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Risk Assessment of Indian Landfill Contaminants using Trapezoidal Neutrosophic Fuzzy Numbers and Fuzzy Inference System

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Abstract

Objectives: To evaluate and prioritize Indian landfills according to the health risks, they pose to people, taking into account the contamination brought on by heavy metals and their physicochemical pollutants. **Methods:** A hybrid method integrating Trapezoidal Neutrosophic Fuzzy Numbers with Mamdani-Fuzzy Inference System was used to analyse twelve landfill sites based on their heavy mental and indicator presence in each landfill sites. To obtain a comparative risk ranking from transformed fuzzy output a score function was applied. Python code was implemented, the comparison of risk scores was done among the twelve landfill sites. **Findings:** Ghazipur was identified as the site with the highest risk by the assessment, with a risk score of 0.5813, followed by Narela- Bawana, Hyderabad, Gurgoan, Kadapa, Ariyamangalm, Okhla, Kodungaiyur, Silchar, Perungudi, Raipur and Ahmedabad. Significant health risks were indicated by the other sites, which also displayed notable high scores. The model's ability to handle ambiguous environmental data allowed for a more accurate assessment of landfill risk, as demonstrated by the results. The results enabled clear differentiation and comparative prioritization among the rank-based interpretation of landfill sites. The findings offer a scalable and quantitative method. With limited data, this framework offers practical insights to direct waste management and environmental health policies. **Novelty:** An integrated model for evaluating landfill health risk ranking that uses rule-based and neutrosophic score-driven site prioritization to improve decision-making with incomplete and uncertain environmental data.

2020 Mathematics Subject Classification: 90B50, 90C70.

Keywords: Metal Contaminants; Trapezoidal Neutrosophic Fuzzy Numbers; Risk Assessment; Fuzzy Inference System; Environmental Uncertain Data

1 Introduction

Landfill leachate is recognized as a major carrier of toxic metals into surrounding soil and groundwater, posing long-term ecological and human health hazards. Studies worldwide have reported the presence of elements such as As, Hg, Cu, Cr, Pb, Zn, and Ni in municipal landfill sites, with links to adverse physiological and carcinogenic effects [1]. To address such risks, recent research has introduced various uncertainty-based modeling frameworks. Methodological advances in neutrosophic optimization [2], effective algorithm for making decisions based on multiple criteria using decision-making measures demonstrate the growing relevance of fuzzy–neutrosophic approaches in environmental and decision-support problems [3]. Trapezoidal fuzzy numbers combined with Monte Carlo simulations have been used to evaluate groundwater health risks [4]. Further adaptive neuro-fuzzy inference integrated with GIS has been explored for predicting heavy metal contamination in arid ecosystems [5], and neutrosophic entropy indices have been employed to assess water quality in the Sirsa River [6]. Despite these advances, most existing studies relies on precise approximations for incomplete data and simplifies indeterminacy. This study ranks the health risks associated with twelve landfill sites in India using a trapezoidal neutrosophic fuzzy inference system (TrNFIS). In order to prioritize sites and inform environmental management and policy, it integrates fuzziness, indeterminacy, and inference-driven reasoning to provide a strong decision-support tool.

2 Methodology

2.1 Preliminaries

2.1.1. Neutrosophic Set:

Let U denote a universal set. The relation $B = [T_B(x), I_B(x), F_B : x \in U]$ where $T_B(x), I_B(x), F_B : U \to -]0,1[+$ that represents the level of enrollment, indeterministic, and non-participation of the component $x \in U$, signifies a neutrosophic set on U, provided that $-0 \leq T_B(x) + I_B(x) + F_B(x) \leq 3 + \forall x \in U$.

