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RESEARCH ARTICLE

Cellular Automata-Based Suitability Analysis for Dense Urban Areas: The Case of Istanbul

Emirhan COŞKUN[1]

[1]Haliç University, Faculty of Architecture Department of Architecture, Istanbul, Türkiye

ABSTRACT

Cellular automata (CA) have emerged as one of the most popular approaches used in recent years to evaluate and predict the development and transformation of cities. Cellular automata approaches have made the complex interaction between urban dynamics and urban sustainability effectively understandable. These models provide a deeper understanding of the complex relationship between land-use changes and urban sustainability. This understanding enables governments, planners, and stakeholders to predict and evaluate the potential consequences of future policy alternatives. It is essential to create scenarios in determining urban policies. The fact that cellular automata models create what-if scenarios makes it an approach that can be used frequently for urban transformation. Thus, the study focuses on the urban development paradigm by interpreting the urban transformation concepts in the historical coastal areas of Istanbul with geospatial techniques, a CA-based urban growth model, and land use data. Reliability is vital for using CA models as decision-support tools in this context. Testing the reliability of CA models, one of the study's aims, is an essential parameter in this respect. For this purpose, the CA model was created by collecting population density, focal points, distance to roads, land uses, and land slope data from different periods (1994 and 2006). The results demonstrated that urban simulation models are effective decision-support tools, promising a more inclusive and explicit planning process.

Keywords: Decision support systems, urban growth, cellular automata, GIS

Introduction

The urban growth model, an interdisciplinary research area, emerges as an important theoretical and practical research area. Social, economic, and political interactions change and transform the physical space. As a result, many cities go through the restructuring process with new roads, infrastructure improvements, and economic purposes. For the sustainable distribution of usable resources, it is necessary to understand the dynamics of the urban growth process and to establish urban growth models according to these dynamics (Batty, 2005; X. Liu et al., 2017; Tripathy & Kumar, 2019).

Understanding urban development requires analyzing the complex relationships that make up urban interactions. This network of relations, which triggers urban change, determines the city's transformation. Since this is a complicated process to define, applying models that will help us to use urban dynamics interactively may allow us to remove the complexity (Sipahioğlu & Çağdaş, 2022). If all the decision makers of urban development and transformation, such as government, planners, stakeholders, etc., are integrated, it will be possible to create a suitable approach. The approaches we use in the computing age have a structure that can integrate with the urban development problems mentioned. One of the approaches that can support urban development studies is the CA model. In this context, the study focuses on understanding the urban growth process, making simulations, and measuring the reliability of CA models.

CA has emerged as a suitable urban modeling technique offering a powerful simulation tool to predictand comprehend the complexity of urban systems over space and time (Aburas et al., 2016; Musa et al., 2017; Santé et al., 2010). CA has been widely used for urban development due to its ability to adapt to complex spatial areas, achieved using simple and effective rules. This feature of CA gives it significant advantages. The general features of CA can be listed as follows. (1) CA is an intermittent dynamic system, and due to this structure, it represents complex and dynamic spatial models or is constantly effective in testing its performance (Sietchiping, 2004). (2) The spatial integrity of CA provides an advantage in any geographical area or self-organization, and thus it is possible to reach high-quality outputs (Silva & Clarke, 2005). (3) The adaptability of CA includes the flexibility of its relations

Corresponding Author: Emirhan COŞKUN **E-mail:** emirhancoskun@halic.edu.tr

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with neighboring cells and the size of the cells. In addition, the state of being integrated with different models can be shown as an expansion (Batty, 2005). (4) The simplicity of CA allows it to present spatial complexity intuitively and effectively. At the same time, considering it in the city context reduces the complexity to a level that is easy to handle (O'Sullivan & Torrens, 2001). (5) The lattice structure of CA makes its connection with geographic data completely visual. Due to its character, it can integrate with many virtual applications. In the urban context, CA has a structure that allows monitoring the growth of urban systems over time.

Many applications are created by taking advantage of the convenience and flexibility of CA. CA has four main ways to use in the urban context or to show a developing structure in regions with different urban dynamics. (1) Generating much richer forms of degeneration at the level of individuals: To understand the situation of any urban dynamic at different scales, it is necessary to analyze the individual layer. This is possible by considering spatial areas of different scales as cells and evaluating individuals (such as population and land uses) as factors. Thus, CA cells will encounter different situations at different scales, and sufficient data can be obtained about urban dynamics (Silva& Clarke, 2005). (2) Adaptations of CA Formalism: Changes to CA models or the adaptation process into which the models will enter include changes in the sizes and structures of the cells that make up the model. In addition, cellular states that can expand and extend neighborhood relations also have an important place (Batty, 2005). (3) Increasing the Efficiency of CA Models in the Optimization and Calibration Process (Efficiency and Improvement of CA Models, especially in the Optimization and Calibration Process): Studies on the development of optimization and adjustment play an essential part in this context (O'Sullivan & Torrens, 2001). (4) Linking CA Models to Traditional Cross-Section Approaches such as Transportation Models: Despite all the developments in CA Models, the limitedness of CA, the number of neighborhood functions, and the inertness characteristics are essential to discuss (Sietchiping, 2004).

