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Landfill Site Selection Using Multi-Criteria Decision Making: Influential Factors for Comparing Landfill Locations

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Abstract:

Landfilling stands as the final phase in the continuum of solid waste management, serving as a complement to various disposal methods. In Iran, only 8% of municipal waste is recycled, composted, or reused, while a staggering 92% is sent to landfills. Of this 92%, approximately 25% is disposed of properly and hygienically; the remaining waste is buried unsafely and piled up chaotically. Landfill sites pose potential risks to human health and the surrounding environment, making the selection of these sites a critical process that must be approached with caution. The factors influencing landfill site selection are numerous and the process itself is complex. Despite extensive research focusing on energy recovery and the recycling of valuable materials from waste to alleviate the pressure on landfills, landfilling remains an integral component of solid waste management.

Sanitary landfill operation management involves several key steps: selecting a suitable site, preparing the site, and executing engineering operations at the landfill. The first step in landfill design is the selection of an appropriate site. When choosing a landfill site, several factors are typically considered, including site topography, site geology, regional hydrology, meteorology, required land area, cover soil type, groundwater level, landfill characteristics, nearby land uses, distance from surface water, land price, landfill site lifespan, soil permeability, soil stability, flood susceptibility, lithology, stratigraphy, presence of faults, type of land use, location of the site relative to urban development, proximity to residential and urban areas, proximity to cultural and protected sites, wind direction, access to roads and railways, proximity to construction materials, location of powerlines and pipelines, and proximity to airports.

The present research investigates various methods used for selecting landfill sites with an emphasis on multi-criteria decision-making approaches (multi-criteria decision analysis (MCDA)). The investigations identify the following as the most frequently used methods: grey systems theory, ordered weighted averaging (OWA), weighted linear combination (WLC), analytic network process (ANP), fuzzy-analytic network process (F-ANP), analytic hierarchy process (AHP), fuzzy-analytic hierarchy process (F-AHP), TODIM, and fuzzy TODIM.

Keywords: Sustainable urban planning, waste management, sanitary landfill sites, landfill location, geographic information system

Introduction

Waste management includes various elements such as waste collection, on-site handling and storage, waste transportation and transfer, resource reduction, material and energy recovery, and finally, disposal. Recent decades have witnessed a notable increase in the disposal of municipal solid waste (MSWThis has emerged from a hierarchical process influenced by various solid waste management options, prioritized as follows: incineration or energy recovery, resource reduction, recovery and composting, and finally, landfilling (El Baba et al., 2014; Shobanoglos and Reith, 2002; US EPA, 2010).

Some studies have explored ways to create value from waste, including the bioconversion of biowastes into biochemicals (Han et al., 2019). While incineration, which converts waste into ash, is frequently investigated, it poses risks such as air pollution (Lu et al., 2019) and, to a lesser extent, contamination of surrounding soils (Li et al., 2019). Consequently, despite the exploration of alternative management methods, landfilling remains a crucial aspect of solid waste management (Eskandari et al., 2012). “Sanitary” or “engineered” landfill sites involve strategically placing waste in designated cells, compacting it, and covering it once the landfill's capacity is reached. Landfilling is considered a low-cost and straightforward waste management method (Khorram et al., 2015); however, its associated issues require careful investigation and resolution (Pariya et al., 2019; Top et al., 2019; Zhang et al., 2019). A significant concern with landfills is the production of highly contaminated leachate that necessitates treatment and management. Recent efforts, such as using membrane bioreactors, have shown promise for landfill leachate treatment (Hayeri Yazdi et al., 2019).

Even in areas where incineration and recycling are the primary waste management strategies, effective municipal solid waste (MSW) disposal remains crucial (Chabuk et al., 2016). Utilizing a scientific approach to site selection helps minimize secondary pollution, costs, and social issues, such as the “not in my backyard” (NIMBY) syndrome (Cao et al., 2006; Gorsevski et al., 2012). Consequently, an appropriate landfill site must fulfill hydrological, geological, environmental, and social criteria. To ensure compliance with these requirements, various criteria and constraints need to be established. The chosen sites should be suitable for both pre-closure and post-closure conditions (Raga et al., 2018). Therefore, selecting a proper location for waste disposal is a complex challenge in MSW management (Chabuk et al., 2016). The various conditions, impacts, and complexities involved make the selection of waste disposal sites a significant concern in urban planning (Chang et al., 2008; Krucu and Erdagi, 2012; Qian et al., 2001).

In Iran, optimizing unsanitary landfill sites and upgrading them to internationally accepted standards, while comprehensively addressing health and environmental protection goals, has become a priority. One sustainable method for municipal solid waste (MSW) disposal is the use of bioreactor landfills. Since 1995, many industrialized countries have transitioned from traditional sanitary landfills to bioreactor landfills, which have become recognized as the preferred alternative for municipal waste management. Today, bioreactor landfills are seen as a desirable option due to their adherence to high environmental and health standards, which consider all technical, economic, social, environmental, and health factors. To ensure accuracy and ease throughout this process, multi-criteria decision-making (MCDM) techniques are utilized (Eskandari et al., 2012).

Over the past few decades, numerous studies have focused on landfill site selection. Various methods and procedures employed in this area include the graphing technique (Cao et al., 2006), grey situation decision-making theory (Clustering) (Cao et al., 2006), expert systems (Cao et al., 2016), analytic hierarchy process (AHP) (Bahrani et al., 2016; El Baba et al., 2014; Tavares et al., 2011; Yuyan, 2014), geographic information systems (GIS) integrated with AHP (Eskandari et al., 2016; Bahrani et al., 2016; Khan and Samadder, 2015), analytic network process (ANP) (Bahrani et al., 2016), GIS integrated with weighted linear combination (GIS/WLC) (Bahrani et al., 2016; Gbanie et al., 2013; Khan and Samadder, 2015), simple additive weighting (SAW) (Bahrani et al., 2016), fuzzy logic (Bahrani et al., 2016), ordered weighted averaging (OWA) (Gbanie et al., 2013), fuzzy logic-GIS (Khorram et al., 2015), fuzzy AHP and fuzzy TOPSIS (Beskes et al., 2015), and GIS/SAW/AHP (Rathur et al., 2016). Each method comes with its own set of advantages and disadvantages and can influence the final results regarding the classification of the most suitable landfill sites.

In a multi-criteria decision-making approach, five distinct steps can be outlined: 1) Setting the goal: Identifying the problem, such as finding a new waste disposal site; 2) Identifying criteria: Defining the requirements and translating them into criteria; 3) Determining weights: Assigning weight to each criterion based on its importance using an MCDM technique; 4) Identifying alternatives: Listing practical options for comparison; 5) Evaluating alternatives: Assessing and ranking the alternatives to determine the best option (e.g., landfill sites) (Hanine et al., 2016).

1. Multi-criteria decision-making

Environmental issues are often multidisciplinary and involve social priorities and environmental and economic considerations. There is a lack of specific critical information for some types of risks (e.g., climate change), resulting in uncertainty in the data. In addition, experts in different fields may disagree with each other and propose different alternatives (Hong et al., 2011). In this process, decision-makers will be faced with diverse and conflicting priorities and a complex procedure with a large number of factors that can influence the decision-making mechanism, making the decision-making process complicated. Finally, problems often have multiple objectives or properties, and each objective or property has a specific unit of measurement that prevents their comparison or analysis (Hwang and Yoon, 2012). Therefore, environmental problems require a methodology in which decision-makers can deal with these challenges.

Multi-criteria decision-making (MCDM) (also known as multi-criteria decision analysis (MCDA)) refers to a set of methods for dealing with complex issues with multiple criteria and objectives (Kumar et al. 2017, Majumder and Saha 2016a, Sharifi et al. 2009) to solve complex problems (Afzali et al. 2014, Huang et al. 2011, Malczewski 1999). In the field of landfilling, the location must meet local regulations and take into account environmental, economic, and social issues (Chang et al. 2008, Nass et al. 2010, Samti et al. 2008). Thus, a significant number of criteria must be applied, making the selection of a suitable landfill site a complex and time-consuming process (Chang et al. 2008). To facilitate this complex process, MCDM techniques have been used. MCDM is widely used for many conflicting decision-making processes (Eskandari et al. 2012).

In Multi-Criteria Decision Making (MCDM), the first step involves identifying properties, criteria, constraints, alternatives, and objectives (Hwang and Yoon, 2012; Kumar et al., 2017). Properties refer to a set of criteria and objectives. Criteria are the factors that influence the decision-making process; they are operational parameters that can be weighted and scored by decision-makers. The higher the score, the more suitable the properties are. The evaluated properties provide the necessary data for assessing the alternatives. Constraints are the limits and parameters that must be considered during the process. A constraint can prevent decision-makers from selecting a particular alternative or may restrict them to specific options. Constraints act as binary systems within the decision-making process. Alternatives are pre-existing candidates that aim to achieve the objectives and are ranked based on the established criteria and constraints. Objectives represent the ultimate goals that decision-makers strive to accomplish. For instance, in the context of landfill site selection, access to a road is considered a criterion, avoidance of flood zones is a constraint, designated areas are the alternatives and the optimal location for waste disposal is the objective (Hwang and Yoon, 2012). In essence, MCDM is a five-step method that includes: 1) defining objectives, 2) selecting groups (for criteria), 3) identifying individual alternatives, 4) analyzing through aggregation, and 5) ranking the alternatives against each other (Majumdar and Saha, 2016b).

