A grey wolf optimizer–cellular automata integrated model for urban growth simulation and optimization: GWO–CA integrated model for urban growth

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A grey wolf optimizer–cellular automata integrated model for urban growth simulation and optimization

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Abstract

This article proposes a grey wolf optimizer (GWO) and cellular automata (CA) integrated model for the simulation and spatial optimization of urban growth. A new grey wolf-inspired approach is put forward to determine the urban growth rules of CA cells by using the GWO algorithm, which is suitable for solving optimization problems. The inspiration for GWO comes from the social leadership of wolf groups, as well as their hunting behavior. The GWO-optimized urban growth rules for CA describe the relationship between the spatial variables and the urban land-use status for each cell in the formation of "if–then." The GWO algorithm and CA model are then integrated as the GWO–CA model for urban growth simulation and optimization. By taking Nanjing City as an example, the simulation accuracy in terms of urban cells is 86.6%, and the kappa coefficient is 0.715, indicating that the GWO algorithm is efficient at obtaining urban growth rules from spatial variables. The validation of the GWO–CA model also illustrates that it performs well in terms of the simulation and spatial optimization of urban growth, and can further contribute to urban planning and management.

1 | INTRODUCTION

Urbanization promotes an increasing number of people living and working in cities (Cao, Huang, Wang, & Lin, 2012; Cohen, 2015). Urban expansion has created a series of social, economic, and environmental changes on both local and global scales (Huang, Zhang, & Wu, 2009; Wu, Zhao, Zhu, & Jiang, 2015; Zhang et al., 2014). Studies on the process of urban growth could help us understand urbanization and its impacts on the pattern of urban land use. Urban growth modeling not only explores the process of urbanization, continues the driving force analysis, and forecasts ecological consequences, but also helps to provide strong support for increasingly complex urban planning and management strategies (Li & Gong, 2016).

Urban growth modeling is an important method of urban land-use optimization, which is considered complicated because the decisions on land-use allocation must be made with respect to not only what activities to select, but also how much land to allocate to each and where to allocate the land (Cao et al., 2011; Cao, 2018). Thus far, many optimization algorithms have been employed to deal with land-use optimization problems, for example: the Tabu search algorithm (Qi, Altinakar, Vieira, & Alidaee, 2010), simulated annealing algorithm (Santé-Riveira, Boullón-Magán, Crecente-Maseda, & Miranda-Barrós, 2008), genetic algorithm (Cao et al., 2011, 2012; Cao & Ye, 2012; Li & Parrott, 2016), particle swarm optimization algorithm (Masoomi, Mesgari, & Hamrah, 2013), ant colony optimization algorithm (Liu, Li, Shi, Huang, & Liu, 2012), bee colony algorithm (Yang, Sun, Peng, Shao, & Chi, 2015), and hybridization of these algorithms (Mohammadi, Nastaran, & Sahebgharani, 2016). Spatial optimization methods in urban growth modeling are commonly based on the cellular automata (CA) model, which coincides with the complex theory in which macroscale and global patterns can be generated from the microscale by local interactions of individual cells (Almeida, Gleriani, Castejon, & Soares-Filho, 2008; Cao, Huang, Li, & Li, 2014; Li, Liu, & Yu, 2014; Lin, Huang, Chen, & Huang, 2014; Liu et al., 2014; Li, Chen, Liu, Liang, & Wang, 2017; Liu, Liang, Li, Xu, & Ou, 2017).

The transition rules, which determine the conversion of land-use status during the process of urban expansion, are a critical part of CA models in urban growth modeling. The goal of defining transition rules is to obtain urban growth rules from the large number of spatial variables, which are often hidden within a large collection of GIS data and remote-sensing images. In addition, to the extent that the transition rules of modeling urban growth reflect the objective causes and inner mechanisms of urban growth, the urban growth rules influence the development trends and spatial pattern of a city. Hereafter, the transition rules of CA refer to the urban growth rules. These urban growth rules mainly have two forms: formulaic and non-formulaic. For the former, the urban growth rules are defined via mathematical equations involving parameter estimation problems (Cao, Tang, Shen, & Wang, 2015). For the latter, the urban growth rules indicate complex nonlinear relationships between spatial variables and urban growth in the form of "if–then" statements. These urban growth rules in the form of "if–then" statements are clearer and make it easier for people to understand the process of urban expansion.

In recent years, swarm intelligence (SI) methods have gained increasing popularity for effectively obtaining CA transition rules. These kinds of intelligent algorithms have become very popular over the past two decades because they have the advantages of flexibility, simplicity, mechanism of free derivation, and avoiding the local optimum (Mirjalili, Mirjalili, & Lewis, 2014). These algorithms derive from the burst collective intelligence of simple agent groups (Bonabeau, Dorigo, & Theraulaz, 1999) and are often inspired by natural swarm behaviors of social animals, such as ants, birds, fish, and fireflies. A variety of SI algorithms have been employed to derive the transition rules, such as particle swarm optimization (Feng, Liu, Tong, Liu, & Deng, 2011; Liao et al., 2014), ant colony optimization (Liu, Li, Liu, He, & Ai, 2008; Liu, Li, Yeh, He, & Tao, 2007), simulated annealing (Feng & Liu, 2013), artificial bee colony (Yang, Tang, Cao, & Zhu, 2013), cuckoo search (Cao et al., 2015), and bat algorithms (Cao, Bennett, Shen, & Xu, 2016).

However, these SI algorithms still have some limitations, as follows: (1) Although some algorithms offer positive feedback that can help to rapidly explore the solution and avoid premature convergence by distributed computation, they still lack a centralized processor to guide them toward good solutions and are not efficient when dealing with large amounts of data due to their large search spaces (Agrawal, Kaur, Kaur, & Dhiman, 2012; Selvi & Umarani, 2010); (2) Some algorithms have high mobility in terms of particles converging rapidly in global searches, but they also exhibit reduced convergence speeds in local searches and even cause premature convergence to a local Pareto-optimal front (Bai, 2010; Chang & Yu, 2013); and (3) Occasionally, the algorithm has great flexibility for two parameters, but requires many new parameter fitness tests and function assessments to improve performance (Abu-Mouti & El-Hawary, 2012; Karaboga, Gorkemli, Ozturk, & Karaboga, 2014). (4) Some algorithms behave like multimodal objective functions with fewer parameters. However, these algorithms occasionally lack sensitivity in terms of the convergence rates of the parameters (Yang & Deb, 2013). Research should be conducted on truly novel algorithms with a better balance of exploration and exploitation (Yang, 2014).

