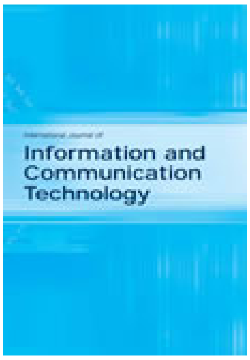

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Multi-objective optimisation for sustainable landscape planning using genetic algorithms

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Abstract: Rapid urbanisation intensifies pressures on urban landscapes, driving sustainability challenges like ecological degradation and unequal green space access. This study develops a genetic algorithm (GA)-based multi-objective optimisation (MOO) framework for sustainable landscape planning in Nanchang City's first ring road. The non-dominated sorting genetic algorithm II (NSGA-II) is adopted to simultaneously optimise ecological, social and economic objectives. Spatial data, including land use and population density, are integrated within a grid-based model, with constraints such as ecological protection lines. In the park green space case, optimisation achieves 100% service coverage, reduces residents' total travel time by 28.2%, increases 15-minute accessible population from 70.35% to 94.31%, and enhances efficiency. The Pareto optimal solution set illustrates critical trade-offs, while the optimised spatial layout demonstrates significant accessibility gains. This approach provides a robust decision-making tool for sustainable urban development, balancing ecological integrity, social equity, and economic viability in high-density environments.

Keywords: multi-objective optimisation; MOO; non-dominated sorting genetic algorithm II; NSGA-II; sustainable landscape planning; genetic algorithm; GA.

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1 Introduction

Rapid urbanisation worldwide has put unprecedented pressure on urban landscapes, leading to a series of sustainability challenges, including ecological degradation, spatial fragmentation of green spaces, unequal distribution of recreational resources, and increased economic costs of land development and maintenance (Bastian et al., 2006; Breuste et al., 2008). As an important component of urban ecosystems and public well-being, urban green spaces (UGS), especially parks and green spaces in urban cores such as the first ring road, play a crucial role in providing key ecosystem services (e.g., air purification, climate regulation, and biodiversity conservation), enhancing human well-being (e.g., recreation, physical and mental health), and promoting social equity. However, the planning and optimisation of UGS usually involves complex spatial decisions that need to balance multiple and often conflicting objectives under strict resource and spatial constraints (Albert et al., 2016; Deng et al., 2022).

The city of Nanchang, especially its area within the First Ring Road, is a prime example of the above challenges (Li et al., 2015). As a rapidly growing city in China, Nanchang is under tremendous pressure to accommodate population growth and economic activities within its limited urban space. The existing green space layout within the First Ring Road area is characterised by an insufficient amount of green space, uneven spatial distribution, and poor connectivity. This has resulted in low coverage of residential services (e.g., many areas lack green spaces within reasonable walking distance), impaired ecological functions (e.g., degradation of habitat quality and landscape connectivity), and inefficient utilisation of land resources.

Traditional landscape planning methods tend to rely heavily on expert experience, qualitative analysis and single-objective optimisation models. These approaches have difficulty quantifying the complexity, multidimensionality (ecological, social, economic), spatial explicitness, and conflicting objectives inherent in sustainable landscape planning goals. For example, maximising ecological protection may conflict with the goal of maximising the area of land available for development or ensuring equitable access to recreational opportunities for all residents. Achieving true sustainability requires a shift to a MOO framework that explicitly addresses these trade-offs and generates a set of optimal compromises.

