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Review

Cellular Automata in Modeling and Predicting Urban Densification: Revisiting the Literature since 1971

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Abstract: The creation of an accurate simulation of future urban growth is considered to be one of the most important challenges of the last five decades that involves spatial modeling within a GIS environment. Even though built-up densification processes, or transitions from low to high density, are critical for policymakers concerned with limiting sprawl, the literature on models for urban study reveals that most of them focus solely on the expansion process. Although the majority of these models have similar goals, they differ in terms of implementation and theoretical assumptions. Cellular automata (CA) models have been proven to be successful at simulating urban growth dynamics and projecting future scenarios at multiple scales. This paper aims to revisit urban CA models to determine the various approaches for a realistic simulation and prediction of urban densification. The general characteristics of CA models are described with respect to analysis of various driving factors that influence urban scenarios. This paper also critically analyzes various hybrid models based on CA such as the Markov chain, artificial neural network (ANN), and logistic regression (LR). Limitation and uncertainties of CA models, namely, neighborhood cell size, may be minimized when integrated with empirical and statistical models. The result of this review suggests that it is useful to use CA models with multinomial logistic regression (MLR) in order to analyze and model the effects of various driving factors related to urban densification. Realistic simulations can be achieved when multidensity class labels are integrated in the modeling process.

Keywords: cellular automata; urban densification; urban models; urban simulation; land use prediction

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1. Introduction

Urbanization is a multifaceted, worldwide process that reveals itself in rapidly changing human population densities and shifting land-use patterns. In the last 30 years, there has been a rapid growth in urban expansion owing primarily to development policies that prioritized urban growth over agricultural and rural development. Large-scale immigration to cities has resulted in rapid urbanization and land-use change [1]. Accelerating urbanization has put a strain on land resources and resulted in a slew of environmental and social issues [2]. In different countries, the shape or pattern of urban growth varies greatly, but in general, city growth is a twofold process of external expansion and rapid physical growth or internal growth and reorganization [3]. This can be further subdivided into two categories: Urban expansion, which deals with horizontal growth and urban densification; or infill development, which is referred as vertical expansion or in-between development [4].

Globally, many cities and regions have enacted policies aimed at encouraging urban densification through a combination of spatial planning and fiscal or economic measures, as well as encouraging infill development and land recycling [5,6]. Urban densification, through infill development, is frequently addressed in urban planning literature as a possible approach to produce compact communities, curb sprawl, and establish urban sustainability [7–9]. For more efficient planning and management, a greater understanding of the process of urban densification and the implications of this growth and land-use change is essential [10]. As a result, several empirical and theoretical modeling tools for the simulation and prediction have recently been developed [11,12].

Urban densification is influenced by various driving factors such as those related to the natural environment, socioeconomics, the built environment, and governance policies, thus making modeling of urban growth complex [13]. Due to their simplicity, versatility, and intuitiveness, CA-based models have been widely used [14]. The application of cellular space models to geographic modeling dates backs to the 1980s [15–17]. Building on these ideas and owing to the fact that new generations of hardware and software to simulate CA have been improved upon since the 1900s, a generic modeling framework based on discrete-time, cell-spaced models was proposed for cellular computation [18,19]. Transition rules are used to calculate development probability as a function of neighborhood, a series of geographical parameters, and stochastics disturbance terms which form the base of CA [1,20,21]. Furthermore, CA is highly compatible with the GIS environment. The nature in which CA works has a natural affinity with raster data, as both treat the input as a representation of cells. As a result of this, ref. [22] stated that CA has a high computational and operational efficiency, and that the neighborhood function has an analogous relationship to focal sum or focal mean function, making it suitable for any kind of simulation. These inherent similarities with GIS helped geographers to quickly adopt it as a framework for modeling spatial dynamics [23,24].

Hence, the nature of the CA model to explicitly consider the spatiotemporal dynamics of urban growth makes it more advantageous than other existing models [25]. Recently, there have been many other developments, such as hybrid CA urban models, which incorporate artificial intelligence based on empirical data such as artificial neural networks [26], case-based reasoning (CBR) [27], and colony optimization [28].The increasing uncertainty due to rapid environmental and societal and technological changes makes it crucial to explore multiple urban models, and driving factors have become important. With urban densification being an innovative yet crucial component of global environmental change, this study reviews the CA model in detail, including various integration approaches with other urban models. Moreover, the CA model facilitates movement toward an environment-sensitive modeling [29] which can be used to establish future development pillars and can be utilized to resolve any limitations or shortcomings. The review also suggests the novel approach of suggesting various dynamic and static drivers for modeling scenarios such as urban densification using CA.

This paper is structured as follows. A brief introduction of CA models has been represented in Section 2. Section 3 gives an overview on the advancement of CA models for studying urban densification. It also details and compares the various types of urban models used for predictions and simulations of future land use. Section 4 describes the methodology used for selecting the works of literature based on bibliometric analysis. Section 5 maps out the usage of CA models in urban simulations over the last 5 decades. Section 6 incorporates the various steps required to design a CA model with respect to urban densification. Various limitations, challenges, and future works have been listed in Section 7.

2. Cellular Automata (CA) Model

Cellular automata (CA) are computational methods for simulating the growth of a complex system by describing it with a set of simple rules [30]. It is a system of cells representing a discrete moment and a set of rules, determining the local transfer function based on the current state of an adjacent cell [31]. In the modeling of urban processes, CA models have a number of advantages, including the ability to perform spatial dynamics and time explicitly [32]. Wagner [33] proposed that CA can be considered an analytical engine of GIS after successfully analyzing the similarities and capabilities of CA.

Sgandurra [34] defined a cell as the smallest unit of space made up of only one component. Each cell in the lattice structure known as cellular space is in one of several predetermined states. The law guiding the change between states is known as the local rule. It is particularly important to choose the optimum transition rules for the phenomenon being studied [35]. Since a cell's finite state machine only accepts input from the neighborhood, it is referred to as "local" in this definition. The term "neighborhood" refers to the cells that are immediately adjacent to a certain cell, and they have the power to affect the subsequent state of that cell. Thus, different states with a CA transition rule will yield different results, but will be similar in statistical form [36].

Understanding the nature of the spatial dynamic requires the use of dynamic models as well as social, economic, and environmental concepts [37]. Over the past few decades, there has been a substantial advancement in various modeling techniques to understand urban expansion [38]. Various simulation and prediction methods have been used in the past to simulate future expansion and a few studies considered densification [39–41]. This paper reviews the use of CA models to understand the dynamics of urban densification and various driving factors associated with it.

