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ARTICLE

Considering Regional Connectivity and Policy Factors in the Simulation of Land Use Change in New Areas: A Case Study of Nansha New District, China

Zehuan Zheng, Shi Xian *

School of Geographical Sciences and Remote Sensing, Guangzhou University-The University of Birmingham Joint Research Centre of Service Industries and Urban Development, Guangzhou University, Guangzhou, Guangdong, 510006, China

ABSTRACT

Numerous emerging development areas worldwide are receiving attention; however, current research on land use change simulation primarily concentrates on cities, urban clusters, or larger scales. Moreover, there is a limited focus on understanding the impact of regional connectivity with surrounding cities and policy factors on land use change in these new areas. In this context, the present study utilizes a cellular automata (CA) model to investigate land use changes in the case of Nansha New District in Guangzhou, China. Three scenarios are examined, emphasizing conventional locational factors, policy considerations, and the influence of regional connectivity with surrounding cities. The results reveal several key findings: (1) Between 2015 and 2021, Nansha New District experienced significant land use changes, with the most notable shifts observed in cultivated land, water area, and construction land. (2) The comprehensive scenario exhibited the highest simulation accuracy, indicating that Nansha New District, as an emerging area, is notably influenced by policy factors and regional connectivity with surrounding cities. (3) Predictions for land use changes in Nansha by 2030, based on the scenario with the highest level of simulation accuracy, suggest an increase in the proportion of cultivated and forest land areas, alongside a decrease in the proportion of construction land and water area. This study contributes valuable insights to relevant studies and policymakers alike.

Keywords: CA model; Land use change simulation; Nansha New District

*CORRESPONDING AUTHOR:
Shi Xian, School of Geographical Sciences and Remote Sensing, Guangzhou University-The University of Birmingham Joint Research Centre of Service Industries and Urban Development, Guangzhou University, Guangzhou, Guangdong, 510006, China; Email: geoshixian@gzhu.edu.cn

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1. Introduction

Land use/land cover change (LUCC) is a significant consequence of human-induced alterations to the natural environment, carrying profound implications for global environmental change [1]. Consequently, understanding and predicting LUCC have become crucial focal points of research. Particularly in developing countries, rapid urbanization [2] has led to dramatic land use changes, intensifying the conflict between human activities and land resources. China, since its reforms and opening up, has experienced rapid urbanization and industrialization, positioning the Guangdong-Hong Kong-Macao Greater Bay Area as the world's fourth-largest bay area [3]. Against this backdrop, the release of the Chinese State Council's "Overall Plan for Guangzhou Nansha to Deepen Comprehensive Cooperation with Guangdong, Hong Kong, and Macao for the World" in 2022 has presented new opportunities. China's dynamic and swift urbanization has given rise to numerous emerging development areas, and among them, Nansha New District, situated in the heart of the Greater Bay Area, stands out as one of the most representative in recent years. The region has undergone rapid and substantial land use changes, largely influenced by policies and increased regional connectivity with surrounding cities. Considering these factors, Nansha New District serves as a typical and ideal case study for simulating land use changes in new development areas.

Commonly employed land use simulation models in existing studies include Markov chain models, system dynamics models, and CLUE-S (Conversion of land use and its effects at small region extent) models [4-7]. Many of these models are founded on the principles of the cellular automata (CA) model and the CLUE-S model, which have undergone further enhancements and refinements [8]. One notable advancement is the future land use simulation (FLUS) model developed by Liu, which effectively addresses uncertainties and complexities associated with interconversions between different land use types, demonstrating strong predictive capabilities in simulating land use patterns [9]. As complex system theory progresses and system simulation platforms are developed, the advantages of complex system simulation methods in land use change research become increasingly apparent [10]. Cellular automata (CA) has emerged as one of the most dominant models for land use simulation due to its remarkable ability to capture the interplay between natural and human-driven factors [1,5,11]. However, despite the prominence of CA models, existing studies on land use and land cover change (LUCC) have primarily focused on cities, urban agglomerations, or larger scales, with relatively fewer investigations specifically examining land use simulation within new areas [3,7,8,12,13]. The rapid and intense land use changes often observed in new areas within cities necessitate close monitoring and thorough understanding. When utilizing CA models for geographic simulation, researchers have found that the expansion of urban areas is influenced by a series of driving factors, including topographic conditions, transportation factors, and socio-economic development [14-16].

Traditional drivers of land use change have been extensively studied, encompassing natural factors, transportation factors, and location factors [17]. Among these, particular attention has been given to natural factors, including terrain conditions represented by the digital elevation model (DEM) [6,7,9,13,18-21], elevation [10,16,22,23], slope [6,7,10,12,13,16,18,19,21-23], and aspect [6,7,16,18], among others. Notably, slope stands out as one of the most significant topographic factors influencing urban sprawl [7].

In land use change studies, traffic factors encompass distance to major roads [13,18,21], motorways [10,18], the city center [13], regional centers [21,22], railways [21], and highways [21]. Additionally, researchers contend that accessibility factors, including public facilities [18] and industrial company density [18,21], play a pivotal role in shaping land use change. Moreover, both population density and the presence of public facilities [21,24] are acknowledged as influential factors in land use change dynamics. Furthermore, economic and social development factors are widely employed in land use change and simulation studies. These factors consist of points of interest (POI) data [6,16,18,22], nighttime lighting (NTL) data [18], GDP [6,18-20], economic development indicators [18], population statistics [6,19,23,25], and population density metrics [13,16,18,20,23].

Scholars are increasingly recognizing the critical role of policy factors in comprehending land use change and simulation [6,25], especially in regions significantly influenced by such policies. Sarah Hasan et al., for instance, highlights the significance of diverse planning policy guidelines and regulations in shaping urban development [7]. In a separate study, Zhipeng Lai et al. utilizes two indicators, namely the Prime Farmland Protection Area and Ecological Sensitive Area, to assess the impact of spatially restricted zones on land use change [18]. Nonetheless, further explicit research is essential to thoroughly investigate the potential influence of government policies on land use [25,26].

Furthermore, there is a growing recognition of the substantial significance of inter-regional connectivity in urban development and land use change. Hence, it becomes imperative to investigate the impact of regional connectivity. Particularly, regional connectivity with surrounding cities acts as a quantitative indicator to assess the degree and quality of interconnectedness between a city and other surrounding cities [27,28], facilitating an analysis of the interconnectivity and interdependence among these urban centers. Moreover, by considering the total connectivity between cities [28-30], we can gauge the overall importance of a city network.

In summary, it is evident that the development of the Greater Bay Area is significantly shaped by both policies and regional connectivity with surrounding cities. Therefore, conducting a comprehensive analysis of land use changes in new areas, considering the influence of policy factors and inter-regional connectivity, becomes of paramount importance in understanding the dynamics of land cover changes and predicting future developments. However, it is important to note that there is a notable dearth of research specifically focusing on the influence of regional connectivity with surrounding cities and policy factors on land use change in new areas [2,6].

