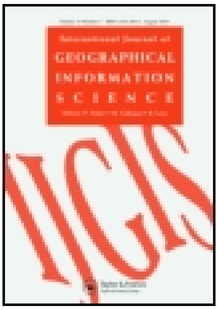


International Journal of Geographical Information Science
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tgis20

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Available online: 17 Jan 2012

*International Journal of Geographical Information Science*
i*First*, 2012, 1–19

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(*Received 25 May 2011; final version received 23 October 2011*)

Optimizing land use allocation is a challenging task, as it involves multiple stakeholders with conflicting objectives. In addition, the solution space of the optimization grows exponentially as the size of the region and the resolution increase. This article presents a new ant colony optimization algorithm by incorporating multiple types of ants for solving complex multiple land use allocation problems. A spatial exchange mechanism is used to deal with competition between different types of land use allocation. This multi-type ant colony optimization optimal multiple land allocation (MACO-MLA) model was successfully applied to a case study in Panyu, Guangdong, China, a large region with an area of 1,454,285 cells. The proposed model took only about 25 minutes to find near-optimal solution in terms of overall suitability, compactness, and cost. Comparison indicates that MACO-MLA can yield better performances than the simulated annealing (SA) and the genetic algorithm (GA) methods. It is found that MACO-MLA has an improvement of the total utility value over SA and GA methods by 4.5% and 1.3%, respectively. The computation time of this proposed model amounts to only 2.6% and 12.3%, respectively, of that of the SA and GA methods. The experiments have demonstrated that the proposed model was an efficient and effective optimization technique for generating optimal land use patterns.

**Keywords:** multi-type ant colony optimization; land use allocation; optimization

## 1. Introduction

In economically fast growing regions, planners and decision makers would frequently face a situation where multiple stakeholders pursue incompatible uses and target the same land parcel (Bojórquez-Tapia *et al*. 1994, Li and Liu 2008). *Land use allocation* is the process in planning that manipulates proportions and locations of different land uses within a defined area, during which the planners try to reconcile conflicting interests or, in other words, achieve an optimal allocation (Carsjens and Van der Knaap 2002). This optimization is particularly challenging for a number of reasons. First, it deals with multiple objectives at different levels. Specifically, at the individual land use level, each use seeks its most suitable location to be geometrically compact; and at the regional level, the objectives may include overall high suitability and low conversion cost. Second, the optimization must take into account both attribute (e.g., physical limitation, socioeconomic and cultural factors,

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ISSN 1365-8816 print/ISSN 1362-3087 online

http://dx.doi.org/10.1080/13658816.2011.635594
http://www.tandfonline.com

and environmental impact) and spatial/geometrical (e.g., distance, shape, contiguity, and compactness) characteristics (Cova and Church 2000). Third, the optimal solution of land use allocation often lies within innumerable combinations of attributes of land unit and alternatives of land use (Diamond and Wright 1989, Aerts 2002), and the complexity of solution search increases in an exponential manner as the region gets large or the spatial resolution of data gets finer (Stewart *et al*. 2004).

A number of algorithms have been developed to achieve optimal land use allocation through computation (WrightCharles and Cohon 1983, Williams and Revelle 1998, Stewart *et al*. 2004). The most commonly used techniques are mathematical programming methods, including linear programming (LP) and mixed-integer programming. LP is powerful in solving high-dimensional problems (Campbell *et al*. 1992), but is limited by assuming linearity for the objective function (Matthews 2001). Mixed-integer programming, as an extension of LP, allows the use of discrete variables and does not need the linearity assumption (Crohn and Thomas 1998). The mathematical programming methods are often computationally intensive, which is a major problem when applying them to land use allocation. To overcome the limitation set by computational capacity, one often resorts to heuristic algorithms (Xiao *et al*. 2007), such as genetic algorithm (GA), simulated annealing (SA), and artificial neural network. A heuristic approach allows trade-off between the quality of solution and the burden of computation, and hence is often used to find near-optimal solutions (Laarhoven and Aarts 1987). For instance, Eastman *et al*. (1995) developed an intuitive solution to the problem of land allocation under the conditions of conflicting objectives within the context of a raster geographic information system (GIS). The limitation of this method is the lack of compactness constraint. A fragmented pattern will be produced without incorporating compactness constraints in land use planning. Gimblett *et al*. (1994) proposed a neural network technique to accommodate a large number of different combinations of interdependent land suitability factors. The limitation with neural networks is that their internal processes are hidden from the planners and tend to have problems of over-fitting (Liu *et al*. 2008a). Recently, the GA method became popular in land use suitability analysis (Krzanowski and Raper 2001). Dibble and Densham (1993) designed a GA process for generating alternative solutions for location problems in spatial decision support systems. Brookes (1997) developed a site allocation method based on region growing, which was further developed by incorporating GA (Brookes 2001). Feng and Lin (1999) proposed a GA-based model that can be used to generate Pareto optimal alternative solutions for land use planning. Xiao *et al*. (2002) also used GA to generate alternatives for multi-objective site search problems. Despite the seemingly popular method of GA in solving spatial allocation problems, a major problem of GA is that one never knows whether the global optimum has been identified with a sufficient precision (Malczewski 2004). A more severe problem with GA is that this method was found to be not efficient when the study area is large with finer resolution (Stewart *et al*. 2004).

Another heuristic method that has been applied to optimal land allocation is SA (Aerts 2002). Martínez-Falero *et al*. (1998) used this method to allocate 10 agricultural activities, during which they took into account 6 sub-objectives. Aerts and Heuvelink (2002) used SA to generate land use allocation alternatives, and a highlight of their model is that it can both minimize development costs and maximize spatial compactness of the land use. Santé-Riveira *et al*. (2008) developed a planning support system for rural land use allocation by integrating the SA method and GIS. Although SA can produce good optimization results, the computational time of SA is much longer than that of GA (Li and Yeh 2005).

Most of these optimization techniques are used to select optimal sites for a single land use (Carver 1991, Church *et al.* 2003, Li *et al*. 2009). Only a few techniques have been proposed to deal with multiple land use allocation problems (Santé-Riveira *et al*. 2008). For example, Stewart *et al*. (2004) designed a multiple land use allocation model by using the GA method. Santé-Riveira *et al*. (2008) developed SA to allocate multiple land use in rural areas based on land suitability values and spatial compactness. Land allocation optimization becomes more complicated when multiple land uses are involved, as different land uses may compete for the same site. Another issue for land use optimization is that conventional heuristic approaches are inefficient in finding good solutions to land use allocation, especially in large areas. Most of the previous studies mainly focus on optimizing land use patterns for a small region. For example, Stewart *et al*. (2004) developed GA to optimize land use planning alternatives, but the experiments were only implemented in $20 \times 20$ and $40 \times 40$ grids. The sketch layout model was proposed by Feng and Lin (1999) to generate alternative land use patterns, the study region having an area of only 40 cells. Santé-Riveira *et al*. (2008) applied the SA method to allocate land units with given areas among the 182,168 cells. However, this method took almost about 5 hours to obtain a land use allocation solution. It is a challenge to solve land use optimization problems with the increase in the size of the study area. Thus, exploration of efficient and effective optimization methods for multiple land use allocation in large areas is academically interesting and may result in useful practical applications as well.

The present study examines the use of ant intelligence for solving multiple land use allocation problems in a large area. Ant colony optimization (ACO) is a computational method inspired by natural biological systems. First proposed by Dorigo (1992), ACO uses a set of cooperating artificial ants with simple intelligence as instruments to incorporate distributed computing, local heuristics, and knowledge from past experience for searching optimal solutions (Eberhart *et al*. 2001). Through the indirect communication among ants by laying pheromone, ACO has a positive feedback mechanism that facilitates the rapid discovery of optimal solutions (Dorigo 1992). Complex tasks, such as finding optimized route to foods, can be effectively accomplished through the cooperation between individual ants, and the integrity of the overall system will not be easily affected by the failure of one or several agents (Dorigo *et al*. 1996).