Multi-Criteria Decision Making (MCDM) utilizes information and opinions from experts to create a systematic approach to decision-making. The process involves collecting the necessary data through a specific protocol, analyzing and interpreting that data using algorithms, and ultimately ranking alternatives based on their merits (Huang et al., 2011; Sharifi et al., 2009). One of the key features of this methodology is its incorporation of both qualitative and quantitative information. This combination allows for an abstract evaluation while maintaining an objective decision-making process (Ekmekcioğlu et al., 2010).

The MCDM matrix is processed by two different models: compensatory and non-compensatory models. In compensatory processing, the model attributes are quantified to provide comparable data for trade-offs between attributes. While, in non-compensatory processing, there is no trade-off between attributes, and each attribute is considered on its own, regardless of other ones. Thus, undesirable attributes cannot be equal to desirable ones. This is an attribute-to-attribute comparison, so it is a simpler form of MCDM (Hwang and Yoon 2012).

For site selection, MCDM includes multi-criteria methods, mathematical programming, and stochastic programming (Sultani et al. 2015). MCDM can be divided into two categories: multi-attribute decision-making (MADM, for evaluation), and multi-objective decision-making (MODM, for design). MADM is a method with finite, pre-estimated alternatives and a large number of criteria, while MADM has unlimited alternatives that emerge as the process proceeds (Aragonés-Beltrán 2010, Hwang and Yoon 2012, Kumar et al. 2017).

Numerous studies have demonstrated that Multi-Criteria Decision-Making (MCDM) methods can enhance decision-making processes related to environmental issues, such as landfill site selection (Huang et al., 2011). For instance, Vatalis and Manoliadis (2002) implemented a two-stage MCDM approach for selecting landfill sites. In the first stage, they identified suitable locations using overlapping techniques. Subsequently, they applied 21 equally weighted criteria to determine the optimal alternative. To mitigate pollution in aquatic ecosystems and effectively manage resources, Linkov et al. (2006) utilized MCDM to select the most appropriate remediation process for a contaminated site. Additionally, many studies on landfill site selection have integrated Geographic Information Systems (GIS) to support the decision-making process (Gbanie et al., 2013).

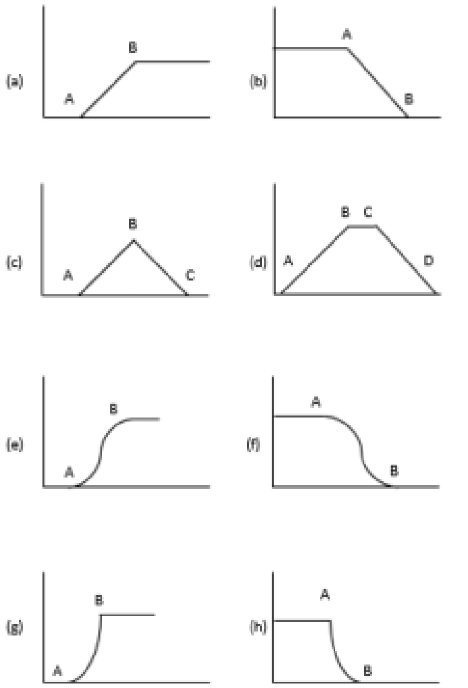

Fig. 1. Graphical forms of a criterion; (a) linear increasing, (b) linear decreasing (c) linear triangular (d) linear trapezoidal (e) sigmoidal (S-shaped) increasing (f) sigmoidal decreasing (g) J-shaped increasing (h) J-shaped decreasing.

(Figure 1)

2. Factors

Various studies have examined different factors that influence waste management decisions. These factors are a function of the type of waste—whether it is municipal, industrial, or hazardous—and the ecological conditions of the region being studied (Bahrani et al., 2016). Decision-makers need to evaluate factors associated with each alternative and present them numerically; when faced with uncertain data, these factors can be represented as linguistic variables. Factors can serve either as constraints or criteria. A constraint limits the available alternatives and categorizes locations into suitable (1) or unsuitable (0) groups. Consequently, constraints are expressed through Boolean maps (Mahani and Gholamali Fard, 2006). In contrast, a criterion assigns a numerical value to a factor. Graphical representations of criteria are displayed in Figure 1 (Eastman & Zimmerman, 2011). As illustrated, the values assigned to criteria do not necessarily follow a linear pattern and can vary based on different functions.

2.1- Physical and Environmental Factors-

2.1-1- Groundwater Depth

Leachates from landfills pose a long-term threat to groundwater resources, making it essential to establish a buffer zone between the groundwater table and the leachates produced (Chabuk et al., 2016; Gorsevski et al., 2012). The appropriate and inappropriate groundwater depths are largely defined based on regional characteristics. Given the significance of this factor, it is important to use monitoring wells both upstream and downstream to detect any anomalies or incidents (El-Magouri et al., 2016). Table 1 presents the scoring values for different buffer zones utilized in various studies regarding groundwater depth.

2.1.2- Surface water

Landfills pose a potential threat to lakes, marshes, wetlands, and rivers due to the production of leachate and gaseous pollutants. Therefore, it is essential to establish a buffer zone between landfills and surface water. The recommended distance between a landfill and surface water should be no less than 500 meters. Typically, a buffer zone ranging from 500 to 1000 meters is implemented. For sites located within 500 meters of surface water, the lowest value (0) is assigned. Conversely, for sites that are over 1000 meters away, the highest value is assigned. For distances falling between 500 and 1000 meters, a median value is given (Chabuk et al. 2016, Djokanović et al. 2016, Nass et al. 2010, Seddiqi et al. 1996). Table 2 presents the buffer zones used in various studies concerning the distance from surface waters.

2.1.3- Soil permeability

In cases where the landfill cover fails to prevent leachate leakage, the underlying soil needs to minimize the potential for leachate to penetrate the groundwater. In landfill design, soil with a $K_f < 1 \times 10^{-7}$ is considered impermeable (Djokanović et al., 2016). Generally, soils with low permeability, such as clay, receive the highest value, while soils with high permeability, like sand, receive the lowest. Other types of soil receive the median value (Bahrani et al. 2016). Table 5 summarizes the scoring values used in various studies concerning soil permeability.

2.1.4- Soil stability

The long-term stability of soil is a critical concern. Unstable areas are at risk of liner failure, which can lead to the leakage of leachate and contaminants into groundwater. Therefore, it is essential to choose locations with stable soil. So, unstable soils such as loose soils receive the lowest value (0), medium-stability soils such as sandy clayey diluvial soil, receive the median value, and sand, sandy clay, silty sand, and loess sand receive the highest value (Djokanović et al. 2016).

(Table 1)

Table 1
Suggested scoring for groundwater depth buffer.

Suggested buffer to groundwater (m)	Scoring	Membership function	Comments	Reference
$a = 1.5$, $b = 2.5$	As per Fig. 1e	Graphical form	Groundwater depth: 0.7–8.4m	(Alves et al., 2009)
<6 6–25 25–110 >110	0 1 5 10	Custom	Arid climate characterized by long hot, rainless summer and mild winter	(Effat and Hegazy, 2012)
<1.5 1.5–3 3–4.5 >4.5	1 4 6 10	Custom	Average groundwater depth: 2m	(Chabuk et al., 2016)
<3 3–7 7–10 >10	0 0.25 0.5 1	Custom	Moderate continental climate	(Djokanović et al., 2016)
<5 5–20 20–50 50–70 >70	1 2 3 4 5	Custom	Groundwater depth: 10–100m	(Arkoc, 2013)
<2 2–5 >5	1 4 7	Custom		(Zelenovic Vasiljevic et al., 2012)
$a = 10$, $b = 50$	As per Fig. 1e	Graphical form		(Afzali et al., 2014)

(Table 2)

Table 2
Suggested scoring for distance from surface water.

Suggested distance (km)	Scoring	Membership function	Reference
$a = 0.2$, $b = 2$	As per Fig. 1a	Graphical form	(Alves et al., 2009)
$a = 1$, $b = 2$	As per Fig. 1a	Graphical form	(Bahrani et al., 2016)
1	Constraint		(Chabuk et al., 2016)
$a = 0.3$, $b = 1$	As per Fig. 1e	Graphical form	(Charnpratheep et al., 1997)
0.5	Constraint		(Djokanović et al., 2016)
<0.5	1	Custom	(Sener et al., 2010; Uyan, 2014; Wang et al., 2009)
0.5–1	2		
1–1.5	3		
1.5–2	4		
>2	5		
$a = 0.5$, $b = 0.8$	As per Fig. 1e	Graphical form	(Donevska et al., 2012; Gorsevski et al., 2012)
<0.5	1	Custom	(Zelenovic Vasiljevic et al., 2012)
0.5–2	4		
>2	7		
$a = 0.6$, $b = 3$	As per Fig. 1a	Graphical form	(Isalou et al., 2013)
<0.3	0	Custom	(Ersoy and Bulut, 2009)
0.3–0.4	2		
0.4–0.5	5		
>0.5	10		
$a = 0.1$, $d = 1$	As per Fig. 1e	Graphical form	(Afzali et al., 2014)
$a = 0.25$, $b = 2.5$	As per Fig. 1e	Graphical form	(Motlagh and Sayadi, 2015)

(Table 3)

Table 3
Suggested scoring values for elevation above sea level.

