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Integrating fuzzy logic into life cycle assessment for sustainable municipal solid waste management in Metro Cities

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ABSTRACT

This study presents an integrated decision-support framework that combines fuzzy logic with life cycle assessment (LCA) to evaluate sustainable municipal solid waste management (MSWM) strategies under data uncertainty, using Delhi as a representative metropolitan context. Seven MSWM scenarios, from conventional composting and incineration to hybrid systems involving anaerobic digestion and mechanical-biological treatment (MBT) with energy recovery, were modeled using fuzzy triangular numbers applied to key parameters such as waste composition, treatment efficiency, and emissions. A fuzzy-TOPSIS method was employed to rank scenarios based on environmental and operational performance indicators. The results indicate that scenarios involving MBT with energy recovery and anaerobic digestion outperform traditional greenhouse gas reduction, energy yield, and landfill diversion methods. Waste quantity was found to have a more significant impact on system performance than treatment capacity, highlighting the model's sensitivity to real-world variability. Although the study focuses on a single urban region and incorporates expert-derived fuzzy ranges, its methodological framework is adaptable to similar urban contexts. By embedding fuzzy logic into LCA for urban MSWM, the research addresses a critical gap in current modeling approaches. It offers a novel, uncertainty-resilient tool for municipal planners and environmental policymakers.

Keywords: solid waste management, life cycle assessment, fuzzy logic, sustainability, greenhouse gas emission.

INTRODUCTION

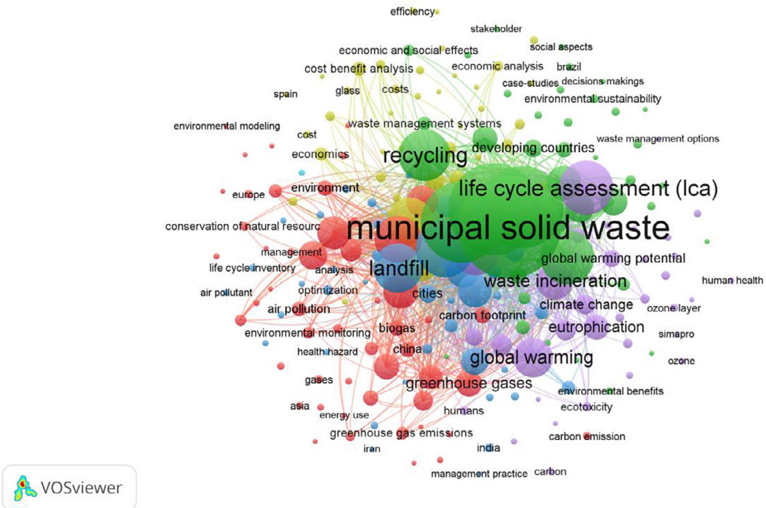
Global population growth has made solid waste management (SWM) an increasingly essential concern in recent decades. The global population is projected to rise from 8.2 billion in 2024 to a peak of approximately 10.3 billion by 2084, followed by a slight decline to 10.2 billion by 2100, according to United Nations projections (Lam, 2025). Uncontrolled urban solid waste growth, especially in megacities like Delhi, outpaces current infrastructure, creating severe public health and environmental risks. This intensifies the demand for scientifically informed decision-making frameworks to ensure long-term sustainability. The increase in population has a significant impact on solid waste output, especially in metropolitan areas. Global research interest in sustainable solid waste management has grown significantly in recent years, particularly in rapidly urbanizing regions such as China and India. This trend reflects increased demand for innovative tools that can address waste management challenges under uncertain and evolving conditions. (Rajpal et al., 2024) This investigation concentrated on Delhi, the densely populated city in Northern India. In 2022, the population of Delhi's metro area reached 32 million people, growing by 2.84% compared to the previous year. In 2021, Delhi faced the challenge of needing new landfill sites to accommodate the increasing amount of waste generated by its residents. The present endeavour sought to identify the most suitable new landfill locations by the Central Pollution Control Board (CPCB) guidelines. These guidelines ensure that landfill sites are selected based on environmental and social criteria to minimize negative impacts (Patil and Endait, 2021; Paul and Ghosh, 2022). Artificial intelligence (AI) models have been successfully applied to urban environmental monitoring, enabling high-accuracy predictions under complex and dynamic urban conditions (Himeur et al., 2022). Fuzzy logic, as a rule-based uncertainty modeling tool, enables city planners to deal with incomplete, imprecise waste data in decision-making—particularly valuable for complex systems like MSWM. Recent research has highlighted that an AI-enhanced framework for air quality forecasting demonstrates the potential of machine learning (ML) in environmental decision-making (Halaktionov et al., 2025; Miller et al., 2025). Such techniques provide a strong precedent for integrating fuzzy logic within LCA for waste management (Dewalkar et al., 2022).

