Land-use zoning in fast developing coastal area with ACO model for scenario decision-making

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Potential ecological environment risks have been emerged as the result of land-use change (e.g. urbanization) in coastal areas. Conflicts between urban growth and ecological conservation should be brought to the forefront especially in the fast developing coastal areas. An optimized landscape pattern for land-use planning could reduce the risk at the regional scale. The cell-based allocation of different land use into the geospace (i.e. land-use spatial zoning, LUSZ) to form optimal pattern with planning objectives and constrains could be viewed as a spatial optimization problem. This study aims to develop a framework incorporated with ant colony algorithm optimization (ACO) to solve LUSZ problem based on the planning guideline of China. Three planning scenarios (i.e. development focusing on urban growth, development considering ecological conversion, and coordinative development between growth and protection) were devised and analyzed with the study area of Doumen District. Comparative analysis with landscape metrics and suitability evaluation indicates that scenario of coordinative development is more available and plausible for land-use change management. This study provides a quantitative and feasible procedure to achieve optimal development pattern on given planning objectives. Moreover, it also demonstrates that cell-based spatial optimization model can generate optimal planning scenarios for decision-making.

Keywords: land-use planning; urban growth; spatial optimization; coastal area

1. Introduction

With the fast development of economy and society, a large amount of ecological land has been converted into construction land especially in the fast developing coastal areas. The land transformation has caused a series of environmental problems, e.g. deterioration of water quality, wetland reduction, and so on (1). In this case, it is an urgent task to make sustainable planning of land use for coastal development (2). Regional land-use planning can be defined as a process of arranging specific land-use types, e.g. urban land, agriculture land, etc. for different land units according to the established rules such as maximum land-use suitability and the most compacted landscape pattern (3,4). In actual, it is difficult to assign every unit with a specific land-use type because the most likely allocation for each type cannot be predicted exactly during the planning process, so regional land-use planning is generally performed at the scale of function zone. This can be defined as land-use spatial zoning (LUSZ), which originated in the late nineteenth century and was ubiquitous in most major cities of US from the 1920s (5,6). As an effective means for management of land resources, LUSZ can reduce the spatial uncertainty of land-use management, and it has been implemented in many countries or regions (7–9). To meet the requirement of land-use planning, the region can be generally discriminated as many different zones with the probability derived from the spatial factors (e.g. the suitability, development state, and dominant utility) (10). Both objectives and constraints of land use should be considered for LUSZ (11). This is obviously a complex spatial optimization problem (12). Therefore, it is necessary to develop efficient quantitative tools for assisting decision-makers in solving such planning problem (13–16).

When zoning of land use at the regional scale (e.g. at a county level or at a city level), there are two main aspects to be considered. The first one is quantity assignment for different land-use activities, and the second one is how to allocate different amount of land use in geospace appropriately (13). These two aspects can be named quantity assignment and spatial allocation. As for the harmonious quantity, it can be assigned according to the regional socio-economic development, and ecological conservation demand. A series of methods have been used to obtain the optimal quantity structure such as the linear programming (17), multi-objective optimization (18), and so on. When considering how to assign those utilities into the space, the framework of land-use suitability evaluation has been used to guide the land-use arrangement for a very long time (19–21). However, optimized land-use zoning cannot be well achieved only with the suitability maps. The key problem of spatial zoning is how to arrange dominant land-use types for each zone on the condition of objectives and constraints (13). More information such as the shape and contiguity of each land-use zone also should be considered (22). It may be easy even for simple method (e.g. enumeration)
to solve such spatial optimization problem if the study area is limited to small spatial units. However, when zoning a county territory or even a larger area at a high spatial resolution (e.g. 100 m × 100 m), it may be more complicated, simple method will pose the problem in retrieving satisfied solutions in a reasonable time.