Cellular automata models can integrate into geographic information systems and simulate complex urban dynamics by processing remotely sensed data with simple rules. These features of cellular automata; combined with the parameters of simplicity, flexibility, and controllability; make it an effective tool that combines spatial and temporal dimensions in urban development processes (Musa et al., 2017; Santé et al., 2010; Yeh et al., 2021). In urban studies, cellular automata show a feature with more potential than agent-based models (Table 1) (Wu & Silva, 2010). One of the critical factors is that it can easily integrate with geographic information systems (GIS). Integration with GIS facilitates using local data to make complex calculations encountered in urban dynamics, resulting in more effective results than mathematical models (Musa et al., 2017).

Table 1. Comparison of CA and Agent-Based Systems (Wu & Silva, 2010).

	CA	**Agent-Based Systems**
Focus	City-level and regional level Landscape and transition Urban simulations	Household and family; vehicles Human actions Population dynamics
Status change	Exchange data with neighborhoods Navigation	Alter attributes and behaviors by themselves
Mobility	Immobile entities	Mobile entities
Representing	Spatial dynamics Geographic factors	Aspatial Dynamics Social-economic factors
Character	Affinity with raster data and GIS Evolution Systems	Freedom for proper spatial mobility Complex Systems

Urban simulation models are considered decision support systems due to the complex nature of urban systems, incomplete or inaccurate local data, and uncertainties in planning policies introduced by all stakeholders involved in the urban design process (Poelmans & Van Rompaey, 2010; Yeh et al., 2021; Yeh & Li, 2006). These models aim to establish a process for how a city will transform concerning urban growth (Camacho Olmedo et al., 2018), allowing us to comprehend urban dynamics in advance and create development scenarios. The cellular automata approach is similarly unconcerned with the cause of urban growth and instead provides results for understanding how urban growth occurs. This study was motivated by the need to analyze the trend of urban growth and comprehend its future consequences by investigating the transformation and spatial changes of Istanbul's urban coastal areas, which have undergone dramatic changes due to urban policies and social and economic transformation. The region where the most significant change in Istanbul's urban coastal areas has occurred is the Marmara Sea coast between the Historical Peninsula and Atatürk Airport. The land use changes due to the filling areas made in the 2000s, the acquisition of new urban areas, and neo-liberal urban policies have been influential in determining the study area (Usanmaz Coşkun, 2020). In this context, the area between the historical peninsula and the airport was determined by creating a 10 km buffer zone (Figure 1).

Figure 1. Study Area.

Method

CAs are computational tools that simulate complex systems through simple rules. It is a system of cells representing a particular moment and local interactions through rules based on the current state of adjacent cells (Chakraborty et al., 2022; Y. Liu & Feng, 2012; Mantelas et al., 2012). The ability of CA to represent spatial dynamics and to incorporate time into the process are essential advantages in urban growth models. The spatial and temporal characteristics of CA make it easy to be an analysis tool for GIS systems. Before moving on to urban studies, defining the cell structure (the smallest unit of CA) is crucial to understand the model. Each cell that composes the cellular fields contains features belonging to one of the certain predefined states. The rule that provides the transition between states is defined as the local rule. Optimizing the transition rules according to the urban scenario for the cellular automata model is essential. This process is known as calibration. Since the finite state machine of a cell receives input from the neighboring cell, a local rule definition is crucial. Neighborhood refers to other cells in the adjacent position of a cell that can cause or influence the cell to move to the next state. For this reason, local rules represent transitions between states that will produce different results for different situations (Chakraborty et al., 2022; Puente et al., 2015).

Cell space, cell, neighborhood, time states, and transition rules form the essential components of a CA model. In urban models, each component has geographical effects and reflections. In urban models, the cell area represents the two-dimensional geographical area brought together by the cells, while the states of the cells indicate different land uses. Transition rules provide transitions between states with different land uses. Transition rules also form the core of the CA model. The autonomous structures of cells enable cells to change state according to transition rules as time progresses (Hashemi & Meybodi, 2009; Wu & Silva, 2010; Triantakonstantis & Mountrakis, 2012; Yeh et al., 2021) (Figure 2).