3. Evolution of Urban Growth Models

Over the last few decades, several empirical and theoretical urban growth models have been introduced to predict and simulate future urban expansion [42]. Models allow us to focus on different future development paths in different places, at different scales, and under different conditions [43]. There has been a significant advancement in Remote Sensing (RS) and Geographic Information Sciences (GIS), thus enabling urban modelers to conduct sophisticated modeling and simulation. RS technologies aid in the collection of various essential data such as spatial and temporal information on land-use patterns and urban morphologies. On the other hand, GIS provides the tools and platform for data visualization and management. Modeling of urban growth patterns using remote sensing (RS) and GIS techniques is performed to better understand the spatial process of urban movement over time in order to develop future sustainable development policies [44].

Traditional models, such as the CA models, have been used in studies that rely on assessing the dynamic growth of urban areas [45]. Empirical estimation models such as logistic regression use statistical techniques for growth modeling [46]. Various types of models, such as the CA and the Markov Chain (MC) models, have been used in other studies to achieve accurate and realistic results [47]. These models have helped urban planners and policy makers to better understand spatial uncertainty and temporal randomness [48].

Many innovative urban growth models have been developed and implemented over the last few decades based on their addressing of various urban problems [49]. A number of scholars have proposed various approaches to model the spatial urban growth. Liu [50] classifies urban growth models into two approaches: process-based and transition-based. Process-based models are mostly dependent on several submodels. The submodels run sequentially, based on some selected number of change processes, and these inputs interact between each other. On the other hand, the transition-based model can be defined as an outcome of probability to summarize the temporal variation. It helps to understand the changes brought by the process-based outcome under a statistical approach to define the underlying complexity of modeling urban dynamics well. Another classification by [51] was based on a basic separation between substantive difficulties related to the system being represented and design issues related to modeling techniques and styles. The modeling approaches were grouped into perspective and descriptive models [43]. The literature review on urban growth focuses on modeling approaches including cellular automata [52], agent-based [53], land-use spatial optimization [54], and machine learning [55].

Figure 1 shows a geographic distribution of all the different urban growth models based on the area of study. Based on these studies, we can suggest that recently, CA models have gained an upper hand over other models due to their reliability for spatial and temporal studies. CA's appeal stems from its capacity to simulate proximity, which is seen as an important spatial aspect that reflects land-use change dynamics. The prominent advantage of a CA model framework lies in the fact that it can incorporate both spatial and nonspatial data for simulating physical and social system processes.

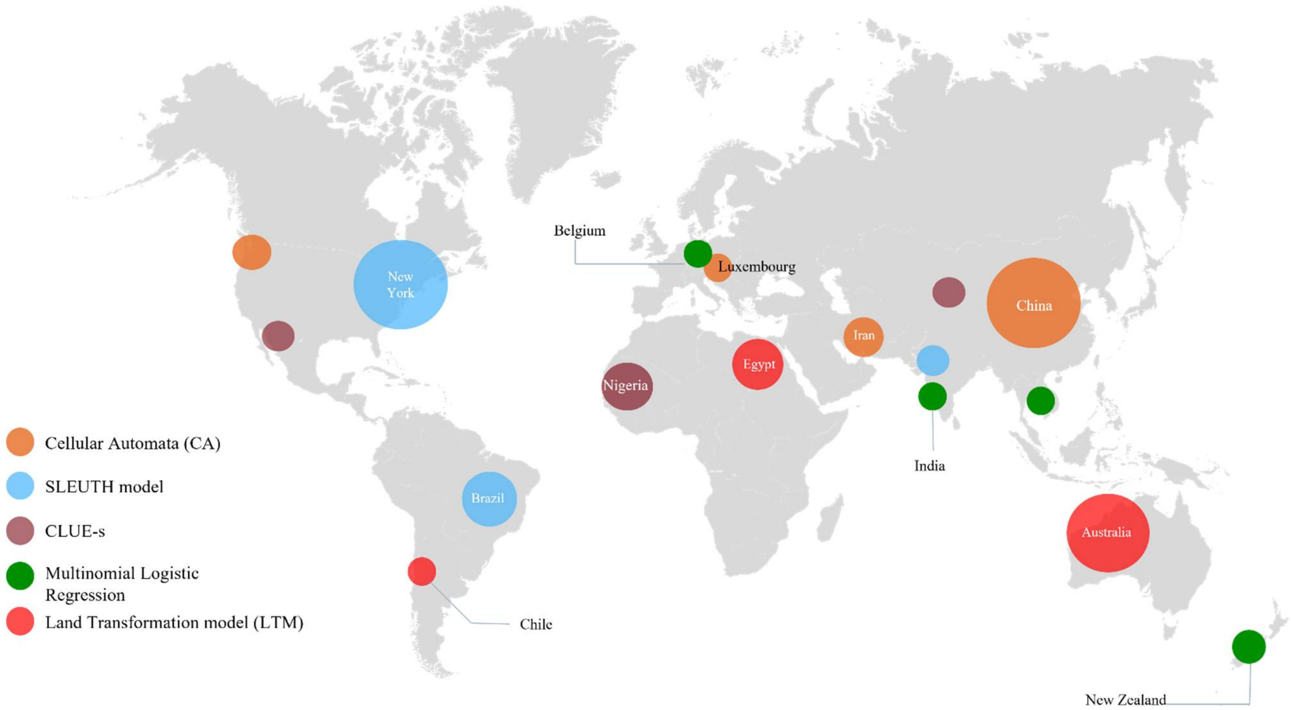

Figure 1. Global distribution of different urban growth model.

The Conversion of Land Use and its Effects (CLUE) model is based on a dynamic simulation of land use competition, with spatial allocation rules determined by empirical analysis, user-specified decision rules, or neighborhood characteristics [43]. The model was developed to empirically quantify the relation between land use and the driving factors on a national scale. Due to the use of data with coarse spatial resolution, a wide knowledge of the study area was required for the use of this model. A dynamic model for analysis of land use at a regional scale was developed later on as the CLUE-S model. The land transformation model (LTM), which amalgamates GIS and artificial neural networks (ANN), can be configured to use a variety of socioeconomic, political, and environmental factors in order to forecast land-cover changes over large regions [55]. It showed a high level of prediction at larger scales with the ability to use a scalable moving window metric. Since it involved an ANN, the steps were complex and large, and this model was confined to the role of a tool for environmental impact assessment. The findings from the LR–CA model which integrates static and dynamic factors helped to overcome the limitation of LR and CA individually [42]. On the other hand, the UrbanSim model [56] pursues a discrete approach based on predicting changes over small time intervals. The model was developed to support land use and transportation planning and growth management. However, this model had limitations, such as being unable to incorporate social and environmental externalities along with demographic processes. This model is still under development and requires added environmental components to simulate land-cover change. Rahnama [57] used an integrated model, a CA–Markov chain, to detect land-use change and simulation as it considers spatial and temporal aspects of urban dynamics. These models generate a better spatiotemporal pattern by considering various factors to improve the accuracy of the model.

