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# Temporal-VCA: Simulating urban land use change using coupled temporal data and vector cellular automata

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A R T I C L E I N F O

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A B S T R A C T

Vector cellular automata (VCA) are effective models for cadastral-scale land use change modeling, leveraging fine spatial granularity information from cadastral plot data. The temporal dimension has the potential to improve the performance of VCA further. However, it is challenging to precisely capture long sequence information of cadastral plot temporal data for VCA while ensuring accurate capture of fine granularity information simultaneously. Our paper introduces the Temporal-VCA framework, which fully utilizes fine spatial and temporal granularity information of cadastral plot temporal data to enhance the accuracy of VCA. Applying Shenzhen's annual cadastral plot data from 2009 to 2014, this study shows how deep learning techniques can elucidate the temporal aspects of VCA models. Temporal-VCA notably improves precision by up to 22.12 %, outperforming the regular VCA models and traditional raster CA models. It reveals the complex nonlinear temporal patterns within cadastral-scale urban development processes. Designed simulations for 2030, including scenarios of disordered development and ecological protection, highlight the benefits of fully leveraging fine temporal granularity information of temporal data into urban planning, potentially reducing ecological damage by 70 %. Our findings offer a novel methodology for urban land use simulation, with significant implications for urban planning and the advancement of sustainable cities.

## 1. Introduction

In recent years, global cities have experienced a rapid development stage and have had a significant impact on the ecological environment (Deng et al., 2020; Zhang, 2016). The report "Cities and Pollution" issued by the United Nations in 2016 (UN Habitat, 2016) pointed out that global cities only cover less than 2 % of the earth's surface but consume 78 % of the world's energy and generate over 60 % of greenhouse gas emissions (Gago et al., 2013). Therefore, understanding the changes in urban land use has become a hot topic for researchers worldwide (Chaturvedi & de Vries, 2021; Hasan et al., 2020; Wu, 2014).

Urban land use change refers to the changes in spatial distribution and functional structure of various types of land within and around a city that occur with urbanization (Cengiz et al., 2022). Simulation of urban land use change can help optimize the structure and spatial layout of urban land use, and deepen the understanding of the impact mechanism of urbanization on land use change. Cellular Automata (CA), as a classic type of spatial dynamics model, has a "bottom-up" characteristic and can retain more foundation and details in the dynamic system, gradually occupying a dominant position in urban land change simulation (Li & Yeh, 2002; Liu et al., 2008). Traditional CA models are based on regularly shaped raster-format units (pixels or patches), setting

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specific transformation rules to change cell states and simulate the spatiotemporal dynamic changes of urban development (Chen et al., 2016; Liu & Phinn, 2003; Tian et al., 2016). Due to the spatial heterogeneity of land use characteristics, boundary conditions usually need to be considered in simulations. In raster CA models, handling boundary conditions can be a challenge (Zhu et al., 2020). The vector CA (VCA) model is more accurate in simulating geographical features and land use boundaries at small cadastral scales. Furthermore, by using spatial units of different shapes and sizes, the spatial heterogeneity of different regions can be more accurately represented (Zhou et al., 2023).

Time could be a potential dimension to further improve the performance of VCA in simulating land use change (Liu & Andersson, 2004). The different potential temporal periodic patterns exist for different land use changes and affect the overall dynamics of urban land use (Liu et al., 2012). The temporal dependence on land use change refers to the trend and pattern of changes in land use types and patterns over different periods, and both the current and historical states and conditions influence the land use change. For example, suburban land used for urban expansion is undergoing rapid and sustained land use transformation, while the land use patterns in ecologically protected areas remain unchanged over time. Researchers regard these patterns as the temporal dependencies of land use change (Asabere et al., 2020). Previous research has made efforts on the temporal dependencies of traditional raster CA models (Li et al., 2020; Wang et al., 2019; Zhou et al., 2023). However, the time dependence in VCA model still needs to be further explored. Therefore, incorporating the ability to capture time series information into VCA models is of great significance for accurately achieving land use prediction and enhancing the sensitivity of model information capture.

Further, it is still challenging to mine and reveal the time-dependent characteristics of land use change for VCA models because its temporal dynamics are intricate (Kumar et al., 2021). Time and space of land use changes have a strong interaction (Wu et al., 2015). It is more challenging for such fine-grained VCA models to precisely decouple the time dependence of cadastral-scale land use time series while ensuring the accurate capture of fine spatial granularity information simultaneously. Traditional methods of revealing temporal patterns include geographic weighted regression models (Mustafa et al., 2018), land use change simulation based on random forests, neural networks, etc. (Xing et al., 2020). However, the lack of mining for multiple temporal drivers and simulation at finer scales cannot effectively explore the time-dependent mechanisms in land use change. Research has confirmed that deep learning models can effectively mine time series information and achieve the expected results (Chung et al., 2014; Hochreiter & Schmidhuber, 1997; Zhao et al., 2017). Thus, deep learning techniques provide an opportunity to enhance VCA's ability to capture long sequence information, thus further improving the performance of VCA to simulate cadastral-scale land use changes accurately.

In order to enhance VCA's ability to capture long sequence information of cadastral plot time series data while ensuring accurate capture of fine granularity information simultaneously, this paper proposes a Temporal-VCA framework for simulating urban land use change, which couples long sequence of cadastral plot data and VCA. This framework takes Shenzhen, Guangdong Province, as the study area, based on fine-spatially-grained and long-sequence cadastral land use time series data. By coupling multiple machine learning, deep learning models, and VCA models, it effectively explores the time-dependent mechanism and dynamic characteristics of land use change based on vector plots, simulates and predicts urban land use change, and improves simulation accuracy. In order to verify the effectiveness of the model and evaluate the implementation effects of different policies, this paper conducted long-term land use development simulations based on different development scenarios. This framework aims to analyze the time-dependent mechanism of urban land use change based on cadastral plots, reveal the laws and future trends in urbanization development, and provide a new approach and method for simulating urban land use change.

## 2. Literature review

### 2.1. Vector cellular automata models for urban land use simulations

With the refinement of simulation methods, vector CA (VCA) models based on irregularly shaped vector-format cells have been proposed and proven to be a more advanced model for urban change simulation (Pinto et al., 2017). Urban land renewal typically occurs on cadastral land parcels (Irwin et al., 2003). However, traditional raster CA models based on grid-shaped raster-format units often have inherent limitations, such as sensitivity to pixel size and fixed unit shape with the inability to accurately express objective geographical entities (Pan et al., 2010; Sante et al., 2010). The VCA model based on cadastral plot data can accurately represent the irregular shape of actual land use (Jjumba & Dragicevic, 2012; Yao, Sun, et al., 2023; Yao, Zhang, et al., 2023), leveraging the high spatial granularity of cadastral-scale land use data (Abolhasani & Taleai, 2020; Barreira-Gonzalez et al., 2015).

In the research of VCA models, Zhuang et al. accurately mined CA conversion rules based on the random forest algorithm and simulated urban land use changes at the cadastral data level, improving the accuracy of model simulation (Zhuang et al., 2022). The HGAT-VCA model proposed by Guan et al. effectively expresses spatial interactions and improves the accuracy of land use simulation by combining VCA with graph convolutional neural networks (Guan et al., 2023). However, most of the existing studies focus on how to improve the accuracy of VCA simulation, ignoring that time is another important dimension of urban land change (Guan et al., 2023; Xu et al., 2022).

In summary, the current VCA model lacks the ability to capture time series information in land use change. Integrating time series information into the VCA model can more accurately capture the historical trends and cyclical patterns of land use change, thereby better understanding the future trends of land use change and assisting urban planners in making better land use planning and management decisions.

