Dynamic Monitoring and Simulation of Urban Land Use Based on Remote Sensing

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Abstract
The remote sensing image and the land cover classification are studied by using the middle resolution image. Firstly, the pre-processing work of radiometric calibration, atmospheric correction and resolution fusion are carried out for the middle resolution remote sensing image. Based on the spectral analysis of ground objects, the decision tree classification model is established based on the idea of hierarchical classification, and the threshold of the branch points of the decision tree classification model is determined by the maximum interclass variance method so as to recognize the residential place. Finally, the classifications results are analyzed and discussed. The geographical area of the urban built-up area and the surrounding area is used as the cellular space, and the research area is divided into a square grid generally. Since the complexity of the transformation rules usually increases exponentially with the number of cells in the neighborhood, the complexity of the rules may not be accepted if the neighborhood is too large.

Key words: Dynamic Monitoring, Dynamic Simulation, Remote Sensing, Otsu Algorithm, Cellular Automaton

1. INTRODUCTION

In order to strictly control the scale of urban land, each city needs to scientifically and rationally formulate urban construction land planning, which is an important measure to implement the most stringent land management system (Xu, Yang, Wang and Yang, 2015). The traditional urban land use scale is determined by prediction technique based on historical statistics (Appiah, Bugri, Forkuo and Boateng, 2014). Under the new situation, the scale of urban land use is affected by various factors, such as population scale, economic level, capital investment, industrial restructuring, geographical position, ecological environment, policies and so on(Liu, Gao, Zhao, Zhang and Yu, 2015). The use of traditional methods to determine the scale of construction land is often unable to meet the real needs of the national economic and social development (Pan, Tian, Lu, SRS Dangal and Liu, 2015). Therefore, how to use satellite remote sensing and other high-tech to have accurate access to urban expansion of information, master the law of urban expansion and reasonably determine urban land use scale is a topic worthy of in-depth study and is of important practical value and application prospects(Carrero, Navas, Malvárez and Guisado-Pintado, 2014).

Many foreign scholars have carried out research in this field. Masek et al. (2000) carried out dynamic monitoring of urban expansion in Washington area by using MSS image and TM image in 1973, 1985, 1990 and 1996, set a limitation to eliminate the change information of agricultural land by using the spatial texture information based on NDV1 different value and accurately extracted urban expansion area from 1973 to 1996(Wang and Xiong, 2015). Karathanassi et al. (2000) proposed a classification method for urban land use(Hosseinali, Alesheikh and Nourian, 2015). The urban building density was determined by image texture through this method and the land use type was determined. The Athens area in Greece was tested by using SPOT panchromatic spectral image. The accuracy of classification is 83.40%-89.61%, which is higher than the traditional maximum likelihood method (79.7%). This method can be used in urban land use change, urban expansion, illegal building monitoring and other urban remote sensing monitoring. Yang X, et al. (2002) studied the land use and land cover of Atlanta with multi-temporal remote sensing images (Pan, 2015).

In this paper, the remote sensing image and the land cover classification are studied by using the middle resolution image. Firstly, the pre-processing work of radiometric calibration, atmospheric correction and resolution fusion are carried out for the middle resolution remote sensing image. Based on the spectral analysis of ground objects, the decision tree classification model is established based on the idea of hierarchical classification, and the threshold of the branch points of the decision tree classification model is determined by...
the maximum interclass variance method so as to recognize the residential place. Finally, the classifications results are analyzed and discussed. The most basic unit of cellular automaton consists of four parts, cellular, cellular space, neighborhood and rule. In addition, it should also include the state and time of cellular. Simply speaking, it can be considered as a cellular space and a transformation function which is defined in the space. As is shown in Figure 4-1, the black cellular represents the center cellular, the grey cell is the neighborhood and their states determines the state of cellular at the next moment. Spatial discretization: Cellular distribution in a discrete cellular space is divided by a certain rule and spatial computing is carried out among cellular. Temporal discretization: Morphological evolution is carried out at equal time intervals, and the time variable can only take the time step of equal steps. State Discretization: The states of all cells are discrete and finite, so a state space \{s1, s2, ..., sl\} can be defined. The state of a cell can be taken only in the state space at any time. In practical applications, it is often necessary to discretize some continuous variables, such as dispersion or classification, in order to facilitate the establishment of CA model. Evolutionary Parallelism: All cells evolve synchronously in time, that is, the state change of each cell at time t + 1 is independent behavior and has no influence on each other, so it is particularly suitable for parallel computation. Temporal and spatial locality: The state of each cell at the next instant t + 1 depends on the state of cells in the neighborhood of radius r of the cells at time t, and cells outside their neighborhood do not work. Global Consistency: All cells are in accordance with the same state of the development of changes in the rules of change. Cells’ size, shape, distribution way are the same and spatial distribution rules are neat. High dimensionality: In dynamic systems, the number of variables is generally referred to as the number of dimensions. Since the cellular space of any complete cellular automaton is an infinite set defined in a one, two, or multidimensional space, the state of each cell is a variable of the dynamical system. Therefore, cellular automaton is a kind of high-dimensional dynamic system.

