Science of the Total Environment 807 (2022) 150813

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Urban expansion simulation and development-oriented zoning of rapidly urbanising areas: A case study of Hangzhou

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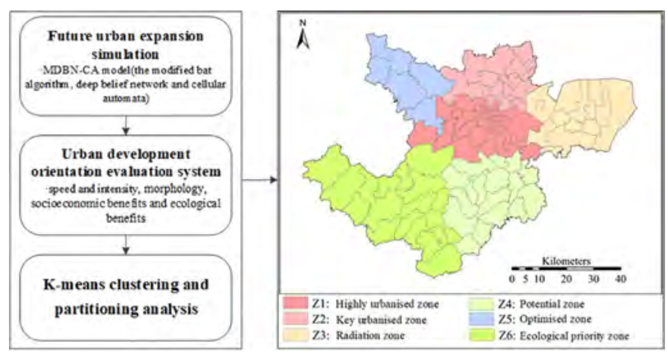
HIGHLIGHTS

- A CA model is proposed by integration with BA, DBN for urban expansion simulation.
- An urban development-oriented zoning framework was established at township scale.
- Based on the proposed method, future urban expansion can be predicted and analysed.

GRAPHICAL ABSTRACTS



ARTICLE INFO

Article history:
Received 17 May 2021
Received in revised form 24 September 2021
Accepted 1 October 2021
Available online 6 October 2021

Editor: Martin Drews

Keywords:
Urbanisation
Sustainable development
K-means clustering
Spatial zoning

ABSTRACT

Sustainable urban development is the key to regional urban development policy-making. Therefore, the comprehensive spatial zoning of rapidly urbanising areas is important. In this study, a novel spatial zoning framework was established based on the future urban spatiotemporal pattern and multidimensional dynamic index system at the township scale. First, the urban expansion of Hangzhou in 2025 was simulated based on a new method in which the hybrid bat algorithm and deep belief network (DBN) are coupled with the cellular automata (CA) model (MDBN-CA). Second, an urban development-oriented evaluation system was established at the township scale based on urban expansion simulations and indicators, including the speed and intensity, morphology, socioeconomic and ecological benefits. Finally, Hangzhou was zoned by using the K-means method. The results show that: (1) The MDBN-CA model effectively overcomes the limitations of traditional neural networks, yielding an increase in the simulation accuracy and spatial pattern similarity of 3.70% and 10.11%, respectively; (2) Hangzhou can be divided into six zones according to the 2025 urban expansion, that is, the highly urbanised, key urbanised, radiation, potential, optimised, and ecological priority zones; (3) Based on the current development trends, urban expansion in Hangzhou will have relatively large benefits by 2025. However, problems with respect to the unbalanced development of land urbanisation and population urbanisation, as well as the low efficiency of land use, were identified. Based on the results of this study, suggestions are provided with respect to spatial pattern reconstruction, urban function transformation, efficient land use, and green and healthy development;

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https://doi.org/10.1016/j.scitotenv.2021.150813

(4) Based on the combination of the MDBN-CA and K-means models with the zoning framework of the comprehensive benefits evaluation system of urban expansion, future urban expansion can be predicted and analysed.

1. Introduction

Land use/land cover change is one of the most direct manifestations of the interaction between human activities and the natural environment and is the core subject of global environmental change research (Fiener et al., 2011; Haase et al., 2012; Qian et al., 2020). Since the reform and opening-up, China has achieved long-term and sustained ultra-high-speed economic growth and large-scale urbanisation. This is especially reflected in the continuous expansion of urban land, which leads to many challenges such as the exhaustion of natural resources and degradation of the ecological environment (Aburas et al., 2019; Huang et al., 2017; Wu, 2010; Zhao et al., 2016). Because of the acceleration of urbanisation, increased attention has been paid to urban land use change/urban expansion, and urban space research has focused on rapid urbanisation areas (Banzhaf et al., 2017; Gu et al., 2016; Hu et al., 2017). Due to the dynamics of urban expansion, the comprehensive spatial zoning of rapidly urbanising areas can be regarded as the basic work for establishing urban development strategies and developing ecological civilisation.

The development-oriented comprehensive zoning of rapid urbanisation areas based on urban expansion simulations is based on more comprehensive studies of the 'process' of its evolution. Establishing a development-oriented zoning model is more in line with future urban land use change without departing from the thorough evaluation of urban space. However, there is a lack of studies evaluating the benefits of zoning future urban expansion areas. Therefore, intelligent urban expansion simulations, development-oriented zoning based on the simulation results, and trend evaluation have become the foci of current land use planning. Mainstream urban zoning tends to be the main function zoning based on historical data, land use zoning, and urban function zoning based on new open data (Chen et al., 2017; Fang et al., 2020; Luescher and Weibel, 2013; Zhong et al., 2014). However, there is a lack of urban development-oriented zoning studies based on forecast data.

In the past few decades, scholars have established various models to simulate urban expansion and land use changes such as system dynamics, Markov chain, agent, and cellular automata (CA) models (Kazemzadeh-Zow et al., 2017; Noszczyk, 2018; Ralha et al., 2013; Rasmussen et al., 2012; Ren et al., 2019). The CA models have attracted increased attention, and rule mining has become a hot topic. A variety of rule mining methods have been proposed, including logistic, Markov, intelligent algorithms, artificial neural networks (ANN), and machine learning techniques (Azari et al., 2016; Gounaridis et al., 2019; Liu et al., 2017; Mustafa et al., 2018). However, the complex relationships among variables cannot be effectively determined with logistic models. Intelligent algorithms are required to improve the accuracy of the models based on the precise pruning of rules. Conventional ANNs are weak in global searching and fall more easily into local optima during CA transition rule mining (Pacelli et al., 2011). With the development of artificial intelligence, deep learning has attracted increasing attention because of its good feature detection and prediction capabilities and has been successfully applied to urban expansion simulations. Recent studies have shown that the use of deep learning models to mine the transition rules of CA outperformed the traditional models such as ANN-CA, random forest - CA, and logistic regression - CA (He et al., 2018; Xing et al., 2020; Zhai et al., 2020; Zhou et al., 2017).

The DBN, which is among the mainstream methods of deep learning, has excellent feature detection abilities. The DBN can easily express the non-linear, complex structures of the data in deep hidden layers. A fast, greedy, unsupervised learning algorithm that can initialise the weights of conventional ANN was recently introduced (Shen et al., 2015). The problem with such a deep learning approach is that it has a large number of critical hyperparameters which are commonly tuned by experienced practitioners, which makes it difficult to find an optimal model architecture (Pham et al., 2021). Among various optimisation algorithms, the bat algorithm (BA) and its improved version is efficient, robust, and straightforward, which is mainly used to solve problems where it is difficult to find an exact mathematical model and can be used to automatically obtain the network structure of DBN to avoid the complexity of manual parameter tuning. However, only a few studies have combined BA, DBN with the CA model to simulate urban expansion. Hence, developing a new method that can be coupled with CA might provide better simulation precision.

The purpose of comprehensive urban space zoning, which is a type of spatial development zoning, is to divide the urban area into multiple comprehensive areas with homogeneous and functional attributes as well as more prominent functional attributes, and it has been used for a long time in urban research and planning (Chen et al., 2017). In early studies, remote sensing images and static models were widely used to describe the comprehensive division of urban functions based on small and medium-scale areas (Heiden et al., 2012; Van de Voorde et al., 2011). At present, the comprehensive zoning of urban space mainly focuses on constructing an indicator system and improving technical methods. On the one hand, the indicator system has evolved from a static system constructed using social economy, land use, and natural factors to a system based on new open data (Chen et al., 2017, 2021; Qian et al., 2020). However, the indicator system establishment lacks a multidimensional and dynamic description. On the other hand, partitioning technology has gradually developed from traditional Geographic Information System (GIS) modelling to spatial clustering analysis, intelligent and optimisation algorithms, nonparametric models, Tyson polygons, and so on (Kazemzadeh-Zow et al., 2017; Qi et al., 2019; Santé et al., 2016). For instance, Chen et al. (2017) proposed functional city zoning based on building-level social media data and applied the k-medoids method based on the dynamic time warping (DTW) distance to analyse the urban spatial structure of the Yuexiu District, Guangzhou.

