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Intelligent Algorithms for Rural Landscape Design: A Closed-Loop Approach

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Abstract: To tackle three key issues prevalent in contemporary rural landscape design, low plant survival rates, high maintenance costs, and severe landscape homogenization, a closed-loop optimization model based on the Rhino-Plantkit graphical algorithm is proposed. This model adjusts critical parameters in real time through environmental response mechanisms. Specific applications include automatically adjusting planting density based on topography, optimizing light distribution in shaded areas, and coordinately regulating the color composition of plant communities. By employing intelligent algorithms, the system is able to harmonize ecological, functional, aesthetic, and cultural objectives within community planning. For instance, by preventing spatial conflicts caused by excessive planting density and optimizing light distribution. Field tests confirm that the approach significantly enhances environmental benefits (soil erosion reduced to 84mm/year, a 45.5% decrease), economic efficiency (maintenance frequency cut to 1.45 times/year, lowering full-cycle costs by 25.1%), and natural affinity (spatial conflict rate lowered to 0.09, color regional compatibility ΔE reaching professional-grade 3.97). This approach overcomes the fragmentation issues in traditional design across ecological adaptability, cultural heritage, and sustainability dimensions.

Keywords: Closed-loop design model, ecological adaptation, intelligent algorithms, parametric plant layout, rural landscape optimization.

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1. Introduction

Rural landscapes serve as vital carriers of nostalgia, embody regional characteristics, and enhance quality of life, making their planning and design increasingly important (Wei, 2024). However, traditional rural landscape design, especially plant configuration, faces multiple challenges. For instance, overlooking "locality" and "adaptability" often results in homogenized landscapes or poor ecological fit. Plant spatial structure design still depends on empirical manual methods, leading to low efficiency and difficulty in growth simulation (Hu and Hu, 2023). More critically, regional cultural traits such as distinctive forms and color schemes are mostly described qualitatively. There is no effective way to embed these elements quantitatively into digital workflows, making cultural expression subjective and difficult to optimize collaboratively. Digital technologies such as parametric design, algorithmic generation, and simulation offer potential to overcome traditional limitations (Aryavalli and Kumar, 2023). Nonetheless, current digital design has its own issues. Plant form modeling relies on static rules, and community configuration lacks an integrated mechanism for ecology, function, aesthetics, and culture. Additionally, subjective goals, such as cultural heritage, remain inadequately quantified or optimized. This makes it difficult to scientifically ensure and express regional characteristics in design solutions (Li and Gu, 2024). Researchers in intelligent construction and human settlement are tackling these problems. Zhang (2024) proposed a path optimization method based on swarm intelligence to enhance design efficiency. Kang (2025) integrated particle swarm optimization with knowledge graphs to optimize park layouts. Li and Fan (2022) employed neural networks to construct evaluation models, strengthening the scientific rigor of proposals. Li and Sharma (2022) utilized interactive genetic algorithms to improve visual reconstruction quality. Ma (2025) optimized ecological layouts through an improved ant colony algorithm. Li and Li (2025) combined support vector machines with remote sensing technology to assist rural landscape identification and planning. Feng et al. (2024) employed Generative Adversarial Networks (GANs) to construct a generative mechanism that synergizes ecology and aesthetics. Using its adversarial training, the model learned both ecological data features and visual composition rules, producing plant layouts that respect topography, soil, and climate while remaining artistically expressive. Senem et al. (2024) used FastGAN to learn quantitative features like functional layout and land use from a courtyard dataset, generating basic spatial frameworks, and then improved visual quality and details with stable diffusion models. In summary, existing studies have made notable progress in digital landscape design via swarm intelligence for path optimization, neural networks for multi-indicator evaluation, and interactive genetic algorithms for feature reconstruction. These approaches yield optimized spatial structures, scientifically sound planning assessments, and high-precision extraction of architectural traits. Nevertheless, they still have weaknesses. They lack dynamic environmental adaptation, insufficient multi-objective (especially cultural) synergy, and limited integration with practical needs (e.g., precise preservation of local cultural heritage). Most methods focus on quantifiable indicators like ecology and function, while ignoring soft objectives such as culture and aesthetics. Consequently, they have failed to establish a comprehensive technical pathway encompassing "cultural feature extraction, quantification of design parameters, multi-objective coordination."

Rhino (Rhinoceros) and its Grasshopper plugin, as a powerful parametric design platform, have shown great potential in architecture and urban design through accurate modeling, rule definition, and logic-driven operations (Armstrong et al., 2023). The Grasshopper plugin Rhino-Plantkit (PlantKit), specializing in plant ecological simulation and parametric configuration, offers a graphical algorithm toolkit based on plant physiological and ecological traits (e.g., growth rates, light needs, spatial competition). It can simulate growth rules, spatial distribution, and interactions with environmental factors for complex plant communities (Wu, 2023). However, PlantKit lacks modeling capabilities for microecological processes like allelopathy and root competition. It also fails to quantify or optimize subjective design elements, such as cultural and aesthetic considerations, thereby restricting the accurate simulation of complex ecological relationships and cultural imagery (Dasari et al., 2022). Therefore, this study focuses on PlantKit's strengths and limitations, further optimizing and refining it to build the Rhino-PlantKit Rural Landscape Closed-loop Optimization Model (RP-RLCO). This research aims to build a closed-loop, optimized rural landscape design model that overcomes two technical bottlenecks: plant ecological adaptability and the synergistic integration of cultural heritage expression with multi-objective community design. The innovation lies in establishing an environmental feedback L-system (Lindenmayer systems) -driven plant-adaptive generation method. Allowing the deep integration of PlantKit with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to achieve multi-objective static spatial optimization across ecological, functional, visual, and cultural dimensions.

2. Method Overview

This section is divided into two parts. First, it develops a plant growth simulation module using L-systems that incorporates environmental response mechanisms. Second, it builds a community-scale intelligent optimization module centered on the Plantkit spatial engine, combined with multi-objective static optimization strategies. Together, these form the RP-RLCO rural landscape design model, which helps designers tackle challenges in ecological adaptability, cultural expression, and multi-objective coordination for plant configuration. The entire process forms a dynamic, closed loop of environmental data-driven plant morphogenesis, while optimized community schemes feed back into environmental simulation, allowing continuous iterative evolution of design proposals.

2.1. Plant Growth Simulation Module: Environmentally Responsive Morphogenesis

To achieve optimal spatial, functional, and visual configuration of landscape plant communities, a diverse parametric library of plant morphologies is needed as design building blocks. This study employs L-systems as the core algorithm to achieve this objective. The main strength of L-systems is their ability to efficiently generate plant topologies from simple to complex using compact generative rules (Wei and Hao, 2023). This provides designers with a parametric generation tool that directly controls key morphological characteristics such as branching density, crown size, and growth posture. The parametric morphology generation process is illustrated in Fig. 1 (Lee et al 2023).

