



Demand prediction and regulation zoning of urban-industrial land: Evidence from Beijing-Tianjin-Hebei Urban Agglomeration, China

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Abstract As a main type of urban construction land, urban-industrial land is used to provide the judging criteria for construction land scale in the planning period when urban population, industrial development, investment scale, and other conditions are uncertain in China; however, research on expected indicator such as urban-industrial land in overall land use plan mainly focuses on qualitative analysis; quantitative analysis research has not yet been carried out. Using MATLAB R2016a software modeling tools to establish GM (1, 1) model

and RBF neural network model, respectively, this paper predicted the demand of urban-industrial land in Beijing-Tianjin-Hebei Urban Agglomeration. Comparing the predicated results with the actual value of urban-industrial land in Beijing, Tianjin, and 11 prefecture-level cities in Hebei Province, we determined the reasonable prediction model for urban-industrial land after testing the accuracy of the two prediction models. The results showed that the RBF neural network model was the more reasonable prediction model for urban-industrial land. Using the predicted results of the RBF neural network model, combining expected indicators of overall land use plan (2006–2020) in Beijing and Tianjin, as well as 11 prefecture-level cities in Hebei Province in the planning target year, determined remaining usable time of urban-industrial land. Finally, combined with the actual scale of urban-industrial land in 2015 and the predicated scale of urban-industrial land in 2020, the remaining usable time of each city's urban-industrial land was calculated in terms of the average annual growth rate of urban-industrial land from 2009 to 2015. According to the comparative relationship between the remaining usable time and the remaining time of the overall land use plan (5 years), urban-industrial lands were divided into three kinds of regulation zones: reasonable reduction zone, optimized adjustment zone, and core development zone. The policy implications for urban-industrial land in each regulation zone were also provided. This paper can provide reference for regulation zoning of urban-industrial land in developing countries and regions.

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Introduction

Land is a precious resource. Pressures on land use have inevitably intensified with the land being a fixed resource and with a growing population (Maria et al. 2016; Yang et al. 2018a, b, c; He et al. 2019). In order to adapt to the new norms of economic development, optimize the land supply structure, and ensure the rational and healthy development of urban and rural construction lands, China has successively issued a series of related policy documents. According to the “Guidance on Land Conservation and Intensive Use” released by the Ministry of Land and Resources, China, in 2014, transformation and optimization of land use patterns and structures should promote transformation and optimization of economic development. Based on coordination of urban space, scale, and industry proposed by Chinese government in 2015, urban land supply structure and industrial structure evolution should match each other. According to the “National Overall Land Use Plan (2006~2020)” released by the Ministry of Land and Resources in 2016, Beijing-Tianjin-Hebei Urban Agglomeration should coordinate industrial land allocation and control urban-industrial land sprawl.

According to the “Code for Classification of Urban Land Use and Planning Standards of Development Land (GB 50137–2011)” (Ministry of Housing and Urban-Rural Development of China 2011), urban construction land can be subdivided into multiple categories. Research on specific urban construction land prediction is increasing gradually. Nevertheless, a comprehensive study on the prediction of total urban construction land and specific urban construction land is yet to be carried out. Moreover, specific urban construction land prediction not only emerges late but also the research methods and contents need to be improved. Urban-industrial land is the main type of urban construction land (Lin 2009; Xiao 2012; Shu and Xiong 2019) and is also the main space for urban non-agricultural activities (Zhao 2012; Xie et al. 2014; Yong et al. 2018). As an expected indicator in land use planning, urban-industrial land is used to provide the judging criteria for construction land scale in the planning period when urban population, industrial development, investment scale, and other

conditions are uncertain (Qiu et al. 2015). Regulation zone refers to further arrangements of land use, population distribution, public facilities, and urban infrastructure allocation in local areas based on the overall urban planning (Panigrahi and Mohanty 2012). After the completion of the urban master plan, large- and medium-sized cities can prepare regulation zoning plans according to their needs. The regulation zone should be carried out simultaneously within the urban area. The zone should be coordinated in time during the preparation process (Pignatti et al. 2016).

Land demand prediction is a complex decision-making process with many random and disorderly factors (Bartoli et al. 2016; Hermanns et al. 2017; Yang et al. 2018a, b, c). Agricultural land allocation involves assessing land potential and land demand for various crops to determine the best land unit for each type. The current allocation model tends to focus on the perspective of land demand growth (Pilehforooshha et al. 2014). In order to achieve the above objectives, scholars used Markov chain (Aurbacher and Dabbert 2011), GIS raster analysis (Pilehforooshha et al. 2014), cellular automata (Kelly et al. 2018; Yang et al. 2019), goal programming (António et al. 2018), fuzzy rule-based system (Reshmidevi et al. 2009), etc.

The rapid urbanization makes urban construction land demand increasing, so it is of great significance to predict urban construction land growth (Kun et al. 2018; Yang et al. 2018a, b, c). The prediction of urban construction land growth is the basic work of urban overall land use plan. At present, research on urban construction land growth forecast can be divided into two types: (1) simulation of land temporal and spatial sprawl and (2) prediction of land scale. As early as the 1960s, urban models were widely used in urban development research, and with the support of new technologies, it was gradually possible to simulate the future development of cities. However, it was not until the CA (cellular automata) model appeared that the two-dimensional spatial feature of urban sprawl was realized. The prediction research mainly depends on spatial data and is constrained by the expansion rules. The scale prediction of urban construction land growth is based on different prediction indexes and mathematical models. The main predictors are population and socioeconomic indicators, such as non-agricultural population, total fixed assets, and GDP (Hao et al. 2014). In addition, urban construction land growth is realized by the occupation of some or most of the cultivated land, and some scholars predict

urban construction land growth in respect of conversion between cultivated land and urban construction land (Zhai et al. 2015; He et al. 2018). In sum, urban construction land growth is a nonlinear and complex process influenced by various factors, and some rules, indicators, or models are needed in the prediction process, although the prediction is uncertain (Yang et al. 2019). Therefore, it provides a scientific reference for the study of land scale demand in urban development.

