Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

AN AGENT-BASED MODELLING FRAMEWORK FOR URBAN AGRICULTURE

Adam Ghandar
Georgios Theodoropoulos
Miner Zhong
Bowen Zhen
Shijie Chen
Yue Gong

Dept. of Computer Science and Engineering
Southern University of Science and Technology
Shenzhen 518055, P.R. CHINA

Ayyaz Ahmed

Al-Khwarizmi Institute of Computer Science
University of Engineering and Technology
Lahore, PAKISTAN

ABSTRACT

Agricultural innovation is imperative in order to meet global challenges to sustainably feed large urban populations. This paper contributes a modelling framework for urban agriculture, and an implementation in a scenario based on the fast growing mega city of Shenzhen located near Hong Kong in southern China. We also review related work and provide a gap analysis between requirements for modelling modern urban agricultural systems versus related work that looks at agricultural supply chains, production, and land use. The proposed framework will facilitate developing a novel decision support system to coordinate decentralized urban agricultural production units in order to realize, at scale, numerous benefits from co-locating production and consumption in the urban environment.

1 INTRODUCTION

Ensuring global food security with a growing population in an uncertain world is an important challenge. Cities are responsible for approximately 70% of total global energy usage which places a significant strain on the earths resources (Musa 2018). Agriculture, particularly transport and storage, uses a significant proportion of energy (Smith et al. 2005), as well as consuming land and degrading the wider environment. At the same time consumers demand higher quality nutrition. Technology is an important means to increase the quantity and quality of production. An attractive concept is situating farming inside cities and using various technologies to scale up the potential yield and feed large numbers of people (Despommier 2013). Vertical farming is a technique in which stacked units are used to grow food indoors with hydroponics, LEDs, and robotic material handling systems; in a closed system the growing environment can be adjusted in real time to tailor production to precise specifications (Castelló Ferrer et al. 2019). Having intensive production taking place physically close to the concentrated consumption of the produce can reduce transportation and storage requirements; there are also further benefits from releasing agricultural land outside cities from the burden of agriculture. A higher quality and more customized product is possible because of elimination of pesticides and contamination from pollution. Diversification of the type of produce can be matched to the needs of local consumers at a finer level of granularity than is possible in traditional agribusiness models. Intergovernmental organizations such as the World Bank (World Bank 2017), the EU (Lohrberg et al. 2016), and others have recently promoted initiatives that include urban agriculture for these types of reasons.

Urban agriculture can take many forms, for instance vertical farming, roof-top farming, controlled environment agriculture, vacant lots, and others. Combining – and coordinating – producing units of varying scales is a novel approach to enhance the viability of feeding large populations with urban farming.

It may not be desirable, or even be practical, to construct massive centrally managed farms within cities to replicate the agribusiness forms that are widely applied today. A future food production system in a smart city context calls for a new type of decision support system (Benke and Tomkins 2017).

Urban farming practices have inherent benefits in social, environmental, and economic dimensions (Specht and Sanyé-Mengual 2017). Examples of environmental benefits include food saving and recycling (as fertilizer), reduced food miles (Manos et al. 2013), and a smaller footprint of land needed to grow food for cities. Social advantages are in education, intrinsic value to well being from linking city dwellers to food production, as well as food security, dietary diversity, and nutrition. Economic benefit occurs through entrepreneurial opportunities and providing public benefits (Lohrberg et al. 2016). Currently the most common type of agriculture practiced in cities is not high tech and consists of roof-top farming either with hydroponics or open air farms with soil in planters (Buehler and Junge 2016). Indoor systems can increase production in small spaces (Despommier 2013; Thomaier et al. 2015) and the technologies related to urban farming are rapidly developing.

The simulation approach described in this paper hopes to provide a way to design a new type of farming paradigm by giving detailed answers for stakeholders such as policy makers, entrepreneurs, and citizens. This is by answering questions such as: "What is the population size that urban farming systems can support"; "How might it change in the future as technology develops?"; "How resilient is the food supply to risk X?"; and on a shorter time scale, "When should producer X plant a crop of type Y to be ready for consumer/retailer Z?".

Simulation is promising because urban systems are complex and simulation can capture emergent behaviour in natural and human systems arising from complex interactions of non-linear dynamics, e.g., thresholds, inventory capacity at many locations, transport bottlenecks, food spoilage rates, and myriad of other factors. What-if analyses could be applied to support design, policies, and long-term strategies taking into account change over space and time in urban systems and allow evaluation of risks such as natural disasters or equipment and other failures. Simulation could also support the near-term operational coordination of food production and distribution using dynamic data-driven application systems to synthesize information about the day-to-day city context, urban producers, and consumers, with multiple data sources connected via a network gateway in a smart city interface. In this way, heterogeneous urban farming projects would be able to anticipate demand at a fine level of granularity based on local conditions, and also could be coordinated with other utilities such as water, energy, and waste disposal (Ghandar et al. 2018).

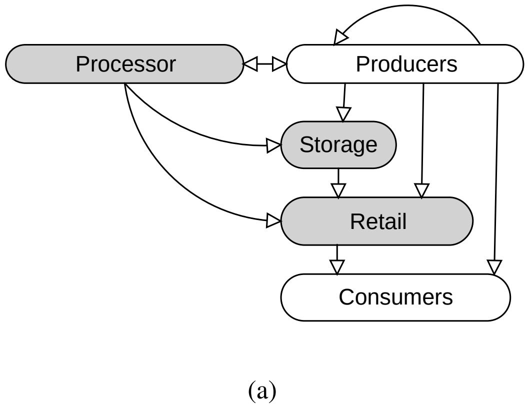
The rest of this paper is organized as follows: Section 2 describes related work in modelling agricultural production including gap analysis of the requirements to model traditional food systems and the requirements to model urban agriculture; Section 3 presents the framework; Section 4 presents a prototype implementation and empirical analysis; Section 5 concludes the paper.

2 RELATED WORK

Supply chains for urban agriculture differ from traditional agriculture. Tsolakis et al. (2014) describe non-urban agricultural supply chains and decision points in depth. Figure 1 highlights key differences between the logistics and product flows in urban agriculture. The co-location of producers and consumers leads to a flatter, less hierarchic, demand chain.