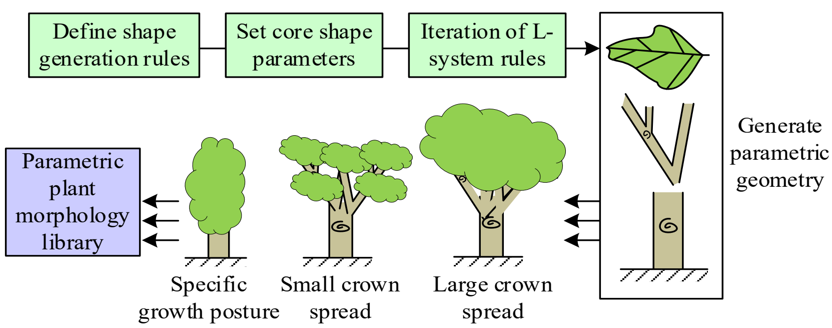

Fig. 1. Workflow of parametric plant form generation using L-system

As shown in Fig. 1, the L-system systematically develops complex spatial structures from an initial morphology (axiom) through its iterative mechanism, thereby generating a series of plant models that vary in size, density, and form. Thus, in this study, the L-system primarily serves as a parametric generator for morphogenesis, offering a library of "digital plant assets" for batch creation and laying the morphological groundwork for subsequent designs. However, L-systems rely on static rules for morphogenesis, so they cannot respond in real time to changing environmental factors such as light and moisture. This shortcoming prevents them from capturing the adaptive growth behavior of plants under real-world ecological conditions (Kökçam et al., 2025). Therefore, this study introduces an environmental adaptation mechanism to optimize the rule-generation process of L-systems. The goal is to produce plant morphologies that are not only ecologically responsive but also act as visual primitives conveying regional culture through their structural features. The underlying principle is illustrated in Fig 2.

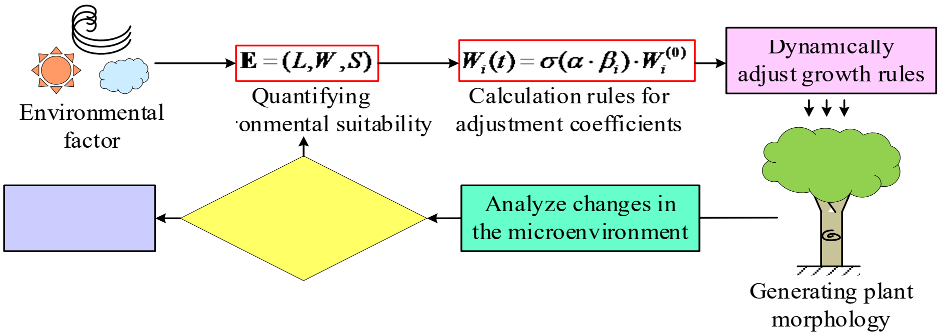

Fig. 2. Schematic diagram of the principle of the environmental adaptation mechanism

In Fig. 2, the study quantifies field measurement data (light intensity L, soil moisture W, terrain slope S) into an environmental vector matrix, as shown in Eq. (1).

$$\mathbf{E}=(L,W,S) \tag{1}$$

In Eq. (1), $\mathbf{E}$ is the environmental vector matrix. This is then mapped via an S-shaped function Φ (e.g., Sigmoid) to a normalized adjustment coefficient $\alpha\in[0,1]$. This coefficient dynamically controls parameters such as branching probability and internode length in the L-system, endowing the generated plants with "environmental intelligence." The activation weight of the i th rule in the rule set is adjusted according to the α adjustment rule (Wan and Wan, 2023), as shown in Eq. (2).

$$W_i(t)=\sigma(\alpha\cdot\beta_i)\cdot W_i^{(0)} \tag{2}$$

In Eq. (2), β_i represents the environmental sensitivity parameter of the rule, and σ denotes the Softmax normalization function, ensuring a reasonable weight distribution. After generating preliminary morphology, the light variation caused by leaf shading is calculated as shown in Eq. (3).

$$\Delta L=L_{\text{initial}}-L_{\text{shaded}} \tag{3}$$

In Eq. (3), ΔL is the light variation; L_{initial} is the initial light intensity; and L_{shaded} is the light intensity after shading. Subsequently, the overall environmental change $\|\Delta\mathbf{E}\|$ is evaluated (He et al., 2022). If exceeding threshold ε, update environmental inputs and return for iteration, achieving synergistic optimization of morphology and environment. Meanwhile, the model quantifies regional pest and disease risks as constraints by establishing a plant disease resistance database that assigns a resistance coefficient R_i to each species, it introduces a disease sensitivity factor δ_j into the rule set weight calculations to reduce the selection priority of highly susceptible species when environmental humidity continuously exceeds thresholds, and optimizes ventilation through canopy density control during the spatial configuration phase, thereby systematically reducing the occurrence risks of pests and diseases such as aphids and powdery mildew. Therefore, this research establishes a plant growth simulation module based on L-systems, integrated with an environmental response mechanism. Its core functionality enables digital plants to dynamically adjust their growth morphology in response to environmental factors like light intensity, soil moisture, and terrain slope, mimicking real biological organisms. The module structure is illustrated in Fig. 3.

As shown in Fig. 3, through real-time data acquisition, this module quantifies and maps environmental factors (e.g., light intensity, soil moisture, and slope) into regulatory coefficients, which are then used to dynamically update key parameters in L-systems, including branching probability and internode length After generating an initial morphology, it calculates local microenvironmental changes and validates environmental adaptability through feedback loops until morphological convergence is achieved. The final output is a set of parameters for a plant model that matches real habitats and whose morphological features can be recognized and utilized by subsequent cultural objective functions.

2.2. Colony Intelligence Optimization Module: Multi-Objective Coordination and Closed-Loop Iteration

The "digital materials" generated by the environmental feedback L-system module possess ecological adaptability and morphological diversity. However, they require scientific configuration at the colony scale to address issues such as spatial overlap between plants, light competition, and inconsistencies with the overall design intent. Plantkit, a powerful parametric plant configuration plugin, provides the computational foundation for resolving spatial configuration conflicts in large-scale scenarios through its built-in efficient spatial indexing and collision detection engine (Benliay and Soydan, 2022). Therefore, this study leverages Plantkit to achieve configuration from individual plants to plant communities. The Plantkit workflow is illustrated in Fig. 4.