A new, efficient, nature-inspired algorithm, termed the grey wolf optimizer (GWO), imitates the rigid social hierarchy of grey wolves and their natural hunting mechanism. Agents are rigidly divided into different levels of a hierarchy, where they play different roles in the process of finding the optimal solutions for prey. The GWO algorithm and its new variants have been widely used in different areas, including dispatch problems (Jayabarathi, Raghunathan, Adarsh, & Suganthan, 2016; Sulaiman, Mustaffa, Mohamed, & Aliman, 2015), vehicle path planning (Zhang, Zhou, Li, & Pan, 2016), and scheduling problems (Komaki & Kayvanfar, 2015). The GWO is not only a stochastic operator helping to search the search space both randomly and globally in the phases of exploration, but also has the exploitation capability of local search around the up-and-coming area obtained in the phases of exploration. At the same time, the adaptive parameters in GWO are advantageous for promoting a balanced development of exploration and exploitation.

Despite its widespread application, the GWO algorithm has not been reported to obtain the urban growth rules for CA that are used in simulation and optimization of urban expansion. As a matter of fact, discovering the urban growth rules for CA is equivalent to an optimization problem. The GWO algorithm, with inspiration from the collective intelligence of groups of simple wolf agents, is a “bottom-up” method that performs complicated tasks through full cooperation among grey wolves. This “bottom-up” idea may enable GWO to discover the optimized urban growth rules for CA. The purpose of this article is to explore the feasibility of applying the GWO algorithm to obtain the urban growth rules of CA for urban growth simulation.

In this article, a GWO–CA integrated model is put forward for simulation and optimization of urban expansion. The remainder of the article is structured as follows. In Section 2, the city growth rules for CA are constructed and expressed as the optimal solutions in GWO. Then, GWO methods are designed to discover the city expansion rules. The GWO–CA integrated model is presented in Section 3. By taking Nanjing City as an example, the proposed GWO–CA model is employed for urban growth simulation and spatial optimization, and model validation for the simulated results is depicted in Section 4. Finally, Section 5 describes our conclusions and indicates some possible future work.

2 | DISCOVERING CITY GROWTH RULES BY GWO

2.1 | General idea of the grey wolf optimizer

Grey wolves always like living in family groups with a rigid social dominance hierarchy. To formulate the theoretical social hierarchy, the population of grey wolves is split into four groups: (1) The leaders, called alphas (α), are mainly in charge of decision-making in terms of hunting, place to sleep, time to wake, etc; (2) The second level, called betas (β), have a lower position and less authority than alphas and often provide decision support for alphas; (3) The third level, called deltas (δ), have to obey alphas and betas. Deltas include hunters, scouts, elders, caretakers, and sentinels; and (4) The lowest-ranked grey wolves are omegas (ω). The role of scapegoat has always fallen to the omegas; they have to obey all other categories of wolves (Mirjalili et al., 2014).

In addition to the rigid social hierarchy, GWO also mimics the hunting behavior of grey wolves and has another interesting characteristic. The group hunting of wolves includes the following major phases (Muro, Escobedo, Spector, & Coppinger, 2011): (1) tracking, chasing, and approaching the prey very closely; (2) pursuing, surrounding, and harassing the prey until it stays where it is; and (3) attacking the prey.

The mathematical GWO algorithm is designed and implemented by imitating the group hunting behavior and leadership hierarchy of grey wolves. Related studies have shown that the high level of exploration involved in the GWO algorithm helps it to avoid local optima. Additionally, the ability to seek a good balance between exploration and exploitation makes GWO advantageous for addressing challenging and complex issues in accordance with actual results (Mirjalili et al., 2014).

2.2 | Expressing city growth rules in GWO

Studies have shown that the impact factors for urban growth can be described by a large number of spatial variables such as distance, neighbors, and some physical properties (Cao et al., 2016). In this study, the GWO algorithm is employed to discover optimal urban growth rules from the spatial variables by simulating the social behavior of grey wolves, including hierarchy and group hunting. During the optimization process, the urban land-use space is presented in the form of raster datasets. Each pixel corresponds to a cell with a series of attribute conditions, which are used to describe the spatial variables that affect the probability of urban growth. The cell status indicates the type of the current cell during the process of urban growth. When the cell is developed into urban, the cell status will be assigned as 1; otherwise, the cell status will be assigned as 0. In the CA model, the next status value of the center cell is determined according to the current attribute conditions of the center and neighbor cells.

The minimum and maximum thresholds of the attribute condition constitute the attribute condition item. The GWO algorithm is utilized to seek the optimal minimum and maximum thresholds for the attributes. Grey wolves can find the optimal link between the attribute condition items and a cell status item. Each link, shown in Figure 1, relates to an urban growth rule of CA. The process of deriving an urban growth rule can be viewed as seeking the optimal link between the attribute condition items and a cell status item, that is, seeking the optimal minimum and maximum thresholds for the attribute conditions. This explicit representation of the transition rules makes them easy to understand and implement in urban land-use planning.

2.3 | GWO method to discover city growth rules

In the mathematical model, if there are *n* grey wolves and *k* cell attributes, then the solution for the *i*th grey wolf is expressed as $A_i = (A_i^{1low}, A_i^{1up}, A_i^{2low}, A_i^{2up}, \ldots, A_i^{klow}, A_i^{kup})$. An optimal solution refers to one urban growth rule. Each

