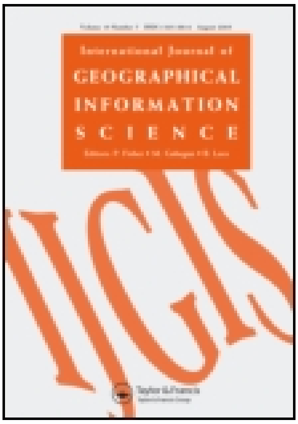

International Journal of Geographical Information Science
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tgis20

Zoning farmland protection under spatial constraints by integrating remote sensing, GIS and artificial immune systems

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Available online: 23 Aug 2011

To cite this article: Xiaoping Liu, Xia Li, Zhangzhi Tan & Yimin Chen (2011): Zoning farmland protection under spatial constraints by integrating remote sensing, GIS and artificial immune systems, International Journal of Geographical Information Science, 25:11, 1829-1848

To link to this article: http://dx.doi.org/10.1080/13658816.2011.557380

International Journal of Geographical Information Science
Vol. 25, No. 11, November 2011, 1829–1848

Zoning farmland protection under spatial constraints by integrating remote sensing, GIS and artificial immune systems

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(*Received 4 October 2010; final version received 19 January 2011*)

Currently, with rapid expanding of urban area, the rate of conversion of agricultural land to nonagricultural uses in China is increasing. Zoning farmland protection is an important measure to protect limited land resource. This article presented an innovative approach based on the integrated use of remote sensing, GIS, and artificial immune systems (AIS) for generating farmland protection areas. Some modifications have been made for conventional AIS so that it can be further extended to the solution of zoning problems. The optimal objective is to generate farmland protection areas that minimize development potential and maximize agricultural suitability and spatial compactness. First, utility function by addressing the criteria of farmland protection is incorporated into AIS algorithm. Second, encoding and mutation of antibodies is modified so that it can be suited to the solution of spatial optimization problems. The AIS-based zoning model was then applied to a case study in Guangzhou, Guangdong, China. The experiments have demonstrated that the proposed method was an efficient and effective spatial optimization technique, which took only about 194 seconds to generate satisfied farmland protection patterns. Furthermore, the AIS-based zoning model can explore various alternatives conveniently, and it can yield better performances than nonprotection scenario in the utility efficiency of land resources and the site condition for farmland.

Keywords: artificial immune systems (AIS); farmland protection; compactness; GIS

1. Introduction

Following the 1978 reforms, China's rapid urbanization has resulted in a series of environmental and ecological problems (Seto 2002, Li and Liu 2008). One problem is that a large amount of farmland was converted to urban uses and lost to agriculture forever (Yeh and Li 1999). According to official government statistics, China lost over 14.5 million hectares of farmland between 1979 and 1995 (Lichtenberg and Ding 2008). Most of the loss had occurred in coastal and central cites, where land is relatively fertile and climate is benign. It is well known that China is a country with the largest population and far below average per capita farmland resource (Li and Yeh 2001). Therefore, the encroachment of urban development onto farmland has placed a tremendous pressure on limited farmland resources (Yang and Li 2000). Farmland is an irreplaceable and nonrenewable natural resource, which contributes to the economic and ecological value of a community (Chang and Ying 2005). The combined effects of the continuous increase in population

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ISSN 1365-8816 print/ISSN 1362-3087 online

http://dx.doi.org/10.1080/13658816.2011.557380
http://www.tandfonline.com

and national food security have led to an urgent demand for farmland protection. Indeed, the preservation of farmland has become a fundamental national policy in China (Brown 1995). Many benefits can be derived from the protection of productive farmland, including local and national food security, the protection of rural and environmental amenities, the promotion of compact pattern in reducing environmental costs, slowing suburban sprawl, and providing wildlife habitat (Gardner 1977, Daniels and Bowers 1997).

The greatest loss of farmland has increasingly become an issue of local, regional, and national concern in China. To guarantee national food security, the Central Government had to implement specific policies aimed at protecting farmland, especially farmland with the greatest production potential. In August 1994, the State Council promulgated *the Basic Farmland Protection Regulation* to zone the best farmland for strict protection. *The New Land Administration Law*, which was promulgated in August 1998, is also intended to protect agricultural lands in the legislative process. In 2008, the State Council promulgated *the National General Land Use Planning (2006–2020)*, which pointed out that tough measures should be taken to ensure the warning line of farmland with an area of 1.8 billion *mu*. These legislations or measures have played a crucial role to control conversion of farmland with high productivity to nonagricultural use. However, the amount of farmland has continued to decrease, especially in expanding metropolitan areas and coastal regions. Perhaps the lack of a scientific method for zoning protected farmland is one of the major reasons. Local government officials generally carried out the zoning in an arbitrary manner (Li and Yeh 2001). Although some brief guidelines have been given in the legislation, they are difficult to follow in practice because of the lack of quantitative criteria. Therefore, there is a need to provide a more scientific and effective framework to assist local government officials in zoning protected farmland.

Farmland zoning usually involves the analysis of a large amount of spatial data. The integration of remote sensing and GIS can provide the spatial data and the spatial analyst tools. Internationally, GIS and remote sensing technologies have been used in the assessment, zoning, and planning of farmland. For example, Li and Yeh (2001) demonstrated the potential of integrating GIS, cellular automata (CA) model, and remote sensing for zoning farmland protection. Carsjens and Van Der Knaap (2002) explore the utility of GIS to help solve problems of farmland spatial allocation. Tulloch *et al.* (2003) describe their attempt to integrate GIS into farmland preservation policy and decision making. Dung and Sugumaran (2005) combined the Land Evaluation and Site Analysis (LESA) system with GIS to provide decision support tools for mangers in farmland protection. LESA, which is developed by the US Soil Conservation Service, has been widely used to guide agricultural zoning and to implement farmland protection. Machado *et al.* (2006) developed an approach that integrated GIS, remote sensing, and the LESA to zoning farmland preservation for multiple objectives. However, most of these approaches did not take into account spatial constraints, such as patch size and compactness. A fragmented pattern will be produced without incorporating spatial constraints in the farmland zoning. Fragmentation of farmland may lead to declining agricultural productivity and profitability (Levia 1998). Moreover, the isolated farm parcels have negative impacts on rural scenic quality and protected areas management (Brabec and Smith 2002).

Difficult decisions must often be made that evaluate the trade-off between farmland potential and development potential in farmland zoning. Farmland preservation plan should consider urban development potential because land consumption is crucial for sustaining economic growth in China. However, the very qualities that make some lands the most productive for agriculture also make them highly suitable for urban development. Unfortunately, urban development and farming are incompatible land uses. As development encroaches upon agricultural areas, it becomes irretrievably lost. In this situation, optimal farmland protection is a complex multi-objectives problem because some conflicts are inevitably involved. Moreover, farmland zoning should take into account spatial constraints, such as patch size and compactness. Farmland zoning under spatial constraints belongs to the NP-hard problem with a huge complex search space and therefore requires efficient optimization methods. Heuristics should be adopted because exact enumeration methods are impossible to solve such hard combinatorial optimization problems in a reasonable amount of time.

