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An Evaluation Model of Urban Green Space Based on Residents' Physical Activity

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Abstract: Urban green spaces (UGSs) possess a status in improving public health; thus, it is crucial to emphasize the evaluation of UGSs in terms of residents' physical activity (PA). This study utilizes the semantic segmentation method and Geographic Information System tools to quantify the key values of UGSs, including aesthetic and attractions, natural world experience, nature conservation, encouraging physical activity, cultural value, and social value, which are set as the evaluation indexes to investigate their impacts on residents' PA based on the six UGSs in Changsha city, Hunan Province, China. The PA-oriented UGS evaluation model is realized through the index optimal combination weights obtained by the Improved Combination Weighting Method of Game Theory, combining the subjective and objective weights from the Uncertainty Analytic Hierarchy Process method and Entropy Weight Method, respectively. By collecting and analyzing the exercise data of residents, we can accurately assess the level of residents' PA and frequency within various UGSs. The proposed model herein has a positive significance for evaluating the value of public green space in residents' PA in Changsha city and provides a reference for the construction of an urban green space evaluation model from multiple perspectives in the future.

Keywords: urban green space; physical activity; evaluation model; GIS; semantic segmentation; improved combined weighting method of game theory (ICWGT)

Citation: Dong, T.; Feng, C.; Yue, B.; Zhang, Z. An Evaluation Model of Urban Green Space Based on Residents' Physical Activity. *Sustainability* **2024**, *16*, 4220. https://doi.org/10.3390/su16104220

Academic Editors: Guangyu Wang, Jiang Liu, Xin-Chen Hong, Jinda Qi, Baojie He and Shi Cheng

Received: 28 April 2024
Revised: 14 May 2024
Accepted: 15 May 2024
Published: 17 May 2024

1. Introduction

It is generally acknowledged that urban green space (UGS) is an available resource, which usually includes parks, gardens, street greening, natural woodland, etc. Urban green space not only provides urban residents with places for leisure, entertainment, exercise, social interaction, and various collective cultural activities but also plays an important positive role in residents' physical health [1–3]. According to the World Health Organization (WHO), the development of green spaces and other nature-based construction solutions can improve the quality of the urban environment, leading to the promotion of sustainable lifestyles and the enhancement of the physical and mental health of urban residents, as well as bringing many other benefits [4]. People who visit the parks benefit from UGS to obtain higher sociological capability in cognitive, emotional, and psychological aspects, significantly reducing stress and mental fatigue while enhancing attention and memory ability [5]. Relevant studies have shown that urban green space can optimize the human living environment and life quality. Some scholars found that there was a significant positive correlation between the time residents spent in green space and their physical and mental health [6]. According to demographic data, outdoor daily physical activity (PA) has a significant effect on the physical health of residents, which can also prevent mental illness to a certain extent [7,8]. In 2023, the Australian Sports Medicine Association and the Australian Psychological Society put forward guidelines on how to maximize the physical and mental benefits of physical activity. It was clearly stated that some physical activity should be carried out outdoors in a pleasant natural environment [9]. From this perspective, urban green spaces (UGSs) are the ideal places offering a safe, accessible, and attractive environment to encourage urban residents to engage in physical activity. Meanwhile, UGSs which provide necessary services also could increase the time spent on outdoor activities, which in turn helps to reduce the occurrence of chronic diseases and mortality among participants [10]. Overall, the quality of UGSs reflects the attractiveness to residents living nearby, which is related to the frequency of visiting green spaces and is a key factor affecting the physical and mental health of urban residents [11]. Hence, objective and reasonable evaluation can contribute to focusing our understanding of UGSs, enabling the implementation of corresponding measures to improve the quality of the urban environment, thereby effectively enhancing the well-being of urban residents.

The accelerated process of urbanization is associated with severe environmental problems, such as noise, traffic, and social pressure [12], which promote people to seek solace in green space and other natural environments. At the same time, the positive and attractive aspects of the UGS (e.g., pleasant experience in nature, spacious sports fields, meeting places) are also one of the reasons attracting visitors. Furthermore, other values of UGSs including educational value and ecological protection value also have an impact on the choice of visitors. Therefore, the evaluation of UGSs should be carried out from multiple aspects. Among published literary works that focused on the health benefits and equity of parks, researchers have adopted the Community Park Audit Tool (CPAT), Environmental Assessment of Public Recreation Spaces (EAPRSs), and other methods to evaluate the quality of urban green space [13,14]. Evaluation indexes of UGS are widely acknowledged in previous studies, such as aesthetics value, ecological value, public service quality, tourist experience quality, and other factors [15–18], which are mostly related to internal park details and comprehensive indexes with emphasis on the management and construction of UGSs, however. In a recent study, Markevych et al. [19] proposed and emphasized the necessity of research on UGSs and health, considering the accessibility, quality, scale, and pattern use of UGSs comprehensively, in order to maximize the health benefits of building environment interventions. However, to date, few UGS evaluation systems have worked on the health of residents around green spaces based on research on PA. In this study, we analyze factors, including aesthetic and attractions, natural world experience, nature conservation, encouraging physical activity, cultural value, and social value, of urban green space based on the residents' daily activities in UGSs and correspondingly establish a residents' physical activity-oriented UGS evaluation system.

Despite the scale, type, and surrounding environment of green space, the potential effects of a UGS on residents' health may also be different based on its internal landscape structure [20,21]. It has been proved that the size of green space brings different perceptions to visitors. Visitors prefer to head to larger urban green spaces, as small-scale green spaces are more likely to be perceived as private properties [22]. Of the various types of green space cover that have been studied (e.g., forests, wetlands, farmlands, rangelands), forested areas provided visual stimuli and significant stress reduction, which have the most significant impact on mental health [5]; however, distinct studies may yield dissimilar outcomes. Though the criteria of landscape structure evaluation are different, landscape diversity and the percentage of each component are the important aspects. The increased complexity and variability resulting from landscape diversity contribute to a stronger visual preference effect and foster an emotional and spiritual connection between visitors and the environment [23].

The social value of UGSs can be reflected in the initiative and frequency of people visiting green space [24], which could contribute to residents' health positively [25]. From this aspect, the accessibility of a UGS may greatly affect the willingness of residents to visit the green space [26–28], which means it is necessary to be able to approach or enter it more conveniently in order to make effective use of the public UGS system. For example, the WHO proposed a method for measuring the health benefits of public UGS systems based on data from the residential population area within a radius of 300 m (or a 5 min walk) around green space in 2016 [29], which indicates that residents living at a certain distance to the green space can easily enter into it. It is reported that residents who live near green spaces engage in a variety of activities such as daily sports and dog walking, while people tend to stay longer and are more likely to engage in active recreational or social activities when visiting distant parks, especially larger city parks [30]. In other words, the frequency of residents visiting green areas for activities and the type of sports they play are related to the distance from the UGS.

Quantitatively investigating the quality of UGSs is facilitated through the utilization of some computer technologies such as big data analysis, image processing, and machine learning [31,32]. Image-based semantic segmentation technology can be used to distinguish different landscape features and provide effective guidance on future urban planning and design combined with public perception, which is a new development trend that is more applied to natural landscapes at present. For example, Chen et al. created a dataset of community-scale UGSs based on the semantic segmentation method to facilitate green space design in future community planning [33]. Wang et al. collected street view images and evaluated the quality of green space using machine learning algorithms to analyze the relationship between street view greening and the social economic conditions of communities [34]. The application of machine learning technology provides effective technical support for the realization of high-precision resolution for natural elements. Based on the selection of models and datasets adapted to describe various landscape elements in UGSs, the application of semantic segmentation in different application scenarios can be widely expanded, where a large experimental space for exploration is promising.

It is necessary to determine the corresponding weights of indexes when constructing an evaluation model for UGSs. Former evaluation models have relied on subjective approaches such as satisfaction surveys, questionnaire surveys, and field investigations, which lack accuracy and objectivity in index weights calculation. In this study, the Uncertainty Analytic Hierarchy Process (UAHP) and Entropy Weight Method (EWM) are used to determine the subjective and objective weights of evaluation indexes to balance the subjectivity and objectivity of the results. The UAHP method is a multi-criteria decision-making method that can comprehensively consider the uncertainty and fuzziness of index factors [35]. Its interval judgment matrix can reduce aleatory uncertainties in the index weight determination compared to the more commonly used Analytic Hierarchy Process (AHP) method [36]. However, the UAHP method can only calculate interval weights, which need to be turned into crisp values for subsequent evaluation. To address this issue, we incorporated the concept of deviation degree into the UAHP to construct an optimization model for resolving the subjective weights. Subsequently, we employed the Genetic Algorithm (GA), which can solve the optimization model accurately and quickly, to determine the optimal subjective weight. The Genetic Algorithm (GA) is an efficient and parallel heuristic global optimization algorithm, which can control the search process adaptively in the solution space to approach the optimal solution successively and finally obtain the approximate optimal solution [37]. On the other hand, the Entropy Weight Method (EWM) is an objective weighting method, which mainly measures the disorder level of the index system through the information entropy and evaluates the distribution of each evaluation index from an objective perspective [38]. Game theory is a branch of modern mathematics capable of considering the predicted and actual behavior of individuals under study while searching the optimization strategies [39]. Herein, a combinatorial weighting method, named the Improved Combined Weighting Method of Game Theory (ICWGT), is employed to combine the index weights obtained by the subjective and objective weighting method, thus aiming to achieve the most reasonable index weights in the end.

Overall, this study aims to establish a UGS evaluation model oriented by residents' physical activity, and the steps and contents of each chapter are distributed as follows: Section 2 of this paper mainly describes the selection of target green spaces, as well as the process and method of obtaining data. Section 3 describes the construction process of the entire evaluation model: Section 3.1 mainly focuses on the selection of evaluation indexes of UGSs; Section 3.2 describes the determination process of evaluation index weight and the construction of the model. Section 4 describes the analysis of the results, including the comparative analysis of the weights of the solved indexes. Section 5 includes the conclusions and future prospects.

2. Research Area and Data Acquisition

2.1. Site Selection

This study was carried out to establish a framework for assessing UGSs by focusing on the residents' physical activity levels in the Changsha City of China. As shown in Figure 1, Changsha City is the capital of Hunan Province, located in the central part of China. The city is renowned for its plentiful water resources and favorable geographical setting, earning it the moniker "City of Mountains and Water". It is noteworthy to highlight that the urbanization rate of Changsha has achieved 77.59%, indicating the rapid progression of its urbanization process [25]. Additionally, Changsha City boasts a forest coverage rate of 55%, positioning it within the top three provincial capitals nationally according to pertinent statistics. The health literacy rate is a comprehensive indicator that reflects economic and social development and the health level of the residents of China. In 2022, the residents' health literacy rate of Changsha attained a level of 31.24%, indicating that 31 out of every 100 residents aged 15-69 possess fundamental health literacy here. Moreover, more than 40 percent of residents participate in physical activities, achieving the target level outlined in the Healthy China 2030 Plan ahead of schedule.

