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Article

Developing a Cell-Based Spatial Optimization Model for Land-Use Patterns Planning

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Abstract: This study developed a cell-based spatial optimization model compatible with the ArcGIS platform, termed Dynamically Dimensioned Search Landscape Optimization Planning model (DDSLOP), for landscape planning. The development of the proposed model was based on the Dynamically Dimensioned Search Algorithm, which can efficiently find an optimal global solution within the massive solution space inherent to multi-dimensional analysis. Therefore, the DDSLOP model can reveal landscape pattern scenarios suited to specific managerial purposes at a cellular level. To evaluate the DDSLOP model, we applied it to a landscape planning initiative that focused on the conservation of three bird species in the National Taiwan University Highland Experimental Farm (NTU-HEF). We compared the proposed model with the Land-Use Pattern Optimization-library (LUPOlib), which was used in the optimization of landscapes at a patch level. The results of the comparison revealed that our fine scale optimization method has better flexibility, and can therefore form landscape structures, which, overall, provides not only better individual habitats for the target species, but also landscape patterns that foster high habitat connectivity, both important aspects of conservation efforts.

Keywords: spatial optimization; landscape; dynamically dimensioned search; scale

1. Introduction

Spatial optimization methods have been used to investigate spatially explicit problems in a wide range of different fields, including: urban planning [1,2], habitat reconstruction [3–6], wildlife reserve selection [7,8], *etc*. Spatial optimization methods are popular because they can provide insights into the implications of landscape designs [9]. As such, many landscape optimizations have been used by decision makers, providing them with additional options to spatial problems at various scales within the cell-patch-class-landscape hierarchy. For example, the habitat reconstruction problems, which focus on the configuration and composition of suitable patches for mammals, can be analyzed at a patch level. On the other hand, the fine scale heterogeneity of small habitat islands within agricultural landscapes, which might be suitable for certain species such as edge-preferring bird species [10–12] or insect species [13,14], could be explored at the cellular scale. Therefore, the scale at which the land-use allocation problems are explored significantly influence the effectiveness and/or appropriateness of spatial optimization models.

Spatial optimization problems analyzed at finer scales may run into restrictions because of increasing resolution. The solution space increases exponentially as the scale of specific analysis decreases over the landscape-to-cell continuum. In other words, the size of solution space represented by K^N rises rapidly while the number of planning units N increases under a certain number of land use options K [15]. Although a wide range of heuristic-based methods have been developed and widely used to overcome, or at least lower, the computational restrictions imposed by massive solution spaces [9], very little comparative research has been done on the effectiveness of landscape optimizations at different scales. Holzkämper *et al.* [3] developed a spatial optimization model, termed Land-Use Pattern Optimization-library (LUPOlib) for which the model units corresponded to patch types in a landscape. This was done in order to both decrease the computational effort in the optimization process and also to avoid unrealistic land-use patterns. Nevertheless, it is unclear whether or not a patch topology approach is optimal for all environments and species, particularly because finer landscape modifications are less likely at such a coarse resolution. Meaning that the creation of small habitat islands, which serve as stepping stones for some species, narrow wildlife corridors, and the consideration of fine scale habitat edge dynamics, *etc.* may be missed during patch-level optimization.

The Dynamically Dimensioned Search (DDS) algorithm [16] is a novel heuristic method, which can be used to find a good global solution by progressively fine tuning a solution from a global scale to an increasingly more localized scale through a series of searches with a pre-specified maximum number of iterations. In so doing, the algorithm incorporates both diversification and intensification mechanisms [17] in a computationally cost effective manner. To discover the differences of spatial optimizations at different scales, we developed a practical land-use allocation model based on DDS, termed Dynamically Dimensioned Search Landscape Optimization Planning model (DDSLOP), which can effectively deal with complex landscape planning problems with huge solution spaces, *i.e.*, finer resolutions, or a greater number of land-use types. The DDSLOP model provides a method of landscape pattern optimization

tailored in accordance to specific criteria at a cellular level. In order to both better capture the needs of the species in question and incorporate the gradient concept of landscape structure [18], a moving window analysis embedded in the DDSLOP model estimated habitat suitability across the study area based on different local landscape metrics (*i.e.*, patterns of sub-landscapes). The optimization process then optimized the landscape structure in reference to the resultant habitat suitability. We used the proposed model to optimize the National Taiwan University Highland Experimental Farm (NTU-HEF) in accordance to the preferences and conservation of three bird species. The optimized landscape patterns formed from cell-level DDSLOP were then compared with those generated by patch-level based LUPOlib landscape patterns. The comparison was done in terms of each resultant average Habitat Suitability Index (HSI) for representing overall habitat suitability of the species in question. As suspected the proposed model efficiently searched an optimum from a massive solution space to render landscape patterns at a finer resolution promoting higher overall HSIs. Consequently, the proposed model has the potential to deal with spatial optimization at a finer scale.

2. Methods and Materials

2.1. Dynamically Dimensioned Search Land-Use Optimization Planning Tool (DDSLOP Tool)

DDS is designed for the efficient search of a good global solution for optimization problems, which simultaneously deal with multiple control variables and their resultant massive solution spaces [16,19,20]. DDS searches the solution globally by adjusting most of the control variables at the outset of the model, then becomes progressively more localized by gradually decreasing the number of control variables as the iteration number approaches the maximum number of pre-defined iterations [16]. This mechanism implies that the DDS algorithm has the ability to escape from the local optima and, consequently, enhances the quality of the global solution through the incorporation of both diversification and intensification processes [17].

Based on this key feature of DDS, the DDSLOP model stochastically modifies most of the cells within the target landscape from the original land-use types (control variables) to other land-use types at the beginning of the optimization process (Figure 1). As the iteration count increases, however, the DDSLOP model only modifies those cells, which contribute to relatively lower evaluated suitability of habitat (criteria) for the species in question. In this way, a general reformation of the landscape ensues, resulting in a good habitat structure for the target species. Furthermore, a user-friendly interface compatible with the ArcGIS platform is provided for planners and researchers (see Supplementary 1).

Due to the complexity of spatial optimization problems, the proposed DDSLOP model has a double loop iteration process, which optimizes not only the composition of different land-use types (first loop), but also the spatial configuration of land-use types (second loop), throughout a given landscape. A series of outer optimization processes progressively modify the overall ratios of different land-use types (composition of the landscape) while iterative inner optimizations then modify the spatial configuration of the landscape based on the habitat suitability of selected cells, the new overall ratios of land-use types, as well as the ratio of land-use types of selected cells if restrictions on final land-use type ratios are predefined (Figure 2). In other words, each of the resultant outer iteration land-use type ratios then undergoes a certain number of inner iterations, which modified the spatial pattern of land-use types.

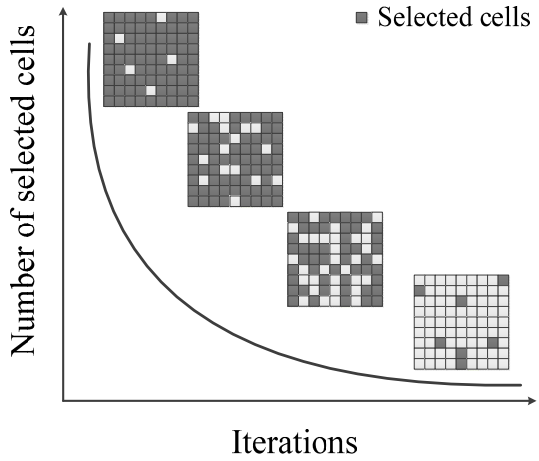
Since the objective is to modify the overall landscape in such a way as to maximize the suitability of habitat for the specific target species in question based on modifications to landscape structure, the fitness function is given as:

$$f_{inner} = \max_{\bar{M}_i}\{HSI_{mean}\} \tag{1}$$

$$f_{outer} = \max_{\bar{p}_t}\{f_{inner}\} \tag{2}$$

where f_{inner} represents the inner fitness evaluated based on the resultant average habitat suitability index; HSI_{mean}. $\bar{M}_i$ represents the spatial configuration of land-use types at count i of inner iterations. While, f_{outer} denotes the outer fitness and $\bar{p}_t$ represents the ratios of land-use types at outer iteration count t.

