Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Research on urban landscape path planning and spatial optimization algorithm based on hierarchical grid model

Weitao Ren[1,✉], Fangsheng Liu[2], Jie Xiang[3]

[1] Department of Modern Agriculture, Jiaxing Vocational & Technical College, Jiaxing, Zhejiang, 314036, China
[2] Zhejiang Urban and Rural Planning Design Institute, Hangzhou, Zhejiang, 310013, China
[3] Zhejiang A & F University Landscape Design Institute Co., Ltd., Hangzhou, Zhejiang, 311300, China

ABSTRACT
In order to improve the planning efficiency of urban landscape, this paper proposes a combination design method of urban landscape construction based on grid division and a spatial optimization model of urban landscape based on particle swarm algorithm to optimize the spatial and pathway layout of urban landscape that takes both economy and ecology into account. The original landscape image was mapped with 3D remote sensing image to generate a 3D image model, and the gradient decomposition method was used for image sampling. Then the multi-dimensional dynamic feature distribution model of urban landscape was constructed, on which the urban landscape area grid was divided to realize the landscape construction combination design. Using particle position to simulate the meta-space layout results of landscape type raster images, the optimization of landscape pattern space and path is completed. The experiment proves that the algorithm in this paper reduces the influence of multiple types of perturbations on the landscape layout results, and the spatial optimization model of urban landscape pattern based on particle swarm algorithm realizes the organic coupling of quantitative and spatial optimization, which not only improves the utilization rate of the urban land, but also substantially reduces the risk index of the urban landscape, and meets the design expectations.

Keywords: urban landscape, particle swarm algorithm, grid division, spatial layout optimization

1. Introduction

In the process of urbanization, urban planning and design and urban landscape design have become important links in shaping the image of the city and improving the quality of the city. Although they have different focuses, they are jointly committed to building a functional, beautiful and culturally rich urban space. The urban planning design focuses on the overall layout of the city, traffic organization,

✉ Corresponding author.
E-mail address: 18768103623@163.com (W. Ren).
Received 20 December 2024; Revised 05 February 2025; Accepted 25 March 2025; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-031

public facilities configuration and other macro-level, while the urban landscape design focuses more on the micro aesthetics of the city and people's perceptual experience [1-4]. Urban planning design and urban landscape design are interdependent, and they complement each other to promote urban construction and development. Urban planning design establishes the overall layout of the city and constructs the main structure of the city [5-7]. Urban landscape design is a delicate depiction of this grand scroll, through the vegetation, water bodies, vignettes and other elements of the clever combination, so that the urban space becomes vivid and rich sense of hierarchy [8-10]. Through clever landscape design, the core concept of urban planning can be visualized, so that every corner of the city is full of cultural characteristics.

Specifically, with the help of GIS technology, scenario analysis, spatial optimization model and other methods, the landscape quantitative structure and spatial layout can be optimized and adjusted, which can form a landscape spatial configuration scheme with the greatest ecological, economic and other comprehensive benefits [11-13]. The resulting landscape planning path can protect and restore biodiversity as well as realize the functional integrity of the city, including the type, number, and spatial distribution and configuration of landscape constituent units [14-15]. The macro-concept of urban planning is refined into perceptible spatial forms, so that each landscape no longer exists in isolation, but becomes an organic part of the overall urban landscape and cultural veins [16].

Literature [17] explored the use of digital landscape design methods and techniques in the landscape design process, based on design logic, design basis, environmental analysis and result presentation, using parametric and visual programming software to establish an analysis model to quantify the relevant information of the urban space, and to formulate a reasonable urban landscape path planning. Literature [18] designed an urban landscape design optimization model with wall position, height and building texture as key features, and used interactive genetic algorithms to evaluate residents' opinions and continuously iteratively optimize the urban landscape design model to obtain urban landscape planning results that meet residents' preferences. Literature [19] also emphasized the key role of 3D landscape visualization technology in urban landscape planning, which can present a more intuitive urban development and planning design for decision makers to make rational judgments, based on which accelerated algorithms to accelerate 3D drawing and improve the quality of 3D design are proposed to optimize the reconstruction process of the urban 3D space. Literature [20] proposed a healthy landscape design optimization strategy for residential parks based on intelligent algorithms, using artificial intelligence theory to analyze the key factors affecting the demand for landscape design, and the landscape design strategy based on intelligent algorithms showed good performance in terms of precision and time optimization of the influential variables under specific evaluation conditions. Literature [21] based on improved BP neural network learning algorithm and geographic information system, constructed a city landscape spatial intelligent design model, improved the model's network convergence effect and generalization ability, to provide a new simulation method for urban landscape planning path. Literature [22] proposes a multi-gradient neutral landscape model based on interactive genetic algorithm, which can successfully simulate the real landscape in complex environment by solving the optimal solution of the model that satisfies the midpoint displacement condition.

The urban landscape design method based on grid division carries out feature extraction and spatial localization of the urban landscape to realize image sampling of the landscape. A dynamic feature distribution model based on multi-dimensional landscape images is constructed to realize the digitization of urban landscape. The urban landscape is spatially divided and the characteristics of each grid cell are analyzed to further grasp its complex spatial structure. Particle swarm algorithm is applied to construct a spatial optimization model of urban landscape pattern to optimize the spatial layout of urban landscape, and examples are taken to demonstrate the effect of the method in this paper, in order to provide a scientific basis for urban land use planning and green ecological construction planning.

2. Design of urban landscape construction combination method based on hierarchical grid modeling

2.1. Urban landscape image sampling

In the process of designing the combination of urban landscape construction, the original image of the city should first be obtained by remote sensing technology [23] and parametric analysis and feature extraction should be performed to realize spatial orientation, and then the landscape image should be sampled to facilitate the subsequent design of the combination of landscape construction and mapped into the 3D remote sensing image. Internal orientation of the digital image is performed based on the 3D coordinates of each surface building to form a 3D auxiliary film, which is combined with the original image to form a 3D model.

Sampling the image based on the orthophoto generated from the original remote sensing image of the city, the edge information of the nonlinear landscape image is obtained as:

$$\begin{cases} G_x = \dfrac{x_0 \times g_0 \times t_0}{\sqrt{2\alpha_1}} \\ G_y = \dfrac{y_0 \times g_0 \times t_0}{h_0\sqrt{2\alpha_1}} \end{cases} \tag{1}$$

where G_x and G_y denote the edge information of the image on gradients x and y, respectively, x_0 and y_0 denote the horizontal and vertical scale parameters of the image, respectively, g_0 denotes the gradient parameter, t_0 denotes the sampling time, h_0 denotes the adjustment constant, and α_1 denotes the random vector.

