Journal of Engineering, Project, and Production Management
2026, 16(3), 2025-197

# Urban Landscape Design Optimization Using Multi-Objective Particle Swarm Algorithms

Qingxuan Li
Lecturer, College of Art and Design, Communication University of China, Nanjing, 211172, China, E-mail: li152qingxuan@163.com

Project Management
Received September 4, 2025; revised October 23, 2025; accepted October 27, 2025
Available online April 8, 2026

**Abstract:** Optimizing land use in urban landscape design can improve the efficiency of urban land use, enhance the attractiveness of urban landscape, and guarantee the ecological and economic benefits for the city. However, many current urban landscape design methods still suffer from low land utilization and poor urban landscape coordination. To solve these problems, this study combines a multi-objective particle swarm algorithm with a Multi-Objective Optimization Problem (MOP). It proposes an innovative urban landscape design method by constructing and solving a multi-objective optimization model for landscape design and land use. The study analyzes the practical effects of the landscape design method. The results indicated that the method increased the urban land utilization rate from 78.3% to 93.7% and the forest coverage rate from 34.2% to 47.6%. Moreover, the city's ecological environment and landscape coordination scores both increased to more than 90 points. Public satisfaction with the landscape design also increased, reaching 92.7%. In summary, the proposed urban landscape design method improves the urban land resource utilization rate while also ensuring landscape coordination and high-quality urban ecological environment. It can also provide urban landscape design references for urban planners.

**Keywords**: Urban landscape design, land use, optimization model for multi-objective problems, multi-objective particle swarm optimization.


DOI 10.32738/JEPPM-2025-197

## 1. Introduction

With the acceleration of global urbanization, the urban population is growing, and the scale of cities is expanding continuously, which leads to land resource tension (Darem et al., 2023). An urgent problem is how to plan for limited urban land in a reasonable way by optimizing spatial layout, enhancing urban landscape quality, and improving the urban land resource Utilization Rate (UR) (Ouma et al. 2023). Many scholars have studied Urban Landscape Design (ULD) and land utilization methods. For example, Sun et al. (2023) proposed a spatial-scale-based ULD method to improve ecosystem services quality. land UR and land cover. When tested in real situations, the outcomes revealed that the method could increase the vegetation cover of the city by 12.3%, but the landscape design of the method was time-consuming. To address poor land use rates in sub-Saharan Africa, Tamirat et al. (2023) developed an urban and rural landscape planning system using satellite imagery and support vector machines. The planning method was tested by using it in a real situation. According to the findings, the technique could raise the rate of land resource use by 10.2%. To optimize urban land use and reduce carbon emissions, Mirici et al. (2024) proposed a land use model based on carbon service. They also constructed a land design planning method based on this model, and the method was used in real situations for testing. The outcomes revealed that this method reduces carbon emissions by 12.2%. To address these problems, Tariq et al. (2023) suggested a land cover prediction model based on a Markov chain and a support vector machine to optimize land use. Their outcomes revealed a 9.7% increase in resource utilization. However, the above method is unable to guarantee high land resource UR as well as the coordination of the urban landscape at the same time, and needs to be optimized (Gottero et al., 2023).

The MOP is an important research area in optimization, focused on optimizing Multiple Objective Functions (MOFs) simultaneously to find an Optimal Solution (OS) (Jangir et al., 2023). MOP models are also often used in various fields due to their advantages. For example, Rahimi et al. (2023) proposed an MOP-based method for multi-objective crowd classification to address poor accuracy and large errors. The method was compared with the traditional classification method. The results showed that the classification accuracy of the method was increased by 21.2%. In addition, Ma et al. (2023) designed a classification framework based on the MOP model in order to classify Multi-Objective Problems (MPs) in the engineering community and used the framework in real situations for testing. The results showed that the classification accuracy of the framework was able to reach 90.2%. Multi-Objective Particle Swarm Optimization (MOPSO) is a swarm intelligence algorithm that simulates bird flock foraging behavior. It finds an OS by the movement of particles in the solution space (Faria et al., 2023). The MOPSO algorithm is also frequently utilized across many domains. For instance, to balance equilibrium strategies among different regions within an MP, Han et al. (2023) proposed a balancing strategy model based on the MOPSO algorithm. The model was tested in real situations. The outcomes revealed that it improved the convergence of strategies within different regions by 12.3%. Moreover, to improve the effectiveness of solar energy utilization in solar energy systems and to reduce energy losses, Zhang et al. (2023) designed a solar energy usage based on the MOPSO algorithm. The method was used in real situations for testing. The outcomes revealed that the utilization of solar energy reached 92.1% after using this method.

In summary, the current land use optimization methods for ULD remain time-consuming and result in poor urban landscape coordination. To develop a planning technique that can account for both urban land use and landscape coordination, this study builds an MOPSO-MOP model by combining the MOP model with the MOPSO algorithm. This research aims to reduce the time required for ULD and planning, improve the coordination of urban landscapes, and increase residents' satisfaction with urban landscapes. This study's innovation involves constructing an MOP model for ULD and land use and then using the MOPSO algorithm to solve it, thereby identifying an optimal method for ULD land use. This is the optimal method for ULD land use.

## 2. Methods and Materials

### 2.1. Construction of the MOP Model

The demand for building land is rising due to a sharp increase in the urban population brought about by the acceleration of global urbanization. However, urban land resources are in short supply, resulting in a contradiction between supply and demand (Akaateba et al., 2025). Moreover, irrational land use can lead to the heat island effect, air pollution and other ecological problems, which affect the health of urban residents. Therefore, it is necessary to optimize the land use method in ULD. Through the optimization method, this study seeks to increase the city's land use efficiency while simultaneously lowering carbon emissions and improving the urban ecological environment (Usman et al., 2023). The MOP model is a method for solving practical, complex optimization problems. It refers to the model that optimizes these Objective Functions (OFs) simultaneously in the case of MOFs in the optimization problem. Moreover, the OS is sought by considering MOFs together (Khalid et al. 2023). In land use optimization for ULD, there are MOFs such as ecological benefit, economic benefit, social benefit, and so on. The MOP model can be used to integrate these OFs to obtain the OS. Fig. 1 depicts the MOP model's basic structure.

