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A Comprehensive Review on the Development and Evolution of Urban Growth Models and Current Challenges

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Abstract

Prediction of urban growth is vital in planning for the future in terms of socio-economic indicators as well as ensuring growth of urban areas meet sustainability goals. The objective of this paper is to provide a comprehensive review on the evolution of various urban growth models and try to provide a narrative on why applicability and acceptability of such models remains limited. We explore and discuss the models since the first application in urban planning to currently used models. Through this discussion, analysis on reasons of evolution and improvement of these models has been done. Three popular models for urban growth modelling namely Cellular Automata (CA), Agent Based Model (ABM), and Artificial Neural Networks (ANN) have been described briefly. The explanation on why and how these models were improvised to better simulate urban growth has been discussed. The inefficiencies of these models as individual models and how integrated models have resolved these issues have been highlighted. This paper summarizes that evolution and development of models has mainly focused to improvise the model component inefficiencies and to reflect the true nature of growth. The inability of current urban growth models to incorporate policy scenarios as driving factors has been discussed and this has been highlighted as a reason for lack of global acceptability of such models. This paper thus recommends the application of different urban growth models based on the generalized objectives of modelling to enhance their credibility as well as bringing a uniformity in modelling approaches around globe.

Keywords

Urban Growth Modelling, Land Use Change Modelling, Cellular Automata, Agent-Based Models, Neural Networks, Artificial Intelligence

1. Introduction

Urban growth is a continuous, dynamic, and complex process (Batty, 2009; Batty, 2015; Wang et al., 2019). The process of urban growth brings significant land-use changes in the vicinities of the cities. The dynamics of land-use change affects the environment and the resources over time (Kushwaha et al., 2021). Lack of prior knowledge on these consequences of land-use has made it difficult to balance between urban growth and urban sustainability. The bulging issues of infrastructure shortages, population density management, provision of essential services in an accessible way are inherent in urbanized environments either in developing or developed nations. Part et al. (Park et al., 2011) have highlighted how severe land disturbance and environment pollution have degraded South Korea's environment quality due to rapid urbanization and industrialization. Relevant research has shown that understanding urban growth is important for sustainable development, estimating future growth and applying alternative policies in development to reduce the impacts on the environment (Aburas et al., 2016; Akyol Alay, Tuncay, & Clarke, 2021; Arasteh & Farjami, 2021; Cui et al., 2019). Therefore, urban planning needs to address these issues through comprehensive policies and strategies. This can only be possible if a precise prediction of the urban growth is done in a more scientific way (Cheng, 2003; Batty, 2020).

The process of land use change is described using theories that encompass mathematical analogies and formulations and visualized, analyzed, and predicted using physical models or computer simulated models (Batty, 2008; Heppenstall et al., 2012). Concepts from linear static theories used in development of early models, to concepts from dynamic systems theory, complex systems theory, played an important role in development of various models of urban growth over time. The application of concepts from these theories also delineates a shift in temporal development of nature and characteristics of models from static to dynamic and from macro to micro level.

Especially, the development of understanding that cities are systems combined of many sub systems and processes and the cumulative interaction between these gives rise to an emergent form or structure was vital to development of micro-dynamic urban growth models. This concept help bring forward the visualization that cities are formed of various physical, social, economic elements, and there are corresponding processes and activities that define the structure of city at a time and interaction of these elements and processes dictates the evolution of morphology of cities (Batty, 2015; Heppenstall et al., 2012). Over the last few decades, much research has been done in understanding how the cities change spatially and temporally via the process of land use and land cover change using different statistical and complex systems based computational models. Among the models, Cellular Automata (CA) (Batty & Xie, 1994; Batty, Xie, & Sun, 1999; Maria de Almeida et al., 2003; Couclelis, 1985; White & Engelen, 2000), Agent Based Models (ABM) (An et al., 2005; Coelho et al., 2016), Machine learning models like Artificial Neural Networks (ANN) (Grekousis, 2019), and integrated Models (Dahal & Chow, 2014; Tan et al., 2015) have been the widely used for research. **Figure 1** shows the evolution timeline of urban growth models along with the direction of modelling approaches.

The purpose of most of the models developed so far is to understand the historical track of growth and to simulate the future urban growth (Wang et al., 2019; Li & Gong, 2016). The selection of an appropriate model is vital, as an inappropriate selection of model may result in large-scale errors (Zhang, Kwan, & Yang, 2023). These errors may be due to inherent model uncertainties and due to issues of model transferability in varying geographic and spatial domains (Yu et al., 2022; Tan et al., 2015; Liu et al., 2021). Also, some models require extensive data and enormous computational power, whereas the others are more empirical, and less data driven. There is a need to identify the most suitable model considering the study objectives, available data, resources, and computational capabilities. However, urban growth domains remain limited mostly in delineating urban growth morphology which cannot widen the scope of modelling practice and usability (Liu et al., 2021). This may require a thorough understanding about various theories that drive the models, their evolution process, and the characteristics of various urban growth models.

Another, hindrance to the applicability of the models is due to the lack of application of models in incorporating and testing various policies and scenarios (Sohl & Claggett, 2013; Batty, 2020). Especially, considering current awareness and practice of sustainability measures and scenarios of global climate change impacts on future of urban areas are yet to be integrated in a systematic way in the scope of urban growth models.

Current literature lacks narrative review and mostly published reviews are systematic but largely limited reviews on approaches and components (Aburas et al., 2016; An, 2012; Berling-Wolff & Wu, 2004; Hassan & Elhassan, 2020; Kim & Newman, 2020; Li & Gong, 2016; Matthews et al., 2007; Santé et al., 2010; Grekousis, 2019; Wang, Murayama, & Morimoto, 2021). This study reviews the evolution of urban growth models, and describes this evolution based on the competencies and drawbacks of the models. Hence, the objectives of this research are to provide an understanding on evolution and development of various urban growth models, discussing the application based on objectives of study, data, and complexity, driving factors incorporation, and incorporating policy scenarios. Finally, providing suggestions for future research to identify appropriate modelling approaches based on clearly defined and classified objectives to unify modelling practice.