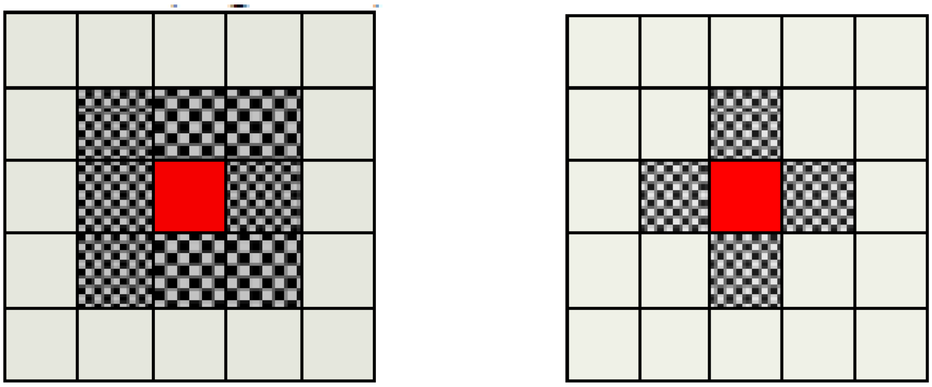

Figure 2. Neighborhood in Cellular Automata Cell. Left: Moore neighborhood; Right: von Neumann neighborhood (Hashemi & Meybodi, 2009, p. 413).

In a basic CA model, a regular grid system of square cells allows computation and works in harmony with the remotely sensed data. When the neighborhood of the cells is homogeneous, the hexagonal cell system can be used instead of the grid system. 3D cell systems can simulate vertical developments in urban systems. As in Voronoi systems, cell types with irregular areas can be used for scenarios with different spatial values (Iovine et al., 2005; O'Sullivan & Torrens, 2001; Shi & Pang, 2000; Yeh et al., 2021) (Figure 3).

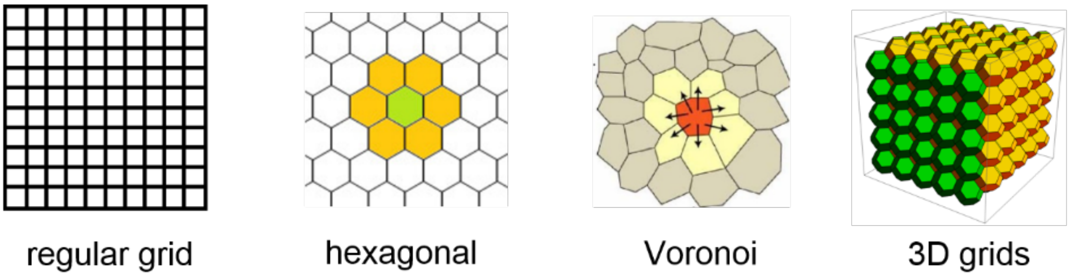

Figure 3. CA Grid Types (Wallentin, 2020, p. 97; Wolfram, 2002, p. 159).

Factors such as urban dynamics, changes in land uses, physical conditions, transportation, and population create complex neighborhood relations. Using non-uniform cell areas may occur because the variables are effective in urban models. The fact that transition rules form the core of cellular automata is vital to consider when describing complex relationships. In a basic CA model, the transition rules depend only on the state of a cell and its neighbors. However, in urban models, the large number and complexity of urban dynamics require consideration of external factors in addition to the states of neighboring cells. The flexible nature of CA models allows us to make these changes. While constructing the model, the randomness of urban growth and urban theories adopted throughout history can be reflected in the model. Another point is that the transition rules in basic CA models are static. It is the same at every moment of the model. Since urban processes change over time, it reveals the necessity of changing and calibrating the transition rules depending on the time factor (Li et al.,2008).

The simple and ordered nature of cellular automata models may need to be revised to represent the real world where geographic data is concerned. A disordered cell structure is needed to adapt the standard cellular automata approach to urban studies. When constructing cell structures and states, features of geographic processes incorporate into transition rules and neighborhood relations. Integrating the cellular automata approach with geographic information system data allows the development of an urban model with constraints. Thus, urban planning scenarios can be formulated more easily (Sıpahıoglu & Çağdaş, 2022). The fact that many factors in the local, regional, and global context are influential in the development of cities reveals the importance of constraints in increasing model performance. The urban model will reveal generic patterns in a scenario without constraints and geographic data.

For this reason, it is vital to determine urban model scenarios and simulate the urban development model with the proper constraints. Constraints are necessary for accurate predictions rather than affecting the production of cellular automata models.

Constraints also allow the provisioning of systematic data to see the reflections of environmental and sustainable policies on urban growth. In this context, systematically taking data from the transformations of the selected urban area in the historical process is critical in adapting the restrictions. Such constraints are frequently encountered in studies such as environmental suitability, urban forms, development density, economic development, and sustainable development (Yeh et al., 2021) (Figure 4).