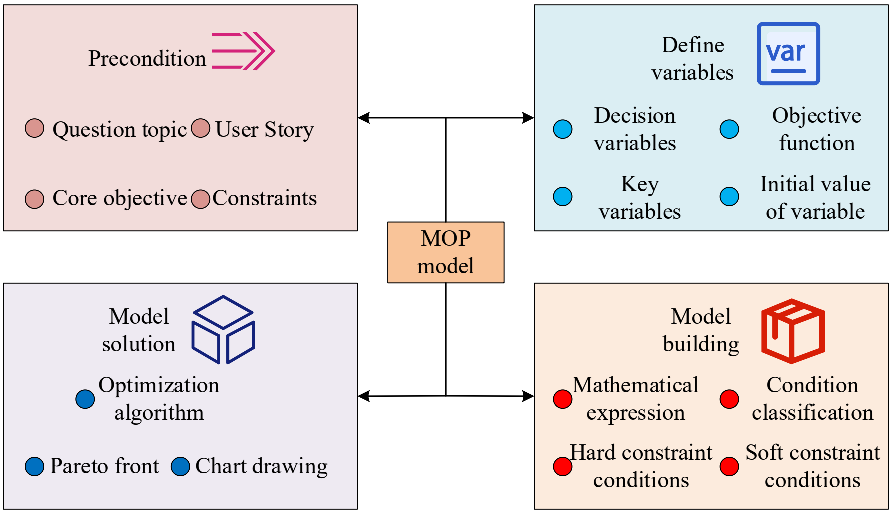



**Fig. 1.** Basic structure of MOP model

In Fig. 1, when constructing the MOP model, the first thing that needs to be clarified is the topic of the problem and the user requirements. The core objectives and constraints of the problem are clarified to ensure that the model is closely integrated with the actual requirements. The Decision Variables (DVs) are defined as follows: the key variables affecting the OFs and constraints are identified, and a reasonable range of values is set for each. Then, based on the user's needs, multiple objectives are transformed into mathematical expressions in order to minimize costs and maximize ecological and social benefits. This creates a trade-off relationship between the objectives. The constraints are categorized as hard and soft constraints. Hard constraints are conditions that the solution must satisfy, while soft constraints are adjustable within a certain range. These constraints are then transformed into inequalities or equations. Next, based on the number of variables and OFs, the best optimization method is selected to solve the MOP model and produce the Pareto frontier. This frontier is plotted as a graph to facilitate the decision maker's choice. The specific formula of the MOP model is shown in Eq. (1).

$$min\, F\,(x) = \sum_{i=1}^{n} K_i X_i\,, (k = 1,2,\dots r) \tag{1}$$

In Eq. (1), $F(x)$ means the OF. $K_i$ means the coefficient of the DV. $X$ means the DV. $i$ means the serial number of the $i$-th DV. $r$ means the number of the OF. The expression of the constraints is shown in Eq. (2).

$$s.t.\begin{cases}\sum_{i=1}^{n} C_{ij}X_i = (\geq,\leq)\, d_i, (j = 1,2,\ldots m) \\ Xi \geq 0, (i = 1,2.\ldots, n)\end{cases} \tag{2}$$

In Eq. (2), $C_{ij}$ means the coefficient of the $i$-th DV in the $j$ the constraint. $d_i$ means the constraint value of the $i$-th DV. The MOP model on land use optimization for ULD is constructed by the above steps. Fig. 2 depicts the fundamental framework of the built MOP model.

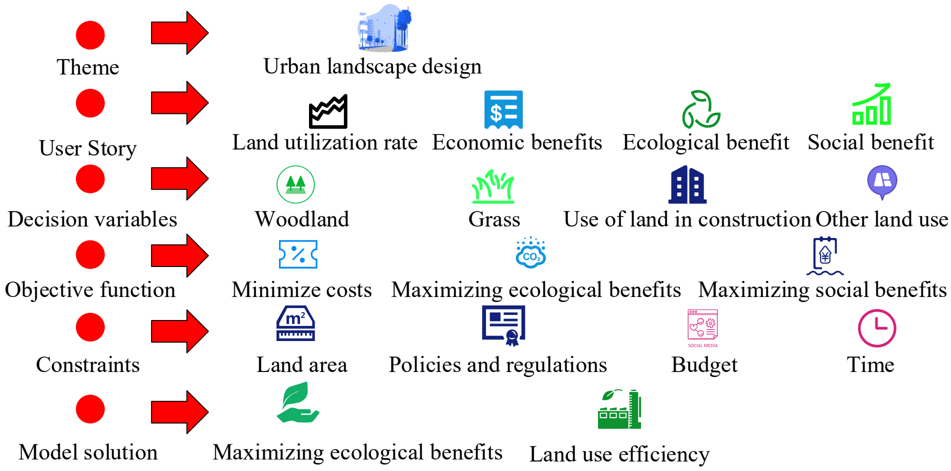



**Fig. 2.** MOP model for urban landscape design

In Fig. 2, the problem topic of the model is ULD. The user requirements are to improve urban land utilization, economic efficiency, social efficiency and ecological efficiency. The DVs are forest land, grassland, water, construction land, and other land. The OF of the MOP model is to minimize cost, maximize ecological efficiency, and maximize social efficiency.

$$\begin{cases} f_1(x) = L_1 + L_2 \\ f_2(x) = M_1 + M_2 \\ f_3(x) = (Y_1 + Y_2 + \ldots Y_n)/n \end{cases} \tag{3}$$

In Eq. (3), $f_1(x)$ denotes minimization cost. $L_1$ is the urban construction cost. $L_2$ is the maintenance cost. $f_2(x)$ is maximizing ecological benefits. $M_1$ is green space coverage. $M_2$ is the biodiversity index. $f_3(x)$ is maximizing social benefits. $Y_n$ is the satisfaction score of residents. $n$ is the total number of residents. This model's hard constraints are the total land area limit, policy and regulatory requirements. The soft constraints are the budget ceiling and the time limit. The constraint limit of total land area is shown in Eq. (4).

$$X_1 + X_2 + X_3 + X_4 = X_A \tag{4}$$

In Eq. (4), $X_1$ is the urban green land area. $X_2$ is urban construction land. $X_3$ is an urban arable land area. $X_4$ is urban industrial land. $X_A$ denotes the total urban land area. The expression of constraints of policies and regulations on green space is shown in Eq. (5).

$$\sum x_i \geq X_1 \tag{5}$$

In Eq. (5), $\sum x_i$ total area of urban green space. Then the appropriate optimization algorithm is selected to solve the MOP model. A series of related solutions are obtained, and the optimal program is selected comprehensively.