The original landscape image is decomposed along the horizontal and vertical directions to obtain the edge pixel components in different gradient directions. Then the dynamic pixel parameters of the landscape image were modeled using the pixel reconstruction method to obtain the scale space of the image as:

$$L_c = \frac{G_z}{G_y}\sqrt{\frac{x_{i,j}}{H \times W \times E}} \tag{2}$$

where $x_{i,j}$ is the set of edge pixel distribution at the position of center pixel point (i, j), and E, W and H are the length, width and height of the landscape area, respectively.

The landscape area is chunked, and the raw landscape data are normalized by the standard normalization process, then the obtained normalization formula for the positive indicator is:

$$Y = \frac{m_0 \times L_e}{b_c} \times \frac{n_0}{A_0 \times \beta_0} \tag{3}$$

where, m_0 is the data extreme value, b_e is the empirical constant value, n_0 is the number of chunks, A_0 represents the transformation matrix, and β_0 is the data eigenvector.

Combining the above formulas, the sampling result of the landscape area image is obtained as:

$$u_0 = -Y\sqrt{\frac{g_t}{h_1}} \tag{4}$$

where g_t is the set of pixels between frames and h_1 is the attribute constraints of pixel points. According to the collected remote sensing images of the landscape region, orthographic projection is performed to obtain the image digital elevation model. Then the image sampling of the regional landscape is realized by gradient decomposition of the graph, which lays the foundation for the next construction of the dynamic feature distribution model of the multi-dimensional landscape image.

2.2. Modeling the dynamic feature distribution of multi-dimensional landscape images

Under the premise of ensuring the wholeness of landscape planning, multi-dimensional landscape data are extracted and the landscape images are processed using the information fusion method [24] to construct the dynamic feature distribution model of multi-dimensional landscape images.

Based on the distribution of the pixel points of the landscape image, the similarity is analyzed by using the spatial region matching equation, the expression of which is:

$$F_c = p\left(c_1, c_2\right)\left(\frac{u_0}{v_y}\right)^{1/2} \tag{5}$$

In the formula, $p\left(c_1, c_2\right)$ is the coordinate position of the neighboring adjacent points of the center pixel point, u_0 is the image sampling result of the landscape area, and v_y is the entropy weight feature distribution set of the pixel point.

For the combination design of urban landscape construction, the spatial scale and pattern of road landscape can be accurately represented through rational layout. The characteristic factors of spatial scale information element mainly include enclosure, openness and spatial order. The degree of landscape enclosure affects the psychological feeling of road users and their sense of intimacy with the environment, etc. The formula for calculating the degree of landscape enclosure is:

$$T_1 = \frac{\frac{1}{n'}\sum_{n=1}^{n} R_n + p_l \times r_n}{f_n \times F_c} \tag{6}$$

where n' is the proportion of building pixels to the road image, R_n is the proportion of plant pixels to the streetscape image, $p_i \times r_n$ is the vertical interface and horizontal interface of the road respectively, and f_n is the scale factor.

The openness in landscape design can effectively enhance the spatial openness feeling of the crowd, and its calculation formula is:

$$T_2 = \frac{S_n \times F_c}{m'} \tag{7}$$

where m' represents the proportion of road pavement pixels in the streetscape image, and S_n represents the resolution coefficient of the landscape as a whole.

Combined with the above analysis to get the dynamic distribution of landscape image feature analysis results. Landscape features include main features, attached features, mixed features, and variant features. Among them:

1) Characterization factors of main features include: arterial road, branch road, enclosure, openness, building form.

2) The feature factors of attached features include: architectural thought, culture, folklore. The feature information element it belongs to is architectural culture, and the feature resolution category it belongs to is layout gene.

3) The characterization factors of mixed features include: plant vegetation, the characteristic information element belonging to which is secondary environment, and the characteristic analysis category belonging to which is environment gene. Sequence composition, which belongs to spatial order and layout genes. Organizational techniques, the feature information element is spatial order, and the feature analysis category is layout genes.

4) Characterization factors for variant features include: commercial, landscape, living, and specific. Its belonging feature information element is road type, and its belonging feature resolution category is functional gene, synthesizing the above, it can be seen that the main feature of urban landscape is the key factor of landscape design, then the pixel covariance function of the multidimensional landscape under the feature resolution model can be expressed as:

$$c(x)=\sqrt{\frac{k_1\left(T_1+T_2+T_3\right)}{2w_0}} \tag{8}$$

where k_t is the feature state function, T_1, T_2 and T_3 are the enclosure, openness and spatial order of the landscape space, and w_0 is the effective activation function.

The extraction results of the fine-grained feature points of the landscape image are thus obtained as:

$$I_1=\frac{n'\cdot c(x)}{E_0\times l_o} \tag{9}$$

where, n' denotes the number of pixel points of the landscape image, E_0 denotes the deviation degree function, which is used to represent the degree of deviation of the landscape data; E_0 denotes the diagonal matrix; l. Denotes the data decay constant.

In turn, the parameter distribution matrix of the landscape design is obtained as:

$$Q=\begin{bmatrix} I_1\delta_1 & I_1\delta_2 & I_1\delta_3 \\ -I_1\delta_1 & -I_1\delta_2 & -I_1\delta_3 \\ 0 & 0 & 0 \end{bmatrix} \tag{10}$$

where δ_1, δ_2 and δ_3 represent the momentum coefficient, discretization factor and variation factor of the landscape data, respectively. From this, the dynamic feature distribution model of multidimensional landscape image is constructed with the expression:

$$M_q=Q\times c_p\times v_k/b_n \tag{11}$$

where c_p denotes the green area ratio, v_k denotes the green vertical projection area, and b_n denotes the adjustable parameter.