ACO has been used in the traveling salesman problem, data clustering, combinatorial optimization, and network routing problems (Lumber and Faieta 1994, Kwang and Weng 2002). Studies indicate that ACO can be superior to other nature-inspired algorithms, for example, SA and evolutionary computation, in solving complex combinatorial optimization problems (Dorigo and Gambardella 1997). Recently, ACO also found its applications in geographical problems, including urban simulation (Liu *et al*. 2008b), remote sensing classification (Liu *et al*. 2008c), and site selection (Li *et al*. 2009). These studies have demonstrated that ACO is a potentially useful algorithm to tackle complex spatial optimization problems. Multiple land use allocation is a complex optimization problem involving conflicting objectives. ACO should be a useful optimization technique for solving this spatial decision problem. Previous studies have demonstrated that ACO is an efficient algorithm in solving multi-objective problems, and hence we have considered it to have potential in tackling land use allocation problems.

However, we then realized that the conventional ACO, which only implements one type of ants, is not sufficient for dealing with a problem like land use allocation. In this study, we extend the single-type ACO to multi-type ACO (MACO) for solving the multiple land use allocation problems in a large area. The modifications include the use of multiple types of ants equipped with a spatial exchange strategy. Different types of ants are used to represent the competition mechanism in the formulation of optimal land use allocation. Moreover, a spatial exchange strategy is designed to deal with competition between various types of land use. The objective is to generate a land allocation pattern that minimizes the converting costs and meanwhile maximizes the land use suitability and compactness. As a case study, we applied this MACO model to the creation of land allocation alternatives in Panyu, a rapidly developing region in Pearl River Delta, China. The model validation was further carried out by comparing the MACO method with the two conventional methods, the SA and the GA.

## 2. Ant intelligence for solving land resource allocation problems

### *2.1. Concepts of ACO*

With ACO, the optimization is carried out by simulating the natural behavior of ant colonies in their search for food, including mechanisms of cooperation and adaptation (Dorigo 1992). When searching for food, the initial path taken by individual ants starting from the nest is essentially random. Once the ants find a food source, they evaluate the distance and the quality of it and deposit pheromone on the ground in order to mark a favorable path that should be followed by other members of the colony. The deposited pheromone trail will evaporate as time passes. Later when an ant goes out to search for food, it will most likely follow an existing pheromone trail, and the ant's own pheromone will reinforce the existing trail (Bell and McMullen 2004). The amount of deposited pheromone will increase when the number of ants increases in selecting a certain path. If the path is shorter, the ants will move along the path, and more ants are attracted to follow the trail. As a result, more amount of pheromone is deposited on this path. At the final stage, all the ants will be attracted to the shortest path. In this way, ants are capable of finding the shortest path from their nests to food sources by exploiting pheromone information and without using visual information. This process can be described as a loop of positive feedback, in which the probability that an ant chooses a path is proportional to the number of ants that have already passed that path (Dorigo 1992).

### *2.2. Land allocation model formulation*

The land source allocation problem can be defined as (Aerts 2002)

$$M = (S, \Omega, f) \tag{1}$$

where $S$ denotes the set of candidate solutions, $\Omega$ is the set of constraints, and $f$ is an objective function. This problem can be formulated as a maximization problem, which is to find a solution $i_{\mathrm{opt}}$ that satisfies (Aerts and Heuvelink 2002)

$$f(i_{\mathrm{opt}}) \geq f(i) \quad \forall i \in S \tag{2}$$

If we represent the study area as a two-dimensional grid with $R$ rows and $C$ columns, then technically the problem is how to allocate $K$ different land uses to the cells in the grid or, in other words, how to assign a specific land use to each individual cell $(i, j)$, so that the resulting land use map optimally achieves the decision maker's objectives. For algorithmic purposes, it is useful to define a binary decision variable $x_{ijk}$, with 1 indicating that land use $k$ is to be allocated to cell $(i, j)$, and 0 otherwise.

Three objectives of land use allocation have been proposed (Siitonen *et al*. 2003, Stewart *et al*. 2004). The first is to maximize land suitability, that is, it is considered optimal that each land use is allocated to the most suitable land. When there is competition for the same piece of land from different land uses, the objective becomes to maximize the total suitability of the land use map (Yeh and Li 1998). The second objective is to maximize the spatial compactness of a land use, that is, a compact shape is more desired than a fragmental shape. This is because a compact shape requires less infrastructure and services, and thus can improve the efficiency in land and energy utilizations (Gabriel *et al*. 2006). The third objective is to minimize the total cost of converting the current land use into a new land use. The costs of various land use conversions are different. For example, converting urban land into grassland is expensive, while the cost of converting agricultural use to urban use is relatively small. The three objectives can be expressed as follows (Stewart *et al*. 2004, Sante´-Riveira *et al*. 2008):

$$\text{Max} \sum_{k=1}^{K} \sum_{i=1}^{R} \sum_{j=1}^{C} \text{Suit}_{ijk} x_{ijk} \tag{3}$$

$$\text{Max} \sum_{k=1}^{K} \text{Comp}_k \tag{4}$$

$$\text{Comp}_k = \frac{L_{k\text{MaxSum}} - L_{k\text{Sum}}}{L_{k\text{MaxSum}} - L_{k\text{MinSum}}} \tag{5}$$

$$\text{Min} \sum_{i=1}^{R} \sum_{j=1}^{C} \text{Conv}_{um} x_{ijum} \tag{6}$$

$$\sum_{k=1}^{K} x_{ijk} = 1 \quad \forall i = 1, \ldots, R,\ j = 1, \ldots, C,\ x_{ijk} \in \{0, 1\} \tag{7}$$

$$\sum_{i=1}^{R} \sum_{j=1}^{C} x_{ijk} = Q_k \quad \forall k = 1, \ldots, K \tag{8}$$

where $\text{Suit}_{ijk}$ *is the suitability of cell* $(i, j)$ for the $k$th land use, $\text{Comp}_k$ *is the compactness of the* $k$th land use in the resulting land use map, and $L_{k\text{Sum}}$ is the sum of perimeter of the $k$th land use. Once the area is known, the most compact form would be circular and the minimum sum of perimeter of the $k$th land use ($L_{k\text{MinSum}}$) can then be calculated. On the contrary, if the selected sites separate from each other, the maximum sum of perimeter of the $k$th land use ($L_{k\text{MaxSum}}$) can then be obtained. $\text{Conv}_{um}$ *is the cost of converting land use from* $u$ to $m$; and $x$ is the binary decision variable discussed earlier: $x_{ijum} = 1$ indicates that the current land use $u$ at location $(i, j)$ is converted to $m$ ($u \neq m$), and $x_{ijum} = 0$ otherwise; and $Q_k$ is a prespecified percentage of land use $k$ in the entire area. Equation (7) ensures that only one land use can be allocated to each cell. Equation (8) specifies percentages of different land use types for the allocation to meet. Since the three objectives may conflict with one another, we employed a weighting method to deal with the multi-objective situation:

$$U = \sum_{k=1}^{K} (a \cdot \text{Suit}_k + b \cdot \text{Comp}_k - c \cdot \text{Conv}_k) \quad \forall a + b + c = 1 \tag{9}$$

where $U$ is a composite score incorporating all three objectives; $a$, $b$, and $c$ are the weights for suitability, compactness, and converting cost, respectively.

