

1 Quantifying meteorological impacts on local landfill methane 2 emissions by using field measurements and machine learning

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9
10 **Abstract.** Landfills are a major anthropogenic source of methane (CH₄), contributing up to 20%
11 of global CH₄ emissions. Although CH₄ emissions from landfills are highly sensitive to
12 meteorological conditions, their response to climate variations remains not fully understood,
13 leading to substantial uncertainty in emission projections under climate change. This study
14 evaluated the impact of meteorological factors on landfill CH₄ generation, using a site-specific
15 machine-learning-based model optimized for temperature and precipitation. The model
16 optimized for meteorological conditions performed better than conventional models such as
17 LandGEM and the IPCC model, with a root mean squared error (RMSE) of 6.57 million m³
18 CH₄, a mean absolute error (MAE) of 4.91 million m³ CH₄, and Pearson correlation coefficients
19 of 0.89, when compared with field measurements. CH₄ generation exhibited a linear correlation
20 with increasing temperature, and a parabolic response to increasing precipitation.
21 Quantification of the contributions of the meteorological variables, revealed that temperature
22 accounted for 5.96 ± 3.06 %, and precipitation for 7.38 ± 0.58 % of the total modeled CH₄
23 generation. These results highlight the high importance of incorporating meteorological
24 variability into landfill CH₄ estimation to improve predictive accuracy, and emphasize the need
25 for stronger and faster CH₄ mitigation efforts under climate change.

26
27 Keywords: Methane; Landfill gas; Emissions; Machine learning; Climate change

1. Introduction

Methane (CH₄) is a major greenhouse gas (GHG) emitted into the atmosphere from various natural and anthropogenic sources (Saunois et al., 2024). CH₄ has a high global warming potential (GWP), 28 times greater than that of carbon dioxide (CO₂) over a 100-year period (Myhre et al., 2013). It accounts for approximately 16 % of anthropogenic GHG emissions (US-EPA, 2012), and has contributed to approximately 30 % to global warming since the Industrial Revolution (IEA, 2022; Masson-Delmotte et al., 2021). Owing to its relatively short atmospheric lifetime (approximately 9–12 years) (Prather et al., 2012; Solomon et al., 2007) and strong GWP, reducing anthropogenic CH₄ emissions is one of the most effective strategies for mitigating climate change (Montzka et al., 2011). Consequently, the number of countries participating in the Global Methane Pledge has increased from about 100 to 159, with all committing to a 30 % reduction in CH₄ emissions from 2020 levels by 2030 (European Commission and United States of America, 2021). To achieve this goal, it is essential that a considerable number of countries accurately monitor, estimate and verify their CH₄ emissions.

Approximately 60 % of global CH₄ emissions originate from anthropogenic sources, including natural gas facilities, agriculture and waste management (Saunois et al., 2024). Of these, landfills represent a significant source, accounting for approximately 19 % of anthropogenic CH₄ emissions, making them the third-largest source after agriculture and the fossil fuel sector (Saunois et al., 2024). Moreover, rapid population growth, industrialization, and urbanization have led to the accumulation of large amounts of waste in landfills, and the contribution is even greater at the urban scale (Kumar et al., 2016). For example, in certain megacities, including Buenos Aires and Seoul, the contribution of landfills to total CH₄ emissions is up to 50 % (Maasackers et al., 2022; SCNSC, 2024), which is as high as the CH₄ emissions from the oil and gas industry (Wang et al., 2024). Furthermore, it has been estimated that future CH₄ emissions from landfills in urban areas will increase considerably due to ongoing waste generation, rapid urbanization, and population growth (Kaza et al., 2018).

Landfill gas (LFG) is generated via the anaerobic decomposition of organic waste by microorganisms (Kim & Townsend, 2012; Themelis & Ulloa, 2007). The produced LFG typically contains 40–60 % CH₄, which is used as an energy source or burned in flares (Tchobanoglous et al., 1993; Themelis & Ulloa, 2007). However, some gases escape into the

1 atmosphere through soil pores, contributing to CH₄ emissions (Fjelsted et al., 2020). Owing to
2 the low efficiency of LFG collection systems, as well as inadequate landfill site management,
3 an estimated 12.4 % to 74.1 % of CH₄ emissions can be released into the atmosphere (Bian et
4 al., 2021). Even after landfill closure, the decomposition process continues until the major
5 organic materials are completely degraded (Mønster et al., 2019). Therefore, an accurate
6 estimation of LFG generation, collection efficiency, and fugitive CH₄ emissions is required for
7 effective landfill management and GHG regulation (Amini et al., 2013).

8 Various measurement methods have been used to quantify landfill CH₄ emissions,
9 including the flux chamber method (Jeong et al., 2019; Reinhart et al., 1992; Yilmaz et al.,
10 2021), differential absorption light detection and ranging (LiDAR/DIAL) (Innocenti et al.,
11 2017; Robinson et al., 2011), unmanned aerial vehicles (UAVs/drones) (Daugėla et al., 2020;
12 Kim et al., 2021), airborne (Cusworth et al., 2024) and satellite technologies (Maasakkers et
13 al., 2022; Nesser et al., 2023). These methods have been shown to directly measure CH₄
14 emissions from landfills, thereby providing more accurate estimates through measurement-
15 based quantification (Mønster et al., 2019). Recent studies have demonstrated significant
16 improvements in the quantification of CH₄ emissions by using observation-based methods
17 (Fosco et al., 2024; Tyagi et al., 2025). For example, satellite observations have identified
18 substantial CH₄ emission hotspots at major landfill sites worldwide, contributing to more
19 comprehensive emission assessments (Maasakkers et al., 2022). Furthermore, the use of
20 multiple field measurement techniques has proven beneficial, as each method complements
21 another (Cambaliza et al., 2017). However, accessibility limitations, labor requirements, and
22 financial constraints make the continuous monitoring of landfill measurements difficult (Kormi
23 et al., 2018; Mønster et al., 2019).

24 To address this measurement difficulty, numerous studies have been conducted on
25 numerical models for estimating CH₄ generation. First-order decay (FOD) models have been
26 developed to estimate LFG and CH₄ generated in landfills. These models assume that the
27 degradable organic matter in waste decays at a relatively slow rate over several decades.
28 Because of their easy applicability and user-friendliness, FOD models, including the
29 Intergovernmental Panel on Climate Change (IPCC) Waste Model, Landfill Gas Emission
30 Model (LandGEM), and Capturing Landfill Emissions for Energy Needs (CLEEN) models, are
31 the most widely adopted approaches (Vu et al., 2017). The IPCC guidelines proposed an IPCC

1 waste model, which is based on the FOD, to support countries in estimating landfill CH₄
2 emissions. The model's individual values for the CH₄ generation potential and CH₄ generation
3 rate constants are derived from the degradable organic carbon (DOC) contained in various
4 waste fractions (Eggleston et al., 2006). The LandGEM model was developed by the United
5 States Environmental Protection Agency (US EPA) for the estimation of landfill emissions and
6 is typically applied using information on the amount and composition of municipal solid waste
7 (MSW), as well as its treatment methods. LandGEM provides an estimate of the evolution of
8 cumulative LFG emissions over time (Alexander et al., 2005). Meanwhile, the CLEEN model
9 is an experiment-based model that estimates CH₄ generation as a function of waste composition,
10 the ambient temperature, and landfill precipitation in the landfill. Based on microbial
11 degradation reactions observed in municipal solid waste experiments, the CLEEN model
12 proposes an equation that links the rate of waste decomposition in landfills to meteorological
13 conditions (Karanjekar et al., 2015).