This research proposes an approach based on the integrated use of remote sensing, GIS, and artificial immune systems (AIS) for zoning farmland protection. AIS, a new computational method inspired by the biological immune system, was first proposed by Jerne (1974). As a heuristic method, AIS can learn new information, recall previously learned information in a highly decentralized fashion, and can tackle complex real-world problems. Since its proposal, AIS has been applied to solve various problems, such as pattern recognition (Carter 2000), intelligent optimization (Chun *et al*. 2002), machine learning (Timmis 2000), adaptive control (Kumar and Neidhoefer 1997), and fault detection (Dasgupta and Forrest 1995). Many studies have demonstrated that AIS possesses several attractive immune properties that allow it to get out local optima and avoid premature convergence (Bersini and Varela 1991, Fukuda *et al*. 1998). Actually, the features of self-adapting, diversity, dynamic learning, distributed computation, and memorizing of AIS make it promising in solving complex geographical problems (Liu *et al*. 2010). In recent years, AIS has been used successfully to solve geographical problems, such as urban simulation (Liu *et al*. 2010) and remote sensing classification (Zhong *et al.* 2007). These researches have demonstrated that AIS is a potentially useful algorithm for providing an acceptable solution to complex geographical problems.

This article will explore the integration of GIS, remote sensing, and AIS as a planning tool for zoning farmland protection. AIS will be modified so that it can be suited to generate farmland protection areas. The objective is to generate protected farmland protection areas that minimize development potential and maximize agricultural suitability and compactness. It is expected that the attractive immune properties of AIS can produce better performance in handling complex heterogeneous spatial data for optimal solution search. The proposed AIS method is then used to zone protected farmland areas in Guangzhou, a rapid growing region in the Pearl River Delta, China, and it can yield good performances. Lastly, the proposed method can explore various alternatives conveniently by using different combinations of weights.

2. Natural and artificial immune systems

Biological systems are serving as inspirations for a variety of computationally based learning systems, such as artificial neural networks, genetic algorithms, and swarm intelligence. Recently, there has been increasing interest in using the biological immune systems as a metaphor for computational intelligence approaches. From a computing standpoint, natural immune systems can be viewed as a parallel, self-adapting, self-learning, self-organizing, and distributed system that has the capability to control complex systems over time (King 2001). Inspired by theoretical immunology and observed immune system function, AIS is rapidly emerging as a kind of soft computing methods. It is capable of offering powerful and robust information processing capabilities for solving complex real-world problems (Tarakanov and Dasgupta 2000).

Natural immune system consists of a complex of cells, molecules, and organs that aim to protect the body against infection (Castro and Timmis 2002). AIS mimics the defense mechanism of the body by means of adaptive immune responses. The main component of adaptive immune response is lymphocytes, which divide into two classes as T and B cells. The main functions of the B cells include the production and secretion of antibodies as a response to exogenous proteins such as pathogens, bacteria, and other toxins that may be harmful. The B cells that are not stimulated as they do not match any antigens in the body will eventually die. On the contrary, the activated B cells with high antigenic affinities are selected to become memory cells. If the same antigens invade once again, the memory cells rapidly divide into plasma cells, and a large quantity of antibodies is generated in a very short period (Castro and Timmis 2002). The functions of the T cells include the regulation of actions of other cells and direct attack of the host-infected cells; the T cells can either help or suppress the B cells' response to a stimulus. Many immune response phenomena, such as clonal selection, immune memory, and negative selection, can be modeled as corresponding reactions and added to AIS algorithm.

Among the AIS methodologies, clonal selection algorithm (CSA) is perhaps the most popular immune-inspired method in current use. CSA evolves the antibodies inspired by the abstraction of the clonal selection principle, which was first proposed by Burnet (1959). The clonal selection theory is used to describe the basic properties of an adaptive immune response to an antigenic stimulus. It establishes the idea that only those cells with high affinity to antigens are selected to proliferate. These selected cells can easily recognize antigens and are subject to an affinity maturation process. The process of improving their affinity to the selected antigens is called clonal selection (Secker *et al*. 2003). CSA mimics the clonal selection mechanism and advocates iteratively improving candidate solutions through a process of accumulated mutation and affinity-based selection.

3. AIS algorithm for zoning farmland protection

3.1. Formulation of zoning protected farmland under spatial constraints

Zoning protected farmland is one instance of the more general problem of land use planning, which can be formulated as spatial optimization problems. There are three planning objectives in prioritizing sites for the preservation of farmland. These objectives include the following:

(1) Maximize agricultural suitability.

This objective tends to focus on preserving high-quality farmland. Agricultural suitability serves as a crucial aid for zoning farmland protection, and it can be estimated from a series of spatial factors that are retrieved from remote sensing and GIS data. Criteria for measuring agricultural suitability are typically related to soil quality, irrigation status, site condition, and slope. Soil quality is based on soil biophysical and chemical properties, including soil fertility, soil depth, and pH value. Site condition is determined by the number of farmland and the number of urban in neighboring areas. Sites in good condition are surrounded by farmland, whereas those in poor condition occur in areas with high proportion of urban. Site condition (C_s) can be calculated using the following equation:

$$C_s = \frac{N_f}{25 + N_u} \tag{1}$$

where N_f refers to the number of farmland in a 5 × 5 neighborhood window and N_u represents the total number of urbanized cells in a 5 × 5 neighborhood window. The equation with the denominator as $25 + N_u$ will guarantee that site condition (C_s) ranges from 0 (poor condition) to 1 (good condition).

The Multicriteria Evaluation (MCE) (Eastman *et al*. 1998) method is used to estimate agricultural suitability according to the above spatial factors, which should be standardized within the range of [0, 1] before the estimation. The total score of suitability is created by a linear weighted combination method:

$$\text{Suit} = w_1 \times F_s + w_2 \times D_s + w_3 \times \text{pH} + w_4 \times I_s + w_5 \times \text{Slope} + w_6 \times C_s \tag{2}$$

where F_s is the soil fertility, D_s is the soil depth, and I_s is the irrigation status. w_1, w_2, w_3, w_4, w_5, w_6 are the weights for each factor, and the total of all the criterion weights is equal to 1.

(2) Minimize development potential.

The potential of urban development should also be taken into account because farmland protection should not totally deny future economic development. Land consumption is crucial for sustaining economic growth in China. Furthermore, close proximity to rural residences, urban service areas, and municipal boundaries may increase development pressures on farmland (Land Information Bulletin 2000). This is generally due to lower development costs. Therefore, there are negative effects if the selected site has high potential of urban development. The development potential is regarded as a negative factor for protection, and it can be estimated as follows:

$$\text{Dev} = b_1 D_{\text{District}} + b_2 D_{\text{Towns}} + b_3 D_{\text{Railways}} + b_4 D_{\text{Expressways}} + b_5 D_{\text{Roads}} + b_6 \rho_{\text{Urban}} \tag{3}$$

where D_{District} is the distance to district center, D_{Towns} is the distance to towns, D_{Railways} is the distance to railways, $D_{\text{Expressways}}$ is the distance to expressways, D_{Roads} is the distance to roads, and ρ_{Urban} is the density of urban land in a 7×7 neighborhood; b_u ($u = 1, 2, \ldots, 6$) is the weight of each variable and is subject to $b_1 + b_2 + b_3 + b_4 + b_5 + b_6 = 1$.

(3) Maximize the compactness of spatial pattern.

