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Fine-grained regional economic forecasting for a megacity using vector-based cellular automata

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ABSTRACT

It is important to measure uncoordinated regional urban economic development to help guide government policy. However, previous models have often struggled to capture the fine-grained spatiotemporal characteristics of economic development, thereby failing to provide insight into the fine-scale patterns. Sectoral structure and its evolution are strongly related to economic development and provide finer spatial information. Therefore, this paper proposes a framework for forecasting the spatiotemporal evolution of urban economic development at the cadastral parcel scale based on sectoral land use dynamics modeling and the S-curve economic model. The results of the case study conducted in Shenzhen, China, show good performance (FoM = 0.182, average R^2 = 0.748, median R^2 = 0.877). The sectoral structure in high-economic-level areas was found to be more balanced, and the economic volume tended to increase more. In contrast, sectoral land use types change more frequently in low-economic-level areas, and the economic growth rates are generally higher due to their lower economic base. Without government intervention, disparities in simulated economic volumes between regions will continue to widen in the short term. Hence, the government is encouraged to consider optimizing the sectoral structure in low-economic-level areas to promote coordinated regional economic development.

1. Introduction

In the 21st century, the problem of uncoordinated regional economic development has become increasingly serious in China as urbanization accelerates (Nishimura, 2020). Most of the regions in China still follow an inefficient land-extensive mode of economic development (R. Yin, Li, & Fang, 2023). The government's excessive focus on economic growth has led to an uncontrolled expansion of urban land. It eventually leads to an imbalance between urban land development and the economic development of cities (Zhu & Du, 2021). However, optimizing the sectoral structure of cities can improve resource utilization and promote high-quality economic development, which is the key to solving the imbalance (Liu et al., 2021). The sectoral structure of cities has evolved dramatically with urbanization, which has given impetus to economic development(Irfan, Razzaq, Sharif, & Yang, 2022). In addition, a change in the major economic sector also affects the change in sectoral structure in terms of production and consumption (Liang et al., 2021a,b). Thus, studying the pattern of urban economic development can provide a reference for governmental decisions in coordinating urban economic development, thereby promoting common prosperity and maintaining social harmony and stability.

Sectoral structure and its evolution are key to measuring and understanding regional economic development. They are highly correlated with the quantity, quality, and spatial patterns of regional economic

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growth (Chen & Peng, 2018). Additionally, they can reveal the relationship between urban land use and economic development (Nasiri et al., 2019). However, the previous urban sectoral structure research faces several issues. First, the evolution of the urban sectoral structure has a significant spatial spillover effect on economic development (Shi, 2020). The previous research on sectoral structure evolution and its relationship with economic development is mainly studied at macro scales, e.g., the provincial, city, and county scales (Liu, Yang, & Chen, 2011; Liu, Xue, Chen, Miao, & Shi, 2022; Wu, Wei, Huang, & Chen, 2017; Yin et al., 2023; Zeng, Hu, & Zhong, 2023).

However, studies at coarse spatial scales often fail to accurately reveal the spatial relationship between sectoral structure and economic development (L. Guo & Liu, 2022; Jun Li, Hu, & Xu, 2010). In addition, a coarse spatial scale will further affect the accuracy of analyzing the urban land-economic impact mechanism and the coordinated development of intracity regions (Hazell & Rinner, 2019). Further, how to model the evolution of the sectoral structure is still not sufficiently discussed. Previous models conducted economic forecasting mostly based on static panel data, without access to the dynamic spatiotemporal evolution of sectoral structure and economic development information (Wang, Ren, & Zhou, 2021). As a result, it is difficult to properly understand micro-scale urban economic change and potential development issues. In short, the study of the sectoral structure and its evolution requires not only further refinement of the spatial scale but also an expansion of its temporal coverage.

Land use and sectoral structure are strongly correlated. Their relationship is important for the coordination of various urban elements, e.g., population, land, and industry (Zhang & Weng, 2022). The development of the sectoral structure can be revealed by the corresponding development of land use (Zhang et al., 2005). The urban land-use system and the economic system together form a typical urban land-economic system. Moreover, an inherent need to coordinate between the two exists because of this interaction (Liu et al., 2014a,b). Cellular automata (CA) models are the most common used and effective computational modeling technique for simulating urban land use system (Barredo, Kasanko, McCormick, & Lavalle, 2003; Liang et al., 2021b; Liu et al., 2014a,b; Santé, García, Miranda, & Crecente, 2010; Wu, 2002a,b). In the actual situation of urban planning, urban land uses are usually planned in terms of the cadasters as the basic units, which are usually irregular shapes (Rabbani, Aghababaee, & Rajabi, 2012). Conventional raster-based CA models struggle to accurately represent the geometric realism of urban land by simply treating urban land as regularly shaped discrete pixels (Barreira-González, Gómez-Delgado, & Aguilera-Benavente, 2015).

Vector-based CA (VCA), a state-of-the-art type of CA models, was proposed to more accurately represent urban land as irregularly shaped cadastral polygons in vector format (Lin, Li, Wen, & He, 2023; Moreno, Ménard, & Marceau, 2008). It shows advantages in simulating the detail and complexity of spatial change in the urban land use system at the cadastral scale. VCA models have been proven to better meet the practical needs of cadastral parcel-based land management in urban planning, and more accurately simulate urban land use dynamics than conventional raster-based CA models (Abolhasani, Taleai, Karimi, & Rezaee Node, 2016; Guan, Xing, Li, & Wu, 2023; Isinkaralar & Varol, 2023). Thus, VCA model can be used to help analyze the distribution pattern of economic development at the fine scale of cities from the perspective of land use and sectoral structure. It has the potential to help urban planners to identify the mechanism influencing economic development and sectoral structure, adjust regional land use policies, improve regional sustainable development performance (Wang et al., 2022), and ultimately achieve efficient, green, and sustainable use of land resources (Li et al., 2021).

This paper proposes a framework for predicting the spatiotemporal evolution of urban economic development at a fine scale. By using sectoral attributes as mediating variables, this paper aims to integrate urban land use dynamic and economic forecasting to achieve the simulation of spatio-temporal change of economic development in mega-cities. In contrast to with current studies, whose results mostly only remain at a coarse spatial granularity, e.g., provinces, cities or districts, this study achieves the fine-grained simulation of economic forecasting at the cadastral parcel granularity. A case study was conducted in Shenzhen. In general, the proposed framework is used to simulate the development of diverse sectoral land use types at the cadastral scale in urban areas. Then, the cadastral-scale economic growth trend of diverse sectoral land use types is predicted. Finally, the spatial pattern of economic growth at the fine scale can be analyzed. The results can help to analyze the impact of economic growth on urbanization at the fine scale and assist decision-making in proposing policies that are appropriate to local conditions.

2. Literature review

2.1. Relationship between sectoral structure, economic development, and land use

The study of the sectoral structure of urban land has positive implications for urban planning and design. An optimal sectoral structuring of urban land can promote positive economic development, provide more jobs, and promote the process of urbanization (F. Lu & Gao, 2008). In terms of research methodology, a combination of qualitative and quantitative analyses is usually used to describe and verify the relationship between urban sectoral structure and economic development (Fang & Sun, 2018; Gregory & Griffin, 1974). From a systemic perspective, the economy shows an important influence on the efficiency of urban land use (Yin, Li, & Fang, 2023). Many methods have been proposed to evaluate urban land efficiency (Guo et al., 2007), the mechanisms of land use evolution (Su, He, & Fang, 2011), and regional differences at different spatial scales (Kline & Alig, 2001; Stoorvogel & Antle, 2001).

The transformation from the inefficient land-extensive mode to the efficient land-intensive mode of urban development can help optimize the allocation of land resources and promote economic development. Therefore, the study of the land-intensive mode has attracted great attention from scholars and governments in China (Liu et al., 2014a,b). Scholars hope to obtain fine-grained regional economic patterns to help analyze the two-way relationship between urban land use and economic development, thereby contributing to regional coordinated development.

2.2. Urban economic modeling

In recent years, traditional quantitative statistical models have been gradually combined with spatial analysis methods, leading to larger spatial scale of analysis (Smętkowski, 2015). In the field of economic forecasting, performance largely depends on the appropriateness of the chosen economic forecasting method (F. Lu & Gao, 2008). Economic forecasting methods include qualitative forecasting methods (e.g., subjective probability methods, cross-probability methods, expert surveys, etc.) and time series forecasting methods (Pesaran, Schuermann, & Smith, 2009), causal analysis methods (Gorus & Aydin, 2019) and neural network modeling methods (Cai, 2021). In the field of time series forecasting methods, the S-curve model has been proposed to describe the phenomenon of initial low growth, followed by faster growth and then slow growth at the end (X. Gao, Wang, Liu, Liu, & Yan, 2019). It has been applied to quantify the relationship between individual sectors such as energy and steel and economic development (Guo et al., 2022). The model has also been applied to studies of economic growth forecasting (Hidalgo & Hausmann, 2009) and urban expansion (Liu et al., 2017). Economic forecasting studies based on time-series data usually have a small sample size of data. It is generally demonstrated through statistical methods, such as significance test, to verify the quality of the data and evaluate the regression model. (Baitinger, 2021; Kouziokas, 2020). However, most current studies focus only on the impact of a single sector on economic development (Gunay, Can, & Ocak, 2021). Additionally, most current studies are conducted at coarse spatial granularities, e.g., nation, province, city scales (Christensen, Gillingham, & Nordhaus, 2018), and metropolitan area (Du, Ge, & Sun, 2021). In summary, the choice of economic forecasting methods should consider the various contributing factors and the spatial granularities.

2.3. Cellular automata models for urban land use simulations

CA models are designed as a bottom-up simulation approach (Li, Yang, & Liu, 2008) to simulate the change in cells based on spatial-related rules (Li et al., 2013; Yang et al., 2015). Traditional Geo-CA models with regular grids are generally considered more suitable for large-scale spatial modeling (Al-kheder et al., 2009; Liang et al., 2021a, b; Liu et al., 2017a,b).However, the basic units of urban planning are usually cadastral parcels, i.e., irregular polygonal blocks (Dahal & Chow, 2015). The value of urban land is not only a key indicator of the economic status of a city, but also has the potential to attract larger populations and businesses, which can further contribute to the economic growth of the city (Peng, Song, & Han, 2017). Such development also has an impact on the demand for urban land for diverse sectors (J. Gao, Wei, Chen, & Chen, 2014; Shu, Xie, Jiang, & Chen, 2018). In this context, the application of VCA is particularly important. Because it is able to model intra- and inter-city land use dynamic by capturing the distances, connectivity, and spatial interactions between different land parcels (Y. Lu, Cao, & Zhang, 2015). By capturing the geographic characteristics based on urban irregular cadasters, VCA can simulate the details and complexity of land use within high-density cities at a fine spatial granularity, and better adapt to the irregularity of sectoral land use dynamics (Moreno, Wang, & Marceau, 2009). Therefore, vector-based CA (VCA) models are proposed to represent irregular geographic cells and to simulate land use changes at a finer scale to predict the evolution of urban development (Moreno et al., 2008).

