

Greenhouse Gas Emission Mitigation in the Municipal Solid Waste Sector in Tangerang Regency: Integrating LMDI, FOD, and System Dynamics

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Abstract: Municipal solid waste management contributes to climate change through greenhouse gas emissions, particularly methane from landfill and unmanaged disposal. This study integrates the Logarithmic Mean Divisia Index (LMDI), First Order Decay (FOD), and system dynamics (SD) to identify historical drivers of MSW-related GHG emissions and evaluate long-term mitigation pathways in Tangerang Regency. LMDI decomposes emission changes into emission intensity, waste-treatment structure, waste-generation intensity, economic activity, and population effects, while FOD captures legacy methane from historical waste disposal. SD was then applied to simulate Business as Usual (BAU), Waste-to-Energy/WTE (S1), CH₄ recovery (S2), enhanced recycling (S3), and lower population growth (S4) scenarios through 2050. GHG emissions increased from 541,155.24 tCO₂e in 2019 to 648,953.80 tCO₂e in 2024. The increase was driven primarily by emission intensity and economic activity, while lower waste-generation intensity and changes in waste-treatment structure partially offset the increase. By 2050, CH₄ recovery (S2) yielded the largest reduction relative to BAU (47.02%), followed by recycling (S3) (9.71%), WTE (S1) (9.46%), and the lower-population-growth scenario (S4) (3.04%). These findings demonstrate that methane control and diversion toward controlled treatment pathways are more influential than isolated end-of-pipe interventions, highlighting the importance of an integrated low-carbon MSW strategy.

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INTRODUCTION

Climate change is a major global environmental challenge driven by rising atmospheric greenhouse gas (GHG) concentrations. Human activities increased global temperatures by approximately 1.1°C in 2011–2020 compared with the 1850–1900 baseline (Intergovernmental Panel on Climate Change [IPCC], 2023). Major emission sources include fossil fuel consumption, industrial processes, transportation, land-use change, consumption patterns, and unsustainable waste management. In Indonesia, GHG emissions primarily originate from the energy, industrial, agricultural, forestry, and waste sectors (Kementerian Perencanaan Pembangunan Nasional/Bappenas, 2023). Globally, emissions are similarly associated with energy production and use, industry, transportation, agriculture, forestry, land-use change, and waste management (IPCC, 2023). The waste sector contributes substantially to CO₂ and CH₄ emissions, while also posing risks to environmental quality and public health (Kementerian Perencanaan Pembangunan Nasional/Bappenas, 2023; United Nations Environment Programme, 2024). Accordingly, waste-sector mitigation is an important component of Indonesia's Second Nationally Determined Contribution (NDC), with priorities including CH₄ reduction, improved waste management, and the development of low-emission waste disposal systems (Republic of Indonesia, 2025).

Municipal solid waste (MSW) management plays a strategic role in climate-change mitigation because improper waste handling, particularly the disposal of organic waste in final disposal sites, generates CH₄ through anaerobic degradation. This issue is becoming increasingly important because waste generation continues to rise in line with demographic and economic dynamics.

Waste generation is closely associated with population size, urbanization, rising income, and consumption, the larger the population and the higher the income level, the greater the potential quantity of waste generated (Prajati et al., 2015; Prajati & Pesurnay, 2019; World Bank, 2018; Zaman, 2016). Globally, municipal solid waste generation is projected to increase from approximately 2.1 billion tonnes in 2020 to 3.8 billion tonnes by 2050 if urgent action is not taken (United Nations Environment Programme, 2024).

This condition is relevant to Tangerang Regency, which is experiencing relatively rapid demographic and economic growth. The population increased from 3,236,700 people in 2020 to 3,400,490 in 2024, while economic growth reached 5.00% in 2024 (Badan Pusat Statistik Kabupaten Tangerang, 2025). These developments have the potential to increase pressure on the waste-management system through higher consumption activity and waste generation.

Low-carbon waste-management policy analysis requires a comprehensive approach that not only calculates GHG emissions, but also identifies the factors driving emission changes and evaluates policy effectiveness over the long term. The LMDI method can explain changes in emissions in terms of driving factors such as population growth, economic activity, waste-generation intensity, and treatment structure (Ang, 2005). Meanwhile, SD can represent cause-and-effect relationships and is therefore suitable for evaluating the behavior of complex waste-management systems that change over time (Darmawan, 2022; Soesilo, 2020).

Previous studies show that waste-sector GHG mitigation can be achieved through complementary interventions. Recycling and material recovery reduce residual waste requiring final disposal (Chen, 2016; Liem et al., 2024), while landfill-gas recovery directly limits methane emissions from disposed organic waste (Kurniawan et al., 2022; Xiao et al., 2021). WTE can also provide mitigation benefits when avoided landfill methane and energy substitution exceed additional combustion-related emissions, although its performance depends on waste composition, energy recovery, and system boundaries (Astrup et al., 2015; Istrate et al., 2020).

