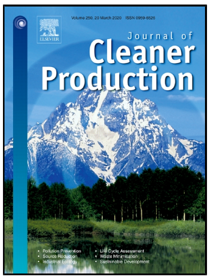

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Sustainable food security decision-making: an agent-based modelling approach.

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Abstract

Ensuring a consistent and regular availability of food is crucial for food security. Food markets, supplied through both domestic production and international trade, are governed by several risks emerging from unpredictable supply chain disruptions, volatility of commodity prices, along with other unforeseen circumstances such as natural disasters. To mitigate the challenges threatening the stability of food systems, decision-making within the food sector should be enhanced and robust to accommodate any changes that might cause food shortages. Dynamic models, that can predict the behavior of food systems in order to avoid potential future knock-on effects and deficits, are incumbent to ensure the sustainable performance of food systems. This study proposes a dynamic decision-making scheme that simulates strategies of the perishable food market under different circumstances. An agent-based model (ABM) is developed and implemented using python MESA library for a case study in Qatar, illustrating the potential performance of tomato under three different scenarios to be considered, namely: (a) baseline scenario - aiming to reflect current production and market conditions; (b) water resource efficiency scenario - basing decisions on crop water requirement (CWR) depending on weather conditions; and (c) economic risk scenario - applying the concept of forward contracts to hedge against future uncertainties in crop prices. The findings of this study demonstrate that under the baseline conditions, a tomato crop can be supplied through a combination of domestic production and imports depending on the available inventories and prices imposed by exporters. The results obtained for the CWR scenario suggest the need for total reliance on imports in order to meet domestic demand, as there is potentially high-water loss, which amounts to an average of 4.9 Billion m^3 per year, if tomato is grown locally. In contrast, the results from the forward contract scenario recommend a 57% dependency on local production in order to mitigate the effects of volatility in global food prices, which contributes to a 63% reduction in environmental emissions. Findings of this research provide insight into the factors that influence strategic decision making by the food sector to enhance its economic and environmental performances under diverse circumstances.

Keywords: Crop water requirement, Nexus, Forward contracts, Virtual water, Food trade.

Nomenclature

Abbreviations

ABM	Agent-based Modelling
CCGT	Combined Cycle Gas Turbine
CWR	Crop Water Requirement
EWF	Energy-Water-Energy
FCM	Fuzzy Cognitive Map
GDP	Gross Domestic Profit
GHG	Greenhouses Gases
GWP	Global Warming Potential
LCA	Lifecycle Assessment
MA	Moving Average
MILP	Mixed-Integer Linear Program

Parameters

d	Monthly demand in kg
D	Distance
e	GWP emissions in kg CO_{2eq}
E	Exporter
ECO	Economic cost in $
ef	GWP factor of GHGs relative to CO_2 GWP
ENV	Environmental impact in CO_{2eq}
g	Monthly grown quantity in kg
imp	Monthly imported quantity in kg
p	Monthly price in $
P	Monthly production capacity in kg
Q	Importer
V	Monthly inventory
X	Monthly exportable quantity in kg

Subscript

G	Grow strategy
i	index of exporting countries excluding Qatar
I	Import strategy
j	index of each strategy either grow or import
k	index of GHG either CO_2, CH_4, or N_2O
n	time step
t	transportation

1. Introduction

1.1. *Background*

Natural resources such as energy, water and food (EWF) continue to experience increasing pressures due to the exponential growth in the world population and anthropogenic activities. Across global markets, industrial sectors mobilise natural resources to generate value-added products and services to meet the demands of the growing population. By 2030, the demand for EWF resources are expected to increase by 40%, 25% and 50%, respectively, thus inducing multiple challenges (Madani *et al*., 2015). For instance, the food sector, comprised of multifaceted systems that involve both water and energy, is continuously stressed due to; continuous population growth; resource scarcity and over-exploitation of resources; vulnerable trade transactions in addition to unforeseen political events (Vieira *et al*., 2018). These stresses, if not handled appropriately, could engender "or propagate" drastic social and economic imparities associated with uneven food availability, accessibility, utilisation and stability. Hence, ultimately the food sector strives to ensure continuous and efficient food production to achieve 'food security', defined as the state "*when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life"*

(FAO, 1996). It is also a fundamental component of the 'Zero Hunger target', part of the sustainable development goals (United Nations General Assembly, 2015). Food security is a multi-dimensional and dynamic concept that requires interconnected entities including producers, customers and policymakers to cooperate within a well-organised and fully-functioning service-oriented supply chain (Moragues-Faus *et al*., 2017). Food security is comprised of four major pillars that define the set of activities contributing to the food delivery framework: (1) food availability, which is related to supply chain activities such as production and distribution; (2) food utilisation, concerned with the safety and nutritional value of the food delivered; (3) food access that represents the economic and social affordability of food products; and (4) food stability that illustrates the resilience of the food system in response to external political, economic and environmental instabilities (Carthy *et al*., 2009). Food systems encompass a range of processes that include production, processing, distribution, retail and consumption of food products (Ericksen, 2008). Products of these steps collectively contribute towards the fulfilment of the four food security pillars.

Currently, global food insecurity exists. The number of undernourished people has increased by 17 million between 2016 and 2017, causing several health and social issues such as hunger. Furthermore, one in every seventh person is 'hungry' (FAO, 2018). As such, a significant percentage of the world's population is likely to be exposed to food insecurity by 2050. Thus, the increasing demand for food necessitates large-scale agricultural intensification to meet the demand for food. The extensive increase in agriculture production will have a positive impact by reducing hunger, such that the average available food for consumption per capita will shift from 2770 to 3070 kcal/person/day between 2007 and 2050 (Alexandratos & Bruinsma, 2012). However, the increase in food production induces intensive resource utilisation to meet the primary raw material requirements in the agriculture sector. As part of the sustainable development agenda, balancing the trade-off between resource and environmental conservation with food demand satisfaction is of the utmost importance. As such, sustainable decision-making practices capable of mitigating risks and uncertainties should be implemented. In fact, the multiple agricultural activities and projects associated with food production are energy intensive and induce irreversible environmental impact. Dynamic decision-making that can accommodate the vicissitudes in food systems should be developed and implemented in order to achieve food security while preserving the environment. In a continuously changing environment, like the food sector, dynamic models have the ability to capture uncertainties associated with food prices risks and fluctuations (Pasqualino et al., 2019), interconnections between the food sector, energy and water sectors, in addition to weather conditions (Bailey et al., 2015), which ensure a holistic analysis of the problem. Some studies in the literature have also depicted the benefits of dynamic decision-making in designing framework and influencing decisions that reduces emissions from the food sector activities, such proposing sustainable water and energy configurations allowing increased food production (Namany et al., 2018).

Food security in the State of Qatar is a pressing concern and is a challenge which requires an intelligent decision-making approach to manage resources. This is because the food sector which is exposed to harsh climates is a major consumer of water. In fact, water consumption in agricultural processes amounts to approximately 40% of the total available quantity, of which, more than 70% is sourced from fresh aquifers (MDPS, 2015). Historically, the food sector has suffered from various obstacles in local food production, in terms of: (a) lack of availability of arable land and suitable soil conditions, which is currently representing only 5.65% of the total area of the state; (b) presence of hyper arid weather conditions; (c) scarce water resources, such as fresh water aquifers, with their extraction rates currently at unsustainable levels surpassing renewal rates (MDPS, 2016); and (d) lack of diversity in the local food production portfolio. Consequently, this resulted in a major reliance on food imports consisting of more than 80% of the total demand for food (QNFSP, 2013). Although globalisation and international trade can prove to be strategic, a heavy dependence on it could be problematic for countries like Qatar, considering the high probability for supply chain disruptions associated with uncertainties and risks governing imports transactions, such as unexpected political events and commodity prices' stochasticity. Therefore, there is an imminent need to design strategies for a self-sufficient food system which is both resilient and sustainable.

This study is a contribution to the existing literature aiming to enhance the food sector performance. It applies agent-based modelling (ABM) to overcome the need for dynamic decision-making in the food system with a focus on food production and availability. It exploits the flexibility associated with agents to simulate real-life decisions within the food sector. This work also investigates economic and environmental implications of applying diverse strategies regarding crops production, through assessing the emissions and costs associated with each decision-making scheme under two different scenarios. The methodology developed adopts a multi-disciplinary approach looking at several assessment criterions to achieve a sustainable crops' provision. The framework introduces two new concepts to the analysis of the food sector's behaviour. First, the effect of water savings is represented through CWR as means to quantify environmental implications of each decision performed by the food sector. Then, forward contracts, one of the most used financial instruments in the commodity markets, is used to evaluate the economic considerations of the food sector while making decisions. This paper is organised such that the following Section 1.2 covers the main topics discussed in this study. The first component highlights relevant studies that have addressed food security from a system modelling perspective, with a focus on the *food availability* pillar of food security. As for the second part of section 1.2, it emphasises the application of agent-based modelling as a resource management tool, particularly, its effectiveness in tackling food sector challenges and opportunities. Section 2 provides a detailed explanation of the methodology and tools developed followed by a thorough description of the case study and scenarios investigated in Section 3. Results of the suggested model are presented in section 4 along with a discussion highlighting the policy implications derived from the findings of the simulated scenarios.

1.2. Literature review

1.2.1. Food availability: optimisation in food production and supply chains

Food security for all is considered a global sustainable development goal, in which the availability of food consisting of production and delivery of good quality and sufficient food is necessary.

However, food availability can be hindered through multiple uncertainties and risks governing the production and provision of food, such as natural and human-driven disasters and supply chain disruptions; unstable international trade policies; and political instabilities and conflict. In the light of such risks, holistic management tools based on dynamic modelling and simulation approaches support understanding the physical, economic and social phenomena associated with food production markets. Such models can benefit the decision-making process in terms of the mitigation or remediation of time-dependent risks induced by external stressors, to ensure a continuous and resilient channel of food products from producers to consumers. As such, it is required that the models developed are able to capture multi-stakeholder requirements, conflicting objectives and constraints, and essentially including provision for food system dynamics using agent-based modelling and game theoretic approaches.

A significant number of studies tackling food security have adopted a EWF nexus perspective to assess food systems as they are intrinsically linked to water and energy systems. The EWF nexus concept was initially introduced in the Bonn conference (2011) and is defined as the system approach highlighting the inherent interactions existing between the EWF sub-systems (Hoff, 2011). In this regard, numerous studies have developed diverse methodologies that could guide decision-making to ensure sustainability and resilience in food availability. Al-Ansari et al. (2015; 2016; 2017) proposed a holistic nexus tool based on life-cycle assessment to assess the environmental performance of some pre-defined food system configurations. A significant portion of these studies have focused on enhancing the food production stage by optimising the agricultural and cultivation practices. This study was further enhanced by Zhang *et al*. (2017) who proposed a simulation-based optimisation framework based on the EWF nexus to reduce the impact of agricultural droughts on crop yields. The study investigated the potential of irrigation in mitigating droughts and enhancing yields under three different scenarios using the GIS-Optice software. The three cases consider the crop yield, water required for irrigation purposes, and energy required for irrigation. The results of the proposed multi-criteria model suggest that the optimal solution does not necessary lead to maximum crop yields, yet it engenders water and energy reductions. The methodology was further developed by Campana *et al*. (2018), who incorporated a minimisation of crops nutrients' intake into the multi-criteria optimisation model proposed by Zhang *et al*. (2017). Aimed at predicting crop productivity, Woldesellasse *et al*. (2018; 2019) conducted a study to model and forecast the crop water demand for Alfalfa crop fields in Qatar using a neural network, considering the impacts of extreme weather and drought conditions on the vegetation health states. A Mixed-Integer Linear Program (MILP) was subsequently applied to identify the optimal water allocation that satisfies the Alfalfa water requirements. Meanwhile, Karnib (2017; 2018) developed a EWF nexus-based tool, called Q-Nexus, consisting of an input-output simulation-optimisation approach that quantifies the interlinkages existing between the three nexus systems through optimally allocating energy, water and food resources to account for additional food demands. The tool was then expanded to be used in solving several scenarios involving decision-making for resources demand, technology selection and resource allocation variabilities. Similarly, Namany *et al*. (2018, 2019a) proposed an integrated nexus systems-based model to identify the optimum mix of energy and water technologies which can satisfy the 40% self-sufficiency for the domestic food demand in Qatar, while reducing the economic cost and environmental impact. The authors also assessed the impact of volatility of gas prices and competition between different power plants through the inclusion of both stochastic and Steckelberg game-theoretic constraints. Karan *et al*. (2018) also adopted a similar approach to study the characteristics of a self-sufficient system that produces its own food, using energy and water at a relatively much smaller scale. Their case was modelled using stochastic optimisation which identifies the optimal sustainable system with the least cost, whilst mitigating discrepancy in food supplies, scarcity of water, and weather conditions that might impact energy generation. Driven by the need to develop local agricultural systems, Govindan and Al-Ansari (2019a) investigated the potential of applying CO_2 fertilisation to improve the productivity of the agricultural sector. The study determines the optimal supply chain network for CO_2 utilisation using a GIS-based simulation.

