Hindawi
Complexity
Volume 2022, Article ID 2291508, 19 pages
https://doi.org/10.1155/2022/2291508

Review Article

State of the Art on Artificial Intelligence in Land Use Simulation

M. Luz Castro[1,2] **Penousal Machado**[3] **Iria Santos**[1,4]
Nereida Rodriguez-Fernandez[1,2] **Alvaro Torrente-Patiño**[1,4] **and Adrian Carballal**[1,4]

[1]*CITIC-Research Center of Information and Communication Technologies, University of A Coruña, A Coruña, Spain*
[2]*Department of Computer Science and Information Technologies, Faculty of Communication Science, University of A Coruña, A Coruña, Spain*
[3]*CISUC, Department of Informatics Engineering University of Coimbra, Coimbra, Portugal*
[4]*Department of Computer Science and Information Technologies, Faculty of Computer Science, University of A Coruña, A Coruña, Spain*

Correspondence should be addressed to Iria Santos; iria.santos@udc.es

Received 1 November 2021; Revised 28 April 2022; Accepted 16 May 2022; Published 26 June 2022

Academic Editor: Haitao Ma

This review presents a state of the art in artificial intelligence applied to urban planning and particularly to land-use predictions. In this review, different articles after the year 2016 are analyzed mostly focusing on those that are not mentioned in earlier publications. Most of the articles analyzed used a combination of Markov chains and cellular automata to predict the growth of urban areas and metropolitan regions. We noticed that most of these simulations were applied in various areas of China. An analysis of the publication of articles in the area over time is included.

1. Introduction

As pointed out by Levy in his urban planning manual [1], planning is an activity that is highly political and inseparable from the legislation. Regional and urban planning decisions often require copious amounts of public and private money, which can bring great benefits to some and losses to others. The complexity of modern communities makes the simplest and most direct approaches inadequate. In recent decades, several modeling techniques have been developed to understand and predict urban growth. In this day and age, much of the planning efforts and modeling are focused on environmental issues to manage development by minimizing environmental damage.

As mentioned earlier, urban growth is a complex process [2], and different approaches have been used to model it. AI-based methods have the advantage of being able to capture the nonlinearities and heterogeneities that exist in urban development. However, a method's superiority depends, among other factors, on how the algorithm's configuration parameters are determined, the size of the teaching and check sets, the architecture of the classifiers, or the selection of the teaching and verification datasets.

Examples of approaches using Markov chain models [3–5], spatial logistics regression [6], cellular automaton (CA) [7–22], agent-based models [23, 24], and artificial intelligence (AI) and machine learning methods such as artificial neural networks (ANNs) [25–28], support-vector machines (SVMs) [29–31], genetic algorithms (GAs) [32–35], particle swarm optimization (PSO) rules [36–38], or data mining [39] can be found in the scientific literature.

The CA is one of the approaches that is most widely used. The CA's ability to replicate urban growth assumes that past urbanism will influence potential trends through interactions with local land use. Its simplicity, flexibility, and intuition, along with its ability to integrate the spatiotemporal dimensions of the mechanism, make CA models competent for sculpting complex dynamic systems like metropolitan systems.

This review article addresses the different applications of AI in urban planning from 2016 to 2020, and particularly, the latest AI techniques for land-use prediction are organized in detail and summarized. This state of the art follows a comprehensive search methodology. We use keywords such as artificial intelligence, urbanism, or urban growth, for example, to search through Google Scholar and ResearchGate. We review the articles found and all their citations, and we collect all relevant information in this study.

We begin by briefly summarizing the previous state of the art on the subject and then delving into the different subsequent articles, which were not included in any of the previous reviews. Before starting this in-depth study, we can find in Table 1 a summary of the different topics covered in the articles mentioned throughout our text. Finally, an objective analysis of the results is reached, which perfectly summarizes the most important aspects that can be observed during the reading, and other relevant aspects. The conclusion highlights the issues that remain unsolved thus far and explains the AI applications that need to be addressed in future research.

2. Literature Review

In 2010, 33 of these models applied to true-world situations were researched by Santé, García, Miranda, and Crecente [63], to show an ordered picture that would facilitate the selection of a certain procedure for a given implementation problem. The authors pointed out that the main flaw is the relative simplicity of CA-based models, while flexibility conditions the model's right to replace events in reality, leading to certain regulatory measures categorized as follows:

(i) Irregular cell space: such as Iovine et al. [64] with their hexagonal cells or Semboloni [65] whose three-dimensional matrices allow to represent the growth of urban areas around their height, and using irregular tessellations such as Voronoi polygons [66] or graphs [67], or cadastral plots instead of regular cells [68], which can provide a representation that is more adjusted to reality.

(ii) Nonuniform cell space: considering other attributes of the land, and examples include accessibility, slope, or elevation.

(iii) Extended neighborhood: districts can be described as adjacent units belonging to spaces made up of irregular units. For example, units that are at a certain distance or employing the Voronoi spatial model [66].

(iv) Nonstationary district: different definitions of slum space for each cell [69]. Models in which each cell is weighted within the neighborhood according to its state and location [70]. This allows the application of districts of various shapes and sizes by adding zero weights.

(v) Transition rules with greater complexity: it may include suitability for land use, accessibility, urban planning, or socioeconomic conditions, reflecting urban theories that are based on theories of microeconomic planning [71], centrality, and potential models [72].

(vi) Transition guidelines (nonstationary): the transition guidelines are adapted to the distinctive properties of the specific periods and areas. This spatiotemporal modification can be obtained via calibration [73, 74], SLEUTH self-modification rules [75], or changes in external parameters and configuration at each stage as suggested by Phipps and Langlois [76].

(vii) Growth constraints: urban demand is often defined by economic, environmental, or social limitations, like urban planning or demographic change, which restrict overall urban development.

(viii) Irregular steps in time: where cells can be aided by different durations [68] or variable steps in time [77] to mimic different durations of specific events.

Other challenges cited for the urban CA models are the need for data and the lack of easily configurable and useable software. Uses of urban CA models were mostly limited to academic exercises because of these shortcomings. The authors concluded that implementing CA models with different techniques, for example, transport models or multiagent systems, could lead to mixed models overcoming some CA difficulties [78].

In 2016, a new literature review on urban cellular automaton (CA) models was published by Aburas et al. [79]. The authors analyzed the data and the most important factors used in CA studies to simulate and predict urban growth patterns and concluded that the model limitations, such as its inability to include the driving forces of urban growth in the simulation process [80] and its implementation with other quantitative models, can be minimized; for example, through the analytical hierarchy process (AHP) [81, 82], the Markov chain models [83, 84], and frequency relationship [85], realistic simulation is achieved when socioeconomic and spatial and temporal factors are integrated into the simulation process.

2.1. Latest Articles (2016–2020). The CA is a discrete cell in which states characterize each cell. The state of each cell depends on its previous state and on neighboring cells according to a set of transition rules. For urban simulation, the different types of the possible cellular automata are as follows: binary values (urban or nonurban); qualitative values representing different land uses; quantitative values representing the degree of development, population density, value of buildings, elevation, or number of roads, for example; or a vector model with several attributes [63].

We will focus our study on the direction taken by land-use prediction research conducted in recent years, as summarized in Table 1, where 19 of the 24 studies have employed some CAs.

Tong published a model in 2016 [40] describing the pattern of distribution of building construction in green spaces that complied with Chinese regulations. The author presented the distribution index (DAI) based on the

Table 1: Summary table of research cited.

Author/s	Year	Objective	Method	Location	Results
Tong [40]	2016	Planning and management of building layout in green zones	GA	Yuhuatai and Qingliangshan Parks in Nanjing (China)	IOD is the only criterion used for assessing results
Naghibi et al. [41]	2016	Predicting urban growth from satellite images	CA + artificial bee colony	Urmia (Iran)	Overall accuracy: 90.1%
Feng et al. [31]	2016	Predicting urban growth from satellite images	CA + LS-SVM	Shanghai Qingpu-Songjiang (China)	Maximum accuracy of 81.2% in the 16th iteration
Perez-Molina et al. [42]	2017	Simulation of urban growth scenarios and their consequent flooding	CA	Kampala (Uganda)	Overall accuracy: 97% *y* 98%. Edge index differential of 0.10 (with a land-cover map index of 49.05)
Chen et al. [43]	2017	Simulation of urban land changes	LP-CA	Shenzhen (China)	Higher average accuracy: 73.08%. Coefficients of correlation of 0.902, 0.883, and 0.881 between the industrial, residential, and commercial land change areas observed and simulated
Jat et al. [44]	2017	Predicting urban growth from satellite images	CA (SLEUTH model)	Ajmer, Rajasthan (India)	Overall accuracy: 80% urban area, 83% urban borders, and 60% for urban clusters
Li et al. [45]	2017	Predicting urban growth from satellite images	Segmentation-Patch-CA	Guangzhou (China)	Overall accuracy: 96%
Liu et al. [46]	2017	Future land-use simulation (FLUS)	CA + ANN	China	Overall accuracy: 84.7%
Feng and Tong [47]	2018	Predicting urban growth from geometric maps and satellite images	DE-CA	Kunming (China)	Overall accuracy: 92.4%
Traore et al. [48]	2018	Predicting urban growth from satellite images	CA-Markov	Conakry (Guinea)	Overall accuracy: 92%
Pazos-pérez et al. [49]	2018	Prediction of urban vertical growth	GA + EC	Minato, Tokyo (Japan)	Overall accuracy number of buildings: 100%, with a 19.5% deviation in building height
Fu et al. [50]	2018	Land-use simulation	CA-Markov	Hamilton County, Ohio (USA)	Overall accuracy: 91,07%
Feng et al. [51]	2018	Land-use simulation	CA + GA CA + PSO CA + GSA CA + LR	Yangtze River Delta (China)	Overall accuracy: 88%
Lipinget al. [52]	2018	Land-use simulation	CA-Markov	Jiangle (China)	Overall accuracy: 92.33%
He et al. [53]	2018	Predicting urban growth and land-use simulation	CA + UMCNN	Pearl River Delta (China)	Overall accuracy: >93%
Yuliantoe et al. [54]	2019	Land-use simulation	CA-Markov	Citarum Watershed, West Java (Indonesia)	Overall accuracy in the most optimistic scenario: merit figure 72.5%, accuracy of producer 78.5%, and accuracy of user 79.6%
Lu and Wu [55]	2019	Land-use simulation	CA-Markov	Hefei (China)	Overall accuracy: 90,48%, 87,76%, 85,1%, and *y* 82,36%, for the 3-, 5-, 10-, and 15-year intervals, respectively
Devendran and Lakshmanan [56]	2019	Predicting urban growth from satellite images	CA-Markov + NNACA	Chennai (India)	Overall accuracy: 84%
Huang et al. [57]	2020	Land-use simulation	CA-Markov	Beijing (China)	Relative error on construction land <0.3%
Khawaldah et al. [58]	2020	Land-use simulation	CA-Markov	Irbid (Jordan)	Overall accuracy: 78.4%
Mohamed and Worku [59]	2020	Land-use simulation	CA-Markov	Addis Ababa (Ethiopia)	Overall accuracy: 87%
Nurwanda & Honjo [60]	2020	Prediction of urban growth and land surface temperature	ANN-Markov	Bogor City (Indonesia)	Overall accuracy >90%

Table 1: Continued.