The rest of the paper is organized as follows: Section 2 starts with introduction to the earliest urban growth models, the theoretical models based on linear static theories. Section 3 introduces urban dynamic models and Section 4 introduces complex dynamic theories-based models. Section 4 details the development, advantages and disadvantages of four types of such models namely cellular automata models, agent-based models, artificial neural networks and integrated models. Section 5 is the analysis and discussion section based on information gathered from earlier sections highlighting the overall advantages and disadvantages of models and what modelling approach lacks in terms of climate change and policy scenario integration into modelling. Section 6 concludes with conclusions and some suggestions for future modelers.

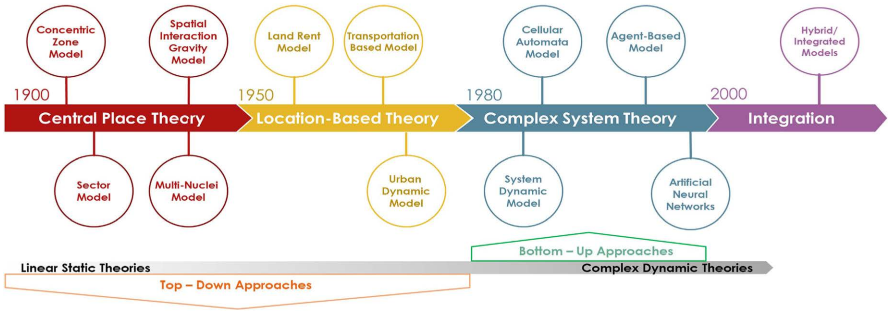

Figure 1. Timeline representing evolution in urban growth modelling. Advancements in theories, models, and approaches. The color code represents the theories, and the shape represents the models.

2. Linear/Static Theories-Based Models for Urban Growth

The early models of urban growth are based on what could be visualized in morphological structure of cities (Berling-Wolff & Wu, 2004). These representations of cities did not consider the dynamics of the processes that shaped the morphology, rather included the representation of what could be seen or visualized on the ground scale (Maria de Almeida et al., 2003; Almeida et al., 2005). The cities were supposed to grow around the centers. This observation formed the basis for the visualization and representation of growth models (Batty, 2020).

The top-down approaches are mostly deterministic in nature and are used highly for prediction of urban growth based on principle of linear system theories (Swannack, 2008). These modelling approaches consider that components of an urban system are static in time, and follow a definite pattern of growth (Verburg et al., 2004).

These models are more representation of urban morphology rather than description of socio-economic rules and components that interact to shape the morphology (Li & Gong, 2016). Theories of Newtons Gravity, theories of systems that always remain in equilibrium like entropy theory, thus were used to build the models for the top down approaches (Tan et al., 2015). These models can be classified into the following two types of models.

2.1. Central Place Theory-Based Models

Prior to 1950s, the concept of growth of cities was limited to assumption that cities grow in a centric way, growth is concentrated around the central business districts or the central zones (Wegener, 1994). Models like concentric zone model (1925) (Brown, 2015), Sector model (Hoyt, 1939), Gravity model (1946) (Zipf, 1946), multi nuclei model (Harris & Ullman, 1945) were developed based on the assumption and mainly categorized under central place theories based models as shown in **Figure 2**. These models mainly focused on spatial interactions where the intensity of two spatially interacting components is closely related to their properties and the distance between them as in gravity model or totally dependent on the attraction of the similar components as in the sector model (Li & Gong, 2016; Batty, 2008).

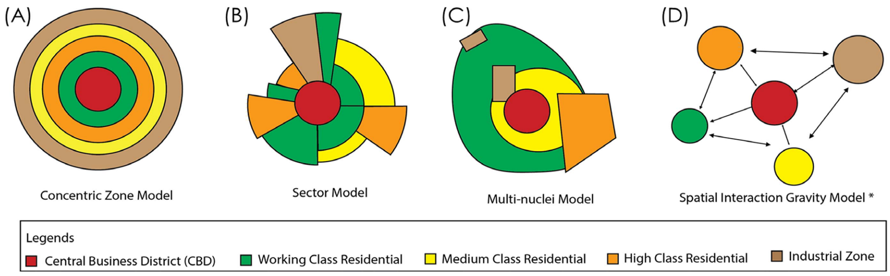

Figure 2. Schematic Representation of Central Place theories based Models with different colors to represent various land use types or social classes; (A) represents concentric zone Model with different concentric zones; (B) shows Sector models with different sectors based on land use class; (C) represents the multi nuclei model where different land sue classes scatter and form different clusters; (D) representation of interaction between different activities in the land use class zones.

2.2. The Models Using Location-Based Theories

Post 1950s, due to rapid development of interstate highways in USA and similar growth in transport infrastructure in Western Europe led to development of growth along the peripheries of highway routes and transportation networks. New cities started appearing along the highway routes as the number of car users increased. Industries started settling around the routes for better access to transportation. This led urban planners to realize the centric models of urban growth are insufficient to predict the land use and trip and location decisions co-determine each other and impact in the rate and density of land use; therefore transport and land use planning needed to be coordinated (Hansen, 1959; Berling-Wolff & Wu, 2004). **Figure 3** represents the models based on the location-based theories.

3. Urban Dynamics Model

Towards the 1960s, people realized that traditional static models of spatial interaction were insufficient to model the dynamic nature of cities. There were emerging concepts which consider cities as systems with various components interacting in a dynamic way as a feedback loop, as shown in **Figure 3(C)**, which drives growth and activities. Forrester (Hester, 1970) in 1969 proposed the Urban Dynamics model based on this concept which is the base model for now called System dynamics Model. However, Forrester Urban Dynamics model was limited due to its fixed boundary conditions, lack of interaction of the system to external environment, and availability of data to incorporate the feedback interactions between different components for modelling, and hence failed to find applications during the period (Shen et al., 2007).