Based on this premise, the present study focuses on the Guangzhou Nansha New District within the context of the rapid development of the Guangdong-Hong Kong-Macao Greater Bay Area. Land cover data from 2015, 2018, and 2021 are utilized to construct three distinct scenarios in the cellular automata (CA) model: Scenario A considers conventional locational factors, scenario A + B incorporates policy factors, and scenario A + B+ C takes into account the influence of regional connectivity with surrounding cities on the study region. The research carefully analyzes the patterns and characteristics of land use changes in Nansha New District and subsequently employs the scenario that yields the highest accuracy of simulation to project its land use data for 2030. By investigating the patterns and influencing factors of land use changes in new areas, this study not only enhances our understanding but also provides empirical support for government policymaking, facilitating more sustainable land use planning in such regions.

2. Research data and methods

2.1 The study area and research data

In 2019, with the establishment of the Guangdong-Hong Kong-Macao Greater Bay Area as a national strategic zone, Guangzhou Nansha New District assumed a central and distinctive role as the sole national new district and comprehensive cooperation best practice zone in Guangdong Province (**Figure 1**). This strategic positioning placed Nansha New District at the geographical heart of the development, resulting in accelerated growth and significant land use changes. As a consequence, the region serves as an ideal research case for examining land use changes within new areas, particularly in the context of regional connectivity with surrounding cities and the influence of policy-driven factors.

The data utilized in this study consisted of five main components, as presented in **Table 1**. First-

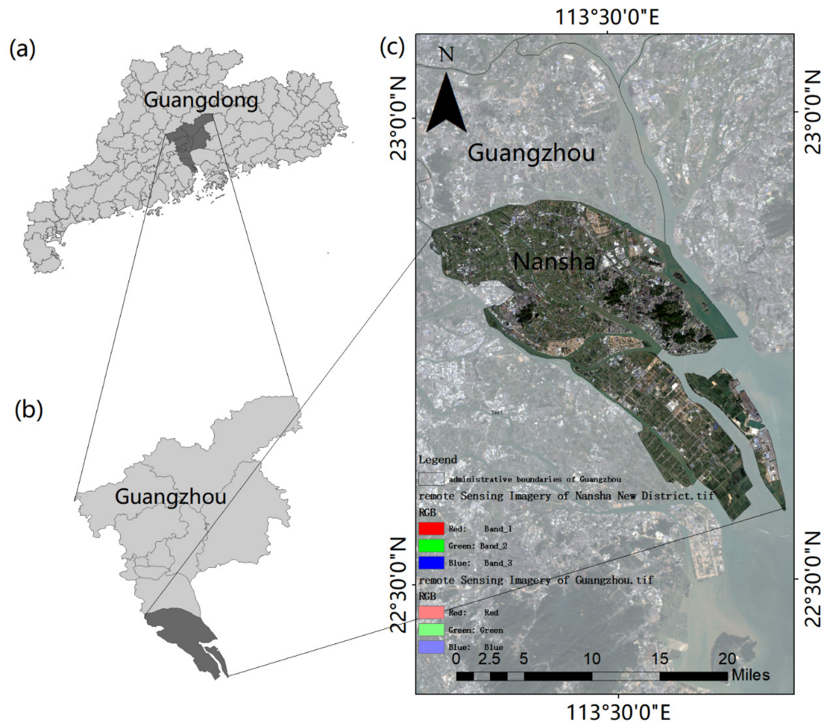


Figure 1. Location of Nansha New District.

Table 1. Data utilized in the study and the data source.

<table>
<tr><th colspan="3">Setting of scenario driving factors</th><th>Classification</th><th>Data type</th><th>Year</th><th>Data source</th></tr>
<tr><td colspan="3"></td><td>Land use data</td><td>Land use vector data</td><td>2015, 2018, 2021</td><td>https://doi.org/10.5281/zenodo.5816591</td></tr>
<tr><td rowspan="5">Scenario A + B + C</td><td rowspan="3">Scenario A + B</td><td rowspan="2">Scenario A</td><td>Data on natural environmental factors</td><td>DEM (including Slope)</td><td>2018</td><td>Resource and Environmental Science Data Center Network (http://www.resdc.cn/)</td></tr>
<tr><td>Traffic elements and location data</td><td>Metro stations, regional centers, urban primary roads, urban secondary roads, provincial roads and highways</td><td>2018</td><td>Guangzhou Municipal Bureau of Planning and Natural Resources (http://ghzyj.gz.gov.cn/)</td></tr>
<tr><td></td><td>Policy planning documents</td><td>The overall land use planning for Nansha New District (2006-2020).</td><td>2006-2020</td><td>Guangzhou Planning and Natural Resources Bureau, Nansha Branch (http://www.gzns.gov.cn/)</td></tr>
<tr><td></td><td></td><td>Socio-economic indicators</td><td>Economic activity indicators: total fixed assets, total production assets; static population indicators: total population at the end of the year, etc.</td><td>2018</td><td>Guangzhou City, Foshan City, Shenzhen City, Zhongshan City, Dongguan City, Zhuhai City Bureau of Statistics (https://lwzb.gzstats.gov.cn:20001/datav/admin/home/www_nj/)</td></tr>
<tr><td></td><td></td><td>Data on indicators related to city connectedness</td><td>Geographical scale indicators: area, population, etc.; Location indicators: i.e. time and distance to the center of a large city; Other indicators: road passenger data, rail passenger data, frequency of place name buzzword searches, etc.</td><td>2018</td><td>Guangzhou, Foshan, Shenzhen, Zhongshan, Dongguan, Zhuhai Bureau of Statistics, Guangzhou Nansha New District Bureau of Statistics (http://www.gzns.gov.cn/), Guangzhou Planning and Natural Resources Bureau, Nansha Branch (http://www.gzns.gov.cn/)</td></tr>
</table>

ly, the land use data① for Nansha New District in Guangzhou City was collected for the years 2015, 2018, and 2021. The land use types in Nansha New District were classified into five major categories, namely cultivated land, forest land, grassland, water area, and construction land, in accordance with the national-level classification standard outlined in the Current Land Use Classification (GB/T21010-2017) by the Ministry of Land and Resources [31]. Secondly, the dataset included information on traffic elements and location data, encompassing metro stations, regional centers, urban primary roads, urban secondary roads, provincial roads, and highways. The European distance tool in ArcMap software was employed to calculate the shortest distance from each image element to the corresponding traffic element within Nansha New District. Subsequently, the traffic conditions were normalized using the raster calculator. Thirdly, the data encompassed natural environment factors, including a digital elevation model (DEM) with a resolution of 30 m, and slope data extracted from DEM. Fourthly, policy factors data involved dividing the study area into four functional areas: permitted construction area, conditional construction area, restricted construction area, and prohibited construction area. Weights were assigned to these functional areas using the analytic hierarchy process. Lastly, urban connectivity indicators incorporated various metrics, such as geographical scale, location, economic activity, static population, and other relevant indicators. Due to limited data availability regarding the regional connectivity between Nansha New District and surrounding cities, this study employed the regional connectivity between surrounding cities and Guangzhou City as an alternative measure for evaluating the regional connectivity of surrounding cities to Nansha New District.