2.1 Overview

A variety of methods have been used to model agricultural systems and supply chains. Some studies consider multiple competing objectives, for instance food safety and profit (Manos et al. 2013; García et al. 2006). Meta-heuristics can provide a way to optimize systems with a global, multi-silo, view (Wari and Zhu 2016). Other techniques focus on specific components such as warehouse stacking, delivery scheduling, etc. Simulation can provide a way to evaluate complex configurations, with multiple silos, or



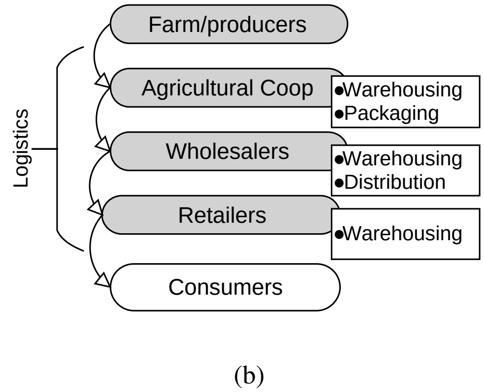


Figure 1: Product flow in traditional, (a), and urban, (b), agriculture supply chains. Co-location of producers with consumers creates new paradigms for production and distribution.

systems-of-systems, to optimize a global representation. Using detailed problem representation rather than an abstract one may enable more accurate conclusions to be drawn due to taking into account the complex interplay of nature, human activity, and technology and resulting emergent system behaviour (Bonabeau 2002). For example, Van Der Vorst et al. (2009) simulate dependencies between logistics, sustainability, and food quality to model dynamics that emerge from changing rules that govern interactions between various interacting entities; Bora and Krejci (2015) also apply simulation in a system for evaluating complex agriculture policies.

In considering urban agriculture it is useful to study factors that cause consumers to select locally grown urban produce instead of possibly cheaper mass-produced goods. For instance local produce may be sustainable, and free of pesticides, but on higher cost. At present, leafy greens are widely grown crops in vertical farming ventures because higher profit margins these crops provide result in feasible business models considering the cost of new technology, not because of any inherent properties of these plants (Frazier 2017). Consumer preference modelling is able to be integrated into complex city and population models to give insights into factors for purchase decisions. For example, North et al. (2010) model individual decision making criteria to determine system-level outcomes such as to determine if a product's market share is increasing or decreasing. Urban agriculture may also provide societal benefits beyond economics, which can also be modelled in a heterogeneous way with agent based-modeling (Poulsen et al. 2015).

Spatial location is another key aspect. Shopping behavior of consumers is highly influenced by spatial location and distance (Vanhaverbeke and Macharis 2011). In urban agriculture scenarios, farms are distributed throughout an urban environment and it would be desirable to reduce transportation overhead and congestion.

There is a large body of work that examines land use patterns and human environment interactions. The concepts and relevant entities share similarities with urban agriculture. As an example, Walsh et al. (2013) model human population and environment interaction in rural settings focusing on relationships between household income and shifts in land use while taking into account a wide variety of endogenous and exogenous factors. Other studies also illustrate benefits of textured models of land use change that use multiple spatial and temporal scales simultaneously (Murray-Rust et al. 2014). The urban environment concentrates many additional systems that also should be considered in modelling human and agriculture interactions and development over time.

Info-Symbiotic or Dynamic Data Driven Application Systems (DDDAS) have been used in other domains as a powerful tool to connect virtual representations of systems with their physical counterparts in real time (Darema 2005). DDDAS provides an adaptive feedback loop framework that covers real-time collection of data for model adaptation and new initial conditions. As ground realities change, streaming data from sensors and external simulations are fed back to continuously refine the models and the simulations. Conversely, simulation outputs can guide data collection. These techniques enable advanced data-driven simulation capabilities that can provide more accurate analysis and prediction through dynamic augmentation of models with dynamic data inputs and can enhance understanding of how social systems respond to policy interventions (Kureshi et al. 2015; Kennedy et al. 2007; Kennedy and Theodoropoulos 2006; Kennedy et al. 2011).

2.2 Knowledge Co-production

Knowledge co-production is a way of generating knowledge in which technical experts and other groups in society produce new knowledge and technologies together, rather than groups with specific expertise deciding what is important for non-experts (Callon 1994). The policies of the United Nations Food and Agriculture Organization recognize the need for technological innovation in agrifood to consider diverse stake holders, including small holders, and to consider issues holistically (e.g., quality, individual preferences, and farmer livelihoods). This is in contrast with past focus on maximizing the amount of food produced (Food 2016). The process of modelling urban agricultural systems can encourage co-production of knowledge by engagement of diverse stakeholders with the modelling process. Stakeholders include policy makers, entrepreneurs, consumers, and producers of all types.

2.3 Complexity of Urban Agriculture

Compared to modelling traditional agriculture, urban agriculture seems more complex mainly because of the need to consider urban systems as well as agricultural, land use, consumer behaviour, and demand. Co-locating producers and consumers of food could also create fluidity between roles of food growers or producers and consumers as occurred in the energy market when consumers started to have a capacity to produce electricity with solar panels and thus become "prosumers" (Kanchev et al. 2011).

There is a limited body of research that studies urban food production and supply specifically. Most related work comprises qualitative studies (see Buehler and Junge 2016; Specht and Sanyé-Mengual 2017; Specht et al. 2014; Warren et al. 2015; Benke and Tomkins 2017; Korth et al. 2014). CoDyre et al. (2015) survey production quantity and requirements for land, labor, and capital in urban farming. A case study of roof-top vegetable production in Bologna finds that roof-top gardening could potentially satisfy 77% of requirements for present inhabitants in that city (Orsini et al. 2014). There are a smaller number of quantitative studies that examine questions related to urban agriculture in terms of measurable quantities. For example, Al-Chalabi (2015) develop a mathematical model to estimate the number of people that vertical farming could support. Another limitation of existing literature is a lack of data on commercial aspects: "there is a reasonable amount of literature available on urban farming that deals with its potential, and its limitations. However, it does not focus on commercial operations" (Buehler and Junge 2016). Recently, some open source initiatives such as Hickem and O'Mara (2019) provide quantitative evaluation in terms of energy, space, and costs at a farm unit level.