Actually, when tackling spatial zoning in a “bottom-up” way at a large scale, it can be taken as a typical non-deterministic polynomial problem (23). The potential huge solutions make traditional optimization algorithms such as linear programming cannot obtain the best solution in a reasonable time. Moreover, LUSZ is not a linear programming problem because the conflicts among different planning objectives (e.g. global best suitability and compact landscape pattern) cannot be obtained simultaneously (24). Therefore, a series of intelligent heuristic optimization methods have been correspondingly developed to solve this problem, such as genetic algorithm (25,26), ant colony optimization (ACO) (27,28), particle swarm optimization (29,30), etc. Previous studies have developed many effective spatial optimization models for land-use allocation, but most of the studies are concern about the strategies for coupling optimization algorithms with GIS to obtain optimal spatial patterns applied in zoning natural protected area and multi-type land-use allocation. Spatial optimization models should be revised to obtain practical results for solving LUSZ problem because most of them are mainly theoretical and focus on improving the algorithms from the perspective of computers.

This study aims to discover the optimal zoning pattern under given planning objectives and constraints with the spatial optimization model. An ACO algorithm is devised to tackle such problem with the combination of modified local heuristic information and global pheromone. By selecting Doumen District, a fast developing coastal area of the Pearl River Delta nearby Macao of China as the sample area, the designed ACO–LUSZ model has been further implemented and validated to generate multi optimal scenarios for land-use planning. We quantitatively compare optimal patterns of land-use zoning derived from three different scenarios with structural metrics at the landscape level and discuss the ability of this approach to guide planning of urban growth. The best optimal scenario which not only reflects the ecological conservation, but also meets the planning demands of urban growth has been selected to discuss the land-use policy in environment-friendly development in this coastal area.

2. Materials and methodology
2.1. Study area and data preparation
2.1.1. Study area
The Pearl Delta of China has experiencing rapid urbanization in the past three decades, which has resulted in a large amount of ecological land converted into urban land. Doumen District (longitudes 113°0.5′–113°25′E, latitudes 21°59′–22°25′N) has been the core region of Zhuhai city in the Pearl River Delta with a total area of 674.8 km². This area is mainly characterized with plains in most regions and mountains in the central part. Figure 1 shows the location of the case study area which is composed of five towns including Jining, Baijiao, Doumen, Qianwu, and Lianzhou. By the year of 2010, the total population has exceeded 350,000 and the GDP has over 15.7 billion RMB Yuan. Because it is the significant area in this coastal region to build the connection among Hong Kong, Macao, Guangzhou, Shenzhen, and Zhongshan, this region has locational advantages for urbanization. However, rapid urbanization has resulted in massive non-urban areas converted into urban lands for the requirement of socio-economic development, limited non-urban land can be used for urban growth in the future, and this region is becoming the backyard (i.e. the region providing important reserve land resources for urban growth) of Zhuhai city. It is important to restrain chaotic urban growth for building environmental-friendly society and reducing environmental risk from land-use conversion. Therefore, discussion and exploration of the optimal landscape pattern for this coastal area is an urgent task for land-use planning.

2.1.2. Data preparation
Remote sensing images and GIS spatial data were used to optimize the LUSZ. Landsat Thematic Mapper (TM) image (122-45) collected in 2005 was used to retrieve land-use information. The spatial dataset was used to build the LUSZ model, including the land-use map (2005), DEM, road networks, transportation centers, administration centers (e.g. town centers), and the agricultural land grading map. The DEM and Landsat TM images were downloaded from the United States Geological Survey website (http://earthexplorer.usgs.gov/). Land-use maps were visually interpreted and classified from Landsat TM images. With the consideration of actual conditions in the study area, the land use was first categorized into seven main types according to the standard for land-use planning at the county level in China (10), including cropland, garden land, forest land, urban & village (e.g. urban construction land and rural residents), non-cultivated agricultural land (mainly developed for farm facilities, ponds, ditches, etc.), traffic, and water land (e.g. river and reservoir). Traffic networks were obtained from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn/). Other spatial dataset was obtained from Provincial Geomatic Center of Guangdong province. And socio-economic data were acquired from the statistical bureau of Zhuhai (http://www.stats-zh.gov.cn/). All spatial datasets were converted into raster format with the same projection, the same size of 377 × 336 pixels and resolution of 100 m × 100 m.

