An Analysis of Simulation and Prediction of Urban Morphology Based on Gray Logistic Cellular Automaton Model

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***Abstract* — Urbanization is accelerating across the globe. In order to achieve healthy urban development, many studies have been devoted to the expansion and simulation of urban morphology. This study makes improvements on the logistic cellular automaton(logistic-CA) model, so as to accurately simulate the evolution of urban morphology in space and quantity, and to explore the rules and characteristics of the evolution of urban morphology under the historical development trend of inertia. By embedding the method of unequal time interval gray combination forecasting into logistic-CA, the modified model achieves the goal of accurately simulating and forecasting urban shape in a given year, which capability has been proven by empirical tests in two forecast years. The predicted result of 2011-2020 is: the spatial layout of Binhai area will gradually develop into a crisscross shape, formed by the main Haihe River development axis and the coastal development belt; the evolution of urban morphology will mainly happen in five clusters: Tanggu City Area, Tanggu Port, Hangu City Area, Binhai International Airport, Dagang City Area and Dagang Oilfield. At the early stage, urban morphology will expand around the five above-mentioned clusters (the expansion of old city areas and ports is especially fast); at the later stage, the expansion will connect the coastal urban development belt and the Haihe River urban development axis to form a crisscross.**

Keywords- grey logistic-CA; urban morphology; simulation and prediction; Binhai area

I. INTRODUCTION

As urbanization accelerates, healthy urban development has become a concern. Simulation of urban Morphology expansion is an important means for the diagnosis of the healthiness of urban development [1,2]. The evolution of urban morphology is complicated and diverse, and the causes and simulation prediction of the evolution have always been heavily studied [3,4]. It is of scientific significant to study the evolution rules of space of urban morphology over time under the influence of different internal and external factors. In these studies, accuracy in spatial and numerical simulation of urban expansion is of great importance. Researches based on simulation and prediction of urban morphology directly influence the urban development strategies and policies, and are extremely significant and meaningful in theories and in reality. The analysis based on simulation and prediction of urban morphology seeks the possible evolution process of city's spatial layout, and the results of the analysis include the identification of each development tendency and its features [5]. Research on urban morphology prediction is propitious for us to master the law of city's development, provide urban planning decision makers with references [6,7], and thus conduct the urban development in a positive and effective way. An appropriate prediction model with high accuracy is highly essential to the urban research and planning.

II. STATE OF THE ART

In 1940s, Ulan and Von Neumann came up with the concept of cellular automation (CA) for the first time. In 1979, Tobler put forward the First Law of Geography. In 1985, Coulers revealed CA's potentiality in urban researches [8-9]. To date, many achievements have been made in urban studies with the applications of CA [10-12]. CA's popularity in the field of urban research and planning is due to its better understanding of the motivation of urban development and its more accurate prediction of the effect of urban planning [13-14]. The core of CA is the transition rules, which mainly include: artificial neural network, logistic, multi criteria decision, ant colony optimization and so on.

One of these rules is logistic cellular automaton (logistic-CA). It has been successfully applied in researches such as: the change of urban land utilization [15], expansion pattern [16], influences of agricultural land use[17], analysis of forest harvesting[18] and so forth. In 1997, Wu put forward the logistic-CA model, using which the simulation of the dynamic process of land utilization was achieved successfully. The research revealed that logistic regression based on land conversion probability explained the urban expansion [19] better. Later a lot of research literature studied the use of logistic-CA. Some typical cases are: the CLUE-S model [20] developed by Verburg from Holland in collaboration with others; enhancement of the prediction accuracy through integration of Logistic and Markov models[21] by Ping; use of this model for simulation and prediction[22] by Jafari; use of this logistic regression in the analysis and predication of the urban expansion of Beijing Zhuhai[23-25] by Yunlong and Zhiqin. Compared with linear regression and log linear regression, logistic regression has several advantages: dependent variable, independent variable and normality assumption. Using the traditional logistic-CA model, this paper are able to simulate the expansion of urban land, but unable to precisely simulate the quantity of urban area in certain year. In this paper, the logistic-CA model is modified to construct a composition gray logistic-CA model. The model is used to predict the evolution of urban morphology by using a small amount of irregular data with rigorous empirical test as the standard, and to accurately simulate the urban expansion area, which is the shortcoming of Logistic-CA model.