Recently, the actual urban-industrial land area of some cities in Beijing-Tianjin-Hebei Urban Agglomeration has exceeded the expected indicators in the overall land use plan (Li et al. 2019b). The expected indicators in the overall land use plan are indicators that should be achieved during the planning period according to economic and social development forecasts, such as total size of construction land (Li et al. 2019a). Research on expected indicator such as urban-industrial land in overall land use planning mainly focuses on qualitative analysis; quantitative analysis research has not yet been carried out. In this paper, the prediction method of mathematical models (neural network model and gray model) is used to predict urban-industrial land demand of cities in Beijing-Tianjin-Hebei Urban Agglomeration. Using MATLAB R2016a software modeling tools to establish GM (1, 1) model and RBF neural network model, respectively, the demand of urban-industrial land in Beijing-Tianjin-Hebei Urban Agglomeration is predicted. After testing the accuracy of the two prediction models and comparing the predicted results with the actual value of urban-industrial land in Beijing, Tianjin, and 11 prefecture-level cities in Hebei Province, the reasonable prediction model for urban-industrial land is determined. Based on the results of prediction, urban-industrial land regulation zones are divided. The policy implications for urban-industrial land in each regulation zone are provided.

Study area and methods

Study area

Beijing-Tianjin-Hebei Urban Agglomeration, covering a surface area of 217,158 km², is an important core area of northern China, including two municipalities directly under the Central Government of

Beijing and Tianjin, and 11 prefecture-level cities of Hebei Province (including Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, and Hengshui) (Fig. 1). According to the overall land use plan of Beijing, Tianjin, and Hebei, there are significant differences in the total amount of urban-industrial land of cities in Beijing-Tianjin-Hebei Urban Agglomeration from 2009 to 2015 (Fig. 2). In 2015, the total area of urban-industrial land in Tianjin, Tangshan, and Beijing reached 1974.67 km², 1747.33 km², and 1452.01 km², respectively. Based on land use survey, problems on scattered layout, irrational structure, and low utilization efficiency of urban-industrial land have emerged in many cities of Beijing-Tianjin-Hebei Urban Agglomeration. Unreasonable use of urban-industrial land has become a roadblock for the sustainable land use in the Beijing-Tianjin-Hebei Urban Agglomeration.

Methods

The mathematical method mainly includes the neural network model and the gray model. Artificial neural network has become an important way to process information. Using the neural network model and the gray model's highly nonlinear mapping ability can predict the construction land demand. Due to the high degree of nonlinear mapping capability, the artificial neural network can realize the nonlinear mapping of the dependent variable and the independent variable without the relationship between the dependent variable and the independent variable (Zhang et al. 2018).

Gray relational analysis

In order to measure the correlation degree of various related factors and overcome the defects of traditional multivariate correlation analysis, gray correlation analysis method was used to select factors for urban-industrial land demand prediction (Hao et al. 2014; Li et al. 2018; Fu et al. 2019). This method mainly includes 3 steps (Yin et al. 2018):

1. Data conversion. Convert raw data into dimensionless and comparable data. Assumed reference data were listed as follows:

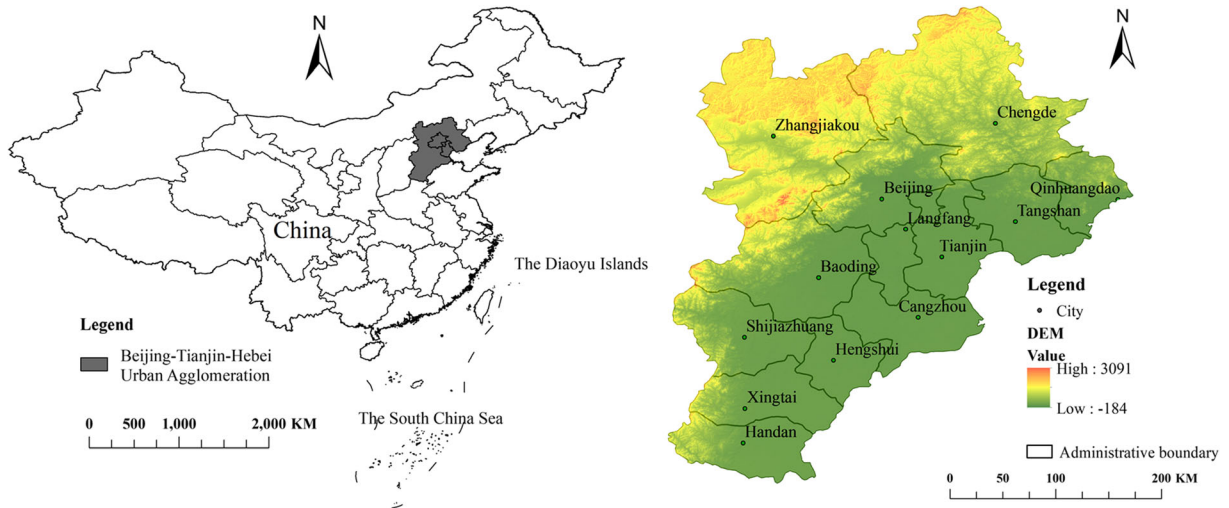


Fig. 1 Location map of the study area

$$x_0 = (x_0(1), x_0(2), x_0(3), \dots, x_0(n))$$

Comparative data were listed as follows:

$$x_i = (x_i(1), x_i(2), x_i(3), \dots, x_i(n)), (i = 1, 2, \dots, n)$$

2. Calculate correlation coefficient in Eq. (1).

$$l_{oi(t)} = \frac{\Delta_{\min} + \rho\Delta_{\max}}{\Delta_{oi(k)} + \rho\Delta_{\max}} \quad (1)$$

where $l_{oi(k)}$ is the absolute difference between two data in time t , namely, $l_{oi(k)} = |x_{0(t)} - x_{i(t)}| (1 \ll i \ll n)$; Δ_{\max} and Δ_{\min} refers to the maximum and minimum values of the absolute differences for all data, respectively. Because comparison data intersects each other, $\Delta_{\min} = 0$ and ρ is the resolution coefficient, it could increase the significance

of difference between the relevant data, $\rho \in (0, 1)$; ρ is used to prefer 0.5 in the previous research (Yin et al. 2018).

