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Improvement of the Reliability of Urban Park Location Results Through the Use of Fuzzy Logic Theory

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Abstract: Green areas, thanks to their relatively unified natural systems, play several key roles. They contribute to the proper functioning and sustainable development of cities and also determine the quality of life for their inhabitants. As a result, urban planners and policy-makers frequently aim to maximize the benefits of green spaces by creating various programs and strategies focused on green infrastructure development, such as the Green City initiative. One of the objectives of this program is to create new urban parks. This research focuses on developing a new method for selecting sites for urban parks, taking into account factors related to the environment, accessibility, and human activity. The research was carried out for the area of Ciechanów city. To make the city areas more attractive to residents, the authorities aim to increase green spaces and also revitalize the existing greenery. The combination of the Fuzzy AHP method and fuzzy set theory (selecting appropriate fuzzy membership for each factor), along with the use of large and diverse geospatial datasets, minimized subjectivity in prioritizing criteria and allowed for a fully automated analysis process. Among the factors analyzed, land use emerged as the most significant, followed by the normalized difference vegetation index (NDVI) and proximity to surface water. The results indicated that 16% of the area was deemed highly suitable for urban park development, while 15% was considered unsuitable. One-at-a-time (OAT) sensitivity analysis, based on changes in the weight of the land-use factor, revealed that a 75% reduction in weight resulted in a nearly 57.2% decrease in unsuitable areas, while a 75% increase in weight led to a 40% expansion of the most suitable locations. The potential park locations were compared with a heat map of urban activity in the city. The developed method contributes to the discourse on the transparency of location decisions and the validity of the criteria used, to promote sustainable urban development that provides residents with access to active recreation.

Keywords: fuzzy set theory; F-AHP; green city; sustainable development

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1. Introduction

With over half of the global population now residing in urban areas, the world has witnessed remarkable urban expansion in recent decades [1]. By 2050, the urban population worldwide is expected to reach 6.3 billion, nearly doubling the 3.5 billion urban residents recorded in 2010 [2]. This swift urbanization has significantly intensified the strain on natural resources and the environment [3], leading to an increase in land use for infrastructure and construction, often at the cost of urban green spaces [4].

According to the definition of Statistics Poland (GUS), green areas are those that are covered with vegetation and located within the boundaries of densely built-up villages or cities. Performing aesthetic, recreational, health, or protective functions, green areas include in particular parks, but also grassy promenades and boulevards, zoological, botanical and historic gardens, playgrounds, cemeteries, vegetation along roads, built-up areas, squares, and historic fortifications, around buildings, landfills, airports, railway stations, and industrial facilities. The World Health Organization (WHO) recommends at least 9 m^2 of green space per capita, with the ideal UGS (Urban Green Space) value of 50 m^2 per person [5]. One such idea promoting the development of green areas is the Green City, caring for the needs of modern man and, at the same time, introducing radical changes in the living conditions of people in growing urban neighborhoods. The Green City is one of the most important concepts within sustainable development. It assumes the possibility of transforming a neglected city into a green urban conglomeration. The beginning of the idea of the Green City (used alternately with Sustainable City) lies at the basis of Howard's concept of the Garden City. The idea is based on creating a central park and green protective belts within the urban area [6].

Urban green spaces, such as city parks, recreational fields, community gardens, forests, and green corridors along waterways, offer a sustainable solution to counter the negative effects of urbanization. They help limit urban sprawl, decrease the need for transportation, and enhance the capacity of cities to address climate change challenges [7,8]. These green amenities can be described as location-specific features that encourage people to visit or spend time in recreational areas [9,10]. Numerous studies have increasingly recognized that expanding urban green spaces boosts physical activity, improves both physical and mental health, and fosters social interaction by strengthening the bond between communities and nature [11,12]. As a result, this has led to a rise in property values in areas situated near urban green spaces [13,14].

Despite the numerous advantages mentioned above, urban green spaces often fail to meet the needs of city residents due to the pressures of rapid urbanization, lack of proper planning, and insufficient attention to population demands [15–17]. In addition, it should be noted that the growth of green resources enhances the overall urban environment, but this improvement may also result in local stratification and a phenomenon referred to as "green gentrification". According to several scholars, including Zheng et al. (2024), Chen et al. (2024), and Russo (2024), green gentrification can boost neighborhood vitality, yet it may also cause certain adverse effects, such as the displacement of long-time residents [18–20]. To tackle these challenges and promote urban justice and equality, attention should be given to the equitable distribution of green spaces in cities, to help overcome neighborhood segregation and foster community integration [19].

Assessing land suitability is a key aspect of planning urban green spaces, as it helps identify the most appropriate locations from a range of possibilities [21]. For selecting suitable sites, the use of the Multi-Criteria Analysis (MCA) approach combined with Geographic Information Systems (GIS) has become increasingly common [10,22,23]. MCA takes into account various parameters, such as biophysical, socio-economic, and policy-related factors, to evaluate different land options during the decision-making process [24]. MCA methods have been widely employed in both developed and developing countries for site selection in agriculture, industry, residential areas, landfills, wind farms, disaster areas, health facilities, and educational institutions [25–27]. In various parts of Europe, North America, and Asia, the integration of MCA with GIS, to identify suitable locations for urban green spaces, has gained significant attention and is now seen as an essential tool for urban green space planning [28,29].

Land suitability analysis serves as an example of a comprehensive approach that integrates Geographic Information Systems (GIS) with the Multiple Criteria Analysis (MCA) framework to evaluate and assess the potential capabilities of land, based on its requirements and qualities [30]. Previous research has integrated GIS with both traditional AHP and fuzzy AHP (F-AHP), two key methodologies developed over recent decades to address complex land-siting challenges [31–33]. Some studies have also explored the application of genetic algorithms in the selection of park sites [34]. Traditional AHP utilizes a weighted overlay tool within GIS to generate the final suitability map after determining the criteria weights through classical set theory [35,36]. Ristić et al. (2018) [37] combined AHP and GIS techniques to develop a land sustainability site selection model for the Sara Mountain National Park, revealing that only 24% of the protected area was suitable for land sustainability, while 36% was unsuitable. In another study, Georgiou and Skarlatos (2016) used traditional AHP to assign weights to four groups of factors—environmental, social, economic, and technological ones—and then incorporated these into GIS for data overlay analysis in a solar park site selection project. Their results showed that only 3% of the area was suitable for a solar park, with over 80% of the land deemed entirely unsuitable [36]. Similarly, Zhang et al. (2019) used AHP and GIS to assess urban park site viability, incorporating factors such as land construction feasibility, air pollution, park accessibility, disaster prevention service coverage, and population distribution, ultimately selecting one large park and seven smaller ones [38]. In the paper [39], the authors focused on analyzing transportation accessibility, population density, and proximity to the cultural, educational, therapeutic, and security centers, as well as proximity to other parks and petrol stations in order to determine the location of new urban parks.

The second approach, known as fuzzy AHP, integrates fuzzy set theory to rank parameters based on their importance and then assigns weights to each parameter [32,40,41]. This method is used to identify suitable locations for park development through GIS-based overlay analysis [41,42]. In their 2020 study, Pakfetrat et al. [41] identified four key factors—physical, environmental, social, and economic ones—to create a model for selecting regional park sites. Their findings indicated that fuzzy hierarchical analysis was an effective tool for determining urban park locations. Zabihi et al. (2020) [42], in their research on ecotourism site suitability, utilized the fuzzy analytic hierarchy process (F-AHP) to assess the impact of physical, natural, environmental, and socio-economic factors on ecotourism site selection. In the paper [43], the authors used 13 factors that influence the determination of urban green space locations. They also supported the analytical process with the F-AHP method. The authors [44] analyzed the application of two different multi-criteria methods, namely AHP and BWM (Best–Worst Method), in the context of supporting decision-making processes for urban park location. The analyzed studies do not take into account the nuisance factors that may have a significant impact on the location of urban parks [43–50]. Moreover, the presented studies are often biased by subjectivity [47–50].

The aim of this paper was to develop a method for selecting a site for a new city park. The research area was the city of Ciechanów, whose authorities aim to improve the quality of life of its residents by investing in the development of green infrastructure. A multi-criteria analysis was applied, considering many possible factors that may influence the location of new green spaces. As a result of a thorough analysis of the study area and the available spatial data, 13 factors were used, including six environmental factors, two related to accessibility, and five related to human activity. The research presented here expands the list of factors previously considered [43–50] by including the impact of nuisance factors (industrial facilities, wastewater treatment plants) as well as flood-risk areas. Then, an integrated approach combining fuzzy triangular sets, fuzzy AHP, and GIS for analyzing land suitability was applied. The proposed F-AHP-GIS method improves upon the traditional AHP-GIS approach by incorporating the fuzzy set theory, which allows for more effective handling of uncertainty. Triangular fuzzy numbers were used to construct a decision matrix, which reduces errors in pairwise comparisons, minimizes subjective bias, and enhances the accuracy of the multi-criteria decision-making model for urban park site selection.

The proposed methodology takes into account the characteristics of the studied area (among others, nuisance factors) and minimizes the influence of subjectivity in determining the potential elements of green infrastructure. Furthermore, the research was enriched by a sensitivity analysis of the land suitability assessment results, as well as an analysis of the obtained results in relation to the phenomenon of the urban heat island.

The main research question stands: what methodology should be developed to select the most appropriate site for a new city park? The additional research question is as follows: what impact does land use have on the choice of location for an urban park? In other words, to what extent does the change in the weight assigned to land use in the F-AHP analysis determine the results of the potential park location analysis?

The method developed is part of the discourse on transparency of location decisions and the validity of the criteria used, with a view to create sustainable and resilient urban development that provides residents with access to active recreation. Moreover, it addresses the needs of cities in Poland and around the world, where authorities are striving to increase the area of green spaces. The use of the presented methodology will certainly improve the planning process.

This manuscript has been divided into five main sections: Introduction, Materials and methods, Results, Discussion, and Conclusions. Section 1 includes a description of the research problem, a review of the literature related to urban greenery planning, as well as the research objectives. The next part describes the study area, the proposed methodology, including a description of the selected factors, and the data used for the research. In the subsequent chapter, the results are presented in the form of maps and tables containing statistical data. Section 3 also includes a sensitivity analysis. The last two parts contain the conclusions drawn from the conducted research and discuss the limitations of the proposed methodology.

2. Materials and Methods

2.1. Study Area

The area of research was the city of Ciechanów, located in the north-western part of the Masovian Voivodeship, less than 100 km north of Warsaw—the capital of Poland (Figure 1). Covering an area of 32.78 km^2, the city is a county seat. Since 2005, a decrease in the number of its inhabitants has been observed [51]. The municipal authorities engage in several revitalization activities, trying to reverse negative trends resulting from the outflow of population and coping with related socio-economic problems.

Although the green area in the city is continuously increasing, it is still far from the ideal value of 50 m^2 of green space per inhabitant. According to the ‘Ciechanów Local Revitalization Program for 2005–2023’ and the ‘Environmental Protection Program for 2026’ [51], the municipal authorities are planning to create new recreational and green areas, whilst at the same time, continue to maintain the existing greenery. Moreover, one of the challenges outlined in the ‘Socio-Economic Development Strategy of the City of Ciechanów until 2035’ is to transform it into a green city—with clean air, lower noise levels, abundant green spaces, efficient energy management, the use of renewable sources, and based on the principles of a circular economy.

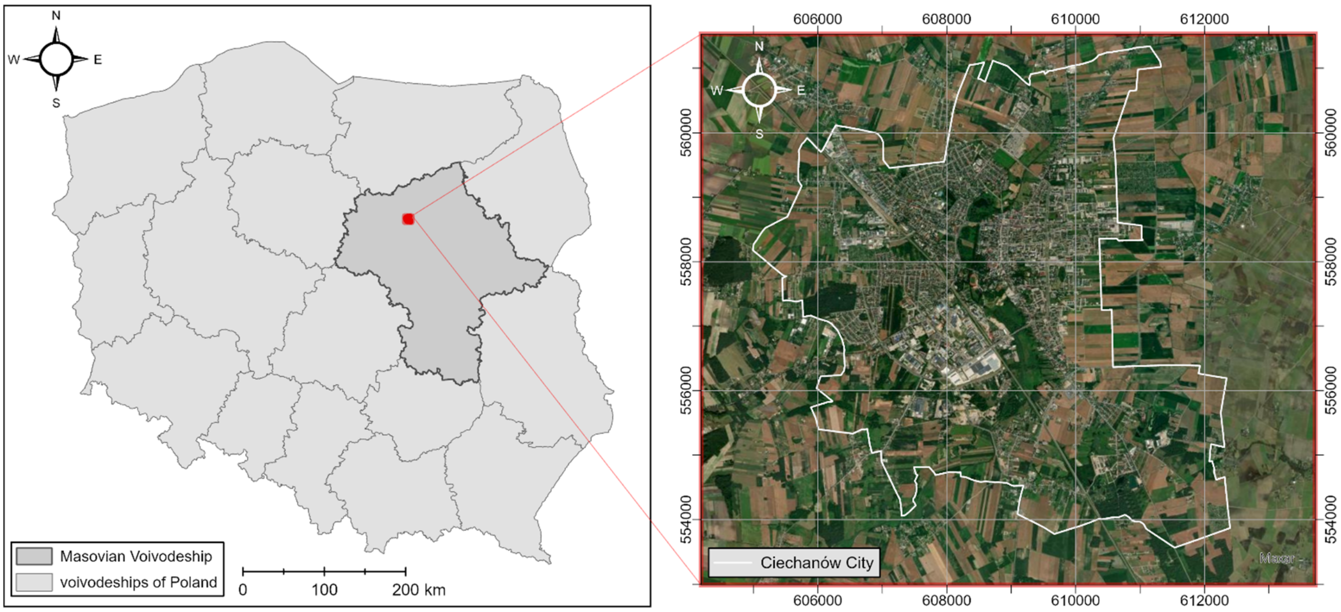

Figure 1. Study area.