In terms of research scales, most urban land use analysis and zoning studies are conducted at the city or county level (Estoque and Murayama, 2011; Frondoni et al., 2011; Sun et al., 2012). However, there is a lack of research on the analysis and comprehensive zoning of rapidly urbanising areas at the township scale (Sakieh et al., 2015; Qi et al., 2019). Townships are the smallest units in China's land use planning. It is of great significance to study the land use changes of towns and thus contribute to the management and planning of urban land.

Therefore, the main purpose of this study was to establish an urban development-oriented zoning framework at the

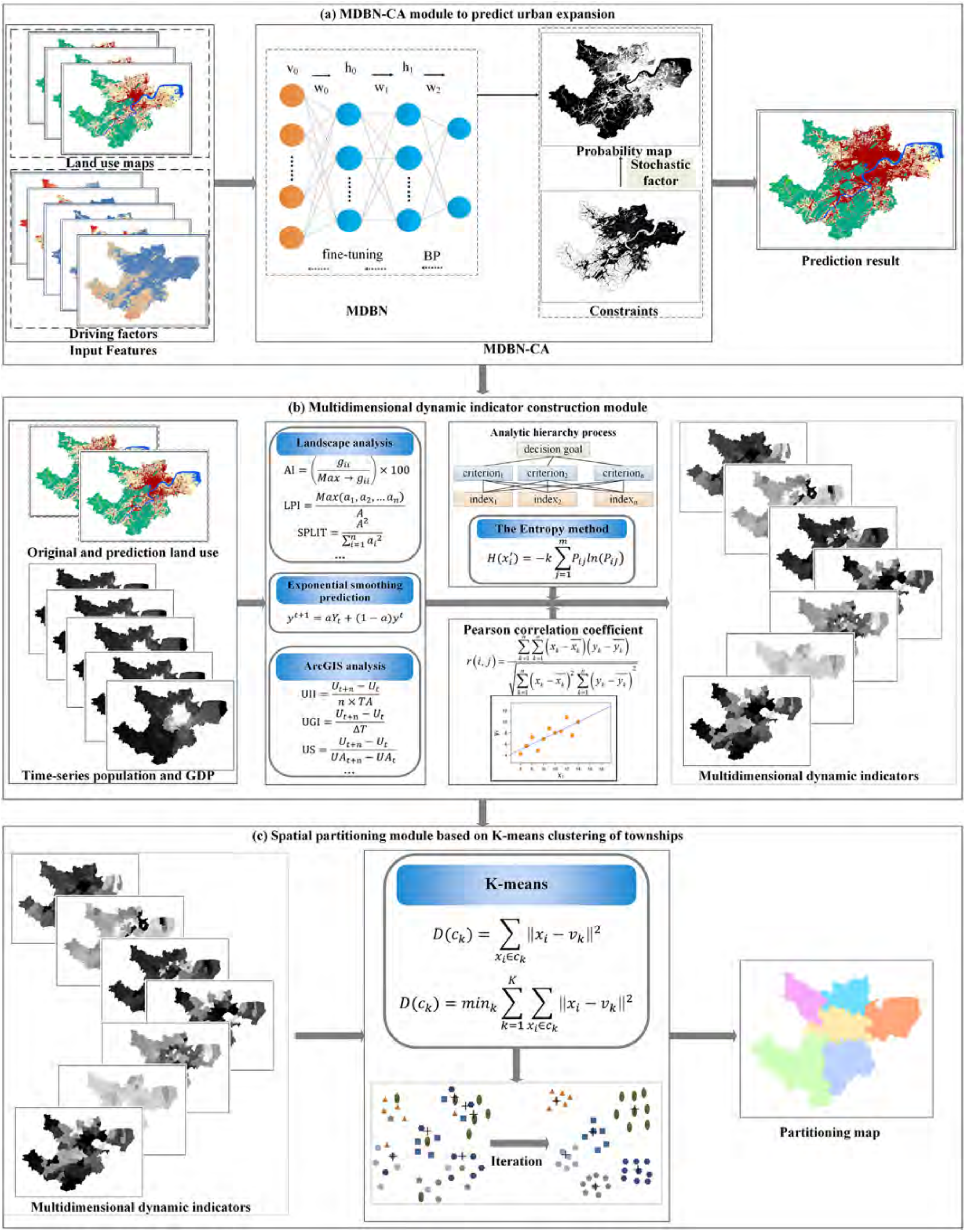

Fig. 1. Urban development-oriented zoning framework.

township scale, considering the future spatiotemporal patterns of rapid urbanisation areas and multidimensional dynamic indicator systems. Hangzhou, one of the rapidly urbanising areas in China's coastal region, was selected as the study area. The main contributions of this paper can be summarised as follows:

(1) We propose the MDBN-CA for future urban expansion simulation, where the optimised DBN obtained by the modified BA (MBA) is used to mine the transition rules of CA.
(2) The multidimensional characteristics of the spatiotemporal evolution of expansion are obtained from forecast data. We establish an urban development-oriented evaluation system based on four-dimensional indicators, including speed and intensity, morphology, socioeconomic benefits, and ecological benefits.
(3) At the township scale, K-means, one of the most popular and simple clustering tools (Jain, 2010; Zhao et al., 2019), is used for the spatial zoning of Hangzhou.

The remainder of this paper is organised as follows: The methods and models used in this study are introduced in Section 2. An overview of the study area and data are provided in Section 3. The implementation and analysis of urban expansion simulation and spatial zoning are described in Section 4. The discussion and conclusions are provided in Section 5.

2. Methodology

The urban development-oriented zoning framework at the township scale for the future spatiotemporal patterns of rapid urbanisation areas mainly includes three modules: (a) MDBN-CA module to predict urban expansion; (b) Multidimensional dynamic indicator construction module; and (c) Spatial partitioning module based on K-means clustering of townships, as shown in Fig. 1. The implementation of the framework will be described in Sections 2.1–2.3.

2.1. Integration of cellular automata with the deep belief network for urban expansion simulation

In urban expansion studies, the future state of a cell can be determined based on the definition of a series of transition rules:

$$State_{ij}^{t+1} = f\left(Neighb_{ij}^{t}, Global_{ij}^{t}, Constraint_{ij}^{t}\right) = \begin{cases} urban, p_{ij}^{t} > p_{threshold} \\ non\_urban, p_{ij}^{t} \leq p_{threshold} \end{cases} \quad (1)$$

where $State_{ij}^{t+1}$ is the state (urban land 1/non-urban land 0) of a cell at location (i,j) at time $t+1$ and $p_{threshold}$ is the predefined threshold for range [0,1]. By adjusting the threshold, the amount of non-urban land converted to urban land is constantly approaching the required amount. In the simulation stage, the number of cells in which non-urban land converted to urban land at the next time is the actual value, and the amount of urban land in the forecast stage is obtained by the Markov chain model. If $p_{ij}^{t} > p_{threshold}$, the non-urban state at time t changes to an urban state at time $t+1$. Otherwise, the non-urban state remains unchanged. $Global_{ij}^{t}$ represents the commonly used driving factors. $Constraint_{ij}^{t}$ are the constraint conditions for urban expansion, $Neighb_{ij}^{t}$ denotes the neighbourhoods, and f represents the transition function used to obtain the best transition rules, which is based on DBN mining and is comparable to ANN in this paper.

2.1.1. Deep belief network

A classic DBN consists of several restricted Boltzmann machines (RBMs) and a backpropagation (BP) network, which are used for pretraining and fine-tuning, respectively (Hinton et al., 2006). The DBN trains the unsupervised RBM network by using the output of the previous RBM as the input of the next RBM. An RBM is an undirected probabilistic graphical model composed of a visual layer (v) and hidden layer (h), trained using the contrastive divergence method. Based on the visible units (v_1, v_2, ……, v_m) and hidden units (h_1, h, ……, h_n), the energy function can be expressed as follows:

$$E(v,h) = -\sum_{i=1}^{m}\sum_{j=1}^{n} v_i w_{ij} h_j - \sum_{i=1}^{m} b_i v_i - \sum_{j=1}^{n} c_j h_j \quad (2)$$

where w_{ij} is the connection weight between visible unit i and hidden unit j, b_i is the bias of unit i, and c_j is the bias of unit j.