Although SD-LMDI has previously been applied to municipal solid waste emission analysis (Xiao et al., 2021), this study extends the framework by integrating FOD-based legacy methane, unmanaged disposal, and long-term policy simulation within a single regional SD model. The novelty therefore lies not in the use of SD-LMDI itself, but in linking historical emission drivers with delayed methane generation from previously disposed waste and future changes in waste-management pathways. Accordingly, this study aims to identify the factors driving changes in GHG emissions from the MSW sector in Tangerang Regency and to evaluate alternative mitigation strategies through 2050.

RESEARCH METHOD

This study uses a quantitative approach. First, the contribution of the waste sector to GHG emissions in Tangerang Regency is analyzed using the LMDI method based on data on waste generation and composition, waste-treatment structure, population, and gross regional domestic product (GRDP). The method analyzes the effects of economic activity (PE), population (PDK), waste-generation intensity (IB), waste-treatment structure (SP), and emission intensity (IE). Using LMDI, GHG emissions from waste are formulated following (Ang, 2005).

$$E_t = \sum_i \frac{E_{i,t}}{W_{i,t}} \times \frac{W_{i,t}}{W_t} \times \frac{W_t}{PDRB_t} \times \frac{PDRB_t}{P_t} \times P_t \quad (1)$$

Total GHG emissions in year (t) are decomposed into five factors, namely emission intensity (IE), management structure (SP), waste generation intensity (IB), economic activity (PE), and population (PDK). The decomposition identity is expressed as:

$$E_t = \sum_i IE_{i,t} \times SP_{i,t} \times IB_t \times PE_t \times PDK_t \quad (2)$$

with $L(x,y)$ being the logarithmic mean, namely $L(x,y) = (x-y)/(\ln x - \ln y)$.

$$IE_{i,t} = \frac{E_{i,t}}{W_{i,t}}, SP_{i,t} = \frac{W_{i,t}}{W_t}, IB_t = \frac{W_t}{PDRB_t}, PE_t = \frac{PDRB_t}{P_t}, PDK_t = P_t$$

The total change in GHG emissions is decomposed into five effects of waste management calculated using the equation:

$$\Delta E = E_t - E_{t-1} = \Delta E_{PE} + \Delta E_{SP} + \Delta E_{IB} + \Delta E_{IE} + \Delta E_{PDK} \quad (3)$$

$$\Delta E_{PE} = \sum_i L(E_{i,t}, E_{i,t-1}) \times \ln \frac{PE_t}{PE_{t-1}} \quad (4)$$

$$\Delta E_{SP} = \sum_i L(E_{i,t}, E_{i,t-1}) \times \ln \frac{SP_{i,t}}{SP_{i,t-1}} \quad (5)$$

$$\Delta E_{IB} = \sum_i L(E_{i,t}, E_{i,t-1}) \times \ln \frac{IB_t}{IB_{t-1}} \quad (6)$$

$$\Delta E_{IE} = \sum_i L(E_{i,t}, E_{i,t-1}) \times \ln \frac{IE_{i,t}}{IE_{i,t-1}} \quad (7)$$

$$\Delta E_{PDK} = \sum_i L(E_{i,t}, E_{i,t-1}) \times \ln \frac{PDK_t}{PDK_{t-1}} \quad (8)$$

with

$EGRK_{i,t}$	=	GHG from waste in year t with processing method i
$E_{i,GRK,t}$	=	GHG from waste processing method i
$SP_{i,t}$	=	proportion of waste allocated to management route (i) in year t
$W_{i,t}$	=	amount of waste allocated to management route (i) in year t
$PDRB_t$	=	Gross regional domestic product in year t
ΔE_{PE}	=	Amount of GHG effect from economic growth
ΔE_{SP}	=	Amount of GHG from waste processing structure
ΔE_{IB}	=	Amount of GHG effect from waste generation intensity
ΔE_{IE}	=	Amount of GHG effect from emission intensity
ΔE_{PDK}	=	Amount of GHG effect from population growth

Table 1. Definition of variables and units

Symbol	Definition	Unit
$E_{i,t}$	GHG emissions from management pathway i	tCO ₂ e/year
$W_{i,t}$	Waste allocated to management pathway i	tonnes/year
$IE_{i,t}$	Emission intensity	tCO ₂ e/tonne of waste
$SP_{i,t}$	Share of waste allocated to pathway i	fraction
IB_t	Waste-generation intensity relative to GRDP	tonnes/Rp
PE_t	GRDP per capita	Rp/person
PDK_t	Population	persons

All variables used in the decomposition have positive values, allowing the logarithmic-mean formulation to be applied directly.