### *2.3. MACO for multiple land use allocation (MACO-MLA)*

While ACO has been successfully applied to spatial optimization problems, such as site selection and route planning (Li *et al*. 2009), conventional ACO, which implements only one type of ants, would not be able to handle the land use allocation problem, which involves multiple land use types. One way for ACO to accommodate such a problem is to expand and include multiple types of ants and use a mechanism to represent their competition and interaction so as to achieve optimization. For that purpose, we developed a spatial exchange mechanism. The details of the procedure are described in the following sections.

#### *2.3.1. Solution construction*

Conventional ACO has only one type of artificial ants. In our MACO, to address the situation of multiple land uses, the types of ants correspond to the types of land uses, and the total number of ants is the same as the number of cells that represent the study region, so that each such cell is occupied by only one ant. The number of ants of a certain type is determined by the proportion of that specific land use in the study region.

In the beginning, the ants are randomly positioned in the region. At the end of the optimization, the final locations of the ants form an optimal solution to the land use allocation problem. As illustrated in Figure 1, the basic process in the optimization is the exchange of ants between two cells. The basic task of an ant in the optimization is to find out if there is a better cell for it to occupy. Whether a candidate cell is better for a searching ant or not is evaluated with an objective function. This function determines if two ants will exchange cells they currently occupy or the searching ant will keep testing other cells.

#### *2.3.2. Improved selection strategy*

Site selection is an important step for ants in optimizing multiple land use spatial patterns. The probability that a cell $(i, j)$ will be selected by the $q$th ant with land use $k$ at time $t$ is defined as follows:

$$p^q_{ijk}(t) = \begin{cases} \dfrac{\left[\tau_{ijk}(t)\right]^{\alpha} \cdot \left[\eta_{ijk}(t)\right]^{\beta}}{\sum\limits_{x \in \text{allowed}_q} [\tau_x(t)]^{\alpha} \cdot [\eta_x(t)]^{\beta}}, & \text{if } (i,j) \in \text{allowed}_q \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

In the above equation, $p^q_{ijk}(t)$ is the probability of cell $(i, j)$ to be occupied by the $q$th ant in iteration $t$, that is, the probability of the cell exchange to occur. This probability is determined by two factors: $\eta_{ijk}$, a heuristic value that guides the $k$-type ant in selecting cells to test, and $\tau_{ijk}$, the pheromone intensity of $k$-type ant, on which the ACO's positive feedback mechanism is based. The constants $\alpha$ and $\beta$ are specified by the user and determine the relative importance of the pheromone density versus the heuristic information. The tabu list ($\text{allowed}_q$) is to mask out the selected cells that should not be visited again by other ants with the same type.

In a naïve process, a searching ant randomly picks a cell to evaluate, which is not efficient. The heuristic value in Equation (10), $\eta_{ijk}$, is for improving the efficiency of the

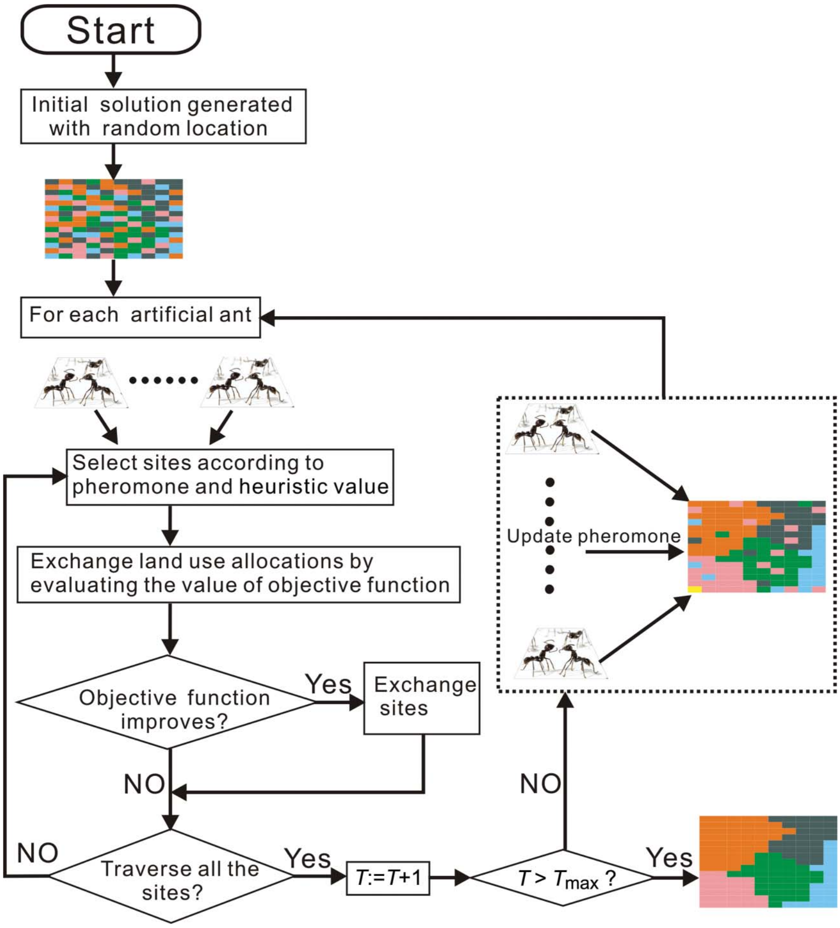


Figure 1. The procedure for optimizing land use spatial patterns using the MACO-MLA model.



selection by giving privilege to certain cells. In this study, we simply used the land use suitability to determine that privilege, and thus define

$$\eta_{ijk} = \frac{\mathrm{Suit}_{ijk}}{\sum_{x} \mathrm{Suit}_{xk}} \tag{11}$$

where $\eta_{ijk}$ is the heuristic value of the $k$-type ants, $\mathrm{Suit}_{ijk}$ is the suitability of land use $k$ at cell $(i, j)$, and $\sum_x \mathrm{Suit}_{xk}$ is the sum of the suitability of land use $k$ for all cells in the study area.

The pheromone intensity in Equation (10), $\tau_{ijk}$, is the unique factor of ACO with which the optimization is achieved. In this study, the pheromone intensity at each cell is initialized to the same value as

$$\tau_{ijk}(t = 0) = \frac{1}{G} \tag{12}$$

where $G$ is the total number of cells in the study region. The pheromone intensity of each type of land use at each cell will be updated at the end of each iteration according to the following mechanism: The pheromone intensity of type $k$ will increase if the cell is occupied by a $k$-type ant; and the pheromone intensity will decrease if the cell is not occupied by a $k$-type ant (i.e., evaporation). Precisely, the updating process is as follows (Li *et al*. 2009):

$$\tau_{ijk}(t+1) = \tau_{ijk}(t)(1-\rho) + \Delta\tau_{ijk}(t) \tag{13}$$

$$\Delta\tau_{ijk}(t) = r \cdot U \tag{14}$$

where $\rho$ is a coefficient specifying the evaporation rate; $\Delta\tau_{ijk}(t)$ is the $k$-type pheromone remaining at cell $(i, j)$, which is determined by the objective function $U$. Objective function is a composite score incorporating land suitability, compactness, and land use conversion cost; and $r$ is a constant. During the optimization process, more $k$-type pheromone deposited on the cells can attract more $k$-type ants to occupy these sites. At the final stage, the optimal land use allocation is identified by these artificial ants according to the pheromone updation.

