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# A user-friendly assessment of six commonly used urban growth models

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ABSTRACT

An accurate grasp of urban expansion patterns is conducive to efficient urban management and planning. Various urban growth models have been developed to meet this need in the last two decades. As more models become available, users increasingly face the challenge of choosing the right one for their purposes. In this study, we first reviewed the recent usage pattern of urban growth models (UGMs) and identified the top ten UGMs accounting for 73.3% of total usage from 2000 to 2021. We then compared the performance of six commonly used UGMs in simulating urban expansion, including the Cellular Automata-Markov model (CA-Markov), Slope, land use, excluded layer, urban extent, transportation, hillshade (SLEUTH), Conversion of Land Use and its Effects at Small extent model (CLUE-S), Future land use simulation model (FLUS), Land Use Scenario Dynamics model (LUSD), and Land Change Modeler (LCM). The behaviors of the six models were verified against descriptions in the model's documentation. We also analyzed the models' documentation, focusing on data requirements and the user's flexibility in the modeling process. The results showed that the validation accuracies of the models varied with the inputted data, indicating a model does not have an intrinsic accuracy. CA-Markov, FLUS, LUSD, and LCM could be verified, while CLUE-S and SLEUTH failed to meet some verification criteria. In addition, SLEUTH has the highest requirement for input data among all studied models. FLUS and LCM allow for higher user flexibility in modeling than others. This study's findings can help users decide which of the six urban growth models suits them.

## 1. Introduction

Urban expansion around the world has modified the global environment profoundly. Projections of urban development and associated environmental impacts have become essential in global change studies (Seto Karen, Güneralp, & Hutyra Lucy, 2012; Zhang et al., 2022). Policymakers and urban planners also increasingly consider future urban growth at the planning stage (Zhang et al., 2021), making urban growth projections essential to long-term urban planning (Huang, Li, Liu, & Seto, 2019; Veerkamp et al., 2020).

Urban growth models (UGMs) are the primary tool for generating urban growth projections. UGMs can simulate the mechanisms of existing urban systems and project the evolution of urban expansion (Wang, Bretz, Dewan, & Delavar, 2022). Researchers and planners use them to predict the amount and spatial distribution of urban growth under different development scenarios (Aburas, Ho, Ramli, & Ash'aari, Z. H., 2016; Harb et al., 2020; Verburg et al., 2019). Due to the intense needs of researchers and practitioners, various UGMs have been made available since the 1950s (Li & Gong, 2016). However, choosing a suitable model for one's work becomes more challenging when more models become available (Li & Yeh, 2002). UGMs have different modeling frameworks and core algorithms (Musa, Hashim, & Reba, 2017). The challenge may partially explain the statement that choosing a particular model is often arbitrary and at the researcher's discretion (Pickard, Gray, & Meentemeyer, 2017).

Studies using UGMs typically provided indicators of model accuracy, such as receiver operating characteristics (ROC), overall accuracy (OA), and Kappa index (Batisani & Yarnal, 2009; Wang, Zheng, & Zang, 2012). However, several studies pointed out the conceptual flaws of using OA and Kappa. They recommended using more proper indexes, such as Figure of Merit (FoM), Hits (area of correct due to reference change simulated as change), Misses (area of error due to reference change simulated as persistence), False Alarms (area of error due to reference persistence simulated as change), quantity disagreement, and allocation

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disagreement (Harati, Perez, Molowny-Horas, & Pontius, 2021; Pontius and Millones, 2011; Varga, Pontius, Singh, & Szabo, 2019). Moreover, accuracy assessments in many studies are limited to the stage of model calibration (Santé, García, Miranda, & Crecente, 2010; Van Vliet et al., 2016). While accuracy at this stage is helpful, it measures a model's performance for learning the historical urban expansion patterns. The value does not tell the user how well the model predicts future expansion, which is the primary goal of model validation. The lack of model validation in past studies leads to the suggestion that separating calibration from validation is an important challenge in land change modeling (Pontius et al., 2018). In response to this concern, land change studies gradually included model validation in the modeling process (Aguejdad, Houet, & Hubert-Moy, 2017; Shafizadeh-Moghadam, 2019; Wang et al., 2022). Validation results from those studies shed light on the performance of a specific UGM in a particular city. For example, Aguejdad et al. (2017) used multiple techniques to validate land changes projected using a Land Change Modeler (LCM) for ecological sustainability in the Rennes Metropolitan Area in France. They found that the LCM performed better at predicting the amount than allocating developed areas. Nevertheless, the estimated accuracies of UGMs in different studies are not directly comparable. The prediction accuracy of a UGM could vary due to uncontrolled factors such as the extent of studied areas and the interval covered by the projections (Li et al., 2021).

Studies have been specifically designed to compare multiple UGMs. For instance, Pontius et al. (2008) used a map comparison method to compare 13 applications of nine land change models for their prediction accuracy. They identified variations in the predictive accuracy of different models. However, variation can be weakly attributed to models because the study areas and inputs vary among models (Li & Gong, 2016). A better way to compare the performance of different UGMs is to subject them to the same simulation task. Several studies followed this approach to compare UGMs (Berberoğlu, Akın, & Clarke, 2016; García-Álvarez, Olmedo, Van Delden, Mas, & Paegelow, 2022; Mondal et al., 2020; Pickard et al., 2017; Qian, Xing, Guan, Yang, & Wu, 2020). While the results from those studies are highly valuable for potential model users, some limitations need to be addressed further. First, models that have been compared in those studies were arbitrarily selected. For example, Qian et al. (2020) stated that they chose four "traditional" models to compare, while Berberoğlu et al. (2016) compared cellular automata (CA) models with machine learning models contained in a modeling platform. Second, the reproducibility of the comparison results is rarely addressed. The set-up of the used models was not fully reported in most studies. Third, a model's structure, data requirements, and flexibility of use were largely overlooked except in a few studies (García-Álvarez et al., 2022). Nevertheless, those factors are often considered by potential users when choosing models. Finally, users who want to use a model to examine different scenarios must be able to control models. In this case, verification is essential. Verification is the procedure to test how a model's actual behavior confirms the stated behavior in the model's documentation (Croks & Heppenstall, 2012; Paegelow, Camacho Olmedo, Mas, & Houet, 2014). So far, comparison studies rarely include verification.

Therefore, considering the above limitations, this study seeks to offer a user-friendly assessment of commonly used UGMs. We have three specific objectives: (1) to reveal the use patterns of different UGMs in recent decades; (2) to examine the data requirements and flexibility of the commonly used UGMs; (3) to evaluate the performance of these commonly used UGMs, including to verify the models' behavior against the descriptions in their documentation.

## 2. Methods

### 2.1. Identify the usage pattern of UGMs

To reveal the usage pattern of different UGMs, we conducted a systematic review following the PRISMA (The Preferred Reporting Items for Systematic Reviews and Meta-analyses) protocol (Moher, Liberati, Tetzlaff, Altman, & Grp, 2009). Two major literature databases, the Web of Science Core Collection and Scopus, were searched for relevant publications. The search string "TS= 'urban' AND ('expansion' OR 'growth') AND ('prediction' OR 'simulation')" was used in the search. We chose the topic words to identify papers focusing on future urban expansion or growth. The query was restricted to articles published between January 2000 and December 2021.

The search yielded 6182 and 4982 papers from the two academic databases. The search results were combined, and duplicates were removed. We screened through the titles and abstracts of the papers to identify papers presenting studies on modeling urban expansion. We then obtained the full texts of the specified documents for further reading. Ultimately, we retrieved 558 publications that used UGMs to simulate urban development (A list of the publications was included in the supplementary files). We summarized the usage of each type of UGM from those publications.

**Table 1**
Information on the six pre-packaged urban growth models.

| Model | Developer | Version | Reference |
|---|---|---|---|
| Cellular automata-Markov models (CA-Markov) | Clark University | IDRISI Selva 17.0 | Eastman, 2006 |
| Conversion of land use and its effects at small extent models (CLUE-S) | Vrije University | CLUE-full version | Verburg & Overmars, 2009 |
| Future land use simulation models (FLUS) | Sun Yat-Sen University | FLUS V2.2 | Liu et al., 2017 |
| Land use scenario dynamics models (LUSD) | Beijing Normal University | LUSD Beta | He et al., 2005 |
| Land change modeler (LCM) | Clark University | IDRISI Selva 17.0 | Eastman, 2006 |
| Slope, land use, excluded layer, urban extent, transportation, hillshade models (SLEUTH) | U.S. Geological Survey and the University of California | SLEUTH3.0 | Clarke, Hoppen, & Gaydos, 1997 |

### 2.2. Qualitative assessment of the commonly used models

Based on the review result (Section 3.1), we selected six urban growth models in five software packages to compare (Table 1). We selected commonly used models available as pre-packed software to compare. We used pre-packed software for two reasons: (1) Practitioners are more likely to adopt them, and (2) the results are more reproducible than unpacked algorithms because the core algorithms and parameters are fixed.