$E_{i,t}$ represents GHG emissions from waste-management category i in inventory year t . For landfill and open-disposal categories, the principal emission calculated under the IPCC framework is CH_4 using the FOD method. This method accounts for the fact that waste disposed of in a given year decomposes and generates methane gradually over subsequent years ((Intergovernmental Panel on Climate Change, 2019b).

$$E_{i,T}^{CO_2e} = CH_{4,i,T}^{emitted} \times GWP_{CH_4} \quad (9)$$

For TPA (final disposal site) and unmanaged waste

$$E_{i,T} = E_{TPA,T}$$

$$E_{i,T} = E_{UM,T}$$

Methane released

$$CH_{4,T}^{emitted} = \left[\sum CH_{4,x,T}^{generated} - R_t \right] (1 - OX_t) \quad (10)$$

$$CH_{4,T}^{generated} = \sum_x \sum_{y \leq T} [W_y S_{x,y} DOC_x DOCf_x MCF_y] e^{-k_x(T-y)} (1 - e^{-k_x}) F \frac{16}{12} \quad (11)$$

$$CH_{4,T}^{emitted} = \left[\sum_x \sum_{y \leq T} [W_y \cdot S_{x,y} \cdot DOC_x \cdot DOCf_x \cdot MCF_y] \cdot e^{-k_x(T-y)} (1 - e^{-k_x}) \cdot F \cdot \frac{16}{12} - RT \right] (1 - OX_t) \quad (12)$$

$CH_{4,T}^{emitted}$	=	methane released in year T ;
$CH_{4,x,T}^{generated}$	=	methane generated from waste type x ;
R_T	=	methane recovered, utilized, or flared;
OX_T	=	oxidation factor in the landfill cover layer;
x	=	waste type, such as food, paper, wood, textiles, and others.
GWP_{CH_4}	=	100-year global warming potential of methane relative to CO_2 , expressed as tonnes CO_2e per tonne CH_4
$W_{x,y}$	=	mass of waste type x disposed of in year y
$S_{x,y}$	=	proportion of waste type x (fraction)
DOC_x	=	degradable organic carbon content of waste type x (ton C/ton waste)
$DOCf_x$	=	fraction of degradable organic carbon in waste type x that decomposes under anaerobic conditions (dimensionless);
MCF_y	=	methane correction factor based on disposal-site conditions;
Y	=	t year in which the waste was disposed.
K_x	=	decay constant for waste type x (yr^{-1});
F	=	methane fraction in generated landfill gas;
$16/12$	=	molecular-weight ratio of CH_4 to carbon.
$W_y, S_{y,x}$	=	Total waste in year y (tonnes/year) and fraction of waste type x in year y

System Dynamics

System dynamics (SD) was employed to represent the dynamic interactions and feedback relationships among population, economic activity, waste generation, waste-management pathways, and GHG emissions over time. The model was developed using Powersim Studio 10 based on stock–

flow structures and feedback mechanisms commonly applied in SD modeling (Darmawan, 2022; Soesilo, 2020). Model validity was subsequently assessed through structural verification, dimensional-consistency testing, and behavioral comparison with historical data. Consistent with Barlas (1989), behavioral validation focused on the model's ability to reproduce the characteristic pattern and dynamic behavior of the real system rather than requiring exact point-by-point agreement between simulated and observed values.

$$GRK_{\text{sampah}} = GRK_{\text{komposting}} + GRK_{\text{TPA}} + GRK_{\text{Unmanaged}} + GRK_{\text{WTE}} \quad (13)$$

Emissions from Composting

$$E_{\text{CH}_4} = \sum_i (M_i \times EF_{\text{CH}_4,i} \times 10^{-3}) \quad (14)$$

$$E_{\text{N}_2\text{O}} = \sum_i (M_i \times EF_{\text{N}_2\text{O},i} \times 10^{-3}) \quad (15)$$

$$GRK_{\text{komposting}} = \text{CH}_{4\text{comp}} \times GWP_{\text{CH}_4} + \text{N}_2\text{O}_{\text{comp}} \times GWP_{\text{N}_2\text{O}} \text{ (tCO}_2\text{e/year)} \quad (16)$$

Emissions from WTE

$$GRK_{\text{WTE CO}_2} = W_{\text{WTE}} \sum_j \left(WF_j \times dm_j \times CF_j \times FCF_j \times OF_j \times \frac{44}{12} \right) \quad (17)$$

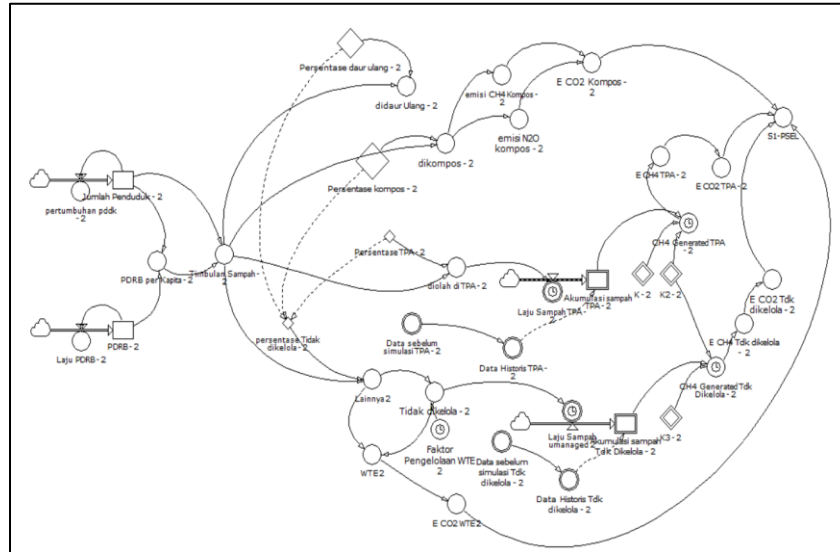
$$GRK_{\text{WTE CH}_4} = \sum_i (IW_i \times EF_{\text{CH}_4,i} \times 10^{-6}) \quad (18)$$