Author/s	Year	Objective	Method	Location	Results
Anand & Oinam [61]	2020	Land-use simulation	ANN-Markov	Manipur River (India)	Overall accuracy: 88%–93%
Mansour et al. [62]	2020	Predicting urban growth from satellite images and land-use simulation	CA-Markov	Nizwa, Al Dakhiliyah, (Oman)	Overall accuracy >80%

geostatistical methods to explain the pattern of distribution of houses in natural areas, and a model based on genetic algorithms that generated the building plan in correlation with a specific DAI. The Nanjing Yuhuatai and Qingliangshan Parks were used as cases for verifying the IOD's effectiveness. The author claimed that the model provided outstanding flexibility in the location of the buildings and that there is organic uniqueness and wide variety in the result of the calculation. He proposed to use it as a guide and reference when planning green spaces during the construction of the building layout. By using just the IOD, the limitation required of the model is relatively restrictive, making the results random and difficult to apply. Besides, the building project will also be influenced by different factors in practical projects, for example, the surface, the shape of the natural zones, the entrances and paths, the terrain and the location of existing buildings, and the practical conditions were not considered under the model presented.

To overcome this disadvantage, the new integrated CA models were recently proposed that were optimized via methods based on the swarm intelligence algorithms.

In 2016, Naghibi et al. [41] proposed a new urban growth model based on CA, using an artificial bee colony (ABC) algorithm to extract optimal transition rules. The ABC is an advanced algorithm based on meta-heuristic swarm intelligence that performs well in solving optimization problems. The authors applied the ABC-CA model to project urban growth with Landsat images from 1997, 2006, and 2015 in Urmia (Iran). The year 1997 was chosen as the base year for simulating future urban growth, and 2006 and 2015 land uses were used, respectively, to evaluate and validate the results. Finally, results for urban growth in 2016 were obtained from the simulation.

The reproduction results were tested using various statistical methods, for instance, overall accuracy, total operating characteristics (TOCs), and total operation Ant colony optimization (ACO) calibrated the CA model to evaluate the productivity of the model raised against similar methods with swarm intelligence algorithms. The authors noted that the ABC-CA model's overall accuracy and merit figure are 90.1% and 51.7%; 2.9%; and 8.8% higher than the ACO-CA model, respectively. In relation, the disparity in the ABC-CA model's allocation of simulation results is 9.9%, which is 2.9% lower than the ACO-CA. To conclude, with fewer allocation errors the ABC-CA model exceeded the ACO-CA model (Figure 1).

In 2016, Feng, Liu, and Batty [31] presented an automatic CA learning model (called MachCA) with nonlinear transition rules based on the LS-SVM to simulate city growth. By launching the input data using the LS-SVM method in a high-dimensional space, a perfect hyperplane is built to move away from the more complex limits between the two terrains (urban and nonurban), allowing the recovery of transition rules from nonlinear CA. For each iteration of the model implementation, the transition rules are dynamically updated in the MachCA model. Applying MachCA to simulate metropolitan growth on China's Qingpu-Songjiang surface in Shanghai revealed that rural-urban trends can be translated into spatial structures. A comparison of the MachCA model with a traditional log-adjusted CA model (called LogCA) resulted in fewer failures and more hits with the MachCA model because of its capability to capture the spatial complexity of urban dynamics (Figure 2). This translated into improvements in the accuracy, however, with a deviation of less than 1% in overall errors produced between the MachCA and LogCA models. However, the way the MachCA model is used to retrieve the rules of transition provided a new way to project the active procedure of metropolitan growth.

Feng and Tong [47] later developed a new mixed model (called DE-CA) that integrated differential evolution (DE) in CA to decipher the objective function and rescue the perfect CA parameters. The DE-CA has been adjusted through spatial data from the past to mimic land use at Kunming in 2016 and to predict many environments for 2026. The quantitative accuracy evaluation showed that the NA-DEC gives an overall accuracy of 92.4%, where 6.8% is the suitably collected growth of the urban area. Besides, the model only reports 2.6% failures and 5% false alarms. The authors projected three scenarios for 2026 with the use of DE-CA to adequately collect reference district development, conservation of the environment, and metropolitan design to explain their new model's robust predictive capabilities (Figure 3).

A comparative study of four CA models incorporating logistic regression (LR) and three metaheuristics was published by the same researchers [51] to simulate the land-use change in the Yangtze River Delta from 2005 to 2015. The metaheuristic methods were driven by an objective function representing the transformation rules' root mean square error (RMSE) and were considerably diverse in terms of optimization iteration, algorithm structure, and computation time. The authors argued that in cases where the complexity of the algorithm and the computation time are not of immense importance, any of the three metaheuristics could be used to build CA models for land use, as equivalent results can be attained (Figure 4).

In 2017, Perez-Molina et al. [42] merged a cellular automaton model with the flood modeling tool openLISEM to

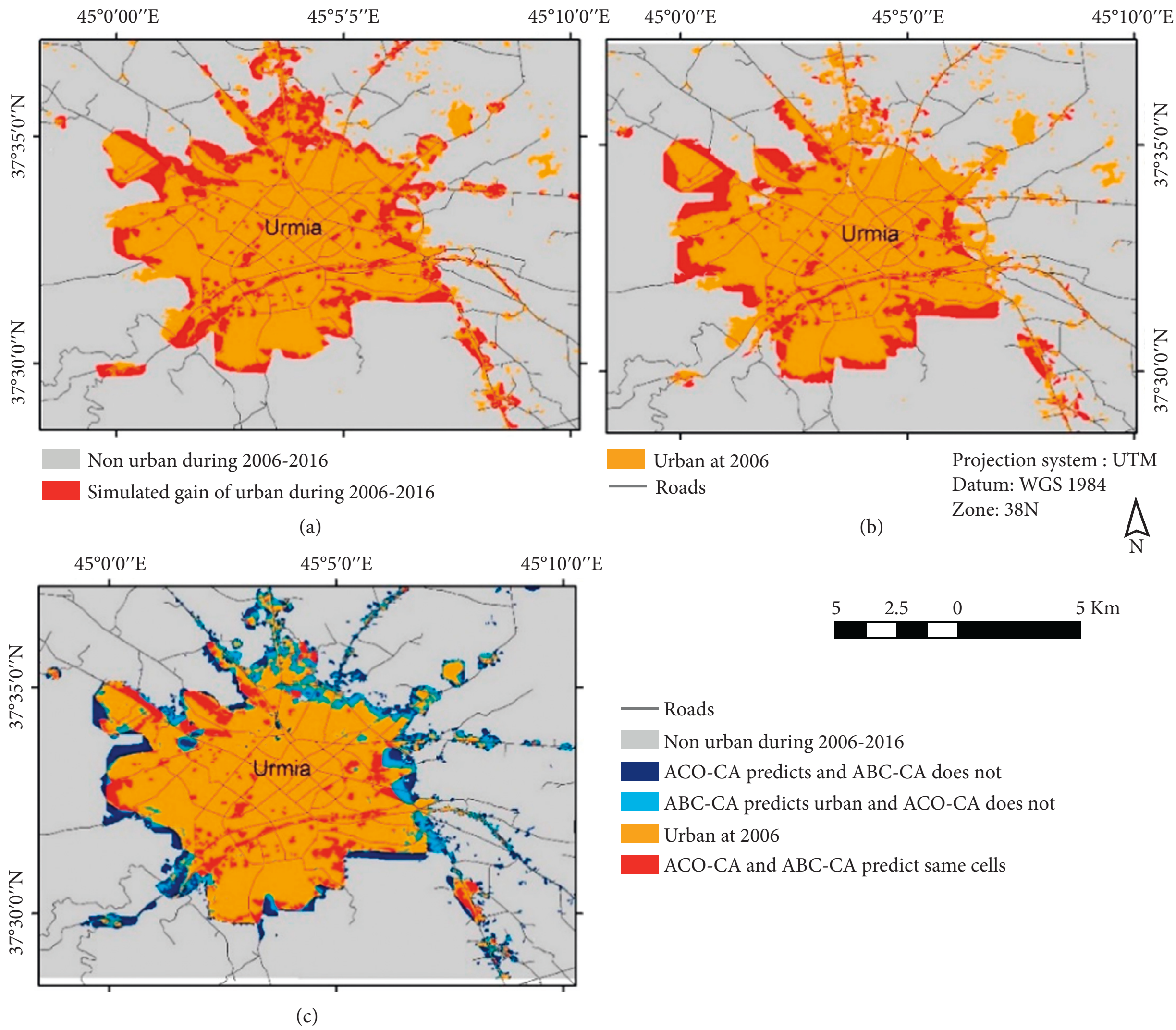

Figure 1: Results of Urmia town prediction for 2016. (a) ABC-CA model; (b) ACO-CA model; and (c) ACO-CA and ABC-CA models' comparison [41].

project district growth and subsequent flooding scenarios. This model was adjusted for the upper Lubigi (Kampala, Uganda), a sub-basin that had rapid metropolitan growth from 2004 through 2010. The model of the cellular automaton has been validated at Nalukolongo (Kampala, Uganda). Then, the authors employed the adjusted model set to project the upper Lubigi district growth contexts by 2020. There were simulations of two atmospheres, predilection requirements, and a strict policy for the protection of existing wetlands. The result of the upper Lubigi-projected scenario showed the ineffectiveness of a policy of exclusive wetland protection; likewise, a significant rise in the impacts of floods due to metropolitan growth is expected for 2020. The authors stated that the tool demonstrated its utility in creating significant land-cover change scenarios and in analyzing flood mitigation measures in a low-data number environment and that this strategy could also be applied to other spatially differentiated hazards that are seen affected by changes in the land cover. Liu et al. also studied simulation models for land-use and land-cover changes (LCCs) considering the background climate effects and proposed [46] a coming land-use simulation model (FLUS) that mimics the long-term spatial trajectories with multiple LCC's. During the projection period, the top-down system dynamics and bottom-up cellular automata interactively docked, and within the CA model, a self-adaptive competition and inertia

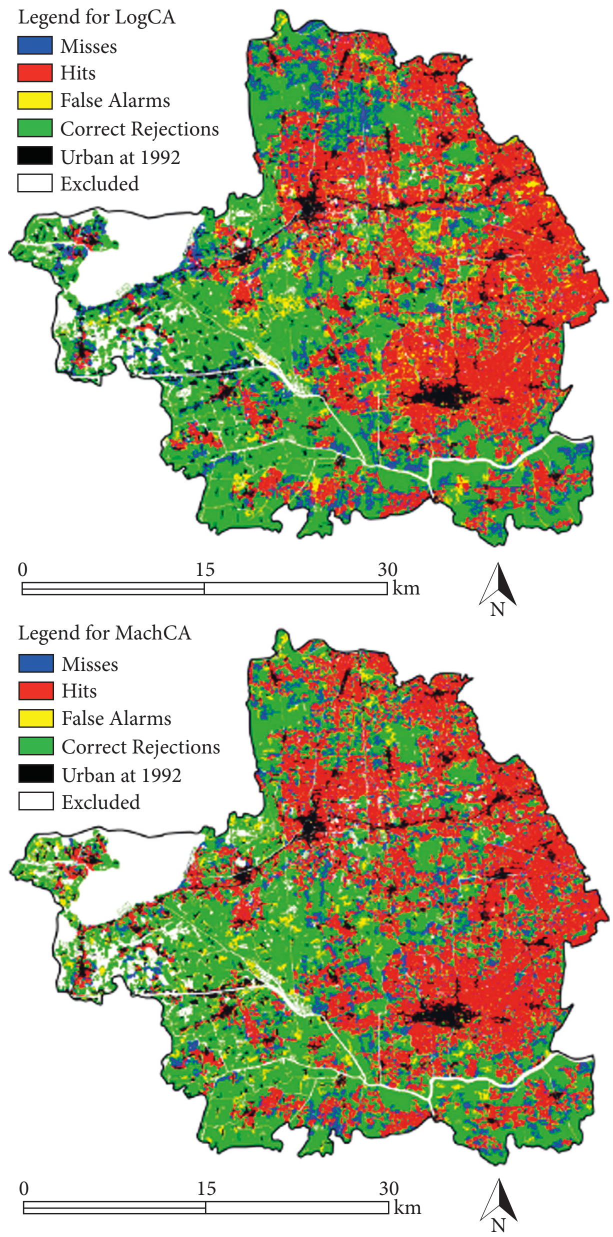

Figure 2: In 2008, metropolitan growth in the Qingpu-Songjiang area was projected using LogCA and MachCA models. Land use whose nomenclature is "excluded" shows water masses and wetlands. Hits (H) show that the increase observed was projected like growth. Misses (M) show that increase observed was projected like persistence. False alarms (FAs) show that the persistence observed was projected like growth. Correct rejections (CRs) show that persistence observed was projected like persistence (after Chen and Pontius 2010) [31].

mechanism was developed to conduct complicated tasks and interactions between several types of land uses. The model was introduced from 2000 to 2010 in China to a LUCC projection where the results indicated a promising agreement between the networks about the actual use of the land, and the precision was higher than other accepted systems like CLUE-S and CA. The model was even better applied to situations from 2010 to 2050 that encompassed various augmentation techniques that consider climatological, natural, and socioeconomic factors. The authors claimed that the simulation results indicated the correct use of the FLUS model in the hot spot regions and examined the causes and effects of potential active uses of land, which could assist academics and judgment-makers to develop correct policies to improve acclimation in the context of global warming to the rapidly changing natural setting.