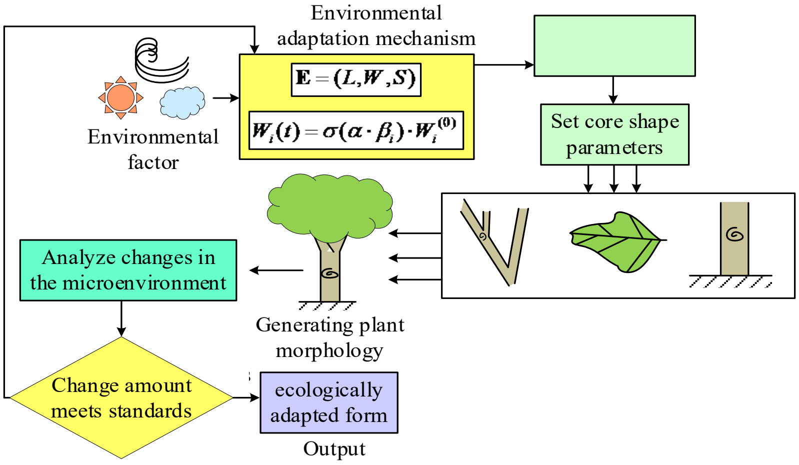

Fig. 3. Schematic diagram of the plant adaptive generation module structure

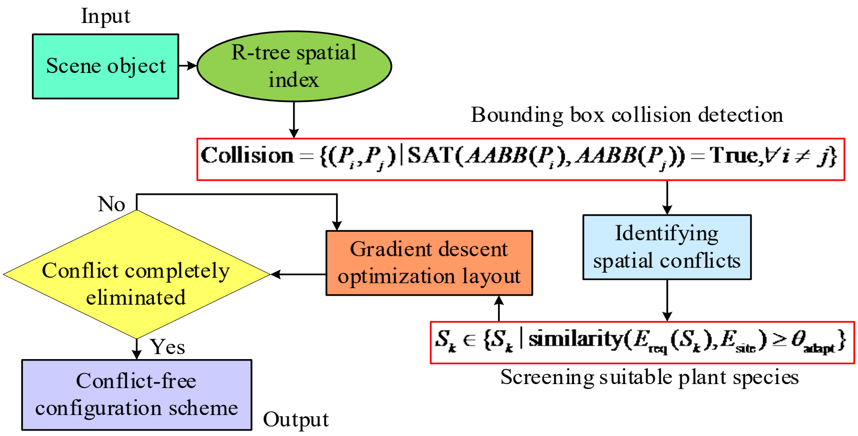

Fig. 4. Schematic diagram of Plantkit's process

As shown in Fig. 4, Plantkit organizes scene objects using an R-tree $B=\bigcup_{i=1}^{N}AABB(P_i)$ -index (where P_i represents the i th plant instance and n denotes the total number of objects). It employs the Separating Axis Theorem to rapidly detect bounding box collisions, with the computation detailed in Eq. (4) (Maged et al., 2025).

$$\text{Collision}=\{(P_i,P_j)\mid \text{SAT}(AABB(P_i),AABB(P_j))=\text{True},\forall i\neq j\} \tag{4}$$

Eq. (4) outputs a set of conflicting plant pairs for subsequent layout adjustments. For instance, when the minimum distance between two tree trunks falls below a preset threshold, the system immediately flags it as a "spatial conflict" and highlights it as a warning in the 3D view. Concurrently, Plantkit can filter suitable plant species based on the site environmental factor vector E_{site}, as shown in Eq. (5) (Zhou et al., 2022).

$$S_k\in\{S_k\mid \text{similarity}(E_{\text{req}}(S_k),E_{\text{site}})\geq\theta_{\text{adapt}}\} \tag{5}$$

In Eq. (5), $E_{req}(S_k)$ represents the ecological requirement index of the species S_k; θ_{adapt} denotes the adaptability threshold. Subsequently, the collision energy function $E_{\text{collision}}$ is minimized via gradient descent until a collision-free state is iteratively achieved. Plantkit bridges the gap from individual ecological modeling to spatial community coordination, ensuring the authenticity and implementability of plant configurations in rural landscapes. However, Plantkit's core capability focuses on resolving spatial conflicts within extensive sites, lacking the ability to jointly balance and synergistically optimize multi-dimensional landscape performance across ecological, functional, visual, and cultural dimensions. To address this limitation, this study introduces a multi-objective static optimization strategy, that constructing a constrained spatial optimization module integrating four-dimensional objectives, as illustrated in Fig. 5.

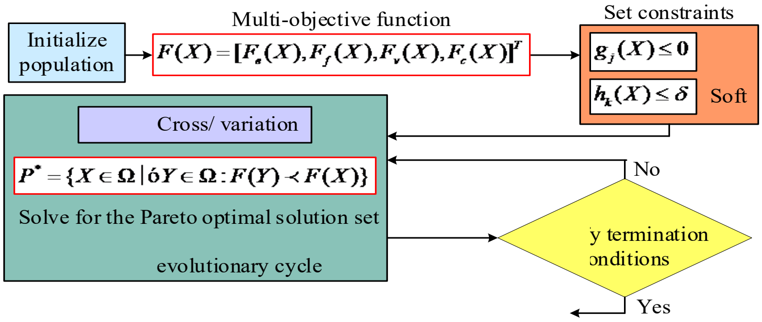

Fig. 5. Schematic diagram of the principle of multi-objective static optimization strategy

As shown in Fig. 5, the core of this strategy lies in establishing an optimization model that incorporates conflicting objective functions and constraints and utilizing the NSGA-II evolutionary algorithm to search for a Pareto-optimal solution set. The study first constructs a four-dimensional objective vector function, as shown in Eq. (6).

$$F(X)=[F_e(X),F_f(X),F_v(X),F_c(X)]^T \tag{6}$$

In Eq. (6), X represents the combination variable of plant location and species; $F_e(X)$ characterizes ecological adaptability (e.g., habitat matching degree); $F_f(X)$ measures functional efficiency (e.g., shade coverage); $F_v(X)$ evaluates aesthetic quality (e.g., seasonal variation richness); $F_c(X)$ is the introduced cultural expression objective, quantifying the design scheme's efficacy in preserving regional cultural heritage. $F_c(X)$ itself is a weighted composite function of multiple cultural sub-objectives, as shown in Eq. (7) (Wolff et al., 2022).

$$F_c(X)=\omega_1\cdot \mathrm{CSS}(X)+\omega_2\cdot \mathrm{RCC}(X)+\omega_3\cdot \mathrm{SN}(X) \tag{7}$$

