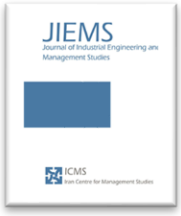
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Optimal Urban Hospital Location Using F-ANP, F-WASPAS Methods, and Spatial Analysis: A Case Study of Arak City

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Abstract

Selecting optimal locations for health and medical facilities is critical for minimizing financial burdens and improving public health outcomes. Hospital siting directly influences accessibility, service efficiency, and overall community well being. This study develops an integrated, uncertainty aware framework to identify suitable hospital locations in Arak City, Iran. The approach combines Geographic Information Systems (GIS) with advanced fuzzy multi criteria decision making techniques, including the Fuzzy Analytic Network Process (F ANP) and the Fuzzy Weighted Aggregated Sum Product Assessment (F WASPAS). Site selection criteria were defined through a comprehensive literature review, national regulatory guidelines, expert input, and local geographic considerations. F ANP was used to derive interdependent criteria weights, while GIS employed multiple fuzzy operators to generate spatial suitability maps. Subsequently, F WASPAS ranked five candidate sites based on their aggregated fuzzy scores. The results identify the most feasible and accessible areas for new hospital development and demonstrate the value of integrating fuzzy logic with spatial analysis in data scarce environments. The proposed framework offers a robust decision support tool for urban planners and health policymakers. Future research may incorporate alternative fuzzy numbers, additional criteria, and broader regional applications to further validate and extend the model.

Keywords: Hospital Site Selection, GIS, Fuzzy ANP, Fuzzy WASPAS, Multi-Criteria Decision-Making, Urban Healthcare Planning, Arak City

Paper Type: Original Research

1. Introduction

Public service infrastructures are vital channels for delivering essential services such as healthcare, education, and banking to the community. Among these, access to medical facilities is particularly critical because reliable healthcare is fundamental to a secure and healthy life. Yet, healthcare services frequently suffer from limited availability, uneven geographic distribution, and elevated costs, making equitable access a pressing challenge (Hu et al., 2024). Rapid urbanization and population growth have intensified the demand for essential infrastructure, including medical centers, emergency response facilities, and parking spaces, resulting in an unprecedented surge in global healthcare needs (Velez et al., 2021). Ensuring universal access to healthcare remains a central objective of national development strategies, but many rapidly growing cities continue to experience disparities in service provision (Tripathi et al., 2020; Shahbod et al., 2020). Despite the importance of healthcare, it often receives insufficient attention in government budgets and infrastructure planning, leading to critical service gaps. In Iran, rapid urban expansion has outpaced infrastructure development, creating disparities in access to essential services, including healthcare. These challenges raise important questions about social justice and sustainable development, as equitable access to healthcare is a fundamental component of urban wellbeing. Social justice emphasizes equal opportunities for all citizens, making the fair distribution of healthcare services a core priority for urban planners (Fang yu et al., 2022). Hospitals, as key institutions in public health systems, provide diagnostic, therapeutic, educational, and research services, and their strategic placement is essential for improving health outcomes and promoting social equity (Dunne, 2018). Given the high costs associated with establishing new hospitals, selecting optimal locations is a critical first step in expanding healthcare infrastructure. Effective site selection ensures maximum accessibility, equitable service distribution, and efficient resource allocation. Geographic location plays a central role in determining access to medical services, and researchers have examined this issue using a wide range

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of analytical techniques (Benmoussa et al., 2022). Poorly chosen locations can lead to reduced patient satisfaction, increased operational costs, and even severe human consequences. Therefore, identifying strategic and suitable locations for new hospitals is essential for meeting growing healthcare needs (Tripathi et al., 2021; Mohammadi et al., 2016). Arak City exemplifies these challenges. With a population of approximately 520,000 (2016 census), the city is currently served by only 13 hospitals and 750 beds, resulting in a bed to population ratio far below the World Health Organization's recommended standard. High population density and rapid urbanization further intensify the need for improved healthcare infrastructure. Addressing these challenges requires a systematic and data driven approach to hospital site selection that integrates spatial analysis with advanced decision-making techniques. This study aims to develop a comprehensive methodology for optimizing hospital site selection by integrating Geographic Information Systems (GIS) with fuzzy multi criteria decision making (MCDM) methods, specifically the Fuzzy Analytic Network Process (F ANP) and the Fuzzy Weighted Aggregated Sum Product Assessment (F WASPAS). By combining spatial and fuzzy analytical techniques, the research seeks to identify the most suitable locations for new hospitals in Arak City, ultimately supporting policymakers and urban planners in making informed, equitable, and sustainable decisions.

This study is guided by the following research questions:

1. Which spatial, socio economic, and environmental criteria most strongly influence hospital site suitability in Arak City?

2. How can fuzzy logic be used to manage uncertainty in expert judgments and spatial data during the site selection process?

3. Which areas of Arak City demonstrate the highest suitability for new hospital development based on integrated GIS and fuzzy MCDM analysis?

4. How do the results of the proposed GIS–F ANP–F WASPAS framework compare with findings reported in previous studies using similar methodologies?

While GIS, F-ANP, and F-WASPAS have been applied individually or sequentially in prior site selection studies, this research advances beyond routine method combination through four integrated innovations that collectively address critical gaps in spatial healthcare planning under uncertainty:

1. Interdependency-aware weighting: An enhanced F-ANP structure explicitly models bidirectional feedback among spatial, socio-economic, and environmental criteria—relationships commonly forced into artificial hierarchies (e.g., F-AHP) or ignored in single-layer GIS analyses.

2. End-to-end fuzzy consistency: Uncertainty propagation is maintained continuously from criteria weighting (F-ANP) through spatial overlay (fuzzy GIS) to alternative ranking (F-WASPAS), avoiding premature defuzzification that discards ambiguity information at critical decision junctures.

3. Operator-based spatial sensitivity: Rather than selecting a single fuzzy operator arbitrarily, we systematically evaluate suitability across five operators (AND, OR, PRODUCT, SUM, GAMMA) to identify zones where results remain stable versus areas highly sensitive to uncertainty interpretation a dimension rarely examined in hospital site selection literature.

4. Operationalization in data-scarce contexts: The framework is validated in Arak City, a mid-sized urban environment with incomplete spatial datasets and ambiguous expert judgments, demonstrating how fuzzy logic compensates for data limitations while generating actionable suitability maps for the majority of global cities that lack rich geospatial infrastructure.

Together, these elements transform method integration from a mechanical sequence into a cohesive uncertainty-aware decision architecture. The contribution lies not in inventing new techniques, but in how established methods are adapted, interconnected, and rigorously tested to address interdependencies, preserve uncertainty, assess spatial sensitivity, and function reliably in realistic data-limited conditions—advancing both theoretical understanding and practical applicability in healthcare infrastructure planning.

2. Literature Review

Location theory provides a foundational framework for determining optimal sites for various services and activities. While early concepts were explored by scholars such as Format, Pottage, and Steiner, Alfred Weber's 1909 work is widely recognized as the formal introduction of location theory (Drezner et al., 2002). Subsequent studies