$$GRK_{\text{WTE N}_2\text{O}} = \sum_i (IW_i \times EF_{\text{N}_2\text{O},i} \times 10^{-6}) \quad (19)$$

$$GRK_{\text{WTE direct}} = GRK_{\text{CO}_2} + (GRK_{\text{CH}_4} \times GWP_{\text{CH}_4}) + (GRK_{\text{N}_2\text{O}} \times GWP_{\text{N}_2\text{O}}) \quad (20)$$

E_{CH_4}	=	CH ₄ emissions from composting, Gg CH ₄ /year
M_i	=	mass of waste composted, Gg waste/year
EF_{CH_4}	=	CH ₄ emission factor, g CH ₄ /kg waste (4 kg CH ₄ /tonnes waste)
$E_{\text{N}_2\text{O}}$	=	N ₂ O emissions from composting, Gg N ₂ O/year
$EF_{\text{N}_2\text{O},i}$	=	N ₂ O emission factor, g N ₂ O/kg waste (0.24 kg N ₂ O/tonnes waste)
GWP_{CH_4}	=	27
$GWP_{\text{N}_2\text{O}}$	=	273
$GHG_{\text{WTE,CO}_2}$	=	emissions from WTE combustion
$WWTE$	=	waste combusted in WTE (tonnes/year)
WF_j	=	fraction of waste component j
dm_j	=	dry-matter fraction
CF_j	=	carbon content of dry matter
FCF_j	=	fossil-carbon fraction
OF_j	=	oxidation factor
44/12	=	conversion of C to CO ₂

Conversion to CO₂e uses 100-year GWP values based on IPCC AR6. Recycling is represented in the model as diversion of waste flow from landfill/unmanaged disposal toward material recovery. Industrial recycling-process emissions and credits from avoided virgin-material production are outside the system boundary and are therefore not included as direct emission components. Based on these formulations, a stock-flow diagram (SFD) was developed for the SD model.



Model Validation and Sensitivity Analysis

Parameters that could not be obtained directly from empirical observations were calibrated using the available historical dataset. In particular, the waste-generation elasticity parameter was calibrated over the 2019–2024 observation period by comparing estimated and observed waste generation. The elasticity value producing the lowest MAE, MAPE, and RMSE was selected for historical reconstruction. The calibration procedure resulted in an elasticity value of $\varepsilon = 0.2$, with MAE of 20,479.73 tonnes, MAPE of 2.23%, and RMSE of 24,985.53 tonnes.

Following calibration, the model was run for the historical period without policy intervention, and simulated outputs were compared with observed population, GRDP, waste generation, and GHG emissions. Behavioral validation was evaluated using mean comparison (E_1) and error variance (E_2). E_1 measures the relative difference between the mean simulated and observed values, whereas E_2 evaluates the difference in their temporal variability:

$$E_1 = \frac{|\bar{S} - \bar{A}|}{\bar{A}} \times 100\% \quad (21)$$

$$E_2 = \frac{|S_s - S_a|}{S_a} \times 100\% \quad (22)$$

where $\bar{S}$ and $\bar{A}$ are the mean simulated and observed values, respectively, while S_s and S_a are their standard deviations. Behavioral validation in system dynamics emphasizes reproduction of the major historical behavior pattern rather than exact point-by-point correspondence (Barlas, 1989). Therefore, the E_1 and E_2 statistics were interpreted together with graphical comparison between observed and simulated trajectories. Operational criteria of $E_1 \leq 5\%$ and $E_2 \leq 30\%$, which have been applied in empirical SD validation studies, were used as reference thresholds (Chumaidiyah et al., 2025; Wahyuni et al., 2021). Because some variables in this study exceeded the stricter E_1 criterion, validation was

interpreted cautiously in terms of historical pattern reproduction rather than exact forecasting accuracy.

Local sensitivity analysis was conducted using the one-at-a-time (OAT) method, which varies one parameter at a time while keeping all others at their baseline values (Pianosi et al., 2016). The analysis examined three key policy parameters: waste-to-energy (WTE) capacity, CH₄ recovery efficiency, and recycling rate. Their effects on projected GHG emissions were assessed for 2030, 2040, and 2050. Since OAT does not account for interactions among parameters, the results were interpreted as local sensitivity estimates rather than a global uncertainty assessment (Saltelli & Annoni, 2010). Probabilistic uncertainty analysis was not conducted because empirical probability distributions were unavailable for several policy parameters. This limitation is acknowledged in the study.