In Eq. (7), $\mathrm{CSS}(X)$ denotes cultural symbol prominence, calculated via OpenVC by measuring shape similarity between the scheme layout and cultural symbol templates; $\mathrm{RCC}(X)$ represents regional color conformity, computed as the reciprocal of the average color difference between scheme colors and regional color systems in the CIELAB color space and $\mathrm{SN}(X)$ signifies spatial narrative, based on spatial syntax analysis of design circulation paths visual connectivity to historical elements. The abstract characteristics of regional culture are translated into cultural and algorithmic parameters through $F_c(X)$ multi-level parameter system. Taking Tianjin's humor culture as an example, its "witty and agile" trait is quantified as visual indicators of color contrast (such as complementary color ratios) and morphological indicators of branch curvature variation coefficients. Meanwhile, its "inclusiveness" is quantified using spatial syntax integration metrics that represent the connectivity strength between public nodes and residential areas. The weight allocation for the four-dimensional objective vector function $F(X)$ is not predetermined with fixed values. Instead, it is comprehensively determined by integrating expert questionnaires from the target region with the Analytic Hierarchy Process. This approach aims to quantitatively reflect the relative importance of each dimension, thereby translating the qualitative value judgments of designers and the community into quantitative constraints within the optimization algorithm. Subsequently, design constraints are established to regulate the output of community configuration schemes, namely design constraints $g_j(X)\le 0$ (hard constraints) and $h_k(X)\le\delta$ (soft constraints). Among these, g_j are hard constraints, such as collision detection, slope restrictions, and cultural preservation redlines. h_k include soft constraints, such as seasonal continuity, fluctuations in species diversity, and native plant ratios, allowing limited deviation δ. The NSGA-II algorithmic workflow includes initializing a random population, performing non-dominated sorting per generation to partition individuals into multiple Pareto fronts, and calculating crowding degree to maintain solution set diversity; parent individuals are selected via binary tournament, and offspring are generated using simulated binary crossover and polynomial mutation. Moreover, it employs a population size of 100, a crossover probability of 0.9, a mutation probability of 0.1, and a maximum iteration limit of 200 generations. Each individual represents a plant community scheme. A hybrid encoding is used: the real-coded part stores the spatial coordinates (x_i,y_i) of each plant. The integer-coded part stores the corresponding species index s_i (from the local adapted plant list). A chromosome for a scheme with N plants can be expressed as $[x_1,y_1,s_1,x_2,y_2,s_2,\ldots,x_N,y_N,s_N]$. The phenotype of this chromosome is the 3D spatial layout, including plant positions, morphological parameters (generated by the L-system based on environmental feedback), and species attributes. Thus, NSGA-II can simultaneously optimize both the spatial arrangement and the species composition. With finite computational resources, the algorithm achieves efficient convergence thanks to its computational complexity of $O(MN^2)$, where M denotes the number of objectives (four in this study), and N denotes the population size. Unlike MOEA/D, which depends heavily on weight vectors, and SPEA2, which involves high computational complexity in archive maintenance, NSGA-II has theoretical benefits in preserving the spread and uniformity of Pareto solution sets. Its crowding distance metric effectively balances soft objectives like cultural expression with quantifiable ecological indicators, thus being selected as the multi-objective optimization engine for this study, with its computation shown in Eq. (8) (Zandniapour et al., 2025).

$$P^* = \{X \in \Omega \mid \nexists Y \in \Omega : F(Y) \prec F(X)\} \tag{8}$$

In Eq. (8), $F(Y) \prec F(X)$ indicates that solution Y dominates solution X. This algorithm generates a set of Pareto optimal solutions for designers. Each scheme represents an optimal trade-off among ecological, functional, visual, and cultural objectives. Thus, the community intelligence optimization module, centered on Plantkit and integrated with a four-dimensional objective static optimization strategy, delivers plant community configuration schemes that harmoniously integrate ecological, functional, aesthetic, and cultural imagery. In summary, this research integrates a plant growth simulation module and a community intelligence optimization module to establish the RP-RLCO model, as illustrated in Fig. 6.

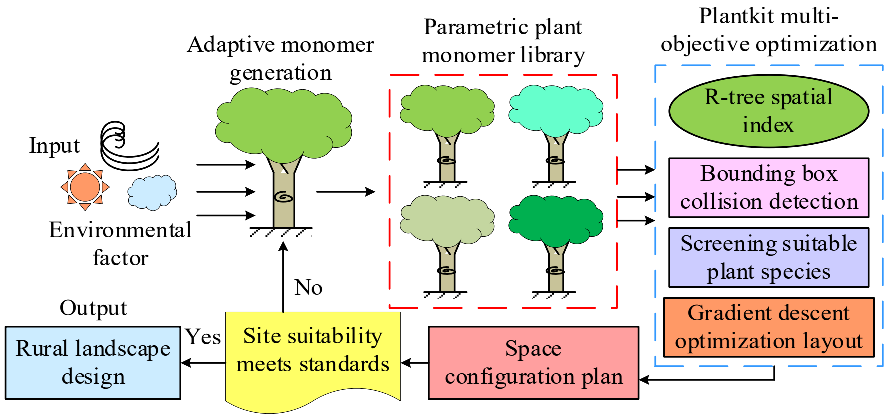

Fig. 6. Schematic diagram of the RP-RLCO model structure

As shown in Fig. 6, initial environmental data (topography, light intensity, soil properties) are first input into the plant growth simulation module to generate an adaptive individual library. Then, Plantkit performs spatial conflict detection across the community, while NSGA-II simultaneously optimizes four-dimensional objectives to produce community design proposals. These proposals are then evaluated within a virtual scenario (e.g., detecting whether light intensity in canopy overlap zones falls below thresholds, or assessing cultural symbol recognition rates at primary viewpoints). Whenever evaluations identify target deviations (e.g., insufficient local scores or excessive maintenance costs), the system automatically extracts environmental parameters and deviation data from problematic regions. This then triggers adjustments to plant morphological rules or a reconfiguration of community layouts.

By dragging Plantkit components inside the Rhino-Grasshopper visual interface, designers construct algorithmic workflows. Real-time input or adjustment of environmental parameters triggers synchronous 3D rendering of plant morphology and community layout. When conflict warnings appear or objective scores are low, designers can manually adjust the NSGA-II objective weight slider. This immediately triggers re-optimization of the design and updates the 3D view.