Farmland that comprises a large contiguous area may be the pattern most worth mapping and preserving. This is because the compact pattern of farmland area is generally more productive and profitable. Moreover, reducing site fragmentation may mitigate urban development pressures, facilitate management, and offer a broader rural aesthetic presence. The compactness index is used to avoid the fragmentation of farmland patterns. It is calculated according to the following equation:

$$C_p = \frac{L_{\text{MaxSum}} - L_{\text{Sum}}}{L_{\text{MaxSum}} - L_{\text{MinSum}}} \tag{4}$$

where L_{Sum} is the sum of perimeter of a protected scenario. It is common sense once the area is known; the most compact form would be circular and the minimum sum of perimeter (L_{MinSum}) can then be calculated. On the contrary, if the selected sites are separate from each other, the maximum sum of perimeter L_{MaxSum} then can be obtained.

According to these objectives of farmland protection, zoning protection problem can be formulated using the following equations:

$$\text{Maximize} \sum_i \text{Suit}_i x_i \tag{5}$$

$$\text{Minimize} \sum_i \text{Dev}_i x_i \tag{6}$$

$$\text{Maximize} \ \ C_p \tag{7}$$

$$\sum_i x_i = Q \tag{8}$$

$$x_i = \begin{cases} 1 & \text{if the site } i \text{ is included in the protection} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where Suit_i is the agricultural suitability of site i, C_p is the compactness index of a protected pattern, Dev_i is the development potential of site I, and Q is the total area of the protection. Obviously, zoning farmland protection is a typical multi-objective problem. Generally, a simple additive weighting method is employed to create a composite score for solving multi-objective problem. Accordingly, the objection function of farmland protection can be defined as follows:

$$\text{Utility} = w_\text{s} \times S_\text{f} - w_\text{d} \times D_\text{p} + w_\text{c} \times C_p \ \ \forall\, w_\text{s} + w_\text{d} + w_\text{c} = 1 \tag{10}$$

$$S_\text{f} = \frac{\sum_i \text{Suit}_i x_i}{Q} \tag{11}$$

$$D_\text{p} = \frac{\sum_i \text{Dev}_i x_i}{Q} \tag{12}$$

where S_f is the average total agricultural suitability; D_p is the average total development potential; w_s, w_d, and w_c are the weight of agricultural suitability, development potential, and compactness, respectively.

3.2. Zoning protected farmland by integrating AIS, remote sensing, and GIS

AIS is a heuristic algorithm that mimics immune theory to solve combinatorial optimization problems. Recently, AIS has been modified to simulate urban development and classify remote sensing data (Zhong *et al*. 2006, Liu *et al*. 2010). This article further modifies AIS algorithm to solve zoning protection problems. Figure 1 illustrates the procedure of zoning farmland protection by integrating remote sensing, GIS, and modified AIS. Remote sensing can be used to obtain the information of land use and urban development. GIS can provide the tools for the analysis of spatial data. AIS is designed to generate protected farmland based on agriculture suitability map and development potential map. The details of AIS algorithm for solving zoning protection problem are provided in the following sections.

3.2.1. Encoding and initialization of antibodies

An initial population of antibodies is generated randomly in a given bound for the zoning problem. Each antibody that represents a candidate solution is encoded by a binary

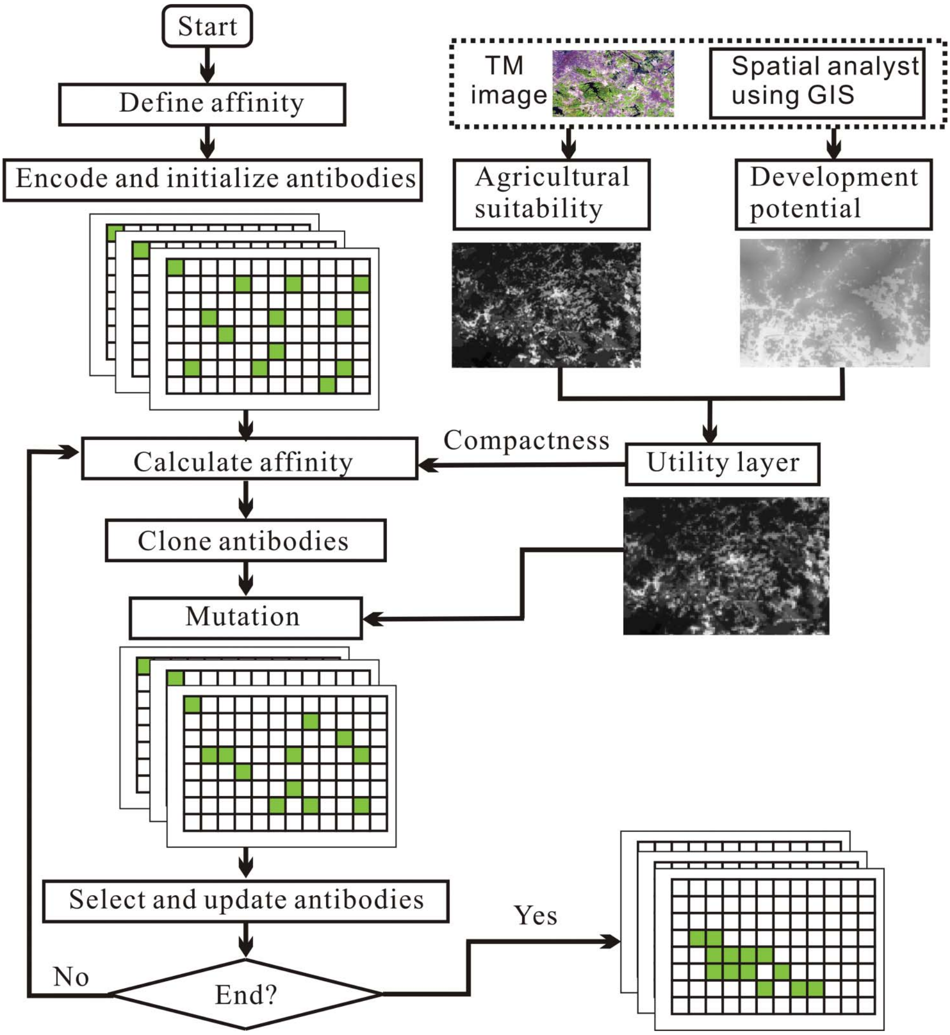

Figure 1. The procedure of zoning farmland protection by integrating GIS, remote sensing, and AIS.

two-dimensional array. In this article, the size of array is equal to the size of the study region ($R \times C$). As illustrated in Figure 2, if the cell is included in the protection, its code is assigned to 1. Otherwise, the code of cell is assigned to 0. At the start of the optimization, these two types of cells are randomly positioned in the study region ($R \times C$) for each antibody.

3.2.2. Clonal selection and mutation

In immunology, affinity is the fitness measurement for an antibody. For the zoning farmland problem, the affinity corresponds to the value of the objection function, Equation (10). The antibodies are ranked in descending order based on their affinity values. The *m* antibodies with the highest affinities are selected for the cloning operation. Each of these selected antibodies receives a number of copies proportional to its affinity. That is, the higher an antibody's affinity is, the more clones it will have. The total amount of clones generated

1	0	0	0	0
0	0	1	0	1
0	1	1	0	0
0	0	0	1	0
1	0	1	0	0

Figure 2. Encoding of antibodies for solving zoning problems. 1: protected farmland, 0: others.

for all these m selected antibodies is given by the following equation (Babayigit *et al.* 2008):

$$M_{\mathrm{c}} = \sum_{h=1}^{m} \mathrm{round}\left(\frac{\beta^{*} M}{h}\right) \tag{13}$$

where round(·) is the operator that rounds its argument toward the closest integer, M is the total number of antibodies, β is a multiplying factor to control the total number of antibodies of the new generation, and h is the antibody's current rank where $h \in [1,m]$, m being the number of selected antibodies for the cloning operation.

