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MODELING FOOD SUPPLY CHAINS USING MULTI-AGENT SIMULATION

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ABSTRACT

In light of the pressures of increasing demands on earth's resources, society faces serious challenges in food production and distribution. Food supply chain (FSC) models are critically important, providing decision-makers with tools that allow for the evaluation and design of FSCs, en route to ensuring sustainable FSC productivity. Multi-agent simulation (MAS) is well-suited to modeling FSCs for this purpose, enabling capture of decision-making, interactions, and adaptations of autonomous FSC actors. However, certain characteristics of FSCs are particularly difficult to model in detail, as data requirements can be intensive. In this paper we highlight some of the challenges modelers face in deciding the most appropriate methods for representing the elements of an FSC in an MAS model. We provide examples from the literature that show how other modelers have chosen to address these challenges. Finally, we discuss benefits and limitations of each example's approach, in terms of realism and data requirements.

1 MODELING FOOD SUPPLY CHAINS WITH MULTI-AGENT SIMULATION

Food supply chains (FSCs) range widely in size and complexity, from subsistence farmers growing their own food to city-dwellers purchasing groceries from a supermarket. Because of food's vital importance to survival, and the multitude of pressures exerted on these systems, methods for producing food more efficiently are an important area of study. One such method to improve food production efficiency is mathematical modeling. FSC models are now potentially more useful than ever before, as human beings face serious challenges with food production and distribution. Worldwide demand for food is growing, but issues such as energy and water resource limitations, agricultural pollutants, and climate change constrain our ability to increase food production. FSC models can help us face these challenges by improving our ability to make decisions that support long-term human and environmental well-being. However, to be useful, FSC models must balance tractability with the ability to realistically capture the essential elements of FSCs.

Mathematical optimization is the most common method of modeling the food production stage of an FSC. Many existing agricultural optimization models are static, deterministic linear programming (LP) models with the single objective of maximizing farm income or profit, subject to constraints of farm input costs and/or availability. However, very few of these models are able to capture stochastic or dynamic elements of FSCs, and most of these models only analyze a single stage of the FSC – food production. Food systems have also been modeled using discrete-event simulation. While discrete-event simulations can explicitly model time dynamics and stochastic behavior, they are incapable of modeling the sociological processes that influence decision-making by individual FSC actors (Higgins et al. 2010). To capture the dynamic, stochastic, and multi-faceted elements of a FSC, recent research suggests that FSCs be modeled as complex adaptive systems (Meter 2006, Higgins et al. 2010). A complex adaptive system (CAS) is a system of interconnected autonomous entities that make choices to survive and, as a collective, evolves and self-organizes over time (Pathak et al. 2007). Thus a CAS framework can be used to study an FSC. Multi-agent simulation (MAS) is a modeling tool that can effectively model the heterogeneous,

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autonomous, intelligent, and interacting actors that comprise a CAS, making MAS a particularly appropriate tool for modeling an FSC.

This paper seeks to highlight some of the challenges that modelers face in deciding the most appropriate methods for representing the elements of an FSC in an MAS model. We also provide examples from the literature that show how other modelers have chosen to address these challenges. Finally, we discuss the benefits and limitations of each example's approach in terms of realism and data requirements.

2 CHALLENGES

Despite the advantages of using MAS to model FSCs, there are very few existing MAS models of multi-stage food supply chains in the literature. The seemingly unbounded capability of modeling details using MAS poses one of the most significant challenges to modelers, who must take care not to overwhelm a model with details and assumptions such that the focus on the original research question is lost or diminished (Johnson 1998). The data requirements for modeling an FSC using MAS are also potentially enormous, and finding sources of high-quality quantitative and qualitative data that fulfill the requirements of the model can be very difficult, particularly at the farming stage. In fact, the substantial data requirements may account for the sparseness of MAS-FSC models in the literature (Higgins et al. 2010). Therefore, model scope and boundary conditions for an MAS-FSC model must be carefully determined. Two main factors will control the boundary conditions: the nature of the research questions being addressed and the availability of good-quality data. In general, as aspects of a model become increasingly detailed, more data is required, which implicitly predisposes the model to be region-specific and potentially less generalizable.

While many MAS models face some or all these challenges to varying extents, here we will address these challenges within the specific context of FSC modeling. A thorough analysis of the literature on food systems and food systems modeling reveals that FSCs consist of a combination of five elements that combine to create significant modeling challenges: 1) the natural environment, 2) planning and decision-making processes, 3) interactions among FSC stages, 4) economic processes, and 5) the political and social environment. Depending on the type of system being modeled, the way that a model includes each of these elements differs. We will discuss each of these elements, provide examples from the MAS-FSC literature, and discuss ways that one might address the challenges of bounding the model and collecting data in a multi-echelon MAS-FSC model. Additionally, using flowchart representations of multi-echelon MAS-FSC models, we will provide examples of how each of these elements might be incorporated into an MAS-FSC model. We begin with Figure 1, which shows the flow of data and materials through a simple "base" model of a three-stage MAS-FSC, which does not explicitly include any of the five FSC elements (see Appendix A for the pseudocode associated with this model). This base model includes farmer agents, who produce food and replenish the inventory of a single distributor agent, who then uses this inventory to satisfy customer demand.

