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Research paper

A Review of Simulation Urban Growth Model

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Abstract

Urban development has become a problem in many cities, especially in developing countries. The availability of areas for development is needed to deal with rapid population growth and urbanization. The purpose of this study was to identify urban growth models. Due to urban growth planning, the city will be more manageable and organized. From the conclusions of urban modeling identification can provide an idea of what model is appropriate for use in urban growth studies. The results of this urban growth model identification could be a reference in urban growth modeling in better urban planning.

Keywords: *Urban Growth; Geographic Information System; Simulation; Modeling.*

1. Introduction

Urban growth is one of the phenomena faced both in developed and developing countries. Urban growth is basically influenced by an increasing rate of economic growth. With increasing economic growth, automatically income levels begin to increase. And that will encourage the growth of population in urban areas as well as the power to pull people to live in the city and the growth is indicated will increase in the future [1]. Economic growth in urban areas is one of the triggers of the urbanization process. With the urbanization process and rapid population growth, demand for land use/land cover for development is increasing.

In determining the proper simulation of urban growth, spatial modeling becomes a serious challenge in urban development [2]. Because, with spatial modeling, it can show the extent to which urban land changes are caused by urban growth, which can later provide information on the investigation of urban ecosystem management [3]. With the urbanization process in urban areas has caused changes in the urban landscape.

In urban growth modeling as well as spatial data management, Geographic Information Systems (GIS) play an important role in their use [4]. Various models and techniques in the Remote Sensing (RS) and GIS strategy are generally used to simulate, predict and demonstrate the design of urban development and the reproduction of land use change [2]. Within coordinating RS and GIS researchers can analyze environmental changes such as identifying land use attributes, land monitoring, land use mapping, and determining a hotspot point [5]. To simulate the change in LU/LC there are various models in urban growth such as Markov chain (MC) model [7], logistic regression model (LR) [8], cellular automata model (CA) [4], artificial neural networks (ANNs) models [10], SLEUTH model [11]. In this paper, our main focus is on describing simulation models of urban growth modeling to find the best model for urban growth.

2. Data Collection Process

Many models are applied to know urban growth by using GIS and RS, one of which is by simulating and predicting urban growth. By approaching the problem from different perspectives as well as from cases occurring in many countries. To prepare good review literature, various electronic sources including search engine database papers such as IEEE, Science Direct, and Web of Science are used by researchers in providing reviews. In determining the appropriate discussion topics on the simulation urban growth model, the researcher follows the guidance standard in determining systematic meta-analysis and PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) [12]. Fig. 1 explains the filtering step of the paper in the order of PRISMA standards, followed by a duplicate selection process, if there is a duplication script it will be deleted. Next to the screening process starts with collecting reference data related to the review. After passing through the stages, the relevant manuscripts to the discussion include urban growth models and components whether they are theoretical discussions or applications of previously published works. And finally, there are 2 papers that serve as a reference and 45 reviews of urban growth simulation model.

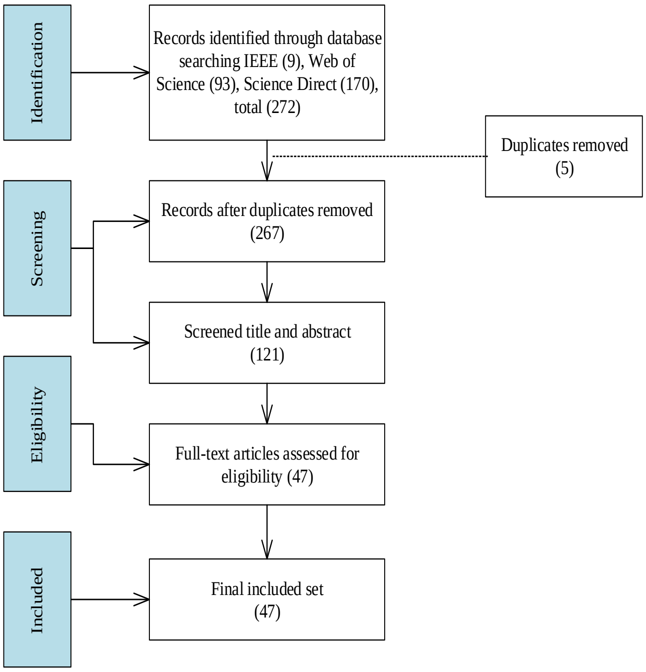

Fig. 1: PRISMA article selection flowchart [1].