### 2.2. Time dependence in land use

In the study of time dependence in land use change, some scholars have constructed a series of methodological frameworks on how to organically integrate spatial region division or time series evolution of land cover for traditional raster CA models. Zhou et al. proposed the KCL-CA model, which integrates K-Means, Convolutional Neural Network (CNN), and LSTM to solve the temporal dependence and spatiotemporal heterogeneity in land use change and improve the accuracy of land use change simulation (Zhou et al., 2023). Li et al. proposed using trend adjusted neighborhood as a weighting factor. They integrated this factor into commonly used Logistic CA models to achieve long-term urban expansion modeling with high accuracy (Li et al., 2020).

However, the issue of time dependence in VCA still needs to be thoroughly investigated. Cadastral-scale VCA models are good at capturing fine spatial granularity information because they can more accurately represent boundary shapes and geometric features to reflect spatial heterogeneity in the real world (Guan et al., 2023). However, regular VCA models lack the ability to exploit long-time series sequence information. Long sequence information can help reveal the VCA simulation of land use change in different periods. Hence, utilizing fully the temporal dependence characteristics of land change can contribute to a more accurate simulation of urban cadastral land use change in VCA models.

### 2.3. Mining land use time series information based on deep learning methods

Deep learning models can learn long-term dependencies in time series, identify the interrelationships between different time points, and thereby enhance the prediction accuracy of land use patterns (Campos-

Taberner et al., 2020). In response to the research on using deep learning to mine time dependencies, a recent study has proposed a cellular automaton model (DL-CA) that integrates convolutional neural networks, random forests, and LSTM (Xing et al., 2020). J. Jagannathan et al. proposed a hybrid heat coding VGG19 deep learning method, which uses mixed logistic regression to classify images and predicts classes based on decision trees. The accuracy of land use prediction is as high as 98.5 % (Jagannathan & Divya, 2021). Existing research mainly combines traditional deep learning algorithms such as neural networks with raster CA models to explore time dependencies in CA models. However, traditional neural networks are not good at processing time series data, and each input is independent, ignoring the pre - and post dependency relationships between data points in time series data (Shen et al., 2020).

LSTM and GRU models can effectively capture and learn long-term dependencies in time series data by introducing gating mechanisms (Lindemann et al., 2021). Scholars have demonstrated the advantages of LSTM and GRU models in mining time series information. Xiao et al. proposed a deep learning model (CNN-GRU) that integrates convolutional neural networks and gated recursive units, combining spatio-temporal neighborhood features to simulate land use change. The study found that CNN-GRU has the highest simulation accuracy (Xiao et al., 2022a). Huang et al. proposed a new model of KCLP-CA, which integrates K-Means, Convolutional Neural Networks (CNN), LSTM, and raster CA models. They confirmed the effectiveness of the LSTM model in addressing temporal dependencies and the impact of temporal dependencies on land use change (Huang et al., 2024). Thus, Deep learning models can extract high-level features and abstract information from data through multi-level nonlinear transformations and can be fully applied in time series prediction tasks (Najafabadi et al., 2015).

## 3. Study area and data

Shenzhen City, China, a single case, is taken as the·study·area in this study. Taking a single case as the study area will help to verify the rationality of the urban land use change model and provide in-depth policy recommendations for future urban development (Wang et al., 2022). Shenzhen, an emerging and rapidly developing city with an area of 1997.47 km$^2$, governs 9 administrative regions and 1 new district (Yao, Sun, et al., 2023). In the process of urbanization, it emphasizes the efficient and intensive use of land resources. However, due to the rapid urbanization process and economic development needs, there is a phenomenon of excessive development and utilization of land resources in some areas, a prevalent predicament in contemporary urban development (Cheng et al., 2023; Pan & Du, 2021; Yu et al., 2019). Research has shown that rapid urbanization in Shenzhen from 1979 to 2017 led to a 3400 % hike in land development, catalyzing prominent urban issues encompassing environmental and infrastructural challenges (Hao et al., 2011; Lai et al., 2017).

Therefore, the·urban·development mode·of Shenzhen is a representative case of China's rapid urbanization, as well as a well-known case of global urbanization (Cheng et al., 2023). Summarizing the development model of Shenzhen can provide reference and explanation for the problems and challenges that other cities may face in similar stages of urbanization, making it an ideal case area for this study (Bao & Lu, 2020; Stark et al., 2020; Tan et al., 2021).

This paper mainly uses two types of data: land use time series data and spatial auxiliary variables from Shenzhen city. Among them, the land use time series data comes from the Shenzhen Planning and Natural Resources Bureau (https://pnr.sz.gov.cn/) cadastral plot data. The land

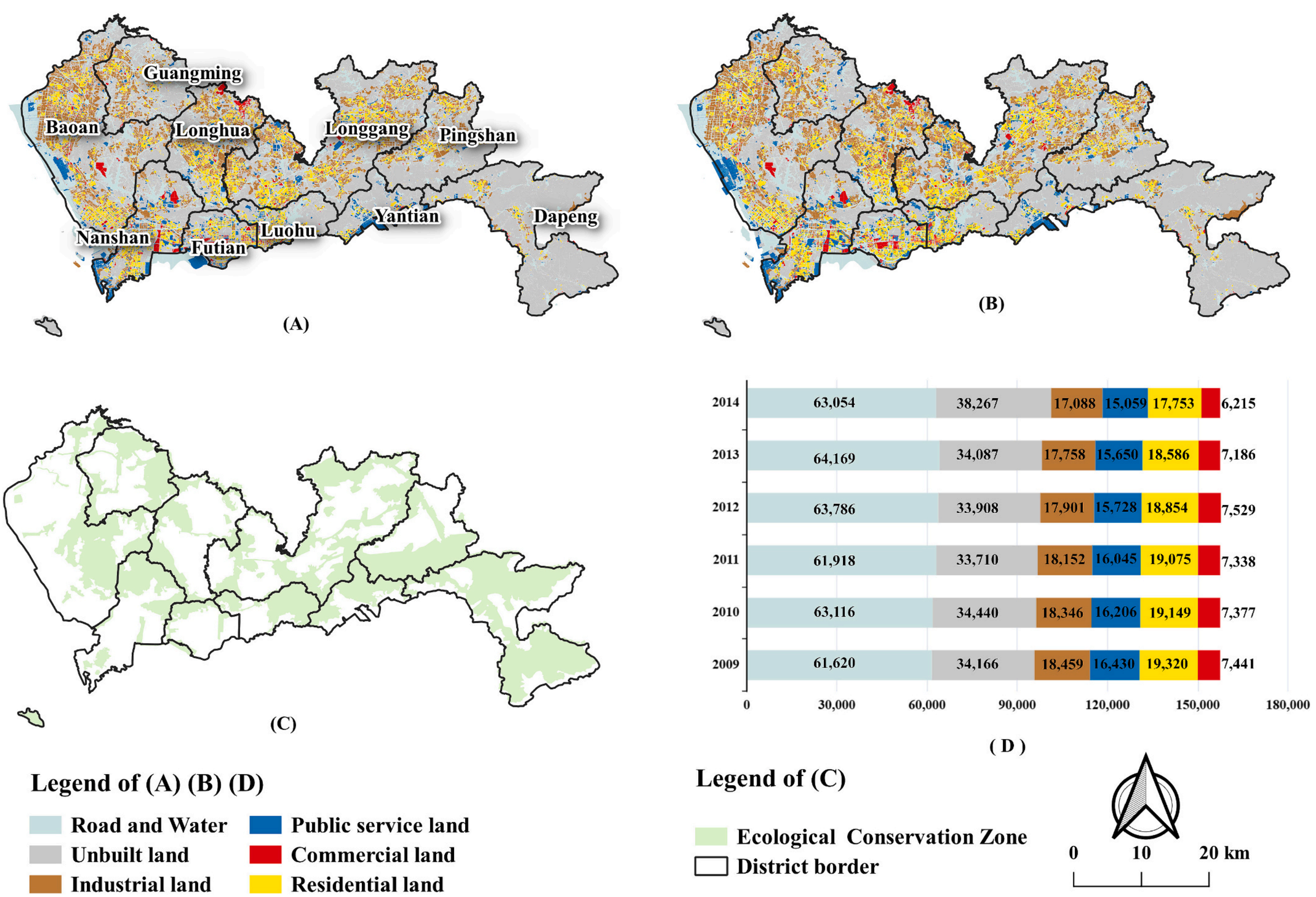


**Fig. 1.** Study area and land use distribution in (A) 2009 and (B) 2014. (C) Ecological conservation zone (D)Comparison of the number of various land use plots from 2009 to 2014.