Figure 1. Dynamically dimensioned search process: The number of selected control variables decreases gradually while the number of iterations increases in the optimization process. These cells are stochastically selected from a target landscape for modification; therefore, the DDSLOP can dynamically scale down the search to find a good global solution throughout consecutive iterations.



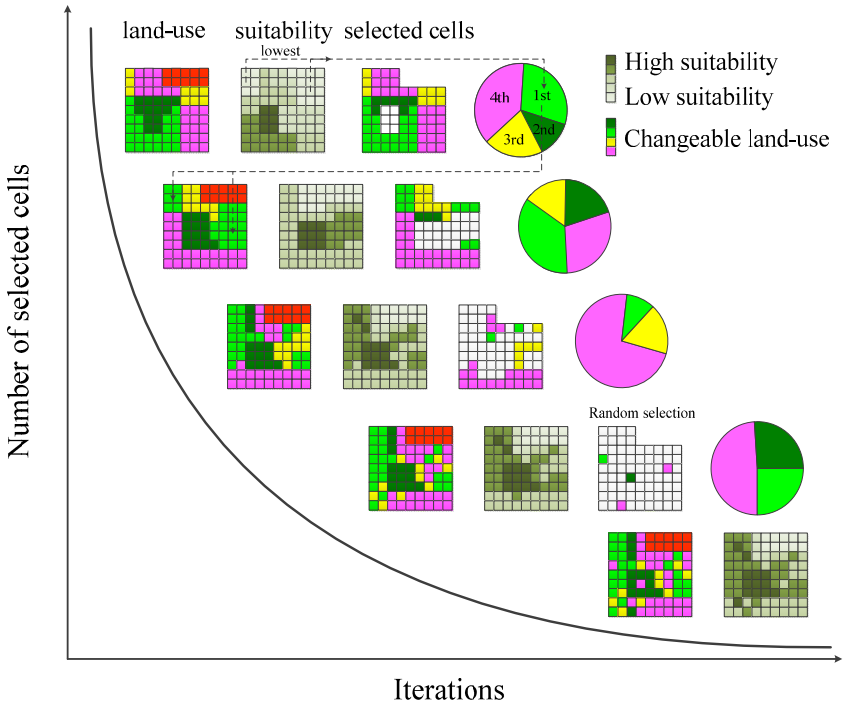
In order to evaluate the inner fitness based on habitat suitability of the target species, we used logistic regression to construct habitat suitability models for each species [3,4,6]. The habitat suitability models were used for estimating the probability of target species occurrence under updated DDSLOP outputs. The model is:

$$HSI_{mean} = \sum_{x}^{x_{\max}}\sum_{y}^{y_{\max}} hsi\ \left(M_{x,y}\right) \Big/ Cells \tag{3}$$

$$hsi\ \left(M_{x,y}\right) = \exp\left(\beta_0 + \sum_{k=1}^{n}\beta_k \times df_k(x,y)\right) \Big/ \left[1 + \exp\left(\beta_0 + \sum_{k=1}^{n}\beta_k \times df_k(x,y)\right)\right] \tag{4}$$

where, $hsi\left(M_{x,y}\right) \in [0,1]$ represents the index of habitat suitability at location (x, y) in a candidate landscape $M_{x,y}$. *Cells* represents the total number of cell grids in the landscape. β_0 is the intercept of the habitat suitability model. β_k is the coefficient of each driving factor $df_k(x, y)$ at location (x, y) in the landscape.

Figure 2. Inner optimization process of the DDSLOP model (Step 5): To promote efficiency of the optimization process, cells with lower habitat suitability are given higher priority for both selection and subsequent exchange, which means that places with higher suitability for the target species have overall lower probabilities of being modified. Based on the updated overall ratios of land-use types selected during the given outer iteration, DDSLOP allocates randomly ranked land-use types to habitat suitability ranked cells during each inner iteration. In the example below, the lawn-green land-use type is stochastically chosen to carry the highest rank in the first inner iteration, and is therefore chosen to replace cells with lowest suitability.



In order to evaluate the effects of spatial patterns on specific species, four types of landscape metrics were considered, including: class area (ca_l), largest patch index (lpi), sum of edge lengths between two land-use types ($es_{l,k}$), and patch cohesion (coh_l) of specific land-use types (see Supplementary 2). The habitat suitability model used each of these metrics as factors contributing to habitability at a territorial scale for each species [3,6], based on presence data correlated with current landscape metrics. A moving window analysis, based on a radius that correlates to the territorial range of the target species [3,6] about each cell, was used to evaluate the landscape metrics and corresponding habitat suitability indexes of each cell. The steps of the DDSLOP model are as follows (modified from [16]) (see Supplementary 3 for the flowchart of the steps):

Step 1. Define DDS inputs:

- Define maximum iteration count t_{max} for outer fitness function evaluations.
- Define maximum iteration count i_{max} for inner fitness function evaluations.
- Define initial solution of outer control variable (composition) $\vec{p}_0 = [p_1,...,p_D]$ and inner control variable (configuration) $\vec{M}_0 = [M_{1,1}, M_{1,2},...., M_{m,n}]$, which denotes the spatial composition and configuration, respectively, of the original-unmodified landscape. Where $M_{m,n}$ represents the land-use type at location (m, n).

Step 2. Set the counter of outer iteration $t = 1$, and evaluate fitness (mean habitat suitability) at initial solution $f_{outer}(\vec{p}_0)$ with respect to the original landscape:

- Current best fitness $f_{outer}^{best} = f_{outer}(\vec{p}_0) = f_{inner}(\vec{M}_0)$.
- Current best solution $\vec{p}^{best} = \vec{p}_0$ and $\vec{M}^{best} = \vec{M}_0$ for outer and inner optimization, respectively.

Step 3. Stochastically place j variables (land-use type ratios) from $\vec{p}^{best}$ (current optimal composition) into the $\{N\}$ set, which will undergo modifications in step 4:

- Calculate the proportion of land-use type ratios, which will be selected for modification, based on a function of current iteration count: $S_t^{outer} = 1 - \ln(t)/\ln(t_{\max})$.
- For $d = 1, \ldots, D$, move p_d from $\vec{p}^{best}$ to $\{N\}$ until j control variables have been selected, ($j < D$) based on the S_t^{outer}.
- If $\{N\}$ is empty, randomly place one element from $\vec{p}^{best}$ into it.

Step 4. In order to get new candidate $\vec{p}_t^{new}$, perturb the selected control variables (land-use ratios), (p_d, $d = 1, \ldots, j$) in $\{N\}$. The perturbation of each variable (land-use ratio) corresponds in intensity proportional to a random sample taken from a standard normal distribution n(0,1), reflecting at bounds of control variables if necessary:

- $p_d^{New} = p_d^{Best} + \sigma_d n(0,1)$, where $\sigma_d = \gamma(p_d^{Max} - p_d^{Min})$.

Step 5. Set the counter of inner iteration to $i = 1$ and perturb the spatial configuration of the landscape $\vec{M}_i = \vec{M}^{best}$ given the new proportions of the exchangeable land-use types $\vec{p}_t^{new}$.