It is found that a significant amount of research has been invested in examining landscape planning approaches and their associated impacts. Leitao and Ahern (2002) proposed integrating landscape ecology metrics into sustainable landscape planning, establishing a core set of nine metrics (e.g., patch richness, edge contrast) to quantify spatial patterns. Their dual-perspective framework (horizontal cross-sectoral integration and vertical planning phases) enhanced ecological decision-making, demonstrated in the Mill River Watershed case where build-out scenarios reduced wildlife habitat by 80% and connectivity (MPI) by 90%. Grahn and Stigsdotter (2003) investigated the relationship between urban open green spaces and residents' stress levels in Swedish cities. They found that individuals visiting UGS more frequently reported lower stress levels, and those living closer to green areas exhibited less stress. The study emphasised the significance of accessible green spaces for stress reduction. von Haaren et al. (2014) explored the divergence between landscape planning and design within the discipline of landscape architecture. They identified substantive and process values distinguishing the two cultures, and proposed a framework for integrating design approaches into landscape planning to enhance communication and understanding of planning objectives. Albert et al. (2014) explored integrating ecosystem services (ES) into landscape planning, synthesising 12 cases across Europe, Australia and Africa. They identified key requirements: adapting ES information to specific planning contexts, diverse participatory approaches (cognitive mapping, scenario planning), and impacts like improved communication and decision-support. Planners found ES useful for communicating nature's value but noted challenges like definition confusion and economic valuation concerns. Neuendorf et al. (2018) reviewed uncertainty in landscape planning, analysing 65 relevant papers (1996–2016). They classified uncertainties into data, model, projection, and evaluation types. Identified assessment methods included Monte Carlo, fuzzy, and sensitivity analyses; coping strategies involved Bayesian Networks, adaptive planning, and scenarios. Findings showed scientific progress on uncertainty assessment, but practical integration into plans and communication to decision makers remained limited. Liu and Li (2020) developed a GIS-AHP method for mountainous city landscape planning, combining GIS-based ecological sensitivity analysis (topography weight: 54%, river systems: 30%) with AHP resource assessment (natural resources weight: 53.9%). Applied in Jiangxi County, China, their approach identified 16.15% of the area as highly sensitive, guiding a 'one-vein, two-belts' spatial structure that retained 91.7% of predictive features while optimising tourism-resource protection. Liu (2020) developed a virtual reality-based 3D visualisation system for urban landscape planning and design, specifically targeting challenges in integrating designs into large-scale scenes and improving planning efficiency. Their approach established 3D databases and virtual scene models, achieving enhanced realism and design quality through spatial roaming algorithms and simulation experiments. Results showed VR technology improved efficiency by facilitating interactive adjustments, with simulation outcomes confirming reduced modelling errors and optimised landscape integration. Haghani et al. (2023) conducted a bibliometric analysis of urban planning research using nearly 100,000 articles, specifically identifying structural divisions and temporal trends through document co-citation and term co-occurrence methods. They identified four major clusters (governance/policy, built/natural environment, economics/markets, housing), with activities shifting towards resilience and smart cities post-2010. International collaboration rose to 21.4% in 2010–2021, outperforming earlier periods by 12.5%, while cluster analysis revealed foundational references influencing modern paradigms like participatory planning and UGS.

In this paper, a sustainable landscape planning model optimised by GA is proposed, with core innovations including:

1 MOO framework: construct a NSGA-II-based optimisation system to balance ecological, social, and economic objectives in landscape planning. Specifically, minimise heat island intensity, maximise green space coverage within 500 m radius, and minimise development costs. This framework addresses the conflicting nature of these objectives by generating a set of Pareto optimal solutions.

2 Quantitative indicator system: develop a comprehensive set of indicators for sustainable landscape planning, including ecological sustainability, social-cultural sustainability, and economic sustainability. These indicators enable systematic evaluation of planning schemes from multiple dimensions.

3 Spatial optimisation mechanism: implement a spatial optimisation process that integrates Future Land Use Simulation (FLUS) simulation for baseline scenario generation and NSGA-II for MOO. Experiments in Nanchang's first ring area demonstrate the model's effectiveness in generating Pareto optimal solutions that achieve a balanced trade-off between ecological improvement, social equity, and economic efficiency. The selected optimal solution achieves 100% green space coverage, reduces total travel time to parks by 28.2%, increases 15-minute accessibility to 94.31%, and improves population served per unit area by 19.7%.

The remainder of this paper is organised as follows: Section 2 introduces the foundational technologies, including the MOO and NSGA-II. Section 3 elaborates on the design and implementation of the NSGA-II model. Section 4 provides a case analysis of MOO of sustainable park green space landscapes using GA. Finally, Section 5 concludes the study.

2 Relevant technologies

2.1 Multi-objective optimisation and NSGA-II

2.1.1 Multi-objective optimisation problems.

A multi-objective optimisation problem is a class of mathematical problems in which multiple conflicting objective functions are optimised simultaneously in the decision-making process (Konak et al., 2006; Gunantara, 2018). Unlike single-objective optimisation, the core challenge lies in the trade-off between the objectives, i.e., improving one objective may lead to degradation of the performance of other objectives, so there is no single optimal solution, but a set of equilibrium solutions, which is called the Pareto set of optimal solutions, should be sought. Its standard form can be expressed as:

$$\min_{\mathbf{x}\in\Omega} \mathbf{F}(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_M(\mathbf{x})\right]^T \tag{1}$$

where $\mathbf{x}$ is the decision vector, Ω is the feasible solution space, $M \geq 2$ is the number of objective functions, and there is usually a conflict between the objectives, for example, the ecological benefits of landscape planning often lead to an increase in development costs.

A solution $\mathbf{x}^*$ is called a Pareto-optimal solution when and only when there is no other solution $\mathbf{x}$ satisfying the following conditions:

$$\begin{aligned} &\forall i \in \{1, 2, \ldots, M\} : f_i(\mathbf{x}) \leq f_i\left(\mathbf{x}^*\right) \\ &\exists j : f_j(\mathbf{x}) < f_j\left(\mathbf{x}^*\right) \end{aligned} \tag{2}$$

This definition suggests that it is not possible to improve any one objective without compromising at least one other objective. The surface formed by all Pareto optimal solutions in the objective space is called Pareto Front, and its shape, convexity, and continuity directly affect the optimisation difficulty. MOO is widely used in scenarios where multiple demands need to be weighed, such as engineering design, resource management, finance and economics, environment and energy.

