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Applicability and sensitivity analysis of vector cellular automata model for land cover change

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ABSTRACT

Urbanization-induced land cover changes significantly impact ecological environments and socioeconomic growth. Vector-based cellular automata (VCA) models are an advanced cellular automata (CA) method that use irregular cells and perform well in simulating land use changes within urban areas. However, the applicability and parameter setting of VCA models for land cover change simulation are still challenging for researchers. To address this issue, this study applied a VCA model and two raster-based models, i.e., a pixel-based CA model and a patch-based CA model, to simulate and compare their performance in simulating land cover changes. The results show that VCA and patch-based CA were superior, with VCA's FoM being 39.74% higher than pixel-based CA and 11.00% over patch-based CA. VCA effectively tracks construction land expansion in rapidly developing areas, while patch-based CA excels in central urban and suburban shifts, fitting broader study scopes. Additionally, a spatial scale sensitivity analysis of the VCA model revealed that a smaller VCA cell size improves accuracy but introduces a risk of spatial pattern errors. Notably, the scope of study impacts VCA accuracy more than cell size. These findings bolster land cover change modeling theory and offer insights for precise future land cover change simulations and decision-making.

1. Introduction

Land cover change is an important issue in sustainable development research (Li et al., 2017; Yang & Huang, 2021). Land cover change modeling and simulation is important research for exploring land cover driving mechanisms, supporting urban planning and policy making, and assessing ecological and environmental impacts (Verburg et al., 2019). Land use and land cover are two key concepts in this field. Land use change simulation studies how human activities affect land resources, while land cover change simulation focuses on the joint effects of natural factors and human activities on surface cover(Feng & Tong, 2017; Zhang et al., 2019).

CA models show good performance in simulating the spatiotemporal dynamic of land use and land cover, making them the mainstream methods in this field(Tong & Feng, 2020; Wang, Zheng, & Zang, 2012). Traditional cellular automaton models use raster cells with regular shapes and sizes to represent cellular space, which have high model efficiency(Clarke & Gaydos, 1998; Feng, Liu, & Tong, 2010; Li & Yeh, 2002). Examples include pixel-based CA models like FLUS and patch-based CA models like PLUS(Liu et al., 2017, Liang et al., 2021b). But it is challenging to use them to obtain high-precision simulation results. Because urban spatial structures often consist of irregular blocks or

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features, not regular units, leading to deficiencies in raster CA's representation of these irregular entities (Barreira-González, Gómez-Delgado, & Aguilera-Benavente, 2015; Moreno, Wang, & Marceau, 2010).

VCA is seen as one direction for CA's future development, aiming to overcome the limitations of traditional raster-based CA models in representing irregular urban spatial structures (Guan et al., 2023; Long, Shen, & Jin, 2016; Shi & Pang, 2000). VCA model uses irregular polygons to form a cellular space. The basic unit of urban planning is the "plot" or "parcel". Given that the main objective of CA models is usually to assist or improve urban planning, it seems appropriate to adopt the same spatial representation method as urban planners (Abolhasani et al., 2016; Barreira-González & Barros, 2017). Building on this approach, Yao et al. (2017) proposed a dynamic land parcel subdivision DLPS-VCA model. This model uses cadastral parcels divided based on natural conditions and land use types as basic units. It adopts a binary recursive partitioning to split cadastral parcels larger than the threshold into smaller parcels, simulating the fragmentation process caused by urban expansion more realistically. Zhai et al. (2020) further proposed the CNN-VCA model, which effectively explored the relationship between land use change and driving factors within the neighborhood of parcels.

However, the applicability of current VCA models for simulating land cover change remains unclear. These models have been primarily used to simulate changes in urban land use types (such as residential and industrial uses) (Yao et al., 2017; Zhai et al., 2020). Unlike the structured land use types in urban areas, natural land cover data may show irregular change patterns and fragmented patches (Liang et al., 2021b). Therefore, it is necessary to further study whether VCA models can effectively capture the complexity and diversity of natural land cover change, as well as reflect the different patterns of urban expansion and spatial structure change. Despite this, the introduction of VCA models undoubtedly provides an effective tool for researchers and policymakers focused on land use and land cover. By deeply comparing and evaluating the applicability and shortcomings of VCA models and raster CA models in simulating different land cover change patterns, important references can be provided for the selection and application of CA models in different cases.

Moreover, the sensitivity of the VCA model in simulating land cover changes is also unclear. In addition to the influence of cellular space, CA models, including VCA, are constrained by parameters such as spatial scale and neighborhood configuration(Tong & Feng, 2020). This makes sensitivity analysis a necessary step in CA modeling, as it can verify the model's credibility and assess the uncertainty of results (Wu et al., 2019). Spatial scale involves both scope and resolution (Gibson, Ostrom, & Ahn, 2000; Gounaridis et al., 2019). Ignoring spatial scale can lead to oversimplification, decreased accuracy, or overly complex issues that are hard to handle and interpret, thereby increasing uncertainty (Verburg et al., 2004). Existing studies on raster CA models have shown a negative correlation between simulation accuracy and spatial resolution (Cuellar & Perez, 2023; Gounaridis et al., 2019; Pan et al., 2010). Unlike traditional CA models, the cells in VCA models are irregular polygons, with shapes and sizes that dynamically change throughout the simulation process. This gives VCA models greater spatial flexibility and data precision, but also introduces more complex scale and neighborhood effects(Zhu et al., 2021). Some researchers believe that VCA models eliminate cell size sensitivity (Dahal & Chow, 2015), but models like DLPS-VCA still consider land fragmentation processes, which involve scale effects (Yao et al., 2017; Zhai et al., 2020). Therefore, this study will explore the VCA model spatial scale sensitivity and provide theoretical support for application.

In summary, studies comparing the applicability and spatial scale sensitivity of VCA models and raster-based CA models in simulating land cover changes are limited. This study uses Shenzhen City as a case study and examines the suitability of pixel-based CA model FLUS, patch-based CA model PLUS, and VCA model in simulating land cover changes. The study also quantifies different urban expansion patterns based on two-phase land cover data and analyzes the suitability of the models under different urban expansion scenarios. Additionally, the study discusses the uncertainty of cell size in the simulation process of VCA models. This study enriches and improves the theory of CA models and provides certain support for land planning and management decisions.

2. Methodology

The study content of this study is divided into three steps, as shown in Fig. 1: (1) Data preprocessing, which converts raster-based land cover data into vector format and splits the land parcels according to the preset iteration times and split thresholds; (2) Land cover simulation, which uses FLUS, PLUS, and VCA models respectively to simulate land cover changes. The simulation effects of the three models are compared through accuracy evaluation, spatial pattern analysis, and model operation time to analyze their respective advantages, disadvantages and applicable scenarios; (3) Scale sensitivity analysis, which compares the simulation accuracy of the VCA model under different cell sizes and explores its uncertainty on spatial scale.

This study used three geographical cellular automata models, FLUS, PLUS and VCA, to simulate land cover changes. These models differ in cellular space, neighborhood effects, data requirements, and methods for computing transition suitability. FLUS and PLUS models used regular pixels, while VCA model used irregular polygons. FLUS model used artificial neural network algorithm and single-period historical data to calculate transition suitability. PLUS and VCA models used random forest algorithm and two-period historical data for simulation. VCA model also used a centroid-intercepted buffer rule based on land parcel area weighting to obtain neighborhood effects. The details of these models are described in Sections 2.2, 2.3 and 2.4.

2.1. Geographical cellular automata model simulating land cover changes

CA models consist of four basic elements: cells, states, neighborhoods, and transition rules (White, Engelen, & Uljee, 1997). In CA models, each cell has a specific state, and future states are determined by transition rules, which can simulate dynamic changes in cell states over a certain period(Feng & Tong, 2017).

