forests

MDPI

Article

Spatial Optimization with Morphological Spatial Pattern Analysis for Green Space Conservation Planning

Jinyao Lin *, Yijuan Zeng and Yuqi He

School of Geography and Remote Sensing, Guangzhou University, Guangzhou 510006, China
* Correspondence: ljy2012@gzhu.edu.cn

Abstract: Conservation areas are essential for preserving green spaces and biological diversity. Although previous studies have demonstrated that spatial optimization techniques are effective for balancing the relationship between ecological importance and spatial pattern during conservation practices, the design of ecological corridors still requires an efficient, intelligent, and flexible workflow. In addition, functional connectivity information is usually unavailable or very difficult to obtain. To alleviate these problems, this paper has developed a new spatial optimization-based model that combines morphological spatial pattern analysis (MSPA) with ecological importance assessment. The consideration of MSPA can guarantee enough ecological corridors in the conservation plan, while the regions with higher ecological importance can be discovered through an ecological importance assessment. This method has been applied to the planning of conservation areas in a highly developed city. Several experiments have indicated that our proposed model could achieve much better performance than conventional models in terms of spatial pattern. Therefore, this new model is expected to assist decision processes during the planning and regulation of green spaces in fragmented urban ecosystems. Furthermore, it can be applied to ecological management and planning in many other aspects because the above-mentioned research gaps are not unique to only Asian or less-developed countries.

Keywords: green space; morphological spatial pattern analysis; land use optimization; spatial planning

check for updates

Citation: Lin, J.; Zeng, Y.; He, Y. Spatial Optimization with Morphological Spatial Pattern Analysis for Green Space Conservation Planning. *Forests* **2023**, *14*, 1031. https://doi.org/10.3390/f14051031

Academic Editors: Cate Macinnis-Ng and Fausto Manes

Received: 20 February 2023
Revised: 19 April 2023
Accepted: 15 May 2023
Published: 17 May 2023

1. Introduction

With urban areas rapidly expanding throughout the world, urban green spaces (e.g., forests, grasslands, wetlands) are substantially shrinking and becoming increasingly fragmented [1–4]. Earlier research has shown that conservation areas should be established to limit the extent of urban sprawl within ecological hotspots [5–7]. The implementation of conservation areas is of great importance for preventing immoderate urban expansion and maintaining green space quality [8–10]. Many countries and regions have designed their own conservation areas over the past few decades [11–13]. For example, the Chinese government has made great efforts toward the development of "ecological civilization" in recent years [14–17].

In practical applications, these tasks are mainly accomplished through a combined use of ecological importance assessment, spatial analysis, and geographical mapping techniques [18–21]. Although such methodological framework has been commonly adopted by land use planners, spatial pattern is easily neglected during the planning procedures [22–24]. In fact, it is very difficult to find out the optimal spatial pattern of conservation areas simply based on manual methods. A disintegrated configuration will be obtained if spatial restraint is not considered. Moreover, the objectivity of conservation area planning is increasingly being questioned in many regions [25–27]. Therefore, in addition to simply increasing the number and size of conservation areas, decision-makers also need to pay enough attention to the quality and rationality of planning.

To tackle the above issues, a number of studies promoted the use of spatial optimization techniques, which can simultaneously consider ecological importance and spatial pattern during conservation planning [28–32]. Multiobjective intelligent algorithms, such as genetic algorithms, are widely utilized to resolve various mathematical optimization problems [33–37]. A fundamental part of optimization is the determination of an objective function, a numerical value to be maximized or minimized under certain constraints. Therefore, a balance between ecological importance and spatial pattern can be effectively achieved by defining a suitable objective function [22,38,39]. While the former can be easily assessed based on ecological importance analysis, the latter is more difficult to characterize.

Some landscape indicators, including edge density and compactness, are regularly utilized to reflect spatial patterns. Notably, Li et al. [40] proposed an effective conservation area zoning method by considering landscape shape index and ecological importance. Lin et al. [38] adopted the compactness metric to characterize the spatial pattern of conservation areas. In addition, some other studies have incorporated connectivity metrics into conservation area planning. For example, Daigle et al. [41] developed a spatial conservation planning model that can consider demographic and landscape connectivity. Beger et al. [42] have incorporated connectivity into spatial decision-making for marine conservation.

However, these traditional indicators could not completely set apart multiple morphological layouts with diverse environmental effects [43,44]. In particular, the connecting passageways that will enable the efficient movement of species between various habitats (i.e., ecological corridors) play a prominent part in the conservation of biodiversity [45–48]. Unfortunately, these narrow-shaped components are very difficult to be automatically generated through spatial optimization techniques [38,49]. This phenomenon will become even worse within a relatively data-poor context, e.g., functional connectivity information is usually unavailable or very difficult to obtain.

In fact, core conservation areas and linear corridors could be distinctly set apart via a morphological spatial pattern analysis (MSPA), which incorporates various geometrical tools that are powerful to characterize land use configuration at a grid-scale [44]. Land-use datasets (conservation area plans) can be categorized into seven morphological layouts building on size, structure, and connectance [43]. This method has been successfully employed in various land-use monitoring and assessments. Notably, Mairota et al. [50] presented a MSPA-based method to monitor conservation areas. Furthermore, Wickham et al. [51] performed a MSPA-based nationwide evaluation of green space throughout the United States. However, MSPA has not been adopted during the intelligent planning of conservation areas. In that case, conventional spatial indicators should be replaced by MSPA so that the spatial pattern of conservation can be described better. That is, the size of corridors can be regarded as an additional criterion for ecological planning. To sum up, the main objective of our paper is to introduce a new spatial optimization-based zoning method by combining MSPA and ecological importance assessment.

2. Materials and Methods

According to previous findings, two fundamental criteria (i.e., ecological importance and spatial pattern) should be carefully considered during the planning of conservation areas [22,40]. Firstly, most land-use pixels with significant ecological importance should be included in the conservation areas. Secondly, high compactness and connectivity degrees are important to the maintenance of biodiversity and ecological sustainability. Therefore, we first performed an ecological importance assessment. Then, the best conservation area plan was determined using an intelligent algorithm (genetic algorithm). Ecological importance and MSPA result were simultaneously considered during the optimization processes. Figure 1 displays the flowchart of this study, and more detailed information is described in the following sections.