The six models can be divided into two groups based on the models' structures. The first group contained two basic modules: non-spatial and spatial modules. The non-spatial module calculates the amount of land-use demand in the future. The spatial module is designed to allocate the pixels that need to be transformed. FLUS, CA-Markov, LUSD, LCM, and SLEUTH models belong to this group. Note that all models can accept externally generated land-use demand except for SLEUTH, which uses land-use demand generated internally. CLUE-S only contains a spatial module that needs land-use demand generated from other models as inputs. More information about the six models, such as the core algorithms and inputs, can be found in the supplementary file.

The six models' documentation was analyzed to provide a qualitative assessment. It is important for users to use a model that they can understand, so a model should have clear documentation. We paid particular attention to the data needs and flexibility of the models. Complicated models may generate better results than simple ones but often require more input data (Gharaibeh, Shaamala, Obeidat, & Al-Kofahi, 2020). A model with many adjustable parameters can give advanced users more flexibility. However, beginners or occasional users may feel overwhelmed when facing the task of tuning the values of many unfamiliar parameters. Information on these two aspects will be helpful

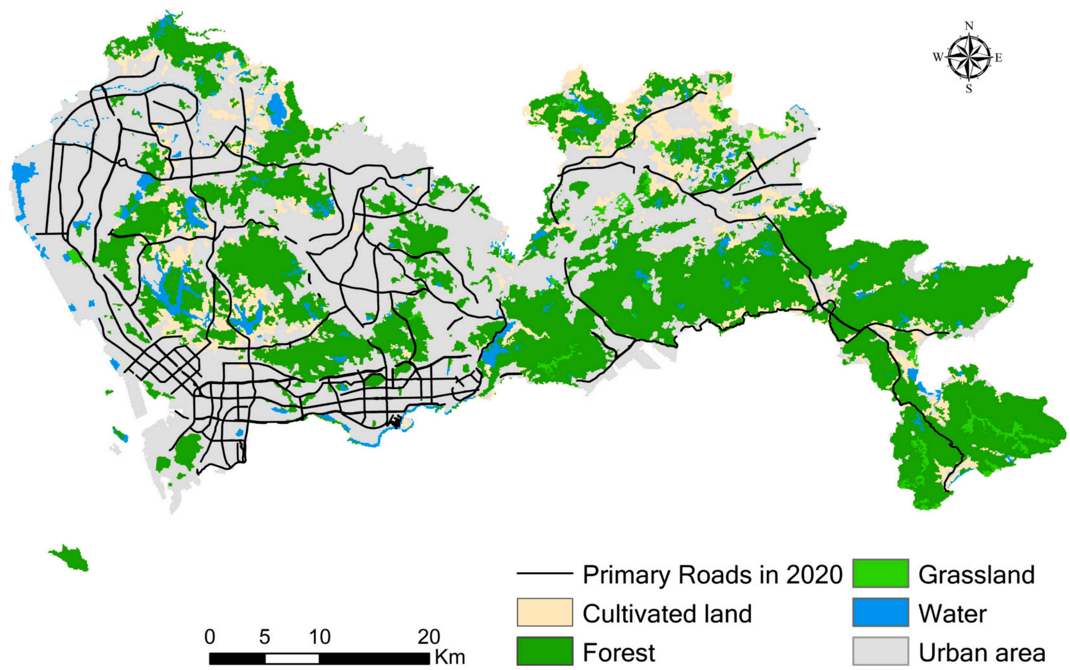


**Fig. 1.** Land use and primary roads in 2020 Shenzhen. The land use data were obtained from the Resource and Environment Science and Data Center, Chinese Academy of Sciences (Liu et al., 2014). The primary roads were obtained from the OpenStreetMap (Scioscia, Binetti, Ruta, Ieva, & Di Sciascio, 2014).

**Table 2**
The primary source of the input data.

| Data | Resolution (m) | Source |
|---|---|---|
| Land use (1995, 2000, 2005, 2015, 2020) | 30 | (Xu et al., 2018) |
| Protected area | Vector | (UNEP-WCMC and IUCN, 2020) |
| Elevation | 30 | (Wang, Zhao, Zhou, & Li, 2014) |
| Population (2015, 2020) | 100 | (Bondarenko, Kerr, Sorichetta, & Tatem, 2020) |
| Distance to roads (2015, 2020) | 100 | (Scioscia et al., 2014) |
| Distance to railways (2015, 2020) | 100 | |
| Distance to subways (2015, 2020) | 100 | |
| Distance to hospitals (2015) | 100 | |
| Distance to markets (2015) | 100 | |
| Distance to residents (2015) | 100 | |
| Distance to schools (2015) | 100 | |

for potential model users.

### *2.3. Compare the performance of the six models*

We compared the performance of the six models by using them to simulate urban growth in the same city. Shenzhen, China, was chosen as the study site for the comparison study (Fig. 1). Shenzhen is located in southern China, adjoining Hong Kong. In four decades, the city has grown from a fishing village to a megacity. Its urban land area increased by a mean annual rate of 11% between 1975 and 2015 (Meng, Sun, & Zhao, 2020). The dramatic change in the urban region makes it an ideal place for testing UGMs.

The model simulation includes four steps: data processing, model calibration, model prediction, and accuracy assessment. The calibration interval was 2005–2015, and the validation interval was 2015–2020 for LUSD, FLUS, CLUE-S, LCM, and CA-Markov models. SLEUTH requires four-time point urban extent data to do the calibration. Therefore, land use maps in 1995, 2000, 2005, and 2015 were inputted for SLEUTH's calibration and simulation. We controlled the factors that can critically impact the simulation results, such as the resolution of the input data (Li et al., 2021). The input data include land-use maps, driving factors, and restriction layers (Table 2). All input data were reprocessed to a resolution of 100 m. The values of driving factors such as elevation, population, and distances to various features were normalized to 0 to 1.

We reclassified the land use data into four types: cultivated land, vegetation, water, and urban land. We merged forest and grassland into a vegetation class because grasslands were scarce in Shenzhen. To remedy the possible misclassification in land use maps, we reformatted the land use data time series to assume zero gross loss of urban lands. We set the 1995 map as the base map and edited the 2000 map by keeping urban lands in 1995 as urban lands in the 2000 map. The land use maps in later times were modified sequentially. In the end, zero gross loss of urban lands was assumed for 1995–2000, 2000–2005, 2005–2015, and 2015–2020. The number of urban pixels increased by 20,326 and 3061 for 2005–2015 and 2015–2020, respectively (Fig. 2).

We simulated two common situations. The first type is that the land-use demand is not predetermined. The UGMs extrapolate the quantity from the calibration interval to the validation interval and allocate it spatially. The second situation is that the future land-use demand is set to match the true quantity of urban gain during the validation interval, and the UGMs are used to allocate the land-use demand.

For the first situation, LCM and CA-Markov extrapolate the land-use demand using a Markov chain module. We set the number of periods between the historical land-use maps and the number of periods to project forward as ten and five for the Markov chain module, respectively. The proportional error expresses the probability that the land use classes in the input maps are incorrect when the land use layers were used for a Markov chain calculation. In this study, we set the proportional error as zero. The module's outputs are transition areas between each of the land use transitions. The land-use demand in 2020 was calculated using the transition areas, which were also used as the land-use demand for FLUS, LUSD, and CLUE-S, as the three models need users to input the land-use demand. SLEUTH does not require land-use demand as it projects urban growth using growth rules.