Previous studies generally calculate the overall transition probability of each cell by integrating four parts: transition suitability, neighborhood effect, constraint factors, and random factors (Chen et al., 2016b). A common cellular automata model framework is shown in the supplementary material (Fig. S1). The transition probability of the i-th cell changing to the k-th land cover type at time t is:

$$P_i^{k,t} = P_{(o)i}^{\ \ k,t} \times \Omega_i^{k,t} \times con\left(S_{ik}^t\right) \times RA \quad (1)$$

where $P_i^{k,t}$ is the transition probability that the k-th land cover change type occurred in cell i at time t. $P_{(o)i}^{\ \ k,t}$ is the transition suitability of the k-th land cover change type that occurred in cell i at time t. $con\left(S_{ik}^t\right)$ refers to the constraint coefficient of the cell's development. $\Omega_i^{k,t}$represents the neighborhood effect of cell i changing to k-th land cover at time t. RA is a random factor value.

Transition suitability reflects the relationship between land cover changes and driving factors. It can be derived from historical data using statistical or machine learning methods such as logistic regression, multicriteria evaluation, and support vector machines (Fu, Wang, & Yang, 2018; Liao et al., 2016; Yang, Li, & Shi, 2008). Among them, the random forest algorithm can effectively mine the relationship between multiple nonlinear variables and quantify the importance of each variable. Many researchers have compared it with artificial neural networks, support vector machines, and other methods, concluding that random forest performs better in prediction ability and interpretability (Lv et al., 2021; Rienow et al., 2021). Neighborhood effect reflects the interaction between different land cover units within the neighborhood range. The neighborhood effect in raster-based CA models is determined by the

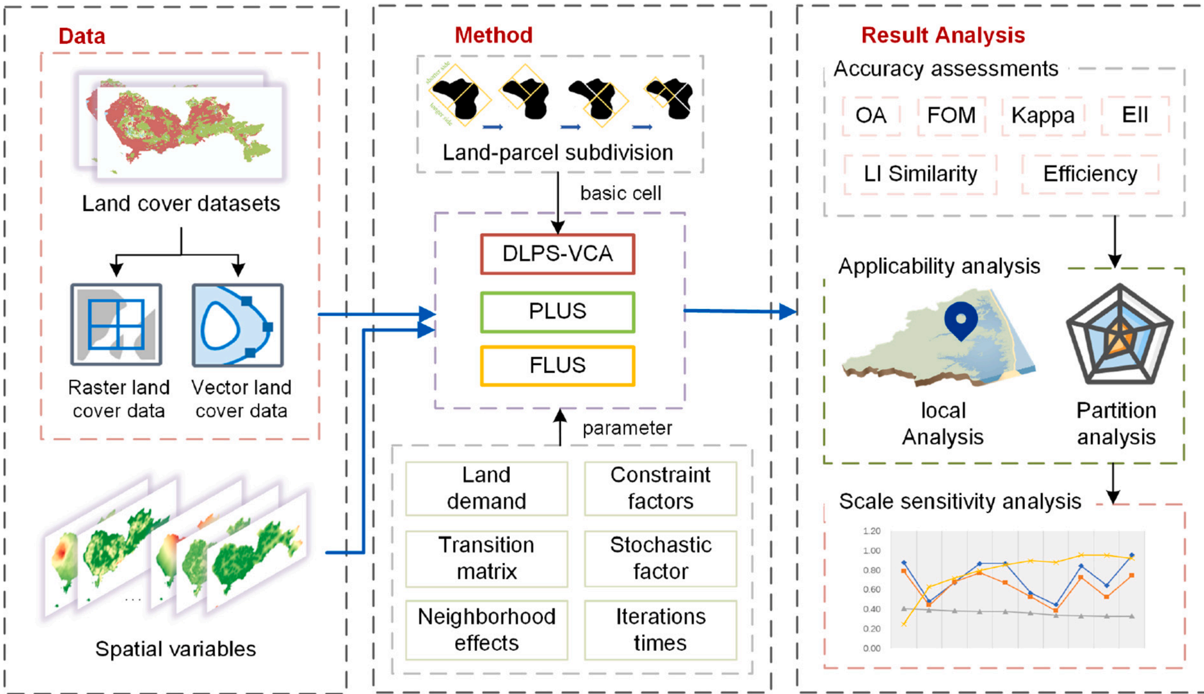


Fig. 1. Flowchart of land cover change simulation via multiple CA model.

following formula:

$$\Omega_{p,k}^{t} = \frac{\sum_{N\times N} con\left(c_p^{t-1} = k\right)}{N \times N - 1} \times w_k \tag{2}$$

where $\sum_{N\times N} \mathrm{con}\left(c_p^{t-1} = k\right)$ represents the total number of grid units occupied by land cover type k in the N × N window at the last iteration time t-1. w_k is a variable weight between different land cover types (Liang et al., 2021b).

Constraint factor refers to the control measures that prohibit specific land cover types (such as water bodies and protected areas) from being converted to other land cover types. The constraint factor of the i-th land parcel at time t is:

$$con\left(S_{ik}^{t}\right) = \begin{cases} 0 \text{ (restricted development area)} \\ 1 \text{ (suitable development area)} \end{cases} \tag{3}$$

2.2. FLUS model simulating land cover changes

The Future Land Use Simulation (FLUS) model is an advanced raster-based CA model(Liu et al., 2017). The basic principle of the FLUS model involves using the Artificial Neural Networks (ANN) algorithm to calculate the transition suitability of each land cover type in the region based on land cover data of the simulation start year and various driving factors. This is then combined with neighborhood effects, adaptive inertia coefficients, and conversion costs to obtain the overall conversion probability of each cell. Finally, simulation results are generated using a roulette competition mechanism.

The self-adaptive inertia coefficient D_k^t can automatically adjust the inheritance of current land cover on each grid unit based on the discrepancy between macro demand and allocated land cover, ensuring that land cover allocations meet macro demand. The adaptive parameter depends on differences between current development and future demand cell numbers, which is defined as follows:

$$D_k^t = \begin{cases} D_k^{t-1} \text{ if } \left|G_k^{t-1}\right| \le \left|G_k^{t-2}\right| \\ D_k^{t-1} \times \dfrac{G_k^{t-2}}{G_k^{t-1}} \text{ if } 0 > G_k^{t-2} > G_k^{t-1} \\ D_k^{t-1} \times \dfrac{G_k^{t-1}}{G_k^{t-t}} \text{ if } 0 < G_k^{t-2} < G_k^{t-1} \end{cases} \tag{4}$$

where G_k^{t-1} and G_k^{t-2} are the differences between the allocated amount of land cover type k and macro demand for the t-1th and t-2th iterations, respectively.

2.3. PLUS model simulating land cover changes

The Patch-generating Land Use Simulation (PLUS) model is developed based on the FLUS model, coupling the Land Expansion Analysis Strategy (LEAS) and the CA based on Multiple Random Seeds (CARS) (Liang et al., 2021b). LEAS samples the land cover data and driving factors of the two periods, and uses the random forest (RF) algorithm to calculate the transition suitability of various types of land. The main differences between the PLUS model and the FLUS model are that the former uses multi-temporal training data and an improved suitability calculation method. According to a study by Liang et al. (2021b), these improvements enable the PLUS model to simulate land cover change more accurately than the FLUS model.