3. Urban Growth Model

Urban growth is a demographic and spatial process that refers to the importance of urban growth where the city as a center of population concentration in the economy and society. Basically, urban growth and population growth are very similar to underlying causes where most of these examples cannot be discriminated because urban growth has important associations with population growth [2]. In this case, the importance of observation in the control of urban growth is to avoid random urban growth. Good and bad urban growth depends on the process, the pattern and its consequences. In addition, there are specific causes responsible for urban growth. In Table 1 is written what are the causes of urban growth, as well as a compact growth in terms of growth that affect the growth of the city with a wide scope.

Table 1: Factors causing urban growth [13].

Urban Growth	Compact Growth	Sprawled Growth
Population growth	✓	✓
Independence of decision		✓
Economic growth	✓	✓
Industrialisation	✓	✓
Speculation		✓
Expectations of land appreciation		✓
Land hunger attitude		✓
Legal disputes		✓
Physical geography		✓
Development and property tax		✓
Living and property cost		✓
Lack of affordable housing		✓
The demand for more living space	✓	✓
Public regulation		✓
Transportation	✓	✓
Road width		✓
Single-family home		✓
Nucleus family	✓	✓
Credit and capital market		✓
Government developmental policies		✓
Lack of proper planning policies		✓
Failure to enforce planning policies		✓
Country-living desire		✓
Housing investment		✓
Large lot size		✓

Basically, simulation techniques are used to test theories about spatial location as well as fundamental interactions on urban models especially land use and urban growth activities [3]. Spatial changes in urban growth especially land use have become a problem as well as one of the interesting concerns to be understood by researchers based on urbanization and development [4]. To know urban growth there are several approaches to study such as population, soil surveys, air surveys, water surveys, remote sensing, and urbanization [16]. Remote sensing in GIS is highly accurate and efficient in assessing urban growth [17]. Along with increasingly sophisticated technological advances especially in technological developments in the field, in use detailed temporal and spatial data on the geographic information system and remote sensing directly lead to an increasing number of model development for land use especially in urban growth [4, 8]. In this case on urban development models such as MC, CA, LR, SLEUTH, ANNs. As urbanization and urban growth impact are important to monitor, research on urban land use extensions, urban growth, and spatial prediction continue [9, 10, 11]. In several years various models in the literature to identify urban growth, including urban change and land use models and models in predicting urban growth [12, 13]. Although, the model must have the same direction and purpose but different in the theoretical implementation and methodology. To assist decision making in the modeling process for urban growth simulations, below are five models to simulate urban growth that can be used by researchers.

3.1. Cellular Automata (CA) Model

In 1940, Ulan and Neuman first introduced the CA Model. The five major components in CA model are Grid: A space in which cells exist [11], Cell state: Cell state of infinite-state [14], Neighborhood (N): Cells adjacent to a particular cell [15], Transition rule: It characterizes the condition of the cell in the following time based on its present state and condition [16], Temporal space/Time: The time advance in which the cell develops [17].

In the CA model, the grid represents space and time by uniform advances and the states inside the system were limited. The smallest spatial unit is the cells and the state is a characteristic that describes the cell for a particular time step. Neighborhood explains the relationship between cells. The state of neighboring cells determines the state of each cell. In characterizing the cell state in each step, a rule is used [18]. CA are broadly utilized as a part of a spatial simulation for its inclination of discreteness in both space and time, the conceivable states of every cell in the lattice are limited. A huge measure of this sort of cells collaborates with each other into a composite of a dynamic system. The associations inside CA models are just nearby. In view of such nearby cooperation, the condition of every specific cell can be just dictated by the states of itself and its encompassing cells at a previous minute as indicated by a progression of composed change rules. Different like a common dynamic model, CA is made by the progress manages as opposed to entirely characterized physical equations or capacities [10]. The state of the cell in the future is controlled by a progression of transitional rules, which think about the underlying condition of the cell, the environment, and other main impetuses [19]. This is formulated:

$$S^{t+1} = f\ (S^t, S^N) \tag{1}$$

where S^{t+1} represents the state of the cell at time t+1, S^t represents the state of the cell at another time t+1, S^N is the set of states of cells in the neighborhood and f is a capacity that addresses to the change rules [20].