Situating agriculture in cities creates layers of complexity that are not present in other agricultural settings. Biological, ecological, social, and economic systems interact together in a concentrated and more dynamic way. It is known that human-natural coupled systems exhibit patterns and processes not evident when studied by considering components in isolation (Liu et al. 2007). Hence, it is necessary to integrate many additional sub-systems together in a coherent meta-model.

3 MODELLING FRAMEWORK

This section describes the proposed framework for modelling urban agricultural systems. The main concepts of the model are production, distribution, market demand, and nutrition. Production creates a "push" dynamic, market demand conversely creates a "pull" dynamic. The model includes the capability

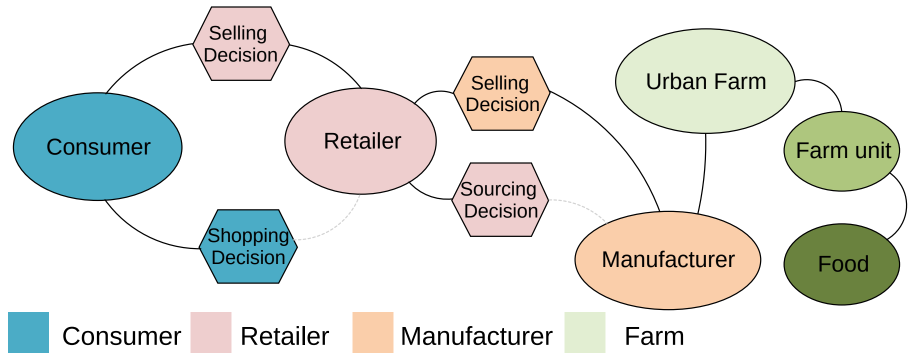


Figure 2: Overview of the framework. In the model, "manufacturers" decide to farm depending on perceived utility.

for consumers and producers to blend roles. Geographic Information Systems (GIS) and demographic characteristics of the urban environment can be included in the farm and agent entities.

Three main types of entity are modelled: farms, retailers, and consumers. A concept of utility assessors allows for specifying various "KPI" measures to evaluate scenarios with regard to economic, social, or environment criteria.

Agent types include producers, consumers, and manufacturers. Passive objects represented include: urban farms, farming-units, and food/produce. Figure 2 summarizes the framework illustrating connections resulting from decision hierarchies and product flow.

The main modules include:

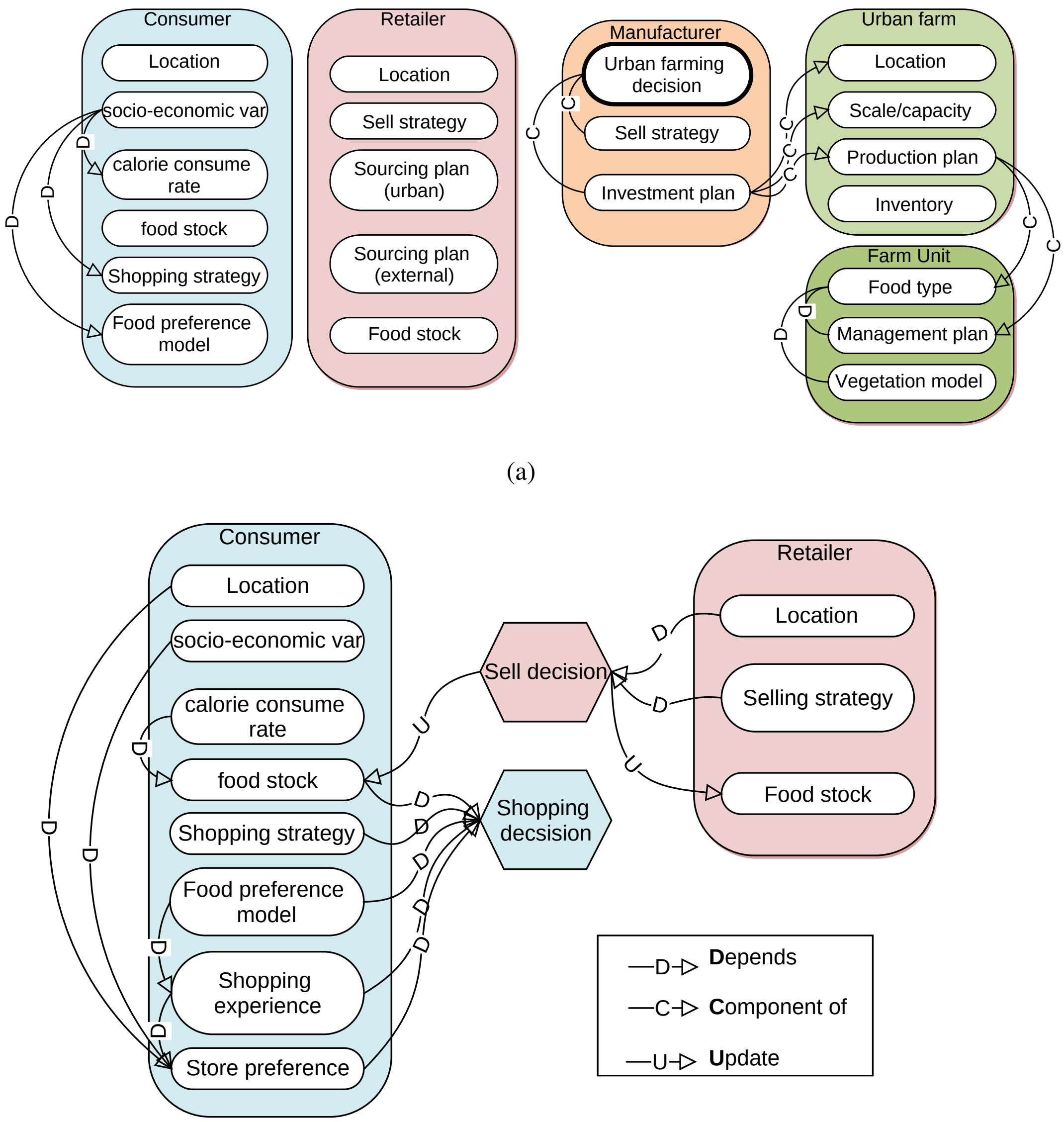
- Initialization module
- Consumer shopping module
- Retailer sourcing module
- Urban farm production module
- Manufacturer update module

Inventory, stock buffers, waste, and spoilage time are handled in what are termed food stock update sub-modules of consumers, retailers, and urban farms. These are scheduled independently but closely linked in order to construct the overall scenario.