2.1.2. Neutrosophic Fuzzy Number:

A set B that is neutrosophic, defined by the full ordering of real numbers R is regarded as a neutrosophic number if, in the remote possibility it has the following properties,

1. B is normal if $\exists x_0 \in R \ni T_B(x_0) = I_B(x_0) = F_B(x_0)$
2. B is a convex set for the truth function with the condition that the set, $T_{\mathbf{B}}(\mu x_1 + (1-\mu)x_2) \geq \min(T_B(x_1), T_B(x_2)) \forall x_1, x_2 \in R, \mu \in [0,1]$.
3. B is a convex set for the indeterministic and falsity function with the condition such that the set has $I_B(\mu x_1 + (1-\mu)x_2) \geq \max(I_B(x_1), I_B(x_2)) \forall x_1, x_2 \in R, \mu \in [0,1]$ and $F_B(\mu x_1 + (1-\mu)x_2) \geq \max(F_B(x_1), F_B(x_2)) \forall x_1, x_2 \in R, \mu \in [0,1]$.

2.1.3. Trapezoidal Neutrosophic Fuzzy Number:

The truth, indeterminacy, and falsity functions of a trapezoidal neutrosophic fuzzy number $B = (b_1, b_2, b_3, u_B, v_B, w_B)$ in R are as follows:

$$T_B(x) = \begin{cases} 0; x \prec b_1 or x \succ b_1 \\ \dfrac{x - b_1}{b_2 - b_1} u_B; b_1 \leq x \leq b_2 \\ u_B; b_2 \leq y \leq b_3 \\ \dfrac{b_4 - x}{b_4 - b_3} u_B; b_3 \leq x \leq b_4 \\ 1; otherwise \end{cases}$$

$$I_B(x)=\begin{cases}0; x \prec b_1 or x \succ b_2\\ \dfrac{b_2-x}{b_2-b_1}v_B; b_1\le x\le b_2\\ v_B; b_2\le y\le b_3\\ \dfrac{b_4-x}{b_4-b_3}v_B; b_3\le x\le b_4\\ 1; otherwise\end{cases}$$

$$F_B(x)=\begin{cases}0; x \prec b_1 or x \succ b_1\\ \dfrac{b_2-x}{b_2-b_1}w_B; b_1\le x\le b_2\\ w_B; b_2\le y\le b_3\\ \dfrac{b_4-x}{b_4-b_3}w_B; b_3\le x\le b_4\\ 1; otherwise\end{cases}$$

2.1.4. Score function:

Let $B=(\langle a,b,c,d\rangle;T,I,F)$ be a TrNFN where $a\le b\le c\le d$ are the parameters and T, I, F are the truth-membership, indeterminacy-membership, and falsity-membership degrees, respectively. Then, the score function is defined as:

$$S(B)=\left(\frac{a+2b+2c+d}{6}\right)\times\left(\frac{T-I(1-F)}{2}\right)$$

where, $\left(\frac{a+2b+2c+d}{6}\right)$ is the centroid trapezoidal represents the central tendency of the fuzzy value and $\left(\frac{T-I(1-F)}{2}\right)$ is the normalized net belief score, which captures the degree of certainty after reducing indeterminacy and falsity from the truth degree[7].

2.1.5. Fuzzy Inference System:

Instead of combining multiple risk variables into a single equation and relying on numerous assumptions, the FIS enables expert judgment to be combined with casual factors in order to determine RM using "if...the..." rules. Two forms of FIS, Sugeno and Mamdani, have been employed in numerous technical and scientific applications. In the literature, Mamdani- FIS models are among the most well-known algorithms. Fuzzification, Knowledge Base, Fuzzy Inference Engine, and Defuzzification are the four stages of the FIS. Table 1 provides the linguistic values for FIS[8].

Table 1. Represents the linguistic values for FIS

S. No.	Parameters	Low (<)	Medium	High (>)
1	Chloride	100	100-250	250
2	Sulfate	100	100-250	250
3	Pb	0.01	0.01-0.05	0.05
4	Cr	0.05	0.05-0.1	0.1
5	Cu	0.05-0.3	0.3-1.0	1.0
6	Zn	1	1-5	5
7	Fe	0.3	0.3-0.5	0.5
8	Ni	0.02	0.02-0.07	0.07

2.1.6. Fuzzification:

The initial phase of FIS is fuzzification which converts crisp values into membership functions for linguistic terms of fuzzy set. The crisp value of measured contaminant concentration is mapped to its corresponding TrNFN based on the Low, Medium, High predetermined values.