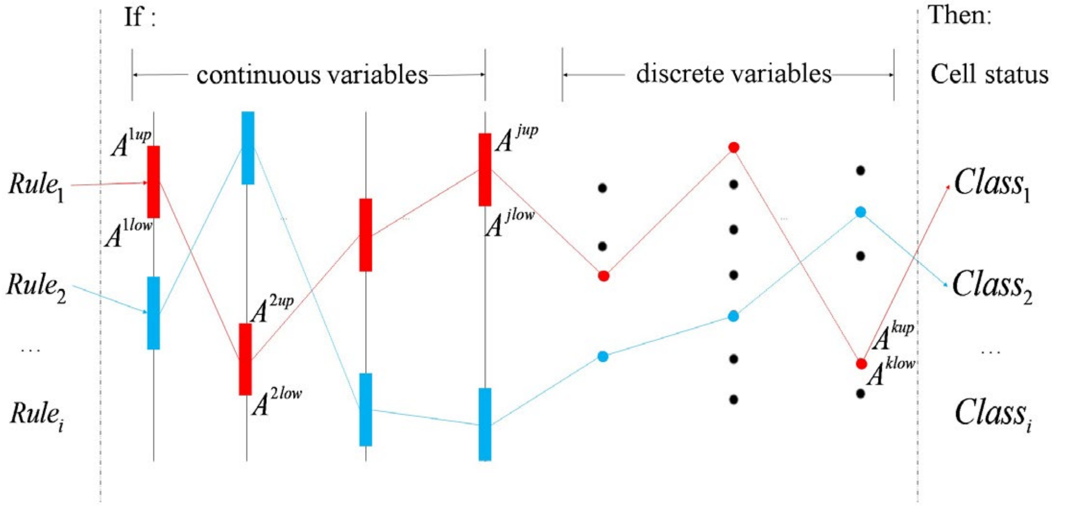

FIGURE 1 Schematic diagram of urban growth rules

grey wolf aims to seek the optimal solution, including minimum (A_i^{klow}) and maximum (A_i^{kup}) thresholds for all attribute conditions, by changing its position. The GWO algorithm is characterized by dimensional equivalence. In this study, all the spatial variables are normalized within the same range between 0 and 1. The process of obtaining the urban growth rules for CA by using the GWO algorithm is summarized in the following key steps.

(1) Solution initialization: initialize a group of n grey wolves $A = \{A_1, A_2,..., A_i,..., A_n\}$, where A_i is the initial solution value of the ith grey wolf. A_i consists of the minimum threshold (A_i^{jlow}) and maximum threshold (A_i^{jup}), which are represented by Equation (1):

$$\begin{cases} A_i^{jlow} = A_{min}^j + rand(0,1)(A_{max}^j - A_{min}^j) \\ A_i^{jup} = A_i^{jlow} + rand(0,1)(A_{max}^j - A_i^{jlow}) \end{cases} \tag{1}$$

where A_i^{jlow} and A_i^{jup} are the optimal ranges, including the minimum and maximum of the ith grey wolf solution vector for the jth attribute condition, $i = (1,2,...,n)$, $j = (1,2,...,k)$; A_{min}^j and A_{max}^j are the minimum and maximum of the jth attribute; and $rand(0,1)$ is a randomly generated value between 0 and 1.

Then, the corresponding objective function value of the initial urban growth rule of each wolf solution is calculated to determine the current global best rule. The objective function of Gini index formulas is shown in Equation (2), which is beneficial for guiding the optimal orientation (Liu et al., 2007):

$$f = \left(\frac{TP}{TP \times FN}\right) \times \left(\frac{TN}{FP \times TN}\right) \tag{2}$$

where TP and FP are the counts for the samples that conform to the urban growth rule and have the same and different cell statuses, respectively, as determined by the rule; FN and TN are the counts of the samples that do not conform to the urban growth rule and have the same and different cell statuses, respectively, as determined by the rule.

(2) Encircling prey: according to the rigid social hierarchy, set the leader alphas, the second-level betas, and third-level deltas of the grey wolves. Omega wolves are assumed to be candidate solutions, which follow all the other categories of wolves. The encircling behaviors for hunting are mathematically modeled as follows (Mirjalili et al., 2014):

$$\vec{D} = \left|\vec{C}.\overrightarrow{A_p}(t) - \vec{A}(t)\right| \tag{3}$$

$$\vec{A}(t+1) = \overrightarrow{A_p}(t) - \vec{B}.\vec{D} \tag{4}$$

where $\overrightarrow{A_p}(t)$ is the solution vector of prey p at iteration t; $\vec{A}(t)$ is the solution vector of an agent at iteration t; $\vec{B}$ and $\vec{C}$ are coefficient vectors calculated by Equations (5) and (6):

$$\vec{B} = 2\vec{a}.\overrightarrow{r1} - \vec{a} \tag{5}$$

$$\vec{C} = 2.\overrightarrow{r2} \tag{6}$$

where $\vec{a}$ is reduced linearly from 2 to 0 during the iteration and $r1$, $r2$ are randomly generated on [0,1]. The wolves are enabled to reorient to any solution within the space near the prey due to the random $\vec{B}$ and $\vec{C}$.

(3) Hunting: based on encircling prey at the current best positions of α, β, and δ wolves, the ω grey wolves are arranged to obtain the renewal of the solutions (Figure 2). Thus, α, β, and δ wolves are responsible for estimating the prey position, and ω wolves obtain the new positions at random surrounding the prey. The ultimate solution is located randomly around the α, β, and δ wolves.

The solutions for the ω wolves are updated with reference to the α, β, and δ wolves. The solutions for the ω wolves are adjusted by using the following three formulas (Mirjalili, 2015; Mirjalili et al., 2014):

$$\overrightarrow{D\alpha} = \left|\overrightarrow{C1}\,.\,\overrightarrow{A\alpha} - \vec{A}\right|, \overrightarrow{D\beta} = \left|\overrightarrow{C2}\,.\,\overrightarrow{A\beta} - \vec{A}\right|, \overrightarrow{D\delta} = \left|\overrightarrow{C3}\,.\,\overrightarrow{A\delta} - \vec{A}\right| \tag{7}$$

$$\overrightarrow{A1} = \overrightarrow{A\alpha} - \overrightarrow{B1}\,.\,\left(\overrightarrow{D\alpha}\right), \overrightarrow{A2} = \overrightarrow{A\beta} - \overrightarrow{B2}\,.\,\left(\overrightarrow{D\beta}\right), \overrightarrow{A3} = \overrightarrow{A\delta} - \overrightarrow{B3}\,.\,\left(\overrightarrow{D\delta}\right) \tag{8}$$

$$\vec{A}(t+1) = \frac{\overrightarrow{A1} + \overrightarrow{A2} + \overrightarrow{A3}}{3} \tag{9}$$

where $\overrightarrow{A\alpha}$, $\overrightarrow{A\beta}$, and $\overrightarrow{A\delta}$ show the position vectors of the α, β, and δ, respectively; $\overrightarrow{C1}$, $\overrightarrow{C2}$, $\overrightarrow{C3}$, $\overrightarrow{B1}$, $\overrightarrow{B2}$, and $\overrightarrow{B3}$ denote the random vectors; $\vec{A}$ denotes the current position vector; $\overrightarrow{D\alpha}$, $\overrightarrow{D\beta}$, and $\overrightarrow{D\delta}$ indicate the approximate distances from $\vec{A}$ to α, β, and δ, respectively, that is, the step length of ω toward α, β, and δ, respectively; $\overrightarrow{A1}$, $\overrightarrow{A2}$, and $\overrightarrow{A3}$ are the updated position vectors guided by α, β, and δ, respectively; and $\vec{A}(t+1)$ denotes the final updated position vector of ω at the next iteration.