2. THEORY AND METHOD OF REMOTE SENSING TECHNOLOGY

2.1 Otsu Algorithm

Otsu algorithm, also known as the Otsu method (Otsu, 1979), is proposed in Japan Otsu exhibition. The Otsu algorithm is derived on the basis of probability statistics and least square method principle with simple principle and clear physical significance. It is based on the statistic property of the image pixel value and the class variance is used as the criterion for judgment. It can realize the automatic selection of the binarization threshold. Therefore, it is well recognized by many scholars.

The basic idea of the between-class variance algorithm is the basic idea of the maximum between-class variance algorithm is to use the maximum gray-scale histogram of between-class variance of a certain target and background to dynamically determine the optimal segmentation threshold, so as to get the corresponding binarization image. The larger the between-class variance between the background and the target is, the larger the differences between the two parts are. When part of target is divided into the background or part of the background error, the differences between these two parts will become smaller. Therefore, the maximum segmentation of between-class variance means that the misclassification probability is the smallest (Qiu, 2011). Its main implementation principles are as follows.

Suppose the span of grey level of an image is \( G = \{0, 1, 2, ..., L-1\} \), \( n_i \) is the pixel number of grey level in an image, the total pixel number of the image is shown in N, then,

\[
N = n_0 + n_1 + n_2 + ... + n_{L-1} = \sum_{i=0}^{L-1} n_i
\]

(1)

Possibility occurrence \( p_i \) of grey level i is:

\[
p_i = \frac{n_i}{N}
\]

(2)

Obviously,

\[
\sum_{i=0}^{L-1} p_i = 1
\]

(3)

Threshold value T divides the pixel in the image into \( C_0 \) and \( C_1 \) \( (T \in G) \), that is \( C_0 = \{0, 1, ..., T\} \), \( C_1 = \{T+1, T+2, ..., L-1\} \)

The possibility occurrence of these two categories can be shown:

\[
a_0 = \sum_{i=0}^{T} p_i
\]

(4)

\[
a_1 = \sum_{i=T+1}^{L-1} p_i = 1 - a_0
\]

(5)

The average grey scale of these two categories can be shown:
\[ \mu_0 = \sum_{i=0}^{L-1} \frac{ip_i}{\omega_0} \]  

\[ \mu_i = \sum_{i=L+1}^{i_1} \frac{ip_i}{\omega_i} \]  

The average value of grey scale statics of the image is:

\[ \mu = \sum_{i=0}^{i_1} ip_i = \omega_0 \mu_0 + \omega_1 \mu_1 \]  

\[ \sigma^2_0 = \sum_{i=0}^{L-1} \frac{(i - \mu_0)^2 \rho_i}{\omega_0} \]  

\[ \sigma^2_1 = \sum_{i=L+1}^{i_1} \frac{(i - \mu_1)^2 \rho_i}{\omega_1} \]  

According to mode recognition theory, \( C_0 \) and \( C_1 \) variances are:

\[ \sigma^2_B = \omega_0 (\mu_0 - \mu)^2 + \omega_1 (\mu_1 - \mu)^2 = \omega_0 \omega_1 (\mu_1 - \mu_0)^2 \]  

\[ \sigma^2_W = \omega_0 \sigma^2_0 + \omega_1 \sigma^2_1 \]  

\[ \sigma^2_r = \sigma^2_B + \sigma^2_W \]  

Among the grey scale of image 0, 1, 2, ..., L-1, to search all the possible grey scale value by using order, to make the between-class variance \( \sigma^2_B \) reach the maximum threshold \( T^* \) and \( T \) is the best threshold, the maximum interclass variance judgment criterion function is:

\[ T^* = \text{Arg} \max_{0 \leq T \leq L-1} \{ \sigma^2 \} \]  

In addition, the optimal threshold discriminant function with the smallest intraclass variance is introduced, even though the threshold with the smallest intraclass variance is the optimal threshold (Qiu, 2011):

\[ T^* = \text{Arg} \max_{0 \leq T \leq L-1} \{ \sigma^2 \} \]  

Considering the computational complexity, the optimal threshold is obtained by the criterion of maximum interclass variance generally.

