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The role of food-energy-water nexus analyses in urban growth models for urban sustainability: A review of synergistic framework

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ABSTRACT

The integration of food-energy-water (FEW) sectors is essential for addressing the co-evolution of urban infrastructure systems during urban growth. But how these evolutionary pathways can affect an urban growth model is unclear. This review paper offers a synthesis of the current philosophy of a FEW nexus in connection with the realm of urban growth models (UGMs) to signify the paradigm collision and shift with interdisciplinary sustainability insights. Findings indicate that urban metabolism and urban ecology in relation to FEW sectors can be incorporated into UGMs with scales via multicriteria decision analysis as FEW technology hub integration can play a critical role in UGMs via a common cellular automata (CA) architecture for both model construction and solution procedure. Synergies between FEW sectors and CA-based UGMs as well as tradeoffs across FEW technology hub integration are highlighted to reflect the cascade effects and higher order impact on urban metabolism and urban ecology. This concept was confirmed with a case study in Miami, Florida, the United States for demonstration. Such synergistic framework is helpful for fostering more sustainable, green, smart, forward-looking, environmentally-sound, socially equitable, risk-informed, resilient, and cost-effective urban growth simulations. It is anticipated that the proposed hybrid FEW-CA-based UGMs can fully account for interactions of context- and culture-driven issues for multi-scale and multiagent urban planning and design in different countries.

1. Introduction

The world's population is expected to grow by more than 2 billion by 2050, resulting in a total population of 9.7 billion (UN DESA, 2019). In addition, about 55 % of the total population currently lives in urban areas throughout the world; this number is expected to increase to 68 % by 2050 (UN DESA, 2018). The process of modern urbanization incorporates many driving forces that vary with time and space exhibiting an unprecedented complexity in human history. Such urban growth pathways are also affected by context- and culture-driven factors, including local/regional economic development, globalization effect, resources constraints, mobility potential, demographic and social networks, educational and social equity, consumer behaviors, governance structures and policies, in additon to climate change impact. Economic development driven by population growth is normally the major driving factor of urbanization, as it is related to rapid land use changes leading to a higher concentration of development activities with economies of scale (PBL, 2014). However, this prediction will be constrained by the imbalance of supply and demand of the food, energy, and water (FEW) resources that has been ignored in urban growth models for decades. This modeling gap is due to a lack of understanding of urban metabolism and urban ecology, which elucidates the flow of resources such as energy and material into and out of cities (Athanassiadis, 2020; Djehdian, Chini, Marston, Konar, & Stillwell, 2019; Kennedy, Pincetl, & Bunje, 2011; Maranghi et al., 2020). It is now acknowledged that large-scale technology adaptation and integration given their associated environmental, economic, and socioeconomic impacts may offer a better chance of success in the context of urban sustainability (Chang et al., 2020a, 2020b; Kurian & Ardakanian, 2015).

The emerging concept of the FEW nexus that accounts for the unique interdependence and interconnection of major resource sectors in a region is closely connected to urban sustainability and may deeply affect future urban growth (Kurian & Ardakanian, 2015). At the global level, the agriculture or food production sector is the prime user of the world's

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freshwater resources, accounting for 70 % of total water withdrawals globally (FAO, 2011a); similarly, about 30 % of global energy consumption is used in food supply chains (FAO, 2011b). While the energy sector accounts for 10 % of total global water withdrawals, 3% of total global water consumption is used for primary energy production and electricity generation (IEA, 2016). These global impacts demand better urban FEW infrastructure systems to accommodate critical needs in service industries with the aid of essential governance organization and managerial policies. An unbalanced condition between land resources and population distribution in an unhealthy urban sprawl can cause significant socioeconomic problems, such as resource depletion and loss of ecosystem services (Chen, Li, Liu, Zhang, & Huang, 2019; Radwan, Blackburn, Whyatt, & Atkinson, 2019; Spyra, Inostroza, Hamerla, & Bondaruk, 2019; Wang, Zhou, Pickett, Yu, & Li, 2019). A novel urban systems analysis in relation to the FEW sectors with the integration of knowledge of urbanism is of critical importance for urban sustainability. This triggers a need to create new social-ecological-infrastructure systems (SEIS) in system science, covering all aspects of science, technology, policy, and planning (Chang et al., 2020a, 2020b, Ramaswami et al., 2012). In a SEIS framework, activities and infrastructures of city boundaries would explicitly integrate with transboundary infrastructures in relation to the FEW nexus. The consequences of SEIS for human health and the environment may span from local to regional scales and beyond. Multiple and multiscale risks must be considered in the context of cost-benefit-risk tradeoffs in decision making when performing technology adaptation and integration (Dai et al., 2018; Zhang, Valencia, Gu, Zheng, & Chang, 2020). For instance, a sound FEW nexus analysis can remediate the intertwined issues of local air pollution, urban heat island (UHI) effect, regional air pollution, and global climate change, which are directly related to fossil derived fuels combustion for energy supply and transportation in urban areas. Interdisciplinary sustainability solutions in a sustainable city for counteracting different scales of such impacts can, in turn, mitigate climate change impacts on regional water, carbon, and ecosystem footprints that can affect water supplies directly and food production indirectly (Bibri, 2018; Chang et al., 2020a, 2020b, Hardin et al., 2017; Tsolakis & Anthopoulos, 2015).

Traditional urban growth models (UGMs) consider spatial land-use variation, temporal dimensions of urban processes, and the intensity of human activities, such as population growth and migration (Crols et al., 2012; Radwan et al., 2019; Sante, Garcia, Miranda, & Crecente, 2010). Amid different types of UGMs, the ability of a cellular automata (CA)-based model to deal with complex cross-scale interactions of urban dynamic elements makes it a feasible tool for urban systems analysis, among others (Batty, 2005). The modeling framework of CA-based UGMs is designed to deal with spatial phenomena and incorporates consideration of timesteps into the simulation dynamically, while the agent's role can be emphasized via a multicriteria analysis (MCA) or others to some extent (Chaudhuri & Clarke, 2013; Chen, Wang et al., 2019). With increased recognition of the importance of FEW nexuses in urban systems, it is crucial to consider the urban dynamics associated with different driving forces, roles of agents, and feedbacks from various FEW systems with scales when modeling urban growth. Such considerations require integrating urban FEW systems with CA-based UGMs in MCA that can simulate urban metabolic patterns, optimize the SEIS frameworks, and choose relevant governance structures and policies (Gragg, Anandhi, Jiru, & Usher, 2018). Most importantly, the connection of FEW systems at different scales with UGMs requires understanding the dynamic effects and higher order impacts of urban resource supply chains and consumption patterns as city structure shapes directional resettlement flows oftentimes to help achieve sustainable development goals (SDGs) (Slavko, Glavatskiy, & Prokopenko, 2020).

The objective of this paper is to provide a thorough review of the possible synergistic framework between CA-based UGMs and FEW systems with a numerical sense to demonstrate an emerging field with interdisciplinary solution. It enables us to answer the following research questions: 1) how can urban growth be modeled numerically by considering the drivers and feedbacks of multiscale and multiagent FEW nexuses? 2) what is an essential way in a mathematical construct when integrating the emerging and existing FEW systems in connection to a CA-based UGM? and 3) how can a CA-based UGM in connection with various FEW nexuses be tackled in response to contemporary calls for sustainable urban development? In the following sections of this paper, we will summarize existing UGM frameworks, discuss recent developments and applications of FEW nexus analyses with possible cost-benefit-risk tradeoffs, present possible multiscale and multiagent FEW nexuses in CA-based UGMs (FEW-CA-based-UGMs) with the synergies of existing and emerging FEW nexuses, and pinpoint future research directions.

2. Background of urban growth models

2.1. Review of existing urban growth models

To model the complexity of urban growth, a suite of mathematical models with different problem-oriented approaches was developed to numerically quantify the urban growth processes in the past few decades. They include, but are not limited to, CA-based models, agent-based models (ABMs) (including decision tree models), spatial statistics models (e.g., Markov chain analysis, principle component analysis, linear or multiple regression analysis, and logistic regression), artificial neural network (ANN) models, and fractal-based models (e.g., Giacomoni, Kanta, & Zechman, 2013; Tian & Qiao, 2014; Xu, Haase, Pribadid, & Pauleit, 2018). Meta-analysis enabled us to summarize the chronological progress and status quo of this field development of UGMs (Fig. 1).

In this meta-analysis, about 270 peer-reviewed studies published from 1990 to 2019 were collected and analyzed for the trend analysis. Different keywords, including *urban growth modeling*, *multiscale*, *cellular automata*, *urban growth models*, *supporting models*, *urban predictive models*, *land use in urban*, *urbanization*, *urban dynamics*, and *spatial models* were used to screen and obtain relevant literature. Articles regarding the CA-based models represent the highest percentage (45 %), while 13 %, 12 %, 7 %, and 6 % are related to ABMs, regression analysis (RA) models, Markov chain (MC) models, and system dynamic models (SDM), respectively. However, significant variations in the study of UGMs were observed over time. For example, most of the studies used CA-based modeling in the 1990s, while research on the topic gradually decreased to 58 % in the 2000s, and 37 % in the 2010s. At the same time, the use of ABM, SDM, MCA, and others has been increasing since the 2000s (Fig. 1). Few studies integrated multiple models collectively in one analytical framework for sustainable urban development. Renewed interest has developed regarding the integration between multiscale FEW nexuses and CA-based UGMs, which may spearhead a new thrust of research, although existing ABM, RA, SDM, MCA, and MC can still act as supporting submodels or modules in an integrated modeling framework congruential with the core part of CA-based UGMs.

2.2. Basic CA-based UGMs

The theory of CA was introduced by John von Neumann in the late 1940s through his work developing an abstract model of self-reproduction in biology and simplifying it as a 2-dimensional CA in 1955 (Neumann & Burks, 1966). CA-based models have attracted attention because of their capacity to model and visualize complex processes that are spatially distributed from simple bio-inspired rules (Takeyama & Couclelis, 1997). The elements of a basic CA model include lattice, cell states, neighborhood, transition rules, and time. In CA-based UGMs, states can be: (a) binary values (e.g., different land uses), (b) quantitative values (e.g., population density), or (c) a vector of several attributes (Sante et al., 2010). Another element is the neighborhood around the automata (Torrens, 2000). The neighborhood is defined as the radius of the affected area (Batty, Xie, & Sun, 1999). There

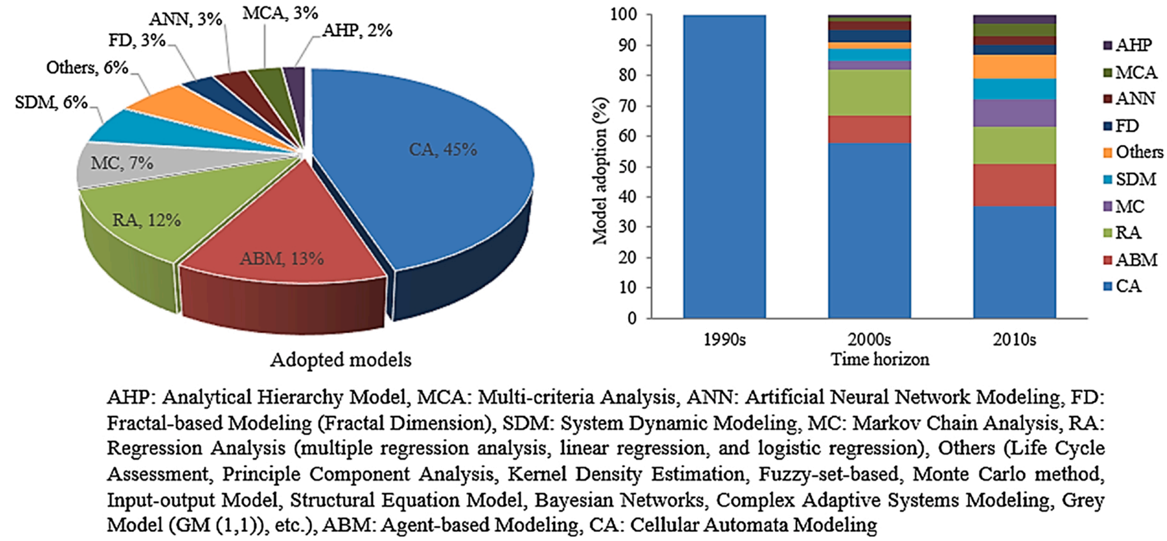

Fig. 1. Urban growth models sorted by (a) popularity (percentage of 270 studies published during 1990-2019); (b) publications of each algorithm in different decades.

are several types of neighborhoods in a 2-dimensional CA, such as: the Von Neumann neighborhood, the Moore Neighborhood, the Margolus neighborhood, the unaligned rectangular neighborhood, the Hexagonal neighborhood, and the small unaligned hexagonal neighborhood. The first two types are more frequently used than others in CA-based UGMs. The engine of changes in a CA-based UGM is transition rules (Jiao, 2003). These rules define the behavior of the automaton (Torrens, 2000).

Cellular automaton can be described as M: (X, S, N, f), in which X is part of the dimensional coordinate space in each cell; S corresponds to the possible set of automaton states; N is the neighborhood template (N={ν_1, ν_2,…, ν_k}); and f is the state transition function described by Eq. (1). The variable S_k^{t+1} represents the cell state at time t and location x+ ν_k.

$$S_k^{t+1} = f(S^t_{x+\nu_1}, \ldots S^t_{x+\nu_k}) \tag{1}$$

A traditional binary CA model is presented in Eq. (2), where S_{ij}^{t+1} represents the cell state at time t + 1; p_{ij}^t (Eq. (3)) corresponds to the probability of transforming the block state at time t, which can be affected by driving factors, constraints, neighborhood factors, and random factors; and p_{thd}^t is the threshold parameter at time t (Liu et al., 2018). The $(P_I)_{ij}$ is the potential for the block to go from non-urban to urban, $(P_\Omega)_{ij}$ is conversion probability, $conc(\cdot)$ are the constraints, and (P_r) is a stochastic variable. Thus, CA can be applied for modeling urban growth dynamics, as the growth process proceeds in each cell depending on the cell state in the neighborhood and is driven by transition rules.

$$S_{ij}^{t+1} = \begin{cases} 1, & if\ p_{ij}^t > p_{thd}^t \\ 0, & else \end{cases} \tag{2}$$

$$P_{ij}^t = (P_I)_{ij}\,(P_\Omega)_{ij}\,(conc(\cdot))(P_r) \tag{3}$$

The core part of a CA-based UGM is transition rules which determine the manner of land use changes from one cell to the next over time. In the file of supplementary materials, a few types of popular transition rules are briefly summarized and explained in Table S1. Characteristics of existing CA-based UGMs such as objective, model input, and growth type are summarized in Table S2, while their advantages and disadvantages are compared in Table S3.

The first step in evaluating a CA-based UGM is identifying the physical and socioeconomic factors that drive land-use/land-cover changes of cities. These driving factors can be either global, regional, or local factors. Global factors focus on recent evolution in cities (e.g., national and international market growth, trade war, extreme weather, immigration, and emigration) (Aguayo, Wiegand, Azocar, Wiegand, & Vega, 2007). However, understanding landscape heterogeneity is also essential for multiscale modeling (Díaz-Varela, Roces-Díaz, & Álvarez-Álvarez, 2016). Local scale factors contribute to the suitability of land for urban development (e.g., land slope, soil, accessibility of transportation systems, land use policy, regional planning strategies) whereas regional drivers provide development trends.

CA-based UGMs have several advantages that make them suitable candidates for modeling urban growth, such as: (1) the capacity to deal with spatial phenomena, especially accounting for the spatial configuration of different cover types, (2) a highly decentralized nature, (3) an affinity with geographic information system and remote sensing to aid in spatial analysis, (4) the capability to handle fine-scale dynamics with computational efficiency, (5) equal attention to space, time, and system attributes, (6) the flexibility to allow multiple timescales to be represented in the simulation, (7) the infusion of complexity theory, (8) simplicity in model architecture, (9) linking macro- to micro-approaches, and (10) easy visualization (Torrens, 2000).