After cloning, the clones are mutated to increase their diversity. Mutation is an important operation in AIS algorithm. Mutation means that random changes take place in a region of the permutation. The mutation rate for an antibody is inversely proportional to the affinity of that antibody: the higher the affinity, the smaller the mutation rate. The mutation rate is given as follows:

$$\theta = \theta_0 \times \left(1 - \frac{A}{\mu}\right) \tag{14}$$

where A is the affinity of antibody. θ_0 and μ are constants to control the mutation rate.

In mutation operation, we randomly select a cell that is included in the protection. Then this cell will be exchanged with another cell that is not included in the protection. The number of cell swaps depends on the mutation rate – the higher the mutation rate, the more cells to be exchanged. After exchange of its sites, the affinity of antibody is calculated newly according to Equation (10). If the affinity is improved, the mutation operation is accepted. Otherwise, the mutation operation is accepted by a small probability:

$$\rho = \gamma \times \left|A_t^{*} - A_{t-1}^{*}\right| \tag{15}$$

where A_t^{*} is the total average affinity of antibodies at time t, A_{t-1}^{*} is the total average affinity of antibodies at time t – 1, and γ is a constant. Thus, if the total average affinity is stable, the mutation rate is very small.

The antibodies in the antibody library will gradually obtain increasingly higher affinities. This process is called affinity maturation, which generates a mature population C^{*}. Then, the individuals in population C^{*} with better affinities are selected to compose the memory set. Finally, those antibodies with low affinity in the initial population are replaced by the improved individuals of C^* to maintain the antibody diversity. The clonal selection and mutation processes repeat until a termination criterion is met or a predetermined generation number is reached.

4. Model implementation and results

4.1. Study area and spatial data

The proposed model was applied to zone protected farmland in Guangzhou, which has an area of 7434 km^2. Guangzhou is located at the center of the Pearl River Delta in Guangdong. The study area consists of 556 $\times$ 761 pixels, with a ground resolution of 200 m. With its combination of fertile soils, benign climate, and good irrigation status, the Pearl River Delta is one of the premier agricultural areas of China. However, because of rapid urban development and poor land management, a large amount of farmland has been converted into urban areas, especially in the metropolitan region of Guangzhou. There is an urgent demand to zoning protected farmland to ensure food security and sustain environmental quality.

Landsat TM images of Guangzhou in 2003 and 2008 were used to obtain the information about land use changes. The classified data reveal the fast farmland lost in this period and provide the empirical information for calibrating the CA model, which was used to simulate future distributions of urban areas. A 30 m DEM data is used to produce the slope data. Soil biophysical and chemical properties, including soil fertility, soil depth, and pH value, are obtained from Guangdong Institute of Eco-environment and Soil Sciences. Five proximity variables (distance to district, distance to towns, distance to railways, distance to expressways, and distance to roads) and density of urban land are used to produce the potential of urban development. All these spatial variables (factors) are converted into a raster format by using GIS (Figure 3).

4.2. Agricultural suitability and development potential analysis

One of the most important steps in the process of land use planning is suitability analysis, which determines whether the requirements of land use are adequately met by the properties of the land (Steiner *et al.* 2000). Suitability analysis involves a number of spatial variables (factors) that are used to evaluate the suitability score. Six factors are selected for agricultural suitability analysis, such as soil fertility, soil depth, pH value of soil, irrigation status, site condition, and slope. Five proximity variables and density of urban land are used to evaluate development potential. All these spatial variables (factors) are integrated into a raster-based GIS software and spatial analysis is performed using overlay techniques. Then, the relative weights of different factors are calculated by using the analytic hierarchy process, which is a theory of measurement through pairwise comparisons and relies on the experiences of experts to derive priority scales (Saaty 1990). Tables 1 and 2 provide these weights of different factors for agricultural suitability and development potential, respectively. Figure 4 demonstrates the final agricultural suitability and development potential map, which was produced by integrating these above spatial variables and weights through overlay techniques.

4.3. Results of protected farmland areas

The modified AIS model was used to generate farmland protection patterns. The required area for the preserved farmland is assumed to be 1123 km^{2}with reference to the strategic

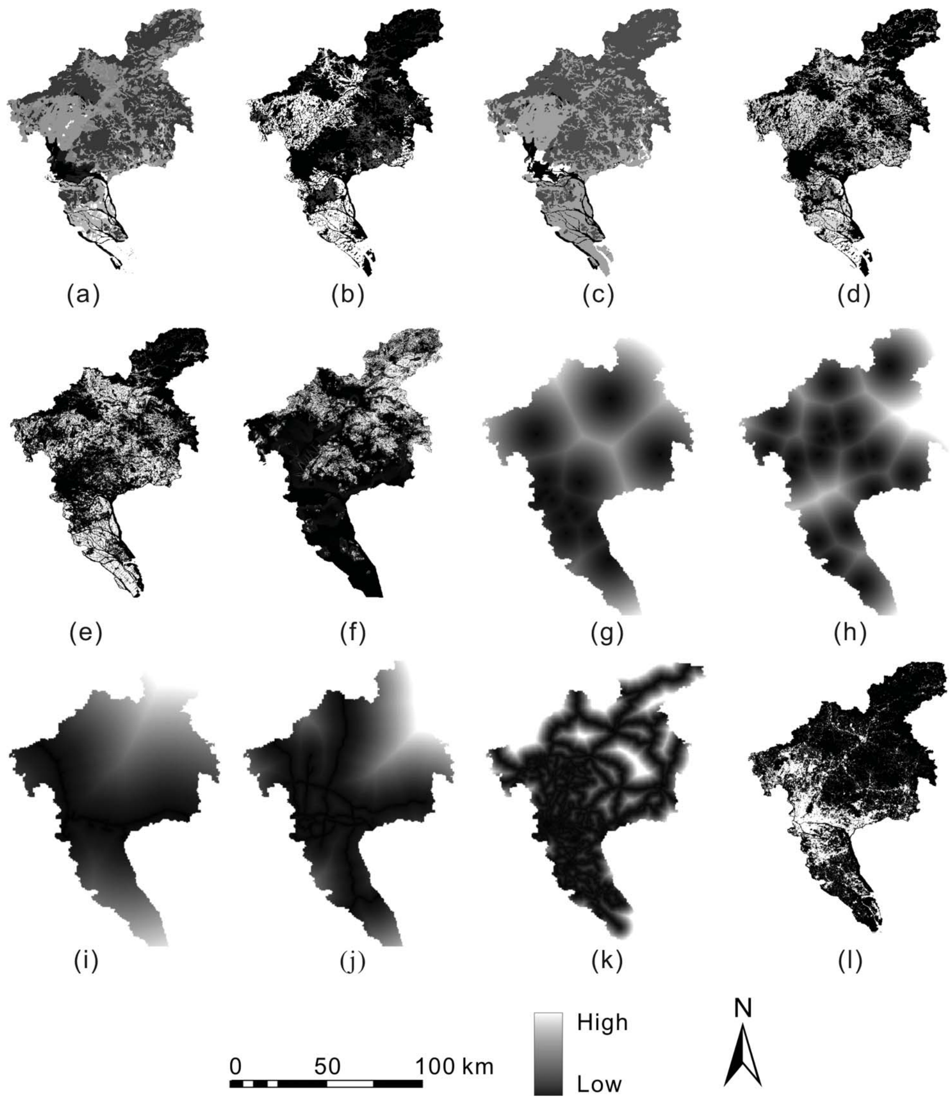

Figure 3. Various spatial variables for agricultural suitability and development potential analysis.