Suggested elevation above sea level (m)	Scoring	Membership function	Reference
$a = 30$, $b = 50$	As per Fig. 1e	Graphical form	(Charnpratheep et al., 1997)
$c = 100$, $f = 200$	As per Fig. 1f	Graphical form	(Charnpratheep et al., 1997)
>2000	1	Custom	(Sener et al., 2010)
1750–2000	2		
1500–1750	3		
1250–1500	4		
1000–1250	5		
$a = 800$, $d = 1000$	As per Fig. 1h	Graphical form	(Donevska et al., 2012; Gorsevski et al., 2012)
17–27	3	Custom	(Chabuk et al., 2016)
27–31	7		
31–70	10		

(Table 4)

Table 4
Suggested scoring values for slope.

Suggested slope (%)	Scoring	Membership function	Reference
$a = 1$, $b = 30$	As per Fig. 1a	Graphical form	(Alves et al., 2009)
>60	1	Custom	(Arkoc, 2013)
40–60	2		
20–40	3		
10–20	4		
<10	5		
>5°	5	Custom	(Chabuk et al., 2016)
<5°	10		
$a = 0$, $b = 2$	As per Fig. 1e	Graphical form	(Charnpratheep et al., 1997)
$a = 7$, $d = 15$	As per Fig. 1f	Graphical form	
<2	0	Custom	(Djokanović et al., 2016)
2–10	1		
>10	0.5		
40–50	1	Custom	(Wang et al., 2009)
30–40	2		
20–30	3		
10–20	4		
<10	5		
$a = 11$, $d = 30$	As per Fig. 1f	Graphical form	(Donevska et al., 2012; Gorsevski et al., 2012)
<10	1	Custom	(Uyan, 2014)
10–20	2		
>20	3		
<2	4	Custom	(Zelenovic Vasiljevic et al., 2012)
2–10	7		
10–20	4		
>20	1		
<5	10	Custom	(Ersoy and Bulut, 2009)
5–10	8		
10–15	6		
15–20	3		
$a = 10$, $d = 20$	As per Fig. 1b	Graphical form	(Sener et al., 2010)
$a = 3$, $d = 40$	As per Fig. 1f	Graphical form	(Motlagh and Sayadi, 2015)
$a = 40$, $d = 10$	As per Fig. 1f	Graphical form	(Bahrani et al., 2016)

(Table 5)

Table 5
Suggested scoring values for soil permeability.

Suggested permeability (cm/sec)	Scoring	Membership function	Reference
$a = 1.0 \times 10^{-6}$, $d = 1.0 \times 10^{-4}$	As per Fig. 1b	Graphical form	(Alves et al., 2009)
$>1.0 \times 10^{-2}$	1	Custom	(Arkoc, 2013)
1.0×10^{-2} - 1.0×10^{-3}	2		
1.0×10^{-3} - 1.0×10^{-5}	3		
1.0×10^{-5} - 1.0×10^{-7}	4		
$<1.0 \times 10^{-7}$	5		
$a = 1.0 \times 10^{-7}$, $d = 1.0 \times 10^{-5}$	As per Fig. 1b	Graphical form	(Djokanović et al., 2016)
$<1.0 \times 10^{-5}$	10	Custom	(Effat and Hegazy, 2012)
1.0×10^{-5} – 1.0×10^{-3}	8		
1.0×10^{-3} – 0.1	6		
0.1 – 1	4		
>1	1		

2-1-5- Flood susceptibility

When a flood occurs at a landfill, it can lead to contamination of the surrounding environment. Additionally, flooding can spread waste downstream. Consequently, areas that are vulnerable to flooding are not appropriate for landfilling. This aspect is considered a constraint, with flood-prone locations assigned a value of zero and areas that are not prone to flooding assigned a value of one (Djokanović et al. 2016).

2.1.6- Lithology and Stratigraphy

Understanding lithology and stratigraphy is crucial for predicting leachate transport, a complex process. Areas with simple lithology are more desirable because they allow for easier predictions of contaminant movement. The most effective geological barriers consist of cohesive and argillic rocks. In contrast, materials such as sand, gravel, sandstone, or highly crushed limestone are considered the least effective. To further clarify, the suitability of different materials is rated as follows: sand, silty sand, and bog are assigned the lowest value (often zero); loess, sandy loess, and sandy clay receive a medium value; while loess clay is given the highest value (Djokanović et al. 2016).

2.1.7- Faults

Earthquakes and ground movements can potentially damage waste landfill sites and release contaminants into the environment. Consequently, the distance from geological faults is a crucial factor in selecting appropriate landfill locations. Typically, a safe distance from a fault line is considered to be 1000 meters. Areas located within 500 meters of a fault are assigned a value of 0, while areas situated further than 1000 meters are given a value of 1 (Gorsevski et al. 2012). Table 6 provides the scoring values used in various studies regarding the distance of landfills from faults.

(Table 6)

Table 6
Suggested scores for distance of landfills from faults.

Suggested distance from faults (km)	Scoring	Membership function	Reference
>0.1	Constraint		(Afzali et al., 2014)
a =0.2, b =1	As per Fig. 1a	Graphical form	(Bahrani et al., 2016)
<1 1–5 >5	0 5 10	Custom	(Effat and Hegazy, 2012)
60–300 300–500 500–1000	2 5 10	Custom	(Ersoy and Bulut, 2009)
a =0.1, b =1	As per Fig. 1e	Graphical form	(Motlagh and Sayadi, 2015)

(Table 7)

Table 7
Suggested scoring values for land type.

Land type	Scoring	Membership function	Reference
Lakes, rivers, wetlands and urban areas Barren land	0 1	Custom	(Bahrani et al., 2016)
Industrial areas, urban centers, villages, universities, rivers, archeological and agricultural lands. Orchards Unused lands	0 5 10	Custom	(Chabuk et al., 2016)
Urban areas Heathland Agricultural areas Rocky areas	2 4 5–7 10	Custom	(Ersoy and Bulut, 2009)

2-2- Social factors

2-2-1- Land use type

Land use is crucial in public affairs, particularly due to the conflicts arising from the NIMBY (Not In My Backyard) syndrome. Generally, wastelands and low-value lands are the most suitable locations for waste disposal. Land can be categorized into six groups: agricultural land, archaeological sites, wastelands, forests, lakes and rivers, and residential areas. Each group should be assessed and valued individually (Chabuk et al., 2016; Gorsevski et al., 2012). Table 7 lists the scoring values used in various research concerning land use type.

2.2.2- Settlements and urban areas

When evaluating the criteria for landfill placement, several important factors must be considered: noise, potential reduction in property values, odor, negative impacts on the aesthetics of the area, the NIMBY (Not In My Backyard) syndrome, possible environmental hazards, and future urban expansion. The landfill mustn't be situated too close to residential areas to mitigate these issues. Conversely, the landfill should also be located close enough to urban centers to avoid excessive transportation costs. Therefore, it is recommended that the minimum buffer zone be at least 5 kilometers from urban areas and 1 kilometer from rural areas. The ideal buffer zone is suggested to be between 5 and 10 kilometers for urban areas and more than 1 kilometer for rural areas (Chabuk et al. 2016, Chang et al. 2007, Gorsevski et al. 2012, Motlagh and Sayadi 2015, Nas et al. 2010, Sener et al.

2010, Seddiqi et al. 1996). The buffers used in the literature concerning the distance from settlements are outlined in Table 8.

2-2-3 Cultural sites

Cultural sites, including archaeological and religious sites, hold significant value for social spirit and the tourism industry. Therefore, areas located near or within a religious site are unsuitable for waste disposal. A common scoring method involves applying a buffer zone of over 1 km. In this system, sites within the buffer zone receive a score of 0, while other sites are assigned a score of 1 (Chabuk et al., 2016; Charnpratheep et al., 1997; Djokanovi´c et al., 2016; Ersoy et al., 2013; Eskandari et al., 2012). A list of possible scoring values based on distance from cultural sites can be found in Table 9.

2.2.4- Protected areas

Protected areas, such as national parks and wildlife habitats, often include a buffer zone and are sometimes viewed as constraints. For instance, if a buffer of 500 meters is established, sites within 500 meters receive a score of 0, while areas located beyond 500 meters are assigned a score of 1 (Djokanović et al., 2016). Table 10 presents a list of scoring values used in various studies regarding the distance from protected areas.