When the state of the visible unit $(v_1, v_2, ……, v_m)$ is known, the activation probability of hidden unit j is as follows:

$$P(h_j = 1|v) = sigmoid\left(c_j + \sum_i v_i w_{ij}\right) \quad (3)$$

Because the RBM is symmetrical, the activation probability of visible unit i can be calculated using Eq. (4) when the hidden units (h_1, h, ……, h_n) are provided:

$$P(v_i = 1|h) = sigmoid\left(b_i + \sum_j w_{ij} h_j\right) \quad (4)$$

During the fine-tuning procedure, the conventional BP network receives the output feature vector of the RBM as the input data for supervised learning training. The RBM training can be regarded as the initialisation of the weight parameters of the BP to avoid the local optimal problem due to the random initialisation of the weights.

2.1.2. Determination of the DBN structure based on the novel bat algorithm

The selection of parameters, such as the number of hidden units and the learning rate of the DBN, directly affects the model performance. The BA, developed by Yang (2010), has been proven to have better performance than the genetic algorithm (GA) and particle swarm optimisation (PSO) in obtaining globally optimal solutions. We introduced the GA's selection, crossover, and mutation operators based on previous studies to optimise the new BA (Meng et al., 2015; Wang et al., 2017), called Modified Bat algorithm (MBA).

In this study, we set the RBM layer number to two and used the MBA model to obtain the optimised DBN parameters, including the number of hidden units ($hidden_1$, $hidden_2$), learning rate [ε_1, $\varepsilon_2 \in (0,1)$], sparsity (s), and the dropout (d) of each RBM layer. Based on the objective function, the minimal error of the training data is obtained. The pseudocode of MBA for DBN using MATLAB is described as Algorithm 1.

Algorithm 1. Integrate Modified bat algorithm with DBN.

Initialise: $\boldsymbol{N}$: the population of bats; **M**: the number of generations; **P**: the probability of selection; $\boldsymbol{w}$: inertia weight; **C**: the compensation rates for Doppler effect in echoes; **θ**: contraction–expansion coefficient; **G**: the frequency of updating the loudness and pulse emission rate; $\boldsymbol{f}$: the frequency; **A**: loudness; $\boldsymbol{r}$: pulse rate; and the constants α, γ.

$\boldsymbol{x}$: the position including the number of hidden units $(hidden_1, hidden_2)$, learning rate $[\varepsilon_1, \varepsilon_2 \in (0,1)]$, sparsity (s), and the dropout (d) of each RBM layer of bats. The initial x is expressed as:

$$x = Lb + (Ub - Lb) \times rand(1, dim)$$

where *dim* is the dimension of *x; Lb, Ub* are the maximum and minimum values for initialising DBN parameters

Fitness: the prediction error on training data of all bats

for t = 1:M

if rand(0,1) < P

generate new solutions by:

$$x_{i,j}^{t+1} = \begin{cases} g_j^t + \theta * \left|mean_j^t - x_{i,j}^t\right| * \ln(\frac{1}{u_{ij}}), if\ rand < 0.5 \\ g_j^t - \theta * \left|mean_j^t - x_{i,j}^t\right| * \ln\left(\frac{1}{u_{ij}}\right), if\ rand \geq 0.5 \end{cases}$$

else

generate new solutions by:

$$f_{i,j} = f_{min} + (f_{max} - f_{min}) * rand(0,1)$$

$$f_{i,j} = \frac{(c + v_{i,j}^t)}{c + v_{g,j}^t} * f_{i,j} * (1 + C_i * \frac{(g_j^t - x_{i,j}^t)}{\left|g_j^t - x_{i,j}^t\right| + \varepsilon})$$

$$v_{i,j}^{t+1} = w * v_{i,j}^t + (g_j^t - x_{i,j}^t) * f_{i,j}$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^t$$

end

if rand(0,1) > r_i

generate a local solution around the selected best solution by:

$$x_{i,j}^{t+1} = g_j^t * (1 + rand\ n(0, \sigma^2))$$

where $\sigma^2 = \left|A_i^t - A_{mean}^t\right| + \varepsilon$, ε is used to ensure $\sigma^2 > 0$. A_{mean}^t is the average loudness of all bats at time step t.

end

evaluate the objective function value of each individual and rank

selection: select the best 50% bats to the next iteration, and use these bats for crossover

crossover: after random pairing, crossover calculations are performed respectively, and the newly generated individuals replace the bat individuals whose fitness function values are ranked in the lower 50%. The number of hidden units is crossed; continuous data is crossed a by:

$$x_{i,j}^{t+1} = rand \times x_{i,j}^t + (1 - rand) \times x_{i',j'}^t$$

$$x_{i',j'}^{t+1} = rand \times x_{i',j'}^t + (1 - rand) \times x_{i,j}^t$$

$$v_{i,j}^{t+1} = rand \times v_{i,j}^t + (1 - rand) \times v_{i',j'}^t$$

$$v_{i',j'}^{t+1} = rand \times v_{i',j'}^t + (1 - rand) \times v_{i,j}^t$$

mutation: select several individuals to mutate, for mutated individual i, when rand>0.5, mutate the number of hidden units; other parameters are initialised randomly

evaluate the fitness function value fitness of each bat, and obtain the optimal individual in fitness and fitness1 as the local optimal in the current iteration

if $rand < A_i$ & $f(x_i) < f(x^*)$

accept the solutions, and update the loudness and pulse rate by:

$$A_i^{t+1} = \alpha A_i^t$$

$$r_i^{t+1} = r_i^0[1 - \exp(-\gamma t)]$$

end

Rank the solutions and find the current best g

if (iteration – g)>G

Re-initialise the loudness A_i and pulse rate r_i

end

end

output: Global optimal solution and corresponding position, fitness function value, and other information

Where the initial value N = 20, M = 100, P □ [0.6, 0.9], w □ [0.5, 0.9], C □ [0.1, 0.9], θ □ [0.5, 1], G = 10, f_{min} = 0, f_{max}=1.5, A_{min} = 1, A_{max} = 2, r_{min} = 0, r_{max}= 1, α, γ = 0.9.

2.1.3. Integration of the MDBN model with cellular automata

The urban expansion simulation model (the first model in Fig. 1) proposed in this study, which couples Markov chains, DBN, and CA, mainly includes the following steps:

Step 1: Data collection and preprocessing. Time series land use maps are collected, and driving factors are determined using GIS and remote sensing technology. Obtaining training and validation samples using the stratified sampling method.
Step 2: MDBN training. Obtain the optimal DBN parameters using the MBA algorithm.
Step 3: Simulation and validation. The optimal DBN structure obtained in step 2 is used to simulate the urban land at time *t*. The observation data at that time are used to perform accuracy validation.
Step 4: Prediction. The Markov model is used to predict the future growth of urban land. The future urban land is predicted using the optimal DBN model.

2.1.4. Accuracy assessment

To test the effectiveness of the model, the accuracy is evaluated as follows:

(1) Pixel dimension. The Overall Accuracy (OA), Kappa coefficient, and Figure-of-Merit (FoM) index are chosen to evaluate the simulation results (Arsanjani et al., 2013; Chen et al., 2016; Yao et al., 2017). The FoM is mainly used to measure the consistency between the actual observation conversion number and the simulation forecast conversion. A higher FoM reflects a higher simulation accuracy. The FoM can be calculated as follows:

$$\mathrm{FoM} = \mathrm{B}/(\mathrm{A}+\mathrm{B}+\mathrm{C}+\mathrm{D}) \tag{5}$$

$$\text{Product}'\text{s accuracy (PA)} = \mathrm{B}/(\mathrm{A}+\mathrm{B}+\mathrm{C}) \tag{6}$$

$$\text{User accuracy (UA)} = \frac{\mathrm{B}}{\mathrm{B}+\mathrm{C}+\mathrm{D}} \tag{7}$$

where A denotes the number of cells that have been predicted to change during the observation but did not change in the simulation; B represents the number of cells that correctly changed both in the simulation and observation; C is the number of cells that incorrectly changed both in the simulation and observation, and D is the number of cells that changed in the simulation but not in the observation.