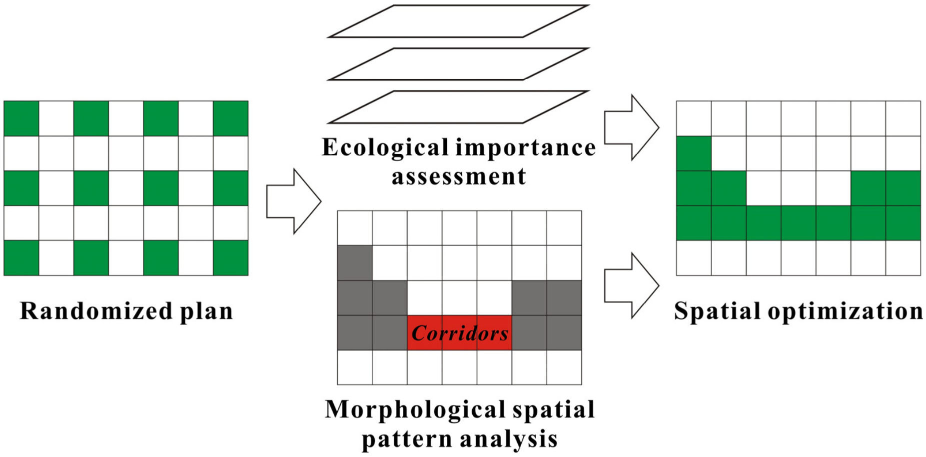

Figure 1. Flowchart of green space conservation planning with MSPA (Red: corridors; Green: conservation areas; Gray: non-corridors).

2.1. Ecological Importance Assessment

As a fundamental part of conservation area planning, an ecological importance assessment was performed to reveal the ecological importance at the pixel level. It should be noted that the meaning of "ecological importance" in this case study draws from the regulations issued by the local government. Generally speaking, the regions with more important ecological functions, higher biological diversity, higher agricultural productivity, and steeper slopes should be protected. According to the findings from previous related studies, ecological importance can be assessed by using a set of ecological spatial factors as follows [23,38]:

(1) Net primary productivity (NPP):

NPP refers to the overall amount of organic matter accumulated by vegetation over a particular area and time period. As an essential element of the carbon cycle, NPP measures the difference between the carbon absorbed by photosynthesis and the carbon released by autotrophic respiration. Therefore, NPP has been commonly used to represent the ability of green plants to fix and convert inorganic carbon into organic carbon;

(2) Habitat heterogeneity (HH):

Habitat heterogeneity can characterize the global configuration of varying environmental situations. Studies have demonstrated that species diversity exhibits a strong positive relationship with habitat heterogeneity in the landscape [52]. Habitat heterogeneity involves three elements: topographic wetness index, aspect, and soil types. Therefore, two major steps were needed for the calculation of this factor: (1) building a binary tree that can interpret "habitats" according to the combination of the above three elements; (2) measuring habitat heterogeneity according to 25 land pixels (30 m $\times$ 30 m) that occupy each grid (150 m $\times$ 150 m) using the Shannon-Weaver index [52].

First of all, the topographic wetness index, which combines the water supply from the upslope catchment area and downslope water drainage for each pixel in a digital elevation model [53], is usually quantified based on the following formula:

$$\text{Wetness index} = \ln\left(\frac{\text{Asi}}{\tan\beta}\right) \quad (1)$$

where Asi means the upslope contributing areas (i.e., the areas that can potentially contribute runoff to the region of interest) [54], and β denotes the slope angle. The output values of this index were then separated into three different categories according to the well-accepted Jenks Natural Breaks method.

In addition, aspects were generated from the digital elevation model, and soil type data were acquired through the department of land use planning. Then, the aspect was separated into four categories: west-facing, east-facing, north-facing, and south-facing slopes, and the study area consists of three major soil types: lateritic soil, waterloggogenic paddy soil, and salt marsh soil. Therefore, there are 36 (3 × 4 × 3) possible combinations (i.e., habitats) among the 3 elements. Lastly, habitat heterogeneity is measured, building upon the Shannon–Weaver index for each grid (150 m × 150 m) [55]:

$$\text{Habitat heterogeneity} = -\sum_i p_i(\ln p_i) \quad (2)$$

where p means the proportion (relative abundance) of each habitat with respect to the total habitats;

(3) Slope:

Topographic situations play an essential role in water-soil protection. Slope, which quantifies the rise or fall degree of land surface, is a useful metric for ecological importance assessment. For example, landslides easily occur in areas with steep slopes (usually greater than 25%). Therefore, although these areas are not "ecologically important", they should still be carefully protected to lessen the potential negative impacts of geologic hazards, such as landslides;

(4) Proximity to aquatic areas (PA):

Aquatic areas are essential parts of ecological conservation areas because water is a vital nutrient to all living things. In addition to the aquatic areas, which are valuable to water supply and sanitation, the regions which are closer to aquatic areas should also be carefully protected since aquatic resources are easily threatened by surrounding socio-economic activities in densely populated areas;

(5) Soil quality (SQ):

Soil quality can reflect the capability of soil to supply ecological and social benefits, such as supporting agricultural production and conserving environmental health [56]. The spatial data about soil attributes (i.e., organic carbon, available water storage, and soil reaction (pH)) were collected through the United Nations' Food and Agriculture Organization. Those land use pixels that are very necessary to be protected were assigned a higher value (closer to 1), while the undesirable pixels were assigned a lower value (closer to 0). For example, the pixels with a pH between 5.5 and 7.2 were assigned 1, the pixels with a pH between 4.5 and 5.5 or between 7.2 and 8.5 were assigned 0.5, and the remaining pixels were assigned 0, according to local field experience. Finally, the average score of the three elements at pixel level was regarded as the soil quality in this study.

All the above spatial factors were rescaled into the range of [0, 1]. Then, they were combined as an ecological importance (S) map using a linear weighted formula [23,40,57]:

$$S = w_1 \times \text{NPP} + w_2 \times \text{HH} + w_3 \times \text{Slope} + w_4 \times \text{PA} + w_5 \times \text{SQ} \quad (3)$$

where w_n denotes the weight for each spatial factor, and $\sum w = 1$. Therefore, the land use pixels with different importance scores can be balanced by using this combination method. The methodological framework is the same if more available spatial data are involved in other applications.

2.2. MSPA

MSPA is a digital signal processing application designed for the presentation of digital remote-sensing images [44]. This method incorporates various geometrical tools that are powerful to characterize land use configuration at a grid-scale, building upon several computer vision algorithms (e.g., eroding, dilating) [43].

The land use grids within areas of interest (e.g., candidate conservation area schemes) were considered "foreground", and the rest grids were considered "background". The area of interest was categorized as seven morphological types in line with the morphological attributes (see Table S1 in the Supplementary Materials). Notably, core ecological habitation and narrow linear corridors could be straightforwardly distinguished through MSPA. Full information about the theory of MSPA was interpreted in the study of Soille and Vogt [44].