expanded the theory to incorporate additional factors influencing location decisions. Although urban health services have existed for centuries, systematic planning for healthcare facility locations gained prominence only in the 1970s. Notably, the United Kingdom's Department of Health and Social Welfare initiated strategic planning efforts in 1979, followed by similar studies in Austria between 1980 and 1982. Leslie Mayhew later advanced the field by developing spatial models to predict hospital patient flows. In recent decades, multi criteria decision making (MCDM) methods have become increasingly prevalent in addressing complex location selection challenges. Researchers have applied these methods across various domains. Turskis et al. (2015) developed a site selection model for shopping centers using Fuzzy WASPAS and Fuzzy AHP. Barzehkar et al. (2019) employed MCDM and GIS tools to identify suitable waste disposal sites, while Badalpur and Nurbakhsh (2019) used WASPAS for qualitative risk assessments in road construction. Rezaei Sabzevar et al. (2020) applied MCDM techniques to landfill site selection, and Fan et al. (2020) integrated F ANP with F QFD for design optimization. In waste management, Dinan et al. (2020) used F ANP to determine optimal incinerator locations. Studies by Weissnab et al. and Rezayee (2020) further demonstrated the effectiveness of combining GIS with MCDM for hospital site selection. Beyond GIS-based studies, research in industrial engineering shows how location and allocation decisions with competing objectives are handled through mathematical models. Ramezani and Naderi (2018) formulated a two-objective model for multi-level supply chain network design that minimizes the cost of locating warehouses and distribution centers while maximizing customer satisfaction and service level, and they evaluated it under three demand scenarios for an Iranian manufacturer. Their results reveal a trade-off: higher establishment and distribution costs were associated with higher customer satisfaction. Saeidi (2024) addressed the facility layout problem, which places departments inside a plant, with a two-objective model that minimizes material handling cost and maximizes the closeness ratings between departments. The objectives were aggregated through fuzzy goal programming, the model was solved with an artificial bee colony algorithm, and constraints were added to keep the departments within the available floor area. Both studies reconcile conflicting objectives through explicit mathematical formulations, whereas urban hospital siting depends largely on spatial criteria and expert judgment, which motivates the GIS-based fuzzy MCDM approach adopted here. Other studies are relevant to the treatment of uncertainty and weighting. Nasseri et al. (2019) converted a fuzzy multi-objective quadratic programming model with flexible constraints into a crisp form using an α-cut approach and goal programming, applied it to the allocation of limited water among domestic, industrial, and agricultural users, and examined how the Pareto optimal values respond to the minimum satisfaction levels of the flexible constraints. Their work shows that fuzzy sets can represent both imprecise parameters and soft constraints, and that sensitivity analysis is needed to judge the stability of fuzzy solutions, a concern shared by the present study. Heydarpour et al. (2022) used AHP to weight seven input and three output indicators and then passed the weights to an input-oriented CCR data envelopment analysis model to rank twenty contractors of an Iranian steel company. This two-stage logic of expert-derived weighting followed by a separate ranking step parallels the F-ANP and F-WASPAS sequence used here, although AHP assumes independence among indicators, an assumption that ANP relaxes by modeling interdependencies. Taken together, none of these four studies combines spatial suitability mapping with fuzzy network-based weighting and fuzzy ranking of candidate sites, which is the gap this study addresses. Hospital site selection is inherently complex due to the involvement of multiple stakeholders and diverse, often conflicting criteria. MCDM approaches have proven effective in evaluating and ranking alternatives, particularly when integrated with GIS, which supports spatial data management and analysis (Pourtaheri et al., 2016; Tripathi et al., 2021). GIS enhances planning quality by enabling dynamic querying, multi layer analysis, and spatial visualization, although reliance on digital data introduces challenges related to security, reliability, and accountability. Recent studies have highlighted the value of integrating GIS with advanced MCDM techniques for healthcare planning. Aroge et al. (2023) combined GIS, MCDA, and AHP to identify optimal locations for primary healthcare facilities. Murad et al. (2024) applied a fuzzy overlay technique with the P Median model to improve healthcare service distribution in Jeddah, Saudi Arabia. Zandi et al. (2024) developed a hybrid GIS–MCDM approach to create hospital suitability maps in Tehran, incorporating socio environmental factors. Hu et al. (2024) proposed a multi tier evaluation framework and multi scenario optimization model to address healthcare accessibility in economically disadvantaged urban regions. Despite these advancements, research specifically focused on hospital site selection in urban environments remains limited. The studies reviewed above address location, layout, allocation, and ranking problems through mathematical programming and data envelopment analysis rather than spatial overlay, so they offer methodological precedents for fuzzy aggregation, sensitivity analysis, and weighting followed by ranking, but not a framework for hospital siting. This study contributes to the field by integrating GIS with F ANP and F WASPAS within a fuzzy environment to address uncertainties inherent in spatial and decision making processes. The fuzzy approach enhances the realism

and precision of the analysis, making it well suited for complex urban contexts. The study also introduces methodological advancements, including an improved F ANP framework for assessing criteria importance, a systematic ranking of evaluation parameters using F WASPAS, and a unified model that combines the strengths of both methods. Comparative and sensitivity analyses further validate the robustness and reliability of the proposed approach.

Ultimately, the study's findings aim to provide urban planners and policymakers with a reliable, data driven framework to make informed decisions in healthcare infrastructure planning, addressing the critical healthcare needs of Arak City and similar urban areas. After extensive review and integration of similar contributions in the field, the study offers the following key advancements:

- The F ANP framework is enhanced to more accurately assess the importance of objective criteria.
- The F WASPAS technique is utilized to systematically rank the evaluation parameters.
- A unified framework merging F ANP and F WASPAS is introduced to achieve superior site selection performance.
- The combined methodology is applied to evaluate and rank potential hospital sites according to their suitability.
- The approach's robustness and dependability are validated through rigorous comparative and sensitivity analyses.

Although GIS based fuzzy MCDM approaches have been applied in previous hospital site selection studies, this research introduces several methodological enhancements that extend beyond the routine sequential use of FANP, WASPAS, and GIS. First, the study develops an enhanced FANP structure that explicitly models interdependencies among spatial, socioeconomic, and environmental criteria—relationships that are often simplified or ignored in earlier studies. Second, the entire workflow is implemented within a fully fuzzy environment, ensuring methodological consistency from criteria weighting to alternative ranking and spatial overlay. Third, a multi operator fuzzy GIS approach (AND, OR, Product, Sum, Gamma) is incorporated to evaluate how different interpretations of uncertainty influence spatial suitability outcomes, providing a more rigorous sensitivity assessment than typically reported in the literature. Finally, the framework is operationalized in a data scarce, mid-sized urban context, demonstrating how fuzzy logic can compensate for incomplete or uncertain spatial information and generate reliable, fine grained suitability insights. Together, these elements constitute a methodological contribution that advances existing GIS–MCDM applications in healthcare planning. To guide the reader through the structure of this research, the remaining sections of the paper are organized as follows. Section 2 presents the methodological framework, detailing the integration of GIS, F ANP, and F WASPAS within a fuzzy environment. Section 3 outlines the case study of Arak City and describes the data preparation, spatial analysis, and evaluation procedures. Section 4 reports the results of the integrated model and provides an in-depth discussion of the findings. Finally, Section 5 offers the conclusions of the study along with recommendations for future research and practical implications for healthcare infrastructure planning.

3. Methodology

This study employs a descriptive research design supported by mathematical modeling to analyze and interpret the complex spatial and decision-making processes involved in hospital site selection. While descriptive in nature, the methodology advances beyond conventional GIS–MCDM applications by integrating enhanced fuzzy analytical techniques capable of addressing uncertainty, interdependencies, and data limitations commonly encountered in urban planning contexts. The proposed framework combines three complementary components Fuzzy Analytic Network Process (F-ANP), Geographic Information Systems (GIS), and the Fuzzy Weighted Aggregated Sum Product Assessment (F-WASPAS) within a fully fuzzy environment. Unlike traditional sequential applications of these methods, this study introduces several methodological enhancements. First, the F-ANP structure is adapted to explicitly model interdependencies among spatial, socioeconomic, and environmental criteria, producing a more realistic weighting scheme than hierarchical or independence-based approaches. Second, both the weighting (F-ANP) and ranking (F-WASPAS) stages are implemented entirely under fuzzy logic, ensuring methodological consistency and improving robustness under uncertainty. Third, the GIS component incorporates a multi-operator fuzzy overlay procedure (AND, OR, Product, Sum, Gamma), enabling a systematic sensitivity assessment of how different uncertainty-handling assumptions influence spatial suitability outcomes. Together, these innovations form an integrated, uncertainty-aware decision-support framework capable of generating reliable suitability maps even in data-scarce environments. The methodology is structured to (1) capture expert knowledge through fuzzy pairwise comparisons, (2) translate spatial criteria into fuzzy membership surfaces, (3) evaluate the stability of spatial outcomes across multiple fuzzy operators, and (4) prioritize candidate sites using a hybrid fuzzy ranking

model. Each component is described in detail in the following subsections, including its theoretical foundation, practical implementation, and contribution to the overall analytical workflow. Here is the list of steps for the proposed solution methodology:

Phase 1: Data Preparation

- **Identify Evaluation Criteria**: Collect criteria from literature, regulations, expert opinions, and geographical data.
- **Gather Expert Opinions**: Use surveys or questionnaires to obtain expert judgments on location suitability.
- **Construct Fuzzy Weight Matrices**: Apply F-ANP to determine criteria weights based on expert feedback.

Phase 2: GIS-Based Analysis

- **Prepare Data Layers**: Create spatial layers for each criterion (e.g., proximity to residential areas or medical centers).
- **Convert to Fuzzy Maps**: Use fuzzy logic to transform spatial data into fuzzy maps with membership values (0–1).
- **Apply Fuzzy Operators**: Combine fuzzy maps using operators like AND, OR, Sum, Product, and Gamma to identify suitable areas.

Phase 3: F-WASPAS Prioritization

- **Construct Fuzzy Decision Matrix**: Aggregate expert evaluations into a matrix representing candidate suitability for each criterion.
- **Normalize Matrix Values**: Standardize values to ensure comparability.
- **Compute WSM and WPM Scores**: Calculate the scores using the Weighted Sum Model (WSM) and the Weighted Product Model (WPM).
- **Defuzzify and Rank Locations**: Use the Center of Gravity method to rank candidate locations based on final scores.