2.1.2 Fundamentals of GA

GA, proposed by John Holland in 1973, is a kind of heuristic search algorithm that simulates the process of biological evolution, and its idea originates from Darwin's theory of 'natural selection', which is to search for the optimal solution or near solution in the solution space by simulating the selection, crossover, and mutation mechanisms in biological evolution (Haldurai et al., 2016; Katoch et al., 2021). By simulating the selection, crossover and mutation mechanisms in biological evolution, it searches for the optimal solution or near-optimal solution in the solution space. The core of the algorithm is to iteratively improve the population through selection, crossover and mutation operations, and gradually approach the optimal solution. GAs are widely used in combinatorial optimisation, function optimisation and machine learning (Alhijawi and Awajan, 2024). The algorithm process includes: encoding, fitness evaluation, selection, crossover and mutation.

- Encoding: represent the solution as a chromosome structure. One common encoding method is binary encoding, which is suitable for discrete variables, e.g., site type selection. Another method is real number coding, which is suitable for continuous variables, such as green space area ratio.
- Fitness evaluation: used to design fitness functions to quantify individual quality. In landscape planning, this can be defined as a weighted combination of ecological, social and economic objectives.
- Selection: selection of high-quality individuals into the next generation according to fitness. One common method is roulette selection, where the probability of selecting an individual is proportional to its fitness. Another method is tournament selection, in which k individuals are randomly selected and the one with the highest fitness is retained.
- Crossover: simulates genetic recombination to generate new individuals by exchanging paternal chromosomes. Typical methods include single point crossover and simulated binary crossover. The former is suitable for binary coding and the latter for real number coding.
- Mutation: randomly changing gene values with low probability to maintain population diversity, which can be achieved by, for example, bit-flipping in binary coding or adding Gaussian noise to real number coding.

2.1.3 Core mechanism and algorithmic flow of NSGA-II

Non-dominated sorting genetic algorithm II is a MOO algorithm proposed by Deb et al. in 2002, which is one of the most influential algorithms in the field of MOO (Yusoff et al., 2011; Ma et al., 2023). It solves the limitations of traditional GA and efficiently solves the Pareto-optimal solution set of multi-objective problems through the three core mechanisms of fast non-dominated sorting, congestion computation and elite strategy. Its specific workflow diagram is shown in Figure 1.

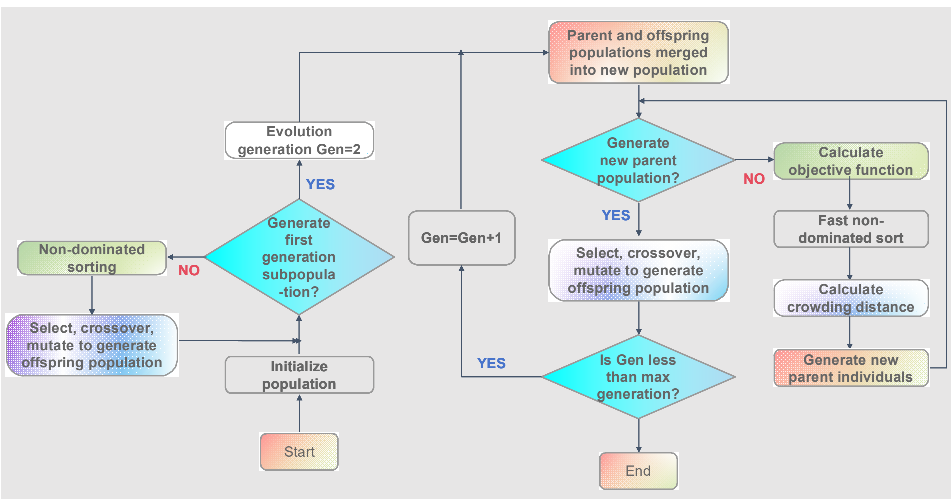
- Fast non-dominated sort: the population is stratified according to the Pareto hierarchy to ensure that high-priority solutions are retained first. First, the dominated count of each individual is calculated at n_i and the dominated set at S_i, then the individuals with $n_i = 0$ are grouped into the first frontier at, then after removing the individuals at F_1, the remaining individuals are updated at n_i, and those with the new $n_i = 0$ are grouped into F_2, and finally the process is repeated until all the individuals have been stratified.
- Crowding distance: used to quantify the distribution density of individuals within the same frontier, to maintain the diversity of solutions within the same non-dominated layer, and to avoid aggregation of solution sets, its formula is:

$$d_i = \sum_{m=1}^{M} \frac{\left| f_m\left(i_{next}\right) - f_m\left(i_{prev}\right) \right|}{f_m^{\max} - f_m^{\min}} \tag{3}$$

where i_{next} and i_{prev} are neighbouring individuals in the target space, and the boundary individual distance is set to ∞. The larger the crowding in the same hierarchy, the sparser the solution and the higher the priority.