2.3. Spatial Optimization Using Genetic Algorithm

As mentioned above, both ecological importance and spatial pattern should be considered during the planning of conservation areas. To simultaneously achieve these two goals, we built upon the genetic algorithm (GA)-based spatial optimization model developed by Lin et al. [38] to figure out the near-optimal plan of the conservation areas. The concept of GA builds upon Darwin's principle of "natural selection" and "survival of the fittest" [58]. Furthermore, numerous research studies have demonstrated that GAs are very powerful for solving many types of mathematical optimization problems [59,60].

The optimization process of GA can be regarded as the process of biological evolution. First, a number of initial individuals (i.e., candidate solutions) are randomly generated. Then, each individual is encoded as a binary matrix, in which 1 represents conservation area pixels, and 0 represents non-conservation area pixels. Next, the new generation of solutions is obtained through selection, crossover, and mutation operations, and those individuals with lower fitness are gradually eliminated. Lastly, highly adaptable solutions can be found after iterative evolution procedures. In fact, the fitness of each individual is assessed through an objective function, in which ecological importance and spatial pattern can be considered simultaneously. In particular, the compactness metric has been largely utilized by much earlier research to reflect the spatial pattern of conservation areas. Therefore, the objective function of the GA model is formulated as follows [23,38]:

$$\text{Objective function} = \text{Maximize } w_s \times S + w_c \times 4\sqrt{A}/P \tag{4}$$

where S is mean ecological importance, A is the size of the conservation areas, P is the perimeter of conservation areas, and w is the weight for each criterion ($\sum w = 1$). The total size of conservation areas (namely, the number of protected land use pixels) was regarded as the constraint of the GA model during the spatial optimization process.

The difference between our proposed method and the above traditional method lies in the indicators of spatial patterns. While traditional methods usually adopted common spatial metrics, we distinguished ecological corridors and core areas using MSPA to characterize the spatial pattern of conservation areas better. Specifically, the size of cores and corridors (both bridges and loops) are considered in the objective function of the GA model. Therefore, ecological importance and spatial pattern were combined using a linear weighted equation, and the improved objective function of the GA model is formulated as follows:

$$\text{Objective function} = \text{Maximize } w_s \times S + w_{c1} \times \frac{A_{\text{core}}}{A} + w_{c2} \times \frac{A_{\text{corridor}}}{A} \tag{5}$$

where A_{core} denotes the size of cores, A_{corridor} denotes the size of corridors, and w denotes the weight for each criterion ($\sum w = 1$). A_{core} and A_{corridor} are two equally important criteria. The consideration of A_{core} can maintain the integrity and compactness of conservation areas, while the consideration of A_{corridor} can guarantee the connectivity degree.

Next, this objective function was utilized to measure the fitness of every candidate solution in each generation. It is expected that the best solution will achieve the largest scores for both mean ecological importance and spatial pattern metrics. Therefore, we employed an "elitism" strategy that directly replicates the current optimal solution to upcoming generations. Such a strategy could ensure that the eventual optimal outcome will not be worse than the best individual ever found.

The GA-based optimization model can discover the optimal conservation area plan by following the objective function after iterative runs of selection, crossover, and mutation processes. To this end, the fitness proportionate selection method was used to select parents for mating and propagating their features to the next generation. Every individual can become a parent with a chance that is proportional to their fitness value (objective function). In addition, a patch-based crossover and mutation strategy was adopted so the parents could produce compact conservation area plans. More details on this strategy can be found in Lin et al. [38] and Cao et al. [61]. The new objective (Formula (5)) can also be achieved by using other multiobjective optimization algorithms.

3. Implementation and Results

3.1. Case Study

Shenzhen, a highly developed megalopolis in Asia, was chosen as the case study region. Shenzhen has developed as an international city after the reform and opening-up policies of China. However, a large amount of ecological space has been encroached upon during the remarkable economic and urban growth. The vegetation coverage rate in Shenzhen is merely 39.2%. Zoning conservation areas in this big city is an urgent need for conserving ecosystem services and biodiversity. Therefore, Shenzhen is a suitable study area through which we could examine the proposed model. In fact, such ecological problems frequently happen in many other countries and regions because an increasing number of residents become permanently concentrated in relatively small, urbanized areas. The United Nations predicted that over two-thirds (about 68%) of the global population will live and work in urbanized areas by 2050. In that case, an effective method designed for conservation area planning is key to the sustainable development of our natural world.

As introduced in Section 2.1, several fundamental ecological factors were utilized for ecological importance assessment. First, we obtained the NPP datasets (MOD17A3H) via the National Aeronautics and Space Administration. Additionally, soil attribute information was collected through the United Nations Food and Agriculture Organization. Lastly, the digital elevation model and ground-truth land-use dataset were collected through the Chinese Academy of Sciences. The ground-truth land-use dataset has been categorized into six types, namely, cropland, forest, grassland, aquatic area, built-up area, and unused area. All these spatial factors have been resampled into a spatial resolution of 1000 m so that the computational burden can be reduced (Figure 2a–e and Table 1).

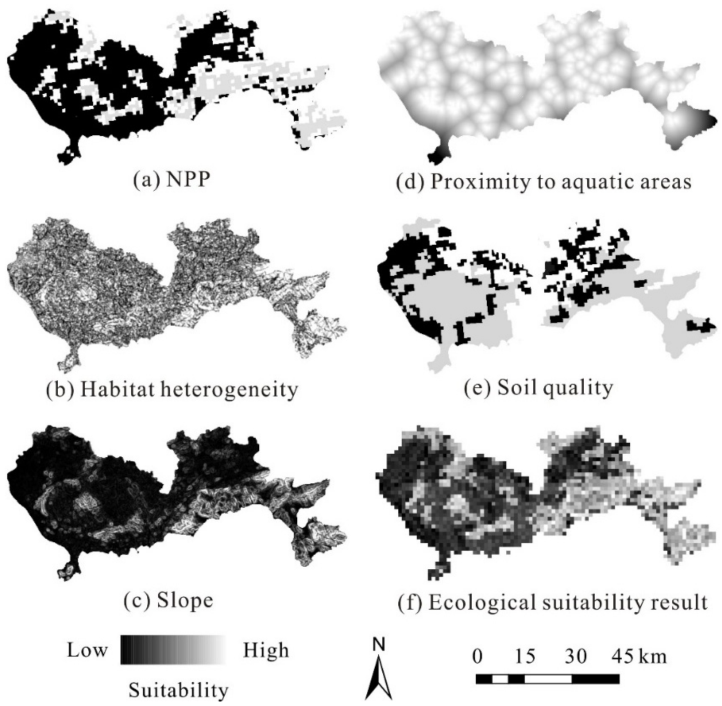

Figure 2. Ecological spatial factors and ecological suitability result: (**a**) NPP, (**b**) Habitat heterogeneity, (**c**) Slope, (**d**) Proximity to aquatic areas, (**e**) Soil quality, and (**f**) Ecological suitability result.