2.2.5- Wind direction

The landfill must be situated in an area devoid of wind (Djokanović et al. 2016). If that isn't feasible, it should be placed in a location that experiences minimal wind to reduce the release of odor and emitted gas into nearby residential zones.

2.3- Infrastructure and economic factors

2.3.1- Roads

The landfill should be situated at a sufficient distance from the road to minimize any negative aesthetic impact. However, economic considerations are also important; the landfill shouldn't be too far from the main road, as constructing new access roads can significantly increase waste disposal costs. Consequently, finding a reasonable distance from the main road is essential. Typically, a distance of less than 500 meters is deemed unacceptable, while a distance between 1000 and 2000 meters is considered optimal (Akbari et al., 2008; Chabuk et al., 2016; Gorsevski et al., 2012; Nass et al., 2010). Another critical factor to consider is the mode of transport. The choice of transportation and the distance from roads can have complex, interrelated effects. For instance, small vehicles and heavy vehicles may require different types of roads and access points, which can influence the selection of an appropriate landfill location. However, these issues are not well-explored in MCDM studies and therefore warrant further research. The scoring values used in various studies regarding distance from roads are detailed in Table 11.

2.3.2- Railways

The negative aesthetic impact of landfills makes their location near railway lines unsuitable, as they can be visible to commuters, and the smell of waste may also reach them. Consequently, a buffer zone of 500 meters is typically recommended. Sites located within 500 meters of a railway are assigned a score of 0, while other locations receive a score of 1 (Nass et al. 2010; Sener et al. 2010; Wang et al. 2009). Additionally, as indicated in Table 12, a buffer zone of 100 meters is also suggested.

(Table 8)

Table 8
Suggested buffers for distance from settlement areas.

Suggested distance from settlements (km)	Scoring	Membership function	Urban/Rural	Reference
a = 1, b = 3	As per Fig. 1a	Graphical form	Urban	(Alves et al., 2009)
1	Constraint		Urban	(Arkoc, 2013)
a = 1, b = 3 a = 3, d = 10	As per Fig. 1a As per Fig. 1f	Graphical form	Urban	(Bahrani et al., 2016)
<5 5–10 10–15 >15	0 10 7 4	Custom	Urban	(Chabuk et al., 2016)
>10	Constraint		Rural	(Chabuk et al., 2016)
a = 0.2, d = 0.5	As per Fig. 1e	Graphical form	Rural	(Charnpratheep et al., 1997)
a = 0.5, b = 2	As per Fig. 1a	Graphical form	Urban	(Djokanović et al., 2016)
a = 0.3, b = 0.5 a = 2, d = 5	As per Fig. 1a As per Fig. 1f	Graphical form	Urban	(Donevska et al., 2012)
<5 5–10 10–20 >20	0 10 7 3	Custom	Urban	(Effat and Hegazy, 2012)
1–2 2–5 5–10 10–20 >30	4 6 8 10 0	Custom	Urban	(Ersoy and Bulut, 2009)
a = 0.5, b = 0.8 a = 2, d = 5	As per Fig. 1a As per Fig. 1f	Graphical form	Urban	(Gorsevski et al., 2012)
<0.5 0.5–1 1–1.5 1.5–2 >2	1 2 3 4 5	Custom	Urban	(Wang et al., 2009)
<0.5 0.5–1 1–1.5 1.5–2 >2	5 4 3 2 1	Custom	Urban economic factor	(Wang et al., 2009)
a = 1, b = 5	As per Fig. 1a	Graphical form	Urban	(Isalou et al., 2013)
a = 0.3, b = 2	As per Fig. 1a	Graphical form	Rural	(Isalou et al., 2013)
a = 3, b = 10	As per Fig. 1g	Graphical form	Urban	(Motlagh and Sayadi, 2015)
a = 0.8, b = 3	As per Fig. 1g	Graphical form	Rural	(Motlagh and Sayadi, 2015)

(Table 9)

Table 9
Suggested scoring values for distance from cultural sites.

Suggested distance from cultural site (km)	Scoring	Membership function	Reference
a = 3, d = 10	As per Fig. 1e	Graphical form	(Bahrani et al., 2016)
<1 1–3 >3	0 5 10	Custom	(Chabuk et al., 2016)
a = 7.1, d = 7.3	As per Fig. 1e	Graphical form	(Charnpratheep et al., 1997)
0.5	Constraint		(Djokanović et al., 2016)
<1 1–5 5–10 >10	0 2 5 10	Custom	(Effat and Hegazy, 2012)
<1 1–3 >3	1 5 10	Custom	(Ersoy and Bulut, 2009)
a = 0.5, b = 3	As per Fig. 1e	Graphical form	(Motlagh and Sayadi, 2015)

(Table 10)

Table 10
Suggested scoring values for distance from protected areas.

Suggested distance from protected areas (m)	Scoring	Membership function	Reference
500	Constraint		(Afzali et al., 2014; Djokanović et al., 2016)
a =1 km, b =10 km	As per Fig. 1a	Graphical form	(Bahrani et al., 2016)
<1 1–5 5–10 >10	0 2 6 10	Custom	(Effat and Hegazy, 2012)
a =0.5, b =1	As per Fig. 1e	Graphical form	(Motlagh and Sayadi, 2015)

2.3.3- Proximity to construction materials

The availability of construction materials, such as borrow pits for liners, daily covers, and final covers, plays a crucial role in reducing costs. Among these materials, borrow pits are particularly significant for covering landfills, as proper covering can minimize leachate production by preventing surface water from entering the landfill (Djokanović et al., 2016; Gorsevski et al., 2012; Sener et al., 2010). Clay, commonly used in liners and drainage systems, is one of these essential materials. Access to clay deposits can significantly reduce transportation costs. Typically, locations within a distance of less than 5 km from the borrow pits receive the highest priority, while locations farther than 15 km are assigned the lowest priority (Gorsevski et al., 2012).

2.3.4- Gas pipelines, oil pipelines, and powerlines

Although spontaneous combustion in landfills is unlikely, it is still a risk; therefore, an appropriate buffer distance from gas pipelines should be maintained. This is considered a constraint in the assessment process. Typically, a value of 0 is assigned to locations with a buffer distance of less than 300 to 500 meters, while a value of 1 is given to locations further than 300 to 500 meters (Chabuk et al. 2016; Djokanović et al. 2016).

Similarly, oil pipelines pose an explosion hazard, necessitating specific restrictions. A buffer distance of 75 meters is recommended for these pipelines (Chabuk et al. 2016).

To mitigate high voltage hazards that could lead to fires at waste disposal sites, it is important to consider buffer distances for power lines. For locations greater than 30 meters from power lines, a value of 1 can be applied. Conversely, locations within 30 meters should be assigned a value of 0 (Chabuk et al. 2016). Table 13 presents the scoring values used in relevant studies regarding distances from pipelines and power lines.

2.3.5- Airports

Waste landfills often attract large flocks of birds, such as seagulls, which can pose a potential hazard to aviation safety. Therefore, it is recommended that landfills be located at a sufficient distance from airports. Typically, a buffer zone of at least 1.5 km is established, with sites closer than this considered unsuitable for landfill construction (Djokanović et al. 2016). Table 14 displays the scoring values used in various studies regarding the distance from airports.

(Table 11)

Table 11
Suggested scoring values for distance from roads.

Suggested distance from roads (km)	Scoring	Membership function	Reference
0.5	Constraint		(Arkoc, 2013)
a =0.3, b =2 a= 4, d =5	As per Fig. 1e As per Fig. 1f	Graphical form	(Bahrani et al., 2016)
<0.5 0.5–1 1–2 2–3 >3	0 7 10 5 3	Custom	(Chabuk et al., 2016)
a =0.1, b =0.4 a =1, d =10	As per Fig. 1e As per Fig. 1f	Graphical form	(Charnpratheep et al., 1997)
a =2, d =5	As per Fig. 1h	Graphical form	(Donevska et al., 2012; Gorsevski et al., 2012)
<0.5 0.5–2 2–5.5 5.5–13 >13	0 10 8 6 4	Custom	(Effat and Hegazy, 2012)
<0.1 0.1–0.5 0.5–1 >1	0 10 5 1	Custom	(Ersoy and Bulut, 2009)
a =0.15, b =6	As per Fig. 1a	Graphical form	(Isalou et al., 2013)
a =0.3, d =2	As per Fig. 1h	Graphical form	(Motlagh and Sayadi, 2015)

(Table 12)

Table 12
Suggested buffers for distance from railways.

Suggested buffer (km)	Membership function	Reference
0.5	Constraint	(Chabuk et al., 2016; Wang et al., 2009)
0.1	Constraint	(Djokanović et al., 2016)

(Table 13)

Table 13
Suggested scoring values for distance from industrial lines.