2.3. Landscape construction portfolio design based on grid division

The combination design method of urban landscape construction using grid division [25] is based mainly on the landscape feature distribution model, and the combination design of landscape construction is realized through the deployment of sampling points in the landscape area. From the grid perspective, the landscape planning space can be regarded as a complete space composed of multiple parcels, which is mathematically defined as

$$C_{ca}=\left(s_d+G_v\right)M_q \tag{12}$$

The deployment model of landscape sampling points is constructed through multiple indicators and applied to road selection and stratification in gridding to obtain a two-layer multilevel grid with the expression:

$$\xi_0=C_{cs}\times\frac{g_p}{D_p} \tag{13}$$

where, g, denotes the landscape element fusion vector, and D_p denotes the indicator importance. Based on the grid division results, the parameterized equations for the multidimensional landscape viewshed are extracted, i.e:

$$P_c = \frac{\xi_0}{j_p} / k_z \tag{14}$$

where, j_p denotes the degree of freedom of the landscape image spatial data, and k, denotes the slack variable. Parametric segmentation of the landscape design model is performed to obtain the result of laying out the sampling nodes of the parametric model of the landscape data, i.e:

$$z(k) = P_c\left[z_1(\omega), z_2(\omega), \cdots, z_{n'}(\omega)\right] \tag{15}$$

In the formula, ω indicates the landscape data sampling node layout, and $z_i(\omega)$ is the data flow.

According to the above calculation and analysis process, based on the grid division to complete the combination design of a city landscape construction in the old city of Hefei.

3. Urban landscape space layout optimization method design

3.1. Calculating the landscape pattern index

Calculating the pattern index of urban ecological landscape space is the main method to quantitatively analyze the spatial layout of the landscape, which can intuitively reflect the specific distribution and information of each element of the ecological landscape in the study area.

Before calculating the ecological landscape pattern index, the quality of urban habitats is evaluated to assess the regional ecological security and resilience. The specific calculation formula is:

$$Q_{xj} = H_j\left(1 - \frac{\sum c_0}{D_k + p_0}\right) \tag{16}$$

where: Q_{xj} - habitat quality factor for raster x in site type j; H_j - ecological landscape adaptation for site type j; c_0 - random vector; D_k - basic probability assignment of the k th plot; p_0 - semi-saturation coefficient.

As can be seen from equation (16), there is a close connection between the quality of regional habitats and the degree of ecological landscape adaptation and half-saturation coefficient, while the degree of ecological adaptation is determined by a combination of biodiversity and the degree of environmental degradation, ie:

$$H_j = \sum\sqrt{\frac{|w_r|}{\sum g_s h_p}} \tag{17}$$

where: w_r - fixation constant; g_s - biodiversity; h_p - degree of environmental degradation.

The land degradation index on position x' in the habitat quality type can be expressed as:

$$D_{x'} = H_j \sum\sum\left(\frac{e_c j_p}{d_f} + \frac{t_y}{\alpha_0}\right) \tag{18}$$

where: D_x - Land degradation index; e_c - Biological abundance factor; j_p - Intensity of threat sources; d_f - Euclidean distance of threat sources; t_y - Resilience of habitats to disturbance; α_0 - Hazard index of threat sources.

From this, the sensitivity parameters of the threat source can be calculated, i.e.:

$$a_i = \frac{D_x \cdot l_p}{\sum \sqrt{f(t) / A_k}} \tag{19}$$

where: a_i - sensitivity parameter; l_p - number of patches in the categorized mosaic; $f(t)$ - inverse tangent function; A_k - positive diagonal weighting matrix.

In turn, the diversity coefficient of the patch landscape shape can be obtained, i.e.:

$$R_u = \frac{\beta_s a_i}{\left\| h_t / \left(s_0 b_c \right) \right\|^2} \tag{20}$$

where: R_u - diversity coefficient; β_s - number of patches per unit area $\left(100\text{hm}^2\right)$; h_t - number of fractal dimensions of landscape perimeter area; s_0 - mixing coefficient, the larger the value, the more complex is the landscape structure; bc - landscape Manifold index.

Calculate the ecological landscape pattern index of the region, i.e.:

$$W_l = \frac{f\left(t'\right)}{v_p} \sqrt{\sum \frac{R_u / G_s}{u_k j_c}} \tag{21}$$

where: W_l - index of urban ecological landscape pattern; $f\left(t'\right)$ - multivariate nonlinear function; v_p - density of patches; G_s - state matrix; u_k - proportion of area occupied by landscape type k; j_c - vegetation cover.

By analyzing and evaluating the quality of urban habitats, calculating the adaptability of the ecological landscape environment, and combining the diversity coefficient of the patch landscape shape, the index of the urban ecological landscape pattern is obtained, which facilitates the construction of the spatial network of the ecological landscape at a later stage.

3.2. Building a spatial network of urban ecological landscapes

Based on the characteristics of the urban ecological landscape spatial pattern and the calculation of the ecological landscape index, the core ecological landscape source points are identified based on the principle of landscape connectivity, and the ecological source points are used as the starting point to construct the urban ecological landscape spatial network.

The sensitivity of ecological landscape is calculated with reference to the bonding index of internal cohesive landscape patches, and the expression is:

$$p_k = \frac{W_l X_t}{\exp\left(-h_r / d_a\right)} \tag{22}$$

where: p_k - sensitivity coefficient; χ - Shannon uniformity index; h_r - empirical constant; d_a - distance between two neighboring patches.

According to the sensitivity of the ecological landscape to determine the comprehensive weight of landscape factors, according to the comprehensive weight of each factor, to determine the core ecological landscape source points, the specific calculation method is:

$$r_k = p_k \phi_0 \omega_\gamma \tag{23}$$

where: r_k - the accessibility of the landscape factor; ϕ_0 - the clustering index of the landscape factor; ω_γ - the combined weight of the γ th ecological factor. The landscape area with accessibility less than the threshold is taken as the core ecological landscape source point, from which the starting point of the ecological landscape spatial network is determined.

The minimum cumulative resistance distance between the core ecological source points is further calculated with the expression:

$$D_e = \frac{r_k}{\theta_0 \varphi_k} \tag{24}$$

where: D_e - minimum cumulative resistance distance between core ecological source points; θ_0 - discrimination coefficient; φ_k - order lag variable.

Taking the screened core ecological source points as the starting point, the minimum cumulative resistance distance between ecological source points and the minimum path between all patches constitute the potential ecological landscape corridor, i.e., the ecological landscape spatial network, so as to complete the construction of the landscape spatial layout network, and to lay the foundation for the final realization of pattern optimization.