(2) Spatial pattern dimension. We used a series of landscape pattern indicators at the built-up land scale and landscape scale to distinguish the differences between the simulated map and observation (Chen et al., 2013, 2016). These indicators include the number of patches (NP), largest patch index (LPI), mean shape index (Shape_MN), and mean Euclidean nearest-neighbor distance (ENN_MN) and can be calculated with Fragstats 4.2. The similarity measurement of the landscape pattern A can be calculated as follows:

$$\mathrm{A} = \left(1 - \frac{1}{n}\sum_{i=1}^{n}\frac{|l_{i,s}-l_{i,o}|}{l_{i,o}}\right) \times 100\% \tag{8}$$

where n is the number of landscape metrics and $l_{i,\,s}$ and $l_{i,\,o}$ represent landscape metrics obtained from the simulation and actual observation, respectively.

2.2. Construction of urban development orientation evaluation system

The development-oriented evaluation system established in this study uses towns as the basic evaluation units. Considering the complex functional structure and urbanisation characteristics of rapidly urbanising areas, as well as the impact of urban expansion on the economy, landscape, and ecological environment, the characteristics and benefits of urban expansion, are used as the two major evaluation themes. Considering the lack of socioeconomic statistical data, substitute indicators or other methods are used to quantify several factors.

The evaluation system includes the system, criterion, and index levels; 21 indicators are preliminarily selected. The system layer includes the characteristics and benefits of urban expansion. The characteristics of urban expansion are divided into the change degree and morphological structure of urban expansion. The benefits of urban expansion are divided into socioeconomic and ecological benefits. The change degree of urban expansion directly reflects the speed and intensity of urban development. Four indicators are selected: urban intensity index (UII), built-up land growth index (UGI), the regional contribution rate of the built-up land expansion (US), and change rate of the built-up land (UC). The morphology of the built-up land expansion reflects the intensive use and characteristics of the built-up land, reflecting the concentration, superiority, and compactness. Therefore, six indicators, that is, the change rate of the patch density (PD) of the built-up land (C_pd), the change rate of the LPI (C_lpi), the change rate of the splitting index (SPLIT) (C_split), the change rate of the aggregation index (AI) (C_ai), the change rate of the morphological compactness (C_cp), and change rate of the mean fractal dimension index (C_fac), were initially selected to characterise the dimension of the morphological structure. Socioeconomic benefits of urban expansion refer to the comparison between input and output in land use, which are reflected by the comprehensive socioeconomic effects of urban development. Considering the availability of data, four indicators were selected: the change rate of the land reclamation index (C_lr), change rate of the land use degree (C_ludc), population expansion index (pop), and economic growth index (gdp). Ecological benefits of urban expansion refer to the effects of land use activities on the urban ecosystem, which are mainly evaluated based on the landscape pattern and ecological effects of urban expansion. Seven indicators were used, that is, the expanded arable land composition index (E_al), expanded green land composition index (E_gs), ecological land coverage change rate (C_ecc), change of mean patch area of green land (C_mp), change rate of Shannon's diversity index (C_shdi), landscape contagion change rate (C_contag), and degree of change in the overall ecological status of the regional land use, which was calculated by referring to the global ecosystem service function evaluation model of Costanza et al. (1997) (C_ec). A detailed description of each indicator is provided in Supplementary Table S1.

The Pearson correlation coefficient was used to analyse the correlation of each indicator. Based on our definition, a correlation coefficient of 0.85 indicates a strong correlation. We eliminated indicators that did not meet these requirements. The range method was then adopted to standardise the original indicator values and convert them into dimensionless values. Finally, the Analytic Hierarchy Process and Entropy method were combined to determine the weight of the influence factor.

2.3. Development-oriented zoning based on K-means clustering

The K-means cluster analysis, one of the most popular and simple clustering algorithms, was employed for development-oriented zoning. At the township scale, the standardised and filtered values of each indicator constitute a matrix, which is used as observation data for the K-means classification. Based on K-means clustering, the observations are divided into k mutually exclusive clusters. The observations within one cluster are close to each other and far from observations in other clusters (Jain, 2010; Carvalho et al., 2016). Determining the number of categories should follow the principles of mutual exclusion of partition objects, the rationality of the number of partitions, and the self-evidence of partition types. Given the observation $X = \{x_i\}$, $i = 1, 2, \ldots n$ (n is the number of towns in the study area) and each town properties of m dimensions, where m is defined as the number of indicators after filtering, all towns will be divided into k clusters $C = \{c_k, k = 1,2,\ldots,K\}$. The goal of K-means clustering is to gather objects into designated k clusters based on the similarity among objects. Each object only belongs to one cluster, with the smallest distance from the centre of the cluster. Based on the assumption that v_k is the mean value of cluster c_k, the Euclidean distance between v_k and all points belonging to c_k is defined as follows:

$$D(c_k) = \sum_{x_i \in c_k} \|x_i - v_k\|^2 \tag{9}$$

The aim of K-means clustering is to solve the optimal problem of all k clusters:

$$D(c_k) = min_k \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - v_k\|^2 \tag{10}$$

The K-means method initialises k cluster centres, compares the distance from each object to each cluster centre, and assigns the objects to the clusters with the nearest cluster centre. Partitions are generated and modified by recalculating the new centroid of each cluster and the new Euclidean distance between each centroid and the point. This process ends when the cluster members are stable or conditionally terminated.

3. Study area and data

3.1. Study area

Hangzhou, in the southern part of the Yangtze River Delta, is the political, economic, transportation, and financial centre of the Zhejiang Province and an important growth core and ecological centre of the Hangzhou Bay Greater Bay Area and Yangtze River Delta urban agglomeration. Without considering the changes in the administrative divisions after 2015, a total of 119 towns in 9 districts under the jurisdiction of Hangzhou were included in the study area in this work, covering a total area of 4876 km^2 (Fig. 2).

Following the market transition and the local policy of 'establishing urban agglomeration around Hangzhou Bay,' Hangzhou has undergone rapid urbanisation. The gross domestic product (GDP) in Hangzhou has significantly grown: it increased from 114.5 billion RMB in 2000 to 872.2 billion RMB in 2015, whereas the population increased from 4.35 to 7.21 million throughout this period. This region experienced a significant expansion of urban land, and the urban landscape configuration dramatically changed. Hangzhou is a typical example of urbanisation.

3.2. Data collection

3.2.1. Land use maps

A Landsat-7 ETM+ image from 2001, Landsat-5 TM image from 2008, and Landsat-8 OLI image from 2015 were used to derive the time series land use maps (30 × 30 m) for Hangzhou. Data preprocessing, including geometric registration, radiometric calibration, atmospheric correction, image cropping, and supervised classification, was conducted using Envi and ArcGIS software. Training and test samples for the supervised classification were obtained using the published land cover data and visual interpretation results of Google Earth historical images. Finally, according to the classification system for remote sensing monitoring of land use of the Resource and Environmental Science Data Center, six categories, including arable land, forest land, grassland, water land, built-up land, and unused land, were selected. After supervised classification and post-classification processing, all overall classification accuracies were higher than 85%, and the Kappa coefficients were larger than 0.82. As shown in Fig. S1, the built-up land expanded rapidly, whereas the arable land decreased.

3.2.2. Driving factors

The process of urban land use change is a complex non-linear system. A single factor cannot accurately reveal the essential relationships and interactions between driving factors and urban expansion. Previous studies showed that the topography, such as the elevation and slope, are prerequisites and important factors limiting urban development (Gounaridis et al., 2019). Transportation accessibility and location conditions often affect the distribution of new urban land; therefore, distance variables are factors that are generally considered in the built-up land expansion (Poelmans and Van Rompaey, 2009). The