2.1 Impact of the Natural Environment

Unlike the stages of many other types of supply chains, on-farm processes directly and strongly influence and are influenced by the surrounding natural environment. Most MAS-FSC models take data inputs from the natural environment into account, and many models also capture farm outputs into the environment, as a means of capturing farm efficiency and environmental impact. For example, Belem et al. (2011) embed the CENTURY carbon cycling simulator in their MAS of a farming community to determine the sustainability of certain land uses and farming practices over time. The CENTURY model and a GIS are used to represent the farm-environment impacts in great detail, and this requires a significant amount of input data: regional demographics, cropping systems, farm economy, biophysical properties (e.g. soil types and climate data), animal characteristics, and spatial data (Belem et al. 2011). Happe et al. (2011) attach the FARM-N fertilizer management model to their MAS of a farming region to assess the relationship between environmental impact and different regional structures and farming practices over time. Given a farming scenario, this model is able to predict very specifically the quantity of resultant polluting outputs. The authors acknowledge that the tradeoff for this high-quality output is that the input data requirements (including number of animals produced, their start and end weight, the quantity of feed consumed per animal and the protein content of that feed) are enormous and highly region-specific (Happe et al. 2011). Many other MAS-FSC models do not model environmental impacts at this level of detail, but most of them include the impact of weather on farm productivity, which can be modeled in detail or very simply. For example, Matthews (2006) uses historical data to generate 100 years of daily weather data with a weather generator, and then uses this data as an input in his MAS-FSC model. In contrast, the weather in the model of Le Bars et al. (2005) has only three possible values (wet, dry, very dry), which are selected randomly in each annual time step.

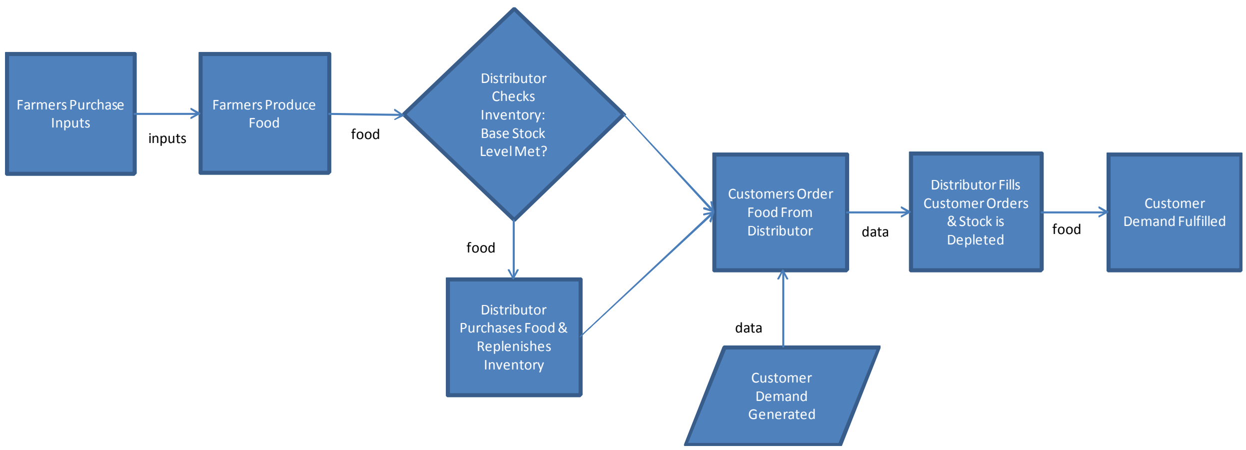

Figure 1: Flowchart representation of an MAS-FSC “base model”

The relationship between biological and ecological processes and crop yields can also be modeled very accurately using crop simulator software (e.g. DSSAT). There are many crop simulators available, and given sufficiently-detailed input data (e.g. land characteristics, soil conditions, weather), these simulators can simulate soil fertility and water dynamics, and then provide data on the resulting crop yields. Matthews (2006) and Schreinemachers et al. (2007) embed crop simulators within their MAS models to achieve a high level of biological realism, capturing soil fertility dynamics. Lynam (2002) also includes detailed models of biological processes in his MAS model of food production, using a geographic information system (GIS) in combination with crop yield equations and soil erosion models. Becu et al. (2003) focus their MAS on studying the impact of different water management schemes on farming systems, and they create their own biophysical simulator to model the effect of water cycling through the soil and atmosphere and the resulting impact on crop yield. MAS models that do not require the details provided by crop simulators may embed simpler yield/ecological functions instead (e.g. Le Bars et al. 2005, Janssen 2001). Although these models may provide less accuracy in their input-output relationships, they also require significantly less input data than the crop simulators. Other models of food systems do not explicitly model the details of the biological processes involved in food production. Polhill, Gotts, and Law (2001) use a database to look up yield values based on a farmer agent’s land characteristics and randomly-generated external conditions. Deffuant et al. (2002) use MAS to model the diffusion of new production practices in a farming region, and model the impact of farmer behaviors on output implicitly (i.e., adopting a new practice carries a risk of lower yields). The amount of detail and the amount of input data required to model the biological processes of on-farm production depends on the goals and intended focus of the modeler.