The traditional ACO depends heavily on cooperation between the ants. In MACO algorithm, the collaborative behavior between identical types of ants is the same as the traditional ACO. However, the different ant types are in direct competition with each other. The modified ACO is equipped with a spatial exchange strategy to solve competition between different types of ants. When an ant selects a site according to Equation (10), this ant may have a probability to give up (exchange) its former location to another type of ant that has already selected a site if there is a significant improvement of the objective function. The spatial exchange strategy is designed as follows: The value of the objective function for the current configuration, $U_c$, is compared with the value of the objective function for the former configuration, $U_f$. If $U_c$ is larger than $U_f$, the selected site is then adopted for exchange. Otherwise, the ant continues to select sites according to Equation (10). The solution was constructed after all ants have located their sites according to the roulette wheel selection principle and exchange strategy. The validity of the solution can be assessed by using the objective function (Equation (9)).



## 3. Model implementation and results

We chose Panyu city in China to test the proposed model. The city, with an area of 786 km$^2$, is situated at the center of the Pearl River Delta in Guangdong Province, one of the fastest developing regions in China (Figure 2). In the past three decades, the region has lost a large amount of agricultural land due to rapid urban development and poor land management (Yeh and Li 1999), which has given rise to a series of land use problems. In this case study, we applied the MACO-multiple land allocation (MLA) model to identify optimal allocation for multiple land uses. The ACO algorithm involves some parameters that can be determined according to previous studies (Dorigo *et al*. 1996, Li *et al*. 2009). Table 1 lists the parameters in Equations (10), (13), and (14) for implementing the MACO-MLA model.

We imposed a grid with 1123 × 1295 cells to the study area, with a ground resolution of 30 m. The study area has seven land uses: agriculture, industry, commerce, residence,

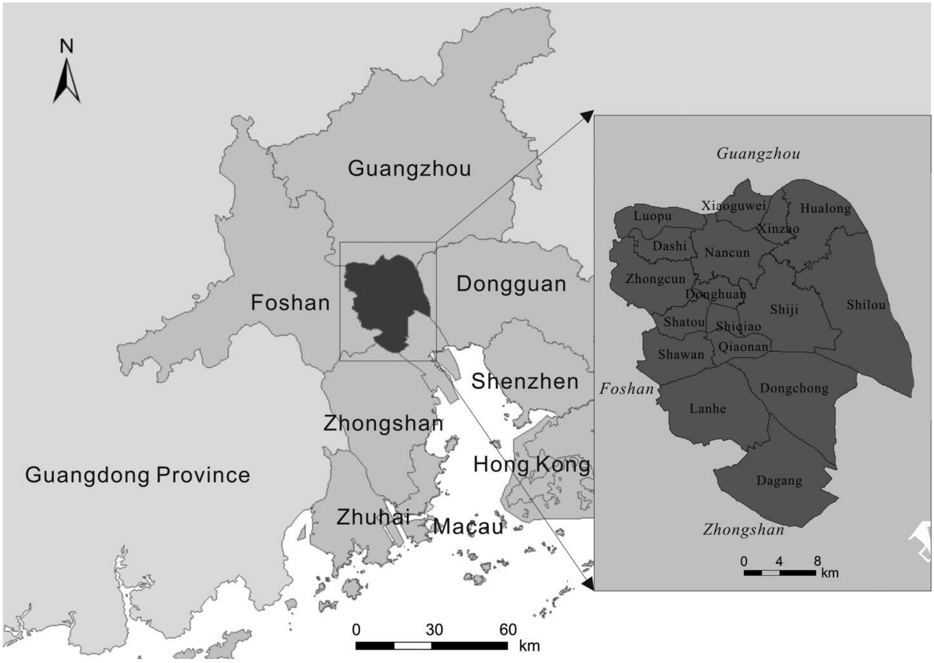


Figure 2. Location of Panyu in the Pearl River Delta.

Table 1. Parameters used in the MACO-MLA model.

| $A$ | $\beta$ | $\rho$ | $Q$ |
|---|---|---|---|
| 5 | 0.75 | 0.01 | 0.15 |

water, forest, and roads (Figure 3). We excluded water, forest, and road from land allocation, as road is usually not convertible and water and forest are important ecological resources for protection that cannot be converted. The modeling contains three general steps: (1) mapping and analysis of land use suitability, which generate suitability value of each considered land use for each cell; (2) projecting land use demands, which generate proportions of different land uses that are to be met by the allocation; and (3) allocating land uses to cells, which was based on the suitability maps and the land use demands.

### *3.1. Land use suitability analysis*

Land use suitability analysis determines to what extent a given piece of land is suitable for a specific use (Steiner *et al*. 2000). In this study, we chose 14 factors to evaluate the suitability. The value ranges of these spatial variables are normalized into 0–1 for calculating the land use suitability map. The suitability value is a weighted linear combination of the factors. The weights of the factors were determined through 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 1980). The analytic hierarchy process can effectively support decision making with regard to complex issues that involve

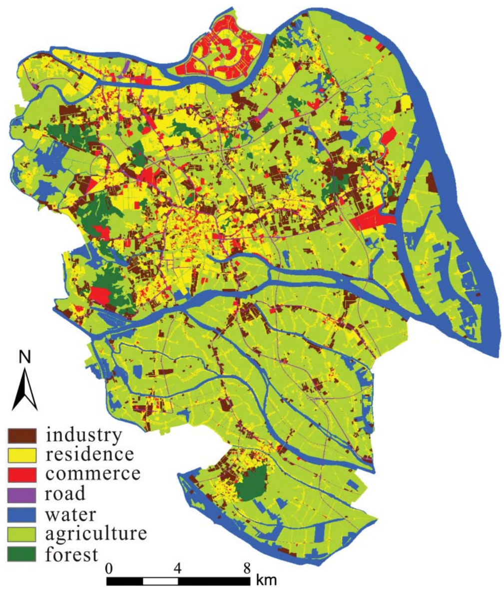


Figure 3. Land use map input in the case study.



Table 2. Weights of factors for each of the four land uses.

| Factors | Agriculture | Industry | Commerce | Residence |
|---|---|---|---|---|
| NDVI* | 0.1385 | N/A | N/A | N/A |
| Slope | 0.0965 | 0.1253 | 0.1266 | 0.1124 |
| Elevation | 0.1097 | 0.0867 | 0.0935 | 0.0827 |
| Fertility | 0.2353 | N/A | N/A | N/A |
| pH value of soil | 0.1598 | N/A | N/A | N/A |
| Geological disaster potential | N/A | 0.1427 | 0.1461 | 0.1479 |
| Distance to towns | 0.0653 | 0.0675 | 0.1251 | 0.1029 |
| Distance to highways | 0.0467 | 0.1669 | 0.0528 | 0.0764 |
| Distance to roads | 0.0585 | 0.1553 | 0.1035 | 0.0886 |
| Density of green surfaces | N/A | 0.0286 | 0.0297 | 0.0923 |
| Proximity to river | 0.0897 | 0.0254 | 0.0169 | 0.0227 |
| Proximity to industry | N/A | 0.1622 | 0.0135 | 0.0119 |
| Proximity to commerce | N/A | 0.0236 | 0.1753 | 0.1054 |
| Proximity to residence | N/A | 0.0108 | 0.1170 | 0.1568 |
| Sum | 1 | 1 | 1 | 1 |

*The Normalized Difference Vegetation Index.

the comparison of decision elements. The factors and their weights for different land uses are listed in Table 2. We constructed a raster layer for each of the factors so that suitability values could be calculated for each cell.

