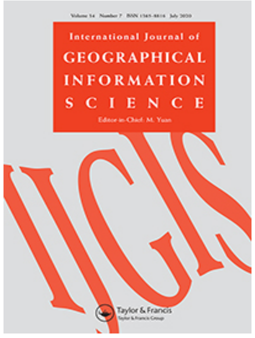

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RESEARCH ARTICLE

Simulating urban land use change by integrating a convolutional neural network with vector-based cellular automata

Yaqian Zhai *[a,b], Yao Yao *[a,b], Qingfeng Guan [a,b], Xun Liang[a,b], Xia Li [c], Yongting Pan [a,b], Hanqiu Yue [a,b], Zehao Yuan[a,b] and Jianfeng Zhou[a,b]

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ABSTRACT

Vector-based cellular automata (VCA) models have been applied in land use change simulations at fine scales. However, the neighborhood effects of the driving factors are rarely considered in the exploration of the transition suitability of cells, leading to lower simulation accuracy. This study proposes a convolutional neural network (CNN)-VCA model that adopts the CNN to extract the high-level features of the driving factors within a neighborhood of an irregularly shaped cell and discover the relationships between multiple land use changes and driving factors at the neighborhood level. The proposed model was applied to simulate urban land use changes in Shenzhen, China. Compared with several VCA models using other machine learning methods, the proposed CNN-VCA model obtained the highest simulation accuracy (figure-of-merit = 0.361). The results indicated that the CNN-VCA model can effectively uncover the neighborhood effects of multiple driving factors on the developmental potential of land parcels and obtain more details on the morphological characteristics of land parcels. Moreover, the land use patterns of 2020 and 2025 under an ecological control strategy were simulated to provide decision support for urban planning.

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Land use change; convolutional neural network; cellular automata; fine scale; urban planning

1. Introduction

Urbanization is a complicated socio-economic process that occurs worldwide (Deng *et al.* 2009). With the increasing urban population and rapid urbanization, urban lands have been gradually expanding, and the patterns of urban landscape change have become complex (Wang *et al.* 2012). Land use changes are related to many factors, such as the topography, transportation, population, location, and public facilities (Li *et al.* 2003, Zhang *et al.* 2018, Wang *et al.* 2017,). How to effectively explore the dynamic mechanism of urban land use changes at fine scales has always been an important problem.

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Geospatial tools and models are useful for understanding the mechanisms and processes of urban expansion and land use change (Li *et al*. 2017). Cellular automata (CA) can be used to model complex geographic processes through a bottom-up approach (Batty and Xie 1994, White and Engelen 2000). Since the 1990s, CA models have been extensively applied in urban expansion and urban land use simulations (Clarke *et al*. 1997, Li and Yeh 2002, Santé *et al*. 2010, Li *et al*. 2017).

Raster-based CA models, which are used in many land use change studies, often use regularly shaped and sized (mostly square or rectangular) grids as the basic cell units (Li and Yeh 2000, Fan *et al*. 2008, Jokar Arsanjani *et al*. 2013, Liu *et al*. 2017). However, ground objects are mostly irregular polyhedrons with different sizes. It is difficult to reflect real shapes by using regularly shaped cells to represent arbitrary geometric entities. Patch-based CA models, in which the entities are represented as patches, have been proposed based on the raster-based CA (Wang and Marceau 2013, Chen *et al*. 2014, 2016). The basic cell units of patch-based CA are still regularly shaped grids, which still have limitations in revealing the actual shapes of land parcels. The deficiencies of the raster-based CA and patch-based CA models become more obvious when simulating complex urban systems at fine scales (Cao 2011, Barreira-González *et al*. 2015).

Vector-based CA models, whose cells are shaped as polygons in the vector data structure to represent arbitrarily shaped land units, have been proposed and applied in urban growth simulation (O'Sullivan 2001, Moreno *et al*. 2008, Lu *et al*. 2015). Among all the vector-based models, those based on cadastral parcels can more realistically represent ground objects, which is conducive to achieving high simulation accuracy in urban areas (Stevens and Dragićević 2016). Urban land use change is a gradual and fragmented process rather than one in which an entire land parcel is completely converted from one land use type to another in a short period (Sun *et al*. 2015). Therefore, Yao *et al*. (2017) proposed a dynamic land parcel subdivision (DLPS)-VCA model, which splits cadastral parcels into smaller parcels that are used as the cell units. Thus, it is able to simulate the land use change process at the land parcel scale.

In many CA models, the transition probability of each cell consists of four parts: the transition suitability, the neighborhood land-use condition, the constraint coefficient and the stochastic factor (Li and Yeh 2002). The neighborhood land-use condition refers to the land use pattern within the neighborhood of a certain cell, and it is often determined by the amounts and distribution of the cells of various land use types inside the neighborhood. The constraint coefficient refers to the control measurements that prohibit specific land use types (e.g. water areas and protected areas) from being converted into other land use types during the simulation. The stochastic factor is a random variable that is incorporated into CA models to reflect the uncertainty and randomness in urban systems (White and Engelen 1993). The transition suitability refers to the combined effect of a variety of driving factors on the land use type of the cell, mainly including topographic, transportation, location and socioeconomic factors (Li *et al*. 2008).

The transition suitability reflects the relationships between the land use types/changes and driving factors, and such relationships can be derived using statistical or machine-learning methods (e.g. logistic regression, artificial neural network, and support vector machine) with historical data (Wu 2002, Li and Yeh 2002, Feng *et al*. 2016). In many studies, the transition suitability of a cell is usually regarded as a local condition, meaning that only the attributes of the driving factors of the cell of interest are considered (He *et al*.

2018). However, the attributes of the driving factors within a cell's neighborhood also have impacts on the suitability of a land use type of the cell, and such neighborhood effects are largely ignored in previous models. A new method that takes into account the neighborhood effects of the driving factors when determining the transition suitability for each cell is therefore needed.

The relationships between multiple driving factors and the development potential of a cell are often complex and nonlinear. Machine learning methods, such as artificial neural network (ANN) (Pijanowski *et al*. 2002), random forest (RF) (Kamusoko and Gamba 2015) and support vector machine (SVM) (Feng *et al*. 2016) have been used to handle these complex relationships, but they are incapable of retrieving the high-level features of the spatial distributions of the driving factors within a neighborhood and discovering their relationships with the land use type/change of the central cell. The convolutional neural network (CNN), a typical deep learning model that has been widely used in image recognition, can provide a promising solution since it is able to extract the high-level features using convolution kernels to process the raw neighborhood information of each pixel of an image (LeCun *et al*. 2015, Rawat and Wang 2017). CNNs are multilayer feedforward networks that allow information to flow from their inputs to their outputs in one direction only. In general, CNN architectures consist of convolutional layers, pooling layers, and fully connected layers. Serving as feature extractors, the convolutional layers can learn the feature representations of their input information (Rawat and Wang 2017).

Besides image recognition, CNNs have also been used in computer vision, speech recognition, document analysis, and natural language processing (Krizhevsky *et al*. 2012, LeCun *et al*. 2015). Many scholars have applied the CNN method in geographic studies. For example, Ding *et al*. (2015) investigated the consumption intentions of individuals using social media data by using a domain adaptive CNN. Du *et al*. (2018) adopted CNN models to analyze the public perception of a measles outbreak using Twitter data.

He *et al*. (2018) obtained better simulation results by introducing the CNN into a raster-CA model for urban expansion simulation, demonstrating the CNN's capability of obtaining the complex features of the driving factors within the neighborhood of each cell. However, He et al.'s study focused only on the urbanization process (i.e. non-urban to urban), and the simulation of the land use changes among multiple types is much more complicated but of great importance for understanding land use dynamics and making sustainable land use plans (Deng *et al*. 2015).

Furthermore, the integration of the CNN and VCA faces a challenge since the CNN is primarily applicable to raster data (e.g. images) with regularly shaped units (e.g. pixels) and the cells of VCA are irregularly shaped polygons. A mechanism is therefore needed to allow a CNN to extract the high-level features of the driving factors within a neighborhood of an irregularly shaped cell and to discover the relationships between multiple land use types/changes and the driving factors at the neighborhood level (i.e. the transition suitability of a cell).

