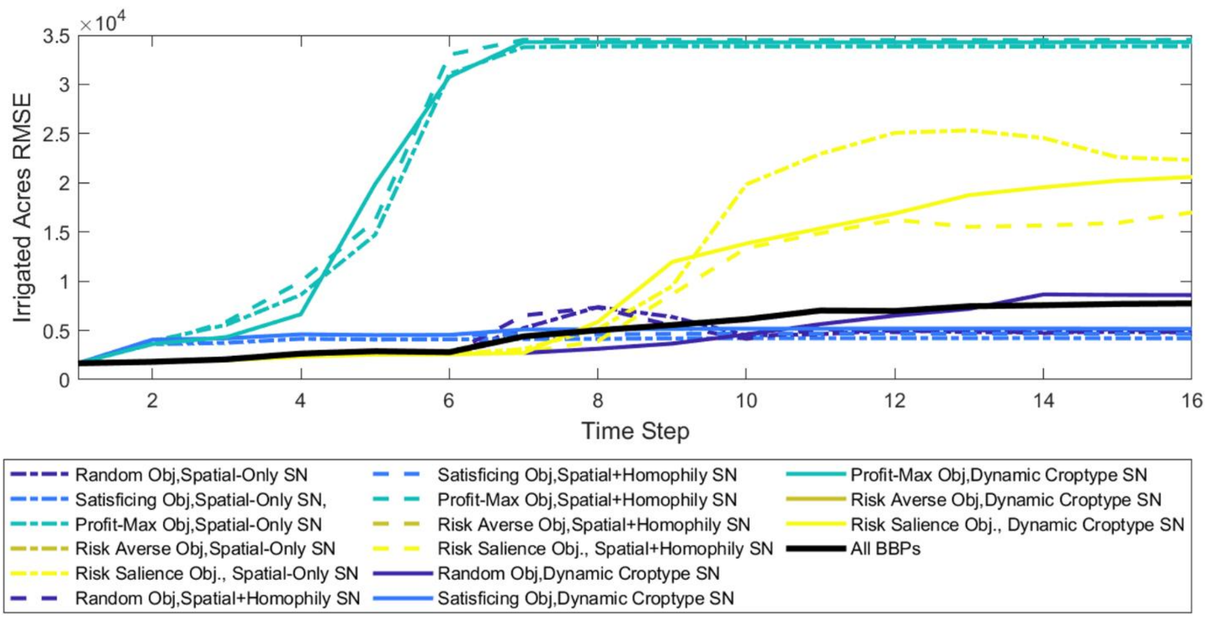

Figure 8: Average root mean squared error (RMSE) of simulated irrigated acreage over the interval of the OSSE for each single BBP combination (color-coded) and all-BBPs (black) simulations with variable precipitation and price conditions.

Assimilation of the IAI data into the all-BBPs model implementation enabled parcel-level evaluation of modeled irrigation decisions. The global accuracy of simulated irrigation decisions was 91.4% of parcels (Table 3). However, irrigation adoption during the study period was limited with only 40 (1.84%) parcels indicated by the OSSE data resulting in 5 (0.23%) correctly predicted irrigated parcels (true positives), 152 (7.00%) parcels incorrectly predicted as irrigated (false positives), and 35 (1.61%) parcels incorrectly predicted as not irrigated (false negatives). Corresponding simulation precision, recall, and false alarm rates were 3.18%, 12.5%, and 7.13%, respectively. The spatial pattern of true and false positive and negative model predictions showed that the irrigation adoption decisions simulated through the OSSE were more spatially clustered than the model predicted (Figure 9). This suggested two possible avenues for improving the model. The contiguous nature of the true positives and false negatives, particularly among smaller parcels, suggested a pattern of land ownership and farm management that was not captured by the model. Parcel ownership information is difficult to obtain and even when it is available from tax assessors or registries farm ownership/management patterns can be challenging to infer (Nolte, 2020). Additionally, calibration of the social network BBPs, such as changing the spatial neighborhood extent or relative weighting of neighborhood information, may be needed to better predict spatially clustered irrigation adoption.

Table 3: Count of true (false) positive (negative) predictions at the final time step of a single execution of the all-BBPs model version and variable precipitation and price conditions compared to instances of irrigation simulated by the OSSE.