The integration of remote sensing and GIS tools can support the planning process of new green urban parks [52].

2.2. Methodology

The primary aim of this research was to apply Fuzzy Logic Hierarchical Decision Analysis along with elements of fuzzy set theory in the planning of urban green spaces in Ciechanów. The study combined Geographic Information Systems (GIS) with fuzzy hierarchical analysis (F-AHP) (Figure 2). By employing the fuzzy approach to determine F-AHP weights and classify GIS indicators, the limitations of the traditional single fuzzy technique—such as data uncertainty and imprecise classification—were reduced. Moreover, the inclusion of criteria that pose threats in the selection process of urban park sites addressed a gap in sustainable urban park development studies. The authors developed a model for selecting urban park locations in Ciechanów and proposed testing its sensitivity through a global sensitivity analysis based on the OAT (one-at-a-time) technique. A map showing suitable sites for urban parks in the Ciechanów area was then created. The methodology adopted in this research enhances the methodological framework by integrating F-AHP and GIS, and the resulting urban park site selection maps provide valuable support to planners and decision-makers, enabling them to make informed and scientifically grounded decisions.

2.2.1. Selection of Urban Park Site Criteria

Most people in Europe live in cities, where conditions unfavorable to human health and well-being such as noise, pollution, or urban heat islands accumulate [53,54]. They negatively affect the health and quality of life of residents.

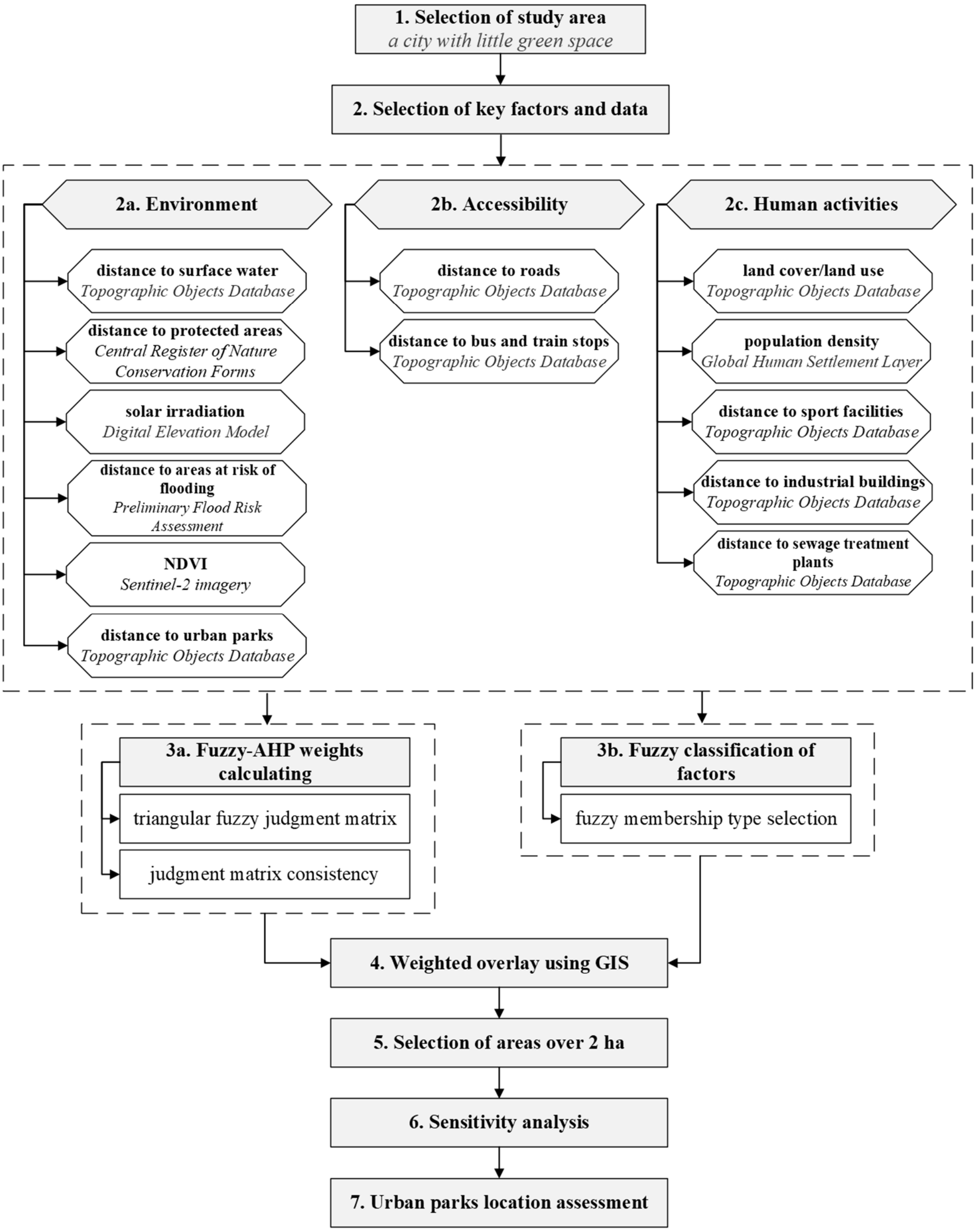

Figure 2. Methodology of urban parks site selection.

The disadvantages of city life are mitigated by creating biologically active areas, including city parks, which improve the quality of living of residents and facilitate the fulfilment of their recreational needs [55,56]. The recreational, aesthetic, and educational functions of parks are extremely important for residents' daily lives, with the vegetation of green areas playing an important environmental role by absorbing pollution, improving climatic, hydrological, and soil conditions, and serving as a habitat for plants and animals [57–59]. Drawing from the reviewed literature [23,41,43,60], the criteria for selecting urban park locations were categorized into three main groups: environmental factors, accessibility factors, and human activity (Figure 3). The environmental factors considered were distance from surface water, distance from protected areas, solar irradiation, distance from areas at risk of flooding, NDVI values, and distance from existing urban parks. Accessibility factors were assessed using distance from roads and distance from bus and train stops, and the following human activity factors were considered: population density, land use/land cover, distance from sports and recreational facilities, distance from industrial buildings, and distance from sewage treatment plants.

Local water resources are important for the urban environment and are also highly valued for recreational and aesthetic purposes. Together with urban green areas, they mitigate the negative effects of city life and climate change. Green and aquatic areas encourage residents to take up recreational activities and attract tourists to the city. Therefore, the distance from water bodies in the study area should be taken into account as one of the factors affecting the suitability of a site for the creation of new green spaces (Figure 3a). It is advantageous if city parks are located near local surface water sites, at a distance of up to 300 m [61,62].

