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# CoCA: Spatial cooperative simulation and future prediction of “land-population-economy” in urban agglomerations

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## HIGHLIGHTS

- Achieving significant improvements in simulation accuracy for land use and population-economic density.
- CoCA more effectively represents the cooperative effects and spatial patterns underlying multiple urban factors.
- Population-economic forecasts enhance land planning, achieving both ecological protection and economic growth.
- Open-source CoCA software enhances decision-making for urban planners.

## ARTICLE INFO

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## ABSTRACT

Urban agglomerations, as complex systems, exhibit co-evolutionary and cooperative effects in land use, population, and economic development. Precisely simulating the dynamic changes of these development factors at the urban agglomeration scale is crucial for formulating effective urban development policies. This study proposes a spatial cooperative simulation and future prediction framework: CoCA, using the Wuhan metropolitan area as a case study. The CoCA framework integrates a patch-generating land use model and a density model based on an S-curve algorithm, employing a dynamic update strategy for driving factors to achieve multi-factor spatial cooperative simulation of land, population, and economy. Compared to traditional single-factor simulations, the CoCA model shows a significant improvement in simulation accuracy. Measuring land use accuracy with Figure-of-Merit (FoM) reached 0.239, enhancing the accuracy by 35%. Meanwhile, the accuracy of population and economic density simulations, assessed using Mean Absolute Percentage Error (MAPE), improved by 38%, with values of 20.19% and 29.59%, respectively. By forecasting future land use patterns in the Wuhan metropolitan area for 2030 under various policy scenarios, this framework further explores the interaction mechanisms among land use change, population growth, and economic development. The CoCA model shows the ability to simulate future urban patterns under different scenarios by considering multiple factors, thereby providing effective supports support to policy makers in promoting balanced plans for sustainable urban growth.

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## 1. Introduction

With the rapid advancement of technology, accelerated global economic growth, and increased population mobility, urbanization has progressed at an unprecedented rate (Usman et al., 2022). Cities are becoming increasingly interconnected, gradually merging into urban agglomeration (Ritchie et al., 2024), which is a key mode for sustainable urban development. However, the mode of urban agglomeration has also exacerbated numerous preexisting space-related challenges, such as population explosions (Deng et al., 2015; Feng et al., 2020), traffic congestion (Chen et al., 2022), and environmental pollution (Liang and Yang, 2019; Vadrevu et al., 2017). Hence, spatial evolution modeling for the essential urban factors (e.g., land use, population and economy) at the scale of urban agglomerations has become a focus of research (Chakraborty et al., 2021; Yang et al., 2019; Zhang et al., 2023). Compared individual cities, urban agglomerations represent a coupled decision-making entity (Fang and Yu, 2017), where resource and spatial cooperative across cities is crucial to find the solutions of sustainable development. For example, urban expansion stimulates economic growth and attracts population, while the growth of population and economy drives the expansion of industrial and public land, accelerating changes in land use patterns (Lei et al., 2021; Deng et al., 2023). Therefore, it's important for spatial evolution models of urban agglomeration to consider the cooperative effects of various driving urban factors such as land use, population distribution, and economic activity (Li et al., 2017).

Cellular automata (CA), a type of advanced spatial evolution models, shows effective performance in simulations of the spatio-temporal evolution of various urban factors, including land, population, and the economy. CA simulates spatial change by estimating the cell state, according to its initial state, neighborhood effects, and transition rules (Liu et al., 2017; Alaei Moghadam et al., 2018). The CA models can generate complex spatial patterns and capture dynamic processes, have been widely applied in simulating land use and land cover(LULC) changes (Shahfahad et al., 2022; Wang et al., 2022), urban expansion (Alaei Moghadam et al., 2018), population dynamics (Sun et al., 2020), and economic development (Liang et al., 2020; Wei et al., 2020). These applications have provided valuable insights into the basic trends of urban development in different aspects, such as the general direction of land-use transformation and the overall population movement trends. Land use change reflects the spatial manifestation of urban expansion, as CA models simulate transitions like agricultural land converting to urban areas or green spaces reducing (Guzman et al., 2020). Population dynamics, closely linked to urbanization, are simulated by CA models considering initial population states and neighborhood influences to predict distribution and density changes over time (Crols et al., 2017; Holko et al., 2016). Economic development is also a vital factor influencing urban changes. CA models integrate economic indicators into spatial transition rules to forecast how economic growth influences the expansion of commercial and industrial zones (Musikhin and Karpik, 2023). The interdependencies among land, population, and economy enable CA models to simulate a multitude of complex urban phenomena. Nevertheless, all the CA models in the abovementioned studies are designed to perform a single task. They have great difficulty in conducting multi-task simulations to take into account the cooperative effects and the inherent complexity of urban space, and are unable to accurately reflect the real-time dynamic interactions among land, population, and economy during the urban development process.

Recent studies have commenced investigations into the incorporation of cooperative effects among multiple urban driving factors into CA-based urban spatial evolution models. For example, the CA-Markov model (Yu et al., 2019) calculates green GDP by integrating ecological value, economic suitability, land use, and neighborhood effects. This integration approach takes into account the interactions between urban economy and environment from a more comprehensive perspective. Guzman et al. (2022) used CA models to estimate population density by integrating land use with population distribution and simulating land use changes, and successfully revealed the close connection between land use and population distribution. Nonetheless, current studies use historical economic, social, and transportation data as static drivers to simulate future development scenarios, neglecting dynamic interactions during the development process (Maerivoet and De Moor, 2005; Okwuashi and Ndehedehe, 2021; Yang et al., 2023). Land use is inherently a dynamic process that evolves over time due to various factors (Deng et al., 2009; Liu and Andersson, 2004). For instance, a tract of land within a city might undergo a transformation from agricultural to industrial and ultimately to residential utilization, propelled by a multiplicity of interacting factors. If the model relies solely on static drivers and fails to account for these dynamic changes, the results may be overly simplistic or fail to capture the actual complexity of urban development (Santé et al., 2010). Thus, the spatial cooperative simulation (SCS) strategy was proposed to take multiple urban driving factors as dynamic variables to consider the dynamic cooperative effects among them (Tu et al., 2024). This SCS method extends the classical CA model to simulate the spatial distribution of multiple factors in a more integrated manner. However, Tu et al. (2024) explored the dynamic cooperative effects by assuming the continuous variables of population and economy as discrete states. It constrains its capacity of the simulation performance for complexity continuous urban phenomena, such as economy and population dynamics. Hence, it remains challenging to incorporate the continuous-state dynamic drivers into the cooperative effects for CA-based urban spatial evolution models (Guan et al., 2023).

The combination of S-curve model and Density CA (DCA) provides a potential to better simulate the complex continuous-state urban phenomena of population and economic dynamics (Haase and Schwarz, 2009). The S-curve model was originally used to describe the pattern of self-limiting population growth and was subsequently adapted for the analysis of urbanization and economic development (Siedlecki et al., 2018). By simulating phases of rapid growth, slowing growth, and eventual stabilization, the S-curve effectively captures changes in urban population and economic dynamics at different stages of development (Wang et al., 2015). The DCA model, specifically designed for continuous variables, introduces "grey cells" to simulate gradual changes in variables like population density and economy density, defined as the GDP or monetary value per square kilometer—within urban areas (Liu et al., 2018). The DCA model dynamically adjusts cell states based on initial density and conversion thresholds, enabling accurate simulation of continuous data (Li et al., 2006). When DCA is combined with the S-curve model, economic density becomes a crucial variable, and detailed growth processes are incorporated into the transition rules. The S-curve provides DCA with precise nonlinear growth patterns, while DCA dynamically simulates economic density, refining predictions of urban economic expansion and spatial layout changes. Some previous models lack this ability to comprehensively and accurately simulate these aspects (Li et al., 2013; Zhu et al., 2024). Therefore, multi-factor collaborative simulation is essential for urban development studies. Integrating the DCA model with the S-curve to simulate population and economic elements can better capture the dynamic nature of urban development, overcome the limitations of traditional models, and lead to more accurate and reliable simulation results.

To fill the gap of continuous-state spatial cooperative simulation, this study proposes a novel spatial cooperative framework CoCA model for simulating and predicting the "land-population-economy" dynamic system in urban agglomeration. Taking the Wuhan metropolitan area as the study area, the CoCA framework is applied to simulate the urban agglomeration's land-population-economy system and predict future land use patterns under various development scenarios. This framework helps reveal the dynamic synergies among urban agglomeration factors, offering a new approach to simulate urban land use changes and improve the accuracy and effectiveness of urban planning for sustainable development.

This paper is structured as follows: Section 2 describes the study area and data. Section 3 details the overall framework of this research as well as the construction methods and principles of the CoCA model. Section 4 shows the simulation results and comparisons. Section 5 discusses the study's significance and offers suggestions for future urban planning. Finally, Section 6 Section 6 concludes, points out limitations and provides future directions.