2.3. Synergies with FEW systems

CA-based UGMs provide the best interface and architecture and can accommodate submodels within a sound analytical framework that exhibits an affinity for synergizing the impact from FEW systems linking macro- to micro-approaches. Yet the dynamic nature of the temporal and spatial complexities of urban growth in association with various FEW nexuses makes it difficult to distinguish the function of transition rules and separate the impact of each driving force, transition factor, resource constraint, policy limitation, or governance structure, especially for simulations of multiscale urban growth facing changing decision making arenas (Lu, Chang, & Joyce, 2018). Nevertheless, the modeling capacity of CA-based UGMS for complex urban growth processes can still tackle evolving FEW systems to some extent when some submodels or modules (e.g., an SDM or others) may come to help for eliciting urban metabolism in different functionalized urban areas, as long as relevant transition rules, such as those forming rule 4 to rule 9 in Table S1, can be properly derived. In synergies with some different decision-making conditions, machine learning may even become applicable to learn historical scenarios in evolving FEW nexuses and aid in the creation of representative transition rules.

In certain cities, however, there is a lack of required data for use within the current CA-based UGMs, particularly those in developing countries, and the resultant modeling philosophy is either limited or increasingly complex. Thus, dynamic simulations of urban expansion encounter a series of challenges when using existing CA-based models to address the complexity and diversity of the driving forces of the urban environment and their interactions in a FEW nexus. Hence, the evolutionary versions of existing CA-based models and even a new prototype of a CA-based model were developed under the impact of environmental changes to respond to different needs of cities in the 2010s (Lu, Chang, Joyce, Chen et al., 2018; Wenhui, 2011). Notwithstanding, a CA-based

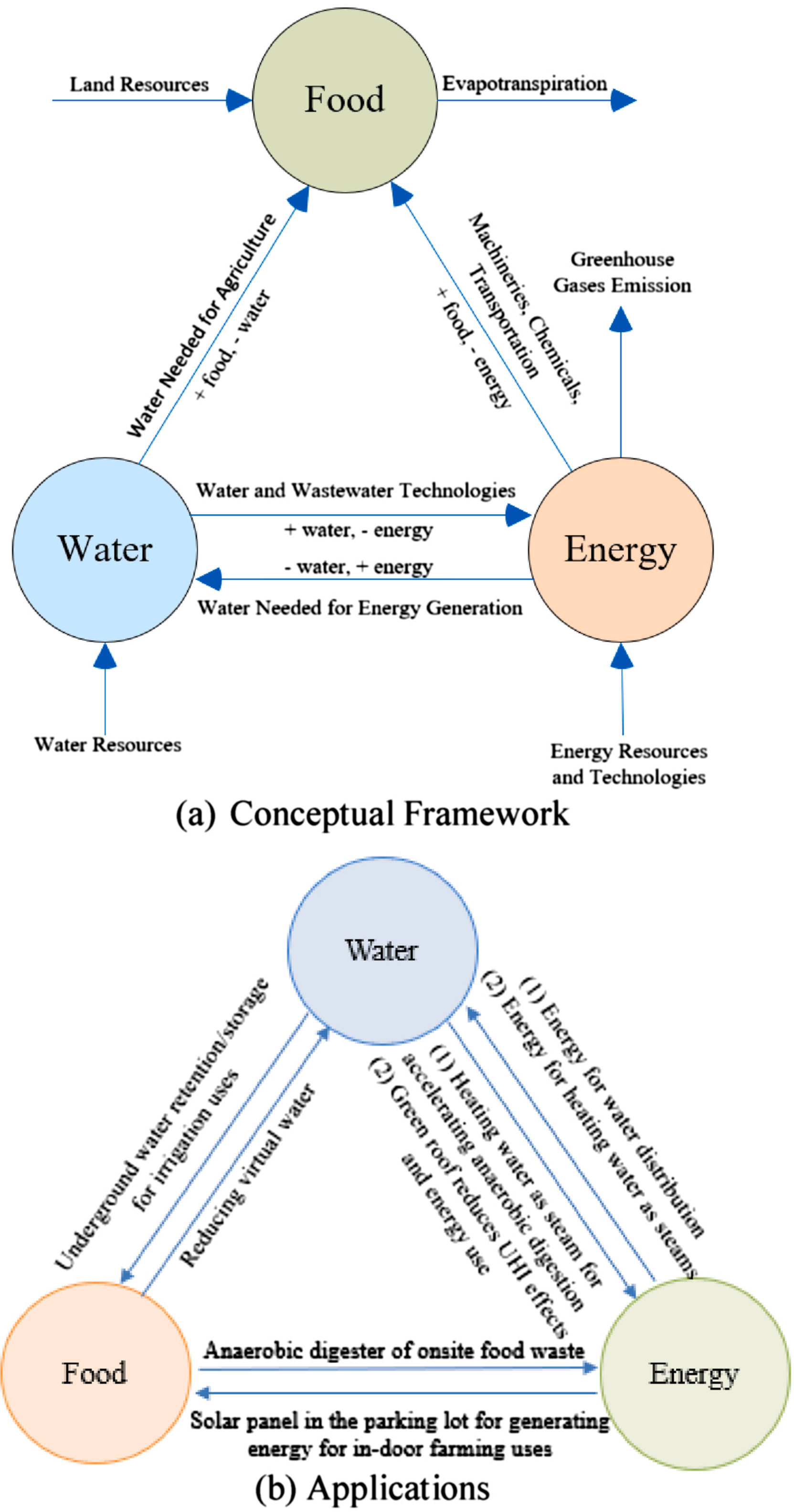

Fig. 2. System framework of a FEW nexus: (a) illustration of the conceptual framework of the FEW nexus and its interlinkages (adapted from Huckleberry & Potts, 2019 with permission) (b) Real world case of technology integration in a FEW nexus and its benefits (i.e., UHI: urban heat island) (Chang et al., 2020a, 2020b).

multiscale and multiagent dynamic modeling system that may enable us to well address urban metabolism has not yet appeared in the "big family" of CA-based UGMs. In the file of supplementary materials, characteristic as well as pros and cons of a few CA-UGMs are briefly summarized and explained in Tables S2 and S3. Integration of the various FEW systems with existing CA-based UGMs has thus become a major research frontier in our scientific community; such integration can allude to both causes and consequences of urban growth and help reconcile the gaps between urban growth and future demands for FEW resources. In the following section, we elaborate on FEW nexus concepts and roadmaps for possible integration with existing CA-based UGMs.

3. The implications of FEW nexus approach

3.1. Incipient stage of FEW nexus

The term nexus was first introduced during the 1980s by the United Nation University (UNU) Food-Energy Nexus Programme (Sachs & Silk, 1990) based on system science theory. This concept is soon connected to the three pillars of sustainable resource management regarding environmental, social, and economic sustainability (Cattano, Nikou, & Klotz, 2011), and attracted scientific interest in the early 2010s (Kulat, Mohtar, & Olivera, 2019). According to the definition from the United Nation University (United Nations University (UNU, 2020):

> "*The nexus approach to environmental resources management examines the interrelatedness and interdependencies of environmental resources and their transitions and fluxes across spatial scales and between compartments. Instead of just looking at individual components, the functioning, productivity, and management of a complex system is taken into consideration.*"

The FEW nexus approach appeared formally in 2011 via the Bonn conference titled '*The Water, Energy, and Food Security Nexus – Solutions for the Green Economy*' - a milestone in international academia and policy circles. Studies began focusing on the nexus approach that can improve water, energy, and food security by integrating management and governance across sectors and scales, reducing unnecessary tradeoffs, and building synergies leading to promote overall sustainability transitioning to green economy (Endo, Tsurita, Burnett, & Orencio, 2017; Hoff, 2011).

In the beginning, the nexus approach was applied to identify and analyze the associated interconnections in FEW systems with interdependent natures at first (Bazilian et al., 2011; Hamdy, Driouech, & Hmid, 2014), as indicated by Huckleberry and Potts (2019) (Fig. 2a). The water-food nexus reflects the water needed for agriculture, as land resources and evapotranspiration come to constrain food production; therefore, the water-energy nexus refers to the relationships between energy required for water and wastewater treatment, as well as water needed for energy generation; the energy-food nexus addresses the interactions wherein energy is consumed to support machineries, transportation, and chemicals for food production at the expense of greenhouse gas (GHG) emissions, although biofuel may possibly aid in energy generation. To consolidate these ideas and make a realistic case, for example, a FEW nexus may involve the optimal integration of technology hubs in association with underground stormwater storage devices, green roofs/roof-top farming, anaerobic digesters, and solar energy harvesting for district heating/hot water distribution as well as food production with feedbacks of food waste for anaerobic digesters to produce biogas toward energy production (Fig. 2b).

To evaluate the synergies of interconnected FEW resources in an urban region with possible cost-benefit-risk tradeoffs, a system engineering-based framework is needed to address the multifaceted challenges in various FEW systems. They are compounded by resource supply and demand with constraints, the type of sustainability indicators selected for decision-making, governance structures and social networks, as well as urban and regional planning policies. All these compounding factors affect urban growth. Recent studies have focused on different perspectives of nexuses to improve individual understanding, including ecosystem services (De Roo et al., 2012; ten Brink et al., 2013), resources eclecticism (Leck, Conway, Bradshaw, & Rees, 2015), process modeling (Garcia & You, 2016), conceptual frameworks with regard to urban/regional context (Foran, 2015), resource security (Allouche, Middleton, & Gyawali, 2015; D'Odorico et al., 2018), and others, such as nexus frameworks, understanding of nexus, governance and policy, decision-making processes, risks and opportunities, possible synergies, and tradeoffs (Bazilian et al., 2011; Bergendahl, Sarkis, & Timko, 2018; Fader, Cranmer, Lawford, & Engel-Cox, 2018; Romero-Lankao, Bruns, & Wiegleb, 2018).

3.2. Studies of FEW nexus with scales

In a recent review, Zhang et al. (2019) estimated a total of 469 related papers from the Web of Science database from 1970 to 2017. The study also related that the majority of these papers were published after the Bonn conference gained extreme popularity. Meanwhile, due to an increasing concern regarding food, water, and energy resources, the FEW nexus has gradually attracted main research interest in the scientific community (Zhang et al., 2019). Identifying and analyzing influential factors may be an effective way to describe and assess the complex FEW relationships in a nexus. Li, Huang, Sun, and Li (2019) developed a conceptual framework for identifying the influential factors of a FEW nexus based on the interpretive structural modeling approach, in which 87 influential factors were identified and classified, and which, in turn, affect urban growth. Some remarkable insights can be found in the following real-world studies as more focal points in different FEW nexuses can be investigated and highlighted below.

By coupling hydrological and crop growth simulation models, Amjath-Babu et al. (2019) developed a hydro-economic model in the transboundary of the Koshi river basin in the Himalayan region to economically optimize FEW systems based on hydroelectric power generation and crop production. Their study observed significant economic benefits from this regional FEW nexus (outweighing US$ 2.3 billion per year, compared to the investment cost of US$ 0.7 billion annually). Falchetta, Gernaat, Hunt, and Sterl (2019) examined the use of hydropower for energy generation in sub-Saharan Africa and its dependence on water availability and climate change. An energy-water-land framework was developed as a tool to safeguard energy security. Besides, by adopting a small-hydropower system, the synergies of the FEW system were evaluated using artificial intelligence in the Shihmen Reservoir and its associated water supply system in Taiwan (Zhou et al., 2019). In this case, water was mainly used for public and agriculture sectors. The study found that optimizing multi-sectoral water allocation could lead to synergistic benefits in the water, food, and energy sectors. For example, water allocation could mitigate the annual water shortage by 40 % and increase the annual food production and energy generation by 10.6 % and 7.5 %, respectively (Zhou et al., 2019). In addition, the use of reclaimed wastewater instead of groundwater and surface freshwater decreases the impact of GHG emissions via increasing the production of lemon, strawberry, avocado, and celery by 7%, 14 %, 9%, and 59 %, respectively (Bell, Stokes-Draut, & Horvath, 2018).

Daher, Hannibal, Portney, and Mohtar (2019), Daher, Lee et al. (2019) highlighted that water resources face multiple challenges in Texas, including increased demand for use in agricultural and energy sectors and urban growth, and thus the gap between water demand and supply is expected to increase 41 % by 2070. Their study identified some potential hotspots in the water-food nexus (e.g., the use of treated water from municipal wastewater treatment plants for dryland farming, adoption of low impact development (LID) options in agriculture, investment in renewable energy, etc.). An example of the interlinkages of LID for irrigation systems and food production with externalities is the reuse of stormwater for food production through the irrigation process, wherein energy is needed for the transport and treatment of irrigation water. The adoption of different LID alternatives in support of irrigation, such as stormwater harvesting, bioretention basin, etc. may improve the system's efficiency and optimize the water and energy use for the irrigation process (Daher, Hannibal et al., 2019; Daher, Lee et al., 2019). The associated externalities affecting the entire system include technology, policy, climate change, and society.

Wicaksono and Kang (2019) proposed a simulation model of a FEW nexus based on a system dynamics concept to simulate the nexus of these three resources for implementing national energy policy changes in South Korea. The model considered the feedback from water, energy, and food sectors with equal weight, and was also capable of identifying influential factors affecting resource availability through feedstock analysis (e.g., interconnection of resources). This type of model can be formulated to address relevant technological and managerial issues at the national level (Wicaksono & Kang, 2019), at the state level (Kulat et al., 2019), or at a city level (Xue, Liu, Casazza, & Ulgiati, 2018). For instance, Kulat et al. (2019) proposed a holistic framework for developing a sustainable scenario for a water-stressed FEW nexus in Texas. Although its focus was primarily placed on water, the interlinkages of other resources were included in the framework in order to quantify the proposed sustainable scenario. The study found that the most sustainable scenarios were associated with infrastructure interventions, including advancing irrigation systems, reusing treated wastewater, building new infrastructure for water storage, improving the cooling system of the power plant, treating brackish groundwater, and adopting solar energy (Fig. 3). The study estimated a \$188-\$239 million annual income from the agriculture sector as well as a potential reduction of the annual water and energy demand by 22 million m^3 and 21 million kWh, respectively.

Liang et al. (2019) assessed the interdependence or interrelatedness of FEW systems by quantifying the materials and flows in the urban FEW nexus in the Detroit Metropolitan Area. The analysis provided four areas for potential improvement, including the maintenance of wastewater collection pipes and the reduction of water utilization in power generation. Despite the economic contribution, there is a paradigm shift that links new urban planning strategies to different sustainable infrastructure transitions based on a FEW nexus approach. Through effective implementation of different intertwined FEW systems in Munich city, more than half of the local demand of fruit and vegetables can be met locally. In addition, about 26 % of the freshwater supply can be reduced by reusing water from a wastewater treatment system coupled with rainwater harvesting, and about 20 % of the current electricity supply can be saved from biogas generated through different sewage systems (Gondhalekar & Ramsauer, 2017). Wang, Fath, and Chen (2019) evaluated the energy–water nexus scenario analysis in China based on future energy scenarios with a focus on total energy generation, non-renewable energy, coal, water pressure, energy-related water, and carbon emission at the national scale. White, Hubacek, Feng, Sun, and Meng (2018) used a multi-regional input-output (IO) approach at the regional scale in a tele-connected FEW nexus analysis in East Asia, and the multi-regional input-output analysis particularly focused on agriculture land use, water scarcity, and emissions of CO_2 and SOx.

While significant contributions of these FEW nexus studies were made possible on the global, trans-boundary, national, and watershed scale, few have focused on the urban scale. Different FEW nexuses have focused on aspects with diverse aims, modeling skills and methods, as well as data requirements and indicators. For example, Moioli et al. (2018) studied the sustainability of bioenergy production under a nexus perspective using generic algorithms based on the data collected from a database - FAOSTAT, World Bank, and other literature, to calculate the nexus index at the global scale. At the local scale, Hanes, Gopalakrishnan, and Bakshi (2018) optimized a food and energy co-production system by employing a mixed-integer linear programming model in an energy-food nexus and highlighted several indicators, such as energy, air quality, water quality, climate regulation, and food production to aid in system optimization. Covarrubias and Boas (2019) discussed the making of a sustainable food city in Barcelona. Very recently, optimal technology hubs integration among the FEW sectors was highlighted by Chang et al. (2020a, 2020b), who categorized technology metrics as either centralized or decentralized to support cost-benefit-risk tradeoffs with respect water, carbon, and ecosystem footprints at the urban scale. The involvement of governments, nonprofits, and private sectors was discussed in a FEW nexus study in terms of comparison between the bottom-up versus top-down approach (Chang et al., 2020a, 2020b; Newell, Goldstein, & Foster, 2019). Thus, integrated urban planning with different FEW nexuses at varying scales can help develop cities with potential synergies of locally available natural resources.