Gathering the necessary data to model the relationships between the natural environment and farm outputs can be challenging if highly detailed interactions are required. Collecting the appropriate primary biological input data may require special equipment and skills, as well as access to farms. Even if large quantities of data on a particular region are available, crop yield functions that apply to that region may be inappropriate in other regions. Therefore, modeling a large, multi-regional FSC with detailed biological processes could be extremely data-intensive. Additionally, the crop yield functions and aggregate data on farm productivity that is available (via USDA and FAO websites, for example) is for conventionally-grown commodity crops, whereas data on yields from farmers that use sustainable practices is not widely published.

The chosen time step depends on the level of detail that a modeler wants to achieve, as well as the types of output in which the modeler is interested. The time step that is selected for an MAS-FSC model also partly determines the amount of input data required. In terms of inputs, the models of Matthews (2006) and Schreinemachers et al. (2007) use data-intensive crop simulators. However, Schreinemachers et al. note that their model is significantly less data-intensive because it runs on an annual time step, rather than a daily time step, as does the Matthews model. In terms of outputs, if the focus of the model is on soil fertility dynamics, a daily time step might be appropriate, whereas an annual time step might be more appropriate for a model focused on farmer decisions that occur only at the end of a farming season. Because most MAS-FSC models in the literature focus on end-of-season farmer decision-making and adaptation, most models use an annual time step.

Figure 2 shows a modification of the base MAS-FSC model (Figure 1), in which the impact of the natural environment on the FSC (weather) and the impact of the FSC on the environment (farm waste outputs) are captured. As with the models in the MAS-FSC literature, the natural environment directly impacts the farming stage of the FSC; however, it does not directly affect food distribution downstream. However, negative impacts of food production on the natural environment (e.g., pollution) could indirectly affect the behavior of the FSC, as consumers become aware of these impacts and modify their buying patterns.

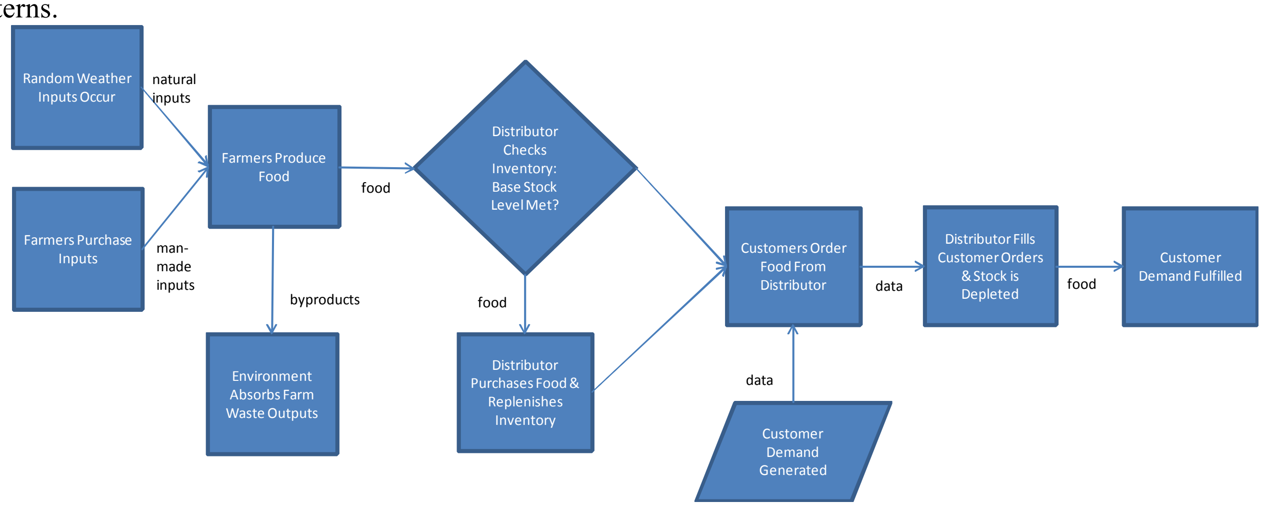

Figure 2: Flowchart representation of an MAS-FSC model with environmental impacts

2.2 Capturing Agent Decision and Planning Processes

Another on-farm modeling boundary decision is the amount of data required for farm planning and land-use decisions. Examples of farmer land-use decisions include quantity/types of crops to plant, alternative land uses, and farm size. MAS-FSC models that focus on land-use decisions can be extremely data-intensive, depending on how many options the farmers have and their capacity to analyze data. Freeman, Nolan, and Schoney (2009) develop a detailed set of farmer decision-making rules that depend on many factors, including the farmer's age and level of risk aversion, the expected yields, prices, and production costs of different crop types, and available credit. In conjunction with an LP used to make crop choices, the farmers use this set of rules to determine in each time step which crops to produce and how much to increase/decrease the size of their farms. Kamusoko et al. (2009) also use a large amount of input data to model land-use decisions. Their model uses Markovian transition probabilities that are based on historical GIS data, which are then used to determine land-use choices. Polhill, Gotts, and Law (2001) also model land-use decisions; in their model, the selection process itself is somewhat complex, but the input data is very simple. In fact, the options available to agents are not representations of real-world land uses – the options simply have attributes that make them more or less desirable to agents, depending on land characteristics and external conditions.