## 2. Study area and dataset

The proposed CoCA model was applied to a simulation of the Wuhan Metropolitan Area (WMA), which is located in central China and encompasses an area of 57,800 km$^2$. Wuhan is the central city of WMA, which is also the biggest city, transportation hub and education center in central China. The WMA contains eight large and medium sized cities around Wuhan (Liang et al., 2021). Fig. 1 shows the overview of the study area. By 2020, the Wuhan metropolitan area had a population of 31.866 million people and a total GDP of 2.63 trillion CNY, which was approximately 0.4 trillion USD (https://www.hubei.gov.cn/). As one of the largest urban agglomerations in China, the Wuhan metropolitan area's urbanization rate exceeds 70 %, characterized by rapid economic development, high population mobility, and frequent land-use changes. This region is a typical case of rapid urbanization in China and a representative case globally (Wang et al., 2022), providing a robust foundation for the model's application (Ma and Wang, 2022). The in-depth study of the Wuhan metropolitan area can offer valuable insights for similar urban agglomerations that may encounter related challenges during their development.

This study uses land use data, population density data, economic density data from the years 2000, 2010, and 2020, along with various spatial auxiliary data. Land use data were sourced from the 30-meter resolution land cover dataset produced by the Chinese Academy of Sciences (https://www.resdc.cn/), which are classified into six categories: cropland, forest, grassland, waterbody, urban land, and unused land. Population data were derived through the Gridded Population of the World (GPW), version 4 (https://sedac.ciesin.columbia.edu/). GDP data were sourced from the Resource and Environmental Sciences Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/). Road network data came from the OpenStreetMap (OSM) platform (https://www.openstreetmap.org/), which includes four types of roads: main roads, first-class, second-class, and third-class roads. Digital Elevation Model (DEM) and slope data were sourced from the global ASTER GDEM (https://www.jspacesystems.or.jp/). The spatial distribution of the ground truth from 2000 to 2020 are shown in Fig. S1.

In total, this study uses 11 types of spatial auxiliary data covering natural features, transportation, locational, and socio-economic factors. Point of Interest (POI) data (https://lbs.amap.com/), road network distance data, and topographic data were resampled to a 1 km × 1 km resolution. Subsequently, the datasets were projected to the same coordinate system, and all variables were normalized to a range of 0 to 1, thus completing the processing of the spatial auxiliary data, as shown in Fig. 2.

## 3. Methodology

Fig. 3 illustrates the process of the Cellular Automata-based "land-population-economy" spatial cooperative simulation and future prediction framework. This framework is composed of three main parts. (1) CA-based Factor Simulation. Using a Density Cellular Automata (DCA) based on the S-curve algorithm to simulate the spatial distribution of population density and economic density, while the PLUS model is employed to simulate land use changes. (2) Multi-factor Spatial Cooperative Simulation. The PLUS model is coupled with the DCA model, and a "hierarchical progressive" dynamic driving factor update strategy is adopted to construct spatial cooperative simulation model. (3) Multi-scenario Future Prediction. Comparative experiments evaluate simulation accuracy, and designing various scenarios to explore the cooperative effects between factors and predict future developments.

### 3.1. Factor simulation based on Cellular Automata

CA models consist of four basic elements: cells, states, neighborhoods, and transition rules (White, 1997). In CA models, each cell has a specific state, and future states are determined by transition rules, which can simulate dynamic changes in cell states over a certain period (Yao et al., 2024a).

For population and economic density simulation, this study employs a Density Cellular Automata (DCA), which represents cell state changes through continuous density values. The DCA model includes suitability functions $Pg_i^t$, neighborhood effects $\Omega_i^t$, and restriction factors $Pr_i^t$. The grayscale value change function is given by:

$$\Delta G_i^t = \frac{\sum_{j\in\Omega_N} Density_j}{Density_{max}\pi l^2} \times Pg_i^t \times \Omega_i^t \times Pr_i^t \quad (1)$$

After multiple iterations, when a cell $G_i^t$ transitions from 0 to 1, this change represents the development of the cell from a non-urban area to an urban area, which allows for the calculation of the urban development density of that cell.

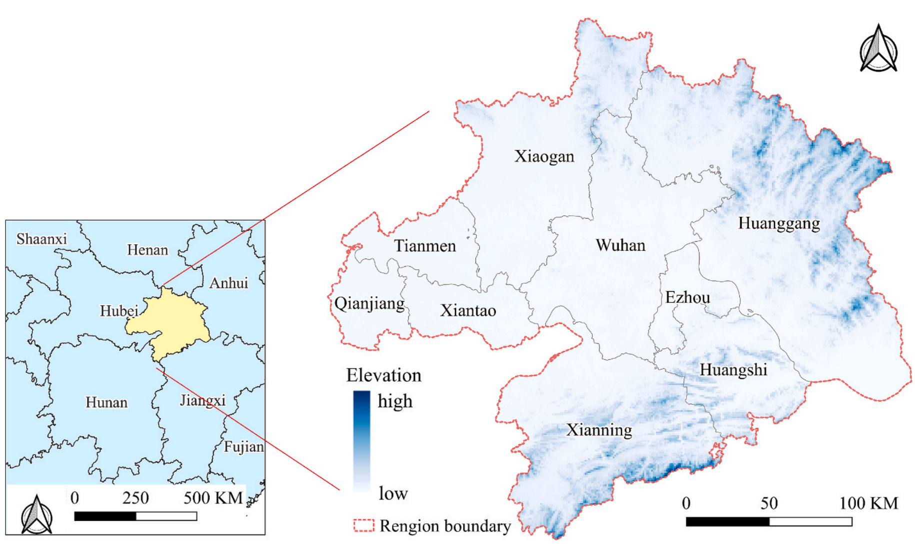


**Fig. 1.** Geographic location and topography of the Wuhan metropolitan area.

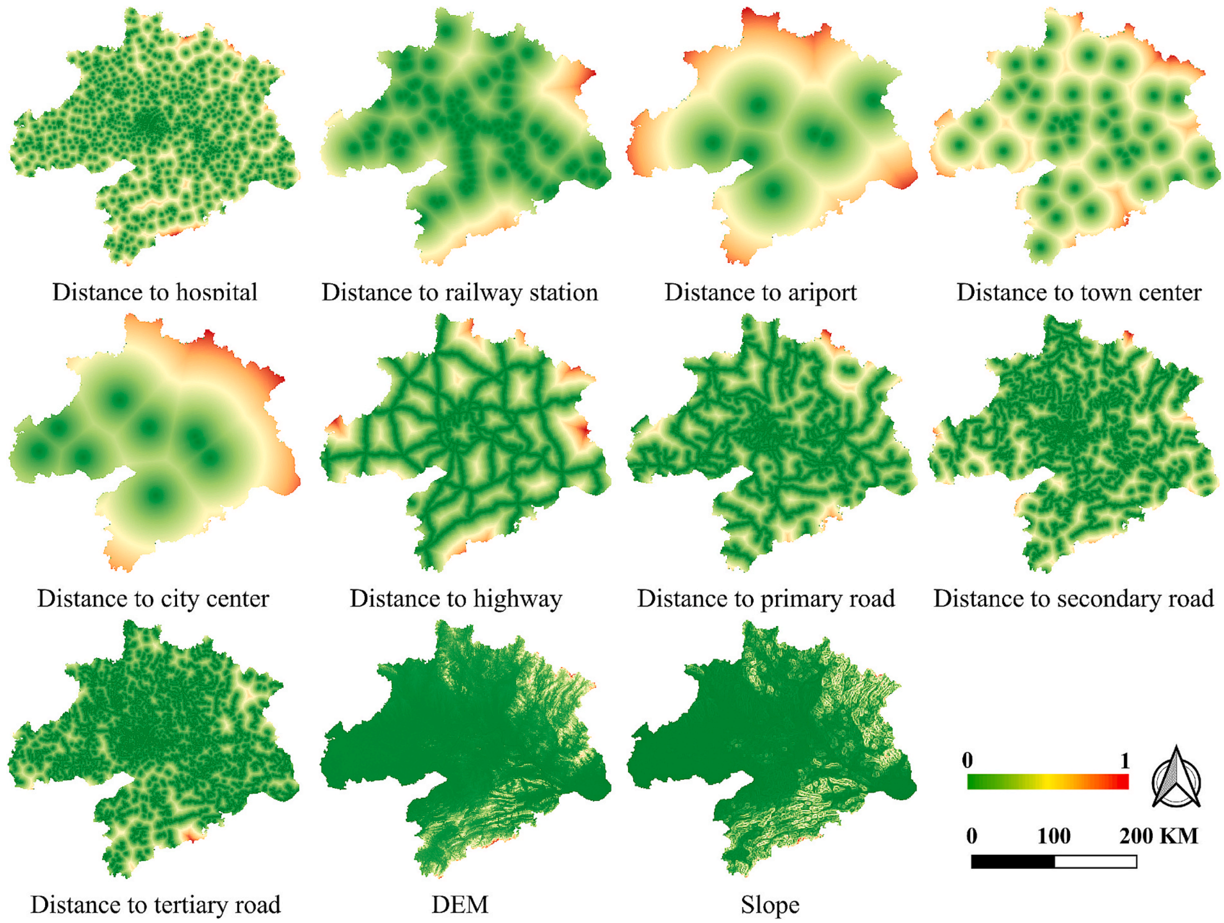


**Fig. 2.** Spatial auxiliary variable data.

The DCA model uses the S-curve algorithm to calculate the development density of the corresponding cell (Liu et al., 2018; Yao et al., 2023). The density value change process is computed as follows:

$$Density_i^t = RA \times \left(Density_i^{t-1} + U\left(Density_i^{t-1}\right)\right) \quad (2)$$

where $U\left(Density_i^{t-1}\right)$ is the initial urban density, $RA$ is a random variable reflecting real-world uncertainties, and $U'(t)$ represents the growth rate of urban density.