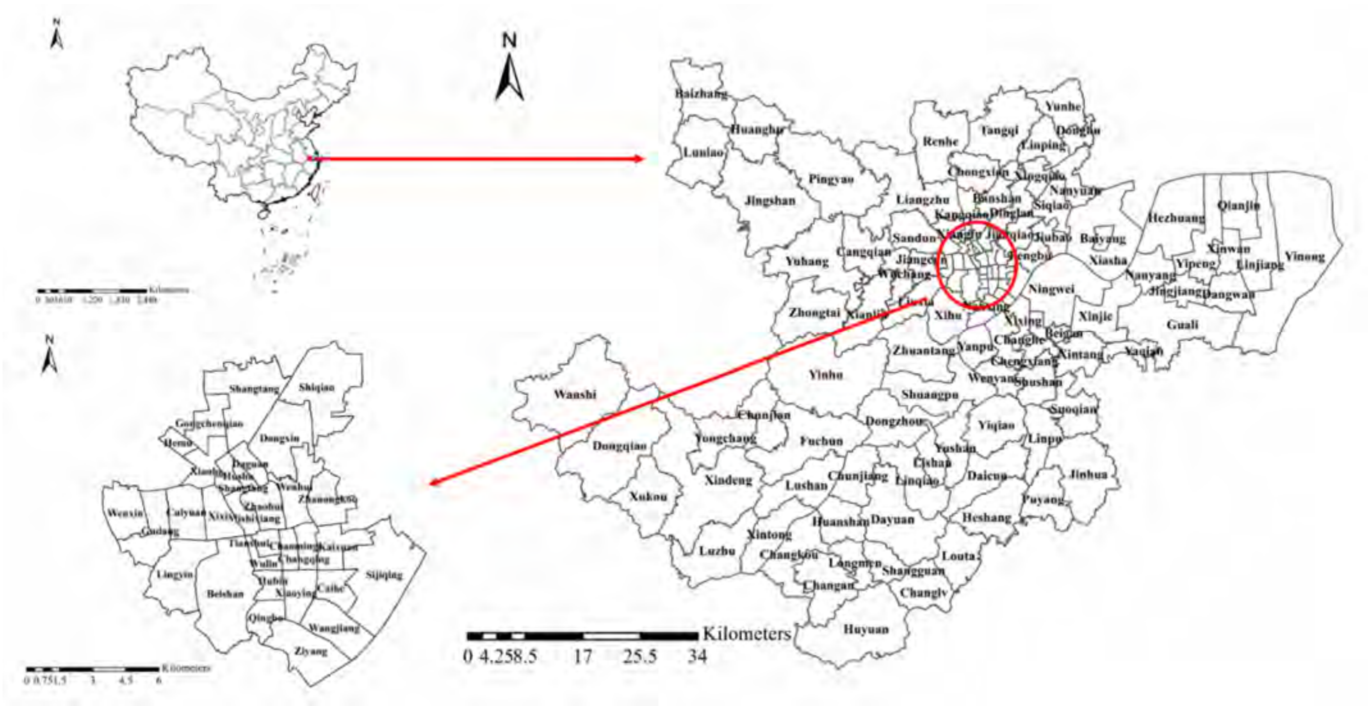

Fig. 2. Location of the study area.

Table 1
List of urban expansion factors used in this study.

Categories	Variable	Data source
Natural conditions	Elevation	Geospatial Data Cloud[a]
	Slope	Geospatial Data Cloud
Accessibility factors	Distance to rivers	Land use maps
	Distance to highways	Openstreetmap[b]
	Distance to primary roads	Openstreetmap
	Distance to secondary roads	Openstreetmap
	Distance to railways	Openstreetmap
	Distance to forest	Land use maps
	Distance to airport	POIs from Baidu Map[c]
	Distance to county centres	POIs from Baidu Map
	Distance to town centres	POIs from Baidu Map
	Density of road network	Openstreetmap
Neighbourhood	Urban neighbourhoods	Land use maps (7 × 7 extended Moore neighbourhoods)
	Non-urban neighbourhoods	Land use maps (7 × 7 extended Moore neighbourhoods)

[a] http://www.gscloud.cn.
[b] https://www.openstreetmap.org.
[c] https://map.baidu.com.

construction of roads, highways, and railways greatly improves the accessibility, especially the construction of roads connecting urban and rural areas, which will allow the development of surrounding areas. A location closer to the city centre means better public infrastructure, greater employment opportunities, and a greater likelihood of development and construction (Zhang et al., 2013). In addition, based on the first law of geography, the spatial correlation indicates that the land use state with a closer distance has a trend similar to that with a farther distance. In summary, a total of 14 driving factors, including natural conditions, accessibility factors, and neighbourhood factors, were adopted (Table 1, Fig. 3). All factors have a spatial resolution of 30 m, calculated with the Euclidean distance equation of ArcGIS 10.4.

3.2.3. Urban development-oriented indicators

The land use maps of Hangzhou from 2008 and simulation results for 2025 are divided by town. The 21 indicators used in this study were calculated as follows:

Based on the 1 km grid population datasets from 1990 to 2015,[1] the population data of each town in Hangzhou in 2025 were obtained through coordinate transformation, resampling, and exponential smoothing prediction. The GDP was obtained with the same method based on the 1 km grid GDP datasets from 1995 to 2015.[2] The change rate of the regional SHDI, the change rate of landscape fragmentation, and all morphological structure indicators for 2008 and 2025 were calculated using Fragstats 4.2. Subsequently, the change rate was calculated. The remaining indicators in the evaluation unit were obtained using ArcGIS statistical methods.

3.2.4. Zoning suitability data

In reference to previous studies, the Minimum Cumulative Resistance (MCR) model was used to partition the suitability of the ecological land in Hangzhou City (Xiao et al., 2020; Xu et al., 2018). Based on land use planning data for Hangzhou, the partition results were revised to obtain the extent of the suitable ecological protection land as the ecological constraint of the CA model, which can be divided into key protection, general protection, and suitable construction areas, as shown in Supplementary Fig. S2.

[1] (http://www.resdc.cn/DOI), 2017. DOI:10.12078/2017121101.
[2] (http://www.resdc.cn/DOI), 2017. DOI:10.12078/2017121102.

4. Implementation and analysis

4.1. Implementation and analysis of the urban expansion simulation

4.1.1. Model implementation

The MDBN-CA model proposed in this study simulates the distribution of the built-up land in 2015 based on the land use map from 2008 and evaluates the accuracy by comparing the results with the observation data from 2015. When the simulation accuracy meets the requirements, the built-up land in 2015 is used to predict the built-up land pattern in 2025.

In the training phase of the MDBN-CA, the numbers of hidden layers, visible nodes, and output layer units are 2, 14, and 1, respectively. We set the learning rate in the fine-tuning stage and iterations of each layer of the RBM to 0.01 and 100, respectively. The number of the bat population is 20; that is, the number of hidden nodes, learning rate, sparsity factor, and dropout of 20 groups of the RBM in each layer were randomly initialised. The selected fitness evaluation function is as follows:

$$f = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(p_{ij}-y_{ij}\right)^2 \tag{11}$$

where $m \times n$ is the number of test samples. When the cell conversion probability obtained by DBN training is greater than the threshold, then p_{ij} is 1, otherwise p_{ij} is 0. The parameter y_{ij} represents observations.

When the number of iterations obtained by MDBN-CA training is 87, the fitness function value drops to the minimum value of 1320 (Fig. S3). The optimal structure of the MDBN-CA is as follows: the number of the two hidden layer nodes and RBM learning rate are 13, 12, and 0.39, 0.44, respectively; the sparsity factor is 0.0043, and the dropout parameter is 0.067.

The number of simulation iterations was set to 50, and the conversion probability threshold $p_{threshold}$ is set to 0.9. The optimal MDBN-CA model was used to obtain the conversion probability of each cell p_{ij}. The conversion probability of the cell can be calculated as follows:

$$p'_{ij} = \begin{cases} 1, p_{ij} \times EC_{ij}^{t} \times con\left(s_{ij}^{t}\right) \geq p_{threshold} \text{ and } rand\,(0,1) > 0.5 \\ 0, otherwise \end{cases} \tag{12}$$

where EC_{ij}^{t} are ecological constraints and $con(s_{ij}^{t})$ are other constraints, which together constitute a global constraint G_{con}. If the cell ij falls in the key protection area, then $G_{con} = 0$. If the cell ij falls in the general protection area, then $G_{con} = 0.5$, the rest are 1. The parameter $rand\,(0,1)$ is a random number in the range [0,1].

Based on the land use maps from 2001 and 2015, the Markov chain was used to predict built-up land area for the next ten years. The transition probability matrix is shown in Table S2. The total built-up land in 2025 was calculated to be 1726.31 km^2.

4.1.2. Comparison and analysis of the simulation results

The null model and traditional ANN-based CA model (ANN-CA) were used to attest to the practicality of the MDBN-CA model. The accuracies are shown in Table 2. The MDBN-CA model yields good results, with the highest OA, Kappa coefficient, and FoM. Compared with the ANN-CA, the simulation results (FoM, PA, and UA) of the MDBN-CA model increased by 3.70%–3.86% in 2015 (Part A in Table 2), which demonstrates that the MDBN-CA model is more suitable for mining the transition rules. Part B lists the results of the comparative analysis of the landscape indices for the two models at the built-up land scale and landscape level. The MDBN-CA performs better with respect to the landscape similarity, which is 10.11% and 13.11% higher than that of the ANN-CA model, respectively, at the two scales. In general, the above-mentioned results indicate that the MDBN-CA model satisfactorily simulates the urban landscape.