3. Case Studies and Applications

To test how well the RP-RLCO model performs in designing complex rural habitats, both typical scenario simulations and real-village case tests were conducted. The former employed terrain gradient perturbations, extreme climate pattern simulations, and multi-objective conflict injection to quantitatively evaluate the synergistic optimization efficiency of ecological, functional, visual, and cultural objectives. The latter used microclimate data from Caocun Village (Jinghai District, Tianjin), together with local plant resources and regional cultural traits, to validate the design scheme's overall effectiveness in habitat adaptation, cultural identity, and user preferences.

Case selection followed principles of representativeness, data availability, and appropriate scale, focusing on typical waterside villages in the North China Plain. It required complete datasets on microclimate, plant species, and cultural symbols, and targeted medium-sized settlements to ensure feasibility. Caocun Village, located on the west bank of the South Canal, exhibits typical characteristics of northern rural settlements. It enjoys transport advantages and ecological sensitivity, covering roughly 445 hectares, mixing built and non-built land, with a registered population close to 1,000. Given its representative scale and structure for the North China Plain, it was chosen as the case study.

3.1. Typical Scenario Simulation

In simulation testing, complex habitat scenes were dynamically tested using the OpenLandscape simulation engine, which supports high-precision terrain generation and microclimate simulation. Parameter settings were consistent with the research methodology section. A benchmark test was performed with the Global Urban and Rural Settlement Dataset (100m resolution, 2000-2020), which contains 44,474 samples integrating data on rural buildings and open areas. A stratified random partition (training: test = 2:8) was applied. For comparison, this study adopted several existing methods to include Collective Intelligence Optimization for Multimedia Landscape Design (CIOM), Particle Swarm Optimization with Polygonal Layout System (PSPL), Particle Swarm-Backpropagation Neural Network Evaluation Model (PSBP), and Interactive Genetic Algorithm for Spatial Environment Optimization (IGAS). To eliminate random errors, 30 independent replicate runs were conducted, each simulating 72 virtual growing months (covering a full seasonal cycle of plants). All quantitative results underwent significance analysis using two-tailed t-tests ($p<0.05$ was considered significant), ensuring the scientific validity and reproducibility of the experimental conclusions. To verify the model's performance in spatial conflict resolution and ecological protection, the study first compared the Spatial Conflict Rate (SCR) and Habitat Coverage Rate (HCR) of landscape design schemes generated by different methods. SCR represents the ratio of plant pairs exhibiting spatial overlap to the total number of plant pairs in the scene. The results are shown in Fig. 7.

According to Fig. 7(a), the average SCR of the RP-RLCO model was as low as 0.09, significantly better than CIOM's 0.18, PSPL's 0.22, PSBP's 0.26, and IGAS's 0.18 ($p<0.01$). This is due to the Plantkit space engine integrating efficient collision detection and NSGA-II multi-objective optimization mechanism to dynamically handle geometric conflicts and hard constraints. However, CIOM relies on swarm intelligence path generation but ignores entity space overlap, and the PSPL polygon layout system has insufficient adaptability in complex terrain, resulting in a sharp increase in conflict rate. According to Fig. 7(b), the average HCR of the RP-RLCO model was as high as 0.93, surpassing CIOM's 0.83, PSPL's 0.74, PSBP's 0.77, and IGAS's 0.85 ($p<0.01$). This is attributed to the real-time response of environmental feedback L-system dynamic rule weights to soil gradients under light conditions. The PSBP neural network evaluation model only quantified static schemes afterward, while the IGAS algorithm optimized visual features but lacked an ecological closed-loop feedback mechanism, resulting in a maximum gap of 0.19. Subsequent research compared the Shannon Diversity Index (SDI) generated by different modeling approaches to quantify the visual richness of landscape layouts. Additionally, color difference (ΔE) within the CIELAB color space was calculated to assess regional color conformity, thereby providing an objective measure of landscape design's artistic quality. ΔE represents the Euclidean distance between the weighted average color value of the primary plant communities in the scheme (e.g., leaf color, flower color) and the corresponding colors in the predefined regional cultural color spectrum. The results are shown in Fig. 8.

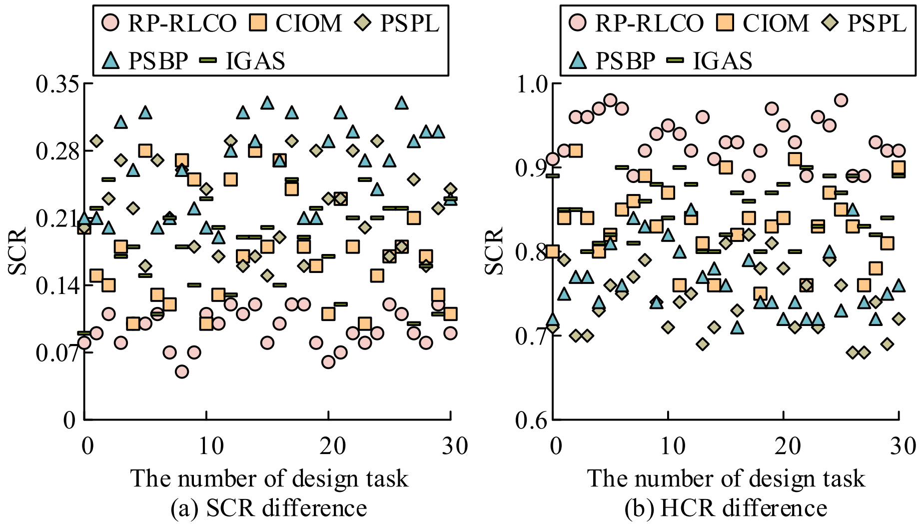

Fig. 7. Verification of spatial conflict resolution and ecological protection performance

As shown in Fig. 8(a), the RP-RLCO model achieved a significantly higher mean SDI of 2.22 than CIOM (1.67), PSPL (1.90), PSBP (1.72), and IGAS (1.96) ($p<0.001$). This stems from the environmental feedback L-system mechanism dynamically adjusting plant morphological rules. Combined with the visual aesthetics objective function in four-dimensional goal optimization, it significantly enhances landscape layout diversity and rhythm. While IGAS achieved a maximum value of 2.22, matching the RP-RLCO mean, RP-RLCO demonstrated markedly superior stability (standard deviation 0.14 vs 0.19). As shown in Fig. 8(b), the RP-RLCO model exhibited a remarkably low mean ΔE of 3.97, demonstrating significant advantages over CIOM (6.99), PSPL (6.35), PSBP (7.42), and IGAS (5.32) ($p<0.001$). This advantage stems from the quantitative constraints imposed by the regional color conformity sub-objective within the cultural expression objective function. By optimizing in the CIELAB color space, the RP-RLCO model produced color schemes that closely align with Tianjin's regional cultural spectrum. Although IGAS's minimum ΔE value of 4.60 approached that of RP-RLCO, RP-RLCO's $\Delta E<3.5$ represented professional-grade color matching (only 41% of IGAS tasks meet this standard). Afterward, to verify the importance of the research selection method, ablation experiments were conducted, replacing NSGA-II with MOEA/D, SPEA2, and Pareto Archived Evolution Strategy (PAES), respectively, as shown in Table 1.