Table 1. Data source and description in this study.

Data	Resolution	Year	Source
NPP	500 m	2018	National Aeronautics and Space Administration
Soil attribute	~1000 m	-	United Nations Food and Agriculture Organization
Soil type	1:1 million scale	2015	Department of land use planning
Digital elevation model	30 m	2018	Chinese Academy of Sciences
Ground-truth land use	30 m	2018	

3.2. Implementation

First, we assessed the ecological importance throughout Shenzhen, building upon a set of ecological spatial factors. The weights for these factors (Formula (3)) were determined based on experts' experiences and domain knowledge. It should be noted that the experts in this study were selected based on their profession and familiarity with the study area. After their group discussion, the pairwise comparison matrix and the resultant weights are presented in Tables 2 and 3, respectively [38]. Figure 2f displays the combined ecological importance result.

Table 2. Pairwise comparison matrix for ecological importance assessment.

	NPP	Habitat Heterogeneity	Slope	Soil Quality	PA
NPP	1	1.20	1.50	2.00	2.50
Habitat heterogeneity	0.83	1	1.20	1.50	2.00
Slope	0.67	0.83	1	1.20	1.50
Soil quality	0.50	0.67	0.83	1	1.20
PA	0.40	0.50	0.67	0.83	1

Table 3. Weights for ecological importance assessment.

NPP	Habitat Heterogeneity	Slope	Proximity to Aquatic Areas	Soil Quality
0.2959	0.2375	0.1907	0.1229	0.1531

Next, the GA-based spatial optimization model was used to search for the best plan of conservation areas based on the ecological importance result. Firstly, several parameters should be defined before running this model. Generally speaking, the GA model with a population size ranging from 20 to 200 can provide desirable outcomes [62]. Additionally, a much longer time is needed for spatial optimization if a larger population size is adopted. Therefore, considering that the optimization task in this study is not too complicated, a medium population size (100) was adopted. Finally, we defined the other parameters for running GA building upon previous relevant research (Table 4) [38]. Specifically, both the crossover and mutation rates were assigned a larger probability score (0.90) to guarantee enough newborn individuals through the crossover and mutation procedures. Additionally, the iteration number was assigned a larger value (10,000) to avoid premature convergence of the GA model.

Table 4. Parameters for the GA-based optimization model.

Population Size	Iteration Number	Crossover Rate	Mutation Rate	w_s	w_{c1}	w_{c2}	w_c
100	10,000	0.90	0.90	0.50	0.10	0.40	0.50

Secondly, the weight for ecological importance assessment (w_s) was set as a fixed value (0.50) to facilitate the comparisons between our method and the conventional method. Thirdly, the weights for the size of cores and corridors (w_{c1} and w_{c2}) were determined through manual tuning (with an interval of 0.05). Lastly, half of the total land area should be protected as stated by local land use regulations. After running the GA-based model, the final optimization result of the conservation areas is shown in Figure 3a.

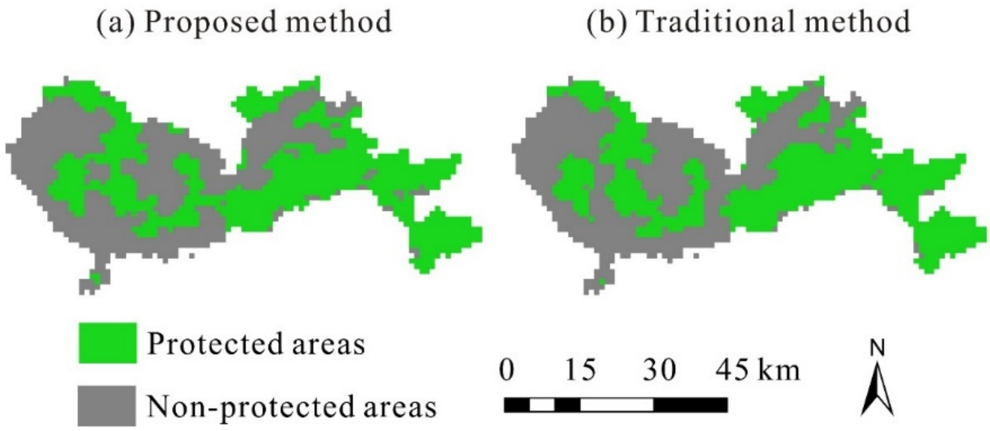

Figure 3. Protected area plans generated by: (**a**) the proposed method; (**b**) the traditional method.

For comparison, we also generated another conservation area plan based on a commonly used traditional method. That is, instead of Formula (5), Formula (4) was adopted as the objective function of the GA. The remaining processes were completely the same as those presented in the above-mentioned spatial optimization model. This traditional result is presented in Figure 3b.

We found that there exist only a few ecological corridors in the plan generated by the traditional method, which implies that such a result is already recognized as well-connected when traditional landscape metrics are used to reflect spatial patterns. This phenomenon happens because most of the land use pixels will gather into several large habitat patches so that the compactness score can be maximized. The planning result will also be undesirable if connectivity indices are adopted since two patches will be considered linked when the proximity between them is less than an established threshold during the calculation.

Next, we calculated a number of metrics (Formulas (4) and (5)) to quantify the performance of the two plans. The results are compared in Table 5. Although the two results share very similar average ecological importance, their spatial patterns vary considerably. Undoubtedly, the pattern produced by the traditional method has a higher compactness score than that generated by the proposed method. However, more importantly, we found that the percentage of corridors in the latter is much higher, which suggests that our new objective has been successfully achieved. The viability of endangered species can be enhanced through the connection of fragmented core habitats.

Table 5. Ecological suitability and spatial pattern of the two protected area plans.

	Average Ecological Suitability	Compactness Score	Percentage of Cores	Percentage of Corridors
Our method	0.6029	0.1816	46.71%	9.63%
Traditional method	0.6021	0.1982	52.19%	3.07%

For further evaluation, those two planning results were also overlaid with the ground-truth land use data (Figure 4). As summarized in Table 6, most of the forest, grassland, and aquatic areas have been included in both results. However, the one generated by the traditional method contains more built-up areas, which may result in more land-use conflicts and social inequality.