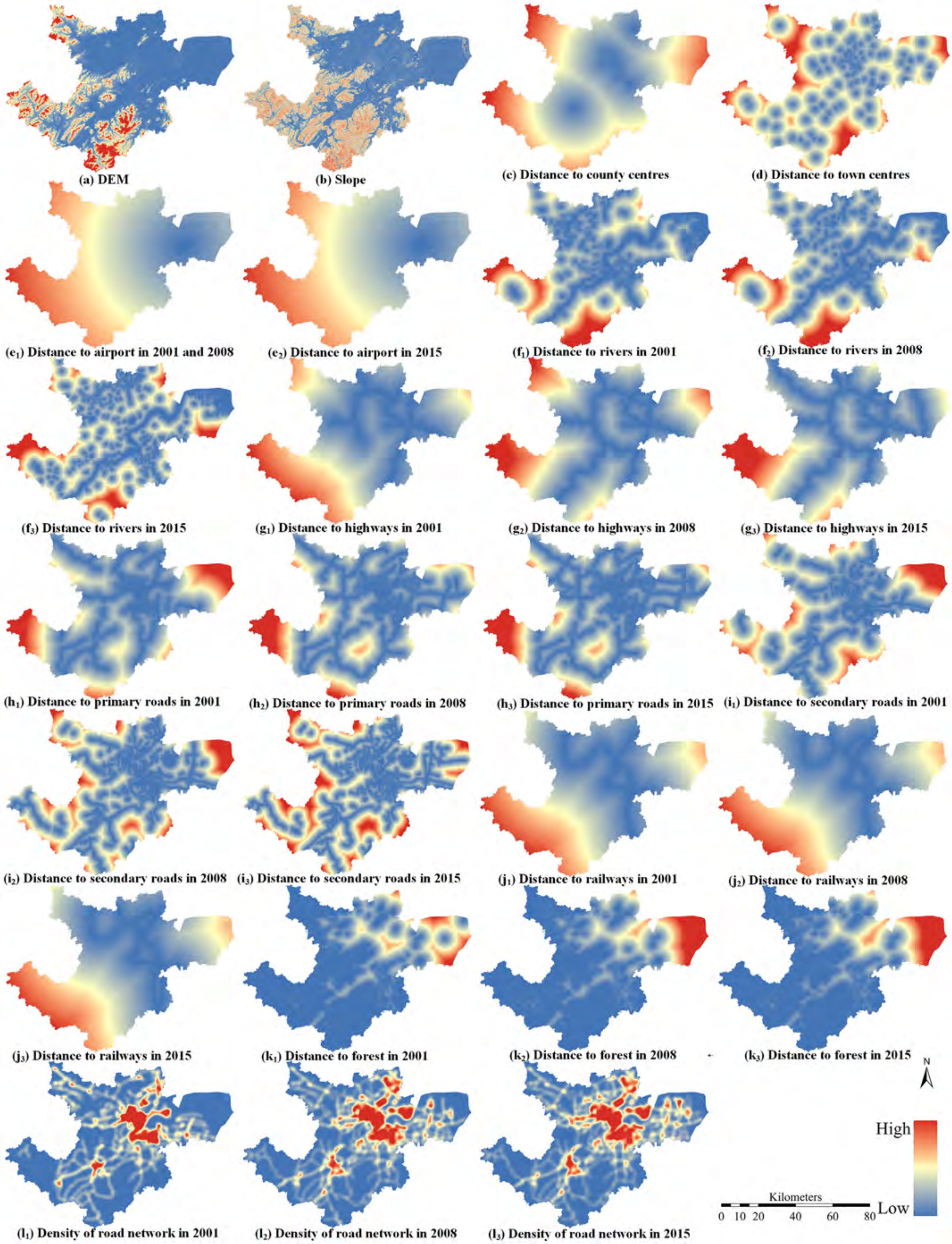

Fig. 3. Global factors.

Table 2
Comparison of the results and landscape metrics simulated for 2015(Part A and B).

Part A	OA	Kappa	FoM	PA	UA
Null	94.01%	0.841	–	–	–
ANN-CA	94.63%	0.867	0.378	54.47%	55.29%
MDBN-CA	95.08%	0.878	0.415	58.27%	59.15%

Part B	NP	LPI	Shape_MN	ENN_MN	A
Built-up land scale					
Observed in 2015	4331	11.766	1.430	166.147	–
Simulated (ANN-CA)	5027	14.078	1.381	143.054	86.74%
Simulated (MDBN-CA)	4121	12.100	1.366	166.897	96.85%
Landscape scale					
Observed in 2015	9708	11.766	1.466	209.587	–
Simulated (ANN-CA)	13,112	14.078	1.398	167.812	80.18%
Simulated (MDBN-CA)	10,708	12.100	1.410	188.858	93.29%

Fig. 4 shows the simulation results and the comparison of the ANN-CA and MDBN-CA models. In part A, the central urban areas of the two models have a clear and consistent outward expansion trend. Based on the overall effect of the simulation, the simulations of the two models in the eastern and southwestern regions are insufficient. In region a1 of part B, the MDBN-CA simulation results are similar to the observations in 2015, whereas the simulation results of ANN-CA in the northeast are insufficient. In regions a2 and a4, MDBN-CA performs better with respect to the overall morphological distribution of built-up land. In region a3, most of the newly added built-up land represents outlying expansion, and the simulations of both models are insufficient. However, the transition rules obtained by these two models effectively simulate urban expansion, and the MDBN-CA model is superior to the ANN-CA model.

4.1.3. Prediction

We predicted the future urban expansion of Hangzhou in 2025 based on the MDBN-CA model under the current development scenario. As shown in Fig. 5, the built-up land in Hangzhou will continuously expand outward. Compared with 2015, the growth rate of newly added built-up land will reach 19.30%.

This is mainly manifested in the trend of the expansion from the urban centre, focusing on infilling and edge expansion. With the acceleration of urbanisation in Hangzhou and the rapidly increasing population and social economy, the built-up area will continue to increase. Given the constraints of ecological land, protection is met, new built-up land will replace a large amount of arable land. Table 3 shows that the NP, PD, and LSI indices will decrease in 2025, whereas LPI and AI will increase, indicating that the urban land in Hangzhou will become more regular and agglomerated. The degree of fragmentation is reduced, the advantage of the landscape is more notable, and the structure tends to be simplified.

4.2. Validation and analysis of the partitioning results

4.2.1. Partitioning results

Based on the land use maps in 2008 and 2025, the indicators of each town were calculated. Pearson correlation analysis was used to remove the very similar indicators. Finally, twelve indicators were obtained (Table S3). After standardisation, the indicators of 119 towns constituted a 119×12 matrix, which was used as the input for the K-means clustering analysis. When the number of categories was six, the categories greatly differed, maintaining the integrity of each category. When the number of categories was higher than 6, the partition results show a greater fragmentation and uncertainty. Based on the combination of the natural environment, socioeconomic conditions, and spatial development planning in Hangzhou with the characteristics four-dimensional evaluation, the 119 towns of Hangzhou can be divided into six regions (Fig. 6): highly urbanised zone (Z1), key urbanised zone (Z2), radiation zone (Z3), potential zone (Z4), optimised zone (Z5), and ecological priority zone (Z6).

4.2.2. Multidimensional analysis

Moran's I index was used to analyse the spatial correlations of the partitioning results. As shown in Fig. S4, at a significance level of 0.01, the spatial distribution of the features in each dimension has spatial clustering characteristics. All Moran's I statistics are positive, proving a significant positive correlation among the 119 towns.