2.1.7. Knowledge Base:

The rule base, which is a collection of if-then rules that relate input variables and output, and the database, which consists of fuzzy sets and membership functions used for the input and output, compose the knowledge base. The following are the general if–then rule structures for the Mamdani FIS:

$$If\ k_1\ is\ B_{i1}\ and\ k_2\ is\ B_{i2}...k_n\ is\ B_{in}\ then\ z\ \ is\ A_i\ \forall i\ = 1, 2, ...r$$

In the rth rule, B_{in} and A_i are linguistic terms for membership function of input variable k_i and linguistic terms k_i for output z, respectively.

2.1.8. Fuzzy Inference Engine:

The fuzzy inference unit uses logical operations, if-then rules, and membership functions to transform fuzzy inputs into outputs. To complete the modeling process, it combines fuzzified data with the pre-established rule base. The widely used maximal composition technique, which is mathematically explained in Eq., is used in this study to implement the Mamdani fuzzy model.

$$\mu_{C_r}(z) = \max[\min[\mu_{B_r}(input(k)), \mu_{A_r}(input(l)), ...]]r = 1, 2, ...$$

where μ_{B_r} and μ_{A_r} are membership functions input (k) and (l) respectively, and $\mu_{C_r}(z)$ is membership of output (z) for the rth rule.

2.1.9. Defuzzification:

Ultimately, fuzzy sets are transformed into distinct values in Mamdani-FIS through the defuzzification process. One of the most popular methods for defuzzification is Centroid of Area (COA). Defuzzification is used in Mamdani-FIS to transform fuzzy sets into discrete values. Every active rule taking part in the defuzzification process is advantageous to the COA technique. Fuzzy sets in the COA approach are converted into crisp values using equation [9].

$$z_{COA} = \frac{\int z\mu_B(z)dz}{\mu_B(z)dz}$$

2.2 Problem Definition

Due to poor dumpsite design and improper landfill site management in developing nations, the environment, especially land and groundwater is contaminated by heavy metals and chemical and physical compounds found in waste disposal sites. The release of hazardous chemicals and leachate from the accumulated solid waste causes various problems for the ecosystem creating risk to public health. This study contemplates twelve Indian sites namely Ahmedabad, Ariyamangalam, Ghazipur, Gurgaon, Hyderabad, Kadapa, Kodungaiyur, Nerla-Bawana, Okhla, Perungudi, Raipur, Silchar for analysis with their metals and indicator parameters gathered from literatures. The metals and indicators include chromium, copper, lead, iron, nickel, zinc, chloride and sulfate. These parameters had uncertain and missing values [10], [11], [12]. A systematic evaluation and juxtaposition of these sites is imperative attributed to the disparity in contamination levels and possible effects across different dumpsites. To effectively allocate resources, policymakers and environmental agencies need a clear setting of these sites based on its potential toxicity order which implements an additional risk attention. In order to help decision makers knowledge sites relative risk levels based on physicochemical properties and make a reliable step for progress this approach is necessary for a sustainable waste management planning process. Using the TrNFN and FIS the ranking is carried out.

3 Result and discussion

First, information about eight heavy metals was gathered from twelve landfill leachate sites. The environmental parameters with indeterminacy and uncertainty were modified into TrNFN. Every TrNFN, using four trapezoidal points (a, b, c, and d) were described with neutroscophic degrees (T, I, and F), known as truth, indeterminacy, and falsity membership. These parameters were quantified by combining their effects and applying a score function to each TrNFN, guaranteeing accurate final score values reflect the level of contamination as well as the data's confidence.

Using the defined score functions, the high truth values and low falsity or indeterminacy of the parameters were estimated. The resulted higher scores indicate a more significant impact of contamination. With the specified parameters, the score values were created using an FIS of Mamdani type. Based on the assigned membership functions, the concentration of metals was classified as Low, Medium, or High. The following three linguistic rules were used to determine the existence of risk in the combined contaminants:

1. The health risk is low if all the parameters are low.
2. A medium health risk is indicated by any parameter that is medium.
3. There is a high risk to health if any parameter is high.