### *3.2. Projecting land use demands*

In this study, we projected land use demands, that is, the proportions of different land uses that the allocation needed to meet, with a two-step procedure: We first used support vector regression (SVR) to project the regional population growth and GDP growth and then

Table 3. The allocation demand for the four urban land uses.

| Land use | Current number of cells (2008) | Demand (2030) |
|---|---|---|
| Agriculture | 381, 117 | 301, 514 |
| Industry | 75, 965 | 97, 513 |
| Commerce | 34, 557 | 47, 255 |
| Residence | 120, 074 | 165, 436 |

project the land use demands based on these growths. SVR is a new learning algorithm for regression that employs structural risk minimization principle instead of empirical risk minimization (Smola and Schölkopf 2004). The so-called structural risk minimization principle means that the model minimizes an upper bound on the generalization error. This strategy provides a well-defined quantitative measurement for the capacity of a learned function to capture the true structure of the data distribution and generalize over unknown test data set. So, SVR can effectively avoid over-fitting and improve generalization performance (Hua *et al*. 2007). SVR has been successfully applied to solve forecasting problems. In this study, SVR is used for forecasting population growth and GDP growth through the machine learning software WEKA (Frank *et al*. 2010). The statistics data required by SVR were obtained from the governmental statistics yearbooks.

The demand for residential use was estimated based on the finding that population growth is strongly correlated with land use changes (Theobald and Hobbs 1998). Population growth will result in more demand for residential areas, and therefore population projections have often been used to establish how much additional residence is required (Pettit 2005). In this study, the demand for residential uses was derived based on the current ratio of population to residential area and the population projection for 2030.

The expansion of industry and the adjustment of economic structure will lead to an increase in demand for industrial and commercial land (Liu *et al*. 2007). In this study, the demands for these two types of land uses were projected based on the ratio of industrial GDP to industrial areas and the ratio of service sector GDP to commercial areas calculated from 2008 to 2030. Lastly, the required area of agriculture is estimated according to the strategic planning of Panyu. Table 3 shows the allocation demand for industry, commerce, and residence in future.

### *3.3. Converting cost*

The converting cost is defined as the total cost of converting the current land use into the future land use. For each pair of land use $u$ and $m$, the cost of changing the land use from $u$ to $m$ is represented as $\mathrm{Conv}_{um}$, which may vary with location because it depends on the soil type, land use type, and elevation (Janssen *et al*. 2008). In this article, the converting cost of each land use is simply estimated based on the local experiences of the experts and urban planners (Table 4). The converting cost ranges from 0 (easy to be converted) to 1 (difficult to be converted). The average converting cost of all cells can be estimated by the following equation:

$$\mathrm{Conv} = \sum_{i=1}^{R} \sum_{j=1}^{C} \frac{\mathrm{Conv}_{um} x_{ijum}}{Q} \tag{15}$$

where $Q$ is the total number of cells in the study region.

Table 4. The converting cost of each land use.

| Future land use | Agriculture | Industry | Commerce | Residence | Water | Forest | Road |
|---|---|---|---|---|---|---|---|
| Agriculture | 0.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Industry | 0.30 | 0.00 | 0.90 | 0.85 | 1.00 | 1.00 | 1.00 |
| Commerce | 0.35 | 0.70 | 0.00 | 0.50 | 1.00 | 1.00 | 1.00 |
| Residence | 0.35 | 0.65 | 0.55 | 0.00 | 1.00 | 1.00 | 1.00 |
| Water | 1.00 | 1.00 | 1.00 | 1.00 | 0.00 | 1.00 | 1.00 |
| Forest | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.00 | 1.00 |
| Road | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.00 |



### 3.4. Results of land use spatial allocation

We implemented MACO-MLA using Visual C# .NET and ArcEngine of ArcGIS. Visual C# .NET is for implementing the modified ACO algorithm and ArcEngine is used for accessing the spatial data and functionality of GIS.

Since the three objectives (suitability, compactness, and converting cost) in the optimization may conflict with one another, we can define the composite optimality score in different ways by emphasizing different objectives and in turn generate alternative land use patterns (Equation (9)). Table 5 lists the weights we have applied to the three objectives for generating different land use patterns. For example, option A is eventually a single-objective optimization that only tries to maximize land use suitability. The relative weights of 3:1:0, 1:1:0, and 1:3:0 were given to generate land allocation patterns that maximize land use suitability and compactness of land masses (options B–D, respectively). The combinations are 2:1:1, 1:1:2, 1:2:1, and 1:1:1 for options E–H, respectively. Options I–K are used to generate land use pattern that both maximizes land use suitability and minimizes converting costs. The relative weights of 1:0:1, 3:0:1, and 1:0:3 for three sub-objectives are given in options I–K, respectively.

As an example, the series of images in Figure 4 show the outputs from different iterations under option H. The first image shows that the artificial ants representing different land uses are randomly located in the study region. As the iterations progress, the formulated patterns appear to be increasingly compact. A close inspection found that after 100 iterations, most ants are at the locations that have balanced combinations of

Table 5. Different sets of sub-objective weights used in MACO-MLA optimization for allocating land units in Panyu.

| Option | Suitability ($a$) | Compactness ($b$) | Cost ($c$) |
|---|---|---|---|
| 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 | .033 | 0.33 |
| I | 0.50 | 0.00 | 0.50 |
| J | 0.75 | 0.00 | 0.25 |
| K | 0.25 | 0.00 | 0.75 |

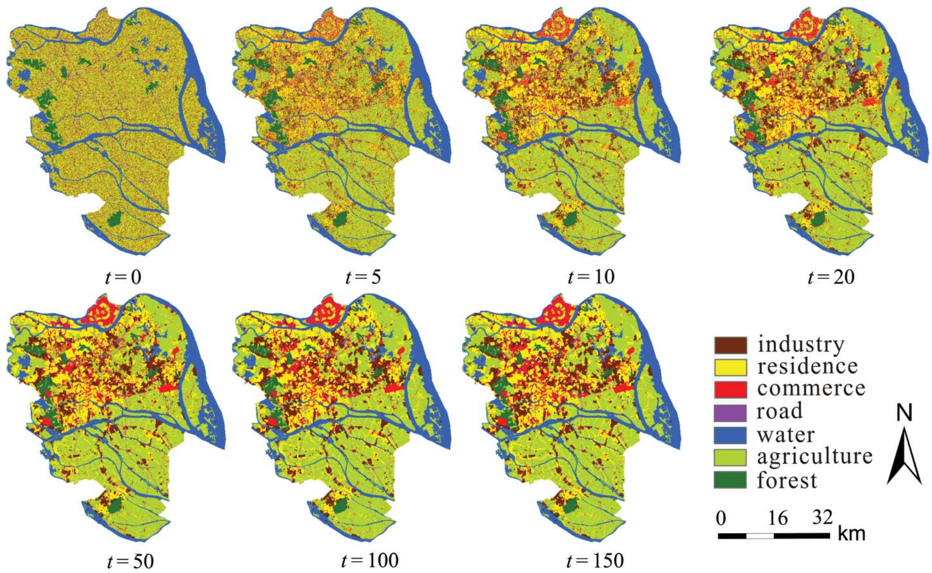


Figure 4. The optimization process of land use pattern by using MACO-MLA model with the defined weights in option H.

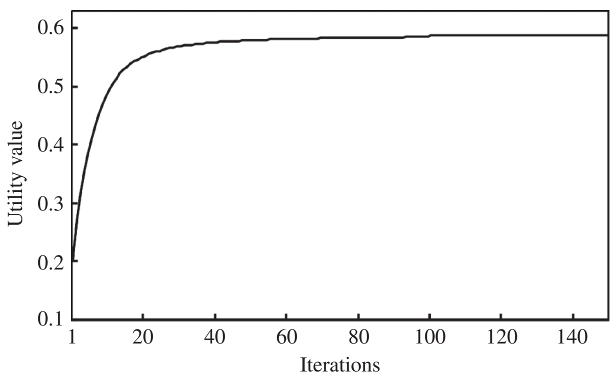


Figure 5. Utility improvement with iterations by the proposed MACO-MLA model.



suitability, compactness, and conversion cost. The land use pattern started to stabilize after 150 iterations. A comparison of the land suitability map in Figure 3 and the last image in Figure 4 shows that in the final result the land uses have been well allocated to their suitable locations.