Based on the analysis of the urban expansion results of each zone according to the weighted average calculation of the township area (Table S4) and the radar chart drawn based on the average of the first-level indicators (Fig. S5), the following observations can be made:

(1) The highly urbanised zone consists of 47 towns, mainly located in the city centre and including the old city of Hangzhou. This zone has a large population, and its urbanisation is relatively mature. The early construction is relatively complete. The patch index, degree of agglomeration, and urbanisation rate are high, as indicated by the relatively large UII (A1) and small C_lpi (B1) and C_ai (B2). The C_ludc (C2) is the largest, indicating more complex socioeconomic activities in the zone and the rapid expansion of built-up land. Except for the highest E_al (D1), all other ecological benefit indicators are low, which means that a large amount of arable land is replaced by built-up land. Ecological land protection measures are in place, but the overall ecological land coverage rate is relatively low. This zone is characterised by a large proportion of built-up land, insufficient vacant land, high land use cost, and low potential for future urban expansion. It is necessary to identify a suitable development model to coordinate the population urbanisation with land urbanisation.

(2) The key urbanised zone, including 17 towns, is mainly located in the flat areas in the northern part of the city. The urban expansion speed and intensity indicators are high, indicating the rapid development during the study period. Similar to the highly urbanised zone, C_lpi (B1) and C_ai (B2) are small and all three socioeconomic benefit indicators are relatively small. The E_gs (D2) and C_ec (D4) are the lowest, implying that the overall ecological land coverage is lower, although the urban expansion occupies less ecological land. Based on the current development model, there will be insufficient green space and ecological land to support the high population density in the future. It is necessary to plan rationally to improve land use efficiency, pay attention to the planning and construction of supporting green spaces, and follow the path of sustainable development.

(3) The radiation zone, including 14 towns, is in the northeast of the city. It includes the 'Qiantang District' established on March 11, 2021 and comprises the Dajiangdong Industrial Cluster Zone. This zone has gentle topography. It is one of the key points of the city's future development. Except for the highly urbanised and key urbanised zones, all built-up land expansion speed and intensity indicators are better than those of other zones. The C_lpi (B1) and C_ai (B2) are high, which indicates that the dominance and agglomeration degree of built-up land in this zone have been improved. The three socioeconomic benefit indicators are relatively high, which shows that arable land use still accounts for a large proportion of the area. The population is rapidly growing due to the radiation of urban expansion and gradually spreads outward. The E_al (D1) and C_ecc (D3) are the smallest, whereas E_gs (D2) is the highest. Due to the relatively effective protection measures of basic farmland areas in this zone, the occupation of arable land in this zone is relatively moderate. As a key area for future development, it is imperative

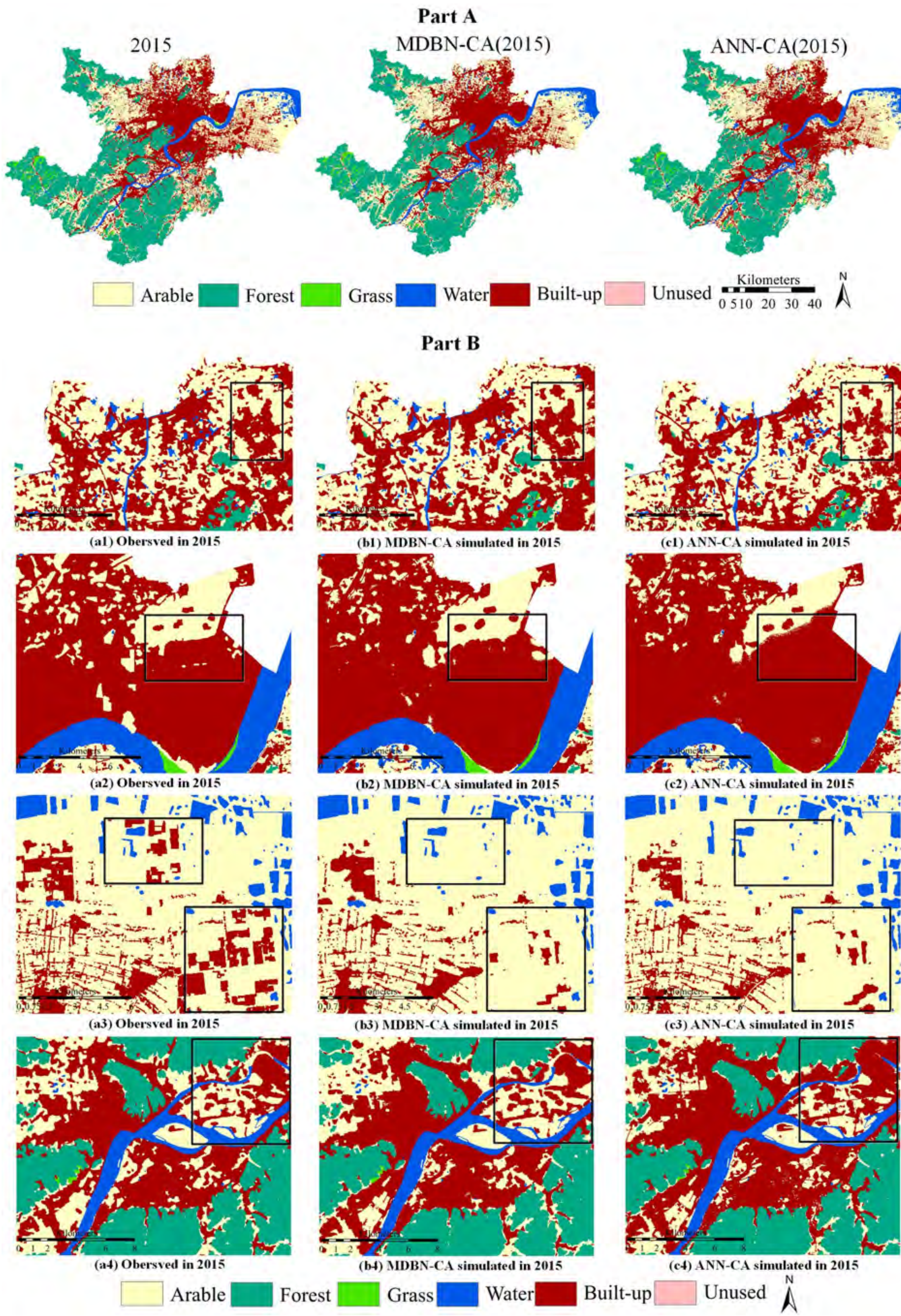

Fig. 4. Results and comparison of simulations of urban expansion based on the two models for 2015.

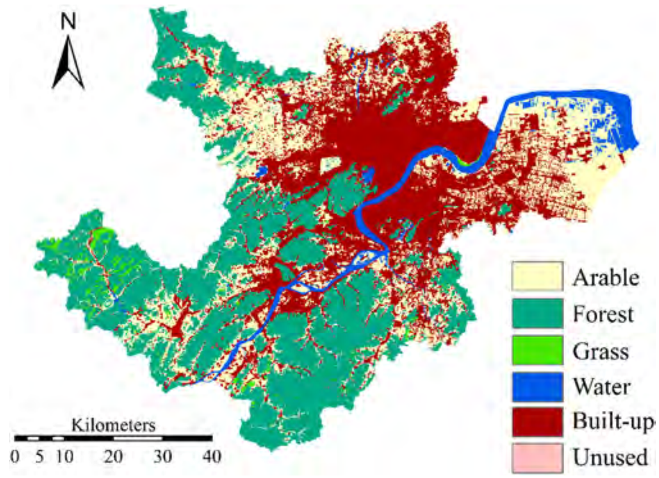

Fig. 5. Simulation of the urban expansion for the year 2025.

to strengthen the protection of ecological land and improve the efficiency and intensity of land use. At the same time, complete industrial functional zones should be built, regional economic development in towns and villages outside industrial clusters should be accelerated to the greatest extent, and long-term development positioning should be completed.

(4) The potential zone includes 17 towns in the south of the city. The urban expansion speed of built-up land is relatively poor; morphological indicators are moderate; and the advantage, concentration, and compactness of built-up land are low. The socioeconomic and ecological benefit indicators are both high, indicating that the benefits of socioeconomic activities in the zone are significant. However, because the ecologically controlled area accounts for a large proportion, the expansion speed and intensity are affected. The future development of the city should be reasonably planned considering the protection of ecological resources. The intensity of urban expansion and degree of land use should be increased.