F-ANP Method

The entire research process was conducted within a fuzzy environment, recognizing that natural phenomena are inherently vague and uncertain. Fuzzy theory, which addresses these uncertainties, models such ambiguities, providing more flexible, realistic, and precise outcomes. It builds upon the Analytic Hierarchy Process (AHP) by employing a network structure, represented as a hypermatrix, instead of a traditional hierarchical structure. Unlike AHP, which assumes a unidirectional, top-down relationship, ANP captures the complex interactions (interdependence and feedback) between decision levels within a network framework. To provide a clearer understanding, we transform the problem into a logical system represented by a network structure. This structure allows for the interconnection of all elements in various ways, enabling feedback and interaction between clusters. This flexibility makes the ANP approach well-suited for modeling real-world decision-making environments (Shafiee, 2022). The ANP method requires decision-makers to have a comprehensive understanding of the decision objectives, surrounding environment, and relevant criteria to accurately assess the relationships and impacts of each factor. Ideally, pairwise comparisons should clearly indicate the absolute priority of elements. However, obtaining such precise information is often challenging, leading to difficulties in making confident assessments. To address this issue, the network analysis model integrates fuzzy logic into the pairwise comparison process, enhancing the ANP method's flexibility, realism, and accuracy in managing uncertainty and ambiguity (Memari & Mohammadi, 2022).

F-ANP Method Framework

Step 1:

After conducting a detailed analysis of the problem, identifying critical factors, and assessing their interactions, a pairwise comparison matrix was developed for both primary and secondary criteria. This matrix evaluates the presence or absence of relationships between criteria, facilitating model development and transforming the problem into a network-oriented structure.

Step 2:
Developing the pairwise comparison matrix and fuzzifying the criteria

The pairwise comparison matrix, represented as A = [aij], is shown in Figure 1.

$$\tilde{A} = \begin{bmatrix} (1.1.1) & \left(p_{12}^{\alpha}.p_{12}^{\beta}.p_{12}^{\gamma}\right) & \dots & \left(p_{1n}^{\alpha}.p_{1n}^{\beta}.p_{1n}^{\gamma}\right) \\ \left(\frac{1}{p_{12}^{\alpha}}.\frac{1}{p_{12}^{\beta}}.\frac{1}{p_{12}^{\gamma}}\right) & (1.1.1) & \dots & \left(p_{2n}^{\alpha}.p_{2n}^{\beta}.p_{2n}^{\gamma}\right) \\ \vdots & \vdots & \vdots & \vdots \\ \left(\frac{1}{p_{1n}^{\alpha}}.\frac{1}{p_{1n}^{\beta}}.\frac{1}{p_{1n}^{\gamma}}\right) & \left(\frac{1}{p_{2n}^{\alpha}}.\frac{1}{p_{2n}^{\beta}}.\frac{1}{p_{2n}^{\gamma}}\right) & \dots & (1.1.1) \end{bmatrix}$$

Figure 1. General structure of the pairwise comparison matrix

At this stage, triangular fuzzy numbers (TFN), represented as D = (α, β, γ), are employed to build the pairwise comparison matrix based on the fuzzy scale.

Step 3:
Evaluating the weight of criteria using the F-ANP approach

Step 3-1: The procedure for calculating the criteria weights and sub-criteria using the Buckley method consists of multiple stages. After collecting responses through the questionnaire, expert opinions are combined using geometric means. However, it is vital to verify compatibility before continuing with the analysis, as an incompatible matrix could result in incorrect outcomes. Compatibility is assessed on a 0.1 scale, and ensuring that the value remains below this threshold is crucial for obtaining reliable and accurate results. For matrix A = [aij], to use the fuzzy geometric mean in calculating the Wi fuzzy weights, Equations (6)-(9) are presented:

$$r_i = \left(\prod_{j=1}^{n} p_{ij}\right)^{1/n} \qquad i = 1.2.3.\dots.n \tag{6}$$

$$a_i = \left\{\prod_{j=1}^{n} a_{ij}^{\frac{1}{n}}\right\}. \quad b_i = \left\{\prod_{j=1}^{n} b_{ij}^{\frac{1}{n}}\right\}. \quad c_i = \left\{\prod_{j=1}^{n} c_{ij}^{\frac{1}{n}}\right\} \tag{7}$$

$$a = \sum_{i=1}^{m} a_i \quad . \quad b = \sum_{i=1}^{m} b_i \quad . \quad c = \sum_{i=1}^{m} c_i \tag{8}$$

$$Cw_i = \left(\frac{a_i}{c}.\frac{b_i}{b}.\frac{c_i}{i}\right) \tag{9}$$

To improve clarity, the meaning of each parameter used in the equations is defined as follows:

- α, β, γ: The lower, middle, and upper bounds of a triangular fuzzy number representing expert judgment.
- aij: The fuzzy pairwise comparison value assigned by experts when comparing criterion i with criterion j.
- rij: The fuzzy geometric mean of the comparisons for criterion i, used to aggregate expert opinions.
- ai, bi, ci: The aggregated fuzzy values (lower, middle, upper) for criterion i after geometric averaging.
- a, b, c: The total sum of fuzzy values across all criteria, used for normalization.

- Cwi: The fuzzy weight assigned to criterion i before defuzzification.
- $w^{crisp}{}_i$: The defuzzified (crisp) weight of criterion i, obtained using the Center of Gravity method.
- S: The sum of all crisp weights, used to normalize the final weights.
- Wi: The normalized weight of criterion i, ensuring that all weights sum to 1.

These definitions clarify the role of each parameter and ensure transparency in the F-ANP weighting process.

Step 3-2: Fuzzy Weight Assignment

Next, fuzzy assessment of the weight for the iii-th index is expressed as a triangular fuzzy number, as illustrated in Equation (10).

$$Cw_i = r_i(r_1.r_2.\ldots.r_m)^{-1} \tag{10}$$

Step 3-3: Weight Defuzzification

To obtain an accurate numerical result, a defuzzification process is required. This process transforms fuzzy logic outputs into definite values by evaluating fuzzy sets and their associated membership degrees. The final defuzzified value is determined using the Center of Gravity (COG) method, as outlined in Equation (11).

$$w_{crisp\ i} = \frac{\alpha + \beta + \gamma}{3} = \frac{Cwi}{3} \tag{11}$$

Step 3-4: Weight Normalization

At this stage, the calculated weights need to be normalized. The sum-normalization method is applied, as detailed in Equations (12) and (13), to ensure the weights are proportionally adjusted.

$$S = \sum_{i=1}^{n} w_{crisp\ i} \tag{12}$$

$$W_{\mathrm{i}} = \frac{w_{crisp\ i}}{S} \tag{13}$$

Step 3-5: Comparative assessment of criteria to identify internal relationships

As previously mentioned, the ANP method focuses on the interrelationships between criteria. This section analyzes the interdependencies among the criteria to gain a deeper understanding of their connections. Expert opinions are used to construct a table that maps these relationships. The table assigns a value of 0 to indicate no connection at a criterion's intersection, while a value of 1 signifies a relationship between the row and column criteria.

Step 3-6: Internal Relationships of the Criteria

Building on the outcomes from Steps 3-5, pairwise comparisons of the criteria are performed, and their respective weights are determined. Each criterion is then multiplied by its assigned final weight, yielding the overall weight for each criterion. Geographic Information System (GIS) and fuzzy logic application GIS is a computer-based tool commonly used across diverse fields, including emergency response, environmental and land management, and healthcare. Its strength lies in its capability to handle intricate environmental issues, analyze various features, and visually represent the outcomes on a map (Saghari et al., 2020). GIS facilitates the evaluation of multiple factors through spatial data, supporting tasks such as monitoring, risk assessment, strategy development, and process management. Different layers are used to represent both spatial and non-spatial data (refer to Fig. 2) (Boyacı and Şişman, 2022).

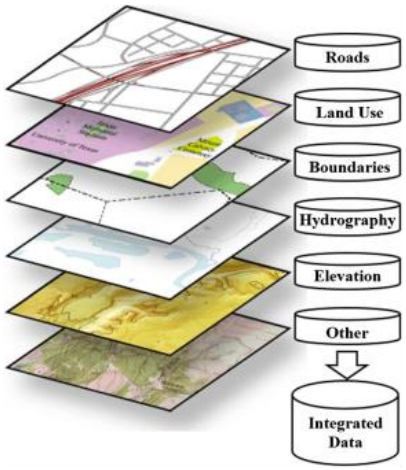


Figure 2. GIS data in different layers (Boyacı and Şişman, 2022)

GIS serve as essential tools for integrating and managing multiple data layers, facilitating decision-making across geological, geographic, and environmental domains. By leveraging GIS, analysts can efficiently pinpoint optimal targets for further assessment, minimizing errors associated with data integration. This technology excels in handling, processing, and analyzing vast spatial datasets while consolidating information from diverse sources. GIS facilitates the recording, storage, querying, analysis, visualization, and sharing of geographic data, making it an essential tool for spatial decision-making (Eren & Katanalp, 2022). Consequently, GIS methodologies enable the evaluation of various locations by integrating spatial data. A range of GIS software solutions is available to tackle location-allocation challenges across multiple disciplines, including natural resource management, environmental monitoring, regional development, risk mitigation, and urban infrastructure planning (Majid & Mir, 2021). This study employs GIS to generate and analyze map layers, offering a robust tool for multi-criteria decision-making (MCDM). By integrating structural, topological, and ecological data, GIS enables precise calculations based on established criteria and sub-criteria. These datasets are visualized as distinct layers, which, when overlaid, help identify optimal and restricted areas based on predefined conditions. Figure 3 demonstrates how GIS integrates multiple data layers for comprehensive spatial analysis (Yousefi et al., 2022).