The suitability of a certain land-use type is generally considered as the key criterion for spatial zoning. Most
2.2. Methodology of optimizing LUSZ

2.2.1. Objectives and constraints of LUSZ model

In order to better understand the LUSZ model, it is assumed that the spatial region can be represented as grid cells distributed in a two-dimensional space with \( I \) rows and \( J \) columns. Land-use type \( k \) ranging from 1 to \( K \) is allocated to the grid cell in the row \( i \) (\( i = 1, 2, \ldots, I \)) and the column \( j \) (\( j = 1, 2, \ldots, J \)) can be defined as \( u_{ij} \). Therefore, the spatial zoning problem can be expressed as a combination of \( I \times J \times K \) binary variables \( x_{ijk} \), such that \( x_{ijk} = 1 \), if \( u_{ij} = k \), otherwise, \( x_{ijk} = 0 \). This can be accordingly transformed to an integer programming problem involving \( I \times J \times K \) binary variables. If the problem is solved explicitly in terms of the \( x_{ijk} \), then by definition we would require \( \sum_{k} x_{ijk} = 1 \) for each grid cell \((i, j)\), which means that each grid should be arranged with only one dominant type of land use. The aim of land-use planning is just to redefine the most probable zoning type on cell \((i, j)\) during the planning period. The final pattern of land-use zoning is determined by both the objectives and constraints of land-use planning.

(1) Objectives of land-use zoning

In this spatial optimization, LUSZ mainly considers the following two objectives: the average total suitability of all the selected cells for a zone and the landscape pattern for zoning. It can be defined as follows (33):

\[
F = \omega_{\text{suit}} \text{Suit}_{I \times J} + \omega_{\text{comp}} \text{Comp}_{I \times J}
\]  

(1)

where \( F \) is the total utility of a land-use zone for the region \( I \times J \), \( \text{Suit}_{I \times J} \) is the average suitability, and \( \text{Comp}_{I \times J} \) is the landscape compactness of the optimal zone. The parameters \( \omega_{\text{suit}} \) and \( \omega_{\text{comp}} \) are the given weights for the suitability and the compactness, respectively. It is expected for optimal zoning pattern to yield the highest total utility.

As shown in Equation (1), compactness index was used to measure the landscape pattern of the optimal zones. It was generally characterized as the ratio of area to perimeter for every land-use patch, and the more compact pattern is more close to a circle (34). However, as for actual land-use planning, more regular shape for each land-use plaque, such as rectangle and square, is to be more expected. Accordingly, the compactness can be calculated as the number of cells belonging to the same land-use type within a given neighborhood, it is expressed as:

\[
\text{Comp}_{I \times J} = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{p,q \in \Omega} x_{pqk}, \text{ if } x_{pqk} = x_{ijk} = 1
\]  

(2)

where \( p, q \) are the indices of cells around cell \((i, j)\) in a neighborhood window (e.g. 3 × 3 Moore neighborhood or expanded Moore neighborhood); \( x_{pqk} \) is also a binary variable, if \( u_{pq} = u_{ij}, x_{pqk} = 1 \), otherwise, \( x_{pqk} = 0 \).
(2) Constraints of land-use zoning

Actually, each type of land use will be assigned with the minimum and maximum quantities determined by social and economic development in any planning period (35). Both the quantity and the spatial structure of land-use types are considered as the main constraints for spatial zoning (36). The optimized quantity for each zone will be adjusted to meet the demands of land use (e.g. agriculture land or construction land) for social and economic development. In this study, we are mainly concerned about how to obtain the optimized spatial pattern of land-use zoning; therefore, the land-use demands for zoning can be restricted to a certain range value according to the Equation (3):

\[
\lambda_k \leq D_k \leq \mu_k
\]

where \( D_k = \sum_{i=1}^{I} \sum_{j=1}^{J} x_{ijk} \), which is the number of grid cells arranged with the dominant land use \( k \). \( \lambda_k \) and \( \mu_k \) are the lower limit value and the upper limit value for the zone arranged with the \( k \)th type of land use, respectively. \( \lambda_k \) and \( \mu_k \) can be predicted according to social and economic development trend in the past periods. And also the quantity of each type can be given for a fixed value, under this condition, \( \lambda_k \) is equal to \( \mu_k \).