The max-min composition method was used to process the fuzzy rules. Using the COA method, as described in the literature, the defuzzification was implemented to produce clear health risk scores with a range from 0 to 100. Each landfill sites, final risk scores were computed. The result shows varying risk degrees, where Ghazipur shows the highest risk score notably due to elevated levels of multiple metals. The lower contamination scores of sites represent its lower inferred risk values. The sites and its rankings are displayed in Table 2.

Table 2. Displays risk scores of landfill sites

S. No.	Sites	Overall Ranking Scores
1	Ghazipur	0.581259
2	Narela-Bawana	0.498241
3	Hyderabad	0.489223
4	Gurgaon	0.477819
5	Kadapa	0.447758
6	Ariyamangalam	0.423233
7	Okhla	0.38611
8	Kodungaiyur	0.323031
9	Silchar	0.321122
10	Perungudi	0.321122
11	Raipur	0.321122
12	Ahmedabad	0.274362

The study's findings show a major improvement in the assessment of environmental health risks, especially when it comes to assessing landfill leachate contamination in the context of uncertainty. Ghazipur (0.581259), Narela-Bawana (0.498241), and Hyderabad (0.489223) were identified as high-risk sites, while Ahmedabad (0.274362), Raipur (0.321122), and Perungudi (0.321122) were classified at the lower end of the risk spectrum, according to the calculated scores, which show a noticeable variation among the twelve landfill sites. Such heterogeneity reflects differences in landfill age, waste composition, and management practices. The risk scores of each landfill site are illustrated below in Figure 1.

This variability is frequently missed by conventional risk assessment techniques, which only use precise values. The indeterminacy in measured concentrations of heavy metals at Kadapa (0.447758) would have probably gone unnoticed by classical models, which could have resulted in an underestimation of risk. In contrast, the current study explicitly accounts for truth, indeterminacy, and falsity by using trapezoidal neutrosophic fuzzy numbers in a Mamdani-type fuzzy inference system. More nuanced results are produced by this enriched representation, especially for locations like Ariyamangalam (0.423233) and Kodungaiyur (0.323031), where uncertain data significantly impacted moderate risk levels.

Significant methodological and practical enhancements are provided by the current study in comparison to previous works. Prior studies that used classical fuzzy sets to apply fuzzy inference to industrial risk only considered truth-membership[(13)]; in contrast, this study contemplates neutrosophic framework providing a robust interpretation. Similarly, a review-based study on the development of neutrosophic set approaches to multi-criteria decision-making emphasized how well they accommodate inconsistent, ambiguous, and incomplete data. Nevertheless, the methods were not applied to site-specific problems; instead, this work concentrated solely on the conceptual development of neutrosophic sets[(5)]. Entropy-based methods used weighted indices (FHCI, NHCI) to categorize contaminated river sampling locations[(4)]. These methods work well for identifying specific points but are unable to continuously rank sites. The current model, on the other hand, combines several heavy metals into a single framework of reasoning, generating risk scores for individual landfills that go beyond single-point analysis and provide useful decision support. Finally, this approach produces continuous scores derived from environmental data, reducing subjectivity and improving transparency in contrast to WASPAS-based neutrosophic applications in FMEA, which rely on discrete expert-weighted rankings[(14)].

Fuzzy-based risk modeling is advanced both theoretically and practically by combining TrNFNs with a Mamdani inference system. The framework not only identifies Ghazipur and Narela-Bawana as immediate priority sites, but it also shows how neutrosophic reasoning can be used to produce reliable, scalable, and useful recommendations for landfill management in