3.3. Cost-benefit-risk tradeoffs in urban FEW nexuses

Functional urban areas are critically important for advancing sustainable development with the aid of FEW systems analysis to address sustainability and resource conservation (Zhang et al., 2019). For

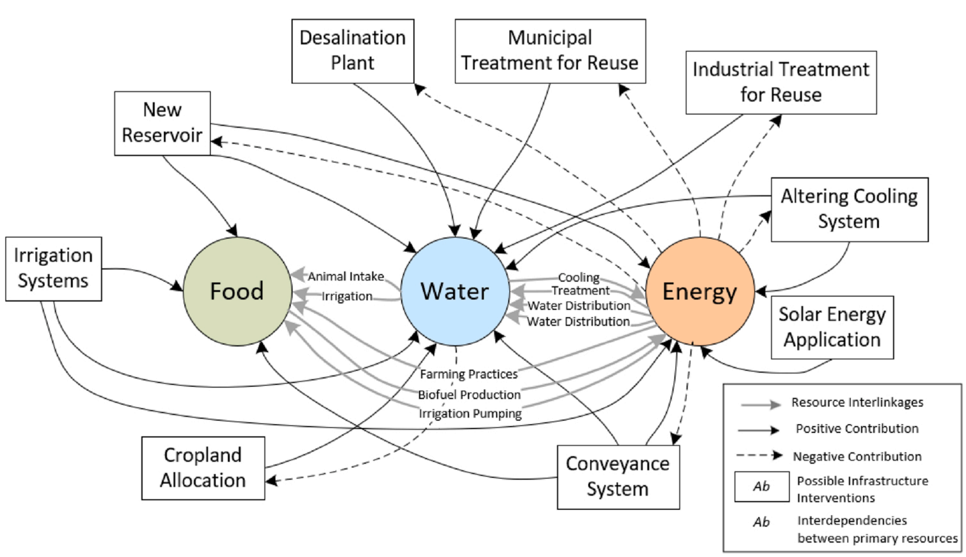

Fig. 3. Infrastructure interventions in a FEW nexus in a case study, Texas (adapted from Kulat et al., 2019 with permission).

example, wastewater treatment and reuse in urban agriculture can reduce GHG emissions, while also directly saving groundwater and freshwater consumption; therefore, a tradeoff does exist in various FEW systems (Miller-Robbie, Ramaswami, & Amerasinghe, 2017). Mohareb et al. (2017) emphasized that benefits such as energy efficiency could be gained through the co-location of urban agriculture operations with different waste streams, including waste heat, emissions of GHG, grey-water, wastewater, compost, etc., while potentially increasing crop yields and reducing pollution impacts compared to conventional agricultural approaches. However, the optimal integration of different urban FEW infrastructures and technologies is an important consideration facing system engineers/scientists, who must consider the impact of such integration on urban growth patterns with different factors and varying constraints. In this context, an appropriate governance structure (e.g., bottom-up, top-down, or mixed) should be constructed within such an infrastructure system, as urban regions struggle to ensure sustainable consumption and distribution patterns of FEW resources when the demand is ever increasing.

Wentz et al. (2018) identified six fundamental aspects of urban form for understanding how urban areas affect and are affected by form, including human constructed elements, the soil-plant continuum, water elements, 2-and-3D space, spatial pattern of urban areas, and time. Therefore, managing complexity in urban growth consists of five levels: policy, actor, behavior, process, and pattern (Fig. 4) with respect to different governance structures (Cheng, Masser, & Ottens, 2003). Policy refers to the most effective factors of urban growth on the macro scale. Actor refers to the agent, and behavior represents the decision made by actors (decision makers). Processes demonstrate the sequence of changes in space (i.e., spatial process) and time (i.e., temporal process) (e.g., land use process, infrastructure expansion process). Pattern is an observable outcome (e.g., developed urban systems), such as centralized ecoindustrial parks (EIPs) versus decentralized ecoindustrial clusters (EICs).

Emerging technological solutions applied to various FEW nexuses with unknown benefit have potential for changing urban growth pathways (Lehmann, 2018). For instance, a network of sensor technologies in concert with the Internet of Things could enhance the operational efficiencies via integrating urban farming (Abegaz, Datta, & Mahajan, 2018) and precision farming (Mekonnen, Burton, Sarwat, & Bhansali, 2018), leading to optimize FEW resources distribution in a timely manner. In this case, information and communication technologies may monitor and control irrigation, electricity consumption, soil moisture, and temperature in smart urban farming for saving energy and water, creating synergies and offering opportunities for minimizing water, carbon, and ecosystem footprints.

More scenario analyses for FEW technology hubs integration with respect to both emerging and existing technologies may result in a suite of possible cost-benefit-risk tradeoffs. For example, a greenhouse is a framed structure with transparent material designed for the optimal cultivation of crops in a controlled or partially controlled environment. Variables for consideration include light, temperature, humidity, moisture, and CO_2 (Asolkar & Bhadade, 2015). A green roof vegetable garden may be employed for backyard farming for producing distinct types of crops, such as fruits and vegetables, under outdoor conditions. Artificial lighting necessary for photosynthesis and controlled environment can be maintained for optimal crop yield at the expense of more energy supply (Kalantari, Tahir, Joni, & Fatemi, 2018). This technology reduces the UHI effect and promotes community involvement, as well as social and economic sustainability (Hui, 2011). More scenarios may arise from the applications of renewable energy technologies, including solar photovoltaic (PV), windmill, and biofuel, which allows for the production of energy that can cover all or part of the urban energy demands. By coupling an energy storage system with renewable energy technologies, the excess energy generated can be stored for future utilization. LID is one of the key technologies in a FEW nexus. Stormwater technologies are divided into distinct types, such as point-based, linear-based, and area-based LID technologies. A common LID is the wet detention pond, designed to attenuate stormwater runoff by storing and collecting runoff, which is therefore used for watershed management and flood control (Harrell & Ranjithan, 2003). Another popular technology is biofiltration systems (rain gardens, biofilters, bioretention systems), which are employed for stormwater quality and flow control by incorporating vegetation, soils, or media mixtures that enhance nutrient removal from sedimentation, adsorption, biological uptake or filtration of runoff (Hatt, Fletcher, & Deletic, 2009). These emerging or existing FEW infrastructure systems could in turn affect urban growth.

Meanwhile, a hypothetical urban FEW nexus that incorporates urban farming, stormwater management, and renewable energy harvesting may be used for demonstration of cost-benefit-risk trade-off below. In Table 1a, alternative 1 proposes a greenhouse system for urban farming with stormwater recycle and reuse aimed for crop irrigation in congruence with solar energy technologies for meeting the necessary energy demands of an urban farming site. Besides food production, the installation of roof-top farming and/or greenhouses can aid in building cooling load reduction by decreasing the temperature inside the building or in the streets, resulting in a reduction of energy cost. An

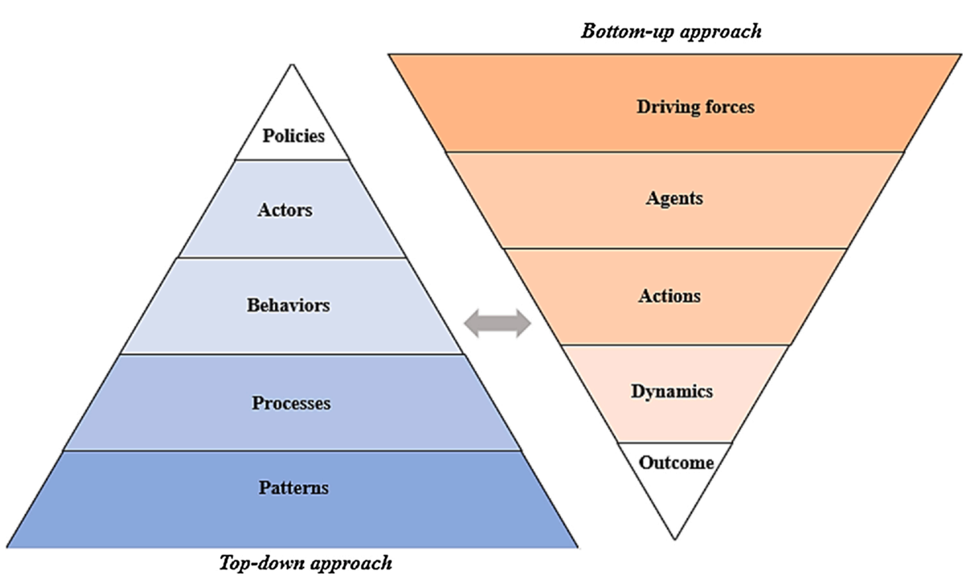

Fig. 4. Levels of systematic perspective to understand urban growth.

Table 1a
Urban FEW System Alternatives (Chang et al., 2020a, 2020b).

FEW System	Food	Energy	Water
Alternative 1	Greenhouse	Solar PV with energy storage	Stormwater storage and harvesting LID technologies (Wet detention pond)
Alternative 2	Green roof vegetable garden	Windmill system with energy storage	Stormwater storage and harvesting LID technologies (biofiltration systems)
Alternative 3	Vertical farming	Biofuels (food and waste-derived-fuel)	Stormwater storage and harvesting LID technologies (pervious pavement)

underground reservoir or an adjacent stormwater wet detention pond can store treated stormwater. The reuse and recirculation of stormwater for irrigation in the FEW system decreases the water demand from surface and groundwater water sources for non-potable water consumption in the agricultural sector. The solar PV can be combined with an energy storage system for carrying out stormwater reuse and essential irrigation in a greenhouse. Any excess energy generated can be either stored in the energy storage system or sold back to the utility grid. Alternative 2 encompasses a green roof vegetable garden with sustained irrigation from a stormwater harvesting and biofiltration system, as well as a windmill system paired with an energy storage unit, whereas alternative 3 incorporates vertical farming sustained by irrigation from a stormwater harvesting and underground storage system via pervious pavement and biofuel production from food. In this system, crops are farmed for biofuel production or local community waste streams are utilized to supply food and waste for biofuel production via anaerobic digesters. These alternatives provide a decision space for multicriteria decision analysis with respect to their associated cost, benefit, and risk factors among multiple stakeholders. Therefore, understanding the cost, benefit, and risk tradeoffs accompanying the integration of a selected FEW nexus alternative supports the decision-making process while rendering a driving force in UGMs for promoting sustainable urban development. A resilient, sustainable, and economically beneficial alternative which minimizes cost and risk and maximizes benefits is desirable. The cost, benefit, and risk associated with the three alternatives in Table 1a are presented in Table 1b, leading to minimize carbon, water, and ecosystem footprints. These multiobjective programming models can be solved through a set of cellular automata-based hybrid methods (Afshar & Hajiabadi, 2019; Afshar & Rohani, 2012; Afshar & Shahidi, 2009). Such synergies between the optimal design of FEW infrastructure and the potential pathways of UGMs via a common cellular automata architecture for both model construction and solution procedure at varying scale are the technical niche in a broader analytical framework of hybrid CA-based UGMs.

4. Driving forces in urban growth processes

Dynamism and urban growth are two common features of urban regions (Barredo, Demicheli, Lavalle, Kasanko, & McCormick, 2004). Dynamism involves urban metabolism and urban ecology, whereas urban growth depends on the stochasticity of an urban system with spatial information and its major urban growth factors (Barredo et al., 2004). Urban development encompasses various physical, geopolitical, and socioeconomic factors, and it is considered a large-scale complex system due to the unknown number of direct and indirect factors and their complex interactions (Li, 2014). Meng, Liu, Liang, Su, and Yang (2019) indicated that about 94 % of existing urban FEW nexus studies focused on only two out of the three sectors, predominantly the energy-water nexus. Sources of complexity in urban growth can be categorized as: (1) spatial complexity, (2) temporal complexity, and (3)

Table 1b
Cost-Benefit Risk Tradeoffs for a FEW System (Chang et al., 2020a, b).

	FEW Resources	Cost	Benefit	Risk
	Food (Greenhouse)	•High capital and O&M costs	•Production is less vulnerable to the environment •Combined with other growing type technologies (vertical farming)	•Continuous maintenance and monitoring
Alternative 1	Energy (Solar PV)	•Requires energy inverter and storage device •High installation cost	•Diverse implementation •Low O&M costs •Reduction of GHG and carbon footprint	•Large ecosystem footprint (e.g. solar PV farm) •Requires sufficient area for PV placement •PV material is fragile •Low energy production efficiency
	Water (Wet detention pond)	•Low or minimal installation costs •Low cost LID technology	•Low O&M costs •Water quality control (pollutant removal) and volume control •Reduces dependence on surface and groundwater sources	•Large ecosystem footprint •Accumulation of pollutants and sediment from stormwater runoff
	Food (Green roof garden)	•Low or minimal installation costs	•Nutrient recycling •Stormwater runoff volume reduction •Reduces water footprint associated with cultivation •Decrease in heat island effect •Building cooling load reduction	•Crop growth competition •Can be time consuming and laborious
Alternative 2	Energy (Wind mill)	•High capital and O&M costs	•High energy production efficiency •Reduction of GHG and carbon footprint	•Noise pollution •Site specific application for energy production •Difficulty in equipment transportation
	Water (Biofiltration system)	•Low capital and operation cost •Low cost LID technology	•Groundwater recharge •Water quality control (nutrient removal) and volume control •Reduces dependence on surface and groundwater sources •Used for landscape and	•Accumulate pollutants from stormwater runoff •Treatment or replacement of soil/ mixture after it is exhausted

(*continued on next page*)

Table 1b (*continued*)

	FEW Resources	Cost	Benefit	Risk
			aesthetic improvements	
Alternative 3	Food (Vertical farming)	•High O&M costs	•Can have small ecosystem footprint •High production yield •Applicable in urban locations •Nutrient recycling •Reduction of irrigation	•Energy consumption •Requires additional technologies and process
	Energy (Biofuels)	•Requires collection and storage units •High investment cost	•Utilization of recycled organic materials and waste •Reduction of GHG and carbon footprint •Alternative transportation fuel	•High water footprint •High ecosystem footprint from deforestation •Promotes competition with food crops •Not applicable at all climates
	Water (Pervious pavement)	•High installation cost	•Restores natural hydrological cycle in urban regions •Water quality control (nutrient removal) and quantity control •Reduces urban heat island effect •Reduces dependence on surface and groundwater sources •Greater durability than porous asphalt	•Possible clogging from accumulation of soil and clay •May be affected by cold climate •Risk of damage from tree roots

decision making complexity (Cheng et al., 2003). The examination of traditional driving forces is also helpful for deepening our understanding of urban growth in different cities with scales. Table 2 summarizes major driving factors including infrastructure systems, demographic level, policy context, transportation, type of economy, available build-up area, type of industry, environment, and topography in different cities to account for different types of urban growth across different continents. The main driving factors shared by most cities are population, policy, transportation, and type of economy. Hosseini and Hajilou (2019) determined 22 factors that drive urban sprawl and development in Iran. In this study, the main 8 factors are the same as the driving factors mentioned in Table 2. However, the level of inclusion of these factors in CA-based UGMs varies with respect to the types of cities.

A list of CA-based UGMs applied in megacities and their corresponding major driving factors are presented in Tables 3a and 4a, respectively. Megacities are defined as urban regions of greater than 10 million inhabitants. Some urban growth factors might not be relevant for an individual megacity simultaneously. For instance, because of the relative flatness (i.e. 0−14 m) of Dhaka, slope or hillshade factor is irrelevant for urban growth. In this case, elevation is considered instead, enabling the determination of which areas are more or less vulnerable to flooding (Ahmed & Bramley, 2015). In addition, distance from water bodies can also determine which areas are vulnerable to flooding (Shafizadeh-Moghadam & Helbich, 2013). However, if the FEW infrastructure systems can mitigate the flooding impact and transfer the flood plains for urban farming, the conventional transition rule needs to be reconsidered in the context of a CA-based UGM. In addition, sea level rise, flood plain, and green infrastructure, which could be linked to local FEW systems, are essential constraints or driving factors of some land use change processes in coastal cities.