SLEUTH considers four types of growth rules: spontaneous growth, new spreading center growth, edge growth, and road-influenced growth, all of which are governed by five coefficients, known as the "urban DNA" [58]. This has been effectively used throughout the world for the past 16 years to forecast changes in land use and land cover. The disadvantages of SLEUTH are that it can only define built-up land and cannot model intraurban categories. Finally, Mustafa [59] used the Multinomial Logistic Regression (MLR) model, a statistical modeling approach using urban density classes to the identify the future trend of each class. According to the results, each governing component exhibited distinct variations dependent on density. Moreover, they indicated the criticality of zoning polices in cases of high density expansions.

3.1. Advancement of Urban CA Model to Study Densification

The emergence and application of CA models designed to simulate urban land-use change from the ground up has dramatically changed the study of urban systems over the last four decades [60]. The recent increase in the number of publications in peer-reviewed journals on CA-based models has been rapid (Figure 2). While most urban growth models are a representation of reality as per definite abstract, most urban CA models to date have only been developed to study the spatiotemporal process of urban expansion. Only a few attempts have been performed to date to understand other continuums of urban change, especially urban densification.

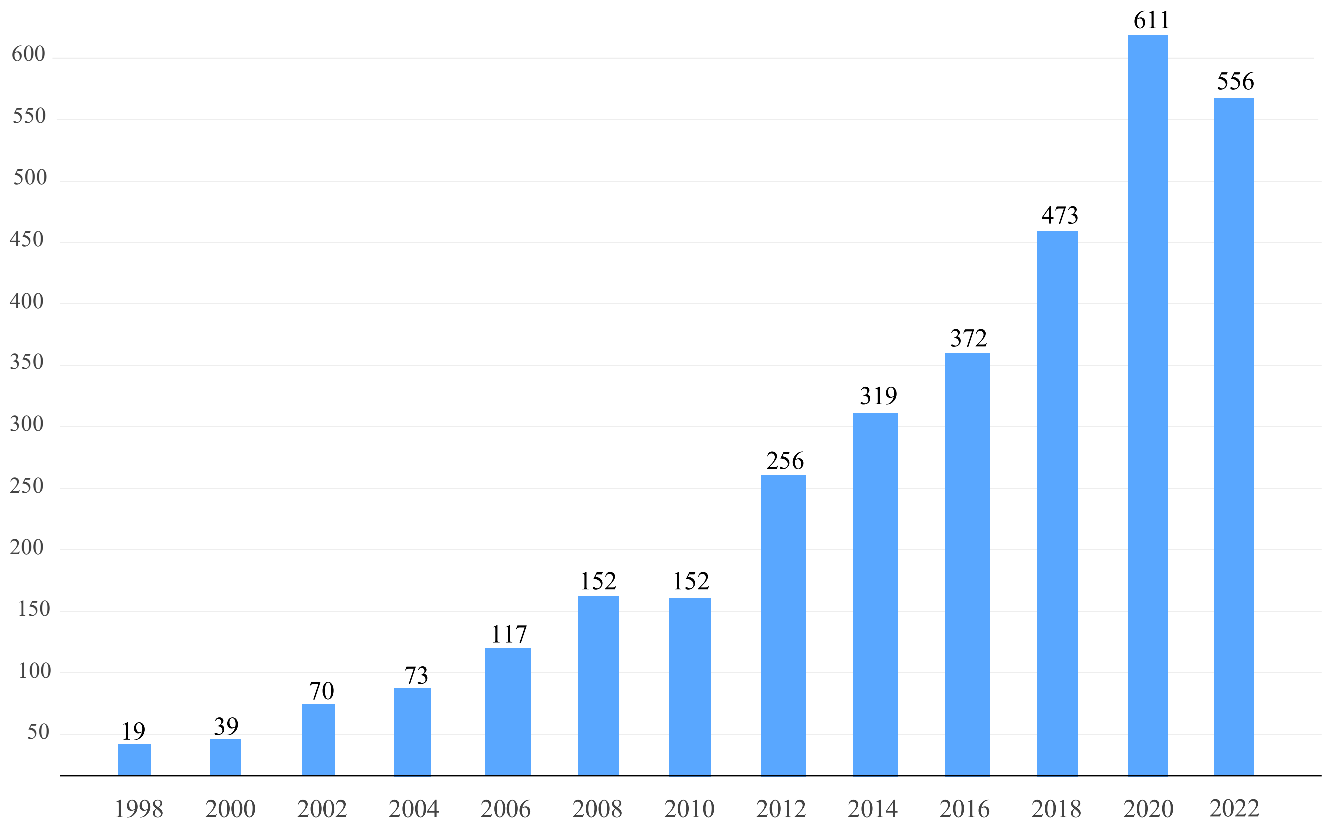

Figure 2. Recent burgeoning in CA-based articles in peer-reviewed journals.

Compact development is one of the most ideal urban forms in terms of land development proximity and clustering [61]. The majority of urban planners and scholars are concerned with the changing shape and size of built-up regions, rather than physical characteristics like density and open space. The total number of people that can be accommodated by a developed cell, also known as urban densification, can be expressed by development density. In an urban CA model, transition rules can be designed with urban densities as a simulation account. If the density factor is taken into account, the chance of development should be proportional to the total density of development (people) in the area. CA models may accommodate a wide range of urban change processes that recognize the bottom-up processes associated with fractal patterns and dynamics, which when combined offer the ability to simulate highly complex urban systems more realistically [62].

3.2. Integrated CA Models

CA-based models are well-known for calculating neighborhood interactions on a dynamic basis in which simulation and prediction are implied at every step based on the neighboring cell rule [52]. However, these models explicitly consider immediate neighbor state to calculate urban transition rather than using an interpretation of densification drivers [63] such as socioeconomic, accessibility, and geophysical factors (Figure 3). To overcome this limitation, several CA-based integrated models were used to demonstrate the effectiveness of hybrid models in the simulation of urban densification and expansion [64].