① The source is the first Landsat-based annual land cover product (CLCD) in China released by Professors Jie Yang and Xin Huang of Wuhan University. The data format is raster data, including nine land types, namely, Cropland, Forest Shrub, Grassland, Water, Snow/Ice, Barren, Impervious and Wetland, with a spatial resolution of 30 m.

2.2 Research methods and data processing

Based on the land use data of Nansha New District for 2015, 2018, and 2021, this study employs the rate of change of land use types to quantify the extent of changes associated with specific land use types within the designated study area over the specified time frame [32]. The rate of change can take on positive or negative values, reflecting the corresponding increase or decrease in the land area occupied by the specific land use type, respectively.

Simulation of land use change trends based on CA model

The cellular automaton (CA) model is a powerful bottom-up approach known for its robust spatial computing capability. Recent research on CA applications has demonstrated its ability to simulate complex systems through the utilization of simple local transformation rules [5,33]. In this study, an extended exploratory investigation was conducted on the definition of CA, particularly focusing on neighborhood configuration and land use conversion rules. Subsequently, a land use evolution model was constructed by integrating artificial neural network techniques [5,7]. The CA model was employed in simulating scenarios of urban expansion pattern changes, with each scenario incorporating different driving factors. Three distinct scenarios were constructed: Scenario A, representing conventional locational factors; Scenario A + B, incorporating policy factors; and Scenario A + B + C, considering the influence of regional connectivity of surrounding cities on land use changes in the study area. Through the analysis of the interrelationships between land use change characteristics and the different driving factors during the years 2015, 2018, and 2021, the CA model yielded valuable insights.

The model scenarios and driving factors

This study aims to investigate the effects of multiple factors on land use dynamics in the Nansha New District. Three scenarios are examined, and cellular automata (CA) models are constructed for each scenario, incorporating factors sequentially as follows: conventional locational factors (Scenario A), policy factors (Scenario A + B), and the influence of regional connectivity with surrounding cities on the study area (Scenario A + B + C). The specific setup of model scenarios and the associated driving factors are detailed as follows:

(1) ***Scenario A: Conventional locational factors***

Considering the land use development characteristics of Nansha New District and drawing from relevant studies and available data, the primary driving factors selected for the cellular automata (CA) model in the conventional locational factor scenario were topographic conditions and traffic factors. These factors encompass DEM data (including slopes extracted from DEM), distances to metro stations, regional centers, urban primary roads, urban secondary roads, provincial roads, and highways (please refer to **Table 1** for detailed information).

(2) ***Scenario A + B: Conventional locational factors overlaid with policy factors***

Against the backdrop of the Guangdong-Hong Kong-Macao Greater Bay Area development, policy factors significantly influence the land use changes in Nansha New District. The policy factors scenario (Scenario A + B) in this study considers the impact of functional area categories in planning policies as a crucial driving factor, while keeping the other driving factors consistent with Scenario A. In existing general urban planning documents, the construction land control area is primarily classified into four types: prohibited construction area, permitted construction area, restricted construction area, and conditional construction area (please refer to **Figure 5**). This research establishes the four types of functional areas based on the information provided in the Nansha District General Land Use Plan (2006-2020).

In Scenario A + B, varying degrees of influence on urban construction land are observed among different functional areas. These degrees of influence are quantified by assigning corresponding weights to each functional area, employing the expert grading method in conjunction with the analytic hierarchy process (AHP). The expert grade method involves statistical processing, analysis, and summarization of expert opinions obtained through anonymous solicitation. To determine ecological sensitivity weights for each factor, AHP is utilized, and the judgment matrix is constructed using the expert grade method to calculate the weights of each functional area.

(3) ***Scenario A + B + C: Conventional locational factors overlaid with policy factors and surrounding cities influence***

Within the context of urban cooperation in the Greater Bay Area, Nansha New District, positioned at the core of this region, is witnessing an increasing level of connectivity with surrounding cities. As a result, the land use changes in Nansha New District may be influenced by the extent of this connectivity. Thus, it is crucial to include the regional connectivity of surrounding cities as a driving factor in the cellular automata (CA) model. The interconnection and influence among cities serve as indicators reflecting the impact of urbanization in peripheral areas surrounding cities. Compared to Scenario A + B, Scenario A + B + C incorporates the driving factor of regional connectivity of surrounding cities while maintaining consistency with Scenario A + B in terms of the remaining driving factors. This addition aims to enhance the accuracy of land use simulation predictions in Nansha New District.

In this study, due to the availability of data regarding the regional connectivity of the surrounding cities in Nansha New District, Guangzhou city was chosen as the focal point for evaluating the city connectivity of these surrounding cities. Specifically, when computing the regional connectedness of cities neighboring Nansha New District, the study incorporated five adjacent cities, namely Foshan, Shenzhen, Zhongshan, Dongguan, and Zhuhai, as factors in the simulation calculation using a cellular automata (CA) model. The approach described by Lin et al. [30] was adopted in this study to calculate the node strength of each city (network node) within the city cluster network, thereby assessing the strength of city linkages using multiple indicators, as outlined in **Table 1**. In accordance with weighted network theory, the city nodal strength is a representation of the sum of weights associated with a nodal bond [34-36]:

$$S_i = \sum_{j=1}^{n} C_{ij} r_{ij} (i \neq j) \tag{1}$$

S_i represents the node intensity of city i. n represents the total number of cities, C_{ij} represents the connectivity score between city i and city j, and r_{ij} represents the relationship between city i and city j. A value of 1 is assigned to r_{ij} if there is a relationship between the two cities, and a value of 0 if there is no relationship.

In this research, the selection of indicators was guided by domain knowledge and expert experience, encompassing several widely utilized socioeconomic indicators, namely gross economic product, fixed asset investment, and year-end resident population (as presented in **Table 1**). A higher average coefficient of determination generally indicates a more reliable dataset [37,38]. To effectively integrate the diverse data sources, an intelligent optimization algorithm known as the selective weighted combination method was employed in this study. Specifically, we utilized the well-established genetic algorithm proposed by Zhou et al. [39] for optimization purposes. This algorithm enabled us to obtain optimal weights and determine the coefficients of determination between different socioeconomic indicators. The adaptability function of the genetic algorithm was calculated as follows:

$$f(x) = \sum_{i=1}^{n} r_i / n \tag{2}$$

r_i represents the coefficient of determination between the weighted result and the ith socioeconomic indicator. n is the total number of indicators.