Chen et al. [43] studied the reliability of fine-scale Earth simulations for raster cellular automaton (CA) models, because regular pixels/grids cannot accurately represent irregular geographic entities and their interactions. The authors proposed that vector CA models can overcome these deficiencies due to the vector data structure's ability to represent realistic urban entities. In their 2017 study, they presented a model of cellular plot automation (LP-CA) to

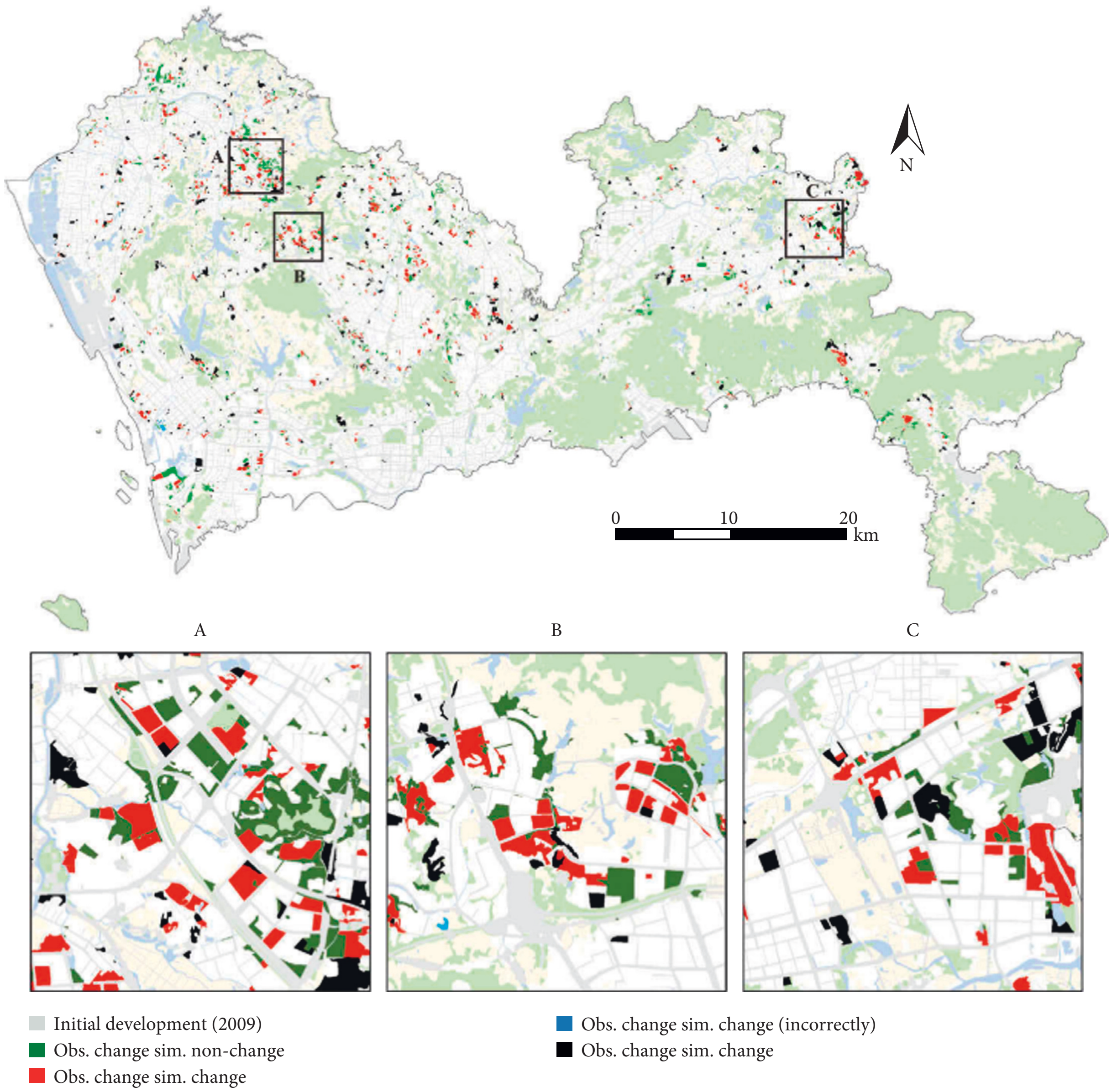

FIGURE 3: Three extended regions displaying the changes between projected and observed results. The disparities between the CA models are marked with circles [47].

simulate changes in urban land, where the model's innovation lies in the use of the automatic calibration joint-learning method. Three commonly used classifiers, Naïve Bayes, neural retro-diffusion networks, and decision trees were chosen to create a joint classifier as the base classifiers. The proposed model was applied in Shenzhen (China), and the experimental results showed the maximum calibration accuracy produced by bagging Naïve Bayes among a selected set of classifiers (Figure 5). District sensitivity assessment suggested that the LP-CA model with a neighboring radius $r = 2$ achieved the highest simulation accuracy. The calibrated LP-CA was used to challenge future changes in urban land use in Shenzhen, and the results were consistent with those specified in the official city plan according to the authors.

Li et al. [45] proposed a new model of metropolitan growth centered on patches with heuristic regulations that used a basin segmentation algorithm (Segmentation-Patch-CA) of the logistic CA model. Section objects derived from the properties of the metropolitan CA model were considered potential conversion patches, when determining a useful function that perceived the suitability and heterogeneity of the internal pixels. Two distinct kinds of metropolitan development were then recognized and individually recreated: organic growth and spontaneous growth, via the implementation of a neighborhood density analysis-based landscape expansion index (LEI). This proposal was applied to the city of Guangzhou, China (Figure 6). The results revealed an improvement in the landscape similarity index (LSI) that reached 20%–50% since the

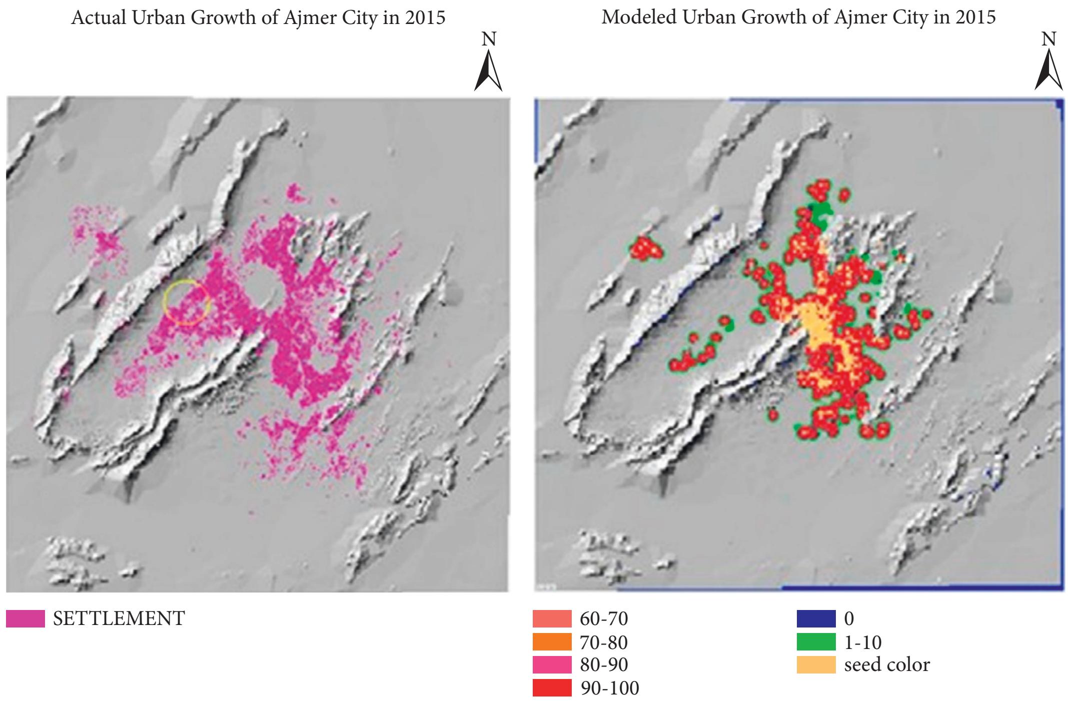

Figure 4: Simulation of 2015 LR-CA patterns and three metaheuristic CA models [51].

proposed system generated a more credible district landscape (96 and 97.38%) than the pixel-based one (45.14% and 74.82%) for two 2003–2008 and 2008–2012 modeling periods.

In 2017, Jat et al. [44] presented a study to evaluate the performance of the CA-based SLEUTH model to project the metropolitan rise of a complicated and slightly more heterogeneous area, the city of Ajmer in Rajasthan, India, which is different from the other areas tested by SLEUTH. Seven multispectral satellite images covering more than 21 years were processed and used for the parameterization of SLEUTH. The results of the urban growth predicted by SLEUTH were compared with other land-use/land-cover extraction methods. The authors stated that the study was successful in offering a meaningful insight into the issues benefiting to the risks in forecasting urban development in heterogeneous metropolitan areas. They have, however, identified some issues related to SLEUTH's sensitivity regarding the scale and spatial resolution of the input variables. Furthermore, the effects of the model indicated that SLEUTH is not capable of capturing the development of small size units, i.e., how unfragmented outdoor expansion is common in developing countries (Figure 7). The model underestimated the fragmented urban growth that can be compared to the approximate resolution implemented throughout the phases, and to the smallest average size below the resolution of the units created and errors in the input data due to classification errors in satellite images. This can be attributed to the heterogeneity of the procedure and the material used for construction.

With the use of the cellular automaton and Markov (CA-Markov) model incorporated with the geographic information system (GIS) and remote sensing (RS) [48], Traore, Mawenda, and Komba simulated land-cover change in Conakry, Guinea. Old information on land-cover modification was taken from Landsat data for the years 1986, 2000, and 2016.

The simulated result was compared for evaluation with the use of the relative operating characteristic (ROC) curve to the land-cover map of 2016. The ROC outcome demonstrated a substantial degree of agreement between both maps. Based on the result, using the CA-Markov model, they simulated the land-cover change map for 2025. The result showed that the metropolitan area ratio was 49% in 2016 and is anticipated to rise to 52% by 2025. On the contrary, the vegetation will fall from 35% in 2016 to 32% in 2025. The authors are optimistic about that study's results. They believe that the model will provide a basis for assessing the sustainability and urban area management and taking measures to mitigate urban environmental degradation.

Liping et al. [52] also used the CA-Markov model to predict potential land-use patterns through remote sensing and geographic information systems based on dynamic changes in usage patterns. They obtained a map predicting land use for 2014 in Jiangle County, China, based on the CA-Markov model, which was validated with actual 2014 results with a Kappa index of 0.8128. The authors also set the 2025 and 2036 land-use patterns.