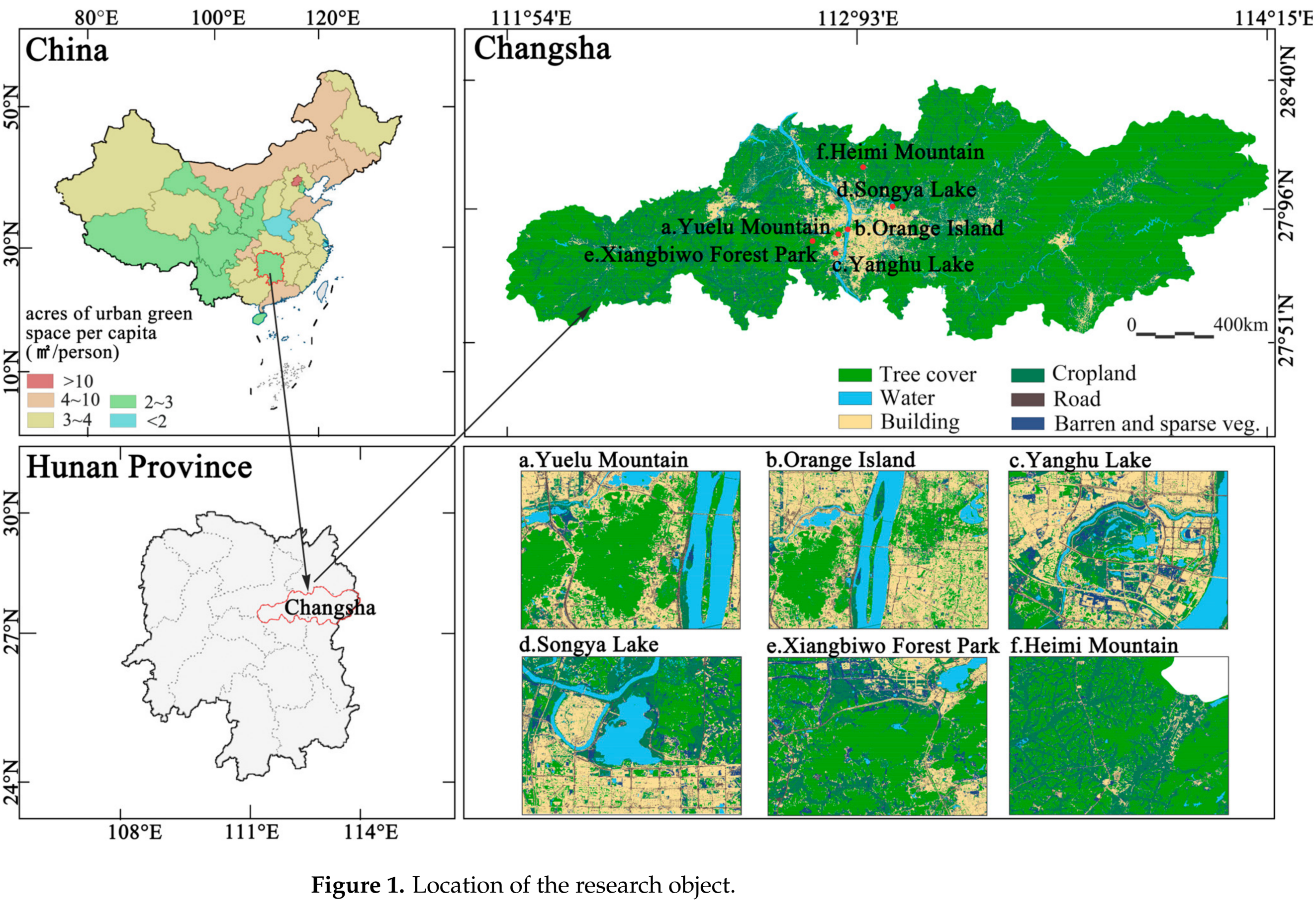

Figure 1. Location of the research object.

Across the city, we selected six UGSs with different proportions of landscape structures for subsequent investigation. Among them, Yuelu Mountain and Orange Island are both characterized by a comprehensive landscape structure and attract a large number of tourists as national scenic spots. Yanghu Lake and Songya Lake are surrounded by residential areas with more convenient transportation accesses, primarily featuring blue space (water body). Xiangbiwo Forest Park and Heimi Mountain are expansive forest parks in Changsha city, boasting abundant vegetation coverage and significant green space (Figure 1). The above target UGSs exhibit a diverse landscape structure that may elicit varying levels of visiting interest/attraction in the surrounding residents. Consequently, these six green spaces were chosen as the subjects of investigation in this paper.

2.2. Image Acquisition

Initially, the target data intended for analysis were acquired from images of the six UGSs through data mining technologies [40]. Previous studies had attempted to obtain and analyze specific data through social platforms such as Twitter and Instagram using data mining technologies [41,42]. The names of the six UGSs were employed as keywords to retrieve publicly available picture data from Weibo ® v13.3, Red® v7.81 (named LittleRedBook in China), and other prominent social media platforms in China. Weibo® v13.3 is the largest social media platform in China, and Red® is loved by younger users, with higher user growth and activity. The data collected cover the period from April 2021 to April 2023, utilizing the Baidu® v13.6 search engine at http://www.baidu.com, accessed on 4 May 2023, and were manually screened, with irrelevant picture data deleted. After the screening process, a total of 2413 images related to the target city green spaces were obtained and further processed.

2.3. Semantic Segmentation

In recent years, deep learning has been widely used in the field of semantic segmentation as a common artificial intelligence technology, which has attracted the attention of researchers. The core technology of this field is the automatic analysis and feature learning based on a large amount of data, which can effectively extract the low-, middle-, and high-level information in the image and realize the prediction classification at the pixel level under the condition of semantic expression [43]. Due to its powerful image processing capabilities, deep learning technology was used to automate the processing of the 2413 images that were collected.

In order to extract urban green landscape features, a Full Convolutional Neural Network (FCN) based on the ADE-20KFootnote1 dataset training model was used to segment the features in each photo semantically and obtain the area ratio of each semantic target. The FCN can predict the semantic properties of each pixel in an image, which can produce the segmentation of natural objects. By segmenting street view images into various detailed sub-scenes using the FCN, including bodies of water, roads, trees, or other natural objects, it is possible to encompass up to 151 categories of green landscape structures (including the "unknown" category). Herein, the ADE-20K dataset published by MIT [44] was used to train the FCN. Then, the well-trained FCN was integrated into a proposed human–machine adversarial scoring framework, which provided 151-dimensional feature vectors for the random forest to fit the scoring preferences of human annotators and gave corresponding recommended scores.

As in the semantic segmentation process shown in Figure 2, the 2413 images covering the 6 UGS areas were segmented and visualized in this study. After classifying the identified information, we distinctly counted the quantity of pixels within each category represented by a unique color. The visual proportion of each landscape feature was precisely determined according to the quantitation results. There were 12 related landscape features finally selected from 151 categories of green landscape structures, which included tree, grass, mountain, plant/plant life, water, rock, river, flower, hill, dirt track, land/ground, and lake. The initial proportions of the corresponding features in the six UGSs after semantic segmentation are shown in Table 1.

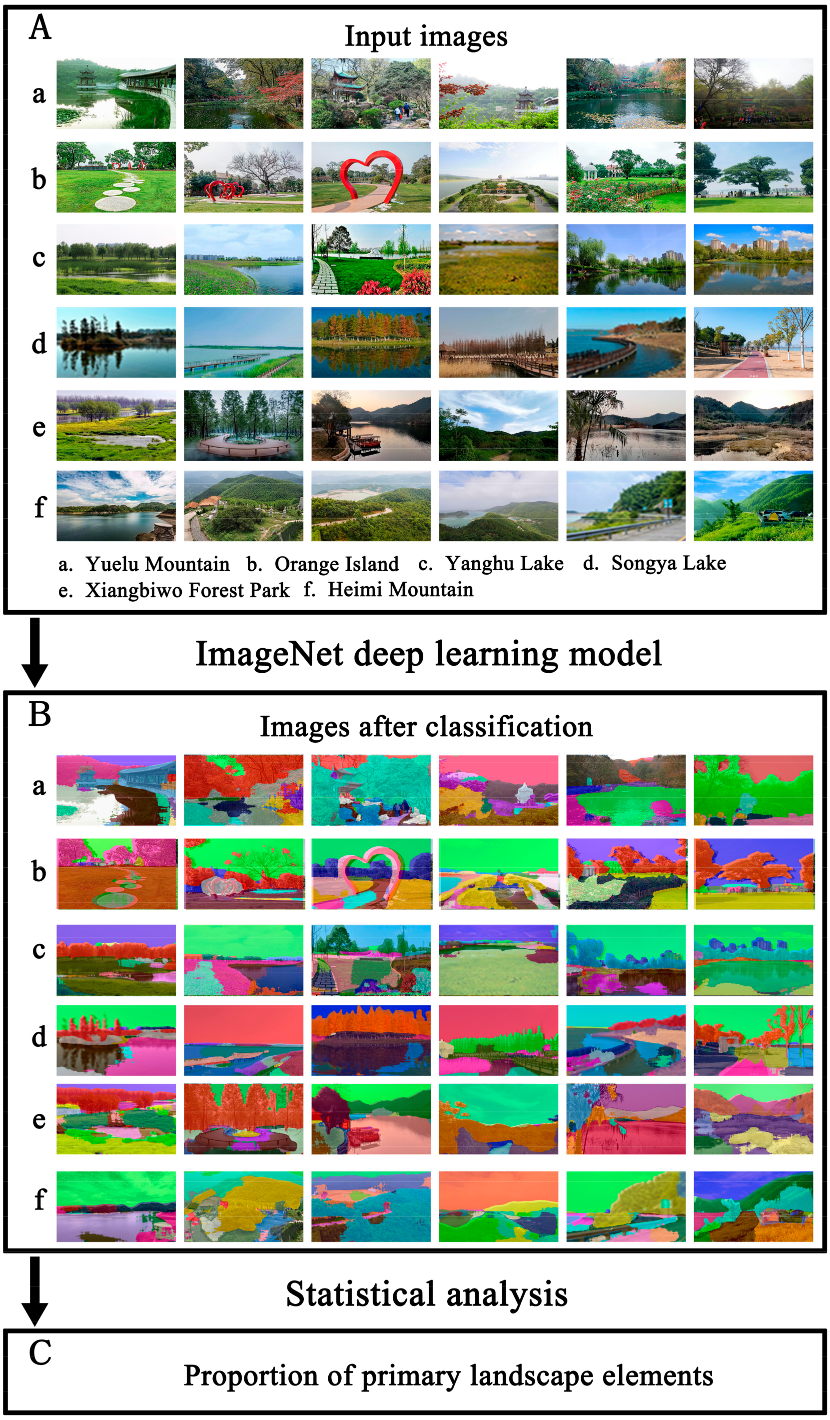

Figure 2. Semantic segmentation process. (**A**) Input images; (**B**) Images after classification; (**C**) Proportion of primary landscape elements.

The data presented in the table represent the initial results obtained after semantic segmentation; with only 12 out of 151 landscape structure categories being considered, the figures may be understated. Within the selected 12 landscape structure categories, there may be significant discrepancies between the data due to individuals' preferences when taking photographs. As a result, a stratified counting approach was employed to reduce errors. The proportion distributions of individual features among the total 12 features are illustrated in Figure 3.

Table 1. The proportion of landscape structure features in the six UGSs.