Meanwhile, not all the cells can be adjusted because of their attributes or ecological services, and some cells are only permitted to be transformed into specified types because of natural conditions. For example, some regions including the natural forest reserves and water areas cannot be alternative into other types for the ecological service (37). The patch with the slope higher than 25° cannot be developed for farm land and so on. Other similar natural conditions of the land-use patch should also be considered when building the LUSZ model. Therefore, not only the quantity constraints, but also the spatial constraints should be incorporated into the LUSZ
model. The spatial constraints should be defined according to the circumstances of the study area and the planning demands.

2.2.2. Modifying ACO for solving LUSZ optimization problem

Ant colony optimization (ACO), which was first proposed by Dorigo in 1990s (38), has proven to be a kind of intelligent computation algorithms for solving optimization problems such as shortest path, land-use allocation, and so on (28,39,40). The optimization mechanism of ACO is generally carried out by simulating the behavior of ants in searching for foods through collaboration. During the searching process, each ant can release a chemical substance named as pheromone trail which will also evaporate with the time going. At the beginning of food searching, an ant selects a path for exploration randomly. The path with a larger amount of pheromone trail will be selected by a certain ant. More ants will move along the path with plentiful pheromone trail. As a result, much more pheromone trail will be deposited on this path. Finally, all the ants will be attracted to the path, that is, the shortest one according to this positive feedback mechanism. Meanwhile, ants can adapt themselves to the changed environment. Once the old path is no longer feasible they can find a new one efficiently. The path selected by all the ants will form a solution for the problem to be optimized. Because of this discrete character, ACO is very suit for solving traveling salesman problems (TSP), and researchers have modified this algorithm for site selection or zoning natural protected areas (27,33).

When ACO is used to solve LUSZ problem, all the ants cooperate with each other to execute evolutionary learning. The optimization process will be terminated on the condition that no optimal solutions (planning scenario) can be obtained, and the ant with the best utility value is the optimal scenario that we want. During the optimization process, a number of unique features should be incorporated and modified for adapting the actual objectives and constraints of LUSZ problem including utility function, probability calculation, and strategies for status updating.

(1) Probability calculation

As for LUSZ in actual planning, the type of land-use allocation depends on two main aspects: (1) the preference of individual behavior. For example, farmers or real estate developers usually make their choice according to local environment. (2) global optimization pattern for the whole region. Although every local developer can obtain the best choice only according to personal demand, the optimized spatial pattern for the whole region could not be achieved. Because if all the ants make their local best choice, there must be a lot of conflicts, and the global utility may be decreased. Therefore, the ant’s choice is also impacted by the global decision information. Accordingly, we could use a sub-window like 3 × 3 to estimate the land-use allocation probability, which can be represented as heuristic information (η) for guiding the ants to make their local choice. During the optimization process, the ants’ pheromone trail (τ) is accumulated based on the utility value variation. This can be calculated by the average suitability and average compactness of the zoning scenario. Optimal zoning pattern can be generated on the condition of retrieving the best utility value. A cell allocated with which type of land use is determined by the two characteristic above, and its status is updated according to the transition probability, which is calculated with the combination of heuristic information (η) and pheromone trail (τ). This modified ACO algorithm is shown in Figure 3 and the main four steps can be described as follows:

\[
\tau_{ijk}(t + 1) = (1 - \rho) \times \tau_{ijk}(t) + \Delta \tau_{ijk}(t)
\]

\[
\Delta \tau_{ijk}(t) = \sum_{n=1}^{m} \Delta v_{ijk}^n(t)
\]