Other models do not model land-use decisions in such a detailed way, but simply model a farmer's choice of crops. Even this simplified approach can require significant data to accurately model the relationship between crop choice and profitability. For example, Sengupta et al. (2005) use an LP to model farmer crop decisions, where farmers select a mix of crops (and crop prices) that will maximize their profits, constrained by the type and quality of soil on their farms. Becu et al. (2003) also use a simple LP to model crop choice where farmers maximize profits subject to cash, labor, and water availability. In both of these models, the relationship between yields and inputs are captured through crop yield functions. The parameters in the LP (e.g. crop prices, water availability) may be expected values, where the farmer bases his decision on historical averages, and so subsequent reality may be different after the decision is made. Other models simply define a static crop rotation, based on actual farmer rotation schedules and without any adaptation to account for changes in the environment. For example, Belem et al. (2011) model two different static crop rotations, and the rotation type that a farmer uses depends on the farmer's strategy (in this case, native farmers use one type and migrant farmers use the other). Other models, such as the model described in Barreteau and Bousquet (2000), do not explicitly model farmer choices among different crop types but simply model the binary decision of whether or not to cultivate a given plot in a given season.

Although it is common to use optimization to simulate farmer planning and decision-making, it is unlikely that farmers behave rationally or always have sufficient information to effectively optimize. In reality, farmers may apply simple rules or heuristics to make decisions, and often adapt the rules over time to account for new information. However, to make farmer behavior more realistic, a modeler must either make assumptions about farmer behavior, or gather and analyze real-life farmer behavioral data. This could require interviews, surveys, and/or interactive simulations. Because real-life FSCs consist of many actors with highly variable attributes (particularly at the farming stage), modeling each actor in the simulation is infeasible for an FSC of any appreciable size. Instead, MAS-FSC models often use data on actor behavior to create categories of agents and then extrapolate to create a simulated agent population. For example, Sengupta et al. (2005) create a typology of farmer agents based on literature and surveys to categorize agents by such characteristics as level of risk aversion, desire for profitability, and environmental ethics. Barreteau and Bousquet (2000) also create different farmer categories based on cultivation objectives and give farmer agents from each category different rules and capabilities for obtaining credit and making strategic decisions. In contrast, Janssen's (2001) model gives each farmer agent only two simple attributes: the ability to earn returns using conservative or intensive fertilizer applications. However, these attribute parameters can take on many different values, allowing the creation of many unique farmers with a wide variety of simulated knowledge and skills.

For a multi-echelon MAS-FSC, different agent planning and decision-making processes would occur based on a particular agent's function. For example, farmer agents would plan crop rotations, but food distribution agents might be concerned with choosing efficient transportation modes and inventory management policies, while retailer agents might focus their efforts on optimizing customer utility. These varied agent objectives throughout the FSC give rise to an important and interesting aspect of supply chain behavior – the potential for suboptimal supply chain performance resulting from individually-optimizing supply chain members. Figure 3 is another modification of the base MAS-FSC model in which farmer and distributor agent planning activities are included. In this version of the model, farmers analyze distributor demand patterns to adjust their land use and crop-choice strategies accordingly, while distributors analyze customer demand patterns to adjust their inventory replenishment levels. Both agent types use historical information with an intent to improve their operational efficiency and their fill rates.

