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A Systematic Review of Methane Emission Estimation Challenges in Open and Unmanaged Landfills

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Systematic Review

Keywords: emissions, lag time, landfill gas, model parameters, unmanaged landfill, traditional models

Posted Date: February 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8913466/v1

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Additional Declarations: The authors declare no competing interests.

Abstract

Landfills generate substantive greenhouse gas (GHG) emissions. Methane is one of the GHGs generated by landfills. The landfill emissions are more pronounced in developing countries where most of the waste disposal sites are open and unmanaged. Unmanaged landfills are non-engineered sites that are poorly managed. This review critically examines the suitability of existing models and algorithms in estimating methane emissions from open and unmanaged landfills. The study reviewed process-based approaches, artificial intelligence (AI)/Machine Learning (ML) methods, and traditional models such as IPCC, LandGEM, and Scholl Canyon. The review revealed that traditional models are based on generalized assumptions that often does not apply to all sites, leading to uncertainties in methane emission estimations. Secondly, improved traditional models such as Capturing Landfill Emissions for Energy Needs (CLEEN) and Solid Waste Emissions Estimation Tool (SWEET) shows reduced estimation errors but have not been validated across regions and sites. Also, process-based approaches like the California Landfill Methane Inventory Model (CALMIM) showed improved estimation of methane emissions but require extensive site-specific data. However, data scarcity in many open and unmanaged landfills inhibits their adaptability. Further, the utilization of machine learning algorithms demonstrated high predictive performance. They have ability to capture nonlinear relationships between methane generation and site conditions. However, they require extensive historical data for model training. The review noted that hybrid physics-AI/ML approaches offer better results than standalone ML because they enhance interpretability of the results. The review concluded that process-based models will be ideal for sites with extensive site-specific data while AI/ML approaches will be ideal for sites with extensive historic emission data. Finally, when methane oxidation and lag time are included in a first order model, it could enhance methane estimation for open and unregulated landfills with limited data. The model is also considered less costly and adaptable when validated using site specific data. The findings provide a basis for improving methane emission estimation from open and unmanaged landfills.

1. INTRODUCTION

Methane production from deposited organic waste is as a result of the anaerobic decomposition of the organic matter. This process is undertaken primarily by microorganisms. It takes place in the absence of oxygen, producing landfill gas (LFG). Published studies have shown that the LFG is composed mainly of methane (CH_4) and carbon dioxide (CO_2). Studies have also shown that CH_4 typically constitutes about 50–60% of the LFG, while CO_2 constitutes roughly 40–50% (Duan et al., 2021; Mønster et al., 2019; Myhre et al., 2013). Other than CH_4 and CO_2, the landfill gas contains traces of non-methane organic compounds (NMOCs), hydrogen sulfide (H_2S), and volatile organic compounds (VOCs). The constituents of the LFG contribute to air pollution (Mohod & Bagal, 2023). Though emitted in smaller volumes as compared to CO_2, methane has a global warming potential about 25 times higher than CO_2 (Majdinasab et al., 2017). Its increase in the atmosphere has been linked to the worsening global warming. Other than being a greenhouse gas, CH_4 causes secondary air pollution such as ground-level ozone formation (IEA, 2022).

Several factors determine the composition of the LFG. They include soil moisture content, waste composition, climate, and the age of the of the deposition site (Un, 2023). As time elapse, less methane is emitted from a particular landfill (Abdel-Shafy et al., 2024). Site factors such as fissures, climate, soil porosity, compaction, and cover material affect oxidation and gas migration and dispersion (Mønster et al., 2019; Yilmaz et al., 2021). The organic content, temperature, and moisture influence microbial activities (Y. Liu et al., 2022; Manheim et al., 2021).

Understanding these factors and their role is key to accurate estimation of methane emissions (Balogun-Adeleye et al., 2019; Nematollahi et al., 2024).