\[
\Delta r_{ijk}^n(t) = \begin{cases} \frac{Q \cdot F^n(t)}{\eta_ijk(t)}, & \text{if } x_{ijk}^n = 1 \\ 0, & \text{otherwise} \end{cases}
\]

\[
F^n(t) = \omega_{suit} \times Sui_{ijk}^n(t) + \omega_{comp} \times Comp_{ijk}^n(t)
\]

\[
\eta_{ijk}(t + 1) = \omega_{suit} \times Sui_{ijk}(t) + \omega_{comp} \times Comp_{ijk}(t)
\]

\[
p_{ijk}^n(t + 1) = \begin{cases} \frac{[\tau_{ijk}(t + 1)]^\alpha [\eta_{ijk}(t + 1)]^\beta}{\sum_{j=1}^{q_{\text{allowed}}[\text{allowed}]} [\tau_{ij}(t + 1)]^\alpha [\eta_{ij}(t + 1)]^\beta} & \text{if } i,j \in \text{allowed} \\ 0, & \text{otherwise} \end{cases}
\]

where \(\Delta v_{ijk}^n(t)\) is the quantity of pheromone trail released on the cell \((i, j)\) for selecting type \(k\) by the \(n\)th ant between time \(t\) and \(t + 1\), \(\tau_{ijk}(t)\) and \(\tau_{ijk}(t + 1)\) are the pheromone deposited by all the ants on cell \((i, j)\) for type \(k\) at time \(t\) and \(t + 1\), respectively. \(\eta_{ijk}(t + 1)\) is a heuristic function related to the neighborhood of cell \((i, j)\) with type \(k\) at time \(t + 1\). \(\Omega\) represents the neighborhood of the cell \((i, j)\). \(p_{ijk}^n(t + 1)\) is transition probability for the \(n\)th ant to allocate type \(k\) on the cell \((i, j)\) at time \(t + 1\). \(Q\) is the amount of pheromone that every ant could release, and \(\rho\) is the evaporation rate of pheromone with time going. \(F^n(t)\), \(Sui_{ijk}^n(t)\), and \(Comp_{ijk}^n(t)\) are the utility, average suitability and compactness of the \(n\)th ant at time \(t\), respectively. \(Sui_{ijk}(t)\) and \(Comp_{ijk}(t)\) are the suitability and compactness of the \(k\)th type on cell \((i, j)\) at time \(t\), respectively. \(m\) is the total amount of ants.

(2) Main procedure of LUSZ optimization

This modified ACO algorithm is then performed for solving the LUSZ problem. The flowchart of the optimization algorithm is shown in Figure 3 and the main four steps can be described as follows:
Step 1: Generating the initial solutions randomly. During the initial optimization process, each cell will be arranged for a certain type of land use using the initialization method.

Step 2: Calculating the probability of each zone. The probability of the cell for an ant allocating a certain type is then calculated with Equation (9). That is, local heuristic information $\eta$ within the observation window and global pheromone $\tau$ from the global solution is, respectively, retrieved with the suitability and compactness.

Step 3: Updating the status of each cell. The status of each cell will then be updated according to the following rules:

(a) **Determining the priority of the land-use type.** A cell may be suitable for more than one type of land use according to the objectives, that is, different types may be of the same allocation probability. That which dominant type will be first selected for the cell rests with actual demand of regional planning.
3.1. Model initialization

3.1.1. Defining the types and quantities of land-use zones

Referring to the standards for land-use planning in China, five types of spatial zones will be accordingly assigned based on the initial classification for the study area: (1) Basic farmland preservation area (BFPA); (2) General agriculture area (GAA); (3) Garden area (GA); (4) Forest area (FA); and (5) Construction area for urban and village (CAUV). The dominate land-use zones mentioned above are usually carried out by the land-use planning of China at the country level (10). This study also provides the relevant regulations for the land-use zones of Doumen District in line with the local conditions (Table 1). For instance, as for BFPA, the dominant type of land use in this zone is cropland; also other types such as pond, rural construction land, and garden plot may be included, whereas land-use type such as water land and traffic land cannot be altered for other utilities.