The final outcome reveals a significantly higher urban connectivity intensity when compared to any individual data source. The urban connectivity values between Nansha New District and the surrounding cities are presented in **Figure 6**. The final connectivity score (C_{ij}) between city i and city j can be expressed as follows:

$$C_{ij} = \sum_{k=1}^{t} W_k C_{ijk} \tag{3}$$

t is the total number of methods. C_{ijk} represents the result obtained from the kth method for the jth observation of the ith variable. W_k represents the weight assigned to the kth method. The sum of all weights, represented by ΣW, is equal to 1.

Accuracy assessment

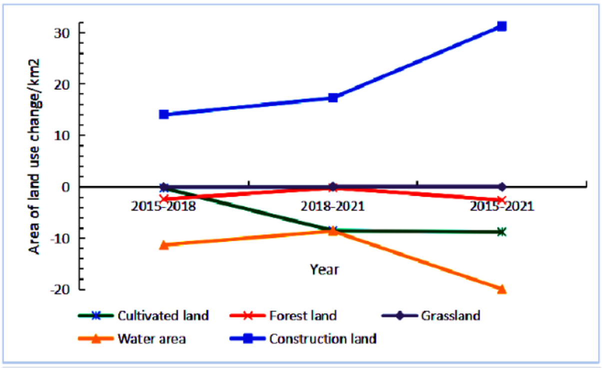
To assess the accuracy of model simulations, previous studies have commonly employed overall accuracy (OA) and Kappa coefficients [33,40]. Additionally, scholars [41] proposed the factor of merit (FoM) as an alternative measure to evaluate simulation accuracy. FoM relies solely on the number of varying cells in the simulated process and offers a more robust assessment of simulation accuracy [13,16]. Building upon this, in this study, historical data was used for simulation, with the 2018 dataset serving as the initial input and the 2021 dataset used for verifying the validity of the CA model [1]. Kappa coefficient, overall accuracy (OA), and FoM were employed to evaluate the accuracy of the model. The Kappa coefficient and OA values range from 0 to 1, with higher values indicating greater classification accuracy achieved by the model. A Kappa coefficient above 0.80 is typically considered indicative of very high simulation accuracy [4,6,9]. As for FoM, values exceeding 0.2 are suggested to indicate an extremely usable model [21,22,42].

3. Simulation results and analysis

3.1 Characteristics and trend analysis of land use change

As discussed in the methodology section, the changes in land area of different land types in Nansha New District were first calculated for the period from 2015 to 2021 (see **Figure 2**).

The findings of the study revealed several noteworthy trends (see **Figure 2**). Firstly, there was a gradual decrease in the area of cultivated land, forest land, and water area in Nansha New District over the specified period. Cultivated land accounted for more than half of the total area during 2015-2021 and served as the predominant land type in the district. However, its proportion experienced a year-on-year decline, with the proportion in 2021 being approximately 1.5 percentage points lower than that



Land use type/km^2			
Year	**2015**	**2018**	**2021**
Cultivated land	314.03	313.78	305.25
Forest land	23.58	21.19	20.99
Grassland	0.12	0.07	0.1
Water area	133.18	121.88	113.28
Construction land	115.58	129.58	146.86

Figure 2. Land use changes in Nansha New District, Guangzhou (2015-2021).

in 2015. The proportion of forest land also exhibited a decreasing trend during the same period. Additionally, the water area saw a reduction between 2015 and 2021, accounting for more than one-fifth of the total area in 2015 and less than one-fifth in 2021. In contrast, the area of construction land exhibited a steady increase, while the area of grassland initially decreased and then showed an upward trend. Construction land accounted for less than one-fifth of the total area in 2015 and surpassed one-fourth in 2021, representing more than one-fourth of the overall growth between 2015 and 2021. In 2015, construction land was primarily concentrated in the eastern and western townships, but it gradually expanded towards the central and northern areas near the center of Guangzhou city after 2015. The proportion of grassland area demonstrated a decrease followed by an increase during the period from 2015 to 2021. During the development and construction of Nansha New District from 2015 to 2021, a considerable amount of cultivated land and water area were converted to meet the demands of urban construction.

To illustrate the changes in land use types within the Nansha New District from 2015 to 2021, this study employs a land use transition matrix to depict the interconversion of land use types in the research area (see **Figure 3** and **Table 2**). The findings indicate that the conversion of land to other use types during the 2015-2021 period is relatively limited. Specifically, between 2015 and 2018, the most significant land use conversion occurred from cultivated land to other use types, followed by water area. Almost half of the grassland area was transformed into construction land, and forest land was predominantly converted to cultivated land, with over 10 percent of the total forest area transitioning to cultivated land, and only a minimal proportion transitioning to construction land. Water area conversions were primarily towards cultivated land, while construction land conversions were limited, not exceeding 0.2 percent. During the 2018-2021 period, the land use conversions remained consistent with those observed in the 2015-2018 period. Notably, there was a significant conversion of construction land to cultivated land. Furthermore, the proportion of water area transitioning to cultivated land decreased from nearly 7.43 percent during 2015-2018 to nearly 4.52 percent during 2018-2021, whereas the proportion of water area transitioning to construction land increased from about 2.23 percent during 2015-2018 to about 3.45 percent during 2018-2021. The examination of the land use transition matrix for 2015-2021 further supports the aforementioned results, indicating that the conversion of larger land areas to construction land predominantly affected cultivated land and water area. Specifically, during the period 2015-2021, about 7.64 percent of the total area of cultivated land was converted to construction land. Similarly, roughly 5.56 percent of the water area underwent a transition to construction land. It is worth noting that this study also reveals a trend of gradual increase in the proportion of cultivated land and water area transitioning to construction land. These findings substantiate the negative impact of urban construction demand on cultivated land and water area during the 2015-2021 period.