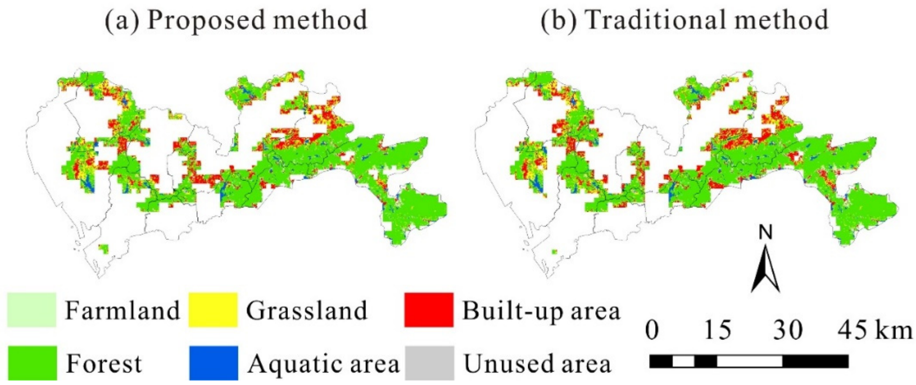

Figure 4. Overlay analysis of the planning results and ground-truth land-use data: (**a**) the proposed method, and (**b**) the traditional method.

Table 6. Land use composition of the planning results.

	Farmland	Forest	Grassland	Aquatic Area	Built-up Area	Unused Area
Our method	2.47%	65.66%	12.56%	3.92%	13.83%	1.55%
Traditional method	2.72%	65.44%	12.14%	3.96%	14.18%	1.55%

3.3. Discussion and Policy Implications

3.3.1. Further Comparisons with Other Methods and Results

To further evaluate the proposed method, we also compared our result with the result generated by a conventional non-spatial optimization method (i.e., density slicing) and the draft plan provided by the local department of land use planning. The density slicing method divides the land use pixel values into two categories (i.e., protected and non-protected), building upon the ranking of ecological suitability scores [23,40]. In other words, the land use pixels with higher ecological suitability scores in this study area were chosen for generating the conservation areas.

As shown in Figure 5a, the result generated by the density slicing method exhibited a very fragmented spatial pattern. This result can hardly be put into implementation because the important connectivity and compactness criteria have not been taken into account in the method. Additionally, compared with the real-world draft plan (see Figure 5b), we found that some narrow-shaped and small land use pixels were not incorporated in our result. This is because these tiny elements are easily ignored by spatial optimization techniques. Nevertheless, generally speaking, the real-world draft plan and our result shared a similar spatial pattern. The differences are in part due to the fact that policymakers can acquire much more detailed and accurate data. Overall, these comparisons have indicated that the proposed method is promising in conservation area planning.

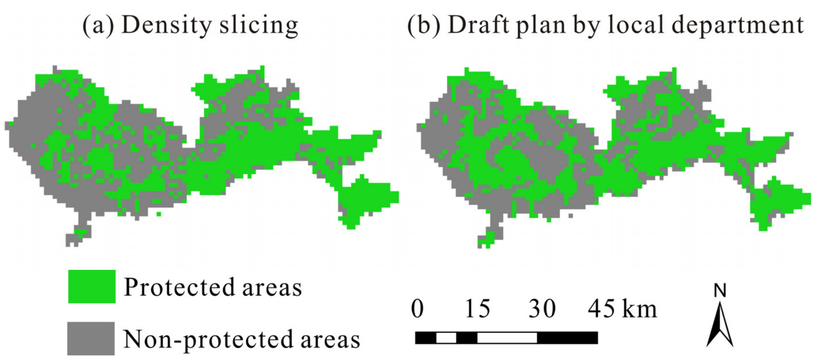

Figure 5. Comparisons with other methods and results: (**a**) density slicing, and (**b**) draft plan by local department.

3.3.2. Advantages of This Study and Policy Implications

Spatial optimization-based models are the current cutting-edge methods for land use and ecological planning. A number of advanced multiobjective intelligent algorithms have been selected to assist the planning of conservation areas. Nevertheless, there is still huge room for improvement because previous studies mainly focused on the upgrade of intelligent algorithms. In fact, the objective function is the core of spatial optimization-based models. Therefore, the resultant conservation area plans can hardly be put into practice if the objective function is not properly designed by policymakers.

To overcome this disadvantage, a novel zoning model with an improved objective function is developed in this study. Our proposed method performs better than the traditional method in terms of the following two points. Firstly, although some popular spatial metrics have been widely considered in the objective function to characterize spatial patterns, linear corridors are still very difficult to generate regardless of the spatial optimization techniques. Fortunately, MSPA is a convenient approach for setting apart core areas and corridors. Considering the size of bridges and loops could guarantee enough ecological corridors in the conservation area planning result. This advantage is particularly valuable within a relatively data-poor context. For example, functional connectivity information is usually unavailable or very difficult to obtain. In fact, animal ecology has been substantially restrained by difficulties in monitoring free-roaming species [63]. This demands a data-driven species-specific field investigation that observes how animals engage with the natural environment [64–66]. Therefore, functional connectivity information is frequently unavailable even in developed countries. Without accurate movement records, local planners struggled to design ecological corridors reasonably [63]. In that case, structural connectivity identified by MSPA is a suitable alternative.

Secondly, some tiny built-up areas (e.g., tiny communities) may be unevenly distributed inside the ecological areas, and some conservation area patches may also be separated by large built-up areas. In such situations, a higher connectivity degree is fundamental for the movement of animals. Unfortunately, many preexisting built-up areas were unreasonably included in the conservation area plan generated by the traditional method since the compactness metric has been overemphasized. As a result, future urban and socio-economic development may be substantially hindered if these plans are put into practice. More detailed real-world examples of the conflicts between conservation and human activities are presented in the Supplementary Materials (see Table S2). By contrast, this disadvantage has been improved in our new planning result. Hence, our method is expected to give helpful support for policymaking in ecological planning and management.

Typically, our proposed model could be applied to the intelligent optimal planning of various similar land use regulations, such as environmental reserves, national parks, ecological greenways, and urban growth boundaries. In particular, many countries and regions around the world, including the European nations, the United States, Canada, and China, have all strongly emphasized the increasing importance of ecological corridors in conservation planning (see Table S3 in Supplementary Materials). Therefore, our proposed model may assist decision processes during the design of ecological corridors in fragmented urban ecosystems. Furthermore, the weights for ecological importance assessment and spatial pattern can also be adjusted by policymakers to explore various conservation scenarios. It should also be noted that although the corridors can still be generated after the zoning of core areas, their objectivity may be severely questioned, especially when the connectivity information is totally missing. Therefore, it is advantageous if the core areas and corridors are simultaneously designed in an intelligent and objective way.