VCA models can better fit the actual urban land use conditions (Dahal & Chow, 2014) and are more advantageous for fine-scale urbanization simulations (Jia et al., 2020). Yao et al. (2021) designed UrbanVCA, a cadastral-scale urban development simulation framework based on the VCA model, which supports various machine learning algorithms to enable the simulation of future land use patterns under diverse scenarios (Yao et al., 2021). Since urban renewal within the city has a strong influence on economic growth, this paper uses the VCA model to simulate the evolution of sectoral land use in our study area.

3. Study area and data

Our study area is Shenzhen, Guangdong Province, China. Shenzhen, located in South China (Fig. 1 (A) (B)), is a special economic zone as well as one of the important national economic centers in China (Zhang et al., 2022). According to official data published by the Shenzhen Bureau of Statistics (https://tjj.sz.gov.cn/), the city had a total area of 1997.47 km^2 and a resident population of 17,763,800 in 2020. Shenzhen is therefore well represented in the changing economic trends of China's megacities.

Land use data are the basis for conducting simulations of sectoral land use evolution, as well as analyzing regional economic patterns. The land use data for this paper are vector-based cadastral land use data obtained from the Shenzhen Municipal Bureau of Planning and Natural Resources (https://pnr.sz.gov.cn/). The 2011 and 2014 land use data were used, containing a total of 120,547 cadastral parcels. The raw land

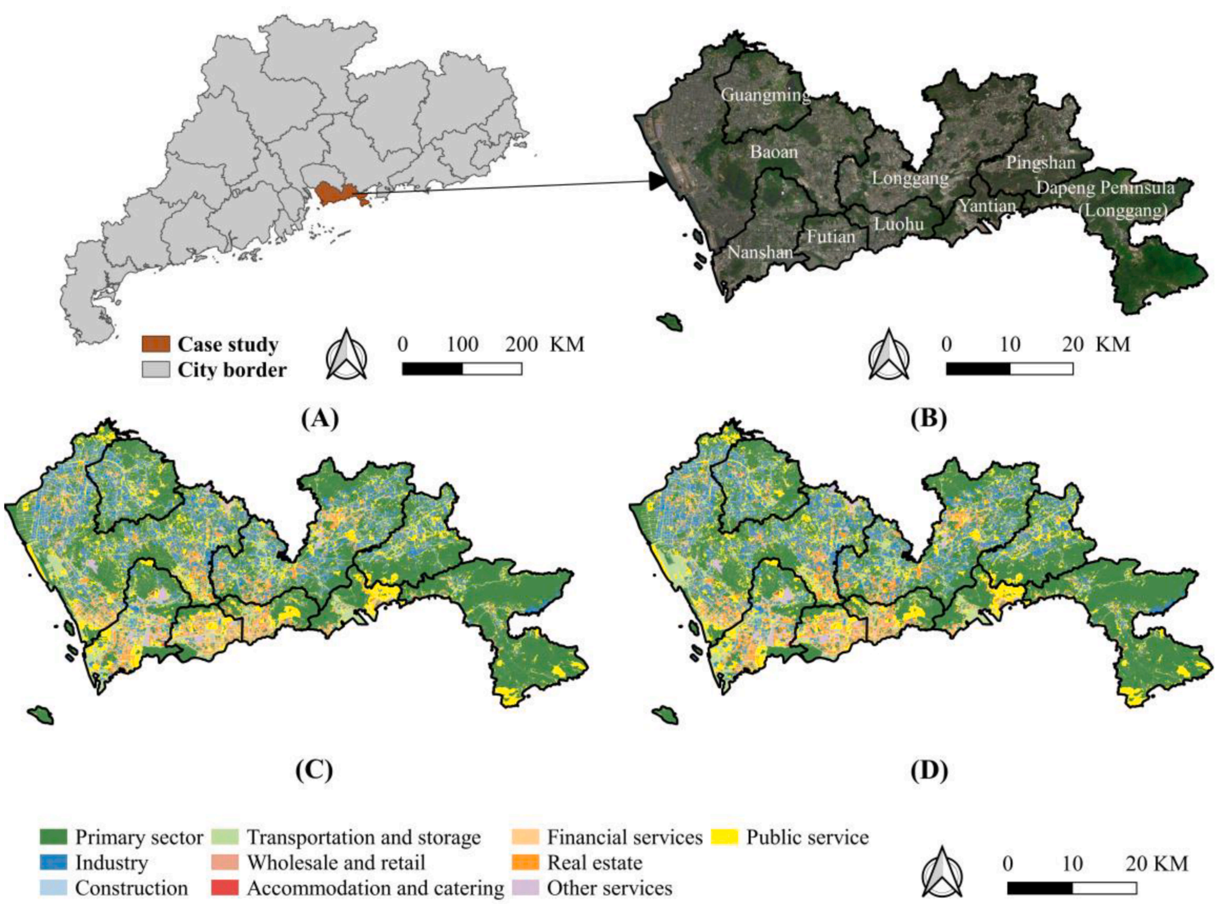

Fig. 1. Study area - (B) Shenzhen, located in (A) Guangdong Province, China, and sectoral land use data in (C) 2011 and (D) 2014.

use types were reclassified into sectoral land use types based on the designed rule (Table S1). The sectoral land use data are shown in Fig. 1 (C) and (D). The county-scale administrative boundaries for 2011 were used since the land use data for 2011 and 2014 were used.

The economic data in this paper are the official gross domestic product (GDP) data of each district and sector from 2011 to 2020. They are obtained from the 2011–2020 Statistical Yearbook issued by the Shenzhen Municipal Bureau of Statistics. The economic statistics of nine sectors are included, i.e., primary sector, industry, construction, transportation and warehousing, wholesale and retail, catering services, finance, real estate, and other services.

The spatial driver data for this paper are a set of contributing factors for sectoral land use evolution in cities. The evolution of urban sectoral land use is often affected by economic and social factors simultaneously

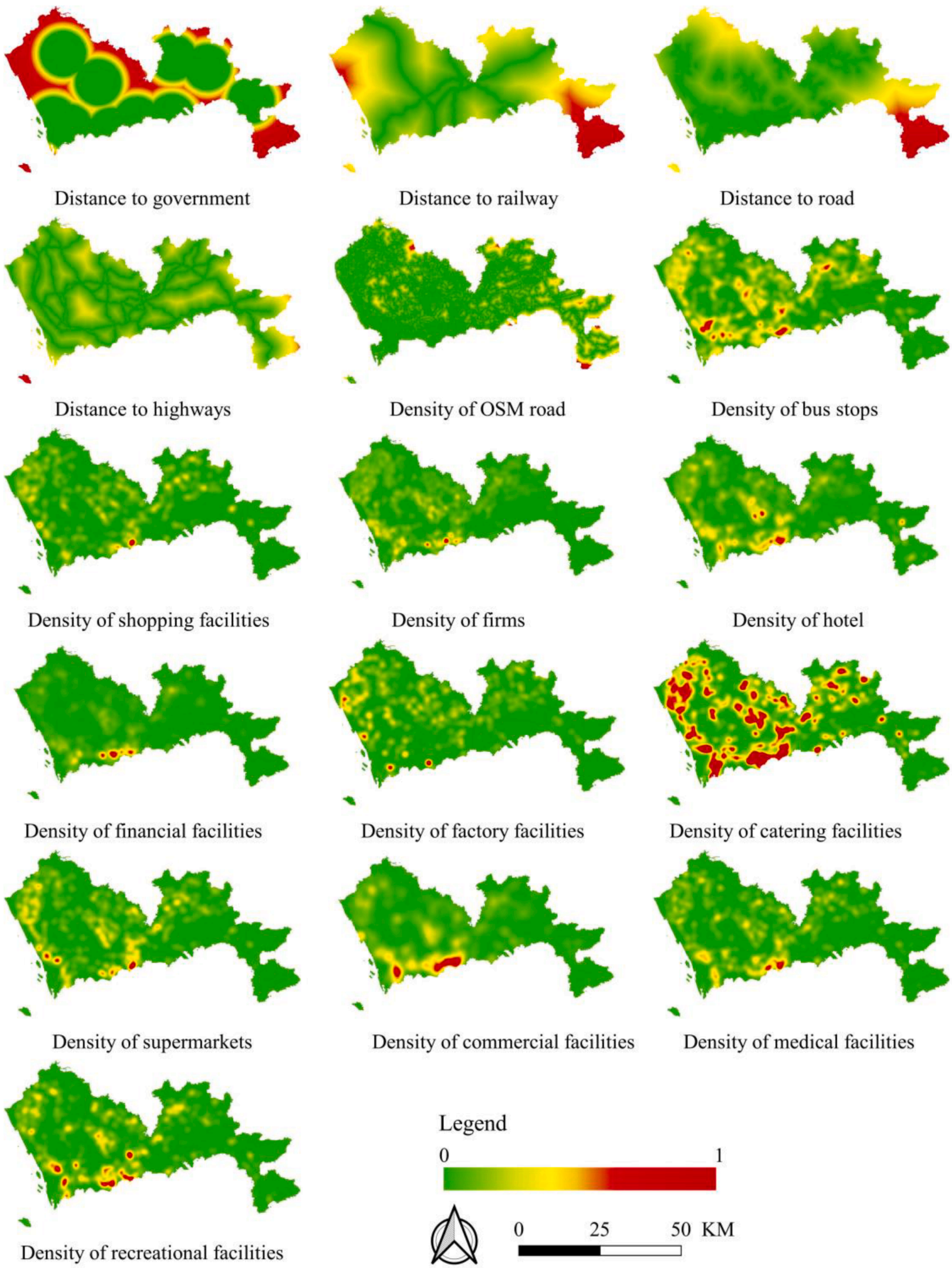

Fig. 2. Spatial auxiliary variables for urban land use dynamic modelling.