3. Relation testing. Based on $l_{oi(k)}$, relation, which is the average value of correlation coefficients, can be calculated in Eq. (2):

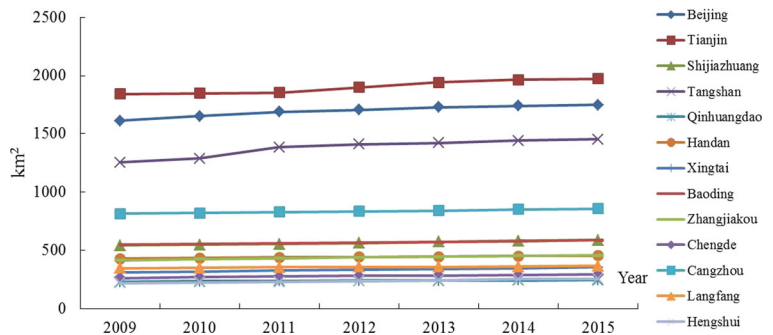
$$r_{oi} = \frac{1}{N} \sum_{k=1}^N l_{oi(t)} \quad (2)$$

where r_{oi} is the relation between sub-sequence i and total sequence o . N is the length of the comparative sequence (number of data).

GM (1, 1) prediction model

Based on gray system theory, GM (1, 1) prediction model can use insufficient information to build a model with possible full information by transforming time series into differential equations through differential

Fig. 2 The area of industrial and mining land of cities in Beijing-Tianjin-Hebei Urban Agglomeration from 2009 to 2015



fitting method (Chen and Pai 2015). GM (1, 1) prediction model could be expressed in Eq. (3):

$$\hat{X}^{(1)}(t) = \left(X^{(0)}(1) - \frac{u}{a} e^{-a(t-1)} \right) + \frac{u}{a} \tag{3}$$

where $X^{(0)}(1)$ is the raw data in urban-industrial land demand system. $\hat{X}^{(1)}(t)$ is the accumulated value of raw data in urban-industrial land demand system. t refers to time. a and u are the development gray number and the endogenous control gray number.

RBF neural network prediction model

Compared with the widely used BP neural network model, RBF neural network prediction model is more advanced in terms of learning speed and parameter settings with a single hidden layer feedforward network (Ghritlahre and Prasad 2018). The framework of RBF neural network prediction model is shown in Fig. 3.

Input Layer Hidden Layer Output Layer

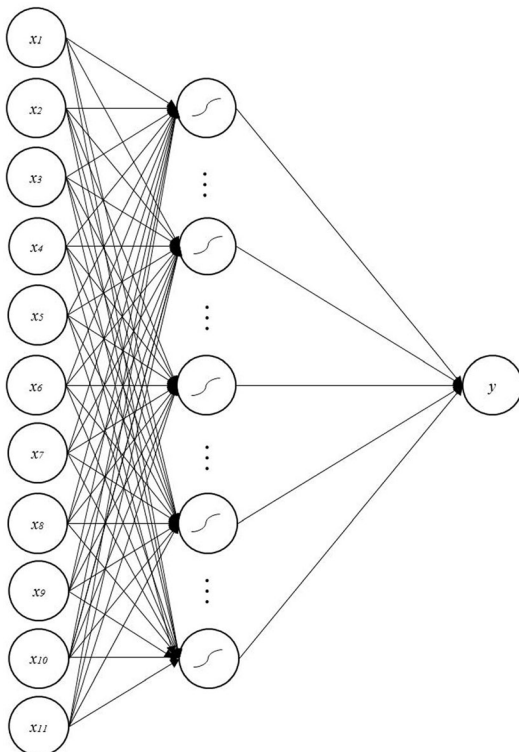


Fig. 3 Framework of RBF neural network model

Learning process of RBF includes two stages: unsupervised learning and supervised learning. The main calculation process includes three steps.

1. Calculate the output value Y_b of the neuron b in the output layer in Eq. (4):

$$Y_a = f\left(\sum_{a=1}^r W_{ba} Y_{ha}\right) \tag{4}$$

where Y_{ha} is the output value of the neuron a in the hidden layer. W_{ba} is the weight from the neuron a in the hidden layer to the neuron b in the output layer. We use Sigmoid to express the function in Eq. (5):

$$f(x) = 1 / (1 + \exp(-x/x_0)) \tag{5}$$

2. Calculate error of the output layer in Eq. (6):

$$\Delta b = Y_b \cdot (1 - Y_b) \cdot (y_b - Y_b) \tag{6}$$

where y_b is the actual value of the neuron b .

3. Adjust weight coefficient ΔW until the error is minimized. It can be express in Eq. (7):

$$\Delta W = \varepsilon \cdot \Delta Y_b (1 - Y_b) \cdot (y_b - Y_b), W'_b = W_b + \Delta W \tag{7}$$

where W'_b is the adjusted weight. ε is the learning rate. ε is selected based on the comparison method. The value of ε ranges between 0.01 and 0.8 (Monteiro et al. 2018). ε is set as 0.03 in this study. The model can be used for prediction when cluster center C_a and weight W_a are defined.

