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RESEARCH ARTICLE

Application of multi-criteria decision-making techniques to develop modify-leachate pollution index

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Abstract

The modify-leachate pollution index (m-LPI) was developed with the help of multi-criteria decision-making (MCDM) technique based on the landfill leachate pollution potential by considering the limitations of traditional methodologies. Across India, twenty major landfill sites (LS) were selected for which m-LPI was assessed. Twenty-five experts' opinions were taken for the determination of nine input criteria weights, such as pH, COD, TDS, Cl, Zn, Pb, Cu, annual rainfall, and landfill age with the help of a questionnaire-based survey. In this context, six MCDM techniques were investigated to develop m-LPI. Among different MCDM techniques selected, weighted aggregated sum product assessment (WASPAS) proved to be an effective one with an R^2 value of 0.828 and IA value of 0.813. WASPAS gave first and last rank to Kadapa, Andhra Pradesh LS (1.677) and Turbhe, Maharashtra LS (2.193), respectively. The investigation revealed that around 90% of LS considered in the present study require leachate treatment. WASPAS sensitivity analysis showed that the least sensitive criteria were pH, followed by Cl and Zn. The m-LPI can be used by researchers and scientists to investigate and evaluate various challenges involved with solid waste management in LS.

Keywords Leachate pollution index · MCDM · Municipal solid waste · Landfill sites · Sensitivity analysis

Introduction

The Indian annual municipal solid waste (MSW) generation is anticipated to be exceeded by 543 million metric tonnes (13% global annual MSW) by the year 2050 with the combined effects of rapid population growth, urbanization, industrialization, and rural-to-urban migration (Somani et al. 2019; Wijekoon et al. 2022). MSWs are generated from various sources including households and commercial or market areas with a percentage of contribution of 55–80% and 10–30%, respectively (Miezah et al. 2015; Abunama et al. 2019; Abunama et al. 2021). The wastes generated from these sources were frequently disposed into non-engineered landfill sites (open dumping sites) due to the low operating costs as compared to composting, incineration, pyrolysis, etc. (Luo et al. 2019; Bisht et al. 2022a, b, c).

Direct disposal of MSW into landfill sites (LS) leads to the production of leachate that can take its pathway to groundwater and surface water bodies, thereby causing a serious threat to the environment and human health (Zohoori and Ghani 2017; Somani et al. 2019). From the literature, it has been observed that the organic, inorganic, and heavy metal pollutants affect the leachate quality, whereas the quantity of leachate can be affected by site hydrology, landfill age (LA), moisture content, and annual rainfall (AR) (Malakahmad et al. 2017; Hendrych et al. 2019). Therefore, quantifying and assessing leachate pollution potential is critical in estimating the potential environmental risk (Rajoo et al. 2020).

Kumar and Alappat (2005) established the Delphi technique-based leachate pollution index (LPI) using eighteen leachate quality criteria to better understand the impact of leachate pollution in LS. LPI can be effectively used to evaluate the pollution potential of LS, and the temporal

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and spatial variation of leachate quality. However, due to its reliability issues, technological advancement, and the emergence of new criteria, this method cannot be applied globally for the accurate representation of landfill leachate properties (Rajoo et al. 2020). In another study, Rajoo et al. (2020) developed the LPI to calculate Leachate Pollution Index in Developing Countries (LPIDC) by considering two additional criteria, such as volume and liner. Different drawbacks, such as inconsistent criteria weights, uncertainty, ambiguity, and imprecision along with the lack of environmental criteria considerations (e.g., AR and LA), lead to ambiguity in the proper estimation of leachate potential (Bisht et al. 2021a, b). Moreover, the correlation between values obtained from LPI and LPDIC indices and treatment requirements is still lacking. Hence, to overcome the aforementioned drawbacks a systematic mathematical approach is requisite for estimating the leachate pollution and deciding whether the treatment is required or not. In this context, multi-criteria decision-making (MCDM) techniques can be used as an effective tool (Mostafaeipour et al. 2020).

MCDM techniques based on mathematical relations gained significant attention recently to solve problems related to water and wastewater management (Anaokar et al. 2018; Golfam et al. 2019a, b; Golfam et al. 2021; Azbari et al. 2022; Goswami and Ghosal 2022), climate management (Golfam et al. 2019a, b), and solid waste management (Garcia-Garcia 2022; Torkayesh et al. 2022). Among different MCDM techniques, simple additive weighting (SAW), weighted product method (WPM), technique for order preference by similarity to ideal solution (TOPSIS), additive ratio assessment (ARAS), evaluation based on distance from average solution (EDAS), and weighted aggregated sum product assessment (WASPAS) are extensively investigated as a decision-making tool in various applications, such as environmental sustainability, operational research, quality management, and soft computing and technology management (Lee and Chang 2018; Xuan et al. 2022). The MCDM techniques have already proven effective in decision-making in various fields by considering the complexities, inadequacies, and uncertainties involved (Sotoudeh-Anvari 2022; Azbari et al. 2021; Ghenai et al. 2020). Unlike LPI, the MCDM techniques can produce good performance scores based on the available number of criteria. For instance, Dehshiri et al. (2022) prioritized the dust sources affecting central Iran using four MCDM methods, including WASPAS, EDAS, ARAS, and TOPSIS. In another study, Sadhya et al. (2022) employed four MCDM techniques to rank the five selected waste-to-energy technology alternatives based on six criteria, such as capital cost, global warming potential, revenue return, operation and maintenance cost, need for segregation, and moisture content.

The objectives of this study were (a) to develop m-LPI using MCDM techniques, (b) to rank and require treatment for LS on basis of m-LPI, and (c) to apply the sensitivity analysis to determine the influence of different input criteria such as pH, COD, TDS, Cl, Zn, Pb, and Cu on m-LPI.

Methodology

In the present study, an attempt has been made to rank and determine the requirement for treatment at twenty LS based on the nine input criteria like pH, COD, TDS, Cl, Zn, Pb, Cu, AR, and LA using various MCDM techniques such as WSM, WPM, TOPSIS, ARAS, EDAS, and WASPAS. One LS named CPCB 2016 leachate permissible values (LS-21) is incorporated in order to determine the treatment requirement for LS.

Study area and data acquisition

A literature survey was conducted where forty influencing inputs criteria were investigated for landfill leachate potential. The availability of data had been a major determining factor in input criteria selection. Thus, only nine input criteria have been chosen from forty criteria for twenty LS in India. The twenty LS were chosen based on the city's socioeconomic condition as well as its geographical location (Fig. 1). These nine input criteria were pH, TDS, Cl, COD, Zn, Pb, Cu, AR, and LA from the organic, inorganic, heavy metal, and other environmental criteria. Eight criteria data were taken from reference literature papers, while the rainfall data for each LS was taken from the Indian Meteorological Department during the respective sample collection year. The complete flow of methodology is shown in Fig. 2. The overall analytical results of input criteria are represented in Table 1 and landfill leachate data characteristics used in the study are shown in Table S1.