(Glaeser & Gottlieb, 2009; F. Wu, 2002a; Xu & Feng, 2022). Thus, the selected contributing factors consist of economic factors (e.g., density of shopping, factory facilities), social factors (e.g., density of transportation, medical facilities), political factor (distance to government) and location factor. Spatial drivers are obtained from the Point of Interest (POI) data in 2015 from Gaode Map (https://lbs.amap.com/), as well as the road network data from OpenStreetMap (https://www.openstreetmap.org/). And then the kernel density analysis is applied to process the above data to obtain spatial auxiliary variables. The bandwidth of kernel density analysis determines the level of details of the generated density raster. This study applied the Silverman's rule of thumb to set an appropriate bandwidth for different datasets (X. Liu et al., 2017a; Silverman, 2018; J.-D. Zhang & Chow, 2015). Next, the spatial ancillary variables were projected and resampled onto the raster layers with the same geographic coordinate system and the 30 m spatial resolution. Last, all the spatial ancillary variables were normalized in a range of [0,1] (Fig. 2).

4. Methodology

The proposed framework includes the following three steps (Fig. 3). In the first step, the overall development probabilities of all sectors were first calculated through a random forest algorithm. The future total land stocks for each sector are then predicted through the Markov chain models. The evolution of sectoral land is simulated based on the VCA model. In the second step, the S-curve model was introduced to construct an economic forecasting model that considers location and sectoral land use type. The spatial patterns of sectoral land use and economic growth in each district are analyzed. In the third step, the economic output indicators for each sector in each district were calculated by combining the predicted sectoral land use data with the predicted economic data for each sector from the zoning statistics. These indicators are then assigned at the cadastral scale based on sectoral land use type, land area, and location attributes. Thus, regional fine-grained economic growth can be obtained.

4.1. Dynamic simulation for urban sectoral land uses

This section describes the details of the VCA model used to simulate the evolution of sectoral land use. The average of the spatial auxiliary variables for each parcel is defined as X. The evolved sectoral land use type is defined as Y. The sectoral land use evolution model is constructed as $Y = f(X)$. The transformation probability for each sectoral land use type Y_i is calculated based on the random forest algorithm. These Y_i are

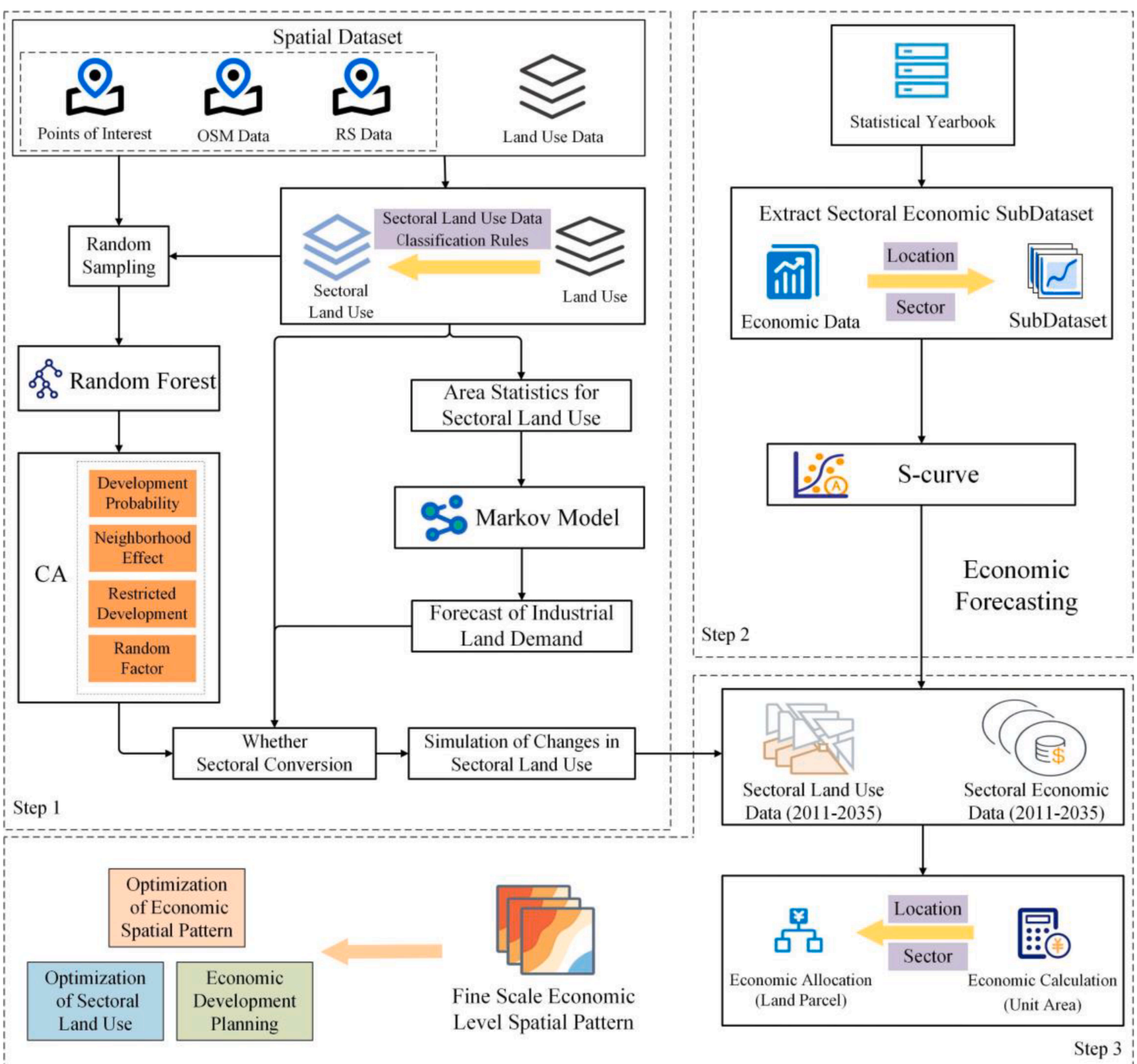

Fig. 3. Workflow of the proposed framework.

taken as the overall development probability of each parcel P_0. Meanwhile, the mass interception buffer method is also used to calculate the neighborhood effect φ for each parcel since the development of the cell's neighborhood also affects the evolution of the cell's sectoral land use. The model introduced a random factor $RA = 1+(-lny)^{\alpha}$ considering the uncertainty in the evolution of sectoral land use. α refers to a parameter between 1 and 10, while y is a random value between 0 and 1.

Here, the VCA model used in this paper, called random forest-based VCA (RF-VCA), can be expressed by the following equation.

$$P_i^{k,t} = P_{0_i}^{k,t} \times \varphi_i^{k,t} \times RA \tag{1}$$

where $P_i^{k,t}, P_{0_i}^{k,t}, \varphi_i^{k,t}$ indicates the transformation probability, the overall development probability, and the neighborhood effect of parcel i transformed into sectoral land use type k at time t, respectively.

Finally, a Markov chain (D. Guan et al., 2011) is used to predict the future total land stock for each sector (Zhang et al., 2011). Therefore, the future evolution of sectoral land use can be simulated based on the total land stocks.

4.2. Fine-grained forecasting of urban regional economic development

4.2.1. Location- and sector-based economic forecasting

Based on the simulated urban sectoral land use, the S-curve model is used to forecast future economic growth using economic data from 2011 to 2020 (Wang et al., 2022a,b). The S-curve regression allows for good control of the maximum environmental carrying capacity of the targeted location. The economic development trend of sectors that are mature in terms of megacities may eventually reach a steady state (Siedlecki, Papla, & Bem, 2018). The equation for fitting the economic growth curve for each sector at each location is as follows:

$$GDP_{ij}^t = \frac{K}{1 + a \bullet e^{-bt}} \tag{2}$$

where GDP_{ij}^t denotes the economic output value of the j-th sectoral land use type in the i-th administrative unit in year t. K indicates the maximum environmental carrying capacity, and a and b control the growth direction and speed of the curve.

The regional curve of overall economic output can be described as follows:

$$GDP^t = \sum_i^n \sum_j^m GDP_{ij}^t \tag{3}$$

where GDP_{ij}^t denotes the forecasted economic output in year t for sectoral land use type j at parcel i, and GDP^t refers to the forecasted economic output in year t for the whole city.

4.2.2. Fine-grained spatiotemporal economic growth calculation

Each region of a city has a different economic development status, sectoral structure, and sector with the highest economic contribution (Jiang et al., 2017). To better adjust the spatial scale of the economic allocation, district- and county-scale land area data and sectoral economic data are used to calculate the economic output at the cadastral parcel scale. First, the land area of each district unit and each sector is calculated based on the cadastral sectoral land use data. Second, the economic data of each sector in each district unit are collected based on official statistical documents. Finally, the economic output of each district unit is allocated based on the area and sector land use type of each cadastral parcel. The equation is as follows:

$$E_{ij}^k = \frac{G_j^i \times S_k}{\sum_k S_k} \tag{4}$$

where E_{ij}^k represents the economic output of the k-th parcel in the i-th district unit with the j-th sectoral land use type. G_j^i denotes the GDP volume of the j-th sectoral land use type officially published in the i-th district unit. S_k indicates the area of the k-th parcel. The spatiotemporal pattern of the urban economic output at the cadastral parcel scale can be obtained based on the above economic output.

4.3. Accuracy assessment

4.3.1. Accuracy assessment of urban sectoral land use simulation

Figure of merit (FoM) can be used to focus more on parcels that have changed sectoral land use type in the simulated urban sectoral land use evolution (Zhai et al., 2020). This paper applies FoM, PA, and UA to evaluate the accuracy of urban sectoral land use evolution simulation. Their equations are as follows:

$$FoM = \frac{B}{A+B+C+D} \tag{5}$$

$$Producer^{'}saccuracy(PA) = \frac{B}{A+B+C} \tag{6}$$

$$User^{'}saccuracy(UA) = \frac{B}{B+C+D} \tag{7}$$

where A, B, C, and D indicate the parcels that remain unchanged in the simulation while in the ground truth the parcels have changed, the parcels that correctly predict land-use change as well as the land-use type, the parcels that correctly predict land-use change but with an incorrect land-use type, and the parcels that have land-use change in the simulation while in the ground truth the parcel remains unchanged, respectively.