3.3.3. Disadvantages of This Study

Nevertheless, several aspects of the proposed method should also be strengthened in future studies. For example, other types of intelligent algorithms can also be used to search for the best plan for conservation areas. In addition, we will try to distinguish further two types of ecological corridors, i.e., bridges (connecting different cores) and loops (connecting the same core). Moreover, local authorities in China are strongly encouraged to replace multiple different conservation-related plans (e.g., national parks, strict nature reserves, forestry ecological red lines) with one top-down master plan. In that case, those previously established key ecologically important areas can be marked out as a baseline conservation framework, which should stay invariable throughout the optimization procedure. Furthermore, to guarantee the performance and efficiency of conservation area planning in much larger study areas, high-performance computing technology should be applied to the spatial optimization process of intelligent algorithms. Lastly, functional connectivity information (e.g., animal migration tracking data), if available, can also be incorporated to assess the quality of ecological corridors during the optimization processes.

4. Conclusions

The major contribution of our research is the introduction of a novel quantitative method for the planning of conservation areas in the absence of connectivity information. Although corridors are fundamental to the interconnection of fragmented green spaces, the design of ecological corridors still requires an efficient, intelligent, and flexible workflow. To this end, a GA-based spatial optimization model is presented, in which morphological spatial pattern analysis and ecological importance assessment are combined. The former can easily distinguish core areas and corridors, while the latter can identify the regions with higher ecological importance. Then, the best solution with the highest scores for both mean ecological importance and spatial pattern metrics can be effectively discovered by GA.

This new method was employed in the planning of conservation areas in a highly urbanized city. Several experiments have demonstrated that our method can provide much better planning results than the traditional method, which uses only common landscape indicators to characterize spatial patterns. The proposed method, which could greatly facilitate the planning of ecological corridors in an objective manner, is more suitable for dealing with land use optimization problems. Our planning results should be much more advantageous in fragmented urban ecosystems.

Despite the fact that this new model was assessed via a case study in Asian cities, it is promising for ecological restoration and management in many other aspects because the previously mentioned problems are not unique to only Asian or less-developed countries. In particular, ecological corridors need to be carefully considered throughout the world during conservation area planning because they allow a safe migration of living beings in densely built-up urban areas. Enhancing ecological connectivities through corridor design is key to the sustainable development of our natural world.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f14051031/s1. Table S1. Definition of the seven morphological types. Table S2. Real-world examples of the conflicts between conservation and human activities. Table S3. Real-world examples of the importance of ecological corridors in conservation planning.

Author Contributions: Conceptualization, J.L.; methodology, Y.Z.; validation, Y.Z.; formal analysis, Y.H.; investigation, Y.H.; data curation, Y.Z.; writing—original draft preparation, J.L.; visualization, Y.Z. and Y.H.; supervision, J.L.; project administration, J.L.; funding acquisition, J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Guangdong Basic and Applied Basic Research Foundation (Grant No. 2023A1515030300), the National Natural Science Foundation of China (Grant No. 41801307), the Guangzhou Municipal Science and Technology Project (Grant No. 202201010289), and the Special Fund for Scientific and Technological Innovation Strategy of Guangdong Province (Grant No. pdjh2022b0420).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. He, C.; Liu, Z.; Tian, J.; Ma, Q. Urban expansion dynamics and natural habitat loss in China: A multiscale landscape perspective. *Glob. Chang. Biol.* **2014**, *20*, 2886–2902. [CrossRef]
2. McDonald, R.I.; Boucher, T.M. Global development and the future of the protected area strategy. *Biol. Conserv.* **2011**, *144*, 383–392. [CrossRef]
3. Astiaso Garcia, D. Green areas management and bioengineering techniques for improving urban ecological sustainability. *Sustain. Cities Soc.* **2017**, *30*, 108–117. [CrossRef]
4. Jiao, L.; Liu, J.; Xu, G.; Dong, T.; Gu, Y.; Zhang, B.; Liu, Y.; Liu, X. Proximity Expansion Index: An improved approach to characterize evolution process of urban expansion. *Comput. Environ. Urban Syst.* **2018**, *70*, 102–112. [CrossRef]
5. DeFries, R.; Hansen, A.; Turner, B.; Reid, R.; Liu, J. Land use change around protected areas: Management to balance human needs and ecological function. *Ecol. Appl.* **2007**, *17*, 1031–1038. [CrossRef] [PubMed]
6. Geneletti, D.; van Duren, I. Protected area zoning for conservation and use: A combination of spatial multicriteria and multiobjective evaluation. *Landsc. Urban Plan.* **2008**, *85*, 97–110. [CrossRef]
7. Gren, Å.; Andersson, E. Being efficient and green by rethinking the urban-rural divide—Combining urban expansion and food production by integrating an ecosystem service perspective into urban planning. *Sustain. Cities Soc.* **2018**, *40*, 75–82. [CrossRef]
8. Peng, J.; Wang, A.; Luo, L.; Liu, Y.; Li, H.; Hu, Y.N.; Meersmans, J.; Wu, J. Spatial identification of conservation priority areas for urban ecological land: An approach based on water ecosystem services. *Land Degrad. Dev.* **2019**, *30*, 683–694. [CrossRef]
9. Önal, H.; Wang, Y.; Dissanayake, S.T.M.; Westervelt, J.D. Optimal design of compact and functionally contiguous conservation management areas. *Eur. J. Oper. Res.* **2016**, *251*, 957–968. [CrossRef]
10. Liang, X.; Liu, X.; Chen, G.; Leng, J.; Wen, Y.; Chen, G. Coupling fuzzy clustering and cellular automata based on local maxima of development potential to model urban emergence and expansion in economic development zones. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1930–1952. [CrossRef]
11. Geneletti, D. An approach based on spatial multicriteria analysis to map the nature conservation value of agricultural land. *J. Environ. Manag.* **2007**, *83*, 228–235. [CrossRef]
12. Asgarian, A.; Soffianian, A.; Pourmanafi, S.; Bagheri, M. Evaluating the spatial effectiveness of alternative urban growth scenarios in protecting cropland resources: A case of mixed agricultural-urbanized landscape in central Iran. *Sustain. Cities Soc.* **2018**, *43*, 197–207. [CrossRef]
13. Zhou, Y.; Li, X.; Liu, Y. Cultivated land protection and rational use in China. *Land Use Policy* **2021**, *106*, 105454. [CrossRef]
14. Bai, Y.; Jiang, B.; Wang, M.; Li, H.; Alatalo, J.M.; Huang, S. New ecological redline policy (ERP) to secure ecosystem services in China. *Land Use Policy* **2016**, *55*, 348–351. [CrossRef]
15. Xu, X.; Yang, G.; Tan, Y. Identifying ecological red lines in China's Yangtze River Economic Belt: A regional approach. *Ecol. Indic.* **2019**, *96*, 635–646. [CrossRef]
16. Lin, J.; He, P.; Yang, L.; He, X.; Lu, S.; Liu, D. Predicting future urban waterlogging-prone areas by coupling the maximum entropy and FLUS model. *Sustain. Cities Soc.* **2022**, *80*, 103812. [CrossRef]
17. Wu, J.; Zhang, D.; Wang, H.; Li, X. What is the future for production-living-ecological spaces in the Greater Bay Area? A multi-scenario perspective based on DEE. *Ecol. Indic.* **2021**, *131*, 108171. [CrossRef]
18. Li, X.; Yeh, A.G.-O. Zoning land for agricultural protection by the integration of remote sensing, GIS, and cellular automata. *Photogramm. Eng. Remote Sens.* **2001**, *67*, 471–478.
19. He, C.; Zhang, Q.; Li, Y.; Li, X.; Shi, P. Zoning grassland protection area using remote sensing and cellular automata modeling—A case study in Xilingol steppe grassland in northern China. *J. Arid Environ.* **2005**, *63*, 814–826. [CrossRef]
20. Bathrellos, G.D.; Kalivas, D.P.; Skilodimou, H.D. Landslide Susceptibility Assessment Mapping: A Case Study in Central Greece. In *Remote Sensing of Hydrometeorological Hazards*; CRC Press: Boca Raton, FL, USA, 2018; pp. 493–512.
21. Li, H.; Zhang, T.; Cao, X.-S.; Zhang, Q.-Q. Establishing and Optimizing the Ecological Security Pattern in Shaanxi Province (China) for Ecological Restoration of Land Space. *Forests* **2022**, *13*, 766. [CrossRef]
22. Shao, J.; Yang, L.; Peng, L.; Chi, T.; Wang, X. An improved artificial bee colony-based approach for zoning protected ecological areas. *PLoS ONE* **2015**, *10*, e0137880. [CrossRef]
23. Liu, X.; Lao, C.; Li, X.; Liu, Y.; Chen, Y. An integrated approach of remote sensing, GIS and swarm intelligence for zoning protected ecological areas. *Landsc. Ecol.* **2012**, *27*, 447–463. [CrossRef]
24. Luo, Z.; Yuan, Y.; Qi, S.; Xu, J. Evaluating the Carrying Capacity and Spatial Pattern Matching of Urban and Rural Construction Land in a Representative City of Middle China. *Forests* **2022**, *13*, 1514. [CrossRef]
25. Liu, X.; Huang, Y.; Xu, X.; Li, X.; Li, X.; Ciais, P.; Lin, P.; Gong, K.; Ziegler, A.D.; Chen, A.; et al. High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015. *Nat. Sustain.* **2020**, *3*, 564–570. [CrossRef]
26. Gao, J.; Zou, C.; Zhang, K.; Xu, M.; Wang, Y. The establishment of Chinese ecological conservation redline and insights into improving international protected areas. *J. Environ. Manag.* **2020**, *264*, 110505. [CrossRef]
27. Feng, Y.; Yang, Q.; Tong, X.; Chen, L. Evaluating land ecological security and examining its relationships with driving factors using GIS and generalized additive model. *Sci. Total Environ.* **2018**, *633*, 1469–1479. [CrossRef] [PubMed]
28. del Carmen Sabatini, M.; Verdiell, A.; Rodríguez Iglesias, R.M.; Vidal, M. A quantitative method for zoning of protected areas and its spatial ecological implications. *J. Environ. Manag.* **2007**, *83*, 198–206. [CrossRef]