CA could simulate framework worldwide complexity viably through neighborhood estimation, belonging turbulent phenomena,

periodical phenomena, natural laws and appearance [10]. This model has strong tempo-spatial evolution prediction ability, it is commonly applied to spatial simulation such as urban growth, land use dynamic, land use prediction and land use change [17, 11, 18, 21].
With simple rules in the space of each cell, CA can produce a complete phenomenon in a simulation of urban growth [36]. Therefore, the CA model is widely integrated with other models as well as the CA model gets a lot of attention in the research because of its accuracy as well as the integration alignment with other simulation models. For example, a two urban growth modeling approach, CA-MC based on the Analytical Hierarchy Process (AHP) and Frequency Ratio (FR) process, is used to compare the performance and accuracy between CA-MC process using AHP and FR. By entering the dataset, a socio-economic, DEM, road network, public service, land use/ cover. From the comparison of the process gets model CA-MC based on AHP process 84.2% and FR 88.2%. From the second validation process, the simulation of CA-MC model based on AHP is lower than using FR process. So, in urban growth simulation planning in that case the CA-MC simulation model based on FR is highly recommended for sustainable urban development in Saremba, Malaysia [22].

3.2. Markov Chain (MC) Model

To perform predictive change modeling techniques, which use macroscopic modeling processes, stochastic as well as MC model aggregates are highly appropriate. Changes in the past serve as a basis for predicting the future [18]. The hypothesis of this model depends on the movement data of MC stochastic process frameworks in anticipating change of status. In each land cover class, this model provides a set of conditional probability images. This model is commonly used on predictive geographic features that have no after effects events and this model has become an important method of prediction in geographic research. In the model proposed by this, to predict future land change, the MC model considers the land cover class obtained from satellite data that will be used to evaluate future land change simulations [23]. In the MC model, there is a transition probability where the probability is a change from one period to another. This MC model calculates the probability of cell change of land within a certain period of time. As well as in the development of the MC model, there is also a transition matrix that contains the probability of land use that may change to other categories such as the use of green land as building land, in any change or land use there is the number of pixels that will change [18]. A Markov transition matrix (P) can be expressed as follows:

$$P = \begin{vmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{vmatrix}, \sum_{j=1}^{n} Pij = 1; i = 1,2,..,n \qquad (2)$$

Where P is the matrix transition, the probabilities Pij are called transition probabilities, and n = the transition probability matrix P. P_{ij} is the probability of change from land use type i to j calculated on a cell-by-cell basis, and the sum of each row always equals to 1 [24]. The basic premise of the Markov chain model is that land use at some point in the future (t+ 1) can be determined as a function of current land use (t), or mathematically

$$X_{t+1} = f\ (X_t) \qquad (3)$$

where X represents t + 1 which is the ending time of the simulation, t represents land use at the beginning time, Xt represents land use at time t and f is the transition rule [25].

3.3. Logistic regression (LR) model

LR models is used to test the relationship between variables based on mathematical calculations. The later of this variable can be fulfilled or independent (experimental). In the application of urban modeling, this variable depends on the possible use of urban land and on experimental variables covering socio-economic factors such as land zoning status, slope, major road distances, development distance to existing areas, accessibility from urban centers, worker potential and factors which affects land use, LR model is used in the calculation of surface probabilities of developmental transitions [26]. LR analysis was used to test the relationship of independent variables and urban land use. The matrix of independent variables becomes the basis of predictive application characteristics in LR, where the dependent variable is a dichotomy. In this case, such dichotomous variables can be urban change where 1 (one) indicates urban change and 0 (null) indicates no change in urban areas [1]. This independent variable can continue, categorically or both. Urban growth modeling has applied many LR models, which accommodates environmental and socio-economic independent variables [26, 27]. In land use utilization model, LR is connected to decide observational weights for the readiness of similarity maps. To analyze and interpret the relationship between forces in socio-economic driving and land change, LR models were chosen to define linear combinations of land use option attributes [28].
The LR model is also possible in visualizing the consequences of development projections in combinations such as zoning and development regulations. This model has capacity in simulating urban growth chamber and vertical growth. As in the example of research modeling of retail, commercial and residential development. In this research LR model shows simulation result at retail location, commercial office, and housing unit tends to grow by considering the aspect of population, tax property, development area, and road network. With that, the structure of this model allows for a fairly flexible and detailed simulation of urban growth, so assisting in urban development planning and decision making by understanding all aspects of growth consequences [26].