This research aims to simulate and predicate the urban morphology of Binhai area in Tianjin from 2011 to 2020, as well as exploring the gray rules and characteristics of urban morphology evolution. The remainder of this paper will present as follows: Section 3 introduces the general situation and data sources of the study area as well as the pretreatment of the data. Section 4 presents the method of the composition gray logistic-CA used in this paper and details how to improve the method. Section 5 focuses on the analysis and practical validation for the simulation results and discusses the rules of urban morphology evolution. The last section summarizes this paper and gives conclusions accordingly.

III. METHODOLOGY

(1) Study area and data

① Overview of the study area

This paper studies the Binhai area of Tianjin, which covers Tanggu, Hangu, Dagang, and parts of Dongli district and Jinnan District. Binhai area is the eastern part of Tianjin with a geographical feature of "a carrying pole with loads at both ends". It is the key development region in Jing-Jin-Tang region's land planning, with a total land area of approximately 2270km^2. In 2011, the resident population of this region reached 2.48 million. Binhai area is located in the east of Tianjin, bordering on Bohai Gulf, with a coastline of 153km. It has the largest comprehensive international trade port in northern China, which is an important gateway to the sea for Beijing, Northeast China and North China. Binhai area has National Pilot Zone for Overall Reform as well as national-level new zones; It is Tianjin's important industrial development region which accommodates major development zones and transportation facilities, such as Tianjin Economic and Technological Development Zone, Tianjin Free Trade Zone, Tianjin Port, Tianjin Binhai International Airport and so on. In those areas, strong economic foundation and well-equipped infrastructures have been established during the past years of development, and they have become important driving forces for the economy of Tianjin. In 2010, Binhai area's GDP reached 503 billion. From 2005 to 2011, land area for construction in urban and rural area expanded from 689km^2 to 1129km^2, a 63.86% increase in 6 years.

Figure 1. The model setting.

② Sources and preprocessing of data

The original data used in the study are from: remote sensing image from Landsat TM5 satellite of August 1998, August 2001, September 2005, August 2009 and August 2011; the 1:100,000 Tianjin topographic map of the year 2010, the 1:100,000 Tianjin map of the year 2005 and 2011, the general urban planning map of Binhai area for 2005-2020 and the general urban planning map of Binhai area for 2011-2030. The space resolution of TM remote sensing image is 30 meters, and image of ALOS satellite 2.5 meters.

The preprocessing of the original data took the following steps: First, scanning and registering the urban planning map and the official map; applying geometric accuracy correction. The discrepancy should be within 1 pixel after correction. Second, calibrating the satellite images and maps into 1:10,000 Tianjin topographic maps; projecting them to WGS_1984_UTM_50N. The error should be controlled within 15 meters. Third, according to domain analysis of urban and rural planning, the land is divided into three categories: construction space, agricultural open space and eco-sensitive space [26]. Considering the geographical situation of the studied area in reality, the land is divided into four categories: construction land, agricultural land, ocean, and water body on land. Fourth, layer stacking the NDVI index and construction index [27] with other wave band; then offering explanation by combining supervised and unsupervised classifications, on-the-spot survey and visual observation. From previous researches land classification can be obtained, and the final accuracy is controlled to be no less than 90%. At last, applying ArcGIS 10 software to establish the data base as well as drawing and statistically analyzing the concerned data from different periods using spatial analysis.

(2) Study Methodology

In this study, this paper simulates and predicates the spatial process of urban morphology evolution using the grey logistic-CA model. The improved model is shown in Fig. 2. The improvements are made based on relative theories of finite-state machine in automata theory[28]. In terms of the ordinary CA, stop of computation subjects to the number of simulated evolution cases. In such cases, the accuracy of computation can hardly be perfect. Based on automata theory, it can introduce the grey prediction method, which is suitable for the urban research, into CA model. The core of the improvement is embedding the unequal interval grey combination model so as to precisely predicate the space and quantity of urban expansion.