Methods for prediction accuracy testing

The accuracy of the prediction model is verified by the mean absolute error (MAE) and the error root mean square (RMSE). They are expressed in Eqs. (8) and (9):

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{Z}_i - Z_i| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{Z}_i - Z_i)^2} \tag{9}$$

where \hat{Z}_i is the predictive value by the RBF model. Z_i is the actual value. n is the total number of samples taken for training and testing. The smaller the value of MAE

and RMSE is, the smaller the error is, and the higher the prediction accuracy of the model is.

Data collection and processing

Data collection

Data about urban-industrial land from 2009 to 2015 were collected from the national land utilization conveyance data. Statistical data related to socioeconomic conditions were collected from Beijing Statistical Yearbook (2010~2016) (Beijing Bureau of Statistics 2017), Tianjin Statistical Yearbook (2010~2016) (Tianjin Bureau of Statistics 2017), Hebei Statistical Yearbook (2010~2016) (Hebei Bureau of Statistics 2017), and China Statistical Yearbook for Regional Economy (2010~2016) (NBSC 2017). Expected data of urban-industrial land in the planning target year 2020 were obtained from the overall land use plan (2006–2020) of Beijing, Tianjin, as well as 11 prefecture-level cities in Hebei Province.

Data processing

According to national land utilization conveyance data originally derived from the first national land survey in 1996, urban-industrial land, including urban land, town land, rural residential land, and independent industrial and mining land, is the space that carries the main production and living activities of urban and rural residents (Lin 2009). Urban-industrial land, similar to urban construction land, including urban land, town land, and independent industrial and mining land, is in line with the urban population in terms of statistical caliber (Li et al. 2018). The main factors affecting urban construction land change are economic growth, the secondary and tertiary industry development, and urbanization (Chen et al. 2017). Eleven indicators, including GDP (x_1), the secondary industry added value (x_2), the tertiary industry added value (x_3), total investment in urban fixed assets (x_4), real estate development investment (x_5), per capita disposable income of urban residents (x_6), per capita consumption expenditure of urban residents (x_7), highway mileage (x_8), number of industrial enterprises above designated size (x_9), industrial output (x_{10}), and the total retail sales of social consumer goods (x_{11}), were selected from four respects of economic growth, industrialization, industrial structure adjustment and upgrading, and urbanization.

Each indicator was converted by using the extremum method. The calculation processes were expressed in Eqs. (10) and (11).

$$x = \frac{[x_{ij} - \min(x_j)]}{[\max(x_j) - \min(x_j)]} \quad (10)$$

$$x = \frac{[\max(x_j) - x_{ij}]}{[\max(x_j) - \min(x_j)]} \quad (11)$$

where x is the value of indicator x_{ij} processed by the extremum method; x_{ij} is the actual value of indicator i in the year j ; $\max(x_j)$ is the maximum actual value of indicator i in the year j ; and $\min(x_j)$ is the minimum actual value of indicator i in the year j .

GM (1, 1) model was established by using the MATLAB R2016a software modeling tool. According to the principle of RBF neural network model, using Newrb toolbox in the MATLAB R2016a software, RBF neural network model, where the SPREAD value in the Newrb function was chosen to be the default value 1 (Morteza et al. 2018), was established by choosing 11 influencing factors as input samples and urban-industrial land demand as output samples. Taking actual area of urban-industrial land from 2009 to 2014 and its influencing factors as training samples, the area of urban-industrial land from 2010 to 2015 was simulated. The simulation results showed that RBF neural network model, of which the output could well approximate the nonlinear function Y_j after repeated tests, was provided with an excellent fitting ability. Urban-industrial land data from 2010 to 2015 of cities in Beijing-Tianjin-Hebei Urban Agglomeration were imported from the GM (1, 1) model and RBF neural network model, respectively. The conditions for the termination of training in the model is set in terms of the actual situation (Morteza et al. 2018). The maximum number of training cycles is 5000 in this study.

Results and discussion

Gray relational grade of the indicators

Gray relational grades of the indicators were conducted by using gray relation system software developed by Liu et al. (2004). The results of gray relational grades showed that the correlation value of each influencing factor, which is greater than 0.7, met three-level precision

Table 1 The gray correlation degree of urban-industrial land and driving factors of cities in Beijing-Tianjin-Hebei Urban Agglomeration

		Indicators										
		x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}
Gray correlation degree	Beijing	0.805	0.710	0.710	0.715	0.706	0.753	0.752	0.995	0.756	0.704	0.804
	Tianjin	0.958	0.925	0.924	0.924	0.881	0.925	0.925	0.924	0.702	0.907	0.926
	Shijiazhuang	0.963	0.988	0.989	0.969	0.987	0.995	0.991	0.948	0.959	0.743	0.988
	Tangshan	0.885	0.715	0.958	0.937	0.927	0.891	0.915	0.809	0.907	0.817	0.950
	Qinhuangdao	0.931	0.973	0.949	0.905	0.977	0.942	0.790	0.754	0.873	0.844	0.950
	Handan	0.966	0.980	0.984	0.957	0.973	0.933	0.967	0.893	0.984	0.767	0.977
	Xingtai	0.830	0.887	0.935	0.839	0.977	0.811	0.838	0.879	0.912	0.737	0.905
	Baoding	0.708	0.947	0.977	0.923	0.970	0.949	0.981	0.887	0.932	0.820	0.968
	Zhangjiakou	0.771	0.853	0.887	0.755	0.902	0.849	0.805	0.802	0.904	0.759	0.886
	Chengde	0.940	0.973	0.982	0.947	0.896	0.957	0.869	0.846	0.979	0.900	0.995
	Cangzhou	0.852	0.828	0.882	0.779	0.757	0.705	0.717	0.746	0.661	0.806	0.858
	Langfang	0.900	0.900	0.899	0.839	0.903	0.849	0.843	0.822	0.854	0.870	0.896
	Hengshui	0.836	0.897	0.926	0.833	0.911	0.932	0.877	0.799	0.870	0.753	0.927

(Table 1). Therefore, there was a relatively strong correlation between the 11 factors and the demand for urban-industrial land, namely, the 11 factors were applicable to the demand prediction of urban-industrial land in Beijing-Tianjin-Hebei Urban Agglomeration.