3.1 Initialization Module

The initialization module, Figure 3a, is responsible for creating and setting starting values and states of attributes and sub-components of the entities. Urban farms are locations where farming can take place and farm units represent different crops or growing methods at farm locations. A key concept here is the decision by "manufacturers" to invest in farming at farmable locations: the agent's decision depends on the trade-off between resources needed to start a farming venture, and the utility that the manufacturer agent determines they would obtain.

Each consumer agent is assigned a location, an initial food stock, and a type which is associated with parameters such as socio-economic attributes (e.g., gender, age, income level, etc.), calorie consumption rate, shopping strategies, and food preference. Dependency between socio-economic attributes and shopping habits has been studied on other research (Ichiminami and Hoshi 1983; Pechey and Monsivais 2016; Turrell 1998). In the proposed framework, retailer agents are assigned a location, initial food stock, selling strategy, and sourcing plan. For manufacturer agents, a decision for starting an urban farm can be implemented initially as a parameter of the simulation or may be determined to take place as the scenario executes (resulting from the simulation dynamics). Investment plans include location, scale, and a production plan. Urban farms themselves comprise a detailed production plan at the level of farm-units. Vegetation models define crop biological characteristics (Sitch et al. 2003). Food stock refers to inventory, and the concept is generalized to entities from consumers to retailers to farms. In the framework, consumers to initiate shopping expeditions when their individual inventory is depleted to a threshold.



(a)

(b)

Figure 3: Components of initialization (a) and shopping (b) modules.

3.2 Consumer Shopping Module

Consumer shopping decisions, Figure 3b, are derived from individual food preferences. Each shopping decision initiates an interaction between the retailer and the consumer that may result in a selling decision. Retailers receive shopping decisions made by a consumer and then check inventory and selling strategies.

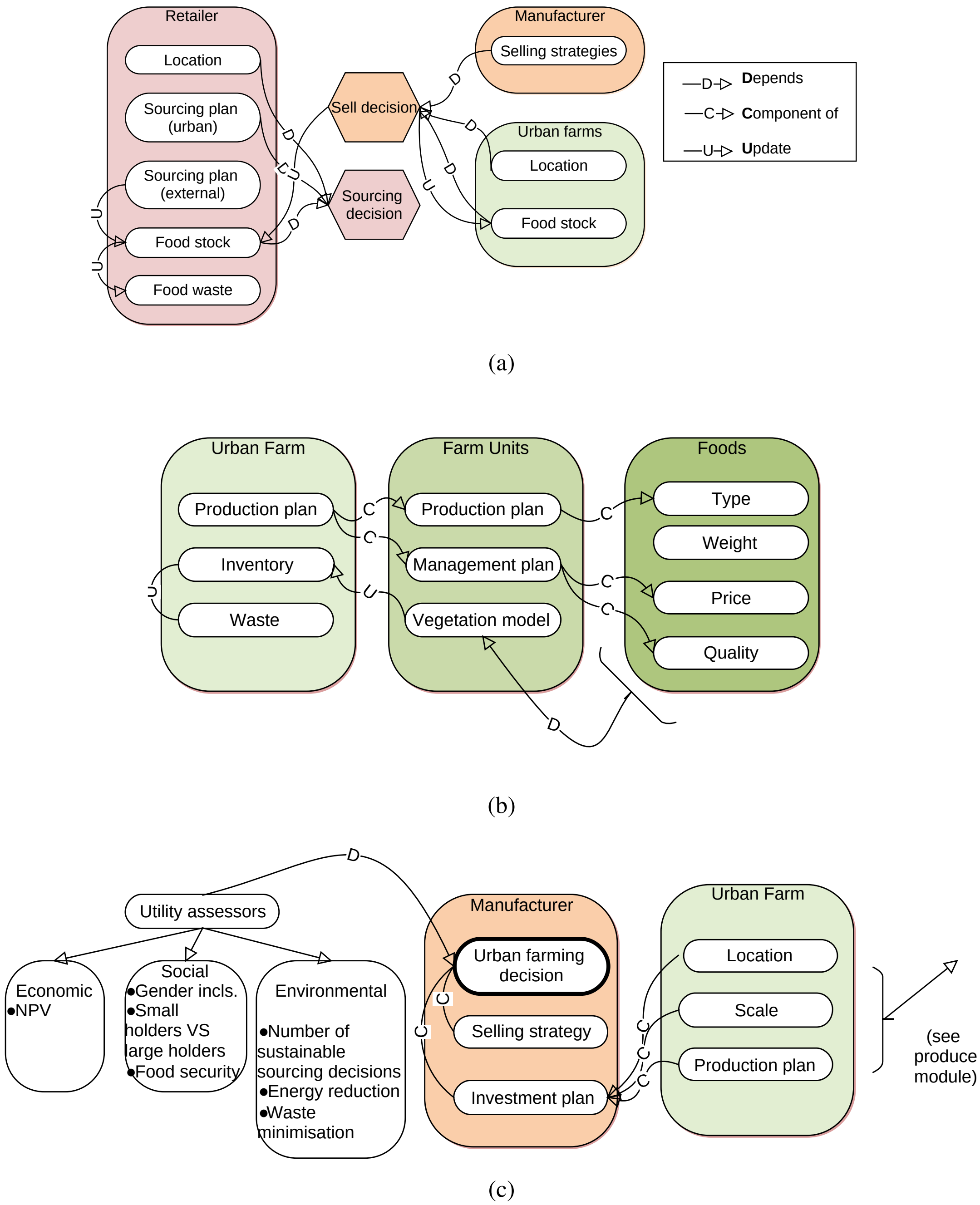


Figure 4: Retail (a), production (b), and manufacturer (c) modules.