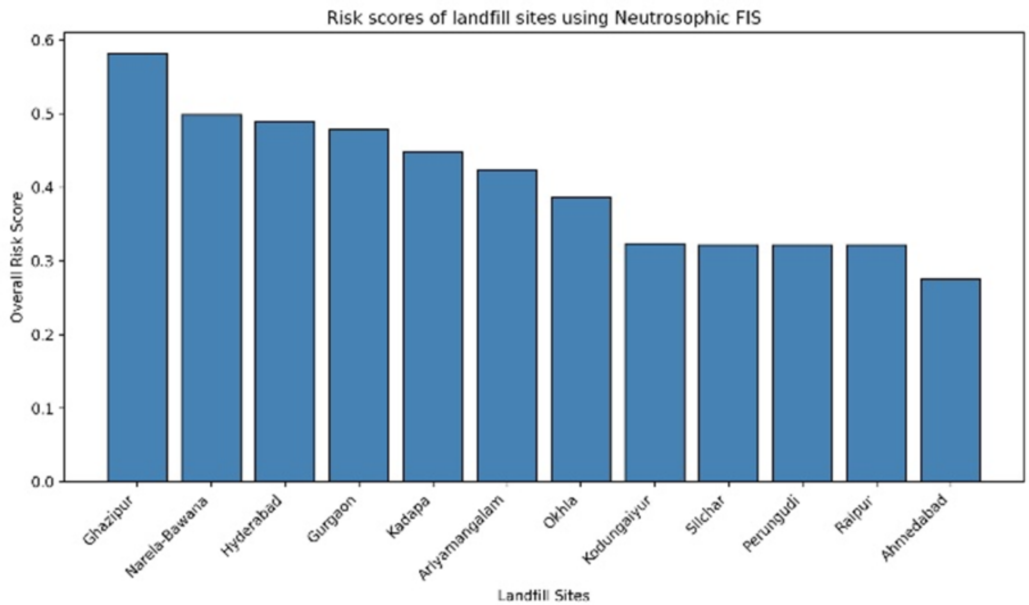

Fig 1. Risk Score of landfill sites using Neutrosophic FIS

complex and uncertain situations. TrNFNs are more effective at capturing indeterminacy than crisp or probabilistic models; however, they are unable to completely handle incomplete datasets or measurement errors resulting from site age, waste type, or climate. The secondary real-world data used in this analysis comes from the literature on landfill leachate measurements. Using primary field data for validation would further strengthen robustness and applicability.

4 Conclusion

This study emphasizes the value of using Mamdani FIS, which incorporates TrNFNs, to assess the health risk status of twelve Indian landfill sites. In this study, indeterminacy is introduced into risk assessment in a novel way by treating missing data as high-indeterminacy TrNFNs and crisp values as degenerate TrNFNs. The unique aspect of this study is the application of TNFNs for landfill risk assessment, which represents an important change from conventional risk assessment models. Being the first thorough application of TrNFN-NFIS to landfill leachate risk in India, this study used a unique in its field and bridges the gap between empirical health risk assessment and theoretical neutrosophic advancements, laying the foundation for future applications in environmental sustainability. According to the model, Hyderabad, Ghazipur, and Narela-Bawana were quantitatively ranked as high-risk locations, while Ahmedabad was deemed the least dangerous. The research's strengths include its ability to apply neutrosophic theory to a real-world environmental problem, transparently model incomplete and uncertain datasets, and produce site-specific prioritization. Its drawbacks include its reliance on expert-derived fuzzy rules, computational complexity for larger datasets, and limited integration of temporal or spatial dynamics. The effects of seasonal variability, landfill layout, and socioeconomic exposure factors on the consequences of neutrosophic risk remain unclear. This study aims to address a gap in previous approaches by introducing a TrNFN–FIS framework that incorporates uncertainty and indeterminacy into landfill health risk assessment. The model provides clear, evidence-based risk prioritization that can direct remediation planning by treating missing data as high-indeterminacy TrNFNs and crisp values as degenerate TrNFNs. This framework's robustness could be increased in future studies by adding temporal and spatial dynamics of contaminant dispersion and expanding the range of environmental and health parameters. This work is novel because it integrates indeterminacy into risk modeling, connecting theoretical developments in neutrosophic theory with real-world waste management applications. Applying this methodology to a different type of ecological risk, like air or water pollution from factories or manufacturing facilities, could further validate its adaptability and applicability. Stakeholder training and simplified tools facilitate implementation; larger, multi-seasonal datasets can lower uncertainties; and comparing NFIS results with epidemiological studies or other models strengthens validation, providing regulators with practical advice to safeguard public health and coordinate landfill monitoring with sustainable development.

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