3.3. PSO landscape pattern spatial optimization model and algorithm

The essence of spatial pattern optimization based on landscape type rasterized data is to adjust the image element position around the optimization goal, so the key to apply PSO for spatial optimization of landscape pattern is to use the particle position to simulate the spatial distribution of landscape type raster image elements. The raster map can be regarded as a real matrix, the raster image elements correspond to the element rows in the matrix, and the image element positions and attribute values (landscape type codes) correspond to the element rows and columns and values, so the processing of the raster image element positions and attribute values is equivalent to the processing of the matrix element rows and columns and values. For this reason, assuming that the matrix $A_{m\times n}$ represents the landscape type raster image, the matrix element row value represents the landscape type coding, the matrix is abstracted as a particle, the matrix element value and row and column number are abstracted as the particle element and position, according to the principle of the particle swarm algorithm, no matter how the spatial position of the particle element changes, the particle element itself, i.e., landscape type coding is unchanged, i.e., a number of elemental values composing the matrix are eternally constant, and the element row and column value is optimized by the PSO algorithm, making the element row and column value optimized. Row and column values are optimized by PSO algorithm, so that the element values are moved from one position to another position and thus combined into a new matrix, when the new matrix corresponding to the landscape spatial pattern can make an optimization goal reach the maximum, that is, to achieve the spatial optimization of the landscape pattern under the goal.

MATLAB is a high-level programming language with matrix as the basic programming unit, which has powerful matrix operation and image processing functions, so the PSO algorithm is designed to realize spatial optimization of landscape pattern using MATLAB, which mainly involves four key technologies.

(1) Spatial mapping relationship between landscape type raster map and particles. Let B be the effective element value storage vector $(\alpha_1, \alpha_2, \cdots, \alpha_N)$ in the matrix $A_{m\times n}$ corresponding to the landscape type map of the base year, which represents a particle, corresponding to a landscape pattern spatial layout scheme; $\alpha_j \in B$ is an effective element value, which represents a particle element, and its row and column number represent the position of the particle element, then the spatial mapping relationship between the landscape type raster map and the particle in the model optimization process.

2) Model optimization objectives and constraints. Landscape pattern spatial optimization is a multi-objective optimization problem, this paper constructs the objective function (fitness function) from the two aspects of the maximum landscape suitability and maximum spatial compactness, in which the landscape suitability is characterized by the product and the sum of the weights of various types of landscapes and their corresponding suitability, and the spatial compactness is expressed by the

shape index of landscape patches. The constraints include area, type and conversion rules. The model objective function and constraints are expressed as:

$$\max F\left(A\right)=w_1\sum_{k=1}^{K}\sum_{1=1}^{Q}\lambda_k p_k+w_2\sum_{k=1}^{K}\sum_{i=1}^{R}c_{kr}/\sqrt{s_{kr}}$$
$$s.t.\begin{cases} d_k(A)=D_k^*,\sum_{k=1}^{K}d_k(A)=\sum_{k=1}^{K}D_k^* \\ \alpha_1\in[1,2,\cdots,K] \\ 0\le T_1\left(k\to k'\right)\le 1 \end{cases} \tag{25}$$

where: λ_k is the weight of k types of landscapes, applying hierarchical analysis to calculate the weights of farmland, orchards, forests, urban and rural habitats, and industrial, mining, and water body landscapes in the economic development scenario. D_k^* is the number of pixels obtained from the optimization of the number of landscapes in category k of a scenario, $D_k^*=z_k^*/e^2$ (z_k^* is the optimal area of the landscape in category k, and e is the size of pixels), $a_j\in[1,2,\cdots,K](j=1,2,\cdots,N)$ is the coded value domain of the corresponding landscape type of the pixels, and $T_j\left(k\to k'\right)$ is the possibility of transforming the corresponding landscape of pixel α_j from k to k'. Combined with the characteristics of landscape pattern changes in the study area, the rules and possibilities of landscape conversion are defined as: urban and rural habitats and industrial and mining and farmland and orchards can be completely converted into each other, water and farmland can be completely converted into each other, forests can be completely converted into each other and farmland and orchards can be completely converted into each other.

3) The initialization of the landscape pattern spatial layout scheme (particles) is to generate initial particles that are equal to the number of optimized image elements of each landscape. Let V be an array of tuples storing the row and column values of the effective elements of each type of landscape and their corresponding landscape suitability values, $\Delta d_k=\left|d_k(A)-D_k^*\right|$ be the absolute difference between the number of image elements in the base year of the k type of landscape $d_k(A)$ and the number of optimized image elements of a certain scenario, $sort\left(Val\right)$ and $sort\left(Val,'descend'\right)$ denote the ascending and descending sorting of the variable Val, respectively, and $A(x,y)=\alpha$ denotes that the image elements of a certain landscape with the line number of x and y in the row and column number in the A are transformed into the corresponding image elements of the landscape coded in the α.

$$V=\left\{\begin{pmatrix} x_1 & y_1 & p_1\left(x_1,y_1\right) & \cdots & p_K\left(x_1,y_1\right) \\ x_2 & y_2 & p_1\left(x_2,y_2\right) & \cdots & p_K\left(x_2,y_2\right) \\ \vdots & \vdots & \vdots & & \vdots \\ x_L & y_L & p_1\left(x_L,y_L\right) & \cdots & p_K\left(x_L,y_L\right) \end{pmatrix},\cdots\right.$$
$$\left.\begin{pmatrix} x_1 & y_1 & p_1\left(x_1,y_1\right) & \cdots & p_K\left(x_1,y_1\right) \\ x_2 & y_2 & p_1\left(x_2,y_2\right) & \cdots & p_K\left(x_2,y_2\right) \\ \vdots & \vdots & \vdots & & \vdots \\ x_W & y_W & p_1\left(x_W,y_W\right) & \cdots & p_K\left(x_W,y_W\right) \end{pmatrix}\right\} \tag{26}$$

where: $V\left\{1\right\},V\left\{2\right\},\cdots,V\left\{K\right\}$ is the row and column values of effective elements of farmland, orchard, forest, urban and rural human settlements, industrial and mining, and water body landscapes and their corresponding landscape suitability values. $p_K(x_L, y_L)$, $p_K(x_G, y_G)$, $p_K(x_S, y_S)$, $p_k(x_c, y_C)$ and $p_K(x_W, y_W)$ are the appropriate values for the K th category of landscape elements corresponding to farmland, orchards, forests, urban and rural human settlements, industrial and mining, and water bodies, respectively.