- Stochastically select k elements from $\vec{M}_i$ (current best land use raster data set) and place these into a pool $\vec{a}_i$. For each iteration, the proportion of selected cells corresponds to the function of current iteration count $S_i^{inner} = 1 - \ln(i)/\ln(i_{\max})$.
  - Rank selected cells in accordance to their relative $hsi(Mx,y)$ at (x,y).
  - Preferentially select cells in $hsi(Mx,y)$ ascending order (lower values first) and place into $\vec{a}_i$, the proportion of selected cells for each iteration is equivalent to the S_i^{inner} function (Figure 2).
- Exchange the land-use type of each element in $\vec{a}_i$.
  - Rank the selected land-use types randomly for land-use reallocation.
  - Cells in $\vec{a}_i$ are chosen for exchange in $hsi(Mx,y)$ ascending order (lower values first) with land-use types in descending order (highest ranked land-use types exchange first) (Figure 2).
- Acquire $\vec{M}_i^{new}$ by updating $\vec{M}_i$ with their corresponding $\vec{a}_i$.
- Evaluate inner fitness and update current best solution if necessary:
  - If $f_{inner}(\vec{M}_i^{new}) > f_{inner}(\vec{M}^{best})$, update $\vec{M}^{best} = \vec{M}_i^{new}$.
  - The size of the habitat suitability moving window (territory range) for each target species in this study was 1 ha. It calculated the habitat suitability of each cell.
- Update inner iteration count $i = i + 1$ and check stop criterion. The maximum inner iteration count $i_{\max}$ was equal to 200 for each of the outer iterations in this study.
  - If $i = i_{\max}$, stop. $f_{outer}(\vec{p}_t^{new}) = f_{inner}(\vec{M}^{best})$.

- Else repeat Step 5.

Step 6. Evaluate outer fitness and update current best solution if necessary:

- If $f_{outer}\left(\bar{p}_t^{new}\right) > f_{outer}\left(\bar{p}^{best}\right)$, update best solution $\bar{p}^{best} = \bar{p}_t^{new}$.

Step 7. Update iteration count $t = t + 1$ and check stop criterion. The maximum inner iteration count $t_{\max}$ was equal to 1000 for each case in this study. Therefore, for each case, the DDSLOP model conducted 200,000 evaluations of fitness.

2.2. Land-Use Pattern Optimization-Library (LUPOlib)

In order to compare landscape pattern optimization at different scales for the target species, we also applied the land-use pattern optimization model LUPOlib [3,4,6] to identify preferred land-use pattern (*i.e.*, habitat structures) at a patch level. The LUPOlib model is a genetic algorithm-based optimization model. The control variables modified by the LUPOlib model were also defined as both the configuration and the composition of different patches in a landscape [6] (Figure 3). The objective was to maximize the habitat suitability of the targeted species. Therefore, the function used for evaluating fitness was identical to that of DDSLOP, Formula (1). We applied the LUPOlib model to optimize the land-use pattern using the following steps [3,6]:

Step 1 A population of 100 candidate solutions of the landscape pattern was randomly generated. A candidate solution is represented using a chromosome in the GA. A chromosome indicates a vector of the spatial configuration of a landscape (Figure 2).

Step 2 The fitness (objective score) of each candidate landscape pattern was evaluated based on the resultant average habitat suitability index HSI_{mean}, which was itself based on a roaming window analysis of landscape metrics.

Step 3 Improvement between iterations (*i.e.*, GA-generations) towards an optimal solution was achieved by two genetic operators, the crossover and mutation (Figure 2). The crossover and mutation operator carried on exchanges of patches in the landscape based crossover and mutation rates of 0.5 and 0.01, respectively.

Step 4 The iteration stopped when it sought the best solution of 1500 iterations, or while the deviation between the 300 previous generations with the current generation was less than 0.01% (such that the convergence ratio equals 0.9999). Steps 2 and 3 were repeated until the criteria were reached.

2.3. Study Site and Data Description

The National Taiwan University Highland Experimental Farm (NTU-HEF) (24°05′N, 121°10′E, altitude 2100 m.a.s.l., size 42.68 ha) was established for academic and educational purposes in horticulture and agriculture. In order to find optimal land-use patterns for bird conservation at a cellular scale, we included: land coverage, the distribution of birds, and geographic data (distance variables) at a 10 × 10 m (Figure 4) resolution. This data was provided by earlier field surveys using a territory mapping method [6,21] from 2005 to 2007 (see Supplementary 4). Additionally, to take species' territorial ranges into consideration, the study area was extended 50 m outward from the boundary of NTU-HEF [6].

In the total 61.61 ha area, about 36.13% was covered by pristine forest. Other land-use types include: buildings, orchards, croplands, conifer plantations, broadleaf plantations, and manmade water bodies. From this description, we can see that the landscape has been markedly influence by human activities.

Figure 3. Crossover and mutation operator in the GA-based LUPOlib model (modified from [3,4,6]): Spatial pattern of a landscape is coded as a vector of the spatial pattern (*i.e.*, a GA genome) based on the patch topology. The crossover operator leads an exchange of selected elements for corresponding elements in another genome. The mutation operator leads to modifications of selected elements to randomly generated land-use types. In the example, land-use type 1 (for red patches) is not exchangeable. On the other hand, land-use types 2, 3, and 4 (for yellow, lawngreen, and purple patches) are exchangeable.

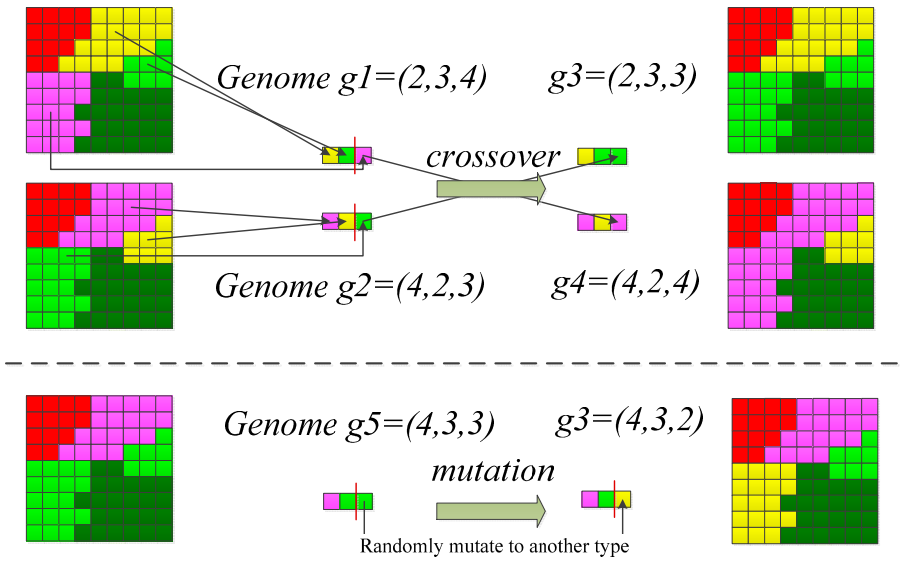
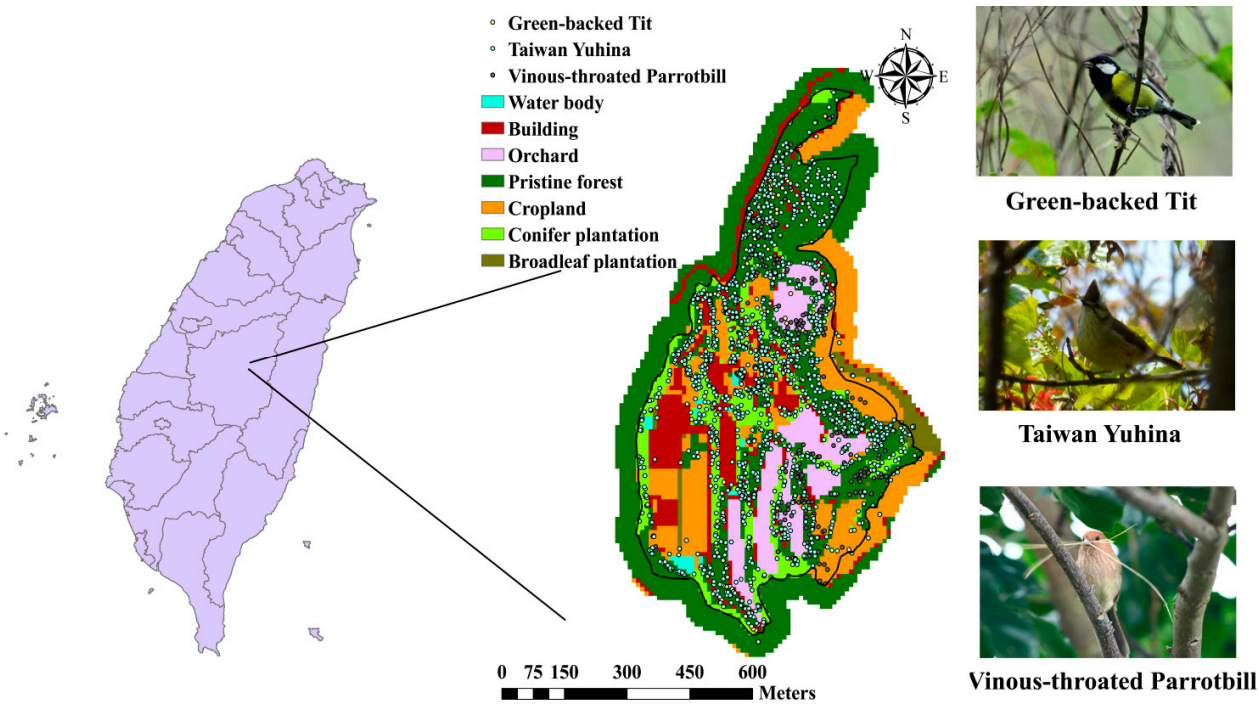