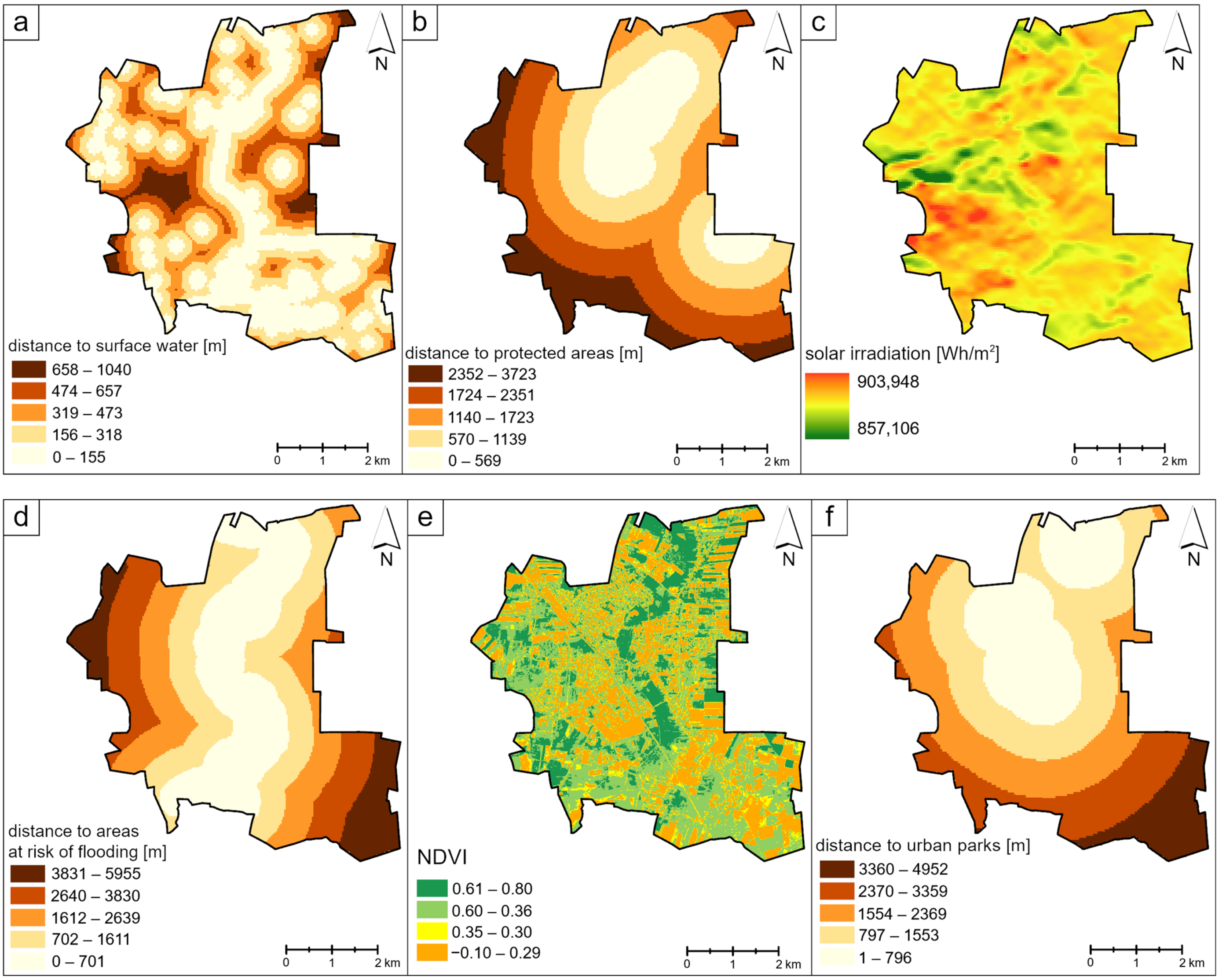

Figure 3. *Cont.*

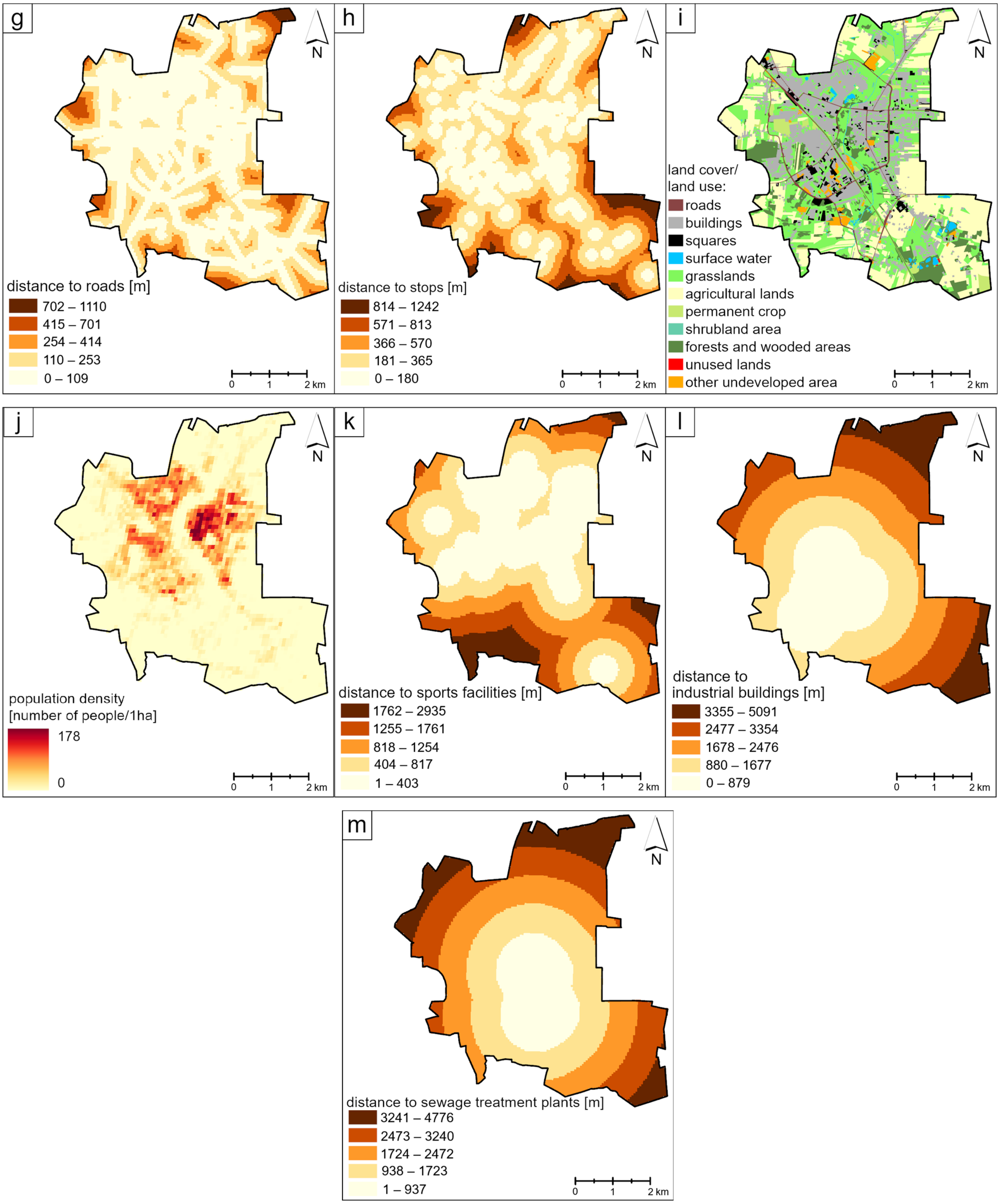

Figure 3. Factors important for determining the location of urban parks in Ciechanów. (**a**)—distance to surface water; (**b**)—distance to protected areas; (**c**)—solar irradiation; (**d**)—distance to areas at risk of flooding; (**e**)—NDVI; (**f**)—distance to urban parks; (**g**)—distance to roads; (**h**)—distance to stops; (**i**)—land cover/land use; (**j**)—population density; (**k**)—distance to sports facilities; (**l**)—distance to industrial buildings; (**m**)—distance to sewage treatment plants.

The distance of a potential site from protected areas (Figure 3b) was also considered. The analyses took into account the distances from ecological sites and landscape and nature complexes. According to the Ciechanów Environmental Protection Program, in force until 2022, the valley of the Łydynia River is the most valuable landscape and natural element of the city, performing important climatic functions, and also determining the natural, environmental, and recreational conditions in the city. In the literature, it is assumed that up to 500 m is the most favorable distance, corresponding to the length of a short walk, and such a distance of a green area from protected areas can be considered highly suitable.

Another environmental factor analyzed in the research was access to sunlight (Figure 3c). Light is essential for the life of plants, which cannot produce oxygen and carbohydrates without solar radiation. Areas with a high level of solar irradiation were used as the most suitable for new urban green areas [63].

According to the ISOK hazard maps, some of the city area is potentially exposed to a risk of flooding, which also affects the potential location of a new urban park. Therefore, distance from areas at risk of flooding was also included in the studies (Figure 3d). Article 175(1) of the Polish Water Law states that to ensure appropriate conditions for the flow of flood water, the competent authorities may, by way of a decision, order to remove trees or shrubs in areas of particular flood risk [63]. Therefore, land at risk of flooding was considered to be less suitable for new green area investment [64].

Li et al. (2022) proposed using the normalized difference vegetation index (NDVI) that determines the amount of biomass produced by plants and their condition, to assess the suitability of a site for a potential urban park [43]. Areas with an NDVI value greater than 0.35 are considered potential locations for an urban park (Figure 3e).

The distance from sports and recreation complexes and existing green areas was also considered in the research (Figure 3f,k). The BDOT10k database includes one sport and recreation center and six parks in Ciechanów, with Maria Konopnicka, Jarosław Dąbrowski, and the Botanical Research Parks of the Academy of Humanities, among others. Green spaces in the city are located in the central part of the study area. The above factors were often taken into account by other authors, including Ustaoglu et al. (2019) [23] and Piran (2013) [65].

The existing transport network significantly influences the accessibility of green urban areas. Distances of potential sites from main, collective, and local roads were taken into account in the research, together with distances from bus and train stops, offering greater accessibility to urban parks (Figure 3g,h).

The land cover of the study area also affects the choice of a suitable site for an urban park. Built-up areas and road infrastructure were excluded. Figure 3i presents the land cover in the city of Ciechanów. New green spaces should be created close to other green areas and sports and recreational complexes and integrate with them. As a result, green areas as potential sites were given higher ratings, while urban agricultural land was assigned lower values.

A socio-economic factor affecting the choice of an area for urban green spaces is population density. Areas with larger population densities require more recreational sites. In Ciechanów, the largest population density is found in the central part of the city, east and west of the Łydynia River (Figure 3j).

The authors also had to consider areas that negatively affect site suitability for an urban park. Areas situated in the vicinity of industrial facilities or sewage treatment plants do not encourage people to go for walks or to engage in relaxation activities (Figure 3l,m). For this reason, distance from large industrial facilities, employing more than 250 people, and wastewater treatment plants was taken into account. Ustaoglu et al. [23] argued that a new city park should be located more than 2500 m from such places.

2.2.2. The Use of Fuzzy Set Theory in the Raster Reclassification Process

It is essential to organize geographical data related to the selection of urban park sites using classification criteria to evaluate the suitability of a site for a park within a given area. There are two main classification methods for GIS raster images: traditional deterministic classification and fuzzy classification. In the deterministic classification, an image element is assigned a value of 1 if it completely belongs to a particular category, and 0 if it does not. However, in remote sensing data analysis, it is common to find image elements that fit into multiple categories. To address this, fuzzy classification is applied, which uses a specific fuzzy membership function to categorize such elements. Fuzzy classification is widely employed in geographic information studies because it allows for the conversion of uncertain geographic features into membership values during classification [66,67].

The concept of a fuzzy set was introduced by L.A. Zadeh in 1965 to address the challenges of uncertainty stemming from the ambiguity and imprecision in human thinking [66]. Its core idea involves relaxing the strict membership criteria of classical sets by allowing partial membership values within the range of [0, 1], where 0 represents no membership and 1 represents full membership. This approach enables researchers to model vague or imprecise concepts in natural language by accounting for uncertainties in observation and measurement [67,68]. Mathematically, the set X = {x} is defined as a finite collection of points, and a fuzzy subset Z can be described as the following:

$$Z = \{x, \mu Z(x)\} \quad (1)$$

for each $x \in X$, where $\mu Z(x)$ is the membership function that specifies the degree to which x belongs to Z. The membership function $\mu Z(x)$ takes values in the interval [0, 1], including 0 and 1. A Z value of 0 signifies that x is not part of subset Z, while a value of 1 indicates full membership. Any value between 0 and 1 suggests partial membership of x in A [67]. This expression demonstrates that the membership function $\mu Z(x)$ reflects the degree to which each x is a member of Z.

The membership function corresponds to a certain proposition; for example, in this study, the proposition relates to the suitability of land for urban green space development, based on factors such as distance from surface water, distance from protected areas, solar radiation, distance from areas at risk of flooding, NDVI values, distance from existing urban parks and existing land use/land cover, distance from bus and train stops, population density, distance from roads, distance from sports and recreational facilities, distance from industrial buildings, and distance from sewage treatment plants. A membership value of 1 indicates optimal suitability, while a value of 0 represents minimal suitability for green space development. The membership function may adopt various forms, whether continuous or discontinuous, linear or nonlinear, symmetric or asymmetric, such as Gaussian, linear, sigmoidal, J-shaped, or other more intricate non-monotonic curves [30,69]. An affiliation value of 1 of raster value indicated the perfect location for an urban park, while a value of 0 denoted the least suitable site. Furthermore, the fuzzy values representing the standards fell between 0 and 1.

This research identified linear, sigmoidal, and inverted sigmoidal functions as the most appropriate affiliation functions for dividing standard spatial data, based on a review of the literature and expert insights (Table 1). A linear function is applied when suitability increases directly with the standard value, whereas a fuzzy sigmoid (increasing) transformation function is used when the larger input values are more likely to be a member of the set. The fuzzy sigmoidal (decreasing) transformation function is used when the smaller input values are more likely to be a member of the set.

Table 1. Parameters of fuzzy membership functions.

Main Criteria	Factor	Fuzzy Membership Type	The Most Suitable Value	Minimum Value	Maximum Value	References
Environmental	Distance from surface water [m]	Fuzzy sigmoidal (decreasing)	100			[61,62,68]
	Distance from protected areas [m]	Fuzzy sigmoidal (decreasing)	300			[21,69]
	Solar irradiation [Wh/m^2]	Fuzzy sigmoidal (increasing)	890,000			[70]
	Distance from areas at risk of flooding [m]	Fuzzy linear (increasing)		100	300	[71]
	NDVI values	Fuzzy linear (increasing)		0.3	0.35	[21,43,72]
	Distance from existing urban parks [m]	Fuzzy sigmoidal (decreasing)	300			[40,69,73]
Accessibility	Distance from roads [m]	Fuzzy sigmoidal (decreasing)	400			[36,43,74]
	Distance from bus and train stops [m]	Fuzzy sigmoidal (decreasing)	400			[36,43,74]
Human activities	Land cover/land use (1—roads, buildings, squares, and other undeveloped areas; 2—permanent crops; 3—arable lands; 4—surface water, bushes, barren vegetation; 5—grasses, forests, and woodlots)	Fuzzy linear (increasing)		1	5	[21,75]
	Population density [number of people/1 ha]	Fuzzy sigmoidal (increasing)	30			[43,75]
	Distance from sports and recreational facilities [m]	Fuzzy sigmoidal (decreasing)	500			[21,28]
	Distance from industrial buildings [m]	Fuzzy sigmoidal (increasing)	2000			[21,75]
	Distance from sewage treatment plants [m]	Fuzzy sigmoidal (increasing)	2000			[21,75]

2.2.3. F-AHP Method

The fuzzy analytic hierarchy process (F-AHP) is a variation of the traditional AHP, which was introduced by Saaty in 1980. This method is used for multi-criteria decision-making (MCDM) and helps rank various significant factors in a specific domain. Fuzzy AHP employs fuzzy numbers to capture the uncertainty in human judgments when comparing different criteria. These numbers are stored in fuzzy pairwise comparison matrices. To begin, the weights are determined from these matrices using one of several algorithms. Zadeh [65] was the pioneer in introducing fuzzy logic, which enables the application of partial truth rather than strictly binary values. In a deterministic framework, decisions are constrained to binary options of 0 or 1, whereas fuzzy logic permits a spectrum of values between them to express 'partial truth'. To quantify this partial truth, a membership function is employed to capture the system's fuzziness [67]. This function was constructed using triangular fuzzy numbers (TFNs), which involve substituting exact values in the decision matrix with fuzzy ones. In the AHP decision matrix, each number is replaced by three values: l, m, and u, representing the lower, middle, and upper bounds. Figure 4 illustrates a TFN (triangular fuzzy number) function, expressed as E = (L_{ab}, M_{ab}, N_{ab}), and is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x - L_{ab}}{M_{ab} - L_{ab}} & , \quad L_{ab} \le x \le M_{ab} \\ \dfrac{x - N_{ab}}{M_{ab} - N_{ab}} & , \quad M_{ab} \le x \le N_{ab} \\ 0 & , \quad otherwise \end{cases} \tag{2}$$

In Equation (2), the TFN is described as $L_{ab} \le M_{ab} \le N_{ab}$, where N_{ab} represents the upper boundary, L_{ab} denotes the lower boundary, and M_{ab} is the midpoint of the triangular fuzzy number M. The difference $N_{ab} - L_{ab}$ indicates the fuzzy interval of M (see Figure 4). The span of this interval reflects the expert's level of confidence in the judgment of the criterion. A wider interval implies a lower degree of confidence, while a narrower interval indicates a higher level of confidence [43].

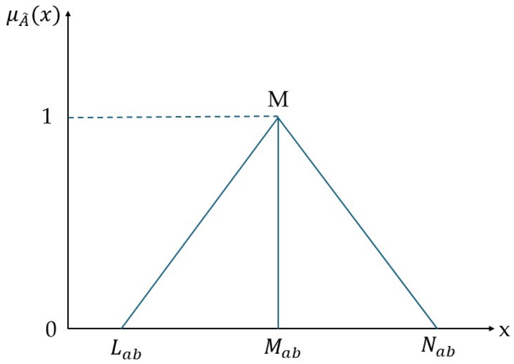

Figure 4. Fuzzy triangular numbers.

In this study, triangular fuzzy numbers are utilized to represent linguistic variables. Additionally, Saaty [76] introduced a 9-point rating scale for AHP. As a result, both approaches are integrated to evaluate genuine human preferences among alternatives. The related fuzzy numbers are shown in Table 2.

Table 2. Fuzzy comparison measures [42].