- Elitism: by merging the parent population with the offspring population, non-dominated sorting and crowding distance calculation are performed on R_t, from which the optimal N individuals are selected to enter the next generation. This prevents the loss of quality solutions and accelerates the convergence to the global Pareto frontier.

Figure 1 Workflow diagram of NSGA-II (see online version for colours)



2.2 *Quantitative indicators for sustainable landscape planning*

The construction of the quantitative index system for sustainable landscape planning originates from the reflection on the traditional planning methods. Early landscape planning overly relied on subjective aesthetic evaluation and economic orientation, and lacked systematic metrics on ecological and social dimensions. In the 1990s, with the popularisation of the concept of sustainable development, the field of landscape planning began to introduce the triple-bottom-line theory, which requires a comprehensive assessment of the planning scheme from the three dimensions of ecological integrity, social fairness, and economic feasibility. After entering the 21st century, the integration of landscape ecology and systems science has spawned innovations in quantitative analysis techniques. For example:

1 landscape pattern indices (e.g., patch density, edge effect index) have realised the objective measurement of ecological spatial structure through remote sensing and GIS technology

2 ecosystem service valuation models (e.g., InVEST) have transformed ecological functions into calculable monetary or physical units.

These advances have laid a methodological foundation for the scientificisation of the quantitative indicator system. This article analyses ecological sustainability indicators, socio-cultural sustainability indicators, and economic sustainability indicators.

2.2.1 Ecological sustainability indicators

Ecological sustainability indicators include thermal environmental regulation efficiency, water sustainability and biodiversity maintenance capacity. Thermal regulation efficiency is quantified by regression analysis of land surface temperature (LST) and green space cover, and the cooling intensity coefficient is defined to indicate the cooling value per unit of green space area. The reference indicators of water sustainability are the reduction rate of rainwater runoff and the proportion of water reuse, which are obtained by simulating the changes of runoff under different green space layouts with the SWMM model. Biodiversity maintenance capacity is quantified by calculating the vegetation community richness using Shannon diversity index, the specific formula is:

$$H = -\sum_{i=1}^{S} p_i Inp_i \tag{4}$$

where S is the number of species and p_i is the proportion of species i.

2.2.2 Socio-cultural sustainability indicators

The socio-cultural sustainability indicators include cultural identity, landscape visual quality and equity of green space services. The indicators of cultural identity are the application rate of native plants and the retention density of historical elements, which are quantified by public questionnaire survey and heritage census. The quantitative model of landscape visual quality is based on the dynamic visual quantification technique, which calculates the proportion of natural landscape in the visual field. It can be realised by combining drone aerial photography and image semantic segmentation algorithm. Green space service equity is quantified by the accessibility coverage ratio, which is expressed as the proportion of population served by green space within a 500-meter radius of a settlement, and is calculated by the formula:

$$C = \frac{N_{covered}}{N_{total}} \times 100\% \tag{5}$$

where $N_{covered}$ is the population covered and N_{total} is the total population.

2.2.3 Economic sustainability indicators

The economic sustainability indicators include resource utilisation efficiency and full life cycle cost-effectiveness. The core indicators of resource efficiency are renewable energy coverage and material recycling rate. The components of total life cycle cost-effectiveness are shown in Table 1.

Table 1 Full life cycle cost effectiveness

Cost type	*Quantitative indicator*	*Calculation basis*
Initial investment	Unit green space construction cost (RMB/m^2)	Reference to regional engineering quotas
Long-term maintenance	Average annual maintenance cost (RMB/year)	Historical operation and maintenance data statistics
Hidden benefits	Property appreciation rate (%)	Comparative analysis of neighbouring property prices

3 Multi-objective GA optimisation model construction and case application

3.1 Research area and database

In this study, the first ring road area of Nanchang City, Jiangxi Province, China, with an area of about 320 km^2, is selected as the object of empirical research, and the basis of its selection stems from the typicality and contradiction complexity of this area in the city cluster of the middle reaches of the Yangtze River in China. As the capital of Jiangxi Province and the core city of the city cluster in the middle reaches of the Yangtze River, Nanchang has both the demand for high-intensity urbanisation and ecological safety barrier functions, with a built-up area density of 78.2% in 2023, a peak heat island intensity of 3.5°C, a superposition of the ecologically sensitive areas of the Ganjiang River and Poyang Lake, and an ecological protection red line accounting for 23.7% of the area. The conflict of 'three districts and three lines' focuses on the game of waterfront space development and ecological protection, and the construction land encroachment on the ecological zone will be 1.2 km^2 per year from 2021 to 2023, which highlights the urgency of the balance between protection and development, and is in line with the core scientific issue of the balance between development and protection in the territorial spatial planning. It is in line with the core scientific issue of 'development and protection' balance in territorial spatial planning. The study area covers three types of spatial units, namely, the old city, the Gan River waterfront and the suburban ecologically sensitive areas, and the spatial resolution is set at 100 m × 100 m raster, with a total of about 32,000 decision-making units, which meets the demand for micro-spatial optimisation and avoids uncontrolled computational complexity. The spatial scope covers three types of gradient differentiation units, namely, the old city (42%), the Gan River waterfront zone (28%) and the suburban ecological zone (30%).