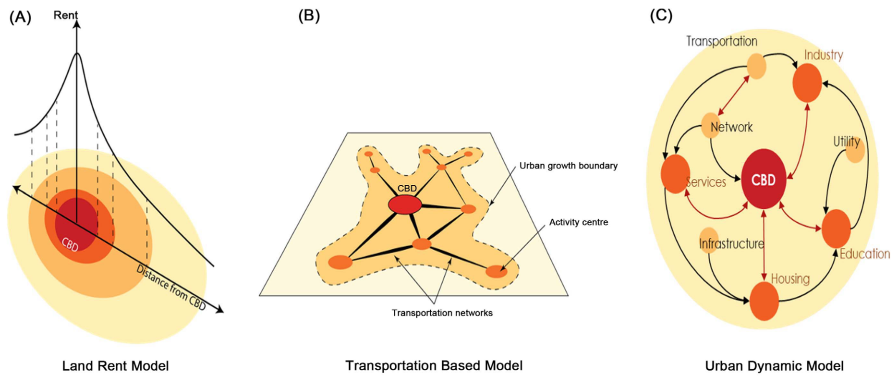

Figure 3. Location-based Theory Models; (A) represents the Land Rent Model demonstrating the value of land decreasing as the distance away from CBD; (B) the Transportation Based Model demonstrating the interactions between activity centres and transportation networks; (C) represents urban dynamic model with interactions between various subsystems.

Lee (Lee, 1973) in 1973 highlighted the lack of capabilities in attempts to model construction of large scale models for urban growth, which became a turning point on the models development. The basic flaws of modelling approaches as the static nature of models, data requirements, inputs, lack of capability of models to handle large number of components and their interactions were the main drawbacks on concurrent models. This helped initiate the concept of cities as dynamic systems and substitute the static system concept at large (Allen & Sanglier, 1978). The development of new models slowed during the following period. However, development of improvised (Land Use based on Transportation) LUT models continued. Some examples of the improvised LUT models include TRANUS (Barra & Rickaby, 2016), MEPLAN (Echenique et al., 1990), MUSSA (Martinez, 1996). Further theoretical description of cities as dynamic entities and cities as systems emerged (Allen & Sanglier, 1978; Chadwick, 1971), however, model development stalled largely.

4. Complex Dynamic Theory-Based Models

With the growth in computer utilization, data availability, and adaptability to modern techniques largely in 80s, researchers were encouraged to apply bottom-up approaches (Batty, 2015; Batty, 2009). This allowed the urban systems to be described as disaggregated structures with varying interaction between their components. This allowed flexibility to describe the dynamicity and integration of local macro and micro level components and their interactions (Tan et al., 2015).

Moreover, towards mid-1980s, the concepts from different fields of science were being merged into the systems theory to describe the complexity observed in natural phenomenon's, especially in biology, ecology, and sociology (Ulysses, 2017). This incorporation of multidisciplinary approach resulted in shift of concepts from general systems theory to complex systems theory. Complex systems theory describes that systems may emerge with different properties other than which can be predicted using their additive properties as in general systems theory. Thus, systems like cities can emerge with different forms geographically or show "emergence" (Clarke, 2019).

Culmination of these concepts led the modelling process in the direction, where cities tend to show a temporal and spatial heterogeneity, emergence, and network connection between processes and elements (Crooks et al., 2021). Parallel to this, development of GIS techniques, object-oriented programming, and advanced computation techniques aided application of bottom-up approaches during 1980-90s. The definition of cities, hence changed as dynamic entities where various components interact and contribute to the growth rates, patterns, and shapes (Batty & Xie, 1994). Cellular Automata (CA) and Agent based (Multi Agent Systems/Individual based system) modelling (ABM) are the examples of models applied in the urban growth modelling domain as a result. These models were the simplest of the models where complexity could be demonstrated (Clarke, 2014).

4.1. Cellular Automata Models

The CA models were first proposed in geographic modelling by Tobler in 1979 and applied in urban growth modelling in the 1980s and 1990s (Batty & Xie, 1994; Couclelis, 1985) and have been widely used in the simulation and prediction of urban-land dynamics since then (Phipps & Langlois, 1997; Feng & Qi, 2018; Liu & Phinn, 2003). These models are based on the concept that the pixels in raster geographical representation also called cells, interact with each other based-on neighborhood rules and transition based on the rule based or probabilistic statistical transition functions as shown in **Figure 4** (Li & Gong, 2016).

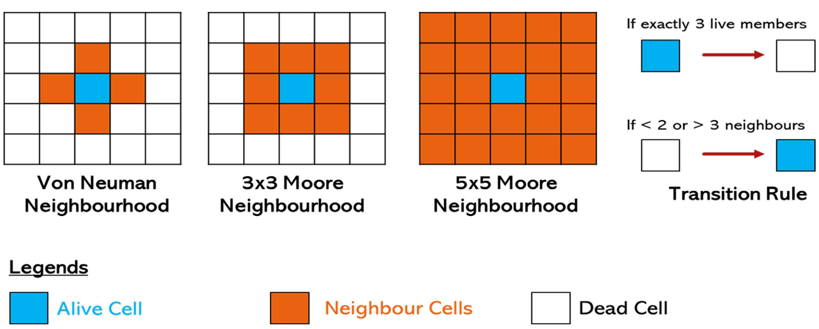

Figure 4. Elements of traditional cellular automata, with cells, cell states, Von Neumann and Moore neighborhood configuration and transition rule based on neighborhood configuration.

(Li & Gong, 2016) described the CA model using Equation (1)

$$s_{ij}^{t+1} = f\left(s_{ij}^{t}, \Omega_{ij}^{t}, T\right) \qquad \text{Equation (1)}$$

where:

s_{ij}^{t+1} is the stage of cell (i, j) at time $t + 1$

(s_{ij}^{t}) is the state of cell representing the stage time t

Ω_{ij}^{t} is state of neighborhood state and transition rules

T is the transition rule by linkage to function f.

The CA models are better at representation of spatial interaction at the pixel level. However, traditional bottom up CA models were not able to capture the macro socio-economic driving factors of growth (White & Engelen, 2000). These models also faced challenges in terms of number of driving factors sensitivity, fixed cellular state, and integration of human decision-making in the change process, thus failing to represent dynamic nature of spatial change (Santé et al., 2010; Liu et al., 2021). The development of CA models in urban growth modelling thus follows the trajectory to rectify and address the issues in the traditional CA modelling approaches including changes in cell shape, cell size, neighborhood configuration, transition rules.