Figure 4. The spatial pattern of NTU-HEF and distributions of each target species (modified from [6]).



We chose three species, the Green-backed Tit (*Parus monticolus insperatus*) (endemic subspecies), Taiwan Yuhina (*Yuhina brunneiceps*) (endemic species) and Vinous-throated Parrotbill (*Paradoxornis webbianus bulomachus*) (endemic species) for conservation scenarios. The presence data included 138 occurrence points of the Green-backed Tit, 1614 occurrence points of the Taiwan Yuhina and 210 occurrence points of the Vinous-throated Parrotbill (Figure 4).

We applied the two optimization models to each species (case 1 = the Green-backed Tit, case 2 = the Taiwan Yuhina, and case 3 = the Vinous-throated Parrotbill) not only to evaluate the proposed model, but also in order to explore the advantages of landscape optimization at both cellular and patch levels. Due to existing land-use policies, which take both species conservation and economic self-sustainability into consideration, certain constraints were placed on the models. For NTU-HEF, land-use types including orchard, cropland, conifer plantation and broadleaf plantation were replaceable; however, the added restraint that 72.5% of the total area of both orchards and croplands need to be maintained for financial purposes was imposed upon the models [6]. Accordingly, 117 patches consisted of 2085 cells were exchangeable in the spatial optimization processes.

3. Results

3.1. Optimal Landscapes Resulted from the DDSLOP and LUPOlib Model

For case 1 to 3, all the results of the DDSLOP and LUPOlib model were compared in order to evaluate landscape optimization for conservation at different scales. In terms of habitat suitability, the DDSLOP model, which modified the spatial patterns at a cellular level, outperformed LUPOlib, which was working at a patch level (Table 1).

Table 1. Comparison of habitat suitability for each study case.

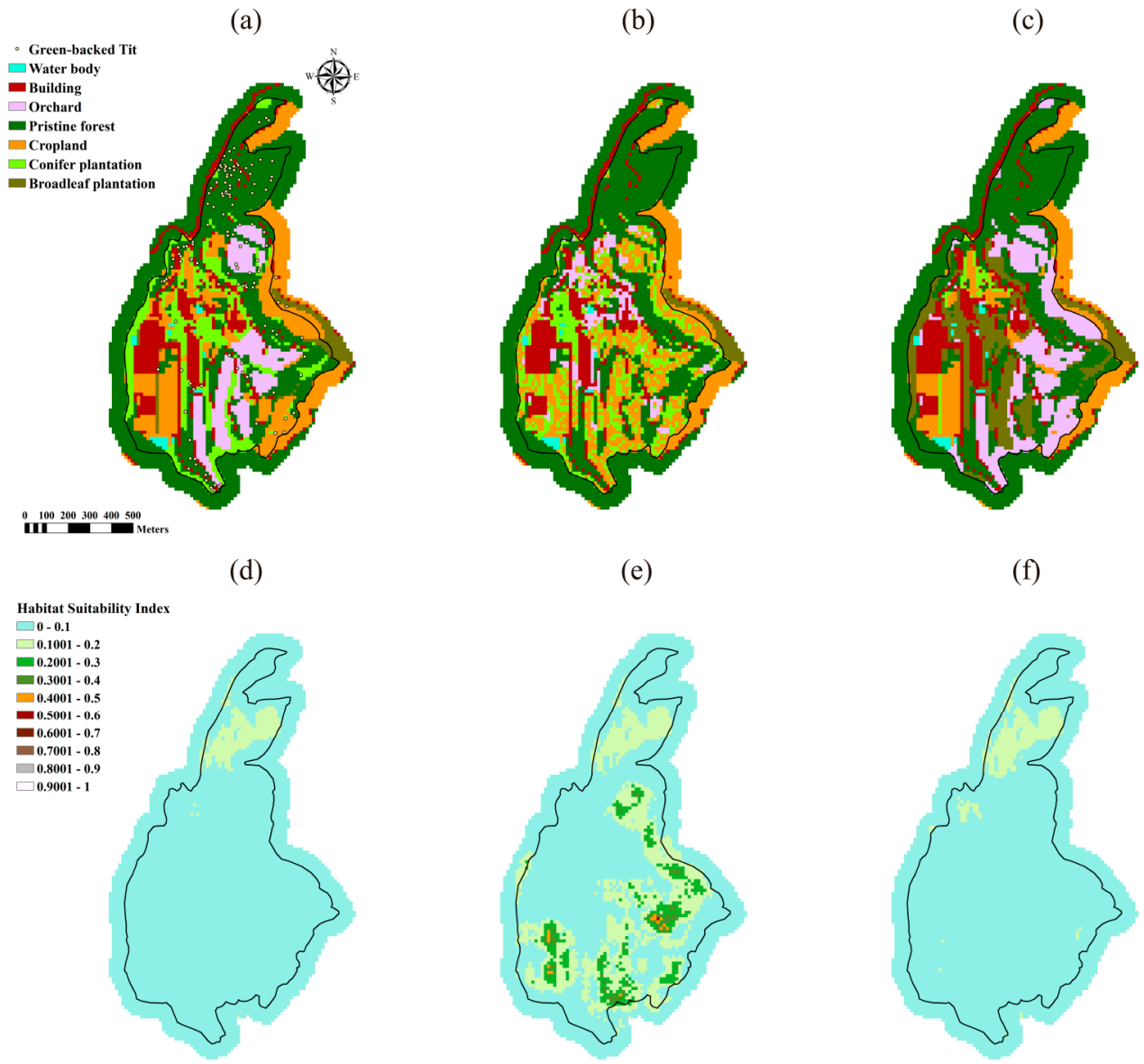
Habitat Suitability	Case 1 the Green-Backed Tit			Case 2 the Taiwan Yuhina			Case 3 the Vinous-Throated Parrotbill		
	Current Landscape	DDSLOP	LUPOlib	Current Landscape	DDSLOP	LUPOlib	Current Landscape	DDSLOP	LUPOlib
Average [a]	0.0282	0.0829	0.0432 [b]	0.2147	0.3668	0.3630	0.0397	0.0789	0.0613
Min	0.0013	0.0014	0.0026	0.0006	0.0006	0.0006	0.0002	0.0005	0.0005
25%	0.0105	0.0315	0.0190	0.1014	0.1781	0.1652	0.0106	0.0223	0.0190
50%	0.0193	0.0650	0.0312	0.2072	0.3725	0.3532	0.0321	0.0582	0.0445
75%	0.0336	0.1139	0.0521	0.3137	0.5367	0.5527	0.0553	0.1193	0.0825
Max	0.1601	0.5071	0.1601	0.7389	0.8774	0.8641	0.3392	0.4866	0.4512