In addition, we ran an independent Markov extrapolation of urban growth during the validation interval to compare with the Markov re-

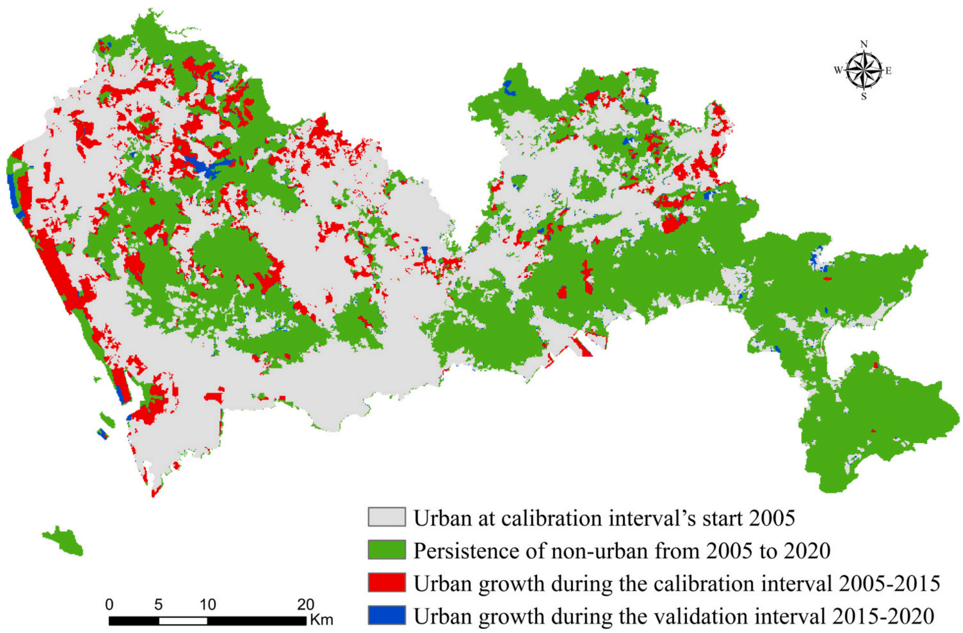


**Fig. 2.** Reference changes in urban growth and persistence of non-urban areas during 2005–2015 and 2015–2020.

sults in LCM and CA-Markov since the duration of the calibration interval does not match the duration of the extrapolation interval. The independent Markov extrapolation was run using the method developed by Takada, Miyamoto, and Hasegawa (2009) (Eq.1).

$$x_{t+c} = x_t \times A^{\frac{c}{c_0}} \tag{1}$$

where $x_t$ is a 1-by-4 row vector that gives the proportion of cultivated land, vegetation, water, and urban areas at the start time $t$ during the validation interval. $c, c_0$ is the time interval during validation and calibration, which was 5 and 10 in this study. $A$ is a 4-by-4 transition probability matrix during the calibration interval, including cultivated land, vegetation, water, and urban areas.

For the second situation, the actual change in urban areas between 2015 and 2020 was input as the land-use demand for all models except for SLEUTH. The models input the information in various ways. LUSD requires users to input only the number of urban pixels in 2020, while FLUS and CLUE-S require the input of the number of pixels for different land use types. In the case of LCM and CA-Markov, the transition probability matrix and the quantities of transition between different land use types were calculated based on the land use in 2015 and 2020.

After setting the land-use demand, Shenzhen's land use in 2005 was used as the initial seed to project land use up to 2015. At the calibration stage, we used land use in 2005 as the initial seed and driving factors in 2015 to simulate urban gain during 2005–2015. The parameters and weights of driving factors during calibration were adjusted according to the documentation of different models. In the LUSD model, we obtained parameter combinations from the model output file "Weight_kappa_max" with a kappa value of 0.743. In the SLEUTH model, we generate parameter combinations using the brute force Monte Carlo method with the highest Lee-Sallee shape index of 0.779 output from the final calibration. For other models, we selected the combination of parameters to maximize the FoM value of the simulated urban map in 2015. The obtained FoM values were 0.343, 0.579, 0.231, and 0.308 for FLUS, CLUE-S, LCM, and CA-Markov, indicating goodness-of-fit for calibration. The tuned models were then used to generate the projections from 2015 to 2020. Detailed information on the model setups can be found in the supplementary file (Table S2).

In addition, we included the ensemble result of the six models in comparison. Using ensemble results of multiple models in land use projection has been proposed to address the uncertainty associated with the individual UGM (Shafizadeh-Moghadam, 2019). We tested this idea in our study. The ensemble method developed by Jung, Henkel, Herold, and Churkina (2006) was used to generate an ensemble map using the outputs of the six models. In the simulation results of the six models, the same pixel may be assigned to different land use types by different models. We calculated the number of times each pixel was classified into the four land use classes by each model and the number of pixels in the 3 × 3 neighborhood classified into the four categories. The frequency value of the central pixel was assigned a weight of eight, while the neighboring pixels were assigned a weight of one. After summing the weighted frequencies of the four land use types, the land use class with the highest frequency was assigned to the pixel. The technique uses a majority vote rule to assign the land use label of a pixel (Eq.2):

$$S_{i,j}^{(u)} = P_{i,j}^{(u)} \times 7 + \sum_{i-1}^{i+1} \sum_{j-1}^{j+1} P_{i,j}^{(u)} \tag{2}$$

where $S_{i,j}^{(u)}$ represents the voting score of the pixel in row $i$ and column $j$ of the ensembled matrix for land use $u$. $P_{i,j}^{(u)}$ denotes the number of votes for the pixel in row $i$ and column $j$ belong to land use $u$ after different model results are superimposed. According to the voting score, the center pixel was reclassified to the land use type with the highest $S_{i,j}^{(u)}$. When there are still multiple categories with the highest number of votes at the same time; we set the following order of priority to transform: urban, cultivated land, vegetation, and water.

We compared the simulated change with the reference change at the validation stage using the three-map comparison method developed for validating spatially explicit land-change models (Pontius, Huffaker, & Denman, 2004). The method compares the projected urban expansion with two reference maps, i.e., Shenzhen's land use maps in 2015 and 2020 in this study. The technique allows one to distinguish the correct pixels due to persistence from those correct due to change (Pontius et al., 2008). The multiple-resolution analysis shows the difference in spatial configuration errors of the UGMs by aggregating pixels at different resolutions (Pontius et al., 2007; Pontius et al., 2011). Indicators including FoM, Hits, Misses, False Alarms, quantity disagreement, and allocation disagreement were calculated for the six models. FoM measures the overlap between observed and predicted changes. The FoM values range between 0 and 1, with one indicating a perfectly accurate

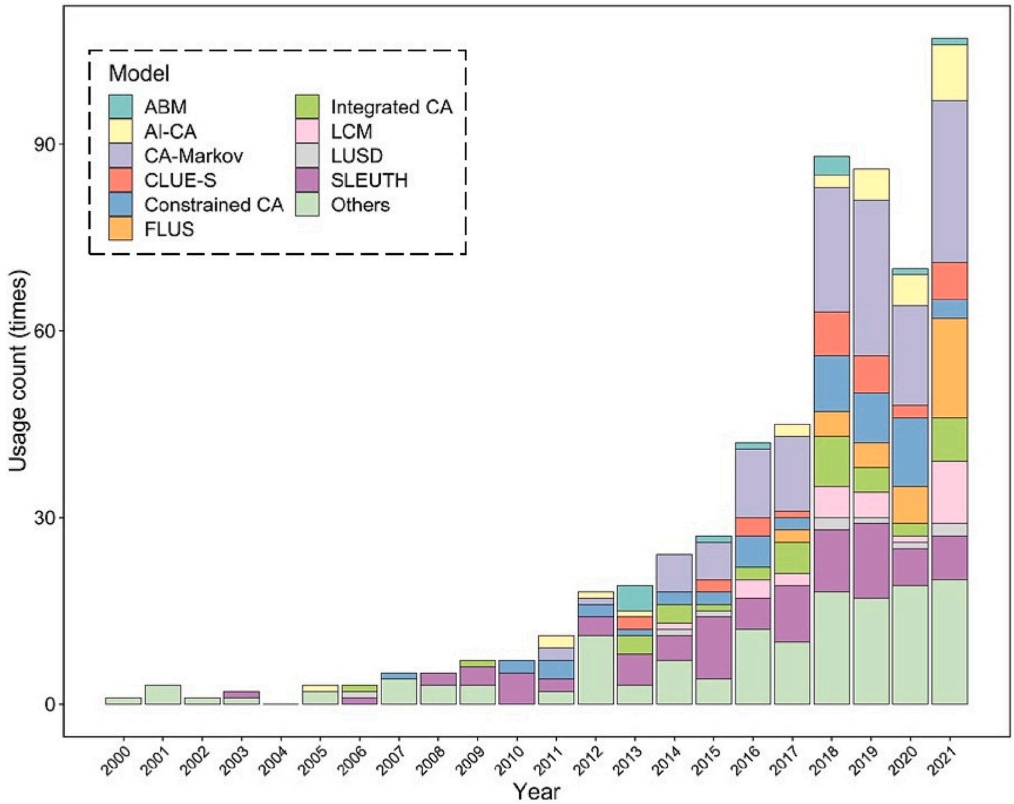


**Fig. 3.** Usage counts of the top ten urban growth models and others between 2000 and 2021.

prediction (Pontius et al., 2008). Quantity and allocation disagreements are essential for comparing a predicted map with the reference map (Pontius and Millones, 2011). Before running the comparison, we merged the cultivated land, vegetation, and water classes of the simulated results and the reference data into a single non-urban class. The results thus only contain urban and non-urban classes. The reclassification allowed us to focus on the simulated urban growth and facilitated the interpretation of results. The three-way map comparison was conducted in R4.1.1 (R Core Team, 2022) using the *lulcc* R package (Moulds, Buytaert, & Mijic, 2015).