For example, solid waste generation has increased from 1.2 kg per day to 1.42 kg per person globally in the last decade, and this pace is expected to grow even more in the future (Alzamora and Barros, 2020). MSW is a significant global problem because of population growth, fast economic development, and growing living standards. The problem is much worse in urban areas because poor management leads to environmental pollution, which poses risks to the health of living organisms (Rajpal et al., 2024). MSW management is a multidisciplinary process that includes making, collecting, moving, processing, and, most importantly, getting rid of the trash, according to Prakash Javadekar, India's Union Minister of State for Environment, Forests, and Climate Change. Now, India produces 62 million tons of garbage annually, of which 5.6 million tons are waste made of plastic and 0.17 million tons are biological materials (Ghosh, 2017). The annual production of hazardous trash is 7.90 million tons, while the yearly e-waste output is fifteen lakh tons. In addition, only around 75 to 80 per cent of the garbage generated in municipal areas is collected; of that amount, only 22 to 28 per cent is processed and disposed of. Waste that is not handled or appropriately managed threatens the environment and could lead to significant medical problems for people (Lee et al., 2004). Due to rapid urbanization and a lack of funding, technology, and governance, the problem of uncontrolled solid waste is especially significant in developing nations (Gupta et al., 2024). Furthermore, most developing-world cities are densely inhabited, unplanned, and lack appropriate road access, making solid waste collection and transportation to disposal locations even more difficult. One of the current challenges of modern civilization is SWM. As with previous disposal practices, various scientific models have been used to solve trash disposal and management issues are during the last few decades (Paul et al., 2019). These models provide critical assistance in the proper management of MSW disposal issues. For MSW sites, the recommended models could be effectively coupled. The connected 1-dimensional method accurately predicted the geographic and temporal distribution of settlement time and gas weight in multi-layered landfills in various operating scenarios (Singh, 2019; Choudhury et al., 2022; Vais et al., 2023) (Figure 1).

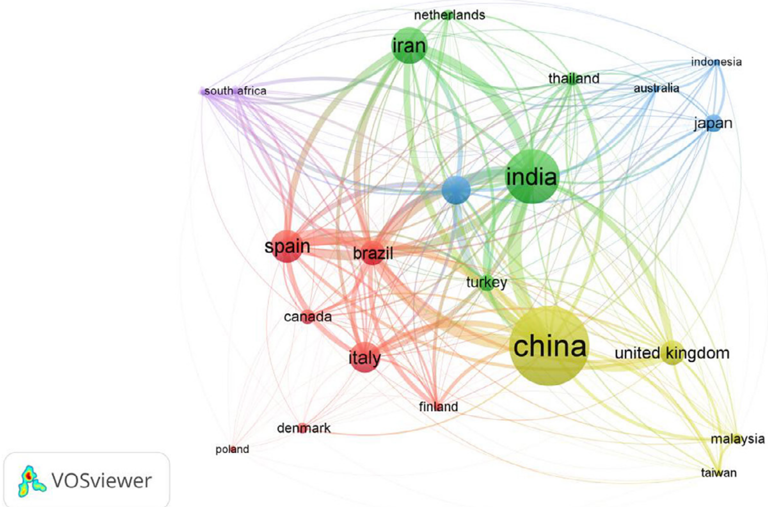
Figure 2a and Figure 2b present a network visualisation graph that illustrates research contributions from various countries in SWM and life cycle analysis. Figure 2 (a) focuses on the most widely used keywords in SWM. Keywords such as "MSW" and "Municipal Solid Waste" emerge as the most frequently utilised, indicating their central role in the literature. This visualisation underscores the primary areas of interest and research trends within the field, offering insights into the thematic focus of recent studies. Figure 2 (b) highlights the country-wise publication analysis, revealing that China, India, and the UK are leading in research efforts on SWM. These countries have made significant advancements in addressing waste management challenges through extensive research and development.

Despite cumulative global attention to SWM, there is a noticeable gap in recent literature

Figure 1. A large pile of municipal solid waste (MSW) being processed by heavy machinery at a landfill site Bhalswa, Delhi, India



(a)



(b)

Figure 2. Network visualization map: (a) keyword-wise distribution, (b) country-wise distribution

concerning applying advanced mathematical methods and decision-making tools, such as fuzzy logic, to address the complex challenges of municipal waste management. Existing studies often focus on isolated aspects, such as treatment technologies, waste reduction, or energy recovery, without a comprehensive combination of these techniques into an efficient framework (Rajpal et al., 2022). Furthermore, the environmental implications of waste disposal in rapidly urbanizing regions like Delhi remain underexplored, as serious environmental implications exist regarding scientifically grounded solutions that control modern analytical methods (Kamboj and Choudhury, 2013).

Existing studies often address individual elements such as treatment, cost, or emissions in isolation. However, few integrate fuzzy logic into a full life cycle assessment (LCA) of SWM systems in real-world metro settings. This study aims to bridge this gap by providing a holistic overview of how advanced mathematical models and MSW techniques can tackle the environmental issues associated with municipal waste disposal. By assessing and comparing existing SWM methods through advanced tools, this article seeks to identify environmentally sound, scalable, and practical solutions tailored to the unique challenges of the North Indian urban landscape. This study integrates fuzzy logic into LCA to develop a robust decision-support framework for MSWM, tested in Delhi, to evaluate climate, cost, and governance outcomes under uncertainty. This study integrates fuzzy logic into LCA to develop a robust decision-support framework for MSWM, tested in Delhi, to evaluate climate, cost, and governance outcomes under uncertainty. The study's findings aim to contribute to developing sustainable waste management practices that align with global environmental and public health objectives.