use time series data used in this study include 6 cadastral-scale land use maps ranging from 2009 to 2014. As shown in Fig. 1, each year's land use time series data is divided into six different types of land use, including water and roads, unbuilt land, industrial land, public service land, commercial land, and residential land. Unbuilt land includes cultivated land, forest land, gardens, and grasslands, while industrial land, public service land, commercial land, and residential land are defined as urban land (Table S1).

Secondly, the study presented in this paper utilizes Gaode's Point-Of-Interest (POI) data (https://lbs.amap.com/). The data encompasses information on various venues, such as catering, bus stops, and daily services. This study also incorporates OpenStreetMap (OSM) data (https://www.openstreetmap.org/). Furthermore, night light data (https://eogdata.mines.edu/) is jointly used to construct spatial auxiliary variables by utilizing driving factors such as terrain, industry, and commerce that affect land use change. Among them, the data age is all 2018, the spatial resolution is set to 30 m, and all variables are normalized to a range of 0 to 1, as shown in Fig. 2.

## 4. Methodology

Fig. 3 illustrates the construction and analysis process of the Temporary VCA model. This framework consists of three steps. (1) Time series model construction. This step uses multiple machine learning models to mine temporal factors and their probabilities in land use change based on preprocessed temporal data of land use change; (2) Model fusion and urban land use simulation. This step combines the prediction probability of the time series model with the prediction probability calculated by the VCA model for different types of land use and selects the final development category through the roulette wheel algorithm; (3) Urban land use prediction under different scenarios. This step involves designing two future scenarios, the disordered development scenario and the ecological protection scenario, to simulate long-term land use development and analyze the temporal characteristics of land use.

### *4.1. Construction of time series model*

Our proposed times series forecasting model employs conventional machine learning and deep learning models to automatically derive features from time series data. This model performs end-to-end training and prediction, ensuring its accuracy (Jiao et al., 2021; Zhang et al., 2022). This paper uses land use temporal data from 2009 to 2013 as training data and land use data from 2014 as accuracy verification data. The training set has a test set data ratio of 7:3 (Fang et al., 2022). To avoid imbalanced samples for the multi-class classification, this paper adopts the method of adjusting the training weight parameters to ensure the model receives relatively balanced training on different classifications (Huang et al., 2020). The equation for training weight parameters calculation is as follows.

$$\alpha^i = \frac{\sum_{j=-1}^{4} n^j}{n^i} \tag{1}$$

In the equation: $\alpha^i$ represents the training weight of the *i*-th type of land use category; $\sum_{j=-1}^{4} n^j$ represents the number of samples for all land use categories within the study area; $n^i$ represents the number of samples for the i-th category of land use. The number and proportion of samples in each category, as well as the adjusted training weights, are shown in Table S2.