The research data system integrates heterogeneous spatial data from multiple sources, and the data integration strictly follows the standard of 'one map' for territorial spatial planning (GB/T 39972-2021). Four types of datasets were constructed through coordinate standardisation (CGCS2000 coordinate system), format conversion (GeoTIFF/Shapefile), and accuracy verification (kappa coefficient ≥ 0.5): basic geographic information, planning constraints, dynamic monitoring, and modelling support.

3.1.1 Basic geographic information data.

For the current land use situation, based on the results of the third survey of China's land (precision 1:2,000), eight types of land information are extracted, such as construction land, greenland, water, etc., and the spatial distribution matrix L_{ij} is generated through rasterisation, i and j represent the raster row and column numbers, with a data volume of about 15.2 GB, and the integrity of the attribute fields is 100%. For the population density distribution, the kernel density model is constructed by integrating the cell phone signalling data (12 million daily sampling points) and the unit statistics of the seventh population census of China:

$$\rho(x, y) = \sum_{k=1}^{n} \frac{1}{2\pi h^2} \exp\left(-\frac{d_k^2}{2h^2}\right) \tag{6}$$

where d_k is the distance from the residential point k to the target grid, h is the bandwidth, which is set to 500 m, to generate the population density map of 500 m × 500 m grid, and the missing values are interpolated by the spatial lag model, $\rho = 0.72$. The 500 m distance is a widely adopted and empirically supported standard for pedestrian accessibility to local public services, especially green spaces. This scale is appropriate for representing the influence radius of local population centres.

For the road network topology, the data of primary and secondary roads are extracted from OpenStreetMap with a total length of 1,850 km, and the road network density index is calculated by:

$$R_d = \frac{\sum L_{road}}{A_{cell}} \tag{7}$$

where L_{road} is the length of roads in the raster and A_{cell} is the raster area.

3.1.2 Planning constraint data

For the ecological protection red line, based on the document 'Nanchang City Land Space Master Plan (2021–2035)', the boundary of the ecological protection zone (area accounted for 23.7%) and control rules were extracted with a spatial accuracy of ±5 m. For the LST, the inversion was performed using Landsat 8 thermal infrared bands (path/row: 123/39), and the summer daytime mean temperature was generated through radiometric calibration and atmospheric calibration to generate the summer daytime mean temperature field. The formula for the heat island intensity index is shown as:

$$\Delta T = \frac{1}{n} \sum_{i=1}^{n} (T_i - T_{base}) \tag{8}$$

where T_{base} is the reference temperature of suburban farmland, 28.5°C is taken in this paper, and the area of $\Delta T > 2.0$°C is labelled as the core area of the heat island, with the inversion error of ±0.8°C (Lütz and Bastian, 2002).

3.1.3 Dynamic monitoring data

For the green space service coverage, combined with the GOOD MAP POI and community boundaries, the green space coverage blind zone of 500 m radius in the residential area was calculated, and the blind zone identification accuracy is 92.1%. For the remote sensing inversion of vegetation biomass, based on the Sentinel-2 NDVI time series data, the vegetation cover is estimated using the image element binary model F_{VC}. The formula is:

$$F_{VC} = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \tag{9}$$

where $NDVI_{soil} = 0.05$ for bare soil and $NDVI_{veg} = 0.75$ for arborvitae canopy.

3.1.4 Model support data.

For the land demand forecast, based on the Nanchang land spatial planning 'one map' platform, the upper limit of construction land increment in 2025 is extracted as 42 km^2. As for the development cost parameters, referring to the 'Jiangxi Province Construction Engineering Standard', the unit development cost of residential land is 1,850 RMB/m^2, and that of industrial land is 1,200 RMB/m^2.

3.2 Model framework design

This study builds a three-stage framework of 'scenario simulation-multi-objective optimisation-decision support', and realises multi-objective synergistic optimisation of land space by coupling FLUS scenario simulation and NSGA-II optimisation engine. The technical routes are as follows:

3.2.1 Basic scenario generation module.

Based on the current land use data of Nanchang and the spatial constraints of three zones and three lines, the FLUS model is used to simulate the land use pattern under the natural development scenario. Its core algorithm is:

$$TP_{k,i}^{t} = P_k \times \Omega_{k,i}^{t} \times \theta_{k,i} \tag{10}$$

where $TP_{k,i}^{t}$ is the probability that the raster i is converted to the type k at the time of t. P_k is the probability of land type demand predicted by Markov chain; $\Omega_{k,i}^{t}$ is the neighbourhood coupling coefficient; $\theta_{k,i}$ is the spatial constraint coefficient, $\theta = 0.01$ within the ecological red line, and $\theta = 0.05$ for basic farmland. This module outputs the 2035 no-intervention scenario as the initial population seed of the GA.