CARS combines a self-adaptive inertia coefficient and multi-type random patch seeding mechanism based on threshold descent. When the neighborhood effect of land cover Ω is 0, the mechanism generates change ‘seeds ‘on the transition suitability surface $P_{(o)i}^{k,t}$ for each land cover type by Monte Carlo method. Seeds can produce new land cover types and grow into new patches of the same land cover type's cells.

$$OP_{i,k}^{d=1,t} = \begin{cases} P_{i,k}^{d=1} \times (r \times \mu_k) \times D_k^t \text{ if } \Omega_{i,k}^t = 0 \text{ and } < P_{i,k}^{d=1} \\ P_{i,k}^{d=1} \times \Omega_{i,k}^t \times D_k^t \text{ all others} \end{cases} \tag{5}$$

where r is a random value ranging from 0 to 1; μ_k is the threshold to generate the new land cover patches for k-type land cover. In order to control the generation of multiple land cover patches, a threshold descending rule of competition process was proposed to restrict the organic growth and spontaneous growth of all land cover types:

$$\text{If } \sum_{k=1}^{N} \left|G_c^{t-1}\right| - \sum_{k=1}^{N} \left|G_c^{t}\right| < \text{Step Then}, l = l + 1 \tag{6}$$

$$\begin{cases} \text{Change } P_{i,c}^{d=1} > \tau \text{ and } TM_{k,c} = 1 \\ \text{No change } P_{i,c}^{d=1} \le \tau \text{ or } TM_{k,c} = 0 \end{cases} \tau = \delta^l \times r1 \tag{7}$$

where *Step* is the step size of the PLUS model to approximate the land cover demand; δis the decay factor of decreasing threshold τ, which ranges from 0 to 1; $r1$ is a normally distributed stochastic value with a mean of 1, ranging from 0 to 2; l is the number of decay steps. $TM_{k,c}$ is the transformation matrix that defines whether land cover type k is allowed to be converted to type c.

2.4. DLPS-VCA model simulating land cover changes

This part uses the DLPS-VCA model that couples the dynamic land parcel subdivision strategy and RF algorithm as the representative of VCA(Yao et al., 2017). This model utilizes multi-temporal land cover data and the same random forest algorithm as the PLUS model to calculate the development suitability. In the DLPS-VCA model, the minimum area boundary rectangle (MABR) is used to iteratively divide the cell unit until all the cell sizes after splitting are less than the set value, obtaining basic cells (Cheng et al., 2008). Secondly, the mean value of spatial variables in each cell after splitting is calculated, and the random forest algorithm is used to calculate the transition suitability. Finally, it couples the neighborhood effect, random value, limiting factor, sets the number of iterations and total growth, and obtains the transition probability. In particular, this study builds a roulette based on the overall probability of all land cover types in the DLPS-VCA model, and selects land cover status in the next iteration.

The cells of the VCA model are irregular polygons, so the raster-based CA neighborhood definition method is no longer applicable. In this study, the DLPS -VCA model adopted a centroid-intercepted buffer rule based on land parcel area weighting to obtain the neighborhood effect of the cell unit. At time t, the neighborhood effect of the jth cell relative to the ith cell can be expressed as:

$$\Omega_{i,j}^{t} = e^{-d_{ij}/d} \cdot \frac{S_j/S_i}{S_{max}/S_{min}} \tag{8}$$

where e is an exponential constant; d_{ij} is the center distance between the i th cell and the j th cell; Si and Sj represent the area of the i th cell and the j th cell, respectively; S_{max} and S_{min} represent the maximum and minimum area of the cells in the study area, respectively.

2.5. Accuracy assessment and landscape consistency analysis

The overall accuracy (OA), Kappa coefficient and Figure of Merit (FoM) were used to evaluate the accuracy of the results. When the Kappa coefficient is >0.75, it indicates that the model has high credibility. The FoM index is also an effective measure to evaluate the accuracy of land cover modeling (Pontius et al., 2008). In large-scale simulations, the FoM index of >0.2 indicates that the model has strong availability (Chen et al., 2014; Yao et al., 2022). The formula is listed as follows:

$$OA = (B + E)/(A + B + C + D + E) \tag{9}$$

$$KAPPA = (OA - P_e)/(1 - P_e) \tag{10}$$

$$FoM = B/(A + B + C + D) \tag{11}$$

Where A indicates the error of actual unchanged land that is simulated as changed; B represents the land that is correctly simulated as changed; C stands for the error that the actual and simulated land has changed but the type does not match; D represents the error of actual changed land that is simulated as unchanged; E represents the land that is actually unchanged and simulated as unchanged; $P_e$is the expected accuracy under random conditions.

The landscape index (LI) is used to describe and quantify the landscape structure and ecological pattern (Haines-Young & Chopping, 1996; Yao et al., 2017). In this study, six landscape indices in Table 1 were used to measure the urban landscape of the simulation results from different aspects (McGarigal, 2015).

landscape pattern similarity can effectively measure the consistency of land cover patterns between simulated data and real data (Chen et al., 2014), and its formula is as follows:

$$\alpha_l = 1 - \frac{1}{n} \sum_i \Delta l_i \tag{12}$$

$$\Delta l_i = \left|l_{i,s} - l_{i,o}\right| / l_{i,o} \tag{13}$$

where $l_{i,s}$ *and* $l_{i,o}$ represent the i th LI of the simulated and real scenarios, respectively, and Δl_i is the normalized difference of the i th LI.

Urban construction land expansion reflects the spatial structure of urbanization process(Wang et al., 2021, Zhou, Wu, & Wang, 2022). This study uses the Expand Intensity Index (EII) to measure the spatial expansion of construction land in different regions of Shenzhen from 2008 to 2018. It analyzes the effects of different models under different urban expansion patterns. The definition is as follows:

$$EII = \frac{U_b - U_a}{U} \times \frac{1}{T} \times 100\% \tag{14}$$

Table 1
Landscape indices for assessing landscape similarity.

LI	Significance	Function
Area_MN	The average area of all patches or a certain type of patch; the smaller the value, the more fragmented the landscape (Wang et al., 2020).	Reflect the fragmentation and continuity of the landscape
Edge density(ED)	The larger the value, the longer the boundary length and the more scattered the distribution of land cover types (Zeng & Wu, 2005).	
Largest patch index (LPI)	The larger the value, the higher the degree of aggregation of the dominant patches (Tong & Feng, 2020).	Measure the aggregation of dominant patches
Aggregation index (AI)	The smaller the value, the more aggregated the patches of the same land cover type, i.e. the easier to form continuous areas. Conversely, the more likely to produce isolated small patches (He, DeZonia, & Mladenoff, 2000).	
Landscape shape index(LSI)	It represents the shape deviation between the simulated landscape and a square with the same area. The larger the LSI, the more complex the shape of the simulated urban patches (Chen et al., 2016a).	Evaluate the shape complexity of the landscape
Perimeter area fractal dimension (PAFRAC)	The larger the value, the more complex the shape of patches in the landscape and the greater the degree of human activity disturbance (Asubonteng et al., 2020).	

where U represents the area of the unit, U_a and U_b represent the construction land area within the same spatial unit in the two periods respectively, and T represents the time interval between the two periods.

3. Results

3.1. Study area and data

Shenzhen is located in Guangdong Province in southern China, with a total area of nearly 2000 km^2. The city has 10 administrative regions, namely Futian, Luohu, Yantian, Nanshan, Baoan, Longgang, Longhua, Pingshan, Guangming and Dapeng (http://www.sz.gov.cn/cn/zjsz/gl/). Futian and Luohu are the political, cultural and commercial centers of Shenzhen. Nanshan is the center of gravity of science and technology and high-end industries (Chen & John, 2015). Dapeng is far away from the city center with many tourist attractions and nature reserves. As the most developed immigrant city in South China, Shenzhen has a complex land cover pattern. With the deepening of urban expansion, little construction land remains, which has a rigid constraint on the social and economic development of Shenzhen (Liu et al., 2016).