### 2.2. MOP Model Solving based on MOPSO Algorithm

After developing the MOP model for land use optimization method for ULD, it is required to choose an appropriate optimization algorithm to solve the OF in the model and obtain the OS. To solve the MOP, the MOPSO algorithm is a population intelligent optimization method that is based on the particle swarm optimization algorithm (Nezafat Tabalvandani et al., 2024). Moreover, compared to Non-Dominated Sorting (NDS) genetic algorithms and other genetic algorithms, the MOPSO algorithm offers high solving efficiency, continuous spatial expression, and interactive parameter tuning. By mimicking the behavior of a population of particles in the solution space, the MOPSO algorithm locates a collection of solutions that are near the OS (Gong et al., 2024). The basic flow of the MOPSO algorithm is shown in Fig. 3.

The parameters, including population size, maximum iteration, and weights, must be established first, as shown in Fig. 3. The fitness value of each particle is then determined once the starting particle population's position and velocity are produced at random. The individual OS is updated based on each particle's current position and its historical ideal position. The particle's unique OS is also used to update the global OS. The particle's position and velocity are then updated using its current velocity, individual, and global OS. Then, to preserve the population's diversity, Non-Dominated Sorting (NDS) determines each particle's crowding value depending on its fitness value. Based on the NDS and the crowding degree value, a new generation of particle population is then selected. These steps are repeated until the maximum number of iterations is reached, yielding a set of optimal solutions. Eq. (6) illustrates how the adaptation of the particles in the particle swarm is determined in the aforementioned procedure.

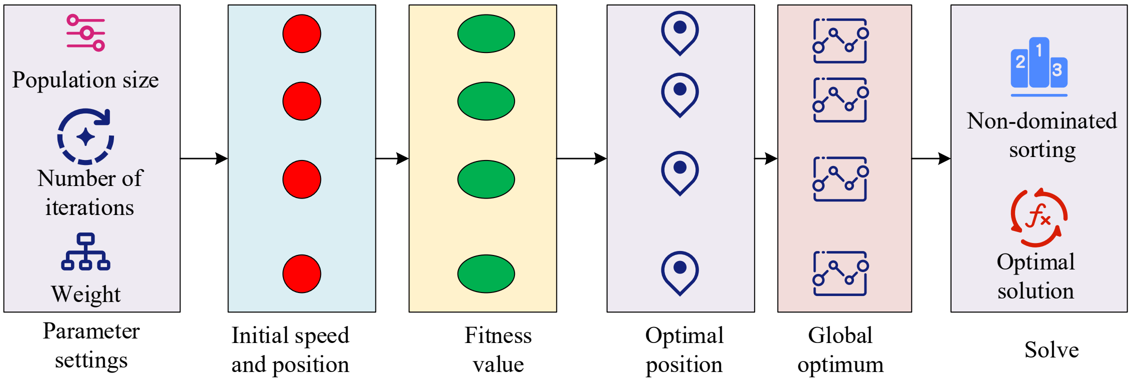



**Fig. 3.** Basic Process of MOPSO Algorithm

$$f(a) = 1/dis * col \tag{6}$$

In Eq. (6), $dis$ is the path distance of each particle in the particle swarm. $col$ is the particle collision frequency. The inertia weights (IWs) are updated as shown in Eq. (7).

$$w_b{}^{(k)} = w_s - (w_s - w_e)(X_a{}^{(k)} - 1)^2 \tag{7}$$

In Eq. (7), $w_a{}^{(k)}$ is the IW of the $a$-th particle at the $k$the moment. $w_s$ and $w_e$ denote the initial and ending values of the particle. $X_a{}^{(k)}$ is the particle position. The particle velocity update formula is shown in Eq. (8).

$$v_{t+1} = wv_t + c1r1(x_{best-}x_t) + c2r2(x'_{best} - x_t) \tag{8}$$

In Eq. (8), $v_{t+1}$ is the velocity at the next moment. $v_t$ is the current velocity of the particle. $w$ is the IW. $c1$ and $c2$ are learning factors. $r1$ and $r2$ are two random numbers. $x_{best}$ is the individual optimal position of the particle. $x'_{best}$ is the global most position of the particle. $x_t$ is the current position of the particle. The position update of the particle is calculated as shown in Eq. (9).

$$x_{t+1} = x_t + v_t t \tag{9}$$

In Eq. (9), $x_{t+1}$ is the updated position. $t$ is the particle movement time. The particles in the particle swarm are continuously adjusted by the above calculation. As for the MOPSO algorithm, the NDS is one of the core mechanisms of the algorithm. This can handle the superiority and inferiority relationships of various solutions computed in the MOP. The basic steps of NDS for the solutions in the MOPSO algorithm are shown in Fig. 4.

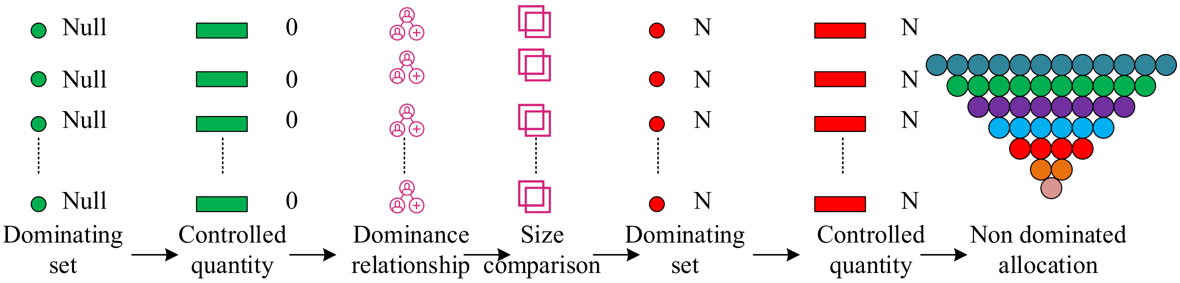



**Fig. 4.** Basic Steps of NDS

As shown in Fig. 4, the NDS process in the MOPSO algorithm first initializes a dominating set and a dominated quantity for each solution. Then, the domination relations are computed. For any of the computed solutions, the dominating set and the dominated quantity of the solution are updated by comparing the magnitude of their values on all objectives. Then, a non-dominated layer is assigned to each solution. The solutions with a dominating quantity of 0 in the dominating set constitute the first layer of the Pareto frontier. Then the number of dominated solution sets for each solution in the first layer is subtracted by one. If, after this operation, a solution's dominated quantity becomes zero, it is classified as a candidate for the second layer of the Pareto frontier. This process is repeated until all solutions are assigned to a non-dominated layer. Within the same non-dominated layer, the congestion of the solutions is computed to further zone the merit of the decomposition. Finally, the index of the dominated layer of each solution is output as an indication of the non-dominated layer in which the solution is located. Generally, the solution in the first layer is selected as a candidate for the global OS. Eq. (10) provides the expression for determining the dominance relationship in the technique described above.

$$\forall q \in \{1,2,\dots. Q\}, f_q(x) \le f_q(y) \tag{10}$$

Eq. (10) denotes that for any individual $x$, its OF is not lower than individual $y$ and at least one OF is better than $y$, then it denotes that individual $x$ dominates $y$. Crowding is calculated as shown in Eq. (11).

$$d(h) = \sum_{z=1}^{Z} \frac{f_z(h+1) - f_z(h-1)}{f_z^{\max} - f_z^{\min}} \tag{11}$$

In Eq. (11), $f_z(h+1)$ and $f_z(h-1)$ are the objective values of $h$'s neighboring individuals on the objective $f_z$. $f_z{}^{max}$ and $f_z{}^{min}$ are the maximum and minimum values of target $f_z$ in the current hierarchy. The MOPSO algorithm solves the OF in the MOP model by the above steps. The solutions obtained are ranked in order of merit, and the best alternative is finally output.