Demand prediction of urban-industrial land

Results of the GM (1,1) prediction model

The prediction results of urban-industrial land area from 2009 to 2015 by using the GM (1, 1) model are shown in Table 2.

Results of RBF neural network prediction model

The prediction results of urban-industrial land area from 2009 to 2015 by using the RBF neural network model are shown in Table 3 and Fig. 4.

Prediction accuracy testing for the two models

Statistic error results of the two models showed that the RBF neural network model, of which the prediction accuracy was greater than that of the GM (1, 1) model, was more suitable for urban-industrial land demand prediction (Table 4). The RBF neural network model was selected to predict the demand of urban-industrial land. Hao et al. (2014) found that construction land demand

could be predicted by using the RBF neural network. Therefore, artificial intelligence approach, including artificial neural network, has been confirmed to be an effective method to predict land resources demand.

Regulation zoning of urban-industrial land

A city is a unified organism, and the various parts of the function which are used in different functions are reasonably organized (Panigrahi and Mohanty 2012). When starting to plan a city, according to the different characteristics and requirements of the city, comprehensive planning should be carried out for the industrial land, residential land, transportation land, etc. However, a series of problems will emerge in cities without a regulation zone of urban land. Li et al. (2019a) proposed that urban-industrial land use efficiency of Beijing-Tianjin-Hebei Urban Agglomeration was relatively low. Therefore, zoning is necessary in urban-industrial land in Beijing-Tianjin-Hebei Urban Agglomeration.

Based on the established RBF neural network model, 13 cities in Beijing-Tianjin-Hebei Urban Agglomeration have been trained and predicted with different models; the urban-industrial land demand of the 13 cities in 2020 was predicted. The comparison of the predicting results and expected indicators of urban-industrial land in the overall land use plan of cities in Beijing-Tianjin-Hebei Urban Agglomeration in 2020 showed that the expected indicator of urban-industrial land is approximately equal

Table 2 GM (1, 1) model prediction results

City	Area/hm ²	2009	2010	2011	2012	2013	2014	2015
Beijing	Actual	161,266.67	165,200.00	168,733.33	170,600.00	172,866.67	173,933.33	174,733.33
	GM	-	-	172,335.00	173,637.00	175,646.00	176,823.00	177,633.00
	Error	-	-	3601.67	3037.00	2779.33	2889.67	2899.67
Tianjin	Actual	184,333.33	184,666.67	185,400.00	189,800.00	194,200.00	196,466.67	197,466.67
	GM	-	-	186,136.00	191,828.00	196,939.00	200,031.00	202,031.00
	Error	-	-	736.00	2028.00	2739.00	3564.33	4564.33
Shijiazhuang	Actual	54,000.00	54,600.00	55,400.00	56,000.00	57,133.33	58,066.67	58,600.00
	GM	-	-	56,210.70	56,746.50	57,864.70	58,889.50	59,602.70
	Error	-	-	810.70	746.50	731.37	822.83	1002.70
Tangshan	Actual	125,400.00	128,600.00	138,333.33	140,933.33	142,066.67	144,133.33	145,200.00
	GM	-	-	148,725.00	148,621.00	148,420.00	149,422.00	147,275.00
	Error	-	-	10,391.67	7687.67	6353.33	5288.67	2075.00
Qinhuangdao	Actual	22,666.67	23,333.33	23,533.33	23,866.67	24,000.00	24,200.00	24,400.00
	GM	-	-	23,734.60	24,117.00	24,272.20	24,453.30	24,643.80
	Error	-	-	201.27	250.33	272.20	253.30	243.80
Handan	Actual	42,866.67	43,266.67	43,800.00	44,133.33	44,333.33	45,000.00	45,400.00
	GM	-	-	44,339.00	44,605.50	44,771.50	45,319.10	45,787.20
	Error	-	-	539.00	472.17	438.17	319.10	387.20
Xingtai	Actual	30,800.00	31,400.00	32,466.67	33,200.00	33,933.33	34,600.00	35,400.00
	GM	-	-	33,566.90	34,192.20	34,879.90	35,537.70	36,290.20
	Error	-	-	1100.23	992.20	946.57	937.70	890.20
Baoding	Actual	54,600.00	55,400.00	55,933.33	56,400.00	56,933.33	57,800.00	58,600.00
	GM	-	-	56,470.70	56,917.90	57,444.00	58,255.80	59,094.40
	Error	-	-	537.37	517.90	510.67	455.80	494.40
Zhangjiakou	Actual	41,266.67	42,333.33	43,000.00	43,800.00	44,466.67	45,200.00	45,666.67
	GM	-	-	43,676.60	44,531.90	45,229.40	45,960.80	46,478.80
	Error	-	-	676.60	731.90	762.73	760.80	812.13
Chengde	Actual	25,800.00	26,666.67	27,400.00	28,000.00	28,133.33	28,533.33	28,933.33
	GM	-	-	28,151.30	28,713.30	28,815.90	29,105.10	29,455.00
	Error	-	-	751.30	713.30	682.57	571.77	521.67
Cangzhou	Actual	81,533.33	82,133.33	82,933.33	83,400.00	84,066.67	85,200.00	85,866.67
	GM	-	-	83,740.10	84,095.80	84,711.40	85,759.00	86,580.00
	Error	-	-	-	-	-	-	-

Table 2 (continued)

City	Area/hm ²	2009	2010	2011	2012	2013	2014	2015
Langfang	Error	-	-	806.77	695.80	644.73	559.00	713.33
	Actual	34,533.33	34,666.67	35,200.00	35,600.00	35,733.33	36,000.00	36,333.33
	GM	-	-	35,740.80	36,098.10	36,206.80	36,407.60	36,586.10
Hengshui	Error	-	-	540.80	498.10	473.47	407.60	252.77
	Actual	22,000.00	22,600.00	22,933.33	23,666.67	24,200.00	25,000.00	25,333.33
	GM	-	-	23,270.50	24,156.40	24,767.70	25,559.00	26,061.00
	Error	-	-	337.17	489.73	567.70	559.00	727.67

to the predicted value by the RBF neural network model. Those indicated that the RBF neural network model was available (Table 5). The predicted values of Tianjin, Tangshan, Cangzhou, Zhangjiakou, and Chengde were obviously different from the expected values, which reflected the deficiency of the overall land use plan.