In the upstream Citarum River Basin (West Java), Yulianto et al. [54] with the inclusion of remote sensing data and the CA-Markov model studied the dynamics of land-use reform and its estimation for the coming year.

Lu & Wu [55] used the method of spatial-temporal data fusion (STF) to obtain summer-scale images of Landsat over the past 30 years in Hefei, China. They used the CA-Markov model to simulate and predict future maps of land-use/land-

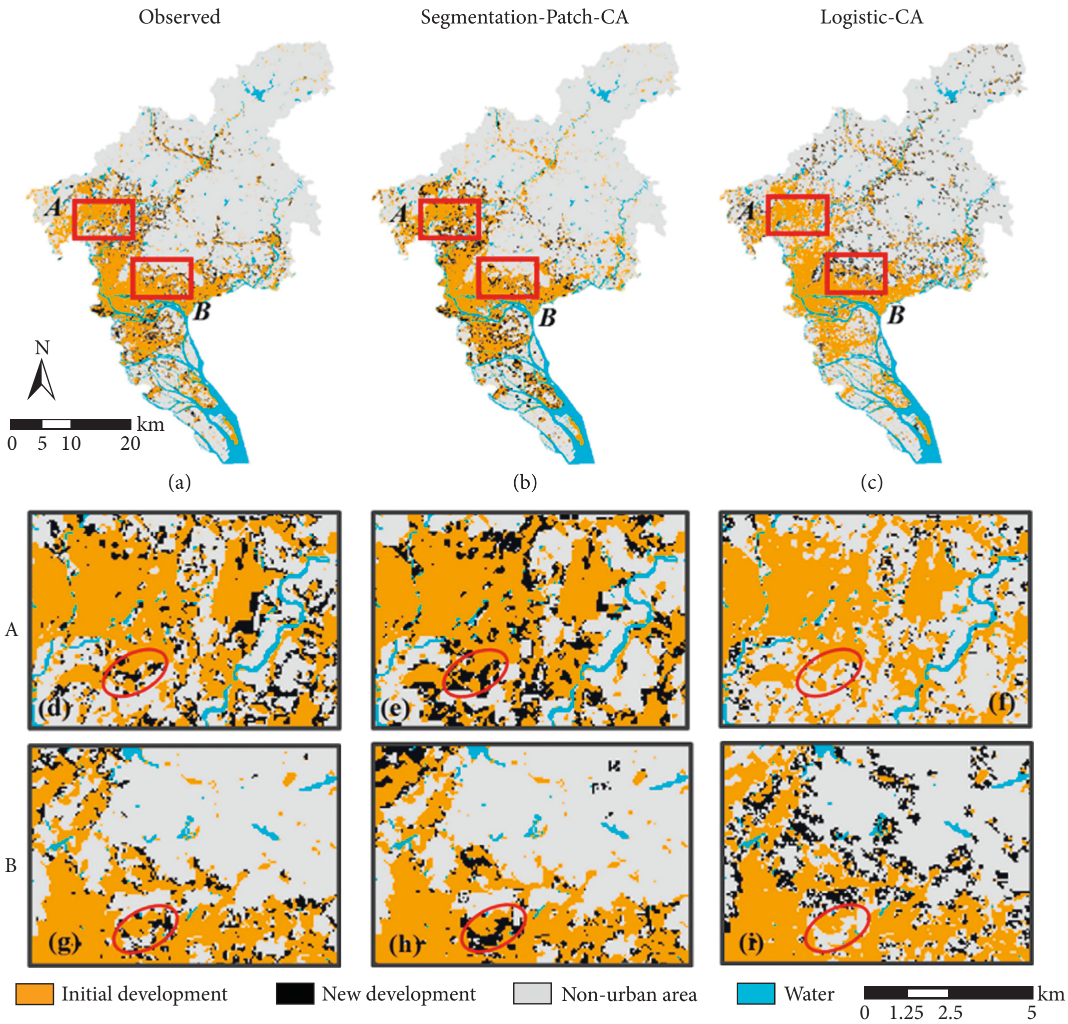

Figure 5: Chen's CA model applied in Shenzhen (China) 100 simulations overlapping ($r = 2$) for (a) industrial land; (b) residential land; and (c) commercial land [43].

cover change (LULC). The authors showed that merged data can improve the accuracy of LULC detection and prediction by shortening the year-to-year interval and obtain results for a specific year from LULC predictions. In their research, they observed that the areas of cultivated land, vegetation, and water declined by 33.14%, 2.03%, and 16.36%, respectively, and the area of land under building extended by 200.46% from 1987 to 2032.

Similar research was conducted by Huang et al. for the Beijing Territory [57]; Khawaldah et al. in Irbid, Jordan [58]; Mohamed and Worku in Addis Ababa and its environs [59]; and Mansour, Al-Belushi, and Al-Awadhi in the Nizwa mountain area of Oman [62].

Anand & Oinam [61] centered their research on the Manipur River Basin (India) wetlands and developed a future area LULC map using the Markov chain and an artificial neuron network. In Bogor City, Indonesia, Nurwanda & Honjo [60] applied the combination of multilayer perceptron and Markov chain (MLP-MC) to predict the future expansion of the city and land surface temperature (SST).

In the multicriteria evaluation (MCE), the Markov model of cellular automaton (CA) was used as a tool for decision-making about land use, analysis, and simulation [50]. Fu et al. explored the possibility of using historical data from a specific area for factor selection, scoring, and quantification. The authors created logistic regression models calibrated to choose and score every potential factor for historical land-use modifications and used the entropy technique for selecting the weights of the chosen variables. The SCM output is used as an input to the CA-Markov model to simulate changes in land use from 2001 through 2011. The simulation result was compared with the land use observed in 2011 to examine the method's performance. The result showed that the use of the SCM factors derived from old data creates a fitness of fit. The biggest advantage of this method is that it derives the selection of variables, ratings, and weights from local data that reflect the actual pattern. This numerical approach leaves for effective adjustment of the CA-Markov model and the growth of various land-use planning scenarios by adapting the rankings and weights of the various issues with the understanding of global change.

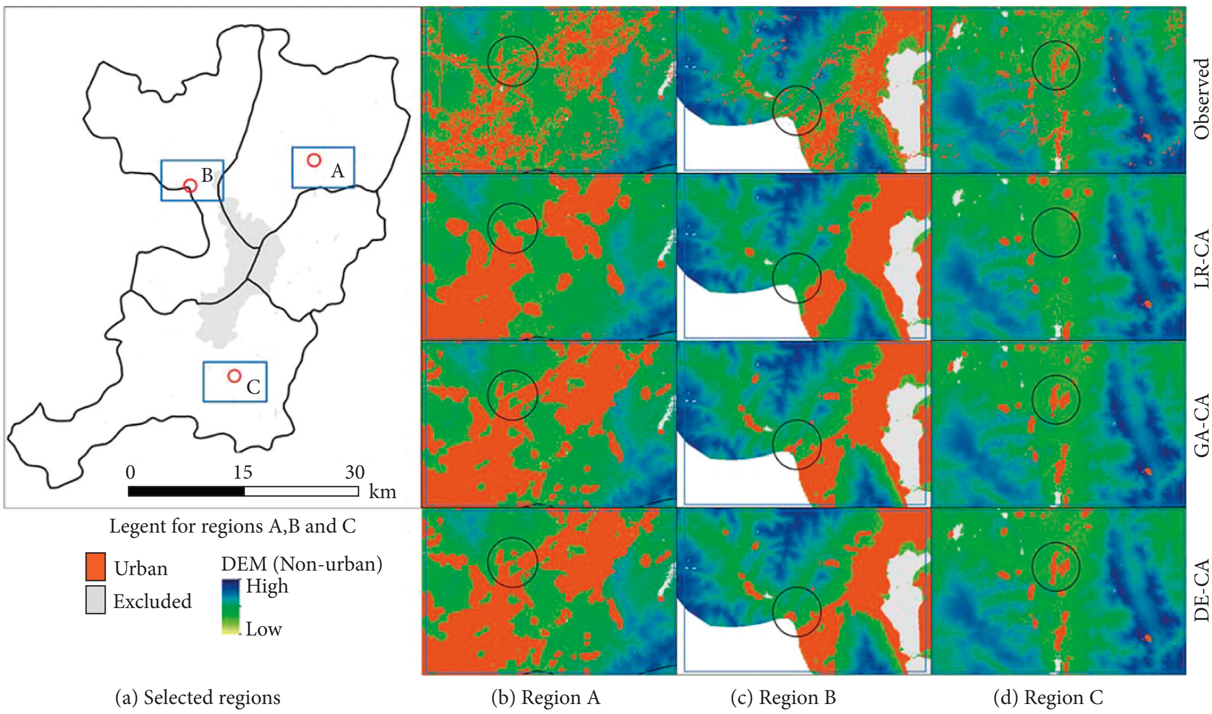

FIGURE 6: Comparison between two different approaches to growth with what was observed in Guangzhou (China), 2012. (a), (b), and (c) are overall results, and fusions of (d), (e), (f) and (g), (h), and (i) are zoomed-in viewpoints, respectively, of local areas A and B [45].

Devendran & Lakshmanan [56] used an urban growth model with cellular automata based on agent-coupled neural networks (NNACA) and historical datasets to forecast the growth of the Chennai metropolitan area (India). The prediction model used eight different urbanization agents, including transport, access points, and industries. Validation of the results showed that the most influential agent was the neighborhood. The authors measured urban expansion through Shannon entropy, and the values obtained suggested the need for more careful planning in the future development of the area.

He et al. [53] also focused on the effects of the neighborhood on the prediction of urban growth and used a CA coupled with a neural convolution network for united mining (UMCNN) and Markov chains to improve the performance of the simulation of urban expansion processes. They chose the Pearl River Delta (China) as a study area with the aim of verifying the effectiveness of deep learning in urban simulation, compared with three machine learning-based CA models (LR, ANN, and RFA). The proposed method achieves the highest simulation accuracy (>93%) and similarity to the landscape index (>89%). However, the authors warn that, although the accuracy of the model is greatly affected by the size of the training window, its lowest result is still higher than the traditional CA model.

Pazos-Pérez et al. investigated the use of evolutionary genetic algorithms to predict metropolitan vertical evolution scenarios in the big central districts [49]. Tokyo's Minato district was used for the case study, as it has rapidly grown over the past 20 years. A genetic algorithm that replicates vertical urbanization was used to make predictions based on initial set parameters, calculating not only the number of potential high-rise structures but also the specific locations most probable to support new high-rise advancements in the future. To assess the accuracy of the genetic algorithm in projecting future vertical district growth, the results of the evolutionary model were compared with continuous high-rise evolutions. After the test, the genetic algorithm's predictions for the period 2016–2019 (Figure 8), and sharing the results with the actual ongoing projects now, the researchers concluded that the algorithm's growth projections were accurate in terms of a complete number of properties and their likely location (±6.67 percent). On the other hand, the algorithm did not accurately determine the year of growth (±1 year) with exactitude and building height (19.5% deviation), indicating that more studies must be carried out in the areas. This experiment proved that the use of evolutionary genetic computation is a method to predict vertical metropolitan growth with a lot of possibilities concerning space and the number of potential edifications.