In terms of land area for each sectoral land use type, the accuracy is assessed at the district scale by comparing the simulated results and the ground truth from the official statistics. The equation is as follows:

$$\text{Accuracy}_{ij} = 1 - \frac{\left|A_{ij}^{simulation} - A_{ij}^{ture}\right|}{A_{ij}^{ture}} \times 100\% \tag{8}$$

where $\text{Accuracy}_{ij}, A_{ij}^{simulation}, \text{and} A_{ij}^{ture}$ indicate the accuracy, the simulated land area, and the ground truth of the j-th sectoral land use type in the i-th district unit.

4.3.2. Accuracy assessment of regional economic forecasting

In this study, the accuracy of the economic forecasting models was evaluated using the coefficient of determination (R2), mean absolute percentage error (MAPE) and symmetric mean absolute percentage error (SMAPE). R^2 is a statistical measure of how well the regression model fits the observations, ranging from 0 to 1. The closer the value of R^2 is to 1, the better the fit of the regression model to the observations. Conversely, the smaller the value of R^2 is, the worse the fit of the regression model to the observations.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{9}$$

$$SST = \sum_{i=1}^n (y_i - \overline{y_i})^2 \tag{10}$$

$$SSR = \sum_{i=1}^n (\widehat{y_i} - \overline{y_i})^2 \tag{11}$$

$$SSE = \sum_{i=1}^n (y_i - \widehat{y_i})^2 \tag{12}$$

where $y, \overline{y}, \widehat{andy}$ represent the economic output to be fitted, the average, and the fitted economic output. *SST, SSR*, and *SSE* indicate the sum of squares total, the sum of squares regression, and the sum of squares error, respectively.

Mean Absolute Percentage Error (MAPE) is a statistical indicator commonly used to measure the accuracy of regression, such as time series forecasts. The MAPE coefficient ranges from [0,+∞]. The smaller the MAPE, the better the model results. A model with a MAPE over 100 % indicates a poor model. SMAPE is a corrective indicator for the possible problems of MAPE, which can avoid the problem of MAPE being asymmetric, i.e., biased towards large values. Their equations are as follows.

$$MAPE = \frac{100\%}{n} \times \sum_{i}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \tag{13}$$

$$SMAPE = \frac{100\%}{n} \times \sum_{i}^{n} \frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2} \tag{14}$$

where $\hat{y}_i$, y_i and n refer to the predicted value, the actual value, and the total sample size.

5. Result

5.1. Result of sectoral land use modeling

5.1.1. Validation of sectoral land use simulation

The VCA model has reached the desired accuracy (Yao et al., 2021). The results show that the FoM, PA, and UA of the simulated sectoral land use evolution in 2014 are 0.182, 0.324, and 0.280, respectively. Overall, these indicators show a good performance of urban land change simulation. Thus, future sectoral land use can be predicted via this VCA model.

To further verify the local accuracy of the land area simulation, the simulated results of each sectoral land use type in each district unit in

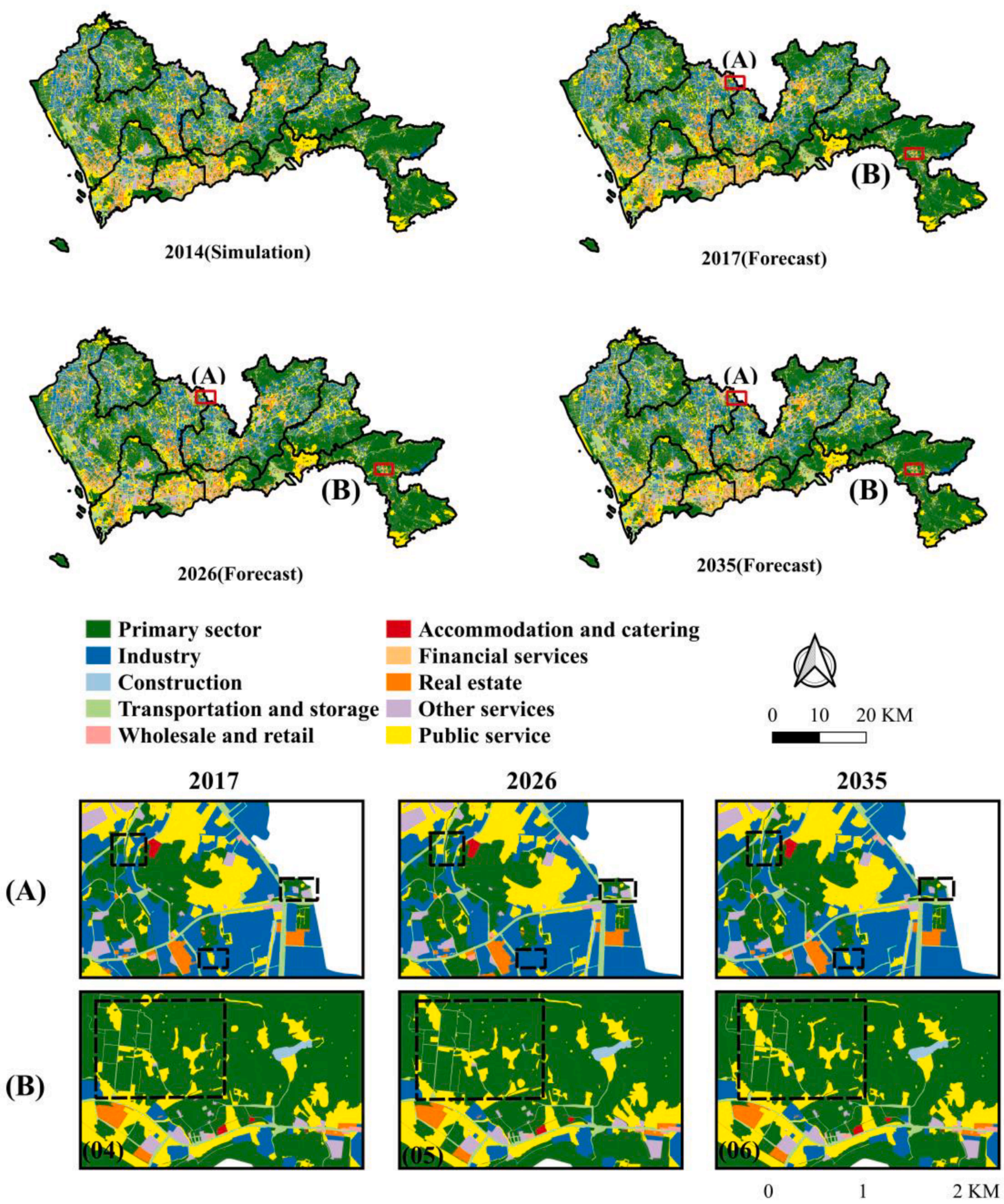

Fig. 4. Results of sectoral land evolution simulation in Shenzhen in 2014, 2017, and 2035. (A) Example in Baoan District, (B) example in Dapeng Peninsula. The black dashed boxes indicate the areas where the sectoral land use types were transformed.

2014 are compared with the ground truth. The majority of the models achieved more than 90 % accuracy. The simulation results of other fitted models also achieved good accuracy and can be used for future sectoral land use change prediction (Table S2).

5.1.2. Spatiotemporal pattern of sectoral land use evolution

The future land stocks for each sectoral land use type in 2017, 2026, and 2035 were predicted through the Markov chain model. The evolution of urban sectoral land use in 2017, 2026, and 2035 was simulated (Fig. 4) based on the future sectoral land stocks. In terms of spatial pattern, the four special economic zones (i.e., Luohu, Futian, Nanshan, and Yantian districts) cover the most diverse sectoral land use types and most balanced sectoral land areas. These are followed by Baoan District and Longgang District, with large and balanced land areas in all sectors except the primary sector. The land area of the primary sector is dominant in Guangming District, Pingshan District, and Dapeng Peninsula, indicating a poor balance of sectoral land areas.

From the perspective of temporal trends, the land area and spatial pattern of sectoral land use in Shenzhen reach a stable state when comparing these three timeframes. In this study, representative high and low economic zones in Shenzhen were selected for comparison and analysis. It was found that the areas of high economic levels (Fig. 4 (A)) have fewer sectoral type changes in land compared to the lower economic level areas (Fig. 4 (B)). This result may reflect that the sectoral structure of land in high economic level areas of megacities is relatively stable; in lower economic level areas, the probability that urban land will maintain a frequent sectoral-type change in the future to better adapt to regional economic development is higher.

5.2. Predicted economic growth considering location and sector

This section aims to analyze the predicted result of location- and sector-based economic forecasting. Since the administrative division in Shenzhen changed after 2014, this paper uniformly follows the eight administrative divisions of the Futian, Luohu, Yantian, Nanshan, Baoan, Guangming, Longgang, and Pingshan districts.

5.2.1. Fitting accuracy

In this study, the significance test was first carried out to verify the validity of the economic data used in this study, followed by the error analysis of the sector-based models and the location-based models. All models passed the significance test with the p-values less than 0.001, proving the reliability of the economic data in this study (Table S3). Both the sector- and location-based economic models show a good performance. Moreover, Table 1 shows that all models can achieve an R^2 of 0.9 or more, except for the model for the primary sector, which has an R^2 of 0.806. The MAPE and SMAPE of all the economic forecasting models in this study are within 5 %, except for the models for the primary and construction sectors, indicating good performance of the models. Thus, these S-curve models have an acceptable degree of accuracy and can be used to forecast the economic growth of each sector in each administrative region. By using this strategy, these S-curve models can address regional and sectoral heterogeneity very well. The predicted results show that all the economic curves are in growth mode, indicating that the future trend of economic development of Shenzhen will continue to increase. At the same time, the economic growth trend can be categorized into three trends: stable growth, decelerating growth, and accelerating growth.

5.2.2. Economic analysis

For comparative analysis of the fitted model parameters for the sectoral economy, Futian District and Pingshan District were selected as representatives of high- and low-economic level areas, respectively (Table 2). Please check Table S4-S11 for the remaining results. Table 2 reveals a Matthew effect in the differences in regional economic growth. The Matthew effect of accumulated advantage refers to the tendency of individuals to accrue social or economic success in proportion to their initial level of popularity, friends, wealth, etc. In the S-curve models, K represents the bounded amount of economic output, revealing the feature of the economic curve. Although the overall economic level of the two regions is different, the economic level of the sectors within each region has the regional strength. Parameters a and b can reveal the growth trend and speed of the curve. The higher the value of a is, the slower the economic growth, indicating that the corresponding sector in the region is entering a mature stage, while b has the opposite effect. Table 2 shows that the overall economic output is higher in the region with a high economic level. Although the economic growth rate may slow down, the value of economic growth will be higher. Thus, the total economic growth in the high economic areas is greater, and the regional gap in economic levels will further widen. Based on the accuracy of these models, the economy of each district and sector in Shenzhen is fitted to predict future economic outcomes (Figures S1-S16).