Table 1. Weights for calculating agricultural suitability.

Factors	Soil fertility	Soil depth	pH value	Irrigation status	Site condition	Slope
Weights	0.303	0.098	0.044	0.124	0.305	0.126

Table 2. Weights for calculating development potential.

Factors	D_{District}	D_{Towns}	D_{Railways}	$D_{\mathrm{Expressways}}$	D_{Roads}	ρ_{Urban}
Weights	0.055	0.142	0.082	0.235	0.402	0.084

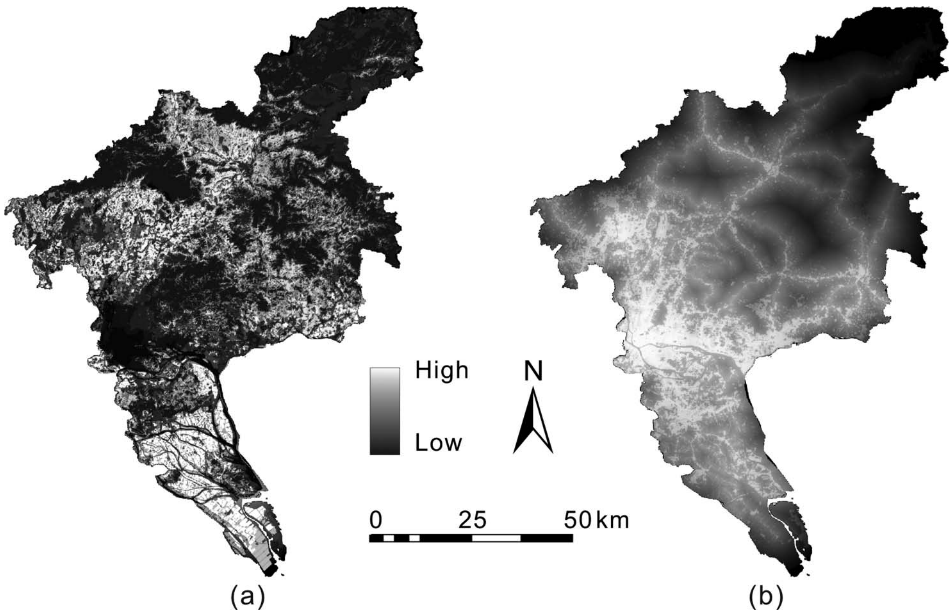

Figure 4. (a) Agricultural suitability and (b) development potential map of Guangzhou. (a) Soil fertility, (b) soil depth, (c) pH value, (d) irrigation status, (e) site condition, (f) slope, (g) distance to district, (h) distance to towns, (i) distance to railways, (j) distance to expressways, (k) distance to roads, and (l) density of urban land.

Table 3. Different sets of sub-objective weights used for zoning farmland protection.

Option	Agricultural suitability	Compactness	Development potential
A	1.00	0.00	0.00
B	0.75	0.25	0.00
C	0.50	0.50	0.00
D	0.25	0.75	0.00
E	0.50	0.25	0.25
F	0.25	0.25	0.50
G	0.25	0.50	0.25
H	0.34	0.033	0.33
I	0.75	0.00	0.25
J	0.40	0.20	0.40
K	0.20	0.40	0.40
L	0.40	0.40	0.20

planning of Guangzhou. This model can be used to generate alternative farmland protection patterns by using different combinations of weights for objectives in Equation (10) (Table 3).

Figure 5 illustrates the optimization process of farmland protection patterns by using AIS algorithm for option H. At the initial stage, farmland cells are randomly positioned in the study region. As the iteration continues, farmland cells are allocated to the sites with high agricultural suitability and low development potential. Furthermore, the formulated patterns become more and more compact. It is found that the protection pattern becomes stabilized when the iteration reaches about 200.

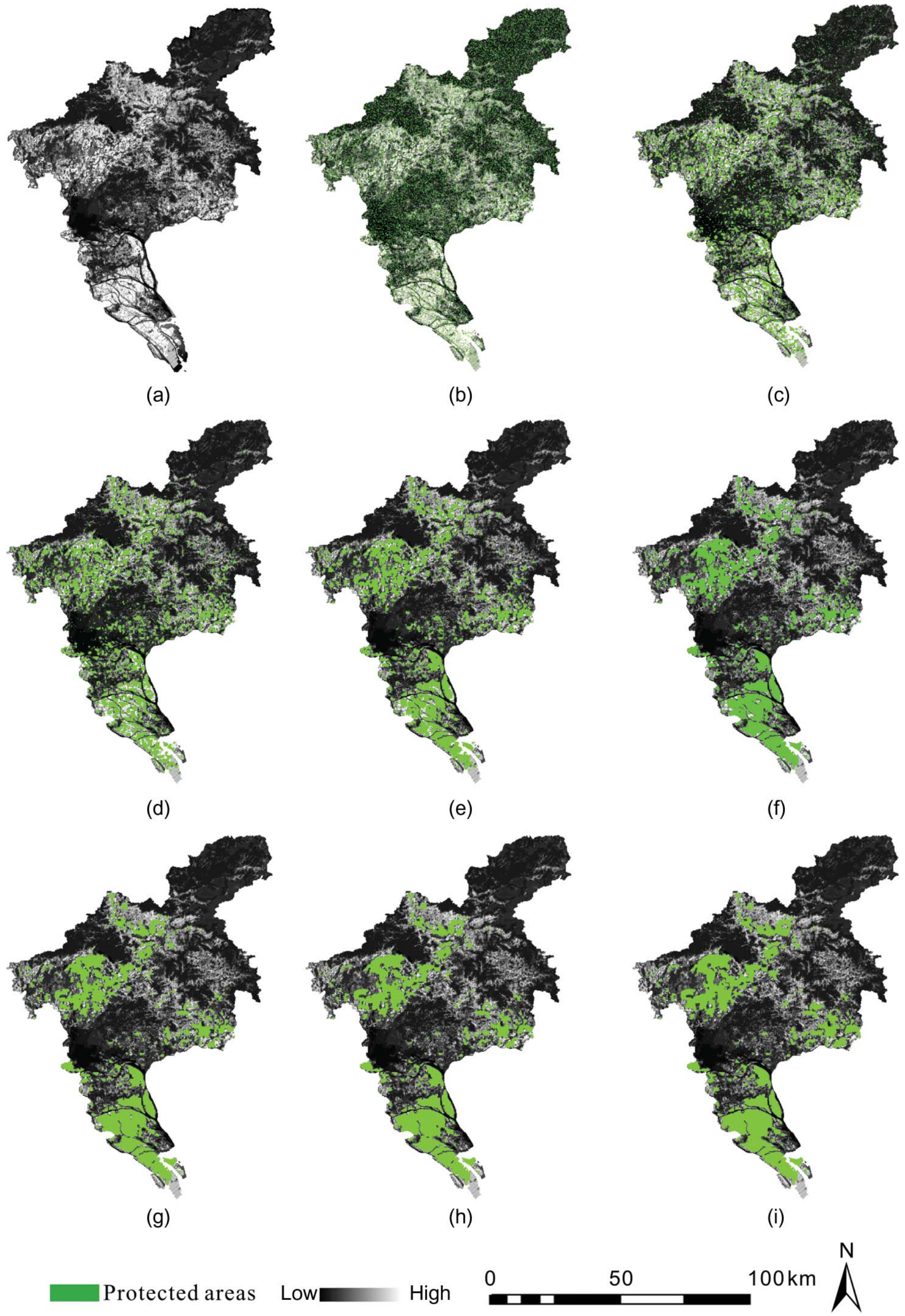

Figure 5. The optimization process of farmland protection patterns by using AIS-based zoning model. (a) Suitability, (b) $t = 0$, (c) $t = 5$, (d) $t = 10$, (e) $t = 20$, (f) $t = 50$, (g) $t = 100$, (h) $t = 200$, and (i) $t = 300$; t: iteration times.