We verified the models' behaviors against the descriptions in the model's documentation based on the simulation result. We focused on

**Table 3**
Data requirements and flexibility of the six models.

| Model | Data requirements | Model flexibility | |
|---|---|---|---|
| | | Mandatory parameters | Optional parameters |
| CA-Markov | Land use at two time points | Neighborhood filter<br>Number of CA iterations | Proportional error |
| CLUE-S | Land use at two time points<br>Driving factors<br>Land-use demand | Conversion elasticity<br>Change matrix | Weights of driving factors<br>Neighborhood setting |
| FLUS | Land use at one time point<br>Driving factors<br>Land-use demand | Sampling percentage<br>Nodes of the neural network<br>Maximum number of iterations<br>Weight of Neighborhood<br>Neighborhood size<br>Cost matrix | Accelerate |
| LCM | Land use at two time points<br>Driving factors | Layer nodes<br>Momentum factor<br>Start and end learning rate<br>Sigmoid constant<br>Sample size<br>Recalculation stages | Change demand matrix |
| LUSD | Land use at two time points<br>Driving factors<br>Predicted urban land area | Inheritance coefficient<br>Disturb Constant<br>Neighborhood size | Weights of driving factors<br>Simulation time steps |
| SLEUTH | Land use at two time points<br>Urban extent maps at four time points<br>Excluded layer<br>Driving factors (Slope, Transportation in two time points) | Thresholds of the urban expansion rate | Coefficients for urban expansion mode |

**Table 4**
Projected urban expansion between 2015 and 2020

| Model | Simulation with simulated land-use demand | | Simulation with actual land-use demand | |
|---|---|---|---|---|
| | Land-use demand (km$^2$) | Projected urban expansion (km$^2$) | Land-use demand (km$^2$) | Projected urban expansion (km$^2$) |
| CA-Markov | 84.04[a] | 84.05 | 30.61 | 30.61 |
| CLUE-S | 84.04[a] | 84.05 | 30.61 | 28.89 |
| FLUS | 84.04[a] | 84.04 | 30.61 | 30.61 |
| LCM | 84.04[b] | 84.04 | 30.61 | 30.61 |
| LUSD | 84.04[a] | 84.04 | 30.61 | 30.61 |
| SLEUTH | NA | 12.77 | NA | 12.77 |
| Ensembled | NA | 65.44 | NA | 32.04 |
| Independent | 87.05 | NA | NA | NA |

two aspects: (1) Does the model behave as told, and (2) Whether users can fully control the model, which is essential for testing urban growth scenarios.

## 3. Results

### 3.1. The trend of commonly used UGMs

The results showed that several types of UGMs dominated the existing studies. The top ten models included agent-based models (ABM), artificial intelligence-cellular automata models (AI-CA), CA-Markov, CLUE-S, constrained cellular automata (constrained CA) models, FLUS, integrated cellular automata (Integrated CA) models, LCM, LUSD, and SLEUTH. They accounted for 73.3% of the total usage of all models in these publications (Fig. 3).

### 3.2. Documentation, data requirements, and flexibility of the six models

The quality of documentation varied among the six models. All models have online resources for users. The websites commonly contain user guides, tutorials, example data, and relevant scientific publications. All models but CA-Markov provide detailed tutorials on running models. Users will have difficulty finding answers for issues related to running

**Table 5**
Model validation results with the simulated land-use demand as input.

| Model | Hits (%) | Misses (%) | False Alarms (%) | Quantity disagreement (%) | Allocation disagreement (%) | Total disagreement (%) | FoM |
|---|---|---|---|---|---|---|---|
| CA-Markov | 0.54 | 0.78 | 3.10 | 2.32 | 1.56 | 3.88 | 0.122 |
| CLUE-S | 0.61 | 0.72 | 9.05 | 8.33 | 1.44 | 9.77 | 0.058 |
| FLUS | 0.34 | 0.99 | 3.30 | 2.31 | 1.98 | 4.29 | 0.074 |
| LCM | 0.30 | 1.03 | 3.34 | 2.31 | 2.06 | 4.37 | 0.063 |
| LUSD | 0.51 | 0.82 | 3.13 | 2.31 | 1.64 | 3.95 | 0.115 |
| SLEUTH | 0.09 | 1.24 | 0.47 | 0.77 | 0.94 | 1.71 | 0.049 |
| Ensemble | 0.49 | 0.84 | 2.77 | 1.93 | 1.68 | 3.61 | 0.119 |

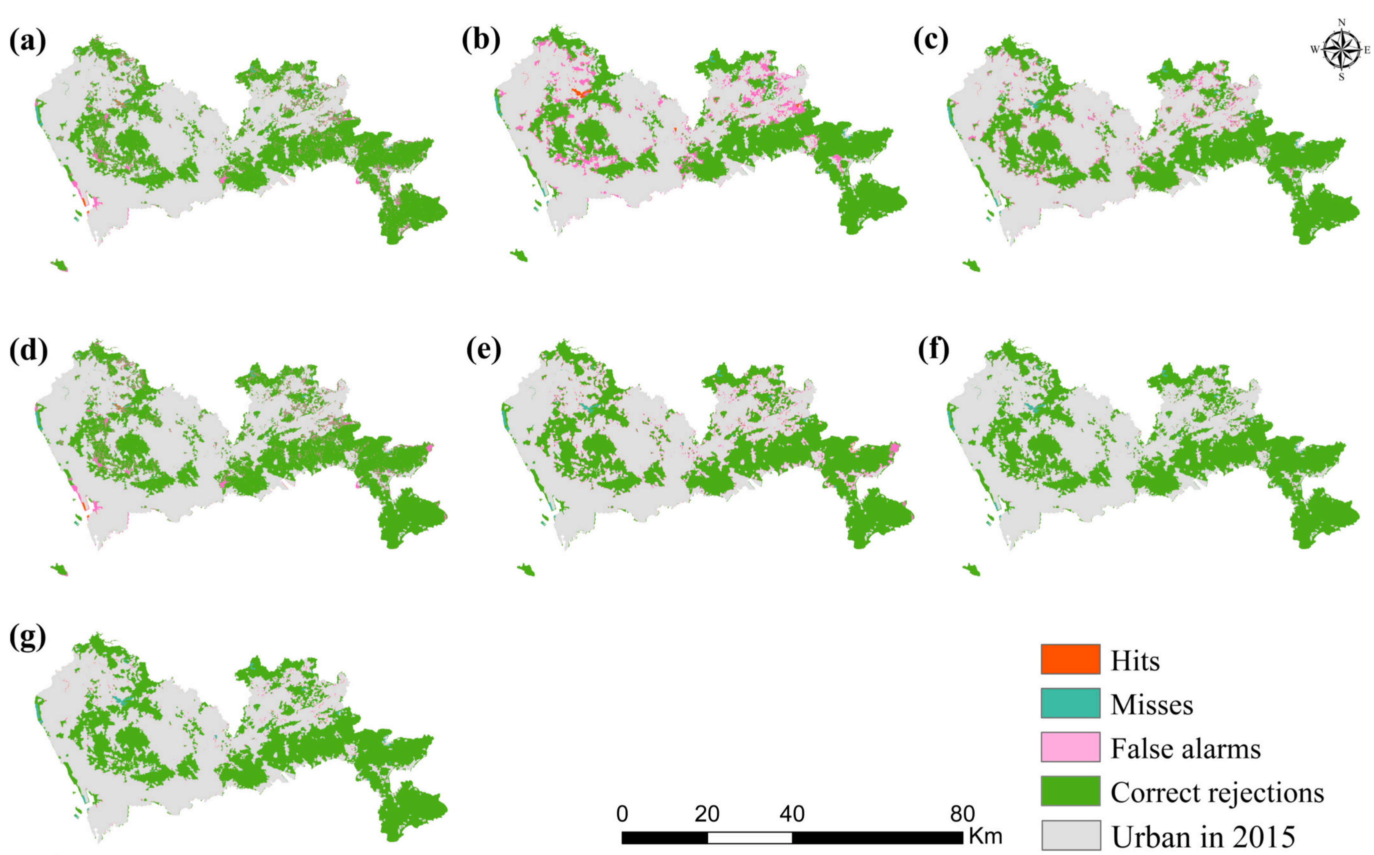


Fig. 4. Three-map comparison between simulated and reference changes during 2015–2020. (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method.