To estimate methane emissions from landfills, researchers and organizations have developed various models. There are traditional time series models some of which consider the half-life of the decaying portion of the waste and the process models that consider the decay process of organic waste (Spokas et al., 2011). Artificial intelligence (AI)/machine learning (ML) approaches have also been developed to enhance methane estimation accuracy (Xu et al., 2025). The traditional models such as the U.S. EPA's LandGEM, IPCC Tiered Models, Scholl Canyon, Solid Waste Emissions Estimation Tool (SWEET), Afvalzorg, and TNO model are simple and require limited data. These aspects make them widely applicable. However, the use of limited data and reliance on generalized model parameters results to uncertainties in the estimates (Majdinasab et al., 2017). Process models such as MODUELO and California Landfill Methane Inventory Model (CALMIM) simulate the methane production process such as hydrolysis, acidogenesis, acetogenesis, and methanogenesis. The approach enables a more realistic representation of methane gas production process. However, they utilize extensive data from the target landfill (Merab et al., 2025). Additionally, the approach is susceptible to uncertainties resulting from input data, such as waste composition. The uncertainties can result to errors in methane emission estimation. Therefore, there is need for uncertainty analysis to evaluate the reliability of the results (Ovodkov et al., 2024; K. A. Spokas et al., 2021). The AI/ML approaches like Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have demonstrated improved accuracy in methane emission estimation. These algorithms are capable of capturing nonlinear relationships between methane emissions and site conditions (Janga & Reddy, 2025). The summary of model categories and variables required is shown in the Table 1.

Table 1
Summary of model inputs, outputs, and applicability

Category	Typical Variables
Inputs	Waste quantity, waste composition, decay constant (k), methane generation potential (L_0), climate parameters
Outputs	Annual CH_4 emissions, cumulative emissions, recovery potential
Validation Data	CH_4 concentration
Best Use Case	National inventories, project-scale estimation, unregulated dumpsites

This review's objective was to critically examine challenges associated with approaches used to estimate CH_4 emission from landfills and their applicability to open and unmanaged landfills. Published studies were drawn from reputable sites such as Google Scholar, ScienceDirect.com, Scopus, Web of Science, and Springer Nature Link. Studies focusing on estimation of methane emissions from landfills were identified. The review considered studies published between 2005 and 2025. Studies that did not discuss methane modelling were excluded. Also, the focus of the review was on model parameters, equations, validation approaches, and applicability of a particular model to open and unmanaged landfill conditions. Comparative analysis was then conducted to outline model limitations, strengths, and applicability to limited data realities of most of the open and unmanaged landfills.

2. METHODS

2.1 Review design and reporting framework

The Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines discussed by Page et al. (2021) were employed by this study to enhance reproducibility in the identification, screening, and synthesis of relevant literature. The review examined existing literature on models used to estimate methane emissions from landfills. The review focused on model equations, parameters, strengths, limitation, and applicability to open and unmanaged landfill conditions. The review intended to identify challenges of existing models and suggest the best approach to estimate methane emissions from open and unmanaged landfills.

2.2 Search strategy

The literature review was undertaken between April and December 2025 across Google Scholar, ScienceDirect.com, Scopus, Web of Science, and Springer Nature Link. The search methodology used by the study combined Boolean operators and keywords related to landfill methane modelling. This study restricted its search to peer-reviewed journal articles, conference papers, and technical reports published by reputable organizations between 2005 and 2025. English- and French-language publications were included with a bias towards English-published papers.

The search string applied were (“FOD models for landfill methane emission” OR “process model for landfill methane emission” OR “machine learning for landfill methane emission” OR “artificial intelligence for landfill methane emission”) AND (“modelling methane emissions from landfill” OR “prediction of methane emissions from landfill” OR “simulation of methane emissions from landfill”) AND (“Methane emissions from landfill” OR “landfill gas emission from landfill”).

2.3 Inclusion and exclusion criteria

The inclusion criteria were defined to ensure the relevance and methodological robustness of selected studies. The studies that focus on modelling of CH_4 emission from landfills were considered. More emphasis was on published studies that compared various models. Additionally, studies conducted on existing landfill sites or validated using ground-based or satellite measurements were included. Further, articles providing quantitative outputs such as R^2, Lo, k-values, and emission rates were viewed as important. Also, conference papers, policy briefs, and publications by international organization such as the IPCC or UNFCCC, which discuss landfill methane emissions were considered. Finally, the regions considered by the study include Africa (Nigeria, Côte d’Ivoire), Europe (Denmark, Netherlands, Sweden, Germany, and Spain), Asia (India, Bangladesh, China, Iran, Malaysia, and Turkey), North America (USA and Canada), and Latin America (Mexico).