The advantage of maximum interclass variance method is that it has little effect on the contrast and brightness of image under certain conditions with small computational complexity. It is widely used in some real-time image processing systems (Qiu, 2011). However, this method has its disadvantages. The method fails when the ratio size between the target and background is small (Kittler, et al., 1985).

### 2.2 Maximum Interclass Variance Method Determines Threshold of the Decision Tree Class Peer

For the remote sensing image, the content of spectral classification is rich and usually contains a lot of spectral information. Due to the universal existence of synonyms spectrum, different objects with same spectrum and mixed pixel, especially the remote sensing image of complex coverage of city and towns, it is difficult to distinguish prospect and background simply. The grey scale histogram rarely shows obvious doublet, but most of them are in normal distribution and singlet form, which makes the complex remote sensing image cannot directly apply the maximum interclass variance method and obtain the optimal segmentation threshold. Therefore, this paper proposes a maximum interclass variance method based on the sample data, that is, by using the maximum interclass variance method of the sample data to determine the segmentation threshold of the branch node of the decision tree and avoid the above phenomenon.

A decision tree classification model is built based on the maximum interclass variance method by using the sample data. The implementation process includes the following steps (Fig. 1):

1) In the remote sensing image, a certain number of samples are selected, and the samples are selected as uniform as possible to ensure the representation of samples.

2) Classification feature selection: Determine the feature image of the current classification node of the decision tree. The feature can enhance the image feature of the target category of the current branch node and weaken the characteristics of other categories.
3) Optimal threshold of segmentation based on sample: The characteristic value of the sample data is extracted. Calculate the optimal binarization threshold value by using the maximum interclass variance method.

4) Image binaryzation segmentation: Use the above threshold value to construct the discriminant rule of the current branch node, the image is divided into two values, and the target category is extracted.

5) Remove the sample data of the current target category, pass the background cell to the next classification node of the decision tree, with repeating steps 2) to 5).

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**Figure 1.** Maximum interclass variance method to determine the decision tree branch node threshold segmentation process

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### 2.2.1 SVM Sorting Algorithm

It is difficult to find one or a few features to separate the feature classes, which are very similar in spectral characteristics and easily confused. The disaggregated model of the decision tree is in the middle node, allowing for the most effective discriminant function or the classification method of the current target category (such as selecting the appropriate wave band and wave band combination, different classification algorithms) so as to reach high classification accuracy.

Support Vector Machines (SVM) algorithm was first proposed by Cortes and Vapnik in 1995 and developed from the optimal classification of linear separable cases (Cortes, C, et al., 1995). Under the linearly separable optimal classification surface, it is required that the classification line not only divides the two classes correctly, but also maximizes the classification interval (Fig. 2). SVM considers a hyperplane \( H \) that satisfies the classification requirements and makes the points in the training set as far as possible from the classification surface that is, searching for a classification surface to maximize the margin on both sides of the classification. The training samples on the hyperplane \( H_1, H_2 \), which are closest to the classification surface and parallel to the optimal classification plane, are called support vectors.

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**Figure 2.** Schematic diagram of the linear separable
Suppose linear separable sample set is \( \{x_i, y_i\} \), among them \( i = 1, 2, \ldots, n \); \( x \in R^d \) are input vectors; \( n \) is sample number; \( y \) is the classification label. For these two problems, \( y \in \{+1, -1\} \) general form of linear discriminant function in dimensional space is \( g(x) = w^T x + b \), classification surface equation is \( w^T x + b = 0 \), among them, \( w \) is weight coefficient vector of optimal classification surface. The interval quantity is equivalent to or minimize \( \|w\| \) or \( \|w\|^2 \). It requires classification of all samples of the correct and it meets the requirements of \( y, [w^T x] + b \geq 1 \geq 0 \). Therefore, to meet the above conditions and make the smallest classification surface \( \|w\| \) is the optimal classification surface. The problem is converted to the minimum value of the function 