14 Although previous models have been useful for estimating landfill CH₄ emissions, they
15 are insufficient for predicting future emissions under changing climate conditions. Landfill
16 CH₄ generation is driven by the anaerobic microbial degradation, and meteorological
17 conditions strongly influence the extent and rate of these biological processes. (Bai et al., 2025;
18 Scheutz et al., 2009; Sacramento et al., 2024). In regions with pronounced seasonality, such as
19 Korea, microbial decomposition rates vary substantially with seasonal changes in temperature
20 and moisture (Kang et al., 2024; Park et al., 2001). In the FOD models, the CH₄ generation rate
21 constants (k) represents the biodegradation rate of organic matter in landfills (Purmessur &
22 Surroop, 2019), however the IPCC and LandGEM models remain too simplified to consider
23 climate impacts, using default k values based on climate zones (Alexander et al., 2005;
24 Eggleston et al., 2006). As climate change is expected to intensify landfill CH₄ emissions,
25 accurately representing and quantifying the impacts of meteorological drivers on CH₄
26 generation is becoming increasingly important (Fei et al., 2021). By contrast, the CLEEN
27 model, which explicitly incorporates temperature and precipitation, appears to reproduce field-
28 based emissions well. However, further calibration and optimization of these parameters are
29 required before the model can be applied to other regions. (Karanjekar et al., 2015).

30 In this study, we aim to assess the impacts of meteorological conditions on landfill CH₄
31 generation and to evaluate their implications for future climate change. Existing models

1 simplify the application of meteorological factors, thereby limiting their ability to fully reflect
2 actual landfill emission dynamics. To address this limitation, we propose a machine-learning-
3 based methodology that optimizes an effective emission factor using field measurement data
4 from the Sudokwon Landfill Site, one of the largest landfills in the world. The optimized model
5 is then applied to quantify the effects of meteorological conditions on landfill CH₄ emissions,
6 identify site-specific features and suggest mitigation strategies.

7 8 **2. Methodology and Data**

9 2.1. Site description

10 The study area was the SLS, the largest sanitary landfill located on the west coast of
11 Incheon, Korea (Fig. 1). It is in a temperate climate zone with an average annual temperature
12 and precipitation of 12.5°C (-18.2°C to 37.2°C) and 1219.7 mm (652 mm to 1777.7 mm),
13 respectively, during 1991–2023. From February 1992, SLS received about 20,000 tons of solid
14 waste daily generated by 5.3 million people in the Seoul metropolitan area, representing the
15 largest amount globally (Owlcation, 2024). The SLS contains two separate closed landfill sites.
16 The Table 1 provides an overview of these two sites. The first landfill site (SLS 1) received
17 approximately 64.25 Mt of waste in an area of 2.5 km² between February 1992 and October
18 2000, while the second landfill site (SLS 2) received 80.18 Mt of waste in an area of 2.6 km²
19 from October 2000 to October 2018.

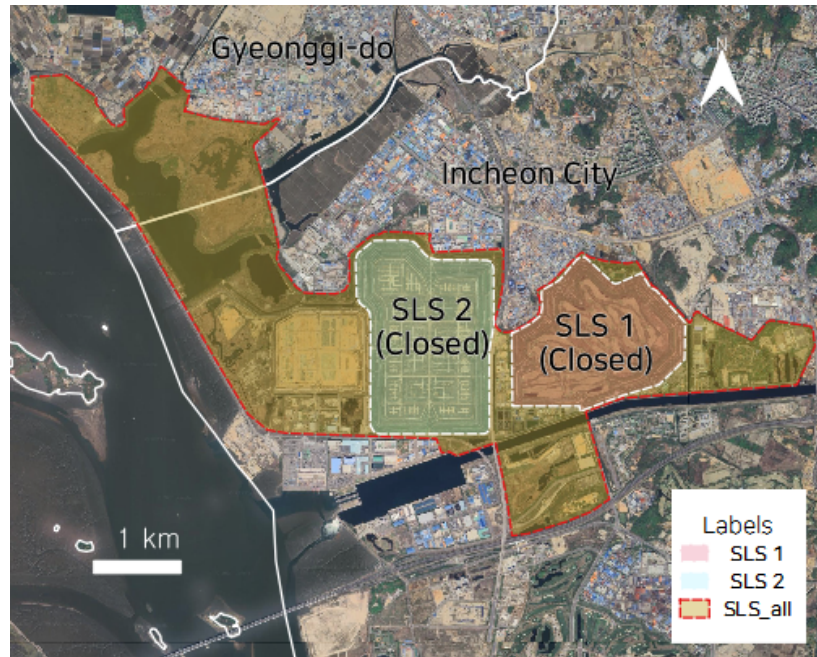


Fig. 1 The Sudokwon landfill site description. The background map is sourced from Google Maps © Google Maps

Table 1. Landfill operational conditions

	SLS 1	SLS 2
Operation Period	February 1992–October 2000	October 2000–October 2018
Landfilled area / Site area (m ²)	2,500,000 / 4,088,832	2,620,000 / 3,778,881
Total waste (tons)	64,250,000	80,180,000
Average waste intake (ton d ⁻¹)	19,560	11,540
Type of waste	Combustible (91.3 %); food (34.1 %), paper (27 %), plastics (18.7 %), textile (4.7 %), yard (1.4 %) and Others (5.4 %)	Combustible (93 %); food (11.8 %), paper (41.4 %), plastics (26.6 %), textile (5 %), yard (1.2 %) and Others (7 %)

2.2. Data

Data on the amount of waste deposited monthly from 1998 to 2021 were acquired from the Sudokwon Landfill Site Management Corporation (SLC) platform (<https://dream-ics.slc.or.kr/>, last access: 1 July 2025). According to a long-term monitoring reports, the yearly composition of waste was examined and collected for the period from 1998 to 2021 (SLC, 2023). The typical MSW composition, along with the mean values, in SLS 1 was: food ($34.1 \pm 2.8 \%$), paper ($27 \pm 2.4 \%$), plastic ($18.7 \pm 3 \%$), textile ($4.7 \pm 0.4 \%$), and wood ($1.4 \pm 0.4 \%$), while the composition in SLS 2 was: food ($14.5 \pm 9.8 \%$), paper ($40.2 \pm 7 \%$), plastic ($26.1 \pm 4.7 \%$), textile ($5.0 \pm 1.1 \%$), and wood ($1.2 \pm 0.6 \%$).