Accessibility of transportation systems, which triggers more rural-urban transitions, is another major driving factor for human settlement. For instance, the ring road system in Beijing accelerates the strong attraction of central areas and linear transport systems (e.g., highway and railway) and unifies the city center with outlying districts (Yi, 2009). Therefore, one of the most important factors is the distance to roads, railway, expressway, shoreline, green infrastructure, airport, harbor, or subway. It should be noted that although expansion of underground space and subways speed up urbanization, they are not revealed in satellite imagery and hence are difficult to consider as driving factors (Yi, 2009). Another important driving factor is the distance to city centers, sub-center cities, or town centers. These areas are considered central business districts and can be expected to provide a reasonable range of services and facilities. This driving factor can affect the urban growth of megacities in Dhaka, Sao Paulo, Jakarta, London, Karachi, Rio de Janeiro, Buenos Aires, New York, Mexico City, Moscow, and Paris. Agglomeration factors in urban dynamics indicate areas close to existing built-up sites that are prone to be developed sooner in the future (Shafizadeh-Moghadam & Helbich, 2013).

In parallel, a list of CA-based UGMs applied to small and medium scale cities and their corresponding major driving factors are presented in Tables 3b and 4b, respectively. Small and medium scale cities are defined as urban regions of less than 1 million and 10 million residents, respectively. Urban growth factors are nearly identical from megacities to medium and small-scale cities (Table 4b). In addition, socio-economic factors including per capita income, living space, housing price, unemployment rate, etc. strongly influence the growth of small and medium scale cities (Xu et al., 2018). Based on non-spatial logistic regression, for example, Liao and Wei (2014) found that accessibility, neighborhood, and socioeconomic conditions are significant factors for small and medium scale urban development. In contrast, the ecological land, such as water body, wetland, and grassland, surrounding the city center has a higher transition probability to urban land in fast-growing cities, and this was evidenced by most fast-growing cities in China (Peng et al., 2017). Hence, socioeconomic factors also strongly influence the pattern of urban growth and the associated ecosystem services (Wang, Chen, Zheng, & Deng, 2018). Consequently, intensification of agricultural land use practices, land use changes for settlement expansion, and farmland abandonment could result in declining habitats and significantly reduce ecosystem services (Drobnik, Huber, & Grêt-Regamey, 2017). In addition, the food production and supply and ecosystem services and conservation are severely affected by land use changes in many of the medium scale cities recently upgraded to mega-cities, such as Wuhan in China (Ke et al., 2018). Development was accelerated by two economic development zones, including the Wuhan East Lake High-Tech Development Zone and the Wuhan Optics Valley of China, and thus, the local economy was stimulated by the investments (Wang et al., 2013). The findings show that the existing CA-based UGMs did not critically consider or highlight the importance of FEW technology hubs integration as a key factor for sustainable urban development (Tables 3a, 3b, 4a and 4b).

Overall, only a few studies have argued FEW infrastructures are one of the key driving factors for urban growth in different cities (e.g., Okata

Table 2
The driving factors of urban growth in different cities.

Cities	Urban Growth Factors										Reference Source
	FEW Infrastructures	Population	Policy	Transportation	Type of Economy	Available build-up area	Topography	Environment	Type of Industry	Other	
America (North and South)											
New York		•	•			•					Judd, Simpson, and Abu-lughod (2011)
Los Angeles		•			•				•	(1)	Dong and Zhu (2015), Scott (1998)
City of Arlington		•				•		•			Giacomoni et al. (2013)
Sao Paulo		•	•								Torres, Alves, and Oliveira (2007)
Rio de Janeiro					•						Smyth and Royle (2000), Tolosa (1996)
Mexico City		•							•		Aguilar (1999)
Buenos Aires			•		•						Pirez (2002)
Santiago Metropolitan		•	•	•		•	•	•			Puertas, Henríquez, and Meza (2014)
Asia											
Tokyo	•	•	•	•							Okata and Murayama (2011)
Osaka	•	•			•						Takashi (2011)
Jakarta	•	•			•						Pravitasari et al. (2015)
Delhi		•				•					Dutta and Bandypadhyay (2011)
Mumbai				•		•	•				Shafizadeh-Moghadam and Helbich (2015)
Kolkata		•	•					•			Bhatta (2012), Mukherjee (2013)
Manila		•	•							(2)	Murakami and Palijion (2005)
Shanghai					•	•			•		Zhang, Min, and Fei (2006)
Beijing		•	•		•						Kuang et al. (2009)
Guangzhou		•		•	•						Ma and Xu (2010)
Shenzhen			•		•						Qian, Peng, Luo, Wu, and Du (2016)
Tianjin		•	•		•						Tan, Li, Xie, and Lu (2005)
Chongqing			•		•						Lamia, Edward, and Zhang (2009)
Karachi		•			•						Afir and Massonma (2003)
Dhaka		•			•		•				Dewan and Yamaguchi (2009)
Fuyang City		•	•	•	•	•		•			Zhang et al. (2013)
Jiangxia, Wuhan		•	•	•	•	•	•	•			Wang et al. (2013)
Europe											
Moscow		•			•						Alexandrov, Markov, and Lachininskii (2014)
Paris				•						(3)	Glaeser and Kahn (2004)
Munich city		•			•	•		•			Xu et al. (2018)
London				•		•	•	•	•		Lu, Chang, Joyce, Chen et al. (2018)
Istanbul		•									Kucukmehmetoglu and Geymen (2008)
Africa											
Lagos			•	•							Braimoh and Onishi (2007)
Cairo	•	•	•	•	•						Yousery and Aboul-Atta (1997)
Kinshasa		•		•	•						Matthieu, Maeyer, and Wolff (2012)

Note: (1) Decentralization and Suburbanization, (2) Past colonial rules, (3) Technological change.

Table 3a
List of previous CA-based UGMs applied to megacities.

CA-Model	Mega-city	Reference	Reference source[b]
SLEUTH	New York Metropolitan Region	Esnard and Yang (2002)	(1)
MOLAND	Lagos	Barredo et al. (2004)	(2)
Markov Chain-CA	Dhaka	Islam and Ahmed (2011)	(3)
Markov Chain-CA		Ahmed and Ahmed (2012)	(4)
DINAMICA		Ahmed and Bramley (2015)	(5)
DINAMICA	Sao Paulo	Almeida et al. (2005)	(6)
		Compos, Filho, and Pedro (2015)	(7)
A CA-based Land-use Model	Tokyo	Arai and Akiyama (2004)	(8)
UES[a]	Beijing	He, Okada, Zhang, Shi, and Zhang (2006)	(9)
UED[a]		He, Okada, Zhang, Shi, and Li (2008)	(10)
BUDEM[a]		Long, Mao, and Dang (2009))	(11)
SLEUTH		Yi (2009)	(12)
Ant Colony Optimization-CA	Guangzhou	Li, Lao, Liu, and Chen (2011), Li, Yang, and Liu (2008), Liu, Li, Shi, Wu, and Liu (2008), Wu (1998)	(13)
An Urban CA model			(14)
Kernel-based non-linear CA			(15)
SimLand			(16)
CA-Support Vector Machines	Shenzhen	Yang, Li, and Shi (2008)	(17)
Markov chain-CA	Mumbai	Shafizadeh-Moghadam and Helbich (2013)	(18)
Models based on CA concept	Shanghai	Han, Hayashi, Cao, and Imura (2009)	(19)
Reg-DUEM	Beijing-Tianjin-Tangshan	Wenhui (2011)	(20)
MOLAND	Buenos Aires	Lavalle, Demicheli, Turchini, Casals-Carrasco, and Neiderhuber (2001)	(21)
MOLAND	Chongqing	Lavalle et al. (2001)	(22)
SLEUTH		Huang, Zhang, and Lu (2008)	(23)
MOLAND	New Delhi	Lavalle et al. (2001)	(24)
MOLAND	Mexico City	Lavalle et al. (2001)	(25)
SLEUTH		Gomez (2001)	(26)
MOLAND	Istanbul	Barranco, Silva, Herrera, and Lavalle (2014)	(27)
LANDSCAPE	Wuhan City	Zheng, Ke, Zhou, & Yang, 2019	(28)
LANDSCAPE	Wuhan City	Ke et al. (2018)	(29)

[a] UES: urban expansion scenario; UED: urban expansion dynamic; BUDEM: Beijing urban development model.
[b] These references are prepared for Table 4a.

& Murayama, 2011; Pravitasari, Saizen, Tsutsumida, Rustiadi, & Pribadi, 2015). This gap would lead to identification of the relationships between integrated technology hubs, as well as the balance of resources in supply and demand (Covarrubias, 2019a; Chang et al., 2020a, 2020b; Kaddoura & Khatib, 2017). This type of systems analysis seeks for interdisciplinary sustainability solutions (Dai et al., 2018).

5. Challenges of CA-based UGMs when incorporating FEW systems

5.1. Spatial resolution, spatial configuration, neighborhood type and size

The outcome of a CA-based UGM can be sensitive to: (1) variation in spatial resolution in the case of constant neighborhood size and variable neighborhood type, (2) variation in neighborhood size in the case of constant spatial resolution and neighborhood type, (3) variation in neighborhood type in the case of constant spatial resolution and variable neighborhood size (Kocabas & Dragicevic, 2006). Pan, Roth, Yu, and Doluschitz (2010) showed that small cell size and neighborhood lead to incorrect expression of land-use transition. However, increasing the neighborhood size with a ring shape first increases the precision of the simulation and then decreases once the neighborhood size reaches a certain value. This issue is also intimately linked with urban FEW systems.

Urban sustainability depends on complex and cross-scale metabolic interactions between the built environment and the natural system, regulated by policies and driven by multiple actors, sectors, and institutions that govern infrastructures such as FEW systems. However, the existing CA-based UGMs may not be capable of accounting for the changing FEW systems with different scales, such as building-scale FEW systems, community-scale FEW systems, urban-scale municipal utility parks (MUPs) (Hauck & Parker, 2012), local-scale EICs, and regional-scale EIPs (Liu, Huang, Baetz, Huang, & Zhang, 2019; Schneider, Folkens, Meyer, & Fauk, 2019). Within this context, spatial configuration (e.g., landscape patches, patch shape, spatial clumpiness, and heterogeneity) is another barrier in CA-based UGMs (Herold, Couclelis, & Clarke, 2005; Sohl & Sayler, 2008), as spatial configuration can be affected by spatial allocation of land use transitions via rezoning, and can manifest spatially at the landscape scale. Moreover, spatial interactions among the districts in a city or multiple cities in a region may be another influential factor, and thus should be incorporated into urban growth modeling (Moghadam, Karimi, & Habibi, 2018).

5.2. Resolving conflict between different transition rules

In a real-world urban development process, modelers may come across a situation in which a single cell has different potential values for different land use patterns. Urban-planning modelers usually develop transition rules based on their own ideas and ignore the decision makers' opinions, governance constraints, and policy limitations (Jiao, 2003). To make a CA-based UGM model practical for urban growth prediction, conflict resolution rules, as well as potential transition rules and how such rules can be affected by a FEW nexus, must be considered; currently, these have not been well defined for the final cell state changes (Jiao, 2003).

5.3. Transition rules elicitation

Possible CA-based UGMs can be divided into two categories in terms of causality vs. uncertainty (Fig. 5a) (Ittersum, 1998). Transition rules of the low-causality CA-based UGM do not consider all the influential factors in urban development, and they only include a few people for

Table 3b
List of previous CA-based UGMs applied to medium and small cities.

CA-Model	Name of city	Scale of city	Reference	Reference source[a]
CAS-CA	City of Arlington, Texas	Small	Giacomoni et al. (2013)	(30)
LUC- ESA	Berlin Metropolitan Region	Medium	Lauf et al. (2014)	(31)
MC-CA-RA	Munich city	Medium	Xu et al. (2018)	(32)
MC-CA-RA	Santiago Metropolitan Area	Medium	Puertas et al. (2014)	(33)
Population Surface Modeling and CA	London	Medium	Wu and Martin (2002)	(34)
ABM-LULC	Municipality of Koper	Small	Robinson, Murray-Rust, Rieser, Milicic, and Rounsevell (2012)	(35)
FS-CA; FSMC-CA; cloud-CA model	Jiangxia, Wuhan	Small	Wang et al. (2013)	(36)
ALUAM- DSA	Inner alpine valley, Valais	Small	Drobnik et al. (2017)	(37)
CA-multi-agent modeling	Fuyang City, Zhejiang	Small	Zhang et al. (2013)	(38)
STF and CA-MC	Hefei metropolis	Medium	Lu, Wu et al. (2019)	(39)
CA-MC	Gorges Reservoir Area, Hubei Section	Medium	Chu, Sun, Wang, Li, and Cai (2018)	(40)
CA-based model (Cellular Automata Dual-DraInagE Simulation (CADDIES)	Wallington area in the London Borough of Sutton	Small	Wang, Guo et al. (2018)	(41)
CA-MC-based modeling	London	Medium	Lu, Chang, Joyce, Chen et al. (2018)	(42)
CA-based land use urbanization level (LUUL) simulation	Zhangjiagang city	Medium	Yang, Gan, Li, and Yang (2009)	(43)

[a] These references are prepared for Table 4b.

decision making with respect to urban development processes (Jiao, 2003). However, the transition rules of high-causality CA-based UGM would consider the influence from a large group of decision makers and different urban development factors. The key driver of urban evolution is "transition potential," which is usually calculated as the weighted sum of several urban development factors, including multi-scale factors (Fig. 5b).

Transition potential can be defined using the MCA method (Wu & Webster, 1998; Yu, Chen, Wu, & Khan, 2011), the regression method (Almeida, Monteiro et al., 2003; Lopez, 2014; Munshi, Zuidgeest, Brussel, & van Maarseveen, 2014), weights of evidence (Almeida, Batty et al., 2003), and complex functions. For instance, principal components analysis (PCA), which is considered a complex function, can identify the major factors used in transition rules (Li & Yeh, 2001). Some methods, such as the MCA, also consider cognitive decision-making processes in different ways, such as the use fuzzy set theory. However, there are a few methods, such as ANN, regression method, and distance curve function, that are not able to consider people's decision-making processes. Transition rules elicited from most of these methods lack conflict resolution rules. Some of the existing hybrid CA-based UGMs, along with their implications, are provided in Table 5.

Notwithstanding, the FEW systems in relation to different scales were not highlighted in the afore-mentioned CA-based UGMs. The decision-making process for promoting urban metabolism and urban ecology via synergized FEW systems when technology hubs integration does matter should employ tools and methods that can consider the natural complexity of systems, harmonize relevant variables as time progresses, treat space as the dimension expands, and integrate different spatial domains and scales, and differentiate temporal spans and inherent dynamicity in urbanism. For example, within the philosophy of spatial and temporal domain and scale, EIPs and MUPs can also be regarded as expanded ideas of FEW systems in representative neighborhood cells for sustainable urban planning in CA-based UGMs. Therefore, it is essential to consider how evolving FEW nexuses with cost-benefit-risk tradeoffs can affect existing transition rules and develop novel transition rules in a suite of hybrid CA-based UGMs. Consequently, temporal and spatial complexities of urban systems should be well described by proper transition rules via machine learning tools such as feature learning or representation learning for harmoniums (Jiao, 2003; Le, Zou, Yeung, & Ng, 2011; Taylor, Fergus, LeCun, & Bregler, 2010). Such CA-based UGMs have a great potential to implement better transition rules of high-causality with the aid of machine learning power and can fill in the gaps of existing transition rules by considering explicit infrastructure development pathways.

Improved transition rules of the hybrid CA-based UGMs with respect to driving forces from feedbacks through evolving FEW systems would be helpful for decision-making processes toward sustainable regional planning. These improved transition rules may help reflect the impact from technology hubs integration between emerging and existing technologies, scaling effects from community to region, optimization of resources distribution, as well as the socio-economic policy interventions that were clearly observed on many occasions. More factors can be included through various submodels, including landscape management, regional planning, economic development, ecosystem services requirements, water resources management, etc., all of which can impact the demand and supply of food, water, and energy resources in response to the predicted urban population growth (see Table 5).