TDS concentration values of 90% LS exceeded the CPCB permissible limit (2100 mg/L) of CPCB (2016). The age of the LS and volatile acid accumulation in the methanogenic bacteria environment were the two major factors that influenced the pH of the leachate (Mor et al. 2018). Twenty percent of the LS were acidic, while the rest were alkaline. Eighty percent of the LS exceeded the permissible limit of Cl concentration (1000 mg/L). Heavy metals in MSW were primarily produced by the electroplating, tannery, and steel industries (Somani et al. 2019). Thirty percent of the LS exceeded the permissible limit of Zn concentration (5 mg/L). Cu concentration in 15% of the LS exceeded the permissible limit (3 mg/L). Pb concentrations in 85% of the LS exceeded the permissible limit (0.1 mg/L). A high biodegradable fraction of MSW was generated in India, implying high COD values (Somani et al. 2019). The COD values of all LS exceeded their permissible limits (250 mg/L).

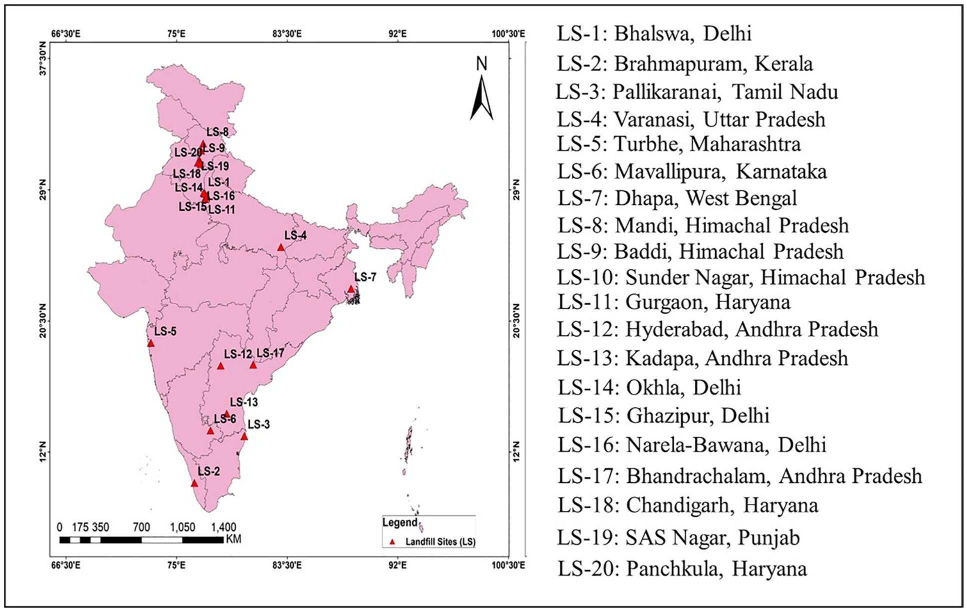


Fig. 1 Locations of the landfill sites across India

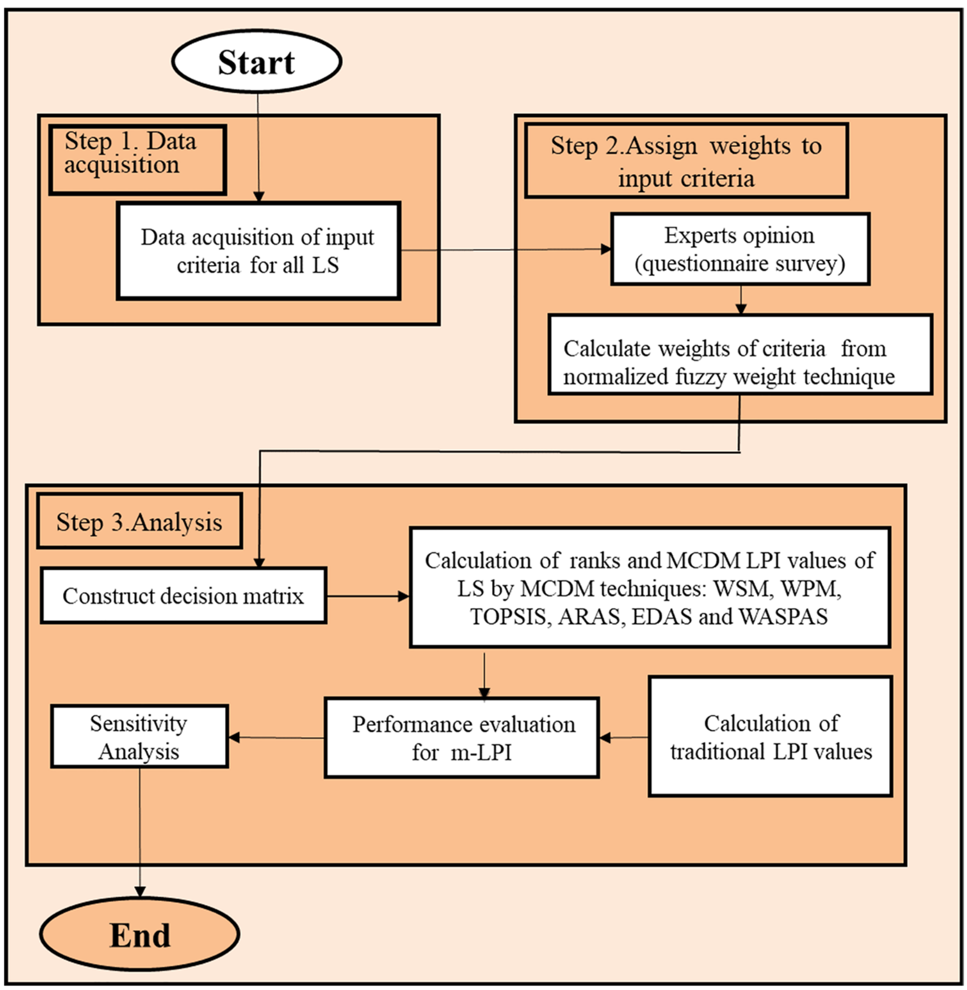


Fig. 2 Complete flow of methodology

Table 1 Descriptive statistics of input criteria of landfill sites

Parameters*	Maximum	Minimum	Mean	Standard deviation
TDS	24,644.3	1156	11,868.447	8265.270
pH	9.6	0.914	7.905	1.982
Cl	11,948.67	150	12,089.421	3925.633
COD	57,300	250	3973.440	13,510.080
Zn	9.8	0.27	3.998	2.843
Cu	3.62	0.07	1.323	1.273
Pb	4.27	0.02	1.007	1.103
AR	2891.5	450	1046.311	622.131
LA	51	5	19.421	13.045

*All the input criteria are mg/L except pH, AR (mm), and LA (years)

Table 2 Linguistic terms and fuzzy numbers

Linguistic terms	Fuzzy numbers
Very high important	(0.7,0.8.0.9,1)
High important	(0.5,0.6,0.70.8)
Important	(0.3,0.4,0.5,0.6)
Low important	(0.1,0.2,0.3,0.4)
Very low important	(0,0,0.1,0.2)

Weights assigned to the input criteria

The literature revealed that the equal weight assigned to the input criteria for the development of indices caused the unevenness and inconsistencies in the index structure (Babcock 1970; Ott and Thorn 1976; Bisht et al. 2022c). Moreover, the assignment of statistical weights might cause irrational weighting, with insignificant criteria receiving a higher relative weight. Hence, expert opinions were taken to the determine weights of the input criteria for this study (Sebastian et al. 2019).