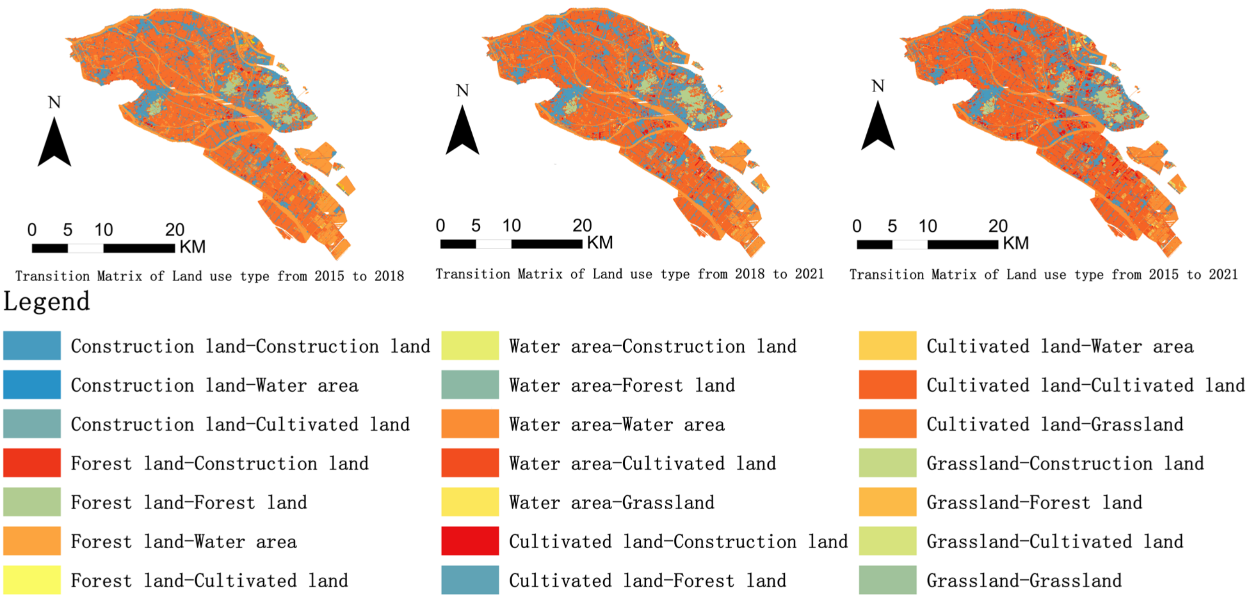


Figure 3. Transition matrix of land use type in Nansha New District from 2015 to 2021.

Table 2. Transition matrix of land use type in Nansha New District from 2015 to 2021.

	Land use type	Grassland (km^2)	Cultivated land (km^2)	Construction land (km^2)	Forest land (km^2)	Water area (km^2)	Total (km^2)
		2018					
2015	**Grassland (km^2)**	0.06	0.00	0.06	0.00		0.12
	Cultivated land (km^2)	0.01	301.33	11.11	0.22	1.37	314.03
	Construction land (km^2)			115.37		0.22	115.58
	Forest land (km^2)		2.54	0.07	20.97		23.58
	Water area (km^2)	0.01	9.90	2.97	0.00	120.29	133.18
	Total (km^2)	0.07	313.78	129.58	21.19	121.88	586.50
	Land use dynamic (%)	–14.22	–0.03	4.04	–3.38	–2.83	
		2021					
2018	**Grassland (km^2)**	0.05	0.00	0.02	0.00		0.07
	Cultivated land (km^2)	0.01	298.83	13.18	0.74	1.01	313.78
	Construction land (km^2)		0.02	129.40		0.16	129.58
	Forest land (km^2)		0.90	0.05	20.24		21.19
	Water area (km^2)	0.04	5.51	4.21	0.01	112.11	121.88
	Total (km^2)	0.10	305.25	146.86	20.99	113.28	586.50
	Land use dynamic (%)	15.81	-0.91	4.44	–0.31	–2.35	
		2021					
2015	**Grassland (km^2)**	0.04	0.01	0.08	0.00		0.12
	Cultivated land (km^2)	0.02	287.24	23.99	0.61	2.17	314.03
	Construction land (km^2)		0.02	115.25		0.32	115.58
	Forest land (km^2)		3.06	0.14	20.37	0.01	23.58
	Water area (km^2)	0.05	14.93	7.41	0.01	110.78	133.18
	Total (km^2)	0.10	305.25	146.86	20.99	113.28	586.50
	Land use dynamic (%)	–2.57	–0.47	4.51	–1.83	–2.49	

3.2 The calculated results for the main driving factors in the three scenarios

In this study, three distinct scenarios were considered in developing the CA models, and the calculation of the main driving factors for each scenario is presented as follows:

The calculated results for the main driving factors in Scenario A

In Scenario A, the driving factors for the CA model consisted of conventional locational factors, including topographic conditions and traffic factors, with the normalized values presented in **Figure 4**.

The calculated results for the main driving factors in Scenario A + B

The calculation results, derived from the implementation of the expert grade method and analytic hierarchy process (AHP), demonstrated that the weights assigned to the permitted construction area, conditional construction area, restricted construction area, and prohibited construction area were 0.538, 0.242, 0.145, and 0.075, respectively (refer to **Figure 5**). Among the functional areas considered, the permitted construction area exhibited the highest weight value, signifying its significant influence on the allocation of construction land within Nansha New District. Conversely, the prohibited construction area had the lowest weight value, indicating its minimal impact on the dynamics of construction land within Nansha New District.

The calculated results for the main driving factors in Scenario A + B + C

Based on the data provided in **Figure 6**, the results indicate that Nansha New District displayed the highest level of connectivity with Shenzhen, surpassing a threshold of 0.6. Furthermore, Foshan City exhibited a connectivity degree exceeding 0.5. In contrast, Zhongshan, Dongguan, and Zhuhai demonstrated comparatively lower levels of connectivity with Nansha New District.

By utilizing the Euclidean distance tool, this study calculated the distances between the cell centers of Nansha New District and its surrounding