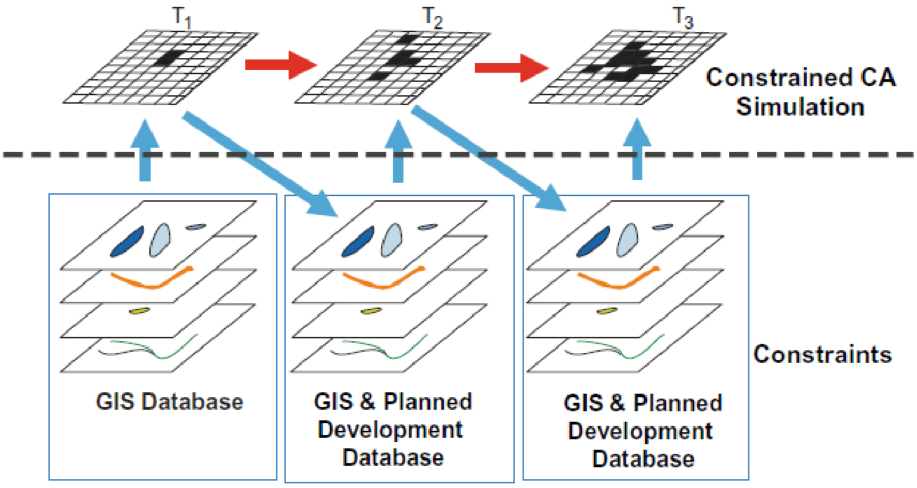

Figure 4. Constrained CA model (Yeh et al., 2021, p.870).

A large and classified data set is needed for urban development models to make accurate predictions within the scope of real-world simulation. The classified data set is vital in defining transition rules and neighborhood relations. In this context, remote sensing data are the most used data in urban development models. Filtering land uses on the earth's surface, and monitoring and measuring changes are possible with remote sensing data. For urban development models to make accurate predictions and to ensure model calibration, data on land uses in different periods are also needed. The remote sensing datasets may include road conditions, traffic networks, distance, natural features (slope and elevation), and physical factors. These data enable us to assess the suitability of land use changes for development. Datasets are classified into three categories: 1) Environmental factors, 2) Built factors, 3) Socio-economic factors. Environmental factors include topographic features. The slope plays a role as a determining factor in the determination of new settlements. Flat and gently sloping lands are simple to develop, while areas with less than 25% slope are considered suitable for vertical growth. Again, environmental factors include data on altitude, distance to coastal areas, green areas, docks, and open areas (Zhou et al., 2021).

Built factors represent the built environment that is independent of the natural environment. Circulation is an important concept. The prominent data are roads, land uses, infrastructure, and public spaces (Mustafa et al., 2018). Socio-economic factors include data such as population density and the number of residences (Poelmans & Van Rompaey, 2009). Using all these data sets contributes to the emergence of realistic simulation results (Chakraborty et al., 2022). Having many data types makes data quality a critical problem area. Calibrating the data is essential for the performance of the model. In this context, while classifying remote sensing data, categorization is provided by using the supervised classification method. Creating maps with different spatial resolutions and eliminating uncertainties is essential for comparative analysis. If there are errors and uncertainties in the data, the results produced by the urban model may be negatively affected and misleading. Creating a process analysis and flowchart is essential for urban models (Figure 5) (Yeh et al., 2021).

Defining and calibrating transition rules in the development of urban growth models is necessary to produce consistent results when generating past data and future forecasts. Since past time data and future predictions will be interpreted on the same rule set, it is essential to establish definitions on correct data sets (Clarke et al., 1997). In most cellular auto-based urban growth models, space reduction to square grids comes to the fore. This reduction ensures that the transition rules are applied iteratively to the spatial model. For this reason, the grid sizes used in the model and the remote sensing data must be the same. Cellular automata-based models developed to simulate urban growth are SLEUTH (Clarke et al., 1997), dynamic urban evolution model (DUEM) (Batty, 1997), multi-criteria assessment model (MCE) (Wu & Webster, 2000), multi-agent system (MAS) (Ligtenberg et al., 2001), Voronoi-based CA model (Shi & Pang, 2000), Markov-CA model (Vaz et al., 2014) (Tripathy & Kumar, 2019). The SLEUTH model, which is one of the oldest and best-known models, uses four essential data sets for the model; land use, slope, transportation, and restricted or protected areas (Clarke et al., 1997); MCE, which is a multi-criteria evaluation model, uses morpho dynamic layers, land use, slope, land carrying capacity, proximity to urban areas, and ecologically sensitive areas as a