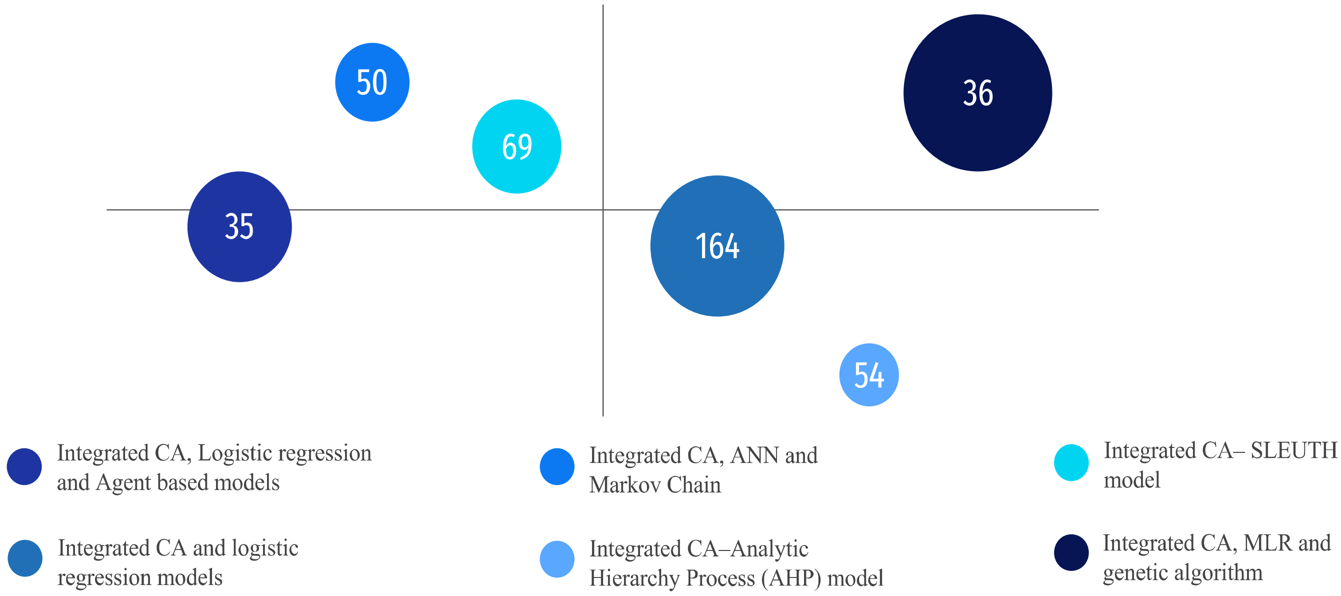

Figure 3. Number of research articles related to integrated CA models.

Previous research on integrated CA models, such as CA–Markov chains (CA–MC) and CA–LR, have strong advantages over the conventional CA models. These models play a significant role in analyzing driving factors for urban growth and densification in developing countries. Logistic regression, a statistical model which explores the association of dependent and multiple independent variables [65] when integrated with the CA model, has the ability to predict a complex reality [42]. The key benefit of combining the CA and LR models is the ability to generate a probability surface with continuous data and a logistic growth function to replicate the ongoing process of urban growth. For modeling the spatial and temporal processes of urban growth, the integration model is highly valid. The hybrid CA–MC models have been most popular in the last decade due to the credibility of it being user-friendly, even for nonspecialist users. In order to validate model simulation, the model used actual land-use data. The drawback of the CA–MC model is that it fails to consider a spatial auto regression in determining the driving forces. Thus, it needs to be integrated with other modeling methods, such as logistic regression models, which consider driving forces [66].

Other models, such as the CA–slope, land use, exclusion, urban extent, transportation, and hill shade (SLEUTH) model and the CA–artificial neural network (ANN), focus on simulation of multiple intraurban land uses in metropolitan areas [67]. The CA–fuzzy logic model's stronger point is that it considers the statistical correlations among predictor components. Furthermore, the model is applicable even in the absence of abundant data. By specifying its transition rules, the CA–adaptative genetic algorithm (AGA) model can be used with sparse data. For better outcomes, this model must incorporate some spatial and numerical elements. A useful model for handling complicated interactions, such as changes in land usage, are the integrated CA–support vector machines (SVM). These can get around several CA limitations. SLEUTH models are significantly useful when it comes to modeling urban densification over a period of time or predicting expansion into the potential. CA transition functions have also been improved by incorporating decision-support tools, such as AHP (analytic hierarchy process-based techniques), which have been made possible by the CA–GIS linkages. There are many benefits to the CA–AHP model, which include the efficient use of probability land suitability maps for urban growth based on a variety of parameters, including environmental, dynamic, social, and economic criteria, as well as factor weights.

4. Materials and Methods

4.1. Bibliometric Analysis

A vital step for any systematic review is the selection and analysis of the available literature and materials depending on the number of studies that would be included in the review. Bibliometric analysis helps in identifying the most active and most cited literature based on the most used keywords in the particular research field. In order to decipher and map the most used works of literature in terms of "CA models" and "urban densification", a bibliometric analysis was performed. This helped us to identify various gaps and work toward a novel approach for our study. Several bibliometric properties of all the gathered papers were analyzed, with the goal of exposing the current state and evolution of knowledge surrounding the topics of urban densification and cellular automata. Several kinds of measurable bibliometric data were examined using statistics-based methodologies, including the evolution of publications per year and the evolution of citations per year.

4.2. Literature Section

To study various models and algorithms in urban growth, a total of 116 relevant works of literature were reviewed by searching urban densification models in scientific search engines through background reviews (to provide theoretical context and to identify gaps in the literature) and stand-alone reviews (summarizing prior works and critically evaluating the work) [68]. Science Direct uses citation metrics and provides introductory overviews; thus, it was used as the primary database. Works of literature were chosen in the period of 1972–2021, as it marks the foundation of applying CA as a real system to cities. Tobler's [15] simulation of the growth of Detroit was the first seminal geographical application of cellular automata. Due to the limitation of accessing Elsevier publications through Science Direct, the authors used other search engines such as Google Scholar for recent publications. The authors have several years of experience working with urban growth modeling. Therefore, the authors used these keywords "**urban growth models**", "**urban densification**", "**infill developments**", and "**urban expansion**" combined with "**Cellular Automata**" for the systematic searches, based on their experience. Structured searches are mostly carried out for the collection of relevant information and research works. The search queries were restricted to a common mode of language, i.e., English. Other languages have not been taken into consideration as per the international standard. Some stringent selection has been made while selecting relevant journals, where peer-reviewed journals, international journals, articles, and review articles have been considered. Very few conference proceedings were considered due to difficulties in locating them.

4.3. Literature Review

A total of 436 articles were searched in the first round, and after reviewing the titles and abstracts, 356 articles were selected. During the full text review, 103 articles were finalized, considering the various growth models and driving factors which were considered in these articles (Figure 4).