5.4. CA-based UGMs associated with urban policy and governance

Urban areas with similar community characteristics (demographics, median household income), and similarities in political institutions and culture can increase the likelihood of building collaborative relationships for policy decisions and effective collaborative governance when more infrastructure systems are considered as major factors and constraints (Hawkins, Hu, & Feiock, 2016; Lee, Lee, & Feiock, 2012). UGMs present a complex multifaceted inter-organizational relationship and help produce shared goals, group decision making, and possible governance structures that are practiced at the local level with implications for the community in an urban environment (Kapucu, 2012). The timescale and the spatial complexity of urban growth makes policy analysis difficult in support of CA-based urban growth simulations because effective modeling of urban growth requires knowledge of complex urban dynamics and their attendant uncertainties. These dynamics under relevant policies and governance structures are especially critical as they are associated with different factors of the FEW nexuses and the capacity to simulate complex interdependencies of urban planning and development processes from local to regional levels. It is important to create a collaborative environment and useful connections and expand these networks of stakeholders for effective policy making and evidence-based decision making.

Greer, Hannibal, and Portney (2020) argued that communication between actors within each policy arena is a critical component of FEW nexus governance, as it was evident that siloed communication in a polycentric and fragmented system could result in inefficient resource management and sustainability efforts. Collaborative motives seem to yield greater results and more desirable outcomes that benefit all actors

Table 4a
List of detailed urban growth driving forces in different megacities.

Megacity	Reference source	Urban Growth Factors													
		Distance to central city	Distance to sub-center cities/ new cities	Distance to large town centers/ services and facilities	Distance to small town center	Distance to subway	Distance to express-way /Highway /ring roads	Distance to Airport	Distance to railway	Distance to waterbody /wetland/ harbor	Slope	Elevation	Restricted Area	Distance from built-up area	Zoning
Lagos	(2)						•								•
Dhaka	(5)	•		•	•		•					•	•		
Sao Paulo	(6)		•	•	•										
Tokyo	(8)						•								
Beijing	(9)	•					•	•	•		•				
	(10)	•	•	•			•	•	•		•				
	(11)	•	•	•	•		•			•			•		
	(12)						•				•		•		
Guangzhou	(14)	•	•	•	•	•	•		•			•			
	(15)			•	•		•		•			•		•	
Shenzhen	(17)	•	•	•			•		•						
Mumbai	(18)						•			•	•			•	
Shanghai	(19)	•	•				•	•		•	•	•			
Beijing-Tianjin-Tangshan	(20)	•	•				•		•	•	•	•	•		
Chongqing	(23)						•				•	•	•		
Wuhan	(28)			•	•	•	•	•	•	•	•	•	•	•	•
Wuhan	(29)			•	•	•	•		•	•	•	•		•	

•Indicates that the factor given in the corresponding column was considered in the model developed for the study given in the corresponding row. Reference sources were obtained from the reference source column in Table 3a.

Table 4b
List of detailed urban growth driving factors in different medium and small cities.

Megacity	Reference source	Urban Growth Factors													
		Distance to central city	Distance to sub-center cities/ new cities	Distance to large town centers/ services and facilities	Distance to small town center	Distance to subway	Distance to express-way /Highway /ring roads	Distance to Airport	Distance to railway	Distance to waterbody /wetland/ harbor	Slope	Elevation	Restricted Area	Distance from built-up area	Zoning
City of Arlington	(30)									•			•	•	•
Berlin Metropolitan	(31)	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Munich city	(32)									•			•	•	•
Santiago Metropolitan	(33)	•	•	•	•		•			•	•	•	•	•	•
London	(34)	•		•			•								
Municipality of Koper	(35)	•		•	•	•	•		•	•		•	•	•	•
Jiangxia, Wuhan	(36)	•	•	•	•	•	•	•	•	•	•	•		•	•
Inner alpine valley	(37)	•	•	•			•			•	•	•	•	•	•
Fuyang City	(38)						•		•	•				•	
Hefei metropolis	(39)									•			•	•	•
Gorges Reservoir Area	(40)	•	•	•	•	•	•	•	•	•	•	•	•	•	•
Wallington area in the London Borough of Sutton	(41)									•		•		•	•
London	(42)	•	•	•	•	•	•	•	•		•			•	•
Zhangjiagang city	(43)						•			•			•	•	•

•Indicates that the factor given in the corresponding column was considered in the model developed for the study given in the corresponding row. Reference sources were obtained from the reference source column in Table 3b.

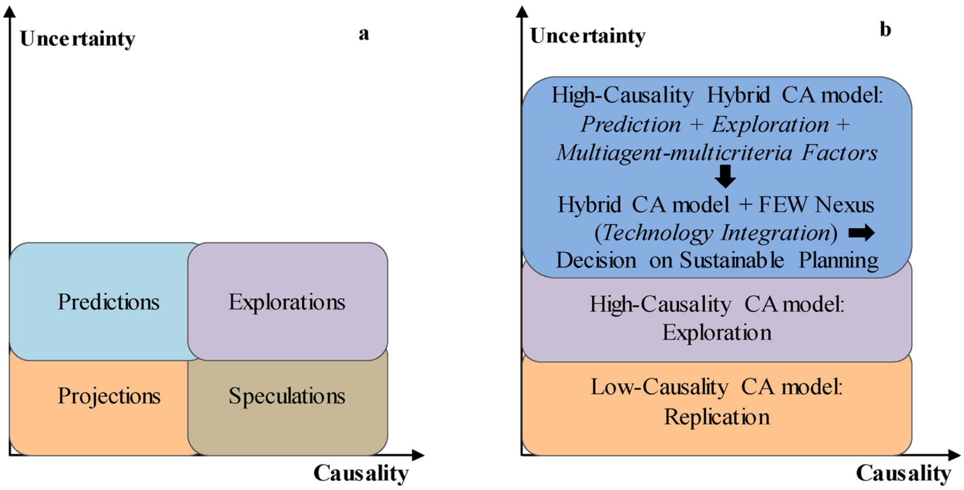

Fig. 5. (a) Different types of land use studies based on uncertainty and causality; (b) possible CA models based on uncertainty and causality (Ittersum, 1998; Jiao, 2003).

collectively. Establishing collaboration is not free of challenges, as it takes time, trust, leadership, and commitment to common goals (Ivanova, Gordon, & Roy, 2007; Lee, Feiock, & Lee, 2012). This is especially critical in privatization processes that were undertaken around the world through various public-private partnerships. Effective collaboration among actors in a FEW nexus can help expand their relation to other areas, as networks involve a multiplexity of relationships across tools, actors, and management strategies (Kapucu & Hu, 2020). Lemaire and Provan (2017) emphasized the importance of the ties of members to influential actors in collaborative networks. Those that would not cooperate if left alone can become stronger participants when they are connected to the lead or influential actor in the network.

Before creating a collaborative network for sustainability specific to a FEW nexus to serve a particular urban area or region, the measures that may decrease the transaction cost and increase social capital should be considered. Feiock, Steinacker, and Park (2009) emphasized that the cost of interlocal cooperation in urban areas is influenced by the characteristics of regional government networks, political institutions in the area, and demographic nature of the community. Economic homogeneity of cities, competition among network nodes, and interactions between members before the establishment of the network are among the factors that contribute to the social capital within a network. This collaborative ecosystem involves actors, including community members and citizens and their multiplex dynamic relationships, along with other environmental factors, in facilitating information and resources sharing with reduced transaction costs (Compion et al., 2015; Smith & Huntsman, 1997; Varda, 2011). Therefore, modern developments in urbanization require a novel urban policy to establish community partners as well as key stakeholders in an urban setting (John & Christopher, 2000).

5.5. Decision making for sustainable development via hybrid CA-based UGMs

Uncertainties within CA-based UGMs can be tied to different aspects such as transition rules, neighborhood configuration, simulation time, and stochastic variables (Yeh & Li, 2006). Sources of uncertainties include: (1) uncertainties from multiple data sources, (2) uncertainties from the elicitation of transition rules, (3) direct and indirect impacts from policy and regulations, (4) multiple decision makers, (5) changing behavioral patterns, (6) scaling issues, and (7) model uncertainties in different hybrid CA-based modeling frameworks.

It is worthwhile to mention that behavioral decision-making via the involvement of stakeholders or policy makers may also be addressed in the proposed FEW-CA-based-UGMs, as the context of FEW policies intended to reduce the use of these resources from a perspective of sustainable development can be thoroughly considered. In such a context, for instance, it is possible to determine the best method for encouraging behavioral changes toward sustainable development and to create a policy for material recycling, recovery, and reuse via a centralized governance structure, such as the USEPA P3 and Total Maximum Daily Load programs. Quantification of existing levels of communication of both researchers and regional stakeholders with identified FEW organizations in the San Antonio region (Texas) can also testify to the feasibility of incorporating behavioral decision-making in a multiagent framework (Daher, Hannibal, Mohtar, & Portney, 2020).

While the role of communication in managing complex FEW governance systems is critical, learning systems with the aid of artificial intelligent have drawn wide attention. When Kennedy et al. (2007) developed a simulation assistance system called Adaptive Intelligent Model-building for Social Science (AIMM) that contains machine learning algorithms to aid in communication became a new focus of research and development. Cao et al. (2011) further introduced the term ‘agent-mining’ to address the interactions between agents and data mining. Therefore, various behavioral interventions (e.g., economic measures, regulations, social communication or enlightenment, or public involvement) may be examined by machine learning or data mining techniques with respect to proper behavioral change theories (Michie, van Stralen, & West, 2011; Michie, Hardeman, & Eccles, 2008). For such behavioral changes, a decision-making process that formalizes the multiagent interaction is more important than system equilibrium that could, in turn, affect the decision making with different scales (Fig. 6). In this decision-making process, there are some stakeholders involved in the decision-making arena, who could be influenced by bureaucratic indifference or motivated by a learning alliance. While some feel that they could lose if something happens, nobody gains unless it is a huge success in a negotiation or even matchup gaming. This is especially true in the decentralization that attempts to result in delegation of many missions from higher to lower tiers of government entities and heighten competition among local governments for central fiscal transfers while having cooperation for management of shared resources (Kurian & Ardakanian, 2015).

A mathematical construct to address such multiagent decision making process would help elicit the bottom up approach. For instance, to address the uncertain impact of climate change on urban growth, Lu, Chang, Joyce, Chen et al. (2018) conducted an integrated model to elucidate the spatiotemporal relationship of urban growth by coupling CA and Markov chain with the aid of a decision-support module. With this foundation, the MCA–weighted linear combination (MCA-LC) can

Table 5
Hybrid CA-based UGMs for sustainable urban planning.

Hybrid Model	Models integrated	Example of study	Scope of study	Implications	Challenges	References
Complex adaptive system (CAS) Modeling; TerraME modeling	CA, ABM, and SDM	City of Arlington, Texas; Brazilian Amazon	Urban water resource systems and urbanization using an integrated complex adaptive systems approach. TerraME is an open access tool that can be used in multi-scale modeling of human-environmental systems by combining ABM, CA, and SDM modeling.	•Includes several components such as land use change, watershed model, water demand, hydrologic process, housing, population growth, etc. •Simple structures and flexibility to represent spatiotemporal dynamics. •Suitable for representing complexity in land systems and able to represent agent heterogeneity.	•Limited set of interactions for a specific resource (e.g., water systems). •Optimization, i.e., the optimal design for water and land use was not considered for long term sustainability of urban water resources. •Computational constraints and limited empirical resources.	de Senna Carneiro et al. (2013), Giacomoni et al. (2013)
Land-use change and ecosystem service assessment (LUC-ESA) Modeling	CA, MCA and SDM	Berlin Metropolitan Region, Germany	Ecosystem services for analysing urban growth and shrinkage scenarios.	•Integrates land use with energy supply, food supply, surface emission, carbon storage, thermal emission and bioclimate comfort, and recreations. •Indicates that land-use transitions from arable land to non-residential uses (e.g., public and private services) most significantly affect ecosystem services. •Simple structures and flexibility to represent spatiotemporal dynamics.	•The adopted model needs to be tested and validated in different regions. •Water resource planning is not considered in the models. •Further efforts are needed for dynamics of parameters. •System dynamics model needs mass information as limited sets of variables are considered. •Computational constraints and limited empirical resources.	Lauf et al. (2014)
Fractal dimension- RA models (FD-RA)	FD and RA	Gold Coast City, Queensland, Australia	Quantitatively assessed the scale effect on landscape patterns using FD-RA models for better understanding the landscape patterns	•Quantifies the effects of changing spatial scales on landscape metrics. •Predicts by extrapolating the historical data.	•Limited to a landscape variable. •Spatial scale range, scale independent interval, and multifractal spectrum in the scale effects needs to integrate in landscape analysis.	Feng and Liu (2015)
CA-multi-agent system (CA-MAS) Modeling	CA and ABM	Tianjin metropolitan region, China	Simulates spatial and temporal dynamics of urban expansion and land use on a regional scale.	•Simple structures and flexibility to represent spatiotemporal dynamics. •Integrates several components including croplands, water bodies, urban lands, rural residential lands, construction lands, un-used lands, etc. •Croplands are the areas most affected by the urban expansion.	•Strong influence of socio-economic variables and dynamism on UGM. •Time domain scenario analysis with landscape patterns are needed to be integrated. •The adopted model needs to be tested and validated in different regions.	Tian et al. (2016)
Integrated urban dynamic modeling based on autologistic RA and MC-CA	CA, MC and RA	Munich city, Germany; Santiago Metropolitan Area, Chile	Analyses urban dynamics based on spatial land use, and then its impacts on green space.	•Multiple scenarios can be evaluated based on urban dynamic modeling. •Predicts by extrapolating the historical data. •Included settlement, gardens, parks, forest, water bodies, etc. •Compact growth was most favorable in terms of green space equity at both regional and local scales. •Urban development and land use change. •Simple structures and flexibility to represent spatiotemporal dynamics.	•Urban dynamic scenario modeling approach was based on only urban green space. •Precise information, i.e. population density, is needed in the model, otherwise, it may induce certain errors when calculating urban green space equity. •Other factors including socio-economic variables need to be included for MCA. •Computational constraints and limited empirical resources.	Puertas et al. (2014), Xu et al. (2018)
Multi-Objective Programming and the Dyna-CLUE model based on Grey model and RA	Grey model (GM (1,1)) and RA	Wuhan city, China	Projected land use changes and ecosystem services with different scenarios through adopting hybrid model based on the Grey model and RA.	•The study concluded that the urbanized area will be increased to 96 %, resulting in the decrease by 18 % of the ecological lands and ecosystem services by 11 % by 2030.	•Optimization is needed in such a model for better understanding the land use changes and ecosystem services. •Computational constraints.	Wang, Li et al. (2018)

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Table 5 (*continued*)

