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Optimization of landfill gas generation based on a modified first-order decay model: a case study in the province of Quebec, Canada

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Abstract

Landfills will likely remain an essential part of integrated solid waste management systems in many developed and developing countries for the foreseeable future. Further improvements are required to model the generated gas from landfills. The literature has not addressed detailed waste characterization in landfill gas (LFG) modeling by a first-order decay model such as LandGEM while using a genetic algorithm. Additionally, little has been done in the literature regarding H_2S generation modeling. This paper uses a genetic algorithm to independently fit parameters to a CH_4 and H_2S generation model based on a modified first-order decay model. In the case of CH_4 generation modeling, biodegradable organic waste (OW) was segregated into food waste, yard waste, paper, and wood. In addition to optimizing the OW fractions, key modeling parameters of OW, such as CH_4 generation potential (L_0) and CH_4 decay rate (k_{CH_4}), were determined independently for different periods in the landfill's life. Similarly, in the case of H_2S generation modeling, the construction and demolition waste (CD) was classified into fines (FCD) and bulky materials (BCD), and H_2S generation potential (S_0) and H_2S decay rate (k_{H_2S}) of FCD and BCD were determined. LFG collection data from a landfill site in the province of Quebec, Canada, was used to validate the LFG generation model. A range of scenarios was analyzed using the validated model, including fourteen scenarios (two benchmark and twelve optimizing) for CH_4 and two for H_2S modeling. The results showed that the differentiation of more waste types improves the modeling accuracy for CH_4. Moreover, within the decade-long lifetime of a landfill, the waste management strategies change, requiring different assumptions for the modeling. Also, the work showed the importance of considering how different landfill sectors are filled over time. Finally, scenario twelve of optimizing scenarios, which assumed four waste types, constant three periodic waste fractions, and six sectors, had the lowest residual sum of squares (RSS) value. For H_2S generation modeling, both scenarios, with or without separate fits of S_0 and k_{H_2S} for FCD and BCD, predicted the generated H_2S well and had a very similar RSS value. Further data could improve H_2S generation modeling.

Keywords Organic waste, Construction and demolition waste, Landfill gas, Parameter fit

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Introduction

Today, more than 90% of waste in low-income countries is still openly dumped or burned, and gaseous emissions from such dumpsites have been poorly studied (Beaven and Scheutz 2019), threatening the environment and human health. In contrast, waste in developed countries is a resource for energy production (Batista et al. 2021), and only 2% is dumped in high-income countries Kaza et al. 2018). Landfills are large and heterogeneous emitting sites that contribute 20% and 17.4% of national methane (CH_4) emissions in Canada (Canada 2017) and the U.S. (USEPA 2020), respectively. Landfills will likely remain essential to integrated solid waste management systems in many developed and developing countries for the foreseeable future (Sun et al. 2019). Understanding Greenhouse Gas (GHG) sources and sinks is a significant endeavour, and many countries have committed to reducing their emissions (e.g., UN COP26 2021, 2021)). CH_4 is a potent GHG with a global warming potential of 28 times that of carbon dioxide (CO_2) over a 100-year timeframe (Monster 2019).

Human-related activities such as fossil fuel production, domestic livestock ranching/farming, manure management, rice cultivation, biomass burning, and waste management cause 60% of global CH_4 emissions compared to natural CH_4 emitters such as wetlands, termites, oceans, freshwater bodies, and wildfires (Figueroa et al. 2009). The waste sector presents an appreciable potential for emissions reduction, particularly in developing countries where emissions from waste can account for 15% of total country GHG emissions due to the higher content of biodegradable Organic Waste (OW) (Maalouf and El-Fadel 2018). If engineered sanitary landfills are managed correctly and Landfill Gas (LFG) collection efficiency improves, emissions from landfills can be decreased.

Originating from waste decomposition, LFG mainly contains CH_4, CO_2, and trace amounts of hydrogen sulfide (H_2S) as an inhibitory (reducing CH_4 generation), odorous and corrosive gas (Flores-Alsina et al. 2016). LFG production occurs in five phases. The aerobic condition in the first phase takes hours to weeks, the anoxic condition in the second phase takes 1–6 months, and the subsequent phases are anaerobic and take several months to years (BCMoE 2010). The anaerobic phases are the ones that LFG generation is usually addressed. Under anaerobic conditions in landfills, CH_4 generation starts and increases, and CO_2 generation decreases (third phase). The trend continues until it reaches a steady state in the fourth phase and finally approaches zero in the fifth phase.

Anaerobic degradation of biodegradable OW (food waste, yard waste, etc.) generates CH_4. There is as low as approximately 0.1% sulphur in Municipal Solid Waste (MSW) (Kaiser et al. 1968). Sulphur-containing materials such as construction and demolition waste (CD) (including bulky materials of construction and demolition (BCD) and fines of construction and demolition (FCD) wastes) can produce H_2S in an anaerobic environment. Compared to MSW, around 1.5–9.1% of CD is sulphate (Hrobak 2009). These wastes are landfilled with MSW in many cases. The byproduct of CD processing facilities is screened materials termed FCD (soil and building material, including drywall). These fines are often used in MSW landfills as alternative daily cover (Anderson et al. 2010) or final cover.

Based on chapter Q-2, r. 19 of the Regulation respecting the landfilling and incineration of residual materials of Environment Quality Act (Quebec 2021), landfills in Quebec must follow the regulation respecting the gas collection system. Chapter II—Landfills, Division 2—Engineered Landfills, Subdivision 32—Collection and Removal of Biogas indicates that "in the case of landfills having a maximum capacity greater than 1,500,000 m^3 or as soon as a landfill receives 50,000 t or more of residual materials per year, the biogas collection system must have a gas pumping device except if such a device is not warranted because of the nature of the residual materials received and the low quantity of biogas likely to be produced."

According to Canada (2022), in Canada, "British Columbia, Alberta, Ontario and Quebec have regulations requiring larger landfills to capture and control or reduce CH_4 emissions, and others include requirements for installing LFG recovery and flaring systems in operating permits. Quebec and Ontario require landfills larger than 1,500,000 m^3 of waste capacity to install systems. British Columbia requires landfills with greater than 100,000 tons of waste or greater than 10,000 tons disposed of per year to evaluate their annual CH_4 generation and install LFG systems if they exceed 1000 tons of CH_4 per year. The lowest regulatory threshold in North America is in California, which requires landfills that generate LFG with a heat input capacity of more than 3.0 MMBtu/hr (~650 tons CH_4 generation per year) to install LFG recovery systems."

The first-order kinetic model [e.g., Landfill Gas Emissions Model (LandGEM)] is the most widely applied model to forecast landfill CH_4 generation (Lima et al. 2018). The U.S. EPA (USEPA 2005) developed LandGEM, which considers the CH_4 generation potential, L_0 (m^3/t biodegradable waste), and the CH_4 generation rate associated with waste decomposition, k_{CH_4} (y^{-1}). Although LandGEM models CH_4 generation from heterogeneous wastes effectively, some input modifications could significantly enhance its accuracy.