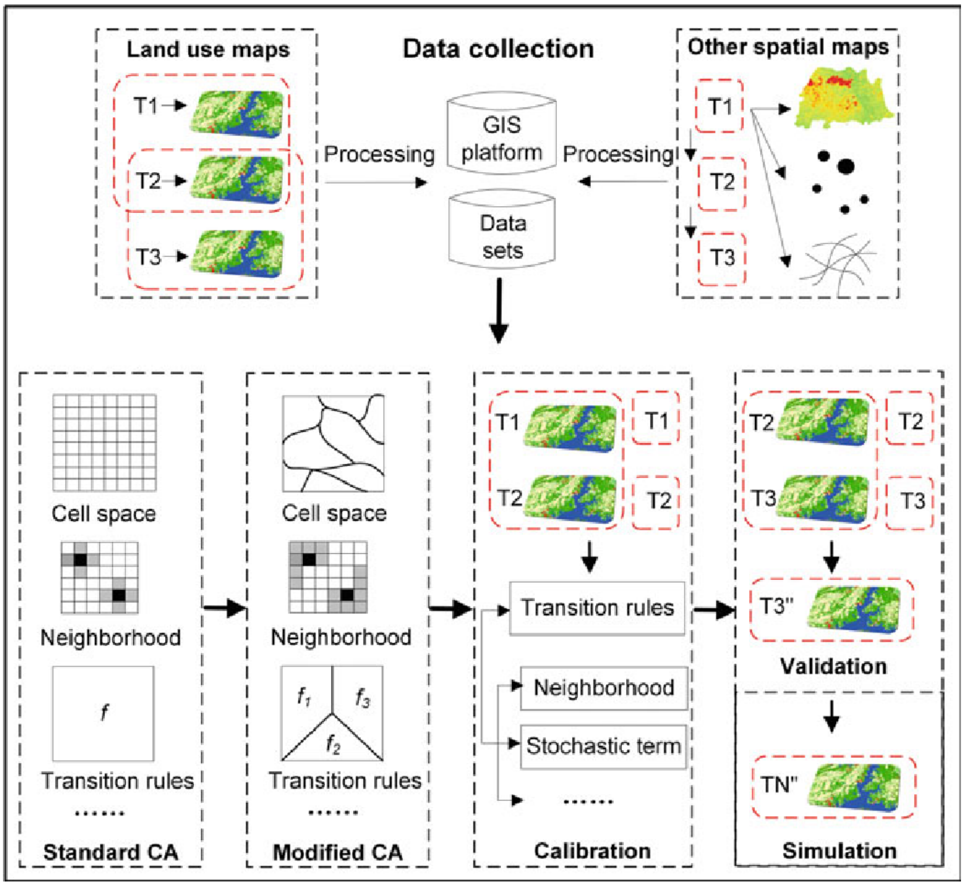

Figure 5. Flow chart of an Urban CA model (Yeh et al., 2021, p. 871).

data set (Bosque-Sendra, 2004). In the multi-factor system, data sets such as land use, population density, and transportation draw attention (Crooks et al., 2014). Since creating a model using a standard rule and data set is impossible, data sets must be prepared according to the determined scenario.

Although urban growth models have gained a versatile structure with technological developments, the selection and application of transition rules are at the center of research as an important problem area. The need for a specific design of transition rules and intensive computation to produce accurate results for urban growth models reveals the importance of developing models that are easy to calibrate and simultaneously apply urban growth's spatial and temporal dynamics. When examining the studies in the literature, it is seen that most models are developed according to individual preferences. For this reason, this study serves two purposes: 1) To accurately describe the function of neighborhood relations of data in an effective CA-based model to simulate urban growth, 2) To test the reliability of a model that considers the spatial and temporal dynamics of urban growth and conclude how it should be calibrated. While locally calibrating site-specific features is vital for spatial calibration, it is essential in terms of temporal calibration to give the model a structure that can adapt to the growth model depending on time. Within the scope of the study, the urban growth model will make this evaluation over two main data sets: Classified land use data for each cell for 1994, 2006, and 2018 and data from population density maps for 1994 and 2006.

Data Preparation

The data sets required for the study were created with remote sensing data as thematic layers. Land use and land cover layers were prepared using satellite data to understand urban growth dynamics for 1994, 2006, and 2018. Another critical data set apart from land use data is the preparation of population density maps. Apart from the land use and population density data, slope analysis, proximity to road networks, focal points, and the determination of the affected areas were prepared in raster layers.

GIS has become an essential tool that can be accessed globally and easily shared in terms of collecting, analyzing, visualizing spatial data, and acquiring new information. The widespread use of geographic information systems also enables spatial data to have increasingly detailed inputs. Thus, it is possible to collect appropriate data to solve complex problems. Although there is much alternative software for GIS that forms the data core of urban growth models, QGIS software, which is open source and free, was preferred within the scope of the study. Land use data was integrated into QGIS software with the Semi-Automatic Classification method. Environmental factors (slope, elevation) were obtained by filtering Shuttle Radar Topography Mission (SRTM) over USGS Earth Explorer satellite images. Data such as roads and focal points were integrated into QGIS software using the Open Street Map (OSM) database.

Land uses, which is the main focus of the study, are an essential source for reflecting built-up features. First, it is necessary to classify the remote sensing data to prepare the land use data of the region where the historical peninsula is located in Istanbul. The classification was prepared using the Semi-Automatic Classification (SCP) Plugin for QGIS. By entering the location information of the determined land, it is possible to download satellite images, process images and make raster calculations through the SCP plugin. While making the classification, four main categories were determined: 1) Built-up areas (such as residential areas, commercial areas, and public buildings), 2) Vegetation areas (such as parks and open public spaces), 3) Water-related areas, and 4) Other layers (Table 2) (Chakraborty et al., 2022; Yeh et al., 2021).