Intensity of Importance	Linguistic Definition	Fuzzy Triangular Numbers
$\tilde{1}$	Equal importance (EI)	(1, 1, 1)
$\tilde{3}$	Weak importance of one over the other (WI)	(2, 3, 4)
$\tilde{5}$	Strong importance (SI)	(4, 5, 6)
$\tilde{7}$	Very strong importance (VSI)	(6, 7, 8)
$\tilde{9}$	Absolute importance	(9, 9, 9)
$\tilde{2}$, $\tilde{4}$, $\tilde{6}$, $\tilde{8}$	Intermediate scales	(1, 2, 3) (3, 4, 5) (5, 6, 7) (7, 8, 9)

In the next step, a fuzzy pairwise comparison matrix is performed and presented as follows:

$$\tilde{A}^k = \begin{bmatrix} \tilde{a}_{11}^k & a_{12}^k & \cdots & a_{1n}^k \\ a_{21}^k & a_{22}^k & \cdots & a_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}^k & a_{n2}^k & \cdots & a_{nn}^k \end{bmatrix} \tag{3}$$

where

$\tilde{A}^{k}$ represents the fuzzy pairwise comparison matrix;
a_{nn}^{k} is a triangular fuzzy mean value for comparing priority pairs among elements.

Regarding fuzzy decomposition, the defuzzification process is described as follows [73]:

$$t_{\alpha,\beta}= [\beta f_a(Lab) + (1-\beta) f_a(N_{ab})], \quad \alpha \in [0,1] \quad \beta \in [0,1] \tag{4}$$

where

$$f_a(L_{ab}) = (M_{ab} - L_{ab}) \times \alpha + L_{ab} \tag{5}$$

$$f_a(N_{ab}) = N_{ab} - (M_{ab} - L_{ab}) \times \alpha \tag{6}$$

and where

L_{ab} is the lower bound value of the triangular fuzzy number;
M_{ab} represents the median value of the triangular fuzzy number;
N_{ab} is the upper bound value of the triangular fuzzy number.

When the diagonal matrix is matching, the result is as follows:

$$t_{\alpha,\beta}(\overline{a}_{ab}) = \frac{1}{t_{\alpha,\beta}(\overline{a}_{ab})}, \quad \alpha \in [0,1] \quad \beta \in [0,1] \quad \mathrm{i} > \mathrm{j} \tag{7}$$

After completing the process of fuzzy decomposition, the de-fuzzified pairwise comparison matrix is represented as shown below:

$$(a_{ab})_{nxn} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n1} & \cdots\cdots & 1 \end{bmatrix} \tag{8}$$

The consistency index (*CI*) and consistency ratio (*CR*) were introduced by Saaty [70] to evaluate the consistency of the comparison matrix. The *CI* and *CR* are determined using the following formulas:

$$CI = (\lambda_{max} - n)/(n-1) \tag{9}$$

where

$\lambda_{\max}$ represents the maximum value of the matrix;
N represents the number of indicators.

$$CR = CI/RI \tag{10}$$

where

CI represents the consistency index;
RI represents the random index.

The random index (RI) is a consistency measure derived from positive reciprocal matrices of varying sizes. Table 3 presents the corresponding values for the random index. According to Saaty [76], when the consistency index (CI) is lower than or equal to 0.1, it indicates an acceptable margin of error. Similarly, when the consistency ratio (CR) is less than or equal to 0.1, it signifies that the matrix's consistency is adequate.

Table 3. Random indexes (RIs).

The Order of Matrix	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RI	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49	1.52	1.54	1.56	1.58

2.2.4. Sensitivity Analysis

Although the triangular analytic hierarchy fuzzy process (F-AHP) is more objective in assigning weights to indicator criteria compared to the deterministic approach, it is still subject to some degree of expert judgment in decision-making. One-at-a-time (OAT) sensitivity analysis was used to analyze the impact of weight values on the final analysis result. In this method, the weight of a single element was changed at a time to assess the extent and pattern of how changes in the weights of individual factors affect the results, while keeping the other factors as constant as possible [77].

The sensitivity analysis of the urban park siting criteria system involves evaluating a limited set of RPCs (Relative Percentage Changes) with discrete percentage changes, starting from the original base data. As outlined by Ustaoglu and Aydinoglu (2020) [23], the RPC range for this study was set at ±75%, meaning that the weights could vary between −75% and +75% of their initial values. The results must ensure that the total sum of all criterion weights remains 1. Following the approach of Saatsaz et al. (2018) [78], the criteria with the highest standard weights were selected for the sensitivity tests. Consequently, the land-use factor, which had the highest weight, was the focus of the sensitivity test in this study. In a manner consistent with Saltelli et al. (2010) [77], a 25% variation in the IPC of the standard weights was consistently observed, showing that the original weights fluctuated by 25% at each step. The weights were adjusted by ±25%, ±50%, and ±75% over six iterations, with the other weights adjusted proportionally each time the main weight was modified.

2.3. Data

The data used in the analyses are presented in Table 4. Vector data were downloaded free of charge from administrative data collections, i.e., from Geoportal—a central node of the Polish Spatial Information Infrastructure, from ISOK—the IT System for National Protection (Country Protection Against Extreme Hazard), as well as from GDOŚ—Geoservice of the General Directorate for Environmental Protection [79–82].

Elements of the Topographic Objects Database (BDOT10k) and the National Register of Boundaries (PRG) were obtained from Geoportal resources. The Topographic Objects Database contains the spatial location of topographic features with their basic descriptive characteristics. The content of the BDOT10k database generally corresponds to a traditional topographic map at a scale of 1:10,000. The following objects were obtained from BDOT10k: roads (all classes), bus and railway stops, surface water (standing and flowing water bodies), buildings, woods and shrubs, permanent crops, agricultural land, grassy vegetation, parks/squares, unused land, squares, industrial buildings, sewage treatment plants, sports areas, and other non-built-up areas. The administrative boundaries of the Voivodeship and the city of Ciechanów were downloaded from the National Register of Boundaries. It is a reference database used by other spatial information systems, with data on the country's territorial division and records of towns, streets, and addresses [83].

Table 4. Data source.

Factor	Data Source Name	Main Parameters
Distance to surface water	Topographic Objects Database (BDOT10k) (Layers: PTWP—surface water, KUSK—sports and recreation complex, SKDR—road, OIKM—object related to communication, PTWP—surface water, PTZB—buildings, PTLZ—forest or wooded area, PTRK—shrubland area, PTUT—permanent crops, PTTR—grassland or agricultural area, PTKM—roads, PTGN—unused lands, PTPL—squares, PTNZ—other undeveloped areas, BUSP—sports building, BUBD—building, KUPG—industrial and economic complex)	vector layer, SHP format
Distance to urban parks		
Distance to roads		
Distance to stops		
Land cover/land use		
Distance to sports facilities		
Distance to industrial buildings		
Distance to sewage treatment plants		
Distance to areas at risk of flooding	Preliminary Flood Risk Assessment (WORP)	
Distance to protected areas	Central Register of Nature Conservation Forms (CRFOP)	
-	National Register of Boundaries (PRG)	
Population density	Global Human Settlement Layer (GHSL)	raster layer, TIF format, GHS-POP product, 2020 epoch, 100-m spatial resolution
NDVI	Sentinel-2a dataset	raster layer, JP2 format, Level 2a product, orthorectified atmospherically corrected surface reflectance, visible and NIR bands at 10 m
Solar irradiation	Digital Elevation Model (DEM)	raster layer, ARC/INFO ASCII GRID, 1-m spatial resolution

The classes of protected objects located in the study area were obtained from the Central Register of Nature Conservation Forms (CRFOP) of the General Directorate for Environmental Protection. The Register is the only official source of protected objects and areas in Poland [82].

The research also made use of spatial data with areas exposed to the risk of flooding, obtained from the Preliminary Flood Risk Assessment (WORP) dataset. This dataset was developed by Polish governmental and scientific institutions as part of the ISOK project. It contains, in particular, information on areas with a significant flood risk or where flooding is likely [79,80].

The 10-m Sentinel-2 multispectral satellite imagery recorded on the 15 August 2021 was also used in the research. The level 2a product was downloaded, atmospherically corrected, and orthorectified [84]. The research was conducted using Sentinel-2 data because they are free of charge and cover the necessary spectral ranges (blue, green, red, and near-infrared), with a relatively good spatial resolution. From Geoportal, the Digital Terrain Model, with a spatial resolution of 1 m, was obtained. The Digital Terrain Model is a discrete (point-based) representation of the topographic height of the terrain together with an interpolation algorithm that allows the reconstruction of its shape in a specific area [85]. The research also used data on population density in Ciechanów, available from the Global Human Settlement Layer (GHSL) project. The project provides global data on human presence on Earth in the form of built-up maps, population density maps, and settlement maps [86].

3. Results

3.1. Weight Calculation and Data Processing

The weights of the selected criteria were determined using hierarchical decision analysis. Factors were compared in pairs using the dominance scale with scores ranging from 1 to 9. The highest value meant absolute dominance of one factor over the other, and the lowest was a lack of dominance. The F-AHP method was employed to determine three main categories of criteria for selecting urban park sites: environmental factors, those related to accessibility, and human activity. Additionally, 13 sub-criteria were identified. Experts in the field were invited to score the triangular fuzzy judgment matrix (Table 5), and the average score was utilized to calculate the weight of each factor. The weights were computed by applying a refined version of the triangular fuzzy hierarchy method. Table 5 presents the consistency test outcomes and the resulting weights of the factors. The findings revealed that land use received the highest weight (19%), while distance from sports and leisure facilities was assigned the lowest (2%).

Environmental criteria, such as NDVI, distance to surface water, and distance to existing parks had significant weights, indicating that the quality of the ecological environment is an important factor in determining the location of urban parks. The land-use factor and distribution of population are the first and third most important factors, suggesting how important access of populated areas to the city park is. The greater the population, the greater the need for places where people can rest and spend time outside their place of residence.

Regarding park accessibility, the distances to underground stations, bus stops, and main roads showed similar weights. Among human activity factors like distance from sports and recreational facilities, distance from industrial buildings, and distance from industrial buildings, were assigned lower weights compared to other elements affecting urban park site selection.

As it had been previously assumed, the highest weights were assigned to the dominant factors in this research topic. The weight of the land-use factor was 19.50% and that of NDVI was 16.91%. The least important criterion of those selected for analysis was distance from sports and recreational facilities, with a weight of 1.72%.

The consistency of pairwise comparisons was then verified with the CI conformity index and the CR conformity ratio. The assessment was reiterated, and its correctness was confirmed. The maximum eigenvalue of the pairwise comparison matrix was approximately 14.378 with 13 factors compared. The value of *CI* was 0.078 and the value of *CR* was 0.114. The results were obtained by applying the following calculations:

$$CI = \frac{14.378 - 14}{13} = 0.114 \tag{11}$$

$$CR = \frac{0.114}{1.58} = 0.078 \tag{12}$$

The raster transformation was performed following the assumptions described in Table 2 and included in Figure 5.

Table 5. Calculated fuzzy aggregated decision matrix and the normalized priority weight.