To obtain the optimized spatial zones, the quantity of each zone should be assigned according to economic and social development as well as ecological status (41). In this study, the optimal zoning problem is more attractive, although there are many models for determining the optimal quantity demand, which was just preset referring to actual land-use planning in the period 2006–2020a of this study area (Table 2). We also defined the minimum sizes for different zones according to planning procedures of China correspondingly. From Table 2, it can be found that water land is not permitted to change for the constraint on ecological protection. Apart from the ecological area, the existing linear infrastructure such as traffic network also should be maintained unchangeable. The optimized structure of spatial zones is seriously restrained within the determined quantity.

3.1.2. Initializing the parameters of the ACO–LUSZ model

Table 3 lists the parameters set for the modified ACO algorithm for solving the LUSZ problem, which was referred to the ACO application in area optimization problems (33). The self-adaptive termination time ($\Delta T$) for ACO was set as 30. Theoretically, more ants will help the optimal searching. However, the more ants are, the more difficult for obtaining the optimized solutions in shorter time because of the increasing computation. As for the population of ants, it was set as 20 in this study. Another parameter is the evaporation rate $\rho$, which was set as 0.7. Parameters of $\alpha$ and $\beta$ is, respectively, used to determine the importance of $\eta$ and $\tau$. For ants, searching the optimized route, $\alpha = \beta = 1$, means both of them are same important. While $\Omega$ was set as the window with the size of $7 \times 7$ cells considering minimum area of landscape patch.

At the beginning of this optimization process, initial types arranged to the cells by the ants should be presented. The technique for initializing the distribution randomly has been widely used in most optimization problem (39). However, in actual land-use planning, most of the existing land use should maintain unchangeable in the future. In this study, the initialization was performed according to the following rules: (1) Spatial constraints described in the Section 2 for land-use planning. That is, such existing land-use patches as natural protection areas cannot be readjusted; (2) Initialization with the random mechanism. The transformable cells were selected randomly, and then the type of the highest suitability was allocated to the selected cell. And then its neighborhood was allocated with a type under the crite-
ria of suitability and minimal size requirement. With this heuristic initialization method, both the initialization mechanism of optimization algorithm and the constraints for land-use planning were effectively considered. A reasonable initialization map will help the ants to find the global best landscape for zoning quickly. Figure 4 shows the present land-use pattern, random initialization pattern, and initialized zones with heuristic information. Through the comparison, we can find that initialization map based on heuristic information method seems more reasonable (Figure 4(c)).

3.2. Results of land use spatial zoning with the ACO model

3.2.1. Deriving the best weights combination for LUSZ

The two main objectives may conflict with each other, and the combination of suitability and compactness will influence the final pattern of spatial zoning (42). The weights $\omega_{\text{cost}}$ and $\omega_{\text{comp}}$ in the Equation (1) are used to control the relative preference to suitability and compactness during the land-use planning. Different weights
combination will generate dissimilar patterns for LUSZ. Figure 5 lists the zoning patterns derived from the ACO model with different combinations of $\omega_{\text{cost}}$ and $\omega_{\text{comp}}$.

Obviously, the spatial zoning pattern may tend to be more fragmented with the increasing weight for suitability, whereas the zoning pattern shows more compact with the increasing of $\omega_{\text{comp}}$. The total and single utility values also vary with the different combinations of weights given for suitability and compactness. Figure 6 illustrates the variation trend of the average suitability and compactness when the value of $\omega_{\text{comp}}$ is increasing. According to the experiment, it is found that the utility value of suitability is decreasing, whereas that of compactness is increasing, and a balance point between the two objectives was obtained under the condition of $\omega_{\text{suit}} \in [0.6, 0.7]$ and $\omega_{\text{comp}} \in [0.3, 0.4]$. In actual, it is not merely expected for planning makers to obtain the zoning pattern showing most compact or the highest

Figure 5. Zoning results with different weights for the objectives. (a) $\omega_{\text{suit}} = 0.9$; (b) $\omega_{\text{suit}} = 0.8$; (c) $\omega_{\text{suit}} = 0.7$; (d) $\omega_{\text{suit}} = 0.6$; (e) $\omega_{\text{suit}} = 0.5$; (f) $\omega_{\text{suit}} = 0.4$; (g) $\omega_{\text{suit}} = 0.3$; (h) $\omega_{\text{suit}} = 0.2$ and (i) $\omega_{\text{suit}} = 0.1$.