[a] The average habitat suitability was used as the objective score throughout the spatial optimization processes;
[b] The results are from [6].

For the Green-backed Tit, the DDSLOP model greatly improved the suitability of habitat when compared to both the current landscape pattern and the LUPOlib model, especially in the southern and eastern parts of NTU-HEF (Figure 5e); as can be seen, the LUPOlib model only slightly increased the suitability value over the same areas (Figure 5f). The DDSLOP model modified orchards to croplands and created edges between conifer plantations and croplands (Figure 5b). However, a contrasting spatial

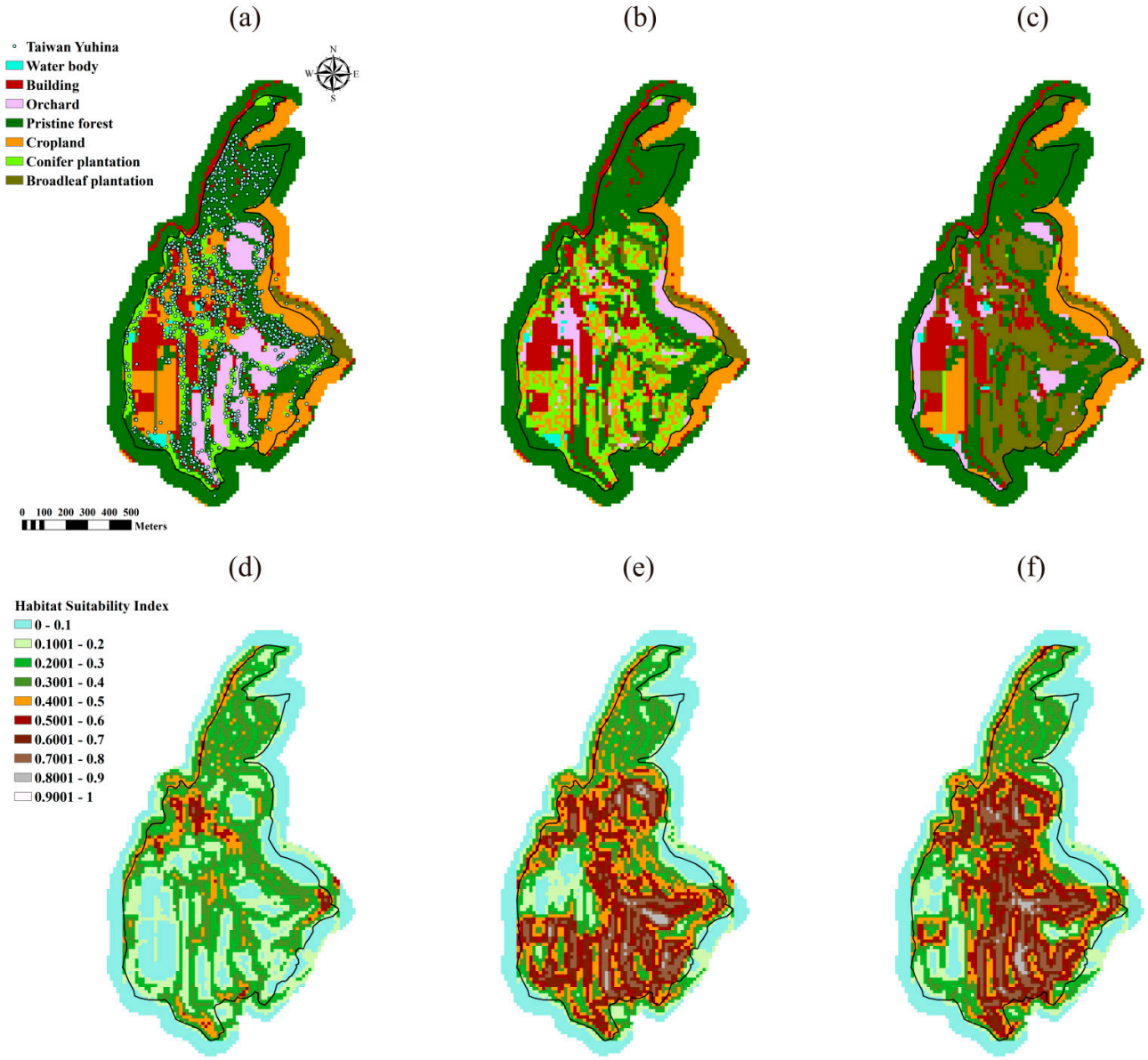
composition was instructed by the LUPOlib model, in which the area of cropland and conifer plantation decreased (Supplementary 5).

Figure 5. Comparison of model outputs for case 1. (**a**) Distribution of the Green-backed Tit over the current landscape; (**d**) Habitat suitability of current landscape pattern; The landscape optimization and corresponding habitat suitability resulting from the DDSLOP (**b**,**e**) and LUPOlib model (**c**,**f**) the result is from [6]).