The FLUS, PLUS, and VCA models used in this study were consistent in terms of the study area, land cover data, spatial auxiliary data, and some parameter settings, in order to control for the effects of other variables. Land cover raster data is an important data set used in this study. The dataset is derived from the China Multi-period Land Use and Land Cover Remote Sensing Monitoring Data Set (CNLUCC) released by the Resource and Environmental Science Data Center (RESDC) of the Chinese Academy of Sciences (https://www.resdc.cn/). The CNLUCC adopts a two-level classification system (https://www.resdc.cn/DOI/DOI.aspx?DOIID=54). Detailed explanations regarding specific classification information can be found in Table S1 of the supplementary materials. To simplify the analysis, we redefined the land cover types in Shenzhen according to the first-level classification criteria of this system, which are: cultivated land, non-construction land (including forest land, grassland, and unused land with <1% proportion), water area, and construction land (Fig. 2). This strategy aims to more intuitively compare the performance of different land cover change simulation models.

Previous studies show that raster-based cellular automata models perform better with higher data resolution(Cuellar & Perez, 2023; Samat, 2006). Therefore, this study used 30 m resolution land cover data as input for FLUS and PLUS models to obtain the best accuracy, without conducting scale sensitivity analysis. However, VCA model required separate scale sensitivity analysis, as its cell size was independent of data resolution. In this study, the reclassified raster data was converted into a vector format, represented by polygonal blocks. Each irregular block has a unique ID and an attribute indicating the land cover type. These vector-based blocks were utilized as inputs for the VCA model.

Land cover change is a complex phenomenon caused by the interaction of natural and human factors. This study used 14 spatial auxiliary data as driving factors influencing land cover change, as shown in Fig. 3. They are divided into natural factors (elevation, slope, distance to river, distance to coastline), traffic factors (distance to main roads, railways, subway stations, distance to road network and bus station distribution

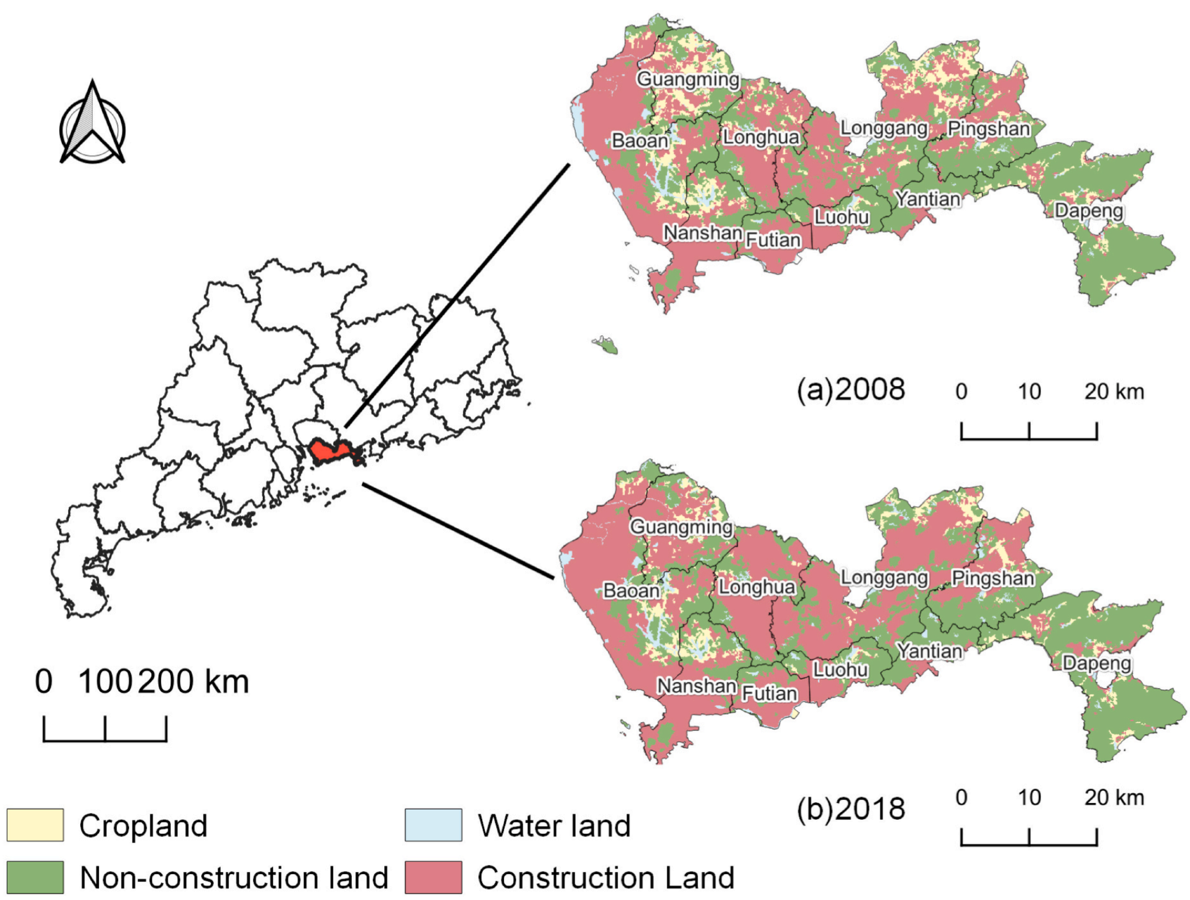


Fig. 2. Land cover data of Shenzhen.

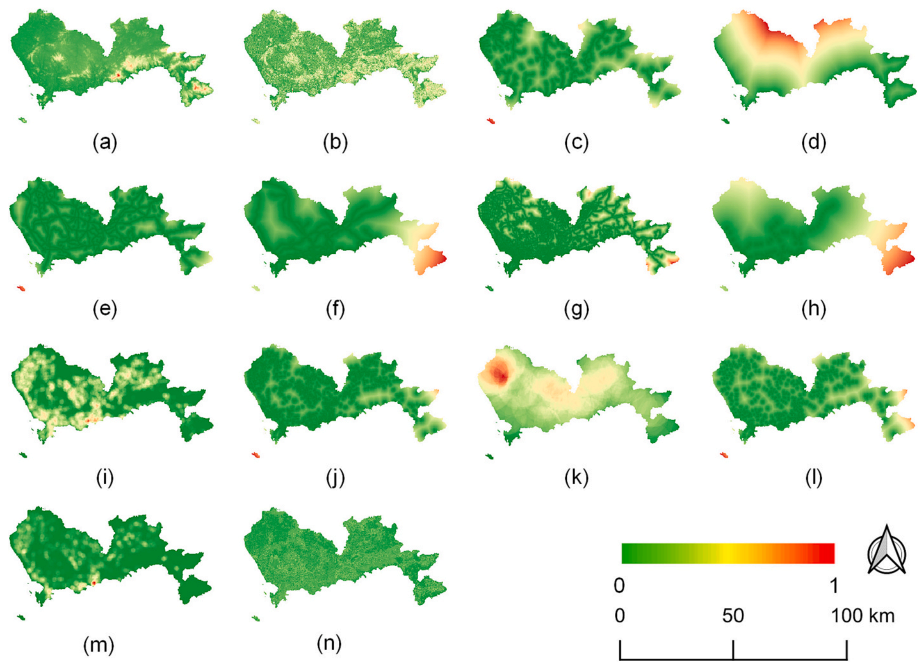


Fig. 3. Auxiliary dataset ((a) DEM, (b) slope, (c)distance to river, (d)distance to coastline, (e) distance to main roads, (f) distance to railways, (g)distance to the road network, (h)distance to subway station, (i) Density of bus stops, (j) distance to hospitals, (k) distance to district centers, (l)distance to school, (m) density of entertainment facilities, (n)housing Prices.)

density), and social and economic factors (distance to medical facilities, district and county centers, schools, entertainment venues, housing price distribution). The data comes from Gaode POI data and OpenStreetMap data in 2018. In this study, spatial auxiliary data were constructed based on these data. This study converted these data into raster data with the same row and column numbers and a resolution of 30 m through spatial analysis. Additionally, the spatial auxiliary data was normalized to a range of 0 to 1.