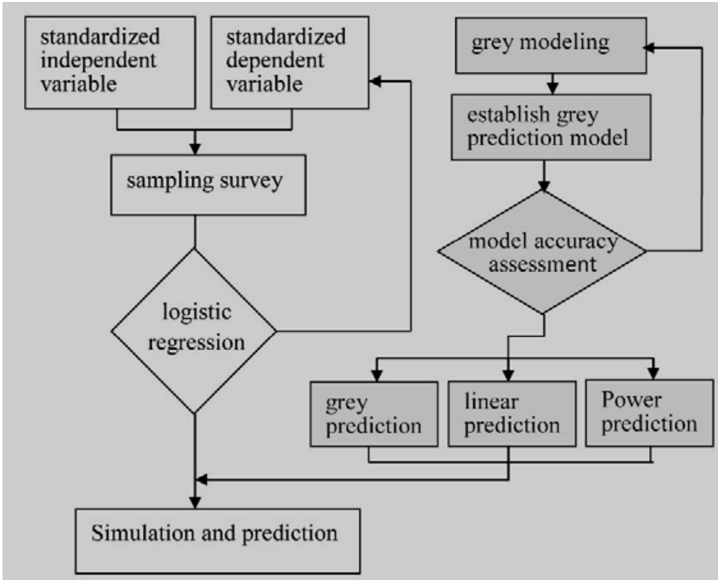

Figure 2. Structure of modified logistic-CA model

① Cellular Automata

The cellular automaton is a dynamic model with dispersed space, time and state, and has the ability to simulate spatial-temporal dynamic evolution process of complex urban systems. Typical CA model consists of four parts, namely, cell, condition, neighborhood and rules, and can be represented by the following formula:

$$S_{ij}^{t+1} = f(s_{ij}^{t}, \Omega_{ij}^{t}, Con, N) \tag{1}$$

In this formula, S_{ij}^{t+1} and s_{ij}^{t} respectively represents the conditions of Cell ij at time t+1 and t, “f” represents the transition rule function; Ω_{ij}^{t} is the spatial expansion situation of neighborhood at the location of ij; Con is the general condition, and *N* is the number of the Cells.

Due to the fact that CA model is established based on dispersed and regular spatial division, the size of spatial resolution ratio influences the accuracy of simulation. In this study, this paper adopt the 30×30m spatial resolution[29-30] which accuracy has been proven. Generally speaking, the urban Cell conditions only fall into two kinds, urban land and non-urban land. Considering that the design standard is 100-200 meters for urban planning and construction, and that the size of Cell in this research are 30 meters in size, the size of neighborhood 5×5Moore, the neighborhood made up of 24 neighborhood units, the neighborhood function formula can be described as:

$$\Omega_{ij}^{t} = \frac{\sum_{5\times5} con(s_{ij} = urban)}{5\times5-1} \tag{2}$$

In the formula, Ω_{ij}^{t} is the urban Cell density in the 5×5 neighborhood; con is a conditional function: if s_{ij} stands for the urban land, con( ) will return true; otherwise, it will return false. The transition rule is the core of CA, for it determines the process and result of CA dynamic evolution.

② Transition rule

The transition rule of grey logistic-CA model herein adopts the binary logistic regression method. The features and advantages of this method are: first, Logistic regression is the regression analysis reacting to the dummy variable of 0 and 1. Therefore, it is perfectly suitable for nonlinear questions such as whether the land converts into urban land; second, it has a high accuracy rate of simulation[31], and it is also convenient for auditing the computation process.

The logistic transition rule can be presented as:

$$P_{d,ij}^{t} = (1+(-\ln r)^{\alpha}) \times \frac{1}{1+\exp(-z_{ij})} \times con(s_{ij}^{t}) \times \Omega_{ij}^{t} \tag{3}$$

In the formula, $\frac{1}{1+exp(-z_{ij})}$ is the feasibility of land development in an area; b_0 is a constant; b_K is a regression coefficient; x_k is a group of variables affecting the transition; $z = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k$ is the vector describing the features of development of unit(i, j). $1+(-ln\,r)^{\alpha}$ is a random entry [32]; the value of γ is random between 0 and 1; α is the parameter controlling the degree of influence brought by random variables, its value being the integer between 1 and 10. The introduction of α is to make the computation conform to the reality, and to reflect the influences and interferences of various political, humanistic, random factor and haphazard events in urban morphology evolution. Taking into consideration the implementation situation of the urban planning in the research area, and after consulting experts, this paper decided to adopt 8 as the value of α for this paper.