For instance, da Silva et al. (2020) concluded that LandGEM overestimated CH_4 generation. One reason could be that LandGEM only includes one type of waste, which includes inerts. Reformulating the model by involving different types of biodegradable organic wastes, such as fast decaying refuse (FDR) and slow decaying refuse (SDR) improves the model's accuracy. IPCC (2006;2019) further divided the biodegradable OW into rapidly degrading waste (food waste, sewage sludge), moderately degrading waste (other (non-food) organic putrescible, garden and park waste), slowly degrading waste (paper/textile and wood/straw), and bulk waste (Additional file 1: Table S1 in supplementary material). Besides, LandGEM does not address the interactions of different waste components interfering with the LFG generation rate. Although sulfate-reducing bacteria help to maintain pH within a reasonable range for methanogenesis [under neutral pH conditions, not acidic ones (Mora-Naranjo et al. 2003)], methanogens and sulfate-reducing bacteria compete for common substrates (i.e., hydrogen and acetate) to generate CH_4 and H_2S, respectively. According to Flores-Alsina et al. (2016), sulfate-reducing bacteria outcompete acetogens and methanogens for electron equivalents (e.g., hydrogen or organic acids), leading to sulfide production, which is inhibitory and causes odour and corrosion. Low concentrations of H_2S could inhibit the growth of microorganisms and suppress the CH_4 forming processes in the presence of sulphate and sulphate-reducing conditions effectively (Mora-Naranjo et al. 2003). In addition to CH_4, H_2S generation is best modeled with a first-order decay equation, similar to LandGEM (Anderson et al. 2010). Therefore, a first-order kinetic model, similar to LandGEM, could evaluate H_2S generation from sulphur-containing wastes: BCD and FCD. An optimization algorithm, such as a genetic algorithm, could also be implemented to estimate H_2S generation potential, S_0 (m^3 H_2S/t sulphur), and H_2S generation rate, k_{H_2S} (y^{-1}) of BCD and FCD. Li et al. (2011) combined artificial neural networks with genetic algorithm to simulate the gas generation in landfills. They found that artificial neural networks is efficient in providing accurate short-term predictions. At the same time, the genetic algorithm can generate a precise model of a landfill for long-term forecasting and planning. The genetic algorithm can navigate large complex search spaces to deliver near-optimal solutions (Kormi et al. 2018).

Nikkhah et al. (2018) used the LandGEM model to calculate landfill emissions and CH_4 generation, which uses one type of waste (i.e. MSW) for the whole landfill and the studied period. The model used a first-order decay equation in which CH_4 generation depended on the CH_4 generation rate (k_{CH_4}), CH_4 generation potential (L_0), and the mass and age of waste. They considered the range of k_{CH_4} and L_0 between 0.02 and 0.70 y^{-1} and 96 to 170 m^3 CH_4 per ton of MSW, respectively, and concluded that for 400 t MSW per day landfilled, 652,836 t CH_4 generated from 1984 to 2124, assuming the value of k_{CH_4} and L_0 equal to 0.70 y^{-1} and 170 m^3 CH_4 per ton of MSW, respectively. Based on their study, each ton of MSW generated 0.03 tons of CH_4 (42 m^3 CH_4 considering CH_4 density to be 0.7157 kg/m^3). A study by Ramprasad et al. (2022) estimated CH_4 generation in a landfill from 2010 to 2060, considering the value of k_{CH_4} and L_0 equal to 0.05 y^{-1} and 110 m^3 CH_4 per ton of MSW, respectively. According to their study, the least and the most CH_4 generated were 256,000 m^3 in 2010 (receiving 30,768 ton MSW or 84 t MSW per day) and 16,600,000 m^3 in 2042 (receiving 3,126,706 ton MSW or 8566 t MSW per day). Hence, each ton of MSW generated 8.3 (2010) to 5.3 (2042) m^3 CH_4. Another study (Sauve and Acker 2020) applied the LandGEM model, assuming k_{CH_4} to be 0.09 y^{-1} and L_0 between 18 to 138 m^3/t MSW and achieved higher LFG generation with higher CH_4 generation potential. Their results confirmed the dependence of landfill environmental impacts of waste composition, particularly the amount of biodegradable OW. Kumar and Sharma (2014) compared the LandGEM model results with other models and proved this model's better ability to estimate GHG emissions from MSW landfills. Various studies [e.g., (da Silva et al. 2020;Fallahizadeh et al. 2019;Sil et al. 2014;Toha and Rahman 2023)] used LandGEM to estimate CH_4 generation from landfills, yet they did not consider waste characterization, parameter fitting of k_{CH_4} and L_0, and applying a genetic algorithm in their work. The same research gap exists for H_2S generation modeling even further as it has been rarely addressed in the literature. Waste characterization, parameter fitting of k_{H_2S} and S_0, and applying a genetic algorithm can not be found in other studies [e.g., (Shaha and Meeroff 2020;Xu et al. 2014)].

Using a genetic algorithm, this study fits parameters to a CH_4 and H_2S generation model according to a modified first-order decay model. Model validation was done using the LFG collection data from a landfill site in the province of Quebec, Canada. The data contained thirty-nine years of measurements of OW, BCD and FCD quantities and twenty-four years of LFG amounts, and was used to evaluate the performance of first-order decay models to estimate CH_4 and H_2S generation. In the case of CH_4 generation modeling, food waste (FDR), yard waste (FDR), paper (SDR), and wood (SDR) were assumed to address OW segregation. In addition to optimizing the OW fractions, key modeling parameters of OW (L_0 and k_{CH_4}) were determined independently for periods in the life of a landfill. Similarly, for H_2S generation modeling, the CD was classified into FCD and BCD, and S_0 and k_{H_2S} of BCD and FCD were determined. A range of scenarios were analyzed, including two benchmark and twelve optimizing scenarios for CH_4 and two scenarios for H_2S modeling.

The novelty of this study is that it differentiates the OW and CD into four and two types to estimate CH_4 and H_2S generation, respectively, and enhance modeling accuracy. Additionally, it applies a genetic algorithm to fit various parameters, which has never been done in the literature. The methodology could be used in other landfills using their waste characterization and gas collection data.

Methodology

Landfilled mass and landfill gas collection trend

The studied landfill was in a wet boreal climate in the province of Quebec, Canada. The landfill had six landfilled sectors, namely 1, 2, 3, 4, 5, and 6, in which only landfilled OW, BCD, and FCD were considered (Table 1). Sectors 1, 2, 3, and 4 only received OW, but sectors 5 and 6 received OW and CD. Sector 5 of the landfill received BCD and FCD, and sector 6 received only BCD (Fig. 1a, b in relative values as they are the confidential data of this landfill). Although waste quantities landfilled could be found for the entire site lifetime, waste composition data were unavailable.

