



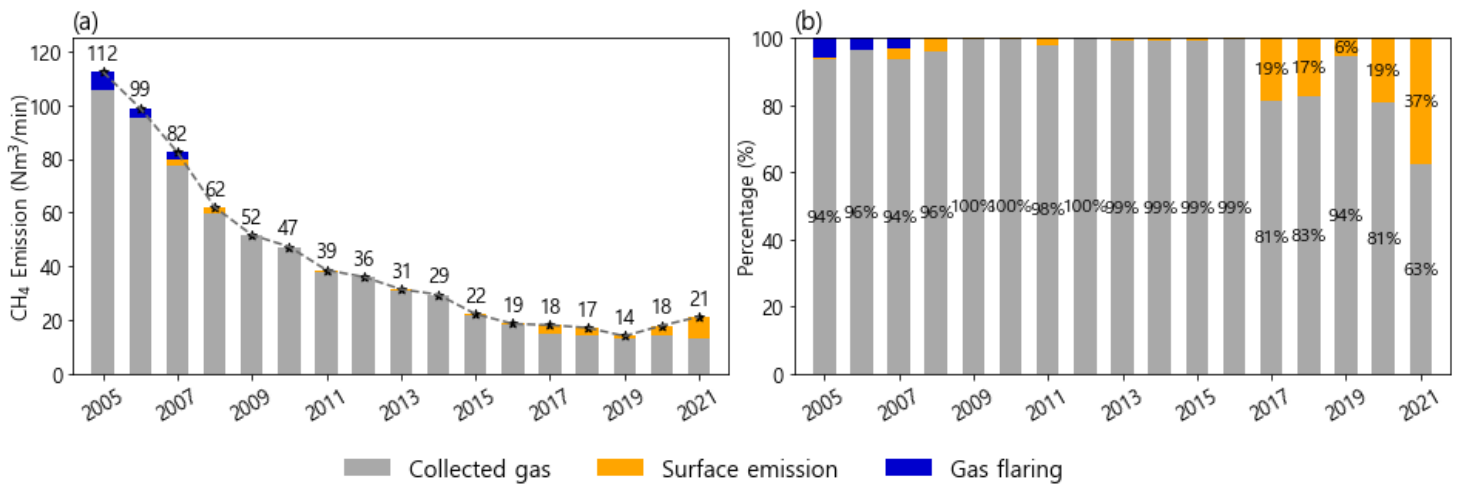
*Supplement of*

## **Quantifying meteorological impacts on local landfill methane emissions by using field measurements and machine learning**

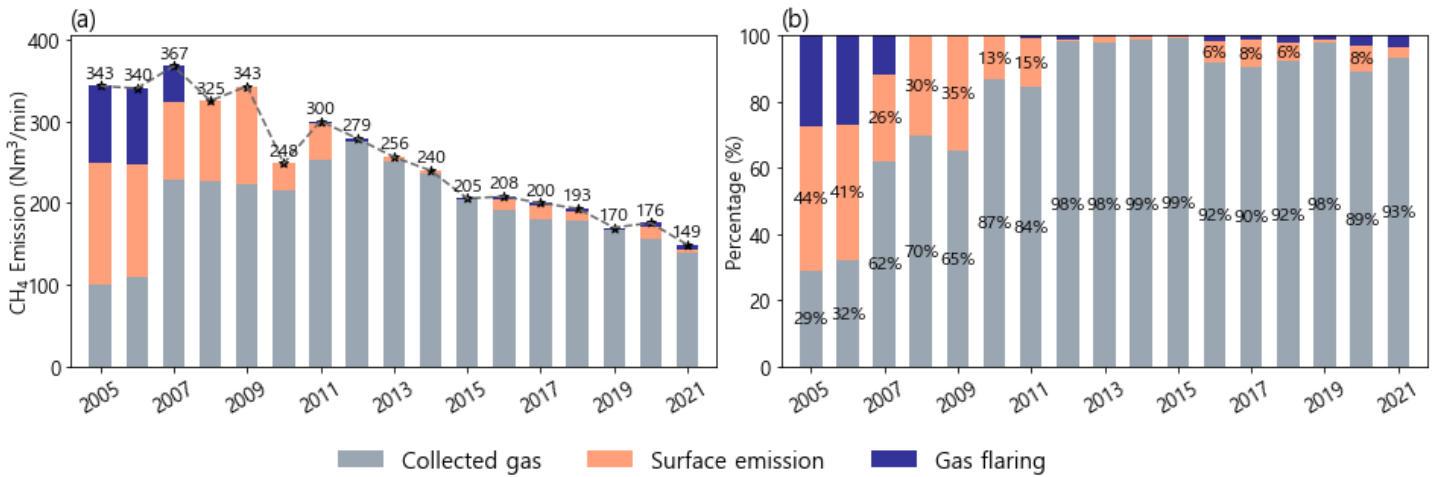
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1 **Fig. S1. (a) Annual CH<sub>4</sub> emission fluxes by pathway at SLS 1, and (b) the corresponding**  
 2 **contribution of ratios of each pathway.**



3 **Fig. S2. (a) Annual CH<sub>4</sub> emission fluxes by pathway at SLS 2, and (b) the corresponding**  
 4 **contribution of ratios of each pathway.**