Landscape Structure Features	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain
Tree	0.4418	0.1370	0.1429	0.1022	0.2646	0.1948
Grass	0.0116	0.0596	0.0503	0.0573	0.0214	0.0156
Dirt Track	0.0006	<0.0001	<0.0001	0.0001	0.0006	0.0004
Land	0.0010	0.0038	0.0013	0.0004	0.0034	0.0120
Stone	0.0074	0.0052	0.0036	0.0045	0.0065	0.0062
Plant	0.0466	0.0265	0.0507	0.0190	0.0252	0.0257
Flower	0.0044	0.0018	0.0023	0.0028	0.0009	0.0006
Mountain	0.0208	0.0306	0.0038	0.0126	0.0680	0.1015
Hill	0.0036	0.0031	0.0001	0.0011	0.0089	0.0148
River	0.0220	0.0128	0.0360	0.0169	0.0324	0.0085
Water	0.0397	0.0594	0.1245	0.0632	0.1018	0.0326
Lake	0.0030	0.0020	0.0105	0.0048	0.0099	0.0023

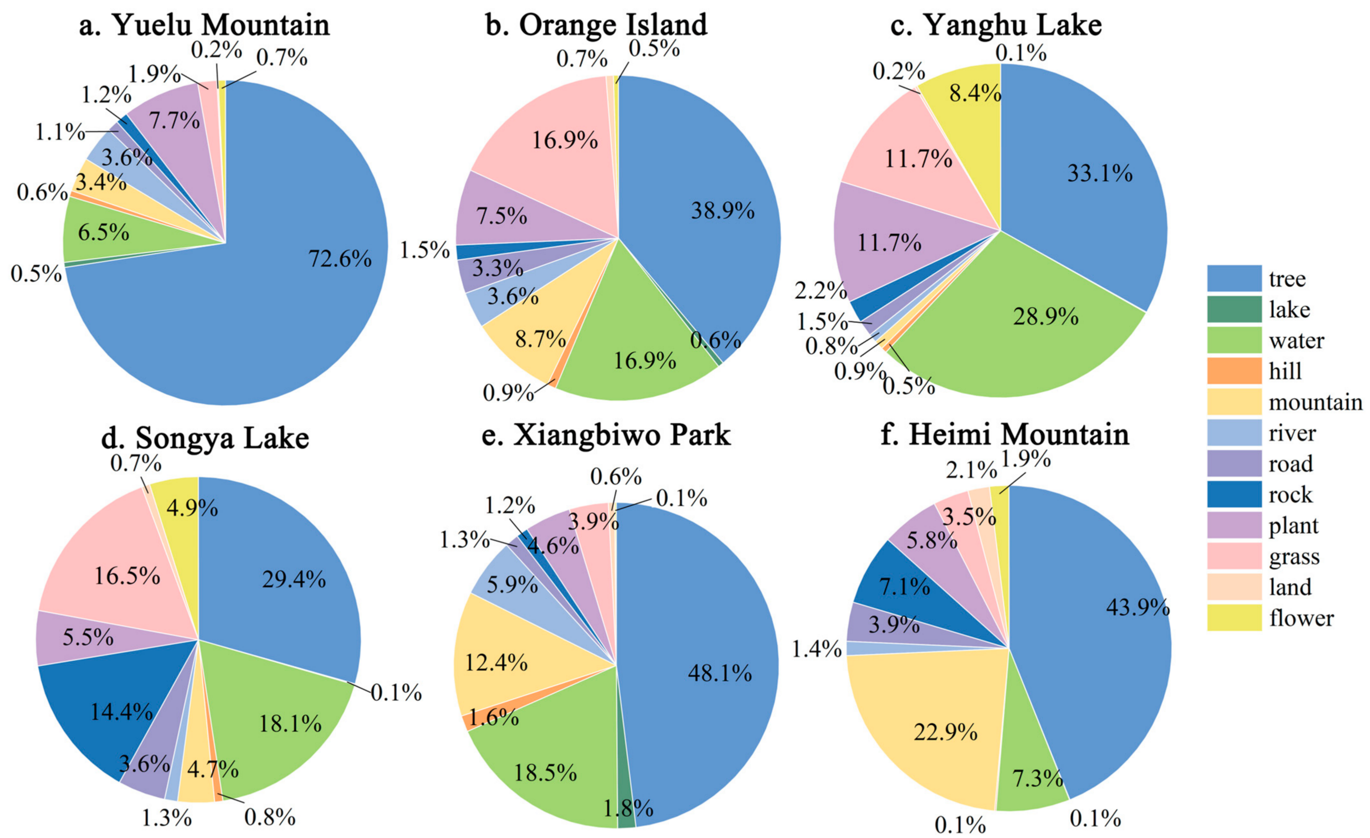

Figure 3. The proportion distribution of individual features in the six UGSs.

2.4. Data on Residents' Physical Activity

The community life circle generally refers to the spatial range composed of activities that occur to maintain the daily life of residents. As an important space carrier to meet the needs of residents' daily public services and diversified activities, the planning practice of the living circle has become increasingly extensive around the world in recent years. At the same time, the planning concept and corresponding practice of "15 min city" and "15 min community life circle" were produced [45]. As China's urban development strategy turns to "people-foremost", there has been an increased focus on investigating and discussing urban community life circle planning.

Keep® v7.47is a widely used and versatile App mainly used for fitness and dating in China with more than 200 million registered users. This study quantitatively assessed the distribution characteristics of urban physical activity by using public records of track information and exercise frequency in the software. The software offers a feature for creating routes, allowing users to generate a new movement route mode while enabling other users to synchronize their movement data upon finishing the same route type. So, it is feasible to make statistics of various movements of surrounding residents based on the documented routes within the software. According to the route data collected, running, walking, and bike-riding are the most frequently recorded route types within the data in the Changsha urban area (in the six UGSs of Changsha). This study only collected the number of completions and respective proportion of the routes that were publicly disclosed within the software and used ArcGIS10.2® to picture the route trajectories for subsequent studies, without any potential invasion or conflicts of personal privacy of the users. In accordance with the principles of the "15 min community life circle", this study focused on the route data within a 1.5 km radius surrounding the six UGSs mentioned above. The research data were collected in October 2023, and by the end of the data collection, a total of 99 routes and 1,697,043 exercise records were obtained, including 1,437,988 running, 166,683 walking, and 73,753 bike-riding records. The relevant data are reflected in Table 2.

Table 2. Statistics of recorded physical activity data.

	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain	Total
Total sports attendance [person-time]	888,012	311,080	230,176	256,058	11,607	110	1,697,043
Number of trajectories	33	20	23	14	8	1	99
Frequency of running [person-time]	781,929	261,581	205,913	178,976	9576	13	1,437,988
Frequency of walking [person-time]	102,769	36,042	20,689	23,773	2018	12	166,683
Frequency of bike-riding [person-time]	3315	13,457	3574	53,309	13	85	73,753

Figure 4 depicts a trajectory route map obtained by picturing the movement trajectories within a 1.5 km radius around the target green space in ArcGIS. The more the line's color approaches red, the higher the number of individuals observed exercising along this trajectory.

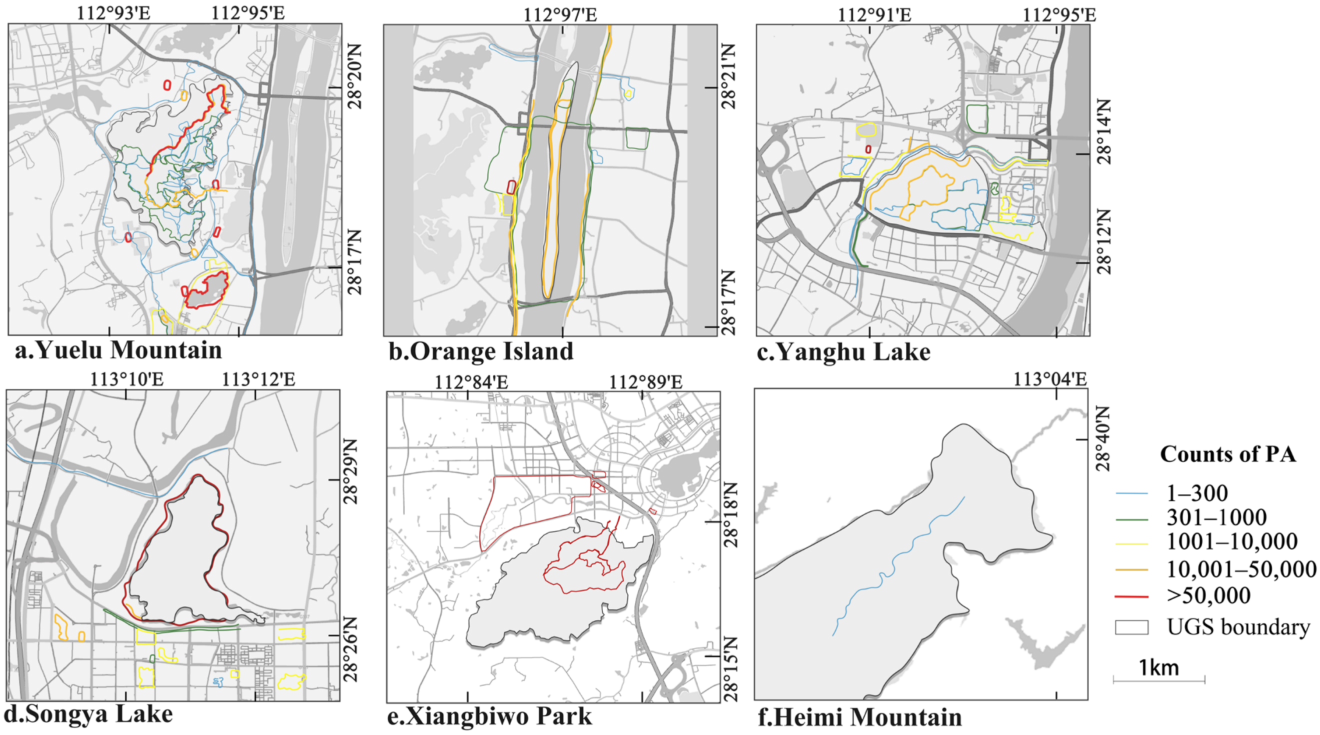

Figure 4. Route records and their frequency in the six UGSs.

3. The PA-Oriented UGS Evaluation Model

The construction of the UGS evaluation model was conducted in two parts, as follows:

1. For the selection of UGS evaluation indexes, the scale of the green space itself and the impact of different types of landscape structures on residents' movement were considered firstly. The statistical analysis of the landscape structure of the target green space was conducted by Python® 3.1.15 and semantic segmentation technology. Secondly, the accessibility of roads within 1.5km around the green space was taken into consideration, which can represent the spontaneity level of residents voluntarily visiting the green space. The PAs of surrounding residents were measured using the Keep App to analyze the positive impact of UGS. Finally, we focused on how the cultural value or natural conservation value of the green space itself influenced the PA motivation of residents.
2. In terms of the establishment of the evaluation model, a GA-optimized Uncertainty Analytic Hierarchy Process (UAHP) method and Entropy Weight Method (EWM) were used to determine the subjective and objective weights of the evaluation indexes, respectively. The Improved Combined Weighting Method of Game Theory (ICWGT) realizes the optimal combination of the subjective and objective weights, which can minimize their deviations and ultimately receive the optimal combined weights. In this way, an index-weight-based, subjective, objective-cognition-considered, and residential PA-related evaluation model for UGS was established herein.

The research method and process are shown in Figure 5:

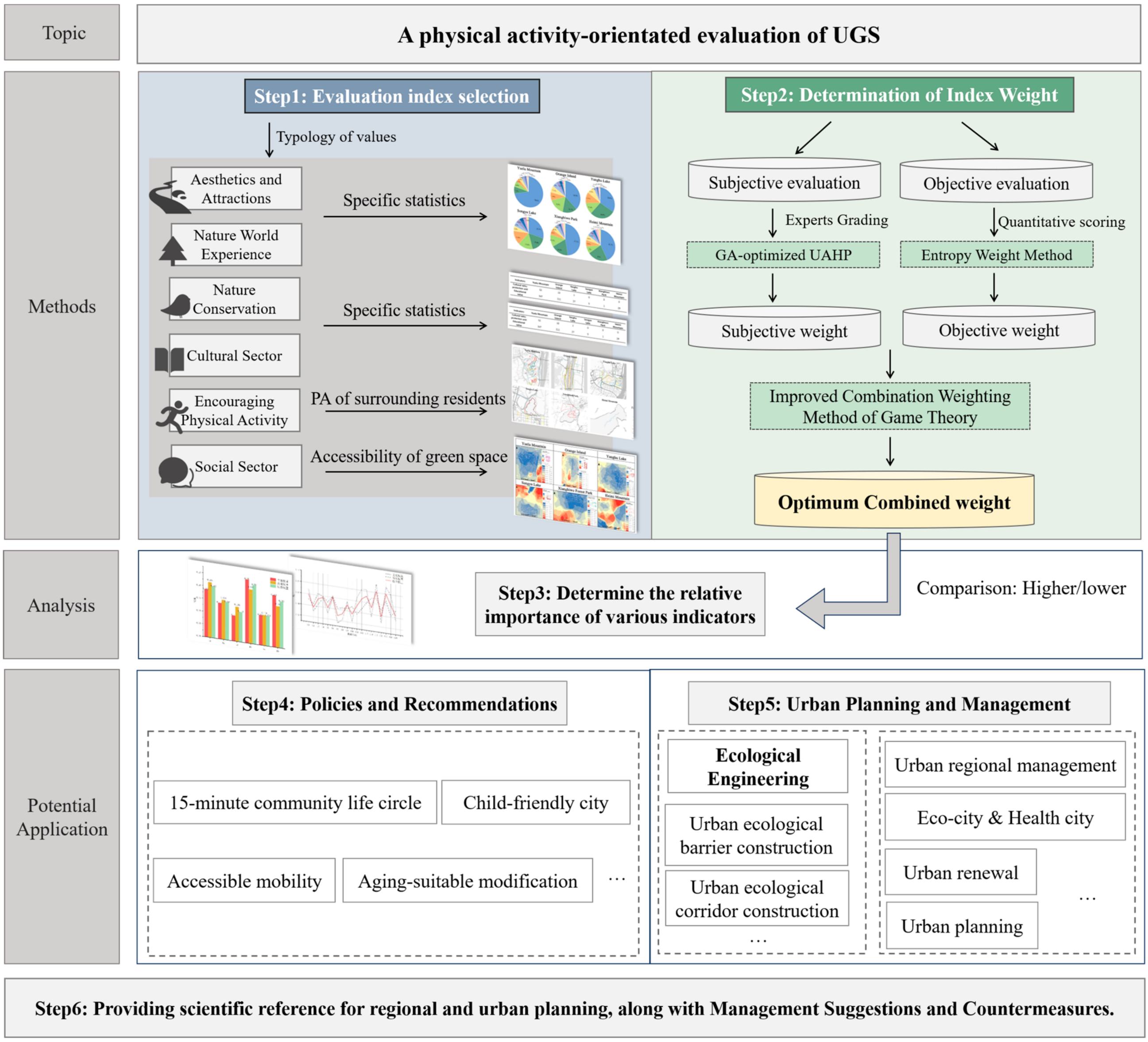

Figure 5. The flowchart of proposed evaluation model.

3.1. Determination and Quantitation Methods of Evaluation Indexes

UGS is considered a crucial component in China's ecological civilization construction; an increasing number of studies have already begun to pay attention to the social value realization and evaluation of UGS, where the relationship between ecosystem social value and environmental landscape features is the current trend in studies on ecosystem cultural services [46]. After discussion and confirmation with experts majored in ecosystem cultural services, we classified the UGS evaluation system from the perspective of ecosystem cultural services as follows:

- Aesthetic and attractions (e.g., places that are visually attractive);
- Encouraging physical activity (e.g., places provide opportunities for physical activity);
- Native conservation (e.g., places' value for the protection of native plants and animals);
- Nature world experience (e.g., places to experience the natural world);
- Cultural value (e.g., opportunities to express and appreciate culture or cultural practices);
- Social value (e.g., opportunities to interact with other people).

Compared with the widely used subjective questionnaire method in previous studies, several quantitative and objective landscape evaluation methods are integrated and employed in the following investigation to reflect the ecosystem cultural service level of UGS. The related public images were gathered by means of image data mining and semantic segmentation technology; then, the visual proportion of different landscape elements was statistically measured by counting pixels, so as to represent the aesthetic value and nature world experience value of UGS. The following are some key indexes which quantify each evaluation dimension: (1) greenery ratio (GR) and green space visual exposure index (GVI) represent the area of natural environment and biological habitat area to a certain extent, which imply positive significance in nature protection; (2) the statistical data of movement routes of surrounding residents can indirectly reflect the value of this green space in PA; (3) the surrounding green space with high walking accessibility can be regarded as capable of providing better neighborhood social services; and (4) the cultural value of UGS can be evaluated by the number of cultural relic protection units and the number of published papers with the target UGS as the key words. The data obtained from all the above methods and their processes are described below.

3.1.1. Aesthetics and Attractions and Nature World Experience Value of UGS

After using the semantic segmentation technology on the acquired images with the method described in Section 2.3, we can calculate the area of different landscape structures in each picture of the target green spaces. According to the UGS landscape classification method proposed by Pablo Knobel et al. in 2021 [47], the 12 landscape elements above are divided into two dimensions: aesthetics and attractions and nature world experience. The former one represents the evaluation of the beauty and attractiveness of the UGS, while the other is used to evaluate the natural attributes of the green space, such as the coverage degree of trees and grassland.

To reduce the influence induced by the uncertainties and potential errors that occurs during program identification, it is stipulated that only non-vegetation landscape elements (mountain, river, etc.) that account for more than 10% of the image area and vegetation landscape features (tree, grass, flower, etc.) that account for more than 20% of the image area will be considered as valid and counted in the total; otherwise, they will not be counted. The statistical results are presented in Table 3:

Table 3. Landscape feature statistics of the six UGSs.

Indexes		YM		OI		YL		SL		XP		HM	
		P	**C**	**P**	**C**	**P**	**C**	**P**	**C**	**P**	**C**	**P**	**C**
Aesthetics and attractions	Plant	0.0466	24	0.0265	9	0.0507	26	0.0190	10	0.0252	13	0.0257	13
	Flower	0.0044	4	0.0018	0	0.0023	0	0.0028	3	0.0009	0	0.0006	0
	Mountain	0.0208	30	0.0306	43	0.0038	2	0.0126	15	0.0680	142	0.1015	73
	Hill	0.0036	3	0.0031	0	0.0001	0	0.0011	0	0.0089	13	0.0148	6
	River	0.0220	35	0.0128	18	0.0360	49	0.0169	24	0.0324	6	0.0085	38
	Water	0.0397	56	0.0594	99	0.1245	163	0.0632	117	0.1018	43	0.0326	111
	Lake	0.0030	2	0.0020	4	0.0105	1	0.0048	1	0.0099	1	0.0023	11
Nature world experience	Tree	0.4418	375	0.1370	115	0.1429	76	0.1022	77	0.2646	151	0.1948	158
	Grass	0.0116	3	0.0596	51	0.0503	21	0.0573	43	0.0214	4	0.0156	7
	Dirt Track	0.0006	1	<0.0001	0	<0.0001	0	0.0001	0	0.0006	0	0.0004	0
	Land	0.0010	1	0.0038	1	0.0013	1	0.0004	1	0.0034	1	0.0120	3
	Stone	0.0074	8	0.0052	4	0.0036	2	0.0045	5	0.0065	7	0.0062	6

Note: YM refers to Yuelu Mountain; OI refers to Orange Island; YL refers to Yanghu Lake; SL refers to Songya Lake; XP refers to Xiangbiwo Park; HM refers to Heimi Mountain. P = each landscape feature's pixels/total pixels of all of pictures; C is the picture counts of each landscape feature.

3.1.2. Nature Conservation Value

Within the urban landscape, destinations such as Yuelu Mountain, Orange Island, Yanghu Lake, Songya Lake, Heimi Forest Park, and Xiangbiwo Forest Park draw considerable foot traffic from locals and tourists alike. To gauge the scale of the natural environment and the richness of biological habitats, metrics like the green space coverage ratio (GR) and the green space visual exposure index (GVI) serve as reliable indexes. Likewise, the diversity of plant species within these green areas underscores their significance in terms of nature conservation. In light of this, the evaluation of green spaces' conservation value revolves around three key indexes: GR, GVI, and the diversity of plant species, each offering valuable insights into the ecological significance of the UGS.

The index for green space coverage rate has the capability to indicate the proportionate expanse of greenery. To obtain relevant data regarding the GR, the ArcGIS 10.2® model was utilized, and the Baidu map was analyzed following geometric coordinate correction and projection conversion. All urban green spaces, agricultural green spaces, forests, and nature reserves are considered green spaces. The index for green space coverage rate had the capability to indicate the proportionate expanse of greenery. Residences and their immediate surroundings within a 10 m radius fall under the urban infrastructure designation; consequently, the foliage adjacent to dwellings did not contribute to the calculation of green space coverage rate.

There are various methods that can be employed to assess the extent of ecological exposure; this study utilizes the GVI assessment tool to quantify the visible greenery from diverse vantage points at ground level. As the snapshots sourced from social media were typically captured through a human lens, the quantification of greenery within a particular location is indicative of its GVI. The number of plant species in the green space was acquired through the Google Scholar data retrieval tool. The statistics are shown in the following Table 4:

Table 4. The nature conservation indexes and corresponding values of each UGS.

Indexes of Nature Conservation	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain
GR	92%	86%	90%	91.80%	85.40%	73.90%
GVI	50.45%	22.49%	24.62%	18.13%	31.21%	23.67%
Number of plant species	977	>1000	639	489	430	673

Notes: GR is the vertical projection area of all vegetation excluding superimposed situations to the total area in a certain range; GVI is the vegetation area in the human view to the total human view area.

3.1.3. Value of Encouraging Physical Activity

Based on the exercise-related route data obtained with Keep® (during the period from April to October 2023), the present physical activity value and potential movement possibilities of UGSs were systematically analyzed. The person-time of individuals utilizing the movement routes, together with the quantity of the routes, was used to convey the movement patterns of the nearby inhabitants. The overall movement in the area can be reflected by adding up the mileage of all users; the greater the total mileage, the better the PA is considered in general. Simpson's diversity index is a reliable metric for determining the variation in physical activities such as running, walking, and bike-riding in the given region. The index is an accurate reflection of the level of diversity present therein; specifically, the closer the index is to 1, the lower the rate of diversity in sports present in that area. The degree of difficulty in traversing is indicated by computing the proportion of the cumulative altitude gain to the overall distance. Essentially, the more challenging the task, the more rigorous the expectations are for the fitness of the individual engaging in it.

Simpson's diversity index was initially implemented to evaluate the variety of species within an ecosystem. Its fundamental concept is to determine an index that characterizes the diversity level of a given sample, taking into account the proportional degree of contribution that each species in the sample holds and assigning a quantifiable measure of the likelihood of randomly extracting two individuals from this sample that will belong to the same specific species. The formula is as follows:

$$\text{Div} = \sum_{i=1}^{S} \left(\frac{n_i(n_i - 1)}{N(N - 1)} \right) \tag{1}$$

where S is the total number of species; N signifies the total number of individuals across all the species found, while n_i denotes the count of individuals for the i-th species within the population. The index is evaluated on a scale of 0 to 1, whereby 0 indicates an infinite range of diversity, and 1 indicates no diversity. A higher index value is indicative of lower diversity within the ecosystem. Table 5 presents the data concerning the promotion of the physical activities of neighboring inhabitants, after data preprocessing.

Table 5. Indexes of residents' physical activity.

Indexes of Residents' PA	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain
Residents' participation in PA [person-time]	888,012	311,080	230,176	256,058	11,607	110
Outdoor activities [km]	769,853.12	686,567.55	283,398.00	1,636,319.28	13,008.35	293.70
Sports diversity (Div)	0.785	0.722	0.809	0.541	0.711	0.616
Difficulty of PA	0.061	0.020	0.014	0.018	0.072	0.041

Note: difficulty of PA = cumulative altitude gain/the overall distance.

3.1.4. Accessibility of UGS

The accessibility of green space is an important component in evaluating the quality of UGS. The accessibility of green spaces is the key standard indicating the disparity of surrounding environmental construction quality and directly impacts on the inclination of residents towards such areas for exercise and social requirements [48,49]. Generally, the ones which are not easily accessible are scarcely frequented and satisfy fewer social needs.

This study employs Origin–Destination cost matrix solver within the GIS framework to calculate and analyze the accessibility of residents commuting on foot to green space, which can identify and measure the shortest path from multiple initial and final access points along a network. After the urban road network was imported, the main roads, secondary roads, and branch roads were selected as the viable computation paths, and all the intersection junctures were set as both the starting and the destination point. The normal walking pace of 6 km/h was set as the computation standard of velocity, whilst the target area was confined within a radial distance of 1.5 km to the target UGS. As a result, the average time from each intersection to other destinations is the criterion for evaluating the accessibility of the particular point. The analysis results of the six target UGSs' accessibility are shown in Figure 6. The statistical chart depicts the varying levels of accessibility across different locations, ranging from maximum to minimum values, along with the average accessibility within the specified range. These data are further detailed in the accompanying Table 6.

