Integrated modeling of extended agro-food supply chains: A systems approach

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Abstract

The current intense food production-consumption is one of the main sources of environmental pollution and contributes to anthropogenic greenhouse gas emissions. Organic farming is a potential way to reduce environmental impacts by excluding synthetic pesticides and fertilizers from the process. Despite ecological benefits, it is unlikely that conversion to organic can be financially viable for farmers, without additional support and incentives from consumers. This study models the interplay between consumer preferences and socio-environmental issues related to agriculture and food production. We operationalize the novel concept of extended agro-food supply chain and simulate adaptive behavior of farmers, food processors, retailers, and customers. Not only the operational factors (e.g., price, quantity, and lead time), but also the behavioral factors (e.g., attitude, perceived control, social norms, habits, and personal goals) of the food suppliers and consumers are considered in order to foster organic farming. We propose an integrated approach combining agent-based, discrete-event, and system dynamics modeling for a case of wine supply chain. Findings demonstrate the feasibility and superiority of the proposed model over the traditional sustainable supply chain models in incorporating the feedback between consumers and producers and analyzing management scenarios that can urge farmers to expand organic agriculture. Results further indicate that demand-side participation in transition pathways towards sustainable agriculture can become a time-consuming effort if not accompanied by the middle actors between consumers and farmers. In practice, our proposed model may serve as a decision-support tool to guide evidence-based policymaking in the food and agriculture sector.

Keywords: Multi-agent systems, Organic food, Environmental behavior, Sustainability, Supply chain management.

1. Introduction

The dramatic growth of the world population and consumption has tripled demand for food over the past 50 years and led to increased pressure on the natural environment (FAO, 2017). The contribution of agro-food production-consumption to eutrophication of surface water is estimated at 30% (Tukker & Jansen, 2006). According to The Intergovernmental Panel on Climate Change (IPCC) (2019), this sector alone accounts for 25-30% of the total global anthropogenic greenhouse gas emissions. Despite irreversible impacts on environmental resources and biodiversity, a growing number of farmers adopt intensive agriculture methods. Primarily, they intend to minimize the production costs and inputs, maximize the yield of crops, achieve economies of scale, run their family business, and in some cases raise mega industrialized farms. Recent studies show that not only the farmers and food suppliers but also distributors, retailers, and consumers are responsible for the environmental impact of global food systems (Notarnicola et al., 2017). Therefore, it is required to broaden the consideration of sustainability issues from an individual farm to the entire agro-food supply chain (SC).

The sustainable supply chain (SSC) concept has emerged as a result of incorporating environmental and social concerns into the economic management of production and distribution, from the point of origin to the point of consumption (Seuring & Müller, 2008). Later, the concept of the circular supply chain (CSC) has been introduced to the field, which focuses on the after-consumption phase of products (Guide Jr & Van Wassenhove, 2009). More recently, the concept of extended sustainable supply chains (ESSC) has been introduced by Taghikhah et al. (2019), which goes beyond the pure operational view and accommodates the behavioral dynamics of production and consumption. The ESSC approach recognizes that sustainable consumer behavior is essential to drive the decision-making process along the whole SC for improving socio-environmental performance.

In this paper, we demonstrate an approach for modeling the ESSC and its operationalization. This study includes a multi-echelon supply chain network according to the ESSC framework in the context of the agro-food industry. It is composed of a set of farmers, processors, distributors, retailers, and customers; producing and consuming both organic and conventional food. We assess the SC performance in terms of economic, environmental, and social metrics. Our aim is to investigate the impact of shifts from conventional to organic food consumption on the underlying SC activities and behaviors.

In our literature survey, on the one hand, we found few examples of SSC studies paying attention to the preference of consumers. For example, Fan et al. (2019) discuss the influence of the altruistic behavior of retailers on the willingness of consumers to purchase low-carbon products. They further study the effect of retailers' behavior across the entire SC to find out the dynamics of the economic and environmental performance of manufacturers. Tobé and Pankaew (2010) empirically study the influence of green practices of the SC on pro-environmental behavior of consumers. They conclude that a quarter of the Dutch population seems to be green consumers. Nevertheless, when it comes to buying decisions, the degree of environmental friendliness of products is not a significant determinant. Coskun et al. (2016) develop a model that considers the green expectations of consumers as a criterion for making decisions about the SC network configuration. They show the assets of the model in a hypothetical example where the consumers are categorized into the green, inconsistent, and red segments. Focusing on agro-food SC literature, Miranda-Ackerman et al. (2017) evaluate different pricing strategies based on consumer willingness to pay more for green food products. Sazvar et al. (2018) investigate the effect of substituting conventional product demand with organic assuming a percentage of consumers are willing to shift their preferences. Similarly, Rohmer et al. (2019) show the impact of possible consumers' shift from meat-based to plant-based diet on the underlying production system.

On the other hand, there are studies from the economics and behavioral science discipline that consider some aspects of SCs. In the field of economics, for example, Wen et al. (2020) and Sabbaghi et al. (2016) discuss the impact of consumer participation on pricing and collection rate decisions in CSC. The study of Safarzadeh and Rasti-Barzoki (2019) is another example of such analysis, which models the interactions between consumers, government, manufacturers, and energy suppliers for assessing residential energy-efficiency program. Regarding the behavioral studies, as a few examples, we point out to the impact of consumer choices on the retailing sector (He et al., 2013; Schenk et al., 2007), energy market (Xiong et al., 2020), housing market (Walzberg et al., 2019), and so on. While researchers have taken initial steps in highlighting the role of consumers in managing SC operation, they are far behind in analyzing the behavior of various consumers and the collective impacts of changing their preferences on enhancing SC sustainability.

The main finding that can be drawn from the reviewed papers is that there is a lack of research that analytically considers the role of green consumer behavior in SCM. Moreover, as there is no experimental or analytical study on the application of the ESSC framework, it still requires further investigations to be accomplished (Ferrari et al., 2019). According to Taghikhah et al. (2019), the complexity of relationships and the uncertainties involved in the ESSC requires a more comprehensive approach.

In developing the proposed ESSC model considering the heterogeneity of consumers, we take an integrated modeling approach combining agent-based modeling (ABM), discrete event simulation (DES), and system dynamics (SD) to simulate both production and consumption side of the operation and the feedbacks between them. ABM is a useful modeling approach for understanding the dynamics of complex adaptive systems with self-organizing properties (Railsback & Grimm, 2019). It allows us to study emergent behaviors that may arise from the cumulative actions and interactions of heterogeneous agents. In the proposed model, we make use of ABM to define each supply chain echelon/actor as an agent with specific behavioral properties and scale. The dynamics of consumer behavior and buying patterns is also modeled using individual households as agents who decide what they buy. DES is used to define the behavior of farmer and processor agents (responsible for production and distribution) as a series of events occurring at given time intervals accounting for resources, capacities, and interaction rules. SD is employed in examining the behavioral patterns and interactions between farmers and market using aggregated variables. The decisions to be explored in the proposed model are related to land allocation, production planning, inventory control, pricing, and demand management under uncertainty. The model accounts for different temporal (from short-term to long-term decisions) scales and multiple objectives in supply chains. The applicability of the proposed model is illustrated in the particular case of the Australian wine industry. The rest of the paper is organized as follows: Section 2 presents a background on the wine SC characteristics and the modeling techniques applied in designing agro-food SC. Section 3 describes the model framework and method. Section 4 explains the details of a case study. Section 5 presents the calibration and validation results, the uncertainty analysis, and findings from the model. Finally, Section 6 derives conclusions and some practical and managerial perspectives.

2. Background

2.1 Sustainability considerations in agro-food supply chains

Farming, processing, distribution are the main functional areas of decision making in the agro-food SC. Strategic and operational farming decisions are about the time of planting and harvesting crops, the land allocation to each crop type and the resources and agro-technologies to be used at the farm. Processing decisions refer to the scheduling of production equipment and labor, selecting production-packaging technologies, and controlling the inventory along the supply chain. The distribution related decisions involve designing the logistics network, scheduling the product shipping, and selecting the transportation modes and routes. The studies by Miranda-Ackerman et al. (2017), and Jonkman et al. (2019) are recent examples of models addressing a range of decisions from farm level (e.g., organic versus conventional farming) to the production (e.g., technology selection) and distribution level (e.g., transportation route). Although studies addressing SC decisions simultaneously are still lacking, the literature trend is towards more integrative, holistic agro-food models.

Strategies aimed at reducing the environmental footprints of agro-food SC are mainly focusing on the production side, designing low-carbon logistics networks, and improving the resiliency and reliability of food delivery (Soysal et al., 2012). These improvements alone may not bring considerable emission savings to agro-food sector. For example, in the case of meat production, which is responsible for approximately 14.5% of total global GHG emissions (e.g., Mohammed and Wang (2017)), even more than the transportation sector (Gerber et al., 2013), introducing green logistics and optimizing energy consumption in the SC will hardly make a significant difference in its overall impact. Regarding the food miles and local sourcing, new studies show that imported food products do not necessarily have higher environmental impacts than locals (Nemecek et al., 2016). Using eco-friendly processing technologies (Aganovic et al., 2017) and utilizing novel packaging options (Licciardello, 2017) are examples of efforts to reduce the environmental footprint of food processing. An insightful discussion on these strategies can be found in (Li et al., 2014). Among the strategies examined in the literature (Beske et al., 2014), demand-side solutions such as consumer preferences for sustainable food or vegetarian diets and their influence on the overall configuration and performance of the SC have been largely ignored.