Figure 1c, d shows the amount of generated CH_4 from all the sectors during thirty-nine years and H_2S from sectors 5 and 6 during eleven years in relative values as they are the confidential data of this landfill. It was assumed that CH_4 generation is associated with OW and H_2S generation with BCD and FCD. LFG flow and CH_4 concentration were measured automatically by onsite flowmeters and infrared analyzers. H_2S concentration was measured by the electrochemical analyzer. Micro 3000A, manufactured by Agilent, measured both CH_4 and H_2S. Also, 62–9/9500 flowmeter, manufactured by Thermal

Table 1 Landfill sectors (1 to 6), landfilled wastes (OW, BCD and FCD) and landfilling years in each sector

Sector	1	2	3	4	5	6
Waste type	OW	OW	OW	OW	OW, BCD, FCD	OW, BCD
Years	4–13	0–3, 13–14	14–22	22–27	28–34 (OW), 27–35 (BCD & FCD)	35–46 (OW & BCD)

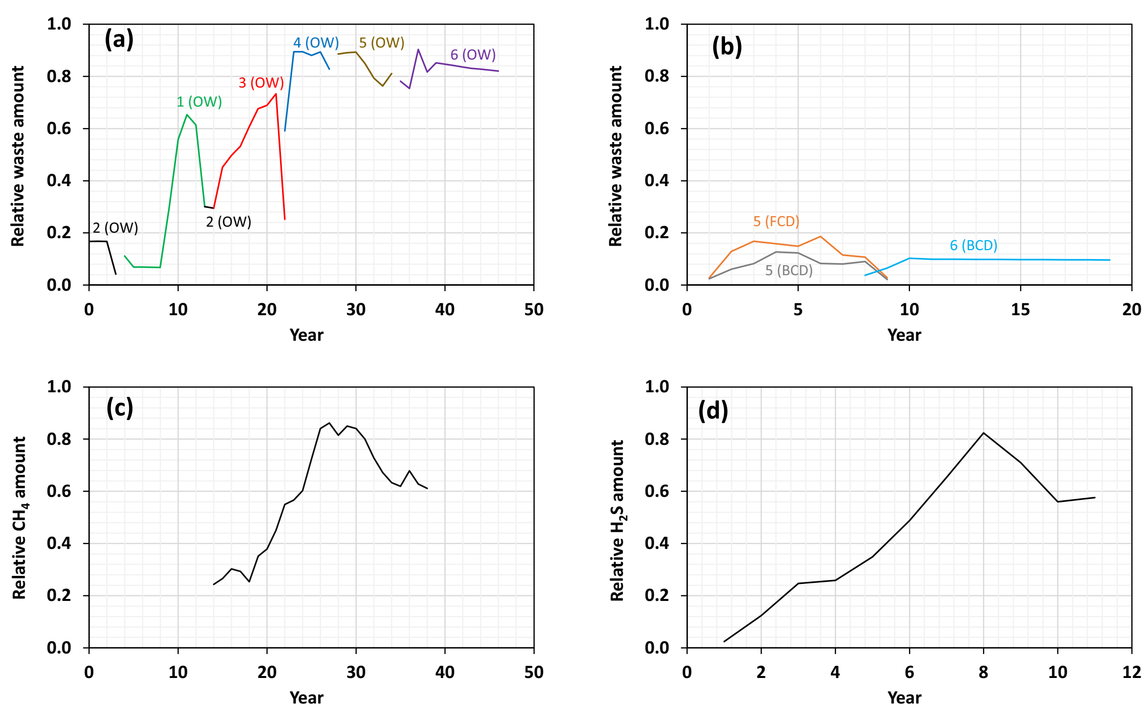

Fig. 1 **a** Landfilled waste (OW) from sectors 1, 2, 3, 4, 5, and 6, **b** Landfilled waste (BCD and FCD) from sectors 5 and 6, **c** Measured CH_4 from all the sectors, and **d** Measured H_2S from sectors 5 and 6, all in relative values due to data confidentiality

Instrument, was used. Data were recorded daily by the landfill operator and were available monthly. Monthly data was compiled annually for this study.

Societal changes in landfilling practices resulting from stricter legislation in Quebec (enhancements in recycling, higher raw material value, etc.) led to considering the subdivision of the landfill's lifetime into three distinct periods—Periods 1, 2, and 3—reflecting the specific history of refuse admittance based on changes in waste characteristics. For instance, Quebec targeted the recovery ratio for recyclables, OW, and construction and demolition waste to be 70%, 60%, and 70%, respectively, and the province aims to increase bioenergy production by 50% through various methods such as bio-methanation of OW by 2030 (Montréal 2017; Québec 2016). Different optimization scenarios were posed in which the variables were time-independent (constant in periods) or time-dependent.

First-order decay model

The first-order kinetic equation, LandGEM (USEPA 2005), was applied to evaluate CH_4 generation from OW (Eq. (1)). And a first-order kinetic equation, similar to LandGEM, was used to estimate H_2S generation from BCD and FCD (Eq. (2)) (Shaha and Meeroff 2020).

$$Q_{CH_4} = \sum_{i=1}^{n} \sum_{j=0.1}^{1} k_{CH_4} L_0 \left(\frac{OW_i}{10} \right) e^{-k_{CH_4} t_{i,j}} \tag{1}$$

where Q_{CH_4} (m^3/y) is the annual CH_4 generation after n years, L_0 (m^3 CH_4/t *biodegradable waste*) is CH_4 generation potential from biodegradable waste, k_{CH_4} (y^{-1}) is the CH_4 generation rate, OW_i (t) is the quantity of biodegradable OW landfilled in year i, $t_{i,j}$ is the age of the j^{th} section of landfilled OW at the i^{th} year, $j = 0.1$ year time increment and n is the number of years calculated (year of calculation—initial year of waste acceptance).

$$Q_{H_2S} = \sum_{i=1}^{n} \sum_{j=0.1}^{1} k_{H_2S} S_0 \left(\frac{CD_i}{10} \right) e^{-k_{H_2S} t_{i,j}} \tag{2}$$

where Q_{H_2S} (m^3/y) is the annual H_2S generation after n years, S_0 (m^3 H_2S/t *sulphur*) is H_2S generation potential, k_{H_2S} (y^{-1}) is the H_2S generation rate, CD_i is the quantity of CD landfilled in year i (t), $t_{i,j}$ is the age of the j^{th} section of landfilled sulphur at the i^{th} year, $j = 0.1$ year time increment and n is the number of years calculated (year of calculation—initial year of waste acceptance).

Parameter fit

A genetic algorithm optimization aims to fit the generated CH_4 or H_2S data with modeled ones. The generated data was obtained from the collected data using a collection efficiency of around 92% (collected gas divided by generated gas). Hence, it was implemented to estimate various parameters, such as L_0 (m^3 CH_4/t *biodegradable waste*) and k_{CH_4} (y^{-1}) of OW, and the fraction of each OW type (*1*) for CH_4 modeling, and S_0 (m^3 H_2S/t *sulphur*), and k_{H_2S} (y^{-1}) of BCD and FCD for H_2S modeling, based on the modeling scenarios. The objective was to minimize the residual sum of squares (RSS) of estimation between two sets of data (Eq. (3)) (Wu and Luo 1993).

$$RSS = \sum_{i=1}^{n} \left(y_{g_i} - y_{m_i} \right)^2 \tag{3}$$

where y_{g_i} is the generated value, y_{m_i} is the modeled value of CH_4 or H_2S, and n is the number of years in the optimization.