Table 6. Accessibility of six UGSs.

Indexes of Accessibility	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain
Accessibility Mean [min]	47.83	39.04	32.63	41.47	45.80	51.69
Accessibility MIN [min]	38.64	20.09	23.67	15.12	29.74	1.09
Accessibility MAX [min]	77.02	70.2	63.76	77.55	118.8	71.3

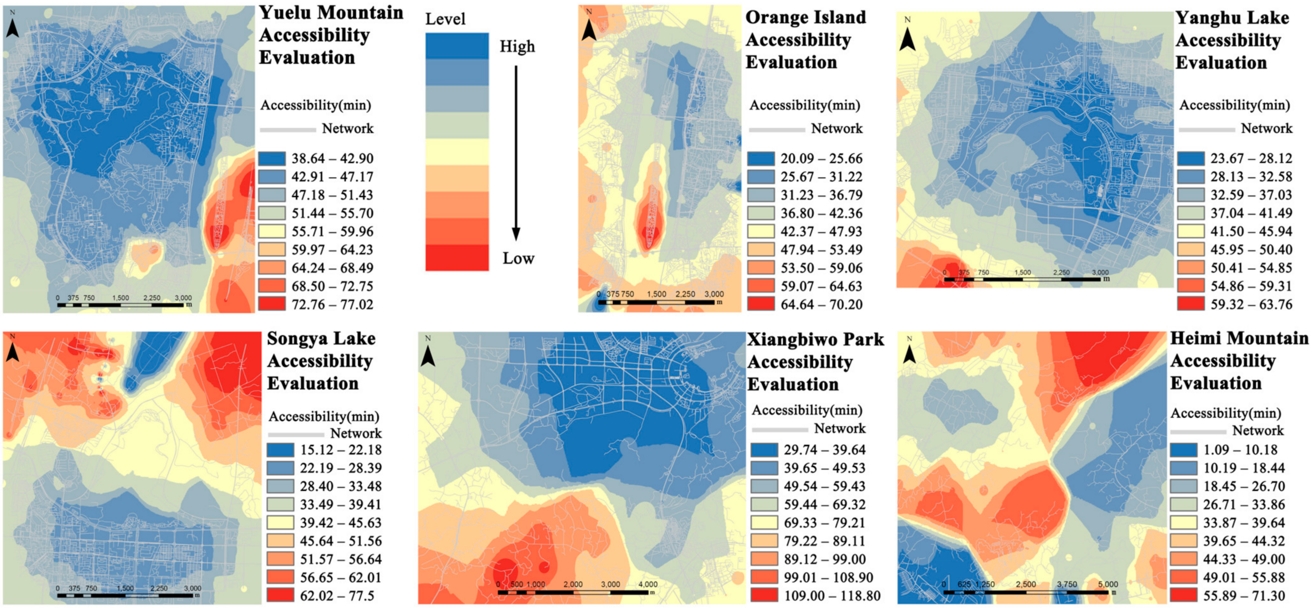

Figure 6. Accessibility map of six UGSs.

3.1.5. Culture Value of UGS

When assessing the humanistic worth of a green space, the quantity of cultural relics that are preserved, the prevalence of cultural allusions pertaining to the area, and the level of cultural and educational importance of the place are typically taken into account. Among these factors, the number of cultural relics safeguarded and the cultural and educational significance bear considerable weight as major draws for individuals who patronize the location. Therefore, this study represents the cultural value of the UGSs by counting the number of cultural relic protection units and the number of publications (both in Chinese and English) with the keywords of the urban green space. The statistical results are presented in Table 7:

Table 7. Indexes of cultural value.

Indexes of Culture Value	Yuelu Mountain	Orange Island	Yanghu Lake	Songya Lake	Xiangbiwo Park	Heimi Mountain
Cultural relics protection units [num]	52	10	1	0	0	0
Educational value [num]	347	211	27	5	1	29

3.2. Construction of Evaluation Index System and Corresponding Weights Calculation

To guarantee the scientific precision and reliability of evaluating the value of UGSs, the approach utilized in this study involved conducting both subjective and objective evaluations on six target green spaces through the UAHP and EWM. This enabled the acquisition of corresponding subjective and objective weights, reducing the margin of error caused by subjective evaluations. The weight of the UAHP technique was evaluated by experts and optimized through GA. The primary purpose of the EWM is to derive an objective targeted value via an assortment of appraisal techniques for green space; some of these methods include green space accessibility, greenery ratio, the extent of residents' involvement in green space recreational activities, etc. After a thorough analysis and evaluation of the value of green space in physical activities, the ideal weight for a combination of subjective and objective factors was derived using the Improved Combination Weighting Method of Game Theory (ICWGT). This achieves the goal of a comprehensive and holistic approach to the assessment of green spaces in PA, providing an all-encompassing perspective.

3.2.1. Uncertainty Analytic Hierarchy Process

The Uncertainty Analytic Hierarchy Process (UAHP) can resolve uncertainties such as randomness, ambiguity, and incomplete information in decision making [50]. In this paper, the UAHP method is used to calculate the subjective weight of each index. Contrary to the conventional AHP approach, the UAHP method employs interval numbers for the resolution of the weight vector instead of specific values. The UAHP technique is more precise and impartial in comparison to the AHP approach, as it can effectively reduce the errors and bias arising from the single subjective evaluation value. For example, J. Awad and C. Jung [51] used the AHP to study the planning elements of sustainable urban renewal in Dubai, and Wang et al. [35] used the UAHP to evaluate the possibility of human error in the fracturing process in drilling operations. The key step of the UAHP is the pairwise comparison of specific items (evaluation indexes) in the same layer to calibrate their relative importance. The comparison results are usually determined using SAATY's "1–9" scale approach [52] based on experts' scoring, which can be expressed as an interval number:

$$I_{ij} = [p_{ij},\ q_{ij}] \tag{2}$$

The interval number I_{ij} represents that the importance of the j-th object relative to the i-th object is between p_{ij} and q_{ij}, where p and q are the adjacent integers according to the "1–9" scale approach.

In this study, it is used to calibrate the relative importance of PA-oriented indexes, which could assess which factor is more positive to the promotion of physical activities in subjective knowledge. And the final relative importance interval number judgment matrix of all the indexes is constructed by the median judgment matrix from multiple experts' scores. Since the interval number judgment matrix obtained by the UAHP cannot obtain the specific weight value, the concept of the deviation degree is therefore introduced into interval numbers to search the potential optimal subjective weights for subsequent evaluation.

Based on the deviation degree, the interval numbers are set to $I_1 = [p_1, q_1]$ and $I_2 = [p_2, q_2]$, and the deviation degree D (I_1, I_2) can be obtained by Equation (3):

$$D(I_1, I_2) = \sqrt{(p_1 - p_2)^2 + (q_1 - q_2)^2} \tag{3}$$

The larger D is, the greater the deviation degree between interval numbers I_1 and I_2. The corresponding optimization model for determining the optimal value of interval weights is as follows:

$$\begin{aligned} &\min F(w_n) = \sum_{i=1}^{n}\sum_{j=1}^{n} D^2(I_{ij}, W_{ij}) = \sum_{i=1}^{n}\sum_{j=1}^{n} D^2(I_{ij}, w_i/w_j) \\ &s.t.\begin{cases} 0 < w_i \le 1, i = 1, 2, \cdots, n \\ \sum\limits_{i=1}^{n} w_i = 1 \end{cases} \\ &D(I_{ij}, w_i/w_j) = \sqrt{(p_{ij} - w_i/w_j)^2 + (q_{ij} - w_i/w_j)^2} \end{aligned} \tag{4}$$

where wn is the optimal subjective weight of each index, Wij is the judgment range of the importance of index i and j, wi is the optimal subjective weight of index i, and wj is the optimal subjective weight of index j.

To solve the above model accurately and quickly, the solution of the model is realized by the Genetic Algorithm in this study. The Genetic Algorithm (GA) is an efficient, parallel heuristic global optimization algorithm inspired by biological evolution [53]. The Genetic Algorithm, with its impressive versatility, advanced evolution, and widespread practicality, has emerged as the preeminent methodology for tackling intricate models. Its exceptional capability to optimize search operations within the solution space leads to successive approximations of the optimum solution. Consequently, it streamlines the quest for the optimal solution by adapting and enhancing the search process. The GA-toolkit built in MATLAB R2021b is employed for the calculation in this paper. The process of solving the optimal subjective weight of the UAHP based on GA is as follows:

1. Construct the objective function and adopt the above formula as the fitness function of the GA.

$$f(X_P) = \sum_{i=1}^{n}\sum_{j=1}^{n} D^2(I_{ij}, W_{ij}) = \sum_{i=1}^{n}\sum_{j=1}^{n} D^2(I_{ij}, w_i/w_j)$$
$$X_P = [w_1, w_2, \cdots, w_n] \tag{5}$$
$$s.t.\begin{cases} 0 < w_i \leq 1, i = 1, 2, \cdots, n \\ \sum_{i=1}^{n} w_i = 1 \end{cases}$$

2. Solve the optimal subjective weight.

The fitness function calculates the fitness values for all corresponding objective functions in each generation, enabling the selection of an optimal solution for the population. As the population continues to evolve towards the final generation, the optimal fitness value for the objective function becomes the global optimal value, and the corresponding parameter or solution vector wbest represents the optimal subjective weights' value for the interval number judgment matrix.

$$X_{P,n} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,n-1} & w_{1,n} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,n-1} & w_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{p,1} & w_{p,2} & \cdots & w_{p,n-1} & w_{p,n} \end{bmatrix} \tag{6}$$

where P is the population size generated in each generation, and $X_i = [w_1, w_2, \ldots, w_n]$ is the solution vector of each individual represented in the solution space.

This study has categorized the UGS evaluation indexes based on the aspects mentioned in Section 3.2, taking into account the theme/target layer (A), the primary indexes layer (B), and the secondary indexes layer (C) as the hierarchical structure of the index system. The details of the hierarchical structure for these evaluation indexes can be viewed in Table 8 below. Layer A contains the main objectives of this study and thus determines the quality of the green space overall.

Table 8. Hierarchical structure of evaluation indexes.

Primarily Index Layer B		Secondary Index Layer C		Description of each Index
B1	Aesthetics and attractions	C1	Plant/flower	Plant and flower cover
		C2	Mountain/hill	Mountain and hill in view
		C3	River/lake	River and lake in view
		C4	Water	Water in view
B2	Nature world experience	C5	Tree cover	Tree cover in view
		C6	Grass cover	Grass cover in view
		C7	Land cover	Dirt track, stone, and land in view
B3	Nature conservation	C8	GR	Area covered by green space
		C9	GVI	Green Visual Index
		C10	Amount of rare species	Amount of rare species
B4	Encouraging physical activity	C11	Residents' participation in PA	The number of times residents participated in PAs
		C12	Outdoor activities	Total mileage of physical activities
		C13	Sports diversity	Simpson's diversity index
		C14	Difficulty of PA	Ratio of road climb height to length
B5	Cultural sector	C15	Cultural relics protection units	Number of cultural relics protection units
		C16	Educational value	The number of publications with the keyword
B6	Social sector	C17	Accessibility (Mean)	The average of the accessibility of the area
		C18	Accessibility (Max)	The maximum of the accessibility of the area
		C19	Accessibility (Min)	The minimum of the accessibility of the area

3.2.2. Entropy Weight Method

The Entropy Weight Method (EWM) evaluates the level of disorder in the index system by analyzing the information entropy value of each index. The higher the entropy value of the assessment index, the lesser the dispersion among the indexes, revealing the insignificant impact of the index in a comprehensive evaluation and a smaller weighting [54]. When dealing with the problem of multi-index weighting, EWM has the capability of eliminating the result deviation caused by subjective evaluation and improving the objectivity and accuracy of evaluation results. In this study, the assignment method was utilized to carry out unified dimensionless quantization of each index at first. Then, the Entropy Weight Method was used to obtain a more objective index weight after quantization. The main calculation steps of the EWM are as follows:

1. Build a dimensionless initial matrix:

$$Y = \left[y_{ij}\right]_{m \times n} \tag{7}$$

where m is the number of objects intended to be evaluated, n is the number of evaluation indexes, and y_{ij} needs to be processed in a dimensionless way.