3.2. Implementation results and comparisons

In this study, the ANN module in the FLUS model contains one input layer, 14 hidden layers, and one output layer, with a neighborhood window size of 3. For the PLUS model, the neighborhood window is also set to 3, while the VCA model uses a neighborhood radius of 600 m. When calculating transition suitability, we used 70% of the training data and 30% of the validation data in the PLUS and VCA models. We also set up 100 decision trees and used out-of-bag cross-validation with boosted random sampling and iterated 100 epochs for reliable average accuracy. The FLUS model follows the original author's procedure, using 70% of the data for training and 30% for validation without cross-validation due to the ANN algorithm(Liu et al., 2017). All parameters were set using a trial-and-error approach. Simulating with the VCA model, the basic unit size is set to 1 ha, 3 ha, 5 ha, 7 ha, 9 ha, and 11 ha, respectively, and the cell size represents the corresponding VCA models. The subsequent sections will discuss the influence of cell size on simulation accuracy. Considering the accuracy of simulation and landscape pattern similarity, this section uses a 5 ha basic unit size example to explore the differences in simulation results of various models.

This study simulated land cover changes in Shenzhen from 2008 to 2018 to evaluate the effects of different models in the same study area and dataset. Table 2 shows model accuracy. The PLUS model has the highest overall accuracy, with OA indices about 1.4% and 2.5% higher than the VCA and FLUS models. All models have a Kappa coefficient exceeding 0.75, indicating overall solid consistency between simulation results and observations. The VCA model has the highest FoM, 39.74% and 11.00% higher than the FLUS and PLUS models, respectively.

Table 2
Accuracy of simulation results via different models.

Accuracy	OA	Kappa	FoM
VCA (5 ha)	0.866	0.768	0.373
PLUS	0.878	0.788	0.336
FLUS	0.857	0.752	0.265

Table 2 shows that the OA and Kappa of the VCA model are lower than those of the PLUS model, while the FoM is higher. According to Fig. 7 analysis, this is mainly because the VCA model tries to simulate more actual changes and reflect more non-construction land transformation to construction land. This leads to a higher FoM for VCA model. However, some originally stable non-construction lands are wrongly identified as construction land by this model, resulting in lower OA and Kappa. Considering all indicators, this study confirms the effectiveness of each model in simulating land cover change data, with VCA and PLUS models performing best.

Table 3 shows the LI of the three models' simulation results. The AREA_MN and ED indices of all three models differ significantly from the actual values (AREA_MN deviation >56.1%, ED deviation >22.2%). Over the past decade, Shenzhen's construction land expanded significantly, filling the gaps and fragments between existing construction land patches, and making the urban form more compact. However, none of the models fully simulated this feature. Compared to the PLUS and VCA models, the FLUS model better simulates urban landscape fragmentation, aggregation and shape complexity. Compared to the VCA model, the PLUS model more accurately reflects the aggregation degree of dominant patches, while the VCA model simulates a more compact landscape that better maintains urban landscape regularity.

3.3. District differences in model accuracy

This study conducted experiments in different districts of Shenzhen to explore regional differences. Fig. 4 shows that the FoM significantly differs from OA and Kappa. Areas with lower FoM (FoM $<$ 0.2) have higher OA and Kappa (OA $>$ 0.90, Kappa$>$0.85). Areas with the highest

Table 3
LI of the simulated results based on different models.

	AREA_MN	ED	LPI	AI	LSI	PAFRAC	α_1
Actual	218.624	17.831	45.709	97.217	22.615	1.300	/
VCA(5 ha)	83.066	23.156	49.161	96.417	28.396	1.325	78.71%
PLUS	64.337	23.372	45.544	95.960	34.520	1.321	73.74%
FLUS	96.028	21.778	46.095	96.624	26.888	1.294	83.49%

FoM (FoM > 0.26) have lower OA and Kappa (OA < 0.85, Kappa<0.75). This is mainly because the OA and Kappa only evaluate the overall quantitative consistency between the simulation results and the actual land cover (Li et al., 2021b). Significant land cover changes make achieving overall classification result consistency challenging, leading to lower OA and Kappa values. The FoM pays more attention to the ability of the model to identify and measure land cover changes (Liu et al., 2017), which can provide a more accurate model effect judgment in this case. Therefore, this study focuses more on FoM accuracy, comparing OA and Kappa between different models in the same region to evaluate model simulation result differences.

Building on this, we compared the FoM obtained by each model in various districts with the EII index (Fig. 5). Fig. 4 shows that the VCA model exhibits excellent simulation results in Guangming, Longhua, and Longgang districts (exceeding the average by 45%), while the FoM in districts such as Futian, Luohu, and Dapeng is lower (FoM < 0.2). This closely correlates with the EII index (correlation of 0.79), as Guangming, Longhua, and Longgang have rapidly expanded construction land over the past decade with high EII values of 2.05%, 1.16%, and 1.00% respectively. These districts are less influenced by government policies. The high FoM values in these fast-growing districts is consistent with previous studies (Yao et al., 2021). In contrast, central urban districts like Futian and Luohu are nearing development limits, with a low EII value of only 0.15%. Development focus has shifted to urban renewal (Li, Chen and Grant, 2021a), such as the transformation of old neighborhoods and industrial areas, making accurate simulation difficult. Dapeng district, located on the islands in the southeastern part of Shenzhen, has limited construction land expansion (EII = 0.14%) and is heavily influenced by marine conservation policy (Zhai et al., 2020), further reducing the FoM accuracy of the simulation.

Although the FLUS model correlates best with EII (0.91), its overall FoM is lower than PLUS and VCA models, as it cannot capture land cover changes over specific time intervals with a single land cover map, leading to lower simulation accuracy. In fast-growing districts like Guangming, Longhua, and Longgang, VCA outperforms PLUS, while PLUS is slightly better in economically and socially developed districts like Nanshan, Futian, and Luohu. This aligns with the EII index, indicating PLUS is more suitable for simulating land cover in mature urban districts, while VCA better simulates rapid outward expansion of construction land, like in emerging urban districts. VCA correlates strongly with EII (0.79) compared to PLUS (0.67), demonstrating its superiority in modeling urban growth.

3.4. VCA spatial scale sensitivity analysis

Fig. 6 shows the influence of cell size on VCA model simulation accuracy. Results show the VCA model is susceptible to cell size. As cell size increases, OA, Kappa and FoM indices gradually decrease. FoM decreases significantly within 5-7 ha (48.7% of the total decrease). When the cell exceeds 6 ha, Kappa drops below 0.75. However, the landscape pattern similarity of results increased markedly with increasing cell size, reaching the highest value of 94.6% at a cell size of 10 ha, then started to decrease. At relatively small cell sizes, the rapidly increasing number of patches and edge density led to landscape fragmentation, thus resulting in a sharp decline in landscape similarity (reduced by 73.4% in the study area). However, excessively large cell sizes could also cause the simulated landscape pattern to deviate from reality, thus leading to the decreased landscape pattern similarity when cell size was >10 ha. Therefore, considering simulation accuracy and landscape pattern similarity, this study selected a cell size of 5 ha as the basic simulation unit, enabling simulation results to match actual data well and express land cover structure and spatial distribution characteristics well. This size is also one of the basic units for large-scale land development and management.