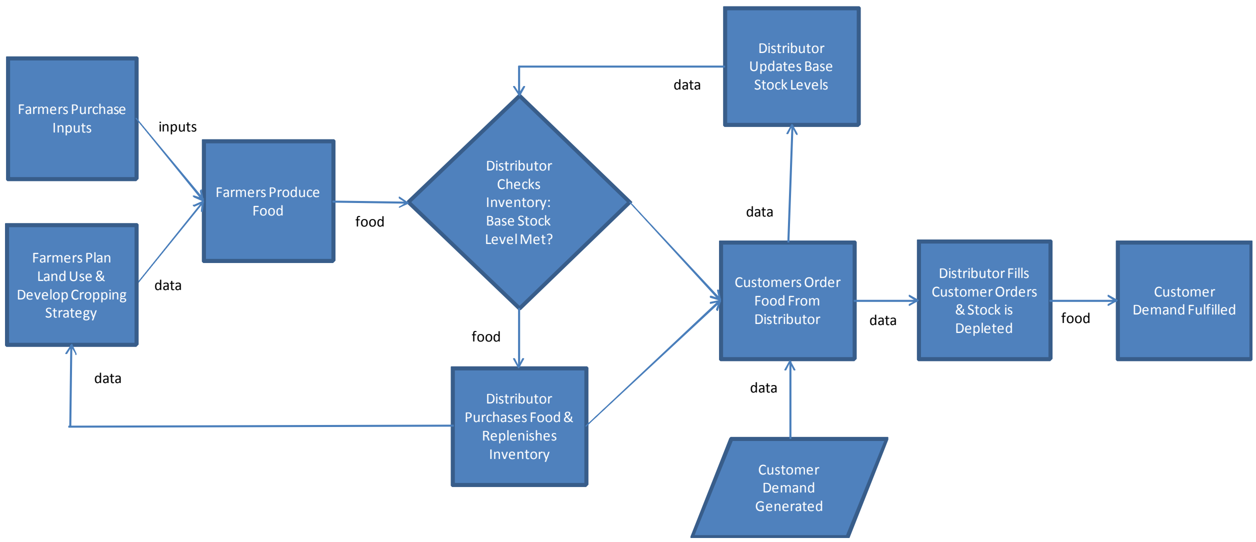

Figure 3: Flowchart representation of an MAS-FSC model with agent planning

2.3 Modeling FSC Interactions

MAS-FSC models of a food-producing region must capture the interactions that occur among multiple farmer agents. In some models in the literature, particularly those models that focus on land use, agents interact only indirectly through markets (e.g. Happe et al. 2011). Other models give agents the ability to interact directly. For example, the communication of information among farmers occurs in many MAS-FSC models in the literature. Deffuant et al. (2002) model complex communication of information among farmers, in which farmers receive information on the economic and social benefits of organic farming and share this information across their social network. In this model, a farmer's social network is determined by geographic proximity, with farmers in the same town communicating more frequently than with distant farmers, and farmers with similar farming systems having greater influence over one another. The geographic locations and farming system types were determined using census data from an actual region in France. An interesting feature of this model is the inclusion of uncertainty in whether or not information is modified during the agents' interaction, which captures the difficulty of communicating complex ideas accurately. Polhill, Gotts, and Law (2001) model indirect communication among land-managing agents through various forms of imitation among neighboring agents. These imitations range from simple indiscriminate mimicry of other agents' behaviors to complex evaluations of other agents before imitation. Janssen's (2001) model also uses imitation to model indirect communication among farmer agents, but in this case farmers choose to imitate only other farmers that have farming abilities that are similar to their own. In both of these models of imitative behavior, it is assumed that the agents have perfect global knowledge of their imitation group's behavior and abilities.

In addition to communication of information, farmers in real-life FSCs can also interact through cooperation, particularly if they share a common goal or a resource. This type of interaction has been modeled most frequently as a negotiation processes among agents. For example, Le Bars et al. (2005) model farmer agents that share a water resource for crop irrigation. The farmers take turns requesting shares of water from a single regional water manager, who responds to each request with a proposed share. Each farmer will accept or reject the proposal, based on his current negotiation strategy, which evolves over time as the farmer gains new information. This negotiation cycle continues until all farmers are satisfied. An interesting component of these negotiations is the farmer types: some farmers are "selfish" and ask for more water than they know they actually need, whereas other farmers are "reasonable" and ask for only what they need. Becu et al. (2003) also model the negotiation of a shared water resource, but in this case the management of the resource is decentralized, and the negotiations occur within pairs of upstream and downstream canal managers.

A model of a multi-echelon FSC would likely include more interaction among agents than the models of the farming stage, because agents in a given stage can potentially interact not only with another but also with other stages. The rules for trade among stages must then be determined, which could include pricing, rules for negotiation, supply and demand values, and the effects of competition on these values. The flow of material (inputs and outputs) and information among different stages must also be managed. Additionally, the rules for evolving relationships among different FSC stages, and therefore the feasible structure of the FSC, must be developed. Figure 4 shows a variation of the base MAS-FSC model that captures agent information-sharing. In this model, the customer estimates its expected demand and informs the distributor agent, which shares that information with the farmer agents. This type of information-sharing would allow the distributor and farmer agents to make better-informed planning decisions and would likely improve the overall performance of the FSC. However, adding even this simple interaction to the model creates new modeling complexities – the modeler must determine the mechanism through which the information-sharing occurs, any costs associated with this interaction, the quality/value of the information that is shared, and whether the farmer agents interact among themselves on the basis of this information.