In addition, for time series prediction, this paper adopts a fixed width

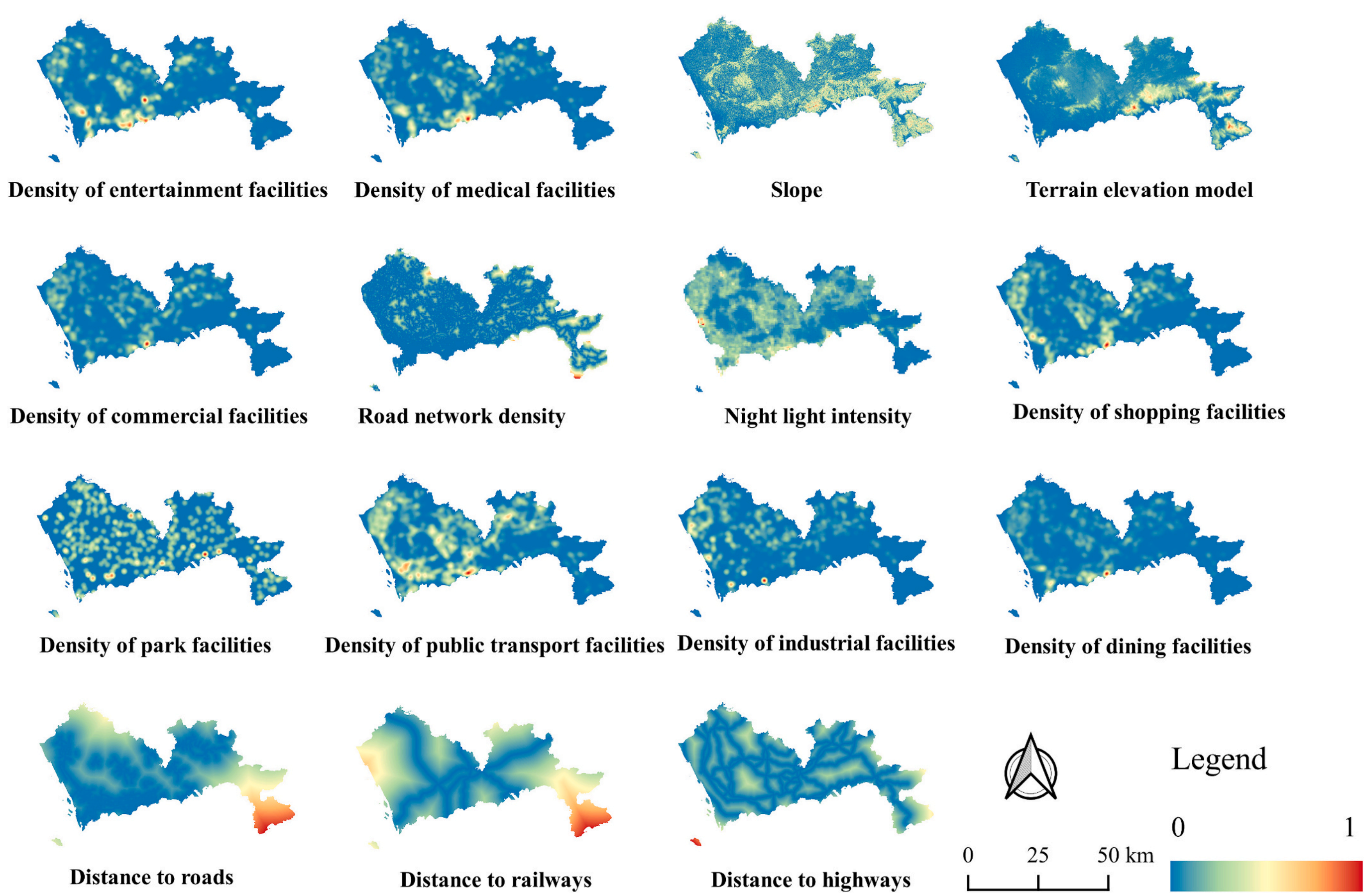


**Fig. 2.** Spatial driving factors calculated for the urban land use change.

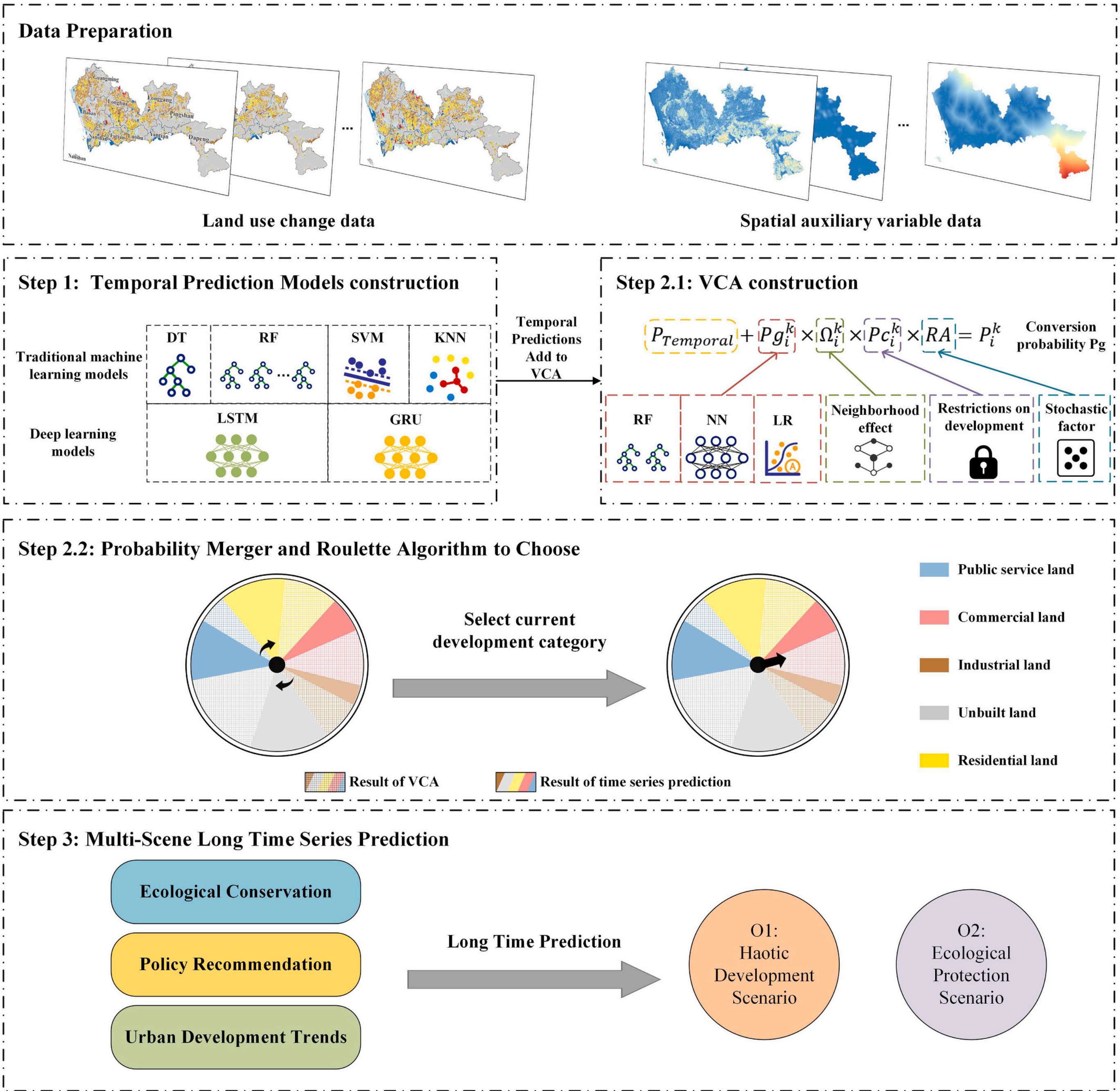


**Fig. 3.** Workflow of the proposed Temporal-VCA framework.

sliding window technique (Chengcheng Chen & Chau, 2022; Roodposhti et al., 2020), which trains the model with fixed-length historical data at each time step and predicts the last time point within the window. After completing the prediction, slide the time window forward by a fixed step size to prepare for the next time step prediction. Using the latest generated land use map as input data for the model can effectively capture the dynamic characteristics of time series data. At the same time, this method allows us to simulate land use changes over a long period and make predictions based on past data, providing valuable information for land planning and decision-making.

*4.1.1. ML-based overall probability calculation*

To thoroughly compare the predictive performance of various time series prediction models in this multi-classification task, this paper selects four machine learning models, including Decision Tree (DT) (Song & Ying, 2015), Support Vector Machine (SVM) (Sapankevych & Sankar, 2009), Random Forest (RF) (Kane et al., 2014), and K-Nearest Neighbor (KNN) (Xu et al., 2020), and two deep learning models, including LSTM (Fischer & Krauss, 2018) and GRU (Dey & Salem, 2017), to explore the temporal factors and their probabilities in the process of land use transformation.

Due to the different basic mathematical principles of different machine learning methods, the six classifiers mentioned above calculate the prediction probability of each category differently, with the prediction probability p of category i in the DT model. The equation is:

$$p_i = \frac{n_i}{N_L} \tag{2}$$

In the equation: $L$ represents the leaf node that satisfies the propagation path of the individual decision tree for the probability sample to be calculated,$N_L$ represents the number of samples contained in leaf node $L$, $n_i$ represents the number of $i$-class samples contained in leaf node $L$.

The RF model, as an ensemble learning method, consists of multiple DTs, each of which can output the probability of each category of sample data. The equation for its prediction probability $P$ is:

$$\mathrm{P} = \frac{1}{\mathrm{N}}\sum_{\mathrm{n}=1}^{\mathrm{N}} \mathrm{p_n} \tag{3}$$

In the equation: $N$ is the total number of DT trained by RF,$p_n$is the probability vector of the $n$-th tree.

SVM was originally a binary classification model. We can use it for multi-classification problems through the one vs the rest method and employ Platt scaling to calculate the probability of categories (Melvin et al., 2007). The original output of the classifier can be mapped to the probability estimation of the class, making these probabilities more in line with the proper class probability distribution. The probability calculation equation after Platt calibration is:

$$\mathrm{P(Y = 1|Z)} = \frac{1}{1 + \mathrm{e}^{\mathrm{A^*Z+B}}} \tag{4}$$

In the equation: $P(Y = 1|Z)$ indicates the probability that the sample belongs to a positive category, $Z$ represents the raw output of SVM, $A$ and $B$ is a calibration parameter, estimating through training datasets.

KNN predicts the category of the tested sample based on the category of the nearest K individuals (Xu et al., 2020). The probability calculation equation is:

$$\mathrm{P_i} = \frac{\sum_{\mathrm{m}} \mathrm{w_m} \times \mathrm{m_Y}}{\sum_{\mathrm{y}}\sum_{\mathrm{m}} \mathrm{w_m} \times \mathrm{m_Y}} \tag{5}$$

The equation for the weight coefficient $w_m$ is:

$$\mathrm{w_m} = \frac{1}{\mathrm{d_m}} \tag{6}$$

In the equation: $m$ represents the K individuals closest to the sample,$d_m$ represents the Euclidean distance from the individual $m$ to the predicted individual,$m_Y$ is an individual with a classification label of Y, y represents all values of the classification label.

#### 4.1.2. DL-based overall probability calculation

Existing research suggests that GRU and LSTM models can capture long-term temporal dependencies for land use classification and prediction performance, effectively improving classification accuracy and establishing more comprehensive land use conversion rules (Xiao et al., 2022b; Xing et al., 2020). Among them, LSTM has a similar structure to GRU. Therefore, This paper takes the LSTM neural unit proposed by Hochreiter and others (Hochreiter & Schmidhuber, 1997) as an example. Fig. 4 shows the LSTM and GRU training models constructed regarding time dimension.