Suggested distance from industrial lines (m)	Membership function	Industrial line type	Reference
30	Constraint	Powerlines	(Arkoc, 2013)
a =500, b =4000 a= 4000, d =10,000	As per Fig. 1e As per Fig. 1f	Powerlines	(Bahrani et al., 2016)
>300	Constraint	Gas pipelines	(Chabuk et al., 2016)
>75	Constraint	Oil pipelines	(Chabuk et al., 2016)
>30	Constraint	Powerlines	(Chabuk et al., 2016)
>500	Constraint	Gas and oil pipelines	(Djokanović et al., 2016)

(Table 14)

Table 14
Suggested scoring values for distance from airports.

Suggested distance from landfills (km)	Scoring	Membership function	Reference
a =3, b =7	As per Fig. 1a	Graphical form	(Motlagh and Sayadi, 2015)
1.5	Constraint		(Djokanović et al., 2016)
<5 5–10 >10	0 5 10	Custom	(Effat and Hegazy, 2012)
3	Constraint		(Ersoy and Bulut, 2009)
<3 3–6 6–9 9–12 >12	1 2 3 4 5	Custom	(Wang et al., 2009)
a =3, b =7	As per Fig. 1a	Graphical form	(Motlagh and Sayadi, 2015)

3- Sensitivity analysis

To investigate how the factors mentioned above affect the results of Multi-Criteria Decision Making (MCDM) and the stability of the resulting rankings, a sensitivity analysis is conducted. Sensitivity analysis helps determine whether the obtained results are stable and how responsive they are to changes in the factors. By making certain adjustments, we can examine the level of uncertainty in the results (Bahrani et al., 2016; Belton and Stewart, 2002; Chang et al., 2008; Eskandari et al., 2013; Kahneman and Tversky, 2013). Sensitivity analysis plots illustrate how variations in the weights impact the final results. The lines in these plots represent different alternatives, and the intersections of these lines are known as "trade-off points." At each trade-off point between two alternatives, the option with a higher priority may be downgraded to the same level as the alternative with a lower priority. For instance, Eskandari et al. (2013) found that ±20% changes in the weights for surface water, land use, and wind direction did not affect the top-ranked alternative, although other alternatives might have been impacted.

In a different study, Eskandari et al. (2015) examined several influential factors, including distances from rivers, springs, wells, and aqueducts, as well as groundwater quality, soil permeability, faults, groundwater depth, proximity to the nearest city (Marvdasht, Iran), land use, distance from roads, soil depth, distance from historical sites, wind direction, and distance from residential areas. They selected four factors for sensitivity analysis: distance from faults, groundwater depth, distance from the nearest city, and distance from residential areas. Their findings indicated that ±30% changes in the weights of all factors had a limited influence on the final result. Figure 2, derived from the sensitivity analysis by Eskandari et al. (2015), depicts the relationship between the alternatives and each selected criterion, with the X-axis representing the weights of the selected criteria and the Y-axis representing the value of each alternative concerning these weights.

Similarly, in a study focused on waste landfill site selection, Chang et al. (2008) considered ten factors: distance from the river, distance from the lake, distance from the wetland, land use, distance from roads, groundwater wells, distance from residential areas, soil type, slope, and distance from the city. They reported that ±20% changes in the weight of each factor did not alter the results; the best site for the waste landfill remained unchanged. Figure 3 illustrates the sensitivity analysis for 100 simulations conducted by Chang et al. (2008), showing that the rankings of the other alternatives largely remained stable despite variations in weights.

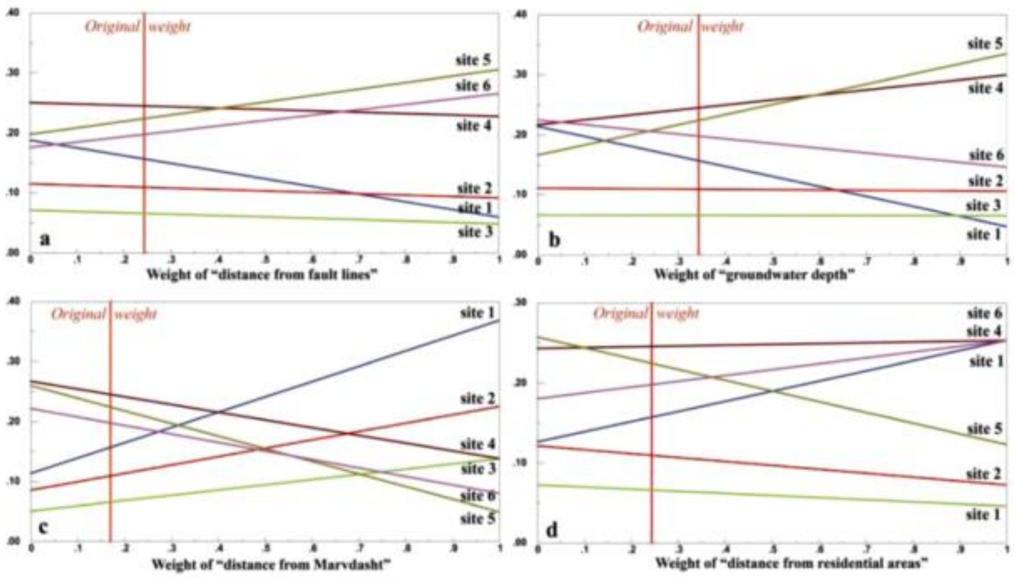

Fig. 2. Sensitivity analysis of Eskandari et al., 2015 for distance from faults, groundwater depth, distance from the nearest city (Marvdasht, Iran), and distance from residential areas. Used with permission (Eskandari et al., 2015).

(Figure 2)

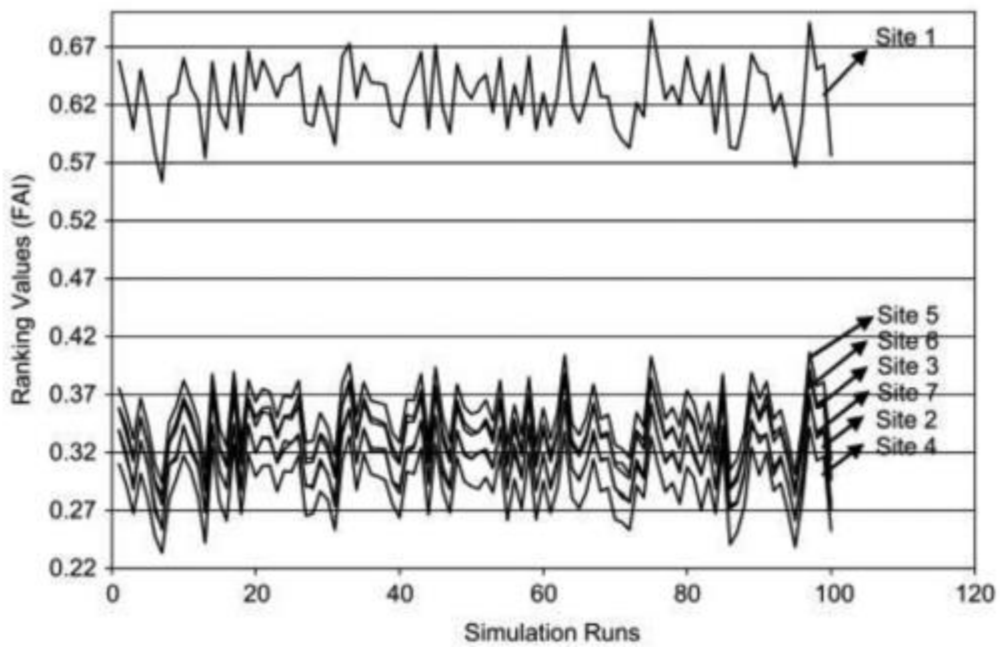

Fig. 3. Sensitivity analysis of Chang et al. (2008) running 100 simulations with various weights. Used with permission (Chang et al., 2008).

(Figure 3)

Aragonés-Beltrán et al. (2010), in their study, introduced a unique approach to sensitivity analysis by examining environmental issues that were unweighted for two specific alternatives and their impact on the Analytic Network Process (ANP). The effect sizes were varied by ±50%, resulting in a total of 81 possible outcomes. They concluded that the rankings remained stable as long as the new values did not significantly deviate from the initial values. Figure 4 summarizes the findings (Aragonés-Beltrán 2010).

4- Multi-Criteria Decision Making (MCDM) Techniques

This section reviews various multi-criteria decision-making (MCDM) techniques used for landfill site selection.

4-1- Weighted Linear Combination (WLC)

Weighted linear combination (WLC) (Voogd, 1983) is the simplest MCDM method for assigning weights to criteria in landfill site selection. Initially, weights are derived from pairwise comparisons, then these calculated weights are assigned to the relative criteria (Donevska et al. 2012; Gorsevski et al. 2012). The WLC equation is as follows:

$$S = \sum_{i=1}^{n} W_i X_i \prod C_j$$

Where S is the total score of location, W is the weight of criterion i, X_i is the criterion score (can be a fuzzy factor), and C_j is the constraint score (0 or 1) (Donevska et al., 2012, Motlagh and Sayadi 2015). In WLC, the best alternative is selected based on the total score of each alternative. This approach provides a complete trade-off between criteria by assigning weights to them (Gorsevski et al. 2012).