A Google form was created which was sent via email to a list of experts around 60 who were primarily academicians, Ph.D. scholars, and consultants in the field of environmental engineering. Saaty (1977) developed fuzzy numbers for seven linguistic terms to describe the degree of satisfaction with decision-making criteria for alternatives. In general, there were no concrete sentences to support the idea that the best linguistic terms were three, five, seven, and nine (Chen and Hwang 1992). Hence, a five-point Saaty scale with five linguistic terms and their respective fuzzy number had been selected for understanding the importance of the inclusion of each criterion in the development of the modify-leachate pollution index (m-LPI) for the LS (Khambete and Christian 2014). The linguistic term and their respective fuzzy number on the five-point Saaty scale are represented in Table 2. The normal weights of criteria for m-LPI were evaluated with the help of the normalized fuzzy weights technique. The paper explains all steps for calculating weights, such as fuzzification and defuzzification (Khambete and Christian 2014).

MCDM techniques

Six MCDM techniques such as SAW, WPM, TOPSIS, ARAS, EDAS, and WASPAS were employed to rank and determine the requirement of treatment for LS. The high and low leachate degree of potential of the LS represents the lower LPI and rank and higher LPI and rank, respectively for six MCDM techniques.

Simple additive weighting (SAW)

In 1968, Fishburn introduced the SAW technique (weighted sum method), which was one of the simple as well as mostly applied MCDM techniques (Fishburn et al. 1968). Generally, in SAW, cost criteria were converted to benefit criteria whereas non-cost criteria were converted into non-benefit criteria. With the normalization step, the largest criterion changes to the lowest and vice versa. In the final step, the alternative total score is to be multiplied by the weight of

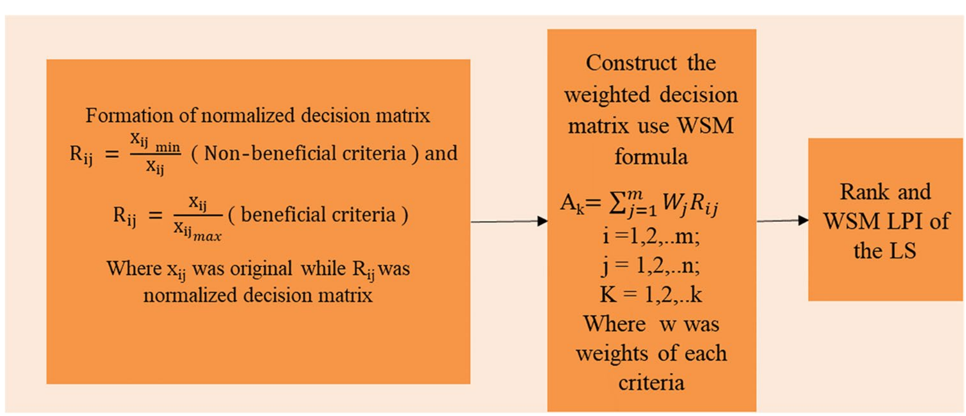


Fig. 3 Complete steps for SAW

each criterion (Roozbahani et al. 2018; Akras et al. 2022). Figure 3 depicts the complete SAW procedure.

Weighted product method (WPM)

In 1969, Bridgeman anticipated WPM, which is similar to SAW (Bridgman 1992). The main difference was that in the mathematical process the number of ratios was multiplied in order to compare each decision alternatively with others. In WPM, each criterion's ratio was increased to the power equivalent of its relative weight of criteria (Triantaphyllou and Mann 1989). This step allows the dimensionless analysis by removing the measurement units, allowing this technique to be applied to both single as well as multidimensional decision hypotheses (Mulliner et al. 2016). Figure 4 depicts the complete WSM procedure.

Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS technique evaluated the best option by considering the basis of local to the positive ideal solution (PIS) and non-local from negative ideal solution (NIS) (Hwang and Yoon 1981). PIS gives the solution, which maximizes profit criteria and minimizes cost criteria, while NIS was the exact opposite. The PIS was created from all of the great achievable qualities of criteria, while the NIS constitutes bad achievable values of criteria. This method took into account the specific scores received from each criterion for evolution and normalization of the decision matrix. The order of priority of the options was finalized by taking into account the distance coefficient of each option (Sadhya et al. 2022). Figure 5 depicts the TOPSIS procedure in detail.

Additive ratio assessment (ARAS)

Turskis and Zavadskas invented ARAS in 2010. To select the best alternatives, quantitative measurements and utility theory were used for the assessment of optimality function values and ranking (Sivalingam et al. 2022). Its widespread use and explosive growth were the results of its simple as well as direct and easy steps, producing reasonable and relatively accurate results to rank various alternatives as per their performance based on selected weighted evaluation criteria (Ghenai et al. 2020). Figure 6 depicts the ARAS procedure in detail.

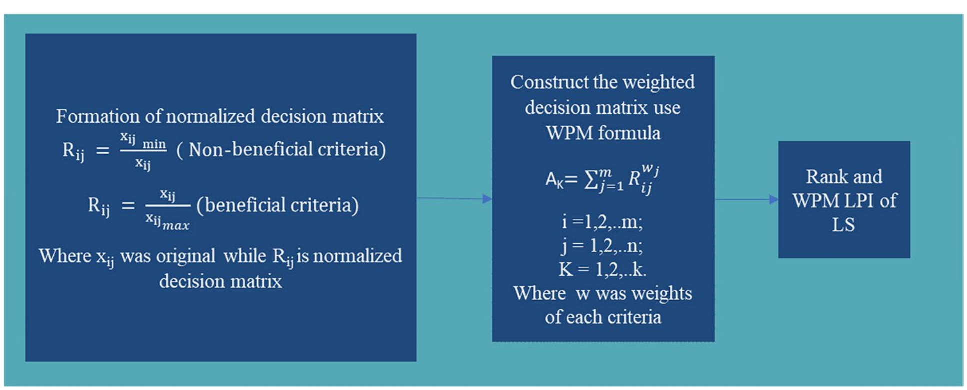
Evaluation based on distance from average solution (EDAS)

In 2015, Ghorabaee proposed the EDAS. It had to be a novel MCDM technique that assessed positive and negative distances from solutions rather than ideal and non-ideal solutions to assess conflicting criteria (Feng et al. 2018; Orji et al. 2022). This technique employed two actions to assess the applicability of the alternative: the positive distance from average (PDA) and the negative distance from average (NDA). These calculations could be used to determine how different each solution (alternative solution) was from the average solution. The alternatives score higher on PDA and lower on NDA. A higher PDA and/or lower NDA value indicated a better (alternative) solution than the general solution. This technique was extremely useful when there were conflicting standards (Mostafaeipour et al. 2020; Mishra et al. 2020). The EDAS's statistical advantages were in providing a robust and accurate ranking of alternatives (Behzad et al. 2020). Figure 7 depicts the EDAS procedure in detail.