Initial CA models were developed in the raster-based GIS platforms where each cell shape representation is a regular rectangular or square lattice (Yi, Min, & Lei, 2015; Stevens, Dragicevic, & Rothley, 2007). To address this shortcoming, the patch-based raster cells are proposed (Chen et al., 2019; Wang & Marceau, 2013). Patch represents a block or parcel of land as combination of cells with homogenous land use type as in **Figure 5** and conversion is on the patch rather than cell by cell basis (Yang et al., 2020). However, patch based simulations still represents the regular and fixed neighborhood, and hence cannot represent heterogeneity of space (Zhai et al., 2020).

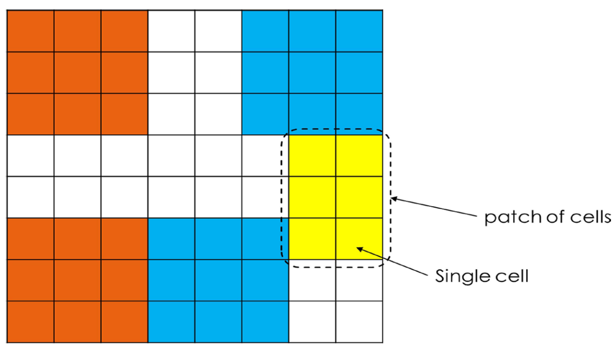

Figure 5. Grid of Cells where each block represents a cell, various color representing various land use classes and the group of same color coded cell represents a patch.

Change in spatial heterogeneity was done using vector based cellular automata. The vector-based CA allowed the representation of land use classes as Voronoi polygons, Delaunay triangles, spatial polygons, irregular automata in forms of cadastral land parcels, census parcels and planning zones (Lu et al., 2020; Zhuang et al., 2022). This approach also provides links between varying land classes, socio economic information and spatial information which makes the model more realistic and allows simulation in much finer spatial scales improving the simulation accuracy (Zhu et al., 2021).

However, in vector-based CA models the definition of neighborhood becomes complex as the size and shape of cells vary. (Stevens, Dragicevic, & Rothley, 2007) have proposed three alternative solutions to this problem, defining the neighbors of each parcel as: a) adjacent parcels only, b) those parcels that are totally or partially covered by a distance buffer, or c) the area within a buffer. (Dahal & Chow, 2014) proposed another neighborhood definition based on topological relations, proximity and intercepted buffers, and the extended neighborhood, where every other parcel acts as a neighborhood. (Barreira-González & Barros, 2017) proposed the use the spatial metrices to characterize and measure the neighborhood effect in irregular cells.

Moreover, transition rules are the most important aspect of CA models and determine the evolution of a cell. Transitional rules are a set of functions either deterministic or probabilistic based on which a cell changes its state (Roodposhti, Aryal, & Bryan, 2019). Traditional CA models use neighborhood influence rules as the benefactor to determine the transition rule (Roodposhti, Hewitt, & Bryan, 2020). As in Von Neumann or Moore Neighborhoods in raster-based CA, there is a certain combination of number of cells defined that determines the evolution of the target cell also shown in **Figure 4**.

To make CA models more efficient in simulation, in addition to neighborhood transition rules, different statistical, probabilistic, machine learning and heuristic methods are introduced to determine the change of cell state/transition rules. **Figure 6** shows the classification of the CA models based on used of different methods to define the transition rules. Various statistical methods like Markov Chain (Feng et al., 2018; Aburas et al., 2021; Rimal et al., 2018; Aburas et al., 2017), regression methods (Long et al., 2014; Cao et al., 2020), decision trees (Basse, Charif, & Bódis, 2016), fuzzy sets (Liu, 2012) have been used in the determination of transition rules in CA models.

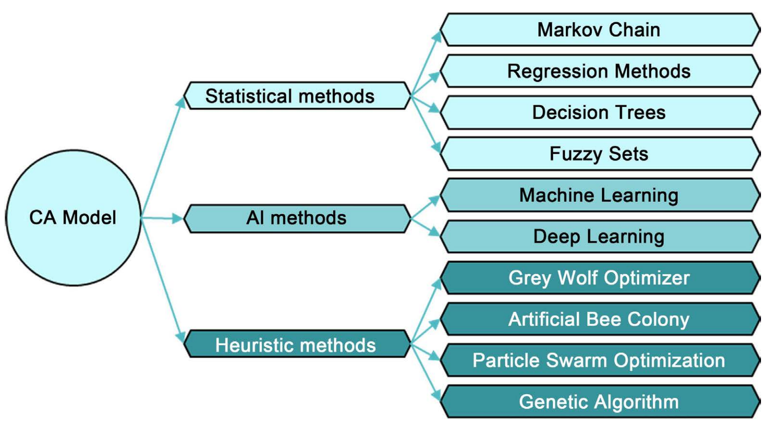

Figure 6. Developments in CA model with the inclusions of statistical, artificial intelligence, and heuristic methods.

With the evolution of CA models and use of variable influence factors, it was essential that transition rules be determined based on the influence of the driving factors that play a significant role in change of urban geography (Hewitt, van Delden, & Escobar, 2014). This means that a cell will change from non-urban to urban if it meets the required neighborhood transition rule and has higher influence of the driving factors like proximity and accessibility to different biophysical and socioeconomic factors.

Also, to address challenges in addressing correlation in interaction of influencing factors, spatial and temporal heterogeneity of spatial growth; variable machine learning methods like Artificial neural networks (Li et al., 2013), Support vector machines (Okwuashi & Ndehedehe, 2021), and heuristic methods like Genetic Algorithm (Liu, Feng, & Pontius, 2014), Artificial Bee colony(Feng & Tong, 2020), grey wolf optimizer (Cao et al., 2019), Particle Swarm Optimization (Feng et al. 2022) are used to mine the transition rules. (Feng & Tong, 2019) used three different methods to quantify spatial heterogeneity of land use classes in the neighborhood cells and used genetic algorithm to mine the transition rules. (Pinto, Antunes, & Roca, 2017) used Particle Swarm method in irregular cell CA to deduce transitional rules. (Yan et al., 2021) used eigenvector spatial filtering techniques in CA modeling to reduce the spatial autocorrelation in driving factors and spatial interactions in urban growth simulation of Suzhou, China. (Gao et al., 2020) used three spatial regression methods to address spatial heterogeneity: a spatial lag CA model (SLM-CA), a spatial error CA model (SEM-CA) and a geographically weighted regression CA model (GWR-CA) for simulating urban growth at Nanjing, China.