Modeling scenarios

CH_4 modeling

This study proposes distinguishing seven categories of landfill waste herein: food waste, sludge, paper, yard waste, wood, textile, and other OW (Table 2). However,

Table 2 Lower bound and upper bound of k_{CH_4} (y^{-1}) and L_0 (m^3 CH_4/t *biodegaradable waste*) for optimizing scenarios of CH_4 modeling

Waste type		k_{CH_4}			L_0				
		(IPCC 2019)	(ECCC 2021)	This study	(IPCC 2019)	(USEPA 2018)	(Krause et al. 2016)	(Park et al. 2018)	This study
FDR	Food	0.17–0.70	0.185	0.17–0.70	77–192	–	12–248	45–301	12–301
	Sludge	0.17–0.70	0.185	0.17–0.70	38–48	–	23–230	19–70	19–230
	Yard	0.15–0.20	0.10	0.10–0.20	173–211	63–104	104	31–136	21–211
SDR	Paper	0.06–0.085	0.06	0.06–0.085	247–309	57–194	66–387	67–296	57–387
	Wood[1]	0.03–0.05	0.03	0.03–0.05	53–63	15–24	–	86–130	15–241
	Textile	0.06–0.085	0.06	0.06–0.085	137–274	172–191	189–216	73–216	105–274
	Other OW	0.15–0.20	0.10	0.10–0.20	82–192	–	22–150	75–109	22–241

[1] Wood of construction and demolition waste

for the parameter fits, only four categories were considered: (1) food waste, (2) yard waste, (3) paper, and (4) wood. The reason is to decrease the optimization variables and categorizing the biodegradable OW into different types: easily (e.g., food waste), slowly (e.g., paper), and hardly (e.g., wood, textiles, and leather) biodegradable wastes. k_{CH_4} is the biodegradation half-life in years^{-1} for OW in a landfill and, based on the U.S. EPA, can range between 0.02 y^{-1} (less than 635 mm of precipitation) and 0.04 y^{-1} (more than 635 mm of precipitation) (Thompson et al. 2009). IPCC reported various ranges of k_{CH_4} (0.01 y^{-1} to 0.70 y^{-1}) for different climatic conditions (IPCC 2006;2019). L_0 depends on the type of waste deposited and some landfilling conditions described below. It can range vastly between 6–270 m^3 CH_4/t MSW (USEPA 2018). Fécil (2003) reported L_0 and k_{CH_4} of MSW to be 78 m^3 CH_4/t and 0.0427 y^{-1}, respectively.

Table 2 shows the waste segregation, k_{CH_4} and L_0 in the literature and the ones considered in this study. In the case of L_0, the minimum and maximum L_0 values were also calculated based on the mass of degradable organic carbon (DOC) following IPCC recommendations for each kind of waste [Eqs. (4) and (5)] (IPCC 2006;2019).

$$DDOC_m = W \times DOC \times DOC_f \times MCF \tag{4}$$

where $DDOC_m$ (t) is the mass of decomposable DOC deposited, W (t) is the mass of waste deposited, DOC (t $carbon/t$ $waste$) is the degradable organic carbon in the year of deposition, DOC_f (1) is the fraction of DOC that can decompose, and MCF is the CH_4 (1) correction factor for aerobic decomposition in the year of deposition (1 (IPCC 2019)).

$$L_0 = \frac{DDOC_m \times F \times 16/12}{W} \tag{5}$$

where L_0 (t CH_4/t $waste$) is the CH_4 generation potential, $DDOC_m$ (t) is the mass of decomposable DOC deposited, F (1) is the fraction of CH_4 in generated LFG, and 16/12 is the molecular weight ratio of CH_4/C. CH_4 density was assigned to 0.554×10^{-3} t/m^3.

The landfill's lifetime was subdivided into three periods reflecting the specific history of refuse admittance based on changes in waste characteristics. Accordingly, various scenarios were defined to improve the fitting of the CH_4 generation model to real generated data using the genetic algorithm. In this study, the optimization of first-order kinetic equation coefficients (k_{CH_4} and L_0) and the

Table 3 Lower bound and upper bound of k_{CH_4} (y^{-1}) and L_0 (m^3 CH_4 t^{-1}) and periodic waste fraction (-) for optimizing scenarios of CH_4 modeling, (a) FDR and SDR, (b) food, yard, paper, and wood

(a) Optimization variables	k_{CH_4}	L_0	k_{CH_4}	L_0	*PWF_FDR*		
Waste type/period	*FDR*	*FDR*	*SDR*	*SDR*	*1*	*2*	*3*
Default							
Sc1 & Sc 4	0.70	62.86	0.03	62.86	0.10	–	–
Sc2, Sc 3, Sc 5 & Sc 6						0.60	0.30
Lower bound							
Sc1 & Sc 4	0.10	12.00	0.03	15.00	0.10	–	–
Sc2, Sc 3, Sc 5 & Sc 6						0.30	0.30
Upper bound							
Sc1 & Sc 4	0.70	300.70	0.20	387.00	0.40	–	–
Sc2, Sc 3, Sc 5 & Sc 6						0.60	0.60

(b) Optimization variables	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	*PWF_food*			*PWF_yard*			*PWF_paper*		
Waste type/period	**Food**	**Food**	**Yard**	**Yard**	**Paper**	**Paper**	**Wood**	**Wood**	*1*	*2*	*3*	*1*	*2*	*3*	*1*	*2*	*3*
Default																	
Sc7 & Sc 10	0.70	62.86	0.15	62.86	0.03	62.86	0.03	62.86	0.10	0.10	0.10	–	–	–	–	–	–
Sc8, Sc 9, Sc 11 & Sc 12												0.30	0.30	0.30	0.15	0.15	0.15
Lower bound																	
Sc7 & Sc 10	0.17	12.00	0.10	21.00	0.06	57.00	0.03	15.00	0.10	0.10	0.10	–	–	–	–	–	–
Sc8, Sc 9, Sc 11 & Sc 12												0.15	0.15	0.15	0.15	0.15	0.15
Upper bound																	
Sc7 & Sc 10	0.70	300.70	0.20	211.00	0.09	387.00	0.05	241.00	0.40	0.40	0.40	–	–	–	–	–	–
Sc8, Sc 9, Sc 11 & Sc 12									0.20	0.20	0.20	0.30	0.30	0.30	0.30	0.30	0.30

Sc optimizing scenario, *PWF* periodic waste fraction proportions of the different types of waste are considered to best fit the measured LFG using a genetic algorithm in MATLAB. The purpose of this study was not to compare different numerical optimization methods or CH_4 generation models. The objective was to compare different scenarios of modelization using different types of waste, different values of k_{CH_4} and L_0, different periods of landfilling and different proportions of waste. Yet, a benchmark study showed that a genetic algorithm performs better and is faster, and LandGEM is well known to be a reliable first-order decay model and was therefore considered an excellent candidate for this study.

Scenarios were divided into two series: benchmark and optimizing. Two benchmark scenarios with no optimization were considered for testing the model's superiority. These scenarios assumed one type of waste (MSW), one periodic waste fraction, and considered the entire landfill as one sector. The first benchmark scenario assumed k_{CH_4}=0.70 y^{-1} and L_0=170 m^3 CH_4 t^{-1} *MSW* (Nikkhah et al. 2018) and the second one assumed k_{CH_4} =0.05 y^{-1} and L_0=110 m^3 CH_4 t^{-1} *MSW* (Ramprasad et al. 2022).