### 2.3. MOPSO-MOP based Land use Optimization Approach

After constructing the MOP model for the land use optimization method for ULD, the constructed model is then solved using the MOPSO algorithm. This is the best planning method for ULD to guarantee the rationality of landscape design. Its ecological benefits are guaranteed while improving land utilization. The basic flow of the land use optimization method for ULD based on the MOPSO-MOP model shown in Fig. 5.

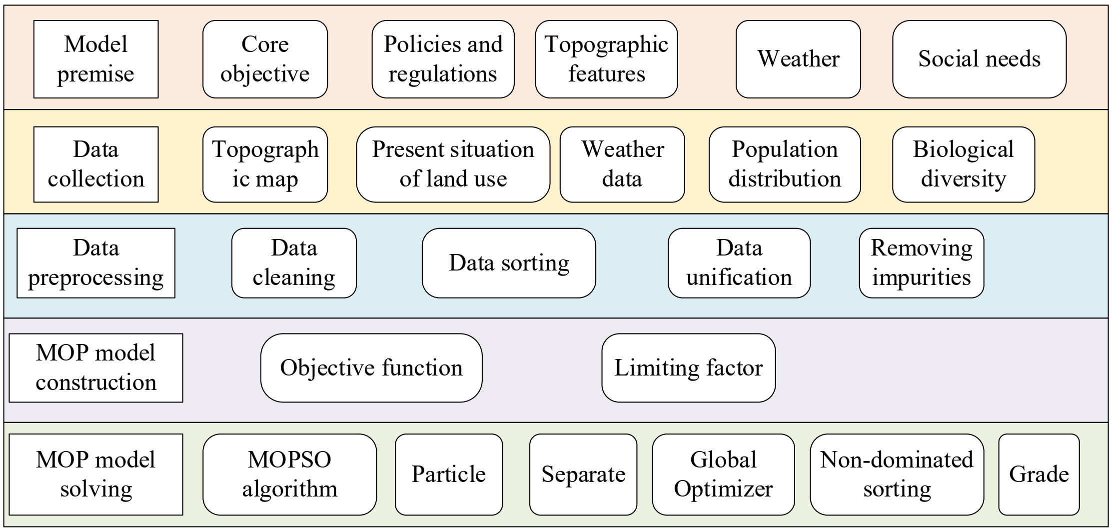



**Fig. 5.** Land use optimization method for urban landscape design

In Fig. 5, the core objective of this ULD land optimization needs to be clarified first. Then the local policies and regulations, topography and geomorphology, climate conditions, social needs, and other factors are considered. After that, data are collected according to the objectives, and the GIS system is used to obtain a local topographic map and the current land use status. Then, remote sensing technology is used to collect remote sensing images and climate data. In addition, local population distribution, traffic flow, hydrological characteristics, and various data about biodiversity are also needed. Then, the data are organized and cleaned to make the data uniform and remove the impurities. Based on the collected data and optimization objectives, the optimization function of the MOP model for the MP and the constraints are obtained. Finally, the MOPSO algorithm is used to solve the optimization function of the MP in MOP. Each particle in MOPSO is treated as a solution in the MOP model, and the individual OS and the global OS are tracked by updating the position and velocity of the particle. Meanwhile, NDS is utilized to classify and store the particles to facilitate the subsequent selection of the global OS. Finally, an OS on land use optimization method for ULD is obtained. This can provide a scientific and efficient land optimization solution for ULD. Furthermore, it can analyze whether the design method is reasonable by comparing the UR of urban land resources, Forest Coverage Rate (FCR), and land construction UR before and after the optimization design. Its calculation formula is shown in Eq. (12).

$$\begin{cases} \rho_1 = F(s)/S \\ \rho_2 = S_1/S_A \times 100\% \\ \rho_3 = S_2/S_A \times 100\% \end{cases} \tag{12}$$

In Eq. (12), $\rho_1$ is land resource utilization efficiency. $F(s)$ is economic efficiency. $S$ is a unit land area. $\rho_2$ is FCR. $S_1$ is a planned forest land area. $S_A$ is the total land area. $\rho_3$ is land construction UR. $S_2$ is the planning annual construction land. Through the above calculation to get the optimized urban landscape planning and design, the specific situation of the indicators of land UR, in order to judge the specific implementation effect of the planning method. Moreover, when calculating for large-scale urban systems, dynamic priority scheduling is used to allocate tasks in order to ensure the computational efficiency of the model. Task priorities are defined by using the Kubernetes default scheduler (kube scheduler). Furthermore, by using Descheduler to release and recycle unused resources, it can effectively calculate data in large-scale cities and improve their computational efficiency.

## 3. Results

### 3.1. Performance Analysis of the MOPSO-MOP Model

The performance of the suggested MOPSO-MOP model must be assessed in an attempt to confirm the efficacy of the land use optimization approach for urban landscape planning and design. In this study, the ZDT1 dataset, DTLZ2 dataset, WFG1 dataset and UF1 dataset are selected as the experimental datasets. All the above four datasets contain MOFs. These experimental datasets are modeled and solved by MOP using the MOPSO-MOP model. The performance of the model is judged by comparing the classification effect, classification error, classification time, Kappa coefficient (KC), and loss function of the non-dominated solutions of the above four datasets. Table 1 displays the setup of the experiment's environment.

**Table 1.** Experimental environment configuration

| Experimental Environment | Configuration | Type |
|---|---|---|
| Hardware environment | Computer | Windows10 |
| | Memory | 128G |
| | Camera | TP-Link IPC44AW |
| Software environment | Application server | SQL Server2000 |
| | Program design platform | VC++ |
| | Data analysis | MATLAB R2017b |

The particle is set to 100, the iteration is set to 500, the learning factor is set to 2, and the initial value of IW is set to 0.9. Experiments are conducted with the above experimental configurations and experimental datasets. The classification effect of the model in the four datasets is first compared, as shown in Fig. 6.