This study uses the PLUS model to simulate land-use changes (Liang et al., 2021). The PLUS model integrates the Land Expansion Analysis Strategy (LEAS) and the CA based on Multiple Random Seeds (CARS), employing a random forest model to evaluate the driving factors contributing to each land-use type. The CARS module allows new land-use patches to grow probabilistically, effectively simulating various future development scenarios.

### 3.2. Multi-factor spatial cooperative simulation

Compared with the traditional combination of Cellular Automata and density models, the CoCA model proposed in this study aims to transform urban simulations from static to dynamic to achieve the cooperative simulation of multiple elements such as land, population, and economy. In this process, the dynamic update mechanism for calculating the overall development probability of PG is crucial. Previous studies often used methods such as random forests and neural networks to change the calculation method of PG, but they never broke through the bottleneck of static simulations. The CoCA model, however, dynamically updates the overall development probability of PG, fully considering the real-time interactions and cooperative relationships among multiple elements. This enables the simulation results to accurately reflect the dynamic changes in urban development.

Fig. 4 shows the collaborative simulation process, consists of the following steps: (1) Independent land-use simulation with the PLUS model and initial population and economic density simulation with the DCA model. (2) When the number of iterations reaches a threshold, the simulation results are input into the other model to recalculate overall development probabilities. (3) The corrected results replace the original data, and the process is repeated until convergence, completing the cooperative simulation that accounts for land use, population, and economic interactions.

In the CoCA model construction, a hierarchical progressive dynamic driving factor update strategy (Friedman, 2001) is employed to achieve the dynamic cooperation of multiple factors, as illustrated in Fig. 5. This driving factor update strategy adheres to the cyclical interactions between land, population, and economic production (Tu et al., 2024). The core concept is to repeatedly train the CA models using the simulated features, rather than the historical data, to capture the cooperative influence of features.

During the model operation, the PLUS and DCA models perform initial simulations using original data from the previous time step $t-1$ and the target time $t$, with land use $LULC_{t-1}$, population density $POPU_{t-1}$, and economic density $GDP_{t-1}$. Spatial auxiliary data, including natural factors, traffic, and location factors, are also used as driving factors $DF$ to compute the overall development probability, generating initial simulation results: $IS-LULC_t$, $IS-POPU_t$, and $IS-GDP_t$.

After obtaining the initial simulation results, this study employed a stepwise cooperative simulation approach. The results were treated as partial driving factors, fed into the model to learn the transformation rules between various factors, and produced the first cooperative

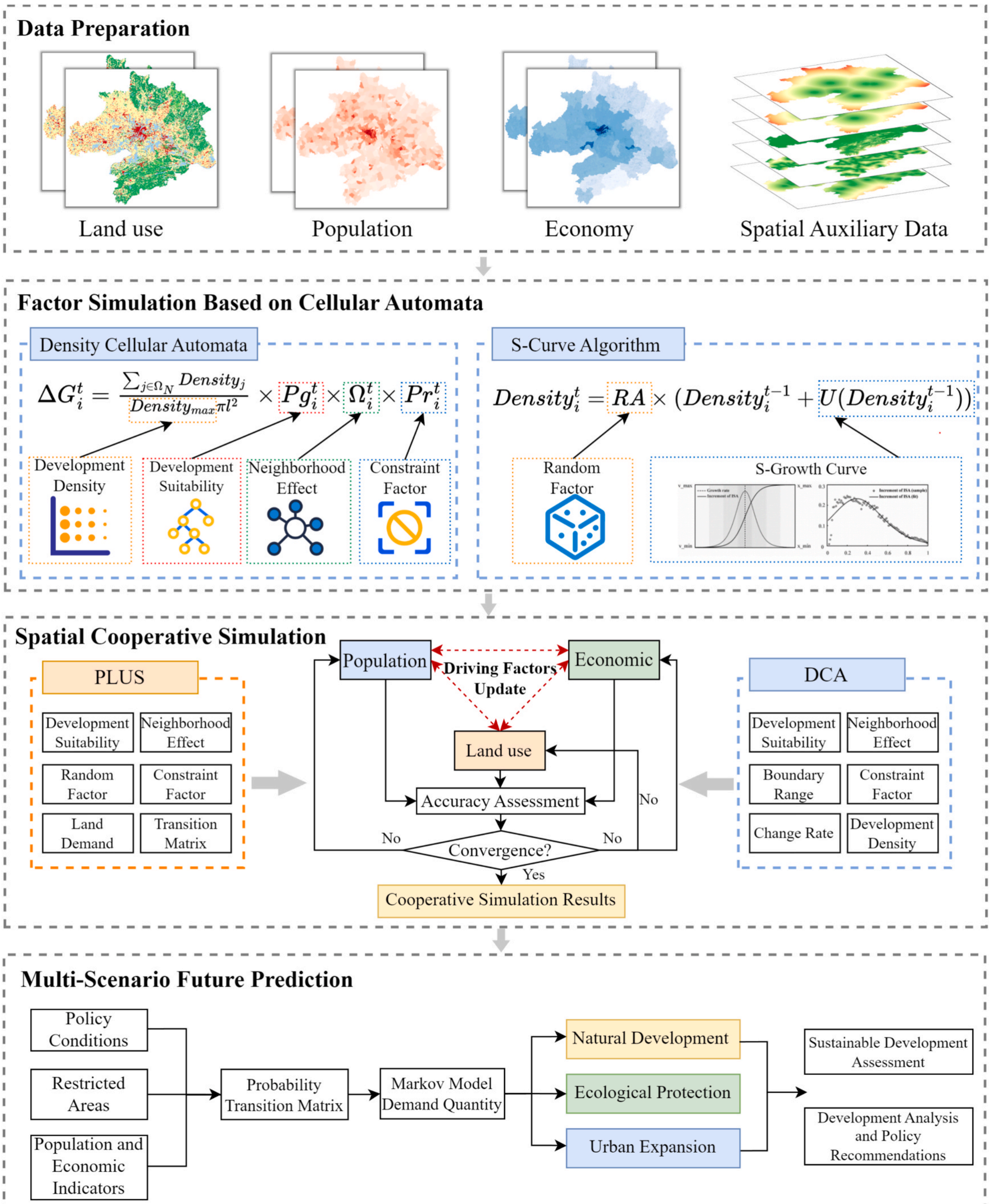


**Fig. 3.** Research framework of the spatial collaborative simulation.

simulation results. For instance, after obtaining the initial simulated land use $IS-LULC_t$, the initial simulated population density $IS-POPU_t$ and economic density $IS-GDP_t$ were used as driving factors. The driving factors were then combined with land use data $LULC_t$ at time $t$, to generate the first cooperative land use simulation result $Co_1-LULC_t$. The process generated the first cooperative population $Co_1-POPU_t$ and economic $Co_1-GDP_t$ simulation results.

Since the value ranges and dimensions of different factors vary, the land use and population-economic density simulation results were normalized before they could be introduced as driving factors into another model. In this study, the min–max normalization method (Henderi et al., 2021) was applied, and the formula is as follows:

$$y_{nor}^i = \frac{y_i - min(y)}{max(y) - min(y)} \tag{4}$$

where $y_{nor}^i$ is the normalized population-economic density value for the $i$ cell, $y_i$ is the actual value, and $min(y)$ and $max(y)$ are the minimum and maximum values within the study area, respectively.