The Biochemical Methane Potential (BMP) values were used to ascertain the CH_4 generation potential (L_0) of the SLS. The BMP assay is a widely used method for predicting the CH_4 generation rate and potential of MSW (Sil et al., 2014). SLS 1 had $40.2 \text{ m}^3 \text{ CH}_4 \text{ Mg}^{-1}$, median value of $33.7\text{--}46.7 \text{ m}^3 \text{ CH}_4 \text{ Mg}^{-1}$ (Park et al., 2019), while SLS 2 had $47.5 \text{ m}^3 \text{ CH}_4 \text{ Mg}^{-1}$, with a median value of $37\text{--}58 \text{ m}^3 \text{ CH}_4 \text{ Mg}^{-1}$ (Jeon et al., 2007).

The field measurement data for CH_4 generation were provided by the SLC (SLC, 2020; SLC, 2022). Observations were conducted on a seasonal basis from 2005 to 2021, along the major LFG emission path: gas recovery, gas flaring, and surface emissions (Fig. S1 and Fig. S2). The SLS operates an electricity generation plant that captures LFG with a 50-MW steam turbine, with an average daily collection rate of $501.5 \text{ m}^3 \text{ min}^{-1}$. Some of the gas that was not injected into the power generation process was transported to a centralized combustion facility for flaring. The gas incinerator at SLS 1 has not been operational since its final decommissioning in 2004, and SLS 2 was operated for a short period between 2004 and 2007, after which it was restarted in 2011. The landfill surface emissions were quantified using the flux chamber method, which offers the advantages of accuracy, simplicity, and flexibility compared to other measurement techniques (Reinhart et al., 1992). The measurements were conducted using the open-flux chamber method, with 39 measurement points at SLS 1 and 130 measurement points at SLS 2. Quantification of oxidized CH_4 is challenging because it was estimated based on stable carbon isotope ratios. Therefore, this model used the fraction of CH_4 oxidized at 10 %, which is the value recommended by the IPCC guidelines (Eggleston et al.,

1 2006).

2 Meteorological data were obtained from the Korea Meteorological Administration
3 (<https://data.kma.go.kr/>, last access: 1 July 2025). To align the temporal resolution of the
4 weather data with the field measurement period, the monthly temperature and precipitation
5 values were aggregated into three-month seasonal periods. Specifically, December–February
6 was defined as winter, March–May as spring, June–August as summer, and September–
7 November as autumn. For each season, the average temperature and precipitation across the
8 three months were used as representative seasonal values. This seasonal aggregation allowed
9 for a consistent comparison with the CH₄ emission measurements, which were available on a
10 seasonal basis

11

12 2.3. Method used to estimate CH₄ generation

13 The proposed landfill CH₄ generation estimation model, CLEEN_{opt}, is a locally
14 optimized model that reflects local landfill environments. The model is based on the FOD
15 equation, which has two critical factors: L_0 and k . L_0 depends on the composition and
16 degradable organic content of the waste, while k depends on the waste composition, waste
17 particle size, temperature, moisture, and pH (Amini et al., 2012; Lay et al., 1996; Machado et
18 al., 2009). The CLEEN_{opt} model calibrates the laboratory-based k_{lab} to reflect individual landfill
19 characteristics, including field measurements and meteorological data. The flowchart in Fig. 2
20 describes the main steps used to implement the improved method for calculating landfill
21 emissions.

22

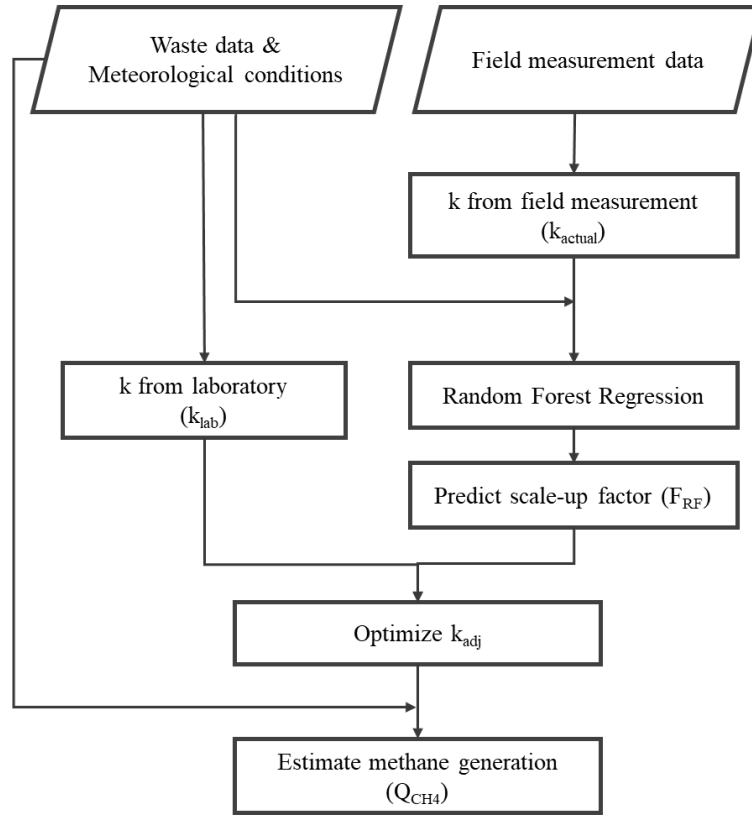


Fig. 2 The CLEEN_{opt} model flow chart

2.3.1. Estimating laboratory-based k_{lab}

The CLEEN model is a FOD-based model that estimates CH₄ generation by using the waste amount, waste composition, ambient temperature, and annual rainfall (Karanjekar et al., 2015). According to a statistical experimental design, the model proposed a multiple linear regression equation relating temperature, precipitation, and waste composition to microbial waste decomposition, as shown in Eq. (1).

$$\text{Log}_{10}k_{lab} = a + bR^2 + c(R \times FD) + dT - eFD + fTX + gY \quad (1)$$

where k_{lab} is the laboratory-scale FOD constant (year⁻¹), R is the average annual rainfall (mm d⁻¹), T is the ambient temperature (K), TX is the proportion of textiles in the landfilled waste

1 (%), Y is the proportion of yards in the landfilled waste (%), and FD is the proportion of food
2 in the landfilled waste (%). The value of a is -3.02658, b is -0.0067282, c is 0.00172807, d is
3 0.01046, e is -0.01152, f is 0.00418, and g is 0.00598.

4 To reflect the relationship between climatic conditions and microbial decomposition,
5 the CLEEN_{opt} model uses the laboratory-based k_{lab} . However, the values obtained under
6 idealized laboratory conditions are generally higher than those in actual landfill sites (Barlaz,
7 2006; Ress et al., 1998). The CLEEN model presents a correction factor (F) to calibrate k_{lab} to
8 the field k values based on the annual temperature and precipitation. However, the field
9 measurement data have been used at selected landfills in the United States and Israel, and its
10 applicability to landfills in other regions is limited. Therefore, we propose the CLEEN_{opt} model,
11 which can be calibrated using landfill-specific field measurements.