LMDI was used to decompose changes in GHG emissions into five contributing factors: economic growth, population growth, waste-generation intensity, waste-treatment structure, and emission intensity. This decomposition follows the integrated system dynamics (SD)–LMDI frameworks applied by Xiao et al. (2021) and Zhang et al. (2025). Combining SD and LMDI enables the identification of key emission drivers and supports the development of mitigation scenarios. Xiao et al. (2021) demonstrated that the contributions of economic growth, population, waste-generation intensity, treatment structure, and emission intensity can be distinguished in explaining changes in waste-sector GHG emissions. Based on this framework, the policy-intervention scenarios were formulated, as presented in Table 2.

Table 2. The policy-intervention scenarios developed from this framework

Scenario	Intervention	Main assumption
Business as Usual (BAU) Scenario 1 (S1)	No additional intervention WTE	Existing waste-management and emission trends continue through 2050. WTE begins operation in 2030 at 360,000 t/year, with capacity increasing by 20% every five years as an exploratory policy experiment.
Scenario 2 (S2)	CH ₄ utilization	CH ₄ recovery starts at 30%, gradually increases over time, and reaches a maximum recovery efficiency of 70% in the later simulation period.
Scenario 3 (S3)	Enhanced recycling	From 2026, 5% of unmanaged waste is diverted to composting and 3% to recycling, with both rates increasing by 1 percentage point annually to maximum shares of 27% and 29%, respectively.
Scenario 4 (S4)	Lower population growth	The population growth rate is reduced by 25% relative to BAU during 2035–2044 and by 35% during 2045–2050.

The scenario magnitudes are used as policy experiments rather than deterministic predictions of conditions in 2050. The initial WTE capacity was selected to represent a facility of approximately 1,000 tonnes/day, while increases in capacity, recycling rate, CH₄ utilization, and lower population growth were used to evaluate system responses to gradual intervention levels that remain plausible within policy and literature ranges. Scenario results are therefore interpreted as relative changes from BAU.

GHG emissions from landfill and unmanaged solid-waste disposal, represented in this study as unmanaged disposal sites, were estimated using the FOD method in accordance with the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, Volume 5: Waste (Intergovernmental Panel on Climate Change, 2019b). The FOD calculation incorporates key parameters including degradable organic carbon (DOC), the fraction of DOC that decomposes (DOC_f), CH₄ correction factor (MCF), decay constant (k), CH₄ recovery, and oxidation factor (OX), thereby accounting for the gradual generation of CH₄ from waste disposed of in previous years.

Because historical waste-generation data prior to 2019 were incomplete, the 2010–2018 time series was reconstructed following the IPCC guidance on time-series consistency and the use of surrogate or extrapolated activity data (Intergovernmental Panel on Climate Change., 2019a). Waste generation was reconstructed using an elasticity-based relationship with population and GRDP per capita, consistent with reported relationships between demographic, economic, and waste-generation dynamics (Beigl et al., 2008; Blagoeva et al., 2023; Mazzarano et al., 2021; World Bank, 2018). The elasticity coefficient was calibrated against observed waste-generation data for 2019–2024 rather than adopted as a universal default. Among the tested values, $\varepsilon = 0.2$ yielded the lowest calibration errors, with an MAE of 20,479.73 tonnes, MAPE of 2.23%, and RMSE of 24,985.53 tonnes, and was therefore selected for backcasting waste generation for 2010–2018.

To improve transparency and reproducibility, the principal data sources, technical parameters, calibrated parameters, and scenario assumptions used in the model are summarized in Table 3. The table distinguishes observed historical data from IPCC default parameters and policy-scenario assumptions.

Table 3. Sources of data, technical parameters, and scenario assumptions used in the model

Input/parameter	Value/range	Unit	Type	Source/basis
Population	2019–2024 historical data	persons	Observed	BPS Kabupaten Tangerang
GRDP ADHK	2019–2024 historical data	billion Rp	Observed	BPS Kabupaten Tangerang
Waste generation	2019–2024 historical data	tonnes/year	Observed	Local waste data/study dataset
Waste composition	Local composition	fraction	Observed	Tangerang Regency waste composition data
DOC	By waste type	t C/t waste	IPCC default	IPCC 2019 Refinement
DOCf	Default value	fraction	IPCC default	IPCC 2019 Refinement
MCF	According to disposal-site condition	fraction	IPCC default	IPCC 2019 Refinement
F	CH ₄ fraction in landfill gas	fraction	IPCC default	IPCC 2019 Refinement
k	By waste type/climate condition	yr ⁻¹	IPCC default	IPCC 2019 Refinement
R	Scenario-dependent	fraction	Scenario	Model assumption
OX	According to disposal condition	fraction	IPCC default	IPCC 2019 Refinement
GWP CH ₄	27	tCO ₂ e/t CH ₄	IPCC value	IPCC AR6
GWP N ₂ O	273	tCO ₂ e/t N ₂ O	IPCC value	IPCC AR6
WTE capacity	360,000 from 2030	tonnes/year	Scenario	Policy experiment
WTE expansion	+20% every 5 years	%	Scenario	Exploratory stress test
CH ₄ recovery	CH ₄ recovery: 30% initially, increasing to a maximum of 70%	%	Scenario	Policy experiment
Composting/recycling diversion	Composting / recycling initial diversion: 5% / 3%	%	Scenario	Policy experiment