As shown in Additional file 1: Table S2 in supplementary material and Table 3, twelve optimizing scenarios were determined, from which some scenarios (4 to 6 and 10 to 12) considered different variables for each sector. In contrast, other scenarios neglected such variation and assumed the whole landfill as one sector. Scenario 1, namely Sc1_2WT_1PWF_1S, had 5 variables, including k_{CH_4} and L_0 for FDR and SDR, in addition to one periodic waste fraction for these waste types. This scenario neglected variation in time and assumed one periodic waste fraction for FDR and SDR throughout the landfill lifetime. Scenario 2, Sc2_2WT_3PWF_1S, had 7 variables as it considered variation in time and had three periodic waste fractions. Scenario 3, Sc3_2WT_CPWF_1S, assumed constant three periodic waste fractions throughout the landfill lifetime analysis and has 4 variables. The subsequent three scenarios (Sc4_2WT_1PWF_6S, Sc5_2WT_3PWF_6S, and Sc6_2WT_CPWF_6S) were the same as scenarios 1, 2, and 3, except that they considered different variables for each sector, and had 30, 42, and 20 variables, respectively. Scenarios 7 to 12 were the same as scenarios 1 to 6, except four waste types (food waste, yard waste, paper, and wood) were considered leading to 11, 17, 8, 66, 102 and 48 variables, respectively. Table 4 illustrates CH_4 modeling optimization variables in each scenario. This study applies to well-documented waste management landfills with accurate waste characterization data. Otherwise, the level of error given by the lack of waste characterization overshadows the effort this study is trying to produce.

H_2S modeling

Sulphur content in MSW is about 0.1% (corrugated boxboard: 0.14%, newspaper: 0.11%, mix paper: 0.12%, food waste: 0.25%, grass + dirt: 0.26%, plastic film: 0.07%, plastics, rubber, leather mix: 0.55%, sewage sludge digested: 0.66%, textiles: 0.20%, wood: 0.11%, glass, ceramics: 0.00%, and metals: 0.01%) (Kaiser 1968). However, CD contains around 1.5–9.1% sulphate (Hrobak 2009) and 2.08% of CD, and 5.15% of earth and sand construction waste is sulphur (Chung et al. 2019). Therefore, estimating H_2S generation in landfills containing the CD is important. H_2S is an odorous gas that negatively impacts neighbouring'populations' health and well-being (Heaney et al. 2011). The modeling scenarios in this study considered two variables (k_{H_2S} andS_0) for BCD and FCD in each sector. Table 5 shows the optimization variables and their lower and upper bounds. Although the range of k_{CH_4} and L_0 values for CH_4 modeling exist in the literature, those corresponding to H_2S are relatively much less known. Anderson et al. (2010) evaluated H_2S

Table 4 CH_4 modeling optimization variables in each optimizing scenario

Scenario	WT												PWF		Number of sectors		Maximum total of variables
	FDR		SDR		Food		Yard		Paper		Wood		Three	One	Six	One	
	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0					
Sc1_2WT_1PWF_1S	☑	☑	☑	☑										☑(1PWF×1WT)		☑	5×1
Sc2_2WT_3PWF_1S	☑	☑	☑	☑									☑(3PWF×1WT)			☑	7×1
Sc3_2WT_CPWF_1S	☑	☑	☑	☑									Constant waste fraction			☑	4×1
Sc4_2WT_1PWF_6S	☑	☑	☑	☑										☑(1PWF×1WT)	☑		5×6
Sc5_2WT_3PWF_6S	☑	☑	☑	☑									☑(3PWF×1WT)		☑		7×6
Sc6_2WT_CPWF_6S	☑	☑	☑	☑									Constant waste fraction		☑		4×6
Sc7_4WT_1PWF_1S					☑	☑	☑	☑	☑	☑	☑	☑		☑(1PWF×3WT)		☑	11×1
Sc8_4WT_3PWF_1S					☑	☑	☑	☑	☑	☑	☑	☑	☑(3PWF×3WT)			☑	17×1
Sc9_4WT_CPWF_1S					☑	☑	☑	☑	☑	☑	☑	☑	Constant waste fraction			☑	8×1
Sc10_4WT_1PWF_6S					☑	☑	☑	☑	☑	☑	☑	☑		☑(1PWF×3WT)	☑		11×6
Sc11_4WT_3PWF_6S					☑	☑	☑	☑	☑	☑	☑	☑	☑(3PWF×3WT)		☑		17×6
Sc12_4WT_CPWF_6S					☑	☑	☑	☑	☑	☑	☑	☑	Constant waste fraction		☑		8×6

Sc optimizing scenario, *WT* waste type, *PWF* periodic waste fraction

Table 5 Lower bounds and upper bounds of H_2S modeling optimization variables for Sectors 5 and 6

	Sector	FCD	BCD
Optimization range for k_{H_2S} (y^{-1})	5	0.10–0.90	0.10–0.90
	6	N.A	0.10–0.90
Optimization range for S_0 ($m^3\ H_2S\ t^{-1}$)	5	0.04–7	0.01–10
	6	N.A	0.01–10

generation from nine U.S. northeastern CD landfills and obtained$k_{H_2S} = 0.50 - 0.88y^{-1}$. This study identified some empirical information of the same type through trial and error. As presented in Table 6, the number of variables was 4 for scenario 1 and 6 for scenario 2, and both used a genetic algorithm.

Results and discussion

CH_4 modeling

Figure 2 shows the results of two benchmark scenarios. The unrealistic results of these studies indicate the necessity of considering different waste types, various periodic waste fractions, and several landfill sectors. The first benchmark scenario had a higher k_{CH_4} (0.70 y^{-1}) and L_0 (170 $m^3\ CH_4\ t^{-1}$ MSW) than the second one (k_{CH_4} =0.05 y^{-1} and L_0=110 $m^3\ CH_4\ t^{-1}$ *MSW*), yet both of them led to significantly high RSS values (198,439 for the first and 49,110 for the second).

Figure 3 illustrates the relative measured and modeled total CH_4 generation of optimizing scenarios 1 to 12. Based on the figures, the highest RSS values were obtained for scenarios 1 (two waste types, one periodic waste fraction, one sector for the whole landfill, RSS: 7709) and 7 (four waste types, one periodic waste fraction, one sector for the whole landfill, RSS: 7659), and the lowest RSS values were obtained for scenarios 4 (two waste types, one periodic waste fraction, six sectors, RSS: 785) and 12 (four waste types, constant three periodic waste fraction, six sectors, RSS: 676). Scenarios 1 and 7 considered the whole landfill as one sector, not six sectors, for only one periodic waste fraction. Their high RSS value reveals they do not coincide with measurement and need refining. A comparison of scenarios 2 (two waste types, three periodic waste fractions, one sector for the whole landfill, RSS: 1550) and 3 (two waste types, constant three periodic waste fractions, one sector for the whole landfill, RSS: 1541) shows that the initial input for the waste fraction in scenario 3 was very close to reality, leading to negligible improvement by optimization. These periodic waste fractions were taken from internal reports. Scenario 4 (two waste types, one periodic waste fraction, six sectors, RSS: 785) has the lowest RSS for the two-type waste modeling series. It indicates the importance of considering sectors individually in the analysis. In scenarios 5 (two waste types, three periodic waste

Table 6 H_2S modeling optimization variables in each scenario

Scenario	Sector	FCD k_{H_2S}	FCD S_0	BCD k_{H_2S}	BCD S_0	No. of variables
1	5	☐[1]	☐	☑[2]	☑	4
	6	N.A.[3]	N.A.	☑	☑	
2	5	☑	☑	☑	☑	6
	6	N.A.	N.A.	☑	☑	