In the review of nexus-based optimisation approaches for ensuring food availability, there is a particular emphasis on food production. However, there are countries where the level of production is not sufficient to meet domestic demands, owing to either the lack of resources, infrastructure or natural conditions conducive to growing food locally. Such countries tend to rely partly or solely on imports to ensure the physical availability of food in the market. Thus, analysing and improving the food supply chains is an incumbent step for the consistent and regular supply of food products, especially within uncertain and risky environments. In fact, supply chain disruptions caused by political instabilities, resources price volatility, along with climatic conditions, require proper and accurate modelling to develop plans that can enhance the resilience of supply chains systems through the mitigation of risks governing them. In this regard, Mogale *et al*. (2018) suggested a multi-structural model characterised by multi-period, multi-criterion and multimodal functionalities to remedy shortages and discrepancies in capacitated silos for food storage. The methodology developed essentially solves a location-allocation problem, aiming at minimising the total supply chain network cost. The second objective of the model is to minimise the transportation costs associated with dwell and transit lead times required to ship food grains. In a similar vein, García-Flores *et al*. (2015) investigated the significance of adopting logistical optimisation in their proposed methodology, which supports scheduling and distribution of dairy products for an agribusiness under capacitated vehicles constraint, access to resources and supply constraints. Furthermore, focusing on the governance level of food supply chains as a means to enhance food security, Irani *et al*. (2017) developed a data-driven approach based on a Fuzzy Cognitive Map (FCM) to investigate the correlation that potentially exists between organisational practices and food supply chains behaviours. The results demonstrated that food security levels are highly influenced by bureaucracy levels, policies and regulation within supply chain systems, in addition to the stakeholders' level of consciousness regarding the environmental implications caused by food waste.

When aspiring to achieve food security, issues related to water scarcity and water management constantly arise considering the inherent link between water resources and food products. In this regard, many studies have investigated the relationship between water and food systems to optimally utilise both resources. Virtual water is one concept that is born as a consequence of agriculture activities in terms of crop water requirement, global food trade and food security. It is used to depict the water content in food products (Allan, 1998). Trading virtual water in the form of imported food products is beneficial for countries with high levels of water scarcity, as it reduces the pressure on their depleting water resources. Alternatively, the economy of water-rich countries benefits from the export of water intensive food products. (Chapagain & Hoekstra, 2004). Considering the environmental and economic profits coming from the adoption of the virtual water concept, Wang et al. (2019) proposed an optimisation model to study the flow of virtual water for a grain trade case. The study determined the optimal water flow that engenders economic and environmental benefit while preserving the ecosystem. Similarly, Chouchane et al. (2018) investigated the relationship between virtual water import and some socio-economic and environmental indicators such as population, GDP, precipitation, water scarcity and irrigated land. Findings reveal a strong influence of the GDP, population and irrigated land on the quantity of virtual water imported; however, the water scarcity component does not exhibit any correlation. The management of national virtual water budgets can support national resource management as it is strongly related to the food trade, and the local consumption of energy and water resources for domestic food production.

1.2.2. Agent-based modelling (ABM) for efficient food systems

In an increasingly complex and changing environment, resources and their representative sub-systems demonstrate multi-faceted synergies amongst themselves, which in turn complicates the modelling and simulation of such systems. Models serve as representations of real systems that can be modified or customised to achieve a specific target (McPhee-Knowles, 2015). Traditional modelling techniques, such as mathematical optimisation, usually assumes idealistic settings involving homogeneous entities and perfect markets (Namany *et al*., 2019b). These assumptions allow for the solution of intricate systems to be more tractable in terms of computational complexity, however, they are less illustrative of actual real-world cases (Macal and North, 2006). The classical optimisation frameworks adopt a top-down approach that tackle problems from a high-level approach, where constraints are imposed and their implications on the entire system performance is deduced. Alternatively, ABMs are founded on a bottom-up perspective that enable interaction between different independent agents and then conclude the overall behaviour of the system. In addition, ABMs are considered intrinsically modular systems, which promote the aggregation of sub-systems problems into large-scale problems, thus enabling a holistic and dynamic approach to problem solving (Barbati *et al*., 2012).

ABMs are adaptive modelling tools that can accommodate and simulate potential interactions between miscellaneous agents operating within unsteady environments. The dynamic functionality of ABMs renders them suitable in guiding the decision-making process for complex problems, particularly those that are multi-disciplinary, such as resource management. Bieber *et al*. (2018) utilised ABM to investigate the impact of socio-economic and human behaviours on the demand profile for energy and water resources. The methodology developed estimates the opportunity cost of forgoing a food production system to implement a power generation plant. The ABM was integrated into a scenario-based optimisation framework that considers the opportunity cost of food forgone along with capital and operating cost of energy generation as metrics to determine the least cost and environmentally efficient scenario. Similarly, Marvuglia *et al*. (2017) addressed both environmental and economic concerns for an agricultural case using ABM. The model simulates and predicts the behaviour of crops under pre-defined conditions, consisting of the integration of an environmental consciousness factor that governs the decisions of farmers. In this case, the objective focused on maximising profits and reducing the overall environmental burden associated with their actions. The green component in the model is illustrated using a Lifecycle Assessment (LCA) that was incorporated intothe agricultural system as a criterion to determine the environmental performance. Focusing on farmers' decision-making practices, Murray-Rust *et al*. (2014) developed a novel multi-disciplinary ABM that applies economic, environmental, social along with subsidy factors to the behaviour of farmers. The framework developed aggregates several land-use models and agro-economic data into one holistic and robust system that can support multi-criteria and complex decision-making within land management systems. Other studies adopted ABM to simulate competition and collaboration within food systems and agri-businesses. For instance, Arvitrida *et al*. (2016) adopted ABM to investigate and clarify the impact of competition on the performance of supply chains. As such, their methodology could be applied to any type of business governed by competition, including the food sector. Results have asserted that the market structure and its interactions are not driven by the demand, but by the competition existing amongst diverse stakeholders.

Current literature related to food availability is heavily concentrated in the development of optimisation models that represent food production and agricultural processes. The majority of studies focus on assessing the potential of deploying new technologies to enhance domestic production using classical mathematical optimisation models, which in some cases generate unrealistic results. Other studies focus on the distribution of food products as part of ensuring food availability, through solving supply, demand and storage problems. Optimisation-based methodologies usually assume steady state and do not allow for interactions between all involved stakeholders. To overcome this issue, other studies have shifted to ABM as a decision-making tool allowing more flexibility in the analysis of food systems. However, the majority of ABM based framework developed considers one component of the food availability pillar, either food production or food supply. In both cases, ABM models are used to assess one behavioural aspect of the food sector, either economic, social or environmental, which can misjudge the performance of the system and lead to unfounded decisions. In this work, a multi-dimensional perspective combining the economic and environmental implications of each decision related to food availability is adopted, allowing for a more holistic and realistic planning. Additionally, both sub-systems, food production and supply chain systems, are integrated for a holistic representation of the food system. The purpose of the study presented in this paper is to design a novel dynamic decision-making framework considering two major components within the food production system, namely domestic production and international imports. The framework is based on an ABM that utilises monthly demand data for perishable crops as an input to simulate and forecast the component behaviours and develop sustainable strategies aimed at satisfying the local food requirements. The model is applied to a Qatar case study to further the methodological development from previous efforts by Al-Ansari *et al*. (2015; 2017) and Namany *et al*., (2019a). The framework generated a five-year forecast for Qatar that would inform decision-makers involved in the tomato market regarding the optimal strategies, with due consideration for economic and environmental costs. The analysis is based on three scenario formulations that support the investigation of the influence of commodity prices i.e. spot and forward prices, crop water requirements on the long-term behaviour of the food market. Although the study currently focuses on only one type of perishable crop, the embedded flexibility in the framework can accommodate other crops individually or in combination.

2. Data and methods

The research approach adopted in this study consists of the formulation of an agent-based model that simulates the decision-making behaviour within a food system comprised of local production and imports sub-systems. It uses a scenario-based analysis approach to investigate several factors that can influence strategic decisions for the policy makers involved in the food sector through the prediction of future practices that should be adopted under economic and environmental circumstances.

2.1. Qatar food security

Satisfying the increasing demands for fresh food in the state of Qatar is a pressing concern as challenges loom. In the past, Qatar has imported approximately 90% of the total requirements, while the remaining 10% is fulfilled through local agriculture (QNFSP, 2013). Although there are challenges connected to sustainable domestic production, a high dependency on international trade is in itself associated with uncertainties that threaten food system security. However, considering the challenging domestic climate and finite freshwater resources, it is unlikely that a complete self-sufficiency across all food crops can be achieved, even with large agricultural intensification, which is given a high importance as part of the national priorities of the State. In fact, local agriculture is restricted by limited arable lands, accounting for only 5.65% of the total area of the State (MDPS, 2016). Agricultural activities depend majorly on fresh water sources for irrigation. Approximately, 40% of the available water in the state is utilised in agriculture, from which 78% is withdrawn from aquifers, which are already facing high scarcity levels (MDPS, 2015). The annual aquifer recharge rate is 58 million m^3 yearly, which is relatively narrow considering the required expenditure in the local food production sector (Darwish, 2014). Domestic and international pressures and risks induce the need to design dynamic models that represent and predict emergent behaviors in food systems in the future, as a means to overcome any potential shortages in inventories, which can disrupt the entire food system operations. The ABM developed and presented in the upcoming Section 2.2 is applied to a Qatar food system that enables the basis for food delivery decision making across various scenarios. As such, the model is implemented to simulate the provision of perishable crops in the Qatari market. Tomato is used as an illustrative example in this simulation, where Qatar is the importer (Q), and exporters (E_i) are a set of 10 countries presented in Table 1. The selected countries represent the major exporters of tomato to Qatar during the last four years. Interactions between Qatar and exporting countries do not depend mainly on the monthly demand of Qatar. However, other factors such as water footprint and the price of the crop to be imported are considered in the decision-making process implementation.

Scenarios illustrating two different criteria affecting Qatar's strategic plans are discussed in the scenario formulation Section 2.3.

Table 1. List of exporting countries.

Index (i)	Country Agent (E_i)
1	USA
2	India
3	Turkey
4	China
5	Netherlands
6	Morocco
7	Lebanon
8	Spain
9	France
10	Iran

2.2. Available data

The model developed involves two categories of agents: an importer and a group of exporters. Hence, the data used is related to the variables of each agent based on scenarios formulated. The data utilised, mainly involves economic and environmental information based on historical statistics compiled from governmental reports and local agricultural institutes, from literature and statistical websites, and used either for representing the attributes or defining behavioral rules for the agents. Governmental and statistical reports were used to compile historical data about the tomato crop in Qatar, being the importer. This information included a 3-year monthly data between 2014 and 2016 for the local demand for tomato, the crop water requirement, list of exporting countries with have the most frequent tomato trade activity with the importer. Tables 2 and 3 describe the datasets used in the model and simulation, in addition to the method of compilation and source. The computations of case-specific variables are thoroughly explained in section 2.3.1, the method of derivation along with the source are depicted in detail.

Table 2. Data sets description for the importer's characteristics.

Data set	Description	Source
Monthly demand (*d*)	The monthly demand data used is forecasted over five years representing 60 months (or time steps). It is forecasted using moving average time series analysis technique. A 3-year monthly historical demand data is used for the forecast.	(MDPS, 2017)
Monthly prices (p_G)	The monthly prices data used is forecasted over five years representing 60 months (or time steps). It is forecasted using moving average time series analysis technique. A 3-year monthly historical prices data is used for the forecast. This price includes the cost of growing tomato crop locally.	(MDPS, 2017)
Environmental impact (e_G)	This variable is derived from the total energy requirement to grow the crop, including energy for water and fertilisers. It is estimated based on the crop water requirement for the 3 years of historical data, which	(QNFSP, 2013; Al-Ansari, 2015; 2017)

	is transformed into energy required to provide water and provide fertilisers, which is then quantified as GWP emissions (see section 2.3.1). Historical data of the environmental impact (e_G) is then used to generate forecasted data using a moving average time series analysis technique for 60-time steps.	

Table 3. Data sets description for the exporter's characteristics.

Data set	Description	Source
Distance (D)	The distance between the importer and exporter in Km, used to quantify the economic and environmental costs associated with the import decision.	(Google maps, 2019)
Monthly prices (p_I)	The monthly prices data used is forecasted over five years representing 60 months (or time steps). It is forecasted using moving average time series analysis technique. A 3-year monthly historical prices data is used for the forecast. This value includes both price of growing the crop (p_{gi}) and the price of transporting it (p_t). This data is compiled from local statistical department based on the historical trade history of the importer.	(MDPS, 2017)
Environmental impact (e_G)	This variable is derived from the total energy requirement to grow the crop, including energy for water and fertilisers in addition to the environmental impact associated with transportation. It is estimated based on the crop water requirement for the 3 years of historical data, which is transformed into energy required to provide water and provide fertilisers, which is then quantified as GWP emissions (see section 2.3.1). GWP associated with crop production and GWP from crop transportation are both summed. Historical data of the environmental impact (e_G) is then used to generate forecasted data using a moving average time series analysis technique for 60-time steps.	(QNFSP, 2013; Stajnko et al., 2016)

2.3. *ABM methodology for perishable crops import profile simulation*

Delivering sufficient, continuous and nutritious food products is fundamental for food security. Any potential shortage of raw materials or food products due to supply disruptions or insufficient domestic cultivation could hinder domestic food security aspirations. In some cases, this can lead to economic and social instabilities. As such, developing the capacity to predict the behaviour within food systems under different scenarios could be insightful for policymakers, as it can enhance resilience to unforeseen future events. The ABM model developed in this study simulates the monthly behaviour of a food system configured to secure the monthly demands for a perishable food crop. The model tracks the economic cost and environmental impact for each executed decision as an indicator of the sustainability performance of the food sector. The scope of this study is limited to a single tomato crop which is used as a representative example. However, the framework developed is generic and can accommodate any type of food product. The following section describes the agents involved in the ABM and how they interact with one and another, and with their environment over time.