4) Particle velocity adjustment and position update, let $P_{M\times(4N+1)}$ be M particle position, velocity and current objective function value storage matrix. Among them, $1 \sim 2N$ is the particle position variable $(x_{11}, x_{12}, \cdots, x_{iN}, y_{i1}, y_{i2}, \cdots, y_{iN})(i = 1, 2, \cdots, M)$, $2N+1 \sim 4N$ is the particle velocity variable $(\delta x_{i1}, \delta x_{i2}, \cdots, \delta x_{iN}, \delta y_{i1}, \delta y_{i2}, \cdots, \delta y_{iN})$, $4N+1$ is the current objective function value of the particle pF_i; $O_{(2M+1)\times 2N}$ is the storage matrix for the historical optimal value of M particles, the local optimal value and the global optimal value. Among them, $1 \sim M$ acts as the particle historical optimal value variable $(x_{11}, x_{i2}, \cdots, x_{iN}, y_{i1}, y_{i2}, \cdots, y_{iN})$, $M+1 \sim 2M$ acts as the particle local optimal value variable $(Ix_{(M+1)1}, 1x_{(M+1)2}, \cdots, |Ix_{(M+1)N}, Iy_{(M+1)1}, ly_{(M+1)2}, \cdots, ly_{(M+1)N})$, $2M+1$ acts as the particle global optimal value variable $(gx_1, gx_2, \cdots, gx_N, gy_1, gy_2, \cdots, gy_N)$. The particle continuously adjusts the speed and updates the position according to the historical optimal value and the local optimal value during the flight. The velocity update formula is:

$$\begin{cases} P_t(i,2N+j) = \omega(t)P_{t-1}(i,2N+j) + c_1\mu_1\left[O_{t\text{-}1}(i,j) - P_{t\text{-}1}(i,j)\right] \\ \qquad\qquad +c_2\mu_2\left[O_{t-1}(M+i,j) - P_{t-1}(i,j)\right] \\ P_t(i,3N+j) = \omega(t)P_{t\text{-}1}(i,3N+j) + c_1\mu_t\left[O_{t-1}(i,N+j) - P_{t-1}(i,N+j)\right] \\ \qquad\qquad +c_2\mu_2\left[O_{t-1}(M+i,N+j) - P_{t\text{-}1}(i,N+j)\right] \end{cases} \tag{27}$$

where $P_t(i,2N+j)$ and $P_t(i,3N+j)$ are the longitudinal and transverse velocities of the particle at t iterations, respectively. t is the number of iterations, $t = 1, 2, \cdots, I_{\max}$, of which $I_{\max}$ is the maximum number of iterations. $\omega(t)$ for the t th iteration inertia weights, c_1, c_2 for different acceleration weights, μ_1, μ_2 are $(0,1)$ random numbers, $O_{t-1}(i,j)$, $O_{t-1}(i,N+j)$ are the historical optimal position of the particle in the $t-1$ th iteration, $O_{t-1}(M+i,j)$, $O_{t-1}(M+i,N+j)$ are the local optimal position of the particle in the $t-1$ th iteration, $P_{t-1}(i,j)$, $P_{t-1}(i,N+j)$ are the current optimal position of the particle in the $t-1$ nd iteration. The constraints of the particle vertical change speed are: if $P_t(i,2N+j) > vX_{\max}$, then $P_t(i,2N+j) = vX_{\max}$; if $P_t(i,2N+j) < vX_{\min}$, then $P_t(i,2N+j) = vx_{\min}$; the constraints of the particle horizontal change speed are similar to those of the vertical direction.

The particle position update formula is:

$$\begin{cases} P_t(i,j) = \operatorname{int}\left[P_{t-1}(i,j) + P_t(i,2N+j)\right] \\ P_t(i,N+j) = \operatorname{int}\left[P_{t-1}(i,N+j) + P_t(i,3N+j)\right] \end{cases} \tag{28}$$

where: if particle position $P_t(i,j) > m$, then $P_t(i,j) = m$; if $P_t(i,j) < 1$, then $P_t(i,j) = 1$. Add a constraint: if $A\left[P_t(i,j), P_t(i,N+j)\right] \le 0$, then restore particle position $\left[P_t(i,j), P_t(i,N+j)\right]$ to the initial state.

The PSO landscape pattern spatial optimization algorithm flow is:

Step 1, the particle position is initialized with the effective element row and column values in $E^*_{m\times n}$, and the particle velocity is initialized with a random integer within the particle velocity constraint range rg using MATLAB's own $rand\operatorname{int}(m,n,rg)$ function.

Step 2, the current objective function value pF_i of the particle is calculated, the local optimal value of the particle domain of 1 is extracted using the ring topology, and the global optimal value of the particle is determined according to the maximum value of the current objective function $\max pF_i$.

Step 3, apply the inertia weight linear reduction formula to calculate the particle inertia weight $\omega(t)$.

Step 4, perform particle velocity adjustment and position update.

Step 5, calculate the current optimal function value $pF_i(t)$ and the historical optimal function value $hF_i(t)$ of the particle for t iterations, and if $pF_i(t) > hF(t)$, perform the update of the historical optimal value of the particle.

Step 6, the ring topology is used to extract the local optimum and the optimal function value $lF_i(t)$ in the domain of i particle for t iterations, compute the local optimal function value $lF_i(t-1)$ of the particle for $t-1$ iterations, and update the local optimum of the particle if $lF_i(t) > lF_i(t-1)$.

Step 7, extract the current objective function maximum value $\max pF_i(t)$ and its corresponding particle position in t iteration, calculate the particle global optimal function value $gF(t-1)$ in $t-1$ iterations, and if $\max pF_i(t) > gF(t-1)$, perform particle global optimal value update.

Step 8, if $t \le I_{\max}$, then make $t = t+1$, perform step 3 step 7, otherwise perform step 9.

Step 9, output the particle global optimal value obtained from $I_{\max}$ iterations, and parse the mapping relationship into a graph, i.e., get the spatial optimization map of the solved landscape pattern.

4. Layout planning effect comparison test

Four independent simulation test environments are generated, each with the same configuration, and the four independent simulation environments correspond to the reference method A, reference method B, reference method C, and the method of this paper, respectively. During the layout optimization process, the changes of the following response metrics are recorded: objective function value, search efficiency, following efficiency, global optimal solution updating frequency, and algorithm convergence speed, and the results are shown in Table 1.

The objective function value of this paper's method finally reaches the highest, indicating that it performs best in integrating the multidimensional factors of the landscape. It also shows high efficiency in searching efficiency and following efficiency, and the final efficiency is 0.1 higher than the initial efficiency in both cases, indicating that its searching and following behaviors are more effective in the optimization process. In addition, the global optimal solution of this paper's method is updated the most frequently and the algorithm converges the fastest, stabilizing at 380 iterations, indicating that it is able to reach the steady state faster, i.e., find the optimal or near-optimal layout solution. It indicates that the method in this paper performs best in the layout optimization response test, and its generated layout optimization scheme is more superior in the consideration of multi-dimensional factors of ecological landscape, and the algorithm efficiency and convergence speed are also higher.