2.2 Modeling methods in the agro-food supply chain

From a modeling perspective, mathematical optimization techniques (combined with life cycle assessment) are the dominant approach used for designing SSC for food products (Zhu et al., 2018). Some researchers take deterministic approaches such as linear programming, mixed integer programming, and goal programming (Oglethorpe, 2010) to design and plan SCs. The uncertainty and dynamics in the parameters are addressed by approaches such as stochastic programming (Costa et al., 2014), fuzzy programming, simulation modeling, and game theory. The choice of modeling technique depends on various factors such as problem scope, inherent complexity, and uncertainty in the SC, modelers' skill, and data availability.

Although a decade ago, the increasing necessity of using system science methods, such as ABM, SD, and network theory for studying agro-food SCs have been emphasized (Higgins et al., 2010), not many applications can be found in practice. Authors have applied ABM in developing theories and policies to improve the performance of the agro-food industry (Huber et al., 2018). Theory focused studies aim to explore the application of theories in understanding agents decision-making process (e.g., farmer, government, dealer, etc.) or develop new theories to explain the interactions among individual agents (e.g., Malawska and Topping (2018)). Theories have already helped to describe the formation of cooperation networks, restructuring the partnerships, and rearrangement of the market power (See Utomo et al. (2018)). Policy focused ABMs study the impact of financial (e.g., incentives and subsidies, pricing, credit, and compensation schemes), innovative and technological (e.g., improved seed, tree crop innovations, or environmental (e.g., organic agriculture, organic fertilizers) policies on the performance of food SC (Albino et al., 2016). In a recent review on the application of ABM in agriculture, Utomo et al. (2018) emphasize that important actors of the industry, such as food processors, retailers, and consumers, are rarely modeled in the current ABM literature and call for further research on these areas.

Despite the growing interest in using optimization approaches, the application of simulation techniques in the SSC context is scarce. Recently, Wang and Gunasekaran (2017), Rebs et al. (2018), and Brailsford et al. (2019) have suggested getting the advantages of combined simulation modeling methods in assessing complex SSC problems. In response to this call, our study presents the development of an extended food SC model that incorporates the dynamics of farmers, processors, retailers, and consumers behavior as well as sustainability aspects. For this we used an integrated, or rather an integral (Voinov & Shugart, 2013) modeling approach to link production decisions to consumption choices in a holistic way.

2.3 Behavioral modeling and hybrid simulation

In recent years, the area of modeling behavioral aspects of decision-making has received attention of researchers and practitioners. According to Kunc (2016), behavioral modeling is "the representation of bounded rationality and theories-in-use rather than normative, rational behavior or passive, predictable entities." It embeds the behavioral theories that focus on changing behavior or explaining the decision-making process to improve our understanding of individual and group mental models and decisions. However, we should also remember that while this modeling practice can provide new insights, it may also introduce undesired complexity, higher ambiguity in the environment, and harder interpretation of results. For a comprehensive discussion on this topic, see Kunc et al. (2016).

Not every modeling method (e.g., mathematical modeling and optimization, DES) can be used for developing behavioral models. It instead requires methods (e.g., SD, ABM) that are able to simulate the intangible aspects of the systems such as relationships, feedbacks, and dynamics of the environment. Hybrid simulation is an approach for mixing, combining, or integrating multiple operational research methods such as DES, ABM, and SD (a comprehensive taxonomy can be found in N Mustafee and Powell (2018)). It has a strong practical appeal to deal with the limitations of a single method in developing behavioral modeling (Navonil Mustafee et al., 2017). This approach allows the models with different levels of abstractions to interact seemingly and increases the flexibility of end-users in using them for decision-making. Having said that, the main challenges of hybrid simulation are difficulty in verification and validation, huge computational complexity (Bardini et al., 2017), and low practical application of the models for solving real-world cases. Brailsford et al. (2019) found that among 139 published papers using hybrid simulation, combined SD-DES is the most popular method, whereas a combination of DES, SD, and ABM is the least applied method, only in 14 papers. In this paper, we compared the results of using both approaches and provided insight into their performance in a case study. For in-depth analysis of hybrid modeling, see Brailsford et al. (2019), Eldabi et al. (2018), and Navonil Mustafee et al. (2017).

3. Methodology

In this study, SC is composed of four actors/echelons - farmer, winemaker, retailer, and consumer - collaborating to achieve their various goals (see Figure 1). They may have different functions, complexity levels, temporal dimensions, and spatial scales. In the proposed ESSC model, ABM is used together with DES and SD to model the behavior of each actor. The model is programmed in AnyLogic 8.3 Software and it is openly available at Comses (https://www.comses.net/codebase-release/eeb3cd12-91ac-4ba7-81f7-8c8bfe7bd804/). It is built in a GIS computational environment enabling users to adjust the resolution and scales during the run time.

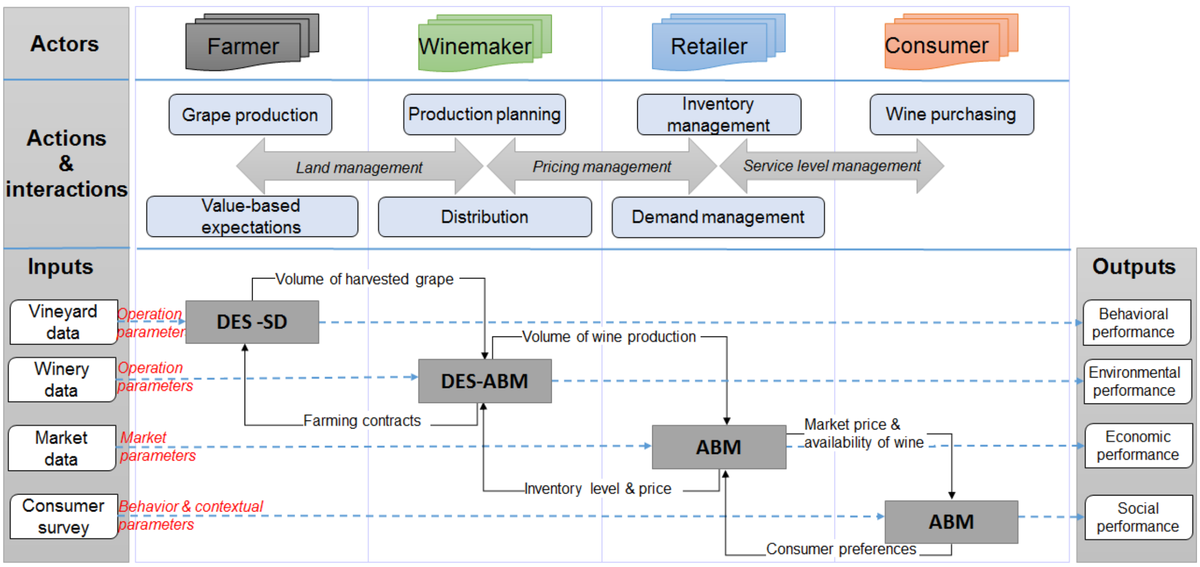

Figure 1. Conceptual framework of ESSC for the wine industry.

The wine market studies reveal that retailers have high bargaining power (Australian competition and consumer commission, 2019). Recently, concentration in most of the retail industries including liquor has increased, with only a few retailers controlling the large market share and setting the prices and quantities strategically. The oligopolistic behavior of retailers significantly reduces winemakers' power in their negotiations and turns them into price takers. Having said that, winemakers still have a significantly stronger bargaining position compared to grape growers. In other words, farmers cannot merely pass higher grape prices and other costs along the supply chain to wineries. These considerations justify the assumptions of hierarchical structures and central control changes to collaboration between actors to maximize the profit.

3.1 ESSC inputs

Both historical and empirical data are used to parameterize, calibrate, and validate the model. The data on crop scheduling, vineyard costs, farming practices, grape types, and land yield describe the farmer agents. The winemaker agents use historical data on numbers and capacities of machinery, production processes, time, costs, and grape requirements. The information collected from liquor retailers' annual reports and the wine industry reports including the prices, market structure, export and import, sales, and profit of retailing addresses the data inquiry of retailer agents. Finally, consumer surveys about wine preferences provide data for the behavioral (e.g., beliefs, goals, experiences, and perceptions) and contextual factors (e.g., price, availability, accessibility) of the consumer agents.

3.2 ESSC methods

An integrated ABM-DES-SD method is employed for the ESSC model development. We use ABM for simulating consumer behavior and retailer operation. It is a bottom-up method suitable for modeling complex social, behavioral dynamics to study heterogeneity and the emergence of collective actions. In facing the same situation, every consumer and retailer agent has a unique reasoning mechanism and they act based on predefined decision rules. A combination of DES and ABM is employed for modeling the dynamics of wine production and distribution operations. DES presents (discrete) sequence of wine processing events in time. Finally, a combined DES and SD method simulates the annual growth cycle of grapevines and predicts farmers' expectations about the value of organic farming (Figure 1).