As shown in Table 1, the full model RP-RLCO achieved a low mean SCR of 0.09, a high SDI of 2.22, and a low ΔE of

3.97 due to its integration of environmental feedback L-system and Plantkit multi-objective optimization. Disabling the L-system (A2) reduced HCR to 0.80 and SDI to 1.82 (p<0.01), revealing that the absence of morphological modeling significantly diminished visual diversity. Disabling Plantkit (A4) worsened SCR to 0.20 and ΔE to 5.65 (p<0.001), validating the spatial engine's central role in conflict resolution and cultural expression. Among alternative approaches, MOEA/D (R1) increased SCR to 0.10 and ΔE to 4.20 (p<0.05) due to the decomposition strategy limiting objective synergy. SPEA2 (R2) failed to adequately preserve archives, causing SCR to rise to 0.11 and SDI to drop to 2.10. PAES (R3) lacked diversity mechanisms, resulting in SCR reaching 0.12 and ΔE increasing to 4.45 (p<0.01), highlighting the superiority of NSGA-II's crowdedness distance calculation in maintaining visual diversity and cultural expression.

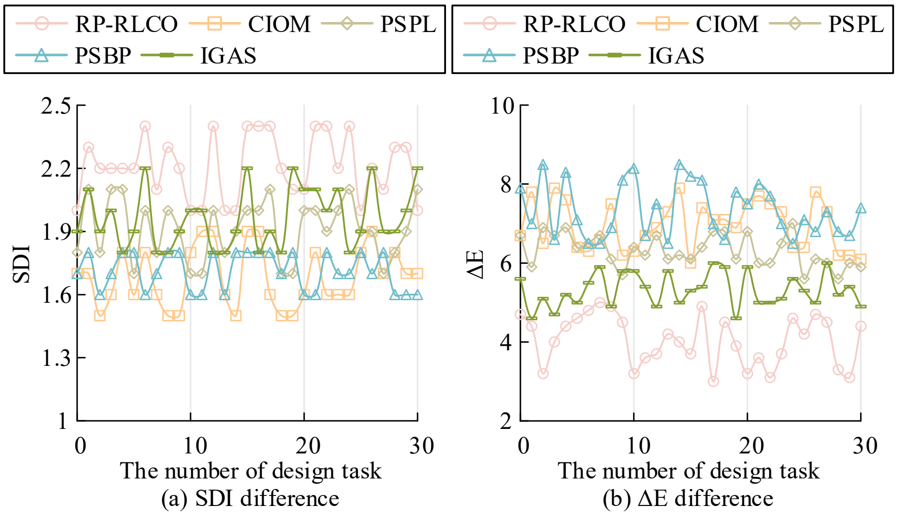

Fig. 8. Verification of ecological stability

Table 1. Validation of the effectiveness of the basic module

Plans	Full	Ablation plan				NSGA-II replacement scheme		
	RP-RLCO	A1	A2	A3	A4	R1	R2	R3
L-system	√	√	×	√	√	√	√	√
Environmentally adaptive mechanism	√	×	×	√	√	√	√	√
Plantkit	√	√	√	√	×	√	√	√
Multi-objective static optimization strategy	√	√	√	×	×	MOEA/D	SPEA2	PAES
SCR	0.09	0.12	0.15	0.14	0.20	0.10	0.11	0.12
HCR	0.93	0.88	0.80	0.85	0.75	0.91	0.90	0.89
SDI	2.22	2.00	1.82	2.05	1.78	2.15	2.10	2.08
ΔE	3.97	4.85	5.20	4.50	5.65	5.65	4.35	4.45

3.2. Actual Village Measurement

CIOM and PSPL, which performed well in the simulation validation, were selected as benchmarks. The field testing was deployed on a provincial smart rural cloud platform, using microclimate data and functional requirement parameters collected from Caocun Village over a 12-month continuous monitoring period. A strict closed-loop workflow ("data input, model computation, 3D generation, field verification") was followed: elevation, soil moisture, native plant species lists, and villager functional demands (e.g., drying area ratio ⩾15%) were fed into the RP-RLCO model as hard constraints. Multi-objective solutions were generated via the cloud-based NSGA-II engine, and IoT sensors continuously collected canopy light intensity and soil temperature/moisture data to verify ecological adaptability. Finally, the model's real-world performance was systematically assessed through a comparative analysis of resident satisfaction surveys and performance indicators across different solutions. The study presents the original pond landscape of Caocun before and after the model design, as shown in Fig. 9.

As shown in Fig. 9, before optimization by the RP-RLCO model, the Caocun pond area had an irregular natural shape Its surrounding vegetation was sparse, lacking clear spatial organization and human activity facilities, which made the environment desolate and weakly functional. After the design, a clear ecological and landscape integration strategy emerged. Algorithm-optimized pond contours became more regular, while transitional zones between water and greenery were enriched with layered, water-friendly plant communities. Concurrently, pedestrian pathways and recreational platforms were introduced. These enhancements respected the original topography and significantly improved spatial visual order, ecological service capacity, and appeal for human activities, fully demonstrating how intelligent algorithms can synergistically optimize natural foundations and human needs. Next, the Importance-Performance Analysis (IPA) method (maximum score 100) was used. Ten local villagers performed double-blind evaluations of the original pond and the proposed designs across five dimensions: cultural symbol prominence (A), color regional compatibility (B), spatial narrative coherence (C), seasonal plant rhythm (D), and material regionality (E). By constructing an IPA four-quadrant matrix to analyze group preference differences, the social acceptability and comprehensive effectiveness of the landscape design were assessed. Sample size was determined based on the data saturation principle in qualitative research, referencing the common range (8-15 participants) in similar rural landscape IPA studies. The responses from ten interviewees, covering key demographics like age and gender, stabilized after the fifth participant, indicating that the sample size was adequate for preliminary analysis of group preferences. The results are shown in Fig. 10.