\[
\phi(x) = \frac{1}{2} (w^T w) = \frac{1}{2} \|w\|^2
\]

minimum value, this is quadratic programming problem. The overall optimal solution is obtained \( w = \sum_{i=1}^{n} a_i y_i x_i \rightarrow w = \sum_{i=1}^{n} a_i x_i \), among them, \( sv \) represents the support vector, if \( a_i \) is the optimal solution, Optimal classification function after the solution of the above problem is

\[
f(x) = \text{sgn} \left\{ (w^T x) + b \right\} = \text{sgn} \left\{ \sum_{i=1}^{n} a_i y_i (x_i \times x) + b \right\}
\]

In the formula, \( \text{sgn}\{\} \) is symbolic function; \( b \) is the threshold for classification. For the unknown sample given \( x \), we need to calculate \( \text{sgn}\{w^T x + b\} \) to judge the classification of \( x \).

In many cases, the training data set is linearly indivisible and can be transformed into a linear problem in a high-dimensional space by non-linear transformation (Zhao et al., 2009). The finding of the optimal classification surface in this high-dimensional space can be realized by inner product of training samples using kernel function, and the computational complexity is not increased (Zhang et al., 2008). The non-linear mapping \( \phi(x) \) is selected and is mapped to the high-dimensional feature space in which the optimal hyperplane is constructed. Similar to the linear case, the optimization function becomes.

\[
Q(a) = \sum_{j=0}^{n} a_i - \frac{1}{2} \sum_{i=0}^{n} \sum_{j=0}^{n} a_i a_j y_i y_j \langle \phi(x_i), \phi(y_j) \rangle \]

Among them, \( \langle \phi(x_i), \phi(y_j) \rangle \) is the inner product of the transformed space. The corresponding discriminant function should also be.

\[
f(x) = \text{sgn} \left\{ \sum_{i=1}^{n} a_i y_i \langle \phi(x_i), \phi(y_i) \rangle + b \right\}
\]

This is the support vector machine. When solving the optimization problem and calculating the classification plane, we only need to calculate the kernel function, \( K(x \times x_i) \), commonly used kernel functions are polynomial, Radial Basis Function (RBF) and Sigmoid. These kernel functions have been shown to be suitable for most nonlinear classification problems (Zhang et al., 2008).

### 2.2.2 Remote Sensing Extraction Technology of Residential Area

In this paper, the remote sensing image and the land cover classification are studied by using the middle resolution image. Firstly, the pre-processing work of radiometric calibration, atmospheric correction and resolution fusion are carried out for the middle resolution remote sensing image. Based on the spectral analysis of ground objects, the decision tree classification model is established based on the idea of hierarchical classification, and the threshold of the branch points of the decision tree classification model is determined by the maximum interclass variance method so as to recognize the residential place. Finally, the classifications results are analyzed and discussed, the technical route are shown in Figure 3.

### 3. LAND MONITORING MODEL BASED ON CELLULAR AUTOMATON

#### 3.1. Cellular automaton

It is also known as cells, cells or basic element, the most basic components of cellular automaton. Cellular is distributed in the space grids of Euclidean space. The shapes of the cellular are different with cellular space. At a certain moment, each cellular has its own state.
Figure 3. Technical route in residential area based on Landsat-8 OLI image data extraction

The set of lattice points in which the cellular is distributed in space is the cellular space. Theoretically, it can be a regular partition of Euclidean space of any dimension. At present, the research work is focused on one dimension and two dimension cellular automaton. For one dimensional cellular automaton, there is only one square arrangement in cellular space. Two dimensional cellular automata are usually arranged in triangular, square or hexagonal grids, as is shown in Figure 4.

Each cellular $l$ can have multiple state variables, but only one state at a time. The set of all states constitutes the property of the cellular system.

It is based on the current state of the cell and its neighborhood determines the state transition function of the cell state at the next moment. At $t$ moment, $i$ cellular state is $S_i^t$, its neighbor state is $S_N^t$, at $t+1$ moment, $i$ cellular state is $S_i^{t+1}$, it can be described in a set-oriented language.

$$S_i^{t+1} = f \left( S_i^t, S_N^t \right)$$  \hspace{1cm} (19)

In the formula, $f$ is cellular state transition rule, $S$ is finite set, representing cellular state, $N$ is cellular neighborhood, $t$ is time. Rules are the most important part of cellular automata, and the advantages and disadvantages of rulemaking are very important to whether CA model can achieve the expected results.