3.3 Actions and behavior of agents

3.3.1 Farmer agent

Farmers act as the first-tier suppliers in the model. They grow two types of grapes - organic and conventional, which are harvested once a year. Depending on the availability of arable land and the farming practice (organic versus conventional), each farmer agent has a distinct production capacity and unit operating cost. Figure 2 presents a simplified schematic of farmer operations.

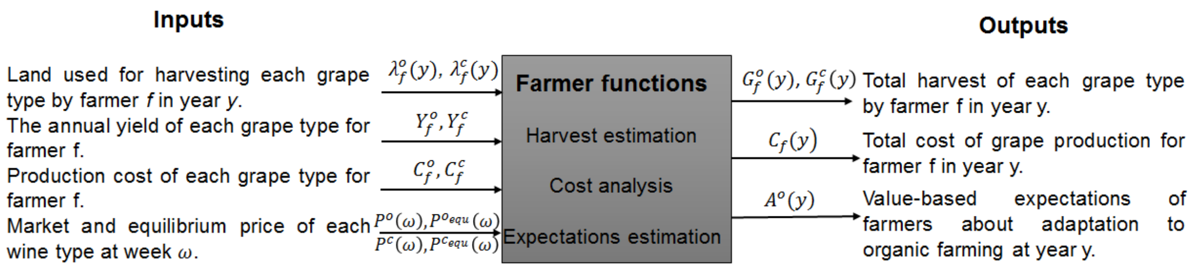

Figure 2. Schematic of operations in farmer agents.

The model assumes that farmers have fixed land area available to supply the grape requirements of wineries. Farmers are contracted by winemakers to grow grapes under a capacity guarantee contract-farming scheme. This contact determines the approximate volume and the type of grapes - organic and conventional - required for production. In this study, organic farming refers to a method of crop production that relies on biological pest controls (e.g., cover crops, crop rotation), and organic fertilizers (e.g., manure). Conventional farming, in contrast, uses synthetic fertilizers, fungicides, and pesticides to maximize the vineyard yield. The organic farming system is considered more sustainable since it can keep soil healthy and maintain the productivity of land. The simulation begins in springtime when the grapevines are in the bud break phase. In this phase, tiny buds start to swell and eventually shoots grow from the buds. Approximately 40-80 days later, small flower clusters appear on the shoot, and the flowering phase starts. Soon after, 30 days on average, the flowers are pollinated, and the berries start to develop. This crop phase determines the potential yield of the vineyard. In the next phase, veraison, the color of grape berries changes after 40–50 days signaling the beginning of the ripening process. Following veraison, within 30 days, farmers complete the harvest, remove grapes from the vine, and transport them to wineries for further processing. Due to the variation in climate conditions over the years, we consider a stochastic crop growth process where the annual harvest of organic and conventional grapes is:

$$G_f^o(y), G_f^c(y) = \{\lambda_f^o(y)Y_f^o, \lambda_f^c(y)Y_f^c\}; \qquad (1)$$

Where, $\lambda_f^o(y), \lambda_f^c(y)$ are grape yields and Y_f^o, Y_f^c are cultivated areas at year y for organic and conventional grapes at farm *f*. The annual production cost at farm *f* ($C_f(y)$) varies depending on the production cost of organic and conventional grapes.

Farmer agents make judgmental assessments of the value of organic and conventional farming systems. The hypothesis of adaptive expectations (Nerlove, 1958) states that the expectations of the future value of the interest variable depends on its past value and adjusts for the prediction error. Thus, the calculation of progressive expectations or error learning hypothesis is derived from observing the difference between past and present market values. The market and equilibrium price of organic and conventional wine (discussed in Section 3.4) guide farmers' expectations of adaptation to organic farming (shown in Figure 3).

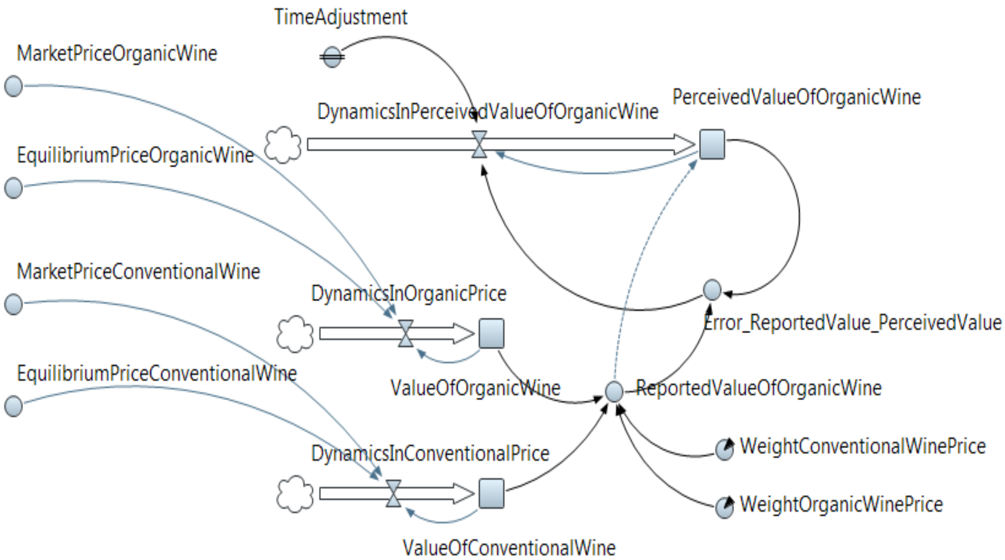

Figure 3. Value-based expectations of farmers about organic farming.

The current expectations of the value of organic farming in the future is calculated as:

$$A_f^o(y) = \int_0^{\omega} \varphi_f^{O_{out}}(\omega)d\omega; \qquad (2)$$

$$\varphi^{O_{out}}(\omega) = \begin{cases} 0, & if\ (\varphi_f^{O_{out}}(\omega) \leq\ 0\ and\ \varphi_f^{O_{err}}(\omega)/t < 0)\ or\ if\ (\varphi_f^{O_{out}}(\omega) \geq 1\ and\ \varphi_f^{O_{err}}(\omega)/t\ > 0); \\ \varphi_f^{O_{err}}(\omega)/t, & else; \end{cases}$$

$$\varphi_f^{O_{err}}(\omega) = \varphi_f^{O_{in}}(\omega) - \varphi_f^{O_{out}}(\omega)\ \ \varphi_f^{O_{in}}(\omega) -\ \varphi_f^{O_{out}}(\omega);$$

Where $\varphi_f^{O_{out}}(\omega)$is the past perceived value of organic wine, $\varphi_f^{O_{err}}(\omega)$is the partial adjustment, which describes the gap between reported value ($\varphi_f^{O_{in}}(\omega)$) and the perceived value of organic wine. A full description of sub-models and their equations is available in Appendix A.1.1.

3.3.2 Winemaker agent

Winemaker agents process grapes to produce two types of products, organic and conventional wines. They are responsible for storing and dispatching final products to retailer agents. The total production capacity per agent is fixed, but periodically, the capacity ratio for organic and conventional wine production can adapt to the size of retailer orders. Figure 4 presents the operations in winemaker agents.

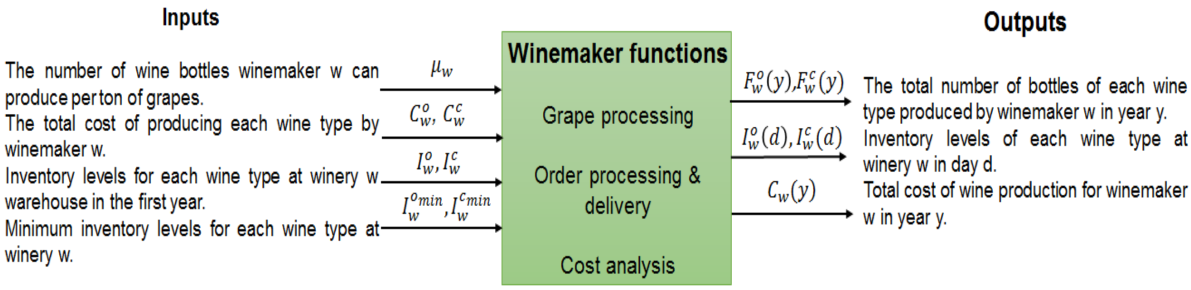

Figure 4. Schematic of functions in winemaker agents.

Due to perishability issues, winemakers try to process the grapes straight away after the harvest. The grapes get sorted, crushed and pressed, fermented, matured, and bottled as organic and conventional wines. Assuming winery *w* purchases all the farmer *f* yield, their annual production is:

$$F_w^o(y), F_w^c(y) = \{G_f^o(y)\mu_w, G_f^c(y)\mu_w\}; \quad (3)$$

Where $G_f^o(y)$and $G_f^o(y)$ are the availability of raw materials from (1) and μ_w is the capacity of processing facilities. While the same type of machinery can be used for producing organic and conventional wines, the processes (e.g., excluding sulfate during fermentation and bottling for organic wine) and associated costs might be slightly different. Upon order arrival from retailers, the winemakers check for the stock availability and follow a rule-based reasoning approach to best fulfill them as described in Appendix A.1.2.