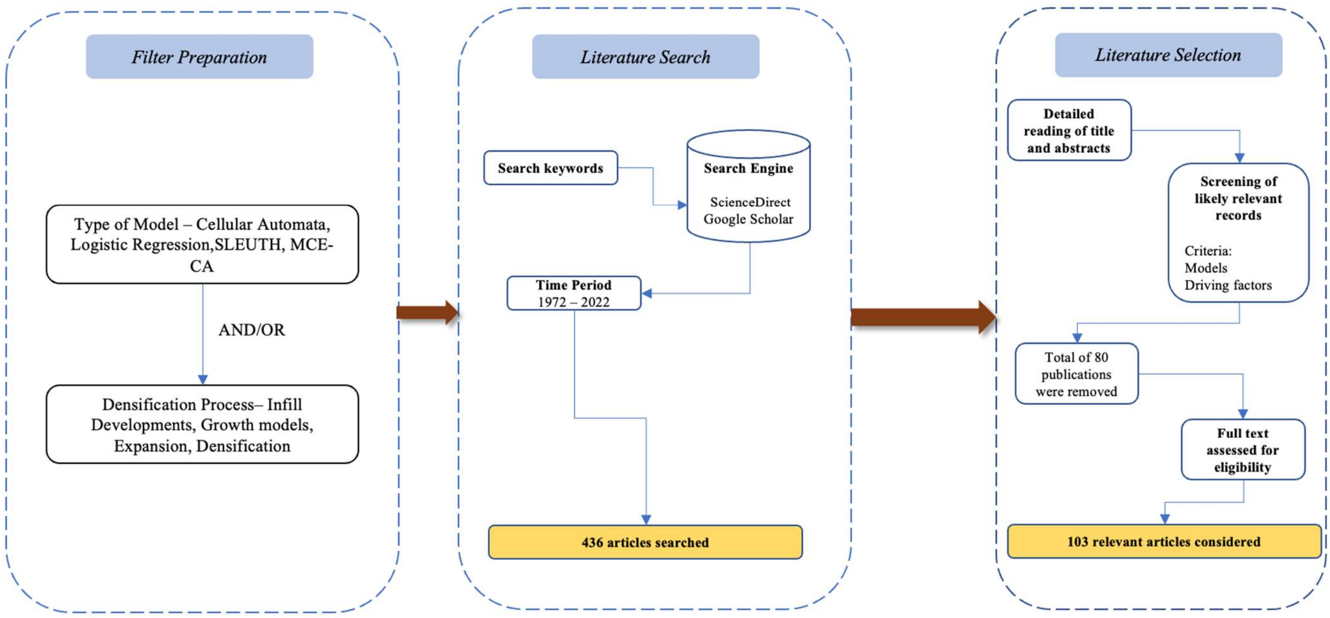

Figure 4. Methodology for literature search and evaluation.

5. Key Findings: Mapping the Landscape of CA in the Five Decades since 1971

Bibliometric Analysis

Several bibliometric properties of all the gathered papers were analyzed, with the goal of exposing the current state and evolution of knowledge surrounding the topics of urban densification and cellular automata. Several kinds of measurable bibliometric data were examined using statistics-based methodologies, including the evolution of publications per year, the evolution of citations per year, and so on. The authors have several years of experience working with urban growth modeling. Therefore, authors use the following keywords: "urban growth models", "urban densification", "infill developments", and "urban expansion" combined with "Cellular Automata" for the systematic searches, based on their experience, as shown in (Table 1). This has been extracted from the titles, abstracts, keywords, and extended subject terms of the 103 research articles. There is a linkage between the most frequently used terms as visualized in the word cloud. It was mentioned earlier that there has not been significant research in modeling urban densification. However, there have been several works of literature that have used CA for modeling urban growth [69].

Table 1. Keyword combination of systematic literature search.

		Type of Model		Densification Process
Urban	AND	Cellular Automata	AND	Infill developments
	OR	Logistic Regression	OR	Growth models
	OR	SLEUTH		Expansion
	OR	MCE-CA (Multicriteria Evaluation-Cellular Automata)		Densification

Between 1972 and 2019, the number and types of publications were analyzed to see the changing trend. Only the two highest forms of publications, journal articles and conference papers, were examined when it came to the source of publications. Because of the large number of journals, Figure 5 only shows the journals that have published two or more publications, as well as the total number of articles presented at conferences.

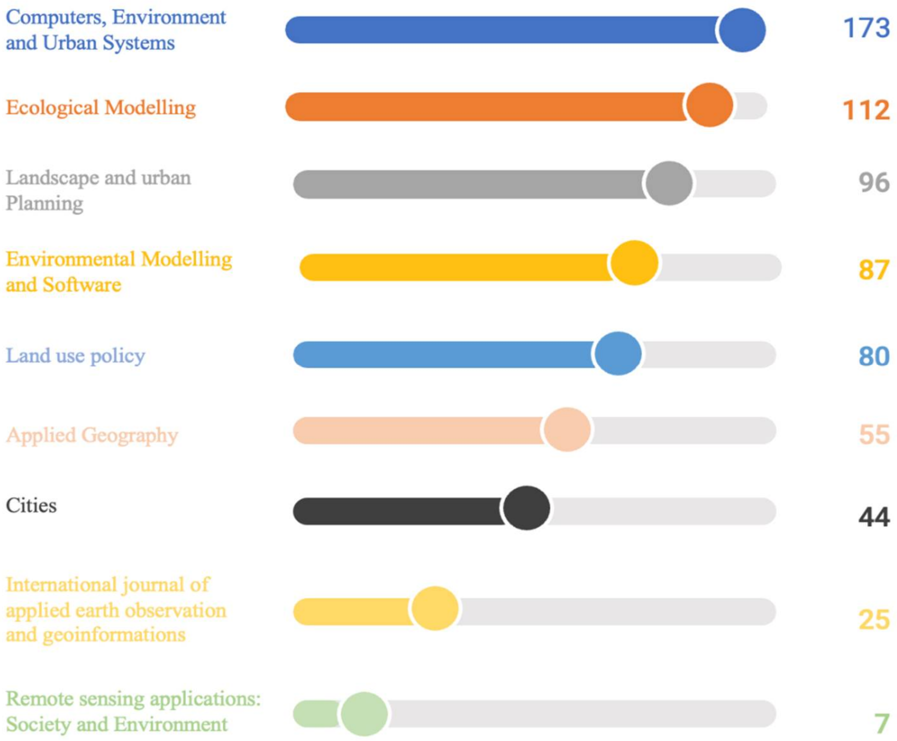

Figure 5. List of selected publication sources.

6. Cellular Automata in Urban Densification

The introduction and implementation of CA models designed to simulate urban land-use change from a bottom-up perspective has radically altered the study of urban systems over the last four decades. While models (in general) are abstractions of reality, few attempts have been made to capture the wider chaotic dynamics of urban densification to date [69]. Due to CA models' inability to represent entities at the most disaggregated levels, current urban models focus on horizontal urban growth. Recent studies [70,71] have made it more evident that CA-based urban models mainly focus on urban sprawl and expansion.

Traditionally, CA models simulate the spatiotemporal dynamics of land-use structures using grid units that are the same size as a cell lattice, similar to raster pixels or patches [72]. The transition rule is the most significant element in the CA model, and researchers have utilized a variety of methods, such as artificial neural networks [52], genetic algorithms [59], Markov models [73], the Bayesian method [74], kernel functions [28], and support vector machines [75] to produce transition rules.