Composting/recycling diversion	Annual increase: +1 percentage point/year to maximum shares of 27%/29%	%	Scenario	Policy experiment
Population growth reduction	25% and 35% below BAU	%	Scenario	Policy experiment

Based on these data and parameter definitions, the system boundary was specified to include direct emissions from composting, landfill, unmanaged disposal, and WTE pathways. Landfill and unmanaged-disposal emissions are calculated using the FOD method. Benefits from avoided landfill emissions are captured endogenously through changes in waste flows among management pathways. Avoided grid electricity from WTE and avoided virgin-material production from recycling are not included within the model boundary. Accordingly, the results represent a sectoral waste-management assessment rather than a full life-cycle assessment.

RESULTS AND DISCUSSION

The study was conducted in Tangerang Regency, Banten Province, which covers approximately 942.65 km² and consists of 29 districts, 246 villages, and 28 urban villages, with the administrative center located in Tigaraksa.

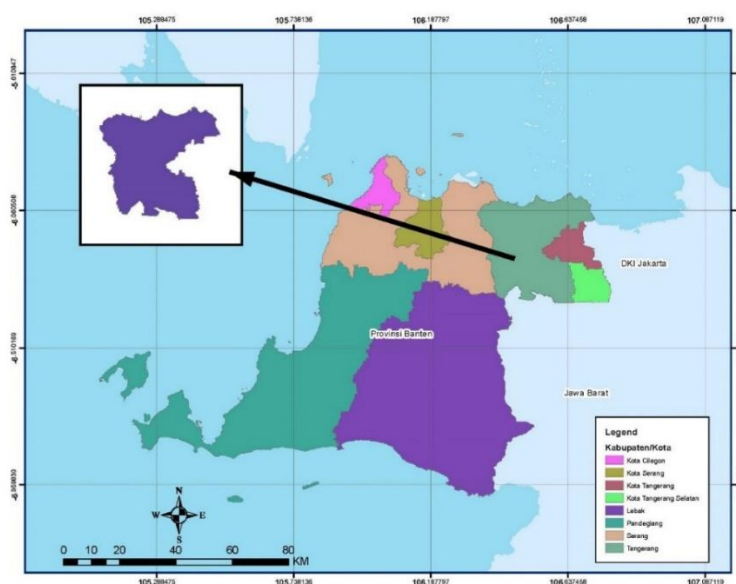


Figure 2. Map of Tangerang Regency

During 2019–2024, the population of Tangerang Regency increased from 3.19 million to 3.40 million. Over the same period, waste generation increased from 862,385.94 tonnes/year to 952,137.20 tonnes/year. Constant-price GRDP also showed an increasing trend, although it declined in 2020 due to the COVID-19 pandemic. These developments indicate that population growth and economic activity place increasing pressure on the waste-management system. Waste composition in Tangerang Regency is dominated by food waste, accounting for 42.15% of total MSW (DLHK Kabupaten Tangerang, 2025). This high organic fraction is particularly relevant to GHG emissions because biodegradable waste disposed of in landfill or unmanaged disposal sites contributes to CH₄ generation through anaerobic decomposition (Intergovernmental Panel on Climate Change., 2019b).

The waste-management structure during 2019–2024 consisted of recycling, composting, disposal to landfill, and unmanaged waste. One of the major issues identified is the persistently high amount of unmanaged waste. Its quantity increased from approximately 434,449 tonnes in 2019 to 666,377 tonnes in 2024. By contrast, waste disposed of in landfill declined from 386,316 tonnes to 229,756 tonnes. Recycling and composting still accounted for relatively small shares. This condition shows that reducing waste sent to landfill does not automatically indicate system improvement, because part of the waste may shift to the unmanaged category, represented in the model as unmanaged disposal, which can still generate GHG emissions.

Table 4. Population, constant-price GRDP, and waste generation in Tangerang Regency, 2019–2024

Year	Population (persons)	Gross Regional Domestic Product (GRDP) (ADHK) Billion Rp	Waste (tonnes/year)
2019	3,194,022	97,129.17	862,385.94
2020	3,236,700	93,480.39	906,276.00
2021	3,279,710	97,869.38	918,318.80
2022	3,321,650	103,219.44	930,062.00
2023	3,362,610	108,569.83	941,530.80
2024	3,400,490	113,998.21	952,137.20

Of the waste generated, food waste represents the largest share (42.15%), while textiles represent the smallest share (0.23%). The waste composition of Tangerang Regency for 2019–2024 is shown in Figure 3.