THE SOLID WASTE MANAGEMENT (SWM) RULES, 2016

Scope and commencement

The SWM Rules came into force on 8 April 2016, after publication in the Gazette. These rules apply to every urban local body (ULB), census town, railway facility, airport, defence area, special economic zone (SEZ), religious or pilgrimage site, and all domestic, institutional, and commercial waste generators. Waste streams already governed by separate rules, such as biomedical and electronic waste, are excluded from this scope (Choudhury et al., 2024). Among the various types of municipal waste, electronic waste presents unique ecological threats due to the presence of heavy metals and persistent organic pollutants (Bhardwaj et al., 2024; Bhardwaj et al., 2025a; Bhardwaj et al., 2025b; Bajpai et al., 2025; Chowdhury et al., 2025). These components have been shown to disrupt biodiversity and pose significant risks to wildlife (Choudhary et al., 2025b). Integrating these aspects into LCA allows for a more comprehensive assessment of environmental consequences.

Segregation and point-of-generations duties

The table below depicts the key responsibilities assigned to different categories of waste generators under the SWM Rules, 2016. It details who is responsible, the timeline, and the corresponding rules. This provides a clear and concise

Table 1. Duties of waste generators

Duty-holder	Quantified duty	Timeline/trigger	Rule	References
All generators	Keep waste in 3 separate bins (bio, dry, domestic-hazardous); never dump/burn; pay user fee	Continuous	4 (1) (a–d)	(Ministry of Environment, Forest and Climate Change, 2016a)
Events ≥ 100 persons	Intimate ULB ≥ 3 working-days in advance & ensure on-site segregation	Per event	4 (4)	(Ministry of Environment, Forest and Climate Change, 2016b)
Street vendors	Maintain own container & hand over daily	Continuous	4 (5)	(Ministry of Environment, Forest and Climate Change, 2016c)
Large generators—RWAs, markets, gated communities > 5 000 m², hotels/restaurants	Segregate, recover recyclables, treat bio-waste on site; partner with ULB	Within 1 year of 8 Apr 2016 (i.e. by 8 Apr 2017)	4 (6–8)	(Ministry of Environment, Forest and Climate Change, 2016d)

view of compliance expectations for each duty-holder (Table 1).

Governance architecture and stakeholder responsibilities under the SWM rules, 2016

The table below presents an overview of the multi-tiered governance framework and market-linked responsibilities under the SWM Rules, 2016. It captures the statutory duties of key actors from government bodies to private sector stakeholders, along with clear timelines and measurable targets. This table shows the coordinated effort required across administrative levels and industries to ensure effective waste management. It underscores institutional accountability and the shared societal obligation to protect public health and the environment (Table 2).

Enforcement framework

The SWM Rules, 2016, derive authority from the Environment (Protection) Act, 1986. Non-compliance may lead to penalties, including imprisonment of up to five years, fines, and continuing penalties for ongoing violations. Many states also strengthen enforcement by empowering local bodies to levy spot fines through municipal bylaws, as permitted under Rule 15(zf), encouraging accountability and sustained public cooperation.

Fuzzy operation

Fuzzy logic has been recognised as a highly effective approach for SWM due to its ability to handle uncertainties and provide a quantitative framework for decision-making. The fuzzy controller operates based on predefined rules, allowing it to evaluate multiple factors and choose the best option for waste processing. Studies have shown that fuzzy logic systems can improve the efficiency and accuracy of waste management practices by dealing with the variability in waste characteristics and generation rates (Giel and Kierzkowski, 2021).

Fuzzy set theory

Fuzzy set theory is a mathematical framework for dealing with uncertainty and imprecision, which is especially useful in complex systems such as waste management. Unlike classical set theory, where an element belongs to a set or does not, fuzzy set theory allows for degrees of membership. It is a powerful tool for modelling real-world scenarios where data is often imprecise or uncertain.