Combined with the actual scale of urban-industrial land in 2015 and the predicated scale of urban-industrial land in 2020, the remaining usable time of each city’s urban-industrial land was calculated in terms of the average annual growth rate of urban-industrial land from 2009 to 2015. According to the comparative relationship between the remaining usable time and the remaining time of the overall land use plan (5 years), the ArcGIS natural breakpoint method was used to divide regulation zones of urban-industrial land. Three regulation zones were obtained (Fig. 5):

- (1) Reasonable reduction zone (0.55 year ≤ remaining usable time ≤ 2.68 years). This zone covers Tianjin, Tangshan, Zhangjiakou, and Chengde;
- (2) Optimized adjustment zone (2.68 years ≤ remaining usable time ≤ 4.36 years). This zone covers Beijing, Cangzhou, and Hengshui;
- (3) Core development zone (4.36 years ≤ remaining usable time ≤ 6.22 years). This zone covers Shijiazhuang, Baoding, Xingtai, Langfang, Handan, and Qinhuangdao.

Policy implications

The policy implications for urban-industrial land in the three regulation zones are put forward as follows:

- (1) Reasonable reduction zone. Covering Tianjin, Tangshan, Zhangjiakou, and Chengde. This zone, of which the actual scale of urban-industrial land has exceeded the expected target of the overall land use plan, should implement measures for reduction of urban-industrial land. Tianjin and Tangshan are important industrial cities in China, and they are also one of the important carrying places for the industrial transfer of Beijing-Tianjin-Hebei cooperative development. The proportion of industrial land among urban-industrial land is relatively high. It is urgent to promote the internal

Table 3 RBF model prediction results

City	Area/hm ²	2009	2010	2011	2012	2013	2014	2015
Beijing	Actual	161,266.67	165,200.00	168,733.33	170,600.00	172,866.67	173,933.33	174,733.33
	RBF	–	165,181.00	168,721.00	170,592.00	172,837.00	173,910.00	174,713.00
	Error	–	(19.00)	(12.33)	(8.00)	(29.67)	(23.33)	(20.33)
Tianjin	Actual	184,333.33	184,666.67	185,400.00	189,800.00	194,200.00	196,466.67	197,466.67
	RBF	–	184,666.00	185,398.00	189,795.00	194,189.00	196,452.00	197,451.00
	Error	–	(0.67)	(2.00)	(5.00)	(11.00)	(14.67)	(15.67)
Shijiazhuang	Actual	54,000.00	54,600.00	55,400.00	56,000.00	57,133.33	58,066.67	58,600.00
	RBF	–	54,597.30	55,399.30	55,995.50	57,125.00	58,050.10	58,586.90
	Error	–	(2.70)	(0.70)	(4.50)	(8.33)	(16.57)	(13.10)
Tangshan	Actual	125,400.00	128,600.00	138,333.33	140,933.33	142,066.67	144,133.33	145,200.00
	RBF	–	128,593.00	138,321.00	140,930.00	142,055.00	144,105.00	145,184.00
	Error	–	(7.00)	(12.33)	(3.33)	(11.67)	(28.33)	(16.00)
Qinhuangdao	Actual	22,666.67	23,333.33	23,533.33	23,866.67	24,000.00	24,200.00	24,400.00
	RBF	–	23,330.00	23,532.60	23,865.60	23,997.30	24,193.90	24,395.50
	Error	–	(3.33)	(0.73)	(1.07)	(2.70)	(6.10)	(4.50)
Handan	Actual	42,866.67	43,266.67	43,800.00	44,133.33	44,333.33	45,000.00	45,400.00
	RBF	–	43,265.30	43,799.50	44,131.50	44,329.90	44,988.70	45,392.00
	Error	–	(1.37)	(0.50)	(1.83)	(3.43)	(11.30)	(8.00)
Xingtai	Actual	30,800.00	31,400.00	32,466.67	33,200.00	33,933.33	34,600.00	35,400.00
	RBF	–	31,397.30	32,459.70	33,194.20	33,921.10	34,587.70	35,384.60
	Error	–	(2.70)	(6.97)	(5.80)	(12.23)	(12.30)	(15.40)
Baoding	Actual	54,600.00	55,400.00	55,933.33	56,400.00	56,933.33	57,800.00	58,600.00
	RBF	–	55,349.10	55,832.00	56,385.80	56,915.00	57,787.70	58,590.10
	Error	–	(50.90)	(101.33)	(14.20)	(18.33)	(12.30)	(9.90)
Zhangjiakou	Actual	41,266.67	42,333.33	43,000.00	43,800.00	44,466.67	45,200.00	45,666.67
	RBF	–	42,328.40	42,998.00	43,792.00	44,456.90	45,183.50	45,660.10
	Error	–	(4.93)	(2.00)	(8.00)	(9.77)	(16.50)	(6.57)
Chengde	Actual	25,800.00	26,666.67	27,400.00	28,000.00	28,133.33	28,533.33	28,933.33
	RBF	–	26,664.30	27,398.80	27,998.40	28,128.70	28,524.40	28,924.80
	Error	–	(2.37)	(1.20)	(1.60)	(4.63)	(8.93)	(8.53)
Cangzhou	Actual	81,533.33	82,133.33	82,933.33	83,400.00	84,066.67	85,200.00	85,866.67
	RBF	–	82,128.90	82,932.30	83,399.30	84,060.00	85,184.90	85,856.10
	Error	–	(4.43)	(1.03)	(0.70)	(6.67)	(15.10)	(10.57)
Langfang	Actual	34,533.33	34,666.67	35,200.00	35,600.00	35,733.33	36,000.00	36,333.33
	RBF	–	34,666.40	35,199.50	35,599.30	35,731.30	35,992.20	36,328.30
	Error	–	(0.27)	(0.50)	(0.70)	(2.03)	(7.80)	(5.03)
Hengshui	Actual	22,000.00	22,600.00	22,933.33	23,666.67	24,200.00	25,000.00	25,333.33
	RBF	–	22,596.90	22,932.50	23,665.00	24,194.30	24,990.10	25,325.60
	Error	–	(3.10)	(0.83)	(1.67)	(5.70)	(9.90)	(7.73)