		Predicted			
		Irrig.	Not Irrig.	Model Evaluation	(%)
Observed	Irrig.	5 (0.23%)	35 (1.61%)	Global Accuracy	91.4
				Precision	3.18
	Not Irrig.	152 (7.00%)	1980 (91.2%)	Recall	12.5
				False Alarm Rate	7.13

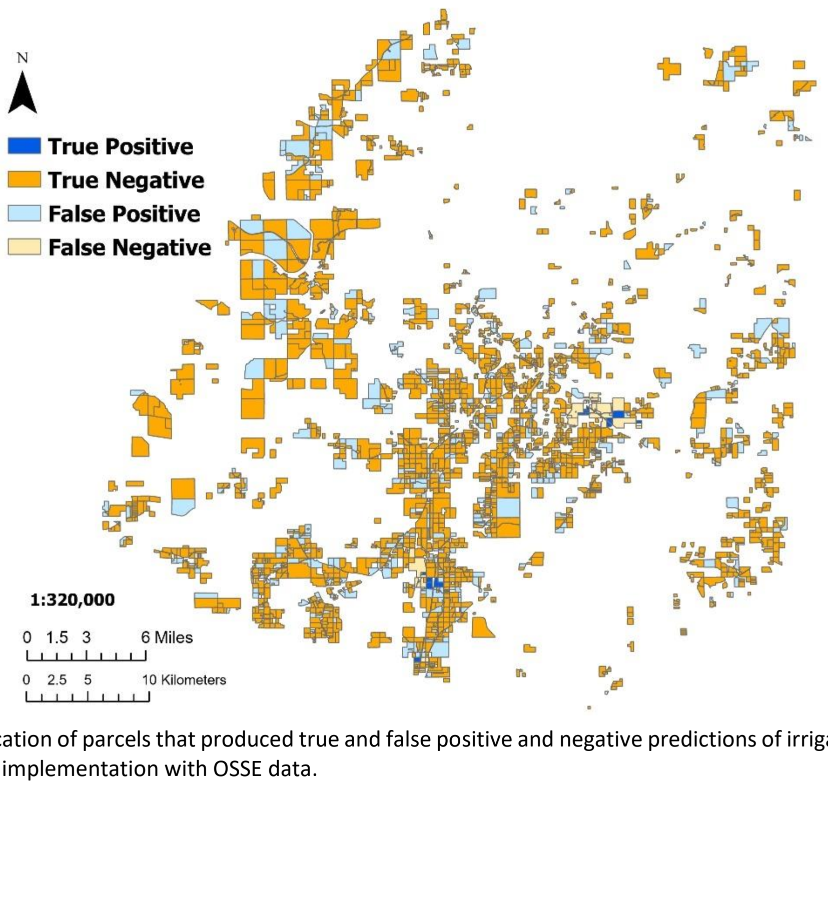

Figure 9: Spatial location of parcels that produced true and false positive and negative predictions of irrigation adoption with the all-BBPs model implementation with OSSE data.

6. Discussion

The results of these modeling experiments should be interpreted through the lens of the three tests laid out in the introduction for assessing the value of increased structural uncertainty. The first and second tests comparing the single BBP versions with more structurally complex all-BBPs implementation assessed the accuracy with which the dynamics and overall levels of observed outcomes were reproduced, respectively, particularly when 'out-of-equilibrium' dynamics would be important. The all-BBPs implementation performed as well as the risk-based models reproducing observed patterns of planted acreage over time subject to large precipitation and price variations (Figure 7). Although a larger improvement in outcome accuracy between the all-BBPs and any single BBP versions would have been desirable, a theoretically richer and more structurally realistic model is preferred over a more stylized version with equal performance because of the mechanistic insights that would not be possible without the presence of behavioral heterogeneity (Overmars and Verburg, 2007). For instance, a noteworthy result was the relatively limited impact of different social network structures Alternative configurations of objective function and social network BBPs produced differences in the time paths of adaptive decisions and final outcomes. The result highlighted the importance of interactions among social network structures and objective functions for either amplifying or dampening shifts in crop choices and farming practices. Specifically, when all agents used a risk-based objective function destabilizing, positive feedbacks were evident that lead to nonlinear shifts in producers' decision-making. Similarly, the dynamic crop type social network BBP acted as a balancing, negative feedback to moderate shifts in producer behaviors through greater information diffusion. This result illustrated the importance of interactions among agents with diverse decision models, rather than a statement about the overall importance of social networks versus other factors in adaptation decision-making, and resonated with broader literature about the importance of behavioral diversity for resilience (e.g., Grêt-Regamey et al., 2019; Haider et al., 2021).