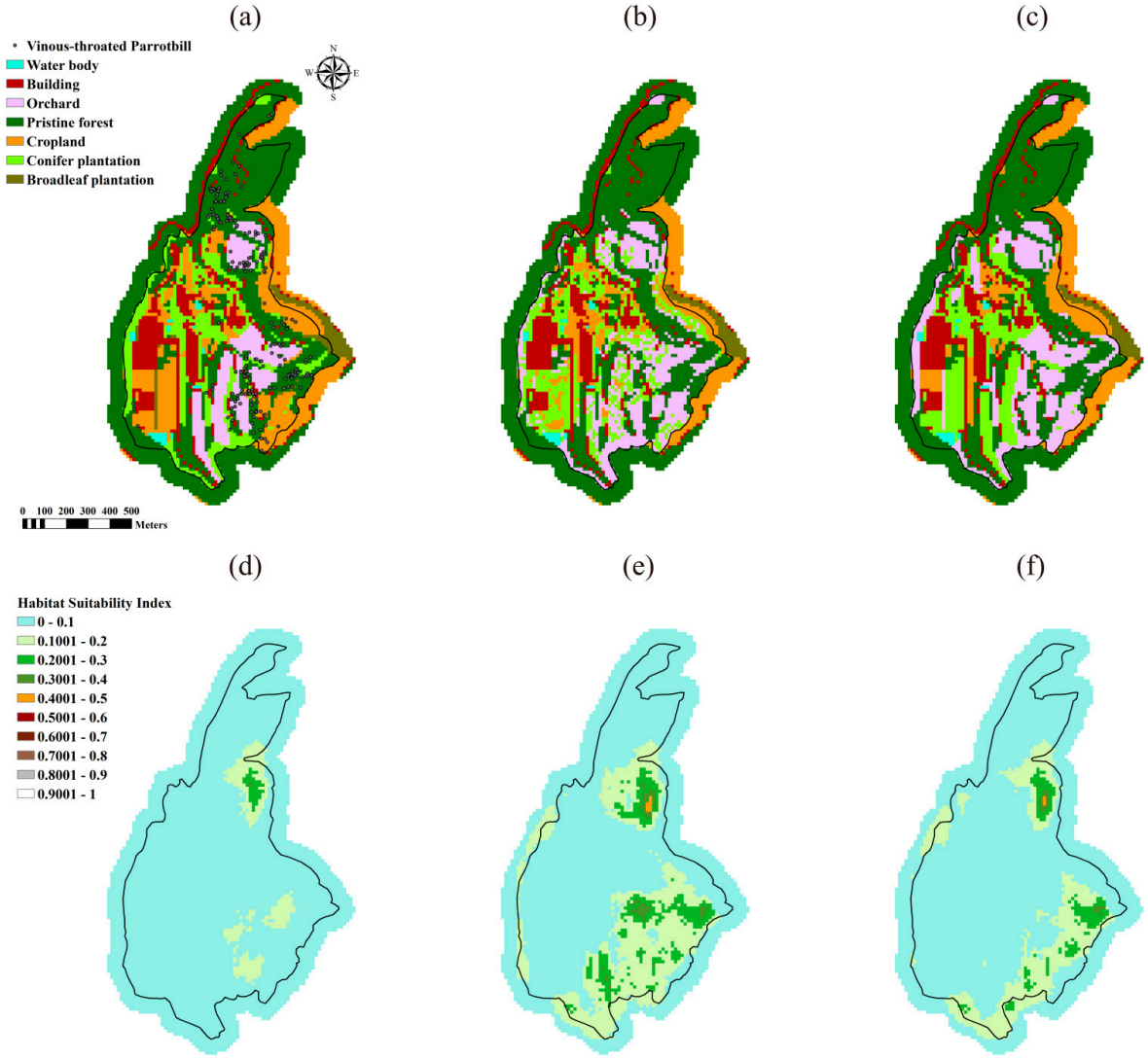
For the Taiwan Yuhina, both of the DDSLOP and LUPOlib model improved the suitability of the habitat over most of the study area (Figure 6e,f). Nevertheless, the two model outputs differed in both spatial composition (Supplementary 5) and configuration. The DDSLOP created a mosaic landscape of croplands, confer plantations, and orchards (Figure 6b). LUPOlib, on the other hand, converted much of the landscape to broadleaf plantations (Figure 6c).

Figure 6. Comparison of model outputs for case 2. (**a**) Distribution of the Taiwan Yuhina over the current landscape; (**d**) Habitat suitability of current landscape pattern; The landscape optimization and corresponding habitat suitability resulting from the DDSLOP (**b**,**e**) and LUPOlib model (**c**,**f**).



For the Vinous-throated Parrotbill, the DDSLOP performed better, particularly in the south-eastern part of the study area (Figure 7e), compared to that of the LUPOlib model (Figue 7f). Although both models yielded similar landscape compositions (Supplementary 5), the DDSLOP model once again created more of a mosaic pattern throughout the landscape. This is particularly apparent in the south-eastern part of NTU-HEF where the conifer plantations were fragmented and embedded within the orchards.

Figure 7. Comparison of model outputs for case 3. (**a**) Distribution of the Vinous-throated Parrotbill over the current landscape; (**d**) Habitat suitability of current landscape pattern; The landscape optimization and corresponding habitat suitability resulting from the DDSLOP (**b**,**e**) and LUPOlib model (**c**,**f**).



3.2. Preferred Habitat Structures of Target Species

In addition to the use of the habitat suitability model for Green-backed Tit on the current landscape from Lin *et al.* [6], we created habitat suitability models for the other two species based on presence/absence data and spatially correlated landscape metrics. In order to compare the fitness of different optimizations, forward stepwise logistic regressions were completed using the Statistical Package for the Social Sciences (SPSS Inc., IL, USA). All the driving factors are listed in Supplementary 6. The results showed that each of the habitat suitability models have AUC values that exceed or are equal to 0.7 (Table 2; for ROC curves see Supplementary 6). The beta value results showed the positive or negative effects of specific landscape metrics (*i.e.*, the driving factors of each habitat suitability model) on habitat suitability (Table 2). For the Green-backed Tit, the results revealed that it preferred not only

pristine forests (ca_{forest}) [6] but also edges between conifer plantations and croplands ($es_{cropland,\ conifer}$). For the Taiwan Yuhina, both broadleaf and conifer plantations ($ca_{broadleaf}$ and $ca_{conifer}$) were preferred. Likewise, the edges between conifer plantations and croplands ($es_{cropland,\ conifer}$) were their favored habitats. For the Vinous-throated Parrotbill three types of landscape metrics correlated with presence data. These included area of pristine forest (ca_{forest}), edge length between pristine forest and orchard ($es_{forest,\ orchard}$), and edge length between orchard and conifer plantations ($es_{orchard,\ conifer}$).

Table 2. Habitat suitability models for target species.

Drivers	Green-Backed Tit		Taiwan Yuhina		Vinous-Throated Parrotbill	
	Beta	**Exp(B)** [a]	**Beta**	**Exp(B)**	**Beta**	**Exp(B)**
Landscape metrics:						
Sum of edge length between building and cropland ($es_{buildind,\ cropland}$)	−0.105	0.900	−0.003	0.997	−0.115	0.891
Sum of edge length between building and orchard ($es_{buildind,\ orchard}$)	-	-	-	-	−0.141	0.868
Sum of edge length between pristine forest and cropland ($es_{forest,\ cropland}$)	−0.089	0.915	-	-	0.103	1.108
Sum of edge length between pristine forest and orchard ($es_{forest,\ orchard}$)	-	-	-	-	0.079	1.082
Sum of edge length between cropland and conifer plantation ($es_{orchard,\ conifer}$)	0.14	1.150	0.062	1.064	-	-
Sum of edge length between cropland and broadleaf plantation ($es_{cropland,\ broadleaf}$)	-	-	−0.066	0.936	-	-
Sum of edge length between orchard and conifer plantation ($es_{orchard,\ conifer}$)	-	-	-	-	0.07	1.073
Cohesion of conifer plantation ($coh_{conifer}$)	-	-	−0.006	0.994	-	-
Cohesion of broadleaf plantation ($coh_{broadleaf}$)	-	-	-	-	−0.03	0.970
Large patch index (lpi)	-	-	−0.016	0.984	-	-
Class area of pristine forest (ca_{forest})	2.305	10.024	2.465	11.763	2.501	12.195
Class area of conifer plantation ($ca_{conifer}$)	−3.575	0.028	3.719	41.223	-	-
Class area of broadleaf plantation ($ca_{broadleaf}$)	-	-	4.796	121.025	-	-
Distance variables:						
Distance to building	-	-	-	-	-	-
Distance to road	−0.028	0.97	−0.058	0.944	-	-
Constant	−3.521		−0.783		−4.542	
Area Under the Curve of ROC (AUC)	0.75		0.70		0.78	