potential of urban-industrial land and improve the level of intensive utilization of urban-industrial land (Li et al. 2019a). Although the intensity of urban-industrial land development in

Zhangjiakou and Chengde is not high, it is very important to have a large number of ecological functions in these regions. With frequent ecological vulnerability and high geological

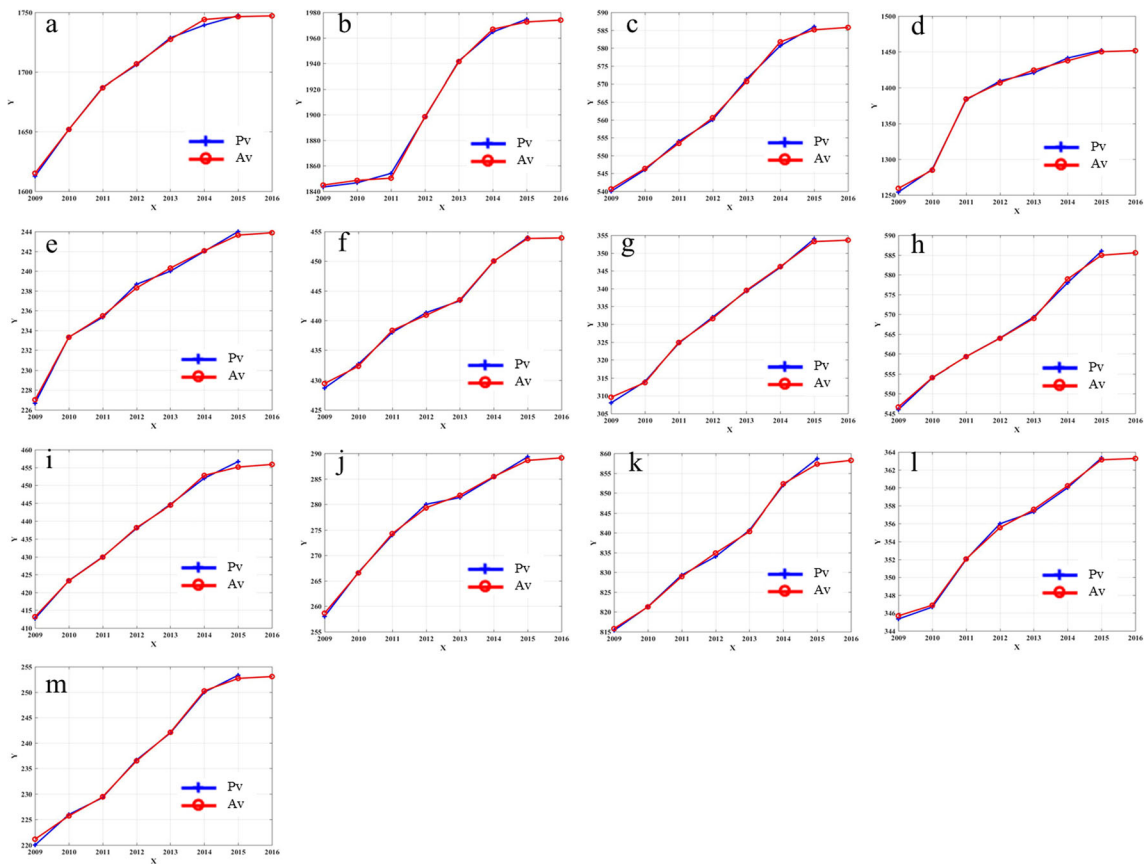


Fig. 4 RBF model prediction simulation results. PV: predicted value; Av: actual value; a–m: Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, and Hengshui

Table 4 Statistical errors of the two models

City	GM (1, 1)		RBF	
	MAE	RMSE	MAE	RMSE
Beijing	3041.47	3055.43	18.78	20.06
Tianjin	2726.33	3023.05	8.17	10.09
Shijiazhuang	822.82	828.47	7.65	9.52
Tangshan	6359.27	6924.27	13.11	15.31
Qinhuangdao	244.18	245.30	3.07	3.59
Handan	431.13	438.03	4.41	5.90
Xingtai	973.38	975.98	9.23	10.23
Baoding	503.23	503.97	34.49	47.69
Zhangjiakou	748.83	750.15	7.96	9.16
Chengde	648.12	653.94	4.54	5.53
Cangzhou	683.93	688.77	6.42	8.22
Langfang	434.55	446.04	2.72	3.90
Hengshui	536.25	550.96	4.82	5.82

hazards, these regions are not suitable for large-scale development and construction of urban-industrial land.