4.2. Agent Based Models

In ABM models the pixels/grids are called agents. These agents are free to move in space unlike the cells in CA models and thus, agents can mimic the interaction between humans and environment and make choices and decisions based on this interaction (Matthews et al., 2007). These agents are given certain attributes based on socio economic formulation of the urban system and interact with each other and transition based on the outcome of the interaction with each other, and via the utility function which is assigned based on preference and suitability of agents to choose a grid or pixel (refer to **Figure 7**) (O'Sullivan et al., 2012). The aggregated behavior of individual agents thus defines the structure of the whole system (Tan et al., 2015).

In urban growth modelling, the development of ABM largely constitutes the definition of the agent type, behavior and the decision-making rules that determines the outcomes of their interaction (Robinson et al., 2012). The agents can be defined and allocated based on the socio-economic formulations of the society or the interactions we intend to model between different land user types (An, 2012). This may include individual households, residential developers, government agencies, and so on and can be defined based on social hierarchy of the urban area (Filatova et al., 2013). These predefined agents are defined with certain attributes using statistical or regression methods, that define their status and suitability at a point in time, based on which they interact with other agent types

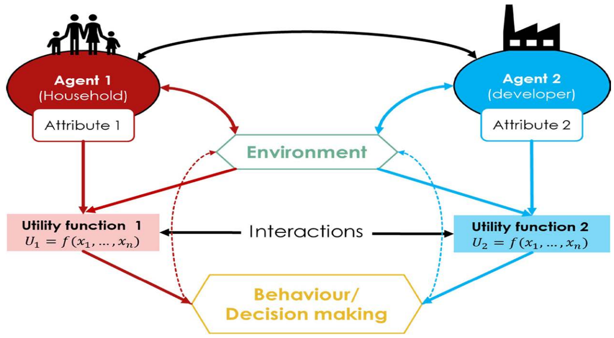

Figure 7. Schematic of agent-based models showing agents with attributes and Utility functions interacting with each other and environment for Decision making/Outcome.

and select a land based on the outcome of those interactions. The decision between two agent types can be decided based on simple argumentative statements of "if and then", case-based reasoning, statistical methods like decision trees (Deadman et al., 2004), theories from social sciences like utility theory (Evans & Kelley, 2004) and interactive decisions theory like Game theory (Tan et al., 2015; Kaviari et al., 2019).

ABM has also been used in combination with various quantitative methods as a hybrid model as shown in **Figure 8**. This has been done to enhance the behavior rules or decision-making rules of agents. (Xu et al., 2015) used ABM with Ant Colony Optimization (ACO) method where ACO was used to define the behavior rules of agents for LULC simulations of Erhai Lake Basin. (Hashemi Aslani, Omidvar, & Karbassi, 2022) used Multi-Layer Perceptron neural network with ABM to predict the future land use transformation of North Ahvaz watershed in Iran. Coelho et al. (2016) used artificial intelligence method call BDI (Belief-Desire-Intention) integrated with ABM, where BDI defines the transitional rules of the ABM for land use transformation studies of Cerrado Biome, Brazil. (Zhang et al., 2013) developed an ABM model integrated with Game theory for the study of urban expansion in Fuyang, China. (Li et al., 2020) used an ABM-Learning model, where learning behavior of human was embedded to study the impact ton land use patterns and simulate the urban growth of Shenzhen, China.

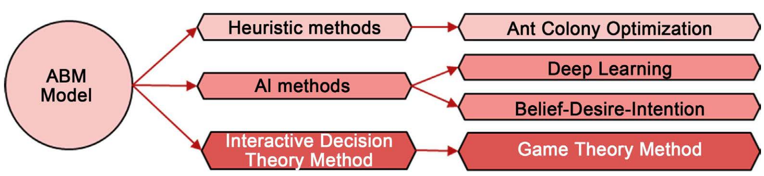

Figure 8. Variants of ABM model by using the heuristic, artificial intelligence, interactive decision theory methods.

The advantage of ABM is that the agents can move in space, interact with other agents based on feedback loop mechanisms, thus representing impacts of individual decision making and representation of socio-economic factors. Thus, Agent based models in urban domain have been used vastly in simulation of human nature interactions and simulation of factors and actors for urban indicators like pollution (Wang, Cao, & Zeng, 2020; Gurram, Stuart, & Pinjari, 2019), water management (Arasteh & Farjami, 2021; Mashhadi Ali, Shafiee, & Berglund, 2017), traffic management (Motieyan & Mesgari, 2018; Filomena & Verstegen, 2021), agricultural land use change Models, case study for Grain for Green Program in China and wide variety of other social and environmental issues including scenario and policy analysis (Dai et al., 2020). However, ABM lack a clear geo spatial representation in simulation environments and are not easily integrable with other methods and techniques, hence, fall behind in application of urban growth prediction to CA models (Heppenstall et al., 2012; Crooks et al., 2021). Also, the data requirements for ABM are large as the agents must be calibrated at the micro level which limits its application on larger scale compared to CA models (An, 2012; Batty et al., 2012; Zhang et al., 2013).

4.3. Artificial Neural Networks

Research in deep learning methods like Neural Networks boomed in decades of early and mid-2000s for image recognition, classification, and pattern recognition (Grekousis, 2019). Important feature of these methods is that they could incorporate any number of inputs, handle large amounts of nonlinear input data and would train themselves to look into the relationships between different input-output parameters in a nonlinear way (Li & Yeh, 2001). This provided urban growth modelers to resolve model sensitivity to number of data inputs and largely to bypass the autocorrelation between different input factors. Figure 9 shows various neural network frameworks currently in use in urban geography. The different layers are represented by nodes, each node acts on its own to determine the relationship between variables in the connected layer to determine the output and acts as an input for the next layer.