Weighted aggregated sum product assessment (WASPAS)

WASAPAS was one of the best MCDM techniques for accuracy and reliability based on two MCDM techniques, i.e., SAW and WPM (Zavadskas et al. 2012; Mostafaeipour et al. 2020). The optimized WASPAS method has a strong benefit over the standard WASPAS method in determining the optimal λ value, which is calculated using the practical concept of variance. Moreover, stochastic errors occur when determining the initial values of criteria. Using the optimal λ value to achieve fall ranking ensures that the estimated variance of the relative importance of each alternative is kept to a minimum. It has been used to solve MCDM problems

Fig. 4 Complete steps for WPM



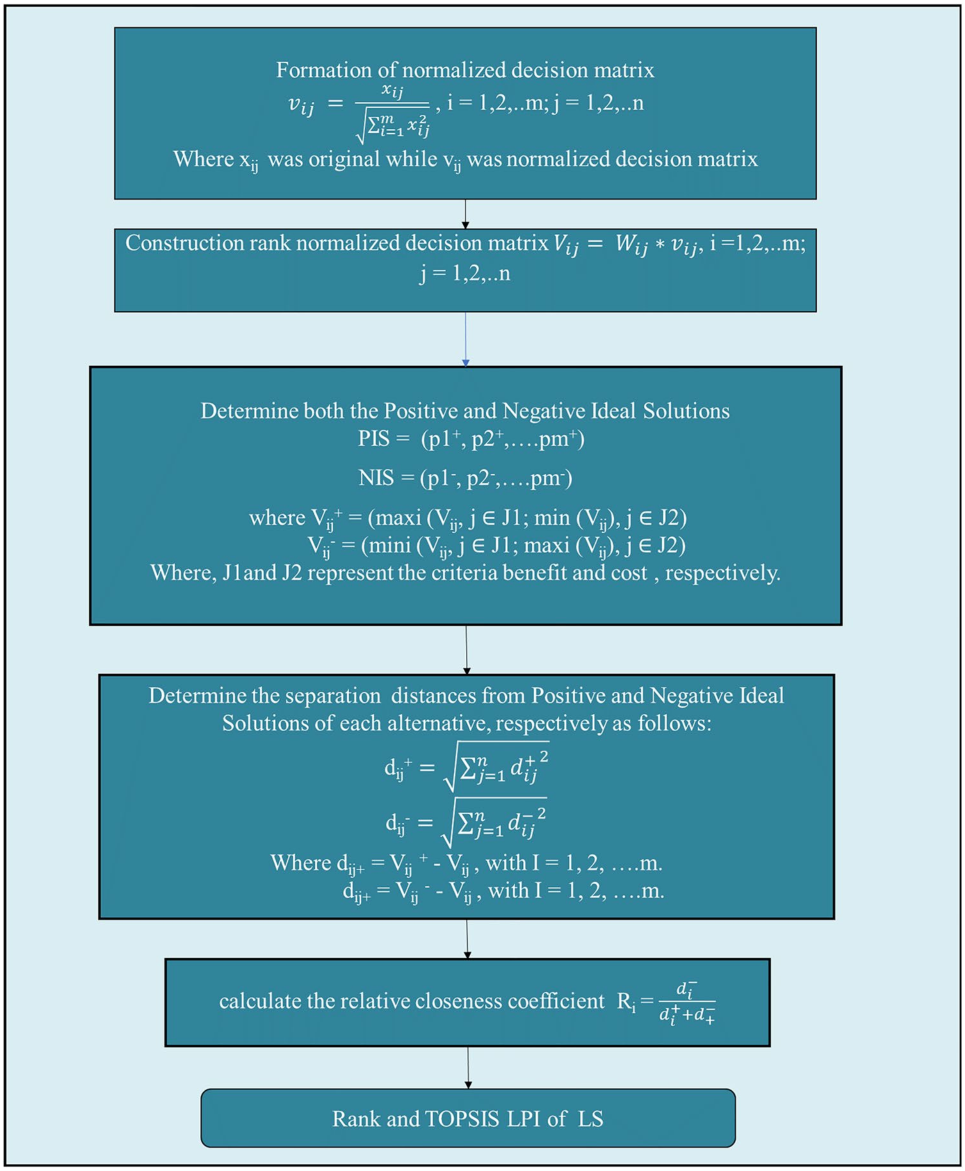


Fig. 5 Complete steps for TOPSIS

to improve ranking accuracy, and it has the highest estimation accuracy (Mishra and Rani 2018). Figure 8 depicts the complete WASPAS procedure.

Leachate pollution index

The traditional approach LPI was proposed by Kumar and Alappat (2005) to calculate the index score for landfill leachate pollution. The LPI is shown in Eq. (1).

$$LPI = \sum_{i=1}^{n} w_i C_i / \sum_{i=1}^{n} w_i \tag{1}$$

where C_i and w_i are the sub-index score and weights for the ith criteria, respectively, and n was the number of input criteria.

Performance evaluation

Performance evaluation techniques such as R^2, RMSE, MAPE, and IA were used in this study to evaluate the best MCDM technique for the m-LPI among six MCDM techniques. The equation of RMSE, MAPE, and IA are expressed in Eqs. (2), (3), and (4), respectively. Furthermore, the impact of seven criteria, such as pH,

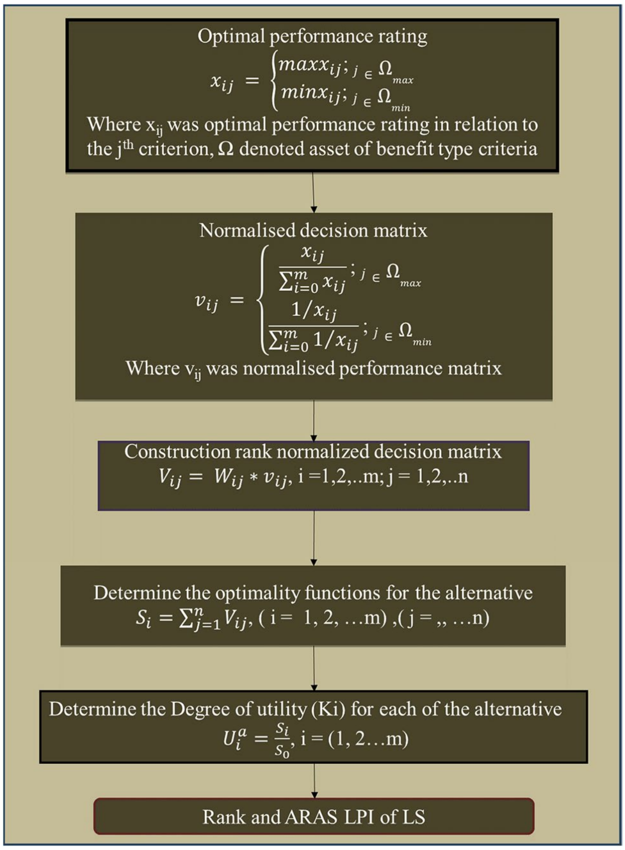


Fig. 6 Complete steps for ARAS

COD, TDS, Cl, Zn, Pb, and Cu, on m-LPI was determined through a sensitivity analysis using a Taylor diagram (Taylor 2001). In this case, one of the criteria was changed at a time while the other remained constant. Based on the study data, the criteria values were changed between their minimum and maximum values, i.e., random values. The other criteria were left of their original values (Radwan et al. 2018). Among the different criteria selected, AR and LA criteria were not considered during the sensitivity analysis due to the no variation in their characteristics throughout the year.