Table 2. Classification of Land Use Classes.

Built-up	• All artificial structures (residential areas, commercial areas, public areas, etc.)
Vegetation	• All green spaces within the urban area and its environments
Water Bodies	• All water bodies, including surface water bodies, lakes, reservoirs, ponds, rivers
Others	• All features, excluding built-up areas, vegetation, and water

After the categories and features were determined for the land use data, the maximum likelihood algorithm produced the classification. Sufficient training data is needed for the maximum likelihood algorithm to produce accurate results. It is possible to preview the training data and to check whether the data to be created is correct. Since the algorithm calculates the spectral distances of the remotely sensed data, training data was needed for each class. More training data is required for classes with close spectral distances (constructed areas and others) than for other classes. Classification is essential in the model as it determines the similarity ratio between the produced result and the actual data. Accuracy rates were determined according to classification. Similarity rates were calculated as 90.27% and 89.35% for 1994 and 2006, respectively. High similarity rates are essential for the reliability of the data.

Apart from land use data, population density is another critical data set for the urban growth model. The population density was prepared as separate data sets for 1994, 2006, and 2018 Population density data were obtained from the open-access Turkish Statistical Institute and World Population Hub database (WorldPop, & Bondarenko, Maksym, 2020). Spatial demographic data, research, and the open-access database made the population density data and population numbers of the desired years editable. The obtained density data were converted into raster layers to match the geometry of other layers required for the model.

Model

The definition of the urban growth model's transition rule, the model's calibration, and the evaluation of the results constitute the stages of the model discussed in the study (Figure 6).

The cellular automata model begins with defining the transitional rules that drive urban growth. These rules act as a function to constrain data such as land use and population density. Transition rules are defined through the neighborhood relation of cells. For this reason, transition rules have been defined over the 3x3 Moore neighborhood, which is observed to give more relevant results in urban studies (Sıpahıoglu & Çağdaş, 2022). By determining the neighborhood relations of the tested cells, the rules simulate their effects in the urban area.

Transition rules can be adapted according to the land uses and strategies for measuring the area where urban growth will be examined. In cellular auto-based urban models, the future state of a cell depends on three factors: 1) Initial state of the cell, 2) Initial states of neighboring cells, 3) Transition rules affecting urban growth. Determining the rules according to land use changes is essential to measure the CA model's reliability. In this context, land use of coastal areas, knowledge of areas to be protected, population density, and road use can be examples of transition rules. According to the transition rules, the transformation matrix of the classes was created (Table 3, Table 4).

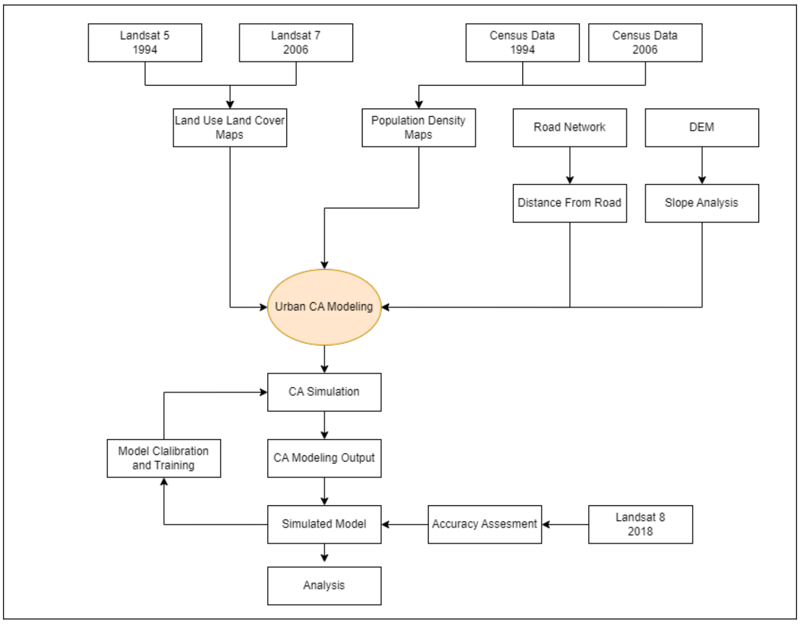

Figure 6. Flowchart of the model.

Table 3. Example of transition rules.

** IF land class is built up (residential, commercial, road, etc.) THEN no change.*
** IF land class is non-built up (vegetation or others), THEN it becomes built up* *if >> Population density is equal to or greater than the defined threshold* *AND neighboring built-up pixel count is equal to or greater than the defined threshold*
** IF the land class is water, THEN no change.*

Table 4. Transformation matrix.