2. Calculate the information entropy S_j of the j-th index:

$$\begin{cases} S_j = -\frac{1}{\ln m} \sum\limits_{i=1}^{m} v_{ij},\ v_{ij} > 0 \\ S_j = 0, \quad v_{ij} = 0 \end{cases} \tag{8}$$

where v_{ij} is the proportion of the j-th index of the i-th evaluation object.

3. Calculate the objective weight w_j of the j-th index:

$$w_j = \frac{1 - S_j}{\sum\limits_{j=1}^{n} \left(1 - S_j\right)} \tag{9}$$

3.2.3. Weight Optimization: Improved Combination Weighting Method of Game Theory

In this paper, the UAHP method is employed to assess the significance of indexes based on expert opinions, which establishes the subjective weight of these indexes. Conversely, the EWM computes the entropy value of indexes by assessing their impact on the entirety, thereby determining their objective weights. There could potentially exist disparities between the outcomes acquired by two methods, and relying solely on a single method for assessment indexes would be biased or inadequate. Therefore, it is necessary to find an appropriate approach to recalculate the weights based on the computed subjective and objective weights, enabling the attainment of the comprehensive weights of indexes.

Game theory is an important subject of operations research. The combinatorial weighting method based on game theory can optimize the index weights calculated by the subjective and the objective weighting method to minimize their deviation, thereby achieving the optimal combination of index weights. However, the weight coefficients derived through the principles of game theory may hold a negative value occasionally. In such instances, the outcome is misguided and at odds with actuality. Therefore, the Improved Combination Weighting Method of Game Theory (ICWGT) [55] is used in this paper to correct the coefficients.

The combinatorial weighting based on game theory can be expressed as follows:

$$w = \sum_{l=1}^{L} \alpha_l w_l^T \tag{10}$$

where α_l is the linear combination coefficient, $\alpha_l > 0$; w is the combined weight vector; and w_l is the weight obtained by the l-th weighting method. L is the total counts of used weighting methods. ICWGT solves the optimization model by establishing the objective function and adding the constraint conditions of the combination coefficients. With the goal of minimizing the deviation of w and all of the w_l and ensuring that the linear combination coefficients α_l are always positive, the optimized model is as follows:

$$\begin{aligned} &\min_{\alpha_1 \cdots \alpha_L} f = \sum_{i=1}^{L} \left| \left(\sum_{p=1}^{L} \alpha_p w_i w_p^T \right) - w_i w_i^T \right| \\ &s.t.\alpha_p > 0, p = 1, 2, \cdots, L, \ \sum_{p=1}^{L} \alpha_p^2 = 1 \end{aligned} \tag{11}$$

The model was tackled using the Lagrange function for its components, with partial derivatives employed to derive the finally corrected coefficients. Following this, a normalization process was implemented. The final weight coefficient for the ICWGT combination was determined as follows:

$$\alpha_p^* = \frac{\sum_{i=1}^{L} w_i w_p^T}{\sum_{p=1}^{L} \sum_{i=1}^{L} w_i w_p^T} \tag{12}$$

After correcting the weight coefficients, the comprehensive weight of each evaluation index in the criterion layer (secondary layer) can be further obtained following Equation (10).

4. Results and Discussion

4.1. Result of Subjective Weights

By comparing the subjective weights of the primary indexes and the secondary indexes, it is possible to investigate which factors have the most significant impact on the phenomenon from the subjective perspectives of professionals. Therefore, the UAHP method was utilized to assess the appeal of UGSs based on their potential contribution towards the recreational wellness of the visitors. The results are shown in Table 9. In this context, the relative weights of secondary indexes (C) were determined within the same framework of corresponding primary indexes (B) firstly. And the relative weights were further normalized to indicate their relative importance among the total secondary indexes.

It can be seen from the results that, in terms of primary indexes, "encouraging physical activities" occupies the largest weight, followed by the "social value" and "aesthetic and attractions". It is basically consistent with the previous research results [51], which highlighted the importance of sports fields and landscape value for UGSs. As our research primarily focuses on the impact of UGSs on residents' physical activity, the degree to which residents engage in exercise by visiting these areas and the convenience of accessing green spaces are relatively more crucial in subjective cognition. This also explains why the subjective weight of "encouraging physical activity" and "social value" is significantly higher than other indexes. The relatively higher ranking of "aesthetic and attractions" suggests that the quality of greenery itself holds stronger appeal for residents to visit, in comparison to other factors of natural environment such as greenery ratio and coverage of grass and trees.

When it comes to the secondary indexes, it appears that mountains hold a greater significance for green spaces in the perspective of individuals. This contribution could be correlated with the fact that Changsha City is located amidst hilly terrain with an abundance of mountains. The extent of grass coverage makes a contribution of over fifty percent towards the "natural world experience", perhaps owing to the fact that the presence of grassland renders it easier for residents to engage in related physical activities. In terms of "culture value", the emphasis placed on the number of heritage conservation units far outweighs that of their research value. This clearly indicates that tangible cultural heritage is more closely intertwined with the lives of residents, underscoring the need to prioritize the conservation value of cultural heritage in urban development. For the accessibility of green spaces, the average and maximum time cost for residents to reach green space have the greatest impact on their decisions.

Table 9. The optimal subjective weights of indexes obtained by UAHP.

B	GA-Optimized Weight of Primary Index	Rank	C	Relative Weight	Normalized Weight of Secondary Index	Rank
B1	0.199	3	C1	0.154	0.031	15
			C2	0.344	0.069	6
			C3	0.218	0.043	10
			C4	0.282	0.056	8
B2	0.106	5	C5	0.289	0.031	16
			C6	0.562	0.060	7
			C7	0.148	0.016	19
B3	0.102	6	C8	0.417	0.042	11
			C9	0.417	0.042	12
			C10	0.167	0.017	18
B4	0.266	1	C11	0.359	0.095	1
			C12	0.205	0.055	9
			C13	0.278	0.074	5
			C14	0.159	0.042	13
B5	0.122	4	C15	0.778	0.095	2
			C16	0.222	0.027	17
B6	0.206	2	C17	0.448	0.092	3
			C18	0.384	0.079	4
			C19	0.168	0.035	14

4.2. Results of Objective Weights

Besides subjective perspectives, objective analysis was conducted through the collected data (refer to Section 3). The objective weights of each index obtained by the EWM are presented in Table 10.

Table 10. The objective weights of indexes obtained by the EWM.

B	Objective Weight of Primary Index	Rank	C	Relative Weight	Normalized Weight of Secondary Index	Rank
B1	0.216	1	C1	0.236	0.051	9
			C2	0.201	0.043	15
			C3	0.292	0.063	4
			C4	0.271	0.059	7
B2	0.154	4	C5	0.325	0.050	10
			C6	0.404	0.062	5
			C7	0.271	0.042	18
B3	0.136	5	C8	0.323	0.044	14
			C9	0.320	0.043	16
			C10	0.357	0.048	12
B4	0.212	2	C11	0.172	0.037	19
			C12	0.223	0.047	13
			C13	0.280	0.060	6
			C14	0.324	0.069	2
B5	0.119	6	C15	0.582	0.069	1
			C16	0.418	0.050	11
B6	0.162	3	C17	0.418	0.068	3
			C18	0.259	0.042	17
			C19	0.323	0.052	8

The findings indicate that the top three influencing factors are "aesthetic and attractions", "encouraging physical activity", and the "social value", which is consistent with the ranking of those obtained by the UAHP but slightly different in the weights' value. When it comes to each secondary index, factors such as the level of difficulty in sports activities, the quantity of cultural heritage sites, and the average accessibility of green spaces hold a correspondingly greater weight compared to other indexes. For landscaping, we have observed that rivers/lakes hold the highest importance among all the landscaping elements. This aligns with the outcomes of prior research [56], indicating that green spaces in proximity to water bodies possess greater value than other types of green areas.

4.3. Comparisons of the Results

Based on the above results, it can be seen that there are still some subjective and objective cognitive biases regarding the relative importance of influencing factors. Thus, this study hopes to adjust the difference in subjective and objective understanding and then obtain more comprehensive, objective, and reasonable weights for evaluation analysis. According to the ICWGT method shown in Section 3.2.3, the combined weight coefficients of the subjective weight and objective weight are $\alpha_S = 0.50564$ and $\alpha_O = 0.49436$, respectively, while the comprehensive weights of primary indexes and secondary indexes are shown in Tables 11 and 12:

Table 11. The comprehensive weight of primary indexes.

B	GA-Optimized Subjective Weight	Rank	Objective Weight	Rank	Comprehensive Weight	Rank
B1	0.187	3	0.216	1	0.202	2
B2	0.141	5	0.154	4	0.148	4
B3	0.100	6	0.136	5	0.118	6
B4	0.250	1	0.212	2	0.231	1
B5	0.117	4	0.119	6	0.118	5
B6	0.203	2	0.162	3	0.183	3

Table 12. The comprehensive weight of secondary indexes.

C	Subjective Weight	Rank	Objective Weight	Rank	Comprehensive Weight	Rank
C1	0.069	15	0.051	9	0.060	7
C2	0.031	6	0.043	15	0.037	16
C3	0.044	10	0.063	4	0.053	9
C4	0.056	8	0.059	7	0.057	8
C5	0.031	16	0.050	10	0.040	14
C6	0.060	7	0.062	5	0.061	5
C7	0.016	19	0.042	18	0.029	19
C8	0.023	11	0.044	14	0.033	18
C9	0.057	12	0.043	16	0.050	12
C10	0.023	18	0.048	12	0.035	17
C11	0.066	1	0.037	19	0.051	11
C12	0.082	9	0.047	13	0.065	4
C13	0.082	5	0.060	6	0.071	3
C14	0.035	13	0.069	2	0.052	10
C15	0.095	2	0.069	1	0.082	1
C16	0.027	17	0.050	11	0.038	15
C17	0.092	3	0.068	3	0.080	2
C18	0.079	4	0.042	17	0.061	5
C19	0.035	14	0.052	8	0.043	13

Comparative analysis was performed on the subjective weight obtained from the UAHP method, the objective weight obtained from the EWM, and the combined weight obtained from the ICWGT. The results are presented in a visual format in the following Figures 7 and 8:

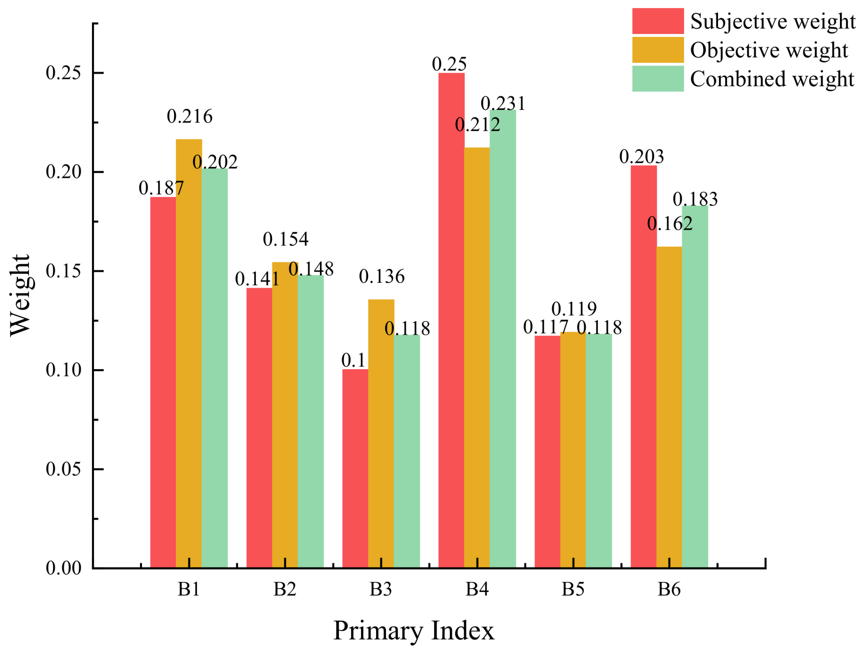

Figure 7. The comparison of obtained weights of primary indexes.