4.2- Ordered Weighted Averaging (OWA)

The ordered weighted averaging (OWA) method was first introduced by Yager in 1988 as a procedure for ranking criteria. Since then, OWA has been applied to various problems, including land-use suitability, residential land assessment, urban water management, and landslide hazard mapping (Bell et al., 2007; Boroushaki and Malczewski, 2010; Gorsevski et al., 2006; Jiang and Eastman, 2000; Makropoulos et al., 2003; Malczewski, 2006). This approach utilizes continuous scaling scenarios to balance risk-taking and risk-averse decision-making through the use of local and global weights. Global weights are assigned based on the judgments of decision-makers, using pairwise comparisons to control the relative importance of each criterion. In contrast, local weights can be gradually added or removed from the criteria, allowing for adjustment in the order of aggregation of the weighted criteria (Gorsevski et al., 2012; Jiang and Eastman, 2000; Malczewski, 1999, 2006). By manipulating local weights, decision-makers can effectively reduce uncertainty within the process. OWA provides a set of tools to adjust the trade-offs between criteria to evaluate potential alternatives. Additionally, this method facilitates the integration of heterogeneous data, enables changes in the order of importance of criteria, and supports various modeling scenarios (Gorsevski et al., 2012).

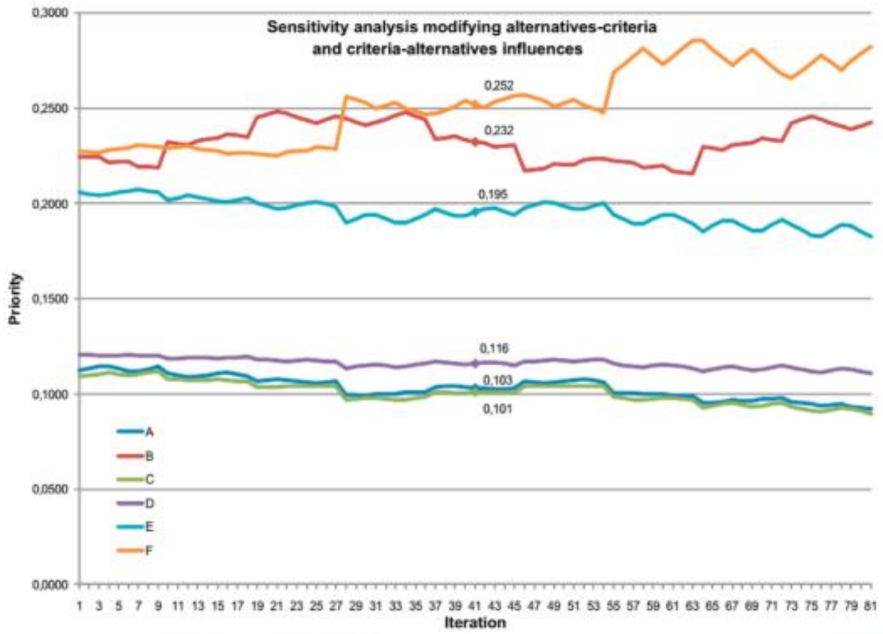

Fig. 4. Sensitivity analysis of Aragonés-Beltrán et al. (2010) for landfill site selection. Used with permission (Aragonés-Beltrán et al., 2010).

Figure 4

4.3- Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a MCDM method first developed by Saaty in the 1980s. Its mathematical foundations have been outlined in various works by Saaty (1980b, 1994). AHP is utilized in numerous complex decision-making scenarios and has been widely applied to waste landfill selection (Chabuk et al. 2016, Donevska et al. 2012, El Baba et al. 2014, Ersoy et al. 2013, Hanine et al. 2016, Rahmat et al. 2016, Torabi-Kaveh et al. 2016). In most decision-making problems, it is essential to consider both quantitative and qualitative information, resulting in complex data. AHP simplifies this complexity by transforming the decision-making process into a hierarchical and binary structure, featuring a one-way hierarchical relationship between levels. In this hierarchy, the final level represents the goal, while the first level consists of the factors involved (Aragonés-Beltrán et al. 2010). This hierarchical transformation and assignment of levels assist decision-makers in assigning weights to intricate problems with multiple attributes (Aragonés-Beltrán et al. 2010; Bozbura and Beskese 2007; Donevska et al. 2012). The AHP process includes four steps: 1) Establishing a hierarchical framework for the problem, encompassing the main objective and the associated criteria and sub-criteria; 2) Developing a pairwise comparison matrix based on experts' evaluations; 3) Calculating the weights; and 4) Determining the consistency ratio (CR) (Moineddini et al. 2010; Saaty and Vargas 2012; Senar et al. 2010).

At each level of the hierarchy, a pairwise comparison matrix is created to evaluate each criterion in relation to others at the same level. A 9-point scale is typically employed (ranging from 9 to 1/9), where 9 indicates the highest importance and 1/9 signifies the lowest.

The AHP process includes four steps: 1) Establishing a hierarchical framework for the problem, encompassing the main objective and the associated criteria and sub-criteria; 2) Developing a pairwise comparison matrix based on experts' evaluations; 3) Calculating the weights; and 4) Determining the consistency ratio (CR) (Moineddini et al. 2010; Saaty and Vargas 2012; Senar et al. 2010). At each level of the hierarchy, a pairwise comparison matrix is created to evaluate each criterion in relation to others at the same level. A 9-point scale is typically employed (ranging from 9 to 1/9), where 9 indicates the highest importance and 1/9 signifies the lowest.

4.4- Fuzzy AHP

One of the drawbacks of the classical Analytic Hierarchy Process (AHP) is the uncertainty in human judgment, which can make the data inappropriate for some situations. In response to this issue, Zadeh proposed the fuzzy method in 1965, and later, in 1983, Van Laarhoven and Pedrycz introduced Fuzzy AHP (F-AHP) (Hanineh et al., 2016; Van Laarhoven & Pedrycz, 1983). In this approach, data regarding landfill site selection are often expressed in linguistic terms, which helps researchers address the uncertainty present in the data (Beskes et al., 2015; Hanine et al., 2016). F-AHP employs fuzzy set theory to scale the criteria into equivalent units. Each criterion is assigned a value between 0 (indicating complete non-membership) and 1 (indicating complete membership) (Gorsevski et al., 2012; Zadeh, 1965, 1999).

Fuzzy logic has been applied to various decision-making problems, including landslide hazard mapping (Gorsevski et al., 2006), industrial allocation (Jiang & Eastman, 2000), water resource systems management (Li et al., 2009), and waste prediction (Ren et al., 2011). The simplest and most commonly used fuzzy numbers for decision-making processes are triangular and trapezoidal numbers, as shown in Figure 5 (Eastman, 2003; Zimmerman, 2011). Instead of assigning single numbers between 0 and 1, a range of values is provided for each objective. More complex forms of membership functions include S-shaped (circular), J-shaped, G-shaped, and linear functions (Figure 6) (Motlagh & Sayadi, 2015).

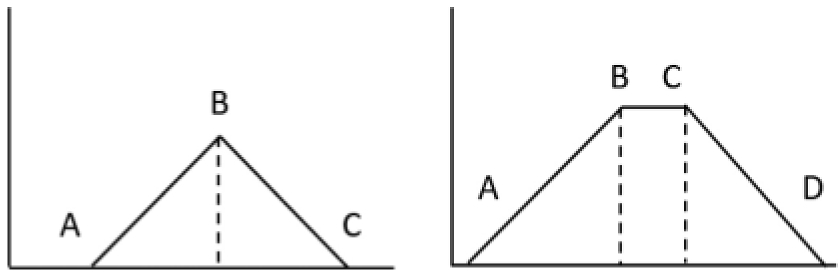

Fig. 5. The membership function of triangular and trapezoidal fuzzy numbers.

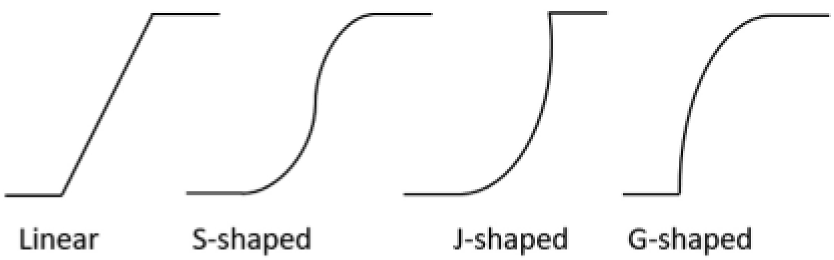

Fig. 6. Complex forms of membership functions.

(Figure 5)

Although the AHP method is a simple and easy procedure, it fails to solve some complex problems. Therefore, other methods have been proposed to solve more complex problems.