As seen in the previous section, there are different variables that affect the prediction. The studies mentioned above have used different input variables for their predictions. These data can be seen in Table 2. Although the variables used are different depending on the study, there are a number of factors that stand out because they are present in many of them: population, race, diffusion, elevation, slope, environment, density, accessibility, constraint factors, stochastic or random factors, probability of development, socioeconomic changes, DEM, and historical land use through neighborhood factors and distances (between urban or nonurban spaces), roads, rivers, railroads, etc. We can appreciate the predominance of qualitative and quantitative

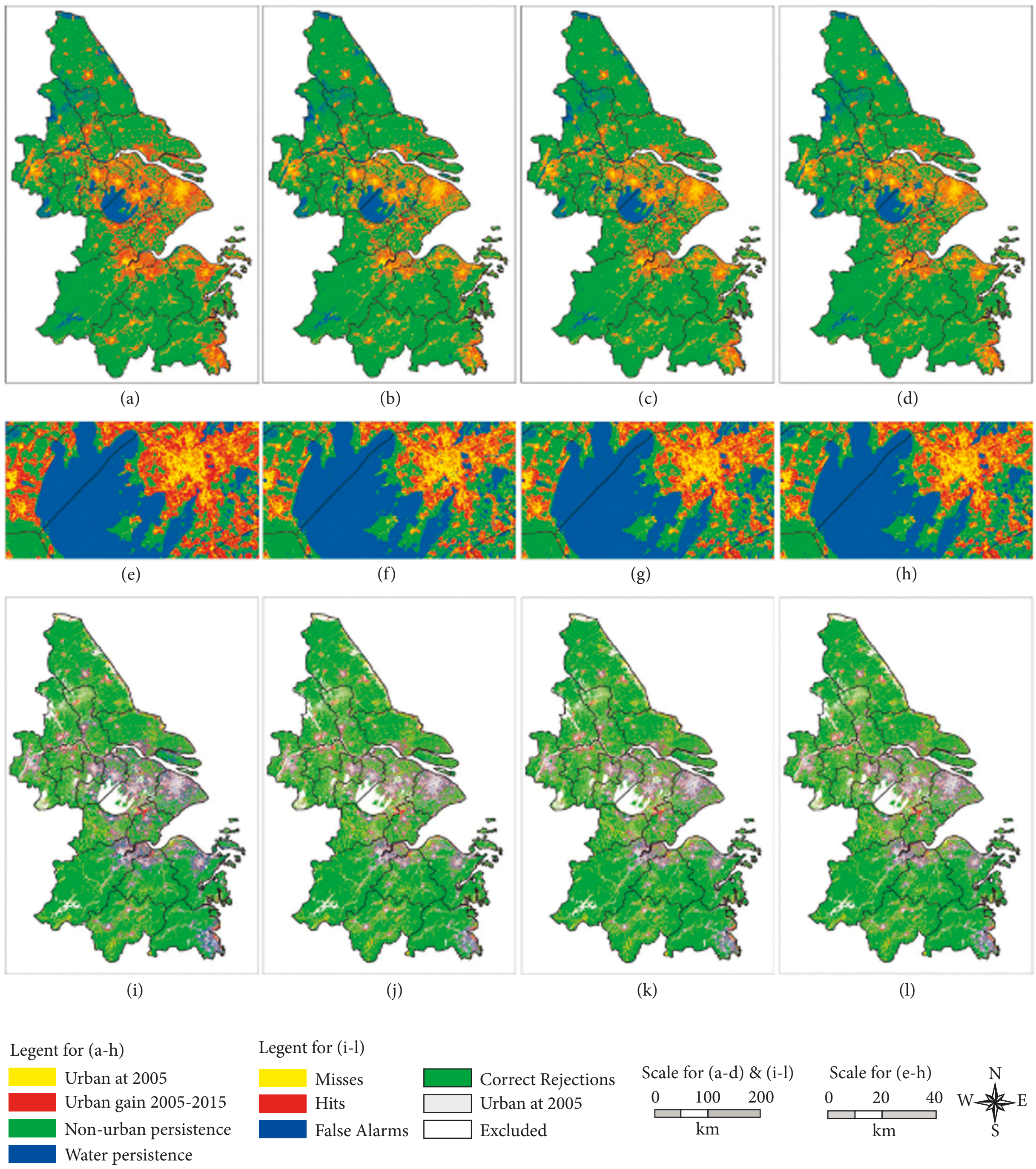

FIGURE 7: Modeled and actual urban growth in Ajmer (India) [44]. (a) Stimulated change by LR-CA. (b) Stimulated change by PSO-CA. (c) Stimulated change by GSA-CA. (d) Stimulated change by GA-CA. (e) Enlarged area of LR-CA. (f) Enlarged area of PSO-CA. (g) Enlarged area of GSA-CA. (h) Enlarged area of GA-CA. (i) Stimulation success and error by LR-CA. (j) Stimulation success and error by PSO-CA. (k) Stimulation success and error by GSA-CA. (l) Stimulation success and error by GA-CA.

CA models, to the detriment of the use of binary or vector CA models or other methods (ANN, GA, etc.).

2.2. More Relevant Data. The implementation of AI for urban planning is a flourishing field with an increasing number of researchers studying and publishing papers in this field. If we consider the different articles mentioned, we can see that since 2016 the number of research articles published in this regard has been increasing, with a decrease in 2018, which equals the number of publications with 2016 (3), but again the course of studies on the subject is redirected in 2020. We have not included the year 2021 within this state of the art, since it is the year of data collection and no results were found in this regard. The year with the highest number of publications was 2018 (7) followed by 2020 (6).

In addition, when it comes to the use of AI for urban planning, it is worth highlighting the countries used in the

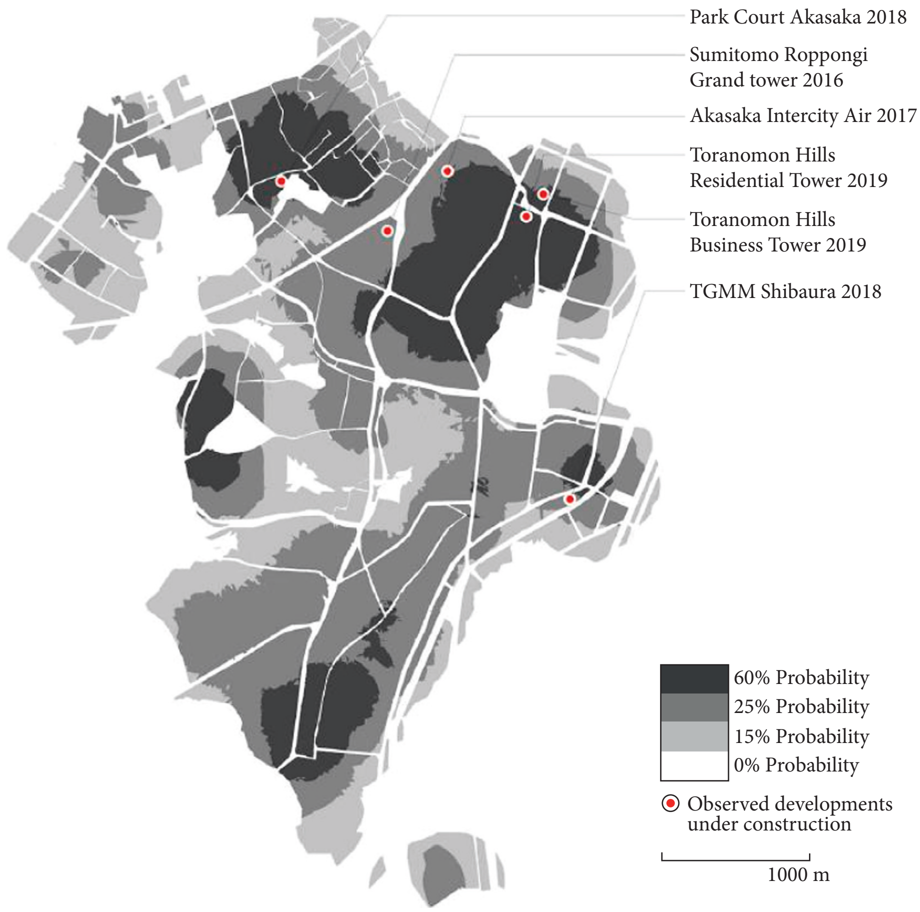

Figure 8: Genetic algorithm prognostications on a probabilistic grayscale in Tokyo's Minato district. Darker tones indicate a greater probability of new high-rise advancements (130 m approximately). Dots constitute discharge structures already planned for completion between 2016 and 2019 [49].

Table 2: Variables used for prediction in the articles of this review.

Author/s	Variables
Tong [40]	IOD is the only criterion used. The study mainly focuses on the geometric importance of the building, and the building types are ignored. The existing buildings in green spaces should also be taken into account in the calculation, but these constraints and practical conditions are not taken into account.
Naghibi et al. [41]	Remote sensing image (Landsat images) to land-use maps; distance to roads map; distance to business center map; distance to population center map; environmental-sensitive area map; slope map; and elevation map.
Feng et al. [31]	Conversion label; distance to urban center; distance to town center; distance to commercial housing area; distance to main roads; distance to agricultural land; and stochastic.
Perez-Molina et al. [42]	Spatial factors: calibrated model suitability, neighborhood factor, travel time to CBD factor, and wetland factor + 0,25 ∗ random.
Chen et al. [43]	Model control parameters: diffusion, breed, spread, slope, and roads.
Jat et al. [44]	SLEUTH parameterization with supervised classification (land use and urban) and the use of statistical measures: sng (cumulative number of urbanized pixels by spontaneous neighborhood growth), og (cumulative number of urbanized pixels by organic growth), rt (cumulative number of urbanized pixels by road influenced growth), area (total number of urban pixels), edges (number of urban to nonurban pixel edges), clusters (number of urban pixel clusters), rad (radius of cluster, which encloses the urban area), slope coefficient, spread coefficient, breed coefficient, road gravity coefficient, percent urban (percent of urbanized pixels divided by the number of pixels available for urbanization), urban growth rate, and number of growth pixels each year.
Li et al. [45]	Two different urban growth types: organic growth (based on segment) and spontaneous growth (based on pixels), which where identified and separately simulated introducing a landscape expanse index (LEI) that built on neighborhood density analysis. CA components: suitability surface, neighborhood, stochastic perturbation, and development probability.

Table 2: Continued.