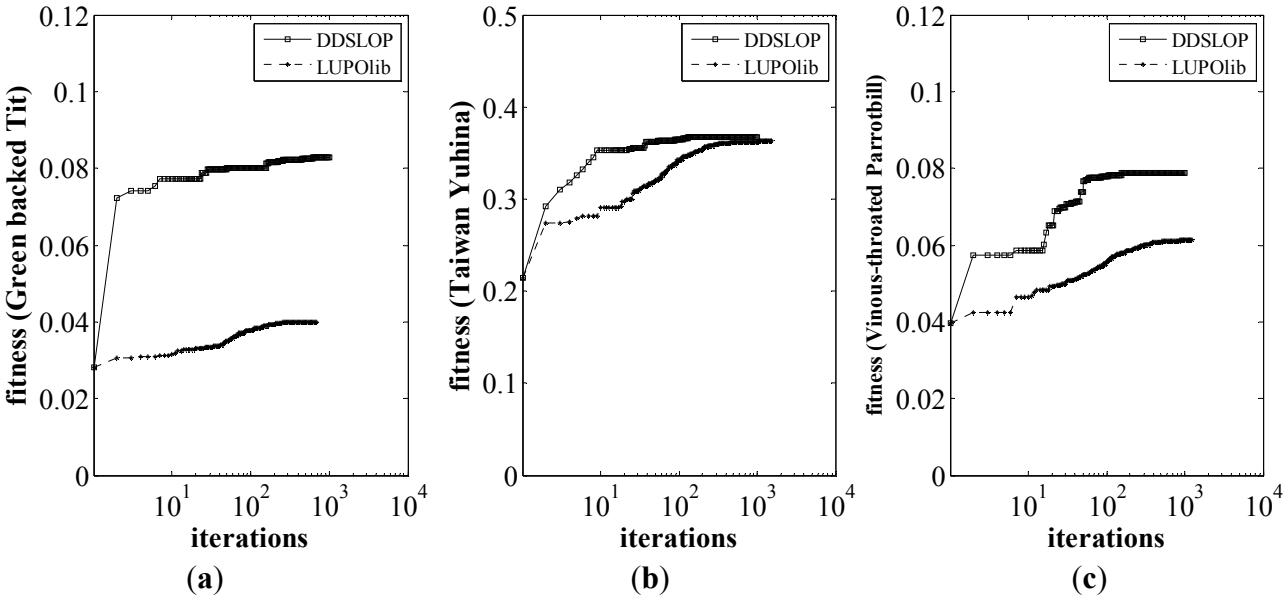
[a] The Exp(B) values indicated the changes in odds upon one unit change of the independent variable.

3.3. Performance of the DDSLOP and LUPOlib Model

The Model performance was plotted against iterations using a base 10 logarithmic scale for the x-axis (Figure 8). In each case, the performance graphs indicated that the cell-based DDSLOP model converged on a better solution in comparison to the solution delivered by the patch-level LUPOlib model (Table 1). In total the DDSLOP model conducted 200,000 evaluations of fitness within 1000 iterations

(outer iteration) for seeking a globally optimal solution from a solution space of 4^{2085} (4 land-use types were allocable for each of 2085 cells). Conversely, the iteration number conducted by the LUPOlib model varied due to its predefined stop criteria. Despite a far smaller solution space of only 4^{117} at patch level (four land-use types for 117 individual patches), the total number of iterations required by the LUPOlib model to reach a solution did not, by any means, reflect the magnitude of difference between solution spaces. This finding suggests that the DDSLOP model has the ability to reach solutions in a more computationally efficient manner.

Figure 8. The performance graphs of the DDSLOP and LUPOlib model. (**a**) Case 1 (the Green-backed Tit); (**b**) Case 2 (the Taiwan Yuhina); (**c**) Case 3 (the Vinous-throated Parrotbill). The iteration number on the x-axis represents the count of outer iteration for DDSLOP and total iterations for LUPOlib. Please note, for the DDSLOP model each of the outer iteration was followed by 200 inner iterations.



In case 1, the DDSLOP model improved fitness rapidly at the beginning and then converged on a globally optimal solution (Figure 8a). However, the fitness of the LUPOlib model grew gradually from the initial value (current landscape) and converged on an optimum, which ensured the stop criteria after 68,600 evaluations of fitness. In case 2, both DDSLOP and LUPOlib models increased fitness rapidly at the beginning and converged on similar closing values of fitness (Figure 8b). The LUPOlib model's stop criteria restricted the model to 150,300 evaluations of fitness. In case 3, the DDSLOP model displayed steep improvement at the outset and ultimately converged on a better solution compared with the LUPOlib model, which conducted 121,900 evaluations of the fitness (Figure 8c).

4. Discussions

4.1. Comparison of Optimal Landscape Planning Using the DDSLOP Model and LUPOlib Model

Spatial optimization conducted at a cellular level delivers a finer perspective for coping with the conservational needs of target species. Here, we demonstrated that the DDSLOP model can deliver better

habitat structure results in a computationally cost effective manner, which is important when dealing with the huge solution space of cellular level optimization. Landscape structures with higher suitability were attained due to the fact that the DDSLOP model can efficiently create more diversified land-use patterns, which provided better habitats for edge preferring species, as well as plenty of stepping-stones for the target species. The DDSLOP model was not only able to identify the necessary land-use types in key patches, but also created more diverse features within or between patches in order to provide an optimal habitat structure. In contrast, the results from the LUPOlib model reveal that a patch-level optimum of habitat reconstruction may be restricted to a given spatial structure with fixed patch shapes and lengths of boundaries between patches. For instance, for the Green-backed Tit (case 1) or the Vinous-throated Parrotbill (case 3), the observed flat improvement of habitat suitability could be attributable to the limitation of simply increasing the preferred boundary, such as the edges between conifer plantations and croplands. It is possible that this flaw could be an intrinsic feature of patch-level spatial optimization. Consequently, land cover that was identified as less favorable to specific species was simply converted to types that were either more favorable or relatively neutral to the species. This is clearly demonstrated by the increase of orchards and broadleaf plantations, which were relatively neutral for the Green-backed Tit, using the LUPOlib model (see Figure 5c). While this type of coarse manipulation may be a suitable solution for core loving species, it is not suitable for all landscape planning scenarios or species. What is instead needed in many situations is a model that can restructure the overall habitat, creating favorable landscape structures for target species within other land-use patches. Moreover, even for species that are not edge-preferring, such as the Taiwan Yuhina (case 2), the DDSLOP model captured more of the replaceable space and created preferred structures by relocating less preferable patches jointly (*i.e.*, the orchards in between buildings) or by moving these patches to the fringes. Therefore, it seems evident that the DDSLOP model can efficiently seek better overall solutions whereas a patch-level model often tends to merely convert less favorable land-use patches to more favorable or neutral land-use patches.

4.2. Spatial Patterns Resultant from the DDSLOP Model

The determination of specific habitat type ratios and their spatial configuration is required in many conservation strategies for the reconstruction of landscapes [5,22]. In many cases, the configuration of habitat structure should be considered at a finer scale, particularly in terms of both composition and functional connectivity for ecological integrity [23]. Although the resultant spatial pattern from the DDSLOP model appears more fragmented for the edge-preferring species, the overall connectivity of suitable habitats did not, by any means, decrease. The concentration of higher habitat suitability sites in specific areas may be an artifact of the moving window analysis in the spatial optimization process [3,4,6], since the suitability of neighboring cells within a species' territory (*i.e.*, sub-landscape) will be promoted simultaneously while a better pattern of the sub-landscape is reorganized. The results reveal that isolated land-use types (*i.e.*, plantations) within other land-use types could also provide suitable habitats for different species. For instance, isolated habitats become more valuable as they function as stepping stones, which make up larger proportions of pristine forests [24]. In other situations, habitat structures with isolated trees or artificial perches may increase bird visitation as well as consequent dispersion of seeds in degraded habitats [24,25]. Accordingly, habitat islands can in many instances have

high conservational value in landscape reconstruction projects, even though they appear fragmented and isolated [12]. In this study we considered each of the target species separately. While our analysis indicates that landscape structural preferences of specific species may conflict in some cases, the results also reveal matching preferences for other species (see Supplementary 7); suggesting that in an actual conservation initiative, multiple species may be grouped together in accordance to their individual landscape structure preferences. In so doing a given landscape can be partitioned into distinct areas which cater to the needs of specific groups of species. Furthermore, trade-offs between habitat suitability of different species which have specific habitat preferences [3,6] should be considered in future studies.