To tackle the aforementioned challenges, this study proposes using a CNN-VCA to simulate the land use changes of land parcels. First, the land parcels were split into smaller parcels as the cell units of the VCA. The driving factors are organized as raster datasets, and a CNN is constructed to extract the high-level features of the driving factors within the neighborhood of each cell. The random forest (RF) is then used to derive the relationship between the land use changes of cells and the neighborhood-scope features of the driving factors. Once trained using historical samples, the CNN-RF module is used to calculate the transition suitability of every cell, which is then combined with the neighborhood land-use condition, constraint coefficient, and stochastic factor to generate the transition probability of each cell during the VCA simulation. The proposed CNN-VCA model was used to simulate the urban land use changes from 2009 to 2012 in Shenzhen, China, and the performance was assessed. Also, the land use patterns of 2020 and 2025 under an ecological control strategy were simulated using the proposed model combined with a constrained Markov chain method.

2. Methods

In this study, a CNN-VCA model is proposed to simulate the land use changes in urban areas. As shown in Figure 1, our proposed model contains four main parts. (1) Basic cell unit of the VCA model: The land parcels are divided into smaller parcels as the basic cells using a binary recursive strategy. (2) Transition suitability using the CNN: With the constructed driving factors dataset within the neighborhood of each parcel and sampled land use change data, a CNN is built to extract the high-level features of the driving factors within the cell's neighborhood. Then, the softmax classifier in CNN is replaced by an RF classifier to excavate the relationships between the land use changes of cells and the

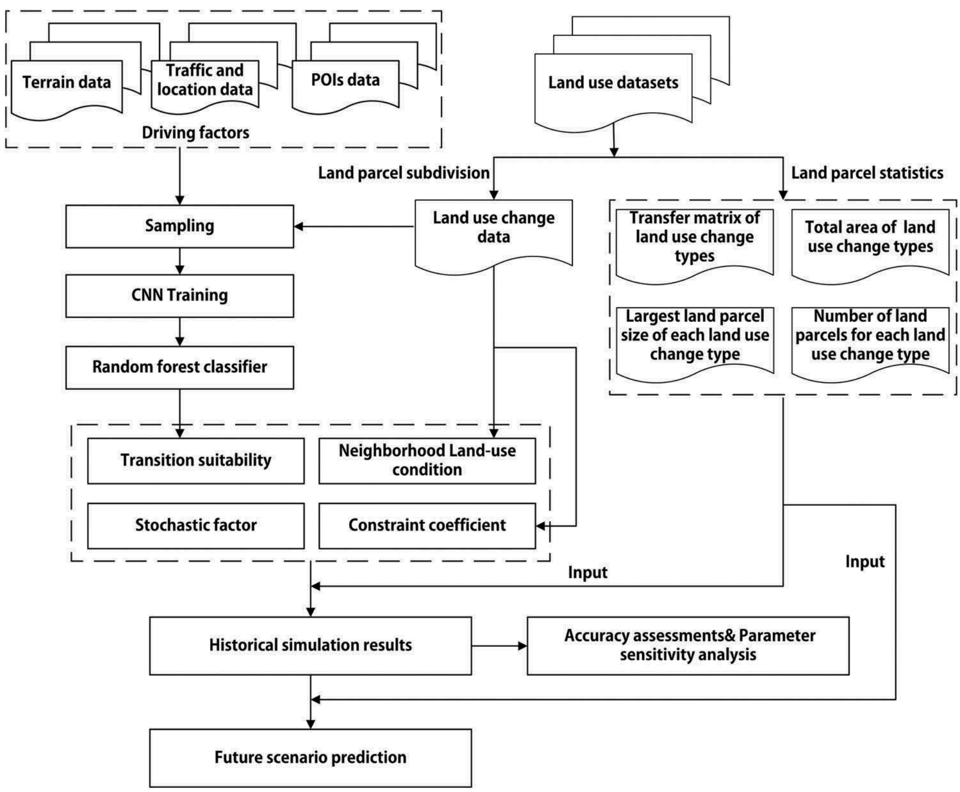

Figure 1. Flowchart of urban land use change simulation via the proposed CNN-VCA model.

neighborhood-scope features of driving factors. Once trained using historical data, the CNN-RF module can be used to calculate the transition suitability of each cell. (3) CNN-based VCA simulation: The transition probability of each cell during the VCA simulation is calculated through the combination of the transition suitability, neighborhood land-use condition, constraint coefficient and stochastic factor. The parameters of the CNN-VCA model are calibrated through statistical methods using historical data. (4) Accuracy assessment and future prediction: The calibrated model is used to simulate the past land use change history, and the modeling performance is assessed. Then, the model can be used to generate future land use patterns under various scenarios to test planning decisions and policies.

In this study, the CNN and RF methods were implemented using the Python language and several open-source libraries, such as Keras, Sklearn, Numpy and Pandas. The VCA model was implemented using the C++ language and several open-source libraries such as GDAL and QtCore.

2.1. Transition suitability by CNN

The land use change data are obtained based on historical data, and the change types are encoded into five categories: 0, 1, 2, 3, and 4. Code 0 represents unchanged, code 1 represents nonurban land converted to public management-services land, code 2 represents nonurban land converted to commercial land, code 3 represents nonurban land converted to residential land, and code 4 represents nonurban land converted to industrial land. Then, a binary recursive strategy is adopted to divide the land parcels into smaller parcels as the basic cell units of the VCA model (Yao *et al*. 2017).

The driving factors dataset within the neighborhood of each parcel is constructed with a regular sampling window. First, the data of each driving factor are organized as a raster layer. Then, the centroid of each parcel polygon is extracted, and the row-column position within the raster driving factor data corresponding to the centroid of each parcel is obtained. Then, the driving factor dataset is constructed using an $N \times N$ sampling window around each central pixel (i.e. the centroid of each parcel polygon) over the raster layer of the driving factor such that each parcel will have $N \times N$ features for each driving factor. The size of the sampling window is determined by the combination of the influence distance of the driving factor and the spatial resolution of the driving factor data. Therefore, when a total of M driving factors are used, after sampling, the number of driving factor features corresponding to each parcel would be $N \times N \times M$ (Figure 2).

Then, the CNN network structure is built to extract the high-level features of the constructed driving factors dataset. The structure of the CNN model consists of seven network layers: 3 convolutional layers, 2 pooling layers, 1 fully connected layer and a softmax classifier layer (Yao *et al*. 2018). The first layer is the convolutional layer consisting of sixteen 3×3 convolutional kernels, and a $(N\text{-}2) \times (N\text{-}2) \times 16$ feature map is obtained. The second layer is the 2×2 pooling layer, generating a $(N\text{-}2)/2 \times (N\text{-}2)/2 \times 16$ feature map. The third layer is constructed as thirty-two 3×3 convolutional kernels, and the fourth layer is also a 2×2 pooling layer. The fifth layer is also a convolutional layer similar to the third layer, producing a $(N\text{-}14)/4 \times (N\text{-}14)/4 \times 32$ feature map. The next layer is the fully connected layer with 96 neurons. Finally, a softmax layer is adopted to calculate the probability for each land use change type. The specific structure and the