Upon completing the above processing, the first cooperative simulation results were used as new driving factors to retrain the CA model, calculate new overall development probabilities, and proceed to the next cooperative simulation. This loop continued until the changes in the factors converged. In this study, the S-index was adopted to assess whether the cooperative simulation had converged, calculated as follows:

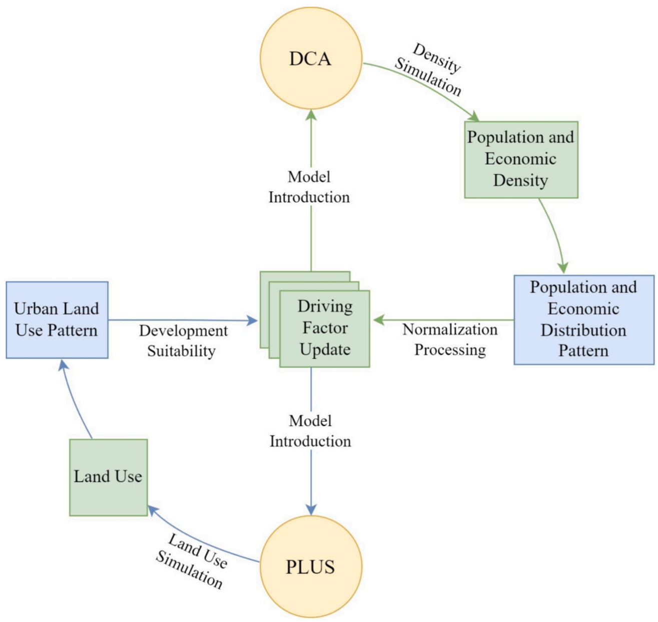


**Fig. 4.** Process flow of the collaborative simulation model.

$$S = W_c P_c + W_z(1 - P_z) + W_e(1 - P_e) \tag{5}$$

where $P_c$ represents land use simulation performance, $P_z$ is the population density simulation error, and $P_e$ is the economic density simulation error. $W_c$, $W_z$, and $W_e$ are the corresponding weights, where $0 \le W_c, W_z, W_e \le 1$ and $W_c + W_z + W_e = 1$. If the comprehensive error $S$ does not show significant changes over $n$ consecutive iterations, the cooperative simulation is considered converged. The final cooperative simulation results, $Co_n - LULC_t, Co_n - POPU_t$ and $Co_n - GDP_t$ are then output.

For future scenario predictions, the land use, population, and economic data at the current time $t$, along with the driving factors, are combined in the same manner. Based on the specified forecast year and demand quantities, the final output for the prediction scenarios will include $Co_n - LULC_{t+1}, Co_n - POPU_{t+1}$ and $Co_n - GDP_{t+1}$.

### 3.3. Multi-scenario prediction

The Markov chain model effectively handles transition probabilities between states in dynamic systems, making it suitable for complex and stochastic land use change processes. This study employs the Markov chain prediction model, using different thresholds and probability transition matrices to simulate various future development scenarios. The Markov model is widely applied to forecast next states of real-world processes in many fields (Girma et al., 2022; Himeur et al., 2022; Zhang et al., 2022). In a finite time sequence $t_1 < t_2 < t_3 \cdots < t_n$, the state at any time $t_n$ depends only on the state at the previous time $t_{n-1}$, independent of both the initial and future states. Land use changes and various factors can thus be effectively predicted within the Markov chain model (Sathees et al., 2014). The random process in the Markov chain model can be represented by the following equation:

$$S_{t+1} = P_{ij} \times S_t \tag{6}$$

In the context of future land use prediction, $S_{t+1}$ represents the land use state at time $t + 1$; $P_{ij}$ is the state transition matrix for land use; and $S_t$ represents the land use state at time $t$. The state transition matrix primarily describes the likelihood of land use transitioning from one type to another, expressed as:

$$P_{ij} = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \left\{ \begin{array}{c} 0 \le P_{ij} < 1 \\ \sum_{j=1}^{n} P_{ij} = 1(i,j = 1, 2, \cdots, n) \end{array} \right. \tag{7}$$

Where, $P_{ij}$ represents the probability of land use type $i$ transitioning into land use type $j$, and n indicates the number of land use types. It is worth noting that the Markov model is discrete, so population and economic data need to be discretized using natural breakpoints. In this case, $S_t$ represents the value state at time $t$, and $P_{ij}$ indicates the state transition probability.

In the context of global environmental change and the promotion of sustainable development, predicting urban land use change is of great significance for guiding land resource management, urban planning policies, and sustainable development (Wang et al., 2021; Zhang et al., 2020). This study aims to explore the synergistic effects of land, population, and economic growth on urban land use changes through simulations of different development scenarios. The scenario predictions simulate and compare different land use development paths, assess the impact of policy measures and planning strategies on urban land use changes, and aim to optimize land resource use and protection, providing a basis for more precise land use and ecological protection policies (Yao et al., 2024b; Zou et al., 2021).

The study focuses on the effects of ecological protection policies on urban land use and the ecological environment, providing a basis for more precise land use and protection policies. The ultimate goal is to achieve sustainable urban development and optimal spatial layouts through the coordinated development of population, economy, and land resources. Three future development scenarios are designed based on

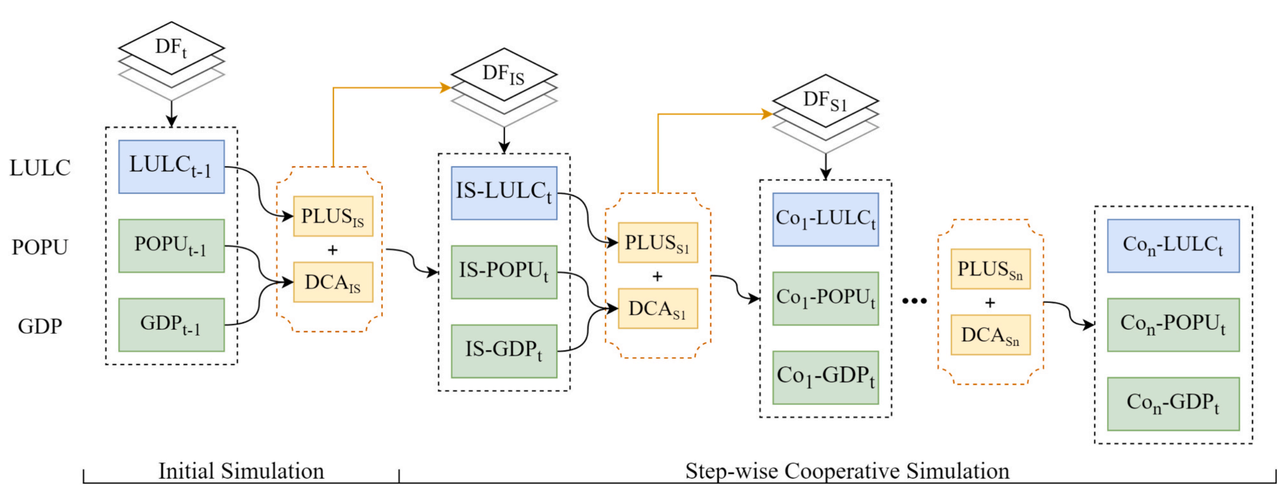


**Fig. 5.** Stepwise dynamic driving factor update process flow.

policy and development goals. Natural Development Scenario (O1): no additional restrictions are applied, and land types can convert freely, reflecting historical land-use change trends. Ecological Protection Scenario (O2): Ecological reserves and agricultural land are protected, reducing the conversion probability of forests and water bodies. Urban Expansion Scenario (O3): Ecological reserves and agricultural land are protected, while development density is increased based on population and economic indicators, expanding construction land allowances. Specific parameter settings for each scenario can be found in Tables S1, S2, S3, and S4.

### 3.4. Accuracy evaluation metrics

This study uses the Figure of Merit (*FoM*) and Overall Accuracy (*OA*) metrics to evaluate the accuracy of the land-use simulation results. The *FoM* measures the ratio of correctly predicted changes to all predicted changes, providing a comprehensive evaluation of model performance (Li et al., 2020). The *OA* metric indicates the proportion of correctly simulated cells out of the total, widely applied for model evaluation (Liu et al., 2007).

$$FoM = \frac{B}{A+B+C+D} \tag{8}$$

$$OA = 1 - \frac{A+C+D}{N} \tag{9}$$

where $A$ represents the number of cells where the simulated type remained unchanged; $B$ represents the number of cells where the simulated type changed correctly; $C$ represents the number of cells where the simulated type changed incorrectly; $D$ represents the number of cells with changes in type; and $N$ represents the total number of cells in the study area.

To evaluate the accuracy of simulating population and economic density, the Mean Absolute Percentage Error (*MAPE*) and Root Mean Square Error (*RMSE*) are used to assess continuous factors' simulation performance (Willmott and Matsuura, 2005):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{10}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

where $n$ is the number of samples, $y_i$ is the actual value, and $\hat{y}_i$ is the predicted value.