③ Grey calibration of the prediction results concerning quantities

Since the design of Cellular Automation can hardly make accurate quantitative forecast[33], this study tries to imbed the unequal interval grey combination forecast method into the logistic-CA model and uses the forecast result as the stopping condition for CA simulation and prediction so as to realize the accuracy of areas simulated by CA model. Unequal time-interval combination gray forecasting model combines the optimal linear and power curve models with the original gray unequal time-interval prediction model. After being compounded, the model can not only improve the prediction precision, but also continue to have gray system play its unique role in urban research[34].

The approach of topology grey forecast is often used for unequal time interval grey prediction. It assumes that the original objective equal interval databases are there but some data is missing for some reason, which results in the original unequal time interval sequences. Our acquired datasets conform to the GM(1,1) curve with its discrete form as $\hat{x}^{(1)}(k+1)=(x^{(0)}(1)-\frac{u}{a})e^{-ak}+\frac{u}{a}$, where $c=x^{(0)}(1)-\frac{u}{a}$. The initial time series is set as 0 and the time series as $T^{(0)}(i)=\{0,t_2,t_3,...,t_m\}$, then can have $x^{(0)}(t_i)=c(1-e^{a})e^{-at_i}$. In the formula $t_i = t_2, t_3,...,t_m$ (m is the number of the initial sequence.). The following equation set put forward by Hu Bin is often used to evaluate the values of *c* and *a*[35].

$$\begin{cases} x^{(0)}(t_i)=c(1-e^{a})e^{-at_i} \\ x^{(0)}(t_j)=c(1-e^{a})e^{-at_j} \end{cases} \tag{4}$$

It leads to:

$$a=\frac{1}{t_i-t_j}ln\frac{x^{(0)}(t_j)}{x^{(0)}(t_i)} \tag{5}$$

The value of a is ai,j, and the number of $a_{i,j}$ is c^2_{m-1}. It can be work out the average value as follows:

$$\hat{a}=\bar{a}=\frac{1}{c^2_{m-1}}\sum_{i=2}^{m-1}\sum_{j=i+1}^{m}a_{i,j} \tag{6}$$

Then it can get the following equation set:

$$\begin{cases} x^{(0)}(t_2) = c(1-e^{\hat{a}})e^{-\hat{a}t_2} \\ x^{(0)}(t_3) = c(1-e^{\hat{a}})e^{-\hat{a}t_3} \\ \quad\cdots\cdots \\ x^{(0)}(t_m) = c(1-e^{\hat{a}})e^{-\hat{a}t_m} \end{cases}$$

(7)

It can get a value for c according to each equation and achieve its average value:

$$\hat{c}=\bar{c}=\frac{1}{m-1}\sum_{i=2}^{m}c_i \tag{8}$$

At last, it can be make the unequal interval grey forecast model by the values of $\hat{c}$ and $\hat{a}$:

$$\hat{x}^{(0)}(t_i)=\hat{c}(1-e^{\hat{a}})e^{-at_i} \tag{9}$$

and the prediction value can be obtained by the equation (9).

IV. CALCULATION AND DISCUSSION

(1) Regression analysis on the historical evolution of urban morphology from 2005 to 2011

①Selection and quantization of driving factors

Various factors influence the evolution of urban morphology. Based on relative researches [36-38], researches on the driving force of construction land growth as well as the universality of urban development, the author selects 15 influencing factors in this study as most representative: expressway, high-speed entrances and exits, railways, railway stations, waterways, rivers, national highways, provincial roads, county and township roads, urban roads, downtown impact, planning layout effects, airports, planning railways and planning roads.

Firstly, distance specification for each point is worked out by ArcGIS 10 with the maximum value standardized. Next, this study get the dimensionless data between 0 and 1, which guarantees the comparability in the computation. Then, it can be assign the spatial values for the construction land, the development standby and other land in the study as 1, 0.6, and 0 respectively, which shows urban planning's overall guidance and control over the urban morphology and ensures that urban planning is comparable and consistent with other influencing factors or variables. Lastly, it can be project all data in WGS_1984_UTM_50N and resample them at a resolution ratio of 30 meters.