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1           To quantify the uncertainty in landfill CH<sub>4</sub> generation estimates, a Monte Carlo  
2 simulation was conducted. For each simulation run, uncertain inputs were randomly sampled  
3 from pre-defined probability distributions (Herrador & González, 2004; Kalos & Whitlock,  
4 2009; Papadopoulos & Yeung, 2001). The methane generation potential ( $L_0$ ) was assumed to  
5 be uniformly distributed within the range derived from the BMP test. For the first sudokwon  
6 landfill site (SLS 1), the waste composition of food, textile and yard waste ( $F$ ,  $TX$ ,  $Y$ ) were  
7 sampled from uniform distribution with a  $\pm 10\%$  uncertainty range, following the IPCC  
8 guidelines (Eggleston et al., 2006), due to the lack of period-specific composition data. In  
9 contrast, the second sudokwon landfill site (SLS 2) had annual waste composition data, a  
10 normal distribution was used to reflect the observed inter-annual variability. For seasonal  
11 variables, the values followed a normal distribution with the seasonal mean ( $\mu$ ) set to the  
12 observed seasonal value and the standard deviation set ( $\sigma$ ) to measurement error. The mass of  
13 waste ( $M$ ) was varied only during the actual landfilling duration. Temperature ( $T$ ) and  
14 precipitation ( $P$ ) data were sampled within each season to reflect seasonal characteristics. A  
15 total of 1,000 iterations were performed to ensure a stable and statistically significant sampling  
16 distribution. The model uncertainty was summarized using the empirical distribution of  
17 simulated CH<sub>4</sub> generation values, and the reported uncertainty bounds corresponds to the 2.5<sup>th</sup>-  
18 97.5<sup>th</sup> percentiles (95% interval).

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2 **Table S1. Probabilistic characteristics of the random variables**

Input ( $x_i$ )	SLS 1					SLS 2				
	Mean	Standard deviation	Min	Max	Distribution	Mean	Standard deviation	Min	Max	Distribution
$L_0$ (m <sup>3</sup> /Mg)	40.2		33.7	46.7	Uniform	47.5		37	58	Uniform
F (%)	34.1		30.7	37.5		13.7	8.3	6.8	38.7	
TX (%)	4.7		5.1	4.2		5	0.8	3.1	6.9	
Y (%)	1.35		1.2	1.5		1.2	0.6	0.5	2.9	
M (Gg/season)	1,827	711	136.08	3454.3	Normal	1,155.2	342.9	311.1	3454.3	Normal
T <sub>spring</sub> (°C)	11.7	0.85	9.7	12.9		11.6	0.8	9.67	12.9	
T <sub>summer</sub> (°C)	23.8	0.88	21.8	25.3		23.9	0.8	22.3	25.3	
T <sub>fall</sub> (°C)	15.0	0.74	13.6	16.1		15.2	0.7	13.6	16.1	
T <sub>winter</sub> (°C)	-0.05	1.16	-2.7	2.4		-0.03	1.3	-2.7	2.43	
P <sub>spring</sub> (mm/d)	2.2	0.92	0.4	4.4		2.2	1.0	0.4	4.4	
P <sub>summer</sub> (mm/d)	7.7	2.81	3.1	15.0		7.6	3.0	3.1	15.0	
T <sub>fall</sub> (mm/d)	2.6	1.20	0.7	5.5		2.5	1.3	0.7	5.5	
T <sub>winter</sub> (mm/d)	0.7	0.39	0.2	1.6	0.7	0.4	0.1	1.6		

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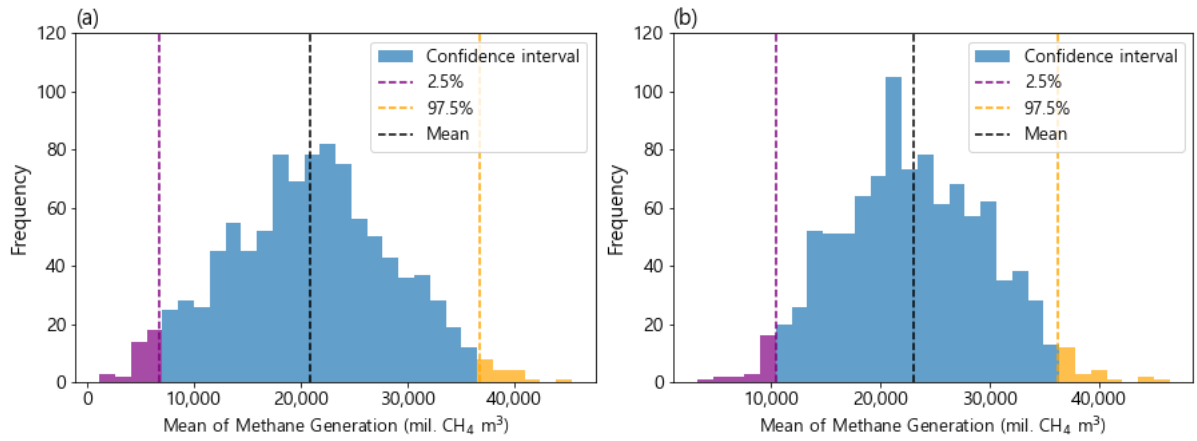
$$y = f(x_i) \quad (\text{Eq. S1})$$

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$$Y = (y_1, y_2, \dots, y_M) = (f(x_1), f(x_2), \dots, f(x_M)) \quad (\text{Eq. S2})$$

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2 **Fig. S3. Histogram representing the result for the error of measurement estimated by**  
 3 **Monte Carlo simulation. The confidence interval (Blue bar), under 2.5% range (purple**  
 4 **line), upper 97.5% range (orange line) for (a) SLS 1 and (b) SLS 2.**

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## 1 **References**

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