Hybrid Model	Models integrated	Example of study	Scope of study	Implications	Challenges	References
				•Predicts by extrapolating the historical data.		
Urban metabolism and life cycle assessment (UM-LCA)	SDM and LCA	Lisbon, Portugal	Integrated system dynamics UGM based on lifecycle thinking to improve sustainable urban planning.	•Energy use and carbon metabolism, and urban planning.	•Complexity in defining the system boundary as urban system is open, inflows and outflows of materials. •Difficult to include socio-economic factors, hydrological dynamics, land use changes, housing dynamics, etc. •MCA-SDM based UM-LCA is needed for comprehensiveness and robustness.	Elliot et al. (2018)
The Land Use Scenario Dynamics-urban (LUSD-urban) model	CA and SDM	Beijing-Tianjin-Hebei (BTH) urban agglomeration, China; northern China	Simulated the urban expansion in the BTH with the potential impacts on ecosystem services based on the LUSD model (a CA based SDM model); Evaluated climate change impacts on urban growth and expansion in Northern China.	•Included several components such as urban expansion, food production, carbon storage, water retention, and air purification, cropland conversion, etc. •Ecosystem services can lose 83.66–97.11 % of the total losses due to the urban conversion of lands in BTH regions. •Simple structures and flexibility to represent spatiotemporal dynamics.	•Limited ecosystem services were considered into the models. •Future socio-economic and policy interventions were not included. •Socio-economic driving mechanisms, land use policy, urban planning and urban land suitability were not considered in future climate change impact model. In addition, complex dynamic water resources consideration is needed instead of linear based modeling.	He et al. (2017), Liu, Huang et al. (2019), Liu, Yamg et al. (2019), Zhang et al. (2017)
Integrated GIS, SD and 3D visualization (GISSD) modeling	AHP, SDM and MCA	Stuttgart Region, Germany	GISSD was developed for assessing the sustainability of urban residential development, spatial distribution, and decision-making processes based on AHP and MCA.	•Considered comprehensive economic-environmental-social variables. •Can be used as decision-support modeling tool for urban residential development based on the criteria developed and adopted in the modeling approach.	•Focused on residential development only. •Evaluation and aggregation of indicators, and weighting for factors, are challenging in such a method. •Computational constraints and limited empirical resources.	Xu and Coors (2012)
Spatial simulations for urban systems (SimUSys)	SDM, ABM and RA	Herdecke, Germany	SimUSys is developed based on SDM-ABM and RA for smaller urban administrations for UGM modeling.	•Quantitively assessed several interconnected entities such as social, environmental, and technical within an urban region. •Easy to use a web-based user interface that includes data such as environment and services, networks, planning entities, etc. •User friendly as no special knowledge is required.	•Applicable to small scale urban regions. Complicated modeling, and thus, knowledge of several modeling and integration approaches is required for this hybrid model. •Computational constraints and limited empirical resources.	Mueller et al. (2018)
ABM based land-use and land-cover change (ABM-LULC)	ABM, CA and RA	Municipality of Koper, Slovenia	ABM based hybrid model consisting of CA and RA was used to model the decision-making strategies of different agents for UGMs.	•Suitable for multi-agent decision-making process. •Integrates land use, infrastructural facilities, noise pollution, etc. into the model.	•Limited set of variables was considered. •Trade-off between multiple resources system with diverse agents and indicators is needed to integrate in ABM-LULC models.	Robinson et al. (2012); Sohl and Claggett (2013)
The Logic Scoring of Preference-ABM (LSP-ABM)	MCA and ABM	Clayton-Cloverdale neighbourhood, BC, Canada	LSP-AMB hybrid model was used to simulate land-use change in supporting the decision-making process.	•Multiple agents, such as city planner, developers, residents, etc. •LSP can capture different agents in the decision-making process through a wide range of input variables and scoring based on preference. •The model showed that residents' intention of choosing mid- to high-rise buildings is highest for a longer time period.	•Model validation and verification associated with agents' reasoning is needed for enhancing the LSP-ABM geosimulation models. •The selection of input variables, scoring techniques, and integration is a challenging task for this model.	Dragicevic and Hatch (2018)

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Table 5 (*continued*)

Hybrid Model	Models integrated	Example of study	Scope of study	Implications	Challenges	References
Hybrid CA model based on fuzzy set (FS-CA) and the fuzzy set-Monte Carlo method (FSMC-CA), and cloud-CA model	CA and Others	Jiangxia, Wuhan, China	Hybrid CA-based models were used in simulating the urban expansion and associate uncertainties.	•Case study results showed that the cloud-CA model has the better performance (simulation accuracies) than the CA-FS and FSMC-CA models.	•Limited ability to integrate socio-economic networks. •Socio-economic factors, including the spatial pattern of urban expansion, are lacking in the model, and thus are needed to integrate comprehensively.	Wang et al. (2013)
Multi-model's hybrid UGM	ABM, AHP, MC and RA	Guangzhou metropolitan area, China	Hybrid model integrating ABM-AHP and RA-MC was used to analyse the decision-making process based on complex urban dynamic systems.	•AHP was used to simulate the behavior of different agents including residents, regional authorities, developers, and farmers in decision making. •For acquiring the agent preferences and their interactions to determine the driving factors, pairwise comparisons were used.	•The classification of agents, integration of multiple agents based on classification and agent-based spatial model, are needed for further improvement of the model. •Computational constraints and limited empirical resources.	Tian and Qiao (2014)
Land Change Modeler for Ecological Sustainability model (LCM)	MC and RA	Rennes metropolitan, France	Land transition from agricultural to urban area was studied by adopting the LCM based on multi-layer perceptron neural network and RA-MC.	•Integrates change analysis, change prediction, transition potential, implication, and planning. •LCM can better perform to predict the amount than the allocation of developed areas. •It can also predict a fragmented urban form effectively.	•In addition to spatial patterns depending on the local characteristics of urban development, the rate of urban expansion needs to be integrated in the model. •SDM and MCA can be integrated for improving the assessment and dynamism.	Aguejdad et al. (2017)
The alpine land-use allocation model and dynamic settlement allocation model (ALUAM- DSA)	CA and ABM	Inner alpine valley, Valais, Switzerland	Coupled with ABM, agro-economic optimization and CA, ALUAM- DSA hybrid model was used to evaluate the settlement growth and ecosystem service in a mountainous area.	•Integrates land use, food production, water supply, forest, recreations, habitat function, etc. •Suitable for small scale local or regional planning. •The model can provide a better understanding of land-use processes in mountainous landscapes.	•Complexity in adoption, especially for lack of spatially explicit data on a parcel level for direct use in the design of zoning plans.	Drobnik et al. (2017)
Spatiotemporal data fusion method (STF) with CA-MC models	CA and MC	Hefei metropolis, China; Three Gorges Reservoir Area, Hubei Section	STF method was used to predict the land use changes in Hefei metropolis based on CA-MC hybrid model.	•Simple structures and flexible enough to represent spatiotemporal dynamics. •Integrates land use, water, vegetation, construction, and housing. •The model estimated that more than 30 % of cultivated land, 2% of water, and 16 % of vegetated areas will decrease. In addition, it was predicted that more than 200 % of the construction area will increase by 2032 compared to 1987, although the urban growth rate will slow down after reaching its peak by 2020.	•Limited ability to integrate socio-economic networks. •Uncertainty factors could potentially affect the prediction results, including uncertainty related to the STF method, variation of data of STF due to different remote sensing images, and the quality of remote sensing images.	Chu et al. (2018), Lu Wu et al. (2019), Lu, Laffan et al. (2019)

help make a systematic decision regarding the change of land use and land cover (LULC) (Shafizadeh-Moghadam & Helbich, 2013). The coupled MCA and CA model can work with fuzzy membership functions to reflect the plausible uncertainties embedded in stepwise decision analyses (MCA-LC), and has been successfully adopted for LULC changes modeling at different scales globally (e.g., Arsanjani, Helbich, Kainz, & Boloorani, 2013; Chen, Yu, & Zhang, 2013; Mitsova, Shuster, & Wang, 2010).

The inclusion of one or more external or internal supporting models such as machine learning may lead to a better understanding of urbanization processes and aid in urban planning and decision-making processes. For instance, in most of these multiscale studies, spatial modeling and simulations were used to address land use change through zoning or rezoning via scenario or variance analyses. However, some spatial, social, cultural, economic, and environmental indicators are rarely combined within such a systematic approach (Hély & Antoni, 2019). The integrated philosophy of multiagent interaction model with the aid of machine learning may provide a platform that allows interactions among actors, tools, patterns, and policies/strategies to collide with other for having deepened comprehension.

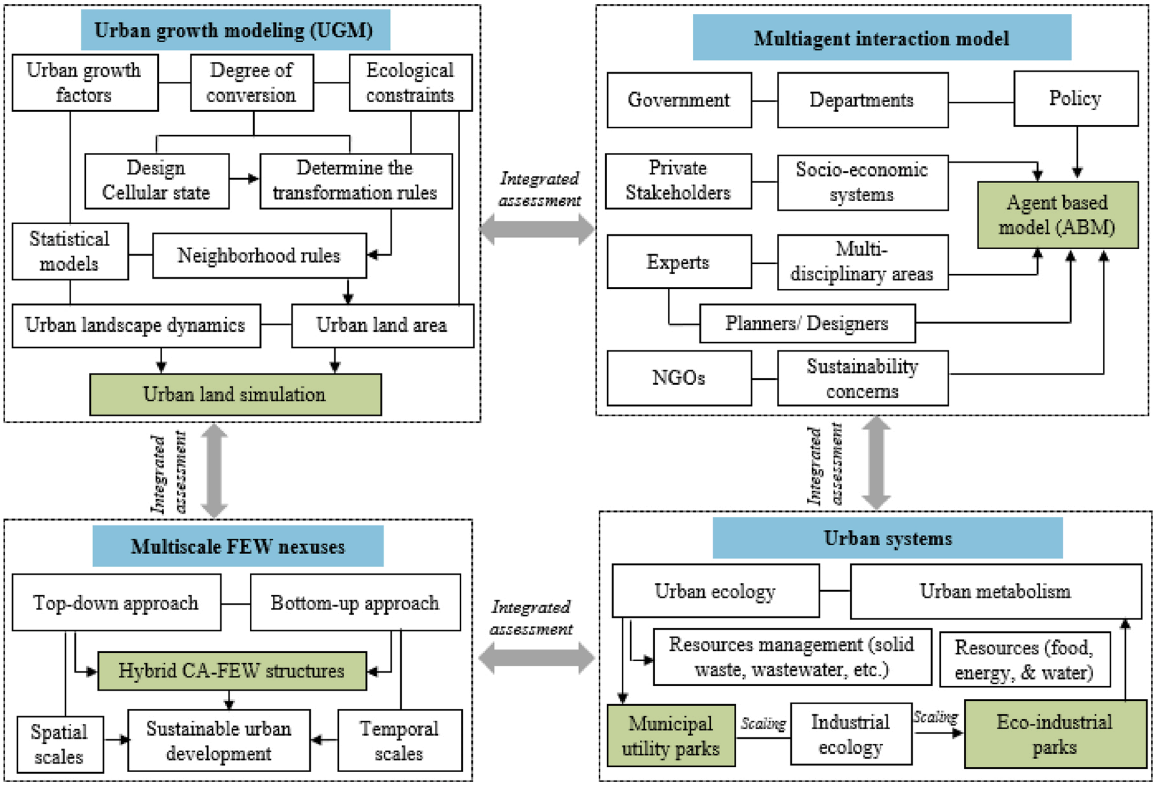

Fig. 6. The integrated philosophy of multiagent interaction FEW model in a CA-based UGM (NGOs: Non-Governmental Organizations).

In a multiagent interaction FEW model in a CA-based UGM, the causes and consequences of urban growth can be described as "input-process-outputs-outcomes," especially for policy making processes, similar to the driving forces, pressures, states, impacts, responses, capacity (DPSIR + C) framework, in which one can observe and analyze the important and interlinked relationships among social, economic, and environmental factors (Kristensen, 2004). According to the DPSIR + C framework, social and economic developments exert pressure (P) on the environment, resulting in the state (S) of the environmental changes (adequate conditions for health, resource availability, and biodiversity, etc.). This leads to the impacts (I) on human health, ecosystems, and materials that may stimulate a societal response (R), which directly feeds back to the driving forces (D), the state (S), or impacts (I), through adaptation or restorative action (Gupta et al., 2020; Zhang et al., 2018). Population growth and developments are the primary driving forces that lead to changes in lifestyles, consumption, and production. Yet capacity (C) in any form (government, public, private firm, etc.) is the basis of having good responses to the DPSIR elements (Zhang et al., 2018). The environmental sustainability index of any system can be evaluated using the structural equation model based on indicators of DPSIR + C elements (Zhang et al., 2018). Nevertheless, it is still difficult to include all uncertainties and associated complexities, such as changing policies, multiagent interactions, and stakeholders' behavioral patterns embedded in transition rules in decision making for sustainable development. Therefore, some external submodels are required to address such concerns. There is a need to develop an advanced (e.g., all-in-one) analytical framework for FEW-CA-based-UGMs by considering all critical and relevant driving forces and their consequences in FEW systems with feedbacks to enrich the classical CA-based UGMs.

6. Featuring the FEW-CA-based UGMs with internal or external supporting modules

6.1. Featured modules

The integration of MCA, the analytical hierarchy process (AHP), ABM, SDM, etc. to address missing links with essential social, economic, and environmental indicators would be very useful for more comprehensive analyses (Mueller, Klein, & Hof, 2018; Xu & Coors, 2012). For instance, several advanced techniques, such as the logic scoring of preference (LSP) technique for identifying the priority factors within ABM, can be useful for MCA-based decision analysis (Dragicevic & Hatch, 2018). Others may have more sophisticated modeling frameworks, such as complex adaptive system (CAS) modeling and TerraME modeling (CA, SDM, and ABM) (de Senna Carneiro, de Andrade, & Câmara, 2013; Giacomoni et al., 2013), LUC- ESA (CA, SDM and MCA) (Lauf, Haase, & Kleinschmit, 2014), CA, ABM and RA (Sohl & Claggett, 2013), CA and SDM (He, Li, Zhang, Liu, & Zhang, 2017; Liu, Yang, He, & Tu, 2019; Zhang, Li, Zhang, & Ouimet, 2017), CA and ABM (Tian et al., 2016), and CA and others (ANN, Monte Carlo, MC, RA, and so on) (Lu, Wu, Ma, & Li, 2019; Lu, Laffan, Pettit, & Cao, 2019; Xu et al., 2018). In addition, some other hybrid CA-based UGMs have adopted different supporting submodels for characterization, trend analysis, planning, and decision-support, such as the Grey model and RA by Wang, Li, Zhang, Li, and Zhou (2018); SDM and life cycle assessment (LCA) by Elliot, Rugani, Almenar, and Niza (2018); integrated AHP, SDM, and MCA by Xu and Coors (2012); integrated SDM, ABM, and RA by Mueller et al. (2018); integrated MC and RA by Aguejdad, Houet, and Hubert-Moy (2017); integrated ABM, AHP, MC, and RA by Tian and Qiao (2014); etc.

Most importantly, FEW-CA-based UGMs are expected to reduce the limitations of individual approaches and integrate existing theories into an all-in-one framework for adjusting necessary conditions and addressing complexity. Nevertheless, these next generation UGMs may be constrained by the multidisciplinary domains of applications, complexity of technology adaptation and integration, data acquisition, evaluation of different sustainability indicators, and unexpected difficulties in model calibration and validation collectively (Ren et al., 2019; Ronchi, Arcidiacono, & Pogliani, 2020) as indicated by Table 5. Existing data base, such as FAOSTAT, can be of some help.

To get through this hurdle, the concept of convergence science must be employed. As indicated by the National Research Council (2014), "Complex research problems require that expertise from formerly distinct academic disciplines be brought to bear in a coordinated way, and convergence is an approach to problem solving that cuts across disciplinary boundaries." Indeed, assessing the impacts of such interlinkage, tradeoffs, and synergies among FEW resource systems with the aid of convergence science would certainly promote increased resource efficiency and social equity with minimized environmental consequences through integrated or group decision making (Engström et al., 2017). For example, by considering the transition of renewable energy from a sewer heat recovery system in the city-wide energy management system in Seoul, significant carbon emissions and energy intensities in the water sector could be reduced. In addition, more than 8% of the total energy used in the water sector could be saved in 2020 compared to the current level, in which an estimated 18.4 million m^3/year of water is reused and 2.40 million m^3/year of rainwater are harvested in the city (Kim & Chen, 2018).

Thus, the inclusion of the impact of FEW systems into the hybrid CA-based UGMs would significantly improve the decision-making process and sustainable urban planning. This can be further expanded to tackle the complexity of FEW systems via CA-based UGMs via coupling different agents' decision-making systems. The land use information was incorporated in the variable grid CA when calculating the individual cell's propensity to change by zooming in on the neighborhood cells in a nested form (Fig. 7). The neighborhood template, shown in Fig. 7, is relative to each individual cell, and therefore moves cell by cell in a nested form over the entire grid, wherein certain cells may be regarded as agents (van Vliet, White, & Dragicevic, 2009). These agents may be decision makers in the food, energy, and water sectors affected by the goals of economic decisions, environmental concerns, and social considerations for sustainable development simultaneously. External or internal supporting submodels, such as SDMs in this context, can feature the individual cell evolution affecting urban metabolisms to account for spatial interactions of total population, material and energy flows, and capital distribution at different scales (Qi & Chang, 2011). In turn, the common architecture of CA-based model construction and solution procedure (Afshar & Hajiabadi, 2019; Afshar & Rohani, 2012; Afshar & Shahidi, 2009) serves as a numerically scalable platform for linking technology hub integration in a FEW nexus and a CA-based-UGM of concern.

These FEW-CA-based UGMs can be effective for modeling urban growth potentials by considering neighborhood factors, and they enable the consideration of resource flows in the systems. The use of scale-dependent contributing factors in a nested form (Fig. 7) to portray possible pathways of urban expansion similar to a biological reproduction process may be configured to reflect population growth, FEW initiatives, economic development, capital investment of urban infrastructure, and so on in such FEW-CA-based UGMs. However, the decision-making for sustainable development may be compromised by some factors, such as geopolitical decisions.