LSTM and GRU use the Softmax function to calculate the probability distribution of categories (Kumar & Abirami, 2021). The equation is as follows:

$$\mathrm{P(Y = i|Z)} = \frac{\mathrm{e}^{\mathrm{z_i}}}{\sum_{\mathrm{j}=1}^{\mathrm{C}} \mathrm{e}^{\mathrm{z_j}}} \tag{7}$$

In the equation: $P(Y = i|Z)$ represents the probability that the sample belongs to category $i$, $z_i$ is the $i$-the value in the score vector logits, $\sum_{j=1}^{C} e^{z_j}$ is the sum of exponentially calculated logits for all categories.

### 4.2. Consolidation of land development probability and simulation of land use

Based on the land use conversion probability calculated by the above model, this study combines the conversion probability of each plot calculated by the time series prediction model and the VCA model (the calculation method in Eq. (S1) through to Eq. (S4)) and obtains the ultimate development probability of the plot, the equation for calculating the development probability of the VCA model is as follows:

$$P_i^k = Pg_i^k \times \Omega_i^k \times Pc_i^k \times RA \tag{8}$$

In the equation: $P_i^k$ is the overall development probability of converting the $i$ plot into a Class $k$ plot,$Pg_i^k$ is the development probability of each plot, $\Omega_i^k$ is the neighborhood effect of the $k$ type of land parcel on the $i$ type of land parcel,$Pc_i^k$ is the development limiting factor, $RA$ is a random value.

Finally, the roulette wheel algorithm is used to determine the final category of land use change (Lv et al., 2021; Xu et al., 2024). The calculation method is:

$$\mathrm{p_i} = \frac{\mathrm{q_i}}{\sum_{\mathrm{i}=0}^{4} \mathrm{q_i}} \tag{9}$$

In the equation: $q_i$ is the sum of the conversion probabilities of land use categories after merging the time series model and VCA model; $p_i$is the probability of roulette wheel selection.

### 4.3. Prediction of urban land use in different scenarios

In the context of global environmental change and promoting sustainable development, urban land use change prediction is of great significance for guiding land resource management, urban planning policy formulation, and sustainable development (Wang et al., 2021; Zhang et al., 2020). The prediction of different scenarios aims to simulate and compare different land use development paths, evaluate the impact of different policy measures and planning strategies on urban land use changes, in order to achieve optimal utilization and protection of land resources, and formulate more accurate land use and ecological

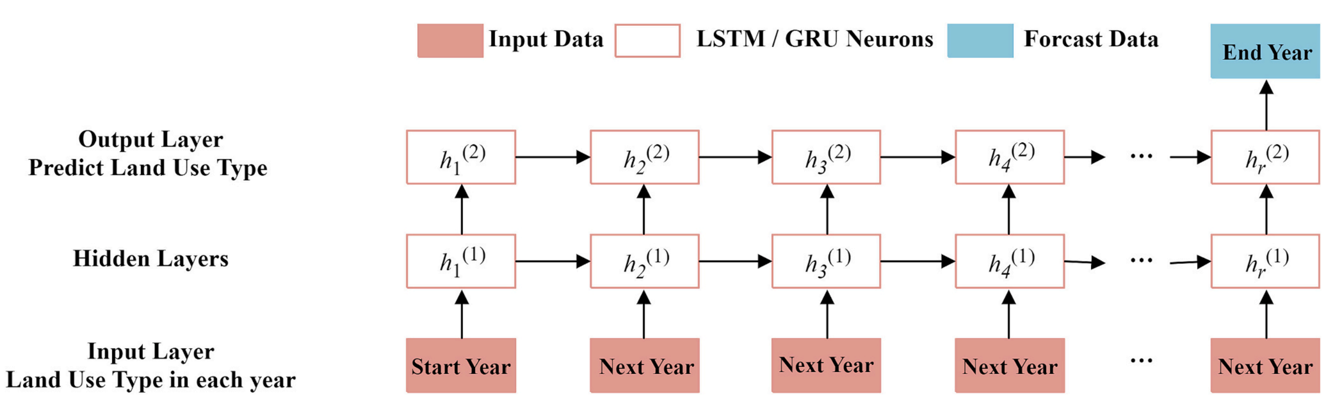


**Fig. 4.** Flowchart of LSTM and GRU Mining Land Use Conversion Probability.

protection policies (Zou et al., 2021).

To compare the land use patterns and trends under different development paths, explore the impact of ecological protection policies on urban land use change and ecological environment. The Temporal-VCA model proposed in this paper can be used to simulate the future urban development of Shenzhen. This study designed two development scenarios: (1) Disordered development scenario (O1), (2) Ecological protection scenario (O2). In scenario O1, following historical development trends, allowing for the mutual transformation of various types of land. Scenario O2 prohibits all plots within the ecological conservation zone from being developed into four types of urban land: industrial land, public service management land, commercial land, and residential land.

### 4.4. Model evaluation

To comprehensively evaluate the simulation performance of the proposed model, this paper applied several evaluation indicators, i.e., Figure of Merit (FoM), Kappa coefficient, and Overall Accuracy (OA). Among them, the Kappa coefficient describes the consistency between two classification datasets. OA is a commonly used indicator for evaluating the performance of classification models, considering the model's accuracy in classifying all class samples. This measure is intuitive, simple, and easy to compare with models (Liu et al., 2007) (the calculation method in Eq. (S5) through to Eq. (S8)).

FoM is a commonly used model validation indicator in land use change simulation. The value range of FoM is $[0, 1]$. Research has shown that (Pontius et al., 2008; Yao et al., 2017; Zhai et al., 2020), If FoM is more significant than 0.2, the land use simulation model has excellent simulation ability. The equation for calculating FoM and its derived indicators is as follows:

$$FoM = \frac{B}{A + B + C + D} \tag{10}$$

In the equation, A represents the area error where the actual land use type changes and the simulation results remain unchanged. B represents the area error of the actual transformation and the correct type transformation in the simulation results. C represents the area error of the actual transformation and the simulated error type transformation. D represents the area error where there is no actual change but the simulated change occurs. N represents the total number of cellular units in the study area.

It's worth noted that the proposed model is only verified in our study area in this study (please check Section 3 for the detailed reasons), but the methodology and the model are applicable to any study area.

## 5. Results

### 5.1. Analysis of simulation results of land use change

Based on machine learning models, Temporal-VCA simulated the urban land use in Shenzhen in 2014 (Fig. 5). Table 1 reveals that the Temporal-VCA model improves the overall simulation accuracy by 19.027 % to 22.124 % compared to the discrete data model PLUS. Among them, the overall simulation accuracy FoM of Shenzhen based on the KNN-VCA model reached 0.276, and even the FoM simulation accuracy of Luohu District, Futian District, and Bao'an District was above 0.290. The results indicate that Temporal-VCA has extreme simulation accuracy in simulating land use changes. In addition, the performance of the models varies significantly in different regions of the study area, with poor simulation results among the models in the Dapeng New Area. This observation signifies that different regions exhibit significant differences in their land use transformation rules and geographical characteristics.