Vertical urban growth or urban densification is one of the most essential parts of 'sustainable, low carbon, equitable, resilient development', as it changes the operation of cities even more [76]. Furthermore, building distribution patterns can have a substantial impact on the nature of the urban heat island effect [77] and can increase pollution levels [78] and road traffic noise levels [79]. Even though CA models for urban densification have recently emerged, there have been studies about 3D CA models [80] which provide an even more realistic representation. As a result, spatial and local variables should be added in order to increase the accuracy of CA simulation [81]. It is significant to understand the various types of drivers and constraints underlying the urban CA models. This would help urban CA modelers to understand the relation between global patterns and local actions, thus acting as a vehicle to construct and validate a new urban model based on "what-if" decision making. CA urban models should also consider qualitative factors such as land ownership and density change by adjusting the models' parameter settings.

There have been few works carried out with CA and densification in recent years, but the number is insignificant, as seen in the Figure 6. As a result of which, it is crucial to review CA-based urban study scenarios based on the data collected, driving factors, and the undergoing process which produces an accurate model. This can open several possibilities and the necessity to expand the horizon of studying different aspects of urban densification.

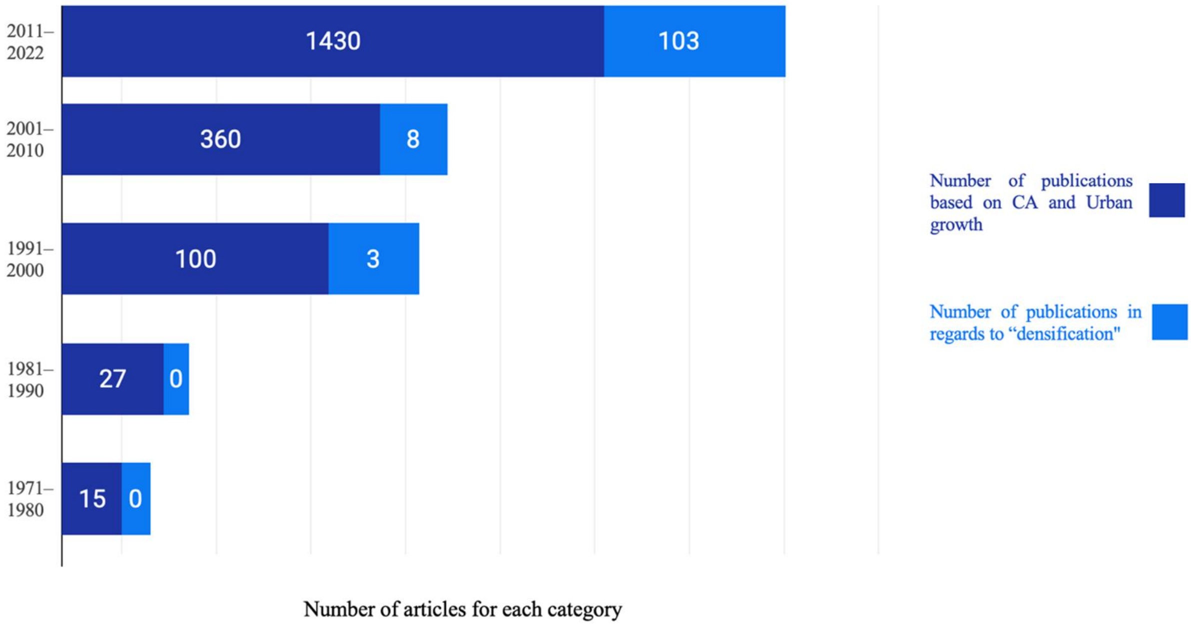

Figure 6. Total number of studies involving CA and urban growth versus studies with respect to CA and urban densification.

6.1. Data Collection

In studies on urban land-use/-cover composition, landscape ecology characteristics, and land surface temperature distribution, satellite image data have received more attention [82]. The remote sensing technique is useful for understanding long-term urbanization and predicting urban sustainability [83]. A similar kind of data can be applied when calculating urban densification for an area. Satellite images' ability to provide temporal and spatial dimensions, as well as their accuracy in visualizing phenomena, have made them necessary sources of data in CA models. In order to avoid inconsistent features over time, various data from sources such as from historical maps, images, and maps from different data and projections need to be standardized [52].

6.2. Driving Factors

A variety of studies have been conducted in order to have a better knowledge of the built-up driving factors [59]. These factors in urban studies can be empirically classified as geophysical factors [84], built factors [85] and socioeconomic factors [86] as mentioned in Table 2. Recent studies on growth models have also included spatial planning policies as an important driving factor due to a large control on the national or regional level [87].

Environmental factors include topographical and amenities factors. The inclination of the landscape, or slope, is a basic criterion for determining a suitable location for future development; flat and gentle-sloped areas are simple to develop and cost less [88]. Cities going uphill with a slope of less than 25° are considered to be on land that is suitable for vertical growth [89]. Elevation, distance to rivers, and distance to amenities such as green spaces, waterfronts, and open spaces can be considered among other topographical factors related to urban densification.

With regards to *build factors*, *accessibility* plays an important role. Mobility (distance to roads, highways, railways), land use (distance to settlements, city centers, residential) and employment opportunities (distance to agriculture, commercial, city center) are considered active drivers for infill development. These characteristics can be used as a proxy for market access and trade opportunities [12]. Additionally, infrastructure development (sewage, water lines) and public facilities are also key elements in future densification [90]. Accessibility to public facilities such as schools, hospitals, and community centers can also be an important determinant in infill growth [13].

In view of *socioeconomic factors*, population density and real estate values play the prime roles. The evolution of population density and number of households are the most active socioeconomic factors for urban densification [91]. High-end, low-pricing real estate values can have development potential and are considered to be important determinants for densification [86]. Low-value agricultural land is more likely to be developed if it has a high potential value when transformed into another use [90].

Table 2. Lineage of works of literature that define driving forces.

Author, Year	Built Factors	Environmental Factors	Socioeconomic Factors
Poelmans and Van Rompaey, 2010 [42]	•	•	•
Al-shalabi et al., 2013 [32]	•	•	
Pijanowski et al., 2014 [55]	•	•	
Liu and Ma, 2011 [91]		•	•
White and Engelen, 2000 [64]			•
Wu, 2002 [92]	•		•
Mustafa et al., 2018 [59]	•	•	•
Shu et al., 2014 [93]	•	•	

Note—The '•' signifies if the particular driving factor is used by the mentioned author or not.