[1] Equal to that of BCD

[2] Optimization variable

[3] Not applicable since Sector 6 did not contain FCD

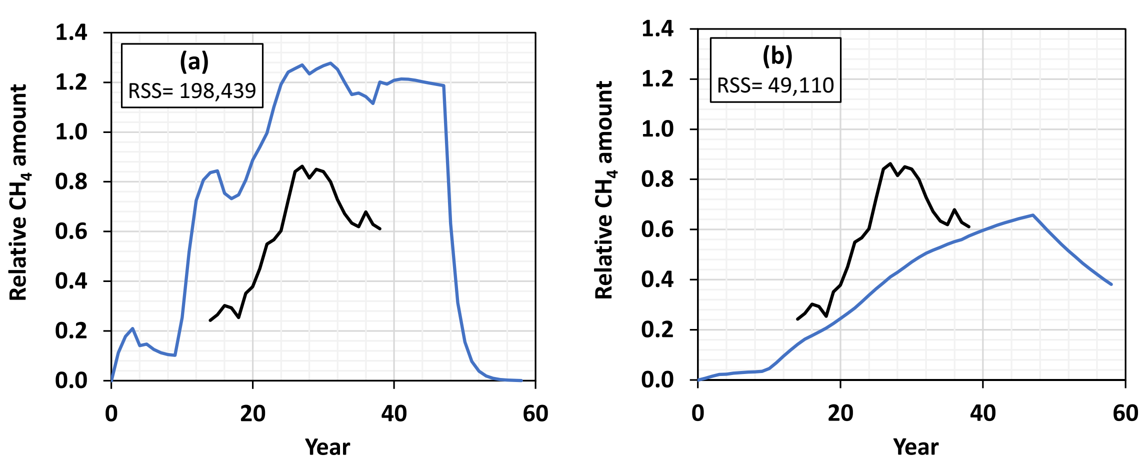

Fig. 2 Benchmark CH_4 modeling using k_{CH_4} and L_0 of **a** Nikkhah et al. (2018) and **b** Ramprasad et al., (2022) in relative values due to data confidentiality (black line is measured and blue line is modeled)

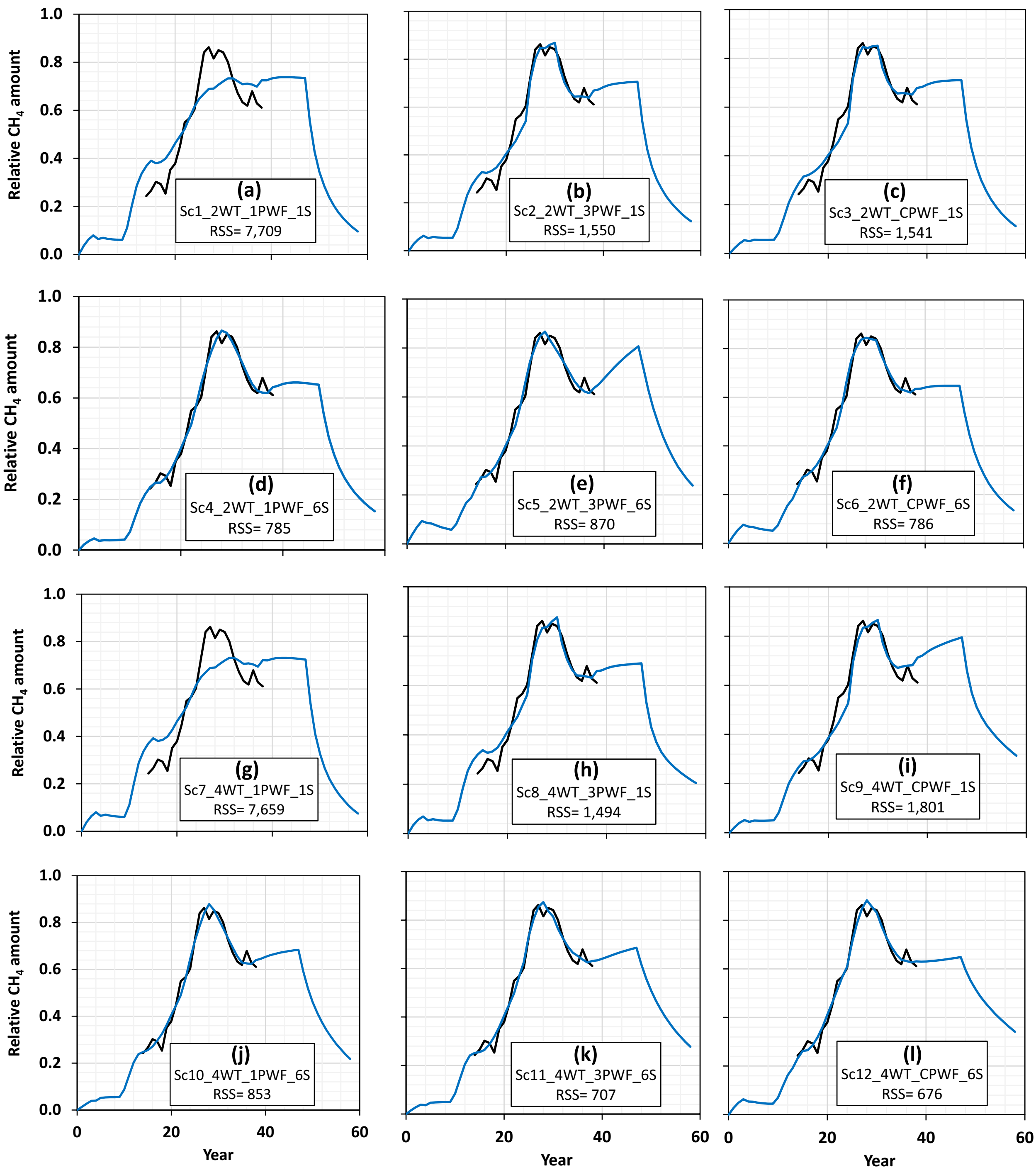

Fig. 3 Measured (black line) and modeled (blue line) total CH_4 generation of optimizing scenarios 1 to 12 (a to l) in relative values due to data confidentiality

fractions, six sectors, RSS: 870) and 6 (two waste types, constant three periodic waste fractions, six sectors, RSS: 786), although multiple variables have been added, RSS is greater than the RSS of scenario 4. Since different sectors are filled with waste at different times, considering six sectors already indicates that we have 6 periods of time. Hence, assuming three additional periods is not necessary. Similar to the two-type waste modeling series, scenarios 8 (4 waste types, three periodic waste fractions, one sector for the whole landfill, RSS: 1494) and 9 (four

Table 7 Optimized k_{CH_4} (y^{-1}) and L_0 (m^3 CH_4 t^{-1}) and periodic waste fraction (-) for optimizing scenarios of CH_4 modeling, (a) FDR and SDR, (b) food, yard, paper, and wood