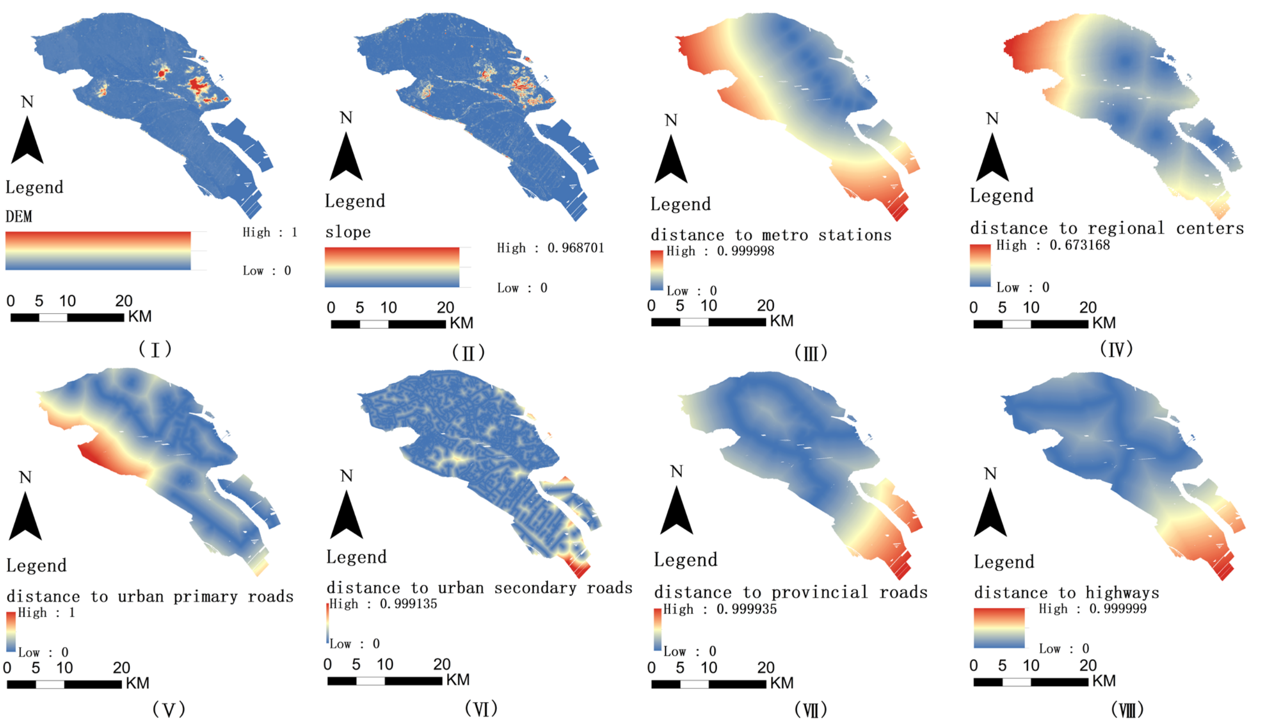
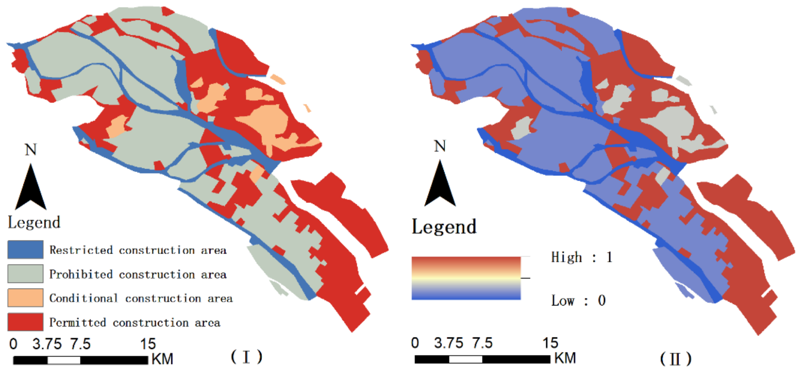
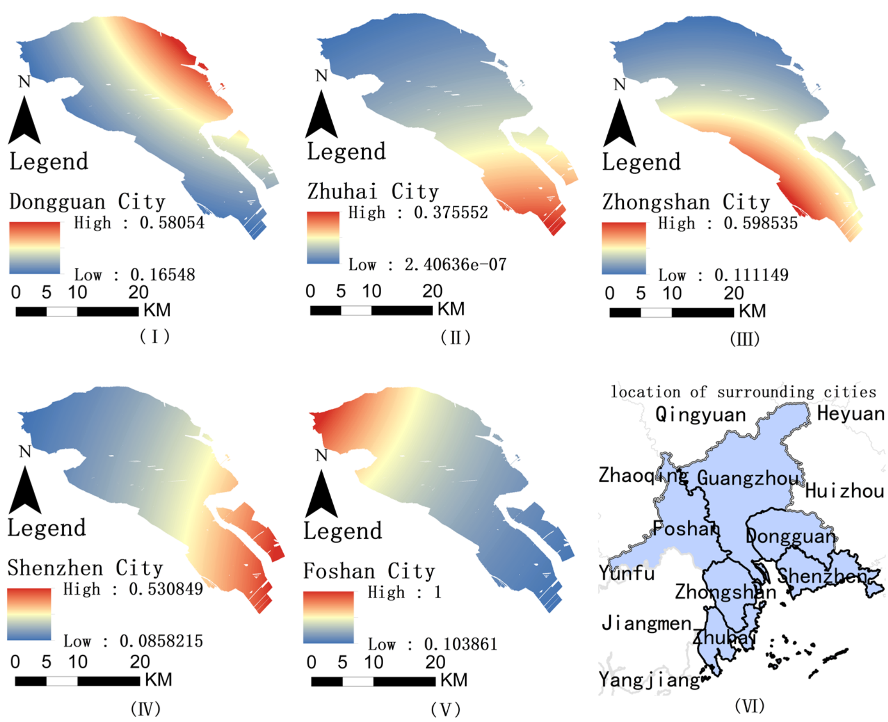


Figure 4. Driving factors used for scenario A: (I) DEM; (II) slope; (III) distance to metro stations; (IV) distance to regional centers; (V) distance to urban primary roads; (VI) distance to urban secondary roads; (VII) distance to provincial roads; (VIII) distance to highways.



Weights of the four functional areas in Nansha New District	
Functional Areas	**Weights**
Permitted construction area	0.538
Conditional construction area	0.252
Restricted construction area	0.145
Prohibited construction area	0.075

Figure 5. Driving factors used for scenario A + B: (I) Planning map of different functional areas in Nansha New District; (II) Degree of land use impact of different functional areas.



Regional connectivity between surrounding cities and Nansha New District of Guangzhou	
City	**Connectivity intensity**
Shenzhen	0.066896
Zhuhai	0.043393
Dongguan	0.047352
Foshan	0.058144
Zhongshan	0.035301

Figure 6. Driving factors used for scenario A + B + C: (I-VI indicate Dongguan City, Zhuhai City, Zhongshan City, Shenzhen City, Foshan City and location of surrounding cities, respectively).

cities. These distances were then combined with the level of city connection to generate **Figure 6**.

The results provide the following insights:

Industrial Development Structure: The land use patterns in Nansha New District exhibit a stronger influence from areas that closely align with its industrial structure.

Economic Development Level: The land use in Nansha New District is more influenced by cities with a stronger economic base. These cities act as development poles, facilitating the exchange of various factors such as human flow, logistics, and capital flow with neighboring urban clusters, fostering positive interactions.

Transportation Accessibility and Population Mobility: Areas with higher levels of traffic accessibility and greater population mobility exert a stronger influence on the land use patterns of Nansha New District.

3.3 Simulation results of land use changes using the CA Model and the accuracy assessment

The land use change simulation in Nansha New District in 2021 was conducted using the cellular automata (CA) model, with the 2018 land use data serving as the baseline. Three distinct scenarios, namely A, A + B, and A + B + C, were established to simulate the land use patterns. These scenarios incorporated conventional locational factors (Scenario A), policy factors (Scenario A + B), and regional connectivity with surrounding cities (Scenario A + B + C). The simulation results depicting the land use changes in Nansha New District in 2021 under the three different scenarios are presented in **Figure 7** and **Table 3**.