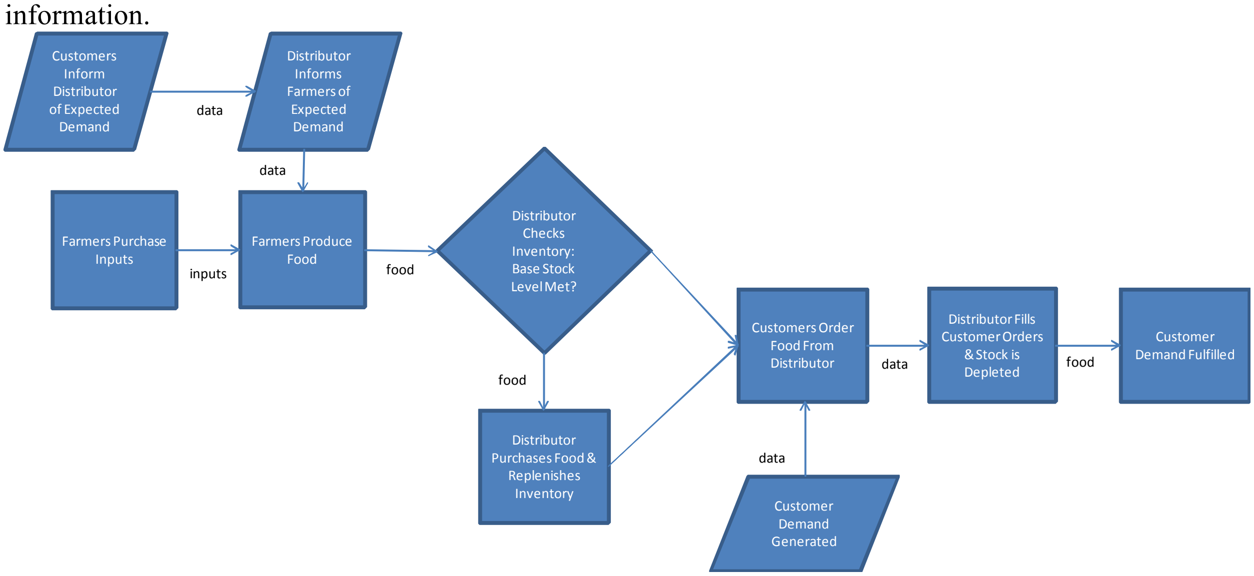

Figure 4: Flowchart representation of an MAS-FSC model with FSC interactions

2.4 Modeling Economic Processes

Crop yield functions, on-farm planning, and farmer-to-farmer interactions are essential elements of FSC models. However, the FSC typically comprises businesses that operate based on profits and losses, and so the economic aspects of FSC processes must also be considered. Modeling these economic aspects can potentially be very complex. For example, at each stage of the FSC, the cost of inputs to that stage must be assigned, but in real-life FSCs, the cost of inputs typically fluctuates over time and may depend on factors within and/or external to the FSC. For example, the cost of agrochemicals and transportation is directly related to energy costs, which can be highly variable and unpredictable. Within the FSC, the cost and/or availability of water for irrigation may depend on the number of farmers that use a shared water source and those farmers' behaviors. The complexities of determining the selling prices of food are even greater. In real-life FSCs, crop prices are influenced by many market factors, such as the demand for the crop at regional, national, and global levels, the available supply (which is often influenced by weather conditions), agricultural subsidies and price supports, and speculations by commodity investors. To capture realistic market behavior, a model would need to include the dynamics of farmer competition and fluctuating demand levels. The availability of credit and an agent's level of debt are also important to consider when modeling FSCs, particularly for farmers. At the start of each growing season, a farmer must typically invest in expensive production inputs (e.g. seeds, fertilizer, equipment) and then wait for a significant length of time (for crop growth) before realizing any returns on the harvest. Therefore, farmers often must have access to credit to cover these up-front input costs.

However, most MAS-FSC models in the literature simply assume that input costs, output prices, and demand levels are exogenous to the model, with values that are either fixed or randomly-determined, although the values may have some basis in historical data. For models of food-producing regions that sell commodities on an open market, these simplifying assumptions may be adequate. However, some MAS-FSC models incorporate some economic data and supply-demand relationships, particularly the models that focus on land use. For example, Freeman, Nolan, and Schoney (2009) model farmer land purchases as auctions, which requires significant data inputs to value the land, such as soil quality, transportation costs, and historic selling prices, as well as data inputs to evaluate farmer creditworthiness. Barreteau and Bousquet (2000) also model farmers' efforts to obtain credit, but use simple rules by which lenders determine the creditworthiness of a farmer.

A multi-echelon MAS-FSC model would likely require more complexity in economic processes than the models of farming regions in the literature, because the exchange of goods and services between stages at different supply chain levels must be explicitly modeled. For example, an MAS-FSC model might include the sale of a farmer agent's crops to a distributor agent. Depending on the power dynamics of this exchange, the farmer or distributor might act simply as a price-taker. However, a more complex exchange might involve a negotiation process between the agents to determine mutually-acceptable prices and delivery quantities. The development of a contract between the farmer and distributor might even occur. In any case, the modeler can choose among game theory, algorithms, or heuristics to model each participating agent. Figure 5 is a variation of the base MAS-FSC model that includes economic processes: when the distributor agent purchases food from the farmer agents, funds flow back to the farmers, and when the distributor sells to the customer, the distributor receives payment. Additionally, this model includes a price-setting mechanism by which the distributor determines how much it will pay farmers for food. Although the flowchart in Figure 5 is not structurally much different from the base model, the modeling logic that determines how the distributor will set purchase prices is potentially very complex.