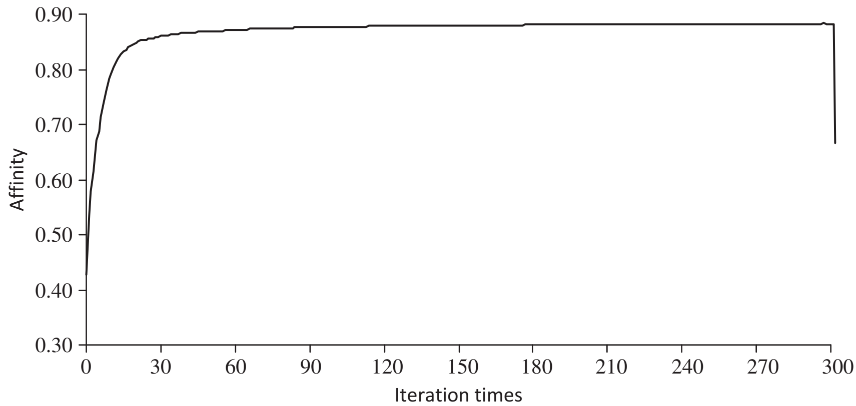

Figure 6. Affinity improvements with iterations by AIS algorithm.

As shown in Figure 6, the affinity will increase significantly at the initial stage. However, the affinity will become stabilized after the iteration is greater than 200, which indicates that the antibodies are matured. The optimization spends only about 194 seconds by using a computer with a Pentium IV 3.2 GHz CPU.

Figure 7 illustrates different optimal farmland protection patterns by using different combinations of weights (Table 3). It is obvious that the compactness factor plays an important role in deriving a feasible protection zone. The first combination is an extreme case that does not take into account the compactness factor and development potential. As a result, the optimal pattern (Figure 7a) is very fragmented because the compactness factor is not included in the objective function. Figure 7b–d is the optimal pattern based on both agricultural suitability and compactness. With the increase in the value of parameter w_c, the patterns become more and more compact. However, the increase of the compactness is at the cost of agricultural suitability (Table 4). Figure 7e–h and j–l are the optimal patterns by considering the trade-off between the agricultural suitability, compactness, and development potential. It is found that the option H can generate a satisfactory protection pattern according to the visual interpretation and comparison of the trade-off (Table 4). The optimal solutions involving a weighted combination of agricultural suitability and development potential are illustrated in Figure 7i. Note that in these solutions, with not considering compactness factor, the optimal pattern is fragmented. As w_d increases, development potential factor becomes more important; the optimal solution allocates farmland where development potential is lower (Table 4).

A further experiment was carried out to compare the performances of the modified AIS model with those of the iterative relaxation (IR) (Eastman *et al*. 1995) and the density slicing (DS) (Li and Yeh 2001). These two methods are applied to the same dataset by using the defined weights in the option H so that the performance can be compared with that of the AIS-based model. As shown in Figure 8 and Table 5, the AIS-based model can generate protected areas with the maximum utility value and compact pattern. The DS method generates the fragmented protected areas with minimum utility value. The performance of IR method is better than that of the DS method, but its spatial pattern is less compact than that of the modified AIS model.

4.4. Estimating the impact of future urban growth on farmland

Future urban growth impacts farmland in two ways. First, urbanized cells will be lost to agriculture forever. Second, the high proportion of urban in neighboring areas for

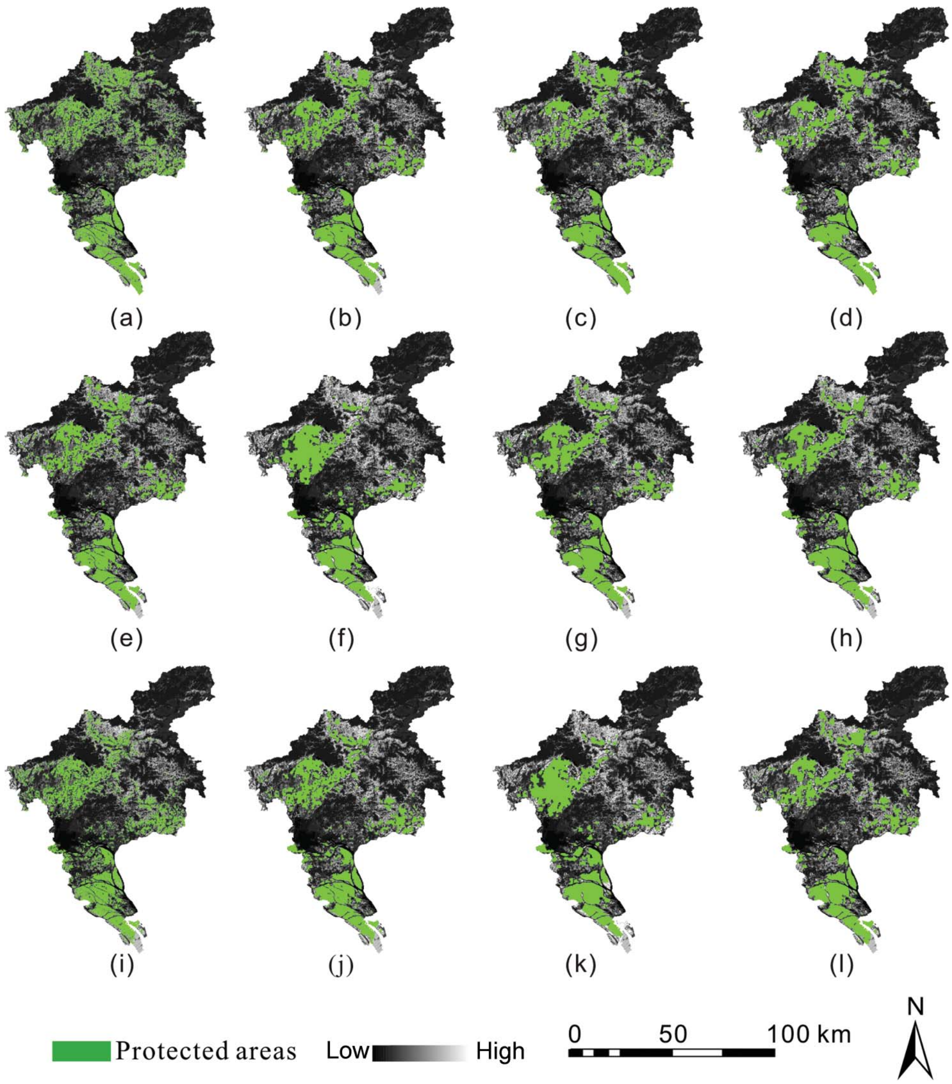

Figure 7. The optimal farmland protection patterns obtained by using AIS method with various weighting scheme options.

remaining farmland will reduce site condition. In this article, we used a Geographical Simulation and Optimization System (GeoSOS) to simulate the spatial pattern of urbanization in 2040 with different optimal farmland protection patterns. GeoSOS is equipped with a number of urban simulation modules that can be used to simulate urban dynamics. The implementation of urban simulation is very convenient by using GeoSOS. The software can be downloaded from http://www.geosimulation.cn. Urban areas in 2003 (Figure 9a) and 2008 were used to provide the empirical information for calibrating the CA model. We selected the module of logistic-CA in GeoSOS to simulate the distribution of urban areas in 2040 without farmland protections. The logistic-CA model is developed by Wu (2002) and applied to simulate rural–urban land conversions in Guangzhou. Figure 9b and c are the simulated urban areas in 2008 and 2040, respectively, by using logistic-CA model. A confusion matrix was calculated to quantify the concordance between the simulated and

Table 4. Total suitability, compactness, and total potential with different sets of weights.