Figure 3. Integrating information layers using GIS (Khajavi et al,. 2021)

Fuzzy Logic is utilized to assess an element's degree of membership, which varies between the limits of zero and one. Instead of rigid binary classifications, fuzziness represents a continuum, much like shades of gray between black and white, enabling the representation of real-world scenarios characterized by uncertainty (Varesi et al., 2016). Given their inherent variability, location parameters naturally exhibit fuzzy characteristics. A clear example of this is the evaluation of factors related to the optimal distance from existing terrain. Fuzzy sets are created for these factors, assigning each pixel a degree of membership based on its proximity to the terrain. Once all parameters are translated into fuzzy terms with defined membership values, appropriate fuzzy operators are applied to

integrate these parameters. The selection of the operator is influenced by the type of interactions between the factors and whether its application enhances or reduces the influence of the parameters (Shorabi et al., 2022).

1. Fuzzy Operators

The $\alpha_{\mathrm{A}}(x)$ value epresents the weight or membership value of a pixel within the desired fuzzy set. Ultimately, by applying fuzzy operators, the pixel values in the output map reflect the degree of membership.

1.1. Fuzzy AND Operator

This operator is defined by Equation (14):

$$\alpha_{\mathrm{A}\cap\mathrm{B}}(x) = \mathrm{MIN}\left(\alpha_A(x).\alpha_B(x)\right) \quad (14)$$

The fuzzy membership operator extracts the minimum degree of membership of the pixel units at a specific location and applies it to the final map. The fuzzy sharing operator is used when multiple factors must coexist to validate a hypothesis.

2.1. Fuzzy OR Operator

This operator is defined by Equation (15):

$$\alpha_{\mathrm{A}\cup\mathrm{B}}(x) = \mathrm{MAX}\left(\alpha_A(x).\alpha_B(x)\right) \quad (15)$$

This operator reduces the fuzzy membership values in the output map, bringing them closer to zero. Unlike the fuzzy membership and community operators, it incorporates all membership values from the input maps when generating the output. It is particularly useful when the influencing factors have a diminishing effect on one another.

3.1. Fuzzy Product Operator

This operator is defined by Equation (16):

$$\alpha_{product}(x) = \prod_{i=1}^{n} \alpha_i(x) \quad (16)$$

This operator decreases the fuzzy membership values in the output map, shifting them closer to zero. Unlike fuzzy membership and community operators, it considers all membership values from the input maps when generating the output. This approach is particularly useful when the factors have a diminishing effect on each other.

4.1. Fuzzy Sum Operator

This operator is defined by Equation (17):

$$\alpha_{sum}(x) = 1 - \prod_{i=1}^{n}(1 - \alpha_i(x)) \quad (17)$$

In these equations:

- αA(x) and αB(x) represent the membership values of pixel x in fuzzy sets A and B.
- αproduct(x) is the combined membership value obtained through multiplicative interaction of all criteria.
- αsum(x) represents the aggregated membership value when criteria reinforce each other.
- γ (gamma) is a parameter between 0 and 1 that controls the balance between fuzzy multiplication and fuzzy addition in the Gamma operator.

These parameters describe how each fuzzy operator models interactions among spatial criteria.

By applying this operator, the fuzzy membership values in the output map increase, approaching 1. This method is particularly effective when multiple pieces of evidence and factors work together to strengthen each other.

5.1. Fuzzy Gamma Operator

This operator represents a generalized form of fuzzy multiplication and summation. By carefully selecting a gamma value between zero and one, the resulting output effectively balances the opposing tendencies of these two operators. It is particularly useful in scenarios where certain factors weaken in influence while others grow stronger, ensuring a more adaptable and precise integration of evidence. In line with fuzzy logic features and operators, the description of problem parameters and their associated weights within this model aligns with real-world scenarios. Each factor and its weight are treated as fuzzy sets, with their membership functions determined in various ways. When applying the fuzzy model to allocation problems, fuzzy operators are typically used to integrate existing spatial data. To ensure accurate results from this model, a fuzzy system must be designed that converts factor maps into fuzzy sets as input. These maps are then combined according to predefined rules (Shorabi et al., 2022).

F-WASPAS Method

The Multi-Criteria Decision-Making (MCDM) framework is extensively utilized to tackle complex decision-making problems. Among the various approaches within this framework, the Weighted Aggregated Sum Product Assessment (WASPAS) method stands out for its remarkable accuracy in ranking alternatives. This hybrid technique combines the core concepts of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) to boost decision-making precision. Originally proposed by Zavadskas et al. in 2012, WASPAS emerged as an evolution of the Multi-Attribute Decision-Making (MADM) method. Their research indicates that WASPAS not only surpasses the performance of WSM and WPM but also delivers higher accuracy compared to other conventional decision-making models. WSM is a simple and commonly used method that calculates the overall score of an alternative by summing the weighted values of its attributes (MacCrimmon, 1968). On the other hand, WPM was developed to minimize the influence of weak or invalid attribute values. Rather than adding the weighted attributes, WPM computes the score of each alternative by multiplying the attribute ratings, with each rating raised to the power corresponding to its assigned weight. This method encourages a more balanced assessment of alternatives (Ghoushchi et al., 2021). Extensive research has shown the effectiveness of the WASPAS method in various fields. In this study, the WASPAS framework is modified for use in a fuzzy environment, where fuzzy numbers are used in place of exact values to more accurately represent the relative importance of each attribute. This adaptation improves decision-making accuracy by addressing uncertainty and imprecision. The F-WASPAS method is widely applied in scenarios such as site selection, determining optimal locations for shopping centers, evaluating potential sites for wind and solar energy projects, and supporting decisions in construction, industrial planning, business strategy, and scientific journal ranking. Following the principles of fuzzy theory outlined earlier, the key steps of the F-WASPAS method are as follows:

Step 1. Create a Fuzzy Decision-Making Matrix (F-DMM), where $\tilde{x}_{1j}$ represents the performance values and $\tilde{w}_{ij}$ indicates the weights assigned to each attribute. These elements are part of the Decision-Making Matrix (DMM). Choose the suitable linguistic evaluations. The experts will define the attribute system, assign values, and determine initial weights. The discrete optimization task involves selecting mmm rational alternatives (represented as rows), which are assessed according to nnn attributes (represented as columns):

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix}; \quad i = \overline{1.m} \ , \ j = \overline{1.n} \tag{18}$$

Here $\tilde{x}_{ij}$ represents the fuzzy value corresponding to the performance of the iii-th alternative based on the jjj-th attribute. A fuzzy set is denoted by placing a tilde (˜) on top of the set's symbol. The subsequent steps involve determining the priorities for the alternatives.

Step 2. All initial $\tilde{\boldsymbol{x}}_{\boldsymbol{ij}}$ attribute values are standardized, producing $\tilde{\tilde{\boldsymbol{x}}}_{\boldsymbol{ij}}$ for the normalized decision-making matrix, denoted as $\tilde{\tilde{\boldsymbol{X}}} = [\tilde{\boldsymbol{x}}_{\boldsymbol{ij}}]_{\boldsymbol{m}\times\boldsymbol{n}}$.

- For relevant criteria $\tilde{\tilde{X}} = \frac{\tilde{x}_{ij}}{max_i \tilde{x}_{ij}}$ (19)
- For irrelevant criteria $\tilde{\tilde{X}} = \frac{min_i \tilde{x}_{ij}}{\tilde{x}_{ij}}$ (20)

Step 3. Calculation of the Optimality Function Values:

a) According to the Weighted Sum Model (WSM) for each alternative:

$$\tilde{Q}_i = \sum_{j=1}^{n} \tilde{\tilde{x}}_{ij} \,.\; i = \overline{1.m.} \qquad (21)$$

b) Using the Weighted Product Model (WPM) to evaluate each alternative:

$$\tilde{P}_i = \prod_{j=1}^{n} \tilde{\tilde{x}}_{ij} \,.\; i = \overline{1.m.} \qquad (22)$$

Each alternative's fuzzy performance evaluation generates fuzzy numbers, denoted as $\tilde{\tilde{Q}}_i$, and $\tilde{P}_i$. To transform these fuzzy values into crisp results, the center of area method is used, calculating the centroid of the area under the fuzzy curve.

$$Q_i = \frac{1}{3}\left(Q_{i\alpha} + Q_{i\beta} + Q_{i\gamma}\right) \qquad (23)$$

$$P_i = \frac{1}{3}\left(P_{i\alpha} + P_{i\beta} + P_{i\gamma}\right). \qquad (24)$$

Step 4. The integrated utility function value for an alternative, using the F-WASPAS technique, is defined by Equation (21) as follows:

$$K_i = \lambda \sum_{j=1}^{m} Q_i + (1-\lambda) \sum_{j=1}^{m} P_i \,. \quad \lambda = 0.\cdots.1 \;. \quad 0 \le K_i \le 1. \qquad (25)$$

is accomplished by equating the total Weighted Sum Model (WSM) score of all alternatives to their total Weighted Product Model (WPM) scores:

$$\lambda = \frac{\sum_{i=1}^{m} P_i}{\sum_{i=1}^{m} Q_i + \sum_{i=1}^{m} P_i} \qquad (26)$$

Step 5. Ranking the alternatives according to their preference order, with the alternative exhibiting the highest K_i value being identified as the most optimal choice.