If the end criterion is satisfied, then a return to the position of the alpha wolf is the best solution. Otherwise, parameters are updated, and the process returns to step (2). During the iteration process, the parameters of

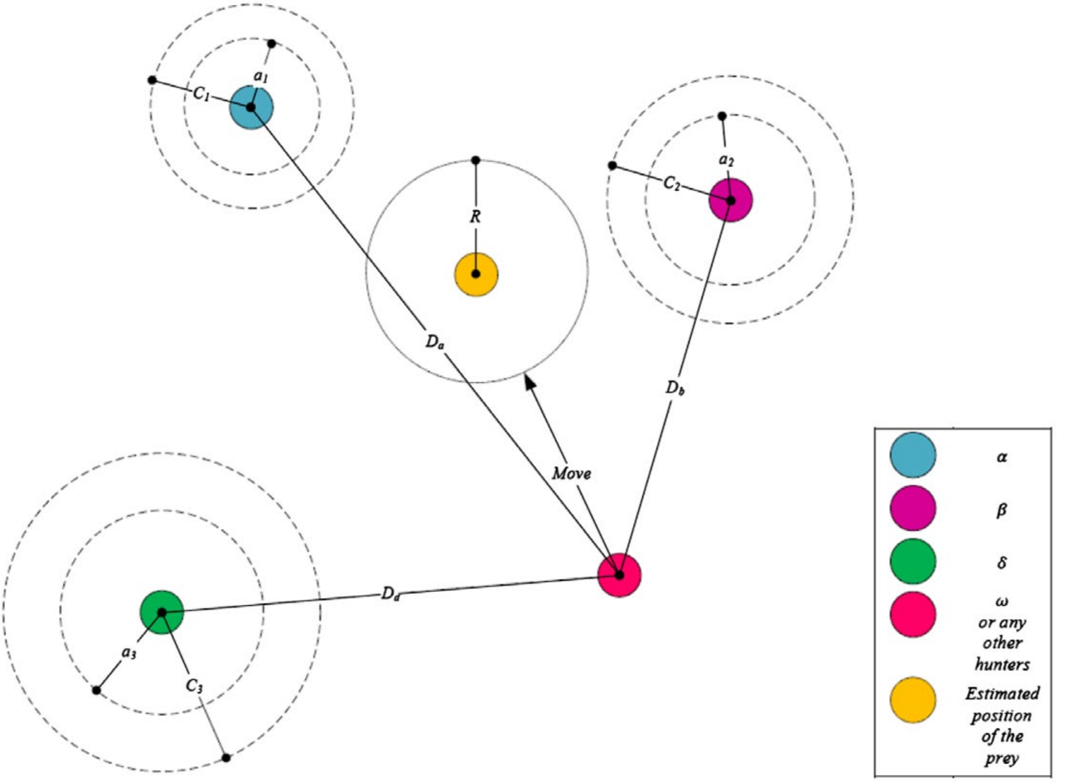

FIGURE 2 Position updating in GWO (Mirjalili et al., 2014)

$\vec{B}$ and $\vec{C}$ are random and adaptive vectors, which are advantageous because they provide the GWO with both exploration and exploitation and help to avoid the local best solution. When $|\vec{B}| > 1$ and $\vec{C}>1$, candidate position vectors are inclined to deviate from the prey, which emphasizes global exploration. In contrast, when $|\vec{B}| < 1$ and $\vec{C}<1$, exploitation is emphasized for position vectors. In particular, $\vec{C}$ decreases nonlinearly with an increase in $\vec{A}$.

3 | THE GWO–CA INTEGRATED MODEL

In this article, the GWO–CA model is proposed by integrating the GWO algorithm and CA for the simulation and spatial optimization of urban growth. There are two main steps for integrating the GWO–CA model. The first step is to optimize the urban growth rules of CA by employing the GWO algorithm. The second step is to address the simulation and spatial optimization of urban growth by using the derived urban growth rules. For the first step, the whole process of deriving the urban growth rules of CA by using GWO is shown as the main algorithm in Figure 3. The core algorithm reflects the flow of optimizing the growth conditions for the urban growth rules, as described in Section 2.3. Some redundant items need to be removed from the discovered urban growth rules to improve their performance. This process of removing redundant items is referred to as rule pruning, which is also carried out to prevent excessive learning from the training data. During the process of rule pruning, the objective function value is recalculated after removing one item at a time. If the objective function value is large after removing the term, then the item would be thoroughly removed from the discovered urban growth rule. Two periods of spatial training data, described in Section 4.1, are used to optimize the urban growth rules for CA.

For the second step, the obtained urban growth rules are utilized for the simulation and spatial optimization of urban growth. Studies have shown that urban areas grow under the influence of various kinds of uncertainties, and the uncertain parts are often located on the edge of the urbanization cluster in small proportions (Liu et al., 2008). A random variable is utilized to reflect the influence of uncertain factors. Meanwhile, CA updates the state of each cell at discrete time steps and local interactions take place at each iteration. Studies have shown that a large enough number of iterations, usually 100–200, is essential to form realistic global spatial patterns (Liu et al., 2008; Yeh & Li, 2006).

4 | CASE STUDY AND RESULTS ANALYSIS

4.1 | Research area and spatial variables

The proposed GWO–CA integration model is employed for the simulation and spatial optimization of Nanjing City, China. Three periods of land-use maps for 2005, 2010, and 2013 are utilized to monitor the process of urban growth. The GWO–CA model is calibrated using land-use data for 2005 and 2010 to determine the urban growth rules of the cell, and its predictability is verified using land-use data for 2013.