However, studies focusing solely on waste management, gas collection infrastructure, or leachate composition and recirculation, without methane modelling component were excluded. Also, publications whose methodologies were not transparent were excluded.

2.4 Study selection process

All retrieved records were exported to Mendeley Reference Manager for organization and duplicate removal. The first correspondent screened the titles and abstracts for relevance. Full-text screening was performed for shortlisted studies, applying the inclusion and exclusion criteria. No automation tools were used in the selection process.

In total, 224 publications were identified across the aforementioned databases. After removal of duplicate and screening as per inclusion-exclusion criteria, 64 studies were included in the final synthesis.

2.5 Data extraction

Information was systematically collected from each study manually. Extracted data included:

1. Model equation and parameters (Lo, k, DOCf, MCF)
2. Reference information: Author(s), year, country.
3. Key findings and implications.
4. Model type: FOD, Process, or AI/ML-based.
5. Validation metrics: RMSE, R^2, MAE, bias.
6. Scale of study: Regional, national, or site-specific.

2.6 Risk of bias and study quality assessment

A formal quantitative-risk-of-bias tool was not used because of methodology diversity. Studies were assessed based on methodological and data clarity. No subgroup, sensitivity or meta-analysis was carried out because quantitative aggregation was not applicable. However, robustness was appraised through comparison of modelling outcomes.

2.7 Data synthesis and analysis

Given the heterogeneity in study designs of the included studies, a qualitative narrative synthesis was considered. The studies were categorized thematically in respect to modelling approach, geographical context and the type of landfill under study. The review focused on the strengths and weaknesses of identified approaches in estimating methane emissions from landfills. The review also compared the performance of studied approaches and their suitability to open and unmanaged landfill conditions. Where applicable, model performance metrics such as R^2, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square (RMSE) were used to compare the performance of identified approaches. The review identified difference in performance, validation levels, and data requirements. The suitability of the study for reproduction was also examined.

Data preparation for synthesis was achieved through standardization of reported of the reported parameters qualitatively rather than statistically. In cases where the model parameters were missing, the studies were retained based on the conceptual methodological contribution.

The results of the included studies were presented using summary tables and narratives. Comparative tables were also used, where applicable, to contrast model limitations, strengths, and applicability to limited data conditions of most of the open and unmanaged landfills.

3. RESULTS

3.1 Overview of study inclusion

Following the study search and selection process discussed in sub-Chap. 2.4, a total of 224 records were identified. After removal of duplicates, where 48 records were removed, 176 records were screened based on abstract and title. This step excluded 56 records. The remaining 120 records were then sort for retrieval. Out of

these, 20 were excluded. Finally, 100 records were assessed for eligibility, where 64 studies published between 2005 and 2025 were included in the final review as shown in Fig. 1 below.

Several studies appeared eligible but were excluded after full-text assessment. Example of studies that were excluded are those that focused on waste management, gas collection infrastructure, or leachate composition and recirculation, without addressing methane modelling. Additionally, studies whose methodologies were unclear were excluded.

The 64 included records entailed studies that focused on modelling of methane emission from landfills. Studies that compared various models and those that validated models were of more interest. Additionally, studies that quantified model parameters and emission rates were considered important. The records also included gray literature such as conference papers and international organization such as the IPCC or UNFCCC, which discuss landfill methane emissions. Finally, the studies span from Africa (Nigeria, Côte d'Ivoire), Europe (Denmark, Netherlands, Sweden, Germany, and Spain), Asia (India, Bangladesh, China, Iran, Malaysia, and Turkey), North America (USA and Canada), and Latin America (Mexico).