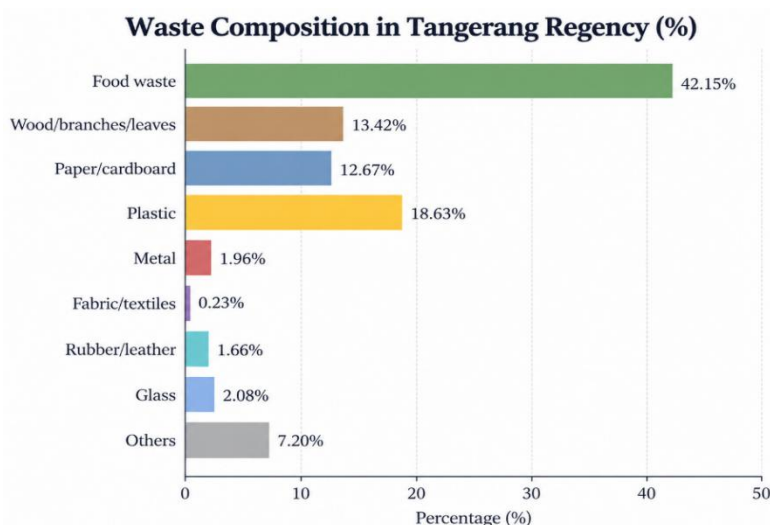


Figure 3. Waste composition in Tangerang Regency

Calculation of CH₄ emissions using the FOD method requires historical waste-disposal data. Because consistently available management data begin only in 2019, waste-generation data for 2010–2018 were reconstructed based on population and GRDP development (Intergovernmental Panel on Climate Change, 2019a). The reconstruction indicates that waste generation increased from approximately 592,416 tonnes/year in 2010 to 839,656 tonnes/year in 2018. The elasticity value ϵ was calibrated using the 2019–2024 observation period by comparing estimated waste generation with actual data. The ϵ value producing the lowest MAE, MAPE, and RMSE was then used to backcast waste generation for 2010–2018. Testing several elasticity values showed that $\epsilon = 0.2$ provided the

best result, with MAE of 20,479.73 tonnes, MAPE of 2.23%, and RMSE of 24,985.53 tonnes. These relatively low errors indicate that the reconstruction approach can be used as the historical basis for FOD emission calculations.

The GHG inventory shows that total waste-sector emissions increased from 541,155.24 tCO₂e in 2019 to 648,953.80 tCO₂e in 2024. The largest emission sources were landfill and unmanaged waste modeled using FOD and assumed to end in open/unmanaged solid waste disposal sites. This is a limitation of the study because data separating unmanaged disposal, open burning, littering, and informal pathways are not available. Therefore, the estimated GHG emissions from unmanaged waste in this study should be understood as an assumption-based approximation of open-disposal pathways rather than an inventory of all forms of unmanaged waste management. In this study, the unmanaged-waste fraction is modeled as unmanaged disposal for FOD estimation. This assumption does not imply that all unmanaged waste actually ends up in open dumping. Landfill emissions reached 308,812.05 tCO₂e in 2019, while unmanaged disposal contributed 231,525.63 tCO₂e. In 2024, landfill emissions declined to 287,949.81 tCO₂e, but unmanaged-waste emissions increased to 360,490.27 tCO₂e. Composting contributed relatively little because the process is predominantly aerobic, while recycling emissions were not counted in the waste sector because industrial processing lies within the industrial-sector boundary.

To identify the factors causing emission changes, LMDI analysis was conducted using five factors: emission intensity, treatment structure, waste-generation intensity, economic activity, and population. The analysis was performed both annually and cumulatively between 2019 and 2024.

Table 5. Quantitative impacts of GHG drivers in Tangerang Regency, 2019–2024

Year	Initial emissions (E ₀)	Final emissions (E ₁)	Actual change (E ₁ -E ₀)	Emission intensity (ΔE _{IE})		Treatment structure (ΔE _{SP})		Generation intensity (ΔE _{IB})		Economic activity (ΔE _{PE})		Population (ΔE _{PDK})		LMDI ΔE _{IE} + ΔE _{SP} + ΔE _{IB} + ΔE _{PE} + ΔE _{PDK}
	tCO ₂ e/yr	tCO ₂ e/yr	tCO ₂ e/yr	tCO ₂ e/yr	%	tCO ₂ e/yr	%	tCO ₂ e/yr	%	tCO ₂ e/yr	%	tCO ₂ e/yr	%	tCO ₂ e/yr
2019–2020	541,155	574,729	33,573	10,832	32.3	-4,946	-15	49,232	147	-28,948	-86.2	7,403	22.1	33,573
2020–2021	574,729	601,157	26,429	47,072	178.1	-28,401	-107	-32,208	-122	32,208	121.9	7,758	29.4	26,429
2021–2022	601,157	615,344	14,187	83,359	587.6	-76,896	-542	-51,565	-363	51,565	363.5	7,724	54.4	14,187
2022–2023	615,344	631,965	16,621	-170	-1.0	9,149	55	-41,498	-250	41,498	249.7	7,641	46.0	16,621
2023–2024	631,965	648,954	16,989	14,914	87.8	-5,098	-30	-38,460	-226	38,459	226.4	7,173	42.2	16,989