We implemented the models on a computer with an Intel(R) CoreTM i7–10,700 2.90 GHz CPU, NVIDIA GeForce GT 1030 GPU, 32GB memory and Windows 10. All models use C++ programming language. Table 4 reports the time overhead of different models. The raster-based CA model has higher computational efficiency than the VCA model. Raster data has a regular structure and less topological information, enabling fast calculation (Lu et al., 2020). Vector data is more complex. The smaller the cell size, the more data and computing resources required for simulation. Therefore, the FLUS and PLUS models are more suitable for large-scale land cover simulation scenarios due to their high efficiency. In contrast, VCA models are more suitable for small-scale simulation scenarios.

Finally, this study conducted a two-way analysis of variance using SPSS Statistics 25 to compare the effects of cell size and study scope on VCA model FoM(Gamst, Meyers, & Guarino, 2008). In the two-factor test, we considered the FoM of the VCA model with different cell sizes from 1 ha to 11 ha in each of the 10 districts of Shenzhen. In statistics, F-value, partial Eta squared and mean square are used as measures of factor effect size. The results demonstrated that both cell size (F = 52.223, partial eta squared = 0.853, mean square = 0.008) and study scope (F = 914.242, partial eta squared = 0.995, mean square = 0.137) significantly affected model accuracy. The F value, partial eta square and mean square corresponding to the study scope factors are much higher than the cell size, indicating that the influence in the model is greater.

3.5. Details of the implementation results of different models

Fig. 7 compares the simulation results of different models and selects four local areas. According to previous studies (Huang, Huang, & Liu, 2019; Zhang et al., 2023), the selected areas are divided into three categories, which are described as follows: 1) Located in the adjacent areas to large existing construction land patch. Newly generated large-scale construction land patch fill the blank between existing construction land patches and connect to each other, such as Part 1, which is located in Guangming; 2) Various forms of construction land growth such as filling and edge expansion, such as Part 2, Part 3 and Part 4, which are located in Longhua, Nanshan and Longgang District respectively. 3) There is a leap-like growth of construction land, where new construction land patches appear far away from the original boundaries, such as Part 5, in Dapeng.

Figs. 4 and 7 show that the smaller the cell size, the higher the simulated construction land expansion and actual value matching degree. Too large a cell size ignores spatial heterogeneity information and produces significant boundary effects, affecting spatial distribution matching degree (Liang et al., 2021a). Too small a cell size also leads to land fragmentation. Therefore, an appropriate cell size should be selected for the VCA model.

Part 1 shows PLUS model land expansion simulation is closer to reality than FLUS. However, both models are limited to simulating the

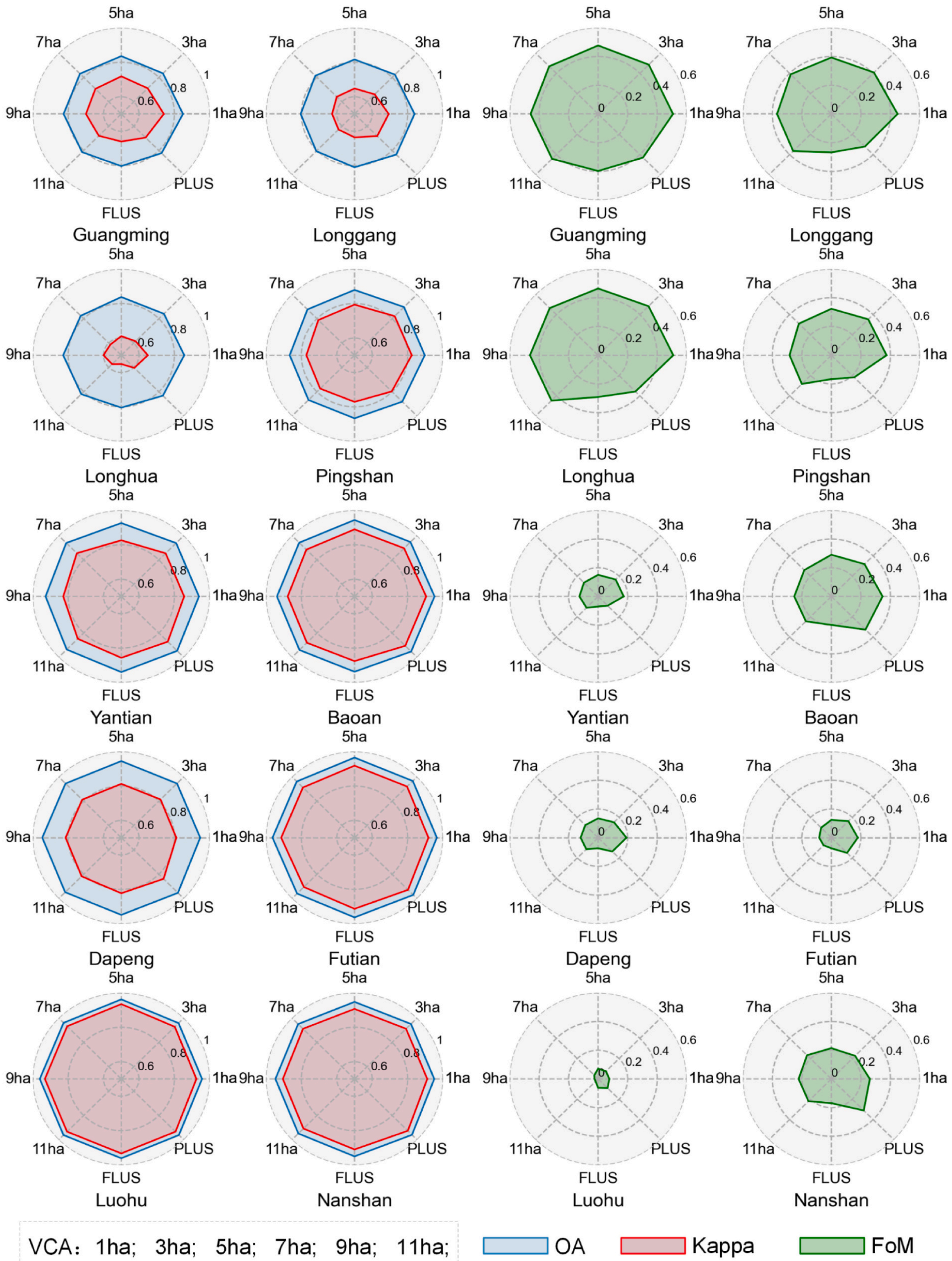
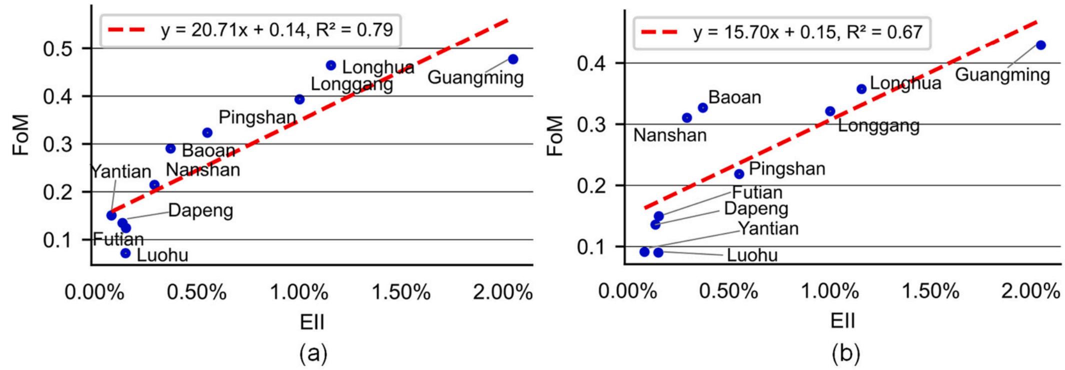
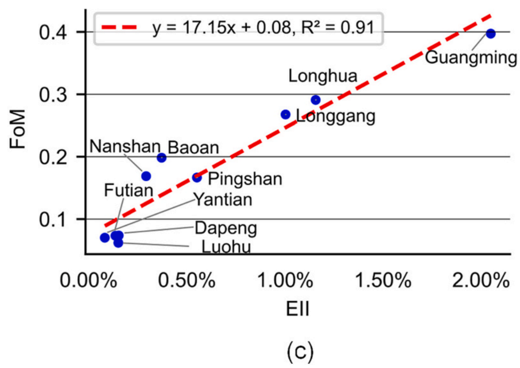