3.2.2 MOO module.

NSGA-II is used as the optimisation engine to set a triple optimisation objective:

- ecological objective: minimise the heat island intensity $\min f_1 = \sum_{i=1}^{n} (LST_i \times (1 - G_i))$, G_i is the green space share of the raster i, LST is derived from the inversion data

- social objective: maximise the green space coverage of 500 m, $f_2 = \frac{1}{N}\sum_{j=1}^{N} I,\ I$ is the indicator function
- economic objective: minimise the development cost $\min f_3 = \sum_k (C_k \times S_k),\ C_k$ is the site type k unit development cost.

3.2.3 Decision output module.

Through the Pareto frontier analysis to identify the non-dominated solution set, this paper adopts TOPSIS to approximate the ideal solution to screen the comprehensive optimal solution, and the weights are set according to the Nanchang City planning guide, and set as ecological: social: economic= 0.5: 0.3: 0.2.

3.3 Coding scheme

The optimisation object of the decision variables is the land use type of the raster unit, in this paper, the set of land use types is simplified into four categories: eco-greenland, residential land, industrial land and commercial land.

This paper adopts the integer coding scheme, each raster as a gene position, the chromosome for the whole domain land use type sequence. The coding is based on:

1 merging the eight types of land in the 'three adjustments' to four types of planning and control types, such as commercial and logistics warehousing merged into 'commercial land', to realise the simplification of the types

2 defining the probability of transferring the types to each other through the matrix to realise the conversion constraint

3 the activation of genetic value of industrial land should meet the distance of road network from the main road ≤ 500 m.

The specific scheme is shown in Table 2.

Table 2 Coding scheme

Gene value	*Site type*	*Conversion rules*	*Economic cost coefficient*
1	Ecological green space	Cannot be converted to building land	0
2	Residential land	Neighbourhood population density > 500 persons/km^2 must be met.	1.0
3	Industrial land use	≤500 m from main roads and avoiding ecologically sensitive areas	0.8
4	Commercial land use	Prioritise the blind area covered by the service radius	1.2

1 Coefficient 0 (ecological green space): this coefficient is assigned based on mandatory planning constraints. Areas within the ecological protection red line are legally prohibited from any development or conversion. Therefore, the effective economic cost for any development project within these zones is considered infinite, which is represented by a multiplicative coefficient of 0 for the developable area, effectively nullifying any development potential in the cost calculation.

2 Coefficient 1.0 (residential land): this is the baseline reference cost. It represents the standard average unit development cost or typical residential land under normal conditions within the study area. The other coefficients are calibrated relative to this baseline.

3 Coefficient 0.8 (industrial land use): this coefficient is derived from a comparative cost analysis. Industrial land development typically requires less investment in certain amenities compared to high-standard residential or commercial areas. The 20% reduction reflects this lower average unit cost.

4 Coefficient 1.2 (commercial land use): this coefficient is applied to high-standard public or commercial green spaces. It accounts for the premium costs associated with higher-quality materials, specialised landscape design, advanced irrigation systems, enhanced maintenance requirements, and the integration of complex amenities. The 20% premium quantifies this additional investment.

The composite objective function *F* is defined as the weighted normalised value of the three sub-objectives and can be expressed as:

$$F = \omega_1 \cdot \frac{f_1 - f_{1,\min}}{f_{1,\max} - f_{1,\min}} + \omega_2 \cdot \frac{f_2 - f_{2,\min}}{f_{2,\max} - f_{2,\min}} + \omega_3 \cdot \frac{f_3 - f_{3,\min}}{f_{3,\max} - f_{3,\min}} \tag{11}$$

where $\omega_1 = 0.5$, $\omega_2 = 0.3$, $\omega_3 = 0.2$, $f_{\min}$ and $f_{\max}$ are pre-calibrated by single-objective optimisation. Meanwhile, the compactness correction operator is introduced to improve the spatial continuity:

$$Comp_{ij} = \frac{1}{M_{neigh}} \sum_{m=1}^{8} \delta\left(type_{ij}, type_{mn}\right) \tag{12}$$

where δ is a Kronecker function with the value of 1 when the neighbourhood raster (m, n) is of the same type as the core raster (i, j). This operator embeds the mutation operation to drive the patch compactness ≥ 0.6.

4 Case study – MOO of sustainable park green space landscape using GA

As an important carrier of urban ecosystem and residents' leisure activities, the rationality of the spatial layout of urban park green space is directly related to the quality of urban habitat and the improvement of residents' well-being. Aiming at the current situation of park green space layout in Nanchang's first ring road area, where there are service blind zones, imbalance between local supply and demand, and service efficiency to be improved, this study is based on the MOO model of 'ecology-society-economy' constructed in above, which is further extended to 'fairness-efficiency-economy' and 'equity-economy'. Based on the 'ecological-social-economic' MOO model constructed in above, this study further extends the model to 'equity-efficiency-economy', aiming to explore the optimisation path of the layout of parks and green spaces in the region through scientific planning. In this section, the core objectives and guiding principles of this optimisation practice are clarified to lay the foundation for the subsequent solving and application of the model.