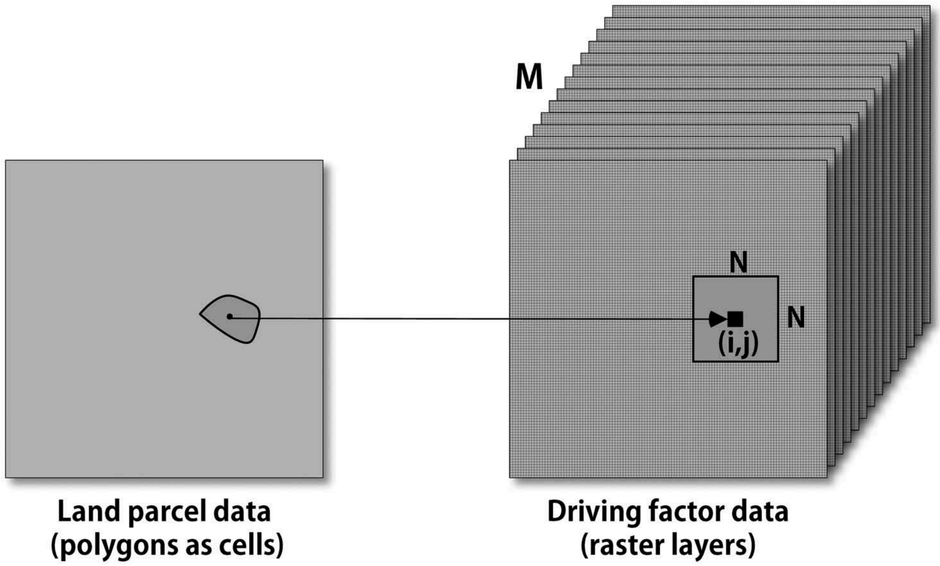

Figure 2. The constructed driving factors dataset within the neighborhood of each parcel.

basic process of the CNN model are shown in Figure 3. Then, the constructed driving factor dataset and land use change data are put into the CNN model for training. After multiple iterations of training and feedback, an optimal CNN model is selected and the complex neighborhood-scope features of driving factors are extracted.

Next, the softmax classifier in the CNN model is replaced with a random forest (RF) classifier to excavate the relationships between the neighborhood-scope features of the driving factors and the land use changes of cells. Previous studies have shown that the random forest is the most effective classifier that can achieve better classification results than other machine learning classifiers (Fernández-Delgado *et al*. 2014). The RF is an ensemble with a set of decision trees that fits on various sub-datasets and uses averaging to improve the predictive accuracy and control overfitting (Biau 2012). Each sub-dataset is generated using the extracted random samples from the original training dataset (Breiman 2001). The final classification results are determined based on the voting record of all decision trees. Therefore, this study replaces the softmax classifier in the CNN model with the RF for land use change classification fitting, and it uses the extracted driving

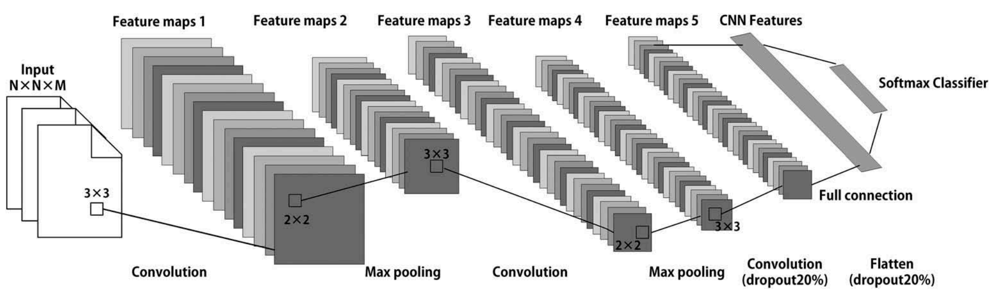

Figure 3. The built CNN model framework.

factor features and sampled land use change data as inputs. After the training with historical data, the CNN-RF module can be used to calculate the transition suitability for each parcel.

2.2. CNN-based VCA simulation

Previous studies have shown that CA models can achieve good performance in urban growth and land use change simulations (Li *et al.* 2017). CA models have four basic elements: cells, states, neighborhoods, and transition rules. In many CA models, the transition probability P of each cell is calculated by integrating four parts: the transition suitability P_g, the neighborhood land-use condition Ω, the constraint coefficient P_c and the stochastic factor RA (Li and Yeh 2002).

The transition suitability P_g for a land use change type g for each parcel is calculated using the calibrated CNN-RF module mentioned above. As an important factor in the CA model, the neighborhood land-use condition Ω is determined by the number and distribution of the land use types within the neighborhood. In vector-based CA models, how to determine the neighborhood land-use condition Ω based on an appropriate rule has always been a difficult issue. Dahal and Chow (2015) study indicated that the neighborhood delineation method of a centroid-intercepted buffer performs better than other methods for urban expansion simulation. Therefore, the neighborhood land-use condition Ω in this study is calculated based on weighting the land parcel areas by using the centroid-intercepted buffer method to delimit the neighborhood range for each parcel (Yao *et al.* 2017). As a vital parameter in calculating the neighborhood land-use condition, the buffer distance is set between 500 m and 1500 m. Based on many trial and error approaches, the calibrated value of the buffer distance would be determined.

The constraint factor controls whether a specific land use type is allowed to change to another type during the simulation. The constraint coefficient P_c of restricted development areas is 0 and that of areas that are suitable for development is 1. According to the historical data, water areas, special land, protected areas, roads, and transportation and logistics land are set as restricted development areas in the simulation procedure. Actually, the influencing factors and dynamic mechanisms of land use change are very complicated. Some urban expansion areas are stochastic and unpredictable. Therefore, the stochastic factor RA is introduced into the VCA simulation as a stochastic disturbance term. $\mathrm{RA} = 1 + (-\ln y)^{\alpha}$, where α is a parameter between 1 and 10, and y is set as a stochastic value between 0 and 1.

In short, the transition probability of the *k*-th land use change type that occurred in the *i*-th parcel at time t is described as follows:

$$P_i^{k,t} = Pg_i^{k,t} \times \Omega_i^{k,t} \times Pc_i^t \times RA \tag{1}$$

where$P_i^{k,t}$ is the transition probability that the *k*-th land use change type that occurred in cell i at time t. $Pg_i^{k,t}$ is the transition suitability of the *k*-th land use change type that occurred in cell i at time t. $\Omega_i^{k,t}$ refers to the neighborhood land-use condition of cell i at time t. Pc_i^t refers to the constraint coefficient of the cell's development. RA is a random factor value. The land use change type is determined by the highest value of the transition probability.

To ensure that the simulation results are close to the actual land uses, the parameters need to be calibrated based on historical data. The total area of each land use change type, the largest parcel size for each use change type, and the number of parcels for each use change type are obtained by applying a statistical method to the land parcels using historical land use data.

In the VCA simulation procedure, the max area of each change type from time t to time t + 1 is set based on the total area of each land use change type. As an important parameter, the maximum area of each change type is set to avoid an oversized parcel from entirely changing from one land use type to another type. This means that if a parcel's area is larger than the maximum area that is set in the VCA model, it will be not allowed to convert to another type. The transition threshold is a crucial parameter that directly determines the simulation results. The transition probability of each parcel is calculated by Equation 1, which was given above. If all the parcels' transition probabilities corresponding to each change type are sorted, then the threshold value of the *k*-th change type is the *S*-th parcel's transition probability value of the *k*-th change type, where S is equal to the number of parcels of the actual change type.

2.3. Accuracy assessment

To quantitatively evaluate the land use simulation results, the figure of merit (FoM) is adopted to conduct the accuracy assessment. The FoM is an indicator that is more focused on the amount of variation in the simulation process (Pontius *et al*. 2008). It is equal to the ratio of the intersection of the observed changes and simulated changes to the union of the observed changes and simulated changes. The equations are as follows (Pontius *et al*. 2008):

$$\mathrm{FoM} = \frac{\mathrm{B}}{\mathrm{A}+\mathrm{B}+\mathrm{C}+\mathrm{D}} \tag{2}$$

$$\mathrm{Producer}'\mathrm{saccuracy}(\mathrm{PA}) = \frac{\mathrm{B}}{\mathrm{A}+\mathrm{B}+\mathrm{C}} \tag{3}$$

$$\mathrm{User}'\mathrm{saccuracy}(\mathrm{UA}) = \frac{\mathrm{B}}{\mathrm{B}+\mathrm{C}+\mathrm{D}} \tag{4}$$

where A denotes the area with an observed change that the simulation predicts to be unchanged. B denotes the area that has an observed change and a simulated change to the correct category. C denotes the area that has an observed change for which the simulation predicted a change to the wrong category. D is the area that is observed to be unchanged for which the simulation predicts a change.