The third test of alternative model structures related to differences in process accuracy when supplied with disaggregate (i.e., agent-level) input data. A model version with heterogeneous behavioral models was hypothesized to have greater process accuracy leading to greater outcome accuracy in the presence of agent diversity. Results of the model comparisons with parcel-level irrigation data assimilation showed that the all-BBPs implementation produced 2 to 3 times less prediction error of irrigated acreage than model versions with the risk-based and profit-maximization objective functions, but the all-BBPs version also generated nearly twice as much prediction error than model versions with the constrained random and satisficing objective functions (Figure 8). At first glance, this would indicate that the increase in structural complexity was not sufficiently compensated by improved performance over simpler models. However, the mechanistic insights gained by implementing a more structurally realistic model with behavioral heterogeneity must again be emphasized. Among the model versions implementing behavioral theories relevant to adaptation decisions (i.e., profit-maximization, risk-aversion/salience), and thus have at least some structural realism, the all-BBPs version performed best. On the other hand, the constrained random and satisficing decision models, by definition, limited change, and in an experimental setting in which adaptation through irrigation adoption was relatively rare (1.84% of all parcels) these decision models produced more accurate outcomes. In this case, the comparative overprediction of irrigation adoption by the all-BBPs highlighted the behavioral origins of a lack of adaptation. Moreover, the implementation of the more structurally realistic all-BBPs model highlighted the impact of biased input data. The parcel-level irrigation adoption data was based on a data product calibrated against aggregate irrigation data which is the best available yet strongly biased toward large-scale irrigation implementation (i.e., omitting smaller-scale irrigation adoption) and known to underreport irrigation overall (Pathak and Magliocca, in review). In the case of such known data biases, a model with structural realism that predicts outcomes in the opposite direction of input data biases is preferrable to a more stylized model that predicts outcomes closer to biased data. Thus, the methods presented here for managing structural uncertainty can have the added benefit of exposing biases in input data, particularly when used in a larger participatory modeling process to evaluate model outcomes against expert and stakeholder experiences.

Of course, this assessment hinges on the overarching purpose of this modeling approach. Insights into the effects of behavioral heterogeneity are particularly important for ABMs seeking to explain differences in decision outcomes (i.e., how differences are produced), in which case the adaptation decision pathways are of particular interest, for example, to analyze adaptation gaps or design behavioral interventions (Taberna et al., 2023; Zagaria et al., 2021). For instance, the comparatively poor performance of model versions assuming homogenous Producer decision models, particularly the profit-maximizing object function that is implemented in the majority of ABMs (Groeneveld et al., 2017), illustrated the limitation of such assumptions. The reliance solely on optimization-based decision models is likely to be more of an issue in diversified, smallholder rather than in large-scale, monoculture production contexts, since the latter production systems are strongly shaped by productivist logic. If the model purpose were to reproduce observed outcomes as faithfully as possible, then the assessment of the presented methods would be different. But given the goal of more realistic representation of human decision-making in a scalable modeling framework, the trade-offs between increased behavioral heterogeneity and structural uncertainty were deemed favorable.

Moreover, the development of methods to identify and manage the impacts of increased structural uncertainty associated with agent behavioral heterogeneity opens new possibilities for scaling-up or scaling-out ABM outputs to extents compatible with macroeconomic and Earth system models. One such approach could be the development of behaviorally rich agent archetypes that reflect heterogeneity in decision models and dynamics of endogenous decision model selection in response to social interactions and environmental changes. Progress has been made with statistically linking cultural factors and behavioral motivations (e.g., Krefeld-Schwalb et al., 2024) and cognitive and spatial factors (e.g., Piemontese et al., 2021) with climate change mitigation and adaptation actions, however these advances lack representation of decision-making processes needed for dynamic simulation. Agent behavioral patterns and adaptation actions generated with a BBPs approach could provide input into archetypes used to scale-out simulation outcomes and initialize a synthetic agent population at the scale needed for scenario analysis with macroeconomic and Earth system models. Similarly, if the BBPs approach was implemented in a 'whole economy' application (e.g., Taberna et al., 2023), the uncertainty analysis method could help identify in what geographic locations and/or segments of the population behavioral heterogeneity is most important to represent.