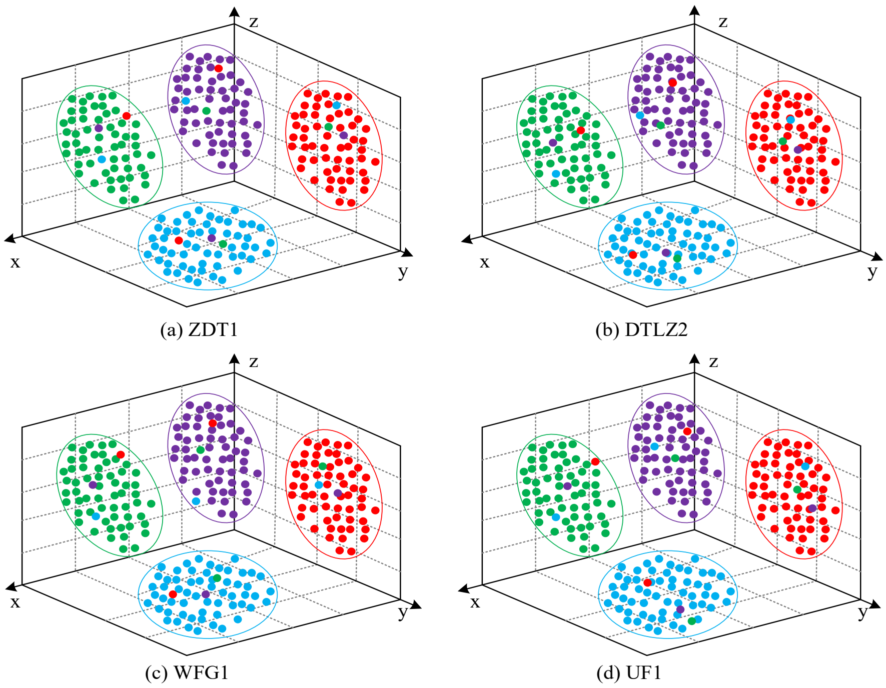
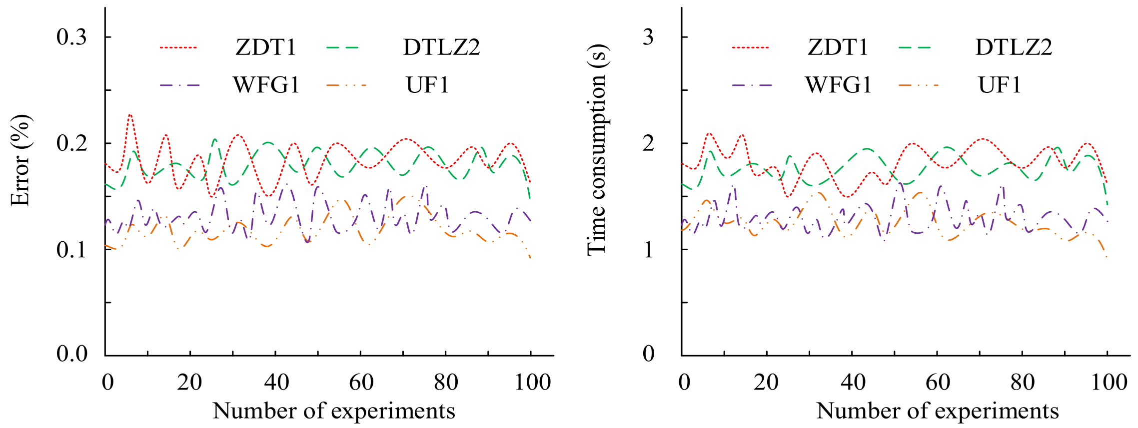



**Fig. 6.** Classification effect

In Fig. 6, a color indicates a class of data in the dataset. In Fig. 6(a), when the MOPSO-MOP model classifies the data in the ZDT1 dataset, only very few data are misclassified, and the classification accuracy is high. In Fig. 6(b), 6(c), and 6(d), the MOPSO-MOP model classifies the DTLZ2 dataset, the WFG1 dataset, and the UF1 dataset with higher classification effectiveness and lower classification error rate. The aforementioned findings demonstrate that the MOPSO-MOP model proposed in the study has a superior impact on categorization. Therefore, when using the MOPSO-MOP model to classify urban land use optimization methods, it can accurately classify decisions based on the position and velocity of the particles obtained from the solution. Moreover, it classifies land use optimization methods into different categories.

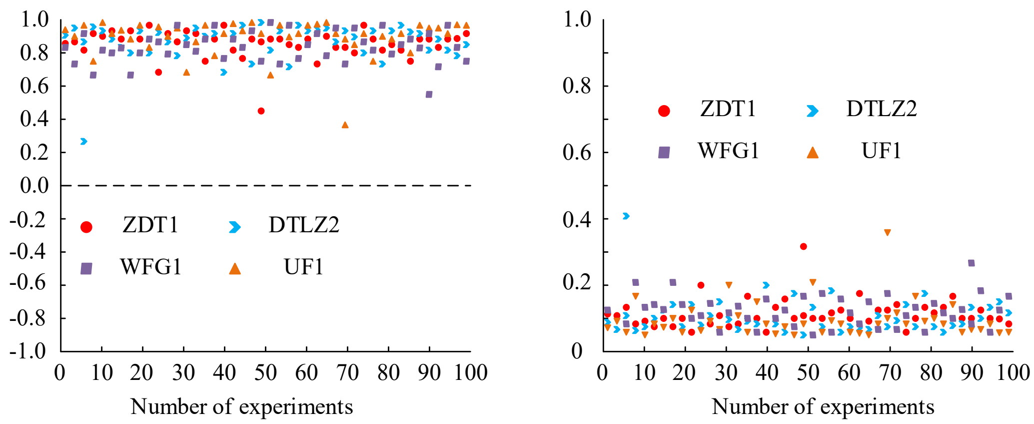
The classification error and classification time results of MOPSO-MOP are shown in Fig. 7.