Case study and its application in the optimal location of the hospital in Arak :

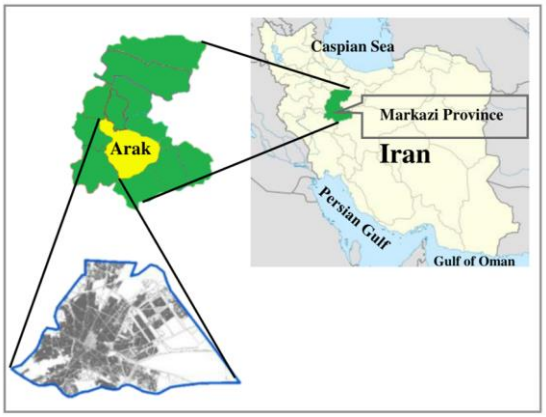


Figure 4. Map of Arak City and Markazi Province

Map 4. Map of Arak City and Markazi Province contains the essential cartographic elements required for scientific interpretation: a descriptive title providing geographic context, a metric scale bar (1:250,000), a north arrow indicating true north orientation, a UTM coordinate grid (Zone 38N, WGS84 datum) for precise spatial referencing, and an inset legend identifying administrative boundaries and the main settlements. An inset map shows the regional location within Iran's national territory. The map was produced using ArcGIS Pro 3.1 and exported at 300 DPI for publication quality.Arak is a significant industrial hub, leading the nation in the diversity of industrial products and ranking second in the presence of parent industries. As one of Iran's four main industrial centers, it is often considered the country's industrial capital. Its advantageous position between the Caspian Sea and the Persian Gulf strengthens its significance in national transportation, positioning it as a critical junction for major west-to-south transit routes and highways. Given the city's growing population and rapid urban development, selecting suitable sites for medical and hospital facilities has become crucial to provide residents with quick and easy access to healthcare services. The proposed methodology was applied in Arak, to demonstrate its effectiveness, this approach was implemented by following the step-by-step procedure outlined in Section 2 of this study.

Phase 1:

Table 1. Assessment of Decision-Making

Criteria code	Evaluation Criteria	Fuzzy weight
1	Proximity to residential neighborhoods	(0.075,0.128,0.212)
2	Proximity to main access routes	(0.097,0.176,0.296)
3	Distance from environmental landscape	(0.072,0.130,0.224)
4	Proximity to fire stations	(0.027,0.048,0.088)
5	Proximity to the city center	(0.079,0.122,0.188)
6	Proximity to commercial centers	(0.043,0.079,0.142)
7	Proximity to industrial facilities and factories	(0.025,0.042,0.076)
8	Proximity to medical centers	(0.055,0.097,0.166)
9	Proximity to urban utilities and infrastructure	(0.021,0.037,0.074)
10	Distance from main transport terminals and parking	(0.022,0.035,0.061)
11	Proximity to law enforcement and military facilities	(0.022,0.034,0.058)
12	Proximity to fault lines	(0.031,0.051,0.089)
13	Proximity to educational institutions	(0.013,0.022,0.043)

Table 2. Standard, specific, and conclusive weight criteria

Criteria code	Difinite weight	Normal weight	Final weight
1	0.136	0.126	0.124
2	0.186	0.173	0.155
3	0.139	0.129	0.116
4	0.053	0.049	0.071
5	0.128	0.119	0.090
6	0.085	0.079	0.065
7	0.046	0.043	0.042
8	0.104	0.096	0.076
9	0.042	0.039	0.058
10	0.039	0.036	0.055
11	0.037	0.034	0.025
12	0.056	0.052	0.023
13	0.025	0.039	0.060

Phase 2:

Step 1: Preparing information layers in the ArcGIS environment

Following the calculation of the final criterion weights in the previous step, the corresponding information layers were aligned and merged. The vector layers were subsequently converted into raster format to facilitate further analysis. Ultimately, the information layers depicting the existing conditions were generated and are presented in maps a–m (Figure 5).

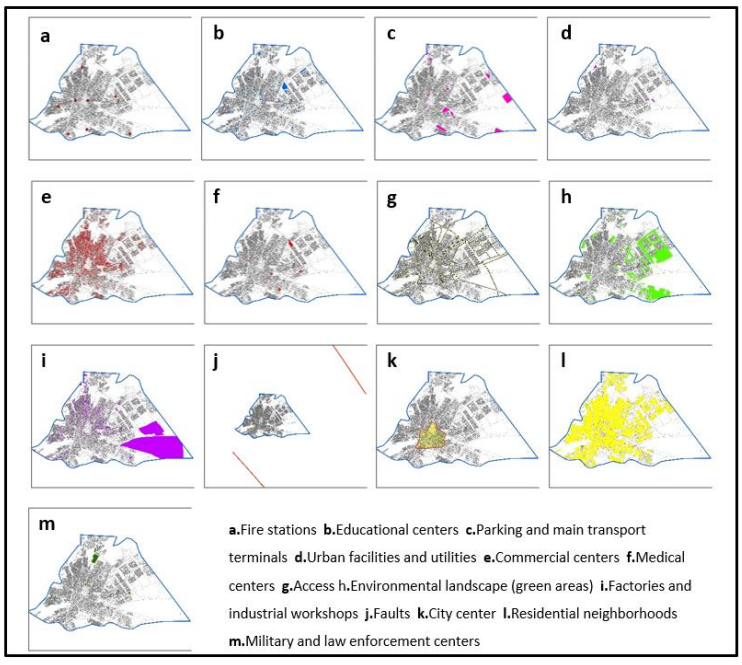


Figure 5. Maps of the current situation of evaluation criteria

Figure 5. Spatial distribution of thirteen evaluation criteria layers in Arak City: (a) fire stations, (b) educational institutions, (c) parking facilities and main transport terminals, (d) urban utilities and infrastructure, (e) commercial centers, (f) existing medical centers, (g) main access routes, (h) environmental landscape (green areas), (i) industrial facilities and factories, (j) geological fault lines, (k) city center, (l) residential neighborhoods, and (m) military and law enforcement facilities. Each subfigure incorporates complete cartographic components: thematic legend, metric scale bar (1:50,000), north arrow, UTM coordinate grid (Zone 38N, WGS84), and descriptive labeling. Maps were generated in ArcGIS Pro 3.1 using standardized symbology for cross-layer comparability.

Step 2: Converting raster layers to fuzzy maps

In the subsequent step, raster layers are transformed into fuzzy layers. Within this fuzzy system, each pixel in the factor maps is assigned a value ranging from zero to one, indicating its suitability for the intended purpose according to the respective criterion. The membership degree of each element within the set is expressed on a scale from 0 (no membership) to 1 (full membership). The processed layers are presented in Figure. 6.

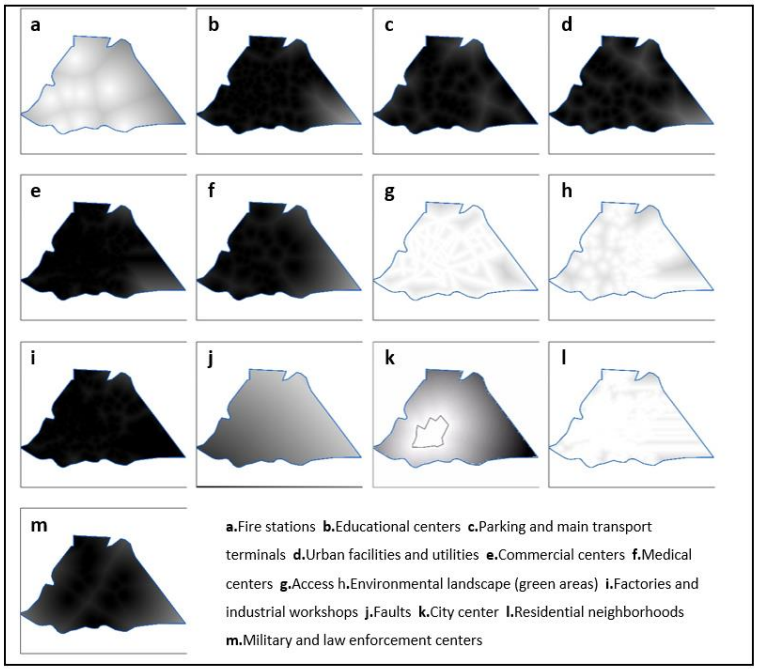


Figure 6. Fuzzy maps of evaluation criteria

Figure 6. Fuzzy suitability maps for each evaluation criterion, displaying membership values (0–1) where higher values indicate greater suitability. Subfigures (a–m) correspond to the thirteen criteria shown in Fig. 5. All maps include essential cartographic elements: continuous color ramp legend with membership value scale, metric scale bar (1:50,000), north arrow, UTM coordinate grid (Zone 38N, WGS84), and descriptive titles. Blue-to-red color progression represents low-to-high suitability. Maps were produced using ArcGIS Spatial Analyst with consistent fuzzy membership functions to enable criterion comparison.