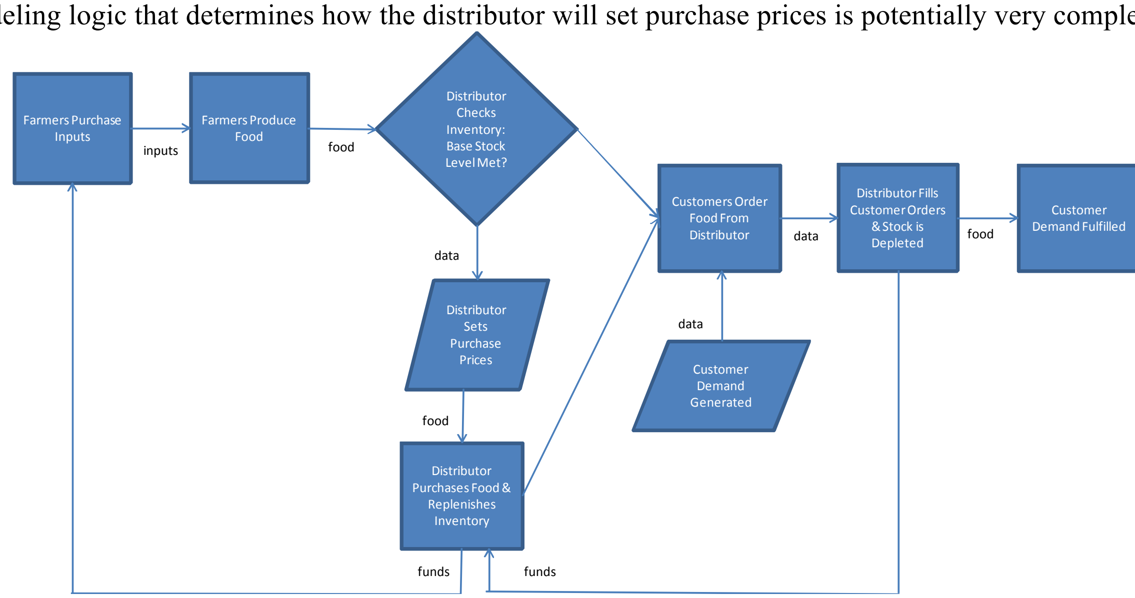

Figure 5: Flowchart representation of an MAS-FSC model with economic processes

2.5 Impact of the Political and Social Environment

The FSC significantly influences and is influenced by the social environment in which it operates. The FSC is also embedded within a political environment, which can strongly influence the behaviors and capabilities of FSC actors. While this is true to some degree for most supply chains, the FSC is particularly intertwined with political systems, through government actions such as subsidies, policies for land use, environmental regulations, and food safety regulations. A model of the FSC would be incomplete without accounting for the influence of the political and social environment that surrounds it.

Accordingly, these elements are often included in MAS-FSC models in the literature. For example, Sengupta et al. (2005) study the effect of government policy on environmental outcomes by modeling the impact of subsidies on farmer agents' decision to fallow highly-erodible land. Using information gathered from farmer surveys, they develop a model of heterogeneous farmer agents to predict the influence of the government program on farmer behavior and thus regional land use. The authors successfully validate their model by comparing its output with the changes in an actual regional land-use map over time. The models of Happe et al. (2011) and Janssen (2001) include elements that simulate environmental regulation to reduce pollution from farms. Happe et al. (2011) use their model to explore the impact of restricting farmers' maximum allowable livestock density on ammonia emissions and farmers' land-use decisions. Janssen's (2001) model includes a "tax payment" parameter with a value that depends on the intensity of a farmer's fertilizer use. The tax value can be varied in different simulated scenarios to study its impact on farmer pollution and subsequent eutrophication in a neighboring lake. Using sensitivity analysis, the author uses his model's output to show that the pollution tax could potentially improve environmental outcomes, but that the effect depends greatly on farmer risk tolerance and utility functions (i.e. farmers who are easily satisfied and risk-averse are not as susceptible to influence). Deffuant et al. (2002) also models government influence on farmer behavior through the inclusion of a Local Chamber of Agriculture. This institution provides farmers with information on organic farming practices, with the intent of encouraging farmers to adopt sustainable behaviors. In addition to this political element, Deffuant et al. (2002) describe farming as a "public act" and model the impact of public opinion (which is transmitted through the media) on farmers' willingness to convert to organic production practices. The authors compare the number of simulated farmers that convert to organic farming with actual historical results for validation purposes. They report that the simulated outputs did not fit the actual data because of the many approximations of model parameter values. However, the general behavior of the model matches the author's qualitative knowledge of the process. Le Bars et al. (2005) do not explicitly include elements of the political and social environment in their model's inputs or structure; however, they analyze the results of various simulation scenarios based on different viewpoints (individual, global, ethical (distribution of wealth), and environmental) that have a basis in political/social concerns.

Figure 6 is a variation of the base MAS-FSC model in which the impact of social pressure for product traceability is included. The demand for traceability is becoming increasingly common in FSCs as consumers have become concerned about food safety and production methods. Although the structure of the model represented in Figure 6 scarcely differs from the base model (farmers now share production data with the distributor, and the distributor shares that data with customer), capturing the implications of this process can be complicated – how exactly will farmers comply with this pressure? Will the farmer face labeling/packaging requirements or audits by the distributor? Will the model allow farmers to transmit erroneous data? The complexity of modeling this element could be potentially significant, depending upon the level of modeling detail.

3 DISCUSSION

MAS is a particularly useful tool for modeling FSCs. However, there are elements of the FSC that can be difficult to capture, because of their complexity and/or the amount of data needed to represent them accurately. A modeler must therefore make decisions on how to bound the level of detail of each of these elements: what should be explicitly modeled, what assumptions should be made, and what can be excluded, depending on the research question and availability of data. Table 1 summarizes the five FSC elements and the previously-discussed examples from the literature of how existing MAS-FSC models address these elements.