2.3.1. Defining attributes and behaviours for an agent-based model development

An agent is an independent entity characterised by specific attributes and behaviours (Lopez-Jimenez *et al*., 2018). Each agent interacts with other agents and its surrounding environment following a specified set of rules, imposed by the agent itself or other external factors (Figure 1). For the purpose of this study, the agents are broadly categorised into two main groups, importer and exporter. Together they interact with one another within a bounded environment representing the local food system. The latter guarantees the production or the imports of perishable food products to satisfy the monthly food demand. The characteristics and specifications of the agents are summarised in Figure 2 and are thoroughly explained in the forthcoming sections.

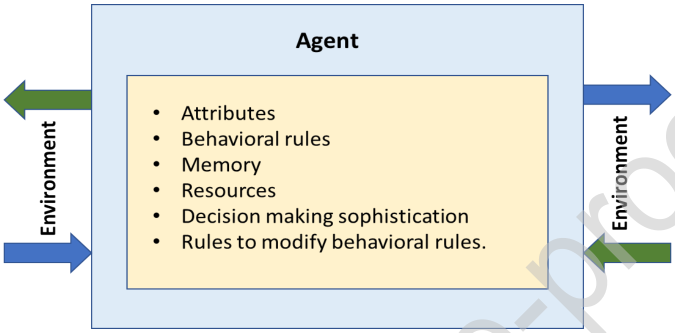


Figure 1. Functionalities of an agent in an ABM (modified from: Macal and North (2006)).

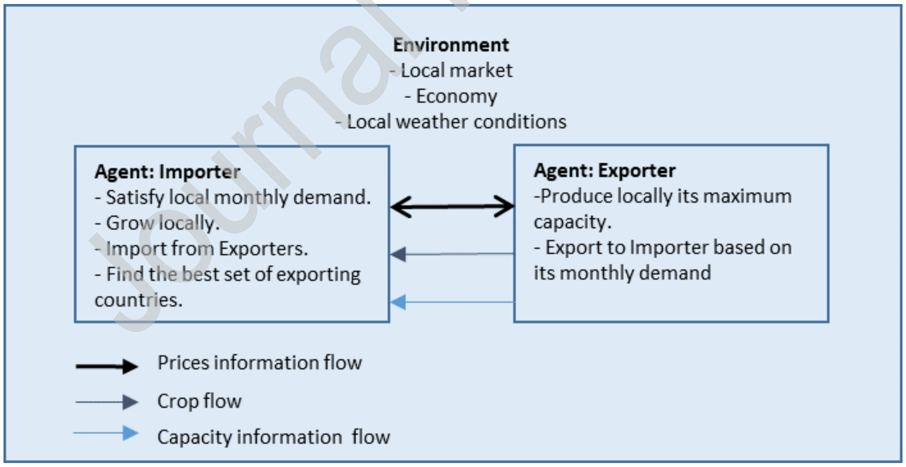


Figure 2. High-level representation of the different components of the ABM.

The model proposed in this study is used to simulate a five-year ($n=60$ months) decision-making profile for an agricultural system represented by an importing country Q interacting with an exporting country $i \in E$, where E is the set of exporting countries. The purpose of the model is to enable the importer Q to meet the monthly demand d, considering the behaviour of the exporter i

and defined internal attributes, such as monthly inventory and growing capacity. Additional scenario-specific attributes associated with the importer are thoroughly discussed in the following scenario formulation section. Table 4 presents the main attributes and behavioural rules characterising agents involved in this study.

Table 4. General features of agents involved in this study.

Agent	Attributes	Behaviours
Importer (Q)	-Monthly inventory V (kg) -Monthly demand d (kg) -Monthly grown quantity g (kg) -Monthly imported quantity *imp* (kg) -Monthly growing capacity (kg)	- Grow strategy (G) - Import strategy (I)
Exporter (E_i)	-Monthly production capacity P_i (kg) -Monthly exportable quantity X_i (kg)	-Produce and export (PE)

Importer Agent

The importer is the core agent, Q, in the model since Q implements strategies for ensuring food availability. The main activities of the importer Q pertain to the satisfaction of the local market demand for tomato crop. To do so, three different strategies are developed and represented as the importer's set of behaviours. Thus, the importer Q is characterised by a monthly demand d that must be satisfied by adopting one or a combination of the following strategies: (a) grow locally (G); and (b) import (I) from exporter agents, $i \in E$. The importer has a monthly inventory variable V which tracks the available monthly quantities of the crops studied. In addition, the assessment of importer's performance is computed using monthly economic and environmental costs in relation to the strategy adopted. Calculations differ depending on the type of the behaviour undertaken. In fact, the crop is characterised by a specific unit cost and environmental impact that are dependent on the country of growth. In this model, the unit costs are expressed as p_j in \$/kg of crops for the economic costs, where j is the set of strategies such that $j = \{G, I\}$, and a unit environmental cost e_j in kg CO_{2eq}/kg of the crop. The following section investigates the difference between strategies, the selection criterion along with the impact of choosing each strategy on the model's parameters.

The model was used to simulate the monthly interactions between the importer and all the available exporters in order to satisfy the monthly demands of the importer, tracking economic costs (*ECO*) and environmental impacts (*ENV*). At each time step n, representing months, the importer checks its current inventory V_n and is compared with the demand for that month d_n; if $V_n > d_n$, the quantity available in the local market is sufficient to meet the demands, else a shortage is detected, and an action is required. Either of the actions, grow (G), import (I) or hybrid (combining G and I) (H) strategies is adopted to compensate for the detected deficit in the inventory. The decision made at this stage primarily depends on economic and environmental factors associated with each scenario developed. Furthermore, the attributes and behaviour of exporters influence the decision of the importer, *e.g.* the restrictions imposed on the exporters' production levels could hinder the imports. Figure 3 illustrates the logic followed by the importer Q to satisfy the monthly demands.

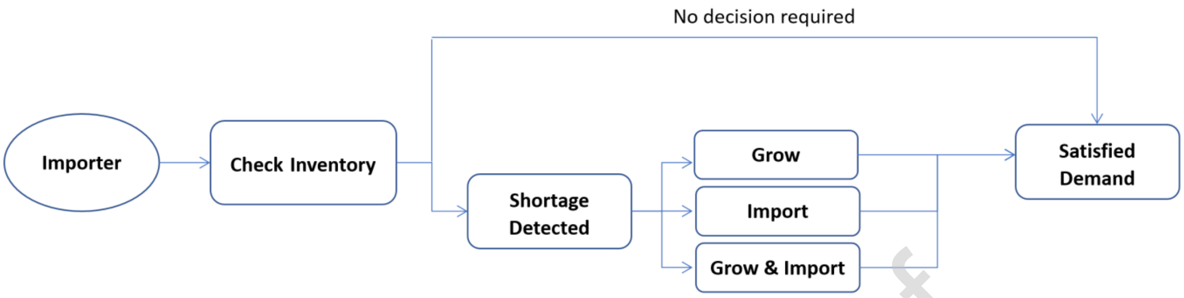


Figure 3. High-level illustration of the Importer's logic.

After determining the best strategy to follow based on the scenario specification, and what it implies in terms of rules and restrictions, the cost and environmental impacts associated with each decision are updated as follows:

*Grow strategy***:** if the grow strategy is selected, the economic and environmental costs are computed using equations (1) and (2):

$$ECO = g \times p_G \tag{1}$$

$$ENV = g \times e_G \tag{2}$$

where g is the monthly grown quantity of tomatoes, which is randomly generated by the model such that it satisfies the local demand, whilst abiding by the capacity constraints of the local farms; p_G is the unit price of tomato grown locally, and it represents the cost of growing one kilogram of tomato taking into account the cost of water and energy required for irrigation and application of fertilisers; and e_G is the unit environmental impact, consisting of the emissions, represented as the global warming potential (GWP) from growing 1 kg of tomato, expressed in terms of 1 kg CO_{2eq}. This impact considers greenhouses gases (GHG), *i.e.* CO_2, CH_4, and N_2O in its computation (IPCC, 2016). In this study, emissions are assumed to be generated from the energy used to produce water and fertilisers, where the energy system is fully operated by a combined cycle gas turbine (CCGT). The method is used to compute e_G, which is expressed by equation (3):

$$e_G = \sum_{k=1}^{3} GHG_k ef_k \tag{3}$$

such that, GHG_k are emissions from GHGs, ef_k is the GWP factor of GHGs relative to CO_2, and k is either CO_2, CH_4, or N_2O.

Import strategy: if the import strategy is selected, the costs are calculated using equations (4) and (5):

$$ECO = imp \times \ p_I \tag{4}$$

$$ENV = imp \times e_I \tag{5}$$

where *imp* is the monthly imported quantity of tomatoes from each country. This value is affected by the monthly quantities demanded. In addition, it is impacted by the behaviour of other exporter agents. As such, *imp* is expressed as a function of the production capacity of exporters P_i, their allowable exportable quantities to the entire world demonstrated by a percentage x along with the maximum amount they are allowed to export to the importer agent, represented by percentage y. For the purposes of demonstration, both x and y were assumed to be fixed. Thus, the general formula for *imp* can be described using equations (6) and (7):

$$imp = X_i \tag{6}$$

$$Ex_i = \ P_i \times x \times y \tag{7}$$

p_I, it is the unit price of tomato, in \$/kg, including the cost of growing tomato (p_{gi}) in addition to the cost of transportation (p_t) that is affected by the distance between importer and exporter. The unit price p_I can be expressed using the following formula:

$$p_I = p_{gi} + p_t \tag{8}$$

and, e_I is the GWP associated with importing 1 kg of tomato. This value encompasses emissions generated from producing the crop in the country of origin (e_{gi}) in kg of CO_{2eq}, in addition to the cost of transporting it across a distance of D_i to the importer (e_t) in kg of CO_{2eq} /km. In this model, e_I is assumed to be uniform for all importers. This value can be represented using the following equation:

$$e_I = e_{gi} + e_t \times D_i \tag{9}$$

Grow and import strategy: in the case of high demand, where the monthly quantity demanded cannot be met through import or grow strategies independently, a mixed or a hybrid strategy involving local production and international imports is adopted. The cost and environmental emissions are added using equations (1) and (4) for the economic cost, and (2) and (5) for the GWP.

Exporter Agents

Regarding, the set of exporter agents E*,* they are denoted by the monthly production capacities P_i, the distance to the importer D_i, along with their monthly allowable exportable quantities X_i. Importer *Q* and exporters *E* interact within an environment represented by the economy. Their decisions are executed simultaneously, such that while the importer adopts one of the aforementioned strategies (Grow, Import, or Grow and Import), and the exporters E produce at each time step based on their monthly capacity, and export according to their allowable exporting quantities along with and the demand of the importer. The logic adopted by the exporters is illustrated in Figure 4.

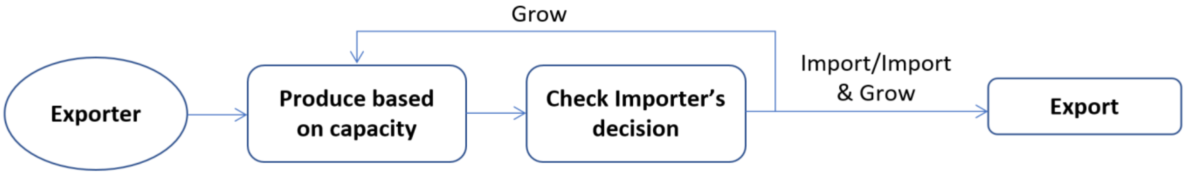


Figure 4. High-level illustration of the Exporter's logic.

2.3.2. Implementation of agent-based modelling and simulation

The ABM developed in this study is modelled using the Python programming language. It is a high-level and general-purpose language that allows the expression of concepts in a concise and representative manner compared to other programming languages (Summerfield, 2014). Python is easily applied to solve practical problems because of its object-oriented characteristic. This feature enables the solution of advanced and multifaceted problems, by dividing them into a set of smaller sub-problems stored in so-called 'objects' (Srinath, 2018). In addition, Python has various open source libraries that can accommodate a large range of problems which makes solutions faster and more practical. In this study, the MESA library (Mesa, 2016) is used to build and simulate the proposed ABM. This library enables building, analysing, and visualising the problem to be simulated, through creating objects representing agents interacting with one and another and with their environment. It enables multiple simulations or runs, in addition to the collection of generated data. Using a JavaScript interface, outcomes can be visualised in an interactive manner (Masad & Kazil, 2015). In the context of this study, MESA modules are mainly used to create agents and environment objects. In addition, a scheduler is used to handle the time component of the model and identify the order of interaction of the agents. The following section details how the different components of MESA library are applied to the case study simulation.

Environment (economy)

The environment is a fundamental component of the ABM system. It is the simulation environment wherein all the global time-dependent variables are defined and tracked using a scheduler process logic approach.

The environment in the proposed ABM is defined by using the economy class defined by the MESA library, wherein the agents were instantiated using an *init()* function and activated simultaneously using the scheduler process, which is in turn called using the function

SimultaneousActivation(). Agents were also created and added to the scheduler to ensure that they are executed at each time step.

Agents

Agents are defined as classes. Attributes and behavioural rules are input as variables and functions. In the ABM model developed, two different categories of agents are defined. Importer (Q) is a unique agent characterised by a set of variables: inventory, monthly CWR, monthly demand, quantity imported in addition to economic cost and environmental impact. *Q* agent is also comprised of a range of behaviours and behavioural rules formulated as part of the subsequent functions implemented in the MESA library:

1-grow (): is a function that creates the grow functionality of the *Q* agent. This function is called when grow or mixed strategies are selected.