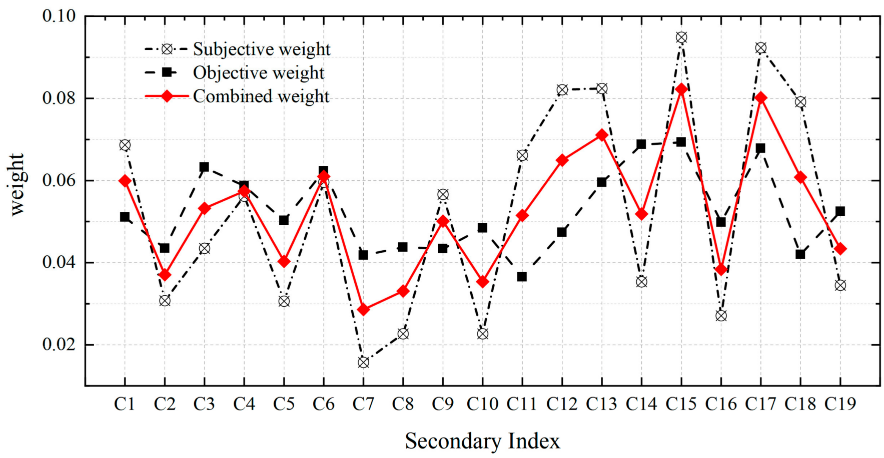

Figure 8. The comparison of obtained weights of secondary indexes.

In Figure 8, the volatility in outcomes derived from subjective weighting in specific project metrics significantly surpasses that of objective weighting. This could be attributed to experts exhibiting notable preferences when scoring certain metric items within the range, thereby resulting in considerable fluctuations in the final outcomes. And it has been found that all of the comprehensive weights by optimized ICWGT lie between the subjective weights and the objective weights. This suggests that an effective balance between subjective evaluation and objective evaluation has been found in the results, by which the subjective nature of UAHP index evaluation has been effectively reduced, while the accuracy of the results has been enhanced through objective statistics.

It can be concluded that "encouraging physical activity" has the greatest weight in all the standard levels. In other words, whether the surrounding inhabitants can voluntarily visit the green space and carry out a series of activities is an important factor in evaluating UGSs when it comes to promoting residents' movement. In the context of policy initiatives like the "National Fitness Campaign" and the promotion of "Healthy Cities", enhancing and refining the sporting facilities within UGSs, such as running tracks and bike lanes, can significantly encourage nearby residents to independently engage in physical activities in these areas. The combined weight of "aesthetics and attractions" ranks second in the results, which indicates that the quality of the UGS landscape structure itself plays an important role in the whole evaluation system. Studies have shown that low-intensity activities (such as strolling and sightseeing) are the most common activities for surrounding people when visiting green spaces [57]. That is, individuals are more willing to go to scenic and ornamental green space for low-intensity activities. The third criterion on the list is the "social value", indicating that green spaces in cities with higher accessibility are more popular among people, and it also means that accessibility is not the primary factor that determines or inhibits the residents from engaging in physical activities in UGSs. The remaining three indexes, namely, "nature world experience", "cultural sector", and "nature conservation", occupy the fourth and joint-fifth positions. Although the influence of vegetation coverage, cultural value, and natural conservation on the assessment is lesser than that of the previous three, their effects regarding citizens' physical activities are still not negligible.

Regarding secondary indexes, it is noteworthy that the category "cultural relics protection units" boasts the highest composite weight value. This could stem from the fact that its subjective evaluation carries more weight than the educational significance within the same category. The specific metrics that closely follow the ranking are the "mean value of accessibility" and "sports diversity", reflecting the extent of accessibility to UGSs and the suitability of these spaces for a variety of activities, both of which play a significant role in the evaluation system. The above findings offer valuable insights for urban green space designs and development. While ensuring the cultural significance and aesthetic quality of green areas, incorporating facilities that encourage physical activity can effectively encourage residents to utilize these spaces.

4.4. Discussion

The aim of this research is to investigate an applicable and comprehensive assessment framework for UGSs with physical activity as a mediator to enhance the health and well-being of inhabitants living near these spaces. This initiative seeks to compensate for the inadequacies of hitherto UGS planning, which has predominantly focused on policy considerations. By improving the design and planning of UGSs, especially with regards to the physical and mental well-being of inhabitants, the results of this research can be leveraged to provide valuable insights into urban renewal, old city reconstruction, and optimization of green space landscapes.

The highlight of this paper lies in its comprehensive assessment process of UGSs, achieved by blending subjective and objective evaluation techniques. By employing the ICWGT method, this paper derives the holistic weighting of these indexes, effectively mitigating the potential distortion of data accuracy caused by single subjective evaluations. Departing from conventional questionnaire methodologies, this paper opts for a more resident-centric approach in selecting and procuring methods and data. It delves into diverse metrics intimately linked to residents' daily lives, including the distribution of green landscapes, the accessibility of green spaces, and residents' mobility patterns. The research methodology employed in this paper offers a more concrete depiction of how the varying quality levels of UGSs impact the daily transportation routines of inhabitants by offering them spaces for outdoor physical activities.

On the other hand, this paper innovates in the objective evaluation of UGSs from multiple perspectives. Using semantic segmentation technology, this research explores the aesthetic and experiential benefits of green spaces. Quantitative analysis is conducted on central network images obtained through the data mining method. Since the majority of photographs on social media platforms depict landscapes from a human viewpoint, they are inadequate representations of the overall structure of green spaces. Nevertheless, this study focuses on the way individuals use green spaces, and the proportions of landscape elements visible to people accurately convey the impact the surroundings have on their users. This study employs sports data from Keep® software to gauge the physical activity value of green spaces, thereby providing substantial backing for the development of an urban green space evaluation model, with a distinct emphasis on sports-centric aspects.

However, in terms of the conservation significance of natural spaces during evaluation, while utilizing GA, GVI, and the diversity of plant species as evaluative benchmarks can partly gauge the conservation merit of green spaces, this overlooks the diversity and safeguarding status of animal species, and the data parameters may not be exhaustive. Given this paper's emphasis on assessing the influence of nearby residents' physical activity on the UGS evaluation framework, the accessibility of green spaces is solely investigated based on pedestrian accessibility, without considerations for vehicular access to these spaces.

5. Conclusions and Suggestions

Based on the proposed evaluation system of UGSs, this paper uses UAHP, EWM, and ICWGT to calculate the combined weights of various evaluation dimensions of green space from the perspective of residents' physical activity and puts forward a novel UGS assessment approach aimed at providing scientific reference for the construction, urban renewal, and transformation of eco-cities and healthy cities.

During the assessment phase, the interval numbers of the UAHP were employed to gauge the significance of indexes, incorporating the deviation degree model and GA for the weights' computation. By delineating the degree of contribution of each index to the final evaluation through the EWM, the objective weights of indexes were quantitatively determined based on the collected data. Finally, the Improved Combined Method of Game Theory (ICWGT) has the capability to combine the outcomes of both subjective and objective evaluations, culminating in more precise and scientifically grounded combined weights for comprehensive evaluation.

Overall, based on the forementioned findings, it was concluded that when evaluating urban green spaces with a focus on the residents' physical activities, residents' engagement in physical activities within green spaces (B4) holds the greatest weight in the overall evaluation index system. In other words, green spaces have a greater appeal to the surrounding residents when they contain suitable sports facilities that meet their needs. Facilities for reference include plastic running or walking tracks, cycling paths, children's play facilities and venues [58], etc. The landscape quality (B1) and accessibility (B6) of green spaces also have a great impact on the evaluation system of UGSs, which is similar to the previous study by Zhang et al. [57]. This suggests that it is important for urban planners to prioritize the enhancement of the linkage between green spaces and residential zones. This involves improving the systematic planning and administration of these green areas and maximizing their capacity to encourage physical activities, enhancing environmental qualities, and fortifying the overall physical and mental welfare of residents. The adoption of such strategies would empower municipal authorities to develop urban areas that are not only more conducive to living but also more dynamic and prosperous.

Author Contributions: Conceptualization, T.D. and C.F.; methodology, T.D. and C.F.; software, C.F. and Z.Z.; validation, C.F., B.Y. and Z.Z.; formal analysis, C.F.; investigation, C.F. and B.Y.; resources, T.D.; data curation, C.F.; writing—original draft preparation, T.D.; writing—review and editing, T.D. and C.F.; visualization, C.F., B.Y., and Z.Z.; funding acquisition, T.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Humanities and Social Sciences Youth Foundation, Ministry of Education of the People's Republic of China. Title: Research on typical urban green space landscape design method based on the relationship between ecosystem cultural services and residents' health. Grant number: 23YJCZH039.