29. Watts, M.E.; Ball, I.R.; Stewart, R.S.; Klein, C.J.; Wilson, K.; Steinback, C.; Lourival, R.; Kircher, L.; Possingham, H.P. Marxan with Zones: Software for optimal conservation based land- and sea-use zoning. *Environ. Model. Softw.* **2009**, *24*, 1513–1521. [CrossRef]
30. Williams, J.C.; Revelle, C.S.; Levin, S.A. Spatial attributes and reserve design models: A review. *Environ. Model. Assess.* **2005**, *10*, 163–181. [CrossRef]
31. Delmelle, E.; Desjardins, M.R.; Deng, J. Designing spatially cohesive nature reserves with backup coverage. *Int. J. Geogr. Inf. Sci.* **2017**, *31*, 2505–2523. [CrossRef]
32. Wang, W.; Jiao, L.; Jia, Q.; Liu, J.; Mao, W.; Xu, Z.; Li, W. Land use optimization modelling with ecological priority perspective for large-scale spatial planning. *Sustain. Cities Soc.* **2020**, *65*, 102575. [CrossRef]
33. Peng, J.; Zhao, S.; Dong, J.; Liu, Y.; Meersmans, J.; Li, H.; Wu, J. Applying ant colony algorithm to identify ecological security patterns in megacities. *Environ. Model. Softw.* **2019**, *117*, 214–222. [CrossRef]
34. Liu, X.; Liang, X.; Li, X.; Xu, X.; Ou, J.; Chen, Y.; Li, S.; Wang, S.; Pei, F. A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landsc. Urban Plan.* **2017**, *168*, 94–116. [CrossRef]
35. Verdiell, A.; Sabatini, M.; Maciel, M.C.; Rodriguez Iglesias, R.M. A mathematical model for zoning of protected natural areas. *Int. Trans. Oper. Res.* **2005**, *12*, 203–213. [CrossRef]
36. McDonnell, M.D.; Possingham, H.P.; Ball, I.R.; Cousins, E.A. Mathematical Methods for Spatially Cohesive Reserve Design. *Environ. Model. Assess.* **2002**, *7*, 107–114. [CrossRef]
37. Zhao, X.; Ma, X.; Tang, W.; Liu, D. An adaptive agent-based optimization model for spatial planning: A case study of Anyue County, China. *Sustain. Cities Soc.* **2019**, *51*, 101733. [CrossRef]
38. Lin, J.; Li, X. Large-scale ecological red line planning in urban agglomerations using a semi-automatic intelligent zoning method. *Sustain. Cities Soc.* **2019**, *46*, 101410. [CrossRef]
39. Du, Y.; Li, X.; He, X.; Li, X.; Yang, G.; Li, D.; Xu, W.; Qiao, X.; Li, C.; Sui, L. Multi-Scenario Simulation and Trade-Off Analysis of Ecological Service Value in the Manas River Basin Based on Land Use Optimization in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6216. [CrossRef]
40. Li, X.; Lao, C.; Liu, X.; Chen, Y. Coupling urban cellular automata with ant colony optimization for zoning protected natural areas under a changing landscape. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 575–593. [CrossRef]
41. Daigle, R.M.; Metaxas, A.; Balbar, A.C.; McGowan, J.; Treml, E.A.; Kuempel, C.D.; Possingham, H.P.; Beger, M. Operationalizing ecological connectivity in spatial conservation planning with Marxan Connect. *Methods Ecol. Evol.* **2020**, *11*, 570–579. [CrossRef]
42. Beger, M.; Linke, S.; Watts, M.; Game, E.; Treml, E.; Ball, I.; Possingham, H.P. Incorporating asymmetric connectivity into spatial decision making for conservation. *Conserv. Lett.* **2010**, *3*, 359–368. [CrossRef]
43. Vogt, P.; Riitters, K.H.; Estreguil, C.; Kozak, J.; Wade, T.G.; Wickham, J.D. Mapping Spatial Patterns with Morphological Image Processing. *Landsc. Ecol.* **2007**, *22*, 171–177. [CrossRef]
44. Soille, P.; Vogt, P. Morphological segmentation of binary patterns. *Pattern Recognit. Lett.* **2009**, *30*, 456–459. [CrossRef]
45. Saura, S.; Bertzky, B.; Bastin, L.; Battistella, L.; Mandrici, A.; Dubois, G. Global trends in protected area connectivity from 2010 to 2018. *Biol. Conserv.* **2019**, *238*, 108183. [CrossRef] [PubMed]
46. Wang, Y.; Fang, Q.; Dissanayake, S.T.M.; Önal, H. Optimizing conservation planning for multiple cohabiting species. *PLoS ONE* **2020**, *15*, e0234968. [CrossRef] [PubMed]
47. Wu, J.; Zhang, S.; Wen, H.; Fan, X. Research on Multi-Scale Ecological Network Connectivity—Taking the Guangdong–Hong Kong–Macao Greater Bay Area as a Case Study. *Int. J. Environ. Res. Public Health* **2022**, *19*, 15268. [CrossRef]
48. Wang, H.; Pei, Z. Urban Green Corridors Analysis for a Rapid Urbanization City Exemplified in Gaoyou City, Jiangsu. *Forests* **2020**, *11*, 1374. [CrossRef]
49. Wu, S.; Wang, D.; Yan, Z.; Wang, X.; Han, J. Spatiotemporal dynamics of urban green space in Changchun: Changes, transformations, landscape patterns, and drivers. *Ecol. Indic.* **2023**, *147*, 109958. [CrossRef]
50. Mairota, P.; Cafarelli, B.; Boccaccio, L.; Leronni, V.; Labadessa, R.; Kosmidou, V.; Nagendra, H. Using landscape structure to develop quantitative baselines for protected area monitoring. *Ecol. Indic.* **2013**, *33*, 82–95. [CrossRef]
51. Wickham, J.D.; Riitters, K.H.; Wade, T.G.; Vogt, P. A national assessment of green infrastructure and change for the conterminous United States using morphological image processing. *Landsc. Urban Plan.* **2010**, *94*, 186–195. [CrossRef]
52. Svoray, T.; Bar, P.; Bannet, T. Urban land-use allocation in a Mediterranean ecotone: Habitat Heterogeneity Model incorporated in a GIS using a multi-criteria mechanism. *Landsc. Urban Plan.* **2005**, *72*, 337–351. [CrossRef]
53. Kopecký, M.; Macek, M.; Wild, J. Topographic Wetness Index calculation guidelines based on measured soil moisture and plant species composition. *Sci. Total Environ.* **2021**, *757*, 143785. [CrossRef] [PubMed]
54. Erskine, R.H.; Green, T.R.; Ramirez, J.A.; MacDonald, L.H. Comparison of grid-based algorithms for computing upslope contributing area. *Water Resour. Res.* **2006**, *42*, W09416. [CrossRef]
55. Shannon, C.E.; Weaver, W. The mathematical theory of communication. *Phys. Today* **1949**, *27*, 379–423.
56. Doran, J.W.; Parkin, T.B. Defining and Assessing Soil Quality. In *Defining Soil Quality for a Sustainable Environment*; Soil Science Society of America: Madison, WI, USA, 1994; pp. 1–21. [CrossRef]
57. Eastman, J.R.; Jiang, H.; Toledano, J. *Multi-Criteria and Multi-Objective Decision Making for Land Allocation Using GIS*; Springer: Dordrecht, The Netherlands, 1998; pp. 227–251.
58. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Application to Biology, Control, and Artificial Intelligence*; University of Michigan Press: Ann Arbor, WI, USA, 1975.