The trends of the fitted curves for the various sectors in Shenzhen are generally consistent with the distribution of sample points (Fig. 5). The economic growth of all sectors and locations in Shenzhen shows an upward trend. However, there are still some differences. For example, the sectoral land uses for industry, wholesale and retail, and other services tend to grow before maintaining stability in future years. This indicates that the development of such sectors tends to be mature and stable. However, the sectoral land use for the primary sector and financial services shows a continuous rapid growth trend in economic development.

5.3. Spatiotemporal pattern of forecasted urban economic growth

The heterogeneity of sectoral economic levels in both spatial and temporal dimensions is revealed by the forecasting of the fine-grained economic levels. Fig. 6 shows the forecasted results of the fine-grained economic levels in Shenzhen for 2017, 2026, and 2035. Several patterns emerged.

From the spatial perspective, the overall economic level of Shenzhen is high in the west and low in the east. The spatial characteristics of economic levels within urban and county-level administrative regions and their association with sectoral structure are linked in some cases. The central part of Nanshan District, which is mainly covered by industrial land and land for other services, shows the highest economic

Table 1
Accuracy of economic fitting S-curve models for different sectors and different locations in Shenzhen.

District	R^2	MAPE	SMAPE	Sectors	R^2	MAPE	SMAPE
Futian District	0.993	1.247 %	1.245 %	Primary sector	0.830	9.705 %	9.443 %
Luohu District	0.983	2.043 %	2.031 %	Industry	0.961	3.192 %	3.176 %
Yantian District	0.994	1.009 %	1.008 %	Construction	0.953	6.013 %	5.977 %
Nanshan District	0.977	3.657 %	3.637 %	Wholesale and retail	0.935	2.950 %	2.936 %
Baoan District	0.983	3.018 %	2.999 %	Transportation and storage	0.904	4.593 %	4.536 %
Guangming District	0.989	2.591 %	2.617 %	Accommodation and catering	0.884	3.600 %	3.568 %
Longgang District	0.976	4.434 %	4.397 %	Financial services	0.980	2.970 %	2.964 %
Pingshan District	0.985	3.192 %	3.186 %	Real estate	0.988	2.703 %	2.725 %
				Other services	0.991	3.133 %	3.144 %

Table 2
Parameters of the S-curve models for Futian District and Pingshan District.

	K		a		b	
	Futian District	Pingshan District	Futian District	Pingshan District	Futian District	Pingshan District
Overall	7.94×10^{7}	2.01×10^{7}	3.17×10^{1}	7.05×10^{1}	1.56×10^{-1}	1.59×10^{-1}
Primary sector	2.53×10^{4}	7.43×10^{7}	2.79×10^{1}	1.34×10^{4}	3.63×10^{-1}	-5.34×10^{-3}
Industry	1.81×10^{6}	1.61×10^{7}	4.32×10^{-1}	8.84×10^{1}	5.93×10^{-1}	1.32×10^{-1}
Construction	7.32×10^{12}	4.50×10^{5}	4.24×10^{7}	1.53×10^{1}	1.61×10^{-1}	4.68×10^{-1}
Wholesale and retail	6.85×10^{6}	4.80×10^{5}	1.69×10^{1}	3.06×10^{1}	9.01×10^{-1}	3.74×10^{-1}
Transportation and storage	5.14×10^{12}	7.24×10^{4}	7.68×10^{6}	2.64×10^{1}	7.61×10^{-2}	4.33×10^{-1}
Accommodation and catering	4.59×10^{10}	8.32×10^{4}	1.14×10^{5}	1.33×10^{1}	4.33×10^{-2}	3.81×10^{-1}
Financial services	2.45×10^{14}	5.30×10^{5}	3.78×10^{7}	8.33×10^{1}	1.07×10^{-1}	2.86×10^{-1}
Real estate	5.90×10^{6}	3.06×10^{12}	4.01×10^{1}	1.35×10^{7}	1.84×10^{-1}	9.87×10^{-2}
Other services	1.56×10^{7}	2.37×10^{6}	3.30×10^{1}	1.82×10^{1}	2.89×10^{-1}	3.32×10^{-1}

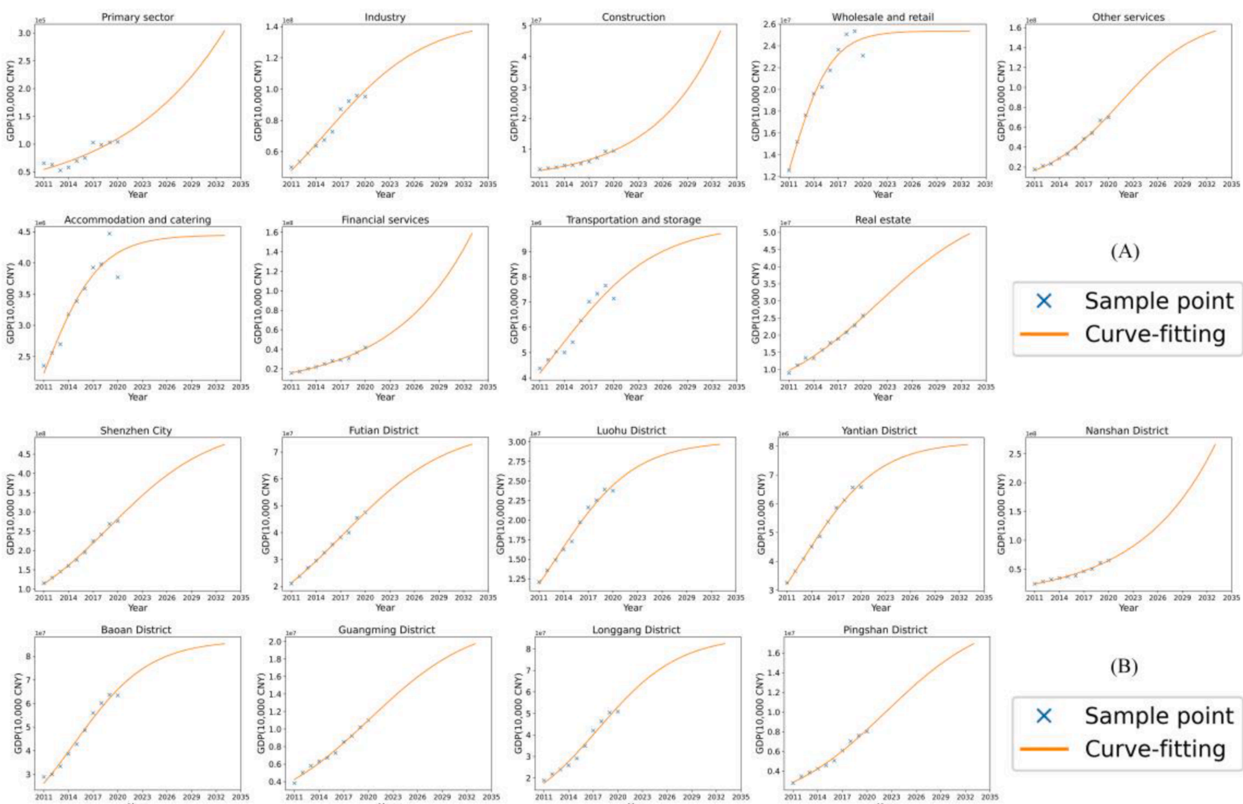

Fig. 5. Forecasted economic growth for each sector (A) in each region (B).

level in the whole city. The western part of Guangming District, which is dominated by industry, has a significantly higher economic level than the eastern part of Guangming District, which is dominated by the primary sector. The lands in Pingshan District and Dapeng Peninsula, which are mainly covered by primary sector land use, generally have lower economic levels, except for a few lands designated for industry and financial services. Moreover, the sectoral structure in the high-economic-level areas such as Futian District, Luohu District, and Nanshan District is more balanced and corresponds to a higher economic level than other districts. The lands in the low-economic-level areas, such as Pingshan District and Dapeng Peninsula, are dominated by the primary sector with a lower economic level.

From the temporal perspective, the overall economic level of Shenzhen has been increasing year by year on the macro scale. However, at the micro scale, the economic level of the low-economic-level regions (Fig. 6 (C) (D)) has been increasing more significantly than that of the high-economic-level regions (Fig. 6 (A) (B)). This may be related to the fact that the low-economic-level regions start from a lower economic base and have a greater potential for development, while the high-economic-level regions tend to be saturated with economic development.

The refined changes in economic levels predicted effectively tap into the spatial heterogeneity at regional economic levels. Fig. 7 shows the differences in the amount and rate of economic growth for each land parcel between 2017 and 2026 and 2035. In terms of the change in GDP volume, a larger increase occurs in high-economic-level areas such as the south-central Nanshan District. Lower-economic-level areas experience a small increase in GDP. A slight decrease occurs in some areas of the Pingshan District. In terms of temporal trends, the GDP volumes from 2017 to 2026 and 2026 to 2035 have their ups and downs. For example, from 2026 to 2035, the western part of Guangming District shows a substantial increase in GDP, while in contrast, the eastern part of Luohu District and the northwestern part of Yantian District show a smaller increase in GDP. In general, larger increases exist in weaker economic areas such as Guangming District, Longgang District, and Dapeng Peninsula.