$$RMSE = \sqrt{\sum_{i=1}^{n} (\hat{Y}_j - Y_j)^2 / n} \quad (2)$$

$$MAPE = 100/n\left(\sum_{i=1}^{n} \left| Y_j - \hat{Y}_j / Y_j \right|\right) \quad (3)$$

$$IA = 1 - \sum_{i=1}^{n} (\hat{Y}_j - Y_j)^2 / \sum_{i=1}^{N} [\left|\hat{Y}_j - \hat{Y}_m\right| - \left|Y_j - Y_m\right|]^2 \quad (4)$$

where Y_j and $\hat{Y}_j$ were the traditional LPI and MCDM LPI values, Y_m and $\hat{Y}_m$ were the mean of the traditional LPI and MCDM LPI values, and n was the number of LS.

Results and discussion

Weights assigned to the input criteria

The use of a questionnaire-based survey response sheet, expert opinions consistency analysis, and geometric mean allowed for the elimination of competing hypotheses and the identification of reliable criteria results (Sadhya et al. 2022). The normal weights of each criterion for the m-LPI have been depicted in Fig. 9. It can be observed that the AR and LA along with Pb scored the highest weight criteria, whereas Cu has the lowest criteria in determining the m-LPI. Similarly, Kumar and Alappat (2005), Mishra et al. (2016), and Gautam and Kumar (2021) studies found higher and lower weight criteria were AR and LA, as well as Cu. The order of the weights of the criteria was AR ≥ LA > Pb ≥ pH > COD ≥ TDS ≥ Cl ≥ Cu. The highest criteria weights for AR and LA attributed to the exudation of the leachate in terms of quantity and quality, while a lower weight for Cu indicates landfill setting.

Correlations between input criteria

As most of the landfill leachate input criteria were normally distributed, Pearsons's correlation matrix was used to analyze the correlation between the criteria as represented in Table 3. The results showed a very strong positive correlation between Cl and TDS (0.852). Some potential reasons include the presence of high concentrations of Cl in the leachate, which could directly lead to increased TDS levels. Moreover, the highest negative correlation between COD and Cu was found − 0.375 respectively. It may be possible that the Cu was binding to the organic matter in the leachate and is not available for COD uptake.

MCDM techniques

SAW

The different MCDM LPI values for respective MCDM techniques and traditional LPI values of LS are represented in Table 4. SAW can develop a clear understanding of the decision-maker and how these alternatives relate to the multiple criteria. The ranking and SAW LPI of the LS were determined by aggregating the criteria of each LS (A_k). SAW LPI values for different LS based on the SAW algorithm

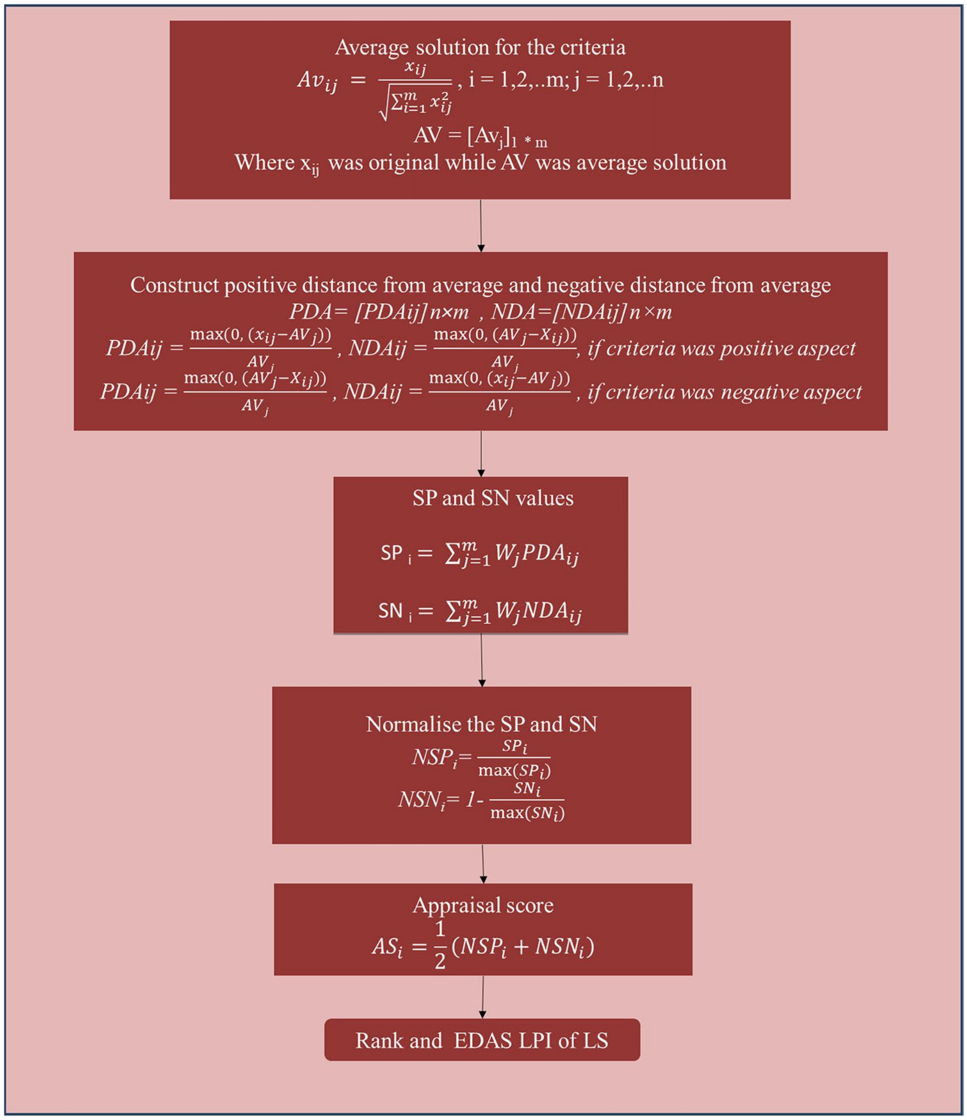


Fig. 7 Complete steps for EDAS

(Fig. 3) are shown in Table 4. The SAW LPI of different LS ranges from 0.261 to 0.635. The highest SAW LPI value was observed for LS-5 (0.635) followed by LS-18 (0.554) and LS-1(0.513), whereas the lowest SAW LPI value was for LS-13 (0.261). It could be due to the SAW LPI of each LS being obtained using the SAW by aggregating the values of that LS in various criteria while accounting for the weight of each criterion.