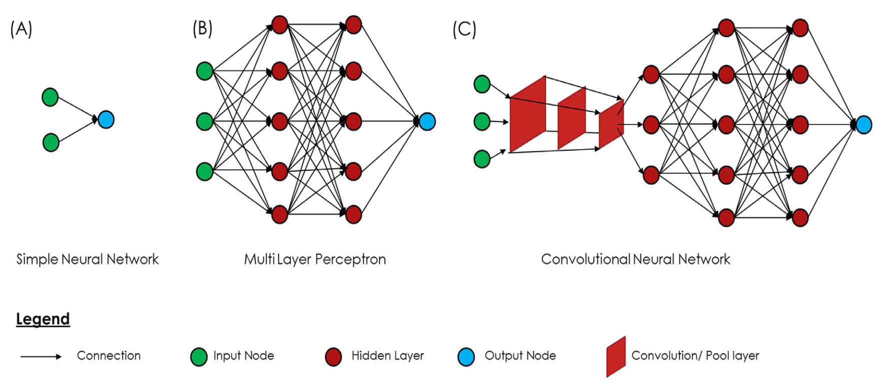

Figure 9. Various Neural Networks used in Urban growth models and their architectures.

The first implementation of ANN methods in urban growth modelling was done in 2002 via integration of GIS with ANN (Li & Yeh, 2001). Since then, ANN has been used widely to simulate and predict urban growth (Basse et al., 2014).

Different ANN models like convolution neural networks, multi layered perceptron neural networks have been used in urban growth modelling area (Omrani, Tayyebi, & Pijanowski, 2017; SİPahİOĞLu & ÇAĞDaŞ, 2022). (Maithani, 2009) used Multi-Layer perceptron network to study the Urban growth patterns in Saharanpur, India. (Alqadhi et al., 2021) used MLP to model the future Land Change in semi-arid region of Asir, Saudi Arabia. (Qiao et al., 2017) used multi-layer back-propagating neural network to study the land use change in Nanjing, China.

The advantage of the neural network-based models is that these models can address the non-linearity in relation between variable driving factors and growth, can handle large amounts and discreet input data types which was a challenging issue for CA, ABM models, meanwhile achieve acceptable simulation efficiencies. These models also addressed the issues of representation of spatial heterogeneity and sensitivity of CA, ABM models to data input. This made ANN one of the frequently used models for prediction of urban land use change (Basse et al., 2014). However, due to the black box nature of operations of ANN, it is difficult to describe the transparency in relationship between input variables and quantize the impact of the factors, and thus hard predicting the error propagation in modelling process (Roodposhti, Aryal, & Bryan, 2019).

4.4. Integrated Models

The basic nature of individual models is that the representation of urban system and growth in simple representation may not describe the broader range of chaotic urban dynamic processes (Liu et al., 2021). Various integration techniques are thus introduced to increase the sensitivity of the models. The models have been integrated to incorporate different transitional rules, different neighborhood configurations, inclusion of varying number and type of driving factors. The CA models are one of the frequently used in integration with other models because of their flexibility, simulation efficiency and representation of geospatial growth (Aarthi & Gnanappazham, 2018; Li & Gong, 2016; Aburas et al., 2016).

Towards the late 2000s to early 2010s, it was realized that combining CA and ABM models with each other as well as with modern statistical and regression approaches have more capabilities to account the complex phenomena. (Mozaffaree Pour & Oja, 2021) used a CA-ABM-Markov model to address spatial heterogeneity; (Kumar et al., 2021) integrated CA-ABM to analyze impact of socioeconomic factors, spatial neighborhoods, stakeholder choices, and development plans on LULC of Dehradun City; (Dahal & Chow, 2014) integrated ABM with irregular CA to determine if integration of these two models improves the simulation efficiency for San Marcos, Texas; (Tan et al., 2015) integrated CA-ABM coupled with Game theory to simulate urban growth of Wuhan; (K Agyemang, Silva, & Fox, 2019) used CA-ABM model to study geospatial behavior of key urban development actors, including households, real estate developers and government in Accra, Ghana. In such integration, CA represents the spatial component, ABM represents the environment and socio-economic variables and thus complementing the deficiencies of individual models by representing landscape as well as human role in urban growth-related decision-making process.

However, with the rise in number of CA-ABM models and their calibration methods, there were some inefficiencies of these integrated models to represent the temporal dynamicity of driving factors (Feng et al., 2019), spatial heterogeneity (Feng & Tong, 2020), model sensitivities to number of driving factors (Wang et al., 2011), multicollinearity between factors (Feng & Tong, 2017). To address this, integration of CA-ANN based models and ABM-ANN, and integration of CA models with different machine learning and heuristic methods was done (Okwuashi & Ndehedehe, 2021). To account for the transparency and black box nature of machine learning, methods like DoT (Dictionary of Trusted Rules), and to increase capability over to ANN, deep belief network (DBN) have been introduced in urban growth modelling (Zhou et al., 2017).

5. Analysis and Discussion

In the above sections we discussed the evolution of various urban growth models. Evolution revolves around better addressing the inherent challenges, shortcomings in the models and simulating urban growth more effectively. Two main problems broadly addressed are:

1) Improving the efficiency of model

2) Representation of true nature urban growth in terms of actual representation of components and process of urban area.

This identification of features, advantages and disadvantages is important when selecting models for the simulation of urban growth. As all the models have specific characteristics, are applicable in certain domains, it is important that relevant models that are suitable for the purpose of the study and applicable for the objective and region of study be used. Even though current modelling calibration and validation efficiencies achieve 85% to 90% accuracy, the applicability of these models in planning and policy making scenarios remain limited in literature. The following sections briefly discuss the models based on why acceptability rather than applicability of models remain limited.

5.1. Modelling Objectives

In urban growth domain, the objectives may include prediction of total land area increase, visualizing human-nature interactions and quantifying the impacts of these interactions, addressing the urban issues related in regional scale like formation of slums, high density growth, peri-urban growth, urban agglomeration etc. or scenario-based analysis like analysis of impacts of climate change in an urban area, analysis of impacts of flood in future urban growth, etc.