4.1 Optimisation goal setting and principles

The core objective of optimisation closely focuses on enhancing the comprehensive benefits of the park green space system, specifically focusing on the following three interrelated dimensions with certain trade-offs: fairness, efficiency and economy.

To achieve these goals and ensure the scientific and implementable nature of the optimisation plan, the optimisation process follows the following core principles: the principle of fairness first, the principle of efficiency enhancement, the principle of economic sustainability, and the principle of coordinated optimisation. The principle of equity priority requires that the optimisation plan must give priority to solving the problem of absolute lack of service coverage, and focus the new park resources on high demand areas (such as densely populated residential areas with a lack of parks) that are currently unserved or seriously underserved, to ensure the equalisation of basic public services. The principle of efficiency enhancement emphasises that the location of new parks should focus on maximising the contribution to the overall service efficiency of the system, i.e., priority should be given to those locations that can significantly reduce the average travel time of the residents, effectively divert the service pressure of high-load parks, and serve more people, to avoid inefficient investment of resources. The principle of economic sustainability requires that, on the premise of meeting the coverage constraints and efficiency enhancement targets, land resources are utilised in a smart way, and by optimising the combination of park scale and location, efforts should be made to achieve the optimal comprehensive benefits with the smallest amount of new land area, reflecting the concept of smart growth. In addition, the principle of coordination and optimisation is also worthy of attention, which requires that the optimisation plan should be coordinated with the city's overall planning, green space system planning, and the current large-scale ecological patches, to ensure that the new parks can be organically integrated into the city's spatial structure, and play a greater ecological and landscape benefits. At the same time, the model sets a clear constraint that the optimisation scheme must achieve 100% service coverage and eliminate service blind zones.

4.2 Model solution

This subsection will elaborate the model solving process and its core output, the Pareto optimal solution set. The core input data of the solution process include:

1. Candidate park sites: through the preliminary GIS spatial analysis, based on the full consideration of the current conditions, planning constraints and potential available open space, 39 potential new park sites with feasibility have been screened and identified within the study area, which serve as the optional range of decision variables for the optimisation model.

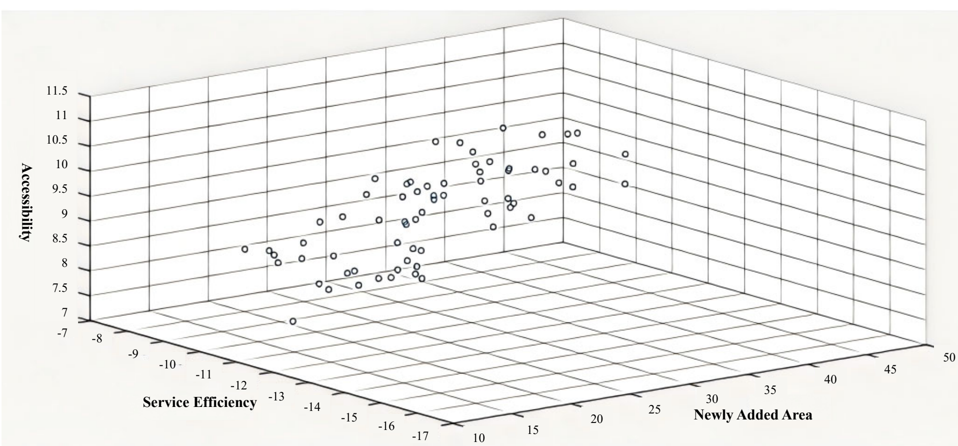
2 Objective function: the three core objectives that need to be optimised at the same time – maximise the overall service efficiency of the park green space system (usually reflected in the service population per unit area or the service efficiency index), minimise the average reachable time for residents to reach the nearest park (or the total time cost, which represents the equity of accessibility), and minimise the total area of new parks (which represents the economy).

3 Constraints: the most important constraint is to ensure that the optimisation scheme achieves 100% service coverage, i.e., eliminating all status quo service blind areas.

In addition, key parameters are set during the algorithm operation, such as the population size is set to 300, the maximum number of evolutionary generations is set to 300, and the crossover probability and the mutation probability are set to 0.8 and 0.1, respectively, which are selected with the aim of balancing the algorithm's searching capability and computational efficiency to ensure that a high-quality solution set is obtained within a reasonable time.