4.5- Interactive and Multi-Criteria Decision-Making (TODIM)

TODIM, a Portuguese acronym, stands for "Tomada de Decisão Iterativa Multicritério," which translates to Interactive and Multi-Criteria Decision Making in English. It was first introduced by Gomes and Lima in 1992 and has been applied to various decision-making problems. The methodology is grounded in Prospect Theory, developed by Kahneman and Tversky in 1979. TODIM takes into account the behavior of decision-makers by considering factors that influence them, such as personal experience and individual concerns. In this approach, the degree of dominance is calculated using a value function with multiple attributes. Attribute values can be expressed in several formats, including definite numbers, fuzzy numbers, interval numbers, or linguistic variables.

4.6- Fuzzy TODIM

Like AHP, the drawback of TODIM is the uncertainty in human judgment, which can make the data inappropriate for some situations. To solve this problem, as in F-AHP, linguistic terms and TFNs are used. Linguistic terms help the researcher to resolve data uncertainty and reduce false judgment. Using TFNs, the gains and losses of each alternative are evaluated with respect to other alternatives. After this evaluation, the dominance of each alternative over other alternatives should be calculated (Hanine et al. 2016).

F-TODIM follows the steps below: (Hanin et al. 2016, Salomon and Rangel 2015, Zhang and Xu 2014) 1) Evaluating criteria and alternatives, 2) Normalizing weights, 3) Calculating weights, 4) Gains and losses, 5) Dominance degree matrix 6) Overall dominance degree matrix 7) Overall value and rank of each alternative.

4.7- Analytic Network Process

The Analytic Network Process (ANP), introduced by Saaty in 1996, modifies the Analytic Hierarchy Process (AHP) by using a non-categorized structure that mirrors how the human brain analyzes problems and decision-making situations (Aragonés-Beltrán, 2010). In ANP, criteria, objectives, and alternatives are represented by nodes, with the influence of each element on the others depicted by direct vectors (Aragonés-Beltrán, 2010; Motlagh and Sayadi, 2015; Saaty, 1996). This method is particularly effective for decision-making problems that can be organized within a network (Chang et al., 2007). All criteria and alternatives, collectively referred to as elements, can be interconnected, allowing for the establishment of an accurate model for complex issues. ANP follows 6 steps: 1) Identify elements, 2) Pairwise comparison of elements, 3) Assign weights, 4) Pairwise comparison of clusters 5) Weighting supermatrix, and 6) Construct weighted supermatrix (Aragonés-Beltrán et al. 2010).

Initially, all criteria are identified and categorized, followed by the identification of elements, clusters, and influence networks by decision-makers. To analyze the influence networks, a zero-one interfactor dominance matrix is created. The elements of this matrix, denoted as aij, can take a value of 0 or 1; a value of 1 indicates that the ith element influences the jth element, while a value of 0 indicates no influence. This numerical data can also be visually represented, which is crucial for accurately modeling the complexity of real-world scenarios. Required data is typically gathered from decision-makers through questionnaires, and the decision-making process is modeled using software tools like SuperDecision and SuperDecisions-Q (Aragonés-Beltrán et al., 2010).

In the subsequent step, priorities are assigned to the relevant elements to create an unweighted supermatrix. Each criterion is analyzed to determine the influence exerted by other criteria. Pairwise comparisons are then made within each criterion group to derive the corresponding eigenvalues. Clusters with specific influences on each group are prioritized using the pairwise comparison matrix. The resulting priority values associated with each cluster contribute to the overall weighting and the formation of the weighted supermatrix (Aragonés-Beltrán et al., 2010).

ANP has been applied in various studies for waste landfill site selection. Its flexibility aids decision-makers in finding optimal solutions to complex problems (Khan and Faisal, 2008). For example, Isalou et al. (2013) integrated ANP with fuzzy logic to select a landfill site in Kahak, Iran, and proposed this model as the most accurate method for landfill site selection. Additionally, this approach has been successfully combined with GIS for landfill site selection in Damaturu, Nigeria, showcasing effective integration (Babalola and Busu, 2011).

5. Grey Systems Theory

Grey systems theory was first proposed by Deng in 1989. This method categorizes data into three groups: white, black, and grey. White data is completely known, black data is entirely unknown, and grey data is partially known (Julong, 1989). Grey systems theory encompasses events, countermeasures, and effects. In this approach, a grey situation represents a pairwise combination of an event and a countermeasure, intending to optimize the selection of the best countermeasure to address the event (Cao et al., 2006). Cao et al. (2006) used this method to select a landfill site in Xuzhou, China, and reported that the grey theory is an effective tool for evaluating different options and identifying a suitable site. However, there is some disagreement about whether grey theory can be classified as a MCDM method.

6- Critical Comparison of MCDM Methods for Landfill Site Selection

Among all multi-criteria decision-making (MCDM) methods, the Weighted Linear Combination (WLC) method is the simplest approach for selecting landfill sites. It provides a complete trade-off analysis among all factors; however, it does not yield highly accurate results, which limits its independent usage (Chou, 2013; Donevska et al., 2012; Gorsevski et al., 2012; Malczewski, 2000; Motlagh and Sayadi, 2012; Voogde, 1983).

The Ordered Weighted Averaging (OWA) method allows for the integration of heterogeneous data and the reordering of criterion importance through various tools. However, this process can become somewhat complex, particularly when dealing with large datasets (Bell et al., 2007; Boroushaki and Malczewski, 2010; Chen et al., 2019; Gorsevski et al., 2012; Gorsevski et al., 2005; Jiang and Eastman, 2000; Makropoulos et al., 2003; Malczewski, 1999, 2006; Volomens et al., 2019). Among the numerous MCDM methods, the Analytical Hierarchy Process (AHP) is the most widely used due to its user-friendliness, flexibility, and ability to incorporate both the relative importance of criteria as well as quantitative and qualitative comparisons. However, it has some notable drawbacks. A significant number of pairwise comparisons must be conducted, which can be cumbersome.

Additionally, AHP does not specifically rank important criteria, and some alternatives may critically influence certain criteria that are not accounted for in the process. Moreover, human judgment can introduce uncertainty, and certain issues cannot be effectively represented in a hierarchical structure, thus limiting the amount of input data (Aragonés-Beltrán et al. 2010, Bozbura and Beskese 2007, Chabuk et al. 2016, Chang et al. 2007, Charnpratheep et al. 1997, Djokanovi´c et al. 2016, Donevska et al. 2012, El Baba et al. 2014, Ersoy et al. 2013, Eskandari et al. 2015, Hanine et al. 2016, Kontos et al. 2003, Li et al. 2008, Majumder and Saha 2016a,b, Moineddini et al. 2010, Rahmat et al. 2016, Saaty, 1980a,b, 1990, 1994, TL 1996, Saaty and Vargas 2006, 2012, Sener et al. 2011, Sener et al. 2010, Seddighi et al. 1996, Torbati-Kavah et al. 2016, Van Laarhoven and Pedriques 1983, Wang et al. 2009). To address the uncertainty in human judgment in the AHP method, the fuzzy AHP method has been introduced. This method retains all the advantages and disadvantages of the AHP method, except for the accuracy and uncertainty of the data (Beskese et al. 2015, Bozbura and Beskese 2007, Chang 1992, D. Y. 1996, Donevska et al. 2012, Gorsevski et al. 2012, Hanine et al. 2016, Jiang and Eastman 2000, Li et al. 2009, Motlagh and Sayadi 2015, Ren et al. 2011, Torbati-Kaveh et al. 2016, Van Laerhoven and Pedriques 1983, Zhou et al. 2016). The TODIM method is unique in its focus on the negative effects of a decision and has the least undesirable impact when seeking the best solution. However, a significant drawback of this method is the uncertainty associated with its inputs and outputs, which makes sensitivity analysis essential (Fan et al. 2013; Gomes and Lima 1992a,b; Hanine et al. 2016; Kahneman and Tversky 2013; Kane et al. 2017; Ren et al. 2016; Salmon and Rangel 2015; Wu et al. 2018; Zhang and Zhu 2014). To mitigate input uncertainty, fuzzy sets can be employed alongside TODIM. Consequently, this combined approach retains the advantages and disadvantages of TODIM while minimizing input uncertainty (Kane et al. 2017; Ren et al. 2016; Salut and Rangel 2015). The Analytic Network Process (ANP) can be viewed as an advanced version of the Analytic Hierarchy Process (AHP), as it attempts to address some of AHP's limitations. However, ANP carries the same advantages and disadvantages as AHP, particularly when dealing with dependent data. The most significant challenges associated with this method include data validation and process complexity (Aragonés-Beltrán et al. 2010; Chang et al. 2007; Isalou et al. 2013; Khan and Faisal 2008; Motlagh and Sayadi 2015; Saaty and Vargas 2006). Grey systems theory is a straightforward approach characterized by simple calculations, especially useful when addressing a single event and one countermeasure. Nevertheless, this method tends to yield lower accuracy in results compared to more complex methods (Cao et al. 2006; Julong 1989).