Table 1. Change results of partial response indicators

Environment		Target function value	Search efficiency	Following efficiency	Global optimal solution update frequency	Algorithm convergence
Reference method A	Initial	0.67	0.34	0.29	10	The stability of the iteration 550 times
	In the end	0.83	0.43	0.38	24	
Reference method B	Initial	0.68	0.38	0.31	11	The stability of the iteration 500 times
	In the end	0.84	0.46	0.37	27	
Reference method C	Initial	0.65	0.38	0.31	11	The stability of the iteration 580 times
	In the end	0.85	0.42	0.38	25	
This method	Initial	0.67	0.39	0.31	14	The stability of the iteration 380 times
	In the end	0.89	0.49	0.41	32	

The four optimization methods were used to carry out their respective layout optimization algorithms at the same time, and the changes in the response indexes in the process of completing the layout optimization were recorded synchronously, and the curve changes in the response indexes are shown in Fig. 1. Comparison and analysis of the index curve changes to draw test conclusions.

From the characteristics of the four curves, it can be found that under the same conditions of the four independent spaces, different layout optimization schemes show large differences in the changes of response indicators. Through observation, it is found that the overall curve of reference method A is relatively smooth, without local jitter, and the overall trend shows an increasing trend, but the momentum of growth is weak, which indicates that the response sensitivity of reference method A reaches the maximum peak, with a maximum value of 12.5. The overall characteristics of the indicator curve of reference method B are the same as those of reference method A, and the difference lies in the fact that the indicator value of reference method B is small, which means that its corresponding response performance is weak. The response index of reference method C fluctuates a lot, and although the response performance grows faster in the later stage, the overall stability is poor. Compared with the above three groups of reference methods, the curve of this paper's method is smoother, the growth trend is more stable, and the performance control performance in the later stage is excellent. Based on the above analysis, it can be determined that the response performance of this paper's method is better than that of the four groups of layout optimization methods, and it can better satisfy the requirements of practical applications.

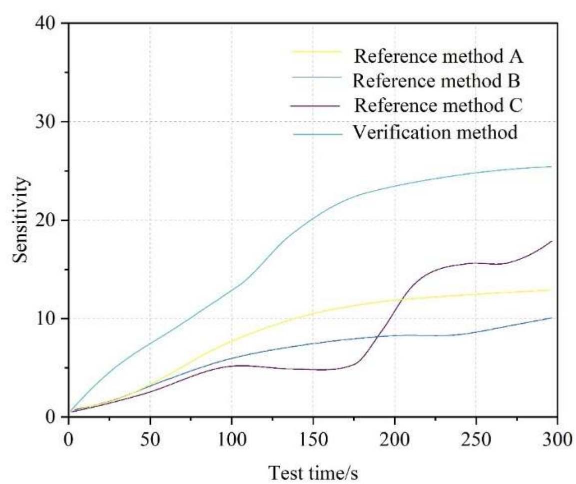

Fig. 1. Response index changes of 4 optimization methods

In order to verify the reasonableness of the above layout results, the above experiments were repeated 15 times to obtain 15 groups of spatial layout response statistical values of ecological landscape land. According to the historical experience, the layout deviation of its response indexes is compared, and if the deviation value is small, it indicates that the layout results of the method have rationality. On the contrary, if the obtained deviation value is larger, it indicates that the layout results of the method do not satisfy the rationality, and the obtained results are shown in Table 2. By observing and comparing the indicators, among the four groups of optimization methods, the deviation indicator value of reference method A is the largest, and the deviation value fluctuates more frequently, indicating that there are limitations in the rationality of the layout of the method. The deviation value of reference method B is smaller compared with the reference method, but the fluctuation frequency belongs to the same level, and the rationality of the layout also has limitations. Compared with the above two, the overall value of reference method C is significantly reduced, and the fluctuation frequency is slowed down, but the overall performance of the indicators reflects a certain gap with the test requirements. On the contrary, the proposed method in this paper has the smallest value of 0.5 without any fluctuation, which indicates that the layout effect is stable and the consistency effect is good. Therefore, the rationality corresponding to the layout results of this paper's method is the best, and it can better meet the test requirements.

Table 2. Statistics of Layout Rationality Test Results

Number	This method	Reference method A	Reference method B	Reference method C
1	0.5	1.2	1.1	1.4
2	0.5	1.3	1.1	1.4
3	0.5	1.1	1.1	1.4
4	0.5	1.2	1.1	1.3
5	0.5	1.1	1.2	1.3
6	0.5	1.1	1.3	1.3
7	0.5	1.5	1.3	1.3
8	0.5	1.3	1.3	1.3
9	0.5	1.1	1.2	0.7
10	0.5	1.2	1.1	0.7
11	0.5	1.5	1.1	0.7
12	0.5	1.5	1.1	0.7
13	0.5	1.5	1.1	0.7
14	0.5	1.5	0.9	0.7
15	0.5	1.5	1.1	1.3

In order to comprehensively assess the practical application value of the layout optimization method, economic benefits are set as the experimental indicators. The economic benefit indicators include maintenance cost, return on investment, land use efficiency, etc., which are directly related to the feasibility and long-term sustainability of the layout optimization scheme. The economic benefit indicators are calculated for each of the four layout optimization methods, and the results are shown in Table 3.

The maintenance cost of this paper's method is the lowest, only 124,000 yuan, indicating that its economic burden in long-term operation is light. The maintenance costs of the reference methods A and C are higher. It may be because their layout schemes require more maintenance work in practice. The method in this paper has the highest ROI of 14.9%, indicating that its layout optimization scheme can bring higher value of ecological services and thus is more attractive economically. Although the reference method C also has a higher ROI, the overall economic benefits are not outstanding considering its higher maintenance costs. The method in this paper has the highest land use efficiency, meaning that more ecological landscape trees can be allocated under the same area, which improves the land use efficiency. The reference method C did not translate into higher economic benefits although the density of forest trees was also higher. Comprehensively, the comparative analysis of the above economic benefit indicators shows that this paper's method performs well in the three aspects of maintenance cost, return on investment and land use efficiency, showing its advantages in economic benefits. This not only proves the effectiveness of this paper's method in ecological landscape layout optimization, but also provides a solid economic foundation for its application in actual urban planning.