A single model even with various techniques may not be able to address all the issues within the localized simulation environment (National Research, 2014). (Liu et al., 2021) reviewed and highlighted how current practice of CA models in limited mostly to urban expansion rather than incorporating broader urban dynamics. (Ren et al., 2019) highlighted reasons for poor validation of models and hence the applicability and lack of global standards in the practice. ML models like ANN have shown great potential in urban growth modelling, however, as with other models a clearly defined objective to guide modelling process has limited their applicability or to larger case acceptability. Moreover, there is a gap in developing a clear classification of objectives on development of urban growth models which certainly has limited their integration in decision making processes. Thus, is necessary to define the modelling objective clearly before a model can be selected. A model should not be taken as a comprehensive tool to address all the issues in the local urban region from delineation of growth forms, morphology, direction of growth, influencing factors of growth, incorporation of any available data and simulation efficiency at the end. Necessary tradeoffs are required, and model selection should be done based on what issue or objective we intend to address through the modelling process.

This will help in increasing the applicability of all model types. Example, the early top-down models like Concentric Zone Model, Sector models or multi nuclei models can still be used in simple scenario analysis, non-vital planning, or reconnaissance survey to study the socio-economic distribution of urban area like distribution of households based on income, family size and other characteristics. Balakrishnan and Jarvis (1991) applied the Burgess CCD model to study the socio-economic status and family size of residents in 14 Canadian cities. The Land Use transportation model can be used in Transport Planning, determination of impacts of use of different modes of transport on housing, employment. Also, the land rent models can be applicable for simple analysis of variations of land prices based on distances, distribution of economic groups based on land use and variations. (Gautrin, 1975) used the simple Land rent model to evaluate the impact of Aircraft Noise on Land Rent Prices. (Park, 2014) reviewed the land rent theory in light of Global financial crisis of 2009 to discuss its applicability on current housing market. These top-down approaches are thus simple in application and may provide a reasonable estimate for simple scenario analysis rather than using complicated, data intensive and time-consuming complex models. Use of complex models like CA, ABM, ANN should be done when the objective is to model influence of various factors on various urban form related changes.

5.2. Data Requirements and Computational Complexity

Another characteristic of urban growth models is the use of variable amounts of input data. Since CA models can be calibrated and validated at the global scale, they are less data intensive and cost less computational power. However, in ABM the data must be calibrated at the local level on the scale of agents. Thus, depending on the number of agents defined and their attributes and utility function, the data demand at the local level can get very intensive and require higher computational power. Whereas models like ANN are flexible in terms of data requirements and computational power, as they can be used with scarce as well as large volumes of data. Depending on the data volumes, their computational requirements can vary depending.

CA and ABM types of models may be susceptible to large amounts of data in terms of simulation times and computational power required to handle the data. With the emergence of big data, the generic CA and ABM models, thus, may be more unfavorable to ML methods like the ANN. This is supported by development of intense data demanding ML methods like RNN, LSTM, GRU (Koumetio Tekouabou et al., 2022). Also, advanced ML models have great potential in addressing several challenges of urban form including spatial and temporal heterogeneity, non-linearity, however, increase in data demand and computational complexity is a challenge in large scale implementation of ANN based models (Koumetio Tekouabou et al., 2022).

5.3. Incorporation of Variable Drivers of Growth

Urban growth is a complex process derived by the combination of biophysical (Geographical and Physical), socio-economic factors, environmental and policy induced factors. The biophysical factors include the proximity to physical infrastructures and characteristics of the geography of urban land like slope, elevation, proximity to road network, health facilities, etc. Socio-economic factors include population density, GDP, household combination and human nature interaction. The environmental factors include proximity to or restricted development to waterbodies, conservation areas, parks, disaster prone areas etc. Policy related factors include policies like zoning, ecological conservation policies, land classification policies, infrastructure development policies that may induce or limit growth in policy implemented areas.

Figure 10 shows that the use of bio physical driving factors is predominant in the last 5 years. Especially proximity and accessibility related factors like distance to roads, city centers, public transportation, slope, elevation, and type of land use more primarily urban land use seem to be more used in delineation of Urban growth. This also provides a picture that the use of CA based models is frequently.

CA models are capable of incorporation of biophysical factors, however, fail to incorporate socio economic factors. Process based models like ABM more easily incorporate the socio-economic factors, however, lag in their spatial representation. This is due to the reason that biophysical factors can be represented effectively as static, whereas socio economic factors are dynamic and the rates of change of such factors are variable with time. This also makes CA models capable of simulation at global scales and thus one model developed can be used in different regions. However, ABM models are generic at the local scales and thus application of the same models at global scales may be inefficient. Hence, individually CA and ABM models cannot comprehensively represent both driving factors during the simulation. However, integrated models like CA-ABM can incorporate

Driving Factors	Frequency	Type of Driving Factors
Any kind of Road	79	
Urban City Centre	48	
Public Transportation	41	
Administrative centres	25	
Service centre(Shopping, restaurant,other indicators)	12	
Close Urban Centre(small /Big)	8	
Airport/Seaport	6	
Density of Industry	1	Physical
Slope	49	
Land Elevation/Altitude	35	
Landsue(Urban, Reidential,Industrial)	32	
Hillshade	7	
Soil type	5	
Vacant land	4	
Direction	2	Geographical
Population/Density	31	
Economy(GDP,un/employment,landprice,Investment)	19	
Education/Health Centres	9	
Tourist/Scenic areas	7	
HDI/Indicators	4	
Canals/Drainage	4	
Religious centre	1	Socio-economic
Water Bodies	28	
Green area/Conservation area/Parks	10	
Excluded areas	8	
Agricultural	4	
Diasaster pron area(flooding, fault)	3	
Annual Rainfall	1	
Average Temperature	1	Environmental
Policy Impact on growth	5	Policy

Figure 10. List and classification of various driving factors analyzed from articles from WOK from 2017-2022.

both biophysical as well as socio economic factors.