According to the composition analysis of the cellular automaton above, the cellular automaton can be summarized as a four-tuple in mathematical notation.

$$A = \left( L_d, S, N, f \right)$$  \hspace{1cm} (20)

In the formula, $A$ represents a cellular automaton system, $L_d$ represents cellular space, $d$ represents the dimension of cellular space, $S$ is the limited discrete set states of cellular, $N$ is a combination of all neighboring cellular, $f$ is transformation rule.
3.2. Establishment of CA model of Urban Spatial Expansion

CA can dynamically simulate the process of urban expansion and GIS can realize the simulation results visualization and spatial analysis. Therefore, this paper builds the urban spatial expansion CA model which is seamlessly integrated with GIS. The technical process is shown in Figure 5. It includes CA definition, cell state database establishment, GIS integration, simulation analysis and prediction of several steps.

Figure 5. Technical process of urban expansion CA model

3.3. CA Element Definition

The geographical area of the urban built-up area and the surrounding area is used as the cellular space, and the research area is divided into a square grid generally. Each grid cell is equivalent to a cell. The spatial resolution of each cell is selected according to the research needs.

In cellular automata, the state of a cell at the next moment depends on the state of its own and the state of the neighboring cell. Therefore, we must define a certain neighborhood range and know clearly which cellular belong to the neighborhood. Cell has a variety of growth rules. For different cell growth rules, different size neighborhoods can be used. Commonly used two-dimensional cellular automaton of the neighborhood type is the Moore neighborhood, as is shown in Figure 6. The center cell is randomly selected as the target cell of urbanization, and the surrounding shadow cell is its neighborhood, and the neighborhood number is 8. Assuming that the central cell is (i, j), then the neighborhood definition is usually as is shown in Figure 7.

Figure 6. Moore neighborhood

<table>
<thead>
<tr>
<th>(i-1, j-1)</th>
<th>(i-1, j)</th>
<th>(i-1, j+1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i, j-1)</td>
<td>(i, j)</td>
<td>(i, j+1)</td>
</tr>
<tr>
<td>(i+1, j-1)</td>
<td>(i+1, j)</td>
<td>(i+1, j+1)</td>
</tr>
</tbody>
</table>

Figure 7. Model Moore Neighborhood Definition

The time in the CA model is an abstract concept of time, and how to correspond to the concept of time measurement in the real world is a difficult problem. In some data, linear control is used to determine the corresponding relationship with the real-time. The concrete method is to determine the correspondence between the model time and the actual time according to the land type data at the initial time point to the second time point. The data of the initial time is selected as the base date and the model parameters such as evolution period and cycle numbers are input. The running model and the simulation result are compared with the actual data at the second time point. After repeated tests and contrast, when the simulation results correspond to the actual data, note the number of cycles the model runs. According to the above method, multiple results are recorded, and finally the mean value is obtained, and the correspondence between the number of model cycles and real
time is obtained. For example, assuming that the model runs 30 times for 10 years, it can be deduced that the model runs three times a year, that is, the model's evolution period \( T = 30/10 = 3 \) years. In order to calculate the trend of urban change in the next 5 years, the model only needs to run \( 3 \times 5 = 15 \) times.

Cellular automaton (CA) is the core part of the definition of conversion rules. The entire simulation process of the CA is controlled entirely by translation rules. At present, there are two methods to determine the city CA model conversion rules. The first is artificial method, such as multi-criteria evaluation method, principal component analysis, 5-factor rule method, gray-scale method, etc. This method is subjective and susceptible to simulator work experience and knowledge level. No matter how rich and complex rules are made, it is impossible to include the diversity of the extension process. The second is automatic acquisition method, as data mining, genetic algorithm, neural network, rough set method, etc. This method is relatively objective and can find the law automatically from the natural complex relation and have access to the model required conversion rules. But it is not mature enough.