Each confirmed shopping decision results in updating consumer shopping experience (in the implementation we rate the shopping experience from the difference between the consumers preferred grocery list and what they actually are able to get). The shopping experience is used to determine store preferences in addition to location and socio-economic attributes along similar lines to Arnold et al. (1983).

3.3 Retailer Sourcing Module

The retailer sourcing module, Figure 4a, controls the process of retailers sourcing farm products. Retailers are an intermediary between farms and consumers. The framework can represent a simple case where produce is directly marketed from farms or a more complex network of grocers and markets. As depicted, within the retailer and farm entities, inventory is transferred to waste based on storage time. Separate sourcing plans are specified for external food sources (e.g., a production schedule could be fixed based on real-world operations). Sourcing decisions depend on marketing plans: pricing, quality information, location, and inventory. Decisions to source trigger a negotiation process between the retailer and a supplier, which – if successful – confirm selling decisions and transactions (the decision "belongs" to manufacturers who control the farms). Manufacturer decisions consider selling strategies and the food inventory in urban farms. Power imbalance and competition between farms or purchasing power of supermarkets or other collectives such as of growers could be considered in the negotiation. Location of farms and retailers is an important consideration. In cities where transportation infrastructure is less developed, or where there are natural obstacles, transportation between some locations may be more expensive.

3.4 Urban Farm Production Module and Manufacturer Update Module

Figure 4b shows the urban farm producing module. Each urban farm is comprised of multiple farming units. A production plan details the operation of production and management for each, individually. The vegetation model defines growth and other properties depending on the type of farm. A plant growth curve can be used to model vegetation as it grows (Murray-Rust et al. 2014) .

The manufacturer update module is shown in Figure 4c. Producers or manufacturers are agents that make decisions to implement urban farming projects based on specific economic or other goals with a utility set by metrics. Farming projects can be initiated in the simulation spontaneously depending on the way producers evaluate projects and conditions that arise.

4 IMPLEMENTATION AND EMPIRICAL STUDY

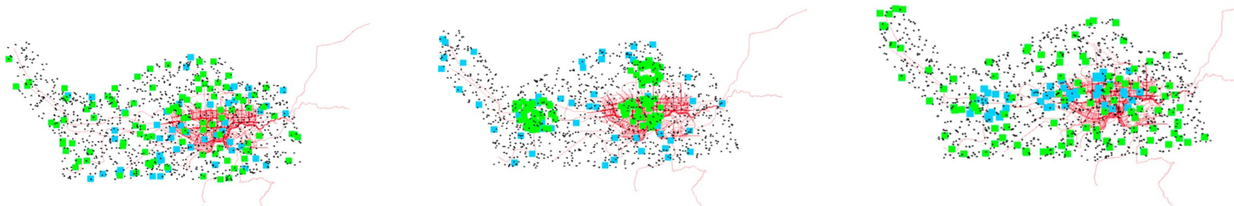
A prototype with demographic and spatial data from the city of Shenzhen, Guangdong Province, China was written using a declarative approach with Repast Simphony (North et al. 2005). Configuration files XML, shapefiles, and CSV set details of the various objects. Utility assessors provide summary data about scenarios. The output metrics were related to consumers, retailers, and urban farms. These metrics include for *Consumers*: overall shopping experience; and for *retailers*: stock level, food waste, fund status, sourcing costs, income, sales records, purchase records; as well as for *urban farms*: inventory, waste, fund status, production cost, energy used, delivery workload, income, sales.

Data used included GIS data for the urban landscape (open source shape file) and demographic information. The following parameters were used in a what-if analysis procedure: *policy* of restrictions on locations of retailers, farms, and farm scale; *food types* including urban and external sources, calories, production pattern, monetary value, and shelf life; *consumer home location* set via a shape file and city census data; *consumer profiles* set using demographic data for sex, socioeconomic status, food preferences, shopping strategies, and store preferences; *retailer* location set from a shape file, and profiles set with stock management plan, sourcing plan and relationships between urban farms predefined; *farm* locations set in a shape file; and farm profiles including inventory, production plans, and crop types pre-configured for the different scenarios.

The source code of these tests is available at https://github.com/drgee1000/urban_farming_abm. The scenarios investigate the spatial distribution of farms and retailers to look at the impact of rules to restrict location; the farm scale, and the effect of co-locating farms with retailers to model farms selling directly to consumers.

Figure 5 shows configurations that test spatial locations of farms and markets. Scenario 1 has farms and retailers distributed evenly throughout the map. Scenario 2 restricts the farms to certain locations.

scenario 3 is the same as scenario 1 with the exception that farms can only interact with retailers within a radius.



(a) (b) (c)

Figure 5: Spatial restrictions on farm location in Shenzhen city scenarios 1-3: (a) random dispersal, (b) concentrations of retailers, and (c) retailers concentrated in a central belt. Green represents urban farm locations and blue retail locations.

Metrics studied relate to *consumers results*: such as consumer satisfaction, defined as the Euclidean distance between consumer preferences for products and the available products at locations, and also the shopping trip distance and time (should be minimized); The *market results*: proportion of food consumed that was grown with urban agriculture; *urban farms results*: cost outputs on average for urban farms, profitability, and cumulative cost of wasted food.

The test scenarios look at effects of varying the number of urban farm projects and altering their production rates and scale (see scenarios 10-13 in Figure 6 for varying the scale of farms). These tests used an equal number of farms with capacities ranging from 1-50 production units per harvest. Additional scenarios looked at variations of the urban farming implementation such as changing retailer sourcing radii (increasing from 5 to 25km in the Shenzhen city map). Here, restricting retailers to interact only with proximate farms results in lower total profit but higher customer satisfaction, also sourcing of produce from urban farms increases. On the other hand, when retailers source produce from a wider area there is increased profit for retailers. The results suggest (given the various assumptions and data used in the model) that to increase the percentage of consumption from urban farms and consumer satisfaction, farms should have higher capacity and be widely distributed in the city with few constraints on movement of product between locations. This also matches general intuition.