4.3. Conservation Actions for Landscape Management Using the DDSLOP Model

The DDSLOP model provides land-use projects with visualizations of optimal landscape configurations based on specific criteria. In this study, we focused on the restructuring of our study area in reference to habitat suitability for specific species. The models created are not only informative for landscape management, but also identify high suitability hot spot habitat areas. This demonstrates that the proposed DDSLOP model provides a quantitative method to measure the effects of landscape reconfiguration on different points of interest. Furthermore, the DDSLOP model provides a robust multi-action planning [15,26] platform by simultaneously reallocating various replaceable land-use types according to predefined criteria. This is in stark contrast to single-action planning, such as simple re-vegetation at a landscape scale [5]. While a number of excellent studies have assessed the influence of landscape configuration on bird diversity in restoration practices [27–29], these studies have generally focused on an individual restoration site rather than on the effects of the land-use configuration in terms of the overall landscape. With the help of the DDSLOP model the results of such studies can be analyzed and applied from the context of total landscape structure. This means that the DDSLOP model has the potential to be a real asset in many landscape management initiatives such as those designed to increase habitat diversity and suitability for different species, including the restructuring of parks and or cityscapes, the re-vegetation of clear cut lands, the design of artificial wetland areas, *etc*. Nevertheless, in most cases it is a complicated task to fragment a landscape in accordance to a specific species' needs. Therefore, we suggest that the modification can initially center on sub-landscapes within hot spot areas. The spatial prioritization can be carried out in reference to habitat suitability as a surrogate of conservation costs [6], in this way, priorities and consequent sub-landscape modifications can be comprehensively considered within a given area. Of course, the restructuring of landscapes needs to take many other factors into consideration as well, such as socio-political constraints, *etc.*, as such, DDSLOP visualizations may not always be directly applicable, but could serve as valuable references for planners.

4.4. Evaluation of the DDSLOP Model

The DDSLOP model provides good global solutions (as opposed to a globally optimal solution) [16] based on the DDS algorithm. The DDS algorithm is an appropriate optimizer suited for problems with huge solution spaces, as it progressively searches the potentialities by narrowing the solutions based on a user-specified number of fitness iteration. In the process, it incorporates both diversification and intensification. However, for a multi-action planning problem, an extraordinarily huge solution space resulted in many useless searches during the diversification process. In order to improve the efficiency

of the diversified search, the DDSLOP model has made DDS more suitable for a greater number of problems by incorporating additional criteria. In this case, the preferential modification of chosen cells with lower habitat suitability for exchanges. In other words, the cells that contribute to lower suitability take priority over others during the adjustment process. This modification successfully increases the efficiency of the search, as evident by a steep gradient of the increased fitness, particularly at the outset of the model. Furthermore, the DDSLOP model has the ability to jump out of the local optimum via the combination of the diversification and subsequent intensification mechanisms. However, the complexity of solution space increases with the number of planning units. As the solution space increases the task of finding a global optimum becomes difficult.

In this study, the DDSLOP and the LUPOlib models were compared at different resolutions. We have not provided conclusive evidence that the DDS algorithm performs better than a GA algorithm in an equivalent spatial optimization problem. Mathematically, the two models solved different optimization problems with different complexities in terms of solution spaces. Furthermore, the two models carried out different strategies in which the DDSLOP searched for an optimal solution by visiting individual points globally at the outset, then moving onto more localized points during consecutive iterations, whereas the LUPOlib drove a multi-point search in order to discover different points of interest during consecutive iterations. However, this study revealed that the DDSLOP model has the ability to efficiently solve spatial optimization problems, which have massive solution spaces in relatively fewer iterations. In addition, this study demonstrated that the habitat structure optimized at a cellular level may be more suitable for certain species than patch-level optimizations. Finally, since the DDSLOP model has less complex stop criteria, simply set the maximum number of inner and outer iterations, we feel as though it provides not only a more user-friendly interface, but also a more standardized solution searching process. As such, though we have not provided definitive evidence of DDSLOPs superiority in spatial optimization, we have rather indicated, quite conclusively, the applicability of DDSLOP as an efficient landscape optimization package suitable for massive solution spaces.

Different species respond to the landscape structure in different ways. In particular, the varying mobility and home ranges of different species means that they experience the landscape at different scales. Most species, however, only directly interact with a small portion of the overall landscape [18,30]. As such, rather than considering the entire landscape structure of a given study area, the DDSLOP model uses a moving window analysis to take the range of specific target species into consideration. In this way, the suitability of habitat within a specified neighborhood around each cell (*i.e.*, territory or home range of a species) is identified and incorporated into the optimization process. As always, the accuracy of survey data of specific species plays a big part in the quality of habitat suitability models, and should be of key concern for users wishing to use the DDSLOP model. In the context of this study, we have high confidence in the presence/absence survey data, which covered the entire study area and was conducted over a three-year period (see Supplementary 4). Based on the presence-absence data, the results indicated that the habitat suitability models are fairly reliable, with AUC values that are equal to or exceed 0.7 [3,31,32]. However, for the Green-backed Tit and the Vinous-throated Parrotbill, the values of average habitat suitability were obviously lower than the habitat suitability of Taiwan Yuhina. This is mainly due to the small number of their presence data compared to that of Taiwan Yuhina. Besides the different number of presence data, the size of moving window also influences the estimated habitat suitability because it decides the habitat composition/configuration to a presence point. In addition, we found that both the

Green-backed Tit and the Taiwan Yuhina share common habitat structure preferences, which differ from those of the Vinous-throated Parrotbill (Supplementary 7). In order to deal with discrepancies between species habitat preferences, we suggest the incorporation of all target species' needs into the same spatial optimization problem, *i.e.*, multi-objective analysis in which the habitat suitability should be normalized in the optimization process to equalize the importance of all species [5], and therefore the varying relative conservational importance of different species can be considered in such initiatives.

5. Conclusions

This study developed a novel spatial optimization model that provides a computationally cost effective approach for landscape planning. The proposed DDSLOP model delivers a practical method for habitat structure optimization at finer resolutions. The case studies conducted indicate the effectiveness of our proposed model in providing good habitat structures for landscape management. As such, the results provide new insights into fine scale spatial optimization, which is becoming increasingly more important when considering appropriate solutions to conflicts between urban sprawl and habitat restoration. As always the willingness of landowners to implement land use changes is crucial in the application of landscape planning initiatives. Therefore, we are planning to analyze the trade-offs at a regional scale by integrating the suitability of urban development into the DDSLOP model in future studies.

Supplementary Materials

Supplementary materials can be accessed at: http://www.mdpi.com/2071-1050/6/12/9139/s1.

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Author Contributions

Main ideas: Chun-Wei Huang, Yu-Pin Lin, Tzung-Su Ding, Johnathen Anthony; Academic writing: Chun-Wei Huang, Johnathen Anthony, Yu-Pin Lin; Data collection: Tzung-Su Ding; Model development: Chun-Wei Huang, Yu-Pin Lin; Wrote for the first draft of the manuscript: Chun-Wei Huang.

Conflicts of Interest

The authors declare no conflict of interest.

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