Option	Total suitability	Compactness	Total potential
A(1,0,0)	22,290	0.7107	6742
B(0.75,0.25,0)	20,936	0.9244	5864
C(0.5,0.5,0)	20,912	0.9294	6554
D(0.25,0.75,0)	20,811	0.9345	6657
E(0.5,0.25,0.25)	21,165	0.9098	5892
F(0.25,0.25,0.5)	18,783	0.9483	4441
G(0.25,0.5,0.25)	20,183	0.9425	5388
H(0.34,0.33,0.33)	20,277	0.9386	5383
I(0.75,0,0.25)	22,199	0.7157	6250
J(0.40,0.20,0.40)	20,708	0.9165	5407
K(0.20,0.40,0.40)	18,768	0.9501	4456
L(0.40,0.40,0.20)	20,672	0.9334	5824

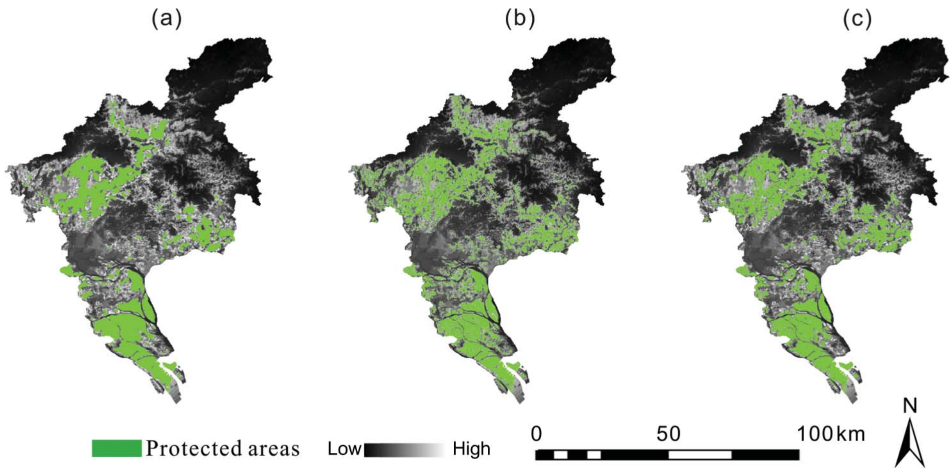

Figure 8. Protected farmland areas using (a) modified AIS, (b) DS, and (c) IR methods.

Table 5. Comparison of performances between AIS, DS, and IR methods.

	Modified AIS	DS	IR
Compactness	0.9386	0.71512	0.8064
Utility value	0.8228	0.7633	0.7898

the actual development patterns (Table 6). The matrix reveals that the total accuracy of the simulation is 82.4%, which means that the simulated image in 2040 is reliable.

Furthermore, different optimal farmland protection patterns are regarded as a constraint factor for the CA model. By inputting different zoning patterns (Figure 7), the CA model will generate different scenarios of urban development (Figure 10). We overlaid the simulated spatial patterns on the distribution of farmland map and the suitability map to identify where farmland will be lost, and estimate the loss of agricultural suitability value. According to Equation (1), site condition for remaining farmland was recomputed based on different scenarios of urban development. The agricultural suitability loss can be calculated using the following equation:

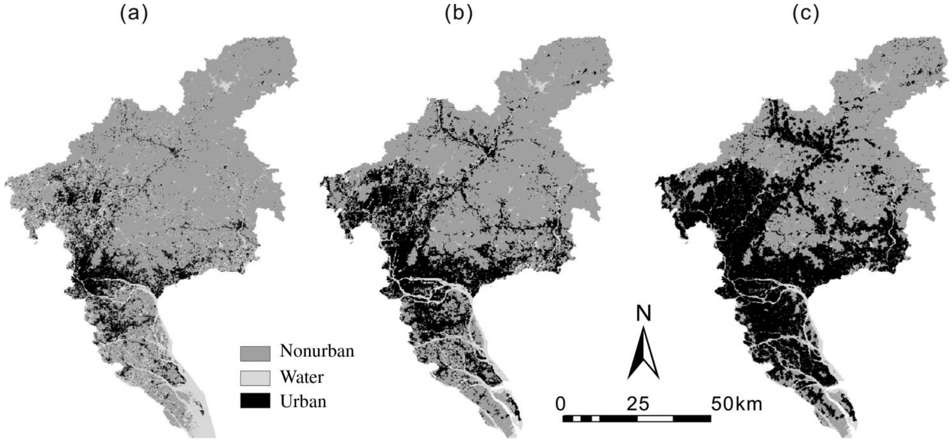

Figure 9. Simulated urban areas in 2008 and 2040, respectively. (a) 2003 (original image), (b) 2008, and (c) 2040.

Table 6. Simulation accuracies of the logistic-CA model for Guangzhou.

	Simulated 2008 nonurban	Simulated 2008 urban	Accuracy
Actual 2008 nonurban	481,322	70,432	87.2%
Actual 2008 urban	57,981	120,186	67.5%
Total accuracy			82.4%

$$A_{\mathrm{loss}} = \sum_i S_{\mathrm{ag}}(i) \tag{16}$$

where A_{loss} is the agricultural suitability loss and $S_{\mathrm{ag}}(i)$ is the agricultural suitability at cell i where land development will take place in the future (2008–2040).

To better evaluate the utility efficiency of land resources, the benefit index is further proposed, which can be calculated by the following equation:

$$S_{\mathrm{B}} = \sum_i (S_{\mathrm{dev}}(i) - S_{\mathrm{ag}}(i)) \tag{17}$$

where S_{B} is the benefit index. $S_{\mathrm{dev}}(i)$ and $S_{\mathrm{ag}}(i)$, respectively, refer to the development potential and agriculture suitability at cell i where land development will take place in the future (2008–2040).