In this study, the processed data were utilized as input for the CA model to simulate and predict the land use change trend of Nansha New District from 2015 to 2021. The findings (refer to **Figure 7** and **Table 3**) revealed that the highest overall accuracy (OA) of the model was achieved when considering the overlay of conventional locational factors, related policy factors, and influence factors of regional

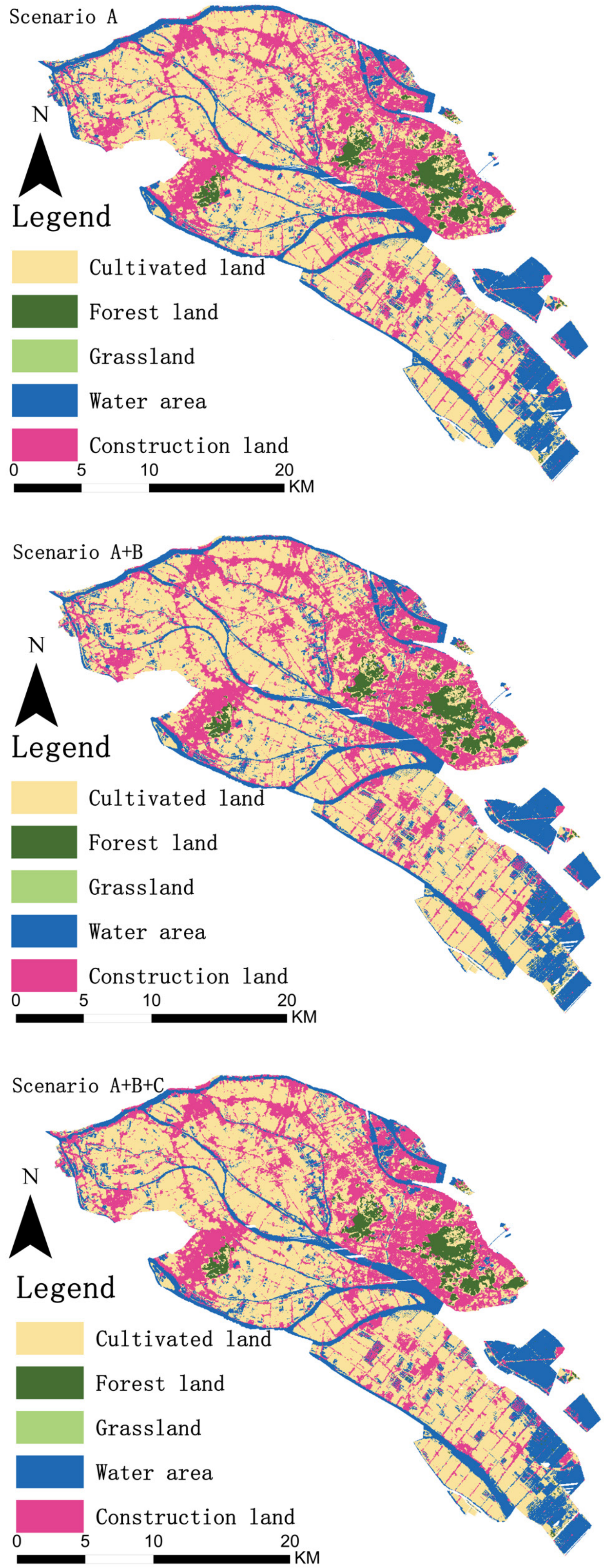


Figure 7. Simulated land use in Nansha New District, Guangzhou in 2021 under scenario A; A + B; A + B + C.

Table 3. Simulation results of land use changes and the accuracy assessment.

Scenario Type	A		A + B		A + B + C	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)
Cultivated land	305.25	52.05	305.25	52.05	305.25	52.05
Forest land	20.99	3.58	21.02	3.58	21.03	3.59
Grassland	0.08	0.01	0.08	0.01	0.07	0.01
Water area	113.31	19.32	113.28	19.31	113.28	19.31
Construction land	146.86	25.04	146.86	25.04	146.86	25.04
Accuracy of land use types in Nansha New District in 2021 for three scenarios						
Scenario type	**A**		**A + B**		**A + B + C**	
Overall accuracy (OA)	0.8933		0.898		0.899	
Kappa coefficient	0.8304		0.8372		0.8394	
FoM accuracy value	0.0554		0.0565		0.0516	

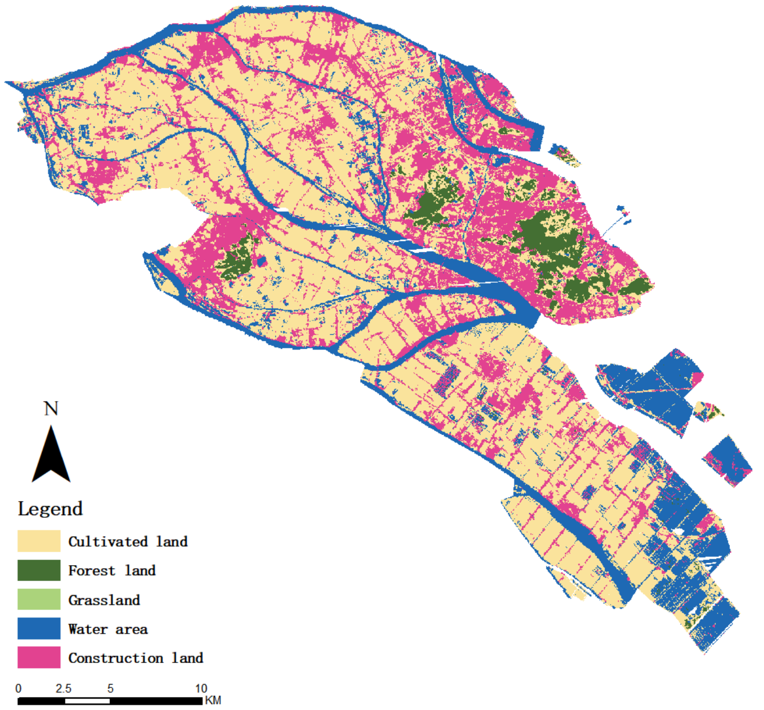
connectivity with surrounding cities simultaneously. This scenario yielded an OA of 0.8990, a Kappa coefficient of 0.8394, and a factor of merit (FoM) of 0.0516. The changes in OA values and Kappa coefficients were more pronounced in Scenario A+B compared to Scenario A, suggesting that policy factors exerted a significant influence on land use change in Nansha New District. However, the changes in OA values and Kappa coefficients in Scenario A + B + C showed subtle variations, which were not as significant as the changes from Scenario A to Scenario A + B, indicating that the influence of regional connectivity of surrounding cities on land use change in Nansha New District was not as prominent as that of policy factors. Nevertheless, the combined OA values and Kappa coefficients indicated that the simulation accuracy of Scenario A + B + C considering multiple driving factors was the highest (refer to **Table 3**).