Class Type	**Built up**	**Vegetation**	**Water**	**Other**
Built up	Can transform	No change	No change	No change
Vegetation	Can transform	Can transform	No change	Can transform
Water	No change	No change	Can transform	No change
Other	Can transform	Can transform	No change	Can transform

After the urban growth model data were prepared, development simulations were produced using the independent software GeoSOS -Future Land Use Simulation tool. FLUS has an infrastructure that can integrate with cellular automata approaches. The results in the study area were compared to historical and today's data, and their relevance and validity were interpreted. GeoSOS-FLUS is an effective interface that calculates urban development by finding complex relationships between human and natural factors to make land use change simulations more convenient and efficient. FLUS can be used for various urban development scenarios as needed: 1) creation of built-up boundaries, 2) high-resolution simulation of land use change within the city, 3) environmental management and urban planning, 4) large-scale land use change and its impact on climate, 5) regional land suitability analysis, 6) early warning for loss of natural and agricultural land cover types, and 7) hotspot recognition for land use change. FLUS offers a suitable interaction environment for measuring and evaluating the effects of urban policies and projects, especially since the beginning of the 2000s.

FLUS integration includes some stages. Firstly, spatial variables and historical land use data were analyzed to predict the transition rules of land uses in the historical peninsula of Istanbul, which has a dense texture, in 1994 and 2006. A development scenario was produced using the analyzed land use data with population density, distance to roads, inaccessible areas, and topography data. Although FLUS offers an environment that allows for multiple scenarios, the primary use case was adhered to as the study aimed to measure the reliability of CA models in a dense and historical area. In the context of the baseline scenario, an urban simulation trial was conducted within the constraints specified for 2018. The year 2018 was chosen because it provides ease of analysis due to the completion of the activities and mega projects in the built environment on the coastline that affects the population and the presence of field studies belonging to the Istanbul Metropolitan Municipality. Since the urban simulation was conducted in 2018, the necessity of having land use data from the 2000s and before, when the activities in the built environment became more frequent, has emerged.

Results

The study aims to test the data from 1994 and 2006 in the CA model to create a simulation for 2018 and test the result's consistency and reliability. Table 5 shows the data on land use in 1994 and 2006.

Table 5. Transformation matrix.

Land Use (1994)	**Percentage %**	**Area [m]²**
Built up (Residential, commercial areas, etc.)	46.20%	108,424,800
Vegetation (Green areas, parks, etc.)	17.09%	40,093,200
Water (Sea)	29.25%	68,640,300
Other (Restricted Areas, Soil, etc.)	7.46%	17,504,100
Total	100.00%	234,662,400
Land Use (2006)	**Percentage %**	**Area [m]²**
Built up (Residential, commercial areas, etc.)	51.48%	120,806,100
Vegetation (Green areas, parks, etc.)	14.99%	35,177,400
Water (Sea)	29.25%	68,640,300
Other (Restricted Areas, Soil, etc.)	4.28%	10,038,600
Total	100.00%	234,662,400

When we look at the change from 1994 to 2006, there is an increase in both area and percentage in the built environment. It is seen that the transformations in the defined transition rules have taken place. The fact that the road data stayed the same and the distances to the roads were fixed ensured that the change was not too much. Interpreting the changes in green areas is more understandable, as the built-up areas currently cover most of them in percentage and numerical terms. It is observed that there is a decrease in the area and percentage of green areas, and accordingly, other data variables and some of the green areas have turned into settled structures (Figure 7 & Figure 8).

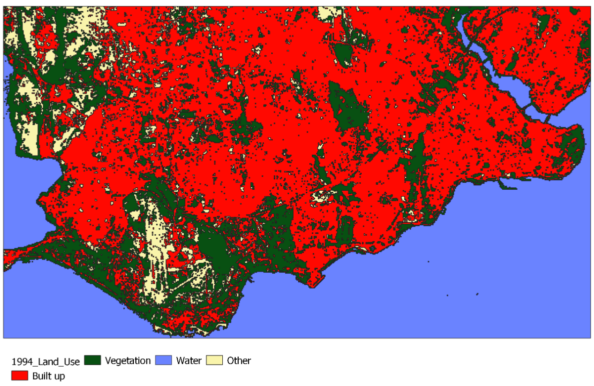

Figure 7. Land use of 1994

With the spatial changes and transition rules analyzed according to the data in 1994 and 2006, the 2018 simulation was made in the second stage. The purpose of the simulation was determined to test the adaptability of CA models as decision support systems in dense urban areas and to measure their reliability. The 2018 simulation produced a result that matched the data and changes in 1994 and 2006 (Table 6). Although the built environment has increased in the area, it has yet to show a significant percentage increase. Transition rules enabled transformations primarily between green areas and elements in the other class.