Author/s	Variables
Liu et al. [46]	Socioeconomic and natural climatic factors: climate change, socioeconomic changes, historical land use, and interactions between variables to obtain land-use demand in each decade. Later, to ANN for land use in 2010: neighborhood influence, weight factor, self-adaptively land inertia, and converting cost. These combined probabilities with probability-of-occurrence surfaces and with roulette wheel selection detect the land use in time.
Feng & Tong [47]	Constrained relations among factors were applied in DE to generate different sets of CA parameters for the prediction of future scenarios. Variables that affect land-use changes: distance to urban center; distance to district center; distance to main roads; distance to the roads along Dianchi Lake; distance to protected areas; and DEM.
Traore et al. [48]	Prior to classifying the images using a supervised classification algorithm, unsupervised classification and normalized difference vegetation index (NDVI) were calculated to help select suitable polygons as training sites and to improve the overall classification process. The classification scheme was established based on auxiliary information from the field survey, local knowledge of the study area, and visual interpretation of the images. Image classification was performed using the maximum likelihood classification (MLC) algorithm, which is a supervised classification, and one of the most widely applied parametric classification algorithms.
Pazos-Pérez et al. [49]	A series of grayscale probabilistic maps with different parameters were produced to be used as the basis for the evolutionary model. The parameters were captured in the following gradient maps: land ownership, regulatory master plans, vertical urban consolidation, accessibility, and allocation. Land ownership: public vs. private; land redevelopment master plans; vertical density; accessibility; allocation parameters; and economic and real estate parameters.
Fu et al. [50]	They used the entropy method to determine weights for the selected factors. Potential factors for multicriteria evaluation: population change; change in employment; population density; median housing income; and highway accessibility, transit accessibility, slope, distance to each of the existing land use types, administrative constraints, and natural constraints.
Feng et al. [51]	Criteria for comparing CA metaheuristic models: best objective function value; iteration or generation; computational time; initial urban area; hit; correct rejection; failure; false alarm; assignment; and quantity. Spatial input variables: distance to city center; distance to country center; distance to main road; distance to railroad; distance to coast; DEM; and restricted areas.
Liping et al. [52]	This study uses remote sensing and geographic information. From 1992 and 2003 Landsat 5 TM images, and 2014 Landsat 8 OLI images and DEM, a land-use classification map was obtained for each year. The cell automaton model is mainly composed of cell, cell space, neighbor, ruler, and time. The closer the distance between the nuclear cell and the neighbor, the higher the weight factor. The weight factor is combined with transition probabilities to predict the state of adjacent grid cells so that land-use change is not a completely random decision. The Markov chain model component controls the temporal dynamics between LULC classes based on the transition probabilities, while the spatial dynamics are controlled by local rules determined by the CA spatial filter or transition potential maps.
He et al. [53]	They use spatial variables in UMCNN. For RFA-CA, the factors used are neighborhood effects, constraint factors, development suitability, and stochastic factors.
Yulianto et al. [54]	Inputs for the training phase of the CA-Markov model: time-1 land-use map; time-2 land-use map; simulated n-time transition area matrix; and simulated n-time Markov conditional probability image. Inputs for the simulation phase of the CA-Markov model: simulated n-time transition area matrix and simulated n-time Markov conditional probability image.
Lu & Wu [55]	Preprocessing tasks, such as radiation calibration, FLAASH atmospheric corrections, image mosaicking, and image cropping, were applied before classifying the images with the ENVI tool.
Devendran & Lakshmanan [56]	Agents of urbanization: existing built-up; hot spots; commutation, high-preference roads; medium-preference roads; least-preference roads; railways; red category industries; orange category industries; green category industries; white category industries; high land prices; low land prices; medium land prices; places of public interests; public utility centers; and population.
Huang et al. [57]	Driving factors: DEM, slope, aspect, GDP, population, highway, rail, river, road, and roc index.
Khawaldah et al. [58]	Image preprocessing techniques include the following: layer stacking; mosaicking; and subsetting or clipping to study area boundaries. The LULC classification scheme comprised seven LULC classes, identified by codes, to prepare different LULCs to simulate future land use.
Mohamed & Worku [59]	The research described the continuing historical increase in built-up space through the consumption of other ecologically valuable LULC classes. Driving factors: elevation, slope, road distance, highway distance, rail distance, and urban centers.
Nurwanda & Honjo [60]	Model control parameters: slope, distance to roads, distance to toll road, and elevation were also used as variables that influenced land-use change.
Anand & Oinam [61]	The ANN was trained with the driver variable, i.e., distance to roads, distance to settlement, elevation, and slope.
Mansour et al. [62]	The analysis was based on three equal interval LULC maps derived from satellite images: Landsat TM for 1998, 2008, and 2018, together with topographic spatial layers (elevation aspects and terrain slopes) derived from the ASTER digital elevation model. Other spatial parameters (population density, proximity to urban centers, and proximity to major roads) were also incorporated into the simulation process.

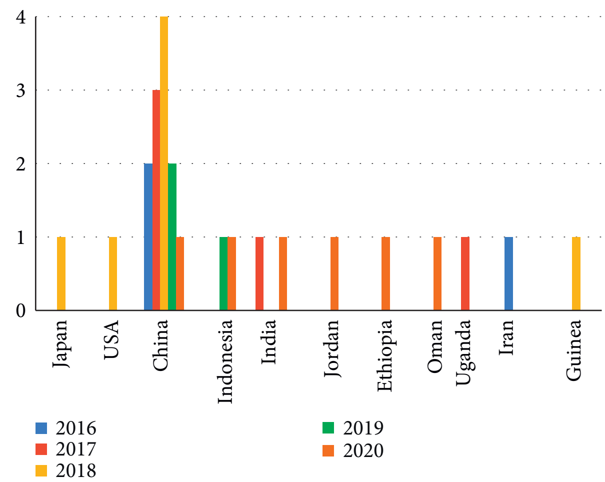

Figure 9: Country of urban development/year.

different works. In the different approaches mentioned in this review, AI techniques are applied to urban planning in large metropolitan areas in various parts of the world, although most papers used in this review focus on urban development in China. For this, Figure 9 is included, which shows the number of articles related to each country per year. In the graph of Figure 9, we can see that most of the works of research urban development in China as mentioned. It is the only country in which investigations have been carried out in all the years included (2016–2020), with 4 of them in 2018. On the other hand, it should be noted the countries used in the scientific research in 2020 (Oman, Ethiopia, Jordan, India, Indonesia, and China).

Perhaps one of the most important pieces of data that we have been able to collect concerns the techniques used in the different experiments. In the papers used in this review, most of the systems combine Markov chains and cellular automata. A less number of papers use other techniques, like artificial neural networks. This contrasts with the substantial number of papers related to architectural design using genetic algorithms [86–93]. You can read more about it in a state of the art that we have previously made [94].

In particular, the AI techniques applied to urban planning used by the authors of the different works that we have found are as follows: the combination between CA and Markov stands out, with three jobs in 2018, two in 2019, and one in 2020. The rest of the jobs in 2020 also use Markov, but in this case, combined with ANN. For its part, the other remaining work from 2019 also uses CA and Markov, but with the peculiarity that it uses neural networks as well.

We can see in Figure 10 that for the rest of the experiments all the works used CA, except [40, 49], which in 2016 used simple GA and combined with EC in 2018, successively. On the other hand, the research that uses CA only has two examples in 2017 of its individual use [42, 44] and the second with a specific model (SLEUTH). In the rest of the studies, they use it in combination with other techniques or the case of [45] use Segmentation-Path-CA.

The best results obtained could be considered by those of [49] with the use of GA + EC, who in 2018 obtained a global precision of the number of buildings of 100%, with a deviation of the height of the building of 19.5%. The results of [42] were also very good with the use of CA achieving an overall precision of 97% and 98%, and an edge index dispersion of 0.10 (with a land cover map index of 49.05), and [45] through Segmentation-Patch-CA obtained an overall precision of 96%. Both are prior to [49], so the work after 2018 has not achieved results that improve the union of AC and EC.

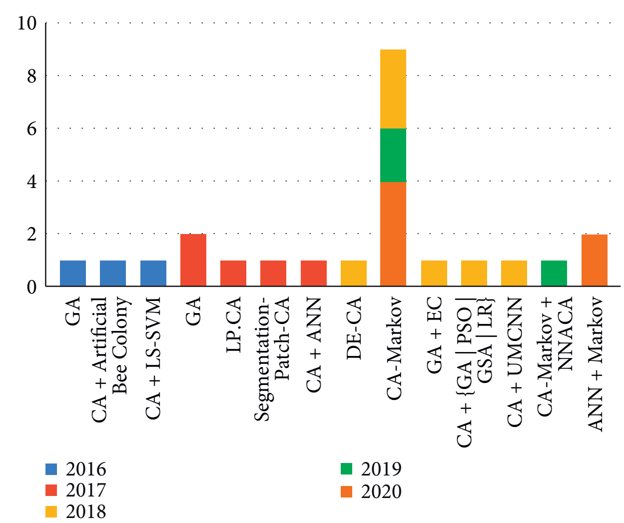

Figure 10: Techniques/year.

3. Conclusions

For years now, CAs have been successfully used in the exploration of a wide variety of urban phenomena [95], from regional-scale urbanization and urban development to traffic simulation [96–98]. The CA models have been developed for topics as varied as sprawl [99, 100] or gentrification [101–103], and simulations of city shape, growth, and location [73, 104–107]. This is because CAs have many advantages for modeling urban phenomena, such as their flexibility, their decentralized and dynamic approach, the relative ease with which model results can be visualized, and also their affinities with geographic information systems and remote sensing data [108]. In our opinion, its simplicity may be its most significant quality. By mimicking the way in which large-scale urban structures can emerge from the myriad interactions of simple elements, CAs provide a framework for the exploration of complex adaptive systems.

We have seen that in recent years these techniques are being used to simulate the urban planning approach and changes in land use, considering population migration or the effects of global warming (such as flooding or the disappearance of water and vegetation, for example), with the aim of planning and achieving sustainable urban development.

Although the best results dating from 2018, it is considered that the other works also obtain satisfactory results, since they are very diverse uses, and as mentioned, different countries and techniques are used.

Among the different deficiencies shown are the following:

(i) The only technique with published examples from a sufficient number of countries to compare the results is the use of CA + Markov.

(ii) This technique has not exceeded the results of the first experiment carried out in 2018 [48] with data from Conakry (Guinea). The results were of an average precision of 92%.

(iii) The only country with which enough techniques have been used to make a comparison between them is China.

(iv) Despite being the same country, the location is different, and therefore, the comparative results will be less consistent.

(v) The use of GA + EC has not been replicated, although it is the option with the best results so far.

(vi) For the most part, the predictive data have not been compared to actual subsequent results.

With the above in mind, we recommend that comparisons be made with actual results when possible. It also makes sense to us that the use of CA has been investigated, as the 2017 results showed its potential. However, following the contained explanation of the literature review we can understand that it does not solve the previous problems. That is why it would also be of interest to show the results of combining CA and EC since it is a combination that has not yet been worked on until now.

We also consider it interesting for future research to carry out more experiments under similar conditions, either of localization and varying the technique used, or of techniques modifying the location. Finally, we recommend promoting the use of GA + EC for its satisfactory results.

Conflicts of Interest

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

Acknowledgments

This project was supported by the General Directorate of Culture, Education and University Management of Xunta de Galicia (ref. ED431G/01 and ED431D 2017/16), the Spanish Ministry of Economy and Competitiveness via funding of the unique installation BIOCAI (UNLC08-1E-002 and UNLC13-13-3503), and the European Regional Development Funds (FEDER). CITIC, as Research Center accredited by Galician University System, is funded by "Consellería de Cultura, Educación e Universidade from Xunta de Galicia," supported in an 80% through ERDF Funds, ERDF Operational Programme Galicia 2014–2020, and the remaining 20% by "Secretaria Xeral de Universidades" (grant no. ED431G 2019/01).

References

[1] J. M. Levy, *Contemporary Urban Planning*, Prentice-Hall, Hoboken, 7th Edition, 2006.

[2] X. Li, Y. Chen, X. Liu, D. Li, and J. He, "Concepts, methodologies, and tools of an integrated geographical simulation and optimization system," *International Journal of Geographical Information Science*, vol. 25, no. 4, pp. 633–655, 2011.

[3] Q. Wu, H.-q. Li, R.-s. Wang et al., "Monitoring and predicting land use change in beijing using remote sensing and GIS," *Landscape and Urban Planning*, vol. 78, no. 4, pp. 322–333, 2006.

[4] D. Guan, H. Li, T. Inohae, W. Su, T. Nagaie, and K. Hokao, "Modeling urban land use change by the integration of cellular automaton and Markov model," *Ecological Modelling*, vol. 222, no. 20-22, pp. 3761–3772, 2011.

[5] H. Shafizadeh Moghadam and M. Helbich, "Spatiotemporal urbanization processes in the megacity of Mumbai, India: a Markov chains-cellular automata urban growth model," *Applied Geography*, vol. 40, pp. 140–149, 2013.

[6] R. Store and J. Kangas, "Integrating spatial multi-criteria evaluation and expert knowledge for GIS-based habitat suitability modelling," *Landscape and Urban Planning*, vol. 55, no. 2, pp. 79–93, 2001.

[7] G. Engelen, R. White, and I. Uljee, "Integrating constrained cellular automata models, GIS and decision support tools for urban planning and policy making," *Decision Support Systems in Urban Planning*, pp. 125–155, E&FN Spon, London, 1997, chapter 8.

[8] K. C. Clarke and L. J. Gaydos, "Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore," *International Journal of Geographical Information Science*, vol. 12, no. 7, pp. 699–714, 1998.