2-import_from_another_country (): is a function relating *Q* agent with E_i agents through imports. This function is called when import or mixed strategies are selected.

3-make_decision (): is a scenario-dependent function restricting the behaviour of importer agent based on the rules set in each scenario. It allows interaction between the two categories of agents amongst each other along with their environment (economy). Being the core of the model, all the other functions are called in *make_decision ()* to coordinate between agents.

*4-step (): i*s a function associated with the scheduler. It is used to call *Q* agent at each time step.

As for the exporter agent ($i \in E$), its class uses only the *step()* function as all rules are set in the *make decision()* of the *Q* agent.

2.4. Scenario formulation

The food system, including domestic production, trade flows and behavior, is influenced by several economic factors, such as GDP and commodity prices (Bahmani-Oskooee et al., 2016). In addition, as anthropogenic activities are increasingly scrutinised for their impact on the environment, an intricate consideration for such activities should be included in any decision-making scheme. In the context of this study, three different scenarios have been formulated to assess the impact of economic and environmental factors on the decision-making scheme as applied to the case study of a tomato market in Qatar. The first scenario represents the baseline case where the decision is fully driven by the need to satisfy the demand at the cheapest price. Whilst in the second scenario, the environmental burden associated with growing tomato has been investigated through analysing the impact of the crop water requirement (CWR) on the selected strategies. The third scenario introduces the concept of forward contracts as a solution to hedge against uncertainty governing the market prices of tomato. In the three scenarios, the economic and environmental costs have been tracked whilst selecting the appropriate strategy. The following section provides a detailed description of scenarios developed for this study.

2.4.1. Baseline scenario

The baseline scenario considers the price of tomato crops as the criterion impacting the choice of the demand delivery strategy, either to produce locally or to import from the trade market. The price of tomato differs from one country to another accounting for several components, including the distance between the importing and exporting countries and the cost of production at the country of origin. The decision to grow locally or to import is primarily driven by price where the economic cost and environmental impacts associated with importing varies depending on the source country. This scenario mimics the current decision-making system adopted in Qatar. In fact, the decision made by the food system is strongly influenced by the need to satisfy the growing population demand, regardless of the economic or environmental cost. When weather conditions and land availability allow for local production to contribute to the supplies, the demand for the crop is also satisfied through domestic products. However, when the local conditions are not appropriate to produce, the food sector relies on imports to partially or fully compensate the shortage in supply. The chronological order followed to formulate the baseline scenario is described in Figure 5.

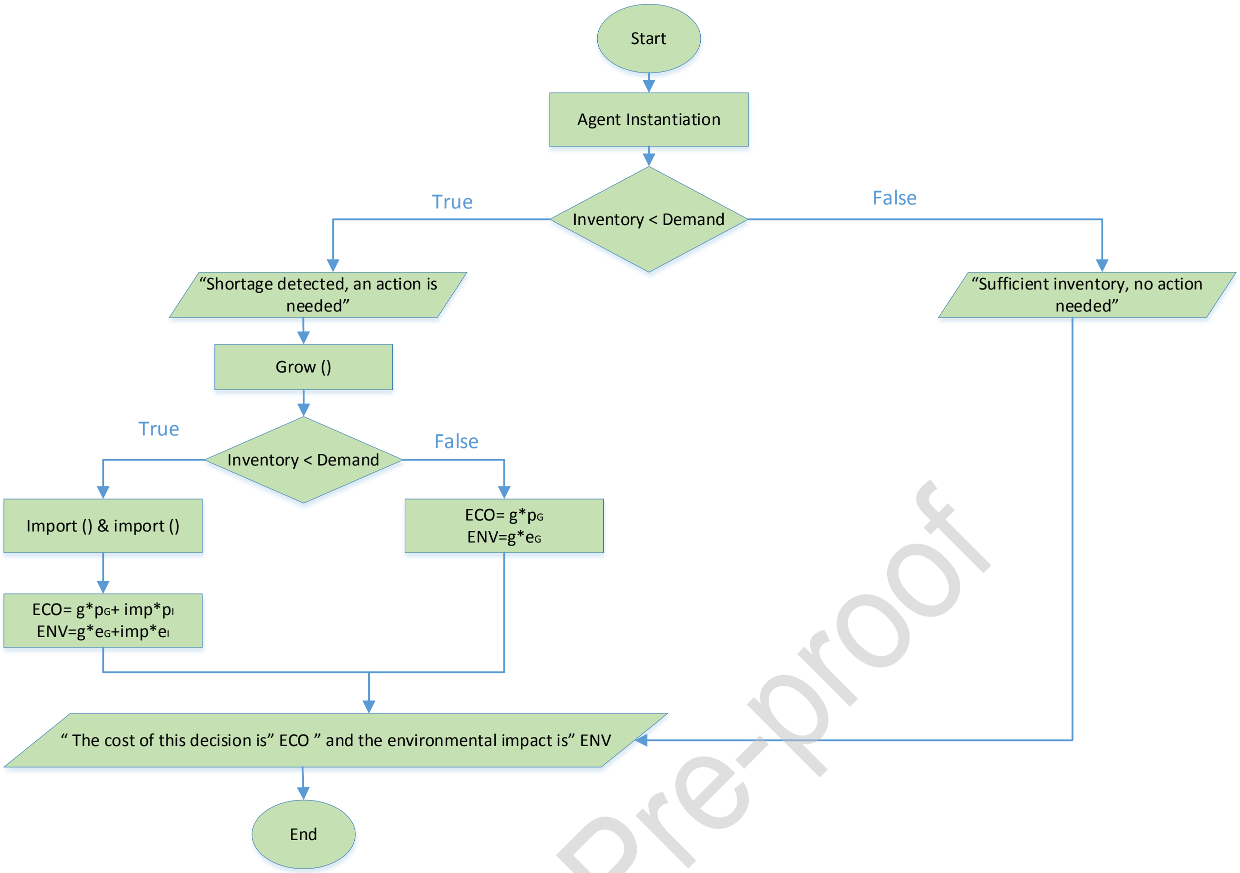


Figure 5. Baseline scenario flowchart.

2.4.2. *Crop water requirement (environmental) scenario*

The scarcity of fresh water supplies is a critical limiting factor to a flourishing agriculture industry in the arid climate of Qatar. Satisfying the complete spectrum of food crops consumed on a daily basis would be extremely difficult if not impossible due to the intense water requirements of some crops such as cereals and barley. Alternatively, reaching 100 % self-sufficiency in certain perishable crops, like tomato, is possible, if economically feasible. However, attaining ambitious yet achievable results will likely stress freshwater aquifers. Therefore, it is necessary to consider the water requirements represented by the *crop water requirement* (CWR) when planning production in domestic agriculture systems. CWR is defined as the amount of water required to compensate water lost through evapotranspiration processes. Essentially, it is the optimal quantity of water that a crop should have in order to grow in healthy conditions (FAO, 2007). Thus, in this scenario, CWR is used to guide the decision-making outcomes and illustrate the water savings from each decision made (grow, import or mixed strategy - grow and import). The quantity of water required to grow tomato locally (CWR_Q) is compared with the water required to produce the crop in exporting countries (CWR_E_i). CWR_Q is forecasted based on 3 years of monthly historical data using the moving average (MA) time series analysis technique. Historical values for CWR_Q are derived using the following equation (Allen et al., 1998; QNFSP & ICARDA, 2010):

$$\text{CWR\_}Q = \frac{A \times ET_c}{1000} \tag{10}$$

Such that A is the area required for production and ET_c is the evapotranspiration.

As for CWR_E_i, it is forecasted using linear regression for the same time period. Due to the lack of data regarding the CWR of each of the exporting countries, the value of this variable is predicted based on a linear regression model linking the water requirement to the temperature of the country. Figure 6 describes the trend of CWR values for exporting countries over a 1-year sample. The purpose of considering the CWR is to factor in the environmental implications of domestic production, in terms of water utilisation. Generally, the smaller the CWR, the higher the water saving. In this scenario, if the import or import and grow strategies are selected, the simulation generates a ranking of the countries to import from based on the amount of water used in the production of tomato. The steps followed for the crop water scenario are illustrated in figure 7.

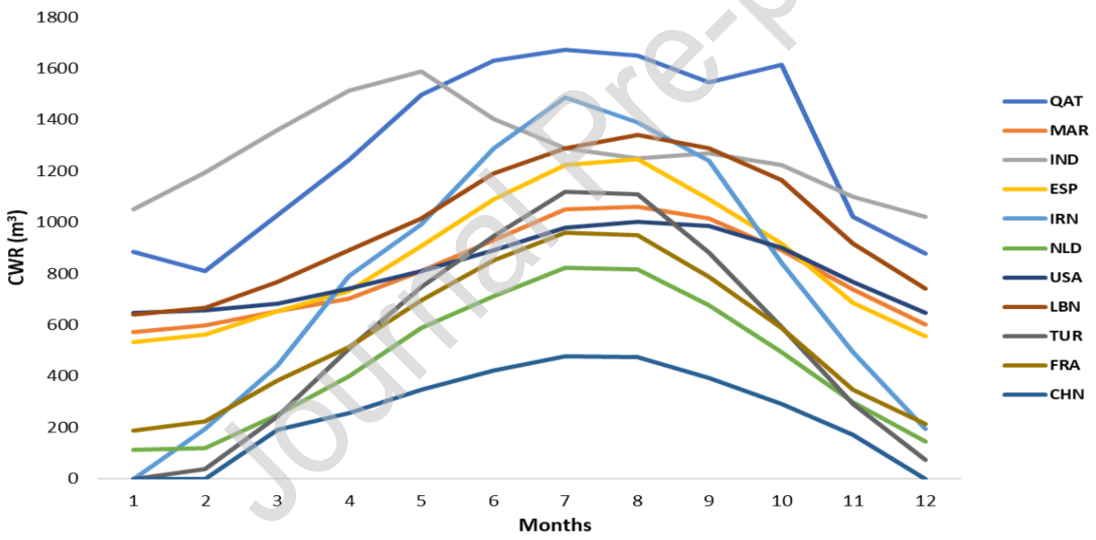


Figure 6. CWR scenario flowchart.

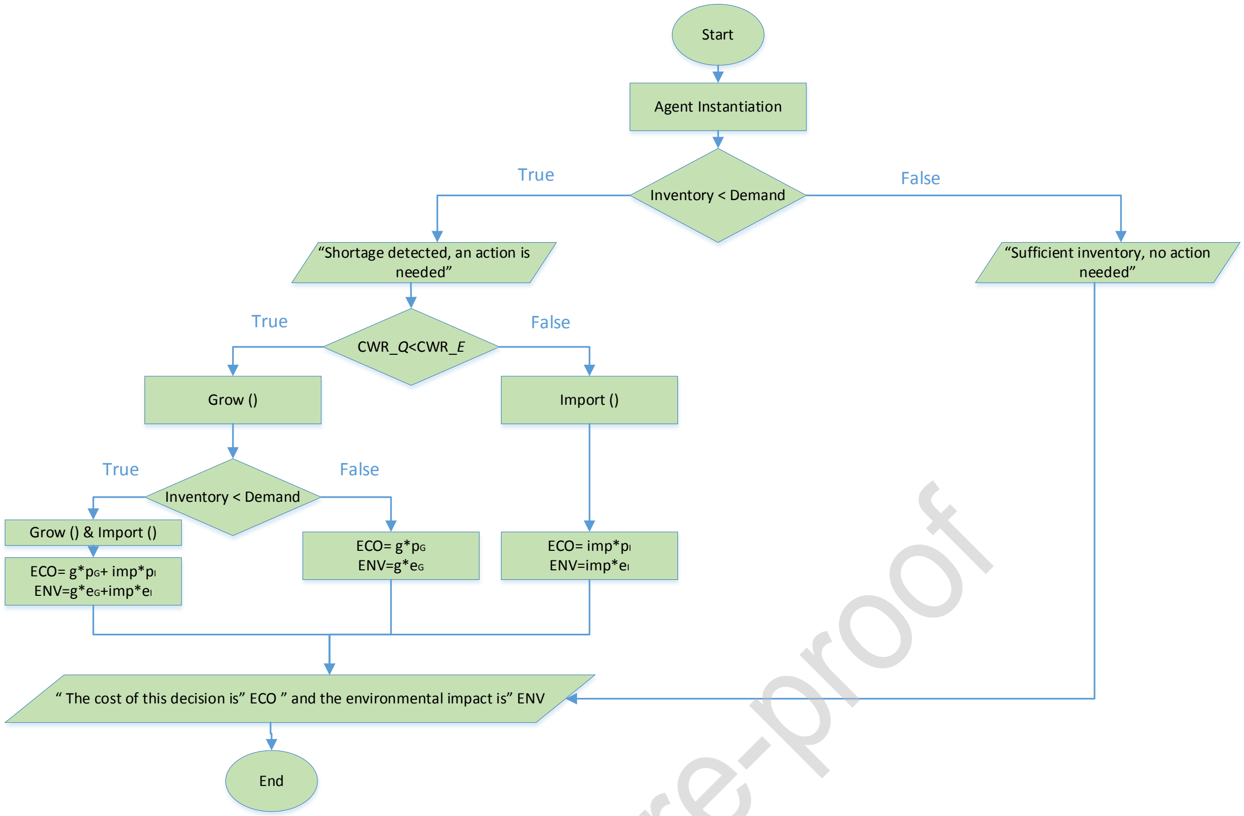


Figure 7. CWR scenario flowchart.