CA models are also susceptible to the number of driving factors input. Thus, generic CA models or CA models combined with statistical methods cannot incorporate large number of driving factors. It is important that the weights of driving factors be determined firsthand and only factors with influence in growth be input in the modelling platform. However, CA-ANN models or CA-heuristic can address this issue effectively. Also, a random selection of articles between 2018-2022 showed that most of articles used driving factors based on past studies of similar models or have not clearly defined the selection of factors. Only about 27% of articles have used a range of driving factors after either correlation analysis or after determining the quantitative impact of these factors. This provides a grim picture as the growth of an area may be dependent on other factors which may be missed in the modelling process. Thereby highlighting the fact that modelling accuracies are more prioritized rather than actual understanding of reasons of growth.

5.4. Urban Growth Models in Policy Based Scenario Analysis

Urban growth is an evolution of various forms of urban areas and relevant policies that shape these forms. Examples include questions like What policies an urban area has adapted for its residential, industrial development, what kinds of housing density to develop, what policies determine the land class for development, what is the socioeconomic policy of urban area that defines health, education, economic growth, and connectivity and many more. However, as these policies vary based on geographical areas, a single standard cannot be used which makes universal modelling of policy scenarios challenging. It may be imperative to use policy scenarios specific to the area being modelled, however, this has hindered practicing uniform modelling approaches.

As briefed in Section 4, evolution of urban growth models has been more focused on improvising models' performance rather than application as decision support systems for various planning and policy scenarios. There is a strong literature understanding on various scenario analysis impacting the urban growth process in terms of land use change (Wang, Murayama, & Morimoto, 2021). Authors have suggested development of relevant policies to manage different forms or rates of growth (Maturana et al., 2021; Kushwaha et al., 2021; Geng et al., 2022; Khan & Sudheer, 2022; Kisamba & Li, 2022). However, there is still limited understanding on how variable policies to manage these scenarios can impact this change after implementation. Recent review on various urban growth models revealed that only 6% of articles have used policy as a variable of change (Wang, Derdouri, & Murayama, 2018). **Figure 10** also supports this fact. Moreover, most of the policy scenarios are focused on bio physical or socio-economic influence related policies (Cheng & Liu, 2022; Spyra et al., 2021; Xu et al., 2020).

Another policy issue largely ignored in urban growth modelling, is the urban sustainability issues (Diehl et al., 2020). Now, as many urban areas are trying to develop sustainable practices and policies to enhance the sustainability of urban areas, urban growth models have largely bypassed this incorporation due to challenges in modelling environment (Sakieh et al., 2015). Widely used CA based model like SLEUTH is able to model different forms and urban change, allocate restricted areas for development for ecological conservation (Akyol Alay, Tunçay, & Clarke 2021; Eyelade, Clarke, & Ijagbone, 2022). However, this model has fixed input layers, which cannot broadly and clearly establish the relation between indicators of sustainability as input and growth as output. Model concepts like CLUE, FLUS have been primarily designed to incorporate various policy scenarios in relation to socio-ecological conservation and protection (Peng et al., 2020; Chasia, Olang, & Sitoki, 2023; Liu et al., 2017). However, large scale applications targeting urban areas still remain limited. Sustainable practice policies change the way urban area's function, hence, what is essential is integrating and testing of these sustainable practices as influence factors of growth.

Also, climate change is a global phenomenon and as most urban areas around globe will certainly be impacted by this phenomenon in one way or the other. The primary impact will be in terms of environmental and ecological parameters within the urban boundary like varying rainfall patterns, rise of sea levels, loss of vegetation and varying frequency of other natural hazards like floods, urban heat, fluctuating temperatures. These parameters will in a closed feedback loop impact the future of growth by influencing adjacent policies, socio-economic distribution and hence changes in patterns of urban growth (Hansen, 2010). Data requirements, computational complexity, and other inherent challenges in models will most likely be not that instrumental compared to challenges possessed by climate change in future. Climate change is one of major problems among current day grand challenges in integration of policy scenarios in urban growth models (Batty, 2011). However, the study on impact of climate change on urban growth is very limited (Liu et al., 2017). As the impacts of climate change get more intense, the necessity to understand this pattern becomes more fundamental. Moreover, CO_2 is main driver of climate change, however, study on impacts of carbon emissions due to different forms of urban growth is limited (Hong, Hui, & Lin, 2022). This consequently limits the application of urban growth models to forecast growth due to carbon emission induced urban change.

6. Conclusions and Recommendations

This study covers a comprehensive review on the development of urban growth models by highlighting and briefly discussing the drawbacks of predeceasing type of models and how new models addressed the drawbacks. It shows paths on which development of urban growth models can be traced. As the capabilities of these models have developed, the data requirements, resource engagement, and complexity of the models have grown manifold at the same time, especially after 1980s when the approach was reversed from static to dynamic.

It is essential that the primary objective of modelling should be a decision support system. Applications like these have been welcoming and hence imperative in advancing the knowledge. However, as long as models cannot incorporate policy making and impacts of policy in future outcomes, the applicability in large scale will remain limited. In addition, there is also a strong need to standardize the modelling approaches globally. However, due to the localized nature of modelling data environments, it possesses a challenge. In terms of policy-based scenario analysis, we propose that these scenarios can be modelled based on the following three classifications:

1) Contemporary policy-based scenario analysis (including biophysical and socioeconomic influence factors related policies);

2) Sustainable practice-based policy scenarios;

3) Climate change-based policy scenarios.

Alternatively, (United Nations, 2015) is a report published by United Nations for commitment towards sustainability and climate change mitigation. Such agendas, and goals tied within the agenda can be used to standardize the future modelling practices.

To conclude, models have evolved to improve simulation efficiency by improving inherent model inefficiencies and to represent the realistic nature of growth. Various models have different features and can address relevant parameters within the modeling framework. Therefore, the applicability of models should be more towards the inherent issues in the local urban domain which it is applied for. And, with emergence of big data and its acceptability, the future models of urban growth may head in a trajectory towards integration with AI based methods.

This presents potential as well as challenges in terms of how future models can integrate policy-based scenarios, and explain future growth based on sustainability and climate change contexts.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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