5 CONCLUSIONS AND FUTURE WORK

The aim of this paper is in addressing the modelling gap between traditional agriculture simulation and the requirements to support urban agriculture with decision support systems. Modelling, evaluating, and optimizing urban agriculture is a challenging problem, because many different systems and entities interact closely (cities, societies, plants, nutrition, business, and others). The paper reviewed related work, and proposed a new framework for modelling urban agricultural systems. Some initial results are provided, a prototype implementation applies the framework to a scenario based on Shenzhen, China.

In future work, we will extend the prototype implementation with additional data and mechanisms for dynamic updates from live sensors. This will form part of an innovative future food production system that is able to coordinate a diverse network of urban agricultural projects to attain high volume, consistent, as well as highly customized production.

REFERENCES

Al-Chalabi, M. 2015. "Vertical Farming: Skyscraper Sustainability?". *Sustainable Cities and Society* 18:74–77.

Arnold, S. J., T. H. Oum, and D. J. Tigert. 1983. "Determinant Attributes in Retail Patronage: Seasonal, Temporal, Regional, and International Comparisons". *Journal of Marketing Research* 20(2):149–157.

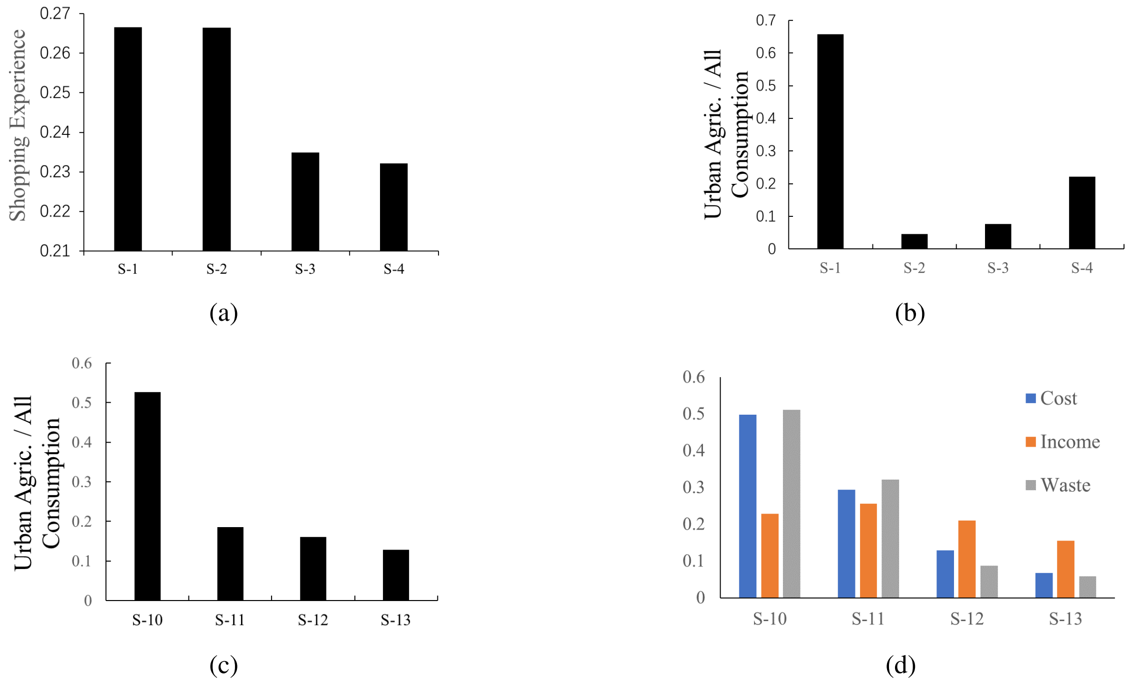


Figure 6: What-if analysis. Scenarios 1 - 4, panels illustrate scenarios configured with different dispersal patterns of farms and retailers: pane (a) shows the consumer shopping experience metric and (b) shows the proportion of all food sold in retailers that sourced from urban agriculture. Scenarios 10 - 13 test having different farm scales: pane (c) shows the food proportion sourced from urban production, and (d) reports metrics of operating expenses, profitability, and wastage for urban farming businesses.

Benke, K., and B. Tomkins. 2017. “Future Food-Production Systems: Vertical Farming and Controlled-Environment Agriculture”. *Sustainability: Science, Practice and Policy* 13(1):13–26.

Bonabeau, E. 2002. “Agent-based Modeling: Methods and Techniques for Simulating Human Systems”. *Proceedings of the National Academy of Sciences* 99(suppl 3):7280–7287.

Bora, H. D., and C. C. Krejci. 2015. “An Agent-based Model of Supplier Management in Regional Food Systems (WIP)”. In *Proceedings of the Conference on Summer Computer Simulation*, edited by S. Mittal and E. Syriani, 514–519. San Diego, CA, USA: Society for Computer Simulation International.

Buehler, D., and R. Junge. 2016. “Global Trends and Current Status of Commercial Urban Rooftop Farming”. *Sustainability* 8(11):1108.

Callon, M. 1994. “Is Science a Public Good? Fifth Mullins Lecture, Virginia Polytechnic Institute, 23 March 1993”. *Science, Technology, & Human Values* 19(4):395–424.

Castelló Ferrer, E., J. Rye, G. Brander, T. Savas, D. Chambers, H. England, and C. Harper. 2019. “Personal Food Computer: A New Device for Controlled-Environment Agriculture”. In *Proceedings of the Future Technologies Conference (FTC) 2018*, edited by K. Arai, R. Bhatia, and S. Kapoor, 1077–1096. Cham: Springer International Publishing.

CoDyre, M., E. D. Fraser, and K. Landman. 2015. “How Does Your Garden Grow? An Empirical Evaluation of the Costs and Potential of Urban Gardening”. *Urban Forestry & Urban Greening* 14(1):72–79.

Darema, F. 2005. “Dynamic Data Driven Applications Systems: New Capabilities for Application Simulations and Measurements”. In *Computational Science – ICCS 2005*, edited by V. S. Sunderam, G. D. van Albada, P. M. A. Sloot, and J. J. Dongarra, 610–615. Berlin, Heidelberg: Springer.