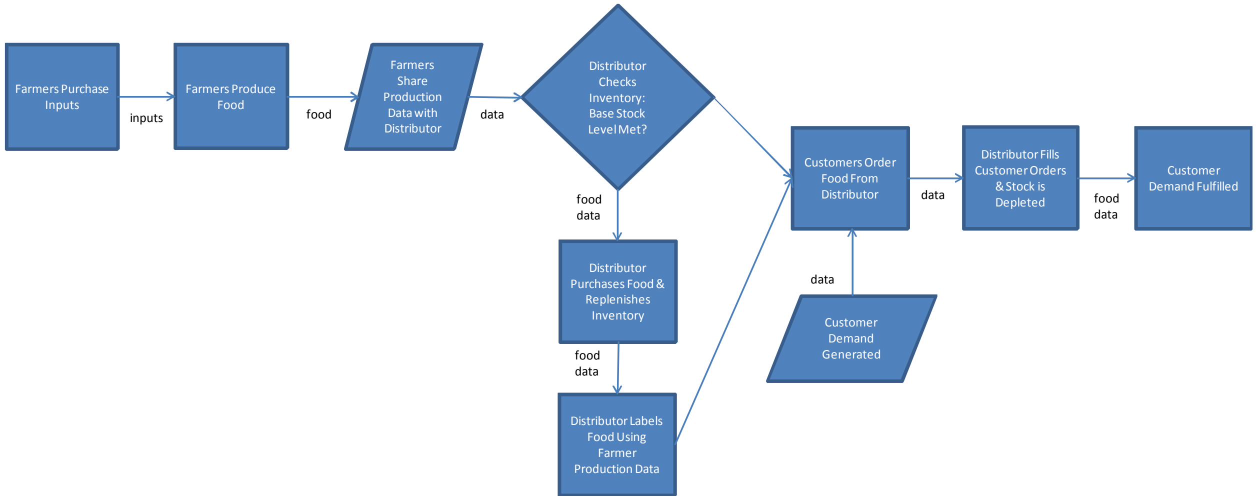

Figure 6: Flowchart representation of an MAS-FSC model with social impact

Table 1: Summary of key elements of FSCs and examples of how they are addressed in MAS-FSC models in the literature

	Explicitly Modeled: High Detail	Explicitly Modeled: Low Detail	Implicitly Modeled or Exogenous
Natural Environment	Belem et al. (2011) Happe et al. (2011) Schreinemachers et al. (2007) Matthews (2006) Becu et al. (2003) Lynam (2002)	Le Bars et al. (2005) Janssen (2001)	Deffuant et al. (2002) Polhill, Gotts & Law (2001)
Agent Decisions & Planning	Freeman, Nolan, & Schoney (2009) Kamusoko et al. (2009) Sengupta et al. (2005) Becu et al. (2003)	Belem et al. (2011) Polhill, Gotts & Law (2001)	Barreteau & Bousquet (2000)
FSC Interactions	Le Bars et al. (2005) Becu et al. (2003) Deffuant et al. (2002)	Polhill, Gotts & Law (2001) Janssen (2001)	Happe et al. 2011
Economic Processes	Freeman, Nolan, & Schoney (2009)	Barreteau & Bousquet (2000)	
Political & Social Environment	Deffuant et al. (2002)	Happe et al. (2011) Sengupta et al. (2005) Janssen (2001)	Le Bars et al. (2005)

A review of the literature has revealed the following insights into the current state and anticipated future of MAS-FSC modeling:

- There is a trend among models in the literature to move toward greater integration of primary simulators (e.g. crop simulators) with MAS models.
- The use of optimization to simulate agent decision-making is common in MAS-FSC models, even though one of the benefits of MAS is that it allows modelers to give agents bounded rationality and limited information/computational abilities.
- Most MAS-FSC models focus on capturing the natural environment and agent decision-making in detail; significant opportunities exist for increasing the level of detail and increased exploration of agent interactions (e.g. communication, cooperation, negotiation, coordination) and their impact on FSC performance.

- Based on the literature, economic processes, when considered, are often assumed exogenous to MAS-FSC models unless they are central to the model (as in land-use models), perhaps because they can be very complicated and may not add much value.
- Nearly all of the MAS-FSC models in the literature use case-study data from a specific region to build their models, although not all models attempt to use this data for validation. As models of multi-echelon FSCs are developed, this will become even more difficult, as the data requirements will be greater.

These insights are based upon an analysis of single-echelon models in the literature. Because multi-echelon FSC models use these single-echelon models as building blocks, these insights can be extended to influence future multi-echelon models. Modelers should keep in mind that adding detail and functionalities to an MAS-FSC model does not necessarily improve its ability to produce useful results and may even reduce its ability to explain relationships between inputs and outputs. It is critical that models are carefully and appropriately bounded.

A BASE MODEL PSEUDOCODE

```
setup procedure:
            create num_farmers farmers
            create 1 distributor
            set demand distribution parameters
            set production distribution parameters
base model procedure:
            generate demand values using triangular distribution random variate generator
            ask farmers
                  if soil_quality < optimal_soil_quality
                        set soil_quality optimal_soil_quality
                  generate yield values using triangular distribution random variate generator
                  set soil_quality (soil_quality * (function of yield values))
            ask distributor
                  if inventory < base_stock_level
                        set order_qty (base_stock_level - inventory) / num_farmers
                        ask farmers with yield <= order_qty
                              set filled_order (filled_order + yield)
                        set remaining_order_qty (order_qty - filled_order) / (count farmers with yield > order_qty)
                        ask farmers with yield > order_qty
                              set filled_order (filled_order + remaining_order_qty)
                        set inventory (inventory + filled_order)
                  if inventory >= demand
                        set inventory (inventory - demand)
                        set current_fill_rate 1.0
                  else
                        set inventory 0
                        set current_fill_rate (inventory / demand)
                  set fill_rate_sum (fill_rate_sum + current_fill_rate)
                  set avg_fill_rate (fill_rate_sum / (season_counter + 1))
```

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