To prevent the issuance of new orders in case of no stock, winery *w* informs all the retailer agents that due to unavailability of stock $\{(I_w^o(d), I_w^c(d)) < (I_w^{o\,min}, I_w^{c\,min})\}$, they would not accept further orders. This is done because wine production can take place once a year at the end of harvest season. Before this time, any new order will be placed in the queue for processing when the product is available.

3.3.3 Retailer agent

Retailer agents have the responsibility of supplying products quickly and reliably, forecasting demand accurately, and controlling the inventory levels continuously. They employ dynamic inventory control models to make a trade-off between SC costs and demand fulfilment. Figure 5 summarises the operations in this agent type.

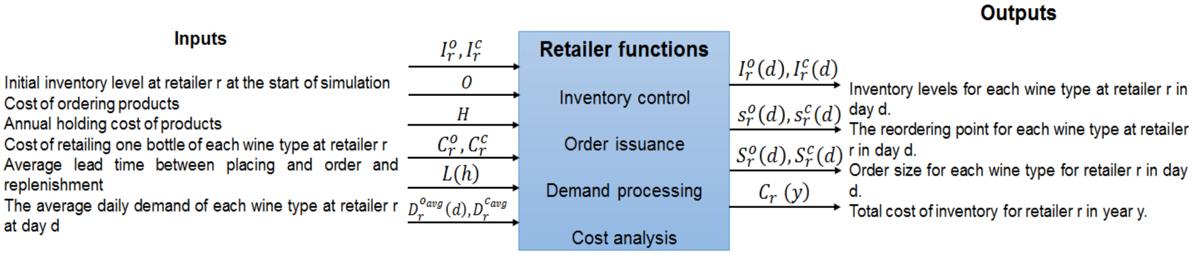

Figure 5. Schematic of operations in retailer agents.

The decisions on when to place an order and how many products to order from winemakers can impact the inventory-related costs. A continuous review inventory policy meets the requirements of retailers in response to dynamic demand situations (Hollier et al., 1995). This policy allows them to review their inventory levels for both organic and conventional products on a daily basis at minimum costs. When the inventory drops to some predetermined level '*s*' (known as reordering point), lot of size '*S*' is ordered. The reordering point ($s_r^o(d)$,$s_r^c(d)$) makes sure that sufficient stocks are available to meet the demand before the order arrives at the retailer *r* to replenish the inventory levels. The order size for retailer *r*, ($S_r^o(d)$, $S_r^c(d)$) is a function of the economic order quantity ($Q_r^o(d)$, $Q_r^c(d)$) and the inventory at hand ($I_r^o(d)$,$I_r^c(d)$). Appendix A.1.3 presents the details of inventory management system.

3.3.4 Consumer agent

Consumer agents follow a certain decision-making process to make choices between organic and conventional wines. ORVin, an ABM developed by Taghikhah et al. (2020), is integrated into our model to estimate the consumer preferences for wine. In exploring the cumulative market consequences of individual consumer choices, factors such as social influence, drinking habits, and behavioral dynamics come into play. Figure 6 presents a summary of the functions used in this agent type.

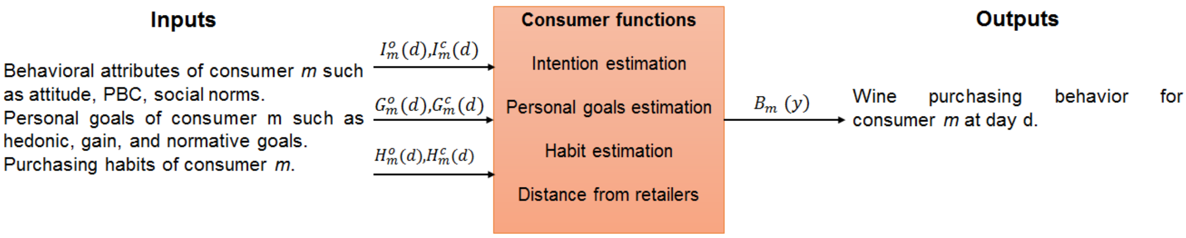

Figure 6. Schematic of functions in retailer agents.

To understand the wine purchasing behavior, the theory of planned behavior (TPB) (Ajzen, 1985) is considered along with alphabet theory (Zepeda & Deal, 2009) and goal framing theory (Lindenberg & Steg, 2007). According to TPB, a particular behavioral choice is preceded by intention, which in turn is influenced by an individual's behavioral, normative, and control beliefs. In addition, Alphabet theory explains the influence of habits on the relationship between intentions and actual behavior. Besides habits, the goal-framing focuses on the impact of environmental-contextual conditions on personal goals (i.e., hedonic-gain-normative goals) when making decisions. This combination provides a theoretical framework for exploring behavioral and contextual factors, including intentions, habits, and personal goals that may influence wine purchasing decisions. Consumers have intentions for purchasing either organic or conventional wine before shopping. When they arrive at the nearest retailer, they first check the availability and price of wine types. If the price of wine is higher than the consumers' spending limit or if no wines are available in stock, they leave the shop without purchasing any wine. Otherwise, they choose wines based on their intentions, habits, observations of what other shoppers buy, and the perceived value of products. During the simulation, the shopping experience, the information about organic wine, and the dynamics of price and availability of wines affect the wine preference of consumers. For a technical explanation of the model, please refer to Appendix C: ORVin model description in (Taghikhah et al., 2020).

When integrating ORVin into the ESSC model, some restrictions of the model could be released as below.

- In ORVin all the retailers have equal stocks of wine. Now, retailers are different, and, apart from price considerations, the product availability on the shelf can affect the perception of consumers about their choice control (i.e., perceived behavioral control (PBC)).
- In ORVin no product shortage is allowed, and the service level is 100%. Now some acceptable level of product shortages can happen, and these are modeled as a service level.

3.4 Agent interactions specification

Figure 7 displays the interactions of agents supporting the operations of ESSC. Three interaction schemes are proposed: service level management scheme, pricing management scheme, and land management scheme.

Retailer agents are gatekeepers between the producer and consumers. In interactions with consumer agents, retailer agents have multiple touchpoints to influence consumer preferences, including prices, and on-shelf availability. There are situations when wines of a certain type, for example, conventional ones, are not available at the shops. If consumer *m* habit of purchasing conventional wine is weaker than their intention to purchase organic wine ($H_m^c(d) < I_m^o(d)$), a shift in their preference (from conventional to organic wine) can occur that may lead to purchasing organic wine (also depending on the other factors). A detailed description of the interactions between consumer and retailer agent is in Appendix A.2.1.

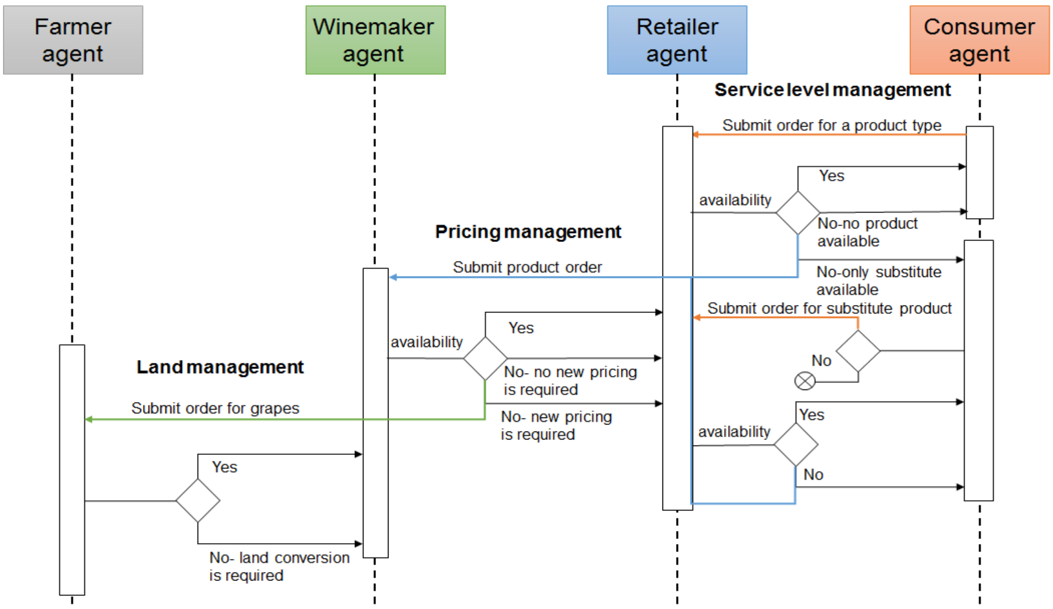

Figure 7. ESSC interactions schemes.

Retailers are also responsive to the changes in the demand for products to keep the profit margin of SC stable. For maintaining high service levels (i.e., acceptable stockout rates), they may adjust inventory policies and set new pricing strategies. They should keep the inventory stock-out at an acceptable level to timely meet customer demand.

The service level at week ω is:

$$\vartheta_{\%}(\omega) = 1 - (N_m^{l_{avg}}(\omega)/N_m^T); \qquad (4)$$

Where $N_m^{l_{avg}}(\omega)$ is the average number of lost consumers and N_m^T denotes the total population of households. $\vartheta_{\%}(\omega)$ should not drop to less than the minimum acceptable level (assumed to be 95% (ϑ=0.95)).