WPM

The ranking and WPM LPI values for different LS were determined by aggregating the criteria of each LS (B_k). WPM LPI values of different LS were generated depending on the steps of the WPM algorithm (Fig. 4) and shown in Table 4. The WPM LPI of different LS ranges from 0.721 to 8.428. The WPM LPI value of LS-17 was observed lowest (0.721) and followed by LS-13 (7.290) whereas LS-5 was the highest WPM LPI value (8.428). It could be due to each ratio being increased to the power equivalent of the corresponding criterion's weight factor, one for each criterion, to compare each possibility to the others.

TOPSIS

The deviation from Euclidian distance from the PIS (d_{ij}^{+}) and separation from the NIS (d_{ij}^{-}) was evaluated for each criterion. The alternatives were ranked concerning their relative closeness value (R_i), with the best alternatives having a lower value (lower LPI and rank) of R_i. TOPSIS LPI values of the different LS are depicted in Table 4 based on the TOPSIS algorithm (Fig. 5). The TOPSIS LPI of different LS ranges from 0.124 to 0.631. It was found that the LS-5 got a high-performance score (0.631) followed by LS-12 (0.545)

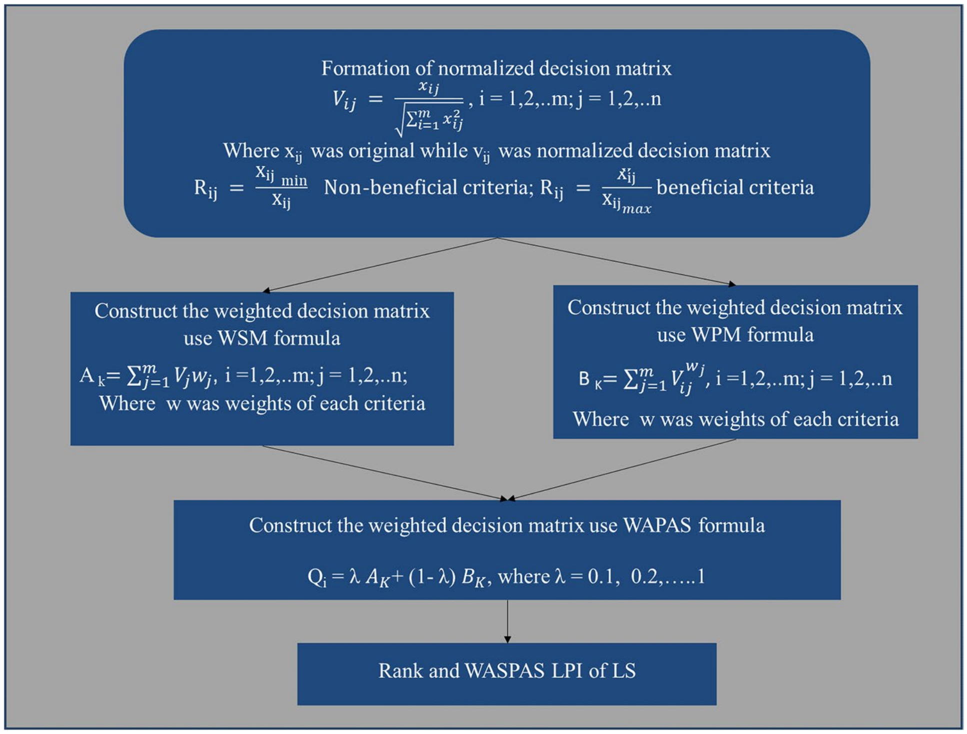


Fig. 8 Complete steps for WASPAS

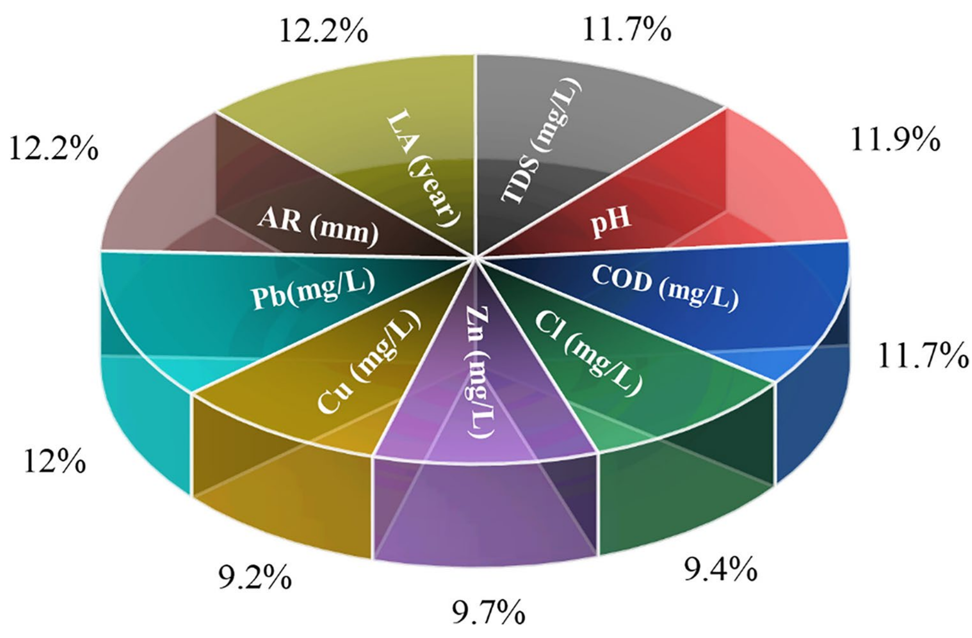


Fig. 9 Weights of the input criteria

and LS-1 (0.513) whereas the lowest performance score was LS-13 (0.124). It could be selected best LS should have the shortest distance from the PIS and the longest distance from the NIS (Hwang and Yoon 1981).

The ranking and ARAS LPI values for different LS were evaluated according to the appraisal score value K_i and the best LS (lower LPI value) were those that have a lower value of K_i. Table 4 depicts ARAS LPI values for different LS that were generated based on the steps of the ARAS algorithm (Fig. 6). According to ARAS, the ARAS LPI values of various LS range from 0.234 to 0.766. The ARAS LPI value was observed lowest at LS-13 (0.234) and followed by LS-17 (0.271) and LS-10 (0.279) whereas LS-5 was the highest ARAS LPI (0.766). It could be due to the complicated relative effectiveness of a feasible LS being directly related to the relative effect of the key criteria's values and weights, with the ARAS relying on quantitative calculations and utility function values of LS.