In this article, spatial variables for deriving the urban growth rules focus on three aspects: distance variables, neighbors, and physical properties. Distance variables are composed of two parts: the Euclidian distance and the road network distance. The Euclidian distance variables mainly include the Euclidian distance to railways (*dis_rw*), to highways (*dis_hw*), to national roads (*dis_nr*), to provincial roads (*dis_pr*), to city roads (*dis_cr*), and to country roads (*dis_ct*). These distance variables, shown in Figure 4, are processed using the ArcGIS Euclidian distance analysis tool.

Since people tend to travel on roads, road network distance variables are used to find and measure the least-cost paths to multiple destinations, including the airport, metro stations, railway stations, and bus stations, along the road network. These road network distance variables, shown in Figure 5, include the road network distance to metro stations (*dis_sw*), airports (*dis_ap*), railway stations (*dis_rwsta*), and bus stations (*dis_bsta*), obtained using

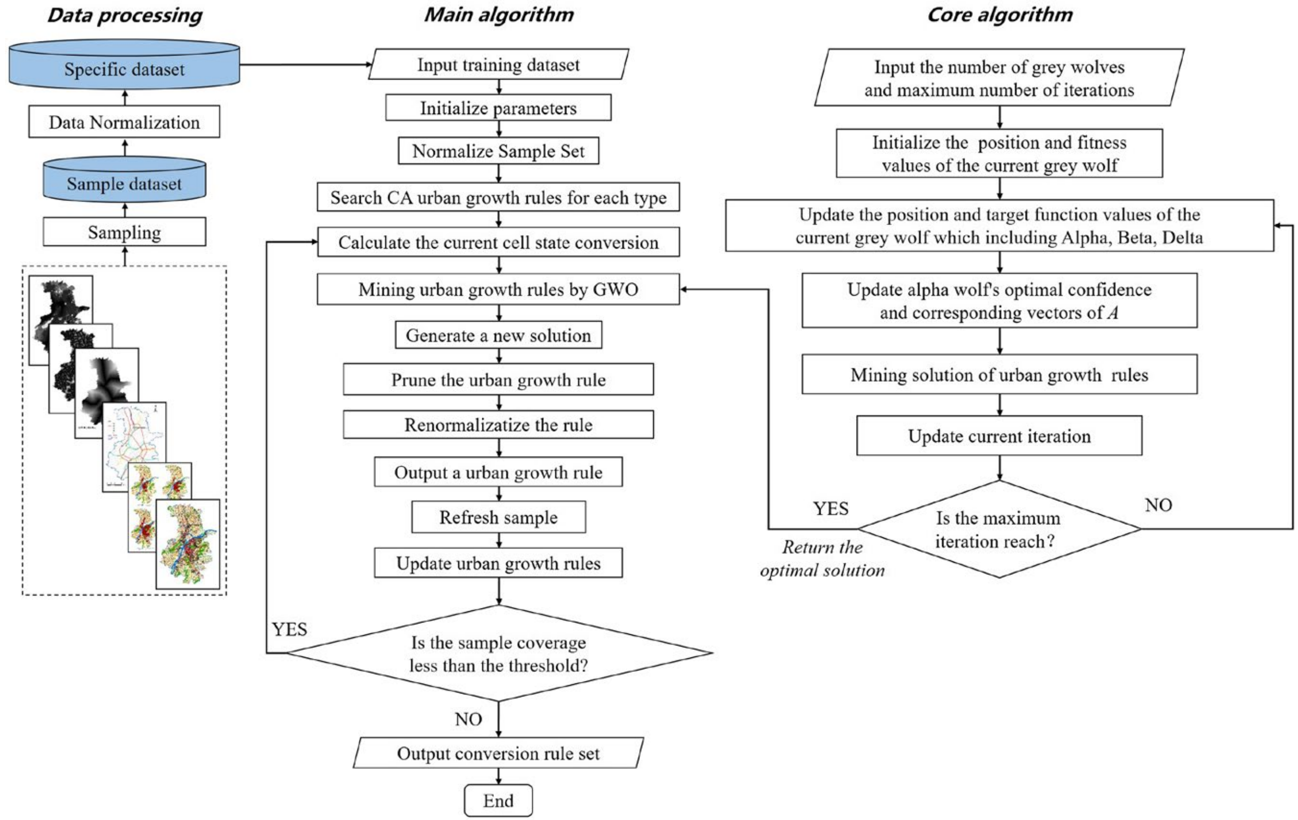

FIGURE 3 Flow chart for optimizing rules by the GWO algorithm

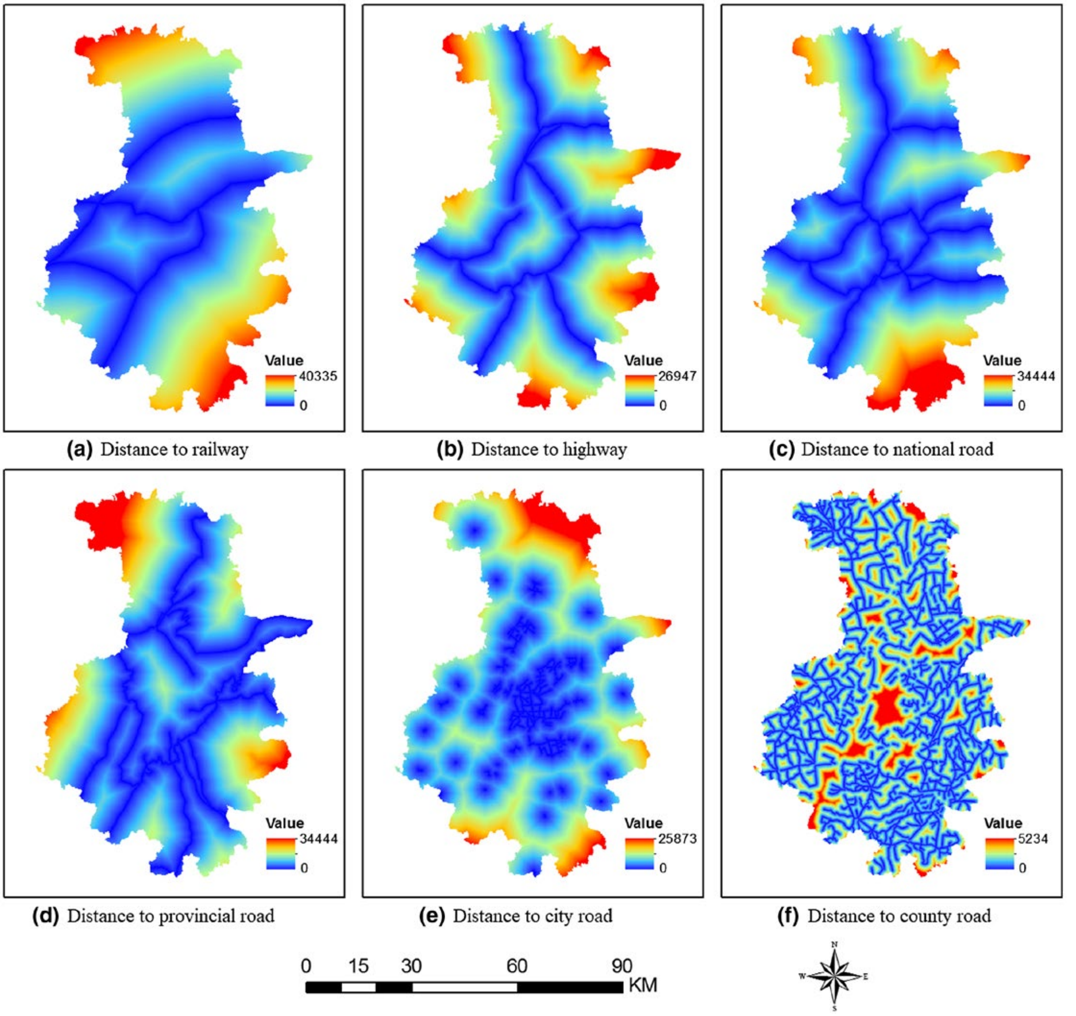

FIGURE 4 Euclidean distance variables

the origin–destination (OD) cost matrix in the ArcGIS Network Analyst extension tool. Better traffic conditions are conducive to urban development, and the distance variables play an important role in determining whether non-urban cells grow into urban cells.