After the calculations, the analysis showed that the simulation changed the coastline and green area very little according to the

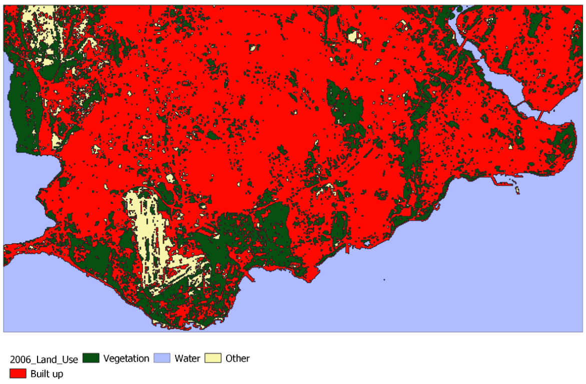

Figure 8. Land use 2006.

Table 6. Land use percentages and area (2018).

Land Use (2018)	Percentage %	Area [m]²
Built up (Residential, commercial areas, etc.)	51.77%	121,475,700
Vegetation (Green areas, parks, etc.)	16.00%	37,537,300
Water (Sea)	29.25%	68,640,300
Other (Restricted Areas, Soil, etc.)	2.99%	7,009,100
Total	100.00%	234,662,400

transition rule. However, the transformation caused by the projects made on the coastline of the historical peninsula as a result of the changing urban policies, especially in the 2000s, provided inconsistency for the model that made the 2018 projection by learning from the 1994 and 2006 data (Figure 8) (Figure 9).

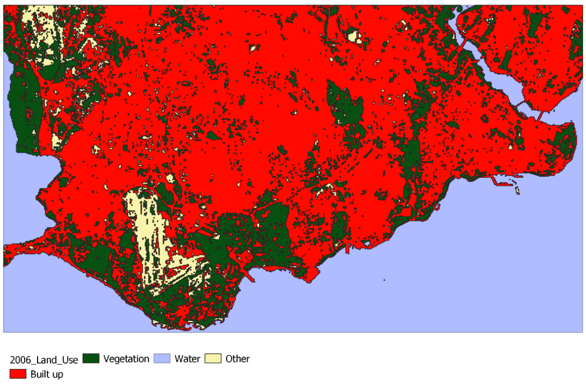

Figure 9. Land use 2006.

As a result of urban policies such as mega-projects and filling areas on the coastline, the decisions that changed the urban texture dramatically did not comply with the transition rules of the model, causing the calculations to be inconsistent. In this sense, although CA models have the power to make accurate urban development predictions with correctly defined rules and correct data sets, the unpredictable elements in urban dynamics have revealed that we need to produce development models with different and multi-layered scenarios. CA models in urban development are a tool with high potential as a decision support system.

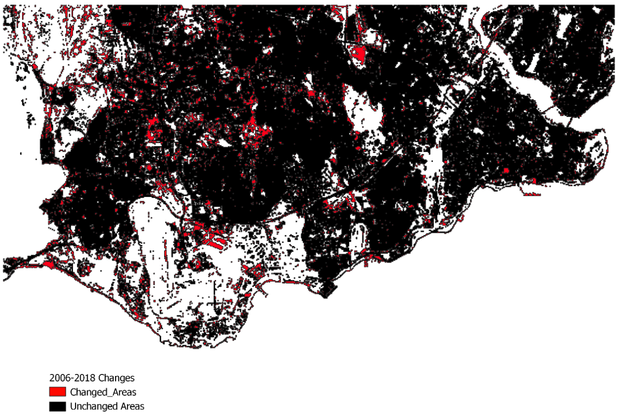

Figure 10. 2006-2018 Land Use Changes.

Discussion and Future Work

Urban CA models try to solve complex problems with a simple system structure. Although the simple structure increases the rapid development of the models and the ability of the models to solve complex problems, constraints arise in real life where urban dynamics are concerned. Extensive modifications are needed to remove the restrictions. On the other hand, since CA models have a flexible framework, they have the potential to be adapted to the desired environment. However, at this point, when dealing with a real problem like urban development, the problem of standardization arises. Flexibility can complicate the situation without a standard approach to the rules. In this respect, a CA model for urban development should be capable of making standard definitions in a simple and flexible framework for real-case scenarios. This study tested the suitability and adaptability of CA models in an area with a dense urban fabric. Although the CA algorithm can produce results suitable for the desired situation, unpredictable urban dynamics can prevent its practical use. They can be used as an interactive urban design tool when all stakeholders active in urban policies are part of the decision-making process. In this respect, urban CA models are descriptive, complementary, and capable tools as decision support systems. This study in the historical peninsula of Istanbul serves as a framework for future studies. Expanding the dataset, increasing the data range, and increasing heuristic learning are necessary to obtain more consistent results and make the model adaptable to different scenarios. Within the scope of the study, an evaluation was made of the local urban texture in 2018 using data from 1994 and 2006. To use CA as a decision support system in the local environment, the need to develop local-specific scenarios and analyses based on these scenarios has emerged. At the same time, for CA to play a more active role in urban development processes, it is necessary to integrate different periods into local scenarios and models. Conducting future simulations on specific scenarios is essential for a clearer understanding of the suitability of CA in a local fabric and the flexibility and adaptability of urban development models.

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