Table 3. Comparison results of economic benefits of different methods

Method	Maintenance cost(10000yuan/a)	Return on investment(%)	Land efficiency (tree number/hm^2)
Reference method A	15.3	12.1	1500
Reference method B	13.9	11.8	1480
Reference method B	14.5	13.5	1580
This method	12.4	14.9	1650

5. Simulation test of spatial layout of land use

The simulation target area has a humid monsoon climate with an average temperature of 17.2°C and abundant annual precipitation at around 978.2 mm. The region is rich in urban landscape plant resources. And the unique climate conditions harbor a variety of grass plants. In addition, trees and shrubs form a beautiful green belt, which has a certain protective effect on the city. The simulation process is completed using the LUSP system, which not only has the function of spatial expansion, but also can dynamically simulate the land use changes. Using this system to simulate the spatial layout of land use in the target area, the land use before and after using the proposed design method is shown in Fig. 2 and Fig. 3, respectively.

Before the design, the city has more unused land, after the redesign using the proposed method, most of the unused land is changed into grassland and woodland, and only a small part of the unused land, which provides space for the expansion of the project in the later stage; in addition, the old buildings around the original unused land are changed into woodland, which increases the greening area, and also reduces the dangers posed by the old buildings, and improves the overall look of the cityscape. Through comparison, it can be seen that after the design of the proposed method, the land utilization rate of the urban landscape is improved.

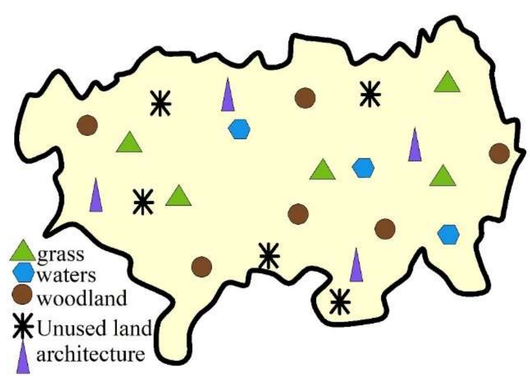

Fig. 2. Layout design before land utilization

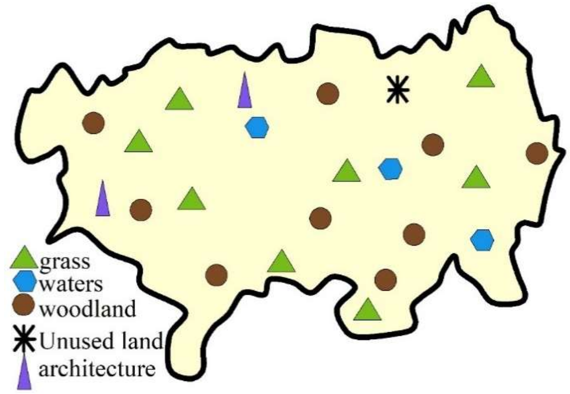

Fig. 3 Layout design of the back soil

In order to more intuitively express the spatial layout of land use before and after the design, the topographic position index, vegetation coverage, landscape risk index and ecological service value are used as quantitative evaluation indexes, and the evaluation results are shown in Fig. 4, and the numbering of the X-axis from 1 to 5 represents five land types, namely, woodland, grassland, water, building and unutilized land, respectively. Before the layout design, the terrain position index was relatively low, indicating the unreasonable application of land types, and the terrain position index increased significantly after the design. The vegetation coverage of each land type was also low before design, and only the grassland and woodland areas met the requirements. After redesign, more attention was paid to the vegetation planning of the water and building areas, such as adding water plants and other landscapes to the water and increasing greening around the buildings. In terms of landscape risk index and ecological service value, the landscape risk after the design was significantly reduced to as low as 2%, and the service value was increased, which resulted in a layout that could realize greater ecological value.

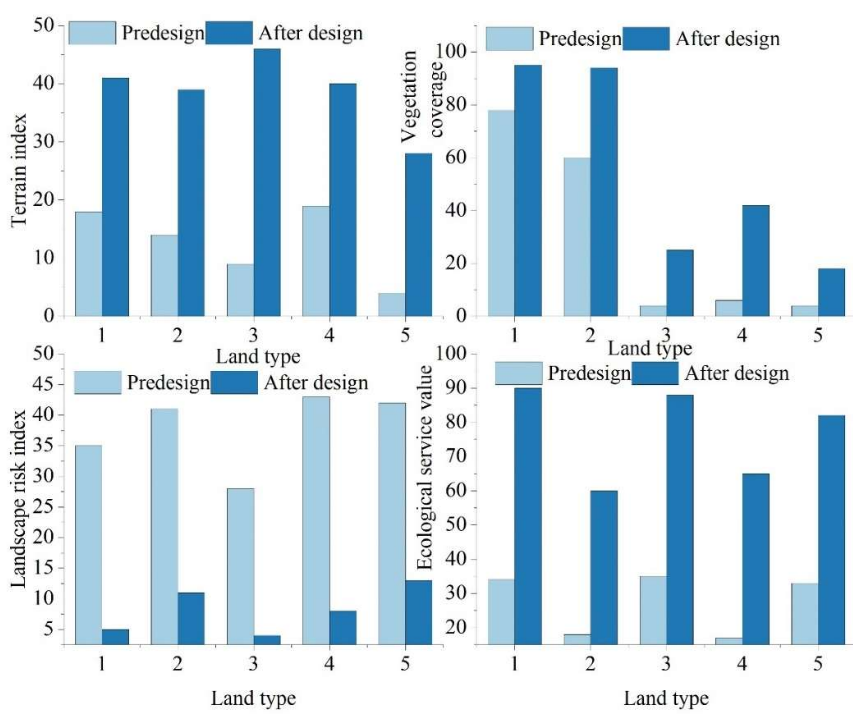

Fig. 4. Evaluation result

6. Conclusion

In this study, a grid division based urban landscape combination design method is proposed to provide a new scheme for urban landscape path planning and design. Then a spatial optimization model of urban landscape pattern based on PSO is proposed to obtain the optimal urban landscape spatial layout optimization scheme.

The comparison results of the four different methods show that the improved particle swarm algorithm performs better in the two indexes of searching efficiency and following efficiency, and the final efficiency is 0.1 higher than the initial one, which proves that the searching and following behaviors in its optimization process possess high efficiency. In addition, the global optimal solution of this paper's method has the highest update frequency and the fastest convergence speed, which converges and stabilizes in 380 iterations, indicating that the layout planning scheme generated by this paper's method is more superior in the multifactorial consideration of urban landscape.