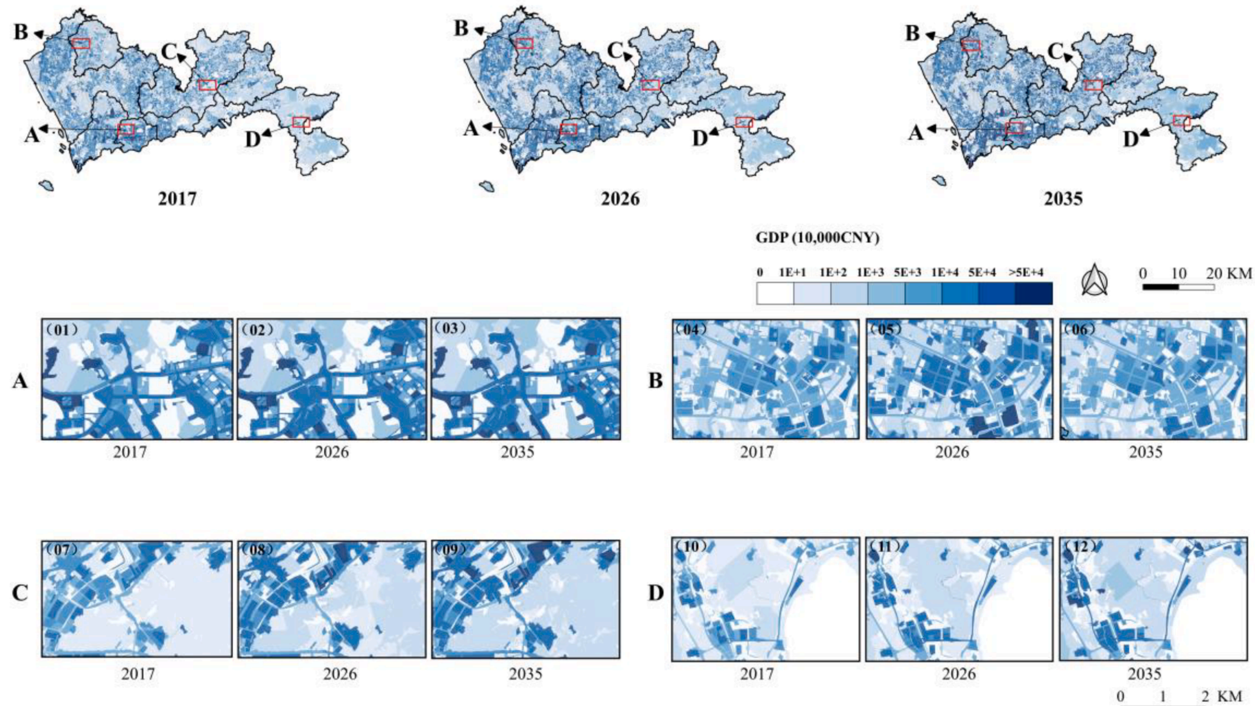

Fig. 6. The fine-grained spatial distribution of economic levels in Shenzhen. (A) Example in Futian District. (B) Example in Guangming District. (C) Example in Longgang District. (D) Example in Dapeng Peninsula.

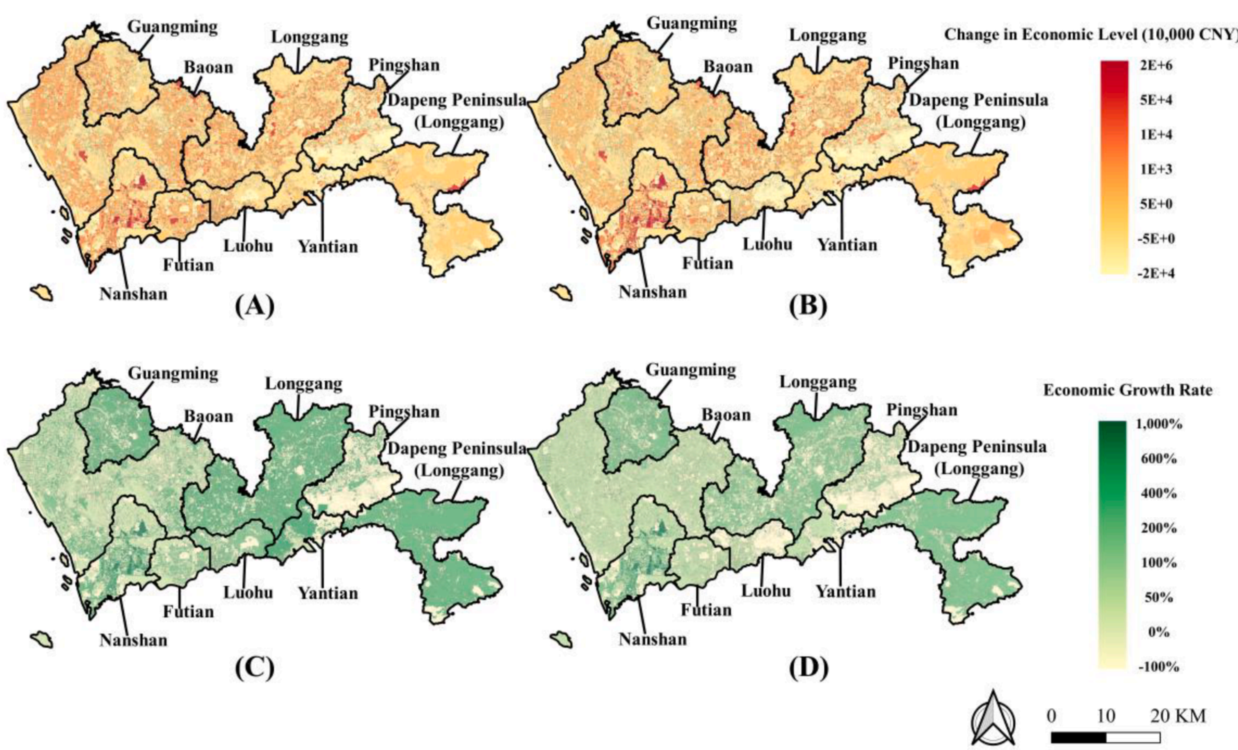

Fig. 7. Temporal changes in economic level and growth rate and their spatial distributions. The change in economic level from 2017 to 2026 (A) and from 2026 to 2035 (B). The economic growth rate from 2017 to 2026 (C) and from 2026 to 2035 (D).

However, the largest GDP increase is found in some strong economic areas (i.e., Nanshan District and parts of Yantian District). The GDP growth rate is significantly lower from 2026 to 2035 relative to that from 2017 to 2026. Most notably, the GDP trend changes from increasing to decreasing in the eastern part of Luohu District and the south-central part of Yantian District. Hence, under the strategy of uncontrolled economic development, the overall economic level of the city will improve in the future, but the gaps in economic volumes between districts will widen further in the short term.

6. Discussion

This paper proposes a framework for predicting the spatiotemporal evolution of urban economic development at the fine-grained cadastral parcel scale, considering sectoral and locational factors, to portray fine-scale economic development. The framework makes the following two contributions: 1) The framework introduces the land use dynamics simulation model for economic forecasting. 2) It can generate an accurate fine-scale spatial distribution of economic development. This study realizes the prediction of the spatiotemporal pattern of urban economic growth at a fine scale by coupling the results of urban land use and economic development forecasting.

This study couples land use dynamics simulation and sectoral structure economy, addressing the problem of the coarse-scale spatial distribution of economic forecasting portrayed in the past. The simulated results of the sectoral land use dynamics indicated a good performance (FoM = 0.182), which shows that the results can be used to analyze the spatial distribution and temporal change characteristics of the sectoral structure of urban land at a fine scale. According to the analysis, the sectoral structure in higher-economic-level areas is more balanced, and development is more stable.

In contrast, the lower economic level areas tend to show a more unbalanced sectoral structure and a higher frequency of adjusting the sectoral structure. For example, the areas of the different sectors in the high-economic level areas such as Nanshan District and Futian District are almost the same, with few parcels undergoing sector changes. Meanwhile, the sectoral structures in the low-economic-level areas such as Dapeng Peninsula, Yantian District, and Pingshan District are dominated by the primary sector. The number of parcels undergoing sector changes is higher. It reveals a general pattern of changing land use sectors in the development process of China's megacities. The framework can provide data references for further exploring the correlation and the driving mechanism of urban economic development changes with sectoral factors.

This study introduces the official statistics of gross economic output and economic volume into the framework to achieve more accurate economic forecasting. By depicting the spatiotemporal evolution of the urban economy, this study identifies a general pattern in which cities will continue to grow in the future. Areas with stronger economies will experience slower but larger economic growth, while those with weaker economies will have faster but smaller economic growth. This pattern describes the spatial distribution characteristics and temporal changes in economic heterogeneity among urban regions in the short run. Uncoordinated regional development will also continue to expand in the short term. This study enriches the theory related to urban economic modeling at the spatial microscale and provides a data reference for guiding policy for coordinated urban regional development.

The linkage between changes in urban sectoral land and economic growth is examined. First, for land parcels whose sectoral land use type do not change, their economic volumes change according to the current sectoral development trend. Since sectoral productivity varies in different administrative districts, the economic levels of land parcels with the same sectoral land use type are not the same. Second, for land parcels with a change in sectoral land use type, the economic level is mainly influenced by the productivity of the two sectors before and after the change, t, and thus changes more notably. For example, most land parcels in Shenzhen are currently experiencing economic growth as the sectoral economy grows.

At the same time, however, some areas in Pingshan District are experiencing a slight economic decline because the majority of the land parcels there are the primary sector land use, whose economic level is slowly declining. In addition, the change in sectoral land use type is also one of the reasons for the economic decline of some land parcels in Pingshan. Despite the economic decline in some of the areas, the overall economic level of Pingshan District is still growing. It further confirms the uncoordinated regional development of China's megacities, which needs to be adjusted through a series of government interventions.

This study needs to be further improved. First, in the process of modeling urban land dynamics, built-up factors, such as commercial facilities and transportation facilities, are seen as the main contributors. However, the influence of some natural factors on changes in sectoral land use types is not considered but may be useful. Second, in the process of modeling the spatial distribution pattern of economic development, the economic levels of each parcel are forecasted according to the three attributes of each parcel, i.e., sectoral land use type, area, and administrative district to which it belongs. However, the spatial neighborhood effect may exist between the economic growth of a parcel and its neighborhood. In the future, the proposed framework will be improved by introducing multisource spatial data, e.g., natural landscape data and urban population data, to determine the spatial neighborhood effect of economic growth to more accurately model economic growth.

7. Conclusion

This paper proposes a framework for calculating and forecasting the spatiotemporal economic levels in megacities at the fine-grained cadastral parcel scale to obtain the fine-scale economic pattern. Taking Shenzhen, Guangdong Province, China, as an example, the results show that the framework can effectively simulate sectoral land use changes (FoM = 0.182) and has significant advantages in economic curve fitting (the mean of R^2: 0.748, the median of R^2: 0.877).

This study found that the spatial distribution of sectoral land in Shenzhen is gradually stabilizing, and the urbanization mode is gradually shifting from urban land expansion to urban sector regeneration. The economic strength of the city continues to increase year by year. The lower-economic-level areas show a more substantial increase due to their weaker economic base and greater development potential. The regional economic gap between regions will continue to widen in the short term if there is no government intervention. Because the higher-economic-level regions have a larger base of economic output, some of them have the highest growth rate. This study reveals the general economic growth of megacities and uncoordinated regional development. We provide a possible explanation for the phenomenon in terms of urban land use change and sectoral structure balance.