Neighborhood condition (*neighbors*) is another important variable determining cell state conversion by counting the urban cells within the surrounding area of 7 × 7 cells. Non-urban cells with favorable neighborhood conditions are more likely to grow into urban cells. In addition, physical properties, including land-use type (*landuse*), DEM (*DEM*), slope (*slope*), and aspect (*aspect*), have a great influence on the development probability. For example, a region in or near a river or an agricultural protection zone has low probability of being developed into urban land.

In this study, the experimental samples from the spatial variables for discovering the urban growth rules are selected by stratified random sampling. There are 10,000 samples in the experiment. Among the samples, 5,000 are taken as training samples for discovering the urban growth rules, and the remainder are taken as test samples for confirming the performance of the discovered urban growth rules.

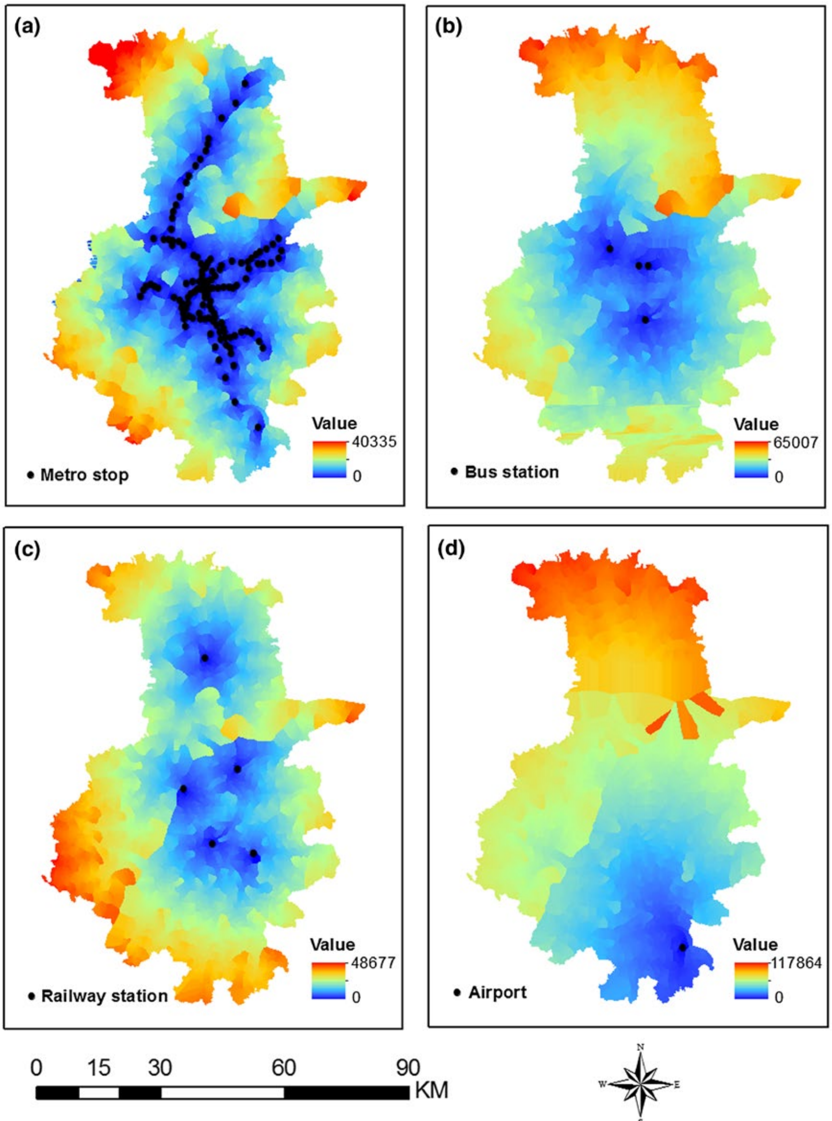

FIGURE 5 Road network distance variables

4.2 | Application of GWO–CA for urban growth simulation and optimization

The urban growth rules of the CA determine whether the non-urban cells can grow into the urban area. If a non-urban cell develops into an urban cell, then the predictive classification of the cells is marked as 1; if not, then the predictive classification of the cells is marked as 0. The predictive classification of cells is affected by a series of attribute values of the center cell and its neighborhood, which are treated as the spatial variables. The parameters of the GWO–CA model are shown in Table 1.