To provide a more comprehensive evaluation of the simulation results, Table 2, displays the assessment of simulation outcomes and the statistical analysis of indicators for each model. Based on the simulation results of land use in Shenzhen in 2014, we found that KNN had a better simulation effect among various models. Among them, FoM is as high as 0.276, PA and UA are as high as 0.596 and 0.327. Secondly, the

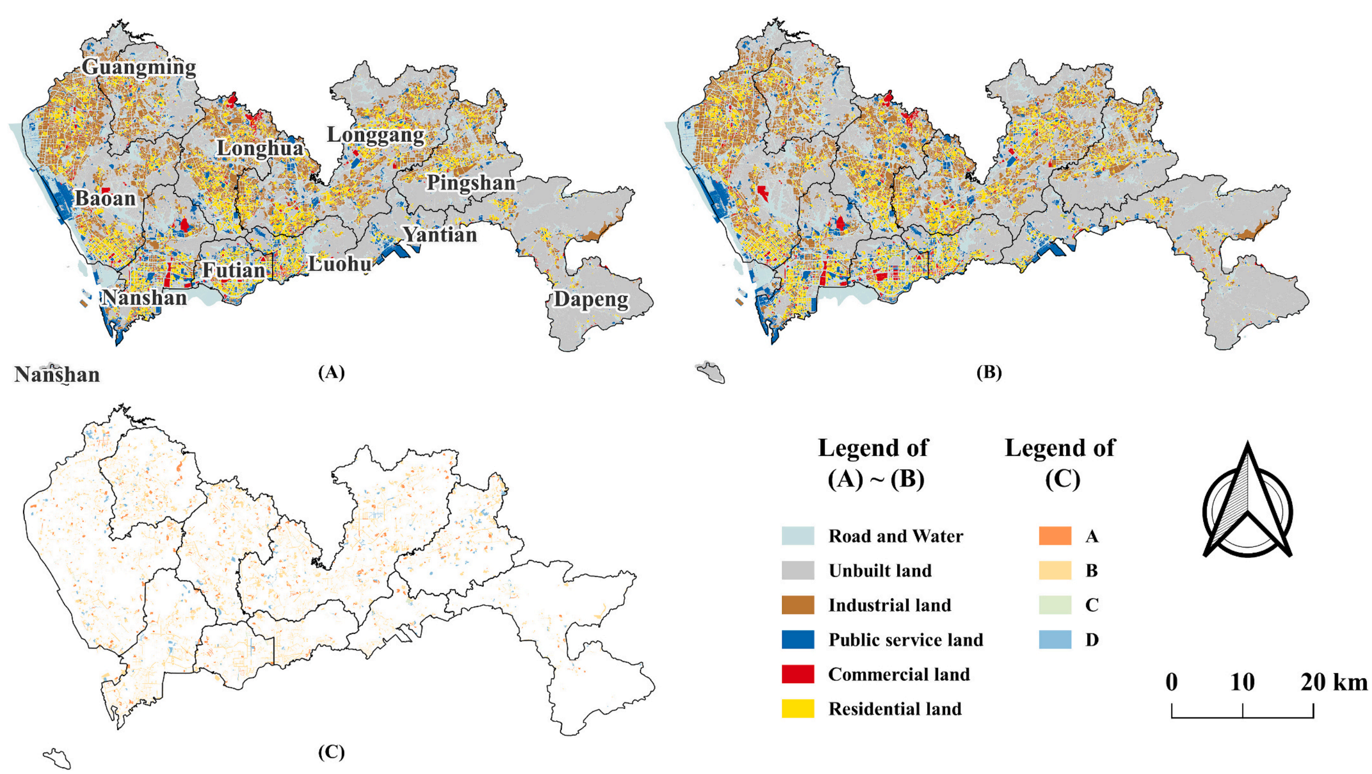


Fig. 5. Simulation result of the land-use dynamic. (A) Ground truth data in 2014. (B) The optimal simulation results of land use change in 2014 (KNN-VCA). (C) The correctly simulated and incorrectly simulated land parcels. A, B, C and D indicate the predicted land parcels in the four situations of FoM metric.

**Table 1**
The simulation accuracy (FoM) of different models based on Temporal-VCA. The up and down arrows represent the maximum and minimum values of the column, with * indicating the model constructed by previous studies.

| | DT | RF | KNN | SVM | LSTM | GRU | PLUS* | RF-VCA* |
|---|---|---|---|---|---|---|---|---|
| Futian | 0.298 | 0.297 | 0.310↑ | 0.307 | 0.294 | 0.305 | 0.133 | 0.241 |
| Luohu | 0.302↑ | 0.306↑ | 0.309 | 0.309↑ | 0.309↑ | 0.306↑ | 0.252 | 0.261 |
| Yantian | 0.242 | 0.242 | 0.274 | 0.258 | 0.249 | 0.251 | 0.115 | 0.252 |
| Nanshan | 0.259 | 0.261 | 0.262 | 0.261 | 0.257 | 0.267 | 0.178 | 0.200 |
| Baoan | 0.295 | 0.294 | 0.298 | 0.298 | 0.298 | 0.293 | 0.258 | 0.215 |
| Longgang | 0.251 | 0.254 | 0.261 | 0.259 | 0.253 | 0.255 | 0.187 | 0.263 |
| Longhua | 0.268 | 0.272 | 0.280 | 0.278 | 0.273 | 0.277 | 0.328 | 0.263 |
| Pingshan | 0.238 | 0.238 | 0.241 | 0.242 | 0.242 | 0.243 | 0.269 | 0.246 |
| Guangming | 0.270 | 0.267 | 0.273 | 0.276 | 0.267 | 0.265 | 0.225 | 0.285 |
| Dapeng | 0.237↓ | 0.231↓ | 0.227↓ | 0.229↓ | 0.222↓ | 0.237↓ | 0.118 | 0.293 |

**Table 2**
Evaluation of simulation results indicators for each model. The up and down arrows represent the maximum and minimum values of the column, with * indicating the model constructed by previous studies.

| | FoM | Kappa | OA |
|---|---|---|---|
| DT | 0.269↓ | 0.979↓ | 0.984↓ |
| RF | 0.270 | 0.981 | 0.985 |
| KNN | 0.276↑ | 0.981 | 0.985 |
| SVM | 0.275 | 0.981 | 0.985 |
| LSTM | 0.271 | 0.982↑ | 0.986↑ |
| GRU | 0.273 | 0.980 | 0.985 |
| PLUS* | 0.226 | 0.783 | 0.863 |
| RF-VCA* | 0.250 | 0.809 | 0.899 |

simulation effect of LSTM is good, with a Kappa coefficient of up to 0.982 and an OA of 0.986. In contrast, the Decision Tree (DT) model underperforms. The subpar performance of the DT model could stem from the influence of multiple factors on Shenzhen's land use changes. Different models, capturing unique features from various data types, consequently produce distinct simulation effects observable in the simulation results.

In addition, the complete model accuracy evaluation and indicator statistics are shown in Tables S3 and S4. Moreover, considering the higher accuracy of KNN, SVM, LSTM, and GRU models compared to other models' FoM, this paper evaluates the refined models of each land use category for the above four models (Tables S5 to S9).

### 5.2. Prediction results in different scenarios

Based on Temporal-VCA and different future development scenarios, this paper conducted a long-term prediction of land use change in Shenzhen in 2030 (Fig. 6) and quantitatively studied the temporal characteristics of land use. Table 3 shows various land use areas under different scenarios in 2030. The results suggest that the effective execution of ecological protection and sustainable development strategies has successfully safeguarded urban green spaces. Nonetheless, these strategies pose significant challenges, as projections indicate a 6 % decrease in public management service land by 2030. Secondly, in all scenarios, the continuous expansion of unbuilt land between 2014 and 2030 will limit the development of urban construction land.

Fig. 7 shows the changes in land use by administrative regions in the O2 scenario compared to each category in the O1 scenario. Comparatively, regional policies in the Pingshan and Nanshan regions prioritize converting ecological land into construction land. In contrast, the ecological conservation zone in the Guangming and Longhua regions have a relatively low proportion. However, the reduction in construction land is relatively high. Simultaneously, ecological strategies can reduce ecological damage by 71.9 % by 2030.