	Population Density	**Distance from Protected Areas**	**Distance from Areas at Risk of Flooding**	**Solar Radiation**	**NDVI Values**	**Distance from Existing Urban Parks**	**Distance from Bus and Train Stops**	**Distance from Roads**	**Land Cover/Land Use**	**Distance from Surface Water**	**Distance from Sports and Recreational Facilities**	**Distance from Industrial Buildings**	**Distance to Sewage Treatment Plants**
Population density	(1; 1; 1)	(3; 4; 5)	(1; 2; 3)	(2.33; 3.33; 4.33)	(0.56; 0.67; 1.00)	(1; 2; 3)	(2; 3; 4)	(2; 3; 4)	(0.33; 0.50; 1)	(1; 1; 1)	(6.33; 7.33; 8.33)	(4; 5; 6)	(3.67; 4.67; 5.67)
Distance from protected areas	(0.20; 0.20; 0.3)	(1; 1; 1)	(0.26; 0.36; 0.61)	(1; 1; 1)	(0.15; 0.18; 0.22)	(0.25; 0.33; 0.50)	(0.78; 0.83; 1.00)	(0.33; 0.50; 1)	(0.13; 0.14; 0.17)	(0.20; 0.25; 0.33)	(1; 2; 3)	(1; 1; 1)	(1.00; 1.67; 2.33)
Distance from areas at risk of flooding	(0.33; 0.50; 1)	(2; 3; 4)	(1; 1; 1)	(1; 2; 3)	(0.25; 0.33; 0.50)	(0.33; 0.50; 1)	(2; 3; 4)	(2; 3; 4)	(0.25; 0.33; 0.50)	(0.33; 0.50; 1)	(3.67; 4.67; 5.67)	(2.33; 3.33; 4.33)	(2.67; 3.67; 4.67)
Solar radiation	(0.23; 0.31; 0.44)	(1; 1; 1)	(0.33; 0.50; 1)	(1; 1; 1)	(0.21; 0.26; 0.36)	(0.28; 0.39; 0.67)	(0.56; 0.67; 1.00)	(0.78; 0.83; 1.00)	(0.17; 0.20; 0.25)	(0.25; 0.33; 0.50)	(2; 3; 4)	(1; 2; 3)	(1; 1; 1)
NDVI values	(1; 1.67; 2.33)	(4.67; 5.67; 6.67)	(2; 3; 4)	(3; 4; 5)	(1; 1; 1)	(1; 2; 3)	(3.33; 4.33; 5.33)	(2.67; 3.67; 4.67)	(1; 1; 1)	(1; 2; 3)	(6.67; 7.67; 8.67)	(5.67; 6.67; 7.67)	(4.67; 5.67; 6.67)
Distance from existing urban parks	(0.33; 0.50; 1)	(2; 3; 4)	(1; 2; 3)	(1.67; 2.67; 3.67)	(0.33; 0.50; 1)	(1; 1; 1)	(1.33; 2.33; 3.33)	(1; 2; 3)	(0.25; 0.33; 0.50)	(0.33; 0.50; 1)	(4; 5; 6)	(2.33; 3.33; 4.33)	(3; 4; 5)
Distance from bus and train stops	(0.25; 0.33; 0.50)	1.00; 1.33; 1.67	(0.25; 0.33; 0.50)	(1.00; 1.67; 2.33)	(0.19; 0.23; 0.31)	(0.31; 0.44; 0.83)	(1; 1; 1)	(1; 1; 1)	(0.20; 0.25; 0.33)	(0.23; 0.31; 0.44)	(2; 3; 4)	(1.00; 1.67; 2.33)	(1; 2; 3)
Distance from roads	(0.25; 0.33; 0.50)	(1; 2; 3)	(0.25; 0.33; 0.50)	(1.00; 1.33; 1.67)	(0.22; 0.28; 0.39)	(0.33; 0.50; 1)	(1; 1; 1)	(1; 1; 1)	(0.17; 0.20; 0.25)	(0.23; 0.31; 0.44)	(2; 3; 4)	(1; 2; 3)	(1; 2; 3)
Land cover/land use	(1; 2; 3)	(6; 7; 8)	(2; 3; 4)	(4; 5; 6)	(1; 1; 1)	(2; 3; 4)	(3; 4; 5)	(4; 5; 6)	(1; 1; 1)	(1; 2; 3)	(9; 9; 9)	(7; 8; 9)	(7; 8; 9)
Distance from surface water	(1; 1; 1)	(3; 4; 5)	(1; 2; 3)	(2; 3; 4)	(0.33; 0.50; 1)	(1; 2; 3)	(2.33; 3.33; 4.33)	(2.33; 3.33; 4.33)	(0.33; 0.50; 1.00)	(1; 1; 1)	(5; 6; 7)	(3.67; 4.67; 5.67)	(2.67; 3.67; 4.67)
Distance from sports and recreational facilities	(0.12; 0.14; 0.16)	(0.33; 0.50; 1)	(0.18; 0.22; 0.28)	(0.25; 0.33; 0.50)	(0.12; 0.13; 0.15)	(0.17; 0.20; 0.25)	(0.25; 0.33; 0.50)	(0.25; 0.33; 0.50)	(0.11; 0.11; 0.11)	(0.14; 0.17; 0.20)	(1; 1; 1)	(0.56; 0.67; 1.00)	(0.56; 0.67; 1.00)
Distance from industrial buildings	(0.17; 0.21; 0.26)	(0.56; 0.67; 1.00)	(0.23; 0.31; 0.44)	(0.33; 0.50; 1)	(0.13; 0.15; 0.18)	(0.23; 0.31; 0.44)	(0.56; 0.67; 1.00)	(0.33; 0.50; 1)	(0.11; 0.13; 0.14)	(0.18; 0.22; 0.28)	(1.00; 1.67; 2.33)	(1; 1; 1)	(1; 1; 1)
Distance to sewage treatment plants	(0.18; 0.22; 0.28)	(0.23; 0.31; 0.44)	(0.22; 0.28; 0.39)	(1; 1; 1)	(0.15; 0.18; 0.22)	(0.20; 0.25; 0.33)	(0.33; 0.50; 1)	(0.33; 0.50; 1)	(0.11; 0.13; 0.14)	(0.22; 0.28; 0.39)	(1.00; 1.67; 2.33)	(1; 1; 1)	(1; 1; 1)
WEIGHTS	0.1247	0.0306	0.0798	0.0378	0.1691	0.0898	0.0428	0.0444	0.1950	0.1195	0.0172	0.0251	0.0243
RANK	3	10	6	9	2	5	8	7	1	4	13	11	12

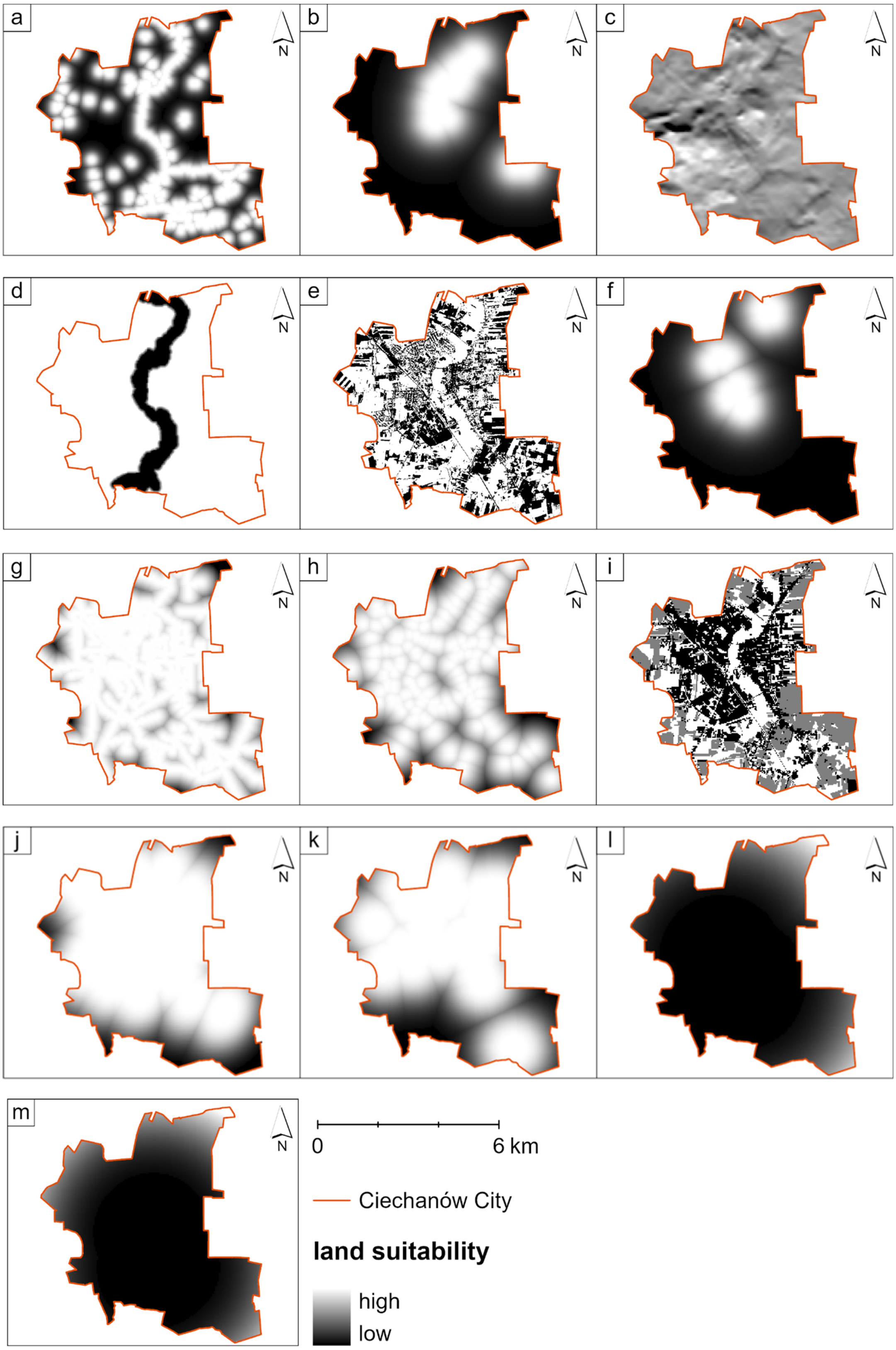

Figure 5. Results of fuzzy logic methods (based on: (**a**)—distance to surface water, (**b**)—distance to protected areas, (**c**)—solar irradiation, (**d**)—distance to areas at risk of flooding, (**e**)—NDVI values, (**f**)—distance to existing urban parks, (**g**)—distance to roads, (**h**)—distance to stops, (**i**)—land cover/land use, (**j**)—population density, (**k**)—distance to sports and recreational facilities, (**l**)—distance to industrial building, (**m**)—distance to sewage treatment plants).

3.2. Site Selection Area in Ciechanów

A weighted sum of 13 images obtained with fuzzy logic methods was calculated. The resulting image was used to develop a map of the suitability of the area of the city of Ciechanów for the site of green infrastructure (Figure 6). The area was divided into five suitability classes, i.e., unsuitable, less suitable, moderately suitable, more suitable, and highly suitable. Areas that are unsuitable for green infrastructure investments are marked in red, while the dark green color represents highly suitable areas. Overall, 14.8% of the city's area (470 ha) was classified as unsuitable, 22.5% (714 ha) as less suitable, 22% (699 ha) as moderately suitable, 23.9% (760 ha) as more suitable, and 16.9% (537 ha) as highly suitable.

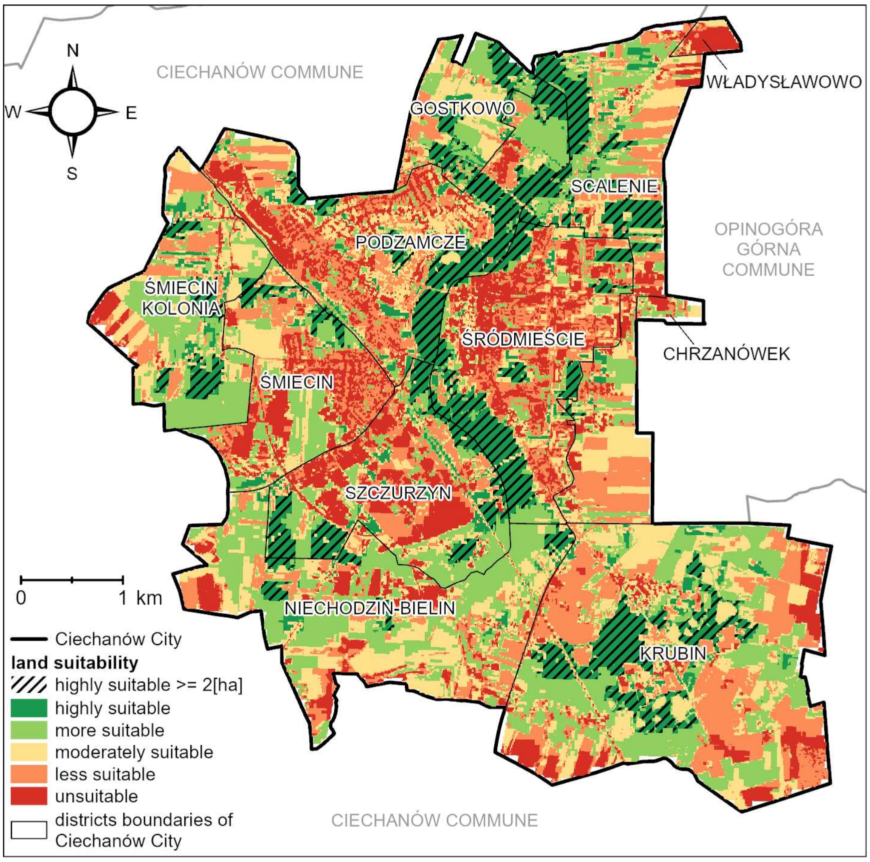

Figure 6. Urban parks location suitability map.

Using population data from 2023 [87], it was possible to select land areas suitable for the site of green infrastructure with over 128 m^2 of greenery per inhabitant of Ciechanów. The highly suitable areas were covered with woodland and grassy vegetation situated around surface water bodies. Those were both sites adjacent to the Łydynia River in the central and northern parts of the city, as well as those with standing water in the south-eastern and western parts.

Considering the administrative division of Ciechanów into 11 quarters (Figure 7), the largest amount of land suitable for the development of green infrastructure is located in Krubin (98 ha), Podzamcze (97 ha), Śródmieście (89 ha), and Scalenie (77 ha). Land designated as unsuitable is usually urbanized or located near city limits. The location of the existing parks in the city coincides with the areas of the greatest suitability, which indicates the high reliability of the research methods. Figure 8 shows the designated sites of the three largest areas that are highly suitable for investments in green infrastructure, against the background of satellite imagery. Sites highly suitable for green infrastructure development are mainly located in wooded or vegetation-covered grassy areas, close to residential buildings and existing water bodies.