Table 3 Correlation matrix between input criteria

Pearson correlation	TDS	pH	COD	Cl	Zn	Cu	Pb	AR	LA
TDS	1								
pH	−0.242	1							
COD	0.427	−0.514	1						
Cl	0.852	−0.193	0.338	1					
Zn	0.041	0.046	−0.185	0.058	1				
Cu	−0.138	0.322	−0.375	−0.277	0.695	1			
Pb	0.312	0.082	−0.192	0.202	0.051	0.222	1		
AR	−0.074	0.063	0.394	−0.264	−0.190	0.196	0.303	1	
LA	0.111	0.111	−0.255	0.094	−0.051	0.137	0.027	−0.106	1

Table 4 Summary of different MCDM LPI with respective MCDM techniques and traditional LPI values of landfill sites

Landfill sites	WSM LPI	WPM LPI	TOPSIS LPI	EDAS LPI	ARAS LPI	WASPAS LPI	Traditional LPI
LS-1	0.513	8.290	0.513	0.569	0.706	2.068	34.501
LS-2	0.405	7.507	0.432	0.509	0.421	1.825	25.206
LS-3	0.365	7.851	0.311	0.391	0.417	1.863	26.064
LS-4	0.360	7.651	0.242	0.377	0.259	1.818	16.567
LS-5	0.635	8.428	0.631	0.766	0.901	2.193	33.001
LS-6	0.341	7.600	0.265	0.355	0.280	1.793	16.189
LS-7	0.437	7.801	0.402	0.505	0.534	1.910	27.799
LS-8	0.350	7.644	0.197	0.349	0.317	1.809	13.161
LS-9	0.404	7.856	0.272	0.429	0.440	1.895	19.703
LS-10	0.329	7.597	0.213	0.279	0.323	1.783	12.980
LS-11	0.510	8.115	0.460	0.558	0.600	2.031	33.214
LS-12	0.489	8.227	0.545	0.576	0.717	2.037	32.769
LS-13	0.261	7.290	0.124	0.234	0.034	1.667	10.129
LS-14	0.512	8.079	0.419	0.528	0.591	2.026	36.060
LS-15	0.458	8.166	0.370	0.500	0.566	1.999	30.614
LS-16	0.511	8.183	0.388	0.521	0.567	2.046	29.543
LS-17	0.305	7.207	0.199	0.271	0.216	1.685	8.344
LS-18	0.554	8.179	0.440	0.574	0.667	2.079	33.187
LS-19	0.493	8.120	0.390	0.510	0.589	2.018	23.631
LS-20	0.362	7.726	0.268	0.361	0.317	1.835	15.543
LS-21	0.325	7.335	0.169	0.300	0.233	1.727	8.663

EDAS

The ranking and EDAS LPI values of the different LS were evaluated on basis of appraisal score value (AS_i) and the best LS (lower LPI value and rank) were those that have a lower value of AS_i. EDAS LPI values (Table 4) were generated based on the steps of the EDAS algorithm (Fig. 7). LPI values of different LS range from 0.233 to 0.901. LS-5 had the highest EDAS LPI value (0.901), followed by LS-12 (0.717), and LS-1(0.706), while LS-21 had the lowest EDAS LPI (0.233). It could be due to the best LS depending upon the positive and negative distance from the average solution than an ideal and anti-ideal solution.

WASPAS

The ranking and WASPAS LPI values for different LS were evaluated by combining the two models, namely WSM and WPM by WASPAS technique. WASPAS LPI values (Table 4) are generated based on the steps of the WASPAS algorithm (Fig. 8). In this study, the optimized WASPAS technique was assessed by considering λ value ranging between 0 and 1 with an interval of 0.1. The WASPAS LPI values with the existing traditional LPI values were compared based on R^2 for each λ value to optimize WASPAS. Hence, the investigation found the optimized value with $\lambda = 0.8$ with an R^2 value of 0.82. Moreover, it was observed

Table 5 Summary of ranks of LS with respective MCDM techniques and traditional LPI

Landfill sites	WSM LPI	WPM LPI	TOPSIS LPI	EDAS LPI	ARAS LPI	WASPAS LPI	Traditional LPI
LS-1	19	20	19	19	18	19	20
LS-2	11	4	16	11	13	8	11
LS-3	9	11	10	9	9	10	12
LS-4	7	8	6	5	8	7	8
LS-5	21	21	21	21	21	21	17
LS-6	5	6	7	6	6	5	7
LS-7	12	10	14	12	12	12	13
LS-8	6	7	3	8	5	6	5
LS-9	10	12	9	10	10	11	9
LS-10	4	5	5	4	3	4	4
LS-11	16	14	18	17	17	16	19
LS-12	14	19	20	20	20	17	16
LS-13	1	2	1	2	1	1	3
LS-14	18	13	15	16	16	15	21
LS-15	13	16	11	14	11	13	15
LS-16	17	18	12	13	15	18	14
LS-17	2	1	4	3	2	2	1
LS-18	20	17	17	18	19	20	18
LS-19	15	15	13	15	14	14	10
LS-20	8	9	8	7	7	9	6
LS-21	3	3	2	1	4	3	2

that if λ is more than 0.5 the R^2 is near 0.82 while λ is ≤ 0.5 the R^2 is close to 0.80. The WASPAS LPI value of different LS ranges from 1.667 to 2.193. The WASPAS LPI of the LS-13 was lowest (1.667) followed by LS-17 (1.685) while LS-5 was found to have the highest performance score (2.193). Moreover, the optimization of λ value directly impacts the performance of decision-making and along used to develop a consensus among decision-makers.

Comparing the ranks of several LS generated by various MCDM methods

A comparative study was performed for ranks of all LS by the six selected MCDM techniques shown in Table 5. It was found that almost all the MCDM techniques gave the first rank to LS-13 whereas last to LS-5. It could be due to landfill leachate input criteria values of AR and LA being more in the LS-13. It was also observed that LS-5 got the last rank by all MCDM techniques while it got the fifth rank by the traditional LPI technique. LS-7 got the twelfth rank by the four techniques like WSM, TOPSIS, ARAS, and WASPAS. It was observed that different LPI values were observed for all selected LS. Tscheikner-Gratl et al. (2017) applied five MCDM models such as WSM, AHP, ELECTRE, TOPSIS, and PROMETHEE for ranking and obtained that the findings of the various models were not similar. Moreover, the author also revealed that employing more than one MCDM technique increases the reliability of the findings and allows for consistency checking. In another study, the wastewater treatment alternative ranking was investigated by Kalbar et al. (2015) considering unequal and equal weights for all criteria revealing different rankings for the alternatives.