CRediT authorship contribution statement

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

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

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jag.2023.103602.

References

Abolhasani, S., Taleai, M., Karimi, M., Rezaee Node, A., 2016. Simulating urban growth under planning policies through parcel-based cellular automata (ParCA) model. Int. J. Geogr. Inf. Sci. 30 (11), 2276–2301. https://doi.org/10.1080/13658816.2016.1184271.

Al-kheder, S., Haddad, N., Fakhoury, L., Baqaen, S., 2009. A GIS analysis of the impact of modern practices and polices on the urban heritage of Irbid, Jordan. Cities 26 (2), 81–92. https://doi.org/10.1016/j.cities.2008.12.003.

Baitinger, E., 2021. Forecasting asset returns with network-based metrics: A statistical and economic analysis. J. Forecast. 40 (7), 1342–1375. Retrieved from. https://econpapers.repec.org/RePEc:wly:jforec:v:40:y:2021:i:7:p:1342-1375.

Barredo, J.I., Kasanko, M., McCormick, N., Lavalle, C., 2003. Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landscape Urban Planning 64 (3), 145–160. https://doi.org/10.1016/S0169-2046(02)00218-9.

Barreira-González, P., Gómez-Delgado, M., Aguilera-Benavente, F., 2015. From raster to vector cellular automata models: A new approach to simulate urban growth with the help of graph theory. Comput. Environ. Urban Syst. 54, 119–131. https://doi.org/10.1016/j.compenvurbsys.2015.07.004.

Cai, B., 2021. Deep Learning-Based Economic Forecasting for the New Energy Vehicle Industry. J. Math. (Wuhan) 2021, 3870657. https://doi.org/10.1155/2021/3870657.

Christensen, P., Gillingham, K., Nordhaus, W., 2018. Uncertainty in forecasts of long-run economic growth. Proc. Natl. Acad. Sci. 115 (21), 5409–5414. https://doi.org/10.1073/pnas.1713628115.

Dahal, K.R., Chow, T.E., 2014. A GIS toolset for automated partitioning of urban lands. Environ. Model. Softw. 55, 222–234. https://doi.org/10.1016/j.envsoft.2014.01.024.

Dahal, K.R., Chow, T.E., 2015. Characterization of neighborhood sensitivity of an irregular cellular automata model of urban growth. Int. J. Geogr. Inf. Sci. 29 (3), 475–497. https://doi.org/10.1080/13658816.2014.987779.

Fang, H., Sun, Q., 2018. Spatial econometric analysis of the relationship between economic growth and industrial structure: Industrial complex network perspective. J. Interdiscip. Math. 21 (5), 1357–1361. https://doi.org/10.1080/09720502.2018.1498307.

Gao, X., Wang, A., Liu, G., Liu, C., Yan, K., 2019. Expanded S-Curve Model of a Relationship Between Crude Steel Consumption and Economic Development: Empiricism from Case Studies of Developed Economies. Nat. Resour. Res. 28 (2), 547–562. https://doi.org/10.1007/s11053-018-9406-3.

Gao, J., Wei, Y.D., Chen, W., Chen, J., 2014. Economic transition and urban land expansion in Provincial China. Habitat Int. 44, 461–473. https://doi.org/10.1016/j.habitatint.2014.09.002.

Glaeser, E.L., Gottlieb, J.D., 2009. The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. J. Econ. Lit. 47 (4), 983–1028. https://doi.org/10.1257/jel.47.4.983.

Gorus, M.S., Aydin, M., 2019. The relationship between energy consumption, economic growth, and CO2 emission in MENA countries: Causality analysis in the frequency domain. Energy 168, 815–822. https://doi.org/10.1016/j.energy.2018.11.139.

Gregory, P., Griffin, J.M., 1974. Secular and Cross-Section Industrialization Patterns: Some Further Evidence on the Kuznets-Chenery Controversy. Rev. Econ. Stat. 56 (3), 360–368. https://doi.org/10.2307/1923975.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., Hokao, K., 2011. Modeling urban land use change by the integration of cellular automaton and Markov model. Ecol. Model. 222 (20), 3761–3772. https://doi.org/10.1016/j.ecolmodel.2011.09.009.

Guan, X., Xing, W., Li, J., Wu, H., 2023. HGAT-VCA: Integrating high-order graph attention network with vector cellular automata for urban growth simulation. Comput. Environ. Urban Syst. 99, 101900 https://doi.org/10.1016/j.compenvurbsys.2022.101900.

Gunay, S., Can, G., Ocak, M., 2021. Forecast of China's economic growth during the COVID-19 pandemic: a MIDAS regression analysis. Journal of Chinese Economic and Foreign Trade Studies 14 (1), 3–17. https://doi.org/10.1108/JCEFTS-08-2020-0053.

Guo, L., & Liu, Y., 2022. Urban-Industrial Development and Regional Economic Growth in a Developing Country: A Spatial Econometric Approach. SAGE Open, 12(2), 21582440221102424. https://doi.org/10.1177/21582440221102425.

Guo, X., Wang, A., Liu, G., Du, B., 2022. Expanded S-Curve Model of Relationship between Domestic Water Usage and Economic Development: A Case Study of Typical Countries. Appl. Sci. 12, 6090. https://doi.org/10.3390/app12126090.

Guo, Q., Xie, J., Yin, J., Wang, L., Zhang, G., 2007. The Evaluation of Urban Land Intensive Use Based on RS. J. Nat. Resour. 22, 775–782. Retrieved from. http://www.jnr.ac.cn.

Hazell, E., Rinner, C., 2019. The impact of spatial scale: exploring urban butterfly abundance and richness patterns using multi-criteria decision analysis and principal component analysis. Int. J. Geogr. Inf. Sci. 34, 1–34. https://doi.org/10.1080/13658816.2019.1675072.

Hidalgo, C. A., & Hausmann, R., 2009. The building blocks of economic complexity. Proceedings of the National Academy of Sciences, 106(26), 10570–10575. https://doi.org/10.1073/pnas.0900943106.

Irfan, M., Razzaq, A., Sharif, A., Yang, X., 2022. Influence mechanism between green finance and green innovation: Exploring regional policy intervention effects in China. Technol. Forecast. Soc. Chang. 182, 121882 https://doi.org/10.1016/j.techfore.2022.121882.

Isinkaralar, O., Varol, C., 2023. A cellular automata-based approach for spatio-temporal modeling of the city center as a complex system: The case of Kastamonu, Türkiye. Cities 132, 104073. https://doi.org/10.1016/j.cities.2022.104073.

Jia, Z., Chen, L., Chen, J., Lyu, G., Zhou, D., Long, Y., 2020. Urban modeling for streets using vector cellular automata: Framework and its application in Beijing. Environment and Planning b: Urban Analytics and City Science 47 (8), 1418–1439. https://doi.org/10.1177/2399808320942777.

Jiang, G., Wenqiu, M., Deqi, W., Zhou, D., Zhang, R., Tao, Z., 2017. Identifying the internal structure evolution of urban built-up land sprawl (UBLS) from a composite structure perspective: A case study of the Beijing metropolitan area, China. Land Use Policy 62 (62), 258–267. https://doi.org/10.1016/j.landusepol.2016.12.014.

Kline, J.D., & Alig, R.J., 2001. A spatial model of land use change for western Oregon and western Washington. U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. https://doi.org/10.2737/pnw-rp-528.

Kouziokas, G.N., 2020. A new W-SVM kernel combining PSO-neural network transformed vector and Bayesian optimized SVM in GDP forecasting. Eng. Appl. Artif. Intel. 92, 103650 https://doi.org/10.1016/j.engappai.2020.103650.

Li, J., Hu, Y., Xu, X., 2010. GIS Based Study on the Spatial Variation of Industry Structure of China. Journal of Geo-Information Science 12, 372–379. Retrieved from. http://www.dqxxkx.cn.

Li, J., Li, Y., Yang, Y., Boldanov, T., Dong, S., 2021. The pattern and driving factors of land use change in the China-Mongolia-Russia economic corridor. Geogr. Res. 40, 3073–3091. Retrieved from. http://www.dlyj.ac.cn.

Li, X., Yang, Q., Liu, X., 2008. Discovering and evaluating urban signatures for simulating compact development using cellular automata. Landsc. Urban Plan. 86 (2), 177–186. https://doi.org/10.1016/j.landurbplan.2008.02.005.

Li, X., Lao, C., Liu, Y., Liu, X., Chen, Y., Li, S., He, Z., 2013. Early warning of illegal development for protected areas by integrating cellular automata with neural networks. J. Environ. Manage. 130, 106–116. https://doi.org/10.1016/j.jenvman.2013.08.055.

Liang, X., Guan, Q., Clarke, K., Liu, S., Wang, B., Yao, Y., 2021b. Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. Computers Environment and Urban Systems 85, 101569. https://doi.org/10.1016/j.compenvurbsys.2020.101569.

Liang, G., Yu, D., Ke, L., 2021a. An Empirical Study on Dynamic Evolution of Industrial Structure and Green Economic Growth—Based on Data from China's Underdeveloped Areas. Sustainability 13, 8154. https://doi.org/10.3390/su13158154.

Lin, J., Li, X., Wen, Y., He, P., 2023. Modeling urban land-use changes using a landscape-driven patch-based cellular automaton (LP-CA). Cities 132, 103906. https://doi.org/10.1016/j.cities.2022.103906.

Liu, W., Bao, Y., Xu, C., 2014a. Empirical Study on the Co-Integration Relationship between Urban Construction Land, Economic Growth and Urbanization Development of Jiangxi Province. 7, 1096–1103.

Liu, H., Chen, N., Feng, C., Tong, S., Li, R., 2017a. Impact of electro-stimulation on denitrifying bacterial growth and analysis of bacterial growth kinetics using a modified Gompertz model in a bio-electrochemical denitrification reactor. Bioresour. Technol. 232, 344–353. https://doi.org/10.1016/j.biortech.2017.02.064.

Liu, J., Hou, X., Wang, Z., Shen, Y., 2021. Study the effect of industrial structure optimization on urban land-use efficiency in China. Land Use Policy 105, 105390. https://doi.org/10.1016/j.landusepol.2021.105390.