[9] F. Wu and C. J. Webster, "Simulation of land development through the integration of cellular automata and multicriteria evaluation," *Environment and Planning B: Planning and Design*, vol. 25, no. 1, pp. 103–126, 1998.

[10] M. Batty, Y. Xie, and Z. Sun, "Modeling urban dynamics through GIS-based cellular automata," *Computers, Environment and Urban Systems*, vol. 23, no. 3, pp. 205–233, 1999.

[11] X. Li and A. G.-O. Yeh, "Modelling sustainable urban development by the integration of constrained cellular automata and GIS," *International Journal of Geographical Information Science*, vol. 14, no. 2, pp. 131–152, 2000.

[12] P. Rocha, "Calibration of stochastic cellular automata: the application to rural-urban land conversions," *International Journal of Geographical Information Science*, vol. 16, no. 8, pp. 795–818, 2002.

[13] S. Leao, I. Bishop, and D. Evans, "Simulating urban growth in a developing nation's region using a cellular automata-based model," *Journal of Urban Planning and Development*, vol. 130, no. 3, pp. 145–158, 2004.

[14] F. Aguilera, L. M. Valenzuela, and A. Botequilha-Leitão, "Landscape metrics in the analysis of urban land use patterns: a case study in a Spanish metropolitan area," *Landscape and Urban Planning*, vol. 99, no. 3–4, pp. 226–238, 2011.

[15] J. Jokar Arsanjani, M. Helbich, W. Kainz, and A. Darvishi Boloorani, "Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion," *International Journal of Applied Earth Observation and Geoinformation*, vol. 21, pp. 265–275, 2013.

[16] Y. Feng and Y. Liu, "A heuristic cellular automata approach for modelling urban land-use change based on simulated annealing," *International Journal of Geographical Information Science*, vol. 27, no. 3, pp. 449–466, 2013.

[17] M. Aljoufie, M. Zuidgeest, M. Brussel, J. van Vliet, and M. van Maarseveen, "A cellular automata-based land use and transport interaction model applied to jeddah, Saudi arabia," *Landscape and Urban Planning*, vol. 112, no. 1, pp. 89–99, 2013.

[18] H. Wang, S. He, X. Liu et al., "Simulating urban expansion using a cloud-based cellular automata model: a case study of jiangxia, wuhan, China," *Landscape and Urban Planning*, vol. 110, no. 1, pp. 99–112, 2013.

[19] J. A. Verstegen, D. Karssenberg, F. van der Hilst, and A. P. C. Faaij, "Identifying a land use change cellular automaton by bayesian data assimilation," *Environmental Modelling & Software*, vol. 53, pp. 121–136, 2014.

[20] Y. Sakieh, B. J. Amiri, A. Danekar, J. Feghhi, and S. Dezhkam, "Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of karaj city, Iran," *Journal of Housing and the Built Environment*, vol. 30, no. 4, pp. 591–611, 2015.

[21] A. Mustafa, I. Saadi, M. Cools, and J. Teller, "Measuring the effect of stochastic perturbation component in cellular automata urban growth model," *Procedia Environmental Sciences*, vol. 22, pp. 156–168, 2014.

[22] J. Liao, L. Tang, G. Shao, X. Su, D. Chen, and T. Xu, "Incorporation of extended neighborhood mechanisms and its impact on urban land-use cellular automata simulations," *Environmental Modelling & Software*, vol. 75, pp. 163–175, 2016.

[23] P. H. Verburg, P. P. Schot, M. J. Dijst, and A. Veldkamp, "Land use change modelling: current practice and research priorities," *Geojournal*, vol. 61, no. 4, pp. 309–324, 2004.

[24] I. Benenson and P. M. Torrens, "Geosimulation: object-based modeling of urban phenomena," *Computers, Environment and Urban Systems*, vol. 28, no. 1-2, pp. 1–8, 2004.

[25] X. Li and A. G.-O. Yeh, "Neural-network-based cellular automata for simulating multiple land use changes using GIS," *International Journal of Geographical Information Science*, vol. 16, no. 4, pp. 323–343, 2002.

[26] B. C. Pijanowski, D. G. Brown, B. A. Shellito, and G. A. Manikd, "Using neural networks and GIS to forecast land use changes: a land transformation model," *Computers, Environment and Urban Systems*, vol. 26, no. 6, pp. 553–575, 2002.

[27] A. Tayyebi, B. C. Pijanowski, and A. H. Tayyebi, "An urban growth boundary model using neural networks, GIS and radial parameterization: an application to tehran, Iran," *Landscape and Urban Planning*, vol. 100, no. 1-2, pp. 35–44, 2011.

[28] Y. Qiang and N. S. N. Lam, "Modeling land use and land cover changes in a vulnerable coastal region using artificial neural networks and cellular automata," *Environmental Monitoring and Assessment*, vol. 187, no. 3, Article ID 57, 2015.

[29] B. Huang, C. Xie, R. Tay, and B. Wu, "Land-use-change modeling using unbalanced support-vector machines," *Environment and Planning B: Planning and Design*, vol. 36, no. 3, pp. 398–416, 2009.

[30] M. Samardžić-Petrović, S. Dragićević, M. Kovačević, and B. Bajat, "Modeling urban land use changes using support vector machines," *Transactions in GIS*, vol. 20, no. 5, pp. 718–734, 2015.

[31] Y. Feng, Y. Liu, and M. Batty, "Modeling urban growth with GIS based cellular automata and least squares SVM rules: a case study in Qingpu-Songjiang area of Shanghai, China," *Stochastic Environmental Research and Risk Assessment*, vol. 30, no. 5, pp. 1387–1400, 2016.

[32] X. Li, Q. Yang, and X. Liu, "Genetic algorithms for determining the parameters of cellular automata in urban simulation," *Science in China - Series D: Earth Sciences*, vol. 50, no. 12, pp. 1857–1866, 2007.

[33] J. Tang, L. Wang, and Z. Yao, "Spatio-temporal urban landscape change analysis using the Markov chain model and a modified genetic algorithm," *International Journal of Remote Sensing*, vol. 28, no. 15, pp. 3255–3271, 2007.

[34] P. Taylor, X. Li, J. Lin, Y. Chen, X. Liu, and B. Ai, "Calibrating cellular automata based on landscape metrics by using genetic algorithms," *International Journal of Geographical Information Science*, vol. 27, no. 3, pp. 594–613, 2013.

[35] Y. Liu, Y. Feng, and R. Pontius, "Spatially-explicit simulation of urban growth through self-adaptive genetic algorithm and cellular automata modelling," *Land*, vol. 3, no. 3, pp. 719–738, 2014.

[36] Y. Feng, Y. Liu, X. Tong, M. Liu, and S. Deng, "Modeling dynamic urban growth using cellular automata and particle swarm optimization rules," *Landscape and Urban Planning*, vol. 102, no. 3, pp. 188–196, 2011.

[37] M. H. Khalilnia, T. Ghaemirad, and R. A. Abbaspour, "Modeling of urban growth using cellular automata (CA) optimized by Particle Swarm Optimization (PSO)," *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. XL-1/W3, pp. 231–234, 2013.

[38] J. Liao, L. Tang, G. Shao et al., "A neighbor decay cellular automata approach for simulating urban expansion based on particle swarm intelligence," *International Journal of Geographical Information Science*, vol. 28, no. 4, pp. 720–738, 2014.

[39] A. Tayyebi and B. C. Pijanowski, "Modeling multiple land use changes using ANN, CART and MARS: comparing tradeoffs in goodness of fit and explanatory power of data mining tools," *International Journal of Applied Earth Observation and Geoinformation*, vol. 28, pp. 102–116, 2014.

[40] Z. Tong, "A genetic algorithm approach to optimizing the distribution of buildings in urban green space," *Automation in Construction*, vol. 72, pp. 46–51, 2016.

[41] F. Naghibi, M. R. Delavar, and B. Pijanowski, "Urban growth modeling using cellular automata with multi-temporal

remote sensing images calibrated by the artificial bee colony optimization algorithm," *Sensors*, vol. 16, no. 12, Article ID 2122, 2016.

[42] E. Pérez-Molina, R. Sliuzas, J. Flacke, and V. Jetten, "Developing a cellular automata model of urban growth to inform spatial policy for flood mitigation: a case study in kampala, Uganda," *Computers, Environment and Urban Systems*, vol. 65, pp. 53–65, 2017.

[43] Y. Chen, X. Liu, and X. Li, "Calibrating a land parcel cellular automaton (LP-CA) for urban growth simulation based on ensemble learning," *International Journal of Geographical Information Science*, vol. 31, no. 12, pp. 2480–2504, 2017.

[44] M. K. Jat, M. Choudhary, and A. Saxena, "Application of geospatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe," *The Egyptian Journal of Remote Sensing and Space Science*, vol. 20, no. 2, pp. 223–241, 2017.

[45] X. Li, P. Gong, L. Yu, and T. Hu, "A segment derived patch-based logistic cellular automata for urban growth modeling with heuristic rules," *Computers, Environment and Urban Systems*, vol. 65, pp. 140–149, 2017.

[46] X. Liu, X. Liang, X. Li et al., "A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects," *Landscape and Urban Planning*, vol. 168, pp. 94–116, 2017.

[47] Y. Feng and X. Tong, "Calibration of cellular automata models using differential evolution to simulate present and future land use," *Transactions in GIS*, vol. 22, no. 2, pp. 582–601, 2018.

[48] A. Traore, J. Mawenda, and A. Komba, "Land-cover change analysis and simulation in Conakry (Guinea), using hybrid cellular-automata and Markov model," *Urban Science*, vol. 2, no. 2, Article ID 39, 2018.

[49] R. I. Pazos Perez, A. Carballal, J. R. Rabuñal, O. A. Mures, and M. D. García-Vidaurrázaga, "Predicting vertical urban growth using genetic evolutionary algorithms in tokyo's Minato ward," *Journal of Urban Planning and Development*, vol. 144, no. 1, Article ID 04017024, 2018.

[50] X. Fu, X. Wang, and Y. J. Yang, "Deriving suitability factors for CA-markov land use simulation model based on local historical data," *Journal of Environmental Management*, vol. 206, pp. 10–19, 2018.

[51] Y. Feng, Y. Liu, and X. Tong, "Comparison of metaheuristic cellular automata models: a case study of dynamic land use simulation in the Yangtze River delta," *Computers, Environment and Urban Systems*, vol. 70, pp. 138–150, 2018.

[52] C. Liping, S. Yujun, and S. Saeed, "Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques — a case study of a hilly area, Jiangle, China," *PLoS One*, vol. 13, no. 7, Article ID e0200493, 2018.

[53] J. He, X. Li, Y. Yao, Y. Hong, and Z. Jinbao, "Mining transition rules of cellular automata for simulating urban expansion by using the deep learning techniques," *International Journal of Geographical Information Science*, vol. 32, no. 10, pp. 2076–2097, 2018.

[54] F. Yulianto, T. Maulana, and M. R. Khomarudin, "Analysis of the dynamics of land use change and its prediction based on the integration of remotely sensed data and CA-markov model, in the upstream Citarum watershed, West Java, Indonesia," *International Journal of Digital Earth*, vol. 12, no. 10, pp. 1151–1176, 2019.

[55] Y. Lu and P. Wu, "Detection and prediction of land use/land cover change using spatiotemporal data fusion and the cellular automata – Markov model," *Environmental Monitoring and Assessment*, vol. 191, Article ID 68, 2019.

[56] A. A. Devendran and G. Lakshmanan, "Analysis and prediction of urban growth using neural-network-coupled agent-based cellular automata model for Chennai metropolitan area, Tamil nadu, India," *Journal of the Indian Society of Remote Sensing*, vol. 47, no. 9, pp. 1515–1526, 2019.