## 4. Results

### 4.1. Results of Multi-Factor spatial cooperative simulation

Table 1 shows the accuracy of the simulations used to validate the performance of the CoCA framework. These simulations focus on the spatial distribution patterns of land use, population density, and economic density in the WMA for the year 2020. The accuracy of the results was evaluated by comparing the simulated data with the actual data. The CoCA model achieved an *OA* of 0.697 and *FoM* of 0.239 for land use simulations. The *MAPE* for population density and economic density were 20.19% and 29.59%, with *RMSE* of 16.75 and 64.86.

To further analyze the simulation performance in different regions, this study calculated the accuracy errors for nine cities within the Wuhan metropolitan area. The *FoM* for land use ranged from 0.214 to 0.247, the *MAPE* for population density ranged from 18.91% to 22.04%, and the *MAPE* for economic density ranged from 28.06% to 31.54%, with error fluctuations within an acceptable range (Karunasingha, 2022).

**Table 1**
Comparison of simulation accuracy for cities in the Wuhan metropolitan area (up and down arrows represent the maximum and minimum values in each column).

| | Land use | | Population | | Economic | |
|---|---|---|---|---|---|---|
| | FoM | OA (%) | MAPE (%) | RMSE | MAPE (%) | RMSE |
| Wuhan | 0.218 | 0.687 | 19.21 | **70.54↑** | 28.41 | **102.34↑** |
| Huangshi | 0.237 | 0.704 | 19.42 | 40.21 | 29.01 | 85.84 |
| Ezhou | 0.242 | 0.764 | 20.19 | 37.65 | 29.47 | 80.73 |
| **Huanggang** | **0.214↓** | **0.683↓** | **22.04↑** | 20.87 | **31.54↑** | 63.87 |
| Xiaogan | 0.226 | 0.716 | 20.07 | 26.45 | 29.48 | 70.68 |
| Xianning | 0.223 | 0.726 | 21.14 | 21.58 | 30.84 | 67.85 |
| Xiantao | 0.243 | 0.786 | 21.42 | 26.78 | 30.67 | 48.94 |
| Tianmen | **0.247↑** | 0.779 | 19.04 | 15.21 | 28.21 | **30.84↓** |
| **Qianjiang** | 0.243 | **0.796↑** | **18.91↓** | **14.84↓** | **28.06↓** | 32.84 |
| WMA | 0.239 | 0.797 | 20.19 | 16.75 | 29.59 | 64.86 |

Compared to the actual 2020 distribution, the CoCA model's simulation results show a strong correlation and consistency with the real spatial patterns of the Wuhan metropolitan area. Fig. 6 shows the 2020 simulation results for land use, population density, and economic density based on the CoCA model. The main urban areas are distributed along the Yangtze River, reflecting the significant influence of water systems on urban development. In terms of population and economic density, the highest concentrations are located on both sides of the Yangtze River within Wuhan's main urban area, particularly in the core zones along the river where population and economic activities are highly concentrated. The southeastern and southwestern regions of the Wuhan metropolitan area also show relatively high levels of population and economic density. These regions closely align with actual urban development trends, and the distribution of land use indicates a logical pattern of urban expansion. Overall, the spatial distribution of land use, population, and economic density in the central areas of Wuhan most accurately reflects the real-world conditions, especially in high-density urban core zones, where the simulation results effectively capture changes in land use and economic activity.

### 4.2. Comparative analysis of simulation results with existing methods

This study designed three sets of comparative experiments to evaluate the simulation effectiveness of the CoCA model. The first group discretized each factor and used the PLUS model to simulate individual factors. The second group used the Clark negative exponential algorithm to simulate population and economic factors and performed multi-factor cooperative simulation in combination with the PLUS model (Clarke and Gaydos, 1998; Tu et al., 2024). The third group used the CoCA multi-factor spatial cooperative simulation proposed in this study. Table 2 shows the simulation accuracy for all three groups is summarized.

From the accuracy of the simulation results obtained by different methods, it is evident that multi-factor cooperative simulation improves the accuracy compared to the individual factor discretization method. The *FoM* for land use simulation using the CoCA model was 0.239, representing an improvement of more than 35%. In population density and economic density simulation, the CoCA model achieved *MAPE* values of 20.19% and 29.59%, respectively, improving accuracy by more than 38% compared to the discretization method. Additionally, when compared to the model using the Clark algorithm, the CoCA model based on the S-curve algorithm also showed significant improvements in accuracy, with *MAPE* values increasing by 45.34% and 14.33%, respectively. These results indicate that the multi-factor cooperative simulation method better captures urban changes, and the S-curve algorithm outperforms the Clark negative exponential algorithm.

This study also selected high-density areas within Wuhan's main urban area, as well as the Ezhou and Huangshi regions, to provide a more detailed comparison of simulation results. Enlarged views of the simulated results from each model were compared with actual land use,

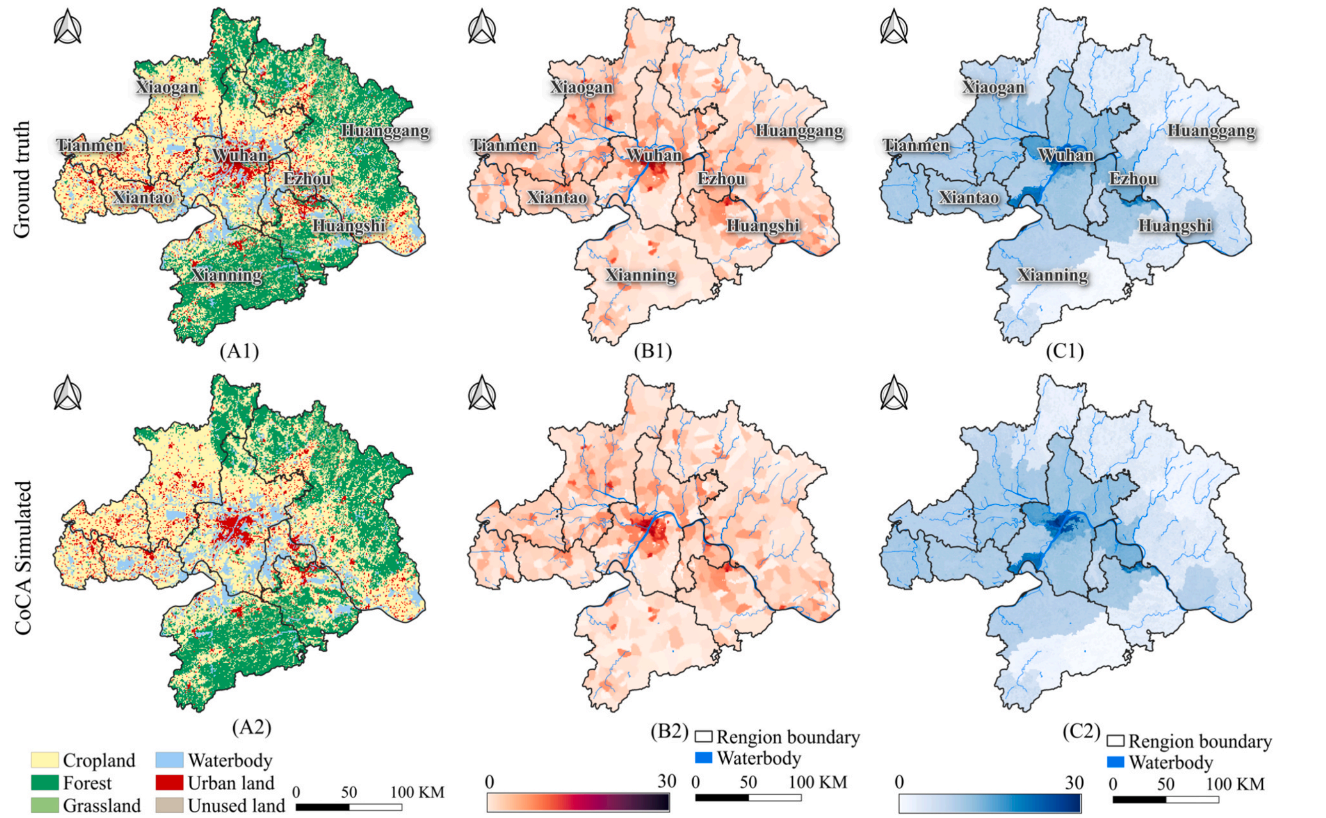


**Fig. 6.** 2020 collaborative simulation results for the Wuhan metropolitan area. (A1-A2) Land use; (B1-B2) Population density (thousand people per km$^2$); (C1-C2) Economic density (thousand CNY per km$^2$).