Fig. 4. The simulation accuracy of different CA models in district.

expansion of construction land changes only in existing urban patch peripheral areas. In contrast, the VCA model better simulates filling construction land expansion patterns. Part 2 is in Longhua District, where construction land expanded significantly, extending outward to form a "peninsula"-like area. The newly added construction land in Part 4 fills the original edge depression and expands outward. In these two areas, The FLUS and PLUS models show only slight expansion along the original boundary in these areas. In contrast, the VCA model with a





Districts	FoM			EII*10
	VCA(5ha)	PLUS	FLUS	
Guangming	0.477	0.430	0.397	20.48%
Longgang	0.393	0.321	0.268	10.01%
Longhua	0.464	0.357	0.291	11.57%
Pingshan	0.324	0.219	0.167	5.50%
Yantian	0.151	0.091	0.070	0.82%
Baoan	0.291	0.327	0.198	3.70%
Dapeng	0.135	0.136	0.073	1.36%
Futian	0.124	0.150	0.074	1.52%
Luohu	0.072	0.090	0.062	1.50%
Nanshan	0.214	0.310	0.169	2.92%

(d) Simulation accuracy and EII of different districts

Fig. 5. The correlation between the FoM (y-axis) of VCA (a), PLUS (b), and FLUS (c) and EII index. (d) Simulation accuracy and EII of the three models in different districts.

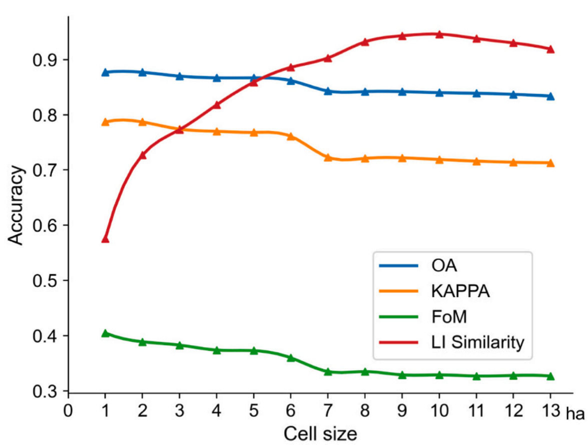


Fig. 6. Cell size sensitivity analysis of VCA.

Table 4
Efficiency of different models.

Model	1 ha	3 ha	5 ha	7 ha	9 ha	11 ha	PLUS	FLUS
Time (Minute)	30.1	14.2	6.5	5.8	5.2	4.9	4.0	4.9

smaller cell size simulates the orientation and amplitude of actual construction land expansion and evolution. This indicates that the VCA model can effectively guide urban growth to concentrate in areas with strong local effects, better simulating urban growth details and diversity and adapting well to complex urban growth patterns.

Construction land growth tends to be stable with a slowing growth rate in Parts 3 and 5. The PLUS model performs well here, while the FLUS and VCA models show insufficient or excessive simulation expansion phenomena. Moreover, the VCA model exacerbates the above defects as the cell size increases. In addition, the PLUS model simulates the approximate location of the newly added construction land block below Part 5, reflecting the model's proposed "multi-type random patch seed mechanism." In summary, most of the construction land growth simulated by the PLUS model is expanding outward along existing construction land edges, indicating this model's neighborhood effect calculation method can better characterize surrounding unit influence, easily capturing edge expansion urban growth characteristics (Zhang et al., 2023).

4. Discussion

Existing research on the applicability and spatial scale sensitivity of VCA and raster-based CA models in simulating land cover change is limited. This study uses Shenzhen as the study area, employing FLUS, PLUS and VCA models to simulate land cover change, conducting in-depth quantitative analysis from multiple perspectives including simulation accuracy, land cover change patterns, and model efficiency. The results demonstrate that both VCA and PLUS models achieved higher accuracy (OA > 0.85, Kappa>0.75, and FoM > 0.3), demonstrating their applicability in handling land cover data. Specifically, the simulation FoM accuracy of VCA model reaches the highest level, increasing by 39.74% and 11.00% over the FLUS and PLUS respectively. Furthermore, findings show the VCA model can guide construction land growth to concentrate in areas with strong local effects, better simulating land cover change spatial heterogeneity and complexity. This provides a new attempt and exploration for scientifically explaining land cover change at the process level.

This study also analyzes the applicability of VCA model and PLUS model in simulating different construction land expansion patterns. The study introduces the EII to measure construction land intensity and evaluates the performance of each model in different regions. The results show that in rapidly expanding newly developed urban areas (i.e., areas with high EII values), VCA model shows the highest FoM value and