12 13 2.3.2. Estimating field-based k_{actual}

14 The CLEEN_{opt} model calibrates k_{lab} to k_{adj} , using landfill field measurements. CH₄
15 generation was calculated as the sum of the recovered CH₄ and CH₄ surface emissions, as
16 shown in Eq. (2) (Eggleston et al., 2006)

$$17 \quad CH_4 \text{ generated} = CH_4 \text{ recovered} + \frac{CH_4 \text{ emitted}}{CH_4 \text{ oxidized}} \quad (2)$$

18 The amount of **CH₄ recovered** was determined based on flow rate and CH₄
19 concentration data obtained from an LFG recovery system. Sanitary landfills are typically
20 equipped with vertical or horizontal wells that collect LFG, which is used as fuel to generate
21 electricity or combusted and released as CO₂. Uncaptured CH₄ gas is oxidized to CO₂ by soil
22 microorganisms or emitted directly into the atmosphere through cracks and pores on the landfill
23 surface. These pathways are referred to as **CH₄ oxidation** and **CH₄ emission**, respectively.
24 Landfill surface emissions can be measured using various techniques, including remote
25 methods (e.g., dynamic tracer gas dispersion, differential absorption Lidar [DiAL], and radial
26 plume mapping) and surface-based methods such as flux chambers (Babilotte et al., 2010;
27 Fjelsted et al., 2020; Mønster et al., 2019; US-EPA, 2006). In this study, CH₄ surface emissions
28 were quantified using the flux chamber method because of its high spatial resolution, which is

1 suitable for site-scale monitoring.

2 To estimate actual CH₄ generation, we applied inverse modeling to derive k_{actual} : by
3 reversing the predictive process of the FOD equation (Eq. [3]).

$$4 \quad \ln(k_{actual}) + k_{actual} = \ln\left(\frac{Q_{CH_4}}{M_i L_0}\right) \quad (3)$$

5 where k_{actual} is the FOD constant that best fits the observed data, Q_{CH_4} is the CH₄ generation
6 estimated from field measurements, M_i is the amount of waste disposed of, and L_0 is the
7 methane generation potential. However, k_{actual} can only be determined when field measurement
8 data are available. For periods without field measurements, we introduced a scale-up factor,
9 F_{RF} , which calibrates the relationship between k_{lab} and k_{actual} , accounting for laboratory-based
10 microbial degradation and landfill environmental conditions.

11

12 2.3.3. Improvement of factor k

13 We selected the random forest RF regression model to estimate the scale-up factors,
14 F_{RF} . RF provides high accuracy and strong generalization, as it does not assume linearity
15 between the predictor and response variables and it is insensitive to outliers. Additionally, RF
16 is a non-parametric model, that is, it does not estimate distributions based on parameters,
17 allowing it to capture complex associations between parameters and observations (Breiman,
18 2001). Therefore, RF is used in the CLEEN_{opt} model to achieve a good performance across
19 various applications.

20 The establishment of a variable was based on the factors related to the landfill organic-
21 degradation environment. The dependent variable, F_{RF} , indicates the calibrated laboratory-
22 based k_{lab} , used to reflect the field characteristics. The explanatory variables consisted of factors
23 directly related to the landfill field environment. **Precipitation** and **temperature** represent the
24 landfill meteorological conditions that affects microbial degradation. **Waste amount** is the
25 amount of waste disposed of that entered the landfill over time. **Lifespan** is the time elapsed
26 from the start of landfilling to the time of the estimation, reflecting the time required for
27 landfilled waste to decompose. L_0 is the CH₄ generation potential, which represents the amount
28 of organic matter that can be decomposed per landfill.

1 The F_{RF} derived from the trained RF model was applied in Eq. (4) to calculate k_{adj}
 2 which reflects the specific landfill environment, as follows:

$$3 \quad 4 \quad k_{adj} = F_{RF} \times k_{lab} \quad (4)$$

5 where F_{RF} is the scale-up factor and k_{lab} was calculated using Eq. (1). k_{lab} can be used
 6 to calculate an optimized k_{adj} , which reflects the field conditions of the landfill.

7 2.3.4. Estimation of CH₄ generation

8 The FOD equation used to estimate the CH₄ generation in the CLEEN_{opt} model is as
 9 follows:
 10

$$11 \quad Q_{CH_4} = \sum_{i=0}^n \sum_{j=0}^a k_{adj} \frac{M_i}{a} L_0 e^{-k_{adj} t_{ij}} \quad (5)$$

12 where Q_{CH_4} is the amount of CH₄ generated (m³ y⁻¹), M_i is the mass of MSW landfilled in
 13 year i within the landfill (Mg), k_{adj} is the calibrated FOD constant (y⁻¹), L_0 is the potential CH₄
 14 generation per waste (m³ Mg⁻¹), n is the total number of landfilling years, a is 1/ a^{th} of the waste
 15 deposited in the year, t_{ij} is the age of the j^{th} section of waste mass M_i in the i^{th} year.

16 To estimate CH₄ generation according to the resolution of the field data, we propose
 17 dividing a year into a month and applying the formula. For example, monthly data can be
 18 calculated by applying 12 to a . Unlike the existing CLEEN model, this method uses the value
 19 calibrated to the landfill by applying k_{adj} by equation (4).

20 L_0 is one of the main factors in the FOD and is defined as the amount of CH₄ that can
 21 be produced per unit mass of waste under ideal conditions for CH₄ formation (Krause et al.,
 22 2016). It can be estimated in various ways, using formulas such as those in the stoichiometric
 23 method, the IPCC method, or experiments such as the BMP test (Eggleston et al., 2006; Symons
 24 & Buswell, 1933).

25 2.3.5. Monte Carlo uncertainty

1 In this study, the Monte Carlo Simulation method was used to evaluate the model
2 uncertainty of the output values for each year. The Monte Carlo method is a sampling-based
3 approach that uses random samples of input parameters to simulate the probabilities of random
4 variables (Herrador & González, 2004; Kalos & Whitlock, 2009; Papadopoulos & Yeung,
5 2001). The probability distribution function of the model uncertainty was obtained from
6 randomly sampled input variables within a range of possible values. The detailed input
7 variables (\mathbf{x}_i) and their distributions are summarized in Table S1. A random experiment was
8 repeated according to the selected number of trials (M), and the output of the corresponding
9 function (\mathbf{y}_M) was determined using the estimation model. To obtain a sufficiently precise
10 sampling distribution, 1,000 random samples were utilized. The calculation for uncertainty is
11 shown in Eq. S1 and Eq. S2. In addition, to obtain a conservative coverage probability for Y ,
12 which has a discrete distribution, a 95 % confidence interval was chosen (Fig. S3).

14 2.4. Model evaluation

15 To evaluate the model performance, we compared the simulated seasonal landfill CH₄
16 generation with field measurements. Because seasonal chamber-based CH₄ surface emission
17 data were only available for the period from 2005 to 2021, the model outputs were assessed
18 over this same period. Three performance metrics were used: the root mean square error
19 (RMSE), mean absolute error (MAE), and Pearson correlation coefficients (r). Low RMSE and
20 MAE values indicate better predictive accuracy achieved by capturing underlying emission
21 patterns, while a high Pearson's r reflects a stronger correlation between the model predictions
22 and observations. In addition, for comparison with conventional models such as the CLEEN,
23 IPCC, and LandGEM models, which estimate annual CH₄ emissions, we aggregated the
24 seasonal outputs to annual scales. This allowed for a direct comparison between the field
25 measurements and existing model estimates.