This paper analyzes the area changes of urban land in Shenzhen (Fig. S2) to clarify the trend of changes in different types of land under O2 scenarios. The results show that under the O2 scenario, unbuilt land grew from 2014 to 2030 and gradually stabilized after 2022, with less change in commercial land. However, the other three types of land, including industrial land, showed a significant decreasing trend from 2020 to 2026 and gradually stabilized.

## 6. Discussion

This paper proposes a Temporal-VCA model for simulating and predicting urban land use change, which couples temporal data with vector cellular automata. It effectively improves the accuracy of urban land use change simulation, reveals the dynamic characteristics of land use change, and clarifies the time-dependent mechanism of urban land use development. This framework provides a new approach for simulating urban land use changes from the perspective of coupling temporal data and machine learning models.

The VCA model integrates temporal land use data and uses Shenzhen city data for simulation validation to better understand the time-dependent mechanism of land use change. This approach enriches the simulation methods of urban land use change. The simulation results show that compared to the discrete data model, Temporal-VCA can improve the simulation accuracy by 19.03 % to 22.12 %, with KNN-VCA having the highest simulation accuracy (FoM = 0.2762). Compared to the current advanced PLUS model and RF-VCA model, the simulation accuracy has been improved by 22.12 % and 10.48 %, respectively. It is worth noting that the simulation accuracy of Luohu District, Futian District, and Bao'an District is all above 0.29, while the FoM accuracy of Dapeng New Area and Pingshan District is around 0.24. Due to the high level of urbanization in Luohu District and Futian District, 90.61 % and 71.01 % of the land areas did not undergo land use category changes from 2009 to 2014, respectively. The land use structure and change trend are relatively stable. So the model can easily record historical status information of different plots under the same conditions and forms a time-dependent mechanism, presenting higher accuracy (Xie et al., 2013). In contrast, Dapeng New Area and Pingshan District are newly established administrative districts in Shenzhen, with frequent land use changes and significant policy impacts (Yue et al., 2013). The dependence of land use time series is relatively diverse, resulting in low simulation accuracy.

Diverse machine learning and deep learning models have been integrated with the VCA framework to analyze land use change extensively. This study has uncovered the time series and nonlinear characteristics of land use dynamic change. This study found that using multiple traditional machine learning models and deep learning models performed similarly on FoM metrics, and even KNN and SVM machine learning models performed better than LSTM and GRU deep learning models. Due to the time-dependent nature of land use change (Jia et al., 2014) and the fact that both KNN and SVM are nonparametric models when dealing with nonlinear problems, they can capture nonlinear features between land use through instance-based learning methods and kernel techniques, adapting to complex decision boundaries and land use change patterns (Liu et al., 2019). The local optimal selection of DT

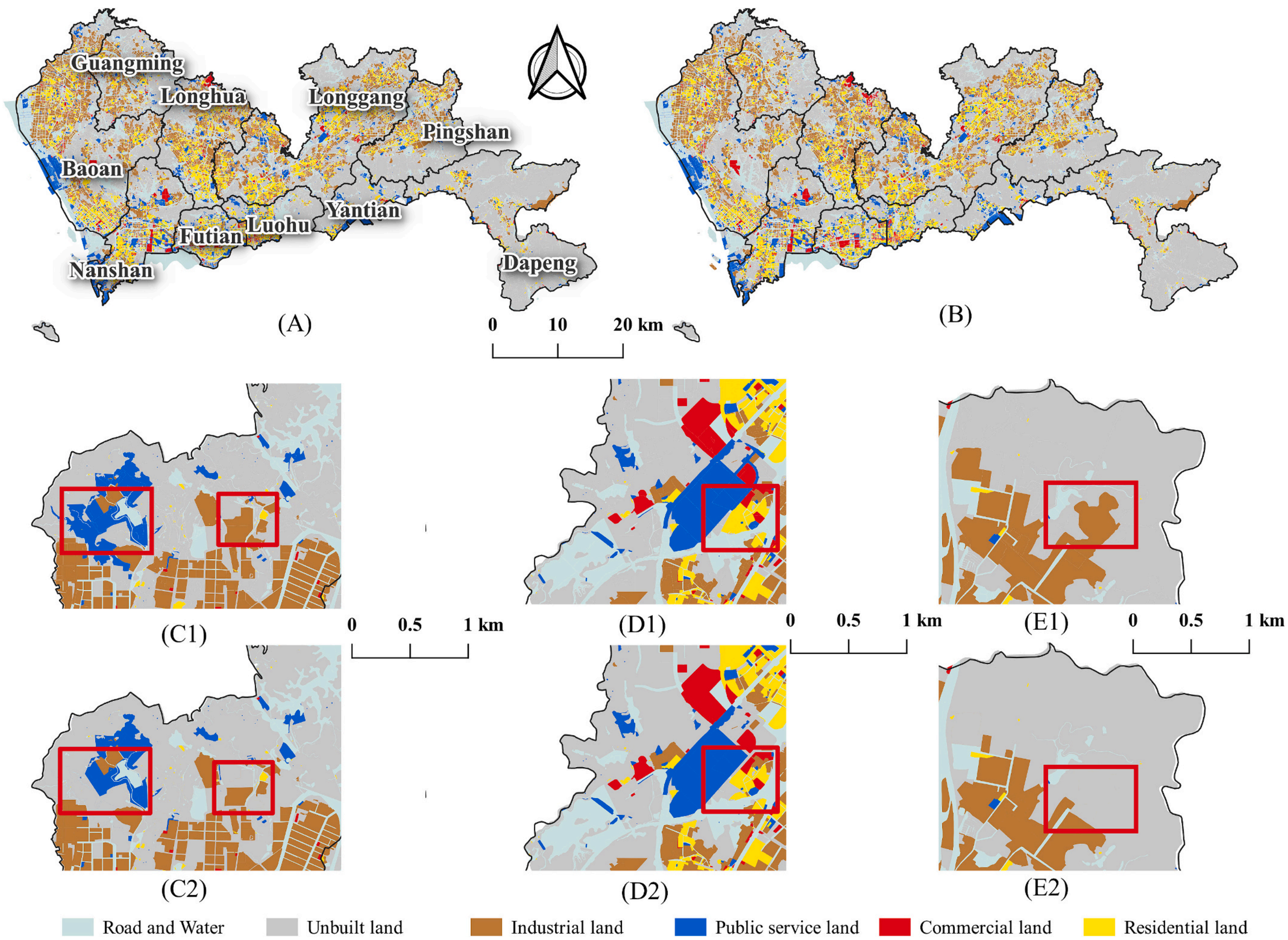


**Fig. 6.** Spatial distribution in 2030 based on Temporal-VCA: (A)O1 Scenario; (B) O2 Scenario; (C1)–(C2), (D1)–(D2), (E1)–(E2) Comparison of details of O1 and O2 in different regions corresponding to the predicted results.

**Table 3**
The total area of each urban land use in 2030 under different scenarios (unit: $m^2$).

| Year | Scenarios | Unbuilt land | Industrial land | Public service land | Commercial land | Residential land |
|---|---|---|---|---|---|---|
| 2014 | \ | 959,506,757 | 299,375,767 | 147,705,670 | 55,746,817 | 212,069,779 |
| 2030 | O1 | 965,279,518 | 299,182,851 | 144,991,972 | 52,525,940 | 215,403,356 |
| 2030 | O2 | 983,063,589 | 289,597,683 | 138,847,167 | 52,205,962 | 211,214,471 |

will result in the inability to capture this nonlinear feature. In addition, LSTM and GRU, as powerful time series and neural network models, can better capture long-term dependencies in time series and memorize and train large amounts of data (Su & Kuo, 2019). The insights extracted from LSTM and GRU regarding time trends can provide valuable supplemental data alongside environmental and socio-economic factors (Patra et al., 2018). This information is vital for departments focused on land resource management and planning, as it aids in comprehending the nature and patterns of land use evolution, allowing for the development of relevant policies and planning strategies.