Figure 5 shows the change of the output value from the objective function as the iterations progress (specified by option H). The curve shows that the value has a rapid increase in the early stages of the optimization, gradually becomes stable, and finally levels out after 120 iterations. The search will spend about 25 minutes by using a computer with a Pentium IV 3.2 GHz CPU.

Figure 6 shows the optimization results generated with different weight settings that emphasize different objectives and their combinations. The letters that label the maps in Figure 6 correspond to the options in Table 5. The pattern shown by option A in Figure 6

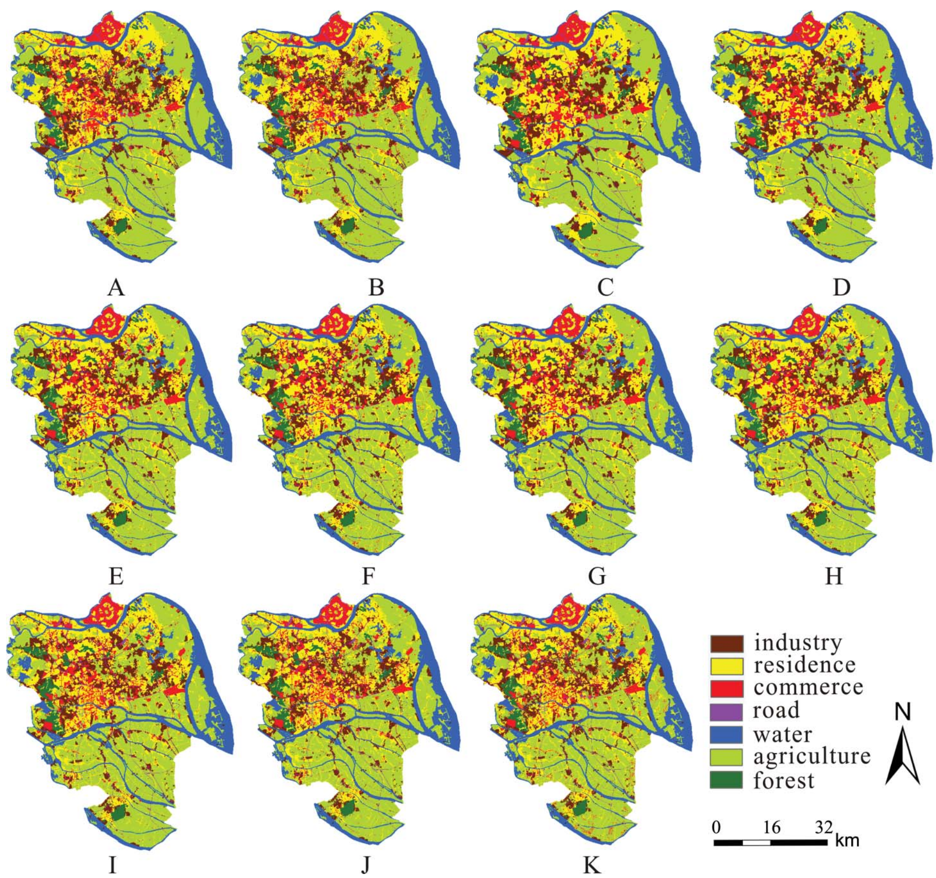


Figure 6. The optimal land use patterns of Panyu obtained by using MACO-MLA model with various weighting scheme options.



is fragmented, because it considers only suitability without including compactness in the objective function. From B to D, as the weight for compactness increases, the patterns become increasingly compact as well, and a close inspection reveals that this is at the cost of ignoring land use suitability (Table 6). Options E–H are the optimal patterns by considering the trade-off between suitability, compactness, and conversion cost. The land use allocation procedure becomes more complicated by considering these conflicting objectives. It is found that option H ($a = 0.34$, $b = 0.33$, and $c = 0.33$) can generate a satisfactory pattern for land use planning according to the visual interpretation and comparison of the trade-off (Table 5). The optimal solutions involving a weighted combination of suitability and converting cost are illustrated in Options I–K. Note that in these solutions, with not considering the compactness factor, the optimal pattern is fragmented (Table 6). As $c$ increases, the converting cost factor becomes more important, and the optimal solution allocates land use where costs are lower. But the decrease of the converting cost is at the cost of suitability (Table 6). Each option takes about 25 minutes for finding a near-optimal solution using a computer with a Pentium IV 3.2 GHz CPU (Table 6).

A further experiment was carried out to compare the performances of this proposed model with those of two conventional algorithms: the SA and the GA. These two algorithms

Table 6. Total suitability, compactness, total cost, and computation time of MACO-MLA solutions with different sets of weights in Table 4.

| Option($a$,$b$,$c$) | Total suitability | Compactness | Total cost | Run time (minutes) |
|---|---|---|---|---|
| A(1,0,0) | 496, 190 | 0.87925 | 113, 812 | 25.3 |
| B(0.75,0.25,0) | 490, 472 | 0.88223 | 120, 702 | 24.8 |
| C(0.5,0.5,0) | 488, 428 | 0.93864 | 129, 511 | 24.3 |
| D(0.25,0.75,0) | 482, 046 | 0.94011 | 131, 188 | 25.5 |
| E(0.5,0.25,0.25) | 486, 229 | 0.90733 | 75, 451 | 24.2 |
| F(0.25,0.25,0.5) | 478, 653 | 0.91921 | 79, 649 | 25.2 |
| G(0.25,0.5,0.25) | 475, 816 | 0.89715 | 64, 557 | 23.9 |
| H(0.34,0.33,0.33) | 480, 547 | 0.90880 | 71, 361 | 24.6 |
| I(0.5,0,0.5) | 485, 520 | 0.84755 | 64, 300 | 25.5 |
| J(0.75,0,0.25) | 488, 205 | 0.82644 | 70, 619 | 24.7 |
| K(0.25,0,0.75) | 479, 500 | 0.81077 | 62, 321 | 25.8 |

have been proved to be useful techniques for solving land use allocation problems (Brookes 2001, Aerts and Heuvelink 2002, Malczewski 2004, Santé-Riveira *et al*. 2008). The SA method and the GA method are applied to the same data set by using the defined weights in option H so that the performances can be compared with that of the MACO-MLA model. Figure 7 shows the optimal results of these three methods. Table 7 depicts the obtained compactness, average suitability, and utility value of these three methods. As illustrated in Figure 7 and Table 7, MACO-MLA yields the greatest utility value. This value is about 4.5% better than that of SA and about 1.3% better than that of GA. Furthermore, MACO-MLA can generate more compact land use patterns; it has an improvement in compactness over SA and GA methods by 8.9% and 1.7%, respectively. However, the average suitability value of the MACO-MLA model is very close to that of SA and GA methods. Table 8 lists the computation time for these three methods in allocating land units using the same computer. Both the SA method and the GA method need more much computation time than the MACO-MLA model. The computation time of MACO-MLA amounts to only 2.6% and 12.3% of that of the SA and GA methods, respectively. This indicates that the performance of MACO-MLA is encouraging in terms of its utility improvement and computation time.