27 2.5. Quantifying the impact of meteorological conditions

28 To assess the individual and synergistic effects of temperature and precipitation on
29 CH₄ generation in landfills, we designed four input scenarios, while all other model conditions

1 were kept constant: (a) using observed temperature and precipitation, (b) using a fixed mean
2 temperature (12.5 °C) and observed precipitation, (c) using observed temperature and a fixed
3 mean precipitation (3.2 mm d⁻¹), and (d) using both fixed mean temperature and precipitation.
4 The influence of each variable was quantified based on the absolute difference in the predicted
5 CH₄ generation between the baseline scenario (a) and each counterfactual scenario (b–d). The
6 mean absolute difference was then normalized according to the total predicted generation under
7 the baseline and expressed as a percentage, representing the relative absolute contribution of
8 the given variable to CH₄ generation.

10 **3. Results**

11 3.1. Optimization of model parameters

12 The RF model was developed using landfill field measurement data from the SLS,
13 with the training dataset including seasonal precipitation, temperature, lifespan, waste amount,
14 and L₀ from 2005 to 2021. A total of 128 data points was used, with 80 % allocated for training
15 and the remainder allocated for 10-fold cross-validation. The hyperparameters were optimized
16 using a grid search. The model demonstrated an R^2 value of 0.86 when evaluated against the
17 F_{RF} and landfill conditions. The significance of each feature indicates the statistical importance
18 of each parameter in the dataset and its impact on the model performance. Among the variables,
19 L₀, precipitation, and temperature were identified as the statistically significant and key
20 predictors, indicating their substantial influence on CH₄ generation. The results demonstrated
21 that CH₄ generation in landfills was primarily determined by waste composition and
22 environmental factors, particularly precipitation and temperature, which affect the waste
23 decomposition process (Krause et al., 2016; Warith & Sharma, 1998).

24 The estimated k values for each model were compared with those of k_{actual} , as
25 summarized in Table 2. The laboratory-based k_{lab} , calculated using Eq. (1), was adjusted to k_{adj}
26 using the field refinement factor (F_{RF}). For comparison, Table 2 also provides the k values used
27 in the LandGEM and IPCC models with country-specific emission factors for South Korea.
28 Among all models, k_{lab} exhibited by far the largest discrepancy from k_{actual} with errors ranging
29 from 2,585 % to 7,269 %. This overestimation arises because k_{lab} is derived under idealized

laboratory conditions, which do not fully represent the heterogeneous and often less favorable conditions in actual landfills. Regarding this, Karanjekar et al. (2015) emphasized that laboratory-derived k values must be calibrated against field data before applied to real landfill systems. The optimized k_{adj} provided the closest approximation to the k value derived from the actual field data, with an average error of 25 %. However, the k values for the IPCC and LandGEM models deviated from k_{actual} by 84 % and 112 % on average, respectively. These results showed that the substantial overestimation of the laboratory-based k_{lab} can be effectively addressed by the k_{adj} .

Table 2. Comparison of actual and modeled k values

Landfill	k values (y^{-1}) (% difference from k_{actual})				
	k_{actual}	k_{lab}	k_{adj}	LandGEM	IPCC
SLS 1	0.034 ± 0.01	0.913 ± 0.539 (+ 2585 %)	0.036 ± 0.003 (+ 6 %)	0.04 (+ 17 %)	0.046 ± 0.05 (+ 35 %)
SLS 2	0.016 ± 0.01	1.179 ± 0.336 (+ 7269 %)	0.023 ± 0.013 (+ 43 %)	0.04 (+ 150 %)	0.046 ± 0.05 (+ 188 %)

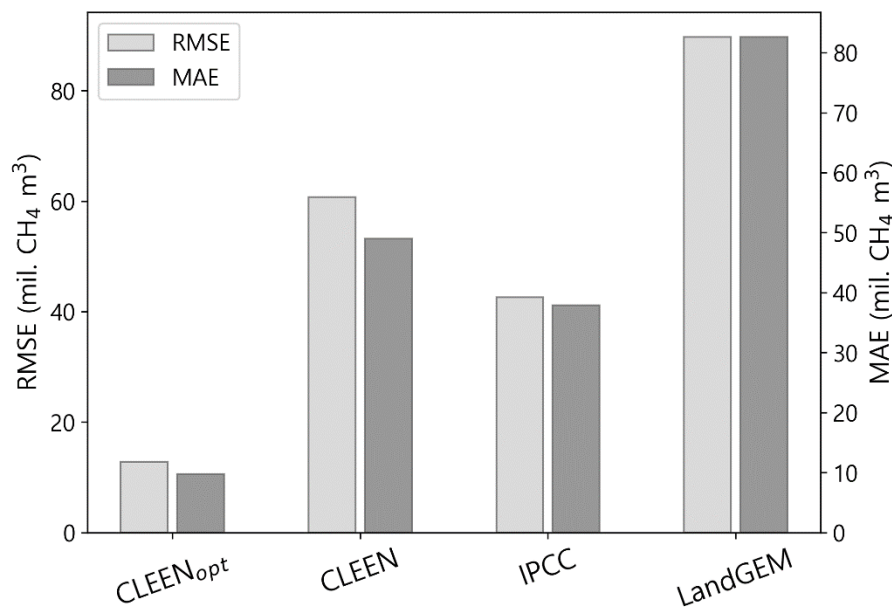
3.2. Evaluation of model performance

To evaluate model performance, CH₄ generation estimates from the CLEAN_{opt} model were compared with the observed seasonal CH₄ generation at two landfill sites (SLS 1 and SLS 2) (Table 3). The model showed strong correlations with field measurements at both sites, with a particularly high correlation at SLS 1 (RMSE = 2.22 million CH₄ m³, MAE = 1.78 million CH₄ m³, $r = 0.96$). In contrast, the model performance for SLS 2 was relatively low (RMSE = 6.48 million CH₄ m³, MAE = 4.81 million CH₄ m³, $r = 0.64$), likely because of the greater variability in field measurements caused by ongoing landfilling activities.