The urban growth rules of GWO–CA are computed through the MATLAB procedure algorithm. There were 58 urban growth rules discovered using GWO in this experiment, and their parts are presented in Table 2. The urban growth rules obtained by using GWO are employed for the urban growth simulation and optimization of Nanjing City, China. The urban growth of Nanjing City from 2005 to 2013 was calculated through 200 iterations, as shown in Figure 6.

TABLE 1 Relative parameters for the GWO–CA

Symbol	Value	Meaning
n	30	Number of grey wolves
m	2	Number of cell states
k	15	Number of attribute conditions
Iter	2,500	Max value of iterations
Cover	0.95	Coverage threshold of the training data
T	200	Number of CA iterations

TABLE 2 Some part of the urban growth rules derived by GWO

Rule 1:
IF *dis_hw > 3387.395 & dis_hw <= 13484.24 & dis_pr > 3134.684 & dis_nr <= 5374.558 & dis_ct > 77.112 & dis_ct <= 1459.412 & dis_sw > 490.463 & dis_rwsta <= 39748.3 & dis_bsta > 14191.34 & dis_bsta <= 49612.71 & landuse = 1 & neighbours > 9*
THEN *class = urban confidence = 0.898*
Rule 2:
IF *dis_hw > 653.831 & dis_pr > 223.449 & dis_nr <= 10788.89 & dis_sw > 3099.352 & dis_sw <= 6269.326 & dis_bsta > 21497.52 & neighbours > 8 & neighbours <= 24* ***THEN*** *class = nonurban confidence = 0.903*
Rule 3:
IF *dis_pr > 151.816 & dis_hw > 1325.382 & dis_pr <= 388.056 & dis_ct <= 1526.587 & dis_sw > 250.596 & dis_rwsta > 7006.605 & dis_bsta > 7844.683 & dis_bsta <= 48532.91 & DEM > 6 & Slope <= 3.2 & neighbours > 4*
THEN *class = urban confidence = 0.884*
… …

4.3 | Model validation

Although conducting a simulation model of urban expansion is very difficult, model validation is still required after running the model for an application (Jenerette & Wu, 2001). A basic method of validating the CA model is to check whether the calculated results are visually in good agreement with the real ones. The comparison shows that the calculated results are visually consistent with the real urban growth (Figure 6).

After spatially overlaying the simulated patterns with the observation in ArcGIS, the spatial distributions of the agreeing and disagreeing patterns are further displayed with different colors in Figure 7. Far more correctly simulated areas can be observed than the incorrectly simulated areas in Figure 7. The spatial overlay further indicates the fact that the simulated result is in good agreement with observation. Moreover, there are also a small number of incorrect simulation areas, which may be caused by the input factors, model parameters, model uncertainties, and other reasons.

For a more quantitative assessment of the GWO–CA model, three quantitative indices, including the confusion matrix, kappa coefficient, and total accuracy, are calculated on a cell-by-cell basis (Table 3). The kappa

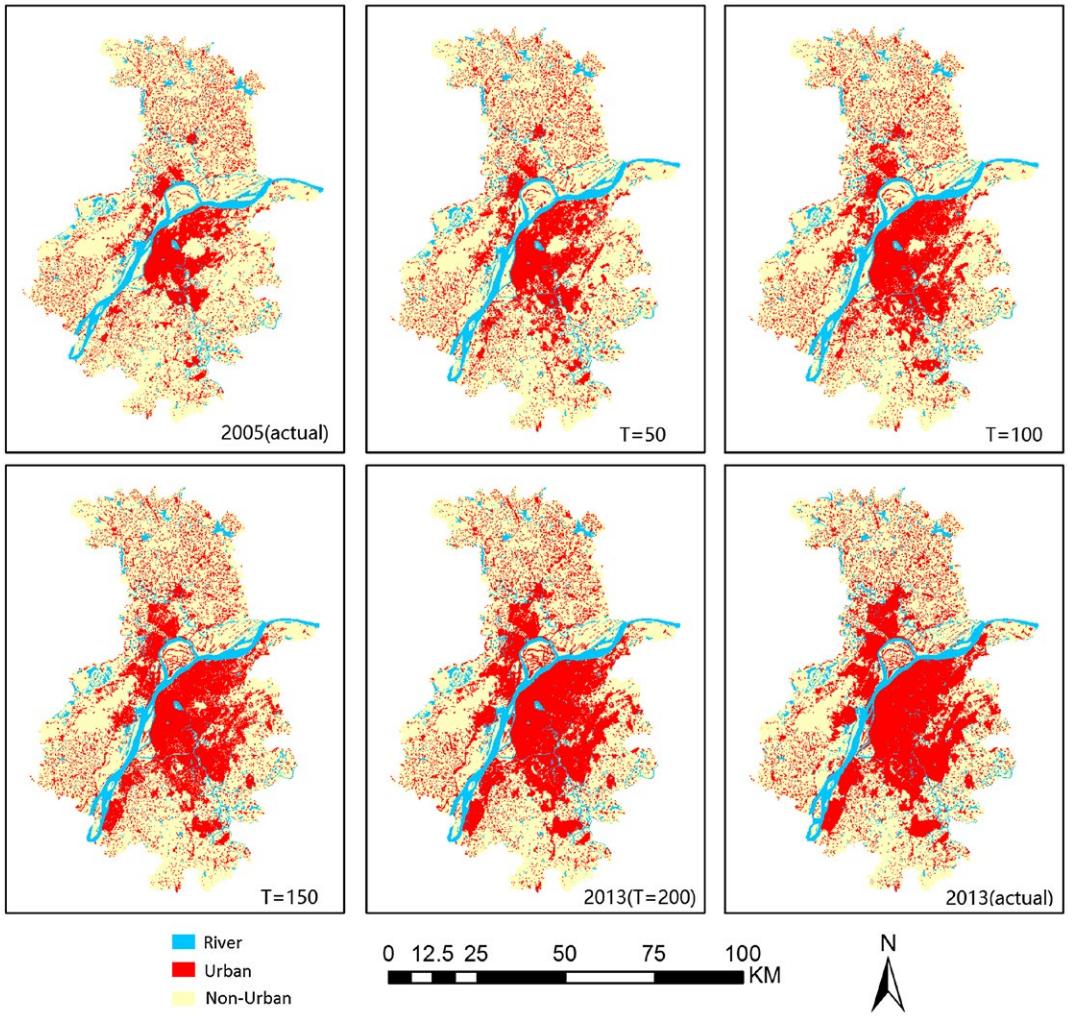

FIGURE 6 Simulation results for Nanjing City

coefficient and total accuracy are 0.715% and 91.9%, respectively. There are 7,815,948 initial non-urban cells, which remain stable during the simulation. After removing the non-urban cells, the simulation accuracy in terms of the urban cells is actually 86.6%. In addition to the above quantitative methods, Moran's *I*, a frequently used statistic to measure spatial autocorrelation, is counted to assess the consistency in spatial patterns (Table 4). The results show that Moran's *I* for the GWO–CA of 0.762 is close to 0.777 for the actual pattern in 2013.