Table 2. Roles, responsibilities, and timelines under the solid waste management (SWM) rules, 2016

Level / entity	Statute hook	References	Chair / lead	Time-bound / quantitative duties
State Urban Development Department	Rule 11	(Ministry of Environment, Forest and Climate Change, 2016e)	Principal UD Secretary	Draft state SWM policy & identify land within 1 year; reserve space in master plans; 5% plot in SEZ/industrial parks for recycling
District Magistrate / Collector	Rule 12	(Ministry of Environment, Forest and Climate Change, 2016f)	DM / DC	Allot land for waste processing within 1 year; review ULB performance quarterly
Central Pollution Control Board (CPCB)	Rule 14	(Ministry of Environment, Forest and Climate Change, 2016h)	Member-Secretary	Review standards annually; set norms for new tech within 6 months; publish national SWM status report annually
Local Authorities / Village Panchayats	Rule 15	(Ministry of Environment, Forest and Climate Change, 2016g)	Municipal Chair / Sarpanch	Prepare SWM plan within 6 months of state policy; door-to-door segregated collection; 1 drop-off/20 km²; bin color code (green/white/black); bye-laws within 1 year; levy user fee
State PCB / PCC	Rule 16	(Ministry of Environment, Forest and Climate Change, 2016i)	Chair, SPCB	Authorise facilities within 60 days; inspect at least once a year; regulate inter-state waste flows
Brand Owners / Sanitary Product Manufacturers	Rule 17	(Ministry of Environment, Forest and Climate Change, 2016j)	—	Finance collection of non-biodegradable packaging; sanitary pad makers to supply a disposal pouch
Industrial Units (within 100 km of RDF/WtE)	Rule 18	(Ministry of Environment, Forest and Climate Change, 2016k)	—	Use ≥ 5% RDF fuel within 6 months (by Oct 2016) if within 100 km of RDF/WtE facility
All Waste Generators (by calorific value)	Rule 21	(Ministry of Environment, Forest and Climate Change, 2016l)	—	Waste with ≥ 1.500 kcal/kg must be used for WtE or co-processing; cannot go to landfill

Fuzzy number in triangle (FNT)

A fuzzy number in a triangle (FNT) is a simple yet effective way to represent fuzzy numbers using three parameters: the lowest possible value (k), the most probable value (m), and the highest possible value (u). The membership function μ(p|M) defines how likely a value p is to be part of the fuzzy number. The primary aim of the Fuzzy set is to indicate how much a value interferes with a specific set value. However, a value for a particular set can be noticed in a typical set. This is a benefit of using a fuzzy-based controller in a waste management system for precise output. Zadeh's "Fuzzy set theory" (Mallick, 2021) is a modeling approach that simulates a complicated system that is difficult to characterize using clear and concise numbers. Modeling governing dependent on vague and equivocal context, i.e., the preferences of control, was a frequent application of the fuzzy set theory. Fuzzy logic is an incredible tool when making sense of ambiguity, imprecision, or a lack of clarity (Balezentiene et al., 2013). In spatial planning, fuzzy logic is employed to judge whether to implement a contiguous object on the map as a variable. In classical set theory, often called crisp theory, an object is a set member, or it is not. "A feature object could be used as a membership value ranging from 0 to 1, which means that the degree of the membership function is indicated by fuzzy set theory." Figure 3 depicts a FNT M as specified below. "There are two ways to express FNTs: the lowest and highest possible values (e.g. (k, m, u)), as well as a linear representation on the right and left sides (Equation 1) of the FNT."

$$\mu(p\backslash M) = \\ = \begin{Bmatrix} 0, p < k, \dfrac{p-k}{m-k}, k \leq p \leq \\ \leq m \; \dfrac{u-p}{u-m}, \; \dfrac{m \leq p \leq u}{p > u} \\ \quad 0, \end{Bmatrix} \tag{1}$$

where: *k, m,* and you are lesser, middle, and upper boundaries are of FNT. Any given component in the domain *p* may fit into the fuzzy number A in a gradation defined by μ, the membership function. Suggestive of a relationship between crisp and fuzzy are numerical values. This equation displays approximate members of every membership level depending on their right and left representations (Kahraman and Kaya, 2010).

$$M = \left(M^{k(y)}, M^{r(y)}\right) = \\ \left((k+m-k)y\right), (u + (m-u)y) \tag{2}$$

where: *M* fuzzy number left and right sides are $k(y)$ and $r(y)$, respectively.

LIFE CYCLE ASSESSMENT (LCA)

The city of Delhi's current waste management system was examined using the LCA technique as part of this investigation. It is a tool that has been shown to give valuable insights into identifying viable outputs for controlling solid waste through its comprehensive viewpoint in measuring environmental consequences (Laurent et al., 2014). When managing solid waste, the old

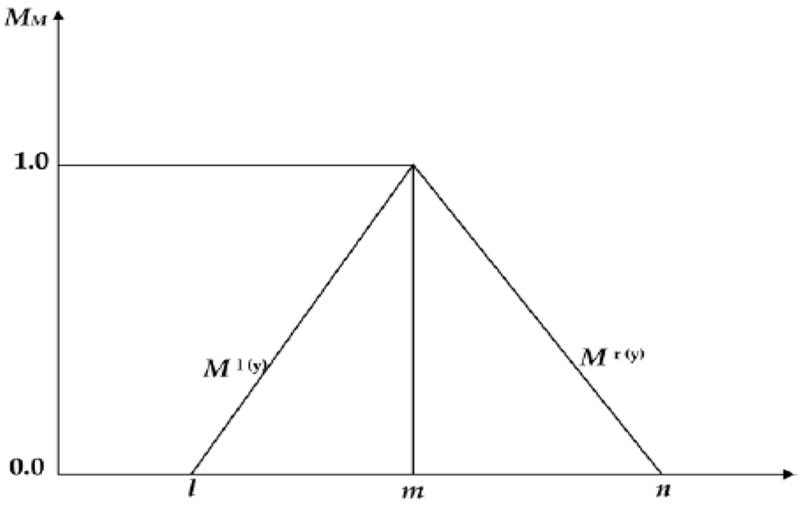


Figure 3. Description of (FNT) "M"