Table 3 The evaluation of the seasonal simulation of the CLEEN_{opt} model for SLS 1 and SLS 2

	SLS 1	SLS 2
RMSE (million CH₄ m³)	2.22	6.48
MAE (million CH₄ m³)	1.78	4.81
Pearson <i>r</i>	0.96	0.63

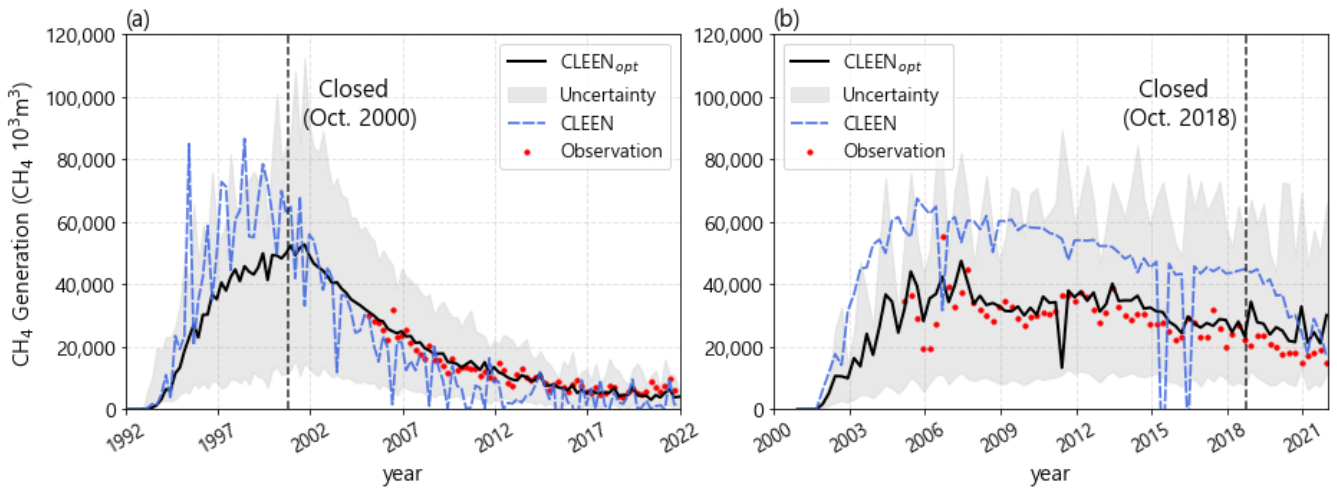
To compare the performance with conventional models such as the CLEEN, IPCC, and LandGEM models, which estimate CH₄ emissions on an annual basis, the annual CLEEN_{opt} model CH₄ generation values were used. As shown in Fig. 3, the CLEEN_{opt} model achieved the lowest RMSE and MAE (values of 12.7 million CH₄ m³ and 9.8 million CH₄ m³, respectively), demonstrating superior accuracy in simulating observed data. In terms of predictive error, the models ranked in ascending order, were IPCC, CLEEN, and LandGEM, with LandGEM exhibiting the highest RMSE and MAE values.



1 **Fig. 3. Comparisons of RMSE and MAE between observed and model estimated CH₄**
2 **generation.**

3
4 3.3. Simulation of model estimates

5 Fig. 4 shows the simulated seasonal CH₄ generation from the CLEEN_{opt} and CLEEN
6 models for SLS 1 and SLS 2. The results indicated that CH₄ generation increased during the
7 active landfilling phase and gradually declined after site closure in both landfills. For SLS 1,
8 the CLEEN_{opt} model estimated the peak CH₄ generation in 2002 at 52.7 million m³, followed
9 by a gradual decline (Fig. 4a). By contrast, the CLEEN model estimated an earlier peak in 1998
10 at 86.6 million m³. For SLS 2, the CLEEN_{opt} model showed a peak in 2007 at 47.5 million m³,
11 while the CLEEN model estimated a peak in 2005 at 67.5 million m³ (Fig. 4b). The sharp drop
12 in the SLS 2 model-estimated CH₄ generation during the summer of 2011 was likely due to
13 extreme precipitation events, particularly in July, when the monthly total rainfall reached 864.2
14 mm, more than twice the climatological average. This anomaly likely caused the model to
15 underestimate the CH₄ generation during this period.



16
17 **Fig. 4. Seasonal CH₄ generation of CLEEN_{opt}, CLEEN, and actual field observation for**
18 **(a) the SLS 1 and (b) the SLS 2.**

1 The CLEEN model showed significant overestimation and variability in the simulated
2 CH₄ generation. This overestimation likely resulted from the use of non-calibrated emission
3 factors despite the incorporation of identical meteorological inputs. In contrast, the CLEEN_{opt}
4 model demonstrated improved reproducibility and alignment with CH₄ generation trends.
5 These results highlight the importance of the site-specific calibration of model parameters with
6 meteorological conditions to accurately estimate emissions.

7 The model uncertainty was assessed using the Monte Carlo method by randomly
8 sampling input variables within their specified value ranges (Fig. S3). Uncertainty was defined
9 as the 95 % confidence interval of the average annual CH₄ generation calculated from 1,000
10 simulation runs. The estimated uncertainty in CH₄ generation at SLS 1 ranged from 75 to 145 %,
11 whereas that at the SLS 2 ranged from 51 to 67 %.

12 13 3.4. Model results based on meteorological condition

14 To examine the response of CH₄ generation to meteorological variability, the
15 CLEEN_{opt} model was applied under an idealized landfill scenario, with a fixed waste input of
16 600,000 tons per month and an L_0 of 100 m³ Mg⁻¹. The ambient temperature and precipitation
17 were varied independently across ranges representative of seasonal conditions in South Korea
18 (-5 to 39 °C and 0 to 16 mm d⁻¹, respectively). For each temperature and precipitation scenario,
19 the model simulated CH₄ generation over a 30-year period, and the total CH₄ generation was
20 compared across all scenarios to assess the relative impact of each variable. The analysis aimed
21 to reflect conditions similar to those of the Sudokwon landfill, using the same modeling period
22 for consistency.

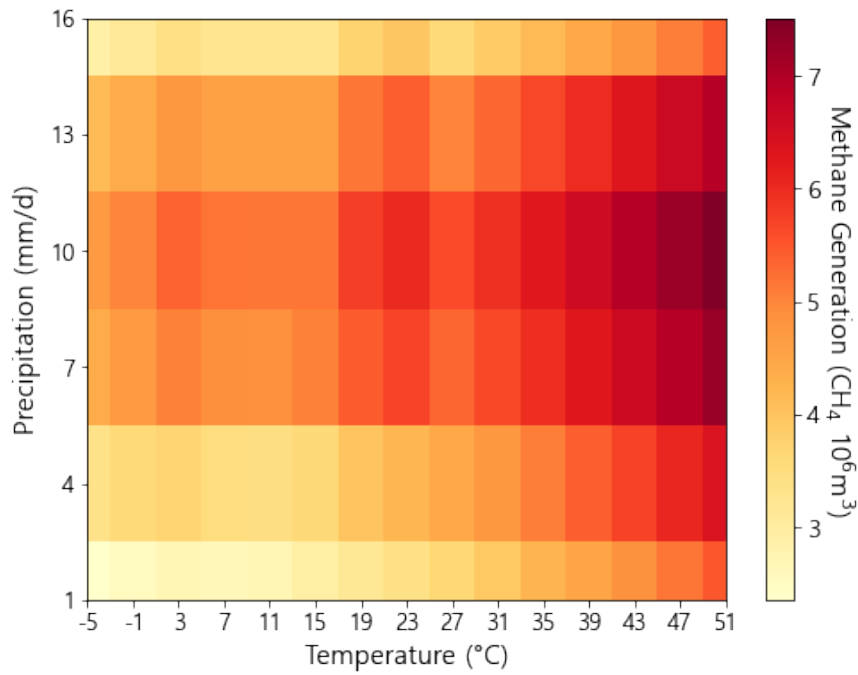


Fig. 5. Heatmap of simulated methane generation as a function of temperature and precipitation.