2.4.3. Forward price (economic) scenario

The current food trade system in Qatar mainly relies on spot prices to provide food products in the market. When import decisions are executed, crops are purchased at the current price set by the market, i.e. exporters, for a delivery date in the future. However, this transaction is governed by many uncertainties associated with market prices and the quality of the commodity. In fact, if prices are reduced between the contract time and delivery time, the transaction is disadvantageous for the importer and the opposite is true in the case of a price increase. To hedge against these risks, forward contracts represents a safer alternative. Forward contracts allow their holder to buy or sell an asset at an agreed price with a predetermined future delivery date, regardless of any future price fluctuations (Black, 1976). In the context of this study, the baseline scenario is reconsidered to include forward prices of tomato as a criterion for the decision-making process. In this scenario, the cost of producing locally (P_G), forecasted using moving average time series analysis and compared against forward prices (F_E) agreed upon with exporting countries. The forward prices are computed using the following formula:

$$F_E = S_E \times e^{rt} \tag{11}$$

where F_E is the forward price of tomato, S_E is the spot price of tomato at the time of the contract agreement, r is the interest rate and t is the delivery time. The purpose of this scenario is to reduce the impact of uncertainty in crop prices on the decision-making process. The logic followed in this scenario is illustrated in figure 8.

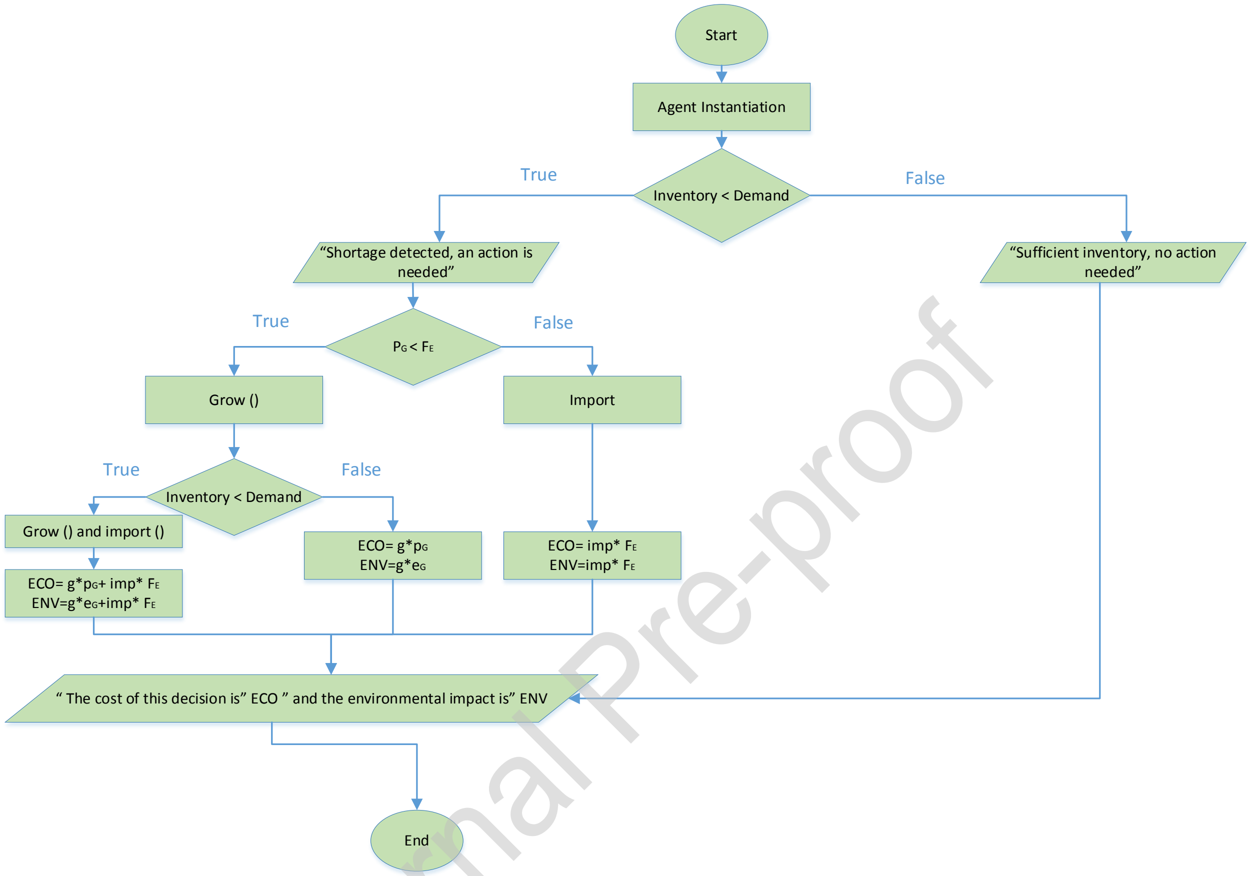


Figure 8. Forward contract scenario.

3. Results and discussion

The ABM developed as part of this study simulates the import/grow profile for tomato crops over 60-time steps representing 5 years of food production. The output from this model is a predicted decision-making profile, which provides advice on strategies for the Qatar food system to satisfy the monthly demand for tomato under various scenarios. It suggests a sustainable planning scheme that reduces uncertainty and manages risks. The model tracks the economic and environmental cost associated with each strategy that is undertaken. The following sections demonstrate the findings of the baseline, environmental and economic scenarios. Furthermore, a thorough discussion on the usefulness of results in directing future practices of the food sector is presented. In fact, the policy implications which enhance the performance of the food sector are also suggested such as reducing potential shortages due to local production restrictions (climate change, resources scarcities) or supply chain disruptions.

3.1. Baseline Scenario Results

The baseline scenario demonstrates a mixed strategy approach. Figure 9 describes the percentage of contribution of each strategy to the fulfilment of monthly demands at every time-step. Results display an average reliance of approximately 95% on imports. The fluctuations represented in Figure 10 demonstrate that in some months both the cost and environmental impact are relatively low when compared to some other periods. The fact is that during those specific months the demand for tomato is mostly satisfied through local production, while a smaller portion is imported. As for the periods demonstrating high costs and environmental burden, the major portion of the available tomato is either fully or partially supplied from other countries. The variability in these decisions is affected by two factors: the monthly demand for tomato, such that, during months experiencing high demand for the crop, the amount grown is not sufficient to meet the demand, hence an additional amount is imported to compensate the shortage. The choice of the exporting countries depends entirely on the unit price of the crop along with the exporting capacity of each country. The second factor impacting decisions taken in this scenario is the growing period of the crop, which in this case is assumed to be two months. In fact, during some months the need to import is imperative as the decision to grow made in a previous month is made but not processed. Consequently, a full reliance on imports is incumbent. While in the case of a partially full inventory, any deficit in the crop supply is compensated through imports. This scheme can provide policymakers the necessary insight into the potential performance of a tomato crop for the upcoming years considering tomato prices and demands. The model was validated using 3-year monthly historical data for all parameters involved in the ABM. Figure 11 describes the imports/grow profile under non-forecasted data. An average reliance on imports amounting to 92% was recorded using historical data for a period of 3 years, which is almost similar to the average reliance generated using forecasted data, equivalent to 94% for a 3-year time span.

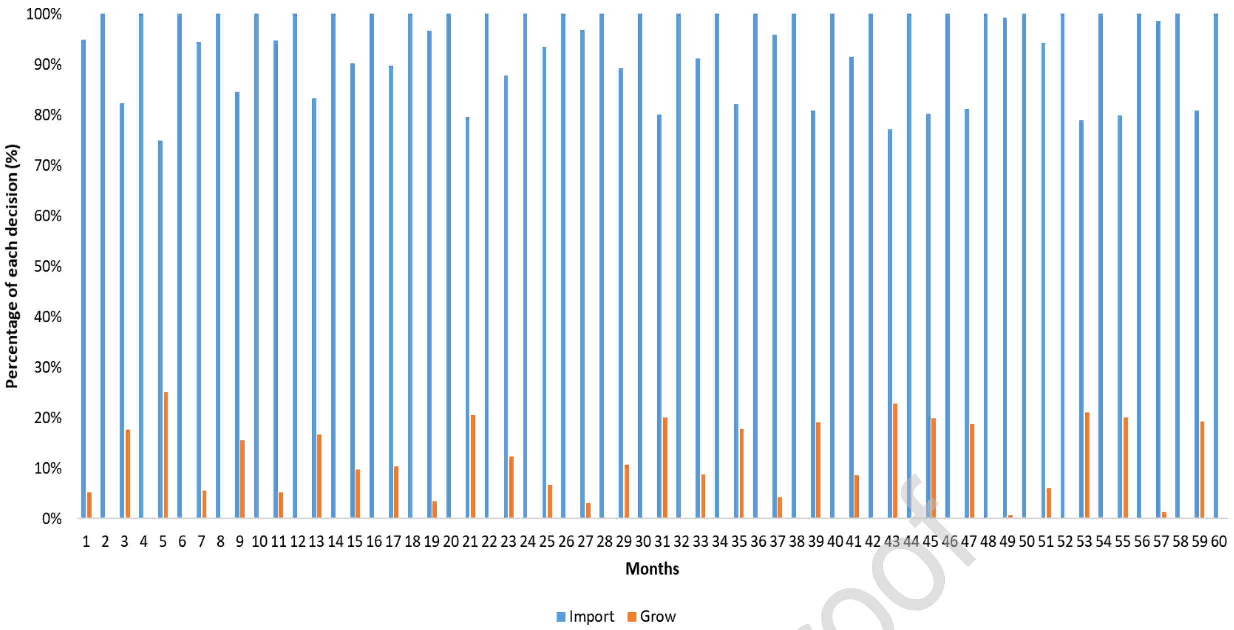


Figure 9. The percentage contribution of each strategy to the fulfilment of the demand.

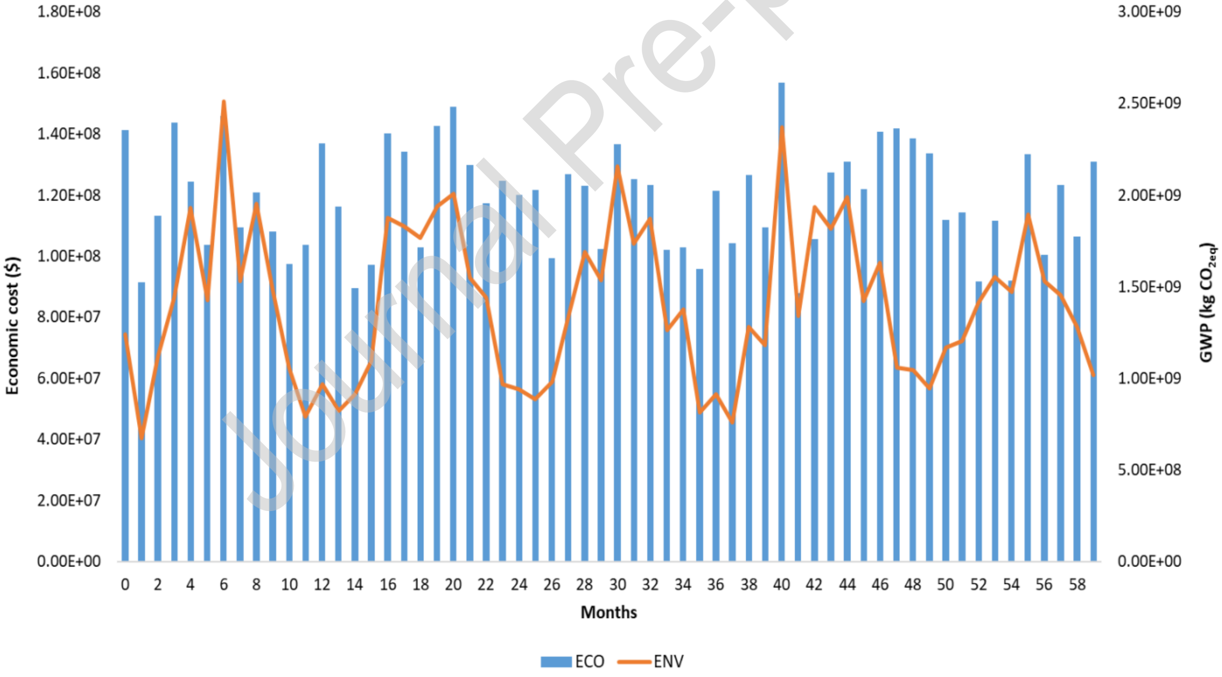
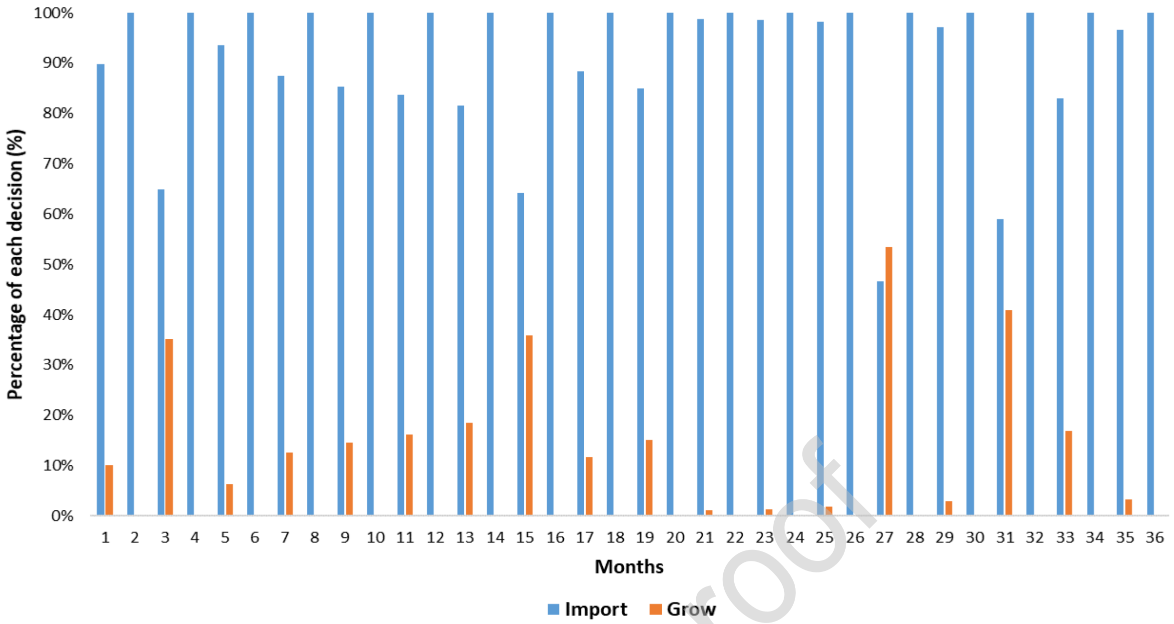


Figure 10. Baseline scenario economic and environmental costs results.