3.2 Risk of bias within studies

Studies that used site-specific model parameters were considered to have low methodological risk of bias whereas studies that utilized default values of model parameters were considered to have a higher methodological risk of bias.

3.3 Results of individual studies

The review identified three main approaches used to estimate methane emissions from landfills. They include traditional models, process-based approaches, and Artificial Intelligence (AI)/Machine Learning (ML) algorithms. Given the difference in the methodology, a wide range of methane emission estimates were reported. The results were analyzed qualitatively because of missing summary statistics and confidence intervals across studies. Tables 2 and 3 summarizes the comparison of key reviewed models, focusing on: key inputs, major assumptions, outputs, data requirement level, strengths, limitation, and suitability for data-scarce region.

Table 2
Models comparative summary

Model	Model type	Key inputs	Major assumptions	Outputs	Data requirement level
IPCC FOD, LandGEM	Empirical	Waste mass, k, DOC	Uniform decay rate	Annual CH_4 emissions	Low
CALMIM, MODUELO 2	Mechanistic/Process	Moisture, temp., kinetics	Detailed processes	Gas fluxes	High
ANN, SVR, KNN, RF	AI/ML	Historical data for data training	Pattern-based learning	Emission forecasts	Medium–High

Table 3
Strengths and limitations of modelling approaches

Approach	Strengths	Limitations	Suitability for data-scarce regions
Empirical (IPCC, LandGEM)	Simple, widely accepted	High uncertainty	High with improvement
Process-based	Physically realistic	Data-intensive	Low
Hybrid / ML	Improved accuracy, adaptability	Interpretability challenges	Medium–High

3.4 Results of synthesis

3.4.1 Characteristic and bias

Analysis of the included studies revealed methodological variability as indicated in Table 4. Traditional models assume that the rate of methane generation at any time is proportional to the amount of decomposable organic material remaining in the landfill. In addition, methane oxidation (by cover soils or bio-covers) and lag time are typically ignored or applied as fixed factor, underestimating complexities of real-world landfill performance. Further, field validation studies revealed systematic over- or underestimations of methane emissions when default parameters were applied.

Process models, on the other hand, simulate the underlying physical, chemical, and biological processes (hydrolysis, acidogenesis, methanogenesis) that drive methane production and transport within a landfill. They explain why and how methane is generated from landfills. Unlike traditional models that rely on statistical relationships and observed data, process models aim to explain the fundamental processes resulting in methane generation, oxidation, and emission. Finally, AI and ML approaches handle nonlinear, multidimensional datasets through algorithm training using historical data. However, in regions where there is limited historical data on emissions, the AI/ML models may not find traction. The review revealed that studies that relied on default parameters contributed to increased bias. This aspect was depicted by the traditional models that were utilized in low data landfills.

Table 4
Summary characteristics of select studies included in the review

Author(s), Year	Region / Country	Landfill Type	Climatic Context	Modelling / Measurement Approach	Key Parameters Reported	Main Focus / Contribution
Thompson et al., 2009	USA	Managed (benchmark)	Temperate	LandGEM	L_0, k	Model development and validation
Oonk, 2010	Netherlands	Managed	Temperate	FOD (TNO model)	DOC, k	Model refinement
Spokas et al., 2011	USA	Managed	Temperate	CALMIM	Oxidation, CH_4 flux	Process-based modelling
Ozcan et al., 2009	Turkey	Unmanaged	Semi-arid	IPCC FOD	DOC, MCF	Emission estimation
Govindan & Agamuthu, 2014	Malaysia	Open dumpsite	Tropical	IPCC FOD	DOC, DOCf	LMIC landfill assessment
Gollapalli & Kota, 2018	India	Open landfill	Tropical	IPCC vs LandGEM	L_0, k	Model comparison
Balogun-Adeleye et al., 2019	Nigeria	Open dumpsite	Tropical	IPCC FOD	DOC, MCF	Data-scarce context
Yapo et al., 2019	Côte d'Ivoire	Unmanaged	Tropical	IPCC FOD	DOC	Regional methane inventory
Vu et al., 2017	Canada	Managed	Cold	Empirical + FOD	k	Climate sensitivity
Börjesson et al., 2009	Sweden	Managed	Temperate	Field measurements	CH_4 flux	Validation study
Fjelsted et al., 2020	Denmark	Managed	Temperate	Tracer gas	Emissions	Measurement uncertainty
Liu et al., 2022	China	Mixed	Subtropical	Modified FOD	DOC, k	Parameter adjustment
Mehrdad et al., 2021	Iran	Unmanaged	Arid	IPCC FOD	DOC, MCF	Parameter uncertainty
Das & Hazra, 2021	India	Open dumpsite	Tropical	LandGEM	L_0	Overestimation analysis
Toha & Rahman, 2023	Bangladesh	Open dumpsite	Tropical	IPCC FOD	DOC	Waste composition sensitivity
Khambekar & Mali, 2024	India	Open dumpsite	Tropical	Hybrid model	DOC, k	Improved prediction
Scheutz et al., 2022	Iceland	Managed	Cold	Empirical	CH_4 oxidation	Climate effects