Figure 6. Variation of suitability and compactness with the growing $\omega_{\text{comp}}$. 

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suitability. That is, the balance between the suitability and compactness is more preferred for land-use planning. Therefore, the combination of $\omega_{\text{suit}} \in [0.6, 0.7]$ and $\omega_{\text{comp}} \in [0.3, 0.4]$ is more suitable for land-use planning in this research.

### 3.2.2. Zoning under multi planning scenarios and results comparison

Meanwhile, a cell may be suitable for different purpose when considering the suitability and compactness, for example, the existing farmland cells around urban land can be developed as construction land or remain unchangeable. The type that the cell should be transformed into is determined by many factors. In this study, only the preference to the two objectives shown by the planning makers was mainly discussed for the spatial zoning. As a tool capable of implementing “what-if” scenario analysis to spatial zoning, the LUSZ model can spatially and explicitly obtain the zoning patterns in the near future according to the various preference between the two objectives. Experiment of these future scenarios will provide scientific information on spatial zoning of the study area for planners. Based on the analysis of optimal weights for the objectives, weights for suitability and compactness were set as 0.7 and 0.3, respectively. Then this weight combination was used to generate land use spatial zoning patterns for the year of 2020 using the ACO–LUSZ model. Accordingly, the following three planning scenarios were set: (1) scenario 1, which aims to give the priority to urban & village. If the cells are most suitable for arranging both urban & village and farmland, then the status of ants will be preferentially updated with urban & village (Figure 7(a)); (2) scenario 2, which focus on ecological conservation. The ecological land such as forest, garden, and farmland protection areas will be adjusted as dominant type with the higher probability (Figure 7(b)); and (3) scenario 3, which seeks the coordinative growth pattern between construction and ecological conservation. Each suitable type for a cell will be updated with the same chance (Figure 7(c)). Figure 7 shows the results of optimal LUSZ under the above planning scenarios for 2020a.

To validate the performance of the LUSZ model, the comparison was carried out quantitatively between the optimized patterns and the current status in the year of 2005. Figure 8 and Table 4 list the comparison results. It is shown that the average suitability and compactness of most optimized zones were increased significantly except for that of GAA. Because the dominant type of GAA is non-cultivated agriculture land, which is mainly composed of ponds, agricultural facilities, etc. Those types will not be generally adjusted for spatial zoning during the planning period. This experiment shows that the average suitability and landscape pattern of most optimized zones derived from the LUSZ model would be either increased or remained stable during the planning period.

The comparison above demonstrates that all the three scenarios for planning will increase the average suitability and compactness. As for the zoning result generated from scenario 1, CAUV was given the priority to be allocated in the study area and distributes with the highest value of compactness, which results in that some ecological conservation areas in most districts will be occupied by CAUV (Figure 7(a)). Scenario 2 was designed that ecological conservation zones such as

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**Figure 7.** Zoning results under multi planning scenarios. (a) Scenario1; (b) Scenario2; and (c) Scenario3.

**Figure 8.** Average suitability and compactness of different optimal zones.
forest, garden, and farmland protection areas were constrained for urban growth. Accordingly, zones dominated with those ecological types show higher compactness than those derived from scenario 1 (Figure 7(b)). When both urban growth and ecological conservation were considered, optimized pattern shows the most equilibrium state among all the zones (Figure 7(c)), which is more regulable for land-use planning in the future. Furthermore, as for actual land-use management, we should choose the best one to guide the future land use. The average suitability and compactness of the three scenarios are further compared. Table 4 shows the single utility values and total utility values generated from the three planning scenarios. It can be found that scenario 3 brings the highest suitability for almost all the zones except GAA and GA, and it also generates the highest total compactness and average suitability. Therefore, scenario 3 is concluded to be most suitable for assisting decision-making.