**Table 2**
Comparison of simulation accuracy across different models (up and down arrows represent the maximum and minimum values in each column).

| Feature | Approach | FoM | OA (%) | MAPE (%) | RMSE |
|---|---|---|---|---|---|
| Land use | PLUS | 0.176↓ | 0.738↓ | / | / |
| | Clark CA | 0.204 | 0.787 | / | / |
| | **CoCA** | **0.239↑** | **0.797↑** | / | / |
| Population | PLUS | / | / | 40.21↑ | 40.92↑ |
| | Clark CA | / | / | 36.94 | 32.51 |
| | **CoCA** | / | / | **20.19↓** | **16.75↓** |
| Economy | PLUS | / | / | 69.38↑ | 119.53↑ |
| | Clark CA | / | / | 34.54 | 102.84 |
| | **CoCA** | / | / | **29.59↓** | **64.86↓** |

population, and economic density patterns to observe the differences between the models. As shown in Fig. 7, the land use simulation results indicate that the cooperative simulation method more accurately captured the expansion of Wuhan's core urban area, and the overall proportion of urban land closely matches the actual situation. In contrast, the PLUS model yielded a smaller core urban area and performed poorly in simulating the expansion of smaller edge regions. In non-core urban areas, the cooperative simulation method better represented the "fragmented" nature of new urban land as observed in real data, while the Clark CA model tended to overestimate expansion in a more continuous manner.

Fig. 8 shows the comparison of population density simulations across different models. The CoCA model better simulated the population convergence trend along the edges of the core urban area, while the Clark model exhibited a more outward spreading pattern from the urban center. Specifically, in the major urban areas of Wuhan, the CoCA model accurately reflected high-density population clusters along the Yangtze River and showed gradual expansion toward the eastern regions. In contrast, the Clark model displayed a more dispersed trend in this area. In the major urban areas of Ezhou and Huanggang, the CoCA model better captured the scattered population clusters in low-density regions, while the Clark model struggled to accurately simulate these areas. The results indicate that the multi-factor collaborative simulation method more accurately captured the distribution of population clusters in the core cities and surrounding areas.

As illustrated in Fig. 9, the CoCA model accurately simulated the GDP distribution in the core area of the Wuhan metropolitan area and showed a similar convergence trend along the edges of the urban area. Both CoCA and Clark models overestimated GDP values in the highly concentrated core regions. However, the PLUS discretization method exhibited a more "fragmented" simulation of economic distribution. For non-core regions such as Huangshi and Ezhou, the Clark negative exponential model underperformed in simulating low-GDP areas.

### 4.3. Multi-Scenario future predictions

Based on optimization objectives and constraints, this study designed three types of future development scenarios to predict the spatial distribution of land use through multi-factor cooperative simulation. Table 3 presents the demand forecasts for different land use types under each scenario for 2030, and Fig. 10 shows the simulation results and detailed comparisons. The trends in land use coverage ratios from 2000 to 2030 under O3 Scenario are shown in Fig. S2.

Compared to the actual land use in 2020, all three scenarios show an increase in urban land and a decrease in other land types to varying extents. Under the O1 and O3 scenarios, there is rapid urban expansion, with a significant increase in urban land and a notable reduction in forested areas. In the O3 scenario, newly formed urban agglomerations are more compact. Meanwhile, in the O2 scenario, large areas of forest and cropland remain unchanged, with urban expansion falling between the patterns of the other two scenarios.

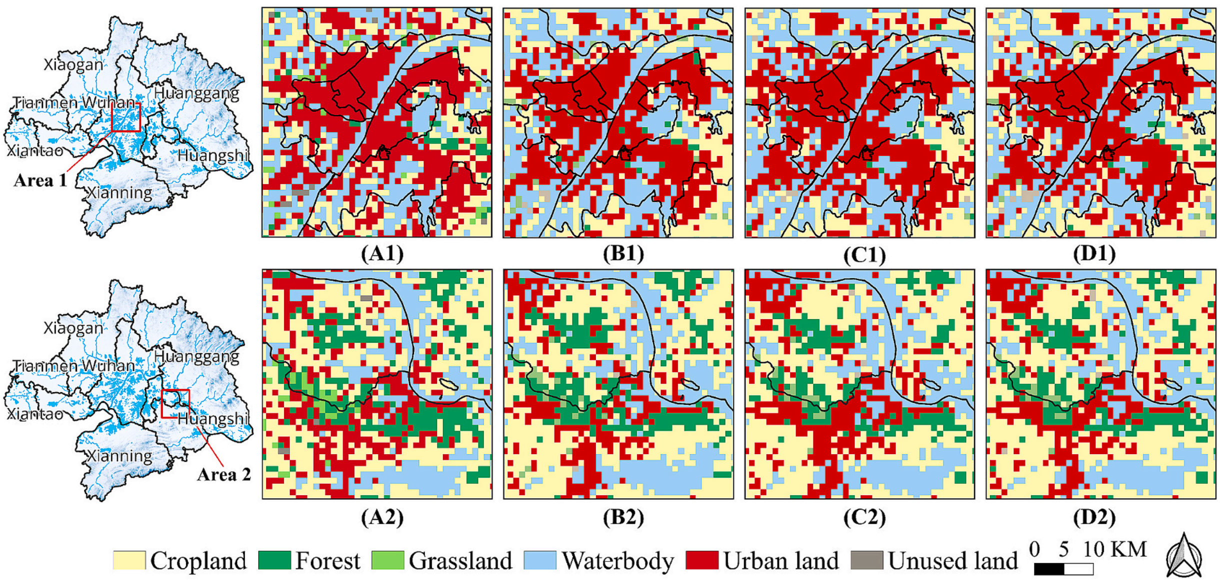


**Fig. 7.** Comparison of land use simulation results across models. (A1-A2) Ground truth; (B1-B2) PLUS simulation; (C1-C2) Clark algorithm simulation; (D1-D2) CoCA multi-factor collaborative simulation. Area 1: Major urban areas in Wuhan; Area 2: Major urban areas in Ezhou and Huanggang.

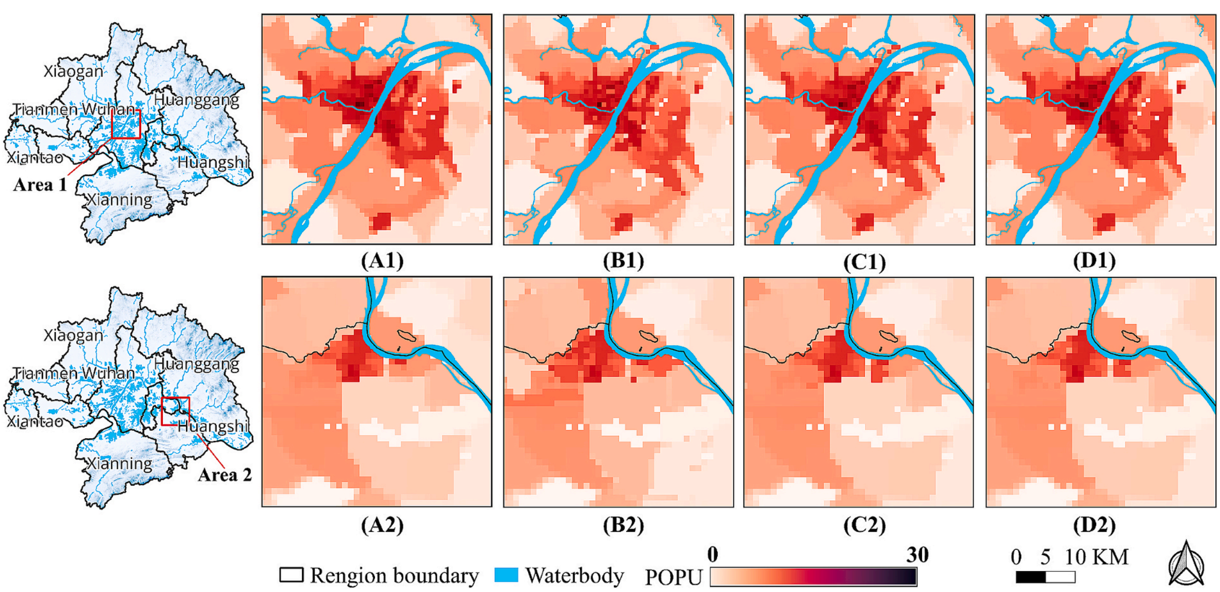


**Fig. 8.** Comparison of population density (thousand people per km$^2$) simulation results across models. (A1-A2) Ground truth; (B1-B2) PLUS simulation; (C1-C2) Clark algorithm simulation; (D1-D2) CoCA multi-factor collaborative simulation; Area 1: Major urban areas in Wuhan; Area 2: Major urban areas in Ezhou and Huanggang.

In the O1 scenario, where there is no policy intervention, land use changes mirror historical trends, with cropland and forestland reduction rates remaining at 2%, and urban land growth continuing at 3%. Urban expansion is most prominent in the core and surrounding areas of Wuhan, especially along the Yangtze River. Although urban land increases, this scenario results in significant consumption of cropland and ecological resources, which could undermine long-term ecological balance.

The O2 scenario effectively limits urban expansion through ecological protection and cropland preservation policies. Although urban land continues to increase, the proportions of ecological protection areas and cropland remain at 47.17% and 29.42%, respectively, demonstrating effective conservation of natural resources. Compared to O1, urban expansion is slower in the Wuhan metropolitan area, especially in the major urban areas of Ezhou and Huanggang, where urban development is restricted, and the ecological environment is well-preserved.