(a) Classification error (b) Classification time consumption

**Fig. 7.** Comparison of classification error and classification time

In Fig. 7(a), the MOPSO-MOP model has a low classification error. The errors fluctuate between 0.1% and 0.3% for all four datasets. The average classification error rate of this model for the four datasets ZDT1, DTLZ2, WFG1 and UF1 is 0.23%, 0.17%, 0.14% and 0.12%, respectively. In Fig. 7(b), the MOPSO-MOP model classifies the four datasets. Its classification time is low for all of them. When classifying the ZDT1 dataset, the average classification time is 1.67s, which is shorter. Moreover, when classifying the DTLZ2, WFG1, and UF1 datasets, the errors are all below 2%. The aforementioned findings demonstrate the accuracy and speed of the MOPSO-MOP model suggested in this study. Therefore, when using the MOPSO-MOP model for urban planning, it can accurately classify urban land optimization methods in a short period of time and select the optimal land optimization method based on the classification results. Finally, the KC and loss function values are analyzed. The results are shown in Fig. 8.




(a) Kappa coefficient (b) Loss function value

**Fig. 8.** Comparison of kappa coefficient and loss function values

The value of KC ranges from -1 to 1. When the value of KC is between 0.8 and 1.0, the dataset is classified with superior accuracy. When the KC is between 0.6 and 0.8, the classification is significantly consistent with the actual situation. When it is less than 0.6, the classification is unsatisfactory, while its value is less than 0, it indicates that the model is extremely poor in classification. In Fig. 8(a), the KC of the MOPSO-MOP model is almost always greater than 0.6 when it classifies different datasets. There are only very few experiments when its KC is lower than 0.6. In Fig. 8(b), the MOPSO-MOP model has low loss function values when classifying the four datasets, and most of its loss function values are lower than 0.2. The aforementioned experimental findings demonstrate the superior classification of the study's suggested MOPSO-MOP model, which has a lower error and a greater classification accuracy. Therefore, when the MOPSO-MOP model is applied to urban land use, it can accurately classify urban land use optimization methods and select the optimal urban land use optimization method based on the classification results. In addition, the convergence and stability of the algorithm are verified. The results are shown in Fig. 9.

In Fig. 9 (a), the MOPSO-MOP model has good convergence in all four datasets and can achieve convergence at around 20 iterations. In Fig. 9 (b), under the addition of Gaussian interference from 0~100Hz, although the classification accuracy of the MOPSO-MOP model is affected, its classification accuracy is still higher than 90%. This indicates high stability.

Therefore, this research constructs a MOPSO-MOP model on land use optimization for ULD, in an attempt to find the optimal planning method.

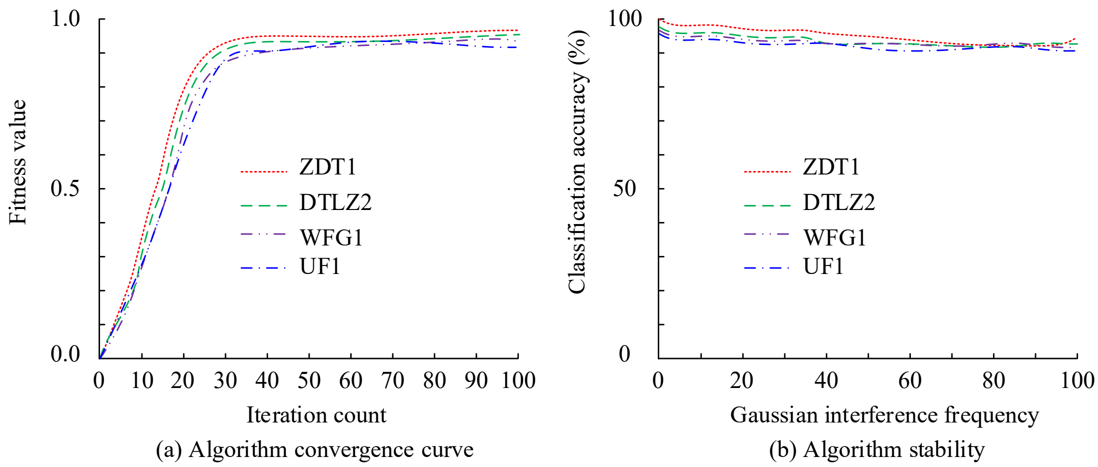



**Fig. 9.** Results of model convergence and stability testing

### 3.2. Practical Effects of Land Optimization Methods

The MOPSO-MOP model's performance is examined, and then the usefulness of the suggested ULD land optimization technique based on the model is examined. Various data on landscape design and land use in four cities A, B, C, and D are collected, including the area of urban forest land, grassland and construction land, the total area of land resources, and various data related to ecology and economy. The MOP model is constructed using the above data and solved using the MOPSO algorithm to obtain the optimal scheme of ULD land planning method. The land resource UR and FCR in this scheme are analyzed. The results are shown in Fig. 10.

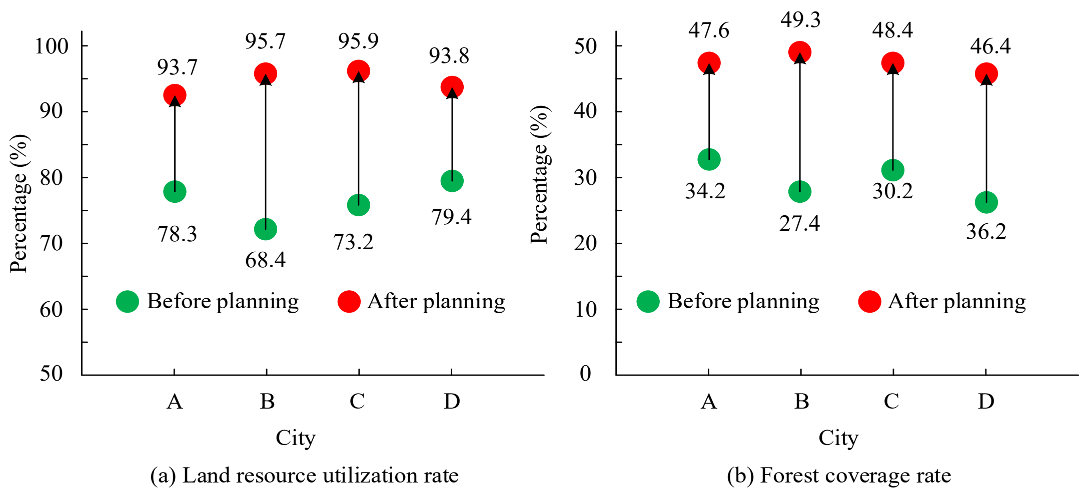
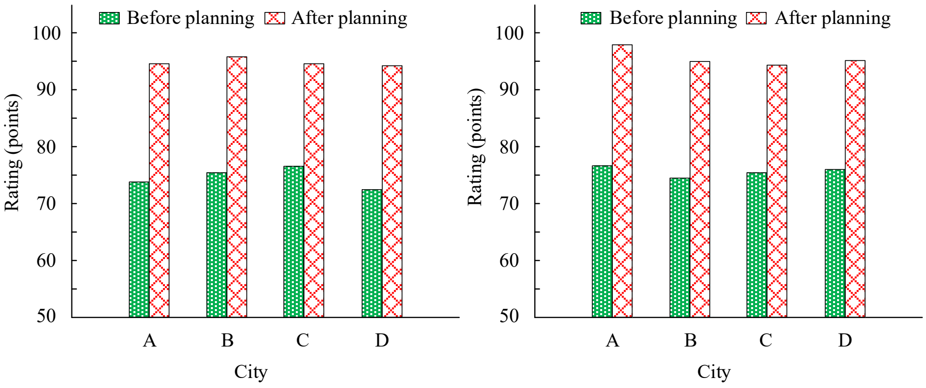