3.4. SLEUTH Model

The SLEUTH urban growth model was utilized to examine the part of various spatial contemplations in creating strategy situations [29]. The SLEUTH model developed by [34] based on the development theory of urban expansion, is applicable to simulating urban development in metropolitan areas [30, 31]. The name SLEUTH itself stands for and comes from the contraction of data input needs is a slope, land use, exclusion/attraction, urban extent, transportation, and hillshade [32].

Table 2: Data requirements for SLEUTH model [29].

Input Layer	Prepared Through	Format
Urban extension	Supervised classification of satellite image	Raster
Transportation network	On-screen digitization from satellite image	Raster
Slope	Derived from DEM (digital elevation model)	Raster
Hillshade	Derived from DEM (digital elevation model)	Raster
Excluded area	Rasterized from vector	Raster

In SLEUTH model implementation, there are two phases: a calibration phase in which the model is trained to replicate historic development trends and patterns and a prediction phase in which historic trends are projected into the future [33]. In this model, each cell can be converted into urban or nonurban use [32]. In this SLEUTH model, five GIS-based inputs are required: urbanization, land use, transportation, areas that are excluded from urbanization that is slopes and hillsides as background. In the input layer must have the same number of rows and columns, have the correct

georeference and precise. For calibration of model statistics, urban levels should be available for at least four time periods [33, 34]. Table 2 explains the data requirements of the SLEUTH model. In Fig. 2, the model overview of SLEUTH [33]. Implementation of the SLEUTH model requires high-end technology in processing because it requires multiple datasets, and this is also a major obstacle when used in developing countries where resources are limited [33].
SLEUTH model in urban growth prediction requires input data such as land slope, land use, exclusion, urban, transportation and hill shadow. In this SLEUTH model, it supports three different modes in urban growth modeling and prediction: test, calibration, and prediction.

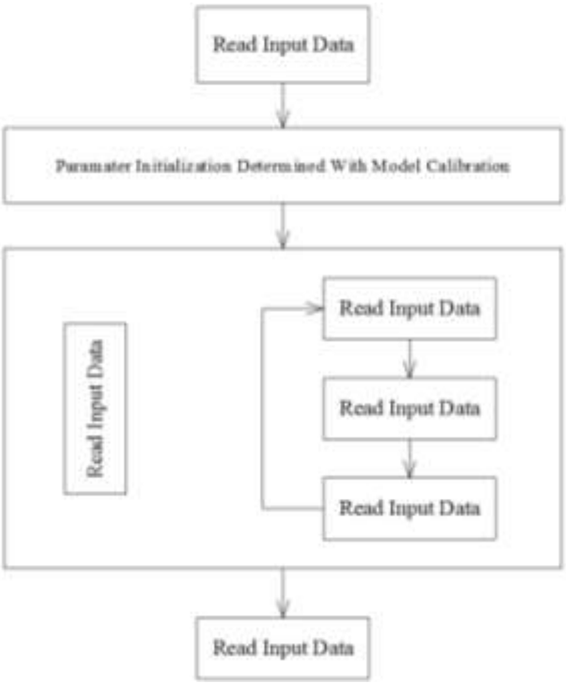

Fig. 2: The general structure of the SLEUTH model [33]

3.5. Artificial Neural Networks (ANNs) Models

ANNs is applied to the impact of land use change and predicting socio-economic patterns. A residential environment consisting of the interaction of parcels of land [20]. ANNs is a machine learning technique capable of capturing nonlinear associations underlying land use transformation by formulating relationships between input variables and output variables [35]. Furthermore, ANNs is known as an artificial neuron in which the computational device operates like a human brain composed of a group of interrelated processing elements [36, 37]. Conceptually, the input and output layers are one or more with hidden layers between them and generally presented by neural networks as in Fig. 3.