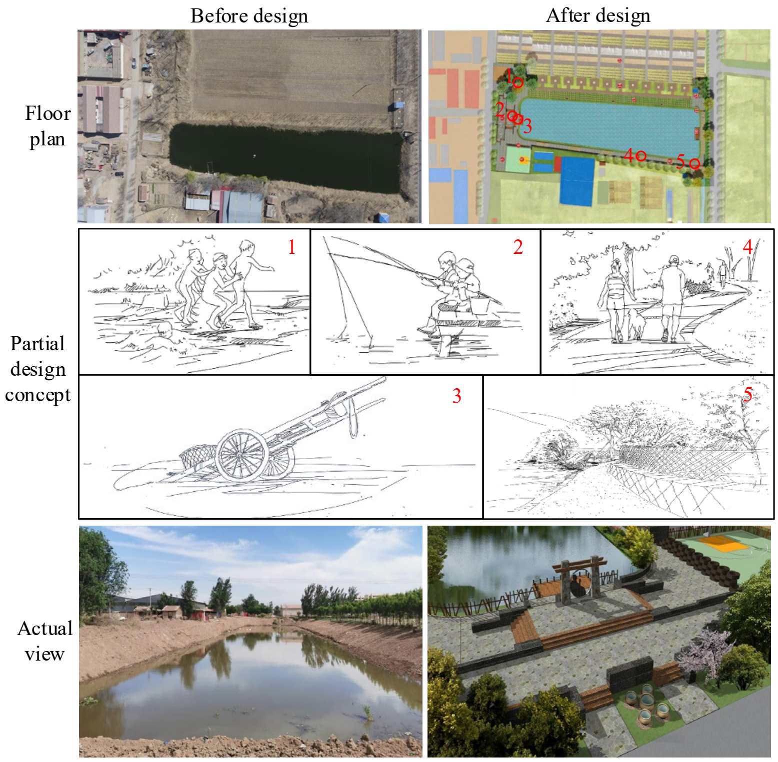

Fig. 9. Schematic of Caocun pond before and after design

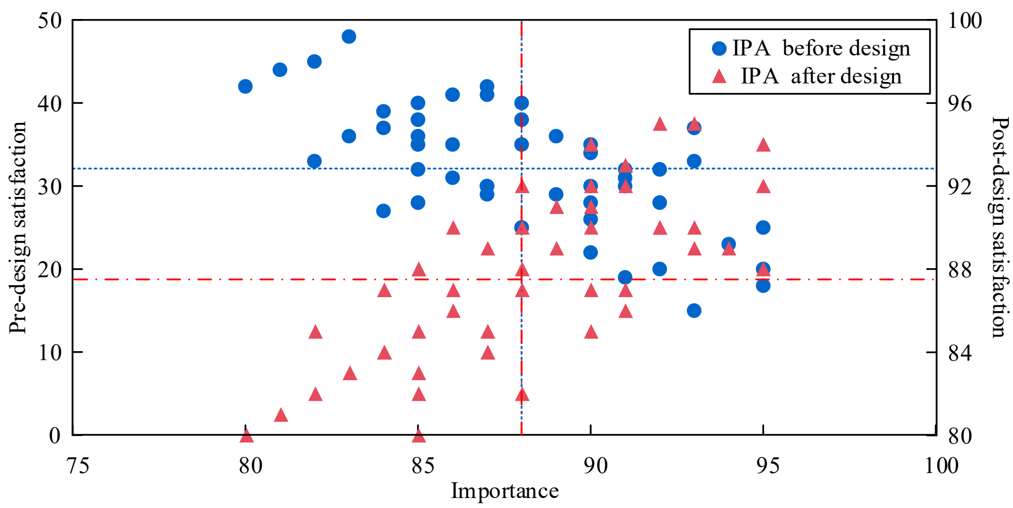

Fig. 10. Validation of IPA group preference differences

According to Fig. 10, cultural Symbol Visibility (A) had an importance score of 90.6, while satisfaction jumped from 28.9 to 86.3, showing that the model effectively boosts regional cultural expression. Color Regional Alignment (B) scored

84.1 in importance, with satisfaction rising from 40.8 to 84.5, reflecting the seamless integration of color strategy with local landscapes. Form Ecological Adaptability (C) scored 89.1 in importance, with satisfaction increasing from 36.5 to 90.9, confirming the synergistic optimization of form and habitat. Functional-Artistic Integration (D) scored 86.5 in importance, with satisfaction rising from 31.6 to 86.6, confirming a balanced functionality and aesthetics. Traditional Craftsmanship Preservation (E) had an importance rating of 89.9, and satisfaction increased from 22.7 to 89.0, underscoring the successful modern adaptation of local techniques. Taken together, these data confirm that the RP-RLCO model can systematically address diverse villager demands. Moreover, the study also compared the Resource Consumption (RC) and Maintenance Frequency (MF) of different model generation schemes in the 3.8ha-5.2ha site to measure the full lifecycle economy of the generation schemes. Maintenance cost statistics, based on Landscape Maintenance Standards and local logs, include replanting, labor, and basic tool wear and tear. Maintenance frequency is measured holistically for the plant community, with calculations accounting for seasonal variations in maintenance intensity (e.g., spring replanting, winter frost protection). Specific data originates from tracking records spanning three consecutive growing cycles. Results are shown in Fig. 11.

According to Fig. 11(a), the RC mean of the RP-RLCO model was as low as 517000 yuan, significantly better than CIOM's 69000 yuan and PSPL's 535000 yuan (p<0.001). This is attributed to the collaborative optimization of local plant configuration and terrain adaptability through the NSGA-II multi-objective module, such as the selection of low-cost wetland plants in riparian zones (as shown in Fig. 12). Although the minimum value of PSPL at 500000 yuan was close to the maximum value of RP-RLCO at 550000 yuan (p>0.05), the standard deviation of RP-RLCO was only 22000 yuan, which proved its cost control stability. According to Fig. 11(b), the mean MF of the RP-RLCO model was only 1.45 times, which had an overwhelming advantage over CIOM's 2.49 times and PSPL's 1.89 times (p<0.001). This is due to the dynamic generation of stress resistant forms through the L-system mechanism of environmental feedback, such as designing shortened internodes in settlement areas to reduce pruning requirements. Although the minimum value of CIOM (swarm intelligence pathway) at 2.1 times was lower than the maximum value of PSPL at 2.4 times (p<0.01), the RP-RLCO standard deviation of 0.18 times verified its ecological adaptability advantage.