② Establishing logistic regression model

To simulate the urban morphology evolution using the grey logistic-CA model, a logistic regression model should be established first. For this purpose, this paper sample at random the target variables (2011 classification table) and the variables of influencing factors for urban morphology. This is achieved through simple programming using the randperm () function offered by matlab2011b software. The random sampling ratio is 20%. Then, this study make logistic regression computation of the sampling data using SPSS 20 software. All influencing factors except for the rivers are tested with 0.05 significance level, and the overall classification accuracy of the model reaches 85%. The regression coefficients this paper worked out are as follows:

TABLE I LOGISTIC REGRESSION DATA

		B	S.E.	Wald	df	Sig.
Expressway	V1	3.282	0.535	37.604	1	0
Outlet & inlet of expressway	V2	-1.325	0.574	5.327	1	0.021
Railway	V3	0.727	0.24	9.204	1	0.002
Railway station	V4	4.335	0.31	195.147	1	0
Sea-route	V5	-1.36	0.124	121.163	1	0
Rivers	V6	-0.479	0.359	2.777	1	0.052
National road	V7	0.428	0.116	13.685	1	0
Provincial road	V8	-1.816	0.224	65.417	1	0
County & township road	V9	-6.246	0.549	129.377	1	0
Urban road	V10	-11.823	0.42	794.005	1	0
Downtown	V11	-4.776	0.308	240.957	1	0
Urban planning	V12	1.612	0.033	2340.421	1	0
Airport	V13	-3.834	0.203	358.068	1	0
Railway planning	V14	0.64	0.218	8.628	1	0.003
Road planning	V15	-10.314	0.593	302.778	1	0
	constant	1.644	0.064	659.804	1	0

The regression function Z is represented like this:

$$Z = 1.644 + 6.282x_1 - 1.325x_2 + 0.727x_3 + 4.335x_4 - 1.366x_5 - 0.479x_6 + 0.428x_7 - 1.816x_8 - 6.246x_9 - 11.523x_{10} - 4.776x_{11} + 1.612x_{12} - 3.834x_{13} + 0.64x_{14} - 10.314x_{15}$$

③ Simulation and evaluation of the results

In order to test the effectiveness of the improved logistic-CA model, the improved model is used to simulate the urban expansion in 2005-2011. Firstly, import the logistic regression coefficients into the grey logistic-CA model and then goes through simulation iterations for 200 times until the simulation area reaches 1072 km². The model allow a deviation of 2% in the computation because some pixel transition probabilities are the same under certain conditions. Then the output would be converted into GIS data by ArcGIS10 and then be further converted as the urban morphology simulation shown in Fig.3. Finally, analyzing the accuracy of the improved model, and use the simulation area and the Lee-Sallle index to do comprehensive evaluation (both the spatial precision of the simulation and the area of the simulation were taken into account). The accuracy comparison results show that the accuracy was high: the accuracy of the simulation area of urban land is 99%; Lee-Sallle index was 0.98.

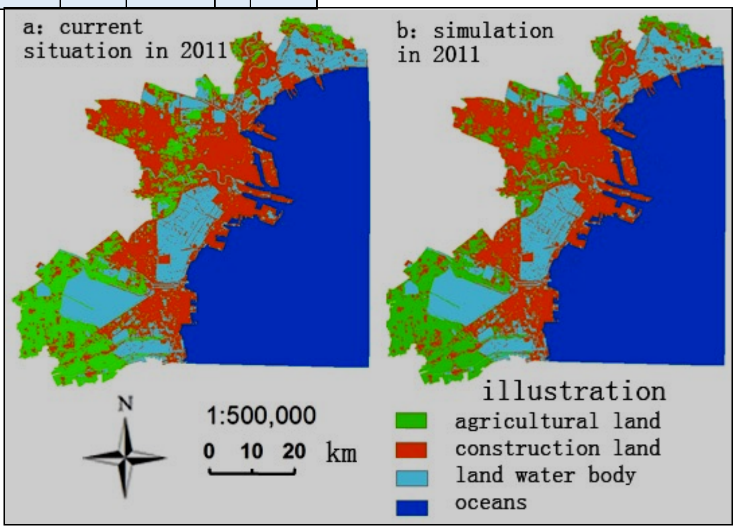

Figure 3. 2011 urban morphology simulation and status quo

Overall, tests on the simulation area and Lee-Salle index prove that the grey logistic-CA model has a high accuracy rate and can be used for analysis, simulation and prediction of the urban morphology evolution from 2005 to 2011.