59. Cao, K.; Batty, M.; Huang, B.; Liu, Y.; Yu, L.; Chen, J. Spatial multi-objective land use optimization: Extensions to the non-dominated sorting genetic algorithm-II. *Int. J. Geogr. Inf. Sci.* **2011**, *25*, 1949–1969. [CrossRef]
60. Lin, J.; Li, X.; Wen, Y.; He, P. Modeling urban land-use changes using a landscape-driven patch-based cellular automaton (LP-CA). *Cities* **2023**, *132*, 103906. [CrossRef]
61. Cao, K.; Huang, B.; Wang, S.; Lin, H. Sustainable land use optimization using Boundary-based Fast Genetic Algorithm. *Comput. Environ. Urban Syst.* **2012**, *36*, 257–269. [CrossRef]
62. Li, X.; Yeh, A.G.O. Integration of genetic algorithms and GIS for optimal location search. *Int. J. Geogr. Inf. Sci.* **2005**, *19*, 581–601. [CrossRef]
63. Stewart, F.E.C.; Darlington, S.; Volpe, J.P.; McAdie, M.; Fisher, J.T. Corridors best facilitate functional connectivity across a protected area network. *Sci. Rep.* **2019**, *9*, 10852. [CrossRef]
64. Carvalho, F.; Carvalho, R.; Mira, A.; Beja, P. Assessing landscape functional connectivity in a forest carnivore using path selection functions. *Landsc. Ecol.* **2016**, *31*, 1021–1036. [CrossRef]
65. Rio-Maior, H.; Nakamura, M.; Álvares, F.; Beja, P. Designing the landscape of coexistence: Integrating risk avoidance, habitat selection and functional connectivity to inform large carnivore conservation. *Biol. Conserv.* **2019**, *235*, 178–188. [CrossRef]
66. Lin, J.; Li, H.; Zeng, Y.; He, X.; Zhuang, Y.; Liang, Y.; Lu, S. Estimating potential illegal land development in conservation areas based on a presence-only model. *J. Environ. Manag.* **2022**, *321*, 115994. [CrossRef] [PubMed]