In this study, we examined the impact of policy factors and regional connectivity with surrounding cities on the land use dynamics of Nansha New District, a burgeoning development area. Our findings revealed that policy factors played a more prominent role in shaping land use changes. When analyzing the simulated area and proportion of different land use types in Nansha New District in 2021 under various scenarios, significant changes were observed in forest land, grassland, and water area. Notably, when considering the overlay of conventional locational factors, policy factors, and the influence of regional connectivity with surrounding cities, the proportion of forest land area was the highest, reaching 3.5858% of the total land area. In contrast, the area occupied by grassland was the smallest, representing only 0.0114% of the land. Regarding water area, the largest proportion was observed when solely considering the conventional location factors, accounting for 19.3197% of the total land area.

3.4 Future land use prediction of Nansha New District in 2030

Based on the significant findings mentioned above, Scenario A + B + C, which encompassed the integration of conventional locational factors, policy factors, and the influence of regional connectivity with surrounding cities, exhibited the highest accuracy in the model simulation. Consequently, this scenario was chosen for predicting the characteristics of land use change in Nansha New District for the year 2030. Using the CA model, the study simulated and predicted the expected land use types in Nansha New District for 2030.

Based on the predicted results (**Figure 8**), several notable observations can be made regarding the anticipated land use changes in Nansha New District between 2021 and 2030. Firstly, the proportion of cultivated land area is projected to increase from 52.05% in 2021 to 53.24% in 2030. Secondly, there



Area and proportion of land use types in Nansha New District in 2030		
Land Use Type	**Area (km)^2**	**Percentage(%)**
Cultivated land	312.26	53.24
Forest land	21.08	3.59
Grassland	0.09	0.02
Water area	111.16	18.95
Construction land	141.91	24.2

Figure 8. Land use predicted results of Nansha New District in 2030.

is a minor decrease expected in the proportion of water area, declining from 19.31% in 2021 to 18.95% in 2030. Thirdly, the proportion of construction land area is predicted to decline, decreasing from 25.04% in 2021 to 24.2% in 2030. Additionally, the proportion of forest land area is projected to exhibit a marginal increase, rising from 3.58% in 2021 to 3.59% in 2030. Lastly, the proportion of grassland area is anticipated to remain relatively stable, with no significant changes expected during the specified period.

4. Conclusions and discussion

The rapid and profound urbanization in China has given rise to numerous new development areas. However, existing research primarily focuses on land use change simulation at the city, urban cluster, or larger scales, offering limited insights into simulating land use change within newly emerging areas. Moreover, there is a notable scarcity of studies that simultaneously consider conventional locational factors, the influence of regional connectivity with surrounding cities, and policy factors on land use change within these new areas. This paper aims to address and critically discuss the limitations identified in the aforementioned relevant studies. Utilizing a case study of Nansha New District in China and employing the CA model, this study simulated the land use changes in Nansha New District for the years 2015, 2018, and 2021, while also predicting its changes in 2030. The CA model was constructed under three scenarios: conventional locational factors alone, conventional locational factors combined with policy factors, and conventional locational factors integrated with policy factors and regional connectivity of the surrounding cities. The latter two scenarios were specifically designed to elucidate the impact of policy factors and regional connectivity on land use changes within Nansha New District. The findings revealed that: (1) significant changes in various land uses in Nansha New District during the period from 2015 to 2021, particularly in cultivated land, water area, and construction land. (2) Comparing the predicted land use data for 2030, generated from the comprehensive model with the highest simulation accuracy, with the current land use status in 2021, it was observed that the proportion of cultivated land and forest land area increased, while the proportion of construction land and water area decreased. The proportion of grassland area showed insignificant changes.

By examining the land use data from 2015, 2018, and 2021, along with the predicted land use data for 2030, several key observations emerge regarding the land use dynamics in Nansha New District. Firstly, the dynamic development of new areas often leads to rapid and significant land use transformations within relatively small areas. Secondly, cultivated land holds a prominent proportion in the current land use pattern; however, it is currently facing challenges such as gradual fragmentation and declining intensification. This fragmentation and declining productivity pose significant obstacles to agricultural activities in Nansha New District, highlighting the impact of urbanization on agricultural land. Furthermore, the expansion of construction land is noteworthy, particularly at the expense of cultivated land. The current distribution of construction land exhibits fragmentation and disorderly spreading, particularly in the eastern part of the district. The predicted spatial distribution of construction land in 2030, especially in relation to the four industrial zones highlighted in the Urban Development Plan of Nansha New District, requires more attention in future planning evaluations.

In the future development of Nansha New District, to formulate policies that effectively address land-use challenges arising from rapid development, decision-makers should promote high-quality development in Nansha New District through enhanced coordination between human activities and land utilization. To address the problem of cultivated land fragmentation, a comprehensive approach focusing on the binding role of policies and regulations is essential. Timely planning evaluation is crucial, and greater attention should be given to the protection of basic farmland and cultivated land. Strictly penalizing violations of the law involving construction on cultivated land should be prioritized. Additionally, leveraging the advantages of regional connectivity with neighboring cities is vital. Mitigating the haphazard expansion of urban construction land requires emphasizing compact land use and effective land use planning. Key strategies include promoting mixed land use, optimizing the integration of above and below-ground space, and exploring untapped urban land potential. Innovative modes of land use planning and management, including evaluating the alignment between planning policies and actual site layout, can enhance the effectiveness of planning decisions.

This study provides support for the argument that policy factors and regional connectivity with surrounding cities exert a substantial influence on the development of new areas. Three scenarios were investigated in this research, each considering different influential factors. The findings reveal that the scenario achieving the highest overall model accuracy was the comprehensive model, which simultaneously considers conventional locational factors, relevant policy factors, and the influence of regional connectivity with surrounding cities. This indicates that policy factors and regional connectivity with surrounding cities significantly impact the land use change in Nansha New District as an emerging area. The study holds noteworthy theoretical and empirical significance, contributing to a comprehensive understanding of the driving forces behind land use changes within flourishing new areas, especially in the context of regional association and cooperation strategies.

Admittedly, this study selected only a limited number of factors as conventional locational factors, and the approximation of the connectivity of surrounding cities to Nansha New District based on their connectivity to Guangzhou might introduce some inaccuracies in the results. Additionally, the consideration of only functional areas in the CA model when analyzing policy factors might be further improved by incorporating additional factors for a more comprehensive analysis to enhance simulation accuracy in future studies. Nevertheless, this research may offer valuable implications for simulating land use change in similar rapidly developing new areas, and it provides valuable insights for policymakers.

Author Contributions

Zehuan Zheng: Conceptualization, methodology, Formal analysis, Data Curation, Writing-Original draft preparation, Writing-Review; Editing.

Shi Xian: Conceptualization, Writing-Review; Editing.

Conflict of Interest

Declaration of no conflict of interest.

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