In transitioning demand from one product type to another, for instance, from conventional to organic wine, the conventional wine stock level grows, and at the same time, the organic wine stock level declines in the SC. This supply-demand imbalance prompts retailer-winemakers interactions, where they take different pricing strategies. Retailer agents monitor the dynamics in the organic and conventional wine inventory stocks using statistical process control (SPC) charts (Oakland, 2007). Upper and lower control limits for the wine inventory SPC charts are yearly determined following a set of production rules, as presented in Appendix A.2.3. Nelson rule checks whether the process is in control/out of control.

According to Nelson rule 8, if the inventory level is out of the defined upper and lower limits for at least nine consecutive time units, then the process is uncontrolled. For example, in situations when due to the changes in the market trend, there is a shortage of products, the prices are subjected to rise to rebalance the demand and supply. Generally, oversupply leads to a drop in the market prices while undersupply increases the market prices of organic and conventional wines ($P^o(\omega)$, $P^c(\omega)$) by a predetermined rate (R^o, R^c). The changes in the market price of wines cannot drop below the minimum ($P^{o_{min}}, P^{c_{min}}$) or go beyond the maximum price of wines ($P^{o_{max}}, P^{c_{max}}$). As the price of products will change temporarily over a short period, it may not be effective in coping with the market price gap when there are significant supply and demand imbalance. Price adjustment is an effective market mechanism aiming to tune the equilibrium prices ($P^{o_{eqb}}(\omega), P^{c_{eqb}}(\omega)$) for increasing or decreasing the sales of a product for longer periods. Instead of a fixed price option, wine equilibrium prices are modified on a γ week-by-week basis at different rates except during the land conversion period from conventional to organic.

A sequence of decisions winemakers and retailers make about the wine prices affects the production plans and supply agreements with farmers. When the price for a certain wine type increases, its production becomes financially more attractive and viable to winemakers. Thus, both parties decide on the volume and selling price of yield in a renewed contract farming agreement as summarized below. Appendix A.2.3 provides a detailed explanation of the farmers' capacity and decisions about fulfilling the winemakers orders for grape.

Convert from conventional to organic farming: No changes in the production plan and vineyard configuration is expected unless the equilibrium price of organic wine increases before the planting season ($\Delta P^o(y)$>0). The organic conversion scale (the amount of land to be converted in year y) is:

$$\Omega^o(y) = \begin{cases} \max\{\Omega^{min}, \chi^o(y)\}, & \text{if } (\delta^o(y) \leq 0.3); \\ \Omega^{min}, & \text{if } (0.3 < \delta^o(y) \leq 0.7); \\ \min\{\Omega^{min}, \chi^o(y)\}, & \text{if } (0.7 < \delta^o(y)); \end{cases} \quad (5)$$

Here, Ω^{min} is the minimum conversion scale, $\chi^o(y)$ is the land required for conversion based on demand estimations, and $\delta^o(t)$ is the perceived failure risk of conversion. The transition from conventional to organic farming takes three years. The yield from transitioning farms can be only sold as conventional products. This long lead time not only adds to the complications of balancing market demand but also gives a bias to farmer judgments about the long-term cost-benefits of their organic vineyards as discussed in Section 3.3.1.

Revert from organic to conventional farming: The decisions on increasing the production volume of conventional wine and reverting from organic to conventional agriculture impose higher risks on the financial performance of SC. In this model, the dynamics of equilibrium price of organic and conventional play the main role in provoking the reversion decisions ($\Omega^c(y) = \Omega^{min}$) as:

- If there is no positive change in organic wine equilibrium price while the conventional equilibrium price is increasing and the SC service level is less than the minimum acceptable level, or
- If there is an oversupply of organic wine and its equilibrium price is at a minimum.

3.5 ESSC outputs

Sustainability objectives, including social, environmental, and economic considerations as well as behavioral considerations, guide the ESSC decisions.

We address the social issues from the public health perspective as a function of organic food consumption. Organic diets expose consumers to fewer chemicals associated with human diseases such as cancer (Chen et al., 2015), autism (Kalkbrenner et al., 2014), and infertility (Chiu et al., 2018). Kesse-Guyot et al. (2017) report the risk of obesity in organic food consumers is reduced by 31% as a result of adopting a nutritionally healthier dietary pattern. In a recent experiment, Hyland et al. (2019) measured the pesticide metabolite levels of 16 individuals before and after switching to an all-organic diet. They surprisingly found that the level of synthetic pesticides in all participants has dropped, on average, 60.5% after eating only organic just for 6 days. A recent comprehensive discussion of organic food benefits for human health is to be found in Vigar et al. (2020). By increasing the consumption of organic food, people can improve their health and well-being. Thus,

(1) **Social performance** accounts for organic product consumption and is defined as:

$$Soc_{sc}(y) = N_m^o(y); \quad (6)$$

Where, $N_m^o(y)$ is the number of organic consumers in year y. Rohmer et al. (2019) and Sazvar et al. (2018) use similar diet-related indicators such as nutritional compliance (i.e., amount of nutrient n consumed) and Individual health-living environmental health (i.e., organic product consumption and production) to assess the performance of SSC in terms of public health.

With regard to environmental issues, this study focuses on the size of land used for organic farming practices. The heavy use of pesticides and synthetic fertilizers in conventional farming is seen as a major cause for more than 40% decline in the number of insects and if this trend continues, there may be no insects left in the next 100 years (Stepanian et al., 2020). Adoption of organic farming can help to: protect soil quality, keep waterways clean, and preserve landscape aesthetics. Certainly, organic farming can reduce environmental impacts related to toxicity and it could also help in the biodiversity preservation.

(2) **Environmental performance** measures the size of organic farming and is defined as:

$$Env_{sc}(y) = \sum_1^{f'} \lambda_f^o(y) \quad (7)$$

where, $\lambda_f^o(y)$ is the total land used for organic farming in year y.

We consider the revenue obtained from the sale of organic food products as an indication of economic performance. While SC cost is the most commonly used indicator, this research focuses on green economic growth and fostering the income from green products. Thus,

(3) **Economic performance** evaluates organic income and is defined as:

$$Eco_{sc}(y) = \sum_1^{r'} P_r^o(y); \quad (8)$$

Where, $P_r^o(y)$ is the total organic food product sales in year y, calculated as $D_r^o(d).P^o(\omega)$.

Given the difficulties associated with the quantification of behavior, farmers' goals and expectations of organic farming adoption can be used as a measure. According to Bouttes et al. (2018), organic farmers' work enjoyment is determined by their expectations of organic farming conversions, "a satisfaction heightened by the positive feedback they already receive for their decision to convert." In transitioning to more ecological farming practices, the market feedback (in terms of price incentives offered by consumers) is essential to enable farmers to enhance adaptive capacity, recover from current setbacks and cope with future change. Thus,

(4) **Behavioral performance** is defined as:

$$Behav_{sc}(y) = \sum_{1}^{f'} A_f^o(y)\,; \tag{9}$$

Where, $A_f^o(y)$ is the value-based expectations of farmers about organic farming in year y from (2).

4. Case study description

The general model described in Section 3 is applied to a case study derived from Australian wine industry, as shown in Figure 8. The SC considered has different aggregation levels varying from the individuals (e.g., consumers) to businesses (e.g., retailers, winery) and farmers. The time step is one week, and the simulation runs for 30 years. For a complete description of data input, please refer to Appendix B.

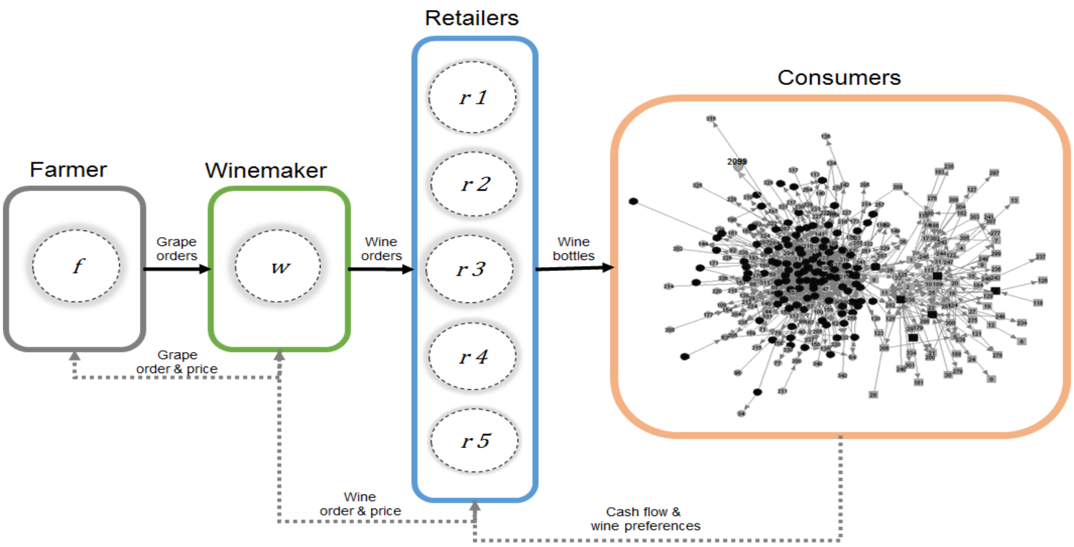

Figure 8. A presentation of ESSC model for the case study; black and grey dots indicate the heterogeneity of consumers and the connections symbolize social networks.