Despommier, D. 2013. “Farming Up the City: The Rise of Urban Vertical Farms”. *Trends in Biotechnology* 31(7):388–389.

Food, F. 2016. “Agriculture: Key to Achieving the 2030 Agenda for Sustainable Development”. *Rome: Food and Agriculture Organization of the United Nations*.

Frazier, I. 2017. “The Vertical Farm”. *The New Yorker*, 9th January.

García, M.-S. G., E. Balsa-Canto, A. A. Alonso, and J. R. Banga. 2006. “Computing Optimal Operating Policies for the Food Industry”. *Journal of Food Engineering* 74(1):13–23.

Ghandar, A., G. Theodoropoulos, B. Zheng, S. Chen, Y. Gong, and M. Zhong. 2018. "A Dynamic Data Driven Application System to Manage Urban Agricultural Ecosystems in Smart Cities". In *2018 4th International Conference on Universal Village (UV)*, 1–7. IEEE.

Hickem, T., and C. O'Mara. 2019. "The Food Wall: Open source Engineering Design Software for Vertical Farming Greenhouse". *https:// www.researchgate.net/ publication/ 335543711_THE_FOOD_WALL_Open_source_Engineering_Design_Software_for_Vertical_Farming_Greenhouse*.

Ichiminami, F., and S. Hoshi. 1983. "On the Relationships Between Socio-economic Characteristics of Consumers and Their Shopping Behavior". *Japanese Journal of Human Geography* 35(3):193–209.

Kanchev, H., D. Lu, F. Colas, V. Lazarov, and B. Francois. 2011. "Energy Management and Operational Planning of a Microgrid with a PV-based Active Generator for Smart Grid Applications". *IEEE Transactions on Industrial Electronics* 58(10):4583–4592.

Kennedy, C., and G. Theodoropoulos. 2006. "Intelligent Management of Data Driven Simulations to Support Model Building in the Social Sciences". In *Computational Science – ICCS 2006*, edited by V. N. Alexandrov, G. D. van Albada, P. M. A. Sloot, and J. Dongarra, 562–569. Berlin, Heidelberg: Springer.

Kennedy, C., G. Theodoropoulos, V. Sorge, E. Ferrari, P. Lee, and C. Skelcher. 2007. "AIMSS: An Architecture for Data Driven Simulations in the Social Sciences". In *Computational Science – ICCS 2007*, edited by Y. Shi, G. D. van Albada, J. Dongarra, and P. M. A. Sloot, 1098–1105. Berlin, Heidelberg: Springer Berlin Heidelberg.

Kennedy, C., G. Theodoropoulos, V. Sorge, E. Ferrari, P. Lee, and C. Skelcher. 2011. "Data driven Simulation to Support Model Building in the Social Sciences". *Journal of Algorithms & Computational Technology* 5(4):561–581.

Korth, M., R. Stewart, L. Langer, N. Madinga, N. R. Da Silva, H. Zaranyika, C. van Rooyen, and T. de Wet. 2014. "What are the Impacts of Urban Agriculture Programs on Food Security in Low and Middle-Income Countries: A Systematic Review". *Environmental Evidence* 3(1):21.

Kureshi, I., G. Theodoropoulos, E. Mangina, G. O'Hare, and J. Roche. 2015. "Towards an Info-Symbiotic Decision Support System for Disaster Risk Management". In *2015 IEEE/ACM 19th International Symposium on Distributed Simulation and Real Time Applications (DS-RT)*, 85–91. Piscataway, NJ: Institute of Electrical and Electronics Engineers, Inc.

Liu, J., T. Dietz, S. R. Carpenter, M. Alberti, C. Folke, E. Moran, A. N. Pell, P. Deadman, T. Kratz, J. Lubchenco, E. Ostrom, Z. Ouyang, W. Provencher, C. L. Redman, S. H. Schneider, and W. W. Taylor. 2007. "Complexity of Coupled Human and Natural Systems". *Science* 317(5844):1513–1516.

Lohrberg, F., L. Lička, L. Scazzosi, and A. Timpe. 2016. *Urban Agriculture Europe*. Jovis, Berlin.

Manos, B., P. Chatzinikolaou, and F. Kiomourtzi. 2013. "Sustainable Optimization of Agricultural Production". *APCBEE Procedia* 5:410–415.

Murray-Rust, D., D. T. Robinson, E. Guillem, E. Karali, and M. Rounsevell. 2014. "An Open Framework for Agent Based Modelling of Agricultural Land use Change". *Environmental Modelling & Software* 61:19–38.

Musa, S. 2018. "Smart Cities-A Road Map for Development". *IEEE Potentials* 37(2):19–23.

North, M. J., T. R. Howe, N. T. Collier, and J. R. Vos. 2005. "The Repast Simphony Runtime System". In *Proceedings of the Agent 2005 Conference on Generative Social Processes, Models, and Mechanisms*, edited by C. M. Macal, M. J. North, and D. Sallach, October 13th-15th, Chicago, Volume 10, 13–15.

North, M. J., C. M. Macal, J. S. Aubin, P. Thimmapuram, M. Bragen, J. Hahn, J. Karr, N. Brigham, M. E. Lacy, and D. Hampton. 2010. "Multiscale Agent-based Consumer Market Modeling". *Complexity* 15(5):37–47.

Orsini, F., D. Gasperi, L. Marchetti, C. Piovene, S. Draghetti, S. Ramazzotti, G. Bazzocchi, and G. Gianquinto. 2014. "Exploring the Production Capacity of Rooftop Gardens (RTGs) in Urban Agriculture: The Potential Impact on Food and Nutrition Security, Biodiversity and other Ecosystem Services in the City of Bologna". *Food Security* 6(6):781–792.

Pechey, R., and P. Monsivais. 2016. "Socioeconomic Inequalities in the Healthiness of Food Choices: Exploring the Contributions of Food Expenditures". *Preventive Medicine* 88:203–209.

Poulsen, M. N., P. R. McNab, M. L. Clayton, and R. A. Neff. 2015. "A Systematic Review of Urban Agriculture and Food Security Impacts in Low-Income Countries". *Food Policy* 55:131–146.