Author(s), Year	Region / Country	Landfill Type	Climatic Context	Modelling / Measurement Approach	Key Parameters Reported	Main Focus / Contribution
Colomer Mendoza et al., 2016	Mexico	Semi-managed	Semi-arid	IPCC FOD	DOC	Inventory development
Forstmaier et al., 2023	Germany	Managed	Temperate	Field + modelling	k	Model validation
Saeedi et al., 2025	USA	Managed	Temperate	ML-enhanced LandGEM	L_o, k	AI-based correction
Merab et al., 2025	Mexico	Mixed	Tropical	Hybrid FOD–ML	DOC, k	Regional calibration

3.4.2 Statistical synthesis

No statistical meta-analysis was undertaken because of the variability in study design, models used, reporting, and outcome of the considered studies. As a result, confidence interval, pooled estimates, or heterogeneity statistics could not be presented.

3.4.3 Heterogeneity of the study results

Differences among study results were primarily attributable to model parameters, input data, and data processing approach.

3.4.4 Sensitivity and robustness

Though sensitivity analysis was not undertaken formally, review of traditional models indicated that methane emission estimates were sensitive to model assumed parameters k, DOC, DOC_f, and MCF, which were sources of uncertainty. For process models, the emission estimates were sensitive to process drivers such as temperature and moisture.

3.5 Reporting bias

Reporting bias in the review could emanated from the preferential of studies that compared performance of various methods. However, the review included gray literature and studies that only focus on a single model to mitigate this type of bias.

3.6 Certainty of evidence

Due to the heterogeneity in modelling approaches, the confidence in the body of evidence was rated as moderate. However, there were clear patterns of the causes of uncertainty and inhibitors of applying existing methodologies to estimate methane emission from open and unmanaged landfills.

4. DISCUSSION

4.1 Interpretation of findings

The review reveals the challenges experienced in estimating methane emission from open and unmanaged landfills. This challenge majorly experienced in low- and middle-income countries whose landfills are mostly open

dump sites. In these sites, the review shows that traditional models like the LandGEM and the IPCC models have been used the most because of low data requirement. However, due to assumptions associated with these models, there output has high uncertainty. This finding indicate supports the evidence that default model parameters validated in engineered landfills do not represent the conditions at the unmanaged landfills. When used, they result to over- or under-estimation of methane emissions from these sites.

4.2 Limitations of the evidence included in the review

This review reveals a persistent challenge of estimating methane emissions from open and unmanaged landfills where data is scarce. The study analyzed the accuracy of various models in quantifying methane emissions from landfills. Four major hindrances to accurate methane emissions in the existing body of research were identified. Firstly, parameter assumptions undermines model transferability. Default decay rate constants (k) and methane generation potentials (Lo) used in first order decay models are derived mainly from temperate climates for engineered landfills. Their application to tropical, open and unmanaged landfills introduces significant uncertainties.

Secondly, limited field validation persists. Only a few models have been validated against field measurements across different climatic conditions. It is not reasonable to rely on model estimates that have not been validated. Most models rely on historical waste inputs and assumed model parameters. Additionally, some studies used site specific data like waste characteristics to calibrate the model parameter but failed to validate the models using measured methane emissions.