Our focus is on understanding the operations of an average farm in the region. So, in the model, we use a representative farmer agent with the characteristics of the cool-climate grape growers in South Australia. This region alone is responsible for more than half of the production of all Australian wines. While we acknowledge that more than sixty different species of grapevines exist in the Australian vineyards, for simplification, we collect data on one popular type, Cabernet Sauvignon (yield of organic/conventional land, resource requirements, and operational costs) (refer to Appendix B.1)

Usually, wineries are established in the grape-producing zones to reduce transportation costs and preserve the quality of crops. The winery warehouses, however, may be located far from production sites and closer to customer zones. We assume that the winery warehouse, located in the vicinity of the retailers, uses a logistic system of the truck scale to distribute the products (refer to Appendix B.2). There are five retailers in the model illustrating major Australian alcohol market players (including Woolworths, Coles Group, Metcash Limited, Aldi, and others). Each retailer has at least one shop in the City of Sydney Local Government Area (LGA). The average price of organic and conventional wines (tax included) across all stores is $13.00 and $10.00 per bottle, respectively. These prices are aligned with the average price of organic and conventional wines presented on Wine Australia website (https://www.wineaustralia.com). On top of retailing costs, the Australian wine retailers should pay Wine Equalisation Tax (WET) (29% of half the price of wine) and Goods and Service Tax (GST) (GST is 10% of the full price) to the governing body (refer to Appendix B.3). The wine preference of 2099 households reported in Ogbeide (2013) is used for the consumer agent. Readers can find the details of ORVin data in Appendix C of Taghikhah et al. (2020).

5. Results and discussion

5.1 Model calibration and validation

Calibration is a vital step in tuning the model to reproduce empirical data by tweaking the values of some of the model parameters. There was only a limited number of experimental results that we could use for this purpose. From Ogbeide (2013), we had the number of consumers having a positive attitude towards organic wine, and from the Wine Intelligence (2018) survey, we could estimate the ratio of organic to conventional wine consumers. These numbers were used for calibrating the model.

The consumer survey by Ogbeide (2013) also contained the number of consumers intending to purchase organic wine, when the price of organic wine is set to AU$12, AU$13, and AU$14. This data was not used for calibration purposes and was set aside to validate the model. A list of calibrated parameters is presented in Appendix C.

According to Brailsford et al. (2019), “Models that use both real-world and illustrative data are categorized as mixed.” As in our model, we use both real world (secondary collected elsewhere for other purposes) as well as illustrative input data (data derived from expert interview and hypothetical data), we position it as a mixed real-world and illustrative model.

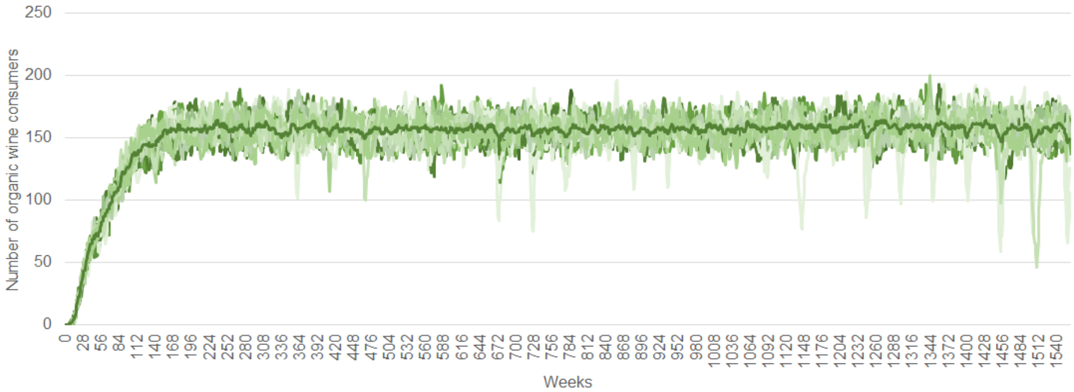

Figure 9. The number of organic wine consumers in the baseline scenario after 20 runs. The considerable variation in output is due to the stochastic nature of some of the parameters.

Figure 9 presents the calibrated number of organic wine consumers (153 consumers equal to 7-8% reported market size) in 20 runs. The variations in the demand are caused by the stochasticity of supply levels, product availability in different shops, and behavioral parameters. The land used for organic farming is 0.58 (hectare) and the annual sales of organic products stay around AU$ 38,334.

A comparison between the estimated number of consumers intending to purchase organic wine and the empirical data from literature is reported in Table 1. The results from the simulation model can estimate the number of organic wine consumers with a significant accuracy of 82% to 97% with respect to different willingness-to-pay settings.

Table 1. Model validation results, when comparing the number of consumers intending to purchase organic wine when its price is set to AU$12 (20% more), AU$13 (30% more), and AU$14 (40% more).

Validation scenarios	**Empirical number of organic wine consumers (Ogbeide, 2013)**	**Estimated number of organic wine consumers (model output)**	**Estimation error (%)**
Willingness to pay 20% more	467	453	-3%
Willingness to pay 30% more	279	258	-8%
Willingness to pay 40% more	150	177	+18%

5.2 Uncertainty analysis

5.2.1 Local sensitivity analysis

Because of the overall model complexity, we used the one-factor-at-a-time (OFAT) method to calculate the sensitivity of model outputs to the input parameters. We analyze the model outputs by varying the model inputs by ±20% of their base case values.

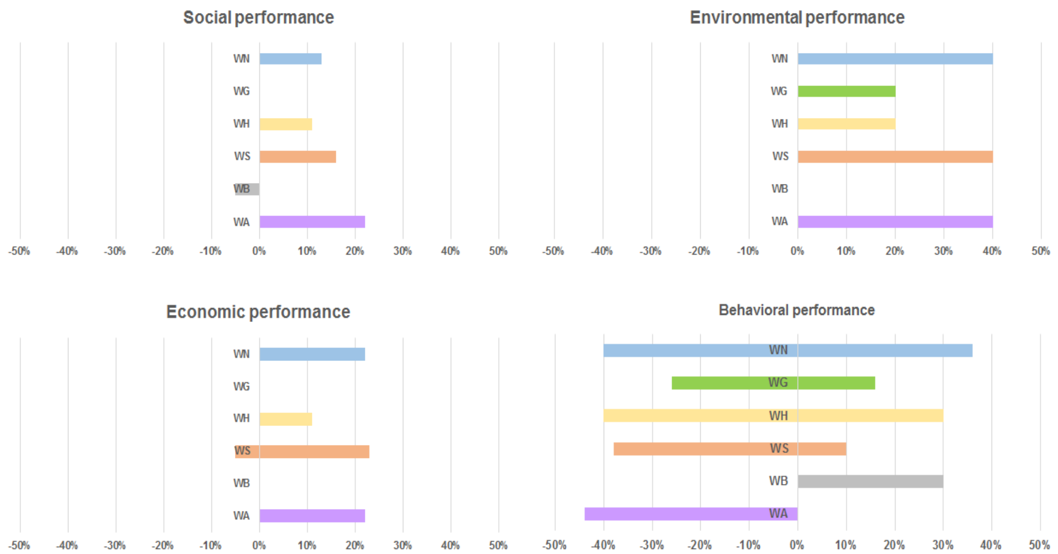

Figure 10. Sensitivity analysis of model estimations to the input parameters (details are presented in Appendix D, Table D1).

For example, Figure 10 presents the sensitivity of model results to variations in the weights of attitude (*WA*), PBC (*WB*), social norms (*WS*), hedonic goals (*WH*), gain goals (*WG*), and normative goals (*WN*). For a detailed discussion on these weights, we refer readers to Appendix C.3.3 in (Taghikhah et al., 2020). Variations of less than 5% are excluded from the charts. Overall, social and economic performance have the lowest sensitivity to the inputs while environmental and behavioral performance undergo significant variations. *WA* and *WS* account for the highest changes in social and economic performance, respectively (+22% and +23% compared to the baseline). The value of environmental performance is equally sensitive to *WA, WS,* and *WN* parameters (+40% ([38, 42] at 95%CI) of the baseline estimation). The behavioral performance shows a high variation, nearly ±40%, to the dynamics of *WN* and *WH*. Appendix D provides a detailed explanation of the modified parameters and their influence on the results.

From this uncertainty analysis, we can conclude that while there is quite significant sensitivity to some model parameters (????), overall, the model output stays within tight 95%CI limits. This also helps us to target particular types of parameters for future refinement in empirical studies. For example, given that the model outputs are especially sensitive to norms, more effort could be spent on improving empirical data about this parameter. As always, conducting a global sensitivity analysis on this model to assess the variations in the outputs to a combination of changing input parameters is certainly desired but requires a high-performance computer with substantial computational resources. The model is programmed in AnyLogic 8.3 simulation software with the help of agent-based, process-centric and system dynamics modelling approaches. See Section 3 for more details on accessing the files.