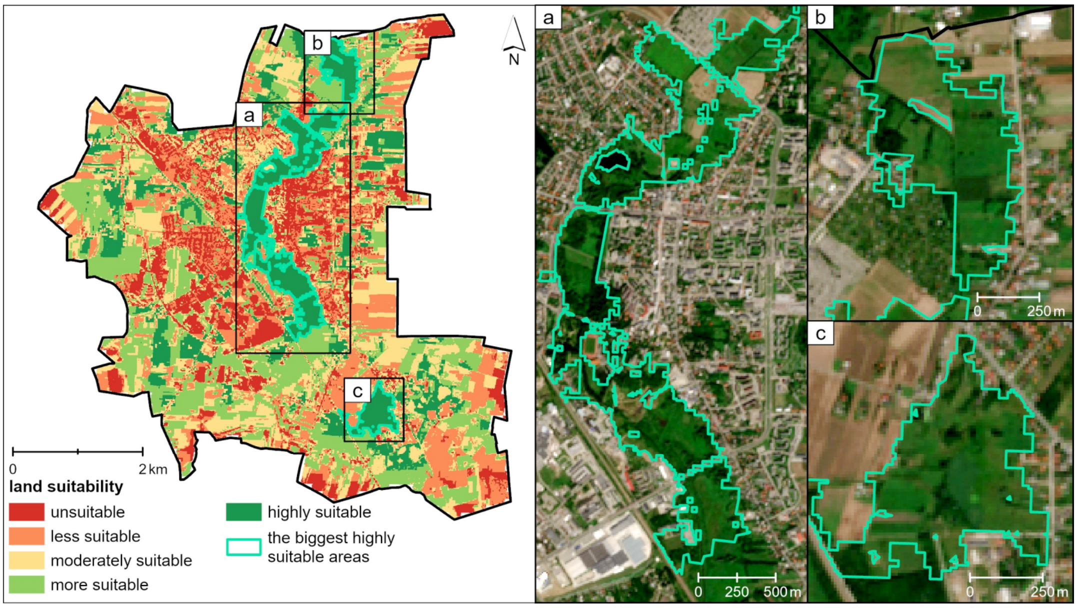

Figure 7. Visualization of the largest highly suitable areas in satellite imagery (Sentinel-2a). (**a**)—areas near the Łydynia River, (**b**)—area in the northern part of the city, (**c**)—in the Krubin district.

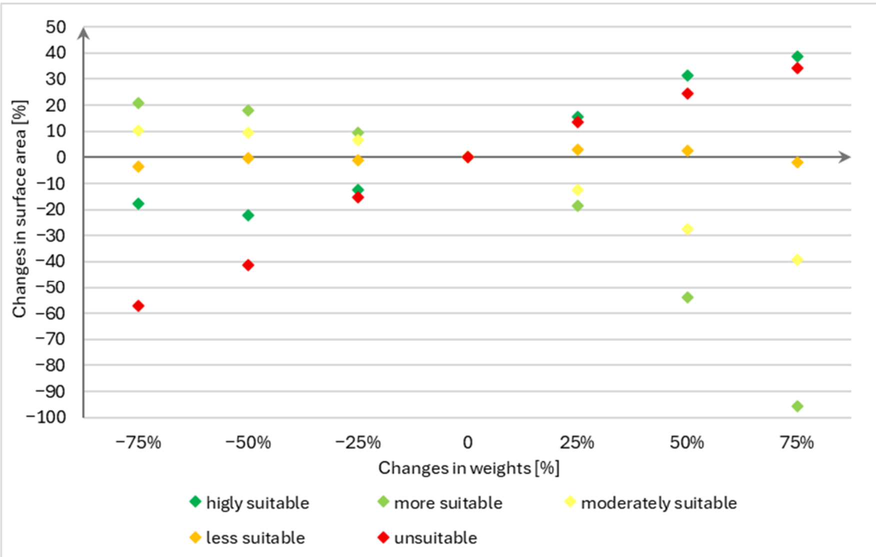

Figure 8. Results of sensitivity analysis—changes in area.

The analysis of the area revealed that there are 29 sites larger than 2 hectares. The largest areas are 84.62 hectares and 63.74 hectares, located near the Łydynia River (central part of the city—Figure 7a). The next largest areas are 33.94 hectares, located along the river in the northern part of the city (Figure 7b), and 31.54 hectares, in the Krubin district (Figure 7c).

3.3. Results of Sensitivity Analysis

Table 6 presents the results of the sensitivity analysis carried out on the factor with the highest importance, i.e., land cover/use. The weight of this criterion has been changed six times, i.e., by −25%, −50%, −75% and +25%, +50%, and +75%. Then, the weights of the remaining factors were proportionally adjusted so that the sum of all weights was 100%. Table 7 contains the values of the adjusted weights.

Table 6. Results on the variation in factors weights.

	Changes in Weight Values						
Factor	**−75%**	**−50%**	**−25%**	**0**	**+25%**	**+50%**	**+75%**
land cover/use	0.0488	0.0975	0.1463	0.1950	0.2438	0.2925	0.3413
NDVI	0.1998	0.1896	0.1793	0.1691	0.1588	0.1486	0.1384
population density	0.1473	0.1398	0.1322	0.1247	0.1171	0.1096	0.1020
distance to surface water	0.1412	0.1340	0.1267	0.1195	0.1122	0.1050	0.0978
distance to urban parks	0.1061	0.1007	0.0952	0.0898	0.0844	0.0789	0.0735
distance to areas at risk of flooding	0.0943	0.0895	0.0846	0.0798	0.0750	0.0701	0.0653
distance to roads	0.0525	0.0498	0.0471	0.0444	0.0417	0.0390	0.0363
distance to bus and train stops	0.0506	0.0480	0.0454	0.0428	0.0402	0.0376	0.0350
solar irradiation	0.0447	0.0424	0.0401	0.0378	0.0355	0.0332	0.0309
distance to protected areas	0.0362	0.0343	0.0324	0.0306	0.0287	0.0269	0.0250
distance to sports and recreational facilities	0.0203	0.0193	0.0182	0.0172	0.0162	0.0151	0.0141
distance to sewage treatment plants	0.0297	0.0281	0.0266	0.0251	0.0236	0.0221	0.0205
distance to industrial buildings	0.0287	0.0272	0.0258	0.0243	0.0228	0.0214	0.0199

Table 7. Results of sensitivity analysis—changes in surface area depending on the weight changes.

	Change in Surface Area [ha]					Change in Surface Area [%]				
Changes in Weight Values	**Unsuitable**	**Less**	**Moderately**	**More**	**Highly**	**Unsuitable**	**Less**	**Moderately**	**More**	**Highly**
−75%	299	690	777	959	456	−57.2	−3.6	10.1	20.7	−17.9
−50%	332	711	771	925	440	−41.4	−0.4	9.4	17.8	−22.1
−25%	407	707	748	841	477	−15.5	−1.0	6.6	9.6	−12.6
0	470	714	699	760	537	0	0	0	0	0
+25%	543	737	622	643	636	13.6	3.1	−12.3	−18.3	15.5
+50%	621	733	547	494	785	24.4	2.5	−27.6	−53.9	31.5
+75%	714	701	501	389	874	34.3	−1.8	−39.4	−95.5	38.5

The modification of weight values led to a change in the surface area of land belonging to all suitability classes, i.e., unsuitable, less suitable, moderately suitable, more suitable, and highly suitable (Table 7 and Figure 8).

The largest changes in the surface area of each suitability class were achieved by increasing the weight of the land cover/use by 75% or by reducing it by 75%. For a change in the weight of −75%, there were the largest changes in the surface area of the unsuitable and less suitable classes, with almost 57.2% and 41.4%. In the other classes, i.e., moderately suitable, more suitable, and highly suitable, the largest area changes were noted after modifying the weight by +75%. Relatively large changes in the surface area were also achieved as a result of a 50% increase in the weight of the factor tested.

The smallest changes in land suitability of less suitable, moderately suitable, more suitable, and highly suitable classes were observed with a modification of the main factor by −25%, while for the unsuitable class, the weight increased by 25%. It was noted that for the unsuitable, moderately suitable, and more suitable classes, an increase in the absolute weight value was related to an increase in the difference in the surface area of the class.

In cases where the weight of land cover/use was increased, the more suitable class was the most sensitive one. Changes in the surface area of this class ranged from −18.3% to −95.5%, leading to its disappearance. Reducing the weight of the main factor resulted in the greatest changes in the surface area of the unsuitable class. A change of −75% resulted in a 57.2% decrease in the surface area of this class. Modifications to the scales also had a significant impact on the area of land considered most suitable for investment in green infrastructure. For a −75% change in weight, the area of the highly suitable class decreased by 17.9%; for a change of −50%, the area decreased by 22.1%; and for a change of −25%, it decreased by 12.6%. For the weight increase of 25%, 50%, and 75%, there was an increase in the area of this class by 15.5%, 31.5%, and 38.5%, respectively. The less suitable class was the least sensitive. Visualization of changes in the distribution of areas of different suitability for the potential location of green infrastructure is presented in the form of maps in Figure 9.

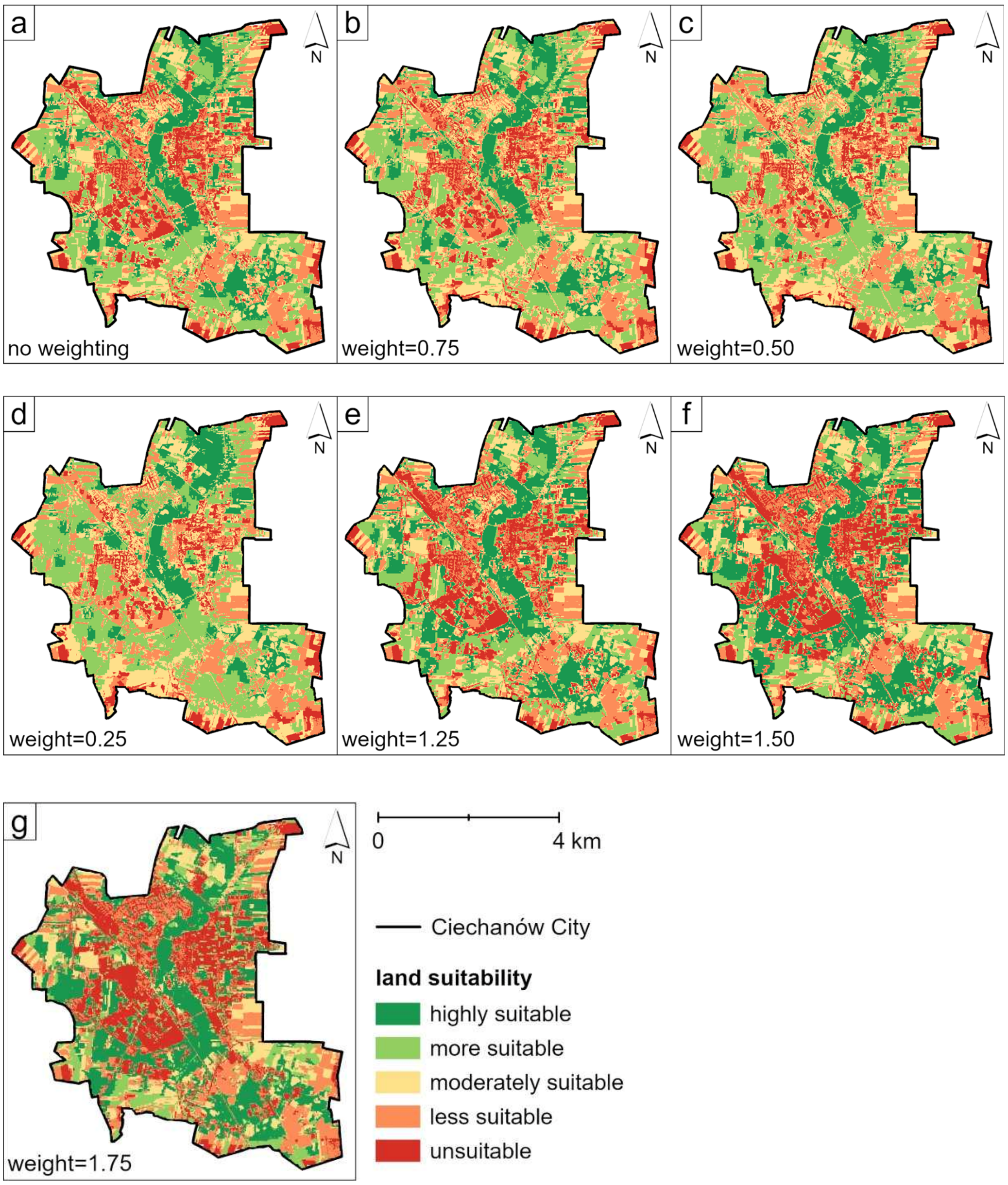

Figure 9. Sensitivity analysis result. The area of land suitability depends on the weight changes (**a**)—no weighting, (**b**)—weight 0.75, (**c**)—weight 0.50, (**d**)—weight 0.25, (**e**)—weight 1.25, (**f**)—weight 1.50, (**g**)—weight 1.75.

4. Discussion

This research presents an integrated approach by combining fuzzy triangular sets, fuzzy AHP, and GIS for analyzing land suitability for urban parks, in the city of Ciechanów. Three main categories and thirteen-factor criteria were systematically established by consolidating earlier research findings. Fuzzy triangular numbers were applied to compute factor weights, to ensure the precision of standardized spatial data sources. Sensitivity analysis was conducted to verify the robustness of the results.