Figure 11. The percentage of contribution of each strategy using non-forecasted data.



3.2. CWR Scenario Results

The CWR scenario resulted in slightly different results (Figures 12). It advises the full reliance on imports to satisfy the demand for tomato. The findings are expected considering the climatic conditions (temperature) in the state of Qatar, which directly affect the water required to grow food. In fact, the local CWR values are always higher than the other countries considered in the model throughout the year. Economic costs displayed significant fluctuations with values slightly similar to the baseline scenario, since the monthly price of the crop remains unchanged. The minimal difference in monthly costs can be explained by the lower price of the growing strategy that implies smaller costs in the baseline scenario compared to the CWR case. However, the environmental impact values experience a significant shift in the CWR scenario. Indeed, an increase in GWP emissions is recorded, especially during the months with larger imported quantities. This rise in environmental impacts is caused by the emissions from transportation associated with the import strategy.

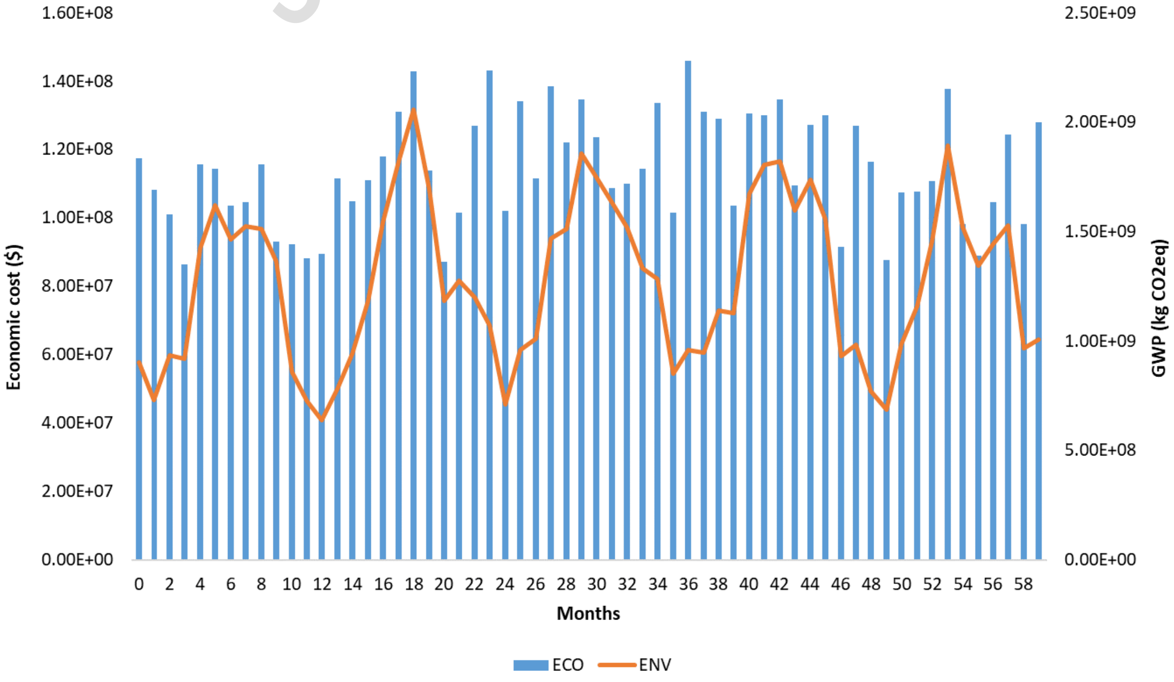


Figure 12. CWR scenario economic and environmental costs results.

This scenario suggests an environmentally friendly decision-making scheme for Qatar as it considers the water scarcity challenge that is threatening the local food sector, through minimising the water footprint. Figure 13 illustrates the monthly water savings of Qatar over the entire period of study. Since Qatar is fully dependent on imports for this CWR scenario, the quantity of water savings is equivalent to the water that would have been used to produce food if the crops were grown locally. Since the water demand is assumed to follow an increasing pattern as a result of the time series forecast, water savings are also expected to increase over the period of study. Figure 14 provides a closer look to the monthly water savings for a period of one year, where the most significant savings are recorded in the in the hot season where the water required to grow food in Qatar is relatively large due to the high temperatures.

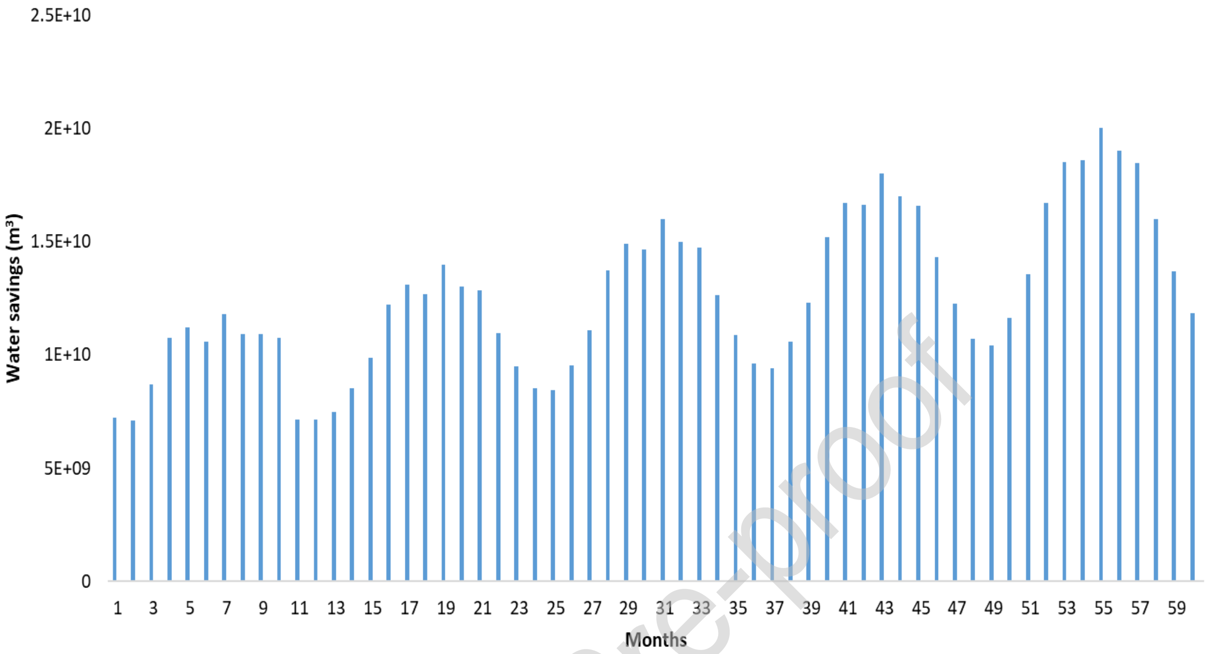


Figure 13. Qatar's monthly water savings over 60 periods.

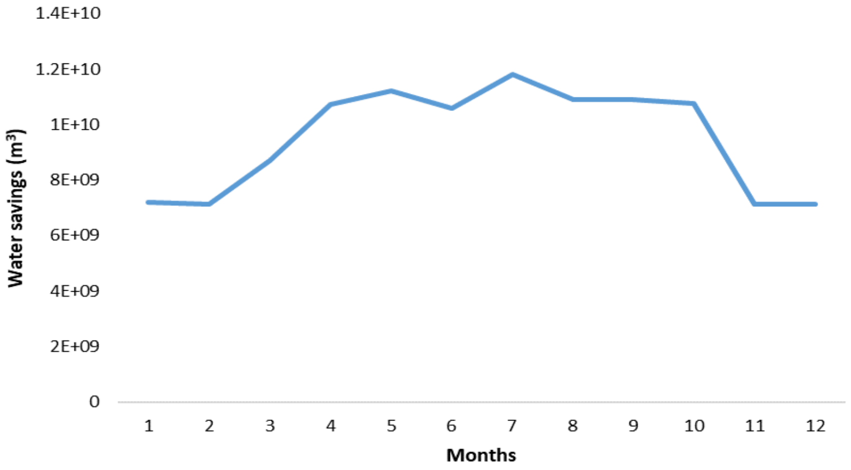


Figure 14. Qatar's monthly water savings over 1-year period.

Globally and considering a one-year sample, water savings exhibit an expected behavior (Figure 15). During the hot season, global water savings are relatively high, whilst in colder periods the savings are less significant. This can be explained by the very high temperature of Qatar during the summer season, which implies more water quantities to grow crops compared to the exporting countries. Therefore, if tomatoes were to be grown locally, it would require tremendous amounts of water amounting to an average of 4.9 billion m^3 per year. In other words, the significant difference in temperature between Qatar and the exporters enlarges the gap between local CWR and exporting countries' CWRs leading to more savings during the hot weather period as displayed in Figure 15. Global water savings are computed using the following formula (Renault, 2002):

Net global water savings = Water savings in Qatar - Water used to grow food in exporting countries.

where the water not used in Qatar is computed through multiplying the quantity of food required with the local CWR, while CWR of exporting countries is used to find the water used abroad in a similar manner.

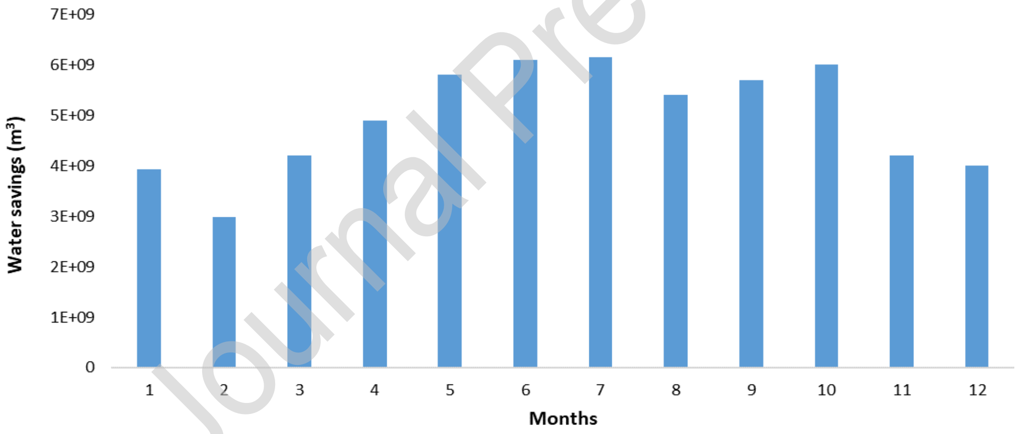


Figure 15. Monthly global water saving over a 1-year period.

While allowing Qatar to achieve significant water savings, this scenario exposes the food system to a higher risk of shortages, which can be caused by supply chain disruptions. In addition, fully relying on imports implies a significant flow of virtual water contained in the crops traded, which can be seen as a threat to the water security of exporting countries. Thus, the CWR scenario also considers sensitivity analysis on the water footprint in making sustainable decisions within the food system. Enhancing the CWR through decreasing its values allows for the integration of the grow strategy and reduce the dependence on imports (Table 5). Results of this scenario and sensitivity analysis outputs can incentivise decision-makers to investigate methods and techniques that could enhance the yield of crops, whilst minimising the water requirement. For instance, as part of the efforts to enhance self-sufficiency, investing in greenhouses and deploying smart agricultural techniques that offer environmentally friendly solutions represent an optimal strategy to control CWR for crops' growth.

Table 5. Sensitivity analysis table for enhanced CWR values.