(2) Calibration of grey prediction

The gray prediction model is used to calculate the urban area in the year of prediction. The composition gray prediction model is calculated as follows:

$$\hat{x}^{(0)}(t_i) = 17.669t_i + 136.792e^{0.058947t_i} + 107.285t_i^{0.4395} + 105.891$$

. Since the first information point is the basic information of the gray system, it does not participate in the prediction. This paper use the prediction model to predict the urban morphology area in 2001, 2005, 2009 and 2011(Table Ⅱ). The average error of the model is 0.003, which is 0.034 higher than that of pure gray forecasting, showing that the accuracy of the model is greatly improved. Using this model, the urban morphology areas can be calculated in 2020 and 2030, which are 1465,2134 km² respectively (Table Ⅱ).

TABLE Ⅱ THE TABLE OF MODEL ESTIMATING ACCURACY

Year	Actual (km²)	Predicted(km²)	Deviation
1998	319		
2001	547	527	-0.001
2005	689	711	0.056
2009	938	959	0.1429
2011	1076	1009	-0.06
2014		1140	
2020		1465	
2030		2134	

Note: Since the first information is the gray system base information, it does not participate in the prediction

③ Urban morphology simulation and prediction

The urban morphology simulation in this paper adopts the loosely coupled system of matlab 2011b and ArcGIS 10, which is flexible, free for enhancement and convenient for checking the calculating process. This model is used to develop the logistic-CA simulation software on the matlab platform, and make visualized processing and analysis using ArcGIS.

This paper import the logistic regression coefficients into the grey logistic-CA model, set the iterative number of the operation as 200 and choose the fifteen driving factors for urban expansion in 2011 as independent variables. With the urban area in 2011 as the prediction base, the predicted urban areas in 2014, 2020 and 2030 should be 1140, 1771 and 2134 km² respectively; the pixels of simulated new urban construction land use should be12300, 713300 and 1116500; and the pixels of new cities at every iteration are 61, 3567 and 5583. Lastly, analyze the results of urban morphology expansion by ArcGIS 10. (see Fig.4,5)

④ Empirical Test of Simulation Results

The quantitative calibration of the model has met the prediction demand for the evolution of the urban morphology. To further verify the predictive effect of the gray logistic-CA model, compared with simulation results of the real year of 2014, this study test the accuracy of the simulation and its validity for the spatial simulation. In 2014, the actual area of urban morphology was 1182km ², the simulated prediction 1140km² and the error 0.3% while the Lee-Sallle index is 0.958, which indicates that the spatial simulation has high trueness.

From the comparison of the simulation results in 2014 and the actual urban morphology, the simulation shows the characteristics of group expansion along favorable locations and achieves the goal of making use of the change of spatial mechanism which is simulated with CA. In the past 10 years, urban expansion has shown a tendency to scatter, mostly relying on the original construction land and infrastructure. Relatively speaking, the expansion is the most concentrated along the Tanggu area. Other expansion points are mainly located in Hangu District, Binhai International Airport, Binhai Recreational Area, Tanggu District and Dagang Oilfield.