(a) Optimized variables	k_{CH_4}	L_0	k_{CH_4}	L_0	*PWF_1*	*PWF_2*	*PWF_3*
Waste type	*FDR*	*FDR*	*SDR*	*SDR*	*FDR*	*FDR*	*FDR*
Sc1_2WT_1PWF_1S	0.70	243.25	0.15	78.23	0.15	–	–
Sc2_2WT_3PWF_1S	0.70	124.10	0.12	91.74	0.22	0.60	0.31
Sc3_2WT_CPWF_1S	0.70	108.39	0.13	98.16	0.10	0.60	0.30
Sc4_2WT_1PWF_6S	0.67	139.56	0.17	62.27	0.11	–	–
	0.70	97.85	0.03	132.55	0.28	–	–
	0.24	190.31	0.07	148.09	0.20	–	–
	0.41	39.52	0.15	167.39	0.27	–	–
	0.70	130.41	0.06	70.80	0.17	–	–
	0.49	91.52	0.11	77.91	0.34	–	–
Sc5_2WT_3PWF_6S	0.64	206.33	0.04	53.40	0.14	0.57	0.45
	0.59	80.69	0.13	197.47	0.27	0.36	0.33
	0.22	148.11	0.10	108.92	0.29	0.58	0.40
	0.50	72.81	0.15	152.99	0.13	0.35	0.31
	0.32	97.36	0.09	37.92	0.32	0.55	0.50
	0.18	129.82	0.05	185.90	0.31	0.42	0.59
Sc6_2WT_CPWF_6S	0.57	169.44	0.16	40.05	0.10	0.60	0.30
	0.58	266.65	0.10	129.90	0.10	0.60	0.30
	0.65	114.21	0.13	115.58	0.10	0.60	0.30
	0.61	50.58	0.12	222.91	0.10	0.60	0.30
	0.44	86.13	0.12	65.70	0.10	0.60	0.30
	0.39	113.80	0.10	87.18	0.10	0.60	0.30

(b) Optimization variables	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	k_{CH_4}	L_0	*PWF_1*			*PWF_2*			*PWF_3*		
Waste type	**Food**	**Food**	**Yard**	**Yard**	**Paper**	**Paper**	**Wood**	**Wood**	**Food**	**Yard**	**Paper**	**Food**	**Yard**	**Paper**	**Food**	**Yard**	**Paper**
Sc7_4WT_1PWF_1S	0.66	104.86	0.18	68.70	0.08	170.07	0.04	240.95	0.39	0.38	0.38	–	–	–	–	–	–
Sc8_4WT_3PWF_1S	0.69	267.53	0.10	21.03	0.08	75.49	0.05	123.80	0.16	0.12	0.12	0.29	0.30	0.29	0.16	0.30	0.27
Sc9_4WT_CPWF_1S	0.70	220.64	0.20	21.00	0.06	57.00	0.05	158.20	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
Sc10_4WT_1PWF_6S	0.62	65.49	0.14	63.90	0.07	156.88	0.04	16.49	0.39	0.20	0.35	–	–	–	–	–	–
	0.47	24.75	0.15	99.51	0.06	98.75	0.05	214.31	0.11	0.27	0.15	–	–	–	–	–	–
	0.53	98.08	0.17	161.56	0.07	288.43	0.04	35.92	0.11	0.11	0.39	–	–	–	–	–	–
	0.20	109.55	0.20	166.45	0.07	182.60	0.03	143.42	0.31	0.32	0.31	–	–	–	–	–	–
	0.67	38.25	0.18	41.89	0.07	98.40	0.05	131.30	0.32	0.31	0.37	–	–	–	–	–	–
	0.61	51.40	0.14	112.65	0.06	331.45	0.04	15.38	0.26	0.38	0.12	–	–	–	–	–	–
Sc11_4WT_3PWF_6S	0.66	161.90	0.11	153.87	0.07	346.58	0.04	17.36	0.16	0.10	0.14	0.21	0.17	0.19	0.21	0.29	0.19
	0.55	109.61	0.14	56.65	0.08	122.27	0.03	185.71	0.12	0.16	0.14	0.18	0.22	0.20	0.15	0.21	0.17
	0.36	82.76	0.12	182.47	0.08	336.13	0.05	154.87	0.14	0.13	0.15	0.24	0.19	0.17	0.21	0.21	0.18
	0.44	191.27	0.18	97.57	0.07	72.54	0.05	121.45	0.15	0.16	0.11	0.28	0.23	0.25	0.20	0.20	0.23
	0.38	146.74	0.11	103.24	0.08	92.89	0.03	82.24	0.19	0.20	0.15	0.25	0.27	0.30	0.16	0.15	0.16
	0.67	18.21	0.17	180.26	0.07	299.47	0.04	78.25	0.19	0.18	0.17	0.17	0.17	0.22	0.29	0.16	0.15
Sc12_4WT_CPWF_6S	0.68	179.35	0.12	173.05	0.06	97.82	0.04	83.87	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
	0.61	297.24	0.18	163.77	0.07	368.73	0.04	83.44	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
	0.17	172.41	0.11	208.26	0.08	321.69	0.05	201.18	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
	0.40	105.71	0.17	114.64	0.07	202.09	0.04	173.17	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
	0.64	33.18	0.12	63.22	0.07	238.09	0.03	25.53	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15
	0.64	54.01	0.12	38.68	0.06	159.64	0.03	167.25	0.10	0.10	0.10	0.30	0.30	0.30	0.15	0.15	0.15

Sc optimizing scenario, *PWF* periodic waste fraction waste types, constant three periodic waste fractions, one sector for the whole landfill, RSS: 1801) were better than scenario 7; however, the constant periodic waste fraction didn't decrease the RSS of scenario 9. Again, similar to the two-type waste modeling series, the impact of considering individual sectors improved the modeling results for scenarios 10 (four waste types, one periodic waste fraction, six sectors, RSS: 853), 11 (four waste types, three periodic waste fractions, six sectors, RSS: 707), and 12 (four waste types, constant three periodic waste fractions, six sectors, RSS: 676). Among these scenarios, scenario 12 had the lowest RSS, indicating the importance of waste segregation and analyzing sectors individually. The slight difference in RSS of scenarios 11 and 12 indicates that considering periods seems unnecessary. Finally, it can be concluded that waste segregation improved the modeling accuracy.

Optimized k_{CH_4} (y^{-1}), L_0 (m^3 CH_4 t^{-1}), and periodic waste fractions (%) of optimizing scenarios 1 to 12 are shown in Table 7. k_{CH_4} values of scenario 4 (two waste types, one periodic waste fraction, six sectors), as the best scenario among the two-type waste modeling series, ranged from 0.24 to 0.70 y^{-1} for FDR and 0.03 to 0.17 y^{-1} for SDR. L_0 values of this scenario ranged from 39.52 to 190.31 m^3 CH_4 t^{-1} for FDR and 62.27 to 167.39 m^3 CH_4 t^{-1} for SDR. Also, the FDR fraction changed from 11% for sector 1 to 34% for sector 6. k_{CH_4} values of scenario 12 (four waste types, constant three periodic waste fractions, 6 sectors), as the best scenario among the four-type waste modeling series, ranged from 0.17 to 0.68 y^{-1} for food, 0.11 to 0.18 y^{-1} for yard, 0.06 to 0.08 y^{-1} for paper, and 0.03 to 0.05 y^{-1} for wood. L_0 values of this scenario ranged from 33.18 to 297.24 m^3 CH_4 t^{-1} for food, 38.68 to 208.26 m^3 CH_4 t^{-1} for yard, 97.82 to 368.73 m^3 CH_4 t^{-1} for paper, and 25.53 to 201.18 m^3 CH_4 t^{-1} for wood. MSW contains inerts, and hence, the L_0 of MSW should be lower than the L_0 of biodegradable waste considered in this study.