The collection of methods implemented here advance current approaches to assess and manage structural uncertainty introduced by multiple, heterogenous decision models within the same agent population. Time series analyses illustrated how decision-making dynamics were influenced by variations in BBPs, which was particularly important for distinguishing between structural variation (among BBPs) and stochastic variation from variable prices and precipitation. Sensitivity analyses using variance decomposition and dispersion indices identified the relative contributions of objective function versus social network BBPs across static and variable price and precipitation conditions and revealed that particular combinations of BBPs and external variable conditions led to either balancing or destabilizing behavioral dynamics. Finally, the OSSE technique enabled validation of modeled irrigation adoption decisions at the parcel level where sufficient empirical data at the regional scale is unlikely to be available. Acquisition of such fine resolution spatial and temporal data, even for this relatively localized landscape, would be extremely time consuming and likely infeasible given the level of community trust and access that would be required for data collection. Scaling-out to larger study extents (e.g., state) would be prohibitive, which is the advantage of the OSSE approach to model evaluation. Thus, we could assess whether and in what ways the all-BBPs model implementation improved upon the single BBP implementations.

Although the accuracy of the all-BBPs model implementation could be improved, these early results demonstrated a tractable way forward for increasing behavioral richness and heterogeneity in ABMs. Increasingly, decision-making and behavioral diversity is at the forefront of challenges facing adaptation and large-scale transformation modeling (Elsawah et al., 2020). Modelers are responding to this challenge by innovating beyond the representative rational optimizer by embracing social science research in this area (Wijermans et al., 2023). However, implementations of boundedly rational and other decision models still rely on a one-at-a-time scenario approach. This approach provides useful comparisons among outcomes enabling quantification of the effects of different behavior assumptions, and can be particularly useful when quantifying uncertainty of physical or external parameters relative to uncertainty produced by alternative behavioral assumptions (e.g., Taberna et al., 2023). Yet this stops short of more realistic representations of multiple, heterogeneous decision models active and endogenously selected among agents in the same population, which can capture the interactions and feedbacks among diverse agent behaviors that are core to adaptation and innovation diffusion processes (Barrett et al., 2020; Schwarz & Ernst, 2009). A robust set of analytical tools, such as those presented here, is needed to quantify and manage the uncertainty introduced by diverse decision models.

7. Conclusion

Interactions among Producer agents able to endogenously select among all of the BBPs, implemented in the all-BBPs model version, created a more realistic, behaviorally diverse population of agents and led to consistently more accurate outcomes than model versions with the same decision model implemented for agents in the population. These results also illustrated the importance of interactions among behaviorally diverse agents for producing more stable and realistic behavioral dynamics. However, such realism comes with the cost of increased model complexity and compounding agent-based modeling's computational and analytical challenges. The uncertainty analysis methods presented also did not directly address the possibility of equifinality among alternative decision model structures. This is a weakness of iGSS methods generally and is a challenge that cannot be tackled without fine resolution panel data for comparison with simulated time series of agents' decisions. In principle, our approach to managing structural uncertainty could be used to discern among the performances of simpler and more complex model structures with the availability of such data. Yet, despite such data and methodological limitations, the need to represent human behavior and agency more realistically in processes of large-scale societal transformation, such as climate adaptation, is clearer than ever.

The BBPs framework and accompanying uncertainty analyses demonstrated here offer a path forward for integrating behaviorally rich ABMs with large-scale economic or Earth system models to investigate behavioral sources of maladaptation (i.e., 'soft' adaptation constraints; Taberna et al., 2023) or possible behavioral interventions to increase future adaptations. The BBPs framework is sufficiently flexible to be implemented in diverse decision-making contexts (Ellis et al., 2018; Magliocca & Ellis, 2016), which must be accounted for when the spatial and/or temporal model scale extends beyond a single community, region, or culture (Noll et al., 2020, 2022). Moreover, the OSSE approach combined with evolutionary programming characteristic of iGSS can provide an empirically-driven method for scaling-up localized adaptation behaviors resulting from heterogeneous decision models to simulate bottom-up impacts on larger natural processes or macroeconomic systems. Such scaling is required to integrate with large-scale models, such as integrated assessment models like GCAM (Calvin et al., 2019) or atmospheric processes models like WRF (Skamarock et al., 2019), which is imperative for modeling societal transformations.

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Supplementary Material

The Supplementary Material can be found online at: https://sesmo.org/article/view/18749/18242.

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