The expansion of the built-up area is mainly caused by the change of the land use type around the city, and there are many ways of transformation. The number of state cells in the front design is 4. According to the combinatorial mathematical principle, the number of conversion rules is \( 4^2 = 16 \) from the initial time to the next time. However, some land types cannot be converted into each other. For example, urban land cannot be converted into agricultural land and non-construction land cannot be converted into urban land. Therefore, according to the actual urban expansion, we should consider on what condition agricultural land can be converted into urban land.

According to the law of urban growth and referring to Clarke's SLEUTH model, four kinds of urban state transition drivers are introduced, namely, growth factors, traffic attraction factors, growth factors along the lines, and center growth factors. The function of the land state transition caused by four factors is set as \( f_1, f_2, f_3, f_4 \) and it will be further explained in the following.

Because the slope of the terrain has an impact on the conversion of urban construction land, here we design an elevation limit function.

The elevation is within the optimum elevation range and the function value is 1. When the elevation value exceeds the maximum limit elevation, the function value is zero. The maximum limit elevation is set as a slope threshold according to the actual situation of urban development.

In order to reflect the uncertainty of urban development, and to bring the results of the model closer to reality, a random term is introduced in the urban CA model. The random term is as follows.

\[
RA = 1 + (-\ln r)^a
\]  

In the formula, \( r \) is a random variable and a parameter for controlling the degree of random variation. The random term can make the simulation result of CA have fractal structure. Studies have shown that the evolution of many natural and geographic phenomena have fractal characteristics.

The state transition rule of the model is as follows.

\[
P = \frac{f_1}{f_2} \times f_{\text{high}} \times RA
\]  

In the formula, \( P \) is conversion probability, showing the conversion possibilities from agricultural land to urban construction land.

Suppose \( P \) valve stands for the state transition probability threshold, when \( P \geq P \), the cell state is converted to urban land.

(1) Spreading growth factors

Urban spreading growth refers to the growth of new urban cells around the original urban cells, which reflects the agglomeration effect of urban development. The neighborhood is defined as a Moore neighborhood. For a cell with a state of agricultural land, if there are more than 3 urban cells in the Moore neighborhood of the cell, the cell can be converted to urban land, as is shown in Fig. 8 (a). It can be expressed in the following mathematical form, namely.

\[
\begin{align*}
\text{if } S_i^t = 0 \text{ then } f_i = S_i^{t+1} = \begin{cases} 
1 & \text{if } \sum S_{S_i}^t \geq 3 \\
0 & \text{if } \sum S_{S_i}^t < 3 
\end{cases}
\end{align*}
\]  

In the formula, \( S_i^t \) shows the cell state \( i \) at \( t \) moment. \( S_i^t \) shows the urban land use state in the neighbor at \( t \) moment center cell. \( S_i^{t+1} \) shows the center cell states \( i \) at \( t+1 \) moment.
Traffic attraction factor

Road traffic belongs to linear geographical elements, the impact of urban expansion is also in a band, in the direction of the road, the impact of urban expansion and its distance from the traffic line is inversely proportional. The urban plots far away from the traffic lines are not easy to be developed into construction land because of the inconvenient transportation. In the vicinity of the roads, the means of transport are developed, the access is convenient and the city expands quickly. The impact of traffic on urban expansion can be divided into two aspects: traffic attraction and traffic growth.

If there are more than two urban cells in the Moore neighborhood, and there are more than one traffic cell (i.e., cells with roads passing through), the cell can be transformed into urban land, as is shown in Fig. 8 (b). The mathematical expression is:

\[
\text{if } S'_i = 0 \text{ then } f_i = S'^{i+1}_i = \begin{cases} 
1 & \text{if } \sum S'_i \geq 2 \text{ AND } \sum S'_t \geq 1 \\
0 & \text{if } \sum S'_i < 1 \text{ OR } \sum S'_t < 1
\end{cases}
\] (24)

In the formula, \( S'_i \) shows the state of center cell at t moment, \( S'_t \) shows the neighborhood urban land state of the center cell at t moment, \( S'_t \) shows the traffic land state of center cell at t moment, \( S'^{i+1}_i \) shows i state of center cell at t+1 moment.