5.2.2 Structural sensitivity of the model

When proposing the ESSC approach instead of the more traditional SSC analysis (Taghikhah et al., 2019), we assumed that the introduction of consumer behavior and preferences can have an impact on the overall performance of the SC. Here, with the model in place, we can actually see how such a structural change in the way the SC is defined impacts the main performance indicators. In the majority of proposed models in the literature on SSC, the demand for products is homogenous. In contrast, the ESSC accounts for heterogeneous demand. To turn our ESSC model into a more conventional SSC one, we replace the heterogeneous adaptive consumers with homogeneous and rational ones using the average weekly demands for organic and conventional wines in each retailer. The SSC assumption is that the demands are constant in time, homogeneous and independent of supply levels, and price of wines.

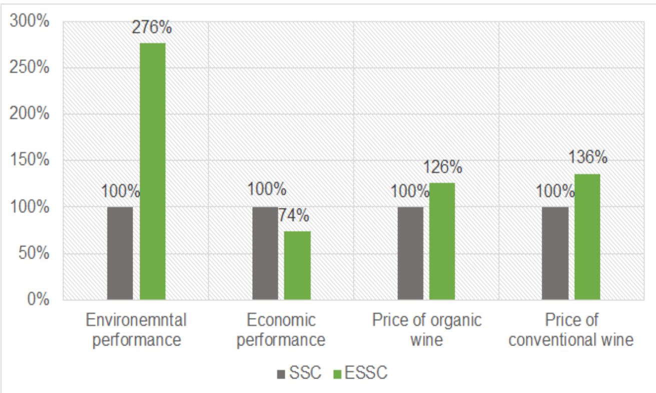

Figure 11. A comparison between the proposed ESSC and SSC (homogeneous demand).

We scale the value of SSC outputs to 100% and compare them with the baseline values of ESSC as presented in Figure 11. Behavioural performance is excluded from the analysis because SSC does not account for farmers' expectations. It can be seen that there are significant differences between the outputs of SSC and ESSC in terms of environmental (+176% points) and economic performance (-26% points). In the case of SSC, since the dynamics of wine prices do not affect the demand, the sales of organic wine would be higher than ESSC, even if the price of products (organic wine (-26% points) and conventional wine (-36% points)) are lower. This analysis shows that in the absence of heterogeneous demand, farmers do not perceive the market value of organic products, and they may decide to revert to conventional farming as reflected in the environmental performance.

5.3 Scenario analysis

Once the model is tested and displays reliable and meaningful performance, it can be used to explore the impact of various control factors on the overall dynamics of the system. This can help us to test how the system reacts to various combinations of input functions and parameters, which we call scenarios, and which describe management decisions and possible system modifications. There are many ways the system can be manipulated, and many policies and management interventions that can be explored. This is a subject of separate research; here, our purpose is only to demonstrate how ESSC can be used in industry and policy design and to show its receptivity to market feedback.

5.3.1 Scenarios related to consumer economic status and social networks

"Combining scenario planning and resource mapping" approach, proposed by Kunc and O'brien (2017), is a practical protocol for supporting strategy development, in particular for hybrid modeling as in the study of Gu and Kunc (2019). On the basis of this approach principles, we design a set of potential scenarios considering the opportunities and threats in the external environment of the SC in conjunction with the dynamics of its strengths and weaknesses. For the purpose of this study, we only discuss the demand-side scenarios describing two possible changes in demographics (economic status such as income) and behavior (social networks such as neighborhood effect) of the consumers and compare the results to the baseline model output presented above in Section 5.2.1. We consider:

Scenario 1: There is a 20% increase in the number of middle and high-income consumers. In terms of model parameters, this means that the income of 14% of consumers earning up to AU$100,000 per year (middle-income group) is increased to AU$150,000 per year (high-income group). At the same time, the income of 6% of consumers earning up to AU$50,000 per year (low-income group) is increased to AU$100,000 per year (middle-income group). The GDP per capita in Australia has shown a growing trend in the last 10 years, and is expected to continue in the coming years. Currently, the production rate of organic wine is low, and on the contrary, the production rate of conventional wine is high. To comply with the possible growth in the consumption of organics in the near future, due to the increasing marginal utility of income, the SC cannot immediately respond to the demand and requires a three-year transition period from conventional to organic wine production. It can be considered as a weakness-opportunity strategy;

Scenario 2: The effect of neighborhood-level characteristics on the wine preference of consumers is restricted because most people moved to apartments and are less likely to interact with each other on a regular basis. Obviously, Sydney’s urban future moves toward apartment living to meet the housing needs of the growing population. This change hinders social gatherings and neighbors’ interactions so that the influence of norms on wine preferences becomes minimal. In terms of model parameters, this means that the weight of social norms on intention is changed from 0.12 to 0.02. As the word-of-mouth effect is small, the SC can shift the norm for conventional to organic wine purchasing, from a vicious into a virtuous cycle. This shift can perhaps bring higher socio-economic benefits for the business. It can be considered as a strength-threat strategy. Appendix E provides a detailed explanation of the neighborhood effect defined in this model.

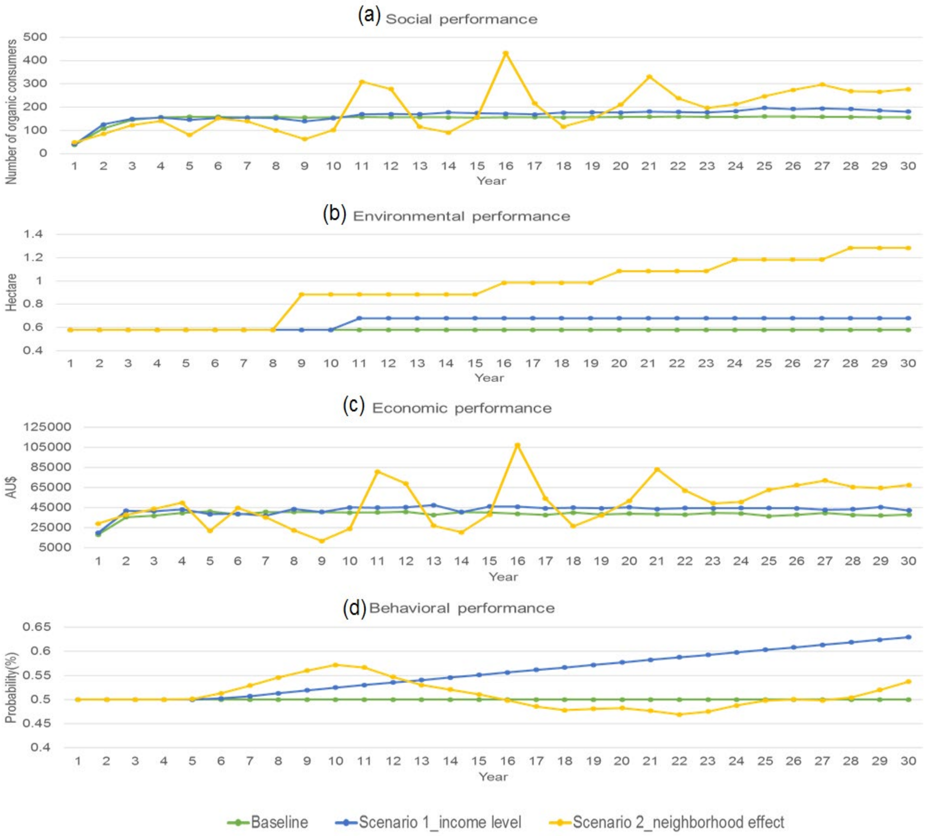

Figure 12. A comparison of scenario results with ESSC baseline.

The results presented in Figure 12 show that in scenario 2 all the indicators, except behavioral performance, perform better than in scenario 1. By reducing the influence of social interactions (among customers living in a neighborhood) on the wine purchasing decisions, the social, environmental, and economic performance of ESSC can be improved by 78%, 122%, and 76%, respectively. However, due to the market volatility caused by variations in the price of organic products and correlated changes of demand and supply, farmers' expectations of the value of organic farming do not grow significantly (Figure 13d). These dynamics are the result of conventional wine overstocking, and organic wine understocking caused mainly by the three year conversion period.

On the contrary, in scenario 1, we observe a growth in the organic market size by 17% in year 14 that eventually leads to a gradual increase in the farmers' expectations of organic agriculture value by 25% in year 30. With regard to environmental and economic performance, there is a 17% and 22% growth in scenario 1. The market financial incentive, in this case, is not good enough yet to meet the expectations of farmers regarding the value of organic farming, and hence government support is required.

From these production-consumption patterns, we may conclude:

- There is a negative impact of uncertain prices on farmers' expectations of organic adoption: The unpredictable and erratic organic prices add uncertainty to farmers' expectations about future returns. As it is unclear when organic wine prices would recover or stabilize, farmers start to prefer conventional markets more. They could choose to enter organic markets if the price for organic wine rose and remained relatively stable following the conversion from conventional farming. Thus, in the periods of the high volatility of organic wine price but the stability of conventional price, farmers tend to perceive the value of waiting to convert higher and risks in the future of organic farming lower.