cradle-to-grave technique must be changed to gate-to-cradle or gate–to–grave, based on whether regeneration or dumping operations are being evaluated. In the case of waste management, it could be trash or reused as a substitute for virgin resources in subsequent life cycles. Substitution refers to replacing primary-source materials with secondary-source materials acquired via recovery and recycling. The original production's environmental duties are ascribed to the recycling system, while the energy and additional materials required for recycling are the system's responsibility. Numerous studies have utilised LCA as a technique for analysing waste management systems. This method allows for deep evaluations of the system's performance, comparisons to other systems, and detection of potential system enhancements. The seven (7) different integrated management systems have been highlighted in this present study. It has been observed that landfills with bio-drying and incineration of leftovers in mechanical and biological treatment (MBT) systems with no energy recovery from landfill gas are more environmentally friendly than aerobic MBT (Koci and Trecakova, 2011). Mechanical pre-treatment is an effective method of recovering a percentage of recyclables from mixed or residual garbage (Di Maria et al., 2013).

Similarly, the creation of raw fertilizer from the organic portion of MST reveals favourable statistics when contrasted with the various alternative management choices (Ferreira et al., 2017). Recycling plastic and paper can be helpful in terms of energy-related GHG emissions, according to the author, who believes it should be promoted more. In addition, they concluded that incineration is preferable to landfilling (Choudhury and Roy, 2025). The combustible use of biomass may help decrease emissions of GHGs (Ferreira et al., 2017). After examining two distinct waste packaging systems, the author concluded that the recycling scenario is the one that is better for the environment. Otoma and Diaz (2017) analysed GHG emissions for six distinct conceivable cases and determined that the biogas production scenario resulted in the lowest emissions. Abduli et al. (2011) compared two approaches to waste management, including separate collection, composting of biowaste, and landfilling of waste (Mondal et al., 2023). The authors highlighted that the most advantageous choice regarding the waste hierarchy was not always beneficial with LCA. Additionally, the authors indicated that with energy recovery by trash, co-incineration correlates with the superior energy performance of dedicated incineration and could be favoured over constructing a new incinerator. The author concluded that the draw-breathe biowaste management system in the Asti area, which is focused on composting, has more advantages than landfilling (Assamoi and Lawryshyn, 2012). Even though the cost of treatment is more significant, it has been proven that incineration is better for the environment than landfilling (Vais et al., 2023). An LCA was performed on the various management strategies at both the urban and the rural levels. The authors examined various disposal and treatment options and recycling for a certain quantity of garbage. The most important takeaways from this research were that recycling has a beneficial impact and that incineration and anaerobic digestion play positive roles. The review is supported by each one of these findings. Because it enables practitioners to analyse many system features from the point of view of the environment, LCA is a valuable technique for designing, implementing, and improving municipal waste (Hadzic et al., 2018).

SOLID WASTE MANAGEMENT

The inputs are required to calculate this system's reference value using fuzzy logic. One of the most significant consumers of plastic is China, whereas India ranks twelfth and generates three percent of the world's plastic garbage. Even though India generates 3% of all plastic garbage, unmanaged plastic waste accounts for about 1.9% of the entire value. China's polymer waste mismanagement rate is around 87 percent, lower than India's (Kibria et al., 2023). Delhi generates around 8300 tons/day of MSW, while Mumbai produces 7000 tons/day of MSW, which is around 18% higher for Delhi than Mumbai (Sathyamurthy, 2018; Randhawa et al., 2020). The reference values are used in this work to simulate Fuzzy logic-based polymer waste management (PWM). The not-managed trash in the United States is around 2%, with unmanaged polymer waste accounting for just 0.9%. This data evaluation of different nations shows that PWM is critical for hygiene and wellness. Other studies suggest that waste management accounts for 6.9% of the worldwide gross domestic product (GDP). Additionally, its applications with plant sludges on anaerobic solid waste degradation in simulated landfill reactors are now under investigation, and cement waste forms (Idachaba et al., 2004). Table 3 shows a brief review of the evaluation of SWM indices in previous research documents concerning their regions. Figure 4 shows the pictorial representations of the reasons that caused solid waste (Abdel-Shafy and Mansour, 2018).

This section summarizes the previous search that has been done about the MSW of SWM using fuzzy logic. Mallick (2021) suggested an integrated framework emphasizing organizing the suitability site map decision-making process for landfills. That might be established using the correct data collection, criteria weighting, and normalization techniques. The GIS-based fuzzy technique was used to choose a landfill site for a location to further understand the mechanisms influencing landfill site appropriateness. These notions were built using remote sensing (RS) and traditional data. This approach and its results could help hydrogeologists, regional planners, and engineers choose a landfill.