Liu, X., Liang, X., Li, X., Xu, X., Ou, J., Chen, Y., Pei, F., 2017b. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. Landsc. Urban Plan. 168, 94–116. https://doi.org/10.1016/j.landurbplan.2017.09.019.

Liu, X.P., Ma, L., Li, X., Ai, B., Li, S.Y., He, Z.J., 2014b. Simulating urban growth by integrating landscape expansion index (LEI) and cellular automata. Int. J. Geogr. Inf. Sci. 28 (1), 148–163. https://doi.org/10.1080/13658816.2013.831097.

Liu, K., Xue, Y., Chen, Z., Miao, Y., Shi, J., 2022. Economic spatial structure of China's urban agglomerations: Regional differences, distribution dynamics, and convergence. Sustain. Cities Soc. 87, 104253 https://doi.org/10.1016/j.scs.2022.104253.

Liu, G., Yang, Z., Chen, B., 2011. A spatial comparative analysis of environmental impacts in Chinese urban metabolic processes. Procedia Environ. Sci. 5, 43–50. https://doi.org/10.1016/j.proenv.2011.03.046.

Lu, Y., Cao, M., Zhang, L., 2015. A vector-based Cellular Automata model for simulating urban land use change. Chin. Geogr. Sci. 25 (1), 74–84. https://doi.org/10.1007/s11769-014-0719-9.

Lu, F., Gao, F., 2008. Economic forecasting research based on artificial neural network technology. Chinese Control and Decision Conference 2008, 1151–1155. https://doi.org/10.1109/CCDC.2008.4597495.

Moreno, N., Ménard, A., Marceau, D.J., 2008. VecGCA: A Vector-Based Geographic Cellular Automata Model Allowing Geometric Transformations of Objects. Environ. Plann. B. Plann. Des. 35 (4), 647–665. https://doi.org/10.1068/b33093.

Moreno, N., Wang, F., Marceau, D.J., 2009. Implementation of a dynamic neighborhood in a land-use vector-based cellular automata model. Computers, Environment and Urban Systems 33 (1), 44–54. https://doi.org/10.1016/j.compenvurbsys.2008.09.008.

Nasiri, V., Darvishsefat, A.A., Rafiee, R., Shirvany, A., Hemat, M.A., 2019. Land use change modeling through an integrated Multi-Layer Perceptron Neural Network and Markov Chain analysis (case study: Arasbaran region, Iran). J. For. Res. 30 (3), 943–957. https://doi.org/10.1007/s11676-018-0659-9.

Nishimura, Y., 2020. New normal and new economy: a new growth engine for China. International Journal of Economic Policy Studies 14 (2), 301–312. https://doi.org/10.1007/s42495-020-00037-y.

Peng, C., Song, M., Han, F., 2017. Urban economic structure, technological externalities, and intensive land use in China. J. Clean. Prod. 152, 47–62. https://doi.org/10.1016/j.jclepro.2017.03.020.

Pesaran, M.H., Schuermann, T., Smith, L.V., 2009. Forecasting economic and financial variables with global VARs. Int. J. Forecast. 25 (4), 642–675. https://doi.org/10.1016/j.ijforecast.2009.08.007.

Rabbani, A., Aghababaee, H., Rajabi, M.A., 2012. Modeling dynamic urban growth using hybrid cellular automata and particle swarm optimization. J. Appl. Remote Sens. 6 (1), 63582. https://doi.org/10.1117/1.JRS.6.063582.

Santé, I., García, A.M., Miranda, D., Crecente, R., 2010. Cellular automata models for the simulation of real-world urban processes: A review and analysis. Landscape Urban Planning 96 (2), 108–122. https://doi.org/10.1016/j.landurbplan.2010.03.001.

Shi, L., 2020. Industrial Structure Changes, Spatial Spillover and Economic Growth in the Yangtze River Delta. J. Coast. Res. 107, 377–382. Retrieved from. https://www.jstor.org/stable/48640726.

Shu, C., Xie, H., Jiang, J., Chen, Q., 2018. Is Urban Land Development Driven by Economic Development or Fiscal Revenue Stimuli in China? Land Use Policy 77, 107–115. https://doi.org/10.1016/j.landusepol.2018.05.031.

Siedlecki, R., Papla, D., Bem, A., 2018. Application of S-Curve and Modified S-Curve in Transition Economies' GDP Forecasting. Visegrad Four Countries Case BT - Contemporary Trends and Challenges in Finance. Springer International Publishing, Cham.

Silverman, B. W. (2018). Density Estimation for Statistics and Data Analysis. In Density Estimation: For Statistics and Data Analysis. https://doi.org/10.1201/9781315140919.

Smętkowski, M., 2015. Spatial patterns of regional economic development in Central and Eastern European countries. Geogr. Pol. 88 (4), 539–555. https://doi.org/10.7163/GPol.0033.

Stoorvogel, J.J., Antle, J.M., 2001. Regional land use analysis: the development of operational tools. Agr. Syst. 70 (2), 623–640. https://doi.org/10.1016/S0308-521X(01)00062-2.

Su, H., He, A., Fang, G., 2011. Study of Urban Land Intensive Use Dynamic and Spatial Difference in Anhui Province. Advanced Materials Research 347–353, 3597–3602. https://doi.org/10.4028/www.scientific.net/AMR.347-353.3597.

Wang, J., Han, Q., Du, Y., 2022a. Coordinated development of the economy, society and environment in urban China: a case study of 285 cities. Environ. Dev. Sustain. 24 (11), 12917–12935. https://doi.org/10.1007/s10668-021-01975-z.

Wang, K., Lin, J., Liu, G., Liu, Q., 2022b. Strategic introduction of logistics retail and finance under competition and channel spillover. Transportation Research Part e: Logistics and Transportation Review 165, 102863. https://doi.org/10.1016/j.tre.2022.102863.

Wang, D., Ren, C., Zhou, T., 2021. Understanding the impact of land finance on industrial structure change in China: Insights from a spatial econometric analysis. Land Use Policy 103, 105323. https://doi.org/10.1016/j.landusepol.2021.105323.

Wu, F., 2002a. China's Changing Urban Governance in the Transition Towards a More Market-oriented Economy. Urban Stud. 39 (7), 1071–1093. Retrieved from. http://www.jstor.org/stable/43196900.

Wu, F.L., 2002b. Calibration of stochastic cellular automata: the application to rural-urban land conversions. Int. J. Geogr. Inf. Sci. 16 (8), 795–818. https://doi.org/10.1080/13658810210157769.

Wu, C., Wei, Y.D., Huang, X., Chen, B., 2017. Economic transition, spatial development and urban land use efficiency in the Yangtze River Delta, China. Habitat Int. 63, 67–78. https://doi.org/10.1016/j.habitatint.2017.03.012.

Xu, M., Feng, Y., 2022. How transportation infrastructure affects firm Productivity? Evidence from China. China Economic Quarterly International 2 (1), 55–69. https://doi.org/10.1016/j.ceqi.2022.02.001.

Yang, J., Xie, P., Xi, J., Ge, Q., Li, X., Ma, Z., 2015. LUCC simulation based on the cellular automata simulation: A case study of Dalian Economic and Technological Development Zone. Acta Geograph. Sin. 70 (3), 461–475. https://doi.org/10.11821/dlxb201503009.

Yao, Y., Li, L., Liang, Z., Cheng, T., Sun, Z., Luo, P., … Ye, X. (2021). UrbanVCA: a vector-based cellular automata framework to simulate the urban land-use change at the land-parcel level.

Yin, R., Li, X., Fang, B., 2023b. The Relationship between the Spatial and Temporal Evolution of Land Use Function and the Level of Economic and Social Development in the Yangtze River Delta. Int. J. Environ. Res. Public Health 20, 2461. https://doi.org/10.3390/ijerph20032461.

Yin, H., Xiao, R., Fei, X., Zhang, Z., Gao, Z., Wan, Y., Guo, Y., 2023a. Analyzing "economy-society-environment" sustainability from the perspective of urban spatial structure: A case study of the Yangtze River delta urban agglomeration. Sustain. Cities Soc. 96, 104691 https://doi.org/10.1016/j.scs.2023.104691.

Zeng, G., Hu, Y., Zhong, Y., 2023. Industrial agglomeration, spatial structure and economic growth: Evidence from urban cluster in China. Heliyon 9 (9), e19963. https://doi.org/10.1016/j.heliyon.2023.e19963.

Zhai, Y., Yao, Y., Guan, Q., Liang, X., Li, X., Pan, Y., Zhou, J., 2020. Simulating urban land use change by integrating a convolutional neural network with vector-based cellular automata. Int. J. Geogr. Inf. Sci. 34 (7), 1475–1499. https://doi.org/10.1080/13658816.2020.1711915.

Zhang, J.-D., & Chow, C.-Y. (2015, August 9). GeoSoCa : Exploiting geographical, social and categorical correlations for point-of-interest recommendations. 38th Annual ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2015), pp. 443-452 BT-SIGIR 2015-Proceedings of the 38th. ACM. https://doi.org/10.1145/2766462.2767711.

Zhang, F., Jiang, G., Xu, Y., Kong, X., 2005. Interactive Relationship between Land Use Change and Industrial Change KONG Xiangbin, ZHANG Fengrong, JIANG Guanghui, XU Yang. Resources Science 27, 59–64. Retrieved from. http://www.resci.cn.

Zhang, R., Tang, C., Ma, S., Yuan, H., Gao, L., Fan, W., 2011. Using Markov chains to analyze changes in wetland trends in arid Yinchuan Plain, China. Mathematical and Computer Modelling 54 (3), 924–930. https://doi.org/10.1016/j.mcm.2010.11.017.

Zhang, M., Weng, A., 2022. Study on the coordination between industrial structure optimization and urban land use intensity in Northeast China. J. Nat. Resour. 37, 734–752. Retrieved from. http://www.jnr.ac.cn.

Zhang, B., Zhong, C., Gao, Q., Shabrina, Z., Tu, W., 2022. Delineating urban functional zones using mobile phone data: A case study of cross-boundary integration in Shenzhen-Dongguan-Huizhou area. Comput. Environ. Urban Syst. 98, 101872 https://doi.org/10.1016/j.compenvurbsys.2022.101872.

Zhu, Z., Du, G., 2021. Coordinated Development of Urban Land Use and Ecological Economics in China. J. Math. (Wuhan) 2021, 5599633. https://doi.org/10.1155/2021/5599633.