- The propagation of consumer organic preferences through agro-food SC is slow: The adaptation of SC operations to the dynamic market trends can be delayed. For example, in both scenarios of simulation, the changes in the environmental and behavioral performance have started 5 to 10 years after the start of simulation. As there are two echelons between the consumers and farmers, transmitting the feedback/ market signals from the preferences of consumers to the land management decisions of farmers comes with a delay. Taylor (2006) and Naik and Suresh (2018) emphasize that the operational and structural factors such as long lead times, absence of long-term demand forecasts, etc. account for this gap between agricultural production and consumer demand.

- Social norms can trigger big shifts in consumer wine preferences: It is interesting to observe that minor changes in the consumption side parameters can help to improve the socio-environmental performance of agro-food SC. The social norms manipulation (reducing neighborhood effect) promotes ecological behavior more significantly than economic factors (consumer income growth). It is quite challenging to motivate consumers to spend more on organic products in the absence of supportive norms, even if their income level is higher. As social norms exert a strong effect on food consumption and production behavior, considering them in the management of SSC can provide new insights.

5.3.2 Single objective optimization

Despite the ESSC model is quite complex, we can still use it for purposes of optimization. In analyzing the possible optimized scenarios, we can find the optimal organic and conventional wine prices for maximizing social, environmental, economic and behavioral performance separately. These experiments demonstrate the capability and flexibility of the proposed ESSC model.

Table 2. Payoff table for single-objective optimization.

	Single objective optimization				**Decision variables**	
	Social performance (%)	*Environmental performance (%)*	*Economic performance (%)*	*Behavioral performance (%)*	*Initial price of organic wine (price at equilibrium)*	*Initial price of conventional wine (price at equilibrium)*
Social performance	**73% (268)**	120% (2.04)	36% (52035)	-54% (0.23)	*10(9)*	*18(7)*
Environmental performance	73% (268)	**120% (2.04)**	36% (52035)	-54% (0.23)	*10(9)*	*18(7)*
Economic performance	-68% (50)	74% (1.01)	**67% (64,139)**	+14% (0.57)	*20(17.35)*	*17(8.5)*
Behavioral performance	-68% (50)	-47% (0.31)	-75% (9,159)	**+100% (1)**	*19(14)*	*7(7)*

Table 2 reports the results of four single-objective optimization tasks (maximizing one at a time) in percentages to baseline values after 20 runs. It should be noted that these best solutions might be local optima, not global solutions, but this does demonstrate how optimization can be used with the model developed. Comparing the results, we see that environmental performance shows the biggest potential for improvement, increasing by 120% from the baseline value, while economic performance has the smallest potential for improvement with only 67% increase. Moreover, the optimal results for social and environmental performance turn out to be the same, indicating that we can simultaneously increase the number of organic wine consumers and expand the organically certified land, while also enhancing the organic sales income by 36% in comparison to the baseline.

6. Conclusions and implications

Organic farming is a promising solution for moderating agriculture impacts on ecosystems and improving human health. Despite the potential benefits that this method has for biodiversity and soil fertility, the global adoption rate of organic farming is still low. It has not become mainstream for two main reasons: (1) lower farm yield and higher production costs in comparison to intensive agriculture (Uematsu & Mishra, 2012), and, as a result, (2) reliance on a niche segment of consumers and a small market share, as compared to conventional food (O'Mahony & Lobo, 2017). A growing number of studies focuses on improving the productivity of organic agriculture from sustainability perspectives; yet, the relationships between the behavior of final consumers and the decisions of upstream supply chain actors, in this case, farmers, have been poorly analyzed (Naik & Suresh, 2018; Taghikhah et al., 2019). We address this void by extending the analysis of traditional food SC to include the dynamics of consumers choices and preferences for organic versus conventional food, as recommended by the ESSC framework (Taghikhah et al., 2019). This study contributes to the existing literature in three ways:

- First of all, it links three very different areas that, to our knowledge, have not yet been synthesized in a modeling study: (i) supply chain design and production economy, (ii) sustainability considerations and, (ii) pro-environmental and pro-health behavior. The model designed to operationalize the ESSC framework in which the SC analysis is extended to consider the buying behavior of consumers. While there are a number of papers that empirically examine the influence of behavioral aspects of demand on a few elements of supply, we are not aware of any published studies that analytically link the heterogeneity of consumers and their preferences to the entire supply chain operation.

- Secondly, to the best of our knowledge, this is the first study that incorporates the preferences of consumers for organic food as well as farmer decisions regarding organic farming adoption into a model of an agro-food SC. Organic supply chain modeling studies for reducing environmental impacts have largely ignored important socio-ecological issues related to consumers. In this study, we include the dynamics of consumer behavior (due to the changes in the social norms, willingness to pay more, the demand substitutions, etc.) and farmers' expectations (due to the changes in the price of products, organic versus conventional production, etc.).

- Thirdly, it contributes to the methodological development in the SSC field by proposing the integration of SD-DES-ABM methods to improve the decisions considering sustainable development goals. So far, systems thinking approaches are underrepresented in the context of SSC research (Rebs et al., 2018), while the filed can benefit from integrated modeling solutions that account for the interplay between SC and sustainability aspects. In particular, the interactions between ABM and SD provide an opportunity for considering the dynamics of social sustainability by developing the direct formulation of population, in our case, both consumers and farmers. According to Brandenburg et al. (2014) and Brandenburg and Rebs (2015), the practice of social simulation in SSC studies is adopted less often.

- The novelty of our model lies in presenting the simultaneous interactions between different SC actors (defined as adaptive systems) at different spatial and temporal scales. In doing so, we provide new insights into how simulation can pave the way towards understanding consumers' preferences and their influence on the choices of producers, in our case, farmers regarding land management and technologies used.

- Fourthly, the novelty of our model lies in presenting the simultaneous interactions between different SC actors (defined as adaptive systems) at different spatial and temporal scales for strategic planning. In doing so, we provide new insights into how integrated modeling can pave the way towards strategic planning. The study of Kunc (2019) was the first study that shows the application of this approach in strategic management and its capability in addressing real-world business challenges. This study can be considered as an extension, where the behavioral aspects, as well as operational characteristics of the SC, are captured in the model simultaneously. The analysis of the model occurs in different levels of details, micro-processes for consumption, and macro-process for production. Businesses and producers can use the model for understanding consumers' preferences, estimate their future influence on the operation, and develop long-term plans for land management and adoption of technologies.

ESSC requires further integration of consumer behavior models as sub-models with traditional SSC models. This integration not only reveals the unobserved heterogeneity of preferences in consumers but also discloses a two-way influence between consumption patterns and production-distribution decisions. We calibrate the proposed model and test the validity of the outputs with available empirical data. The validation process is not straightforward (Bert et al., 2014) and can certainly be improved in the future, as more data becomes available and the model undergoes further testing.

The comparison between the results of ESSC and SSC analyses indicates that the assumptions of homogeneity in consumer preferences may need to be reconsidered and released. The homogeneous demand assumption has the highest impact on environmental and economic performance. Our modeling experiments demonstrate the adaptiveness of ESSC model for market dynamics. The findings with respect to the changes in the financial and behavioral status of consumers, highlight the highest impact of changing social norms on improving the sustainability of the SC. As there are multiple actors between the consumers and suppliers, farmers' perceptions and expectations towards the value of organic-based agriculture may deviate notably from reality. Moreover, the adaptation of producers to market trends takes much time due to the delays in supply. The analysis of optimal scenarios produces solutions that can simultaneously improve the economic, social, and environmental performance but not behavioral performance. This means, that by the expansion of organic farming in response to the growing demands of organic consumers, a significant reduction in the organic wine prices will eventually occur, which may not be favorable for farmers.

Accounting for demand-side heterogeneity provides new insights into addressing sustainability issues in SCs. The results imply that the design of organic food policies aiming at behavioral changes should not be limited to financial incentives. In designing politically feasible policy options, paying attention to the social environment, public awareness, norm support cues, and cultural codes can reinforce the transition to organic agriculture. Accompanying information and value-based policy instruments may not only lead to the diffusion of organic food consumption but also increase the number of organic farms. Having said that, due to the presence of certain constraints and barriers (for example changing price and availability) a quick transition in organic consumption-production cannot be expected. Government price control schemes to control minimum or maximum prices and trade control to balance exports and imports can speed up the contribution from the demand side in reducing the environmental impacts of production.

A future research direction for this study is to apply the model for investigating the impact of different behavior change scenarios. In particular, the influence of green taxation schemes, informational marketing campaigns, and organic food promotions and incentives on the adaptive behavior of farmers and consumers can be further examined and assessed. A potential extension of this model will include agro-ecological models of crop growth to forecast the farm yield with regards to the adopted farming system (i.e., organic, biodynamic, conventional, etc.) under changing climatic factors (i.e., temperature, humidity, rainfall, etc.). The model was developed for the wine case study, yet, it is generic enough to be used for studying a wide range of agro-food SCs that have similar characteristics such as tea and coffee SCs. Another interesting area to explore is the heterogeneity of farmers regarding their expectations of organic farming adoption and their choice between different conversion strategies. With minor modifications, the model can be easily adapted for other agricultural products to explore ways for transitioning to organic farming. The analytical framework and suggested modeling approach can also be adopted by researchers to examine the adaptive behavior of the disaggregated, multi-scale tiers of the SC in other sectors. Finally, the model can be used as a decision support tool to help practitioners in designing evidence-based policies for organic food.

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