Additionally, a set of landscape indices (LIs) are used to assess the landscape pattern similarity between the actual and simulated land use (Seto and Fragkias 2005, Zhao *et al*. 2012, Chen *et al*. 2014). Several LIs (including the number of urban patches (NP), the mean Euclidean nearest-neighbor distance (ENN), the mean perimeter-area ratio (PARA), and the largest-patch index (LPI) were calculated by Fragstats 4.2 (McGarigal *et al*. 2012). The similarity is estimated by the average difference of the above LIs. The equations are as follows (Chen *et al*. 2013):

$$\Delta I_i = \begin{cases} \left|\mathrm{I}_{i,s} - \mathrm{I}_{i,o}\right| / \mathrm{I}_{i,o}, & \mathrm{I} = \mathrm{NP}, \mathrm{ENN}, \mathrm{PARA} \\ \left|\mathrm{I}_{i,s} - \mathrm{I}_{i,o}\right|, & \mathrm{I} = \mathrm{LPI} \end{cases} \tag{5}$$

$$a_l = 1 - \frac{1}{n}\sum_i \Delta I_i \tag{6}$$

where $\mathrm{I}_{i,s}$ and $\mathrm{I}_{i,o}$ indicate the *i*-th LI of the simulated and actual land use, respectively, and ΔI_i represents the difference of the *i*-th LI. In Equation 6, a_l is the landscape pattern similarity between the actual and simulated land use, and n refers to the number of LIs.

3. Case study area and data

Shenzhen is situated in Guangdong Province of China on the east coast of the Pearl River Estuary. It has a residential population of approximately 12.528 million and a total area of 1997.47 km^2 (http://www.sz.gov.cn/cn/zjsz/gl/). Shenzhen had a GDP of 2,243.839 billion yuan in 2017, ranking third among large and medium-sized cities on the Chinese mainland (http://www.sztj.gov.cn/). Shenzhen is one of the economic, financial, and technology innovation centers in China with four pillar industries including the following: cultural and creative, high-tech, modern logistics and finance.

As shown in Figure 4, Shenzhen has ten administrative districts, including Futian, Luohu, Yantian, Nanshan, Baoan, Longgang, Longhua, Pingshan, Guangming, and Dapeng districts. In Shenzhen, Futian, Luohu, Yantian and Nanshan are the primary and most economically developed of the downtown districts. Futian and Luohu, as the earliest-developed areas, are the main financial and commercial districts of Shenzhen (Chen and Zacharias 2015). Nanshan features a large number of listed companies, and it is also an education center. It ranks first among all districts' GDPs and accounts for approximately 20% of the overall GDP of Shenzhen.

Figure 4. Case study area: Shenzhen, China.

This study adopts the cadastral land use data for 2009, 2012 and 2014 from the Bureau of Land and Resources of Shenzhen. The land use data contain five land use types: nonurban land, public management-services land, commercial land, residential land, and industrial land (Figure 5). Among them, public management-services land, commercial land, residential land, and industrial land are urban land types.

According to the statistics of the land use data, the total numbers of land use parcels in 2009, 2012, and 2014 were 104,608, 114,541, and 123,325, respectively. The total area percentages of nonurban land in 2009, 2012 and 2014 were 70.52%, 69.24%, and 68.73%, respectively, which means that the nonurban land area presented an obvious declining trend during 2009 to 2014. Otherwise, the areas of the other four urban land use types all showed increasing trends. As illustrated in Table 1, only 3.08% of the land was converted from one land use type to another from 2009 to 2014. The main change was from nonurban to the other four urban categories (public management-services land,

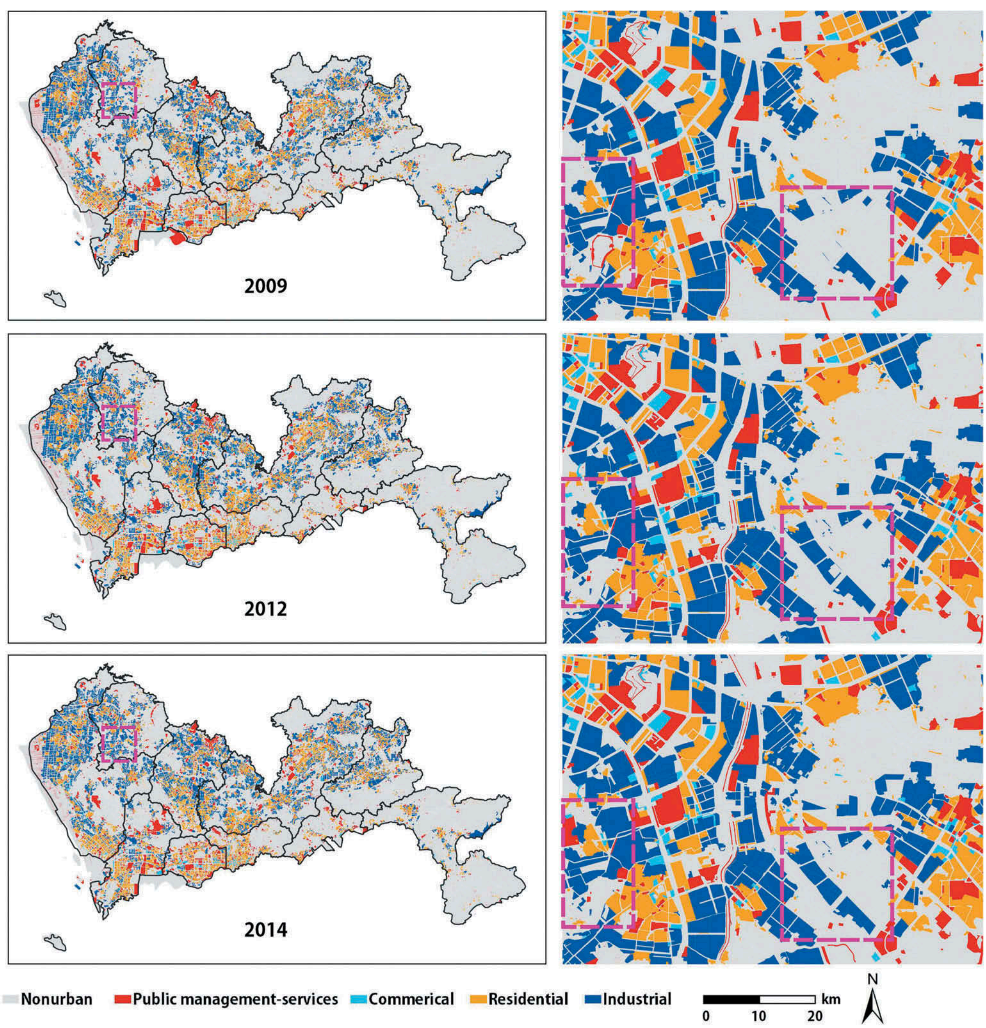

Figure 5. Urban land use data of Shenzhen in 2009, 2012 and 2014.

Table 1. Total areas of different land use change types from 2009 to 2014.

	Nonurban	Public management-services	Commercial	Residential	Industrial
Nonurban	1354.784	16.458	5.513	10.659	16.682
Public management-services	7.472	94.517	0.000	0.018	0.015
Commercial	0.345	0.014	25.998	0.000	0.000
Residential	0.235	0.001	0.000	187.577	0.001
Industrial	3.663	0.270	0.011	0.005	265.918

(unit: km^2)

commercial land, residential land, and industrial land). Few conversions occurred from urban land to nonurban land, and internal conversions among the four urban land use types were almost nonexistent. Therefore, this study only considers the transition from nonurban land to multiple urban land use types, neglecting the internal transition between urban land use types and the reverse urbanization process.