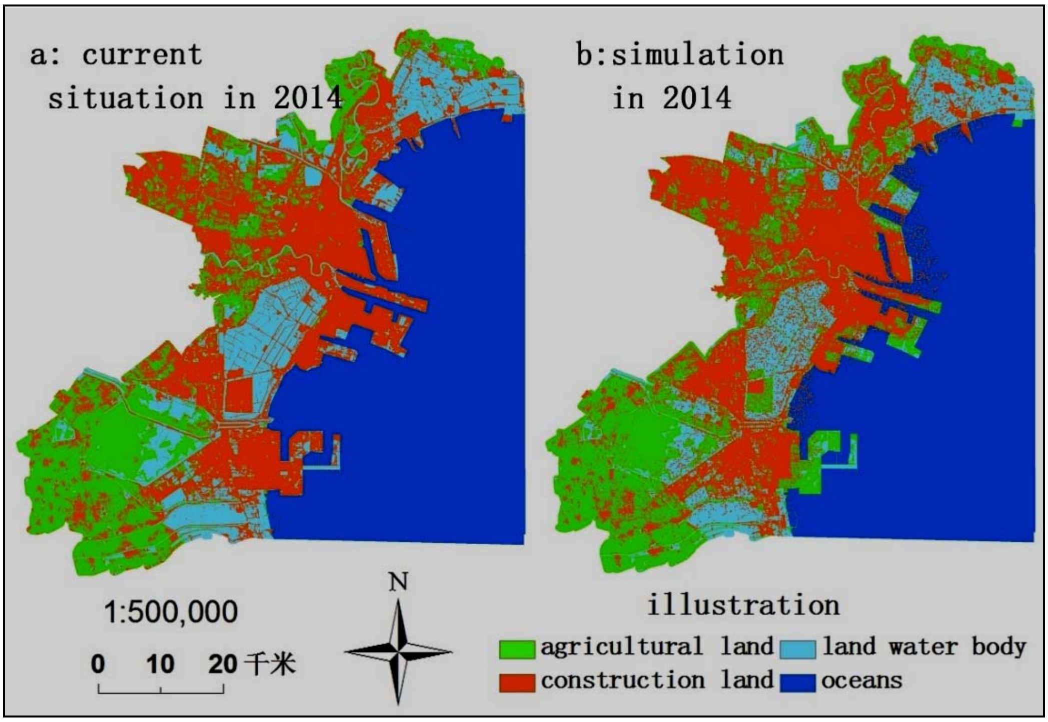

Figure 4. Forecast and Actual Contrast of Urban Morphology.

⑤ Analysis on the predicted results

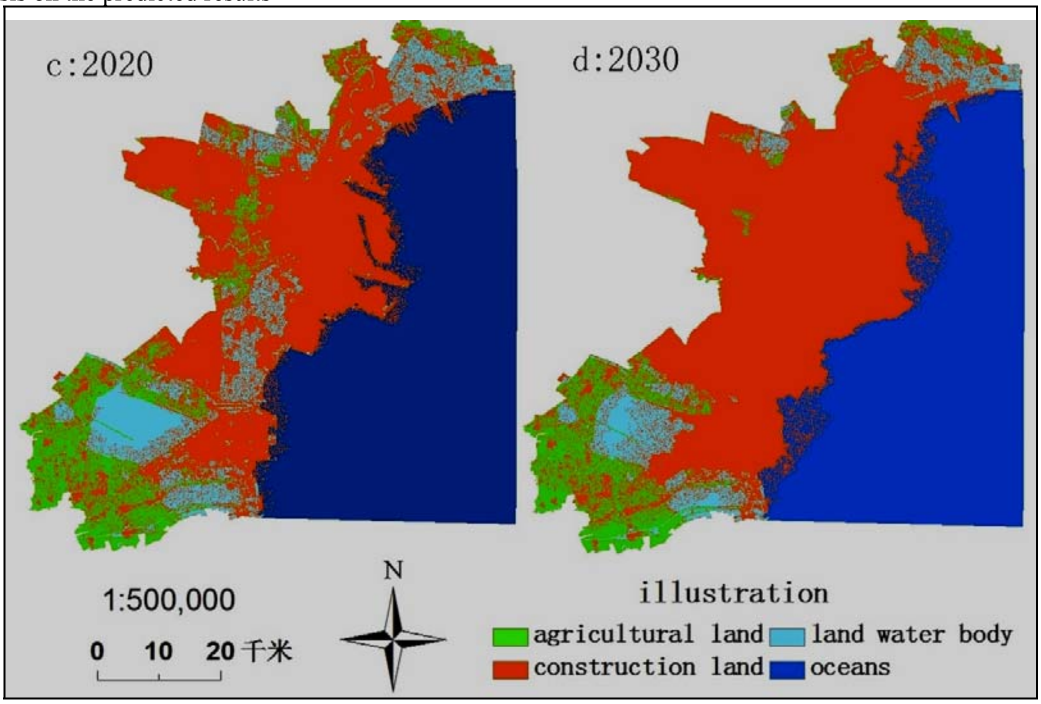

Figure 5. Prediction of urban morphology.