Each Multi-Criteria Decision-Making (MCDM) method has its own advantages, disadvantages, and applications. The choice of the MCDM method can influence the final results of a comparison, although this influence may not be fundamentally significant. In other words, in addition to being dependent on various factors, the ranking of the most suitable sites for waste disposal can also be affected by the selected MCDM method. For example, Bakhtavar and Lotfian (2017) conducted a study on landfill site selection where they compared Fuzzy AHP with Grey System Theory. They evaluated six alternatives and ranked them based on the aforementioned methods, reporting that the results were generally similar, except for the rankings of the third and sixth alternatives. Additionally, the findings from field studies confirmed the priority of the first and second-ranked sites. In another study, Hanine et al. (2016) separately employed Fuzzy AHP and Fuzzy TODIM to rank four candidate waste disposal locations. Their results indicated that although the methods followed different procedures, the final rankings were identical.

Based on the advantages and disadvantages outlined for the MCDM process, it can be concluded that although fuzzy ANP is a complex procedure, it is the most suitable method when all factors and their effects are known. In situations where some data are missing or where there are fewer factors, the AHP method is the best choice. For time-sensitive scenarios that require quick decision-making, the grey system theory is preferable due to its simplicity. Additionally, the TODIM method can be used to validate the results obtained from other procedures. Therefore, when sufficient time, data, and resources are available to make the best possible decision, the order of priority is as follows:

F-ANP> ANP> F-AHP> F-TODIM> TODIM> OWA> Grey Theory>WLC

7- Geographic Information System (GIS)

Recently, Geographic Information Systems (GIS) have become increasingly popular for addressing various management issues, including site selection. GIS is a powerful tool that offers software for spatial analysis. When integrated with Multi-Criteria Decision Making (MCDM), GIS can effectively analyze spatial data, such as maps, aerial photographs, and satellite images, by combining them with quantitative data, including values and weights, to recommend the most suitable site for selection. In particular, GIS can be beneficial for identifying appropriate locations for waste disposal by applying weighting and decision-making methods developed through MCDM. Thus, GIS serves as a valuable aid to MCDM in the process of selecting landfill sites (Kontos et al., 2005; Malczewski, 2000).

When integrating Geographic Information Systems (GIS) with Multi-Criteria Decision Making (MCDM) for the evaluation of landfill sites, MCDM supplies the necessary data values and weights, while GIS processes this information and ranks the alternatives (Chang, 1992; Chang et al., 2008; Djokanovi´c et al., 2016; Donevska et al., 2012; El Baba et al., 2014; Ersoy et al., 2013; Eskandari et al., 2016). Additionally, after combining large amounts of spatial and quantitative data, GIS presents the final results in a simple form (maps), making them easily understandable for both the public and experts (Bahrani et al., 2016).

GIS is a procedure that follows the following steps: data input, data storage, data analysis and processing, and data output. This process has several advantages, including reduced data evaluation time (Djokanovi´c et al. 2016, Donevska et al. 2012, Eskandari et al. 2012, Somati et al. 2008), reduced cost (Jokanovi et al. 2016, Donevska et al. 2012, Eskandari et al. 2012, Soumati et al. 2008), Simplified and objective analysis of graphical data (Djokanovi´c et al. 2016, Ersoy and Bulut 2009), provision of a digital data bank for future monitoring and evaluation (Donevska et al. 2012, Soumati et al. 2008), program globalization (Vatalis and Manoliadis 2002), geographic data storage and management (Arkoc 2013), and optimized data analysis (Miles and Hu 1999, Parsons and Frost 2000).

However, GIS has also several drawbacks, including the need for large databases that may increase cost and time (Eskandari et al. 2015) and errors caused by inadequate pixel size, data availability, and data accuracy (Djokanovi´c et al., 2016). Despite these disadvantages, the benefits of GIS generally outweigh the drawbacks, making it a preferred choice (Djokanović et al., 2016).

GIS has been utilized alongside MCDM procedures in various studies to aid in landfill site selection. Effat et al. (2012), Ayalew et al. (2004), Mahini and Gholamalifard (2006), Malczewski (2000), Shahabi et al. (2014), Gbanie et al. (2013), and Motlagh and Sayadi (2015) have used WLC combined with GIS to select waste landfill sites. Beskese et al. (2015), Rahmat et al. (2016), Sener et al. (2011), Sener et al. (2010), Torabi et al. (2016), Yuyan (2014), Zelenovic et al. (2012), Shahabi et al. (2014), Moineddini (2010), and El-Alfy et al. (2010) combined AHP with GIS to obtain more accurate results. Moreover, Malczewski (2006), Gbanie et al. (20131), and Motlagh and Sayadi (2015) incorporated GIS with OWA to select the best waste landfill site in the study area.

8. Workflow for using MCDM for site selection

This section outlines a workflow for using Multi-Criteria Decision-Making (MCDM) methods. The steps are as follows: 1) Select essential factors (as discussed in Section 2): identify the key factors relevant to the decision-making process; 2) Classify selected factors: Group the selected factors into the following categories: physical, environmental, social, economic, and infrastructure; 3) Prepare a questionnaire: Develop a detailed questionnaire for experts from various disciplines. This questionnaire should include multiple sections, such as identifying constraints, ranking the importance of each selected factor (weighting), and proposing buffer zones and their respective values; 4) Identify potential landfill sites: Note that this step can be skipped if the procedure is integrated with Geographic Information Systems (GIS); 5) Assign weights and values: Based on responses to the questionnaire, assign weights and values to the factors (In some cases, this step may be omitted in favor of using personal knowledge and experience. Additionally, fuzzy sets for values can be utilized at this stage); 6) Prepare GIS maps: Create GIS maps for each selected factor, incorporating the assigned weights and values. This step is relevant only if the procedure is integrated with GIS; and 7) Select the most suitable location: Determine the most appropriate site for waste disposal based on the assigned values and weights. This procedure has been utilized in various MCDM studies to identify suitable locations for waste landfills. Table 15 summarizes the steps employed in different studies.

9- Conclusion

MCDM (Multi-Criteria Decision-Making) methods can serve as an effective screening process to identify solutions for complex problems. These methods provide valuable insights for decision-makers, allowing them to compare and weigh various parameters before reaching a final decision. Selecting the best landfill site is a significant environmental concern that necessitates considering trade-offs among different factors.

Several influential factors must be taken into account when choosing a landfill site, including groundwater depth, proximity to surface water, elevation, land slope, soil permeability, soil stability, flood susceptibility, lithology and stratigraphy, faults, land use types, proximity to settlements and urban areas, proximity to cultural and protected sites, prevailing wind direction, access to roads and railways, closeness to construction materials, pipelines, and power lines, and distance from airports. These factors can be categorized into physical, environmental, social, infrastructural, and economic groups. Achieving a balance among these factors is crucial for sustainable development, particularly when addressing socioeconomic criteria. The final decision must effectively satisfy and balance all of these considerations. Physical and environmental factors evaluate the potential negative impacts of constructing a landfill on the surrounding environment. Social factors assess how the landfill will affect nearby residents. Infrastructural and economic factors examine the project's financial aspects to ensure its feasibility.

(Table 15)

Table 15
The MCDM steps used in various landfill site selection studies.

Reference	Step 1	2	3	4	5	6	7
(Effat and Hegazy, 2012) (Afzali et al., 2014) (Arkoc, 2013) (Donevska et al., 2012) (Eskandari et al., 2015) (Gorsevski et al., 2012) (Wang et al., 2009) (Torabi-Kaveh et al., 2016) (Zelenovic Vasiljevic et al., 2012)	✓	✓	✓		✓	✓	✓
(Aragonés-Beltrán et al., 2010) (Alves et al., 2009) (Bakhtavar and Lotfian, 2017) (Cao et al., 2006) (Hanine et al., 2016)	✓		✓	✓	✓		✓
(Djokanović et al., 2016) (Ersoy and Bulut, 2009) (Motlagh and Sayadi, 2015) (Sener et al., 2010) (Charnpratheep et al., 1997)	✓	✓			✓	✓	✓
(Babalola and Busu, 2011)	✓				✓	✓	✓
(Alves et al., 2009) (Bozbura and Beskese, 2007) (Bahrani et al., 2016)	✓	✓	✓	✓	✓		✓
(Chabuk et al., 2016) (El Baba et al., 2014)	✓		✓		✓	✓	✓
(Vatalis and Manoliadis, 2002)	✓	✓		✓	✓	✓	✓

A variety of selection methods have been employed for optimal site selection in various studies. Some commonly used methods include WLC, OWA, AHP, F-AHP, TODIM, F-TODIM, ANP, F-ANP, and Grey Theory. Utilizing fuzzy theory instead of Boolean theory helps researchers reduce uncertainty in human judgment, bringing more reliable solutions. Among all Multi-Criteria Decision-Making (MCDM) methods, AHP, ANP, and their variants are the most prevalent. When sufficient resources, data, and time are available, ANP (with or without fuzzy elements) is recommended as the best method for landfill site selection, followed by AHP (with or without fuzzy). In time-sensitive situations where quick and straightforward comparisons are necessary, the Grey Theory may be the most suitable choice. Additionally, some studies have utilized GIS to manage large volumes of data from various sources and rank alternatives. Research is ongoing to identify the best methods for selecting a landfill site, with a significant focus on reducing uncertainty in human judgment.

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