Land use change is influenced by transportation factors, location factors, the population density, public facilities, and government planning policy (Zhang *et al*. 2018). In this study, the location and transportation information, basic topographic information, and some POI information are applied as driving factors for the urban development simulation. Specifically, four location and transportation factors (including (a) the distance to district centers, (b) the distance to railways, (c) the distance to highways, and (d) the distance to main roads), two basic topographic factors (including (e) the DEM and (f) the slope), and eight POI density factors (including (g) the density of hospitals, (h) the density of bus stations, (i) the density of restaurants, (j) the density of entertainment facilities, (k) the density of parks, (l) the density of supermarkets, (m) the density of shopping malls, and (n) the density of factories) in study area were collected (14 total factors, M = 14). As shown in Figure 6, the driving factor data are organized as raster datasets with a 30-m resolution. In this study, the distance of the driving factors within the neighborhoods of cells is set as 1500 m so that the sampling window size is 50 × 50 pixels (N = 50). To eliminate the dimensional impacts among the different driving factors, the Min-max normalization method is used to scale all the values of the driving factors to [0, 1].

4. Results

4.1. Implementation results and comparisons

This study proposes a CNN-VCA model for simulating the land use changes of land parcels. The proposed model was applied in Shenzhen, China. Using the historical land use data and driving factors dataset, the CNN-VCA model was constructed and trained. Once calibrated, the proposed CNN-VCA model was used to simulate the urban land use changes from 2009 to 2012 in Shenzhen after three iterations and the performance was assessed. Moreover, three other VCA models (including logistic regression (LR)-VCA, artificial neural network (ANN)-VCA and random forest (RF)-VCA) were constructed and compared to test the effectiveness of the proposed CNN-VCA model. To verify the applicability of the proposed model, a simulation for 2014 was performed by using the calibrated CNN-VCA model after five iterations, and the simulation accuracy of the validation result was evaluated.

In the experiment, 50 × 50 pixels was set as the sampling window size for constructing the driving factors dataset within the neighborhood of each parcel. In the training of the

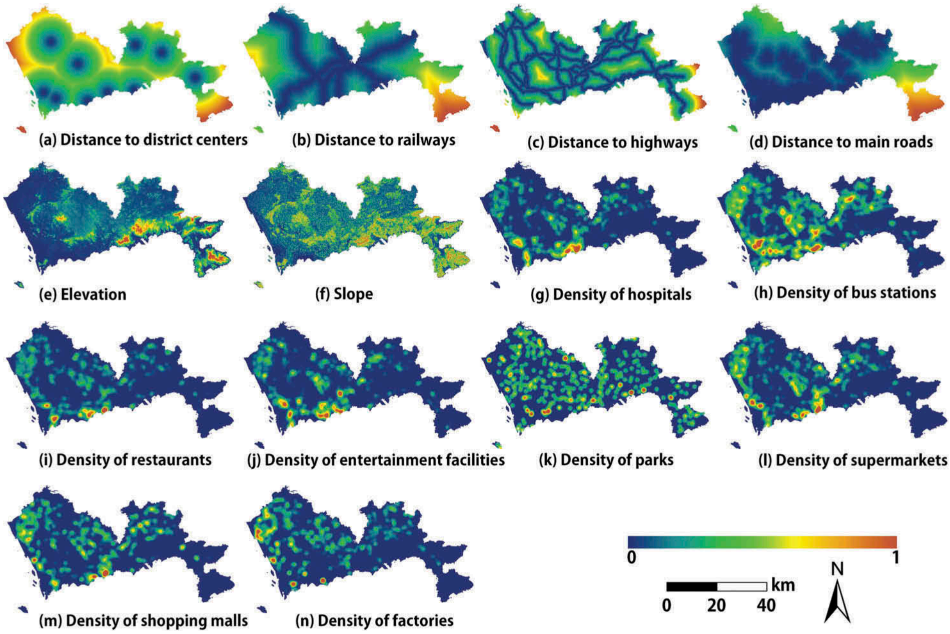

Figure 6. Driving factors dataset. (a) distance to district centers, (b) distance to railways, (c) distance to highways, (d) distance to main roads, (e) DEM, (f) slope, (g) density of hospitals, (h) density of bus stations, (i) density of restaurants, (j) density of entertainment facilities, (k) density of parks, (l) density of supermarkets, (m) density of shopping malls, (n) density of factories.

CNN model, 80% of the sampled data were used as training data, and the remaining 20% were used as validation data to assess the model's accuracy. After multiple iterations of training and feedback, the optimized CNN model was obtained. Then, the original soft-max classifier in the CNN model was replaced with the RF for fitting the land use changes classification. 60% of the dataset was selected as the training set for the random forest classifier, and the remaining 40% was used as the validation dataset to assess the module's classification accuracy.

Figure 7 shows the actual and simulated land uses in 2012 based on the four VCA models that were mentioned above. The results of accuracy evaluations are shown in Table 2. As shown in Table 2, the proposed CNN-VCA model achieved the best simulation result, which is much better than the LR-VCA and ANN-VCA results and is 11.8% better than that of the RF-VCA model. To the best of our knowledge, the reasons for urban land use change are very complicated and unpredictable. Actually, only a few land conversions occurred from 2009 to 2012 in the study area. It becomes more difficult to accurately simulate multiple land use changes within small changes. The results indicate that the CNN-VCA is capable of effectively mining multiple land use change transition rules.

Among the four VCA models that were constructed in this study, the LR-VCA and ANN-VCA models accurately simulate only a few actual converted land parcels. Conversely, the RF-VCA and CNN-VCA models both achieve relatively good simulation results. The simulation result of the CNN-VCA model is approximately 11.8% better than that of the RF-VCA model, which indicates that the CNN method of accounting for the neighborhood driving factor information is conducive to obtaining more accurate transition suitability. Previous

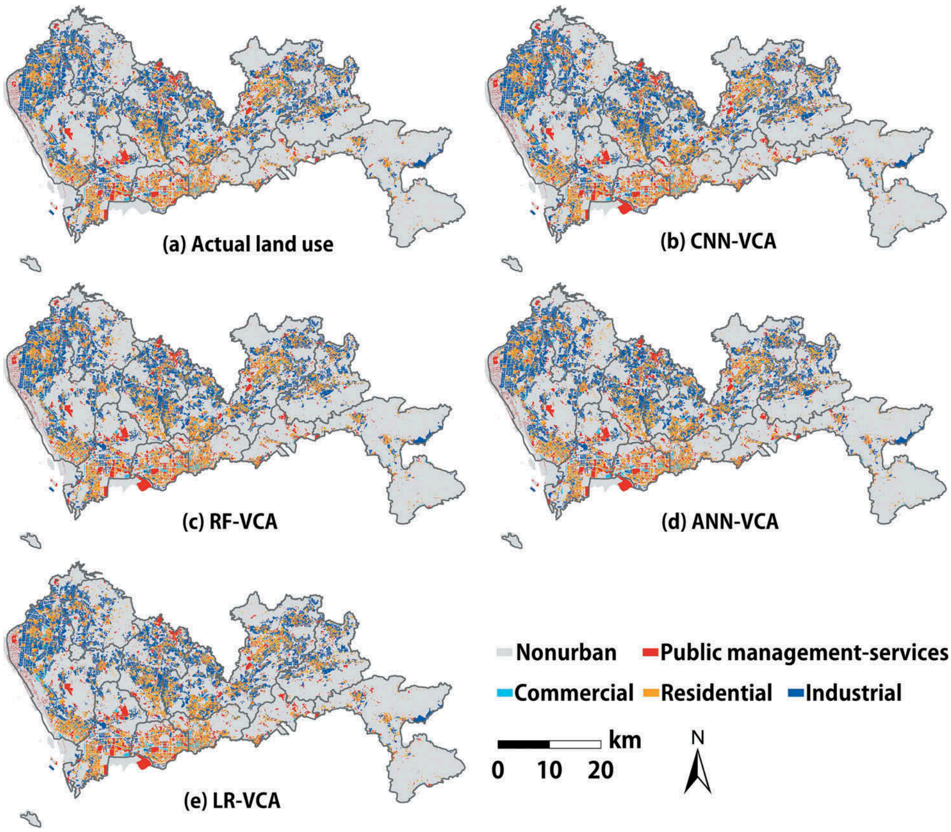

Figure 7. Actual and simulated land uses in 2012 in Shenzhen. (a) Actual land use, (b) simulated land use based on the CNN-VCA, (c) simulated land use based on the RF-VCA, (d) simulated land use based on the ANN-VCA, and (e) simulated land use based on the RF-VCA.