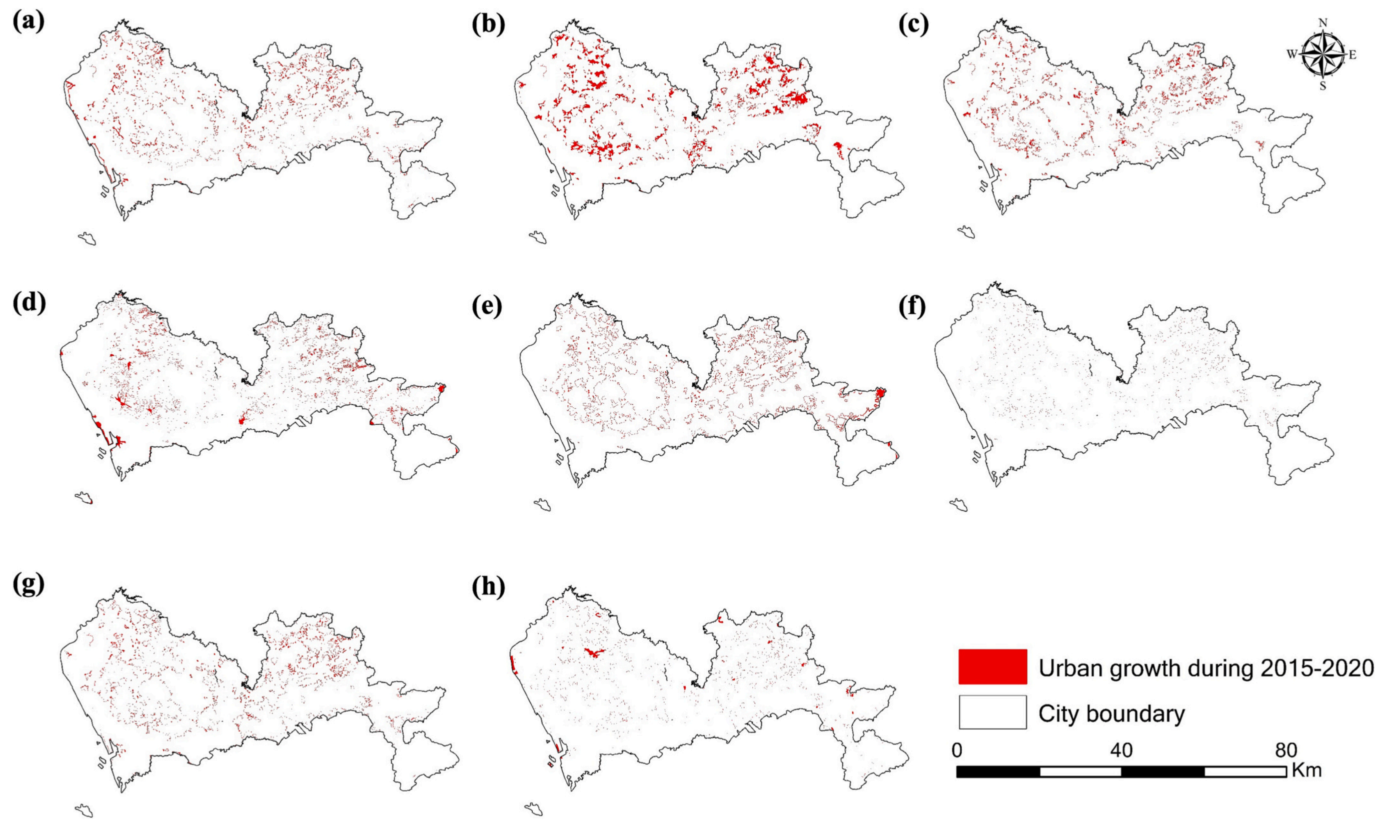


**Fig. 5.** Urban expansion from 2015 to 2020 predicted by using the extrapolated land-use demand: (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method; (h) actual urban gains extracted out from the validation intervals.

CA-Markov from the simple help file provided by IDRISI. LCM supplies detailed text version of the tutorial and videos of key operational procedures. Example data are an important component of tutorials as it allows users to test run the model and format their own data accordingly. All models have specific example data or example data included with the software package for users to get familiar with the models.

SLEUTH has the highest requirement for input data among the six models. Conversely, CA-Markov has the lowest data requirements (Table 3). FLUS has the highest number of mandatory parameters that need to be set among all models.

### 3.3. Performances of the six models

The final projected urban growth from 2015 to 2020 agreed well with the inputted land-use demand among models except for CLUE-S (Table 4). SLEUTH projected the smallest urban growth among all models. It should be noted that half of the reference growth during 2005–2015 and reference growth during 2015–2020 was 101.63 $km^2$ and 30.61 $km^2$, respectively. The urban growth of the city slowed down in the later period.

a. Generated using the Markov chain module
b. Self-extrapolated

The validation results of the projections for 2020 with simulated land-use demand as input are shown in Table 5. CLUE-S had relatively higher false alarms and total disagreement than other models, resulting to a low value of FoM. The simulation errors of CA-Markov, CLUE-S, FLUS, LCM, and LUSD were mainly attributed to quantity disagreement, while SLEUTH showed an opposite result.

The spatial allocation accuracy varied between different models (Fig. 4).

Spatial patterns of urban growth differed among the models as well. They were all different from the actual pattern of urban expansion (Fig. 5).

The multiple-resolution results showed that percentage of hits increased while the misses reduced when the map's resolution became coarser (Fig. 6).

The validation results of using the actual area as the land-use demand were shown below (Table 6). CA-Markov, FLUS, LCM, and LUSD had zero quantity disagreement as expected. Nevertheless, CLUE-S had a high quantity disagreement.

Again, the spatial patterns of projected urban growth were different from that of the actual urban growth (Fig. 7). The results of the three-map comparison between simulated and reference changes during 2015–2020 and the multiple-resolution analysis were also shown below (Figs. 8 and 9).

CA-Markov, FLUS, LCM, and LUSD could be verified because of the consistency of model behaviors. CLUE-S and SLEUTH could not meet the criterion that the users can control the model. CLUE-S obtained allocated urban lands that were 9.46 $km^2$ and less than the inputted quantity, respectively. SLEUTH does not allow users to input land-use demand. Instead, the final quantity of projected urban growth is determined by the model.

## 4. Discussion

### 4.1. Documentation, data requirements, and flexibility of the six models

A model's user guide and tutorial are important for users to understand the model's functions and learn the basic information for model operation. Besides CA-Markov, the user guides and tutorials of other models included in this study have rooms for improvement. For example, while the online guide of SLEUTH covers its development,