(5) The optimised zone includes six towns in the northwestern part of the city. In terms of the speed, intensity, and morphology of the built-up land expansion, the overall trend is similar to that of the potential zone. The ecological coverage change is the highest. Large areas of ecological land affect the intensity and speed of urban expansion. The C_ludc (C2) is the lowest and pop (C3) is the highest, indicating that the land use in this zone is low and the socioeconomic activities are relatively weak. Similar to the development of the potential area, the focus should be placed on balancing the population and land urbanisation and formulating relevant policies to attract talent.

(6) The ecological priority zone includes 18 towns in the southwestern part of the city and ecological protection areas such as nature reserves and forest parks. The ecological conditions are superior, and the natural environment is good, limiting built-up land expansion. The speed and intensity of built-up land expansion are the smallest. The morphological indicators are also low, and the change rate of the ecological benefits of the land use structure is large. The proportion of green space, such as forest land, is replaced during urban expansion. Therefore, the future development in this zone will be based on ecological protection and the rationally planning of land resources. In addition, it is necessary to strictly control the intensity and speed of urban expansion to improve the socioeconomic benefits of urban land use and develop advantageous industries in combination with the characteristics of towns and villages.

Table 3
Landscape indices of built-up land in 2015 and 2025.

	Year	NP	PD	LPI	LSI	AI
Built-up land	2015	4331	0.837	11.766	72.380	94.365
	2025	3926	0.758	17.446	67.402	95.201

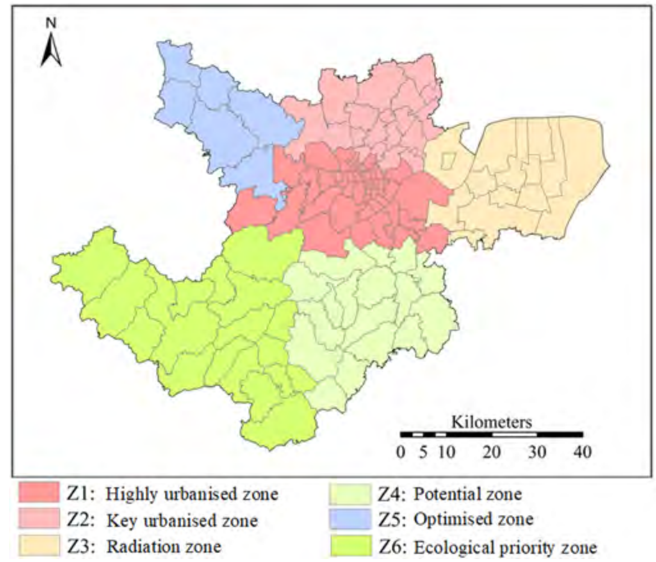

Fig. 6. Partitioning results based on K-means clustering.

4.2.3. Development proposal

In short, the urban expansion in Hangzhou will be highly complementary in the future. The ecological zone and core of the socioeconomic development zone will define clearly, which is in line with the current development plans, and hence the overall benefits will be substantial. However, each zone has its problems that cannot be ignored. There are problems with respect to the coordinated development of land urbanisation and population urbanisation and the inability of ecological benefits to consider the low efficiency of land use. Based on the results of this study, we provide the following suggestions regarding future development strategies in Hangzhou:

(1) Spatial pattern reconstruction. In response to the development of the Yangtze River Delta urban agglomeration and Zhejiang Province's request for 'Construction of the Greater Bay Area, Great Garden, Great Channel, and the Great Metropolitan,' the goal of building a new modern district integrating industry and the city and the harmonious coexistence of man and nature, an urban spatial pattern with Shanghai as the core and Hangzhou as one of the primary nodes should be formed focusing on the integrated development of the Yangtze River Delta, and the future development of Hangzhou should be integrated with the overall plans for the Greater Bay Area, overcoming the constraints of administrative divisions, advancing the construction of the intercity railways and inter-provincial highways in the Yangtze River Delta, jointly building a comprehensive interconnected transportation system, promoting spatial integration and infrastructure sharing, and forming a network integration development model.

(2) Urban function transformation. The highly urbanised zone is responsible for several of the main urban functions. It provides a space for the flow of population, capital, and transportation in the central urban area of Hangzhou, whereas the original industrial and residential auxiliary functions migrate outward. In key urbanisation radiation zones, which are hot areas for economic development in Hangzhou, the focus should be placed on building the dual engines of digital economy and manufacturing,

accelerating the digital transformation of industries, optimising the industrial layout, and strengthening the construction of transportation and public services to form a new urban core of Hangzhou.

(3) Efficient use of land and balancing the land urbanisation and population urbanisation. In the transition zone between the highly urbanised zone, periphery of the key urbanised zone, and radiation zone, a high-level interconnected modern transportation facility network and comprehensive transportation hub system should be constructed, the overall location advantage should be improved, and the coordinated development of the metropolitan area as well as the development of the Yangtze River Delta urban agglomeration should be promoted.

(4) Green and healthy development. The ecological priority zone should be considered the key area for environmental protection, supplemented by the development of the potential and optimised zone, and industrial transformation and upgrades should be promoted based on the development positioning of each district, thereby creating a green and healthy sustainable development model. The quality and equalisation of community services, such as educational facilities and cultural and health facilities, should also be promoted. An ecological, systematic, and humanistic green space system should be established to facilitate green transformation and construct a healthy living environment.

5. Discussion and conclusion

Hangzhou was selected as the study area, and an urban development-oriented zoning framework was constructed in this study based on future spatiotemporal patterns and the multidimensional dynamic indicator system at the township scale: (1) A model integrating the DBN with the CA was proposed, whereas the MBA optimised DBN model was used to obtain the CA transition rules. The results show that the model effectively overcomes the prediction limitations of the traditional neural network. The simulation accuracy (FoM index) and spatial pattern similarity improved by 3.70% and 10.11%, respectively. The model considers the needs of ecological protection and urban development, thus providing a scientific basis for urban planning guided by ecological priority; (2) Based on the speed, intensity, morphology, socioeconomic and ecological benefits of urban expansion, 21 indicators were selected to establish an evaluation system. Twelve independent indicators were obtained after calculation, correlation analysis, and data preprocessing, which reflect the future development trend of the city based on the land use data from 2008 and 2025; (3) A matrix including the evaluation indicators of 119 towns in the study area was used as the input vector for K-means clustering and Hangzhou was divided into six zones: highly urbanised zone, key urbanised zone, radiation zone, potential zone, optimised zone, and ecological priority zone. The analysis results show that the urban expansion in Hangzhou by 2025 and development ideas agree with the local development plan and the overall benefits of expansion are relatively high. However, challenges with respect to the coordinated development of land urbanisation and population urbanisation and the inability of ecological benefits to consider the inefficient use of land were identified. Spatial analysis was used to identify the characteristics of each district in four dimensions, actual conditions were considered to determine the district development status of Hangzhou, and strategies were proposed based on the spatial pattern reconstruction, urban function transformation, efficient land use, and green and healthy development.

In short, the MDBN-CA model proposed in this study performs better than the traditional ANN-CA model. Based on the combination of the MDBN-CA model and K-means clustering with the zoning framework of the comprehensive benefit evaluation system of urban expansion, the future urban expansion can be predicted and analysed, which is of great significance for future urban planning and government decision-making. However, to make the proposed framework more practical, several improvements are necessary:

(1) The MDBN-CA model is less effective in simulating 'outlying expansion.' Land use changes are closely related to socioeconomic development and government policies. The integration of more socioeconomic variables and policy factors will further improve the performance of the model.

(2) The population and economic data of the development-oriented evaluation indicators are based on inversion data, and certain deviations were observed. The use of social statistics and inversion data should be considered to improve the data accuracy. The selection of development-oriented evaluation indicators is not optimal. Therefore, the completion of data or the use of more substitute indicators should be considered to build a more comprehensive evaluation system.

(3) The spatial development-oriented zoning of Hangzhou was only realised at the township scale from 2008 to 2025. In future research, the time scale should be extended, and the fixed boundaries of township administrative divisions should be broken to explore urbanisation.

(4) Considering the impact of all kinds of land use changes on zoning in the future.

CRediT authorship contribution statement

Ye Zhou: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Funding acquisition. **Tao Wu:** Formal analysis, Software, Writing – review & editing. **Yechenzi Wang:** Data acquisition, Formal analysis, Software, Resources.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

This work was supported by the National Key Research and Development Program of China (2019YFC1521303).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.150813.

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