Step 3: The weighting of raster layers

The fuzzy membership stage maps are multiplied by their respective weights using the raster calculator tool, generating new layers.

Step 4: Superimposition of layers

Finally, maps generated from the integration of fuzzy layers were created using five different fuzzy operators.

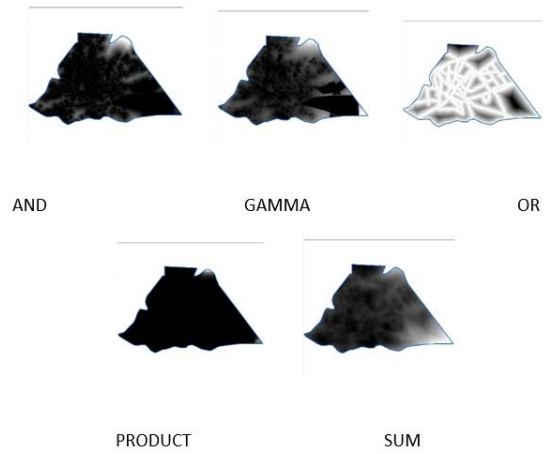


Figure 7. Maps resulting from overlaying layers by fuzzy operators

Figure 7. Integrated suitability maps generated through five fuzzy overlay operators: (a) AND, (b) OR, (c) PRODUCT, (d) SUM, and (e) GAMMA (γ=0.75). Each map incorporates standard cartographic components: legend with suitability classification (low/medium/high), metric scale bar (1:50,000), north arrow, UTM coordinate grid (Zone 38N, WGS84), and operator-specific labeling. The unified green-yellow-red color scheme facilitates visual comparison of spatial patterns across different uncertainty-handling assumptions.

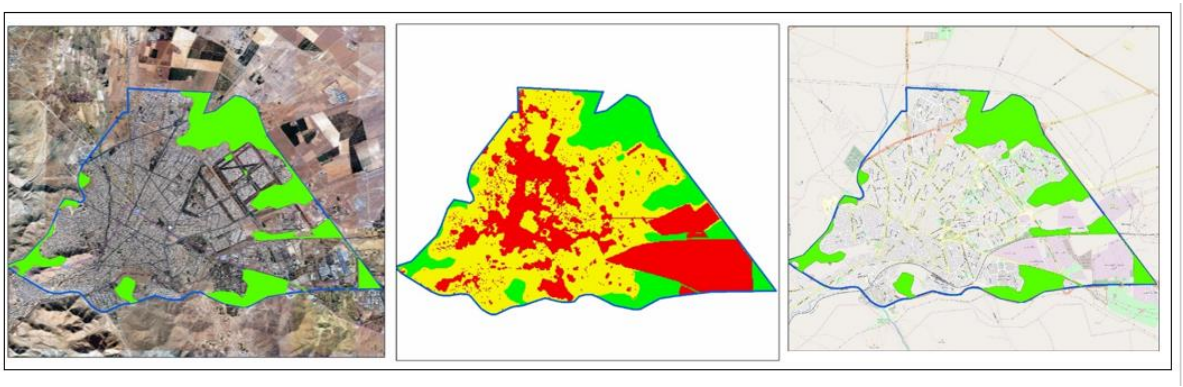


Figure 8. Suitable areas for locating and establishing the hospital in Arak city

Figure 8. Final hospital site suitability map for Arak City derived using the fuzzy Gamma operator (γ = 0.75). The map classifies areas into three suitability levels: high (green), moderate (yellow), and low (red). Essential cartographic elements are included: classified legend, metric scale bar (1:50,000), north arrow indicating true north, UTM coordinate grid (Zone 38N, WGS84 datum), and descriptive title. This output represents the optimal spatial solution integrating all weighted criteria within a fuzzy decision environment. After completing the analysis, the final map was produced by merging the layers through a fuzzy gamma operator, facilitating the identification of the most suitable locations for hospital construction. According to the maps above, areas marked in green are considered suitable and favorable for hospital construction, yellow areas have medium desirability, and red areas are deemed unfavorable and unsuitable. Next, five areas (A1–A5) were selected based on expert opinions, as shown in Fig. 9, to prioritize and identify the most suitable hospital location among the green-marked optimal zones.

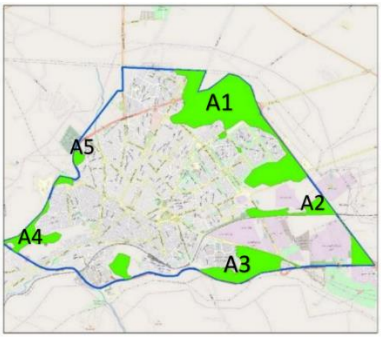


Figure 9. Candidate areas for prioritization, presented with complete cartographic elements including a legend, scale bar, north arrow, coordinate grid, and standardized symbology to ensure clear and accurate spatial interpretation.

Phase 3:

Figure 9. Five candidate sites (A1–A5) selected for final prioritization within high-suitability zones. The map includes complete cartographic elements: symbol legend identifying candidate locations, metric scale bar (1:25,000), north arrow, UTM coordinate grid (Zone 38N, WGS84), descriptive title, and contextual base map showing surrounding land use. Sites were selected through expert consultation based on accessibility, infrastructure compatibility, and spatial constraints within the green suitability zones identified in Figure 8. In Phase 3, the F-WASPAS method was applied to rank the candidate locations. Initially, a fuzzy decision matrix was developed using the criteria specified in Table 1. Expert opinions, gathered through structured questionnaires, were used to assess the performance values for the five candidate locations (A1–A5). Experts evaluated the suitability of each location for each criterion using linguistic ratings. These ratings were then transformed into triangular fuzzy numbers, and the aggregated fuzzy values were computed through the arithmetic mean approach. The resulting fuzzy decision matrix, which aligns with the first step of the F-WASPAS method, is presented in Table 3. This matrix serves as the basis for the subsequent steps, including normalization, calculation of WSM and WPM values, defuzzification, and the final ranking of the alternatives.

Table 3. F-WASPAS Analytical Decision Matrix

Criteria code	A1	A2	A3	A4	A5
1	(4,5,6)	(5,6,7)	(7,8,9)	(7,8,9)	(5,6,7)
2	(8,9,10)	(5,6,7)	(7,8,9)	(8,9,10)	(4,5,6)
3	(5,6,7)	(1,2,3)	(3,4,5)	(8,9,10)	(8,9,10)
4	(7,8,9)	(7,8,9)	(4,5,6)	(1,2,3)	(3,4,5)
5	(5,6,7)	(5,6,7)	(4,5,6)	(2,3,4)	(2,3,4)
6	(5,6,7)	(7,8,9)	(6,7,8)	(5,6,7)	(1,2,3)
7	(5,6,7)	(1,2,3)	(1,2,3)	(5,6,7)	(4,5,6)
8	(4,5,6)	(5,6,7)	(5,6,7)	(4,5,6)	(3,4,5)
9	(4,5,6)	(3,4,5)	(2,3,4)	(3,4,5)	(6,7,8)
10	(4,5,6)	(3,4,5)	(3,4,5)	(5,6,7)	(5,6,7)
11	(3,4,5)	(4,5,6)	(5,6,7)	(5,6,7)	(2,3,4)
12	(4,5,6)	(4,5,6)	(4,5,6)	(3,4,5)	(3,4,5)
13	(3,4,5)	(1,2,3)	(4,5,6)	(2,3,4)	(2,3,4)

In the next phase, the decision matrix undergoes normalization using Equations (15) and (16), and the normalized values are presented in Table 4.