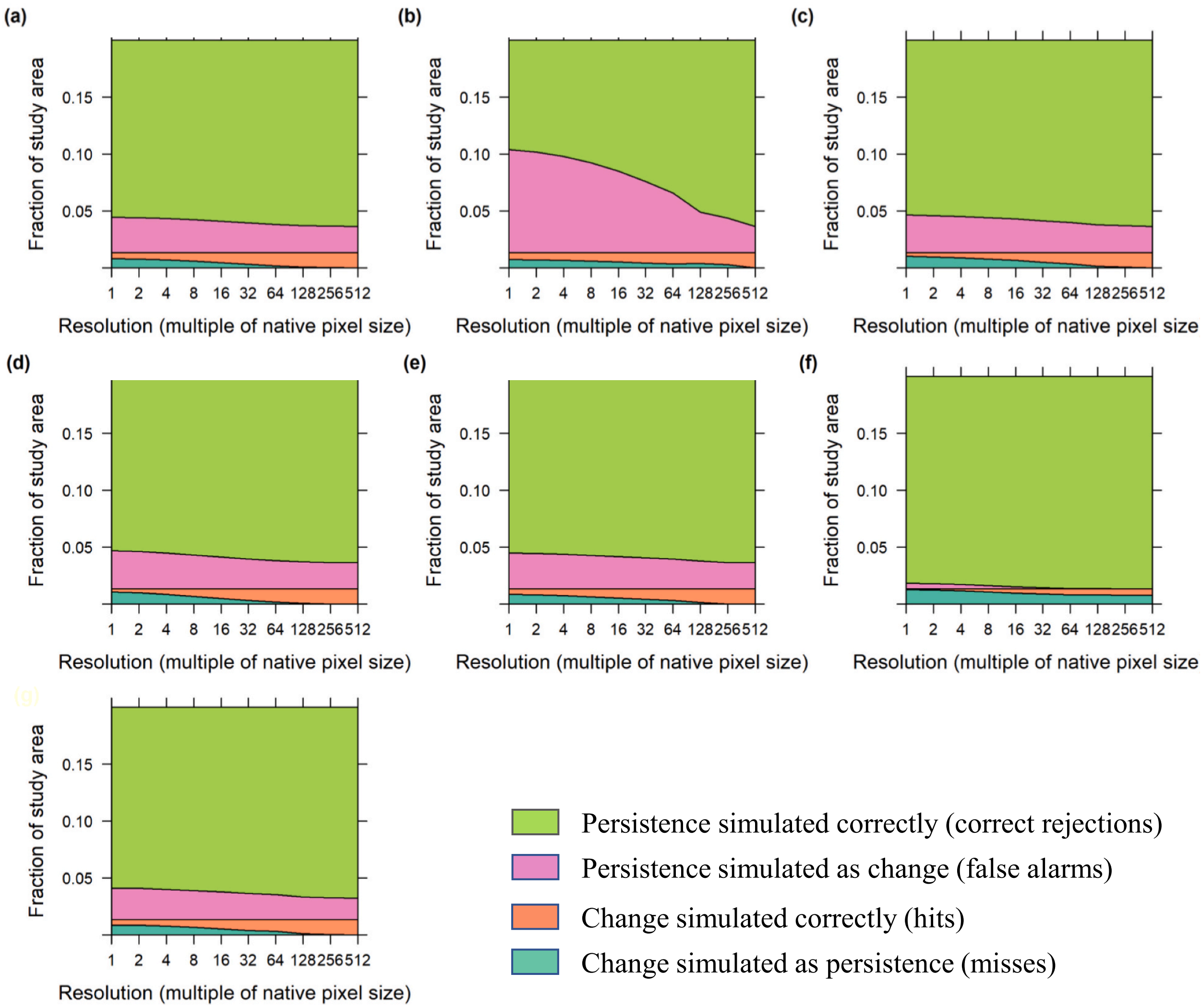


**Fig. 6.** Components of agreement and disagreement for the entire study area at multiple resolutions: (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method.

**Table 6**
Model validation results with actual land use area in 2020 as the input.

| Model | Hits (%) | Misses (%) | False Alarms (%) | Quantity disagreement (%) | Allocation disagreement (%) | Total disagreement (%) | FoM |
|---|---|---|---|---|---|---|---|
| CA-Markov | 0.26 | 1.07 | 1.07 | 0 | 2.14 | 2.14 | 0.107 |
| CLUE-S | 0.49 | 0.83 | 7.88 | 7.05 | 1.66 | 8.71 | 0.053 |
| FLUS | 0.15 | 1.17 | 1.17 | 0 | 2.34 | 2.34 | 0.062 |
| LCM | 0.11 | 1.22 | 1.22 | 0 | 2.44 | 2.44 | 0.042 |
| LUSD | 0.25 | 1.07 | 1.07 | 0 | 2.14 | 2.14 | 0.106 |
| SLEUTH | 0.09 | 1.24 | 0.47 | 0.77 | 0.94 | 1.71 | 0.049 |
| Ensemble | 0.21 | 1.12 | 0.78 | 0.34 | 1.56 | 1.90 | 0.098 |

model structure, data requirements, and the growth rules used in the modeling process, the growth rules are difficult for users to understand due to limited descriptions and the use of pseudo-codes. The user guide of the CLUE-S model describes the principles and process of allocating land-use demand, but no algorithms are available for users to refer to. Among all models, LCM is the most user friendly with its instructions in both text and video formats.

The data requirements for the six models are very similar. Input data typically consists of three main types: historical land use data, the land-use demand, and driving factors such as topographic and socio-economic data. Urban expansion is driven by the interactions of various socio-economic and biophysical factors (Achmad, Hasyim, Dahlan, & Aulia, 2015). Therefore, the data requirements of the six models reflect this view and adopt similar driving factors. Notably, FLUS requires only one land-use map to train the model, giving it an advantage over other models when land use data is difficult to obtain. In contrast, SLEUTH has the highest requirement for input data. It requires urban extent layers at four time points and land use maps for at least two time points. Also, it requires the excluded layer, which is an optional input for other models.

The flexibility of the six models varies widely. FLUS and LCM have higher flexibility than other models. More model flexibility increases the possibility of achieving better simulation accuracies because users can tune more parameters. Nevertheless, the models with high flexibility

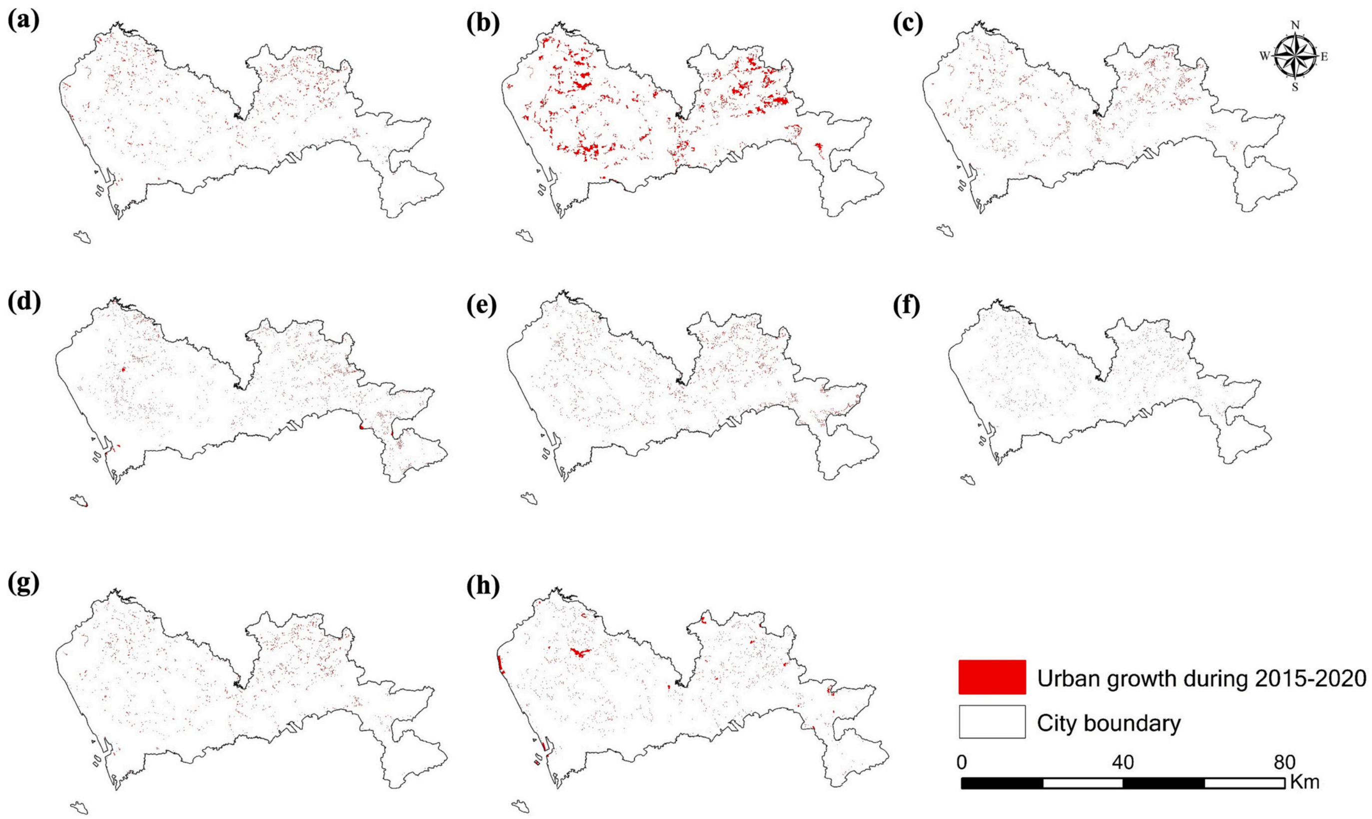


**Fig. 7.** Urban expansion from 2015 to 2020 predicted by using the actual urban growth as the land use demand: (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method; (h) Actual urban gains between 2015 and 2020. Note: SLEUTH does not accept the land-use demand.