In the O3 scenario, the proportion of urban land increases to 10.59%, with urban expansion showing an outward trend. Compared to the O2 scenario, the reduction rates for cropland and forestland are smaller, at just 0.21% and 0.07%, respectively. Urban expansion primarily occurs around existing urban areas, achieving a relatively balanced approach to urban growth and ecological protection. This scenario demonstrates that by increasing urban density, it is possible to achieve urban expansion without significantly damaging the ecological environment.

Overall, O1 sees the fastest urban growth and greatest ecological loss without intervention, O2 controls expansion and protects ecology but limits development, and O3 strikes a balance between growth and conservation.

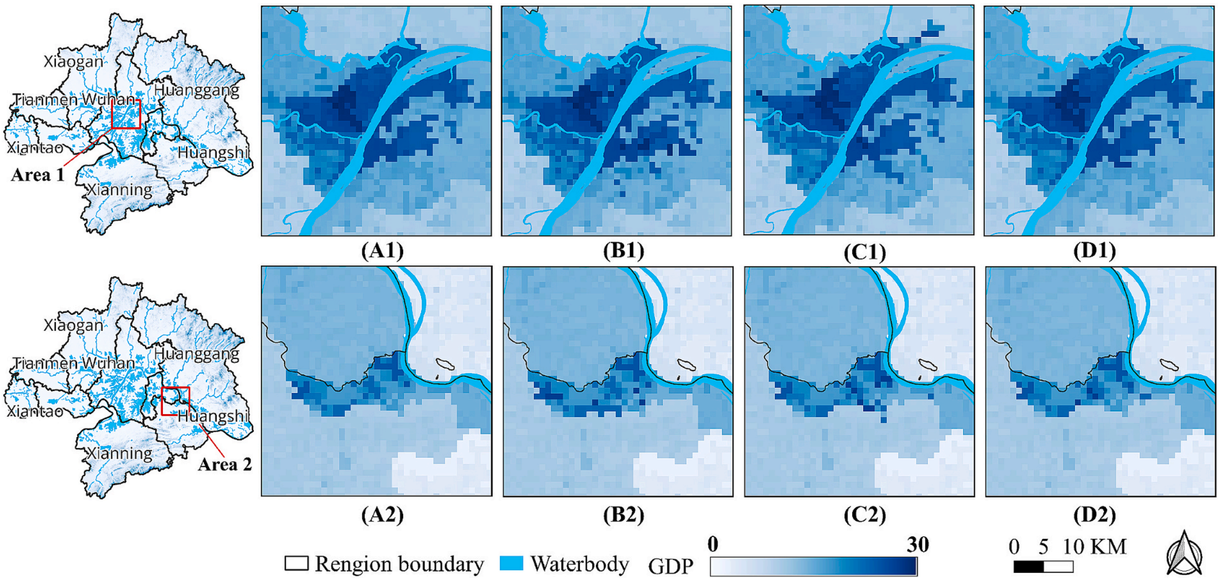


**Fig. 9.** Comparison of economic density (thousand CNY per km$^2$) simulation results across models: (A1-A2) Ground truth; (B1-B2) PLUS simulation; (C1-C2) Clark algorithm simulation; (D1-D2) CoCA multi-factor collaborative simulation; Area 1: Major urban areas in Wuhan; Area 2: Major urban areas in Ezhou and Huanggang.

**Table 3**
Projected land use areas in 2030 in the Wuhan metropolitan area (unit: km$^2$).

| Scenarios | Cropland | Forest | Grassland | Waterbody | Urban land | Unused land |
|---|---|---|---|---|---|---|
| Ground truth 2020 | 27,654 | 17,423 | 1392 | 6409 | 4964 | 159 |
| Prediction 2030 (O1) | 27,180 | 16,921 | 1386 | 6467 | 5937 | 110 |
| Prediction 2030 (O2) | 27,361 | 17,067 | 1284 | 6410 | 5773 | 106 |
| Prediction 2030 (O3) | 27,240 | 17,034 | 1091 | 6407 | 6142 | 87 |

## 5. Discussion

Existing CA models usually have difficulty in simulating complex continuous urban phenomena of population and economic dynamics and ignore the cooperative effects among multiple urban factors. This study proposes the spatial cooperative framework **CoCA** for simulating and predicting the land-population-economy system in urban agglomeration. This framework significantly improves the accuracy of land use change and the development patterns of population and economic density, while revealing the complex interactions among these factors in urban agglomeration. By exploring the dynamic trends and cooperative effects among various factors, this study provides a novel method and technique for research on the cooperative development of metropolitan areas, with significant practical applications.

The CoCA model incorporates interaction mechanisms between multiple factors, significantly improving the accuracy of various simulated factors, overcoming the limitations of traditional single-factor and static simulation models, thereby enhancing the capability to simulate complex urban dynamics. In comparative experiments focused on the Wuhan metropolitan area, the CoCA model outperformed both the single-factor discretization simulation and the Clark algorithm-based cooperative simulation. Specifically, the CoCA model increased the accuracy of land use simulation by over 35%, while reducing the *MAPE* for population density and economic density by over 38%. Furthermore, the results show consistent performance across different regions, with minimal fluctuations in simulation errors. Analysis across the nine cities in the Wuhan metropolitan area reveals that these errors remained within acceptable ranges. Notably, higher accuracy was observed in Wuhan's main urban area and the high-density southeastern region of the urban agglomeration, where clearer development policies and concentrated economic activities contributed to better simulation outcomes (Xing et al., 2019). In contrast, in more remote areas with numerous mountainous regions, such as the western and southern parts, the improvement in simulation accuracy was less pronounced. This variation highlights the differing interaction mechanisms of urban development factors across regions, emphasizing the need to consider these mechanisms to improve overall simulation accuracy. This study underscores the importance of incorporating multiple factors and their interactions in urban simulation models for higher accuracy. The CoCA model demonstrates the ability to adapt to different regional characteristics and accurately simulate complex urban environments.

The integration of the S-curve based DCA model significantly enhances the accuracy of simulating population and economic density for CA, allowing for a more precise representation of the complex distribution of various urban factors. Comparative analysis of different models reveals that the cooperative simulation approach, integrating the DCA model, increased land-use accuracy by 15% in Wuhan's core urban areas and improved the representation of scattered distribution patterns in peripheral regions. The CoCA model effectively captures the interaction between economic growth and land expansion. This results in a land-use distribution that closely matches actual conditions and clearly distinguishes between urban and non-urban areas. This accuracy is achieved by effectively limiting excessive urban expansion through the consideration of urban growth boundaries in simulations of population and economic density, demonstrating a convergent trend during the simulation process. In contrast, the Clark negative exponential model typically assumes that population and economic activity extend infinitely from the urban center and gradually decay outward (Clarke and Gaydos, 1998), leading to an overestimation of GDP and urban land expansion in northern Wuhan. These phenomena indicate that urban development results from the combined effects of natural, social, and economic factors. This further confirms the proposed model's advantage in verifying the effectiveness of cooperative mechanisms (Tu et al., 2024), and in delving deeper into the synergistic interactions among