Table 8 Optimized k_{H_2S} (y^{-1}) and S_0 (m^3 H_2S t^{-1}) of FCD and BCD for H_2S modeling

Optimized variables **Waste type**		k_{H_2S} FCD	S_0 FCD	k_{H_2S} BCD	S_0 BCD
Scenario 1	Sector 5	0.10	15.98	0.10	15.98
	Sector 6	–	–	0.89	1.50
Scenario 2	Sector 5	0.10	3.36	0.10	35.91
	Sector 6	–	–	0.10	4.11

One of the limitations of this study is that the effect of LFG collection efficiency variation was not considered. Hence, it could be optimized within the range of 0.75–0.95 and added to the best scenarios from 1 to 12 based on their results for future studies. Moreover, the waste characterization data is required to model the gas generation. However, landfills usually lack such data and occasionally conduct waste characterization studies. In addition, the interaction of H_2S and CH_4 generation was not considered.

H_2S modeling

Figure 4 shows the relative measured and modeled total H_2S generation of scenarios 1 and 2. Both scenarios estimated the measurement values well and had an almost similar RSS value. Scenario 2 with six variables had a RSS value equal to 1,027,which was 1,049 for scenario 1. Optimized k_{H_2S} (y^{-1}) and S_0 (m^3 H_2S t^{-1}) of these scenarios are shown in Table 8. Optimized k_{H_2S} of FCD and BCD is 0.10 y^{-1} for sector 5 in both scenarios and optimized k_{H_2S} of BCD is 0.89 and 0.10 y^{-1} for sector 6 in scenarios 1 and 2, respectively. The higher k_{H_2S} of BCD

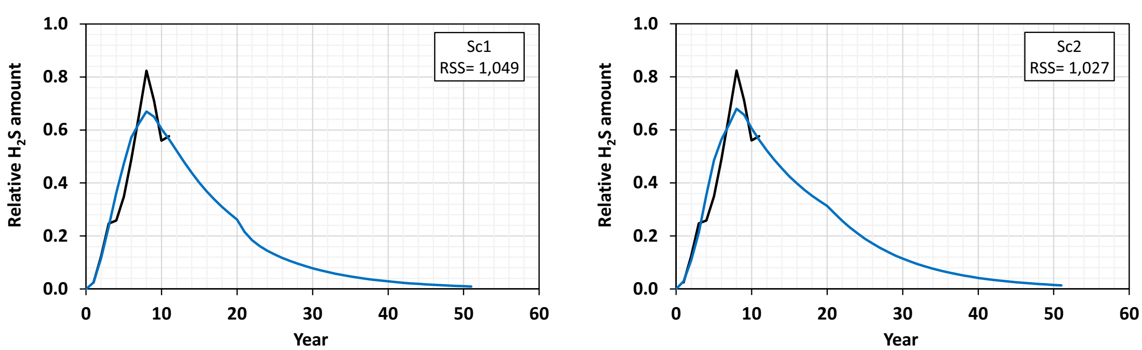

Fig. 4 Measured (black line) and modeled (blue line) total H_2S generation of scenarios 1 and 2 in relative values due to data confidentiality

($0.89\ y^{-1}$) led to a lower S_0 ($1.50\ m^3\ H_2S\ t^{-1}$). Anderson et al. (2010) reported $k_{H_2S} = 0.50 - 0.88y^{-1}$ from nine U.S. northeastern CD landfills. Optimized S_0 of FCD and BCD is 15.98 $m^3\ H_2S\ t^{-1}$ for sector 5 in scenario 1, and 3.36 and 35.91 for scenario 2, respectively. In addition, the optimized S_0 of BCD is 4.11 $m^3\ H_2S\ t^{-1}$ for sector 6 in scenario 2. Further data could improve H_2S generation modeling.

Conclusion

Fitting parameters was done in this paper to a CH_4 and H_2S generation model by applying a genetic algorithm based on a modified first-order decay model. To predict CH_4 generation, two benchmark and twelve optimizing scenarios were considered. The benchmark scenarios did not consider any change in modeling parameters, such as waste type, periodic waste fraction or landfill sectors. These scenarios led to impractical and unworkable residual sum of square (RSS) values. Hence, applying the LandGEM model should be done by considering different parameters to approach the actual condition of landfill gas (LFG) generation in landfills.

In addition to benchmark scenarios, twelve optimizing scenarios were considered. Scenarios 1 to 6 divided the organic waste (OW) into fast decaying refuse (FDR) and slow decaying refuse (SDR). Scenarios 7 to 12 assumed four types of OW: food waste, yard waste, paper, and wood. In all the scenarios, the OW fractions, CH_4 generation potential (L_0), and CH_4 generation rate (k_{CH_4}) were optimized. In addition, some scenarios optimized the parameters mentioned for six landfill sectors, while others considered the landfill as one sector. Moreover, in some scenarios, the landfill's lifetime was subdivided into three distinct periods reflecting the specific history of refuse admittance based on changes in waste characteristics. The results showed that the differentiation of more waste types improves the modeling accuracy for CH_4. Scenarios 11 and 12 considered four waste types of 6 landfill sectors and had the best predictions, proving that waste characterization is a significant factor in gas prediction. Additionally, since different sectors were filled with waste at different times, assuming 6 sectors in the modeling already indicated six periods. Hence, considering three additional periods for the landfill's lifetime was unnecessary. Finally, all the scenarios that assumed 6 landfill sectors had a better parameter fit to real data.

For H_2S generation modeling, H_2S generation potential (S_0), and H_2S generation rate (k_{H_2S}) of fines (FCD) and bulky materials (BCD) of the construction and demolition waste (CD) were optimized. Based on the results, both scenarios had an effective prediction with a similar RSS value. If further data could be provided to the model, more improvements could be achieved.

Abbreviations

BCD	Bulky materials of construction and demolition waste
CD	Construction and demolition waste
CH_4	Methane
CO_2	Carbon dioxide
FCD	Fines of construction and demolition waste
FDR	Fast decaying refuse
GHG	Greenhouse Gas
H_2S	Hydrogen sulfide
k_{CH4}	CH_4 generation rate (y^{-1})
k_{H2S}	H_2S generation rate (y^{-1})
L_0	CH_4 generation potential ($m^3\ CH_4/t$ *biodegradable waste*)
LandGEM	Landfill gas emissions model
LFG	Landfill gas
MSW	Municipal solid waste
OW	Organic waste
PWF	Periodic waste fraction
RSS	Residual sum of squares
S_0	H_2S generation potential ($m^3\ H_2S/t$ *sulphur*)
SDR	Slow decaying refuse

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40068-023-00292-w.

Additional file 1: Table S1. Waste segregation and corresponding k_{CH4} values, biodegradation half-life in years^{-1} for OW in a landfill, based on IPCC recommended ranges [adapted from IPCC (IPCC 2019)]. **Table S2.** Number, name, and description of optimizing scenarios for CH_4 modeling.

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TM prepared the whole article. DL and UE contributed in review and editing. All authors read and approved the final manuscript.

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Declarations

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Competing interests
The authors declare that there are no competing interests.

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