The results indicate that the use of fuzzy-based approaches in assessing urban park site suitability leads to more accurate results compared to traditional methods like the Analytical Hierarchy Process (AHP) [73,74,85]. The application of fuzzy triangular numbers in the judgment matrix allows for the inclusion of uncertainty and variability in factor assessments, resulting in a more precise representation of the actual situation in the analyzed areas, which was also confirmed by many researchers like Zabihi et al. (2020) and Li et al. (2022) [42,43]. Noticeable variations in factor weights (as seen in Table 6) suggest that the fuzzy approach captures nuances that would be difficult to account for if traditional assessment methods were used [78]. In the research three main groups of selected factors were used: environmental factors, accessibility factors, and human activity. The considered environmental factors were distance from surface water, distance from protected areas, solar radiation, distance from areas at risk of flooding, NDVI values, and distance from existing urban parks. Accessibility factors were assessed using distance from roads and distance from bus and train stops. Population density, existing land use/land cover, distance from sports and recreational facilities, distance from industrial buildings, and distance from sewage treatment plants were considered to be human activity factors. The results show that each study area may require the use of a different set of factors, which was confirmed also by Givi et al. [39]. In Ciechanów, due to the presence of flood-prone areas, this factor was specifically considered. In the literature, factors that negatively affect the sustainability assessment of land, like the distance to sewage treatment plants, are often not included [43,44]. Taking such factors into account significantly impacts the accuracy of land suitability evaluation. Changes in factor weights, particularly those with higher values, significantly impact the final suitability map. For instance, when the weight of a factor was reduced by 75%, significant changes were observed in the "unsuitable" and "less suitable" categories, emphasizing the role of key factors in the final classification of areas. On the other hand, traditional questionnaire methods, although widely used, may lead to ambiguities and errors in the judgment matrix, particularly given the multitude of factors and the substantial time required from experts. Research shows that it is, therefore, essential to use sensitivity analysis to examine changes in the results of reliability assessments for urban park location suitability, which was confirmed also by Li et al. (2022) [42].

The proposed methodology for selecting urban park sites has significant practical implications, especially in the context of mitigating the urban heat island effect (Figure 10). Heat island analysis revealed that the best locations for new parks are situated in areas with the highest temperatures, suggesting that establishing parks in these areas could help lower the surrounding temperatures. Creating parks in these areas will provide shade and moisture through transpiration, ultimately reducing the surrounding temperatures. Mitigating the urban heat island effect can significantly improve residents' quality of life and contribute to sustainable urban development.

One of the main limitations of the proposed method is the fact that it is time-consuming, as the factors used in the analysis are not universal and need to be tailored to the specific characteristics of the study area each time. This customization process involves identifying and justifying the inclusion of relevant criteria for each unique location. Access to high-quality and specialized datasets, such as flood hazard information, can be a major constraint. In some cases, the lack of these data sources limits the comprehensiveness of the analysis and may lead to less accurate results. Variations in factor weights, influenced by the preferences or biases of decision-makers, may affect the results. Although the use of the Fuzzy AHP method minimizes subjective weight assessment, discrepancies in weight assignment by decision-makers may still not be fully objective. By acknowledging these limitations, future research can focus on refining the methodology to address these challenges, ensuring its broader applicability and effectiveness in diverse urban contexts.

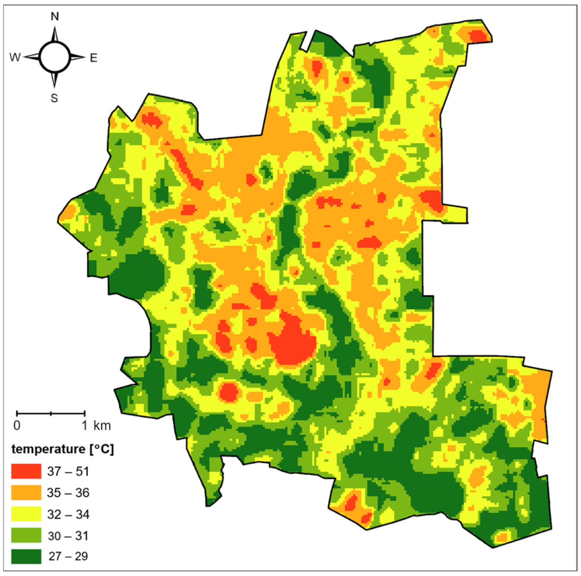

Figure 10. Surface temperature distribution in Ciechanów City on 7 August 2021.

While the proposed methodology has demonstrated its effectiveness, there is room for further development and refinement of the park site selection process. Future research could explore the integration of more advanced methods, such as artificial intelligence or genetic algorithms, to improve the precision of urban park location prediction by considering a greater number of variables. Additionally, accounting for variations in weight preferences among different decision-makers may enhance the flexibility and applicability of this methodology in different cities, adapting it to local conditions.

In conclusion, this study makes a significant contribution to the development of methodologies for selecting urban park sites, particularly through the integration of fuzzy techniques with GIS. This approach has led to more accurate results compared to traditional methods, marking an important step toward better spatial planning and sustainable urban development. The findings of this research have important practical implications and may form the basis for more effective strategies in managing green infrastructure in cities.

5. Conclusions

The proposed F-AHP-GIS method improves upon the traditional AHP-GIS approach by incorporating the fuzzy set theory, which allows for more effective handling of uncertainty. Using GIS spatial overlay techniques, a final map of urban park suitability was generated, categorizing the land into five levels: highly suitable, more suitable, moderately suitable, less suitable, and unsuitable. Approximately 16.9% (537 ha) of the area was found to be highly suitable, 23.9% (760 ha) more suitable, 22% (699 ha) moderately suitable, 22.5% (714 ha) less suitable, and 14.8% of the city area (470 ha) unsuitable.

The OAT sensitivity analysis, based on the maximum weight of a factor, revealed that the heavily weighted land-use factor had a notable impact on the suitability map. In the case of weight change by −75%, the largest changes in the surface area of unsuitable and less suitable were noted, by nearly 57.2% and 41.4%. This led to the conclusion that the highest-weighted factor for urban park site suitability significantly affects the final evaluation. Overall, the presented analysis of existing urban park locations in Ciechanów highlighted that various environmental, accessibility, and human activity-related factors were appropriately taken into account. The currently existing city parks coincided with the areas marked in the analysis as highly suitable, which confirms the correctness of the analysis.

This research might offer a foundation for the planning process by employing GIS and the multi-criteria decision-making (MCDM) method for the urban development of Ciechanów. Consequently, this study highlighted the benefits of conducting GIS-based land suitability assessments and provided an approach to address complex decision-making scenarios. It also serves as valuable guidance for future land-use modifications and presents cost-efficient solutions for cities with conditions similar to those found in Poland.

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References

1. Wu, J. Urban Ecology and Sustainability: The State of the Science and Future Directions. *Landsc. Urban Plan.* **2014**, *125*, 209–221. [CrossRef]
2. World Urbanization Prospects—Population Division—United Nations. Available online: https://population.un.org/wup/ (accessed on 12 September 2024).
3. Rees, W.; Wackernagel, M. Urban Ecological Footprints: Why Cities Cannot Be Sustainable—And Why They Are a Key to Sustainability. *Environ. Impact Assess. Rev.* **1996**, *16*, 223–248. [CrossRef]
4. Benabbou, A. Land Use Suitability Analysis Using an Approach Combining GIS, Regionalization, and PROMETHEE II. *Ann. GIS* **2024**, *30*, 121–136. [CrossRef]
5. Russo, A.; Cirella, G. Modern Compact Cities: How Much Greenery Do We Need? *Int. J. Environ. Res. Public Health* **2018**, *15*, 2180. [CrossRef]
6. Szczepańska, M. Miasto-ogród jako przestrzeń zamieszkania, pracy i rekreacji—Dawniej i dziś. *Stud. Periegenetica* **2011**, *6*, 77–89.
7. Escobedo, F.J.; Kroeger, T.; Wagner, J.E. Urban Forests and Pollution Mitigation: Analyzing Ecosystem Services and Disservices. *Environ. Pollut.* **2011**, *159*, 2078–2087. [CrossRef]
8. Armson, D.; Stringer, P.; Ennos, A.R. The Effect of Street Trees and Amenity Grass on Urban Surface Water Runoff in Manchester, UK. *Urban For. Urban Green.* **2013**, *12*, 282–286. [CrossRef]
9. Waltert, F.; Schläpfer, F. Landscape Amenities and Local Development: A Review of Migration, Regional Economic and Hedonic Pricing Studies. *Ecol. Econ.* **2010**, *70*, 141–152. [CrossRef]
10. Van Berkel, D.B.; Munroe, D.K.; Gallemore, C. Spatial Analysis of Land Suitability, Hot-Tub Cabins and Forest Tourism in Appalachian Ohio. *Appl. Geogr.* **2014**, *54*, 139–148. [CrossRef]
11. Zwierzchowska, I.; Hof, A.; Iojă, I.-C.; Mueller, C.; Poniży, L.; Breuste, J.; Mizgajski, A. Multi-Scale Assessment of Cultural Ecosystem Services of Parks in Central European Cities. *Urban For. Urban Green.* **2018**, *30*, 84–97. [CrossRef]

12. 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]
13. Jim, C.Y.; Chen, W.Y. External Effects of Neighbourhood Parks and Landscape Elements on High-Rise Residential Value. *Land. Use Policy* **2010**, *27*, 662–670. [CrossRef]
14. Zygmunt, R.; Gluszak, M. Forest Proximity Impact on Undeveloped Land Values: A Spatial Hedonic Study. *For. Policy Econ.* **2015**, *50*, 82–89. [CrossRef]
15. Gill, S.E.; Handley, J.F.; Ennos, A.R.; Pauleit, S. Adapting Cities for Climate Change: The Role of the Green Infrastructure. *Built Environ.* **2007**, *33*, 115–133. [CrossRef]
16. Wright, R.; Nebel, B.; Toward, A. Sustainable Future. *Environ. Sci. Policy Sustain. Dev.* **2002**, *44*, 10–15. [CrossRef]
17. Ahmadi, N.; Golestani, M.A.; Bayzidan, M. The Current Status of Urban Parks and Green Spaces in Tehran, Iran. In Proceedings of the VI International Conference on Landscape and Urban Horticulture 1189, Athens, Greece, 20–25 June 2016; pp. 155–160. [CrossRef]
18. Zheng, H.; Jia, H.; Lu, J. Study on Green Gentrification Mechanisms and Residents' Satisfaction in Chinese New Urban Areas: A Case Study of the Area Surrounding Julong Lake Park. *Sustainability* **2024**, *16*, 150. [CrossRef]
19. Chen, T.-L.; Chen, T.-X.; Lin, Z.-H. Rural Gentrification and Its Driving Forces Based on Social Network Analysis: A Case Study of Yilan, Taiwan. *Sustainability* **2024**, *16*, 10460. [CrossRef]
20. Russo, A. Renaturing for Urban Wellbeing: A Socioecological Perspective on Green Space Quality, Accessibility, and Inclusivity. *Sustainability* **2024**, *16*, 5751. [CrossRef]
21. Sahabo, A.; Mohammed, A.B. A GIS Based Multi-Criteria Analysis for Siting Recreational Parksin Yola-North Local Government. *Int. J. Appl. Sci. Eng. Res.* **2016**, *5*, 20–29.
22. Uy, P.D.; Nakagoshi, N. Application of Land Suitability Analysis and Landscape Ecology to Urban Greenspace Planning in Hanoi, Vietnam. *Urban For. Urban Green.* **2008**, *7*, 25–40. [CrossRef]
23. Ustaoglu, E.; Aydınoglu, A.C. Land Suitability Assessment of Green Infrastructure Development. *TeMA—J. Land. Use Mobil. Environ.* **2019**, *12*, 165–178. [CrossRef]
24. Zhran, M.; Ghanem, K.; Tariq, A.; Alshehri, F.; Jin, S.; Das, J.; Pande, C.B.; Pramanik, M.; Hasher, F.F.B.; Mousa, A. Exploring a GIS-based analytic hierarchy process for spatial flood risk assessment in Egypt: A case study of the Damietta branch. *Environ. Sci. Eur.* **2024**, *36*, 184. [CrossRef]
25. Rikalovic, A.; Cosic, I.; Lazarevic, D. GIS Based Multi-Criteria Analysis for Industrial Site Selection. *Procedia Eng.* **2014**, *69*, 1054–1063. [CrossRef]
26. Demesouka, O.; Vavatsikos, A.; Anagnostopoulos, K. Using MACBETH Multicriteria Technique for GIS-Based Landfill Suitability Analysis. *J. Environ. Eng.* **2016**, *142*, 04016042. [CrossRef]
27. Vasileiou, M.; Loukogeorgaki, E.; Vagiona, D.G. GIS-Based Multi-Criteria Decision Analysis for Site Selection of Hybrid Offshore Wind and Wave Energy Systems in Greece. *Renew. Sustain. Energy Rev.* **2017**, *73*, 745–757. [CrossRef]
28. Marsh, K.; IJzerman, M.; Thokala, P.; Baltussen, R.; Boysen, M.; Kaló, Z.; Lönngren, T.; Mussen, F.; Peacock, S.; Watkins, J.; et al. Multiple Criteria Decision Analysis for Health Care Decision Making—Emerging Good Practices: Report 2 of the ISPOR MCDA Emerging Good Practices Task Force. *Value Health* **2016**, *19*, 125–137. [CrossRef]
29. Nowak, D.; Crane, D. The Urban Forest Effects (UFORE) Model: Quantifying Urban Forest Structure and Functions', in Integrated Tools for Natural Resources Inventories in the 21st Century. In Proceedings of the IUFRO Conference, Kuala Lumpur, Malaysia, 7–12 August 2000; pp. 714–720.
30. Malczewski, J. GIS-Based Land-Use Suitability Analysis: A Critical Overview. *Prog. Plan.* **2004**, *62*, 3–65. [CrossRef]
31. Islam, M.; Kashem, S.; Morshed, S. Integrating Spatial Information Technologies and Fuzzy Analytic Hierarchy Process (F-AHP) Approach for Landfill Siting. *City Environ. Interact.* **2020**, *7*, 100045. [CrossRef]
32. Ahmad, N.; Qahmash, A. Implementing Fuzzy AHP and FUCOM to Evaluate Critical Success Factors for Sustained Academic Quality Assurance and ABET Accreditation. *PLoS ONE* **2020**, *15*, e0239140. [CrossRef]
33. Chaabane, F.Z.; Lamine, S.; Guettouche, M.S.; Bachari, N.E.I.; Hallal, N. Landslide Risk Assessments through Multicriteria Analysis. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 303. [CrossRef]
34. Neema, M.N.; Ohgai, A. Multi-Objective Location Modeling of Urban Parks and Open Spaces: Continuous Optimization. *Comput. Environ. Urban. Syst.* **2010**, *34*, 359–376. [CrossRef]
35. Olaniyi, O.E.; Akindele, S.O.; Ogunjemite, B.G. Ecotourism Suitability of Okomu and Pendjari National Parks. *Anatolia* **2018**, *29*, 593–604. [CrossRef]
36. Georgiou, A.; Skarlatos, D. Optimal Site Selection for Sitting a Solar Park Using Multi-Criteria Decision Analysis and Geographical Information Systems. *Geosci. Instrum. Methods Data Syst.* **2016**, *5*, 321–332. [CrossRef]
37. Ristić, V.; Maksin, M.; Nenković-Riznić, M.; Basarić, J. Land-Use Evaluation for Sustainable Construction in a Protected Area: A Case of Sara Mountain National Park. *J. Environ. Manag.* **2018**, *206*, 430–445. [CrossRef]