- (2) Optimized adjustment zone. Covering Beijing, Cangzhou, and Hengshui. This zone, of which the surplus scale of urban-industrial land is relatively insufficient, should activate the existing urban-industrial land, promote the adjustment of industrial structure, and carry out land transformation of old towns, old villages, and old factories with the historical opportunities of industrial transfer and non-capital functions in the coordinated development of Beijing, Tianjin, and Hebei. As the main industry transfer place of Beijing-Tianjin-Hebei coordinated development, Beijing should activate the stock of construction land, reduce the proportion of industrial and storage land, and optimize land distribution with the requirements of “orderly relaxing the non-capital

Table 5 Comparisons between the predicated demand of urban-industrial land and the expected indicators of urban-industrial land in the overall land use plan in 2020

City	Actual value in 2009/km ²	Predicted value in 2020/km ²	Expected value in 2020/km ²	Actual value in 2015/km ²	Modified value in 2020/km ²	Average annual growth rate/(km ² /year)	The remaining usable time/year
Beijing	1612.67	1854.99	1970.00	1747.33	1970.00	51.05	4.36
Tianjin	1843.33	2030.51	1750.00	1974.67	2030.51	26.74	2.09
Shijiazhuang	540.00	615.68	781.00	586.00	781.00	34.43	5.66
Tangshan	1254.00	1468.95	731.00	1452.00	1468.95	30.71	0.55
Qinhuangdao	226.67	251.33	295.05	244.00	295.05	9.77	5.23
Handan	428.67	478.18	603.00	454.00	603.00	24.90	5.98
Xingtai	308.00	386.92	481.89	354.00	481.89	24.84	5.15
Baoding	546.00	632.35	706.00	586.00	706.00	22.86	5.25
Zhangjiakou	412.67	475.25	368.00	456.67	475.25	8.94	2.08
Chengde	258.00	308.81	230.00	289.33	308.81	7.26	2.68
Cangzhou	815.33	900.61	653.00	858.67	900.61	12.18	3.44
Langfang	345.33	433.12	506.00	363.33	506.00	22.95	6.22
Hengshui	220.00	274.87	290.00	253.33	290.00	10.00	3.67

functions of Beijing, optimizing and upgrading the core functions of the capital.” Formulate policies to guide land withdrawal for general industries, especially “two high” industries (high pollution, high energy consumption), labor-intensive industries, partial public service functions, partial service agencies, and enterprise headquarters.

- (3) Core development zone. Covering Shijiazhuang, Baoding, Xingtai, Langfang, Handan, and

Qinhuangdao. The expanding space of urban-industrial land of this zone is relatively larger. At present, the intensity of development is moderate, the resources and environment are relatively low, and there is some suitable space for construction. Meanwhile, according to the industrial belt, the industrial chain, and the specific industrial undertaking platform proposed by the guidelines on industrial transfer among Beijing, Tianjin, and Hebei and the opinions on strengthening the construction of key platforms for industrial transfer among Beijing, Tianjin, and Hebei, the region is along the development axis of Beijing and Tianjin, development axis of Beijing-Bao-Shi, and the development axis of Beijing-Tang-Qin, and is the main region to undertake the industries transfer of Beijing-Tianjin-Hebei. Owing potential for future development and should guide the rational agglomeration of industries, the scale of urban-industrial land should be moderately increased in the region.

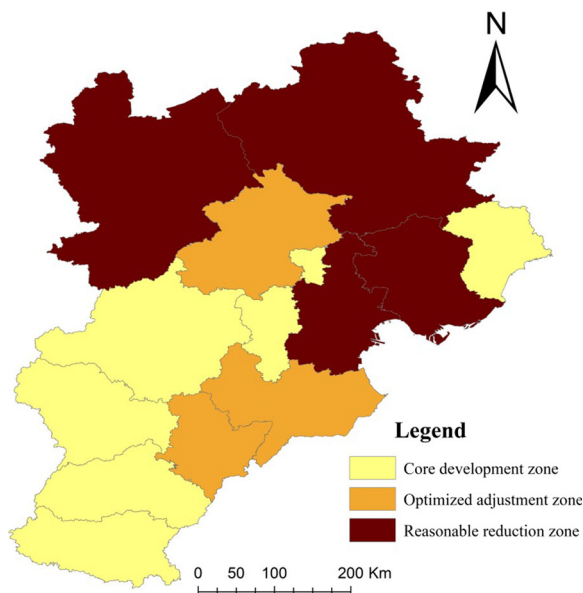


Fig. 5 Regulation zones of urban-industrial land of Beijing-Tianjin-Hebei Urban Agglomeration

Because the spatial data of urban-industrial land of the study area are not available, this paper only predicts urban-industrial land in respect of quantitative scale. It could be studied in respect of spatial scale in the future. The spatial distribution of urban-industrial land could be predicted with the quantitative scale, so as to further improve its effectiveness.

Conclusions

Using the MATLAB R2016a software modeling tools to establish the GM (1, 1) model and RBF neural network model, respectively, this paper predicted the demand of urban-industrial land in Beijing-Tianjin-Hebei Urban Agglomeration. Comparing the predicted results with the actual value of urban-industrial land in Beijing, Tianjin, and 11 prefecture-level cities in Hebei Province, we determined the reasonable prediction model for urban-industrial land after testing the accuracy of the two prediction models. The results showed that RBF neural network model was the more reasonable prediction model for urban-industrial land. Using the predicted results of the RBF neural network model, combining expected indicators of “Overall Land Use Plan (2006–2020)” in Beijing and Tianjin, as well as in 11 prefecture-level cities in Hebei Province in the planning target year, determined remaining usable time of urban-industrial land. Finally, combined with the actual scale of urban-industrial land in 2015 and the predicated scale of urban-industrial land in 2020, the remaining usable time of each city’s urban-industrial land was calculated in terms of the average annual growth rate of urban-industrial land from 2009 to 2015. According to the comparative relationship between the remaining usable time and the remaining time of the overall land use plan (5 years), urban-industrial lands were divided into three kinds of regulation zones: reasonable reduction zone, optimized adjustment zone, and core development zone. This paper can provide reference for regulation zoning of urban-industrial land in developing countries and regions.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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