## 4. Conclusion

The complexities of searching for an optimum land use solution will enormously increase as the number of land uses to be allocated increases and/or the size of the data set increases. Mathematical optimization approaches have difficulties in solving this problem within a reasonable time. This article presents a study of applying the ACO algorithm, a recently developed artificial intelligence approach, to the land use allocation problem. The most important novelty of this study is that we expanded the conventional ACO to include multiple types of ants that represent different land uses and developed a corresponding spatial exchange mechanism, which mimics the competition and interaction of different land uses, through which optimization was achieved.

This modified ACO method was then applied to the creation of optimal land use patterns in Panyu, a rapidly developing region. This large region consists of $1123 \times 1295$ cells. The objective is to generate an optimal allocation pattern that both minimizes converting costs and maximizes land use suitability and compactness. This problem requires a huge amount of computation time to solve by using the mathematical optimization method

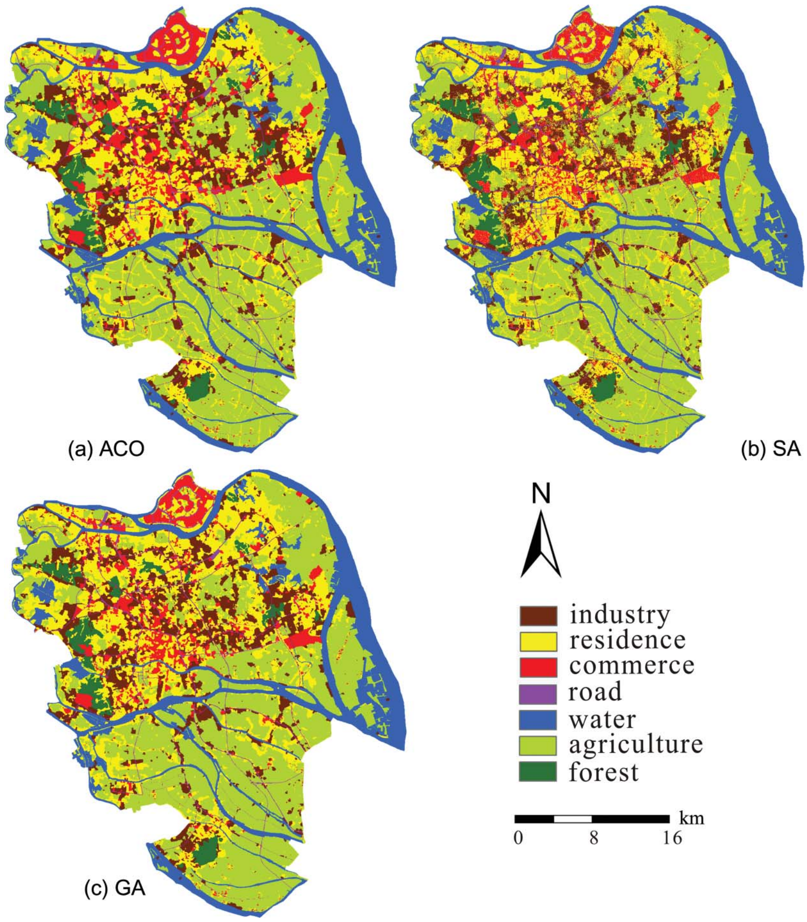


Figure 7. Comparison of optimization results between MACO-MLA, SA, and GA.

Table 7. Compactness, average suitability, and utility for optimization results using MACO-MLA, GA, and SA.

| | Modified ACO | GA | SA |
|---|---|---|---|
| Utility value | 0.64030 | 0.63251 | 0.61279 |
| Compactness | 0.90880 | 0.89341 | 0.83479 |
| Average suitability | 0.92413 | 0.92165 | 0.91837 |

because the combinations are numerous. However, MACO-MLA took only about 25 minutes to find near-optimal solutions. The comparison between the MACO method, the SA method, and the GA method indicates that MACO-MLA can yield a better performance than SA and GA methods. It is found that MACO-MLA can improve the total utility value over the SA method and the GA method by 4.5% and 1.3%, respectively. Furthermore, MACO-MLA needs much less computation time than SA and GA methods, and the computation time of MACO-MLA model only amounts to 2.6% and 12.3% of that of the SA method and the GA method, respectively.

Table 8. Comparison of the computation time using MACO, SA, and GA.

| | MACO | SA | GA | MACO/SA | MACO/GA |
|---|---|---|---|---|---|
| Time (minutes) | 24.6 | 937.4 | 200.8 | 2.6% | 12.3% |

This study should be useful for tackling land use allocation problems involving large amounts of spatial data by adapting and improving ACO-based algorithms. The MACO-MLA method proved to be an efficient and effective optimization technique for generating alternative land use patterns by altering sub-objective weights. It can be used to explore the trade-off between maximizing land use suability, optimizing spatial objectives, and minimizing converting cost. This can allow planners and stakeholders to test and compare what can be gained under different sub-objective weights. It provides a useful exploratory tool for testing various scenarios for land use planning. As such, the MACO-MLA method may make sense to be incorporated as an early planning stage in practical land use planning.

Although the MACO-MLA model can be used to generate alternative land use patterns, there are some limitations in using this model for land use allocation. First, only three objectives have been included in the proposed model, namely, land use suitability, conversion cost, and compactness. However, practical land use planning involves many more factors, such as ecological protection, historical and cultural space protection, governmental planning intention, and landscape aesthetics. Second, the MACO-MLA model lacks a participatory module. Various stakeholders with conflicting interests are involved in land development decision, and an allocation model is required to be participatory so that all the stakeholders' interests are taken into account. Finally, the MACO-MLA model also lacks an interactive tool. A solution that includes all criteria is impossible. Thus, providing an interactive tool is necessary to enable the stakeholders to experiment with criteria, visually explore alternatives, and learn about the problem as they search for feasible solutions (Xiao *et al*. 2007). Future work will extend the capabilities of MACO-MLA for addressing these limitations.



## Acknowledgements

This study was supported by the National Natural Science Foundation of China (Grants No. 40901187 and 41171308) and the Key National Natural Science Foundation of China (Grant No. 40830532).

## References

Aerts, J., 2002. *Spatial decision support for resource allocation*. Thesis (PhD). University of Amsterdam.

Aerts, J. and Heuvelink, G.B.M., 2002. Using simulated annealing for resource allocation. *International Journal of Geographical Information Science*, 16, 571–587.

Bell, J.E. and Mcmullen, P.R., 2004. Ant colony optimization techniques for the vehicle routing problem. *Advanced Engineering Informatics*, 18 (1), 41–48.

Bojórquez-Tapia, L.A., Ongay-Delhumeau, E., and Ezcurra, E., 1994. Multivariate approach for suitability assessment and environmental conflict resolution. *Journal of Environmental Management*, 14, 187–198.

Brookes, C.J., 1997. A parameterized region-growing programme for site allocation on raster suitability maps. *International Journal of Geographical Information Science*, 11, 375–396.

Brookes, C.J., 2001. A genetic algorithm for designing optimal patch configurations in GIS. *International Journal of Geographical Information Science*, 15, 539–559.