Table 2. The overall FoM of the simulated results via different models.

Results	LR-VCA	ANN-VCA	RF-VCA	**CNN-VCA**
FoM	0.023	0.078	0.323	**0.361**
PA	0.038	0.133	0.475	**0.514**
UA	0.054	0.149	0.498	**0.539**

studies have shown that the CNN method can automatically extract the abstract features of neighborhood spatial information, which contributes to obtaining better classification performance (Rußwurm and Körner 2017).

In this study, four landscape indices, including the NP (number of patches), the LPI (largest patch index), the ENN (Euclidean nearest neighbor distance), and the PARA (perimeter area ratio) are combined to evaluate the landscape similarity of the simulated and actual land uses. Table 3 shows the calculated results of the landscape similarity for the four models. Compared to the LR-VCA, ANN-VCA and RF-VCA, the CNN-VCA model obtains the highest landscape similarity (0.948) with the actual land use, and it approximately 2.8%-9.3% higher than those of the other three VCA models.

Table 3. Landscape indices of the simulated results based on different models.

Results	NP	LPI	ENN	PARA	Similarity
Actual land use	28,658	67.566	123.548	907.810	
LR-VCA	28,181	67.036	119.633	908.540	0.855
ANN-VCA	28,089	67.226	119.570	911.376	0.901
RF-VCA	28,246	67.293	119.521	909.212	0.920
CNN-VCA	28,329	67.411	119.762	914.829	0.948

Figure 8 shows the results of the actual and simulated land use changes from 2009 to 2012 using the four VCA models that were mentioned above. Moreover, four typical areas are selected to demonstrate some details of the actual and simulated land use changes of land parcels (Figure 9). The details indicate that the CNN-VCA model and the RF-VCA model both achieve good performance with respect to matching the actual converted land distribution. The ANN-VCA and LR-VCA models have difficulty capturing the location of the actual converted land. Moreover, compared to the RF-VCA model, the simulation results of the proposed CNN-VCA model are more similar to the morphological

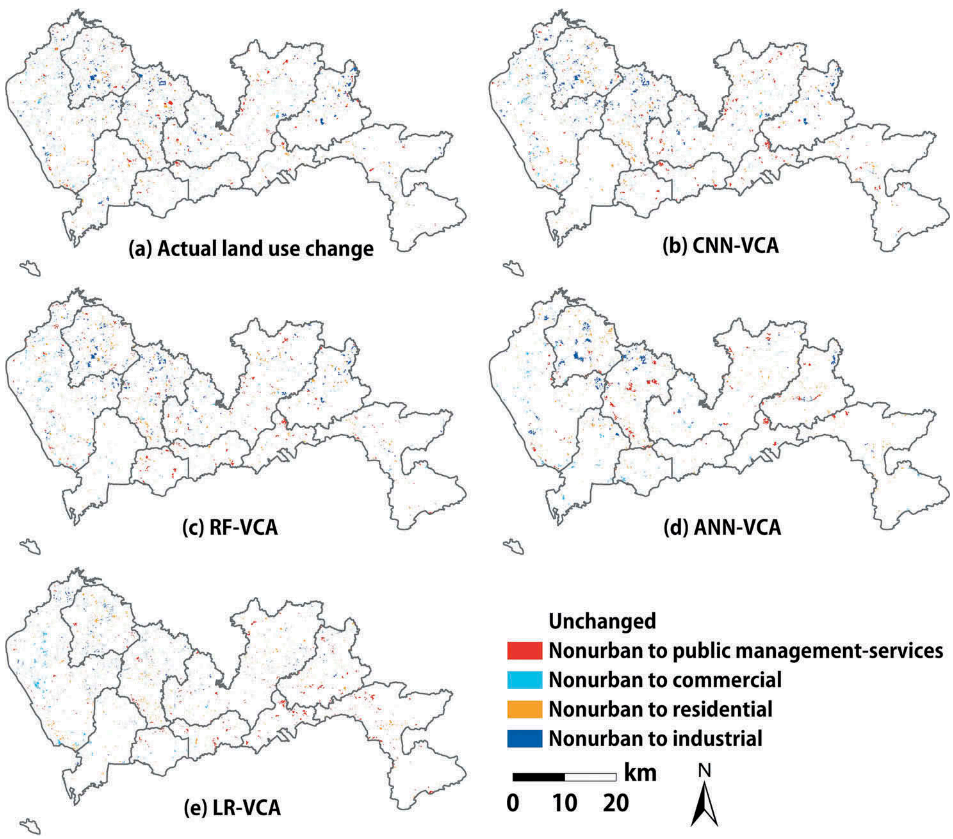

Figure 8. Actual and simulated land use changes in Shenzhen from 2009 to 2012. (a) Actual land use change, (b) simulated change using the CNN-VCA, (c) simulated change using the RF-VCA, (d) simulated change using the ANN-VCA, and (e) simulated change using the LR-VCA.

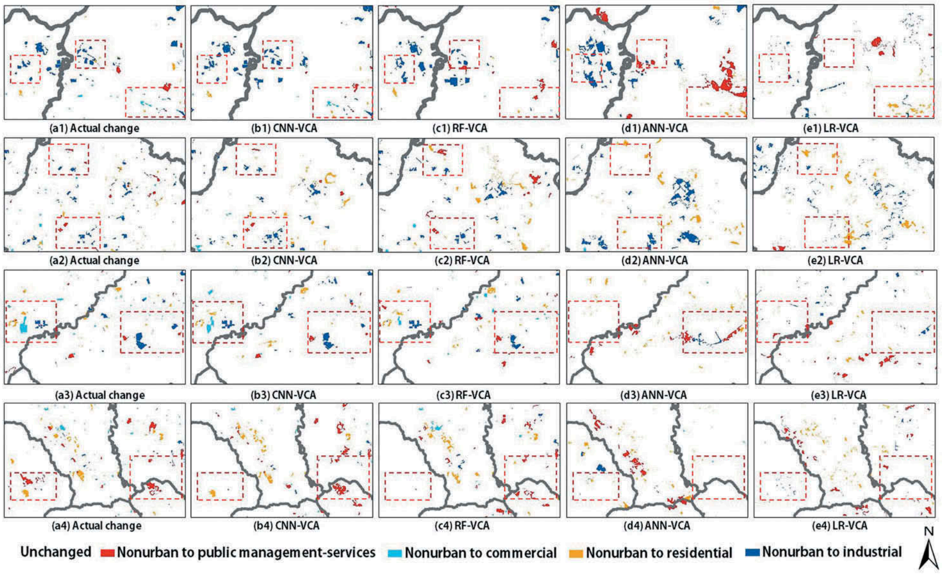

Figure 9. Details of actual and simulated land use changes from 2009 to 2012. (1) Baoan district and Longhua district; (2) Guangming district; (3) Longgang district and Pingshan district; (4) Nanshan district and Luohu district.

characteristics of the actual converted land parcels. Some are almost completely consistent with the actual land edge contours.

4.2. Details of the implementation results of the CNN-VCA

According to the historical land use data, most of the land that underwent conversion from 2009 to 2012 was originally agricultural land or unused land that gradually changed to urban land use. Among the four land use change types, the conversion of nonurban to industrial land has the largest total area proportion with several large concentrated areas, representing a relatively aggregated spatial distribution. The simulation result accuracy for nonurban land converted to industrial land is far higher than those of the other three change types (FoM = 0.466). The CNN-VCA model can achieve better performance at accurately capturing the conversion of nonurban to industrial land.

The distribution of the nonurban land converted to residential land is relatively scattered with no concentrated areas and it is present in small areas with a spatially-sporadic distribution. The change from nonurban to commercial land is the smallest among the four nonurban-to-urban change types, and it has a very scattered spatial distribution, which makes it more difficult to accurately simulate. The FoMs for nonurban land converted to residential land and nonurban land converted to commercial land reached 0.355 and 0.297, respectively, which means that the CNN-VCA model also shows a good ability to simulate these two land use change types.