Growth factor along the traffic line

For cells in the state of agricultural land, if there is more than one urban cell in the Moore neighborhood, there are more than three traffic cells, the cell can be transformed into urban land, as is shown in Figure 8 (c). The mathematical expression is:

\[
\text{if } S'_i = 0 \text{ then } f_i = S'^{i+1}_i = \begin{cases} 
1 & \text{if } \sum S'_i \geq 3 \text{ AND } \sum S'_t \geq 3 \\
0 & \text{if } \sum S'_i < 3 \text{ OR } \sum S'_t < 3
\end{cases}
\] (25)

In the formula, \( S'_i \) shows the state of center cell i at t moment, \( S'_t \) shows the urban land state in the neighborhood of center cell at t moment, \( S'_t \) shows the traffic land state in the neighborhood of center cell at t moment, \( S'^{i+1}_i \) shows the state of center cell at t+1 moment.

Center growth rule

The growth of urban centers reflects the scale effect and agglomeration effect of urban development, that is, when a certain area of the city develops to a certain scale, there will be new urban cells appearing inside and around the area. Within the sphere of influence of the central region of the city, a small neighborhood of the cell is defined as a 3 × 3 neighborhood of radius 1; The other large neighborhood is a 5 × 5 neighborhood with radius 2, as is shown in Figure 8 (d).

For any central cell, if the number of urban cells in its small neighborhood is greater than a specified value (e.g., 8), a cell is randomly selected in its large neighborhood. If the cell has not been urbanized, the cell can be converted into urban land. The mathematical expression is as follows.

\[
\text{if } S'_i = 0 \text{ then } f_i = \begin{cases} 
1 & \text{if } \sum S'_i \geq 8 \\
0 & \text{if } \sum S'_i < 8
\end{cases}
\] (26)
In the formula, $S_t^i$ shows the state of cell in the neighborhood at $t$ moment. $S_N^i$ shows the urban land state in the neighborhood at $t$ moment. $S_t^{i+1}$ shows the state of cell $i$ in the neighborhood at $t+1$ moment.

4. SIMULATION BASED ON CELLULAR SPATIO-TEMPORAL DATABASE

The cellular spatial-temporal database is based on the concept of cell database. It is mainly composed of remote sensing image map, land use vector diagram, DEM data and cell attribute database.

4.1. The Structure of Cell Attribute Database

According to the definition of cellular in the previous, a city cellular property includes land class status, time and elevation attributes. Since the cell data is based on the raster data structure, the spatial position of the property can be used cell where the row number and column number are. Each cell is given a name identifier and the cell has a total of 6 properties. The structure of the cell attribute database can be designed as follows.

<table>
<thead>
<tr>
<th>Property</th>
<th>Name</th>
<th>Line number</th>
<th>Column number</th>
<th>Time</th>
<th>Status</th>
<th>Altitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Hollerith type</td>
<td>Hollerith type</td>
<td>Hollerith type</td>
<td>Period type</td>
<td>Hollerith type</td>
<td>Floating point</td>
</tr>
</tbody>
</table>

4.2. Acquisition of cellular Properties

The cell properties are derived from remote sensing images at different periods. Firstly, the remote sensing images are classified into land use types according to the land use map, and then re-encoded them into urban land, agricultural land, and road and non-construction land. Then the ERDAS software is used to transform polygon vector layers. Each polygon contains attributes of land type, area, and perimeter. The vector layer is led into the Mapinfo software. The use of grid production tools in the vector layer can be generated within the square grid layer and each grid is a cell. The grid size is defined according to the need. The grid layer automatically generates the grid name and row and column number for each grid. The row number is represented by A, B, C, ..., and the column number is represented by 1, 2, 3, .... The time domain, the state and the elevation are added into the grid layer attribute library, so the structure frame of cell attribute database is constructed.

The time value of each cell grid comes from the date of the image, the elevation value comes from the DEM data, and the ground class state is obtained from the polygon vector layer. There are two cases:

1. If a grid is completely contained by a polygon, the polygon's land attribute can be assigned directly to the grid's status field.
2. If a grid covers several polygon boundary lines, the state value of the grid depends on the area ratio of several polygons in the grid. The polygon ground class with large area ratio is the state of the mesh.

4.3. CA and GIS Seamless Integration

CA and GIS seamless integration can take full advantage of the technical advantages of both, so that urban space expansion simulation system is more perfect. The frame structure of the model is shown in Figure 9. CA module and GIS module have a common user interface and a common background database. The function of CA module is to set various conversion parameters, to carry on the city expansion simulation and prediction. GIS module functions are various data input, editing, simulation results display, spatial analysis and so on.