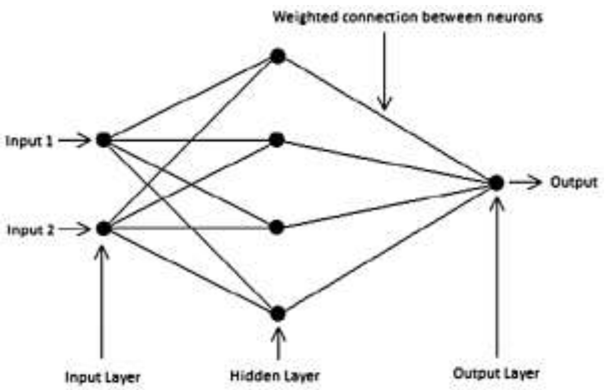

Fig. 3: A multi-layer perception of ANNs architecture [38].

In the above ANNs model showing the neurons in each layer, the layers shown in the drawing have a 2-4-1 architecture pattern where two neurons are in the input layer, four neurons are in the middle layer and one neuron is in the output layer. In the layer has a relationship between one with another [38]. In the above neuron image, the input layer as the data transmission and the output layer as the data processor. Basically, the input relationship of the neuron is used as the transfer function calculated through the output network.

4. Discussion

Urban growth is a problem in developing countries, where each city has its own form and complexity in making simulations and predictions of urban land use. Moreover, it uses only a few approaches in the implementation of the simulation. Urban is an area of complexity that requires the integration of one model with another model. With the RS and GIS in the simulation and prediction will be helpful in handling various phenomena associated with urban growth. With RS and GIS simulations can be done by applying various models of urban growth simulation according to the region as well as the expected output results. For a realistic and idealized simulation can be generated using an integration approach using spatial transition rules over time.
This study reviews from several theoretical modeling perspectives selected from previous studies in the field of urban growth, with the aim of providing references to facilitate subsequent researchers in the field of urban growth. Furthermore, it found five modeling of urban growth in a search that is MC, CA, LR, SLEUTH and ANNs. In the five models of urban growth, there are strengths of each such as shown in Table 3.
Although it has the strength of every simulation model in each model, it also has a lack. The MC model in the analysis is not very sensitive to space or state causing serious problems, hence to integrated with CA models that have spatial elements to cover deficiencies in this model. From five urban growth modeling above, the most generally utilized model is CA model for simulation during 2013 to 2018 in a can from 45 reviews paper as shown in Fig. 4.

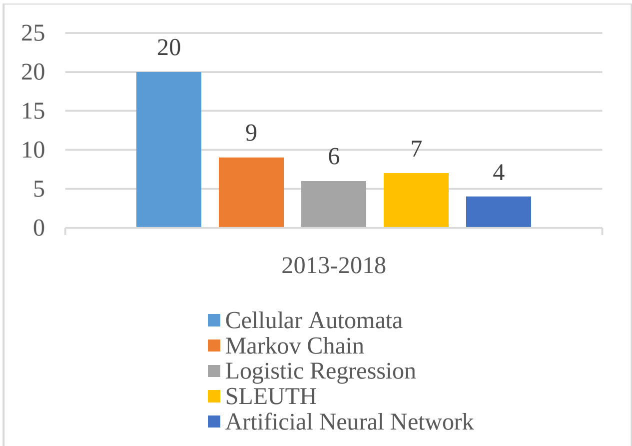

Fig. 4: Modeling of popular urban growth from 2013 – 2018

From Table 5, data model CA most widely used by researchers as the best model to be used as a simulation of urban growth.
Because from some models such as the CA model and others can illustrate future land use, but the model does not have the capability to handle changes in land use transitions and the other categories contained. To handle this requires a combination or integration between one modeling with another modeling in order to handle factors not present in the modeling. In Table 4, some of the integration between the CA model with other models as well as the result of the integration between the two models. In the simulation and prediction of land use changes if the factors that influ-

ence can be identified and incorporated into the model will reinforce the results of the simulations and predictions that researchers do. One of the strengths of the CA model is there of socio-economic aspects, where this aspect is so important in urban growth that many researchers use CA modeling as the main model and then integrated with other models.
In Table 4, there is some integration between the CA model with the other model along with the result of the integration of the model. The result of integration between CA model and other models shows high results, both in projection, simulation accuracy, and prediction as well as in determining an urban planning that will be used as government decision making and policy in managing urban growth.