4. Conclusions

It is an urgent problem to make sustainable planning of land use in coastal areas for tackling the environmental problems resulted from rapid urbanization. The main purpose of regional land-use planning is to assign different land-use types in the geospace. However, it is actually difficult to arrange a specific land-use type for each grid cell. Regional land-use planning is generally performed at the scale of function zone rather than grid cell. The technique of LUSZ is applied to solve land-use allocation during the planning process. The key problem of LUSZ is to achieve the optimized pattern of spatial zoning with the alternative quantity constrains. LUSZ can be taken as a cell-based spatial optimization problem, and the optimal landscape pattern derived from LUSZ model can assist planners to make decision.

In this study, the LUSZ model is devised according to the framework of land-use planning at the county level in China. A modified ACO algorithm is then used to retrieve the optimized layout of spatial zoning. Which dominant type will be allocated to the traveling cell is mainly determined by the transition probability, which is calculated with local heuristic information and global pheromone. Therein, the local heuristic information can be directly obtained from local environment within a neighborhood window. Both the suitability and the landscape pattern of each spatial zone are considered as the main factors for local environment. The value of global pheromone is mainly determined by the solution obtained by each ant. In this optimization process, the status of each ant is then updated according to the transition probability and constraints.

The LUSZ model is validated with the application to the case study area of Doumen District, the core region of the coastal region in the Pearl River Delta in China. It is found that different weights for the suitability and compactness will influence the pattern of spatial zoning. In general, planning makers expect to achieve the optimized balance between suitability and compactness for practical application, the best combination of the weights (e.g. $\omega_{\text{suit}} \in [0.6, 0.7]$ and $\omega_{\text{comp}} \in [0.3, 0.4]$) for suitability and compactness, respectively, is generated to assist decision-making. Based on this, the optimized zones with different planning scenarios are also analyzed to validate the efficiency of the LUSZ model. Compared with the present land use, the suitability and compactness are improved for most types of spatial zoning. Among the three optimal planning scenarios, the coordinative development between construction and ecological conservation scenario could achieve both the highest suitability and compactness. Therefore, the landscape pattern under coordinative development which is generated by ACO–LUSZ is the best choice for this study area.

Ecological and environment risks will become serious if there is no sustainable land-use planning. Developing some planning tools to assist environment management is very important and urgent. The essence of spatial optimization is to generate optimal landscape pattern of land-use allocation under the given objectives, which may conflict with each other. For example, both urban growth and ecological conservation should be considered for sustainable planning. The cell-based spatial optimization methods can retrieve the balance between the above two objectives. From this study, we can find that LUSZ model based on spatial optimization is a powerful assistant tool for land-use planning though there are still some drawbacks to be improved. We hope that cell-based geospatial optimization model will provide a quantitative analysis framework for scenario decision-making in resources and environment management for coastal areas, especially in spatial planning.

### Table 4. Suitability and compactness comparison between present and planning.

|                 | Maps            | BFPA | GA  | FA  | GAA | CAUV | Total   |
|-----------------|-----------------|------|-----|-----|-----|------|---------|
| **Suitability** | Land use in 2005a | 1192 | 328 | 1162| 1667| 1151 | 5500    |
| Scenario1       | 2355            | 477  | 1305| 1164| 1409| 6690 |
| Scenario2       | 2501            | 594  | 1230| 1142| 1377| 6846 |
| Scenario3       | 2534            | 565  | 1382| 1134| 1484| 7109 |
| **Compactness** | Land use in 2005a | 6294 | 1061| 7929| 10,512| 6814 | 32,610  |
| Scenario1       | 10,918          | 1596 | 8613| 5992| 10,161| 37,280 |
| Scenario2       | 11,388          | 1986 | 8818| 6082| 10,146| 38,420 |
| Scenario3       | 11,331          | 1987 | 8529| 9029| 9550| 40,426|
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