This study conducts long-term simulation and prediction based on two future scenarios of the uncontrolled urban sprawl and ecological protection, quantitatively verifying the future implementation effects of different land use policies and further revealing that land use change temporal information can become practical information for predicting future land use changes. The prediction results show that between 2014 and 2030, residential land shows a decreasing trend under ecological protection scenarios, with a decrease in industrial land in Pingshan District (5.8 %) and Nanshan District (4.3 %) and significant changes in the growth of unbuilt land, while the opposite is true under the uncontrolled sprawl scenario. Following policy regulations (SPNRB, 2021), Shenzhen will achieve and promote the redevelopment of small-scale housing by 2035, and strengthen the protection of natural resources and ecological restoration, which indicates that introducing temporal data for land use scenario prediction can effectively evaluate the effectiveness of policy implementation. After 2026, the changes in the area of various land types gradually tend to stabilize. Due to the continuous improvement of land use data accuracy and shortened data update cycles, more abundant time series information is easily accessed. By leveraging these abundant time series information, more clear time-dependence characteristics can be captured to accurately model land use change and develop CA theories. Coupling time series data with VCA models becomes a practical basis and promising direction for land use change modeling and simulation, which can assist decision-makers in making targeted and rational planning and policy recommendations (Jin et al., 2020).

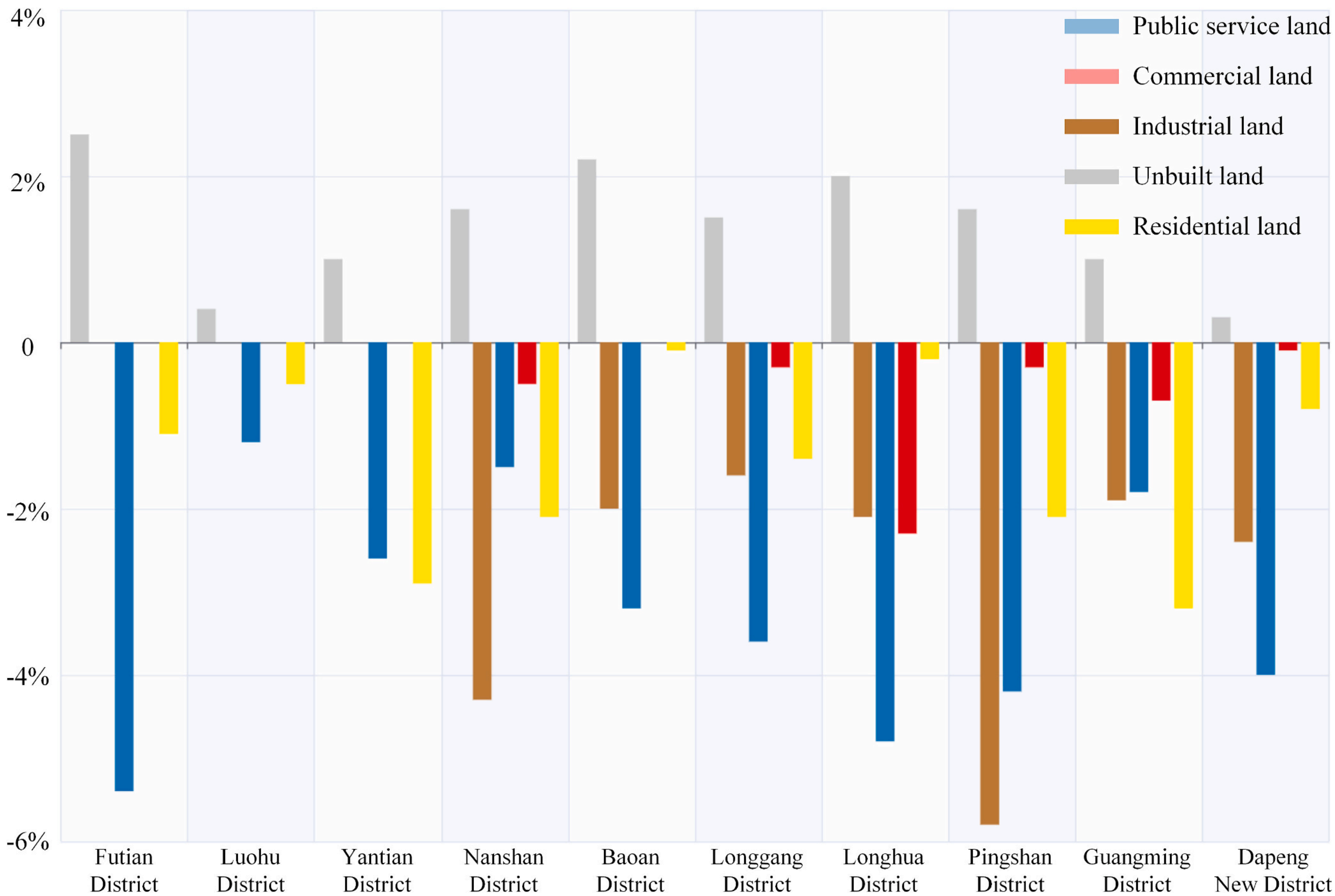


**Fig. 7.** Simulated changes in land use in various administrative regions compared to the uncontrolled sprawl scenario in 2030 under ecological protection scenarios (unit: %).

This study still has some possible opportunities for improvement. Firstly, the model proposed in this paper combines the temporal prediction results with the VCA framework results at the probability level of land parcel conversion prediction. Future research can consider generating temporal conversion factors based on the temporal prediction results to achieve deep coupling at the probability level of VCA conversion. Secondly, there is uncertainty in the model's prediction results. Various uncertain factors like the economy and policies influence urban land use change (Long et al., 2020; Wei et al., 2016). These factors demand more discussions and evaluations during model application and decision-making. Finally, in future research, we will apply the VCA model to the field of urban agglomeration and global land use change to explore its generalizability.

## 7. Conclusion

This paper proposes an advanced framework for simulating and predicting urban land use changes, Temporal-VCA. The framework simulates land use change in Shenzhen by coupling time series data with different machine learning and deep learning models. The results verify that land use change has obvious time dependence and trends. Introducing time dimension information significantly improves the simulation accuracy of the model. It shows that temporal VCA can process high-precision information of time and space dimensions at the same time, providing a feasible direction for the further development of VCA model. The long-term prediction results based on multiple scenarios indicate that combining time series data can assist decision-makers in better predicting and planning the spatial distribution of land use and have a clear understanding of the implementation effects of different policies. This paper suggests that in the future, the Shenzhen Municipal Government should pay more attention to the combination of urban planning and time dependence mechanisms, establish and improve a land use temporal database, strengthen the application of time series analysis in land use planning, in order to accurately predict land use demand, improve urban livability and attractiveness. In the future, this study will consider environmental and economic factors, deeply analyze the driving mechanism of land use temporal factors, and accurately excavate and evaluate the factors affecting urban development in different regions. The study results contribute to a deeper understanding of the temporal dependence mechanism of urban land use and provide a reference for formulating regional development policies.

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## CRediT authorship contribution statement

**Yao Yao:** Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Kun Zhou:** Writing – original draft, Validation, Methodology, Investigation, Data curation. **Chenxi Liu:** Writing – review & editing, Writing – original draft. **Zhenhui Sun:** Writing – review & editing, Software, Methodology. **Dongsheng Chen:** Writing – review & editing, Writing – original draft, Methodology. **Linlong Li:** Writing – review & editing, Validation, Data curation. **Tao Cheng:** Writing – review & editing, Validation. **Qingfeng Guan:** Writing – review & editing, Supervision, Project administration.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2024.104975.

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