**Fig. 10.** Comparison of land resource utilization rate and forest coverage rate

In Fig. 10(a), the landscaping scheme planned by the MOPSO-MOP model is able to increase the land resource UR of the city A from 78.3% to 93.7%. It can increase the land resource UR from 27.3%, 22.7%, and 14.4% in cities B, C, and D, respectively. In Fig. 10(b), the FCR in different cities improves to varying degrees after planning. The FCR of city A has increased from 34.2% to 47.6%. The FCR of cities B, C and D are also increased. The landscape coordination and visual attraction of the scheme are then analyzed. The results are shown in Fig. 11.

In Fig. 11(a), the landscape coordination scores of the cities are all improved after planning by this model. Moreover, after planning, the landscape coordination scores of all four cities are higher than 90. In Fig. 11(b), the visual attraction scores of the cities are also improved after planning. Furthermore, after the improvement, their scores are also all higher than 90 points. Finally, the actual effects of this planning scheme are compared with the traditional artificial planning methods and the more advanced planning methods based on the Interactive Genetic Algorithm (IGA) and the Harmony Search-Artificial Fish Swarm Algorithm (HS-AFS) planning method. Table 2 displays the completed landscape design for City A, which is chosen for the project.



(a) Landscape coordination score (b) Visual attractiveness rating

**Fig. 11.** Rating Landscape Coordination and Urban Visual Attraction

**Table 2.** Comparison of actual landscape design effects

| Planning Methods | Land Utilization Rate | Forest Coverage Rate | State Environment Rating (points) | Landscape Coordination (points) | Visual Attractiveness (points) | Public Satisfaction |
|---|---|---|---|---|---|---|
| Manual planning | 78.3% | 34.2% | 78.3 | 73.4 | 76.5 | 67.8% |
| MOPSO-MOP | 93.7% | 47.6% | 94.7 | 93.9 | 97.4 | 92.7% |
| IGA | 89.7% | 40.3% | 87.3 | 82.3 | 80.5 | 83.4% |
| HS-AFS | 90.1% | 42.3% | 89.7 | 84.9 | 83.1 | 84.8% |

In Table 2, the MOPSO-MOP planning method, the IGA planning method, and the HS-AFS planning method are able to substantially improve the land UR and FCR of the city compared with the traditional manual planning method. However, among the three planning methods, the MOPSO-MOP planning method has the greatest improvement. This method can increase the land UR from 78.3% to 93.7%. It is also able to improve the ecological environment score from 78.3 to 94.7, and the urban landscape coordination from 73.4 to 93.9. The improvement of each index is higher than the IGA planning method and HS-AFS planning method. In conclusion, the suggested land use optimization approach for ULD based on the MOPSO-MOP model has a far better practical impact than both the existing planning method and the conventional design method.

## 4. Discussion

The current ULD method has the problems of low urban land resource UR and poor urban landscape coordination. Aiming at these problems, this study constructed a MOPSO-MOP model on ULD and land resource UR. Based on this model, an optimal urban landscape planning method was found to improve its land resource UR and landscape coordination. To verify the performance of the model, this study constructed the MOPSO-MOP model using the ZDT1 dataset, the DTLZ2 dataset, the WFG1 dataset and the UF1 dataset. The performance of the four models was also analyzed. The results revealed that the classification accuracies of all four models were relatively high, and the classification error of all four models was lower than 0.3%. In addition, the classification time of the models was also shorter, and the classification time in all four models was lower than 3s, which was better. This result was similar to that of Wang et al. (2023). However, the classification error in Wang et al.'s (2023) study was 2.3%, which was larger than the MOPSO-MOP model proposed in this study. This could be due to the fact that the MOPSO algorithm utilized in this study solves the MOP model, which could optimize more than one objective at the same time and could ensure the diversity of optimization objectives. In the study by Wang et al. (2023), only the PSO algorithm was used to solve the MOP model, and the optimization of OFs is prone to conflict with each other. This could result in the phenomenon of objective omission, which leads to a larger classification error. Then the practical effect of the ULD method obtained based on the model was analyzed. The outcomes revealed that the model could increase the UR of land resources to more than 90%. Meanwhile, the FCR of the city could be guaranteed to be more than 40%. Furthermore, the coordination score of the urban landscape planned by this method could reach more than 90 points. The visual attraction of the city could also be improved to more than 90 points. The above results were very similar to the results of Zhang et al. (2023). However, in Zhang et al.'s (2023) study, the effect of landscape coordination was slightly lower than the method proposed in this study. This might be due to the fact that the MOPSO-MOP model utilized in this study was able to incorporate both land use issues and urban landscape coordination issues, as well as ecological issues, into the model. This could lead to an optimal ULD approach. In summary, the land use optimization method proposed in the study can provide urban planners with an urban land planning method that can balance land use and urban landscape coordination.

The MOPSO-MOP model can also be integrated with GIS systems to support spatial data visualization and dynamic adjustment. When coupling the MOPSO-MOP model with a GIS system, it is necessary to develop a GIS-MOPSO-MOP interface module to convert spatial data into model input parameters and generate optimized vector planning maps. Moreover, in practical situations, urban data often suffers from issues such as inconsistent resolution, time lag, or lack of privacy. These issues can lead to model input bias. Consider using Kalman filtering or Bayesian updating to fuse multivariate data and dynamically adjust model parameters. In terms of policy, urban planning needs to be able to balance the government's GDP target, the economic interests of developers, and the ecological demands of residents. The preferences of different subjects are converted into weight vectors, and then the model is solved. At the same time, the planned urban land use methods consider the interests of residents, the government, and developers. It can meet their requirements to the greatest extent possible.