[57] Y. Huang, B. Yang, M. Wang, B. Liu, and X. Yang, "Analysis of the future land cover change in beijing using CA – Markov chain model," *Environmental Earth Sciences*, vol. 79, Article ID 60, 2020.

[58] H. A. Khawaldah, I. Farhan, and N. M. Alzboun, "Simulation and prediction of land use and land cover change using GIS, remote sensing and CA-markov model," *Global Journal of Environmental Science and Management*, vol. 6, no. 2, pp. 215–232, 2020.

[59] A. Mohamed and H. Worku, "Urban climate simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding," *Urban Climate*, vol. 31, Article ID 100545, 2020.

[60] A. Nurwanda and T. Honjo, "The prediction of city expansion and land surface temperature in bogor city, indonesia," *Sustainable Cities and Society*, vol. 52, Article ID 101772, 2020.

[61] V. Anand and B. Oinam, "Future land use land cover prediction with special emphasis on urbanization and wetlands," *Remote Sensing Letters*, vol. 11, no. 3, pp. 225–234, 2020.

[62] S. Mansour, M. Al-belushi, and T. Al-awadhi, "Land use policy monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-markov modelling techniques," *Land Use Policy*, vol. 91, Article ID 104414, 2020.

[63] I. Santé, A. M. García, D. Miranda, and R. Crecente, "Cellular automata models for the simulation of real-world urban processes: a review and analysis," *Landscape and Urban Planning*, vol. 96, no. 2, pp. 108–122, 2010.

[64] G. Iovine, D. D'Ambrosio, and S. Di Gregorio, "Applying genetic algorithms for calibrating a hexagonal cellular automata model for the simulation of debris flows characterised by strong inertial effects," *Geomorphology*, vol. 66, no. 1-4, pp. 287–303, 2005.

[65] F. Semboloni, "The dynamic of an urban cellular automata in A 3-D spatial pattern," in *Proceedings of the XXI National Conference, Aisre: Regional and Urban Growth in a Global Market*, Palermo, 2000.

[66] W. Shi and M. Y. C. Pang, "Development of Voronoi-based cellular automata -an integrated dynamic model for Geographical Information Systems," *International Journal of Geographical Information Science*, vol. 14, no. 5, pp. 455–474, 2000.

[67] D. O'Sullivan, "Graph-cellular automata: a generalized discrete urban and regional model," *Environment and Planning B: Planning and Design*, vol. 28, pp. 687–705, 2001.

[68] D. Stevens and S. Dragićević, "A GIS-based irregular cellular automata model of land-use change," *Environment and Planning B: Planning and Design*, vol. 34, no. 4, pp. 708–724, 2007.

[69] H. Couclelis, "Cellular worlds: a framework for modeling micro-macro dynamics," *Environment & Planning A*, vol. 17, no. 5, pp. 585–596, 1985.

[70] R. White and G. Engelen, "Cellular automata and fractal urban form: a cellular modelling approach to the evolution of

urban land-use patterns," *Environment & Planning A*, vol. 25, no. 8, pp. 1175–1199, 1993.

[71] C. Webster and F. Wu, "Coase, spatial pricing and self -organising cities," *Urban Studies*, vol. 38, no. 11, pp. 2037–2054, 2001.

[72] M. C. Polidori and R. Krafta, "Simulando crescimento urbano com integração de fatores naturais, urbanos e institucionais," *GeoFocus*, vol. 5, pp. 156–179, 2005.

[73] S. Geertman, M. Hagoort, and H. Ottens, "Spatial-temporal specific neighbourhood rules for cellular automata land-use modelling," *International Journal of Geographical Information Science*, vol. 21, no. 5, pp. 547–568, 2007.

[74] X. Li, Q. Yang, and X. Liu, "Discovering and evaluating urban signatures for simulating compact development using cellular automata," *Landscape and Urban Planning*, vol. 86, no. 2, pp. 177–186, 2008.

[75] K. C. Clarke, S. Hoppen, and L. Gaydos, "A self-modifying cellular automaton model of historical urbanization in the san francisco bay area," *Environment and Planning B: Planning and Design*, vol. 24, no. 2, pp. 247–261, 1997.

[76] M. Phipps and A. Langlois, "Spatial dynamics, cellular automata, and parallel processing computers," *Environment and Planning B: Planning and Design*, vol. 24, no. 2, pp. 193–204, 1997.

[77] H. Couclelis, "From cellular automata to urban models: new principles for model development and implementation," *Environment and Planning B: Planning and Design*, vol. 24, no. 2, pp. 165–174, 1997.

[78] P. M. Torrens and I. Benenson, "Geographic automata systems," *International Journal of Geographical Information Science*, vol. 19, no. 4, pp. 385–412, 2005.

[79] M. M. Aburas, Y. M. Ho, M. F. Ramli, and Z. H. Ash'aari, "The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: a review," *International Journal of Applied Earth Observation and Geoinformation*, vol. 52, pp. 380–389, 2016.

[80] N. Bihamta, A. Soffianian, S. Fakheran, and M. Gholamalifard, "Using the SLEUTH urban growth model to simulate future urban expansion of the isfahan metropolitan area, Iran," *Journal of the Indian Society of Remote Sensing*, vol. 43, no. 2, pp. 407–414, 2014.

[81] M. Mohammad, A. Sahebgharani, and E. Malekipour, "Urban growth simulation through cellular automata (CA), analytic Hierarchy process (AHP) and GIS, case study of 8th and 12th municipal districts of isfahan," *Geographia Technica*, vol. 18, no. 2, pp. 57–70, 2013.

[82] S. Park, S. Jeon, S. Kim, and C. Choi, "Prediction and comparison of urban growth by land suitability index mapping using GIS and RS in South Korea," *Landscape and Urban Planning*, vol. 99, no. 2, pp. 104–114, 2011.

[83] S. Q. Wang, X. Q. Zheng, and X. B. Zang, "Accuracy assessments of land use change simulation based on markov-cellular automata model," *Procedia Environmental Sciences*, vol. 13, pp. 1238–1245, 2012.

[84] B. H. Aithal and S. V. T. Ramachandra, "Landscape dynamics modeling through integrated Markov, fuzzy-AHP and cellular automata," in *Proceedings of the 2014 IEEE Geoscience and Remote Sensing Symposium*, pp. 3160–3163, Quebec, Canada, October 2014.

[85] A. A. A. Al-sharif and B. Pradhan, "Spatio-temporal prediction of urban expansion using bivariate statistical models: assessment of the efficacy of evidential belief functions and frequency ratio models," *Applied Spatial Analysis and Policy*, vol. 9, no. 2, pp. 213–231, 2016.

[86] N. Behboudi, F. Butt, and A. Abhari, "Automatic building design with genetic algorithms and artificial neural networks (WIP)," in *Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design*, vol. 7, Society for Computer Simulation International, Orlando, FL, USA, March 2012.

[87] A. Gaspar-Cunha, D. Loyens, and F. Van Hattum, "Aesthetic design using multi-objective evolutionary algorithms," in *Proceedings of the International Conference on Evolutionary Multi-Criterion Optimization*, pp. 374–388, Springer, Ouro Preto, Brazil, April 2011.

[88] C. T. Mueller and J. A. Ochsendorf, "Combining structural performance and designer preferences in evolutionary design space exploration," *Automation in Construction*, vol. 52, pp. 70–82, 2015.

[89] C. Ugurlu, I. Chatzikonstantinou, S. Sariyildiz, and M. F. Tasgetiren, "Evolutionary computation for architectural design of restaurant layouts," in *Proceedings of the 2015 IEEE Congress on Evolutionary Computation (CEC)*, pp. 2279–2286, IEEE, Sendai, Japan, May 2015.

[90] I. G. Dino, "An evolutionary approach for 3D architectural space layout design exploration," *Automation in Construction*, vol. 69, pp. 131–150, 2016.

[91] Z. Guo and B. Li, "Evolutionary approach for spatial architecture layout design enhanced by an agent-based topology finding system," *Frontiers of Architectural Research*, vol. 6, no. 1, pp. 53–62, 2017.

[92] A. De Almeida, B. Taborda, F. Santos, K. Kwiecinski, and S. Eloy, "A genetic algorithm application for automatic layout design of modular residential homes," in *Proceedings of the 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 002774–002778, IEEE, Budapest, Hungary, October 2016.

[93] B. Taborda, A. De Almeida, F. Santos, S. Eloy, and K. Kwiecinski, "Shaper-G. A.: Automatic shape generation for modular house design," in *Proceedings of the Genetic and Evolutionary Computation Conference*, pp. 937–942, ACM, Kyoto Japan, July 2018.

[94] M. L. Castro, A. Carballal, N. Rodriguez-Fernandez, I. Santos, and J. Romero, "Artificial intelligence applied to conceptual design. A review of its use in architecture," *Automation in Construction*, vol. 134, Article ID 103550, 2021.

[95] M. Batty, H. Couclelis, and M. Eichen, "Urban systems as cellular automata," *Environment and Planning B: Planning and Design*, vol. 24, no. 2, pp. 159–164, 1997.

[96] M. Rickert, K. Nagel, M. Schreckenberg, and A. Latour, "Two lane traffic simulations using cellular automata," *Physica A: Statistical Mechanics and Its Applications*, vol. 231, no. 4, pp. 534–550, 1996.

[97] D. E. Wolf, "Cellular automata for traffic simulations," *Physica A: Statistical Mechanics and Its Applications*, vol. 263, no. 1–4, pp. 438–451, 1999.

[98] S. F. Hafstein, R. Chrobok, A. Pottmeier, M. Schreckenberg, and F. C. Mazur, "A high-resolution cellular automata traffic simulation model with application in a freeway traffic information system," *Computer-Aided Civil and Infrastructure Engineering*, vol. 19, no. 5, pp. 338–350, 2004.

[99] B. Wang and F. Qian, "Three dimensional gas dispersion modeling using cellular automata and artificial neural network in urban environment," *Process Safety and Environmental Protection*, vol. 120, pp. 286–301, 2018, ISSN 0957-5820.

[100] F. Wu and C. J. Webster, "Simulation of land development through the integration of cellular automata and multicriteria evaluation," *Environment and Planning B: Planning and Design*, vol. 25, no. 1, pp. 103–126, 2018.

[101] D. O'Sullivan, "Toward micro-scale spatial modeling of gentrification," *Journal of Geographical Systems*, vol. 4, no. 3, pp. 251–274, 2002.

[102] A. Nara and P. M. Torrens, "Inner-city gentrification simulation using hybrid models of cellular automata and multiagent systems," in *Proceedings of the Geocomputation 2005 Conference*, University of Michigan, Michigan, August 2005.

[103] P. M. Torrens and A. Nara, "Modeling gentrification dynamics: a hybrid approach," *Computers, Environment and Urban Systems*, vol. 31, no. 3, pp. 337–361, 2007.

[104] M. Batty, "Cellular automata and urban form: a primer," *Journal of the American Planning Association*, vol. 63, no. 2, pp. 266–274, 1997.

[105] F. Wu, "Calibration of stochastic cellular automata: the application to rural-urban land conversions," *International Journal of Geographical Information Science*, vol. 16, no. 8, pp. 795–818, 2002.

[106] E. A. Silva and K. C. Clarke, "Complexity, emergence and cellular urban models: lessons learned from applying SLEUTH to two Portuguese metropolitan areas," *European Planning Studies*, vol. 13, no. 1, pp. 93–115, 2005.

[107] K. R. Dahal and T. E. Chow, "Characterization of neighborhood sensitivity of an irregular cellular automata model of urban growth," *International Journal of Geographical Information Science*, vol. 29, no. 3, pp. 475–497, 2015.

[108] P. M. Torrens, *How Cellular Models of Urban Systems Work", WP-28*, Centre for Advanced Spatial Analysis (CASA), University College, London, ISSN: 1467-1298, 2000.