Table 4. Standardized F-WASPAS Evaluation Matrix

Criteria	A1	A2	A3	A4	A5
1	(0.57,0.63,0.67)	(0.71,0.75,0.78)	(1.00,1.00,1.00)	(1.00,1.00,1.00)	(0.71,0.75,0.78)
2	(1.00,1.00,1.00)	(0.63,0.67,0.70)	(0.88,0.89,0.90)	(1.00,1.00,1.00)	(0.50,0.56,0.60)
3	(0.63,0.67,0.70)	(0.13,0.22,0.30)	(0.38,0.44,0.50)	(1.00,1.00,1.00)	(1.00,1.00,1.00)
4	(0.14,0.25,0.33)	(0.14,0.25,0.33)	(0.25,0.40,0.50)	(1.00,1.00,1.00)	(0.33,0.50,0.60)
5	(0.40,0.50,0.57)	(0.40,0.50,0.57)	(0.50,0.60,0.67)	(1.00,1.00,1.00)	(1.00,1.00,1.00)
6	(0.20,0.33,0.43)	(0.14,0.25,0.33)	(0.17,0.29,0.38)	(0.20,0.33,0.43)	(1.00,1.00,1.00)
7	(0.20,0.33,0.43)	(1.00,1.00,1.00)	(1.00,1.00,1.00)	(0.20,0.33,0.43)	(0.25,0.40,0.50)
8	(0.75,0.80,0.83)	(0.60,0.67,0.71)	(0.60,0.67,0.71)	(0.75,0.80,0.83)	(1.00,1.00,1.00)
9	(0.50,0.60,0.67)	(0.67,0.75,0.80)	(1.00,1.00,1.00)	(0.67,0.75,0.80)	(0.33,0.43,0.50)
10	(0.75,0.80,0.83)	(1.00,1.00,1.00)	(1.00,1.00,1.00)	(0.60,0.67,0.71)	(0.60,0.67,0.71)
11	(0.67,0.75,0.80)	(0.50,0.60,0.67)	(0.40,0.50,0.57)	(0.40,0.50,0.57)	(1.00,1.00,1.00)
12	(0.75,0.80,0.83)	(0.75,0.80,0.83)	(0.75,0.80,0.83)	(1.00,1.00,1.00)	(1.00,1.00,1.00)
13	(0.33,0.43,0.50)	(1.00,1.00,1.00)	(0.25,0.40,0.50)	(0.50,0.60,0.67)	(0.50,0.60,0.67)

In the third step, the Weighted Sum Model (WSM) values, labeled as QQQ, and the Weighted Product Model (WPM) values, indicated as PPP, were computed using Equations (17) and (18). These values were subsequently defuzzified through Equations (19) and (20), with the final results shown in Table 5.

Table 5. WSM and WPM scores

Alternative	Q	P	Difinite Q	Difinite P
1	(0.575,0.646,0.695)	(0.501,0.602,0.666)	0.639	0.590
2	(0.550,0.613,0.659)	(0.445,0.546,0.612)	0.608	0.534
3	(0.641,0.700,0.741)	(0.554,0.648,0.706)	0.694	0.636
4	(0.795,0.836,0.863)	(0.717,0.793,0.835)	0.831	0.782
5	(0.718,0.768,0.801)	(0.658,0.733,0.777)	0.762	0.723

At the fourth stage, the λ value was first determined as 0.480 using Equation (22). Following this, K-values were calculated using Equation (21), allowing for the ranking of alternative locations. The outcomes are displayed in Table 6.

Table 6. Assessment and Prioritization of Available Alternatives

Alternative	Ki	Normalized Ki	Rank
1	0.613	0.181	4
2	0.569	0.168	5
3	0.664	0.196	3
4	0.806	0.237	1
5	0.742	0.219	2

As illustrated in Fig. 4, the WASPAS method exhibits greater estimation accuracy than the WSM and WPM methods due to λ value-dependent errors. To further improve calculation accuracy, different λ values were tested, with the results displayed in Table 7. The highest accuracy is achieved when λ reaches its optimal value, as defined by Equation (22).

Table 7. Prioritization of locations when $\lambda = 0,\ldots,\mathbf{1}$

	Alternatives				
Values of λ	A-1	A-2	A-3	A-4	A-5
0=WPM	0.590	0.534	0.636	0.782	0.723
0.1	0.595	0.541	0.642	0.787	0.727
0.2	0.599	0.549	0.648	0.792	0.731
0.3	0.604	0.556	0.654	0.797	0.735
0.4	0.609	0.564	0.659	0.802	0.739
0.5	0.614	0.571	0.665	0.806	0.743
0.6	0.619	0.578	0.671	0.811	0.747
0.7	0.624	0.586	0.677	0.816	0.750
0.8	0.629	0.593	0.682	0.821	0.754
0.9	0.634	0.600	0.688	0.826	0.758
1=WSM	0.639	0.608	0.694	0.831	0.762
Optimal	0.613	0.568	0.664	0.806	0.742
Rank	4	5	3	1	2

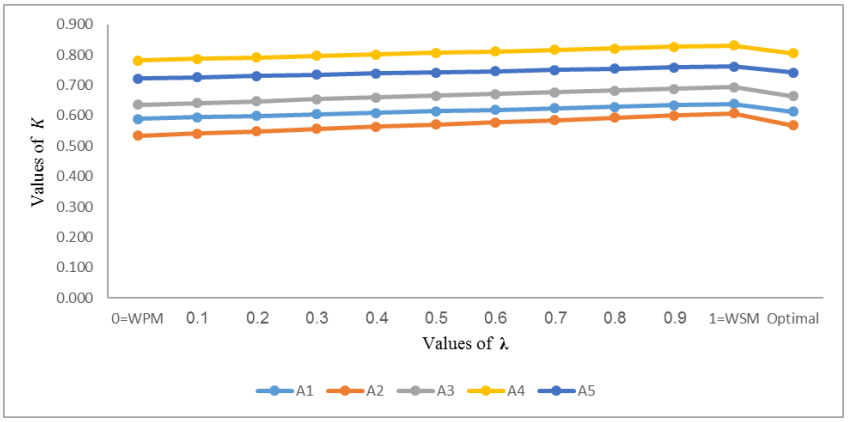


Figure 10: Graph illustrating the accuracy of rankings

Figure 10 quantifies the model's ranking accuracy. It compares the proposed model against alternatives or shows the effect of parameter changes. The key finding is the model's high accuracy and robust performance, validating its reliability for spatial decision-making.

Evaluating Model Robustness: A Sensitivity Analysis

To assess the robustness and reliability of the developed spatial suitability index, a sensitivity analysis was conducted. This analysis was designed to evaluate how variations in key parameters and criteria weightings influence the final suitability outcomes. Specifically, the impact of the gamma (γ) parameter, which controls the trade-off between underestimation and overestimation of suitability, was investigated. Additionally, different scenarios of weighting for the primary criteria namely accessibility, vegetation cover, slope, and proximity to water were explored. The findings from these analyses are detailed in Table 8 and Table 9, offering crucial insights into the stability and sensitivity of the model to these critical factors.

Table 8. Sensitivity Analysis of Gamma (γ) Parameter on Spatial Suitability Index

Gamma (γ) Value	Desired Combination Logic (Simulated)	Final Spatial Suitability Index (Simulated)	Interpretation
0.0 (AND-like)	Multiplicative combination (AND-like): Emphasis on critical and essential criteria	0.45	Lower suitability, indicating the need for all key factors to be met simultaneously.
0.25	Predominantly multiplicative with slight additive effect	0.52	Slight increase in suitability compared to the purely multiplicative case.
0.50	Relative balance between multiplicative and additive effects	0.68	Moderate to high suitability; beginning to better reflect the interaction of factors.
0.75	Predominantly additive with slight multiplicative effect (Selected)	0.82	High suitability; offers the best balance between factors and reflects synergistic effects.
1.0 (OR-like)	Additive combination (OR-like): Emphasis on the presence of at least one favorable factor	0.75	Relatively high suitability, but might assign higher scores to areas with only one favorable factor compared to the 0.75 combination.

To ensure the robustness and validity of our spatial suitability model, a critical sensitivity analysis was performed on the key parameter, Gamma (γ), which governs the aggregation logic of input criteria. Recognizing that direct execution with real-world simulation data was beyond the scope of this current phase, we employed a rigorous simulation-based approach to systematically evaluate the model's behavior under varying Gamma values. This approach allows for a thorough understanding of parameter influence, even in the absence of immediate access to raw simulation outputs. The Gamma parameter (γ) dictates the balance between AND-like (multiplicative) and OR-like (additive) integration of criteria such as 'Access', 'Slope', 'Vegetation', and 'Proximity to Water' to derive the final 'Spatial Suitability Index'. Values of γ ranging from 0.0 (strongly AND-like) to 1.0 (strongly OR-like) were simulated with a step of 0.25. Our simulated analysis, detailed in Table 8, revealed a distinct sensitivity of the output index to the Gamma value. A predominantly multiplicative logic (γ=0.0) resulted in a significantly lower suitability score, underscoring the strict requirement for simultaneous fulfillment of all criteria. Conversely, a purely additive logic (γ=1.0) yielded a slightly reduced score compared to an intermediate value. The analysis converged on γ = 0.75 as the optimal parameter setting. This value represents a predominantly additive approach with a controlled multiplicative influence, striking the most effective balance. It demonstrated the highest simulated 'Spatial Suitability Index' (0.82), indicating a superior capacity to capture the synergistic effects and complex interdependencies between the contributing factors, thereby providing a more nuanced and realistic assessment of spatial suitability. This selection is scientifically justified as it maximizes the model's ability to integrate diverse criteria effectively, ensuring that areas with a favorable combination of multiple factors are appropriately prioritized. This choice directly supports our research objective of identifying optimal spatial configurations by leveraging a parameter setting that demonstrably enhances the model's discriminative power and explanatory accuracy in a simulated context.