The simulation accuracy of the change from nonurban land to public management-services land is the lowest among the four nonurban-to-urban change types (FoM = 0.248). This change type may be greatly affected by national policies and government planning programs, which are very hard to accurately simulate with the constructed model (Huang *et al*. 2015, Qian *et al*. 2016).

The accuracy results of the ten administrative districts in Shenzhen are shown in Table 4. The simulation results in the Pingshan district, Futian district, Longhua district and Baoan district are higher than the average FoM in Shenzhen. The results show that Pingshan, Longhua and Baoan, as the main manufacturing bases, are in line with the current development pattern, and are less subject to government policy intervention. The accuracy of the simulation results in the Guangming district and the Longgang district is consistent with the simulation accuracy of Shenzhen overall. The FoM values for the Luohu district, Dapeng district, Nanshan district and Yantian district are significantly below the average simulation accuracy of the entire study area. As the economically developed downtown districts, nonurban land conversions to urban land use rarely occur in the Luohu, Yantian and Nanshan districts, which enhances the difficulty of accurate simulations. Dapeng, as a newly developing area, is greatly affected by government planning policy.

Moreover, to verify the applicability of the proposed model, a simulation for 2014 was performed by using the calibrated CNN-VCA model, and the performance was assessed. The results show that the validation FoM is 0.286, and the PA and UA are 0.435 and 0.442, respectively. Urban land use change is a complicated dynamic process with a lot of uncertainty and randomness (Ye *et al*. 2015). The predicted result for 2014 is rather weaker that the simulated result for 2012, but still achieves good performance. These results indicate that the proposed CNN-VCA model can be well applied for simulating the land use changes of land parcels.

4.3. CNN-VCA parameter sensitivity analysis

The size of the sampling window directly affects the coupling neighborhood driving factors information of each parcel, which has an uncertain influence on the final simulation accuracy. Therefore, it is necessary to explore the trend in the relationship between different sampling window sizes and the accuracy of the corresponding simulated result. Additionally, in the training process of the CNN module, the batch size is an important parameter that may be related to the final optimal CNN model, which determines the extracted driving factors dataset within the neighborhood of each parcel.

Table 4. FoMs of the simulated results based on the CNN-VCA model for different districts.

Districts	FoM	PA	UA	Actual change (km^2)
Futian	0.419	0.775	0.477	0.674
Luohu	0.259	0.529	0.334	0.831
Nanshan	0.178	0.195	0.671	2.050
Yantian	0.177	0.402	0.239	1.055
Baoan	0.389	0.577	0.528	7.951
Guangming	0.356	0.524	0.515	5.782
Longhua	0.399	0.518	0.621	7.015
Longgang	0.344	0.511	0.503	6.317
Pingshan	0.434	0.535	0.692	4.608
Dapeng	0.215	0.368	0.333	1.880
Shenzhen	0.361	0.514	0.539	38.163

To analyze the effect of the input parameters on the final simulation result, this study conducted a set of experiments with a series of batch sizes based on different window sizes of 30 × 30, 40 × 40, and 50 × 50. Figure 10 shows the FoM results for 2012 with the different batch sizes and different sampling window sizes. The simulation accuracy varies between 0.338 and 0.361 and lacks an obvious trend. The overall simulation accuracies for the three window sizes are not significantly different, and the highest value is 0.361 at the batch size of 640 based on the window size of 50 × 50. This result shows that the distance range for the neighborhood effect of the driving factors on a parcel in the study area is within 1500 meters. How to determine the appropriate impact range is a question worthy of future study.

4.4. Future scenario simulation

The proposed CNN-VCA model can be applied to simulate future urban development in Shenzhen. To effectively predict future land use in Shenzhen, based on the combination of the constrained Markov chain method and the historical data on the conversion of nonurban land to the four urban land types (Fan *et al*. 2008), the future land uses under the scenario of sustainable development with an ecological control strategy are simulated and shown in Figure 11.

The scenario of sustainable development with an ecological control strategy is a Chinese government policy for protecting its natural ecosystems. In this strategy, the land within the ecological conservation red line is not allowed to develop into urban land. According to the historical land use data for 2009, 2012 and 2014, most of the land that has been converted from nonurban to urban land uses was originally agricultural land and unutilized land. However, most of agricultural land is inside the ecological conservation red line data, which means that some land is restricted from developing into urban land, even though its transition probability suggests otherwise.

Based on the proposed CNN-VCA model, the 2020 simulation result is obtained through six iterations starting with 2014. Similarly, the 2025 land use is also obtained

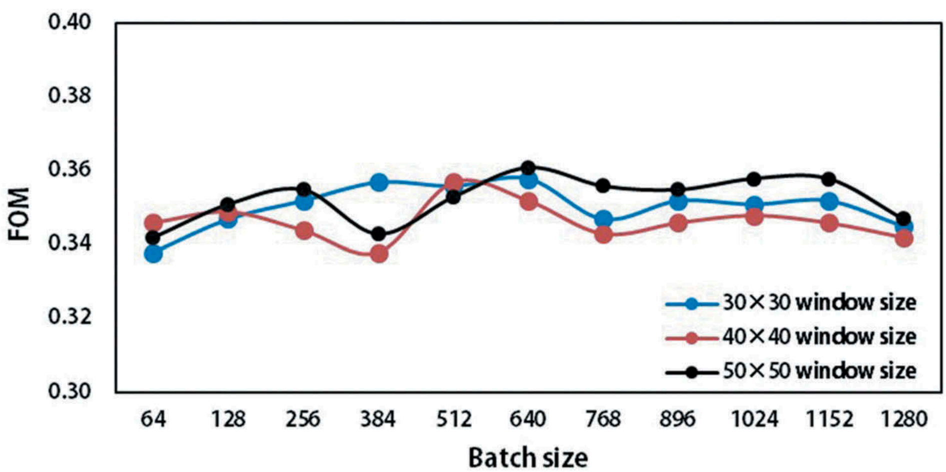

Figure 10. Accuracy assessments for different window sizes with different batch sizes.

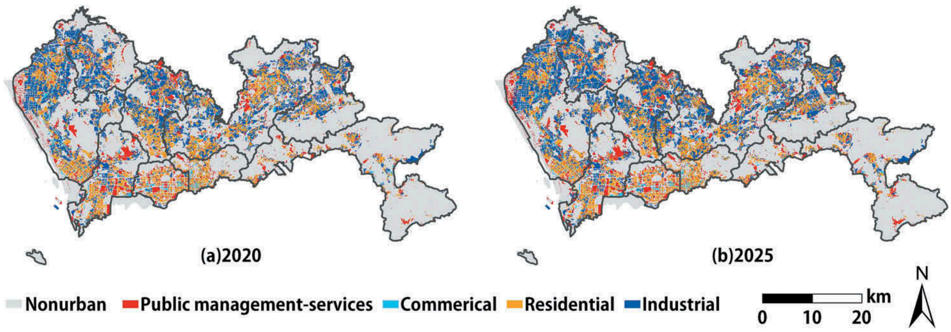

Figure 11. The simulated results for 2020 and 2025 under ecological control.

Table 5. Total simulation area of each land use change type under ecological control.

	Unchanged	Nonurban to public management-services	Nonurban to commercial	Nonurban to residential	Nonurban to industrial
2014–2020	1925.872	21.547	6.999	15.304	25.567
2020-2025	1937.833	17.958	2.583	13.318	23.597

(unit: km^2)

through eleven iterations based on the land use data from 2014. Table 5 shows that the total area of nonurban land that changed to urban land use is 69.417 km^2 from 2014 to 2020 and 57.756 km^2 from 2020 to 2025.