After the iterative operation of the algorithm, the Pareto optimal solution set representing the solution of the MOO problem is finally successfully obtained. To visualise the optimisation results and understand the complex trade-offs between the objectives, the Pareto front is plotted as shown in Figure 2, where each point on the Pareto front represents a feasible layout plan that achieves an optimal balance between resource inputs and benefit outputs. These scenarios provide a rich pool of alternatives for subsequent in-depth analysis and selection of the final scenario.

Figure 2 Optimisation model Pareto optimal solution set



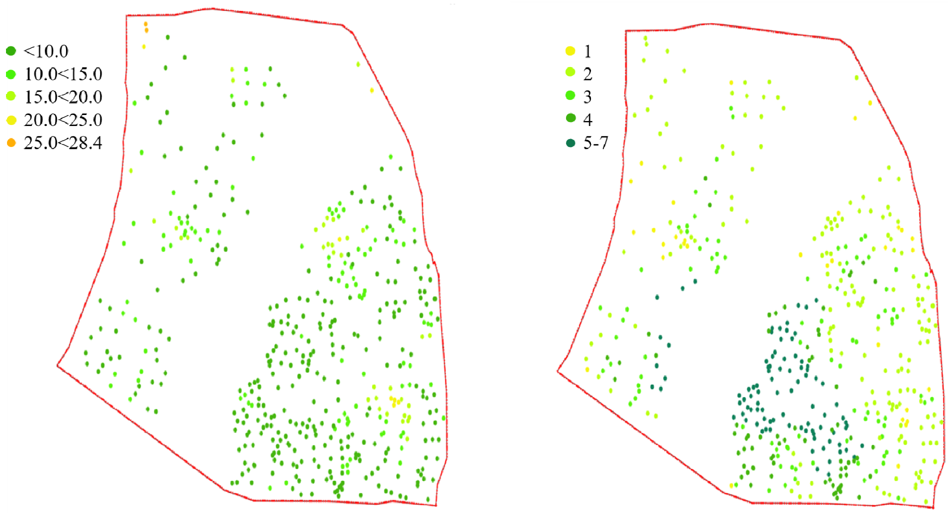
4.3 Result analysis and program selection

Based on the Pareto optimal solution set generated by the MOO model in Figure 2, three typical scenarios are selected for in-depth comparative analysis, namely: scenario 1 (four new parks), scenario 2 (nine new parks) and scenario 3 (14 new parks). These scenarios represent optimisation paths with different trade-offs, aiming to balance the three core objectives of fairness (eliminating service blind spots), efficiency (improving service efficiency) and economy (controlling new area). A comparison of the key indicators of the optimisation schemes is shown in Table 3.

Table 3 Comparison of key indicators of optimisation schemes

Evaluation indicators	*Status quo benchmark*	*Scenario 1*	*Scenario 2*	*Scenario 3*
Service coverage (%)	87.65	100.00	100.00	100.00
Total park area (m^2)	3,407,770	3,715,060	3,750,170	3,864,260
Total time cost from the settlement to the nearest park (min)	89.03	75.66	68.26	63.88
Proportion of residents reachable within 15 minutes (%)	0.35	82.17	89.64	94.31
Average population served per unit area (persons/10 m^2)	1.52	1.68	1.75	1.82

Figure 3 Optimised layout space diagram of scheme three (see online version for colours)



(a) (b)

It can be found through comparison:

1 All the scenarios eliminate the service blind zones and achieve 100% coverage, satisfying the hard constraints of the optimisation model and the preset objectives.

2 The significant improvement in accessibility and service efficiency of the optimised scenarios, with the increase in the number of new parks, the total time cost from the settlements to the parks decreases from 89.03 min to 63.88 min, which is a decrease of 28.2%.

3 The proportion of residents reachable within 15 minutes increased from 70.35% to 94.31%, and the average population served per unit area increased by 19.7%, indicating a significant optimisation of resource utilisation efficiency.

4 After weighing and comparing, option 3 has greater advantages in terms of fairness prioritisation, efficiency breakthrough and economic acceptability, so option 3 is the most appropriate. The spatial map of the optimised layout is shown in Figure 3, in which Figure 3(a) represents the time required for each settlement to reach the parks, and Figure 3(b) represents the number of parks that can be reached by each settlement in option 3.

5 Conclusions

This paper proposes a sustainable landscape planning model optimised by GA to address the challenges of urbanisation in Nanchang. Ecological, social, and economic objectives are balanced by constructing a MOO framework based on NSGA-II. A comprehensive quantitative indicator system for sustainable landscape planning has been established, covering ecological sustainability, social-cultural sustainability, and economic sustainability. This model integrates FLUS simulation for baseline scenario generation and NSGA-II for MOO, generating Pareto optimal solutions. Experiments show that the model can effectively improve the ecological and social benefits while controlling the economic cost. The selected optimal solution achieves 100% green space coverage, significantly reduces the total travel time to parks, increases the 15-minute accessibility, and improves the population served per unit area. This study provides a scientific and effective approach for sustainable landscape planning in urban areas.

Declarations

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The author declares that she has no conflicts of interest.

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