depend more on users' choice and their understanding of urban processes, which may weaken the models' ability to represent the real-world system (Santé et al., 2010; Sathish Kumar, Arya, & Vojinovic, 2013). CA-Markov allows users to adjust the neighborhood filter, the number of CA iterations, and the proportional error in Markov module. Users can also modify the suitability maps in CA-Markov. Besides, the CA-based models are attractive to users because they simplify the complex urban system (Okwuashi & Ndehedehe, 2021; O'Sullivan, 2001). SLEUTH also allows users to make a few modifications. The model relies on the capability of adaptive simulation prediction. Some researchers have concerns that the adaptive approach is time-consuming to calibrate and can increase the stochasticity of the model in the simulation (Berberoğlu et al., 2016). Among the six models, FLUS and LUSD incorporate a stochastic component. FLUS adds randomness to the simulation result through incorporating the "Roulette effect". After calculating the transition probability of every land use type, the final land use type of every cell is determined by a roulette wheel (Liu et al., 2017). LUSD calculates transition probability of every cell from different land use types to urban by considering their suitability, neighborhood effect, inheritance of land use types, constraints factor, and random perturbations (Eq. 3 in the supplementary files). The random perturbations of every cell were determined by a function of a random variable following a uniform distribution (He, Zhang, Huang, & Zhao, 2016). Therefore, models with high and low flexibility both have pros and cons. Users must make an informed choice.

### 4.2. Prediction accuracy of the six models

The validation results show that projections from all models contain considerable uncertainties, i.e., the errors were 7 to 22 times more than hits. Uncertainties in projected urban growth came from two sources: extrapolation and spatial allocation. This fact has been made obvious by inputting the actual growth as the land-use demand; errors due to extrapolation was removed but the models still contained errors due to allocating the land-use demand.

An interesting result is that FoM values of all model results decreased when actual urban growth was inputted as the land-use demand. Normally one would interpret the reduced FoM values as decreased prediction accuracy. The result would be counterintuitive since actual urban growth was used. The drop in FoM was due to the fact that the actual urban gain was less than the extrapolated urban gain. Therefore, reporting a single metric of accuracy has limitations. To show the sizes of misses, hits, and false alarms should be preferred over reporting one metric. The finding raised a concern on judging models by prediction accuracies. The accuracy of a model can be affected by many factors, such as the quality of input data, the representativeness of driving factors, and users' efforts to calibrate the model (Feng & Tong, 2019). The selection of accuracy indicators also influences the accuracy assessment substantially (Pontius et al., 2011).

SLEUTH extrapolated fewer urban gains than models using the Markov chain module. However, the quantity still deviated from the actual growth. Berberoğlu et al. (2016) pointed out that SLEUTH generated predictions without spatial coordinates. The extra georeferencing process needed for SLEUTH may influence the final accuracy.

While the quantities of projected urban expansion were the same except for CLUE-S and SLEUTH, the spatial distribution of urban expansion projected by different models varied visibly. Similar phenomenon was found when comparing the simulation results of LCM, CA-Markov, and GeoMod (Abuelaish & Olmedo, 2016). Even though all models rely on the historical land use change trend and the learned influence of the driving factors to predict urban expansion (Anand, Gosain, & Khosa, 2018; Thapa & Murayama, 2012), a model's specific algorithm can contribute to some regular patterns. Peng et al. (2020) showed that the CLUE-S algorithm tends to predict newly urban pixels around existing urban pixels. On the contrary, Ma, Cai, Ai, Xie, and Zhao (2022) found that CA-based models tend to produce more dispersed and

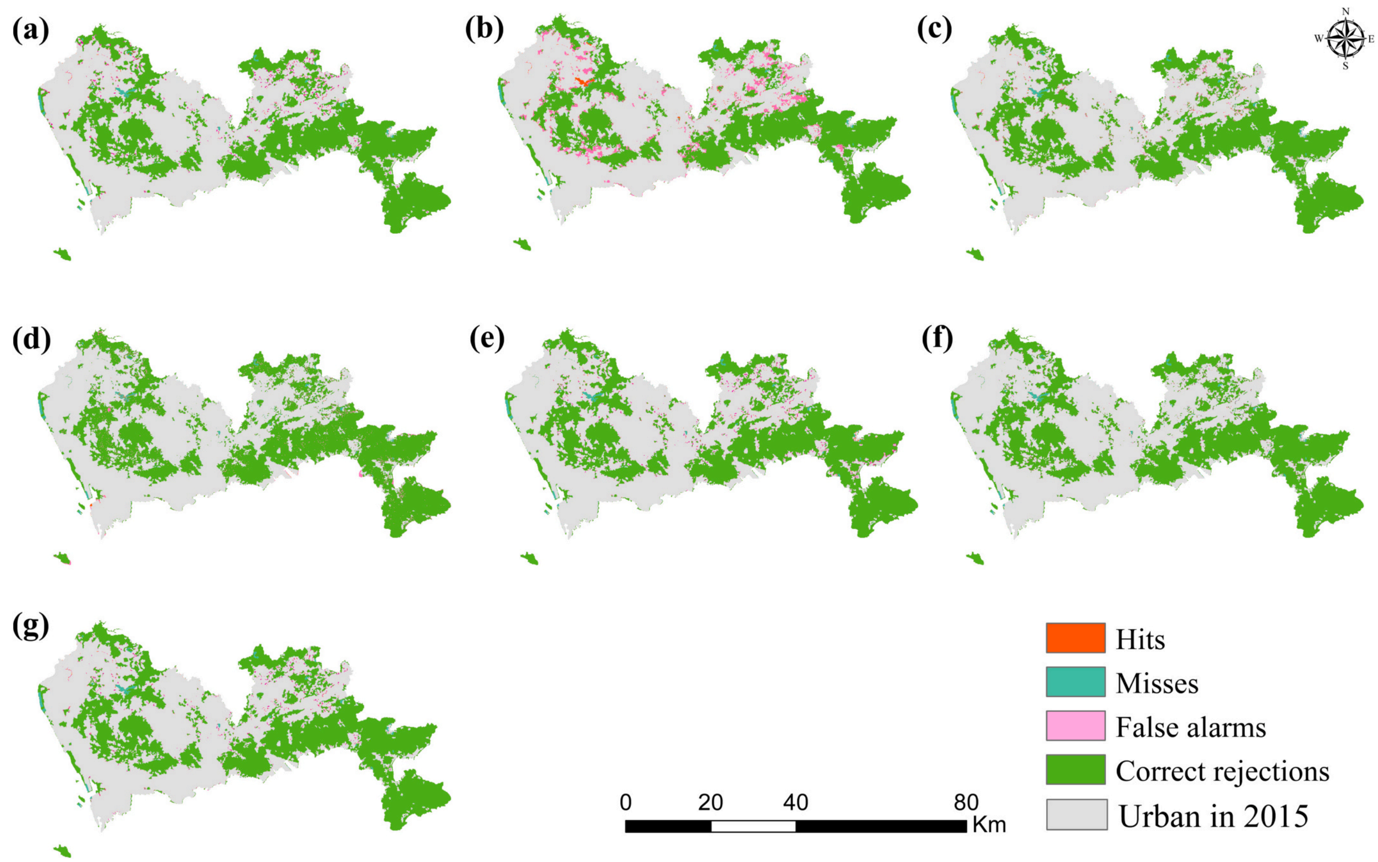


**Fig. 8.** Three-map comparison between simulated and reference changes during 2015–2020. (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method.

fragmented new urban areas. These patterns were observed in our study.

The uncertainties of ensemble results were in the middle range in both experiments. Researchers noted that the simulation uncertainty of a single model can vary in different places (Shafizadeh-Moghadam, 2019), while the ensemble method can provide relatively stable results because it combines the consistent parts of different model outputs. We used a voting approach to ensemble the simulation results in this study due to the restriction of pre-packaged models. Ensemble approaches that integrate multiple transition rules (Li, Liu, & Gong, 2015; Su, Sun, Lei, Weng, & Cai, 2017) can also be tested to see whether the ensemble results can be further improved.