Data Availability Statement: Dataset available on request from the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kondo, M.C.; Fluehr, J.M.; McKeon, T.; Branas, C.C. Urban Green Space and Its Impact on Human Health. *Int. J. Environ. Res. Public Health* **2018**, *15*, 445. [CrossRef] [PubMed]
2. van Dillen, S.M.E.; de Vries, S.; Groenewegen, P.P.; Spreeuwenberg, P. Greenspace in urban neighbourhoods and residents' health: Adding quality to quantity. *J. Epidemiol. Community Health* **2012**, *66*, e8. [CrossRef] [PubMed]
3. Bixby, H.; Hodgson, S.; Fortunato, L.; Hansell, A.; Fecht, D. Associations between Green Space and Health in English Cities: An Ecological, Cross-Sectional Study. *PLoS ONE* **2015**, *10*, e0119495. [CrossRef] [PubMed]
4. Farkas, J.Z.; Hoyk, E.; de Morais, M.B.; Csomós, G. A systematic review of urban green space research over the last 30 years: A bibliometric analysis. *Heliyon* **2023**, *9*, e13406. [CrossRef] [PubMed]
5. Hedblom, M.; Gunnarsson, B.; Iravani, B.; Knez, I.; Schaefer, M.; Thorsson, P.; Lundström, J.N. Reduction of physiological stress by urban green space in a multisensory virtual experiment. *Sci. Rep.* **2019**, *9*, 10113. [CrossRef] [PubMed]
6. Li, Q.; Liu, Y.; Yang, L.; Ge, J.; Chang, X.; Zhang, X. The impact of urban green space on the health of middle-aged and older adults. *Front. Public Health* **2023**, *11*, 1244477. [CrossRef]
7. Firth, J.; Solmi, M.; Wootton, R.E.; Vancampfort, D.; Schuch, F.B.; Hoare, E.; Gilbody, S.; Torous, J.; Teasdale, S.B.; Jackson, S.E.; et al. A meta-review of "lifestyle psychiatry": The role of exercise, smoking, diet and sleep in the prevention and treatment of mental disorders. *World Psychiatry* **2020**, *19*, 360–380. [CrossRef] [PubMed]
8. Zhou, R.; Zheng, Y.-J.; Yun, J.-Y.; Wang, H.-M. The Effects of Urban Green Space on Depressive Symptoms of Mid-Aged and Elderly Urban Residents in China: Evidence from the China Health and Retirement Longitudinal Study. *Int. J. Environ. Res. Public Health* **2022**, *19*, 717. [CrossRef] [PubMed]
9. Vella, S.A.; Aidman, E.; Teychenne, M.; Smith, J.J.; Swann, C.; Rosenbaum, S.; White, R.L.; Lubans, D.R. Optimising the effects of physical activity on mental health and wellbeing: A joint consensus statement from Sports Medicine Australia and the Australian Psychological Society. *J. Sci. Med. Sport* **2023**, *26*, 132–139. [CrossRef]
10. Wolch, J.R.; Byrne, J.; Newell, J.P. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landsc. Urban Plan.* **2014**, *125*, 234–244. [CrossRef]
11. Zheng, Y.; Cheng, B.; Dong, L.; Zheng, T.; Wu, R. The Moderating Effect of Social Participation on the Relationship between Urban Green Space and the Mental Health of Older Adults: A Case Study in China. *Land* **2024**, *13*, 317. [CrossRef]
12. Reyes-Riveros, R.; Altamirano, A.; De la Barrera, F.; Rozas-Vasquez, D.; Vieli, L.; Meli, P. Linking public urban green spaces and human well-being: A systematic review. *Urban For. Urban Green.* **2021**, *61*, 127105. [CrossRef]
13. Lee, C.; Kim, H.J.; Dowdy, D.M.; Hoelscher, D.M.; Ory, M.G. TCOPPE School Environmental Audit Tool: Assessing Safety and Walkability of School Environments. *J. Phys. Act. Health* **2013**, *10*, 949–960. [CrossRef] [PubMed]
14. Rigolon, A. Parks and young people: An environmental justice study of park proximity, acreage, and quality in Denver, Colorado. *Landsc. Urban Plan.* **2017**, *165*, 73–83. [CrossRef]
15. Zhang, Z.; Xu, C.; Gong, L.; Cai, B.; Li, C.; Huang, G.; Li, B. Assessment on structural quality of landscapes in green space of Beijing suburban parks by SBE method. *Sci. Silvae Sin.* **2011**, *47*, 53–60. [CrossRef]
16. Song, Y.; Xu, S.; Liu, Z.; Zhang, Y.; Qiu, P.; Niu, A.; Xu, G. Time and space differences of water environmental quality of the mangrove wetland park in Nansha: Based on the improved twice-slope clustering method. *Sci. Geogr. Sin.* **2016**, *36*, 303–311. [CrossRef]
17. Xu, H.; Li, Q. Analysis of the Evaluative Dimensions and Causal Relationship on Theme Park Visitors' Experience Quality: Based on a C-trip Comments Review of Disney and Happy Valley. *Tour. Sci.* **2017**, *31*, 57–68. [CrossRef]
18. Xiao, N.; Huang, Y.; Liu, J.S. Evaluation and spatial differentiation of tourism experience quality of theme park in China. *Sci. Geogr. Sin.* **2019**, *39*, 978–986. (In Chinese) [CrossRef]
19. Markevych, I.; Schoierer, J.; Hartig, T.; Chudnovsky, A.; Hystad, P.; Dzhambov, A.M.; de Vries, S.; Triguero-Mas, M.; Brauer, M.; Nieuwenhuijsen, M.J.; et al. Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environ. Res.* **2017**, *158*, 301–317. [CrossRef] [PubMed]
20. Lepczyk, C.A.; Aronson, M.F.J.; Evans, K.L.; Goddard, M.A.; Lerman, S.B.; MacIvor, J.S. Biodiversity in the City: Fundamental Questions for Understanding the Ecology of Urban Green Spaces for Biodiversity Conservation. *BioScience* **2017**, *67*, 799–807. [CrossRef]
21. Zhao, X.; Li, F.; Yan, Y.; Zhang, Q. Biodiversity in Urban Green Space: A Bibliometric Review on the Current Research Field and Its Prospects. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12544. [CrossRef] [PubMed]
22. Macintyre, V.G.; Cotterill, S.; Anderson, J.; Phillipson, C.; Benton, J.S.; French, D.P. "I Would Never Come Here Because I've Got My Own Garden": Older Adults' Perceptions of Small Urban Green Spaces. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1994. [CrossRef] [PubMed]
23. Lengen, C. The effects of colours, shapes and boundaries of landscapes on perception, emotion and mentalising processes promoting health and well-being. *Health Place* **2015**, *35*, 166–177. [CrossRef]
24. Jennings, V.; Bamkole, O. The Relationship between Social Cohesion and Urban Green Space: An Avenue for Health Promotion. *Int. J. Environ. Res. Public Health* **2019**, *16*, 452. [CrossRef] [PubMed]
25. Chuang, Y.-C.; Chuang, K.-Y.; Yang, T.-H. Social cohesion matters in health. *Int. J. Equity Health* **2013**, *12*, 87. [CrossRef] [PubMed]
26. McCormack, G.R.; Rock, M.; Toohey, A.M.; Hignell, D. Characteristics of urban parks associated with park use and physical activity: A review of qualitative research. *Health Place* **2010**, *16*, 712–726. [CrossRef] [PubMed]

27. Li, L.; Zheng, Y.; Ma, S. Links of urban green space on environmental satisfaction: A spatial and temporarily varying approach. *Environ. Dev. Sustain.* **2023**, *25*, 3469–3501. [CrossRef]
28. Tian, D.; Wang, J.; Xia, C.; Zhang, J.; Zhou, J.; Tian, Z.; Zhao, J.; Li, B.; Zhou, C. The relationship between green space accessibility by multiple travel modes and housing prices: A case study of Beijing. *Cities* **2024**, *145*, 104694. [CrossRef]
29. World Health Organization. *Urban Green Spaces and Health*; WHO Regional Office for Europe: Copenhagen, Denmark, 2016. Available online: https://iris.who.int/handle/10665/345751 (accessed on 15 March 2023).
30. Schindler, M.; Le Texier, M.; Caruso, G. How far do people travel to use urban green space? A comparison of three European cities. *Appl. Geogr.* **2022**, *141*, 102673. [CrossRef]
31. Li, X.; Zhang, C.; Li, W.; Ricard, R.; Meng, Q.; Zhang, W. Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban For. Urban Green.* **2015**, *14*, 675–685. [CrossRef]
32. Xia, Y.; Yabuki, N.; Fukuda, T. Development of a system for assessing the quality of urban street-level greenery using street view images and deep learning. *Urban For. Urban Green.* **2021**, *59*, 126995. [CrossRef]
33. Chen, J.; Shao, S.; Zhu, Y.; Wang, Y.; Rao, F.; Dai, X.; Lai, D. Enhanced Automatic Identification of Urban Community Green Space Based on Semantic Segmentation. *Land* **2022**, *11*, 905. [CrossRef]
34. Wang, J.; Liu, W.; Gou, A. Numerical characteristics and spatial distribution of panoramic Street Green View index based on SegNet semantic segmentation in Savannah. *Urban For. Urban Green.* **2022**, *69*, 127488. [CrossRef]
35. Wang, Q.; Zhang, L.; Hu, J. An integrated method of human error likelihood assessment for shale-gas fracturing operations based on SPA and UAHP. *Process. Saf. Environ. Prot.* **2019**, *123*, 105–115. [CrossRef]
36. Madzík, P.; Falát, L. State-of-the-art on analytic hierarchy process in the last 40 years: Literature review based on Latent Dirichlet Allocation topic modelling. *PLoS ONE* **2022**, *17*, e0268777. [CrossRef] [PubMed]
37. Wang, S.; Wu, Y.J.; Li, R. An Improved Genetic Algorithm for Location Allocation Problem with Grey Theory in Public Health Emergencies. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9752. [CrossRef] [PubMed]
38. Qin, Y.; He, J.; Wei, M.; Du, X. Challenges Threatening Agricultural Sustainability in Central Asia: Status and Prospect. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6200. [CrossRef] [PubMed]
39. Lai, C.; Chen, X.; Chen, X.; Wang, Z.; Wu, X.; Zhao, S. A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory. *Nat. Hazards* **2015**, *77*, 1243–1259. [CrossRef]
40. Chen, M.-S.; Han, J.; Yu, P. Data mining: An overview from a database perspective. *IEEE Trans. Knowl. Data Eng.* **1996**, *8*, 866–883. [CrossRef]
41. Keeler, B.L.; Wood, S.A.; Polasky, S.; Kling, C.; Filstrup, C.T.; Downing, J.A. Recreational demand for clean water: Evidence from geotagged photographs by visitors to lakes. *Front. Ecol. Environ.* **2015**, *13*, 76–81. [CrossRef] [PubMed]
42. Tenkanen, H.; Di Minin, E.; Heikinheimo, V.; Hausmann, A.; Herbst, M.; Kajala, L.; Toivonen, T. Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas. *Sci. Rep.* **2017**, *7*, 17615. [CrossRef]
43. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef] [PubMed]
44. Zhou, B.; Zhao, H.; Puig, X.; Fidler, S.; Barriuso, A.; Torralba, A. Scene Parsing through ADE20K Dataset. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 21–26 July 2017; pp. 5122–5130.
45. Wu, H.; Wang, L.; Zhang, Z.; Gao, J. Analysis and optimization of 15-minute community life circle based on supply and demand matching: A case study of Shanghai. *PLoS ONE* **2021**, *16*, e0256904. [CrossRef] [PubMed]
46. Huang, R.; Liu, Y.; Liang, S.; Si, J.; Di, S.; Cai, M.; Hu, S.; Hao, C.; Zhao, Z. Social Value of Urban Green Space Based on Visitors' Perceptions: The Case of the Summer Palace, Beijing, China. *Forests* **2023**, *14*, 2192. [CrossRef]
47. Knobel, P.; Dadvand, P.; Alonso, L.; Costa, L.; Espanol, M.; Maneja, R. Development of the urban green space quality assessment tool (RECITAL). *Urban For. Urban Green.* **2021**, *57*, 126895. [CrossRef]
48. Stoia, N.L.; Niţă, M.R.; Popa, A.M.; Iojă, I.C. The green walk—An analysis for evaluating the accessibility of urban green spaces. *Urban For. Urban Green.* **2022**, *75*, 11. [CrossRef]
49. Lu, Y.; Chen, R.; Chen, B.; Wu, J. Inclusive green environment for all? An investigation of spatial access equity of urban green space and associated socioeconomic drivers in China. *Landsc. Urban Plan.* **2024**, *241*, 104926. [CrossRef]
50. Yaraghi, N.; Tabesh, P.; Guan, P.; Zhuang, J. Comparison of AHP and Monte Carlo AHP Under Different Levels of Uncertainty. *IEEE Trans. Eng. Manag.* **2015**, *62*, 122–132. [CrossRef]
51. Awad, J.; Jung, C. Extracting the Planning Elements for Sustainable Urban Regeneration in Dubai with AHP (Analytic Hierarchy Process). *Sustain. Cities Soc.* **2022**, *76*, 103496. [CrossRef]
52. Saaty, T.L. The Modern Science of Multicriteria Decision Making and Its Practical Applications: The AHP/ANP Approach. *Oper. Res.* **2013**, *61*, 1101–1118. [CrossRef]
53. Michalewicz, Z.; Schoenauer, M. Evolutionary Algorithms for Constrained Parameter Optimization Problems. *Evol. Comput.* **1996**, *4*, 1–32. [CrossRef]
54. Ren, J.; Xiong, Y. An optimised method of weighting combination in multi-index comprehensive evaluation. *Int. J. Appl. Decis. Sci.* **2010**, *3*, 34–52. [CrossRef]
55. Li, A.H. Research on Safety Assessment Method of Quayside Container Crane. Ph.D. Thesis, Wuhan University of Technology, Wuhan, China, 2017.
56. Zhou, W.; Cao, W.; Wu, T.; Zhang, T. The win-win interaction between integrated blue and green space on urban cooling. *Sci. Total. Environ.* **2023**, *863*, 160712. [CrossRef] [PubMed]

57. Zhang, W.; Yang, J.; Ma, L.; Huang, C. Factors affecting the use of urban green spaces for physical activities: Views of young urban residents in Beijing. *Urban For. Urban Green.* **2015**, *14*, 851–857. [CrossRef]
58. Bao, Y.; Gao, M.; Luo, D.; Zhou, X. Urban Parks—A Catalyst for Activities! The Effect of the Perceived Characteristics of the Urban Park Environment on Children's Physical Activity Levels. *Forests* **2023**, *14*, 423. [CrossRef]