6.3. Validation and Calibration of Urban CA Models

It is critical to distinguish between the calibration phase of the model and the validation of the model results when evaluating the predictive value of an urban model [94]. Validation is the demonstration that a model, within its domain of applicability, has a sufficient range of accuracy for the model's intended application [95]. Furthermore, calibration can be performed at a state or cell level, allowing for specific conditions to be applied to the standard state transition mechanism for those states or cells. In order to show the scientific significance with respect to real-world conditions and to assess the accuracy of a prediction model, it is necessary to validate the model [96,97]. Among the 116 review papers that have been considered for review, only 80 papers validated their simulations. The percentage of the most used simulation includes 40% of Kappa index of agreement, 15% of goodness of fit, and 20% of receiver operating characteristics (ROC). A detailed overview of the metrics can be seen in Figure 7.

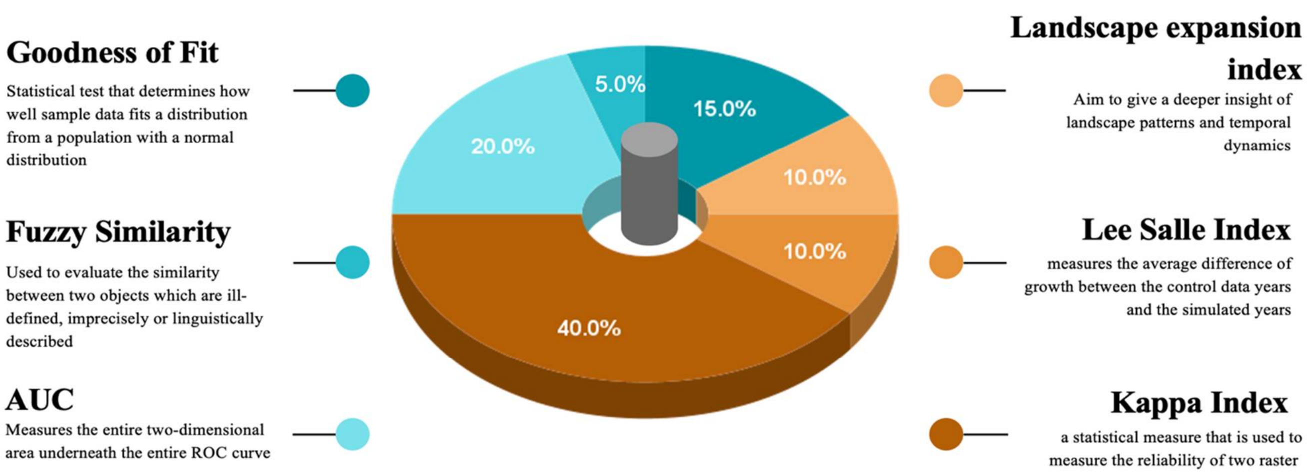

Figure 7. An overview of validation method adopted across considered articles.

The importance of model validation is widely recognized, resulting in a variety of approaches [58]. The most basic approach of model validation is where a predicted map is compared to an actual map [98]. However, this is not universally accepted, as different models serve different purposes or applications. Validation of CA models has been accomplished through a combination of methods such as confusion matrices [23], fractal index and analysis [64], landscape matrix [99], Moran's I [100], and Lee–Sallée index [92]. The generation of an error or confusion matrix is one of the most prevalent approaches for quantitatively measuring the performance of urban CA models. The error matrix is a square matrix where columns represent the observed data and rows represent simulated data.

The landscape expansion index can be used to identify expansion types and its distribution pattern from multitemporal spatial data. The LEI index divides spatial urban patterns into: infilling, edge expansion, and outlying. By comparing urban pixels, the Lee–Sallée criterion assesses the success of the geographic matching of modeled growth with temporal data. The ratio of intersections and combinations of the Existing Urban Area and the Simulated Urban Area is the Lee–Sallée shape index.

Our review, as shown in Figure 7, helps to state that the Kappa index of agreement (KIA), the receiver operating characteristics (ROC), and the goodness of fit curve are the most significant and extensively used coefficients used to validate models for urban densification [64]. The Kappa coefficient of agreement was developed as a discrete multivariate analytic statistic with values ranging from 1, indicating perfect agreement, to -1, indicating no agreement at all [97]. Cohen formulated the Kappa index as

$$\kappa = \frac{\rho_o \ - \rho_e}{1 - \rho_e} = 1 - \frac{1 - \rho_o}{1 - \rho_e}$$

where p_o is the relative observed agreement among raters and p_e is the hypothetical probability of chance agreement.

6.4. Prospects of CA Model in Urban Densification

Study of the CA model has undergone several paradigm shifts over the years. The foundation has been based out of the raster-based CA model for scrutinizing urban growth studies where the study area has been treated as a collection of cells [101]. Nonetheless, several aspects of urban growth modeling, such as the representation of time built into the model and model randomness, raster cellular space does not take into account the real structure of the land, or the use of scales that are inappropriate for urban or regional planning. As a result, only a few models have been integrated into planning decision-making procedures [102]. Thus, CA has an exponential likelihood to imply vector data which will make it realistic and help solve real-world problems, taking the land use and urban scenarios at a simplified level.

6.4.1. Vector-Based CA Model

Though raster-based CA models or Parcel-based CA models are widely used, it raises a question: is it appropriate to use raster surfaces in urban growth simulations? Urban space transformations do not always comply with the pattern of a regular structure, such as that used in a raster data model; rather, they usually fit into the pre-existing land structure. Moreover, raster models are usually a good fit for large-scale urban studies, but when the goal is to describe an urban system and its associated dynamics at a more reduced scale, close to urban planning scales, this representation is less appealing.

In order to address these difficulties, CA has an ability to integrate vector entities. Irregular space structures, such as cadastral parcels or plots, that constitute the geographical space division according to land property, can be taken into account at different scales, such as the municipal and statistical sectors. Efficient usage of this structure to simulate urban growth will yield models capable of working at a scale closer to that employed in urban planning. This is because it will include different neighborhood types and building attributes (height, usage, and surface).

6.4.2. Three-Dimensional CA Model

Urban spatial dynamics are nonuniform in time and discontinuous in space. However, all the past research related to urban CA models have been historic vector-based or raster-based 2D data. Cities, on the other hand, are three-dimensional objects and record just a portion of the nature of urban morphological dynamics [103]. Few attempts have been made to study the growth of cities in 3D in terms of land use [104–106], but none of them have considered urban densification and cellular automata per se. It is possible to convert 2D simulated maps from a CA model to 3D by means of spatiotemporal changes in building heights and volume of buildings. Previous research has been established to model the spatiotemporal dynamics of urban densification using the CA model [103,107]. The result of using this approach resulted in a grid distribution of low resolution due to the usage of raster images. A novel approach can be established to create a 3D vector-based urban CA model using parameters such as building height, usage, and surface for simulating residential densification. These attributes can also be considered to study the impact of densification on land values, urban heat index, and the society. Cadastral parcels act as the fundamental building blocks in urban planning, which can be implemented as an input to model urban densification using CA, as they are of ir-regular shapes and sizes, thus overcoming the limitation of raster images. This can also represent fast growth scenarios for medium- and high-rise buildings in the urban and city center.