Yang et al. (2021) suggested an AI technique to accurately anticipate MSW energy recovery gas yield accurately. A deep neural network (DNN) was used to forecast gas yield in MSW. The moth-flame optimization-deep neural network (MFO-DNN) model is then used to optimize and increase the DNN model's accuracy. Both models accurately forecast gas yield. MFO-DNN outperformed DNN. Using MFO-DNN, toxic gases can be carefully managed and optimized to get the gas

Table 3. Chronological review of global MSW evaluation studies supporting Fuzzy-LCA integration (2010–2025)

S. No.	Author(s)	Evaluation index/method	Region of study
1	Dawar et al., 2025	AI/ML-based decision tools	Global (Review of worldwide applications)
2	Nurzhan et al., 2025	Life-cycle assessment (LCA)	Global (Case studies from various countries)
3	Zhang et al., 2024	Policy & infrastructure challenges	Asia & Africa (Developing cities)
4	Maalouf and Mavropoulos, 2023	Waste generation data & projections	Global (Cross-country data)
5	Ibikunle et al., 2021	Solid waste to energy conversion	Nigeria
6	Kawai and Tasaki, 2016	Per-capita waste generation index	Global (Focus on developing countries)
7	Iqbal et al., 2020	Life-cycle assessment (LCA)	Global (Case studies from various countries)
8	Kokkinos et al., 2019	Processing of waste	Thessaly, Greece
9	Godwin, 2019	Treatment technologies in solid waste	Global
10	Kaza et al., 2018	Waste generation & disposal metrics	Global (217 countries)
11	Sathyamurthy, 2018	Polymer waste management (PWM)	Comparison between India and China
12	Estay-Ossandon et al., 2018	Energy recovery techniques from waste	Canary Islands archipelago, Spanish region
13	Olaniran et al., 2017	Greenhouse gas (GHG) emission	Nigeria
14	Khan and Samadder, 2014	GIS-based siting & routing	India (case context)
15	Guerrero et al., 2013	Sector challenges (Multi-criteria)	Latin America, Africa, Asia
16	Hoornweg et al., 2013	Waste generation, GHG Emissions	Global (152 countries)
17	Pires et al., 2011	Systems analysis (LCA, GIS, etc.)	Europe (EU 27)
18	Su et al., 2010	Waste reduction and treatment	Taiwan

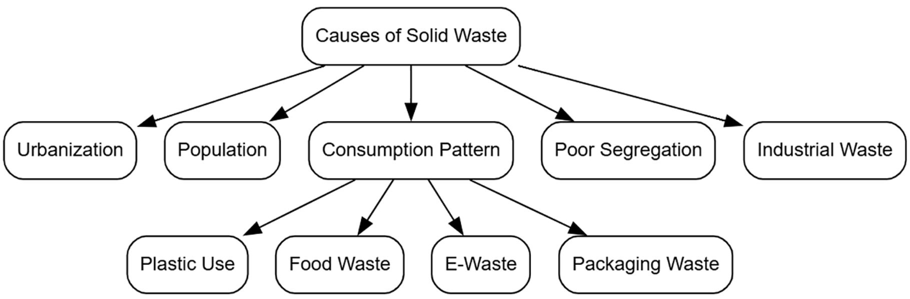


Figure 4. Structure of solid waste causes

field from MSW for use in the treatment of waste facilities, hence reducing the damage done to the surrounding environment.

An analytical hierarchy process (AHP) based framework was recommended for use in this research. Multiple ML methods gradient boosting tree (GBT), decision tree (DT), and support vector machines (SVMs) were used to determine the best site for WtE facilities. Eleven thematic geospatial raster layers included social, environmental, economic, and land cover characteristics. Sharjah, UAE, with a population of 1.5 million, used the recommended structure. Gaussian dispersion modeling was developed for WtE air pollution emissions. GBT, DT, and SVM have respective accuracy rates of 94.6, 93.9, and 91.8 percent. The AHP consistency assessment found a 0.0344 total criterion consistency index and 0.019 ratios. 16.6% of Sharjah was deemed very appropriate (Al-Ruzouq et al., 2022).

Michael et al. (2021) and Makonyo and Msabi (2022) suggested GIS-based multi-criteria decision analysis to choose landfill locations. The AHP was used to integrate fifteen criteria using the AHP. 41,177 hectares (14.7%) of the area studied is exceptionally suitable for landfills. 30% of the region is appropriate, 30.2% is suitable, and 19.1% is less suitable. 16,683 hectares (6%) is inappropriate. Eleven dump sites from the highly suitable region were prioritized using AHP. Geology, hydrogeology, geophysics, and environment experts validated the locations' appropriateness. Developing nations may use these strategies to find acceptable waste locations to reduce health and environmental damage.