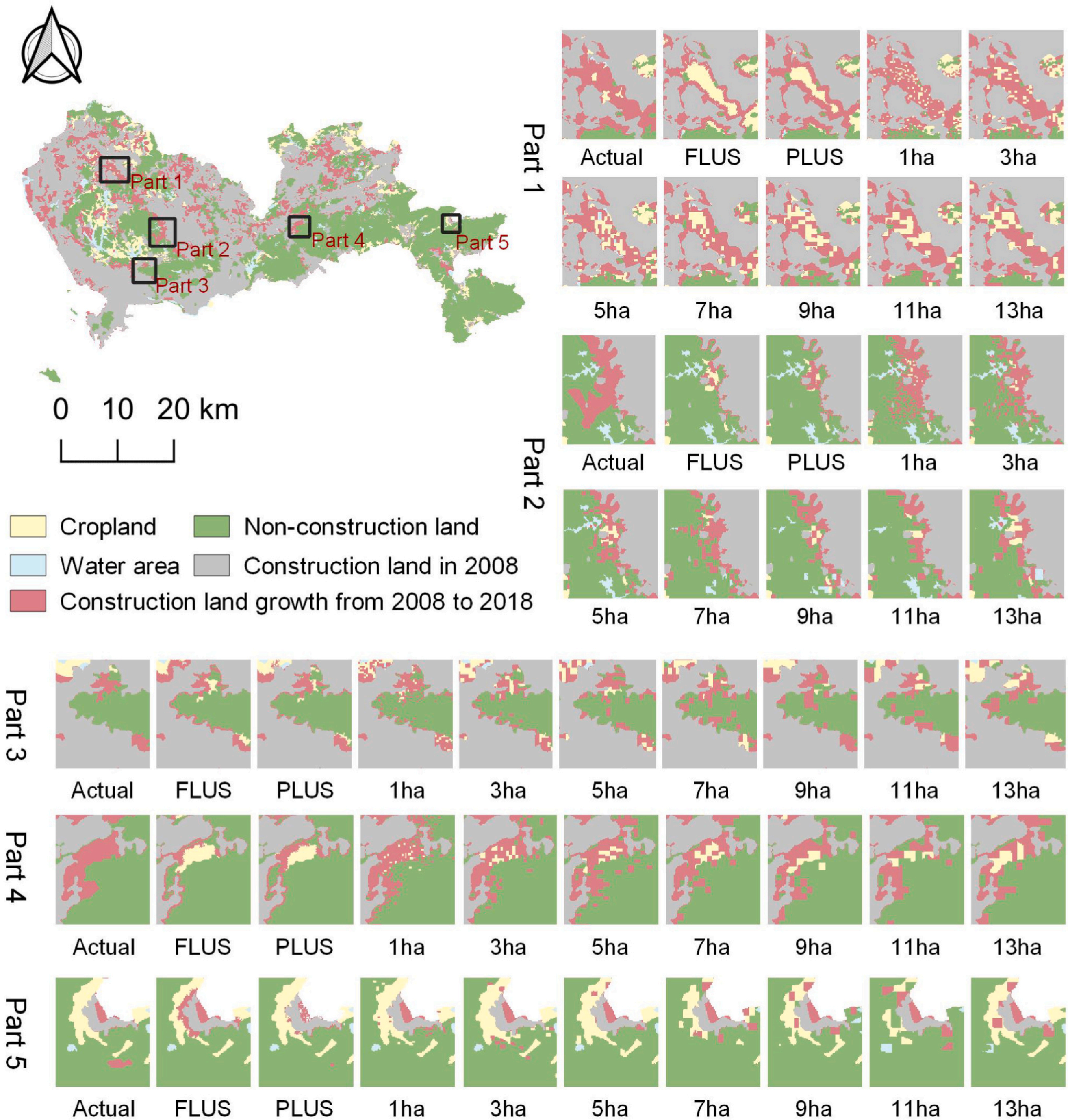


Fig. 7. Details of simulation results of different models.

achieves the best simulation performance. Compared with the FLUS and PLUS models, VCA model has significant advantages in simulating the infill construction land expansion and can more accurately simulate urban expansion direction and scope (Section 3.3). In contrast, PLUS model is more suitable for simulating land cover change in relatively mature central urban districts and underdeveloped suburban areas, which often have lower EII values. The PLUS model can better simulate edge expansion of construction land, and its unique "multiple-type random patch seeding" mechanism can partially capture the leapfrog growth of construction land patches. Moreover, based on raster data, PLUS model runs faster and more efficiently, providing greater simulation superiority over the VCA model in large study areas. Therefore, choosing the appropriate CA model according to the regional development characteristics and model advantages can effectively improve the accuracy and efficiency of urban growth simulation. Furthermore, coupling or integrating different models can be explored to enhance simulation accuracy and flexibility.

This study analyzes the spatial scale sensitivity of VCA model and explores the spatial heterogeneity of land cover change at different scales. The results show that as the cell size increases, the simulation accuracy gradually decreases, while the landscape pattern similarity significantly increases. However, this increase is not unlimited. During urban expansion, new urban spatial elements lead to increasingly scattered and fragmented urban spatial morphology (Shen et al., 2019).

Excessively large cells cannot reflect urban spatial morphology detailed complexity. Excessively small cells lead to overly rich internal details, increasing noise and over-fragmenting the landscape (Liang et al., 2021a). Moreover, reducing cell size requires greater computational power, significantly reducing model efficiency. The study also finds that among the ten districts in Shenzhen, the study scope has a greater impact on the model than the cell size, indicating that considering regional differences is crucial for the model. Therefore, choosing cell size must comprehensively consider study scope and data characteristics, balancing model accuracy and landscape continuity. Land cover change is a complex multi-scale, multi-mechanism system problem. A single modeling or parameter quantification method can only partially capture inherent laws and dynamic characteristics (Li et al., 2023). This study provides scientific methods and data support for land cover change modeling and scale sensitivity analysis.

Some shortcomings remain in this study. The experiments were conducted only in Shenzhen, without examining the influence of different geographic environment and socio-economic factors to test the generalizability of the VCA model. Additionally, this study focused solely on the spatial scale's impact on the VCA model, using simple neighborhood strategy and single conversion rule, without conducting comprehensive impact assessment. Future study can expand in two main directions: First, expand the scope of study and test models in more diverse regions. However, this will face greater challenges as it requires more data sources, which may lead to mismatches and stronger spatial heterogeneity between heterogeneous data. Second, considering not only the cell scale but also other parameters such as neighborhood strategies and transition rules, and performing in-depth sensitivity analysis of parameters. However, considering more parameters may introduce the issue of local minima in the parameter space optimization for comprehensive evaluations. This will pose a more challenging problem of optimizing parameter combinations. In summary, through the optimization of methods and techniques, the model may have greater scientific value and application prospects.

5. Conclusion

Aiming at the applicability and spatial scale sensitivity of the VCA model in land cover change simulation, this study used VCA, PLUS and FLUS models to simulate Shenzhen land cover change and conducted a systematic comparative analysis. Results show that both VCA and PLUS models demonstrate good applicability to land cover data. Different models have their advantages in mining the changes in urban land scale, intensity and spatial distribution. The VCA model is suitable for exploring land cover change mechanisms in newly developed urban areas with rapid construction land expansion, typically characterized by high EII values. The PLUS model suits change patterns of mature central urban or lagging suburban areas, often with lower EII values. Moreover, the PLUS model exhibits high simulation efficiency, particularly in large-scale study areas. Cell size is a crucial VCA model simulation effect affecting parameters. Excessively small cell size leads to improved accuracy but reduces landscape pattern similarity. Additionally, we found that the impact of sdudy scope on the accuracy of the VCA model is greater compared to cell size.

This study provides theoretical and technical support for land cover change research and urban planning management. Based on results, we suggest planners or policymakers fully consider land cover change characteristics and trends in different regions when formulating overall cover planning and construction land scale control planning. Select appropriate CA models and cell size to simulate and predict, to realize the optimization of land cover patterns and the economic and intensive use of land resources. Future study will conduct experiments in more different study areas, and explore multiple parameters in depth, including cell size, neighborhood definition and conversion rule, to reveal the complex synergistic effects, and improve the accuracy of land cover change simulation.

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Author statement

No conflict of interest exists in the submission of this manuscript, and manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part.

CRediT authorship contribution statement

Yao Yao: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Ying Jiang:** Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Zhenhui Sun:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Linlong Li:** Conceptualization, Data curation, Software, Writing – original draft, Writing – review & editing. **Dongsheng Chen:** Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Kailu Xiong:** Formal analysis, Validation, Writing – original draft, Writing – review & editing. **Anning Dong:** Investigation, Methodology, Software, Writing – original draft, Writing – review & editing. **Tao Cheng:** Software, Writing – original draft, Writing – review & editing. **Haoyan Zhang:** Data curation, Writing – original draft, Writing – review & editing. **Xun Liang:** Conceptualization, Writing – review & editing. **Qingfeng Guan:** Conceptualization, Data curation, Project administration, Validation, Writing – original draft, Writing – review & editing.

Data and codes availability statement

The data that support the findings of the present study are available on Figshare at https://figshare.com/s/e340e2e7e70ba9e2fc61. The FLUS software can be downloaded from: http://www.geosimulation.cn/FLUS.html. The PLUS software can be downloaded from: https://github.com/HPSCIL/Patch-generating_Land_Use_Simulation_Model. The UrbanVCA(RF-VCA) software can be downloaded from: https://urbancomp.net/archives/urbanvca-v2.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compenvurbsys.2024.102090.

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