Thirdly, the exclusion of spatial heterogeneity of landfills, methane oxidation, and lag time contribution to methane generated from landfills. Methane oxidation in open and unmanaged landfills is an important factor that should not be excluded in models. The landfill cover or surrounding soils can consume up to 75% of generated CH_4 through oxidation (Fjelsted et al., 2020). Many models do not have this component. Additionally, some model parameter optimizations methodologies did not consider this methane oxidation resulting to errors. Likewise, lag time is an important component to be considered during model development. Organic waste decomposition does not take place immediately waste is deposited at the landfill. Models that do not include lag time assume that emissions started immediately waste is deposited. Also, when lag time and methane oxidation are not included in the model, the model parameters compensate for the resultant errors, leading to inflated model parameters, especially in semi-aerated or partially covered dumpsites.

Fourthly, intensive data requirement. The review found that process-based models and AI/ML approaches demonstrated enhanced precision but they require intensive data. Most open and unmanaged landfills, especially in African region like the Dandora dumpsite in Nairobi City, have limited field measured data. The complexity of process-based models also limits their applicability in such open and unmanaged landfills. Lack of data inhibits calibration and validation. In addition, there is limited historical data for AI/ML model training. The lack of data limits the utilization of the two approaches in open and unmanaged landfill sites. Also, the need for extensive data makes them expensive to implement.

The findings of this review indicates a need for a less data intensive locally calibrated model for estimating methane emissions from open and unmanaged landfills.

4.3 Limitations of the review processes used

The review depicted methodological limitation in terms of the studies included. Only studies published in English or French were included with a bias toward studies in English. Additionally, while many literature sources were included, inaccessible studies were not captured. As a result, the review could have missed out on important literature. Finally, the discussion of the literature is based on the qualitative patterns rather than quantitative comparisons due to variability in the methodologies under review.

4.4 Implications of the results for practice, policy, and future research

The findings of the review indicates that while First-Order Decay (FOD) models remain widely applied due to their simplicity and institutional endorsement, they are limited by their generalization of landfill characteristics. Additionally, most of the existing models were developed to estimate methane emissions from engineered landfills in the temperate climate regions. They struggle to capture the environmental variability and operational realities of open and unmanaged landfills in tropical regions. When employed in such sites, they tend to overestimate or underestimate methane emissions. Because of their unreliability, mitigation efforts and greenhouse gas (GHG) inventory development are compromised.

The process-based models and Artificial Intelligence/Machine Learning approaches demonstrated progress toward estimation of methane emissions from landfills. Process-based models require extensive site specific data while AI/ML algorithms require extensive historical data for model training. The data demand by the two approaches restrict their application in open and unmanaged landfills where data is scarce.

To enhance estimation of methane emissions from open and unmanaged landfills the review suggests the urgent need for a cheap, locally calibrated, adaptive methane emission estimation models. In case the open and unregulated landfill site has historical emission data, then AI/ML-FOD hybrid models will be the ideal approach to estimate methane emissions. Similarly, if the historical emission data is absent but site specific data such as waste composition, rainfall and temperature, cover type, and site management practices are available then a process-based model will be ideal for methane emission estimation. However, in case both historical data on methane emission and site specific data are limited, a first order decay model with calibrated decay constants (k) and methane potential (Lo), with methane oxidation factor and lag time included is perceived ideal for enhanced methane estimation from open and unmanaged landfills. The transition from assumption-based to data-driven methane modelling is essential to improve reliable estimation of methane emissions from open and unmanaged landfills.

Declarations

Registration and protocol

This review was **not registered** in a systematic review registry, and a formal protocol was not prepared prior to study initiation.

Funding

The authorship, research or publication of this study was not funded by any individual or entity.

Declaration of conflict of interest

The authors declare no conflict of interest regarding authorship, research or publication of this study.

Data availability

All data used in this review were obtained from publicly available sources cited within the manuscript. No new datasets or analytical code were generated.

Consent to Publish

Consent to Publish declaration: not applicable.