## 5. Conclusion

In response to the problems of underutilized urban land resources and inadequate coordination of urban landscapes in current ULD methods, this study proposes a MOPSO-MOP model for ULD and land resource utilization. Based on this model, the study identifies the optimal urban landscape planning method to improve its land resource utilization and landscape coordination. Moreover, the research results show that the MOPSO-MOP model has excellent classification performance. The land use optimization method based on this model can improve the urban land resource UR and urban landscape coordination score. In summary, the MOPSO-MOP-based model proposed in the study can provide a ULD method that accounts for both land-use and urban landscape coordination to improve the rationality of ULD and land use. However, the MOPSO algorithm used in this study to solve the MOP model is sensitive to parameters such as weights and acceleration factors. The parameter selection can lead to a decrease in the performance of the algorithm. In the future, the acceleration factor can be adaptively adjusted according to the evolution of the particles, or the IWs of the algorithm can be dynamically adjusted to improve the robustness of the algorithm. In addition, if there are social issues, such as government changes or developer bargaining in the city, the optimal urban land use method obtained may cause problems in urban planning.

## Funding

This research received no specific financial support from any funding agency.

## Institutional Review Board Statement

Not applicable.

## Declaration of Artificial Intelligence (AI) Tools

The author confirms that no AI tools were used in the preparation of this manuscript.

## References

Akaateba, M. A., Akanbang, B. A. A., and Korah, P. I. (2025). Planning public green spaces within customary land tenure contexts: Reflections on the limits to collaborative planning in Tamale, Ghana. *Journal of Urban Affairs*, 47(3), 856–879.

Darem, A. A., Alhashmi, A. A., Almadani, A. M., Alanazi, A. K., and Sutantra, G. A. (2023). Development of a map for land use and land cover classification of the Northern Border Region using remote sensing and GIS. *The Egyptian Journal of Remote Sensing and Space Science*, 26(2), 341–350.

Faria, J., Marques, C., Pombo, J., Mariano, S., and Calado, M. D. R. (2023). Optimal sizing of renewable energy communities: A multiple swarms multi-objective particle swarm optimization approach. *Energies*, 16(21), 7227–7243.

Gong, C., Zhou, N., Xia, S., and Huang, S. (2024). Quantum particle swarm optimization algorithm based on diversity migration strategy. *Future Generation Computer Systems*, 157(8), 445–458.

Gottero, E., Larcher, F., and Cassatella, C. (2023). Defining and regulating peri-urban areas through a landscape planning approach: The case study of Turin Metropolitan Area (Italy). *Land*, 12(1), 217–228.

Han, H., Liu, Y., Hou, Y., and Qiao, J. (2023). Multi-modal multi-objective particle swarm optimization with self-adjusting strategy. *Information Sciences*, 629(6), 580–598.

Jangir, P., Buch, H., Mirjalili, S., and Manohara, P. (2023). MOMPA: Multi-objective marine predator algorithm for solving multi-objective optimization problems. *Evolutionary Intelligence*, 16(1), 169–195.

Khalid, A. M., Hamza, H. M., Mirjalili, S., and Hosny, K. M. (2023). MOCOVIDOA: A novel multi-objective coronavirus disease optimization algorithm for solving multi-objective optimization problems. *Neural Computing and Applications*, 35(23), 17319–17347.

Ma, H., Zhang, Y., Sun, S., Liu, T., and Shan, Y. (2023). A comprehensive survey on NSGA-II for multi-objective optimization and applications. *Artificial Intelligence Review*, 56(12), 15217–15270.

Mirici, M. E. and Berberoglu, S. (2024). Terrestrial carbon dynamics and economic valuation of ecosystem service for land use management in the Mediterranean region. *Ecological Informatics*, 81(3), 102570–102584.

Nezafat Tabalvandani, M. A., Hosseini Shirvani, M., and Motameni, H. (2024). Reliability-aware web service composition with cost minimization perspective: A multi-objective particle swarm optimization model in multi-cloud scenarios. *Soft Computing*, 28(6), 5173–5196.

Ouma, Y. O., Keitsile, A., Nkwae, B., Odirile, P., Moalafhi, D., and Qi, J. (2023). Urban land-use classification using machine learning classifiers: Comparative evaluation and post-classification multi-feature fusion approach. *European Journal of Remote Sensing*, 56(1), 2173659–2173673.

Rahimi, I., Gandomi, A. H., Chen, F., and Mezura-Montes, E. (2023). A review on constraint handling techniques for population-based algorithms: From single-objective to multi-objective optimization. *Archives of Computational Methods in Engineering*, 30(3), 2181–2209.

Sun, X., Ma, Q., and Fang, G. (2023). Spatial scaling of land use/land cover and ecosystem services across urban hierarchical levels: Patterns and relationships. *Landscape Ecology*, 38(3), 753–777.

Tamirat, H., Argaw, M., and Tekalign, M. (2023). Support vector machine-based spatiotemporal land use land cover change analysis in a complex urban and rural landscape of Akaki river catchment, a suburb of Addis Ababa, Ethiopia. *Heliyon*, 9(11), 45–87.

Tariq, A. and Mumtaz, F. (2023). A series of spatio-temporal analyses and predicting modeling of land use and land cover changes using an integrated Markov chain and cellular automata models. *Environmental Science and Pollution Research*, 30(16), 47470–47484.

Usman, A. M. and Abdullah, M. K. (2023). An assessment of building energy consumption characteristics using analytical energy and carbon footprint assessment model. *Green and Low-Carbon Economy*, 1(1), 28–40. https://doi.org/10.47852/bonviewGLCE3202545

Wang, Z., Pei, Y., and Li, J. (2023). A survey on search strategy of evolutionary multi-objective optimization algorithms. *Applied Sciences*, 13(7), 4643–4657.

Zhang, L., Qiu, Y. F., Chen, Y., and Hoang, A. T. (2023). Multi-objective particle swarm optimization applied to a solar-geothermal system for electricity and hydrogen production; Utilization of zeotropic mixtures for performance improvement. *Process Safety and Environmental Protection*, 175(4), 814–833.

Zhang, Z., Wang, X., Zhang, Y., Gao, Y., Liu, Y., and Sun, X. (2023). Simulating land use change for sustainable land management in rapid urbanization regions: A case study of the Yangtze River Delta region. *Landscape Ecology*, 38(7), 1807–1830.

Qingxuan Li, born January 1993, is a female of Han ethnicity, a native of Yangzhou, Jiangsu, China. She holds a master's degree and currently serves as a Lecturer. She completed both her bachelor's and master's studies at Nanjing Forestry University. Her primary research focuses on urban landscape design, landscape planning, and smart design.
Work Experience: Since September 2019, she has been a full-time faculty member in the College of Art and Design at Communication University of China, Nanjing, teaching in the Environmental Design program.