Table 4. Assessment of climate-induced CH₄ generation using OLS regression analysis.

$CH_4 \text{ Generation} = \beta_0 + \beta_T T + \beta_P P + \beta_{TP}(TP) + \beta_{P^2} P^2 + \varepsilon$				
Variables	Coefficient	std err	t-value	p-value
Intercept	5756.798	51.749	111.245	<0.001
T	47.828	1.946	24.575	<0.001
P	38.480	6.565	5.862	<0.001
T × P	-1.035	0.380	-2.724	0.008
P ²	-36.350	1.498	-24.262	<0.001

Fig. 5 shows a 2D heatmap of simulated CH₄ generation as a function of temperature and precipitation. As temperature increases, CH₄ generation consistently rises across the full range of precipitation. In case of precipitation, CH₄ generation increases up to approximately 9–10 mm d⁻¹, but declines at higher precipitation level.

To statistically quantify these relationships, we applied ordinary least squares (OLS)

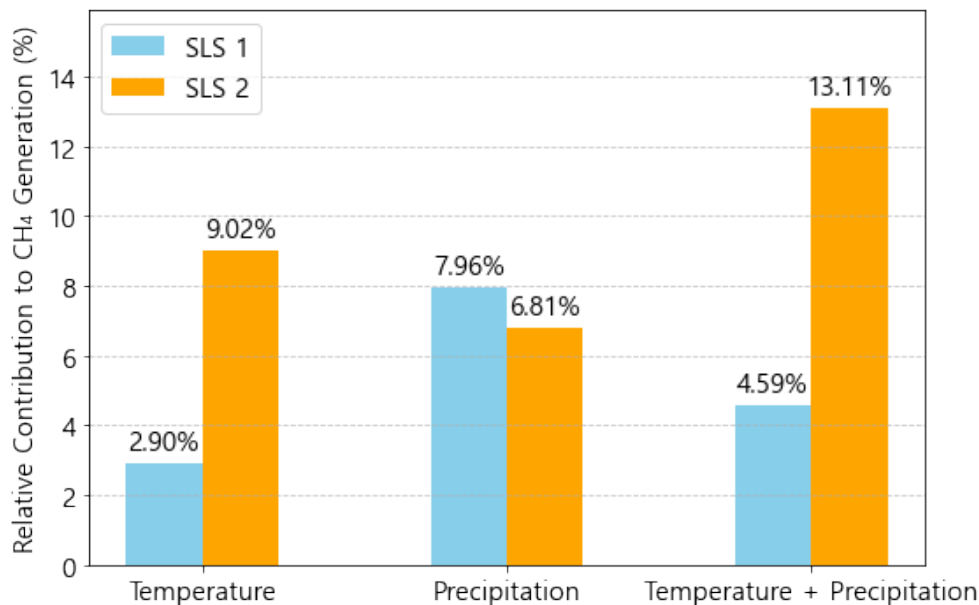
1 using centered predictors to mitigate multicollinearity (Iacobucci et al., 2016; Kraemer et al.,
2 2004). The regression results summarized in Table 4 shows a strong positive association with
3 temperature ($p < 0.001$). Under average conditions, the OLS coefficient for temperature (47.8
4 units per 1 °C) corresponds to an increase of approximately 0.8–1.0 % in simulated CH₄
5 generation per 1 °C warming. In contrast, precipitation indicates a significant nonlinear effect:
6 the combination of a positive linear and negative quadratic term (both $p < 0.001$) produce the
7 inverted-U shaped relationship, with emissions peaking at intermediate precipitation levels
8 around 9–10 mm d⁻¹. In addition, the temperature–precipitation interaction term is statistically
9 significant ($p = 0.008$), indicating that increasing precipitation reduces the effect of temperature
10 on CH₄ generation. In other words, under dry conditions, the effect of temperature on CH₄
11 generation is relatively more pronounced, whereas under moist conditions, the influence of
12 precipitation becomes comparatively more important.

13 Previous studies have reported peak CH₄ emissions at subsurface soil temperatures
14 between 25 °C and 40 °C (Scheutz et al., 2009; Spokas & Bogner, 2011; Whalen et al., 1990),
15 which closely correlate with ambient temperatures (Yesiller & Hanson, 2003). Elevated
16 ambient temperatures provide a favorable environment for the bacterial degradation of waste
17 (Rachor et al., 2013; Wang et al., 2012). Precipitation influences CH₄ emissions by affecting
18 both soil moisture content and water diffusion within the landfill. Although moderate moisture
19 levels support microbial activity and enhance CH₄ production, excessive precipitation can
20 saturate landfill pores, thereby inhibiting gas diffusion and reducing CH₄ emissions (Rachor et
21 al., 2013; Scheutz et al., 2009). These results suggested that optimal CH₄ generation occurred
22 under high temperatures and moderate precipitation, whereas excessive rainfall could suppress
23 emissions owing to pore saturation and limited gas transportation

24 3.5. Analysis of meteorological impacts

25 The absolute contributions of temperature and precipitation variability to the modeled
26 CH₄ emissions across the two landfill sites are shown in Fig. 6. The contrasting sensitivities
27 observed between the two landfill sites suggested that the landfill operational status played a
28 key role in mediating climate-driven CH₄ generation. SLS 1, which reached the post-closure
29 phase and was undergoing stabilization, showed a lower response to both temperature (2.90 %)
30 and combined variability of temperature and precipitation (4.59 %), although precipitation still

1 exhibited a strong influence (7.96 %). In contrast, SLS 2, which remained in an active state
2 with ongoing waste placement, showed greater sensitivity to temperature (9.02 %) and
3 combined variability (13.11 %).



4
5 **Fig. 6. The contribution of temperature and precipitation to CH₄ generation in SLS 1 and**
6 **SLS 2.**

7
8 These differences were likely due to the dynamic microbial and hydrological
9 conditions present in active landfills. The continuous deposition of waste in SLS 2 maintained
10 high levels of organic loading and microbial activity. Given the ongoing operation, the surface
11 has not yet been fully covered, leaving it more exposed to external environmental factors.
12 Conversely, in closed landfills with stable conditions, such as SLS 1, the application of a final
13 cover likely reduces environmental variability at the surface, thereby mitigating the impact of
14 meteorological conditions.