Kumar et al. (2020) suggested the outlines as a time series model for predicting monthly strong trash generation in Noida, India, using artificial neural network (ANN) and an autoregressive approach. From 2012 to 2016, monthly municipal waste perceptions were collected. Better areas have strong waste characteristics. The accurate projection of MSW generation is essential nowadays. Predictions need MSW data. The 60-month data collection comprises forty-two training, nine testing, and nine validation sets. Finally, neural network architecture is improved. The suggested model validates the lowest mean square error of 0.0004, the lowest root mean square error (RMSE) of 0.0203, and the highest regression coefficient of 0.8123 for performance metrics. The ANN model is supposed to deliver exact prophetic results based on the assumption of these execution parameters.

A comprehensive framework for assessing the incineration power plant's performance from a reprobate categorization standpoint was suggested (Wu et al., 2020). The Hesitant Fuzzy Linguistic Term Sets (HFLTS) check all assessment information. The index weights are then calculated using the AHP and entropy methods, eliminating the need for subjective weight judgments. Third, fuzzy synthetic evaluation (FSE) calculates the outcome based on fuzzy relation synthesis. A case study assesses the framework's applicability. The article offers economic, environmental, and social solutions to increase incinerator benefits. This article provides a theoretical reference for future incineration power plant development and increases the benefit assessment literature.

Soni et al. (2019) suggested Discrete Wavelet Theory–Artificial Neural Network (DWT-ANN), ANN, discrete wavelet theory–adaptive neuro-fuzzy inference system (DWT-ANFIS), genetic algorithm–artificial neural network (GA-ANN), and genetic algorithm–artificial neuro-fuzzy inference system (GA-ANFIS), as well as compared them to see how well they could predict how much trash would be made. New Delhi, India, is used to illustrate many models. The models were compared based on their Root Mean Squared and the index of agreement (IA) values. The Genetic Algorithm and ANN hybrid model provides the lowest RMSE, the most considerable IA value, and the highest R2 value.

Soni et al. (2019) describe using scientific models, environmental challenges related to municipal garbage disposal. The investigation's repercussions and municipal garbage disposal difficulties are described. Waste disposal challenges are explained with context. Optimization modeling, multi-objective approach, and ANNs are mentioned in waste management. Single-objective optimization models yielded a fresh optimal solution, but multi-objective difficulties led to compromises. In addition, the investigation revealed that model-based ANN has been used extensively to work with an appropriate prediction for the rate of production of solid waste.

Sebastian et al. (2019) suggested I-Index, as it is a complicated multi-criteria decision-making (MCDM) issue, which consists of the views of over two hundred experts, gathered at various phases of its creation. The AHP was used to compute the relative weighting of the qualities, and rating curves were utilized to standardize. The invulnerability MSW was produced in three economic groupings; the I-Index values were 72.38, 62.08, and 41.94, respectively. A high number suggests more invulnerability since the I-Index is an increasing scale index. This proves how differences in MSW content among economies might alter how MSW can be incinerated.

Singh et al. (2019) developed a mixed-integer linear optimization model, which considered the unpredictability of waste volume and the competence of the waste treatment plant. MSW management was designed to lower the overall cost of SWM, the complete risk of owning environmental cleanup provisions, and the amount of trash at the source. These optimal locations of trash sources and centers were found using a population-weighted vehicle routing (PWVR) optimization model. Single, multi-objective optimization demonstrated that the overall charge fluctuates to a few degrees with the variation of trash amount and quality in incinerators. Three scenarios were explored. Uncertainty analysis found that the waste amount has a more significant impact on waste management planning than treatment/disposal facility capacity. Case 2's overall cost depended more on facilities than trash volume. Only Cases 2 and 3 minimize environmental risk and waste volume. Single-objective optimization costs less than multi-objective and goal programming. Table 4 shows the comparative analysis of the previous research documents in the field of MSW of SWM using fuzzy logic.

COMPARATIVE ANALYSIS

The strategies presented in this article showed that waste material might be effectively transformed into a functional form. Lessons from community-based waste bin systems in rural Ukrainian regions (Bredun et al., 2024) underscore the importance of inclusive, bottom-up waste management practices. Similar participatory models could be adapted to metro cities by combining local stakeholder engagement with intelligent fuzzy logic frameworks for system

Table 4. Comparative analysis of literature review (2019 to 2025)