At the early stage(2014-2020), there is a clustered expansion concerning Tanggu City Area, Hangu City Area, Binhai International Airport, Dagang City Area and Dagang Oilfield. At the same time, the urban morphology will spread from the port onto the sea, mainly centering Tanggu Port, Dagang Oilfield, the Central Fishing Port, International Amusement Port and Binhai Leisure and Tourism Zone.

At the later stage(2020-2030), the urban morphology will link the five clusters of Tanggu City Area, Hangu City Area, Binhai International Airport, Dagang City Area and Dagang Oilfield together, and connect the Binhai urban development belt with the Haihe River urban development axis. During this period, the South will expands faster than the North, and there will be a significant increment of construction land in Southeast of Dagang Reservoir.

On the whole, the urban morphology will mainly center on Tanggu District and spread along the Haihe River Development Belt to Bohai Sea. The urban expansion will be mostly realized through reclamation. As a result, there will be a great deal of seawater reduction; the salt pan in the north will disappear much faster than that in the south. The urban morphology will gradually evolve into a crisscross structure formed by main Haihe urban development axis and the coastal urban development belt. In the crisscross structure, the central node is the old Tanggu City Area and the other four peripheral nodes are Binhai International Airport, Hangu City Area, Tanggu Port, Dagang City Area and Dagang Oilfield. By 2020, there will be only a small area of land preserved in the Haihe development belt, mainly around Huanggang Reservoir and the northeast of Modern Metallurgy Industrial Park, while the ecological land in the south and west of Dagang Reservoir will be well preserved.

V. CONCLUSION

In order to promote the urban construction and development of Tianjin Binhai area to contribute to the city's robust and healthy development, this paper offers a new method for the accurate simulation of urban morphology, exploring the pattern-mechanism of urban morphological evolution and other rules. The composition gray forecasting model with unequal time interval is used to modify logistic-CA model to calibrate the quantity. Having passed two rigorous empirical tests, the model is capable of predicting the evolution of urban morphology by using a small amount of irregular sample data. Based on the urban morphology simulation of Tianjin coastal area from 2011 to 2030, this paper analyzes the process, pattern and mechanism of urban spatial morphology evolution under the gray rule of urban morphology evolution.

Conclusions are as follows:

Firstly, the grey logistic-CA model adopts the method of unequal interval combination grey model, which makes simulation and prediction of urban morphology expansion no longer restricted by regular sample data. Also, the model has a high accuracy rate of prediction for the urban area in a certain year, thus CA's advantage in a bottom-up simulation of the urban morphology evolution is shown more clearly.

Secondly, the urban morphology will gradually expand around five clusters: Tanggu City Area, Binhai International Airport, Hangu City Area, Tanggu Port, Dagang City Area and Dagang Oilfield; it will form a spatial framework of a crisscross structure composed of the main Haihe River urban development axis and the coastal urban development belt. During the urban morphology expansion, the salt pan in the north will disappear much faster than that in the south, while the ecological land to the south and west of Dagang Reservoir will be well preserved.

Thirdly, logistic-CA model should be adopted to simulate and predict the urban morphology, in order to better analyze and study its spatial evolution features under the historical trend, make urban development planning for different phases, and to guide the urban morphology to develop more scientifically.

In this paper, the gray system method is used to calibrate the logistic-CA model. The accuracy and stability of the calibration will improve as the gray system progresses. In CA simulation of urban space, influencing factors are many, including economic factors, social factors, policies, administrative divisions and more. The impact of these various factors on the urban system evolution should be given full consideration. If the date base is big enough and accuracy high enough, it is possible to operate the accurate simulation of urban spatial morphology with big data and ultra-high resolution.To conclude, the results show that, 1) stochastic analysis exhibits H-M coupling behavior in statistical fractures more actually; 2) fluid action on fractures can cut down surrounding wall stress; 3) stress field influences the seepage field by changing the permeability; 4) as the stable state of surrounding wall, the waterhead remains almost the same; 5) with H-M coupling the flow rate shows an obvious increase around the tunnel.

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