Current CWR	Current decision	5% decrease	5% decision	10% decrease	10% decision	15% decrease	15% decision	20% decrease	20% decision
883.5	import	839.325	grow	795.15	grow	750.975	grow	706.8	grow
808.4	import	767.98	grow	727.56	grow	687.14	grow	646.72	grow
1027.256	import	975.894	grow	924.531	grow	873.168	grow	821.805	grow
1241.599	import	1179.519	grow	1117.439	grow	1055.359	grow	993.279	grow
1495.635	import	1420.853	grow	1346.071	grow	1271.289	grow	1196.508	grow
1632.179	import	1550.570	import	1468.961	import	1387.352	grow	1305.743	grow
1671.872	import	1588.278	import	1504.685	import	1421.091	grow	1337.498	grow
1649.644	import	1567.162	import	1484.679	import	1402.197	import	1319.715	grow
1544.854	import	1467.611	import	1390.369	import	1313.126	import	1235.883	grow

3.3. Forward Price Scenario Results

Forward contracts aim at minimising the risk associated with fluctuating market prices. When dealing with an import decision, this scenario assumes the forward price in order to value the crop. Figures 16 illustrate results of the forward contract scenario exhibiting a different decision-making scheme. Unlike the previous scenarios, opting for the forward contract as a criterion to choosing the best strategy recommends a heavier reliance on local production to fulfill the demand for tomatoes. On average, when using forward pricing as a criterion for decision-making, a ratio of 57% of domestic production is recommended. Additionally, in comparison with the baseline case, the forward scenario reduces the recommended percentage of imports from 95% to 43%. Consequently, both the cost and environmental impact display a flagrant reduction in the forward pricing scenario compared to other scenarios, except in some specific months where the demand is relatively high entailing additional provisions from exporting countries for the coming months. Results of this scenario can be explained by the case where the forecasted value of the tomato spot price in Qatar is less that the forward price of the exporting countries (Black et al., 2009). In this situation, it is more beneficial for Qatar to satisfy its inventory through growing food. This is in contrast to the results generated in the case where anticipated spot prices of the crop are higher than future prices. In the context of Qatar, the implementation of the results of this scenario can be unrealistic in the light of climatic conditions in the region that make it less likely to fully rely on agriculture to satisfy demands. However, investigating the potential of integrating forward contracts while taking into account uncertainties associated with weather conditions could achieve more realistic results. In fact, adopting resilient thinking that fosters dynamic decision-making and risk mitigation could lead to robust methods that can enhance the governance and policy-making in food and other resources systems (Govindan & Al-Ansari, 2019b). In addition, and in comparison, with the baseline case, this scenario resulted in a significant reduction in environmental emissions amounting to 63%. Therefore, introducing forward contracts to the baseline case does not only mitigate the risks of fluctuating future prices; yet, it also serves as an environmentally friendly strategy that encourages sustainable local production.

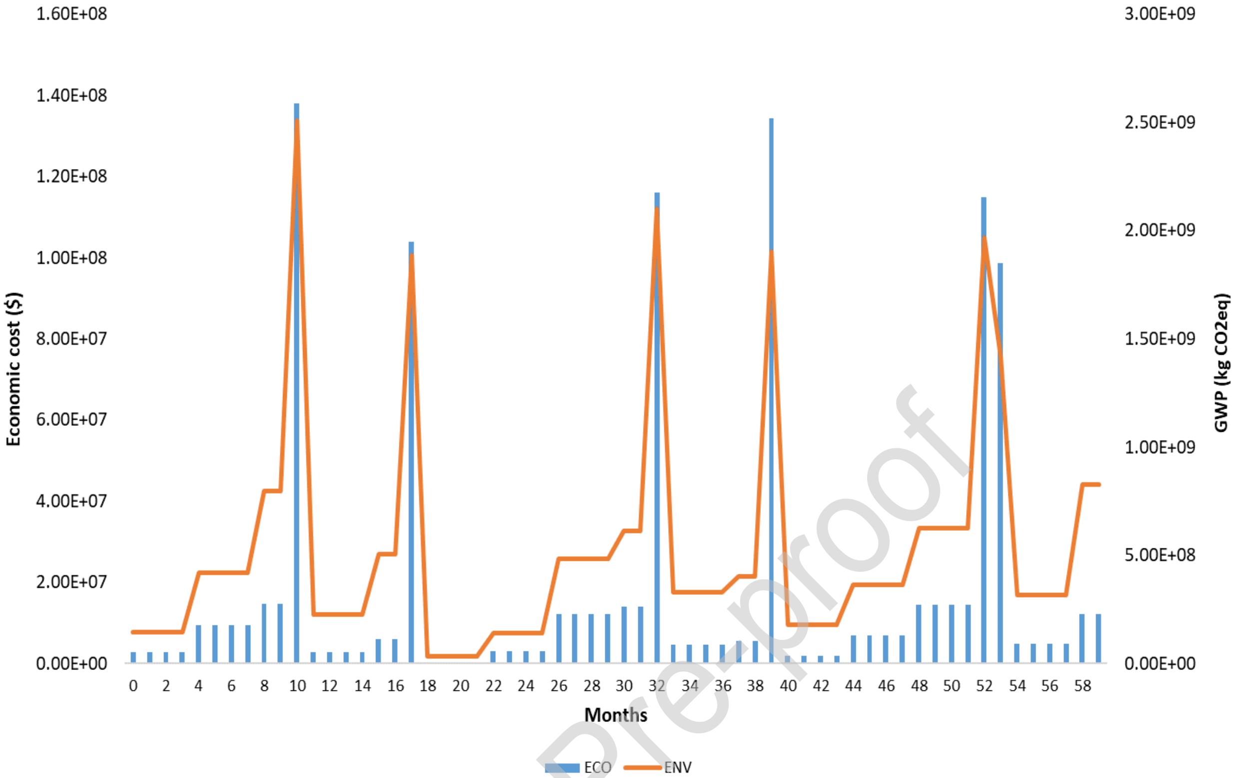
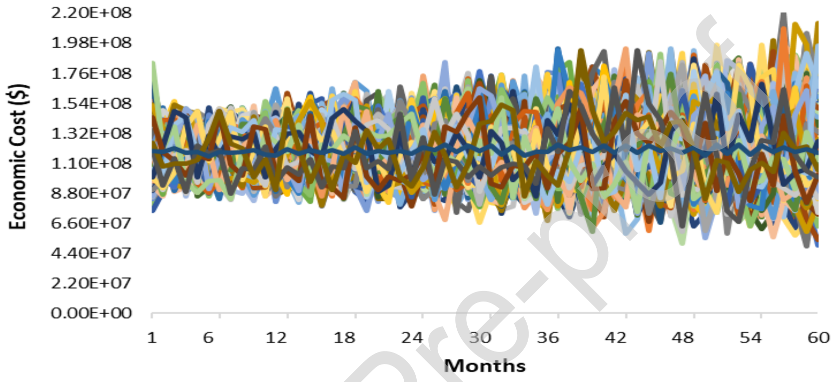


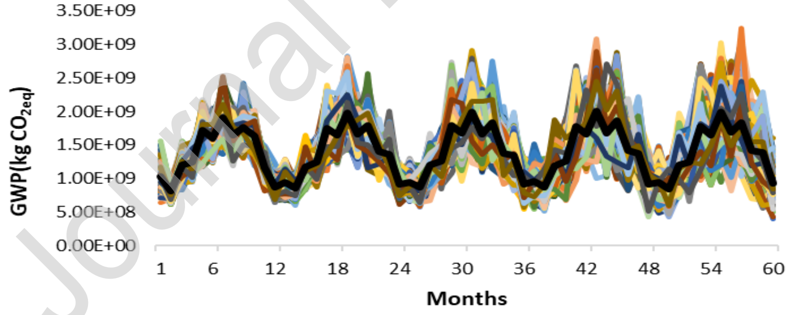
Figure 16. Forward price scenario results.

3.4. *Comparative assessment of scenarios using Monte Carlo simulations*

The first order-moving average model implemented also captures the uncertainties in the forecasted data used in this study. In addition to the trend (average) estimations, the model essentially represents the serial auto-correlations of stochasticities for different techno-economic factors considered with respect to the tomato crop, namely: (a) local demand; (b) local and international prices; (c) water requirements for cultivation locally and internationally; and (d) environmental impacts of cultivation locally and internationally. Monte Carlo simulations were subsequently carried out using these uncertainties, integrated into the ABM model setup, to generate 250 realisations for the planning period of 60 months.

Figures 17, 18 and 19 illustrate the results obtained, indicating the average curves for each of the sustainability dimensions - cost, GWP and water savings. The findings in the outcomes of the uncertainty analyses assert that in comparison with the baseline scenario, although the economic cost on average exhibits a similar behavior to that of the CWR scenario, a significant cost reduction is achieved in the forward price scenario. This can be explained by the full reliance on imports in the CWR scenario, which is relatively similar to the 95% reliance as in the baseline case. Meanwhile, the forward price scenario engendered significantly smaller economic cost since it encourages enhancing the local production, since the import contracts have relatively higher expected prices. Likewise, considering the GWP, the baseline and CWR scenarios exhibit similar behavior, and significantly higher than that of the forward contract scenario which scores an important reduction in environmental emissions at multiple time points during the planning period, once again attributed to the lower reliance on imports. Interestingly, when considering water savings as a performance criterion for decision making, the CWR scenario displays relatively higher water savings on average, since the crop is not grown in Qatar, where the production necessitates the requirement for high amounts of irrigation water.





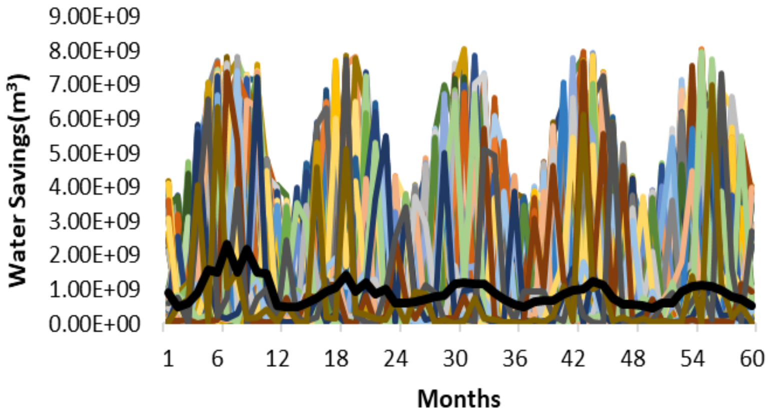


Figure 17. Monte-Carlo simulation results for baseline scenario.

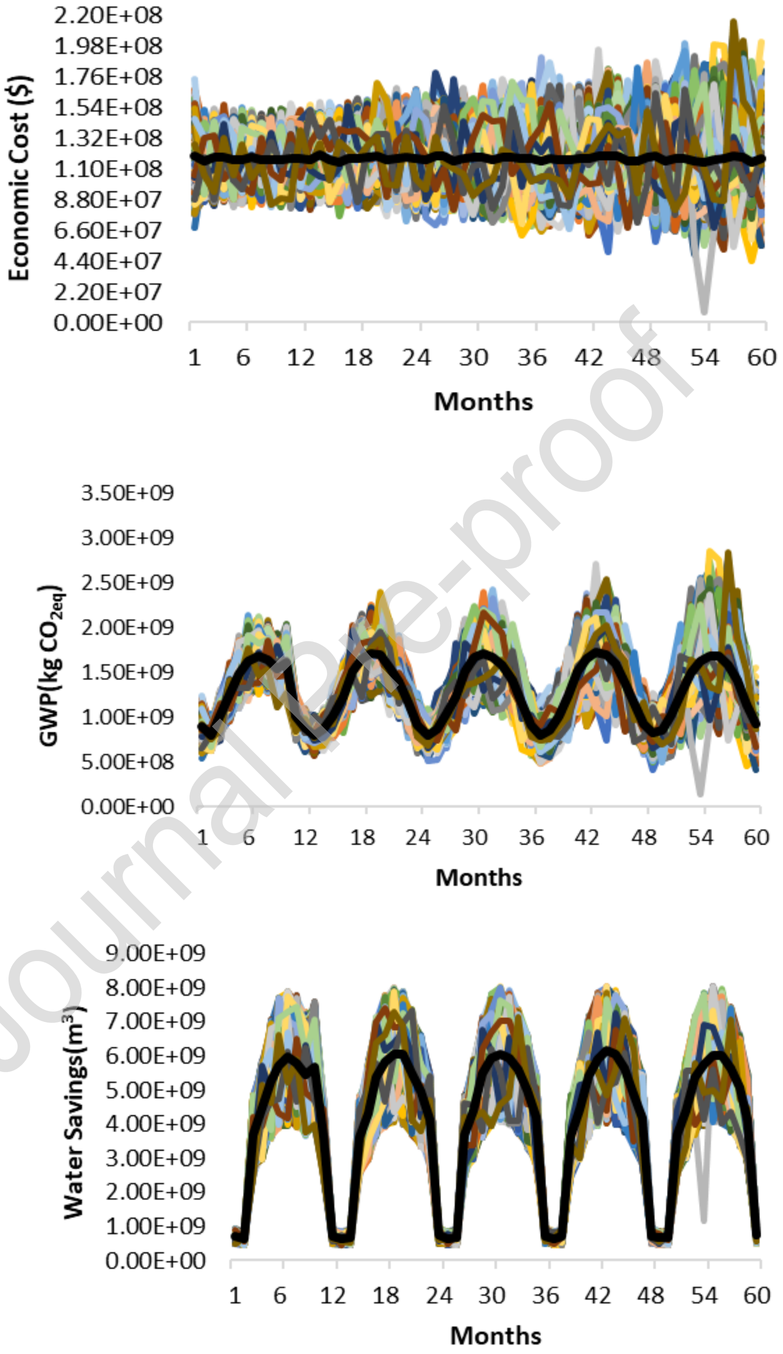


Figure 18. Monte-Carlo simulation results for the CWR scenario.