Ethics Approval and Consent to Participate

Ethics and Consent to Publish declarations: not applicable.

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Figures

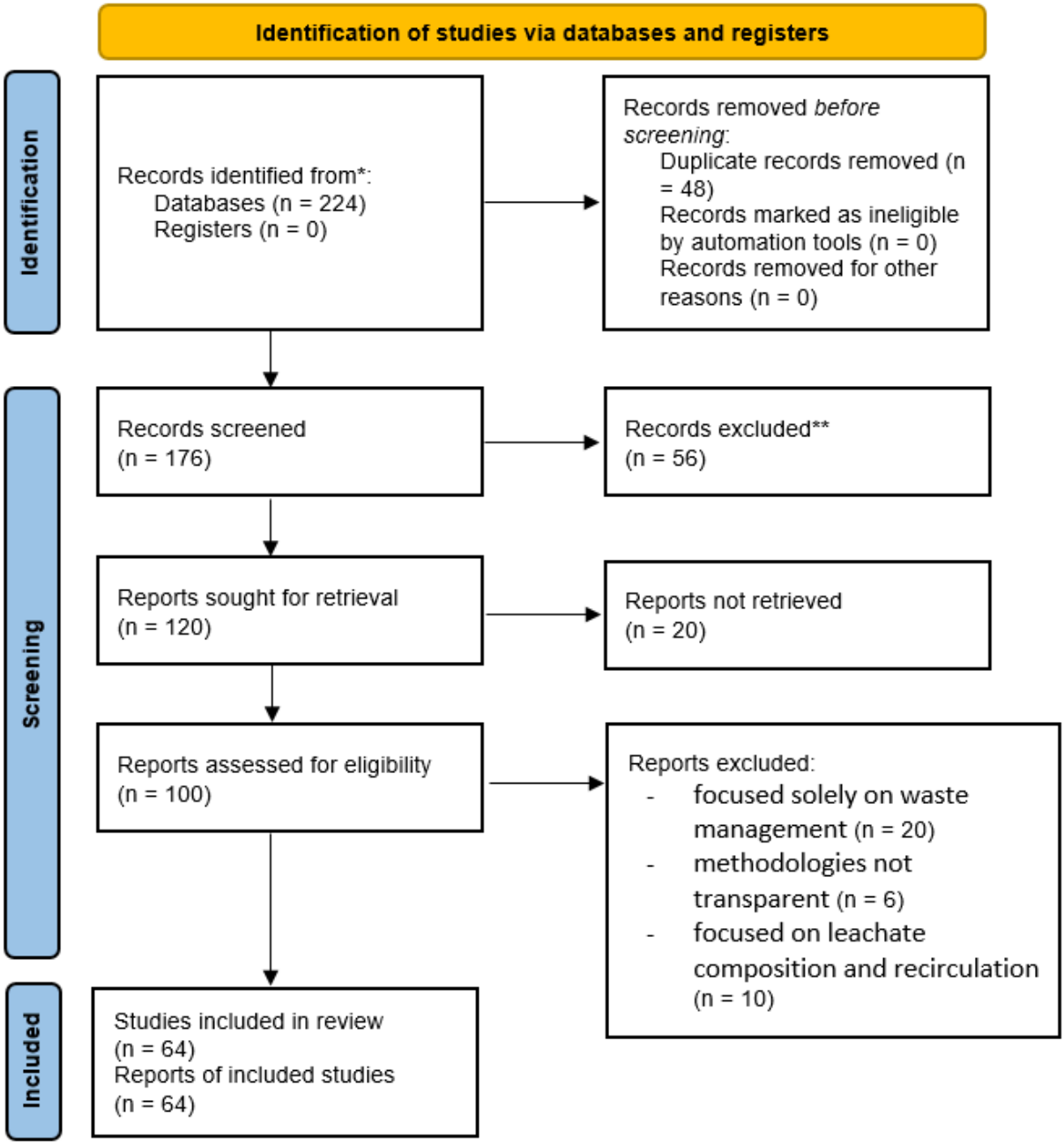


Figure 1

The results of the search and selection process