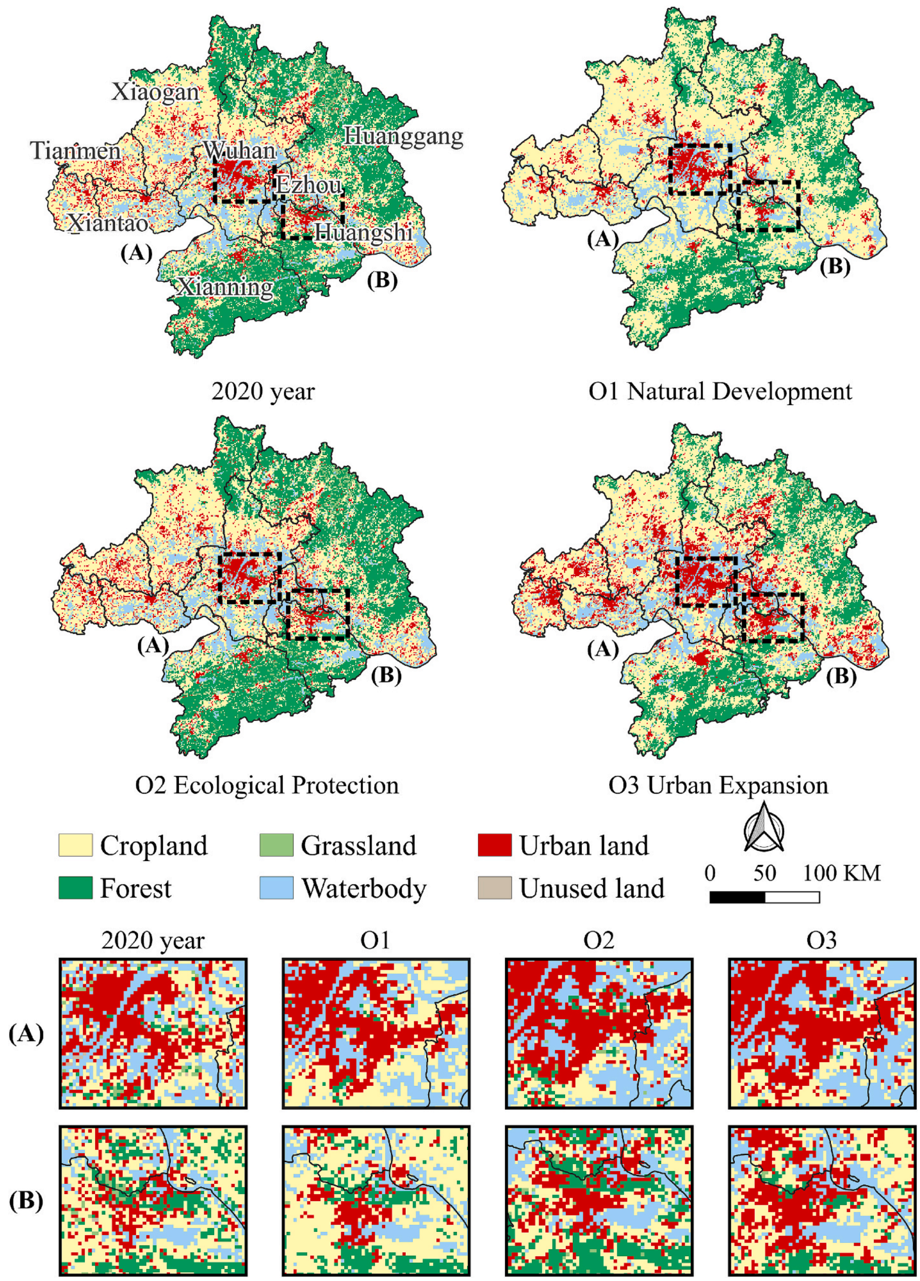


**Fig. 10.** Projected land use distributions in 2030 under different scenarios. (A) Major urban areas in Wuhan; (B) Major urban areas in Ezhou and Huanggang.

multiple factors.

Multi-factor cooperative simulations more effectively predict land use changes, as demonstrated by the quantitative verification of future impacts of different planning policies and comprehensive evaluations for sustainable development. The prediction results demonstrate that under the urban expansion scenario, the proportion of urban land increased to 10.45% compared to 2020, with significant urban expansion in cities like Huangshi and Huanggang. In the southern and northern mountainous areas of the Wuhan metropolitan area, forestland tends to degrade into grassland and cropland. Newly added forestland is primarily located in the eastern region, while other regions exhibit more evenly distributed changes. The overall forestland percentage under the urban expansion scenario is consistent with that of the natural development scenario, aligning with previous research findings (Liang et al., 2021). Furthermore, under the urban expansion scenario, the conversion of arable land to other types is reduced, and the expansion of urban areas at the expense of arable land is controlled, ensuring the protection of arable land area. Compared to the ecological protection scenario, the area of forest and grassland also exceeds the restrictive indicators of the ecological protection red line, with only a 0.98% increase in ecological damage and a 0.22% increase in arable land occupation. This approach ensures a stable ecological environment while supporting continued economic growth, providing a scientific basis for urban planning and sustainable development (Cao et al., 2012). Therefore, setting appropriate ecological protection indicators and economic development control targets based on actual conditions can achieve a balanced development scenario through cooperative simulations.

The results of this study offer valuable perspectives and suggestions for the WMA's sustainable development. The Urban Expansion Scenario (O3), in particular, strikes a balance between urban development and ecological protection, holding great significance for WMA's planning. In Scenario O3, the urban land proportion rose to 10.59%, expanding mainly around existing urban areas. This meets urban development demands while maintaining low reduction rates for cultivated land

(0.21%) and forest land (0.07%). The research results of the WMA show that population distribution and economic development under different scenarios significantly interact with land use changes (Liu et al., 2023). Therefore, during economic development, the WMA should focus on protecting the cultivated and ecological forest land in areas like the western Xiantao and northern Xianning. This can be achieved through strict land use regulations and continuous monitoring (Xing et al., 2019). Our analysis prompts urban planners and policymakers to consider regional characteristics and development needs for coordinated development. For ecologically-fragile yet valuable regions like the southern WMA mountainous areas, explore suitable development models while prioritizing ecological protection. For rapidly-developing regions, enhance development quality via land use layout optimization and infrastructure improvement.

Based on these experiments, this study developed and released the CoCA spatial cooperative simulation platform, which includes modules for data preprocessing, cooperative simulation, and accuracy evaluation. The CoCA platform is equipped with robust data processing capabilities and spatial cooperative simulation functions, with each module operating independently. Constructed on general urban development theories and multi-factor cooperation mechanisms, the CoCA platform is region-independent. Its core algorithms and framework can adapt to diverse urban characteristics in land use, population, and economy, flexibly adjusting simulation parameters according to city-specific data. The platform is highly compatible in data processing and input, accepting various data formats and sources, with built-in conversion and preprocessing functions. It can also dynamically adjust driving-factor weights based on a city's development stage and features, accurately mirroring local conditions for different urban simulation scenarios.

The CoCA model proposed in this study is a powerful and practical tool for urban planning and sustainable development, it is one of the few models that effectively integrates the dynamic interactions among multiple urban factors, such as land use, population, and economy, in a comprehensive spatial simulation framework. By considering the coevolutionary relationships between these factors, it achieves more accurate and realistic simulations of urban development scenarios. The CoCA breaks through the limitations of traditional static simulation models. In previous studies, most models used static data to simulate urban development, neglecting the cooperative effects in urban systems (Guzman et al., 2020; Liu et al., 2017; J. Wang et al., 2022). The CoCA model dynamically updates driving factors during the simulation process. For example, when calculating the overall development probability of land use patches, it takes into account real-time changes in population density, economic development, and geographical conditions. This dynamic approach can better capture the complex and changing nature of urban development, providing a more accurate representation of urban development trends. A significant advantage of CoCA over existing models is that its simulation results can directly inform urban planners and policymakers about the potential impacts of different policies on land use, population distribution, and economic development (Guzman et al., 2022; Yu et al., 2019). This is crucial for supporting the formulation of scientific and targeted urban planning strategies. Hence, we believe this convenient modelling tool can help planners determine the optimal scale of urban expansion, allocate resources more efficiently, and design sustainable land use policies.

## 6. Conclusion

This study proposes a CoCA framework that enables spatial cooperative simulations and multi-scenario predictions of land-population-economy systems at the urban agglomeration scale. The framework combines the DCA model based on the S-curve algorithm with a patch-generation land use model, effectively enhancing the simulation accuracy of various factors. Moreover, by employing a dynamic updating strategy for driving factors, the framework more effectively explores the mechanisms of synergy and mutual influence among various urban development factors. This study provides an effective method for depicting the spatial distribution of multiple factors at the metropolitan scale.

The results show significant cooperative changes and interactions among various factors during urban development, consistent with the principles of urban system dynamics theory. This study contributes to a deeper understanding of the mechanisms of interaction among metropolitan factors and offers insights for regional policy-making. We recommend that future urban planning in Wuhan should focus more on multi-factor cooperative planning and establish and improve dynamic data updating mechanisms for land, population, and economy. Furthermore, urban development plans should be scientifically formulated based on future land use and population-economic development indicators, aiming to promote sustainable urban development under various development objectives.

**Limitations & future directions:** Several aspects of the proposed CoCA remain in need of further elaboration. The development of population and economic is susceptible to various external factors. The causal mechanisms between different urban development factors in the constructed spatial cooperative simulation framework are still unclear, and the analysis methods remain relatively simple. Moreover, the study used raster data, which poses challenges in simulating at a finer scale, leading to less precise delineation of urban boundaries and land parcel divisions. Future research could incorporate more constraint functions to improve the accuracy of continuous variable simulations. Additionally, using vector-based cadastral parcels in cellular automata could refine land-use change simulations. Integrating more detailed economic factors would also help deeply explore the causal feedback mechanisms among urban development factors.

## CRediT authorship contribution statement

**Chenglong Zeng:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Data curation. **Yao Yao:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Jiayao Liu:** Writing – original draft, Validation, Software, Methodology, Data curation. **Zhenhui Sun:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology. **Kun Zhou:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Dongsheng Chen:** Writing – review & editing, Validation. **Qingfeng Guan:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

## 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.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2025.105442.

## Data availability

The data and software (CoCA v2.1.0) that support the findings of the present study are available on Figshare at https://figshare.com/s/

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