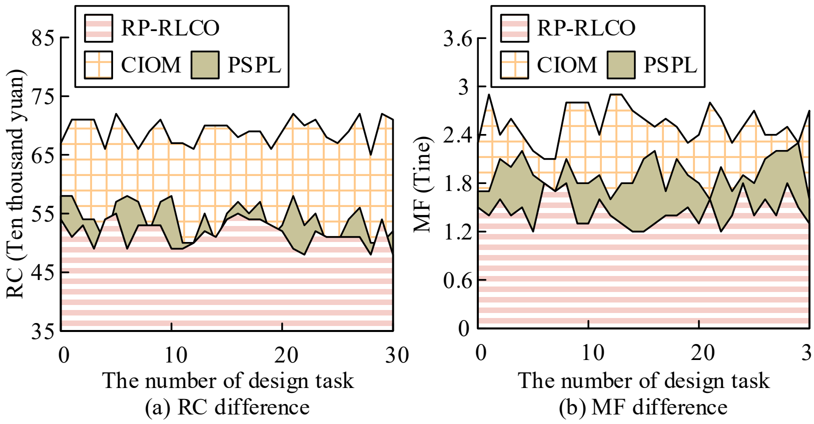

Fig. 11. Verification of economic efficiency throughout the entire life cycle

(a) Conceptual design sketch A for pond plants (b) Conceptual design sketch B for pond plants

Fig. 12. Schematic of plant arrangement for research model output scheme

In addition, the study also compared the Computation Time (CT) and RC required for different model generation schemes to verify the computational efficiency of the model, as shown in Table 2.

According to Table 2, the average CT of RP-RLCO was 94.3 minutes, significantly lower than CIOM's 106.0 minutes (p<0.05), and the standard deviation of 5.6 minutes was much smaller than PSPL's 8.9 minutes, highlighting its closed-loop optimization architecture that dynamically reduced iteration redundancy through environmental feedback L-system and Plantkit/NSGA-II collaboration. In the RC index, both RP-RLCO and PSPL had a mean of 5.6GB, but the RP-RLCO standard deviation of 0.2GB was better than PSPL's 0.3GB (p<0.01), attributed to the lightweight indexing of Plantkit space engine compressing memory requirements, and the CIOM mean of 6.0GB exposed the resource inflation defect of swarm intelligence algorithms.

Table 2. Verification of computational efficiency

Number of design tasks	CT (min)			RC (GB)		
	RP-RLCO	CIOM	PSPL	RP-RLCO	CIOM	PSPL
5	98	99	105	5.4	5.5	5.3
10	91	114	82	5.6	6.3	5.8
15	90	107	99	5.7	6.3	6.1
20	100	104	81	5.6	5.7	5.5
25	101	103	98	5.2	6.4	5.4
30	86	109	93	6.0	5.9	5.3
Means	94.3	106.0	93.0	5.6	6.0	5.6
Standard deviation	5.6	4.8	8.9	0.2	0.3	0.3

4. Significance for Design

The proposed RP-RLCO model contributes not only technical innovation but also practical empowerment for contemporary rural landscape design across multiple dimensions. Experimental results show an SCR as low as 0.09, which is 33.3% lower than that of traditional approaches. On the aesthetic level, the color regional compatibility ΔE reaches 3.97, and the cultural symbol prominence score is 4.62. Field measurements reveal that maintenance frequency drops to an annual average of 1.45 times, and lifecycle costs decrease by 25.1%. This advantage manifests in specific projects through the refined use of local resources and the systematic integration of multifunctional spaces. For instance, in the Caocun Pond Landscape project, the model guides innovative reinterpretations of local materials such as discarded items and fences (as shown in Fig. 13(a)), substantially lowering material procurement and transportation costs. At the same time, the generated design plans diverse functional spaces for recreation, interaction, and wellness (as shown in Fig. 13(b)). By improving spatial efficiency and user satisfaction, it fundamentally reduces the need for later modifications caused by functional mismatches. This approach supports the creation of high-quality rural landscapes that are green, low-carbon, and economically viable.

(a) Innovative application of local pastoral materials

(b) Creation of diverse landscape functional spaces

Fig. 13. Schematic of landscape design practice case for the Caocun Pond area

In the end, algorithms do not replace designers; instead, they extend and enhance their role. The RP-RLCO model frees designers from tedious repetitive modeling and localized adjustments, enabling them to concentrate more deeply on higher-level creative tasks such as interpreting regional contexts, generating innovative concepts, and overseeing overall quality control. This constitutes an important step in exploring human-machine collaboration and intelligently empowering design practice.

5. Conclusion

By leveraging environmental feedback, L-systems, and the NSGA-II multi-objective optimization algorithm, the proposed RP-RLCO model digitally translates and synergistically optimizes both plant morphological ecological adaptability and regional cultural traits, thereby greatly improving the scientific rigor and overall effectiveness of rural landscape design. For project managers, this study will change the following decision processes: at the project initiation stage, managers can use the RP-RLCO model to conduct algorithmic simulations of various plant configuration schemes, comparing full-cycle maintenance costs, ecological benefits, and cultural compatibility across different solutions, thereby transforming traditional experience-based budget allocation into data-driven scientific decision-making. During the construction and maintenance stages, managers can formulate precise maintenance plans in advance based on the model's adaptive layout and stress-resistant species recommendations, reducing trial-and-error costs and later rework. The core objective of this study is not to replace designers or over-technologize, but to provide a scientific and efficient digital assistant for both managers and designers.

Although the RP-RLCO model proposed here has achieved notable progress in static spatial optimization and eco-cultural multi-objective coordination, further refinement and expansion are still needed. At present, the model mainly optimizes plant morphology and layout at a single time point, without fully capturing the long-term succession of dynamic plant growth. As living entities, vegetation undergoes significant changes in morphology, community structure, and ecological benefits over time. Static optimization methods currently struggle to accurately predict or respond to these temporal shifts. While the model has been effectively validated in riverside villages of the North China Plain, its key parameters, such as species ecological niche thresholds and regional color genealogies, rely heavily on the environmental data and cultural characteristics of specific regions. When directly applied to other areas with vastly different climatic and soil conditions, its performance may diminish. Future work will prioritize the integration of a "dynamic succession model." By combining canopy gap models, growth prediction algorithms, and spatiotemporal simulation engines, it intends to develop computational frameworks that can simulate natural vegetation renewal, competition, and decline over decades. This approach will enable scientific assessment and optimization of a landscape's long-term ecological benefits, maintenance costs, and cultural expression sustainability, thereby significantly enhancing the adaptability and reliability of design solutions throughout their entire lifecycle. In addition, there are plans to build a standardized case library that covers diverse climatic zones, soil types, and village scales, which will be used to train and calibrate the model's core parameters. This aims to achieve more flexible adaptation to various rural landscape development scenarios.

Author Contributions

Fan Ding contributes to methodology, software, data collection, and manuscript editing. Xinbing Liu contributes to methodology, validation, analysis, investigation, and manuscript editing.

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