Generally, predictive models perform better than the NULL model, which refers to pure persistence with the initial and final actual land data (Liu et al., 2007). In the study, the accuracy of the NULL model is calculated between the actual urban land use in 2005 and 2013. The kappa coefficient and accuracy in terms of the urban cells of the NULL model are 0.527% and 51.6%, respectively. Additionally, the GWO–CA model is compared with the PSO–CA model to confirm its performance (in Figure 8). The kappa coefficient and accuracy in terms of the urban cells of the PSO–CA model are 0.692% and 85.1%, respectively. Moran's

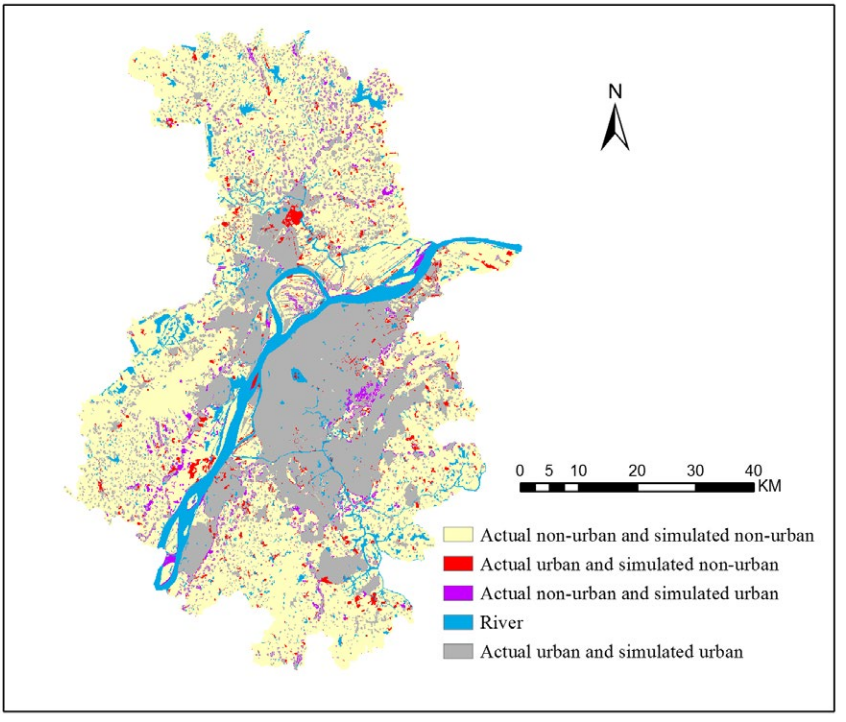

FIGURE 7 Spatial overlay result

TABLE 3 Accuracy evaluation of GWO–CA

	Actual 2013 urban (cells)	Actual 2013 non-urban (cells)	Total (cells)
Simulation 2013 urban	1,242,264	581,786	1,824,050
Simulation 2013 non-urban	193,019	7,578,925	7,771,944
Total	1,435,283	8,160,711	**9,595,994**
Total accuracy	(1,242,264 + 7,578,925)/9,595,994 = 91.9%		
Accuracy of urban cells	1,242,264/1,435,283 = 86.6%		
Kappa coefficient	0.715		

TABLE 4 Comparing Moran's *I* indices

	Actual (2013)	PSO–CA (2013)	GWO–CA (2013)
Moran's *I* values	0.777	0.737	0.762

I for the result of PSO–CA is 0.737, which shows that Moran's *I* for GWO–CA is much closer to the actual index. In summary, the above results show that the GWO–CA model prevails over the NULL and PSO–CA models.

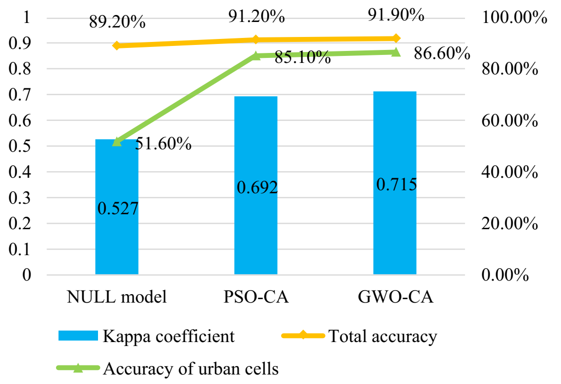

FIGURE 8 Model contrast analysis

5 | CONCLUSIONS

This article constructs a GWO–CA model by integrating GWO with CA to simulate and optimize urban growth. It is demonstrated that the GWO algorithm is advantageous for optimizing the reliable urban growth rules of CA, which are hidden within the large sets of spatial variables. Specifically, under the inspiration of wolf leadership hierarchy and hunting behavior, the GWO algorithm provides solutions to avoid convergence to the local optimum and to achieve the global optimum. By using Nanjing City as an example, the GWO–CA model is applied for urban growth simulation based on the urban growth rules obtained using the GWO. The model validations demonstrate the powerful ability of the GWO–CA model to simulate urban growth. The article demonstrates that the GWO algorithm can optimize reliable urban growth rules, which is conducive to understanding the urban growth mechanism and supporting urban planning and management. Urban forecasting under different land-use planning scenarios could be studied further for the uncertain future. However, during the construction of the urban growth rules, each attribute condition is simply expressed through the minimum and maximum values of the attribute. Occasionally, some other characteristic values are essential to describe the attribute conditions. More research seems necessary to specify the characteristic values for a more effective expression of the urban growth rules. In addition, the mathematical model of the GWO algorithm was designed and established under certain assumptions; the GWO algorithm now has some new variants in which it is applied to different applications. These assumptions and the new variants of the GWO algorithm need to be investigated further.

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