Authors	Method used	Area	Suggested outcome	Future scope
Adekoya and Ogbolumani, 2025	SVM & ANN + IoT smart bins & route optimization	Waste collection optimization (47 urban sites)	89% accuracy; 35% fewer trips; 42% fuel savings	Expand to smart city frameworks with real-time analytics
Zhao et al., 2024	BP Neural Network	MSW prediction (China)	R^2 = 0.969–0.971; 93.8% accuracy in Shandong	Extend to other urban regions for forecasting
Desta et al., 2023	GIS, Remote Sensing, AHP	Landfill site suitability (Ethiopia)	GIS and AHP identified high-suitability zones	Useful for future landfill planning in Ethiopian towns
Al-Ruzouq et al., 2022	GBT, DT, and SVMs	Energy waste	GBT, DT, and SVM achieved 94.6%, 93.9%, and 91.8% accuracy	Identified 16.6% of Sharjah as a highly appropriate area
Makonyo and Msabi, 2022	AHP	Landfill sites	41,177 ha (14.7%) of the study area is suitable for landfills	Applicable in developing nations for health and environmental safety
Mallick, 2021	GIS-based fuzzy-AHP-MCDA	Landfill suitability	Classification between excellent, good, and bad zones	Guide for future landfill site selection
Yang et al., 2021	Gas yield, MFO-DNN	Energy recovery	DNN and MFO-DNN accurately predicted gas yield	Reduces the environmental impact of treatment facilities
Kumar et al., 2020	RMSE, ANN	MSW prediction (NOIDA, India)	MSE = 0.0004; RMSE = 0.0203; R = 0.8123	Supports ANN for future solid waste forecasting
Wu et al., 2020	HFLTS, AHP, FSE	Incinerator performance classification	AHP and entropy reduced bias; FSE synthesized the index	Suggests revising performance indices for broader impacts
Soni et al., 2019	GA-ANN, RMSE	Garbage prediction	GA-ANN is most accurate in RMSE, IA, and R^2.	Promotes the use of hybrid ANN models
Sebastian et al., 2019	MCDM, AHP	I-Index formulation	I-Index values: 72.38, 62.68, and 41.94 for three countries	Recommend standardizing the I-Index methodology
Singh et al., 2019	PWVR	Waste quantity & facility capacity planning	Costs varied with waste volume and incineration quality	Encourages multi-objective optimization modeling

optimization. The most common methods are recycling Plastic, converting organic waste into biofertilizer, and the greenhouse gases generated in the landfill due to anaerobic digestion, consisting of methane, which can be used as a fuel for cooking as well as for energy generation (Hajam et al., 2023). The most crucial factor in choosing a method is waste. Waste with a high percentage of biodegradable and organic material is used to produce biogas and manure. Selecting landfills in the most appropriate locations may be accomplished most efficiently using GIS and other technologies. This study discusses GIS-enabled techniques for locating the ideal dump location. GIS and AHP integration offer a powerful multi-index assessment tool that uses spatial analytic approaches to choose the best dumping location. In one study, Resourcesat LISS-III and SENTINEL -2 multispectral satellite data is used to identify zones in the Delhi area based on various parameters groundwater table, geomorphology data, lithological data, and soil data and found most suitable zone in Delhi is Saket District in the south zone with overall only 0.27% of the area was found ideal in Delhi (Tiwari et al., 2022). While several aspects are considered when selecting a location, the fuzzy set has a robust ranking potential. Qualitative data can also be represented and presented in a variety of membership degrees. The bulk of SWM's resources are devoted to collecting solid trash. After that, it is necessary to get public support for a landfill site that meets environmental standards. This article also fully describes a public acceptability study for proposed dump sites. Numerous forecasting and analysis projects aimed at predicting future solid waste generation in Indian cities and rural areas, including Mumbai and Delhi (Sharma and Mathur, 2020), Mumbai (Sathyakumar et al., 2020), Kolkata (Soren et al., 2023), and Chennai (Partheeban et al., 2020).

CONCLUSIONS

The future of MSWM in metro cities lies in integrating fuzzy logic with advanced technologies such as AI, ML, and geospatial analytics. These hybrid approaches can enhance prediction accuracy, enable real-time decision-making, and support adaptive waste management strategies aligned with dynamic urban growth and regulatory shifts. Incorporating IoT and digital twins will improve monitoring while embedding socio-economic and behavioral factors into decision models, ensuring greater public acceptance and policy relevance. Establishing standardized, open-access waste data platforms will be crucial for scaling and replicating these intelligent systems across diverse urban environments, fostering more sustainable and resilient waste management frameworks.

This study developed an integrated decision-support framework by combining fuzzy logic with life cycle assessment to evaluate sustainable MSWM strategies in a metropolitan context, using Delhi as a representative case. By incorporating uncertainty in waste composition, treatment efficiency, and emission factors, the fuzzy LCA model enabled a realistic assessment of environmental and operational outcomes across seven distinct waste treatment scenarios. The integration of fuzzy logic allowed for dynamic scenario ranking under variable conditions using a fuzzy-TOPSIS approach. Results indicated that hybrid systems involving MBT with energy recovery and anaerobic digestion provided the most effective greenhouse gas reduction, energy recovery, and landfill diversion outcomes. These findings highlight the value of adaptable decision-making tools that reflect real-world uncertainty. The approach addresses a significant gap in current MSWM research by providing an uncertainty-aware framework that moves beyond deterministic modeling. It offers a multidimensional sustainability assessment, integrating technical, environmental, and economic criteria. By embedding fuzzy logic within LCA, the study presents a novel contribution that supports more informed, resilient waste management planning. The findings can assist policymakers and urban planners in developing sustainable, data-resilient strategies tailored to the complexities of rapidly urbanizing cities.

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