Table 3: Strength and recommendations of each model

Model Type	References	Strength	Recommendations
Cellular Automata (CA)	[17, 20, 42, 43]	- Addressing urban growth with digital elevation models in remote sensing useful for the development of land cover data models. - Accuracy in the simulation of land use is more effective because of the spatial area of cells that implement it in various environmental measures. - For indicate socio-economic development and environmental changes.	For cities that have different geographic areas this model is highly recommended because of its high accuracy in support of its correct allocation level.
Markov Chain (MC)	[3, 44]	Local historical data as a search for factors affecting land change.	The existence of an integrated analytical model on GIS, this model is well suited to predict future urban growth with previous simulation data.
SLEUTH	[32]	In the input process SLEUTH model requires less number of input layer and for development of different growth more flexible.	In areas where the socio-economic data is not very broad this model is more recommended.
Logistic Regression (LR)	[7, 29]	- Explaining relationships as well as factors between experimental variables and urban land use - In deciding allocation is dictated by factors as per government regulations. - This model helps in incorporating the effect of growth drivers that contribute to more precise growth projections.	- To improve and assist in decision making with the support of planned thinking. - For further research, aspects affecting urban growth need to be considered again in a simulation so that the resulting data is stronger both in land use and urban planning.
Artificial Neural Networks (ANNs)	[39, 46]	- This model mimics the operating system of human brain operation. - To predict urban growth used multilayer artificial neural network perceptron.	For non-dependent data input this model is very suitable to use.

Table 4: Results integration between CA model with other models

References	Place	Purpose of Application	Technique Used	Result
[47]	Bogor, Indonesia	Prediction Land Cover	Integrated Cellular Automata – Markov Chain	The results from the projection model show that the built-up area will increase almost double from 24 to 53% and in this technique almost all land cover types are accurately predicted except for cultivation and rice fields.
[6]	Gilan, Iran	Dynamic Simulation Urban Expansion	Integrated Cellular Automata-Logistic Regression	Results from the analysis of land change during the years 1989-2013 showed an increase of 1.7% of urban land area 36,012.5 ha to 59,754.8 ha. The predicted results for the year 2025 and 2037 are 0.82% and 1.3%.
[36]	Sana'a, Yemen	Modeling Urban Growth Evolution and Land Use Change	Integrated Cellular Automata-SLEUTH	From the simulation and prediction results with the map dataset for 35 years in Sana'a city showed 99.6% overall high accuracy, 83.3% producer accuracy and 83.6% user accuracy. This integration model can predict and be effective in planning and decision making on urban growth in Sana'a.
[43]	Maragheh, Iran	Urban Planning	Integrated Cellular Automata-Artificial Neural Networks-Fuzzy	The results of a research simulation to determine the impact of urbanization on the orchards area show that CA-ANN-Fuzzy revealed a major loss of 7% in 2025 due to urbanization, with validation kappa coefficient of 83%. In simulation showed that the threatened orchards located in suburban areas.

5. Conclusion

Urban growth especially on land use/land cover is important to observe and investigate. With economic growth and rapid population growth, anticipation is required to avoid irregular urban growth and to simplify city planning. Coupled with the urbanization that adds problems in many cities in developing countries. Various ways are done to overcome urban growth one of them to simulate and predict urban land use that aims to simplify the settings. With the availability of simulation models as well as predictions for urban growth can help plan well and build an organized city.
This review provides an overview of five models of urban growth in which each model has its own power in simulating and predicting urban growth. In this review also explained various aspects and factors that support in a simulation and prediction of urban growth. Such as socio-economic aspects, network road, land use and land change, government policy, property tax and urban development planning. Urban growth modeling is a very important aspect for developing countries. Due to this modeling, both government and policymakers can plan future developments based on land use history data in the latter areas. Given this modeling based on remote sensing in GIS, sustainable urban development planning will be easier to do. The model can be implemented as a reference for urban growth planning. From the above review data, there is a model most used by researchers in simulating and predicting urban growth i.e. CA model. The CA model has good simulation accuracy due to the application of spatial areas of cells that are in various sizes of the environment, as well as taking socio-economic aspects where this aspect is very influential in urban growth.
In addition, CA models can be integrated into other models such as LR, ANNs, SLEUTH, and MC. But, for urban growth the CA

model is heavily integrated with the MC model as it has accurate simulations and predictions of land changes well. Therefore, for the results of simulations and predictions of urban growth have high accuracy, the factors and aspects that affect urban growth can be improved and incorporated into the urban growth model for better identification and planning.

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