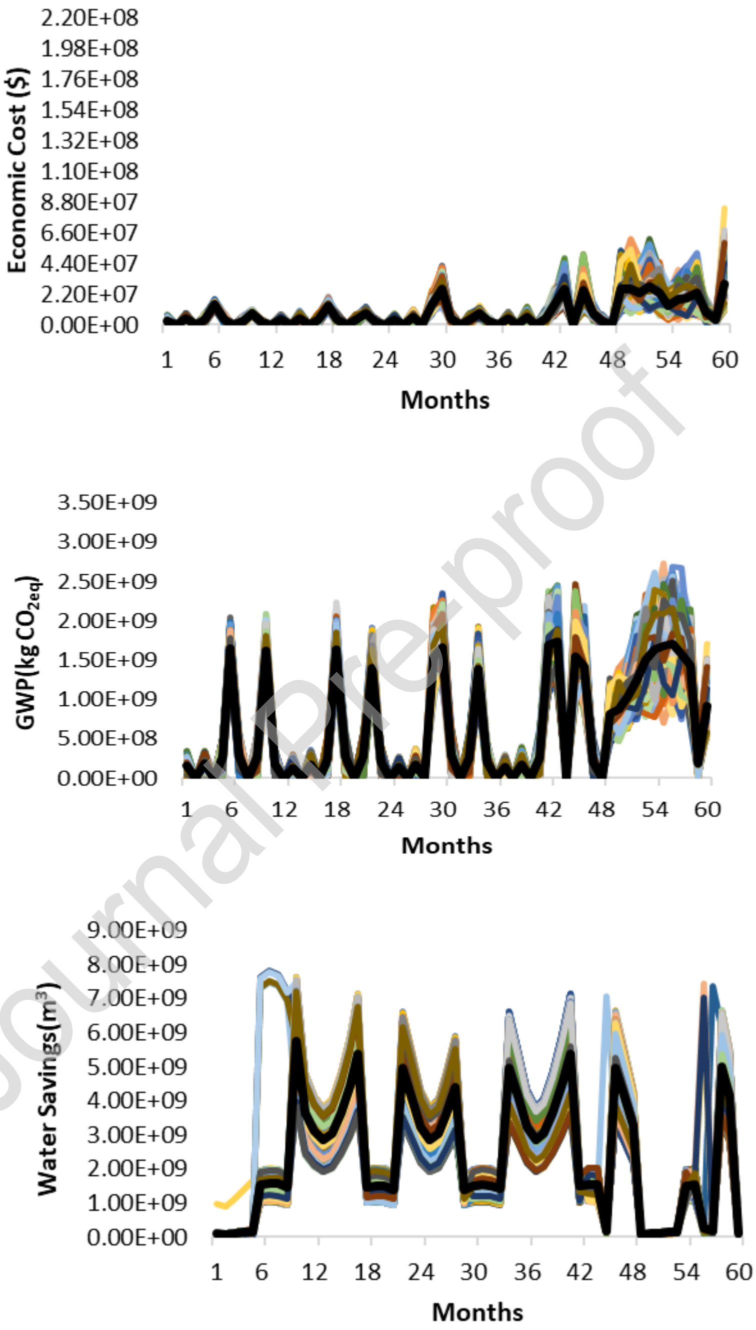


Figure 19. Monte-Carlo simulation results for the forward price scenario.

4. Conclusion and future work

Food availability, an output of food systems, is a critical pillar of food security and is continuously challenged by compounded externalities. This is under stress by the continuously increasing demand for food products and is influenced by several external factors such as uncertain trade transactions, unpredictable climatic conditions, fluctuating commodity prices and scarce resources. The food system in Qatar is under pressure to enhance its efficiency and adopt resilient strategies in order to ensure sufficient quantities of food in the market. Agent-based modeling (ABM) represents a promising tool that can mimic real-life systems in a dynamic manner and predict their future performance as a means to mitigate future risks. The model developed in this work simulates the performance of the tomato market in the state of Qatar under different economic and environmental scenarios. Opting for commodity prices as a decision criterion allows for more flexibility and diversification, as it suggests both growing and importing to meet local demands. The crop water requirement (CWR) scenario, on the other hand, suggests a full reliance on imports as growing locally is not an environmentally conscious strategy considering water scarcity in Qatar. The integration of future contracts for imported crops advises for a heavy dependence on local production to meet the demand, as it is economically less expensive. The methodology developed in this work serves as a decision-making guideline that allows policymakers in the food sector to perform sustainable prediction and planning of future practices that should be implemented in order to achieve enhanced food availability. The model also ensures improved economic and environmental performance of the food sector through quantifying the costs and emissions of each decision undertaken. In the future, other scenarios tackling additional environmental concerns, such as emissions from energy and water systems, could be added to investigate the impact of the performance of other sectors on the decision-making process in the food sector. Furthermore, access to larger data sets could be beneficial to enable the generation of realistic results that can optimally direct future policymaking in the food sector.

5. Acknowledgment

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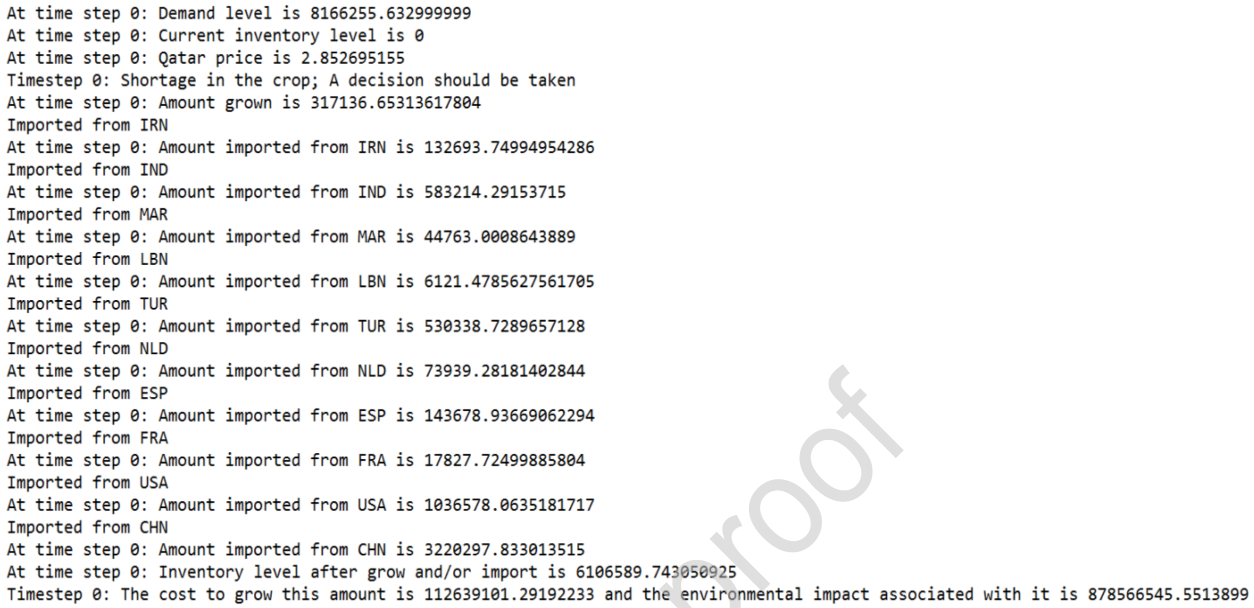
7. Appendix

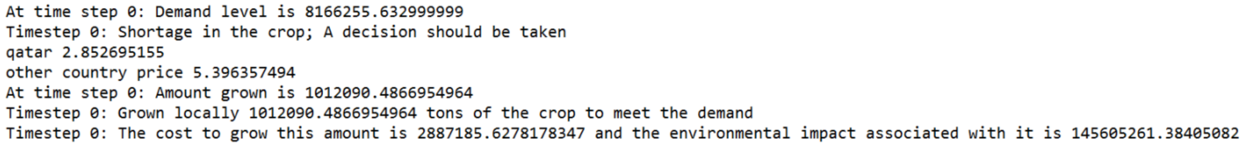


```
At time step 0: Demand level is 8166255.632999999
At time step 0: Current inventory level is 0
At time step 0: Qatar price is 2.852695155
Timestep 0: Shortage in the crop; A decision should be taken
At time step 0: Amount grown is 317136.65313617804
Imported from IRN
At time step 0: Amount imported from IRN is 132693.74994954286
Imported from IND
At time step 0: Amount imported from IND is 583214.29153715
Imported from MAR
At time step 0: Amount imported from MAR is 44763.0008643889
Imported from LBN
At time step 0: Amount imported from LBN is 6121.4785627561705
Imported from TUR
At time step 0: Amount imported from TUR is 530338.7289657128
Imported from NLD
At time step 0: Amount imported from NLD is 73939.28181402844
Imported from ESP
At time step 0: Amount imported from ESP is 143678.93669062294
Imported from FRA
At time step 0: Amount imported from FRA is 17827.72499885804
Imported from USA
At time step 0: Amount imported from USA is 1036578.0635181717
Imported from CHN
At time step 0: Amount imported from CHN is 3220297.833013515
At time step 0: Inventory level after grow and/or import is 6106589.743050925
Timestep 0: The cost to grow this amount is 112639101.29192233 and the environmental impact associated with it is 878566545.5513899
```

Figure A1. Baseline scenario strategies report for the first month.

```
At time step 0: Demand level is 8166255.63299999
Timestep 0: Shortage in the crop; A decision should be taken
monthly cwr less than other countries
At time step 0: Demand level is 8166255.632999999
Imported from IRN
At time step 0: Amount imported from IRN is 109379.71054661648
Imported from IND
At time step 0: Amount imported from IND is 716254.0890638012
Imported from MAR
At time step 0: Amount imported from MAR is 42069.040398311095
Imported from LBN
At time step 0: Amount imported from LBN is 3349.779208738145
Imported from TUR
At time step 0: Amount imported from TUR is 384306.08823898766
Imported from NLD
At time step 0: Amount imported from NLD is 80704.87220591752
Imported from ESP
At time step 0: Amount imported from ESP is 129891.05524318105
Imported from FRA
At time step 0: Amount imported from FRA is 19948.006915633952
Imported from USA
At time step 0: Amount imported from USA is 858233.5898694501
Imported from CHN
At time step 0: Amount imported from CHN is 3701191.6874537277
At time step 0: Inventory level after  import is 6045327.919144365
Timestep 0: The cost to import this amount is 117782864.91661617 and the environmental impact associated with it is 36802.024999999994
```

Figure A2. CWR scenario strategies report for the first month.



```
At time step 0: Demand level is 8166255.632999999
Timestep 0: Shortage in the crop; A decision should be taken
qatar 2.852695155
other country price 5.396357494
At time step 0: Amount grown is 1012090.4866954964
Timestep 0: Grown locally 1012090.4866954964 tons of the crop to meet the demand
Timestep 0: The cost to grow this amount is 2887185.6278178347 and the environmental impact associated with it is 145605261.38405082
```

Figure A3. Forward contract scenario strategies report for the first month.

Author contributions

Use this form to specify the contribution of each author of your manuscript. A distinction is made between five types of contributions: Conceived and designed the analysis; Collected the data; Contributed data or analysis tools; Performed the analysis; Wrote the paper.

For each author of your manuscript, please indicate the types of contributions the author has made. An author may have made more than one type of contribution. Optionally, for each contribution type, you may specify the contribution of an author in more detail by providing a one-sentence statement in which the contribution is summarized. In the case of an author who contributed to performing the analysis, the author's contribution for instance could be specified in more detail as 'Performed the computer simulations', 'Performed the statistical analysis', or 'Performed the text mining analysis'.

If an author has made a contribution that is not covered by the five pre-defined contribution types, then please choose 'Other contribution' and provide a one-sentence statement summarizing the author's contribution.

Manuscript title: **Sustainable food security decision-making: an agent-based modelling approach.**

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☒ Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☒ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☒ Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

☒ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☒ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
Specify contribution in more detail (required; no more than one sentence)

Author 2: Rajesh Govindan

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☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☒ Contributed data or analysis tools
Helped with the python code

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
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☐ Other contribution
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Specify contribution in more detail (optional; no more than one sentence)

☒ Contributed data or analysis tools
Contributed with data related to forward contracts section

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
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Author 4: Gordon McKay

☐ Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☒ Contributed data or analysis tools
Assisted in developing the sceanrios

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
Specify contribution in more detail (required; no more than one sentence)

Author 5: Tareq Al-Ansari

☒ Conceived and designed the analysis
Main suoervisor of the project

☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☐ Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
Specify contribution in more detail (required; no more than one sentence)

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☐ Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☐ Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
Specify contribution in more detail (required; no more than one sentence)

Author 7: Enter author name

☐ Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☐ Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

☐ Performed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Wrote the paper
Specify contribution in more detail (optional; no more than one sentence)

☐ Other contribution
Specify contribution in more detail (required; no more than one sentence)

Author 8: Enter author name

- ☐ Conceived and designed the analysis
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Collected the data
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Contributed data or analysis tools
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Performed the analysis
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Wrote the paper
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Other contribution
  Specify contribution in more detail (required; no more than one sentence)

Author 9: Enter author name

- ☐ Conceived and designed the analysis
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Collected the data
  Specify contribution in more detail (optional; no more than one sentence)
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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Highlights:

- A dynamic decision-making framework to ensure consistent availability of food is developed.
- An agent-based simulated is used to advise the strategic planning of tomato crops supply in Qatar.
- Three different scenarios are investigated to demonstrate the impact of crop water requirement and forward contracts on the strategies of the food sector.
- A yearly average of 4.9 billion m^3 is globally saved while considering the water requirement of the crop in the decision-making.
- A reduction of 63% in environmental emissions is recorded while adopting forward contracts.