6.2. Phased modeling framework of FEW-CA- based UGMs

The phased modeling framework in Fig. 8 encompasses three phases within a typical FEW-CA-based UGM. With consideration of the FEW infrastructure systems, Phase 1 can depict the driving factors and constraints for scaling up or down according to varying socioeconomic conditions, governance structures, management strategies, as well as policies and regulations, at various scales. Submodels or modules can be developed internally or externally to link with Phase 1 and aid in systems analysis. External modules, such as climate change impact assessment, have been proven effective in this phased modeling framework (Lu, Joyce, Imen, & Chang, 2017; Lu, Chang, Joyce et al., 2018; Lu, Chang, Joyce, Chen et al., 2018). These external modules may adopt either bottom-up approaches (e.g., multiagent modelling) or top-down approaches (e.g., SDM) or both. More numerical tools can be used to identify critical FEW factors and define critical pathways of FEW resources delivery to urban regions. This toolbox may include but is not limited to both inductive and deductive tools such as SDM, AIMM, PCA, agro-logistics, and so on. Phase 2 represents the core part of a FEW-CA-based UGM for land use implementation based on several distinct time periods (e.g., two in this diagram) to retrieve the transition probability matrix for Markov chain and help build the Gaussian Markov Random Field for urban growth analyses. Finally, Phase 3 encompasses the calibration and validation of the developed FEW-CA-based UGM by predicting land use for two other distinct time periods comparatively. Markov Chain Monte Carlo (MCMC) may be employed to test the uncertainty of scenarios during and after calibration and validation for uncertainty analyses. Similar to CAS, the phased approach enhances

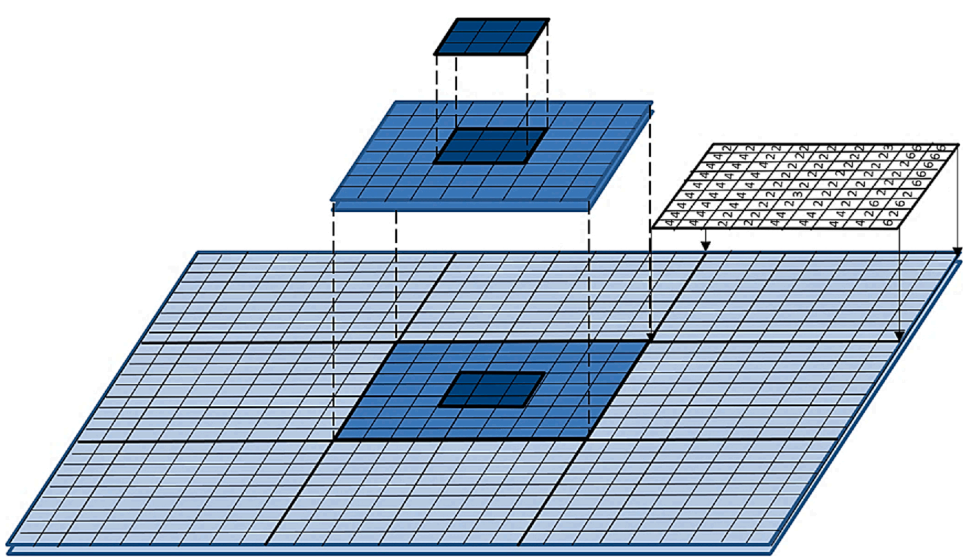

Fig. 7. The philosophy of aggregation level of individual grids relative to the central grid in the neighborhood using a variable nested grid in a multiscale FEW-CA-based UGMs.

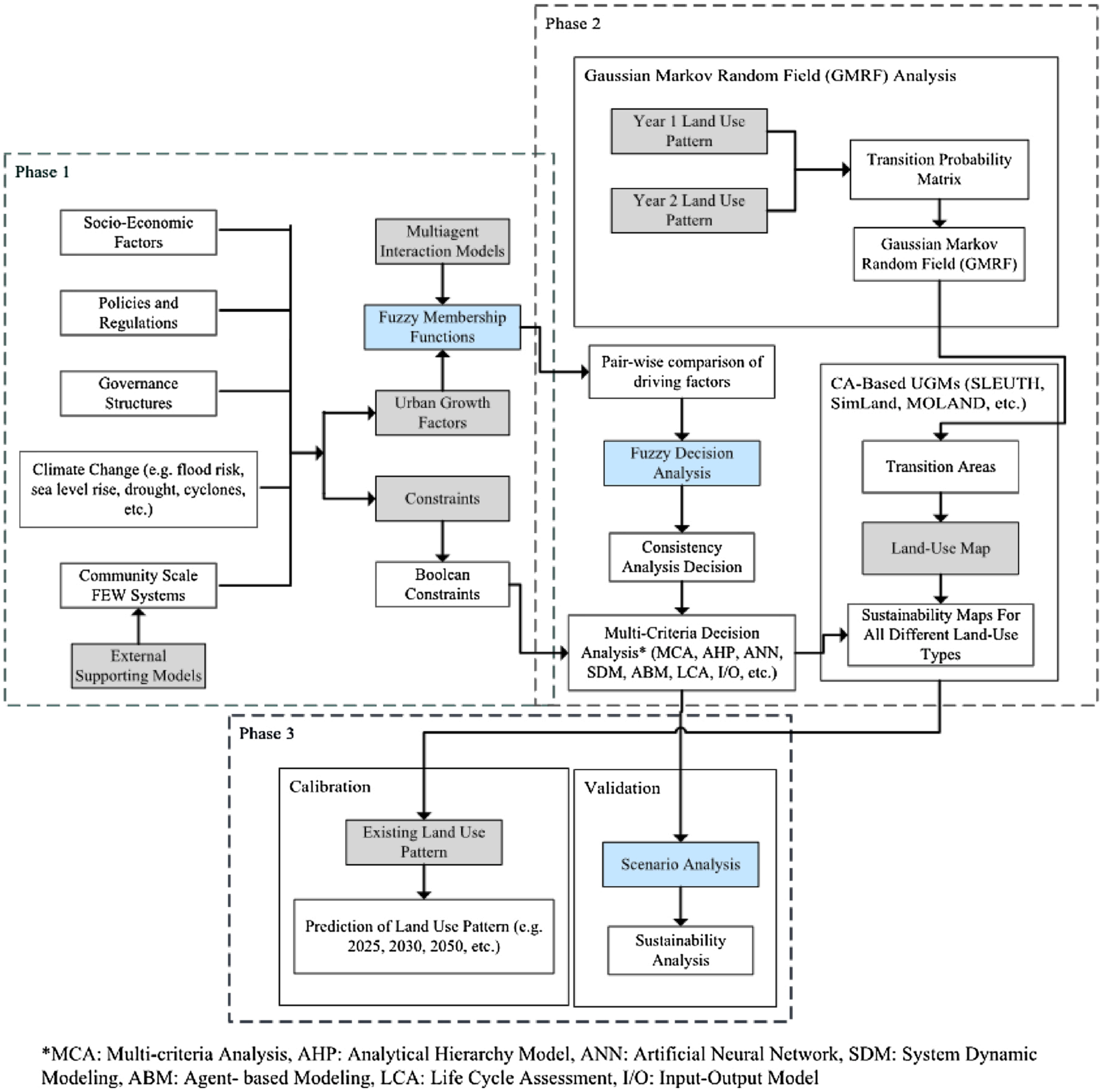

Fig. 8. The phased analytical framework of FEW-CA- based UGMs.

robustness in planning and also gives the planners the flexibility to scale up or down as changes in the FEW systems necessitate while taking the uncertainty into account.

6.3. A case study

With evolving FEW nexuses, the proposed top-down approach (e.g., regional scale MUPs and EIPs) and bottom-up approach (community scale urban farming) can be integrated into FEW-CA- based UGMs for more robust and sustainable urban planning under different governance structures and policies (Fig. 4). In such an analytical framework, different supporting submodels/modules are formulated and adopted for FEW evaluations to generate meaningful transition rules, wherein CA-based UGMs can be featured for spatiotemporal planning in a nested form (Fig. 7). The practical implementation of cost-benefit-risk tradeoffs with technology hubs integration in FEW systems enhances the convergence opportunities (Massachusetts Institute of Technology (MIT, 2016), while behavior interventions respond to evolution through multiagent modeling processes in an attempt to optimize the urban growth pathways (Chang et al., 2020a, 2020b).

Implementation of a FEW nexus in the greater Miami region can be used as an example for demonstration of how community urban farming could affect urban growth from community-scale to urban-scale (Fig. 9). This is a unique region in south Florida where food security is a major concern (e.g., identified >300 "food deserts," where residents have difficulty accessing affordable, fresh, and nutritious food), along with other sustainability challenges, such as threats from climate, sea level rise, and worsened water pollution due to nutrients (Fig. 9). There have been incipient grass-root and booming business interests that have advocated for the development of urban farming. This is especially relevant in this region, where there is a year-long growing season and thus considerable opportunities for urban farming development. In fact, urban farming has gained increased attraction with emerging practices, including community gardens, peri-urban farms, and more recent interests in vertical farming technologies. Different urban farming types have their own benefits, niches, and considerations for scaling-up from local communities to regional landscapes. Community gardens, for example, are common in urban cores, easy to implement, and mostly for personal consumption. Peri-urban farms are normally large-scale operations with commercial potential. Peri-urban farms near Miami can also help preserve high-yielding prime lands and reduce development pressure on the Everglades. Vertical farming, with a controlled environment and enhanced resource efficiency, also has substantial commercial opportunities.

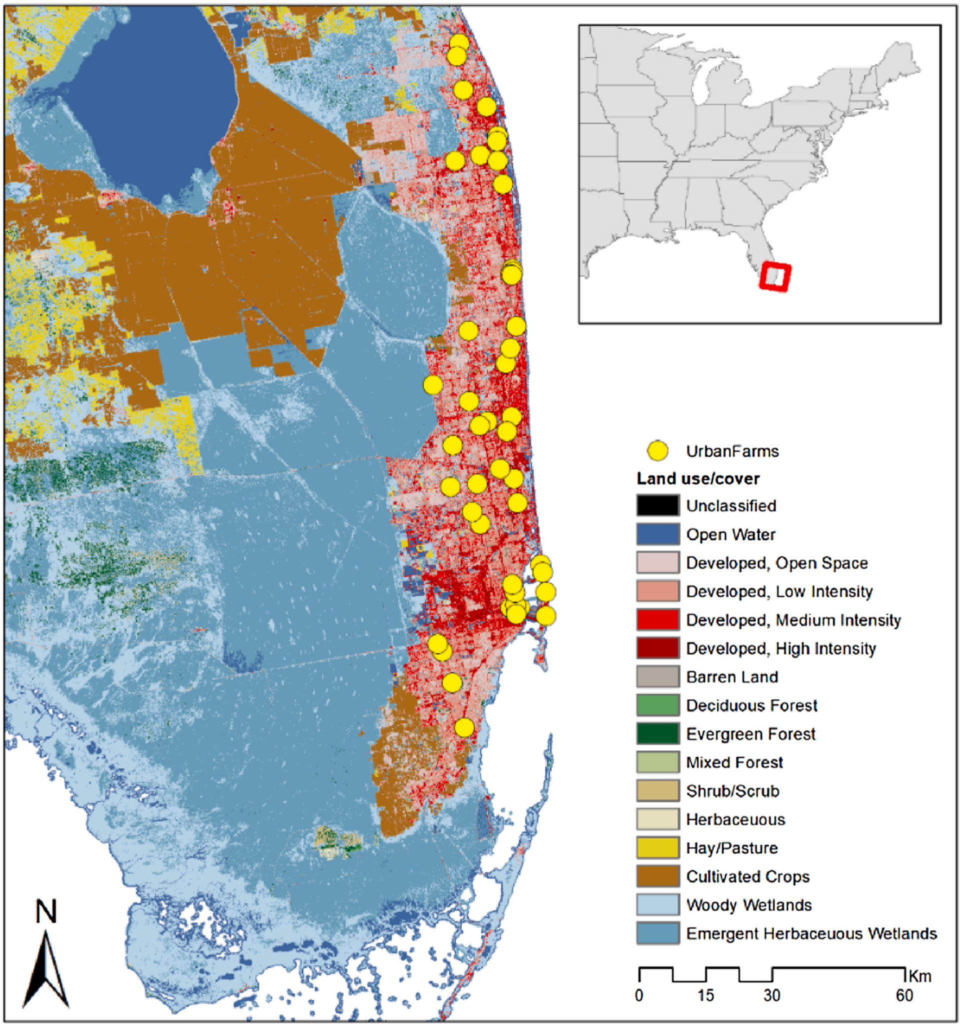

Fig. 9. Land use/cover of south Florida (data source: National Land Cover Dataset –NLCD 2011) and the spatial distribution of urban farming sites in South Florida, USA.

On the other hand, solar energy harvesting has been popular in this region due to ample solar radiation year-round. Hence, the extent to which the scaling up of urban farming sites from the local to the regional scale is sustained by solar photovoltaic technology and smart grid (Zhang, Valencia, Gu, Zheng, & Chang, 2020) has created tremendous niches for integration in the FEW nexus that would, in turn, affect the land-use transitions in urban settings. This extent remains unclear but critical for modeling using the proposed FEW-CA-based UGMs. With the aid of a set of external and internal supporting submodels and MCMC techniques for uncertainty analysis, the proposed analytical framework in Fig. 8 may be applicable to the Miami-Fort Lauderdale-West Palm Beach region (e.g., the greater Miami region), where a lot of urban farming sites (yellow dots in Fig. 9) are active and form a wealth of community-scale FEW nexuses with scales that in turn affect urban growth in this highly-populated coastal metropolitan region (e.g., 7 million residents).

Following the philosophy in Fig. 9, the factors embedded from the FEW systems over time in Phase I may be described via a SDM (Forrester, 1961, 1968, 1969). A SDM encompassing the interaction of distinct FEW components with temporal changes in UGMs is considered an internal supporting submodel in this context (Tang & Vijay, 2001). In Fig. 10, an SDM in support of the FEW-CA-based UGM includes five stocks (stormwater retention pond, cistern, green roof system, energy storage devices, and greenhouse system) and flows for addressing a community-scale FEW system that links the material and energy flows to model the dynamic behavior associated with those stocks over the temporal domain (Lu et al., 2017). The stock denotes a variable that is affected and changed through flows. The flow (inflow or outflow) represents a changing variable over a time interval. As shown in Fig. 9, the formulation of the SDM model is designed to show the interactions and relationships of the stock and flows in a FEW system and model the behavior of the FEW system herein. Therefore, such SDM can be used for identifying and analyzing the resource flows of FEW and can effectively be coupled with some hybrid FEW-CA-based UGMs.

The mathematical equations of the SDM for the five corresponding stocks are described in Eqs. (4)–(8) as an external support model to echo the CA-based UGM defined by Eqs. (1)–(3), through which the hybrid FEW-CA-based UGM modeling framework may be connected, and in which green roof, solar energy, stormwater harvesting and reuse, and roof-top food production are integrated through an SDM (Fig. 10). The SDM modeling system was thus developed to dynamically evaluate the inputs and outputs for a FEW nexus integrated with a green building that might be grouped later into a microgrid system for green energy supply (Zhang, Valencia, Gu, Zheng, & Chang, 2020). This model can be extended to the urban catchment scale, wherein similar equations can be synergized for the evaluation of different inputs and outputs in a LID region in which the stormwater peak reduction and roof-top irrigation might have a conflict; using such a model, the linkage between the green building design and watershed landscape design can be made possible.