Performance evaluation of m-LPI

In order to investigate, the best MCDM technique for the development of m-LPI was evaluated by comparing their MCDM LPI with the traditional LPI values using performance evaluation techniques such as R^2, RMSE, MAPE, and IA (Table 6). According to the performance evaluation techniques, WASPAS was the best-fitting among six MCDM techniques ($R^2 = 0.828$, and IA = 0.813), followed by WASPAS > EDAS > TOPSIS > ARAS > WPM > WSM. The best performance of WASPAS could be due to it being

Table 6 Performance evaluation for m-LPI

MCDM techniques	R^2	RMSE	MAPE	IA
WSM	0.799	24.521	97.940	0.897
WPM	0.796	17.731	58.801	0.314
TOPSIS	0.820	24.582	98.459	0.906
EDAS	0.832	24.422	97.882	0.885
ARAS	0.806	24.486	97.891	0.894
WASPAS	0.828	23.132	90.113	0.813

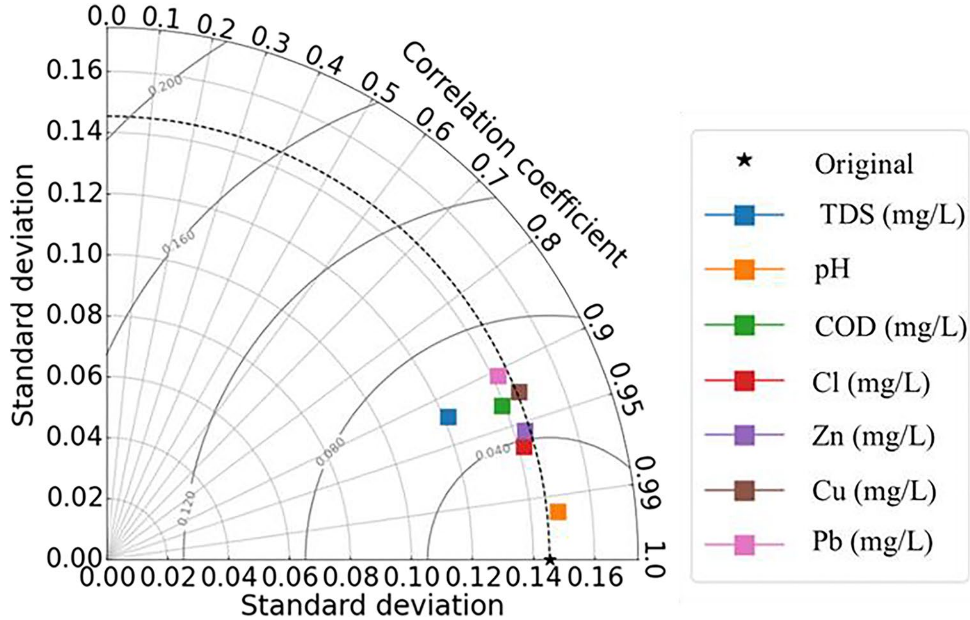


Fig. 10 Taylor diagram for sensitivity analysis of input criteria

one of the newest methods of the MCDM technique and is increasingly used because of its high accuracy and short calculation stages; moreover, its ability to produce an accurate and unbiased solution. In addition, the optimization of λ value in WASPAS directly impacts the performance of decision-making and along used to develop a consensus among decision-makers. The method is useful for the complete ranking of alternatives; however, it only takes into consideration minimum and maximum values (Dehshiri et al. 2022; Firouzi et al. 2021). Xuan et al. (2022) revealed that WASPAS was an efficient MCDM technique among others to determine the most appropriate solar-hydrogen generation region in Uzbek. In another study, Azbari et al. (2022) stated that WASPAS was the best MCDM technique for finding the best alternatives for wastewater reuse allocation alternatives at provinces of Iran.

The WSPAS technique suggested that 90% of LS required treatment whereas 10% of LS does not require treatment (LS-13 and LS-17). Lower criteria values at the LS-13 (1.667) and LS-17 (1.685) were observed which are below LS-21 permissible values (1.727). It could be due to the LA, continuous aeration, and rainfall (Yadav et al. 2014; Somani et al. 2019). WASPAS resulted in lower and higher ranks for LS-13 and LS-5 (2.193). LS-5 was an active landfill cell, and the leachate produced was an acetogenic phase (Mishra et al. 2016). It could be an essential decision-making for policymakers to determine the appropriate treatment of landfill leachates and the ranking of LS. Overall, this study could benefit researchers and scientists in terms of resource allocation, standard enforcement, ranking of LS, treatment requirements, and public information about the quality of leachate for well solid waste leachate management.

Sensitivity analysis

Sensitivity analysis was conducted on basis of the Taylor diagram for the WASPAS technique shown in Fig. 10. It was used to assess the variability of the WASPAS LPI values and ranking of LS as each criterion value was changed, one at a time. The order of criteria sensitivity was found as Pb > TDS > Cu > COD > Zn > Cl > pH. The least influencing criterion found was pH ($R = 0.99$). pH does not affect the ranking and LPI values of LS in the acidic medium, basic medium, and neutral medium. The most influencing criterion found was Pb, which was a highly sensitive criterion because it degraded differently than other heavy metals. Its concentrations in leachate were primarily due to chemicals used for photograph processing, disposal of batteries, pipes and lead-based paints, etc. (Abunama et al. 2019).

Conclusions

This study described a novel approach of m-LPI for the assessment of leachate pollution potential for twenty LS across India with the help of MCDM techniques. The present study considered nine input criteria for developing m-LPI using MCDM techniques which were not explored previously. Among all, WASPAS was proved to be the best technique with $R^2 = 0.828$ and IA = 0.813 for determining the ranking and treatment requirement of leachate compared to the traditional LPI method. However, WASPAS only takes into consideration of minimum and maximum values of the criteria. According to the study, 90% of the LS require leachate treatment based on effectively selected criteria LA and

AR for m-LPI. The sensitivity analysis also revealed that the pH was the least influencing criterion followed by Cl and Zn. In the present study, only seven input criteria were considered due to the availability of limited data on LS across India, which is one of the limitations that need to be considered for future investigations. Furthermore, criteria weights were calculated with a questionnaire survey and normalized fuzzy method; however, entropy methods can be explored to avoid ambiguity during the survey. The findings of this study will assist decision-makers in planning appropriate corrective actions to avoid solid waste leachate pollution. The m-LPI could help urban authorities and policymakers in all the undeveloped and developing nations to decide biomining activity and trend analysis of LS after closure of land filling sites.

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Author contribution Dharmasanam Ravi Teja has done literature survey to identify research gaps for this study. He developed methodology for the research work and collected data. He prepared the manuscript with data interpretation and statistical analysis. Padimala Shanmuka Sai Kumar provided technical support in writing the manuscript along with comments and revisions in the manuscript. Namrata Jariwala provided resources and support for writing the manuscript along with critical comments and revisions in the manuscript. All the authors have read and approved the manuscript.

Data availability All data generated or analyzed during this study are included in this published article (and its supplementary information files).

Declarations

Ethical approval The manuscript has not been submitted to another journal for simultaneous consideration.

Consent to participate All the authors mentioned in the manuscript have agreed to authorship, and read and approved the manuscript.

Consent to publish All authors whose names appear on the submission approved the version to be published.

Competing interests The authors declare no competing interests.

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