15 16 **4. Discussion**

17 In this study, we showed that incorporating site-specific meteorological conditions
18 significantly improved the accuracy of CH₄ generation estimates at the SLS. We further

1 evaluated the influence of meteorological conditions on CH₄ generation at the SLS. The results
2 indicated that CH₄ generation increased with rising temperature, whereas the effect of
3 precipitation increased up to a certain threshold and then decreased. Prior research has also
4 reported such relationships between meteorological variables and landfill CH₄ generation. For
5 instance, Fei et al. (2016) found that higher temperatures were associated with increased waste
6 decomposition, as reflected by elevated k values based on laboratory and field monitoring data.
7 Similarly, Jain et al. (2021) examined 114 closed landfills in the US and found that landfills in
8 regions with adequate annual precipitation emitted more CH₄ than those in arid regions.
9 However, excessive soil moisture has been reported to reduce CH₄ emissions by impeding gas
10 exchange owing to water-filled pore spaces (Rachor et al., 2013). In contrast, some studies have
11 reported a negative relationship between temperature and CH₄ emissions (Rachor et al., 2013),
12 which was attributed to reduced moisture availability under high-temperature conditions
13 (Sacramento et al., 2024; Visvanathan et al., 1999). In the SLS, the positive correlation between
14 temperature and CH₄ generation was likely due to the availability of sufficient moisture during
15 the summer months when temperatures were high.

16 We quantified the relative contributions of temperature and precipitation to CH₄
17 generation in the SLS and highlighted the site-specific differences in climate sensitivity based
18 on the operational status of the landfill. Climate sensitivity can vary depending on the physical
19 and biochemical conditions of landfills, particularly whether active or closed (Barlaz et al.,
20 1990; Karanjekar et al., 2015). Closed landfills are typically capped with cover layers, which
21 reduce exposure to external environmental influences and stabilize organic waste over time
22 (Duan et al., 2022). By contrast, active landfills continue to receive degradable organic waste
23 and remain open to the atmosphere, making them more susceptible to fluctuations in
24 meteorological conditions (Przydatek et al., 2024). Quantifying the effects of meteorological
25 factors can contribute to more accurate estimation of future CH₄ emissions from landfills. In
26 regions where the temperature and precipitation are expected to change under future climate
27 change, the CLEEN_{opt} model can be applied to estimate potential CH₄ emissions. These
28 projections can serve as a scientific basis for informed policy decisions, enabling more effective
29 landfill CH₄ measurements that are tailored to the operational status of landfills and site-
30 specific climatic conditions.

1 The CLEEN_{opt} model estimated CH₄ generation by accounting for key variables,
2 including waste input, waste composition, ambient temperature, and precipitation. However,
3 other environmental and meteorological factors that may influence CH₄ generation—such as
4 soil moisture, atmospheric pressure, wind direction, and pH (Amini et al., 2013; Scheutz et al.,
5 2009)—were not explicitly represented in this study. Furthermore, the CH₄ generated in
6 landfills undergoes microbial oxidation in the cover soil before being released into the
7 atmosphere (Duan et al., 2022; Scheutz et al., 2009). To ensure consistency with national
8 inventory practice, we applied a default oxidation rate of 10%, following the IPCC guidelines
9 (Eggleston et al., 2006). However, this value represents a major assumption and an important
10 source of uncertainty in our emission estimates. In reality, CH₄ oxidation is also strongly
11 influenced by climatic conditions, particularly temperature and precipitation (Christophersen
12 et al., 2000). To achieve more accurate and policy-relevant estimates of atmospheric CH₄
13 emissions, future studies should aim to use oxidation rates that reflect local environmental
14 variability, rather than relying on a default value (Chanton et al., 2009; Scheutz et al., 2009). It
15 is therefore imperative to obtain long-term, site-specific field measurements to enhance model
16 calibration and validation. Expanding field-based monitoring across diverse landfill types and
17 environmental conditions would improve both the accuracy and generalizability of landfill CH₄
18 emission models (Mønster et al., 2019).

19 To extend the CLEEN_{opt} framework to landfills with different climates, waste
20 compositions, and operational practices, sufficient site-specific data are required for model
21 calibration. The most critical inputs are field measurements of landfill gas (including surface
22 emissions, gas collection, and gas flaring), along with detailed records of the amount of waste
23 disposal and local temperature and precipitation. To adequately capture seasonal dynamics,
24 these datasets should ideally have at least monthly or seasonal temporal resolution over several
25 years. In addition, L_0 should be carefully constrained based on the amount and composition of
26 degradable organic matter at the target landfill. In data-limited cases, one might use parameter
27 sets derived from SLS for landfills that share similar conditions and waste management
28 practices. However, such a parameter transfer would likely introduce substantial additional
29 uncertainty, and parameter sets should be rigorously evaluated against local field measurements
30 before being applied. Overall, the transferability of CLEEN_{opt} to other regions depends strongly
31 on the availability of long-term, temporally resolved landfill gas and activity data. Where such

1 data exist, the framework can provide high-resolution and locally optimized CH₄ generation
2 estimates, thereby enabling more robust applications across diverse climatic and waste
3 management contexts.

4 Optimization of the emission factor within the CLEEN_{opt} framework provides a
5 facility-specific approach that is consistent with an IPCC Tier 3 methodology. By calibrating
6 constant k under site-specific meteorological conditions, the model yields facility-level
7 emission factors that can be used to refine Tier 3 parameterization in national landfill CH₄
8 inventory methods. When combined with reliable, high-resolution activity data, CLEEN_{opt} can
9 enhance both the accuracy and transparency of landfill CH₄ emission estimates and support a
10 more explicit quantification of inventory uncertainties. Systematically application of this
11 framework at the national scale would enable country-specific, higher-tier emission estimates,
12 aligning with IPCC guidelines. In turn, this could directly inform the improvement of national
13 GHG inventory systems, support the design of effective CH₄ mitigation strategies, and provide
14 a scientific basis for assessing progress toward national NDC (Nationally Determined
15 Contribution) targets.

17 5. Conclusion

18 This study demonstrated that integrating site-specific meteorological conditions into
19 landfill CH₄ generation modeling significantly improves estimation accuracy. Our results
20 showed that CH₄ generation responded strongly to both temperature and precipitation,
21 indicating an enhanced accuracy of the CLEEN_{opt} model compared to that of conventional
22 models that do not fully account for meteorological variability. The response of CH₄ generation
23 to meteorological variations showed a linear response with temperature and a parabolic
24 response with precipitation. Furthermore, the findings indicated that CH₄ generation increased
25 with precipitation up to approximately 10 mm d⁻¹, but decreased beyond this point, likely due
26 to excessive soil moisture, which inhibited gas exchange. Using the CLEEN_{opt} model, we
27 quantified the relative contributions of temperature (5.96 ± 3.06 %) and precipitation (7.38
28 ± 0.58 %) to CH₄ generation at the SLS. These results highlight the importance of climate-
29 sensitive modeling approaches that account for both seasonal variability and site-specific

1 landfill characteristics. Quantifying the influence of meteorological conditions provides
2 valuable insights into CH₄ mitigation strategies tailored to landfill type, operational phase, and
3 regional climate. Long-term field observations in diverse landfill environments are essential to
4 further enhance the reliability and applicability of landfill emission models.

5

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8

9 **Author contributions**

10 DHK, SJJ and DYC conceived and designed the study. DHK collected and performed
11 the data analysis. SJJ, DYC, and JWJ discussed the results. All authors contributed to the
12 manuscript writing.

13

14 **Competing interests**

15 The authors declare that they have no competing interests.

16

17 **Data availability**

18 The data used in this study could be available upon request from the corresponding
19 author.

20

21

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