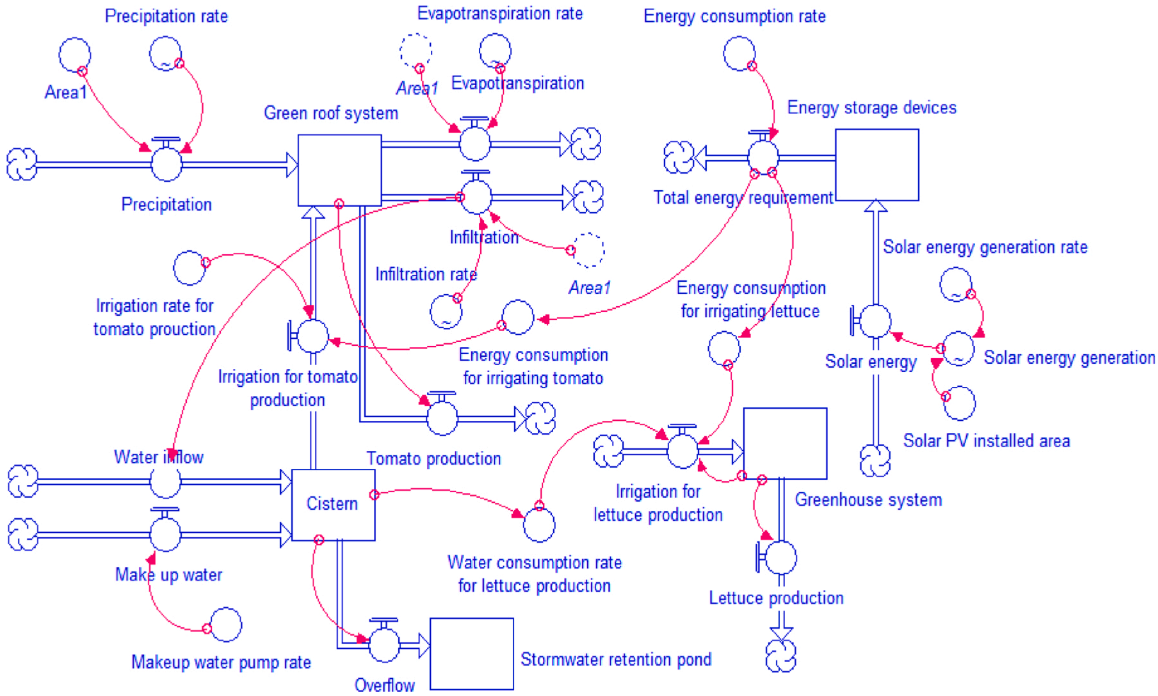

Fig. 10. An analysis of SDM (a Stella model) for the integration of a building-scale FEW system as an internal submodel in a green building with roof-top farming, green energy, and stormwater reuse (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

$$\frac{dC}{dt} = V_{in}C_t + V_{in}W_I + V_{in}M_W - V_{out}I_{TP} - V_{out}O \tag{4}$$

$$\frac{dE}{dt} = \frac{P_{in}}{t_{in}}E_t + \frac{P_{in}}{t_{in}}S - \frac{P_{out}}{t_{in}}E_{TR} \tag{5}$$

$$\frac{dG_H}{dt} = M_{in}G_{H_t} + V_{in}I_{LP} - M_{out}L_P \tag{6}$$

$$\frac{dG_R}{dt} = M_{in}G_{R_t} + V_{in}P + V_{in}I_{TP} - V_{out}I - V_{out}E - M_{out}T_P \tag{7}$$

$$\frac{dS_{RP}}{dt} = V_{in}S_{RP_t} + V_{in}O \tag{8}$$

where C: Cistern, W_I: Water inflow (m^3), M_W: Make up water (m^3), I_{TP}: Irrigation for tomato production (L/kg), O: Overflow (m^3), E: Energy storage devices, S: Solar energy (kWh), E_T: Total energy requirement (*kWh*), G_H: Greenhouse system, I_{LP}: Irrigation for lettuce production (kg), L_P: Lettuce production (kg), G_R: Green roof system, P: Precipitation (in), I: Infiltration (in), E: Evapotranspiration (in), T_P: Tomato Production (kg), S_{RP}: Stormwater retention pond.

For a watershed-scale analysis, the SDM in Fig. 10 may consolidate the use of stormwater collected from a nearby stormwater detention pond within an urban catchment, stored in a cistern, and complemented by rainfall for irrigation of a green roof system and a greenhouse for the production of two crops (e.g. lettuce and tomato). The energy required for irrigation is obtained via solar energy and stored in energy storage devices for further distribution. Thus, in this context, the food, energy, and water are intertwined in a FEW nexus that can be implemented to achieve sustainable development in a community for scaling up. The different metacommunity patterns, Such as EIP and EIC, identified at the increasing geographical scales can accommodate different scale-related urban metabolism and urban ecology. Consequently, as many more communities in an urban region can pursue this type of sustainable development through the scaling up of urban farming efforts, the SDM as a theoretical foundation can further incorporate more cells with multiple objectives for decision analysis in a FEW nexus as described in Fig. 7.

On the other hand, external driving factors, such as urban growth and economic development factors, may affect the land use patterns in sequence; these factors can be addressed by an external supporting submodel (Phase I in Fig. 8) as an integral part of the gravitational field model (Fig. 11), which can be linked to water, carbon, and ecosystem footprints to confirm sustainability criteria. With the aid of all possible supporting submodels, including SDM, AHP, MCA, LCA, etc., transition rules become more flexible, robust, and comprehensive for minimizing decision-making gaps across multiple agents. However, the challenges from handling the uncertainties of numerical planning scenarios require gaining some more insights in large-scale complex systems analysis, leading to better backcasting, nowcasting, and forecasting outcomes.

Finally, determining how those interconnected FEW processes with scaling effects via hybrid FEW-CA-based UGMs with the aid of valid transition rules is critical in decision-making processes. As forward-looking projection and simulation of the future, i.e., forecasting, are emphasized, backcasting is becoming more and more important. Methods for connecting the proposed modeling framework with backcasting related to policy goals has thus become an appealing topic. To elucidate valid transition rules, there is a need to understand such scaling effect since the FEW nexus factors and trends may vary across spatial, temporal, and organizational scales (Fig. 12) (Ramaswami et al., 2012, 2017). The transitions occur from least complexity (no cross-scale interactions among the drivers, and unconnected silos of economic, environmental, and social sustainability), to complex FEW nexuses and decision-making, and then to more complex cross-scale interactions between drivers and FEW systems (Gragg et al., 2018). By considering the scenario analyses (e.g., base case, rapid development, restorative development) under the different policy settings and uncertainty with scaling effect, the proposed modeling framework in Fig. 8 could still be applicable through the use of MCMC techniques. When projection can be done based on the scenario analyses, the same approach can be adopted for simulating the nowcasting and backcasting related to policy goals. This makes Fig. 8 an all-in-one system.

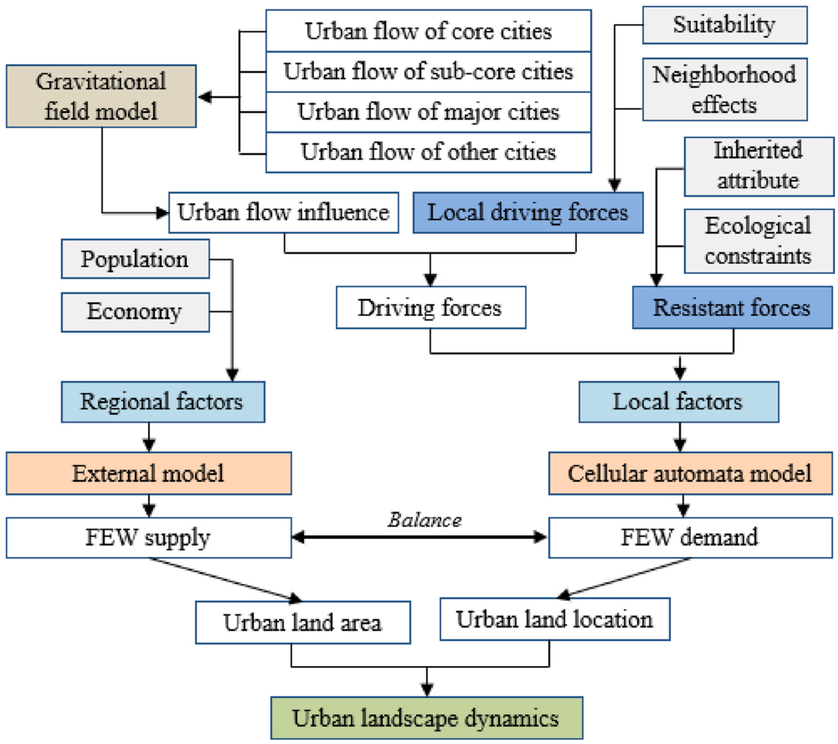

Fig. 11. The role of an external model in connection to a CA-based UGM to address the balance between supply and demand of FEW resources in urban metabolism (adapted from He, Zhao, Tian, & Shi, 2013 with permission).

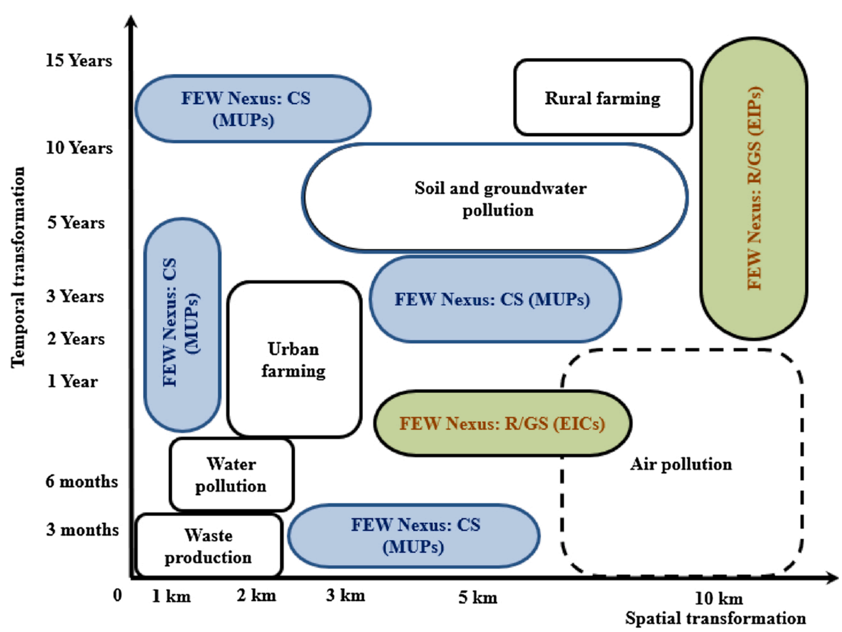

Fig. 12. Different spatial and temporal domains, scales, and granularity of phenomena (adapted from Blecic, Cecchini, Prastacos, & Verigos, 2004 with permission).

7. Global vision of FEW-CA-based UGMs for sustainable development goals

Facing an era of rapid urbanization, the integration of local knowledge and community innovation is important for understanding the associated multitude of interconnected "social-ecological systems" and "socio-technological systems" in urbanized environments (Lindley, Pauleit, Yeshitela, Cilliers, & Shackleton, 2018). Most importantly, among the 17 SDGs provided as part of the global development agenda of the United Nations, 8 SDGs are related directly and indirectly to sustainability, urban growth, and the FEW nexus. Whereas the former include SDG 2 (food security), SDG 6 (water), SDG 7 (energy), and SDG 11 (cities and communities) with direct impact, the latter include SDG 8 (decent work and economic growth particularly for materials footprint, and materials consumption), SDG 9 (industry, innovation and infrastructure particularly for carbon reduction), SDG 12 (responsible lifestyles particularly for materials and wastes), and SDG 15 (land and biodiversity) with indirect impact. However, the achievements of such goals are still quite low. For example, only 23 % among 93 SDGs indicators have made significant progress over the last 15 years globally (UNEP, 2019). It has already been mentioned that about 68 % of the total population is expected to live in the urban areas by 2050, particularly in developing and third world countries. Therefore, the focus on integrated urban development with scales (e.g., landscape planning, management, projection, etc.) and FEW nexuses (ensuring food, energy and water security), including their associated drivers and agents, are of paramount importance for policy making toward a sustainable future. This is particularly important as there are strong interconnections between drivers, such as urbanization, population, economic growth, technology, and innovation with integrated management over soil, water, and waste as an extended soil-water-waste nexus (UN Environment, 2019).

Following the Organisation for Economic Co-operation and Development (OECD) approach to measure the distance to the SDGs (OECD, 2017), the national implementation of the 2030 Agenda for Sustainable Development can be assessed across different OECD member countries. With the same philosophy, the proposed numerical scheme of FEW-CA-based UGMs can become an amiable tool to simulate the urban growth patterns and estimate the distance to the SDGs for cities. For instance, climate impacts on regional water resources can directly affect water supplies, as well as indirectly impacting food production. Different institutions and associated actors can significantly influence water resource distribution in different ways at different scales. Policy implications at different institutional levels are needed for counteracting different impacts with scales. Therefore, the proposed FEW-CA-based UGMs can play a central role in estimating the distance to the SDG 6 (water) for a suite of FEW nexus proposals in alignment with urban growth. This anticipated thrust in convergence science research is consistent with the divergence of megatrends in science and engineering toward sustainable urban development (Roco, 2002).

8. Conclusion

Functional urban areas that are centers of production, consumption, and population settlement constitute a wealth of critical driving forces for social, economic, and environmental stability and sustainability. Given that a huge amount of natural resources is needed to meet soaring demands in urban regions that span hundreds of kilometers, the implementation of UGMs help urban planners and decision makers map the present, reconstruct the historical extent of the urbanization processes, and predict future scenarios regarding factors, processes, and policies from local to regional, to national, to transboundary levels. However, the incorporation of FEW systems at varying scales becomes a key to success in modern UGMs due to the possibilities of social, economic, and environmental consequences, as cities are considered more susceptible to global changes.

This paper provides a comprehensive review of CA-based UGMs and FEW systems with synergies for improving classical urban growth models with different scales. To bridge the gap between the two regimes, however, there is a need to further expand existing hybrid CA-based UGMs with the inclusion of other internal and external supporting sub-models. This advancement leads to enrich the multiscale and multiagent decision support via either a top-down or bottom-up approach or mixed. The proposed hybrid FEW-CA-based UGMs for capturing the patterns and traits of urban growth with spatiotemporal characteristics can share a common architecture of CA during the model construction and solution procedure that is a promising research direction in the future. It may contribute to reshape land use policies and infrastructure management strategies, help allocate budget and financing, examine multilevel governance structures, and create place relevance assessment for developing and developed countries. In addition, the environmental and human health consequences of such systems may span from local to regional scales.

We believe that the proposed analytical framework of hybrid FEW-CA-based UGMs could help understand the contemporary challenges and promote sustainable, cost-effective, environmentally-sound, forward-looking, socially equitable, risk-informed, green, smart, and resilient urban development. The interdisciplinary sustainability solutions produced from this analytical framework will provide stakeholders and decision makers with insightful and constructive information. Future research should consider a full-scale assessment of possible technology hubs integration over a wealth of FEW nexuses to aid in long-term context- and culture-driven sustainable urban planning for land-use transitions, mobility potential, and urban growth toward supporting some of the SDGs.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. List of Abbreviations

ABM	Agent-based model	LULC	Land use and land cover
AHP	Analytical hierarchy process	MC	Markov chain model
AIMM	Adaptive Intelligent Model-building for Social Science	MCA	Multicriteria analysis
ANN	Artificial neural network	MCMC	Markov chain Monte Carlo
CA	Cellular automata	MRIO	Multi-region input-output
CAS	Complex adaptive system	MUP	Municipal utility park
DPSIR	Driving forces, pressures, states, impacts, responses	OECD	Organisation for Economic Co-operation and Development
EIP	Ecoindustrial park	O&M	Operation and maintenance
EIC	Ecoindustrial cluster	PCA	Principal components analysis
FAOSTAT	Food and agriculture organization corporate statistical database	PV	Photovoltaic (solar)
FEW	Food-Energy-Water	RA	Regression analysis
FEW-CA-based UGM	Food-energy-water cellular automata based urban growth models	SDG	Sustainable development goal
GDP	Gross domestic product	SDM	System dynamic model
GHG	Greenhouse gas	SEIS	Social-ecological-infrastructure systems
IO	Input-output	SPT	Solar power tower
kWh	Kilowatt hours	UGM	Urban growth model

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(continued)

LCA	Life cycle assessment	UHI	Urban heat island
LID	Low impact development	UNU	United Nation University
LSP	Logic scoring of preference	USEPA	United States Environmental Protection Agency
LUC-ESA	Land-use change and ecosystem service assessment		

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.scs.2020.102486.

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