Figure 12 shows some of the details of the simulated change results for 2014–2020 and 2010–2025. The area of nonurban land that was converted to industrial land is mainly in the Guangming district, Longhua district, Pingshan district and Longgang district in 2020,

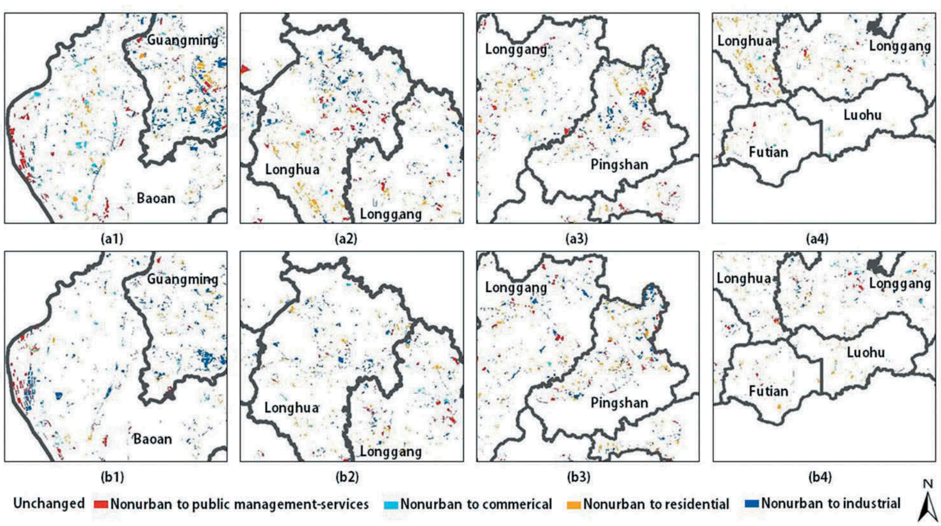

Figure 12. Details of the simulated change results for 2014–2020 and 2020–2025 under ecological control. (a1-a4): Details of the simulated change results for 2014–2020, and (b1-b4): Details of the simulated change results for 2020–2025.

and it is in the Guangming district and the Baoan district in 2025. These districts are in the process of rapid development. The predicted results align well with the actual industrial expansion distribution. The area of nonurban land that changed to public management-services land is sparsely distributed over the entire Shenzhen area in 2020 and 2025. The area of nonurban land that changed to commercial land is mostly in the Baoan district, with some in the Longhua district and the Longgang district in 2020, but little area exists in 2025. The conversion of nonurban land to residential land has several significant aggregated small areas in 2020 but no obvious aggregated areas in 2025.

The simulated results reveal that Shenzhen tends to continue to develop manufacturing around the edge of the existing industrial cluster area in the Guangming, Longhua and Pingshan districts, and a significant shortage of commercial and residential development areas will exist in the future, showing an unbalanced spatial relationship between jobs and housing. To optimize the refined utilization of the existing undeveloped land, the 'job-housing balance' (Peng 1997) should be considered as part of future urban planning in Shenzhen. The reasonable expansion of multilevel housing in the Longgang, Guangming and Pingshan areas, as important industrial and population agglomeration areas, can meet the housing needs in these districts. Meanwhile, the corresponding surrounding public infrastructure should be improved.

5. Discussion and conclusions

To estimate the effect of the driving factors within the land parcel's neighborhood on the land use change of the parcel, this study incorporates the CNN method in the VCA model when computing the transition suitability for each parcel. The proposed CNN-VCA model is applied to urban land use changes simulation in Shenzhen from 2009 to 2012. Our results show that the proposed CNN-VCA model can achieve the best simulation results compared with those of other existing VCA models (LR-VCA, ANN-VCA, and RF-VCA) with a result that is 11.8% higher than that of the RF-VCA model.

Moreover, the simulated land use details that were determined via the CNN-VCA model are mostly consistent with the actual converted parcels with respect to their spatial distributions, and some are exactly the same in terms of the morphological characteristics of the land parcels. Compared to the RF-VCA model, the proposed CNN-VCA model performs better at obtaining the detailed information of a land parcel's edge contour. The results indicate that the CNN method can effectively extract the high-level features of the driving factors within the neighborhood of each cell, which is conducive to effectively determining urban land use change rules and improving the simulation accuracy.

The proposed CNN-VCA model adopts the CNN method to extract the high-level features of the driving factors within the cell's neighborhood and discover the neighborhood's effects on the land use change of the cell, which is not considered in previous VCA models (Yao *et al*. 2017). The CNN can extract abstract and robust features with the help of the raw neighborhood information in the raster-based CA models by using the convolution kernel and local connections (He *et al*. 2018). In this study, the CNN is used to obtain the complex features of the driving factors within a neighborhood of an irregularly shaped land parcel. Additionally, the proposed CNN-VCA model can automatically determine the impacts of the driving factors within a cell's neighborhood on the land use type of the cell, which can effectively avoid the uncertainty that is caused by artificially setting the impact rule.

The CNN parameters are important factors that affect the computational complexity, training speed, extracted features, and classification accuracy (Zhou and Yang 2011, Shin *et al*. 2016). Thus, accuracy assessments based on different sized sampling windows and training batches are contrasted in this study. The results show that the final simulation accuracy varies within a stable range, and the lowest simulation accuracy is still higher than that of other VCA models.

The sensitivity analysis results for different window sizes reveal the maximum distance at which neighborhood land parcels affect the central parcel. Previous studies indicate that the neighborhood land-use condition is an important factor that is driven by urban land use change (Li *et al*. 2017). The attributes of the driving factors within a cell's neighborhood also impact the land use type of the cell. The results indicate that the CNN-VCA model can effectively discover the effects of the driving factors within the parcel's neighborhood on the development pattern of the parcel and obtain better simulation results for the morphological characteristics of land parcels than other VCA models.

By simulating the urban land use for 2020 and 2025 under the ecological control strategy using the proposed CNN-VCA model with the constrained Markov chain method, we obtained the main nonurban land areas that will be converted to multiple types of urban land use, which are aligned with the current development distribution in Shenzhen. The simulated results reveal that Shenzhen tends to have an increasingly unbalanced relationship between jobs and housing under the current land use change pattern. The increasing development of residential land in the Longgang, Guangming and Pingshan districts should be considered in the future. The results demonstrate that the proposed model can be an effective method of anticipating problems as cities expand, and it can support future land use policy decisions.

As a complicated socio-economic phenomenon, urban expansion is influenced by intricate and variable factors with uncertainty and randomness (Ye *et al*. 2015). In China, urban development is greatly related to government policy and urban planning, which increases the difficulty of land use change simulations (Tian and Qiao 2014). It is very difficult to exactly match actual changes, especially when few conversions occur in a large area. The proposed CNN-VCA model has achieved good simulation performance, and it represents an advance in VCA models.

Some shortcomings remain in this study. How to construct an appropriate network structure and adaptively adjust the input parameters to optimize the CNN model is an open question in the field of computer science (Rawat and Wang 2017), which will be considered in future work. Moreover, the spatial variables of the driving factors are assumed to be static during the simulation process, but they are dynamically changing in reality (Liu *et al*. 2017); therefore, dynamic spatial variables will be introduced in future studies. Although the proposed CNN-VCA model can achieve better simulation results, it does not quantitatively reveal the individual contributions of the driving factors during the modeling. How to explain the deep learning model remains a difficult issue in the field of computer science, and it also needs to be explored in our future work. Urban land use change is affected by urban planning and government policy. How to incorporate the policy into the CA model for urban expansion simulations is still a difficult issue. In our further work, how to integrate policy factors into the CNN-VCA model will be considered.

This study proposes a new framework named the CNN-VCA that integrates the CNN method into the VCA model to simulate the land use changes of land parcels. Through comparing several existing VCA models (e.g. LR-VCA, ANN-VCA and RF-VCA), it is found that the proposed CNN-VCA model, which can effectively estimate the effects of the driving factors within the land parcel's neighborhood on the land use change of the parcel, achieves the best simulation results. In addition, the simulated results indicate that the CNN-VCA model can obtain more detailed morphological characteristics of the land parcels. The proposed model can provide a basis for exploring the complicated effects of the driving factors within the cell's neighborhood on the land use patterns in further studies.

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Data and codes availability statement

The data and codes that support the findings of this study are available at figshare.com with the identifier [DOI: http://doi.org/10.6084/m9.figshare.11493660]. The original data that support the findings of this study was provided by the Bureau of Land and Resources of Shenzhen, and cannot be made publicly available to protect the data confidentiality. If necessary, the data can be applied with the Shenzhen Planning and Natural Resources Bureau (http://pnr.sz.gov.cn/).

Disclosure statement

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