Table 7 shows agricultural suitability loss, benefit index, average site condition, and reduced site condition for urban simulations based on different optimal farmland protection patterns. The nonprotection scenario has the largest values for the indicators of agricultural suitability loss because a large amount of farmland is converted into urban land. Agricultural suitability is lost in a large block south of Guangzhou (Figures 7 and 8c). Benefit index for the nonprotection scenario is lowest because agricultural suitability loss is larger than that of other development scenarios. It is obvious that the development scenario with option A has the lowest values for agricultural suitability loss, because this scenario tends to focus on preserving farmland with high agricultural suitability. However, its benefit index is also low. The development scenario with option C obtains the largest value

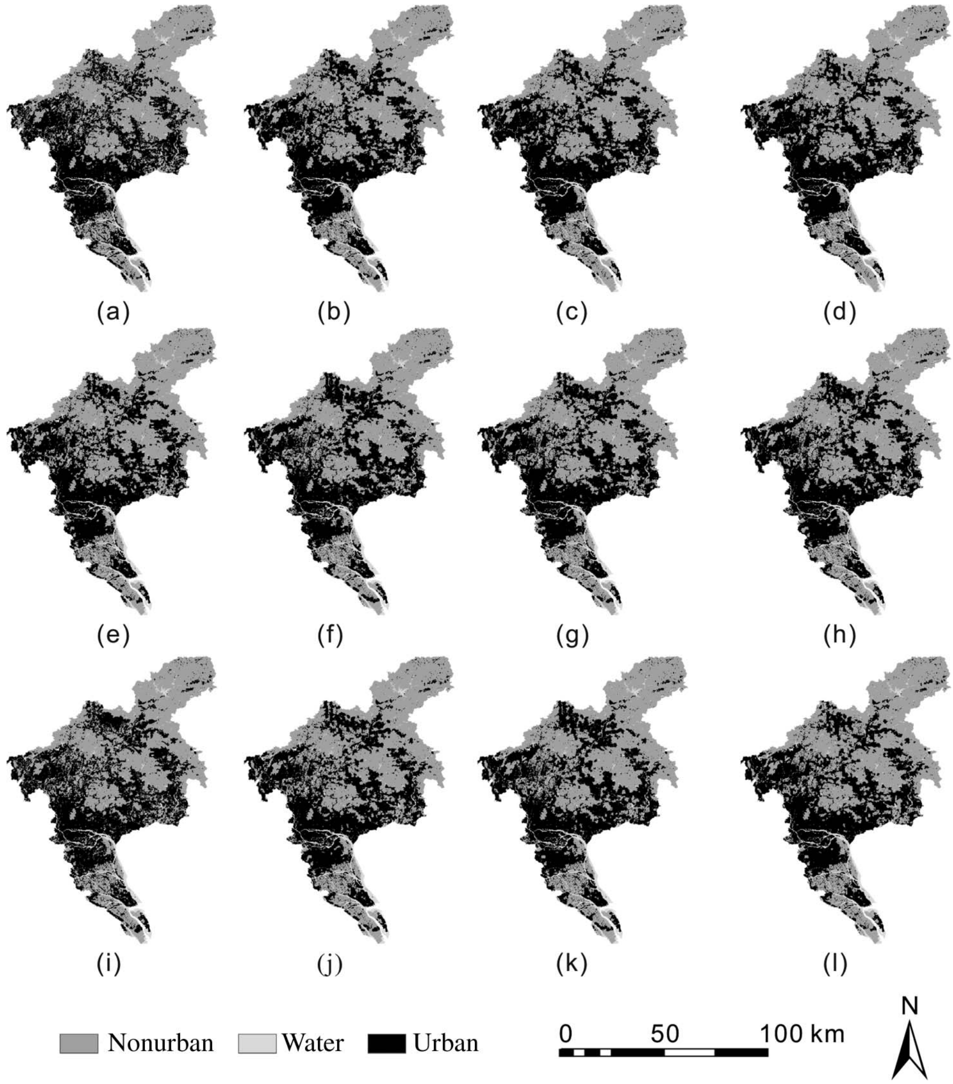

Figure 10. Urban simulations based on various optimal farmland protection patterns.

of benefit index. By 2040, farmland is predicted to have reduced site condition because of urban growth, especially in nonprotection development scenario. The development scenario with option L has the largest value of average site condition, and its reduced site condition is small.

5. Conclusion

Establishing farmland protection areas is an important measure for the Chinese government to protect limited land resource and guarantee food security. This article proposed a scientific, effective, and flexible method to zone farmland protection under spatial constraints by integrating GIS, remote sensing, and AIS. Remote sensing data are capable of

Table 7. Agricultural suitability loss, benefit index, average site condition, and reduced site condition with different development scenarios.

Option	Agricultural suitability loss	Benefit index	Average site condition	Reduced site condition
A(1,0,0)	17,276	24,891	0.1251	0.1194
B(0.75,0.25,0)	18,496	25,332	0.1255	0.1190
C(0.5,0.5,0)	18,520	25,751	0.1272	0.1173
D(0.25,0.75,0)	18,628	25,672	0.1264	0.1181
E(0.5,0.25,0.25)	18,369	25,404	0.1256	0.1189
F(0.25,0.25,0.5)	19,290	24,306	0.1192	0.1253
G(0.25,0.5,0.25)	18,867	24,800	0.1229	0.1216
H(0.34,0.33,0.33)	18,818	24,825	0.1228	0.1217
I(0.75,0,0.25)	17,907	25,507	0.1201	0.1244
J(0.40,0.20,0.40)	19,186	24,276	0.1152	0.1293
K(0.20,0.40,0.40)	19,334	24,254	0.1183	0.1262
L(0.40,0.40,0.20)	18,501	25,424	0.1273	0.1172
Nonprotection	21,901	23,955	0.0999	0.1446

obtaining the information of land use and urban development. GIS is used to overlay spatial variables to make a composite map that acts as an agricultural suitability and development potential map. Zoning farmland protection under spatial constraints belongs to the NP-hard class because of a huge combinatorial solution space. It is impossible to solve such difficult problems in a reasonable amount of time by using exact enumeration method. As a heuristic method, AIS has been proved to be effective algorithm for solving complex combination optimization problems. In this article, AIS is designed to generate farmland protection areas based on agricultural suitability and development potential map. We make some contributions in five aspects by extending AIS to the solution of farmland protection problems. These contributions include the following: (1) An innovative and scientific framework is proposed to support farmland preservation programs in developing countries. (2) Utility function by addressing the criteria of farmland protection is incorporated into AIS algorithm. (3) Encoding and mutation of antibodies is modified so that it can be suited to the solution of spatial optimization problems. (4) Spatial constraints are taken into account for farmland protection. This can avoid generating fragmented patterns. (5) It is important for collaborative planning processes in which planners can explore and evaluate alternatives. The proposed AIS-based zoning model offers opportunities to generate different optimal farmland protection patterns by altering the weights of sub-objectives.

The AIS-based zoning model was applied to the zoning farmland protection in Guangzhou, a rapidly urbanizing region. This large region consists of 556×761 cells. The objective is to generate an optimal allocation pattern that minimizes development potential and maximizes agricultural suitability and compactness. This problem requires a large amount of computation time to solve by using the mathematical optimization method. However, the proposed model took only about 194 seconds to generate satisfied farmland protection patterns. Furthermore, the application shows that the AIS-based zoning model can explore various alternatives conveniently.

A logistic-CA mode is then used to simulate urban development without farmland protections. The experiment shows that simulated Guangzhou growth under current development trend without farmland protection will lead to the loss of a great amount of farmland. Furthermore, we simulate the spatial pattern of urbanization in the future with different optimal farmland protection patterns. The simulated results indicate that the farmland protection measure can preserve farmland with high agricultural suitability. Moreover, farmland protection will obtain better results in the utility efficiency of land resources and the site condition for farmland.

Acknowledgements

This study was supported by the National Basic Research Program of China (973 Program) (Grant No. 2011 CB707 103), the National Natural Science Foundation of China (Grant No. 40901187) and the Key National Natural Science Foundation of China (Grant No. 40830532).

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