38. Zhang, X.; Fang, C.; Wang, Z.; Ma, H. Urban Construction Land Suitability Evaluation Based on Improved Multi-Criteria Evaluation Based on GIS (MCE-GIS): Case of New Hefei City, China. *Chin. Geogr. Sci.* **2013**, *23*, 740–753. [CrossRef]
39. Givi, A.A.; Karimi, S.; Foroughi, N.; Moarab, Y.; Nikzad, V. Using Fuzzy Logic Analysis in GIS and FAHP Method for Parks Site Selection in Urban Environment (Case Study: Region 7, Tehran Municipality). *Curr. World Environ.* **2015**, *10*, 432–444. [CrossRef]
40. Emrouznejad, A.; Ho, W.; St, C. *Fuzzy Analytic Hierarchy Process*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2017. [CrossRef]
41. Pakfetrat, A.; Taghvaei, M.; Zarrabi, A. A Comprehensive Approach in Green Space Site Planning: An Application of a Three-Stage Multi-Criteria Decision Support System. *Urban Res. Pract.* **2020**, *13*, 45–76. [CrossRef]
42. Zabihi, H.; Alizadeh, M.; Wolf, I.D.; Karami, M.; Ahmad, A.; Salamian, H. A GIS-Based Fuzzy-Analytic Hierarchy Process (F-AHP) for Ecotourism Suitability Decision Making: A Case Study of Babol in Iran. *Tour. Manag. Perspect.* **2020**, *36*, 100726. [CrossRef]
43. Li, C.; Zhang, T.; Wang, X.; Lian, Z. Site Selection of Urban Parks Based on Fuzzy-Analytic Hierarchy Process (F-AHP): A Case Study of Nanjing, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 13159. [CrossRef]
44. Srdjevic, B.; Srdjevic, Z.; Reynolds, K.M.; Lakicevic, M.; Zdero, S. Using Analytic Hierarchy Process and Best–Worst Method in Group Evaluation of Urban Park Quality. *Forests* **2022**, *13*, 290. [CrossRef]
45. Chandio, I.; Matori, A.-N.; Lawal, D.; Sabri, S. GIS- Based Land Suitability Analysis Using AHP for Public Parks Planning in Larkana City. *Mod. Appl. Sci.* **2011**, *5*, 177–189. [CrossRef]
46. Srdjevic, B.; Lakicevic, M.; Srdjevic, Z. Fuzzy AHP Assessment of Urban Parks Quality and Importance in Novi Sad City, Serbia. *Forests* **2023**, *14*, 1227. [CrossRef]
47. Wicaksono, A. Priority Modeling for Public Urban Park Development in Feasible Locations Using GIS, Intuitionistic Fuzzy AHP, and Fuzzy TOPSIS. *J. Rekayasa Elektr.* **2021**, *17*, 247–256. [CrossRef]
48. Zięba-Kulawik, K.; Wężyk, P. Monitoring 3D Changes in Urban Forests Using Landscape Metrics Analyses Based on Multi-Temporal Remote Sensing Data. *Land* **2022**, *11*, 883. [CrossRef]
49. Ooshaksaraie, L. Identification and comparison criteria and sub-criteria for siting urban forest parks. *Proc. Int. Acad. Ecol. Environ. Sci.* **2024**, *14*, 75–85.
50. Lotfi, S.; Hoseinzadeh, A.Z.; Faraji Molaei, A.; Ahmadi Firozjaei, M. Investigation of Spatial Distribution of Urban Parks and Site Selections of New Parks Using Fuzzy Logic and Analytical Hierarchic Process (Case Study: Babolsar). *J. Environ. Stud.* **2012**, *38*, 37–39.
51. Program Ochrony Środowiska Gminy Miejskiej Ciechanów. Available online: https://bip.umciechanow.pl/informacje_urzedu/Program_ochrony_srodowiska_GM_Ciechanow_na_lata_2013_2016 (accessed on 14 September 2024).
52. Strategia Rozwoju Społeczno—Gospodarczego Miasta Ciechanów Do 2035 r. Available online: https://bip.umciechanow.pl/informacje_urzedu/strategia-rozwoju-spoleczno-gospodarczego-miasta-ciechanow-do-2035-r (accessed on 16 September 2024).
53. Cao, X.; Onishi, A.; Chen, J.; Imura, H. Quantifying the Cool Island Intensity of Urban Parks Using ASTER and IKONOS Data. *Landsc. Urban Plan.* **2010**, *96*, 224–231. [CrossRef]
54. Kong, F.; Yin, H.; James, P.; Hutyra, L.R.; He, H.S. Effects of Spatial Pattern of Greenspace on Urban Cooling in a Large Metropolitan Area of Eastern China. *Landsc. Urban Plan.* **2014**, *128*, 35–47. [CrossRef]
55. White, M.P.; Pahl, S.; Ashbullby, K.; Herbert, S.; Depledge, M.H. Feelings of Restoration from Recent Nature Visits. *J. Environ. Psychol.* **2013**, *35*, 40–51. [CrossRef]
56. 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]
57. Szumacher, I. Potencjał rekreacyjny parków miejskich. *Probl. Ekol. Kraj.* **2010**, *27*, 487–490.
58. Nesshöver, C.; Assmuth, T.; Irvine, K.N.; Rusch, G.M.; Waylen, K.A.; Delbaere, B.; Haase, D.; Jones-Walters, L.; Keune, H.; Kovacs, E.; et al. The Science, Policy and Practice of Nature-Based Solutions: An Interdisciplinary Perspective. *Sci. Total Environ.* **2017**, *579*, 1215–1227. [CrossRef] [PubMed]
59. Ji, S.; Ma, R.; Ren, L.; Wang, C. How to Find Vacant Green Space in the Process of Urban Park Planning: Case Study in Ningbo (China). *Int. J. Environ. Res. Public Health* **2020**, *17*, 8282. [CrossRef] [PubMed]
60. Zhou, Y.; Shi, T.-M.; Hu, Y.-M.; Gao, C.; Liu, M.; Song, L.-Q. Location selection for Shenyang urban parks based on GIS and multi-objective location allocation model. *J. Appl. Ecol.* **2011**, *22*, 3307–3314.
61. Piran, H.; Maleknia, R.; Akbari, H.; Soosani, J.; Karami, O. Site Selection for Local Forest Park Using Analytic Hierarchy Process and Geographic Information System (Case Study: Badreh County). *Int. Res. J. Appl. Basic Sci.* **2013**, *6*, 930–935.
62. Mahdavi, A.; Niknejad, M. Site Suitability Evaluation for Ecotourism Using MCDM Methods and GIS: Case Study—Lorestan Province, Iran. *JBES* **2014**, *4*, 425–437.
63. Krawczyk, P.; Calka, B.; Bielecka, E. Analiza Zagrożenia Powodziowego Kazimierza Dolnego. *Rocz. Geomatyki* **2022**, *20*, 81–91.
64. Ustawa z Dnia 20 Lipca 2017, r.—Prawo Wodne. Available online: https://isap.sejm.gov.pl/isap.nsf/DocDetails.xsp?id=WDU20170001566 (accessed on 16 September 2024).
65. Zadeh, L.A. Fuzzy Sets. *Inf. Control* **1965**, *8*, 338–353. [CrossRef]

66. Foody, G.M. Fully Fuzzy Supervised Classification of Land Cover from Remotely Sensed Imagery with an Artificial Neural Network. *Neural Comput. Appl.* **1997**, *5*, 238–247. [CrossRef]
67. Zimmermann, H.-J. Fuzzy Set Theory. *Wiley Interdiscip. Rev. Comput. Stat.* **2010**, *2*, 317–332. [CrossRef]
68. Abebe, M.T.; Megento, T.L. Urban Green Space Development Using GIS-Based Multi-Criteria Analysis in Addis Ababa Metropolis. *Appl. Geomat.* **2017**, *9*, 247–261. [CrossRef]
69. Yigitcanlar, T.; Sipe, N.; Evans, R.; Pitot, M. A GIS-Based Land Use and Public Transport Accessibility Indexing Model. *Aust. Plan.* **2007**, *44*, 30–37. [CrossRef]
70. Mierzwiak, M.; Calka, B. Multi-Criteria Analysis for Solar Farm Location Suitability. *Rep. Geod. Geoinform.* **2017**, *104*, 20–32. [CrossRef]
71. ISOK—Country's Protection Against Extreme Hazards. Available online: https://isok.gov.pl/inspire.html (accessed on 29 May 2024).
72. Li, Z.; Fan, Z.; Shen, S. Urban Green Space Suitability Evaluation Based on the AHP-CV Combined Weight Method: A Case Study of Fuping County, China. *Sustainability* **2018**, *10*, 2656. [CrossRef]
73. Mondal, S.; Parveen, M.T.; Alam, A.; Rukhsana; Islam, N.; Calka, B.; Bashir, B.; Zhran, M. Future Site Suitability for Urban Waste Management in English Bazar and Old Malda Municipalities, West Bengal: A Geospatial and Machine Learning Approach. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 388. [CrossRef]
74. Bhattacharya, O.; Sinha, S.; Mishra, V.N.; Kumari, K.; Ben Hasher, F.F.; Barman, J.; Zhran, M. Harnessing geospatial tools to map the forest fire: Risk zonation in Pauri Garhwal, Uttarakhand. *Results Eng.* **2025**, *25*, 103694. [CrossRef]
75. Gelan, E. GIS-Based Multi-criteria Analysis for Sustainable Urban Green Spaces Planning in Emerging Towns of Ethiopia: The Case of Sululta Town. *Environ. Syst. Res.* **2021**, *10*, 13. [CrossRef]
76. Saaty, T.L. The Analytic Hierarchy Process (AHP). *J. Oper. Res. Soc.* **1980**, *41*, 1073–1076.
77. Saltelli, A.; Annoni, P. Sensitivity Analysis. In *International Encyclopedia of Statistical Science*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 1298–1301. [CrossRef]
78. Saatsaz, M.; Monsef, I.; Rahmani, M.; Ghods, A. Site Suitability Evaluation of an Old Operating Landfill Using AHP and GIS Techniques and Integrated Hydrogeological and Geophysical Surveys. *Environ. Monit. Assess.* **2018**, *190*, 144. [CrossRef]
79. Preliminary Flood Risk Assessment. Available online: https://dane.gov.pl/pl/dataset/2181,wstepna-ocena-ryzyka-powodziowego-worp (accessed on 14 September 2024).
80. Bielecka, E.; Dukaczewski, D.; Janczar, E. Spatial Data Infrastructure in Poland–Lessons Learnt from so Far Achievements. *Geod. Cartogr.* **2018**, *67*, 3–20. [CrossRef]
81. Geoportal. Available online: https://web.archive.org/web/20250105185747/https://www.geoportal.gov.pl/ (accessed on 19 July 2024).
82. Central Register of Nature Conservation Forms. Available online: https://www.gov.pl/web/gdos/dostep-do-danych-geoprzestrzennych (accessed on 29 May 2024).
83. National Register of Boundaries. Available online: https://web.archive.org/web/20241114125818/https://www.geoportal.gov.pl/pl/dane/panstwowy-rejestr-granic-prg/ (accessed on 10 May 2024).
84. Copernicus. European Union's Space Programme. Available online: https://browser.dataspace.copernicus.eu (accessed on 29 May 2024).
85. Kaczyński, R.; Ewiak, I. *Fotogrametria*; Wojskowa Akademia Techniczna: Warszawa, Poland, 2016.
86. Copernicus GHSL. Available online: https://human-settlement.emergency.copernicus.eu (accessed on 29 May 2024).
87. Głowny Urząd Statystyczny/Podstawowe Dane. Available online: https://stat.gov.pl/podstawowe-dane/ (accessed on 16 September 2024).