Campbell, J.C., *et al*., 1992. An application of linear programming and geographic information systems: cropland allocation in Antigua. *Environment and Planning A*, 24, 535–549.
Carsjens, G.J. and van der Knaap, W., 2002. Strategic land-use allocation: dealing with the spatial relationships and fragmentation of agriculture. *Landscape Urban Planning*, 58, 171–179.
Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. *International Journal of Geographical Information Systems*, 5 (3), 321–339.
Church, R.L., *et al*., 2003. Constructing cell-based habitat patches useful in conservation planning. *Annals of the Association of American Geographers*, 93 (4), 814–827.
Cova, T.J. and Church, R.L., 2000. Exploratory spatial optimization in site search: a neighborhood operator approach. *Computers & Operations Research*, 24, 401–419.
Crohn, D.M. and Thomas., A.C., 1998. Mixed integer programming approach for designed land application systems at regional scale. *Journal of Environmental Engineering*, 124, 170–177.
Diamond, J.T. and Wright, J.R., 1989. Efficient land allocation. *Journal of Urban Planning and Development*, 115, 81–96.
Dibble, C. and Densham, P.J., eds., 1993. Generating interesting alternatives in GIS and SDSS using genetic algorithms. *In*: *GIS/LIS '93*, C. Dibble and P.J. Densham, eds. 180–89. Minneapolis, MN: ACSM, ASPRS, AM/FM International, AAG, URISA.
Dorigo, M., 1992. *Optimization, learning and natural algorithms*. Thesis (PhD), Department of Electronics, Politecnico diMilano, Italy.
Dorigo, M. and Gambardella, L.M., 1997. Ant colony system: a cooperative learning approach to the traveling salesman problem. *IEEE Transaction on Evolutionary Computation*, 1, 53–56.
Dorigo, M., Maniezzo, V., and Colorni, A., 1996. Ant system: optimization by a colony of cooperating agents. *IEEE Transaction on Systems, Man, and Cybernetics-Part B*, 26, 29–41.
Eastman, J.R., *et al*., 1995. Raster procedures for multi-criteria/multi-objective decisions. *Photogrammetric Engineering and Remote Sensing*, 61, 539–547.
Eberhart, R., Shi, Y., and Kennedy, J., 2001. *Swarm intelligence*. San Francisco, CA: Morgan Kaufmann.
Feng, C.M. and Lin, J.J., 1999. Using a genetic algorithm to generate alternative sketch maps for urban planning. *Computers, Environment and Urban Systems*, 23, 91–108.
Frank, E., *et al*., 2010. Weka-a machine learning workbench for data mining. *In*: O. Maimon, L. Rokach, eds., *Data Mining and Knowledge Discovery Handbook*, 2nd ed, 1269–1277.
Gabriel, S.A., Faria, J.A., and Moglen, G.E., 2006. A multiobjective optimization approach to smart growth in land development. *Socio-Economic Planning Sciences*, 40, 212–248.
Gimblett, R.H., Ball, G.L., and Guise, A.W., 1994. Autonomous rule generation and assessment for complex spatial modeling. *Landscape and Urban Planning*, 30, 13–26.
Hua, X., *et al*., 2007. Modeling of temperature–frequency correlation using combined principal component analysis and support vector regression technique. *Journal of Computing in Civil Engineering*, 21, 122.
Janssen, R., *et al*., 2008. Multiobjective decision support for land use planning. *Environment and Planning B*, 35, 740–756.
Krzanowski, R. and Raper, J., 2001. *Spatial evolutionary modeling*. Oxford: Oxford University Press.
Kwang, M.S. and Weng, H.S., 2002. Multiple ant-colony optimization for network routing. *Proceedings of the First International Symposium on Cyber Worlds*, Tokyo, Japan, 2002, 277–281.
Laarhoven, P.J.M. and Aarts, E.H.L., 1987. *Simulated annealing: theory and applications*. Dordrecht, Holland: D. Reidel Publishing Company.
Li, X., He, J.Q., and Liu, X.P., 2009. Intelligent GIS for solving high-dimensional site selection problems using ant colony optimization techniques. *International Journal of Geographical Information Science*, 23, 399–416.
Li, X. and Liu, X.P., 2008. Embedding sustainable development strategies in agent-based models for use as a planning tool. *International Journal of Geographical Information Science*, 22, 21–45.
Li, X. and Yeh, A.G.O., 2005. Integration of genetic algorithms and GIS for optimal location search. *International Journal of Geographical Information Science*, 19 (5), 581–601.
Liu, Y., *et al*., 2007. An integrated GIS-based analysis system for land-use management of lake areas in urban fringe. *Landscape and Urban Planning*, 82, 233–246.
Liu, X.P., *et al*., 2008a. Simulating complex urban development using kernel-based non-linear cellular automata. *Ecological Modelling*, 211 (1–2), 169–181.

Liu, X.P., *et al*., 2008b. A bottom-up approach to discover transition rules of cellular automata using ant intelligence. *International Journal of Geographical Information Science*, 22 (11–12), 1247–1269.
Liu, X.P., *et al*., 2008c. An innovative method to classify remote-sensing images using ant colony optimization. *IEEE Transactions on Geoscience and Remote Sensing*, 46 (22), 4198–4208.
Lumber, E. and Faieta., B., 1994, Diversity and adaptation in populations of clustering ants. *In*: *Proceedings of the third international conference on simulation of adaptive behavior: from animals to animates*. J.-A. Meyer and S.W. Wilson, Eds., Cambridge, MA: MIT Press/Bradford Books, 501–508.
Malczewski, J., 2004. GIS-based land-use suitability analysis: a critical overview. *Process in Planning*, 62, 3–65.
Martínez-Falero, E., *et al*., 1998. Optimization of spatial allocation of agricultural activities. *Journal of Agricultural Engineering Research*, 69 (1), 1–13.
Matthews, K., 2001. *Applying genetic algorithms to multi-objective land-use planning*. Thesis (PhD). The Robert Gordon University, Aberdeen, UK.
Pettit, C.J., 2005. Use of a collaborative GIS-based planning-support system to assist in formulating a sustainable-development scenario for Hervey Bay, Australia. *Environment and Planning B: Planning and Design*, 32, 523–545.
Saaty, T.L., 1980. *The analytic hierarchy process*. New York: McGraw-Hill.
Santé-Riveira, I., *et al*., 2008. Algorithm based on simulated annealing for land-use allocation. *Computers & Geosciences*, 34, 259–268.
Siitonen, P., Tanskanen, A., and Lehtinen, A., 2003. Selecting forest reserves with a multiobjective spatial algorithm. *Environmental Science and Policy*, 6, 301–309.
Smola, A. and Schölkopf, B., 2004. A tutorial on support vector regression. *Statistics and Computing*, 14 (3), 199–222.
Steiner, F., McSherry, L., and Cohen, J., 2000. Land suitability analysis for the upper Gila River watershed. *Landscape and Urban Planning*, 50 (4), 199–214.
Stewart, T.J., Janssen, R., and van Herwijnen, M., 2004. A genetic algorithm approach to multiobjective land use planning. *Computers & Operations Research*, 31, 2293–2313.
Theobald, D.M. and Hobbs, N.T., 1998. Forecasting rural land use change: a comparison of regression and spatial transition based models. *Geographical and Environmental Modelling*, 2, 65–82.
Williams, J.C. and Revelle, C.S., 1998. Reserve assemblage of critical areas: a zero-one programming approach. *European Journal of Operational Research*, 104, 497–509.
WrightCharles, J. and Cohon, J., 1983. A multi objective integer programming model for the land acquisition problem. *Regional Science and Urban Economics*, 12, 31–53.
Xiao, N., Bennett, D.A., and Armstrong, M.P., 2002. Using evolutionary algorithms to generate alternatives for multiobjective site-search problems. *Environment and Planning A*, 34, 639–656.
Xiao, N., Bennett, D.A., and Armstrong, M.P., 2007. Interactive evolutionary approaches to multiobjective spatial decision making: a synthetic review. *Computers, Environment and Urban Systems*, 31, 232–252.
Yeh, A.G.O. and Li, X., 1998. Sustainable land development model for rapid growth areas using GIS. *International Journal of Geographical Information Science*, 12 (2), 169–189.
Yeh, A.G.O. and Li, X., 1999. Economic development and agricultural land loss in the Pearl River Delta, China. *Habitat International*, 23 (3), 373–390.