Urban density also impacts energy usage and quality of life in urban residents. Due to the demand of more dwelling spaces, levels of CO_2 emissions have increased, thus resulting in high energy consumption [108]. Urban form can also have an impact on the urban microclimate, which includes the thermal environment, ventilation, reflection, and solar radiation absorption [109]. With the growing extent of urban density, urban areas can be configured spatially for the reduction of energy use and CO_2 emissions.

7. Challenges, Limitations, and Potential

Environmental degradation is a growing concern because of the global trend of increasing urbanization. Simulating urban growth patterns is becoming increasingly important for long-term and sustainable development [110]. The integration of RS data with GIS tools creates a vital tool to measure, monitor, and map urban land densities [111]. Despite its importance to the environment and local economies, there have been few studies on what some scholars refer to as the urban densification process [112]. The easy integration of CA models with other urban modeling techniques and its incorporation with geographic information science and remote sensing is the main reason behind such increase. Moreover, urban CA models are capable of predicting infill development through time due to the simple and effective rules. CA models are simple to use, can simulate complex models, have an open structure, and can simulate both spatial and temporal models [19].

CA models overcome their limitations of not being able to include drivers in urban densification simulations by combining other quantitative and space–time methods such as the Analytic Hierarchy Process (AHP) [113]. AHP is a multicriteria decision approach that assists urban planners to analyze all data before making decisions that include competing criteria. According to the literature reviews, the CA model is one of the most powerful models for simulating and predicting the urban growth phenomenon.

Empirical models such as Markov chain and logistic regression can be integrated with dynamic models such as CA and agent-based models in order to improve accuracy [114]. The CA models can be integrated with Markov chain and logistic regression. Because of their ability to reproduce complex dynamics similar to those found in real cities from simple rules, cellular automata (CA) stand out among the most used urban models for simulation and analysis of urban growth [115]. Furthermore, the CA model can be used with existing data. Therefore, several researchers have integrated CA models with other statistical and empirical models such as LR and ANN to overcome the limitation of standalone CA models.

Cellular automata have been widely used in social, economic, military, and scientific study since their inception. In sociology, CA can be employed to explore the social changes in context of social influence [116]. Human brain mechanism exploration [117] and HIV infection studies [118] can be viewed as further evidence of the natural propagation of CA models. In lieu of the recent COVID-19 pandemic outbreak, modeling the spread of the virus through CA has been an important step in learning proper preventive measures. Additionally, residential migration is an important part of city and crime-prevention planning. By examining the influence of social structure on the decision to relocate, CA models are also a suitable tool for analyzing residential migration and neighborhood structure.

The CA-based model may have some limitations, which is common for any land-use model. These limitations are related to the sensitivity of the model due to: cell size (e.g., 20 m; 100 m; 500 m), grid orientation (N-S; NW-SE), and neighborhood configuration (Moore, Von Neumann, etc.). To overcome these limitations, it is recommended to consider recent advances in CA-based models, mainly related to neighborhood configuration. Overall, for the model evaluation, land-use modelers focus on the confusion matrix. Meanwhile, the evaluation (goodness of fit) metrics should cover all four categories with their adaptation to the ML concept: (i) some mix of percent positives/negatives (figure of merit); (ii) an ROC (threshold-independent measure); (iii) pattern (number of patches, shapes, entropy), and (iv) resolution (scalable window).

The assessment of error propagation and uncertainties is also one of the most important factors in understanding the results of simulations of urban CA. Like many other simulation models, urban CA models have inherent issues with data and model uncertainty. Spatial variables retrieved from GIS are prone to errors and can propagate in CA simulations. These errors can be identifying as transformational, positional, and attributional errors. Transition rules, neighborhood cell size, and other parameters can contribute to uncertainties while defining a CA model.

However, very recently, researchers from Europe and the US presented an original modeling framework that allows for multilabel class assignment in land use [119]. This new concept, as well as the use of machine learning [120], will open diverse opportunities of research on both theoretical and empirical sides and will have exciting challenges. In future work, there is a need to tackle other problems (such as: model calibration and evaluation issues, using big land-use data, handling dependence among classes, dealing with class imbalance problems, variable selection, ensemble learning) for further advancement in CA-based land-use modeling.

On the other hand, the size of the raster cell and the fixed neighborhood structure limit the ability to accurately model urban space transformation. Most of the study involves a raster-based CA model which considers each entity as a representation of two-dimensional cells (rows and columns). While doing so, to overcome these limitations, the vector-based CA model can be introduced to study urban densification.

This paper recommends a combination of a nonordered, multinomial logistic regression (MLR) and cellular automata (CA) model to simulate scenarios such as urban densification [63]. The models take in consideration the fact of a transition from low density to high density, which is of the utmost importance for policy makers when it comes to urban sprawl. Apart from showing the utility of the CA model as a collection of 2D cells in raster, this paper will facilitate as an exhortation to the potential of vector-based CA models, which will produce a near-realistic simulation of urban scenarios. This paper will also demonstrate the capabilities of CA in the three-dimensional aspect, which is a trend-setter for the future research potential. The model considers a number of fixed driving factors such as accessibility, geophysical features, policies, and socioeconomic factors, which was a limitation of the urban CA model. Employing a multiobjective genetic algorithm

(MGA) to calibrate the neighborhood interactions on a dynamic basis will maximize the allocation accuracy.

8. Conclusions

CA models have mostly been restrictive toward studying and simulating urban expansion. Very few recent researchers have takes into consideration the study of multidimensional aspects of urban development such as densification, infill development, vertical urban growth, urban shrinkage, etc., [70]. In this paper, we attempted to report on the CA approach over the period of five decades (1970–2020) in order to develop integrated research which will provide in-depth information about the application of spatiotemporal modeling of urban densification using CA. The combination of various dynamic and static drivers that can be accounted largely for modeling densification has been reviewed to lay a foundation on modeling such scenarios using CA. Finally, the evaluation metrics used over all these years have been thoroughly explored to give an idea about the plausible metrics which can be used for the same purposes. Though there have been few works on urban densification modeling in recent years, the number of works related particularly to CA is still insignificant and mostly limited to 2D applications. As a result of this, our paper will help to pave the way for a scientific, systematic method to explore the potential of CA modeling in urban densification and provide the researchers and planners a potential opportunity in the field of urban planning and development by exploring 3D-integrated CA models and simulations at the age of digital twins.

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