In addition, the spatial optimization model of urban landscape pattern based on PSO in this paper can strictly follow the design of the objective function, improve the utilization rate of urban land, reduce the risk index of urban landscape, and the risk index of water landscape is only 2%, which improves the service value of urban landscape.

In the path planning and spatial layout design of urban landscape, in addition to taking into account the above optimization objectives, it should also pay attention to the dynamic and static collocation of urban landscape, adapt to the local conditions, and continuously introduce new concepts of urban landscape layout, improve the level of landscape design, and maintain the order of urban landscape layout.

References

[1] Li, X., Li, X., & Ma, X. (2022). Spatial optimization for urban green space (UGS) planning support using a heuristic approach. Applied Geography, 138, 102622.

[2] Mohammadyari, F., Tavakoli, M., Zarandian, A., & Abdollahi, S. (2023). Optimization land use based on multi-scenario simulation of ecosystem service for sustainable landscape planning in a mixed urban-Forest watershed. Ecological Modelling, 483, 110440.

[3] Feng, L., Mi, X., & Yuan, D. (2022). Optimal planning of urban greening system in response to urban microenvironments in a high-density city using genetic algorithm: A case study of Tianjin. Sustainable Cities and Society, 87, 104244.

[4] Li, Y., Chen, Y., Zhao, M., & Zhai, X. (2018). Optimization of planning layout of urban building based on improved logit and PSO algorithms. Complexity, 2018(1), 9452813.

[5] Yoon, E. J., Kim, B., & Lee, D. K. (2019). Multi-objective planning model for urban greening based on optimization algorithms. Urban Forestry & Urban Greening, 40, 183-194.

[6] Dong, X. (2024). Optimization of landscape garden greening design based on multi objective genetic algorithm. Journal of Electrical Systems, 20(6s), 226-236.

[7] Ban, N., Liu, X., & Zhu, C. (2022). Landscape ecological construction and spatial pattern optimization design based on genetic algorithm optimization neural network. Wireless Communications and Mobile Computing, 2022(1), 4976361.

[8] Chen, M. (2020, October). Research on landscape Spatial Structure Optimization of Garden sculpture based on improved Particle Swarm Optimization algorithm. In IOP Conference Series: Earth and Environmental Science (Vol. 580, No. 1, p. 012009). IOP Publishing.

[9] Deng, Y., Xie, L., Xing, C., & Cai, L. (2022). Digital city landscape planning and design based on spatial information technology. Neural Computing and Applications, 34(12), 9429-9440.

[10] Tian, Z., Wang, Y., & Xue, Q. (2022). Optimization of Urban Landscape Planning and Layout under Multicriteria Constraints. Mathematical Problems in Engineering, 2022(1), 2991188.

[11] Xu, J. (2024, January). Application and Decision Support of Multi-Objective Optimization Algorithm in Urban Landscape Planning. In Proceedings of the First International Conference on Science, Engineering and Technology Practices for Sustainable Development, ICSETPSD 2023, 17th-18th November 2023, Coimbatore, Tamilnadu, India.

[12] Zandniapour, K., Soroush, A., Agdam, E. K., & Sanaieian, H. (2024). Integrating GIS, 3D-Isovist, and an NSGA-II multi-objective optimization algorithm for automation of design process in urban parks and public open spaces. International Journal of Geoheritage and Parks.

[13] Lin, J., Zeng, Y., & He, Y. (2023). Spatial Optimization with Morphological Spatial Pattern Analysis for Green Space Conservation Planning. Forests, 14(5), 1031.

[14] Hou, X., & Shan, Q. (2024). Simulation and Optimization of Landscape Planning and Design Based on Virtual Reality Technology. Journal of Electrical Systems, 20(3s), 1734-1745.

[15] Xu, H., & Diao, J. (2023). Accurate Design and Layout of Landscape Elements Based on Improved Particle Swarm Optimization. Computer-Aided Design and Applications, 49-65.

[16] Ou, D., Yao, X., Xia, J., Gao, X., Wang, C., Chen, W., ... & Yang, J. (2019). Development of a composite model for simulating landscape pattern optimization allocation: A case study in the Longquanyi District of Chengdu City, Sichuan Province, China. Sustainability, 11(9), 2678.

[17] Yu, L., Zhang, L., & Gong, Z. (2022). An optimization model for landscape planning and environmental design of smart cities based on big data analysis. Scientific Programming, 2022(1), 2955283.

[18] Wang, Y., Fang, X., Zhou, T., & Tang, J. (2024, April). Research on Urban Landscape Design Optimization Based on Interactive Genetic Algorithm. In Proceedings of the International Conference on Algorithms, Software Engineering, and Network Security (pp. 22-26).

[19] Wang, L. (2023). 3D urban landscape rendering and optimization algorithm for smart city. Intelligent Decision Technologies, (Preprint), 1-16.

[20] Huang, J. (2024, June). Study on Optimization of Landscape Design Strategy in Residential Park Based on Intelligent Algorithm. In 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS) (pp. 1-5). IEEE.

[21] Wu, G., Miao, Y., & Wang, F. (2022). Intelligent design model of urban landscape space based on optimized BP neural network. Journal of Sensors, 2022(1), 9704287.

[22] Li, G. (2021). Urban Landscape Design Optimization Based on Interactive Genetic Algorithm. In 2020 International Conference on Applications and Techniques in Cyber Intelligence: Applications and Techniques in Cyber Intelligence (ATCI 2020) (pp. 1097-1102). Springer International Publishing.

[23] Di Chen,Qiuzhi Peng,Jiating Lu,Peiyi Huang,Yaxuan Liu & Fengcan Peng. (2025). Assessing effect of water photovoltaics on nearby water surface temperature using remote sensing techniques. Advances in Space Research(1),138-147.

[24] Yang Yu,Qinghua Li,Zhijie Hua,Chongbo Yin & Yan Shi. (2025). An effective multi-source information fusion method for electronic nose and hyperspectral to identify the spring tea quality at different harvesting periods. Measurement116452-116452.

[25] Li Mingxia,Pei Yongji,Wang Hailong,Li Panpan,Feng Yongjun & Huang Xinlei. (2022). Design of Emergency Simulation Training Scene Construction System Based on Grid Model Interactive Correlation Technology. Journal of Nanoelectronics and Optoelectronics(12),1588-1595.