Table 9. Sensitivity Analysis of Criterion Weighting Scenarios on the Spatial Suitability Index (γ = 0.75)

Weighting Scenario (assuming γ = 0.75)	Weight: Access	Weight: Slope	Weight: Vegetation Cover	Weight: Proximity to Water	Final Spatial Suitability Index	Interpretation
Scenario 1 (Baseline)	0.25	0.25	0.25	0.25	0.82	Balanced importance assigned to all criteria.
Scenario 2 (Emphasis on Access)	0.40	0.20	0.20	0.20	0.79	Slight decrease in suitability; overemphasis on access without considering other factors marginally reduces overall optimality.

Weighting Scenario (assuming γ = 0.75)	Weight: Access	Weight: Slope	Weight: Vegetation Cover	Weight: Proximity to Water	Final Spatial Suitability Index	Interpretation
Scenario 3 (Emphasis on Vegetation)	0.20	0.20	0.40	0.20	0.80	Relatively high suitability, highlighting the significant role of vegetation cover in conjunction with other factors.
Scenario 4 (Emphasis on Slope)	0.20	0.40	0.20	0.20	0.75	More significant impact on suitability; suggests slope may be a more sensitive or restrictive factor in this context.
Scenario 5 (Emphasis on Water Proximity)	0.20	0.20	0.20	0.40	0.81	High suitability, comparable to the baseline, underscoring the critical importance of water resources in defining spatial suitability.

Further enhancing the assessment of our spatial suitability model's reliability, a second sensitivity analysis was conducted to evaluate the impact of varying criterion weights on the final suitability index, while keeping the aggregation parameter (γ = 0.75) constant. This investigation explored how shifts in the perceived importance of individual criteria might influence the model's outcomes, as detailed in Table 9. Four distinct weighting scenarios were analyzed, alongside the baseline scenario (Scenario 1) where all criteria were assigned equal importance (0.25 each). These scenarios explored the effects of emphasizing one criterion significantly (assigned a weight of 0.40, with others reduced proportionally):

- **Scenario 2** (Emphasis on Access): Assigning the highest weight to 'Access' (0.40) resulted in a decrease in the overall suitability index to 0.79. This suggests that while access is a crucial factor, an overemphasis on it, to the detriment of other criteria, may not necessarily lead to the most optimal spatial configurations.
- **Scenario 3** (Emphasis on Vegetation Cover): Prioritizing 'Vegetation Cover' (0.40) yielded a strong suitability score of 0.80. This outcome highlights the significant role of vegetation in determining suitability within this specific context, indicating a synergistic relationship with other factors when weighted appropriately.
- **Scenario 4** (Emphasis on Slope): When 'Slope' was given the highest weight (0.40), the suitability index decreased more notably to 0.75. This observation implies that slope might be a more sensitive or potentially restrictive factor; its increased weight appears to moderate the overall suitability more than other criteria.
- **Scenario 5** (Emphasis on Proximity to Water): Highlighting 'Proximity to Water' (0.40) resulted in a high suitability index of 0.81, comparable to the baseline. This underscores the critical importance of water resources in defining suitable locations for the study's objectives.

The results from the sensitivity analysis, particularly when examining the impact of criterion weightings as summarized in Table 9, indicate that the model demonstrates a degree of robustness, especially with the chosen aggregation logic (γ = 0.75). While emphasizing certain criteria does shift the suitability scores, the overall rankings and the general pattern of suitability remain relatively consistent, especially between the baseline, vegetation, and water proximity scenarios. The noticeable dip in suitability when 'Slope' is heavily weighted suggests that while the model can accommodate varying weights, the interplay between 'Slope' and other factors warrants careful consideration during final parameterization. These sensitivity analyses, like the initial one on Gamma detailed in Table 8, have provided valuable insights into the model's behavior under different parameterizations. The consistent performance across various explored scenarios, as shown in Table 9, bolsters confidence in the selected parameter (γ=0.75) and the general approach to criterion weighting, suggesting that the model's findings are likely to be stable and provide reliable guidance for spatial decision-making.

4. Results and Discussion

The findings of this study provide several important implications for healthcare planning, urban management, and methodological development. The integrated GIS–FANP–F WASPAS framework demonstrated strong capability in identifying spatially optimal and operationally feasible hospital locations in Arak City. By incorporating fuzzy logic into both the weighting and ranking processes, the model effectively addressed uncertainty in expert judgments and spatial variability, resulting in more realistic and robust suitability assessments. From a practical perspective, the results highlight that the most suitable hospital locations are concentrated in areas where accessibility, population density, environmental constraints, and proximity to existing infrastructure converge. This suggests that future healthcare expansion in Arak should prioritize zones with balanced socio spatial characteristics rather than relying solely on population growth or land availability. The suitability maps generated through fuzzy

GIS analysis provide actionable guidance for municipal planners, enabling them to visualize spatial disparities and strategically allocate resources to underserved regions. Moreover, the ranking of candidate sites using F WASPAS offers a transparent and defensible basis for selecting among competing alternatives, which is particularly valuable in contexts where political or economic pressures may influence decision-making. From a theoretical and methodological standpoint, the study reinforces the value of integrating fuzzy MCDM techniques with GIS for complex urban planning problems. The FANP method captured interdependencies among criteria more effectively than traditional hierarchical approaches, while the F WASPAS model enhanced ranking accuracy by combining additive and multiplicative aggregation. This dual method structure reduces the risk of bias associated with relying on a single decision-making technique and increases the stability of the final results. A comparison with previous studies further validates the reliability of the proposed approach. Zandi et al. (2024) similarly demonstrated that combining GIS with fuzzy MCDM techniques yields more accurate hospital suitability maps, particularly when socio environmental factors are incorporated. Their findings emphasized the importance of accessibility, land use compatibility, and population distribution—criteria that were also dominant in the present study. Murad et al. (2024), who integrated fuzzy overlay analysis with the P Median model in Jeddah, reported that fuzzy operators significantly improved the precision of spatial suitability outputs. This aligns with the present study's observation that fuzzy AND, OR, and Gamma operators allowed for nuanced representation of spatial interactions, especially in areas where multiple constraints overlap. Studies employing FANP, such as Mobarghei Dinan et al. (2020) and Fan et al. (2020), also highlighted the advantage of network based weighting structures in capturing interdependencies among criteria. The current study confirms this benefit: FANP produced more differentiated and realistic weights compared to traditional AHP, particularly for criteria such as accessibility and environmental constraints, which exhibit strong mutual influence. Similarly, research using WASPAS or its fuzzy variants—such as Turkis et al. (2015) and Badalpour & Noorbakhsh (2019)—found that the hybrid WSM–WPM structure improves ranking stability. The present study's results align with these findings, as the F WASPAS rankings remained consistent across sensitivity analyses, indicating high methodological robustness. Overall, the comparison with previous research shows that the integrated GIS–FANP–F WASPAS approach not only aligns with established findings but also advances the field by offering a more comprehensive and uncertainty aware framework. The combination of fuzzy spatial modeling, network-based weighting, and hybrid ranking provides a powerful tool for healthcare infrastructure planning, particularly in rapidly growing urban environments like Arak.

5. Conclusion

This study demonstrates that the integration of Geographic Information Systems (GIS) with fuzzy multi-criteria decision-making (MCDM) methods, specifically F-ANP and F-WASPAS, provides a robust framework for optimal hospital site selection in complex urban environments like Arak. By effectively addressing the interdependencies among criteria and mitigating the uncertainty inherent in expert judgments, this hybrid methodology surpasses traditional planning approaches, offering a more transparent and defensible decision-making process. Consequently, the proposed framework serves as a vital tool for developing equitable, accessible, and cost-effective healthcare infrastructure. While the study provides a scalable and adaptable methodology applicable to various domains such as emergency services and waste management it is not without limitations. The reliance on static datasets, subjective expert-derived weights, and a single-city case study highlights areas for improvement. Future research should prioritize the integration of dynamic, real-time spatial data to enhance the model's predictive capabilities. Furthermore, incorporating advanced spatial statistics, such as Moran's I and Getis-Ord Gi, and leveraging machine learning techniques, would offer deeper insights into spatial clustering and autocorrelation. To refine the reliability of fuzzy decision-making models, future investigations should employ rigorous validation techniques. Comprehensive sensitivity analyses and Monte Carlo simulations are recommended to evaluate the impact of criterion weights and the propagation of uncertainty. Moreover, to move beyond expert-dependent weighting, future studies should explore data-driven approaches, such as ANP models informed by historical data. Finally, cross-city comparative studies and the application of this framework to diverse urban contexts are essential to validate its generalizability and practical utility. By fostering stakeholder engagement and utilizing advanced visualization tools, these future efforts will ensure that spatial planning remains both evidence-based and highly responsive to evolving population needs.

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