### 4.3. Verification of the six models

In this study, CA-Markov, FLUS, LCM, and LUSD matched the quantities of inputted land-use demand with the final allocated urban lands. The user guide of FLUS suggests that the model iteratively adjusts the number of land use transitions until the macroscopic land-use demand is satisfied (Liu et al., 2017). The user guide of LUSD also indicates that the iteration of model simulation stops until the inputted land-use demand is satisfied. FLUS and LUSD have been utilized for predicting complex urban expansion under various scenarios (Xu, Song, & Tian, 2022; Zhang, Huang, He, & Wu, 2017). Our findings partially explained their popularity as both models had good documentation and could be controlled by the users.

LCM and CA-Markov both allow users to modify the inputted Markov transition matrix of defined land use areas and state the user-specified number of allocations can be obtained using the algorithm in the iterative allocation. In this study, LCM could project urban growth that was the same size as the land-use demand while CA-Markov obtain slightly different result (one pixel). Compared with the result of independent Markov extrapolation, LCM and CA-Markov reduced the influence caused by the mismatch between the duration of the calibration interval and the duration of the extrapolation interval. The two models predicted the transition probability matrix first and then determine the transition areas based on the matrix and the land uses at the start of the extrapolation.

CLUE-S did not generate the predeterminate amount of urban growth. The CLUE-S model accepts the land-use demand and allocates these demands spatially. The user guide of CLUE-S states that when allocation equals demand, the final map is saved. However, the loss of urban land was predicted by CLUE-S among the simulation results of six models, although the conversion from urban to non-urban land was specified as zero in the change matrix file for CLUE-S. To find reasons for this deviance, we reviewed the model's documentation and found one statement in the guide that certain land use conversion settings will have no effect due to being overruled by the conversion elasticity and land requirement settings. This model behavior can cause difficulty for users to maintain the consistence between the inputted land-use demand and the model output. SLEUTH predicts urban growth based on growth rules and cannot accept land-use demand inputted by users.

### 4.4. Recommendations for potential model users

Because a model does not have an intrinsic accuracy, it is unrealistic to find a most accurate model. Instead, potential users should consider if a model provides sufficient documentation to be understand and can be controlled. They should also pay attention to data requirements and model flexibility. Therefore, we made the following recommendations for users based on results in this study. LUSD, FLUS, and LCM can be a good choice when users need good tutorials to get familiar with the models and run simulations. They and CA-Markov are also suitable for

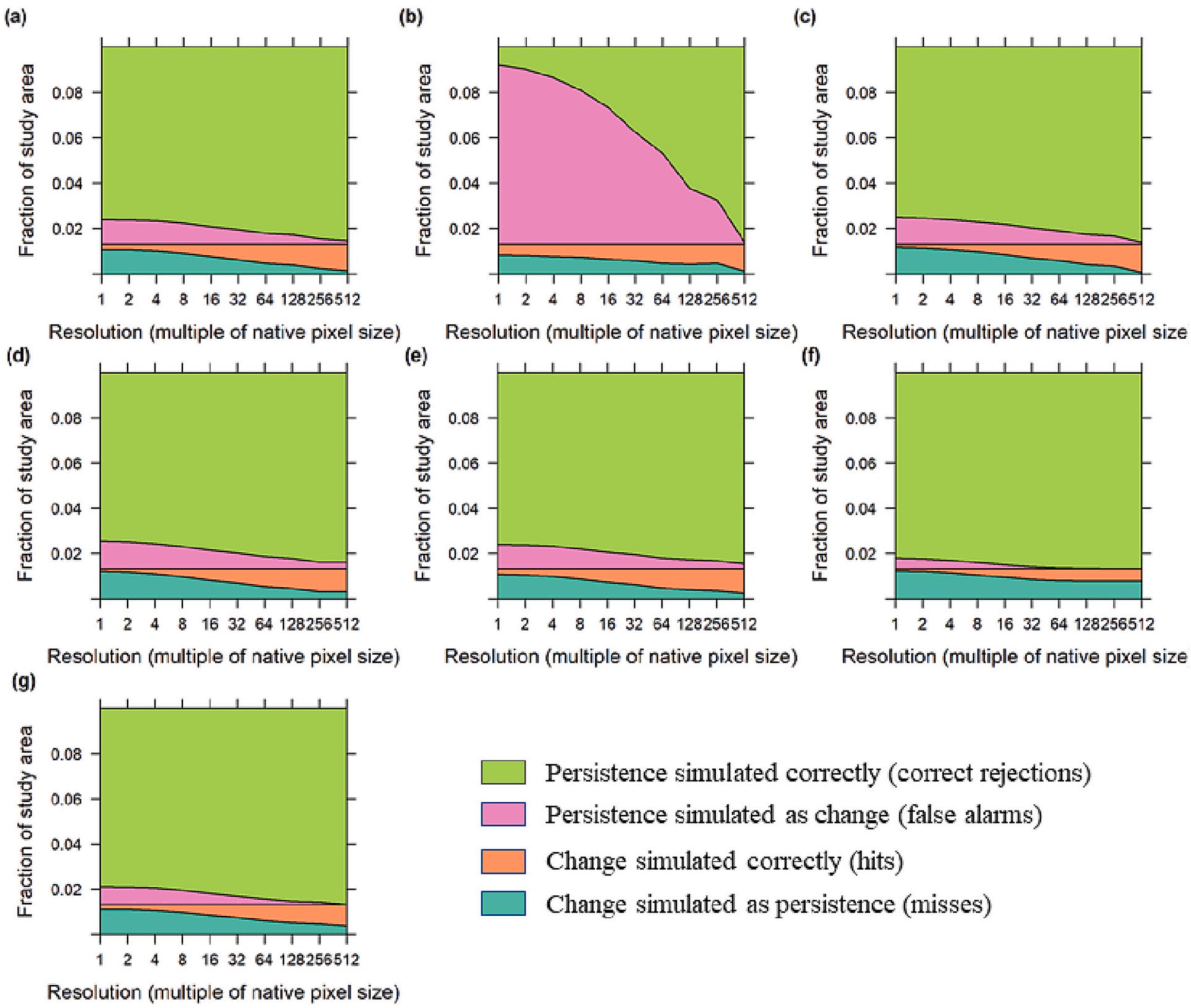


**Fig. 9.** Components of agreement and disagreement for the entire study area at multiple resolutions are shown in: (a) CA-Markov; (b) CLUE-S; (c) FLUS; (d) LCM; (e) LUSD; (f) SLEUTH; (g) Ensembled method.

users who intends to run scenarios with predetermined growth targets. Among those models, FLUS is a better option when historical land use data is not easy to get, while LCM and CA-Markov with their Markov modules are useful when users do not want to input the land-use demand.

SLEUTH cannot be used for simulating scenarios where the amount of urban growth is predetermined. The unique growth rules adopted by SLEUTH can allow users to test scenarios that can be tied to diffusion, breed, spread, slope, and road gravity parameters (Rafiee, Mahiny, Khorasani, Darvishsefat, & Danekar, 2009) or the exclusion layer (Liu, Clarke, & Chen, 2020). CLUE-S can be a challenge for simulating scenarios with predetermined urban growth as well. Although in theory, the conversion elasticity, land requirement settings, and land use conversion settings can be tuned to achieve the inputted land-use demand, the model's documentation does not include instructions on how to do it correctly.

## 5. Conclusion

UGMs play an increasingly important role in scientific studies and urban planning practices. In this study, we reviewed the use patterns of UGMs in the past two decades and compared six UGMs regarding their performance, and model features such as data requirements and model flexibility. The simulation results showed that all models had high uncertainties as they simulated 7 to 22 times more error than hits. Furthermore, a model does not have an intrinsic accuracy and its simulation accuracy was influenced by many factors. Model verification and good documentation are therefore important factors for potential users to consider when selecting UGMs. CA-Markov, FLUS, LUSD, and LCM were verified as they behaved as described. CLUE-S, and SLEUTH failed to meet some of the testing criteria. Besides CA-Markov, user guides and tutorials of those models are comprehensive enough for users to understand and run them. We further made recommendations for choosing the six models for different situations based on the verification results, data requirements, and flexibility of models. Verification of more UGMs can be carried out in future studies to give potential users more choices.

## CRediT authorship contribution statement

**Yuzhi Zhang:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Mei-Po Kwan:** Writing – original draft, Supervision. **Jun Yang:** Conceptualization, Methodology, Writing – original draft, Supervision, Funding acquisition, Writing – review & editing.

## Data availability

Data will be made available on request.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2023.102004.

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