Sitch, S., B. Smith, I. C. Prentice, A. Arneth, A. Bondeau, W. Cramer, J. O. Kaplan, S. Levis, W. Lucht, M. T. Sykes, and S. Venevsky. 2003. "Evaluation of Ecosystem Dynamics, Plant Geography and Terrestrial Carbon Cycling in the LPJ Dynamic Global Vegetation Model". *Global Change Biology* 9(2):161–185.

Smith, A., P. Watkiss, G. Tweddle, A. McKinnon, M. Browne, A. Hunt, C. Treleven, C. Nash, and S. Cross. 2005. "The Validity of Food Miles as an Indicator of Sustainable Development-Final Report". *Report ED50254, AEA Technology Environment, National Academies of Sciences, Engineering, and Medicine, U.S. Department of Transportation*.

Specht, K., and E. Sanyé-Mengual. 2017. "Risks in Urban Rooftop Agriculture: Assessing Stakeholders Perceptions to Ensure Efficient Policymaking". *Environmental Science & Policy* 69:13–21.

Specht, K., R. Siebert, I. Hartmann, U. B. Freisinger, M. Sawicka, A. Werner, S. Thomaier, D. Henckel, H. Walk, and A. Dierich. 2014. "Urban Agriculture of the Future: An Overview of Sustainability Aspects of Food Production in and on Buildings". *Agriculture and Human Values* 31(1):33–51.

Thomaier, S., K. Specht, D. Henckel, A. Dierich, R. Siebert, U. B. Freisinger, and M. Sawicka. 2015. "Farming in and on Urban Buildings: Present Practice and Specific Novelties of Zero-Acreage Farming (ZFarming)". *Renewable Agriculture and Food Systems* 30(1):43–54.

Tsolakis, N. K., C. A. Keramydas, A. K. Toka, D. A. Aidonis, and E. T. Iakovou. 2014. "Agrifood Supply Chain Management: A Comprehensive Hierarchical Decision-Making Framework and a Critical Taxonomy". *Biosystems Engineering* 120:47–64.

Turrell, G. 1998. "Socioeconomic Differences in Food Preference and their Influence on Healthy Food Purchasing Choices". *Journal of Human Nutrition and Dietetics* 11(2):135–149.

Van Der Vorst, J. G., S.-O. Tromp, and D.-J. v. d. Zee. 2009. "Simulation Modelling for Food Supply Chain Redesign; Integrated Decision Making on Product Quality, Sustainability and Logistics". *International Journal of Production Research* 47(23):6611–6631.

Vanhaverbeke, L., and C. Macharis. 2011. "An Agent-based Model of Consumer Mobility in a Retail Environment". *Procedia-Social and Behavioral Sciences* 20:186–196.

Walsh, S. J., G. P. Malanson, B. Entwisle, R. R. Rindfuss, P. J. Mucha, B. W. Heumann, P. M. McDaniel, B. G. Frizzelle, A. M. Verdery, N. E. Williams et al. 2013. "Design of an Agent-based Model to Examine Population–Environment Interactions in Nang Rong District, Thailand". *Applied Geography* 39:183–198.

Wari, E., and W. Zhu. 2016. "A Survey on Metaheuristics for Optimization in Food Manufacturing Industry". *Applied Soft Computing* 46:328–343.

Warren, E., S. Hawkesworth, and C. Knai. 2015. "Investigating the Association Between Urban Agriculture and Food Security, Dietary Diversity, and Nutritional Status: A Systematic Literature Review". *Food Policy* 53:54–66.

World Bank 2017. *ICT in Agriculture : Connecting Smallholders to Knowledge, Networks, and Institutions*.

AUTHOR BIOGRAPHIES

ADAM GHANDAR is an Assistant Professor in the Computer Science and Engineering department at SUSTech. In 2017 he returned to academia after four years as a Principal Scientist at a multinational company, where he mainly worked on open pit mine plan and schedule optimization systems, collaborating closely with customers representing many of the largest mining companies in the world. He is now enjoying developing applications for socially beneficial and interesting applications such as urban agriculture. He is also a member of the IEEE Computational Intelligence Society in Finance and Economics. His email address is aghandar@sustech.edu.cn.

GEORGIOS THEODOROPOULOS is a Chair Professor in the department of Computer Science and Engineering at SUSTech. He joined SUSTech from Durham University, UK, where he was the inaugural Executive Director of the Institute of Advanced Research Computing and held a Chair in the School of Engineering and Computing Sciences. Prior to that he was a Senior Research Scientist with IBM Research. His research work is underpinned by interests and contributions in: Modelling and Distributed Simulation; Complexity and Multi-agent systems; Data intensive computing and Info-Symbiotic Systems; High Performance, Parallel and Distributed Computing; and computational infrastructures for data-driven, prescriptive, System-of-Systems analytics. His email address is theogeorgios@gmail.com.

MINER ZHONG is a graduate student at the University of Queensland getting her Master of Philosophy degree in Civil Engineering (Transportation Engineering). In 2018, she was a research assistant in the department of Computer Science and Engineering at SUSTech. Her research interests include big data analytics and urban mobility prediction. Her email address is miner.transp.seu@gmail.com.

BOWEN ZHEN is a fourth year undergrad at SUSTech. His research interests are deep learning and evolutionary computation. His e-mail address is 11611611@mail.sustech.edu.cn.

SHIJIE CHEN is a fourth year undergrad at SUSTech. His research interests are deep learning and evolutionary computation. His e-mail address is 11612028@mail.sustech.edu.cn.

YUE GONG is a fourth year undergrad at SUSTech. Her research interests are data mining and distributed systems. Her email address is 11611908@mail.sustech.edu.cn.

AYYAZ AHMED is a research officer at the Al-Khawarzami Institute of Computer Science in the University of Engineering and Technology, Lahore, Pakistan. He also worked as Research Intern at SUSTech, Shenzhen, China for 2 months. He won second position in the *Global Huawei ICT Skill Competition 2018*, in which more than 23 countries participated. His main research interest areas are IoT, Telecommunications, Machine Learning, and Simulation. His email address is ayyaz.ahmed@kics.edu.pk.