![Figure 9. Framework of CA model for urban expansion](image)

To achieve the seamless integration of CA and GIS, you can use the control technology for development. GIS control technology has the following advantages. First, it can use their own development interface instead
of professional GIS software interface to reduce the difficulty of user operation. Second, when releasing software, just bundled control released, there is no need to install professional GIS software, reducing the cost of enterprise applications. Third, a different interface can be customized to different users. Fourth, it is easy to be ported to the internet and intranet.

At present, some large GIS software providers can provide control for users, such as ERSI's Map Object, Map Info's Map X and Intergraph's geomedia. These controls have powerful map management and editing functions, which can be directly embedded in the high-level language call and support external database mount. It provides convenience for GIS development.

Through the analysis, it is appropriate to adopt the GM (1,1) model with relatively small standard deviation in the prediction of the built-up area, and the allometric model in the medium term. Logistic model is adopted for long-term development.

![Various built-up area forecast curve (original)](image1)

**Figure 10.** City built area prediction curve comparison (2008 ~ 2030)

After analysis, we can get the scale of land use in the planning period of City built-up area in Table 5-16.

5. COMPARATIVE STUDY OF SIMULATION AND PREDICTION RESULTS OF DIFFERENT MODELS

Parameter determination $r=0.022742818$, The hyperbolic prediction model is established as follows:

$$ P(t) = \frac{1503090}{1-0.022742818(t-1984)} $$

Test of goodness of fit $R^2=0.96694$.  

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Use the hyperbolic model to calculate the planned land use from 1984 to 2015, the results are compared with the actual values to obtain the standard deviation $S=99622$, $S/Y=4.7\%$.

The AR (2) prediction model is obtained by using the data of Prairie-Winsten parameter estimation by using SPSS software from 1984 to 2015.

$$P_r = -14522.81101 + 1.04538P_{r-1} - 0.00531P_{r-2}$$ (28)

Test of goodness of fit $R=0.99035891$; $R^2=0.98081077$; Adjusted $R^2=0.97761257$.

The AR (2) model is used to calculate the planned land use from 1984 to 2015, and the standard deviation $S=75702$ and $S/Y$ average = 3.5% are obtained.

The above six kinds of prediction models are used to forecast the planned land use from 2016 to 2034, and the results are shown in Table 2.

<table>
<thead>
<tr>
<th>Year</th>
<th>Regression model</th>
<th>Compoundin g model</th>
<th>Gray prediction</th>
<th>Logistic model</th>
<th>Hyperbolic model</th>
<th>AR(3) model</th>
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</table>

| Standard deviation | 489781 | 1261955 | 1349848 | 14522.81101 | 1.04538 | 0.00531 | 32553800 | 1380818 |

6. CONCLUSION

The transformation rule of cellular automaton is local, and the state of cell depends on the state of its neighboring cell. The space domain to be searched for in a cellular state is called the neighborhood of the cell. In principle, there is no limit to the size of the neighborhood, and the neighborhood size of all cells is the same. Since the complexity of the transformation rules usually increases exponentially with the number of cells in the neighborhood, the complexity of the rules may not be accepted if the neighborhood is too large.

Therefore, the neighborhood is often composed of adjacent cells. We extend the neighborhood radius of the Moore-type neighborhood to 2 or more, which leads to the extended Moore type neighborhood as is shown in Figure 4-3(c)and it contains the number of cells $(2r + 1)$ 2-1. Obviously, the mesh points of the cell space boundary do not have the same neighborhood as other internal grid points.

In the case of land-type transformations, these areas must be extracted and constrained. In this way, the cell's land state set can be designed as $\{0,1,2,3\}$. Among them, 0 represents agricultural land, 1 represents urban land, 2 represents transportation land and 3 represents non-construction land. The state of each cell is taken from the state set. In addition, because the construction and development of the city is restricted by the slope of the terrain, when the slope reaches a certain height, the possibility of urbanization may be very small. Therefore, each cell should contain the height attribute.

The land use type city model of cells is the status of the city, can be obtained by remote sensing classification technology. According to the nature and driving factors of urban spatial expansion, the land use types can be divided into four kinds of urban land, agricultural land, road and non-construction land. Urban land
refers to the land used to build a land in the present; the road is the main traffic road of the study area; the non-construction land cannot be used as the area of urban construction land.

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