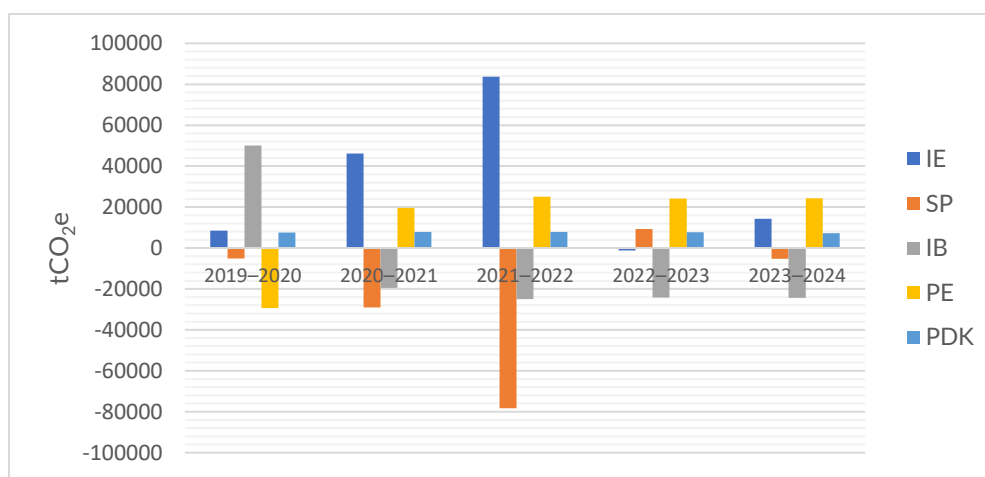


Figure 4. Changes in GHG emissions from waste management in Tangerang Regency, 2019–2024, and the contribution of each driver.

During 2019–2020, emissions increased by approximately 33,573 tCO₂e. The dominant factor was waste-generation intensity at +49,232 tCO₂e, while economic activity had a negative effect of

approximately $-28,948 \text{ tCO}_2\text{e}$ due to the slowdown in GRDP during the pandemic. In 2020–2021, emission intensity became the largest driver at $+47,072 \text{ tCO}_2\text{e}$. This is related to the characteristics of the FOD method because emissions in the current year arise not only from waste generated in that year, but also from the decay of waste disposed of in earlier years.

During 2021–2022, the emission-intensity effect increased sharply to approximately $+83,359 \text{ tCO}_2\text{e}$, but total emissions increased by only about $14,187 \text{ tCO}_2\text{e}$ because this effect was offset by changes in treatment structure ($-76,896 \text{ tCO}_2\text{e}$) and generation intensity ($-51,565 \text{ tCO}_2\text{e}$). In 2022–2023, the emission-intensity effect became negative, indicating a decline in emissions per unit of waste activity during that period. In 2023–2024, economic activity again became one of the drivers, while generation intensity restrained the increase in emissions.

Cumulatively over 2019–2024, GHG emissions increased by $107,798.56 \text{ tCO}_2\text{e}$. LMDI results show that emission intensity was the largest driver, contributing $+138,492.80 \text{ tCO}_2\text{e}$ or 128.47%. Economic activity also made a large contribution of $+126,511.83 \text{ tCO}_2\text{e}$ or 117.36%, while population growth added $+36,967.94 \text{ tCO}_2\text{e}$ or 34.29%. The increase in MSW-related GHG emissions in Tangerang Regency should be interpreted within the broader context of rapid socioeconomic and urban development. Urbanization, industrialization, increasing population density, energy consumption, and economic activity can intensify anthropogenic emissions and increase environmental pressure (Sodikin et al., 2026). This is consistent with the LMDI results of the present study, in which economic activity and population growth acted as positive drivers of emission growth.

In contrast, waste-generation intensity ($-105,048.60 \text{ tCO}_2\text{e}$) and changes in the waste-management structure ($-89,125.39 \text{ tCO}_2\text{e}$) partially offset the emission growth associated with economic and demographic expansion. The mitigating contribution of the waste-management structure indicates the importance of shifting waste flows away from final disposal toward material recovery. This is consistent with Warlina, (2019), who emphasized the transition from linear waste management toward circular approaches based on reduce, reuse, recycling, recovery, and material-value retention. This result suggests that improvements in waste-management efficiency and shifts toward lower-emission treatment pathways can weaken the coupling between socioeconomic growth and MSW-related GHG emissions. For landfill and unmanaged-disposal pathways, the emission-intensity effect should not be interpreted solely as a change in the current-year technical emission factor. Because emissions in the numerator are calculated using FOD, this effect also implicitly reflects the temporal influence of historical waste that is still decomposing.

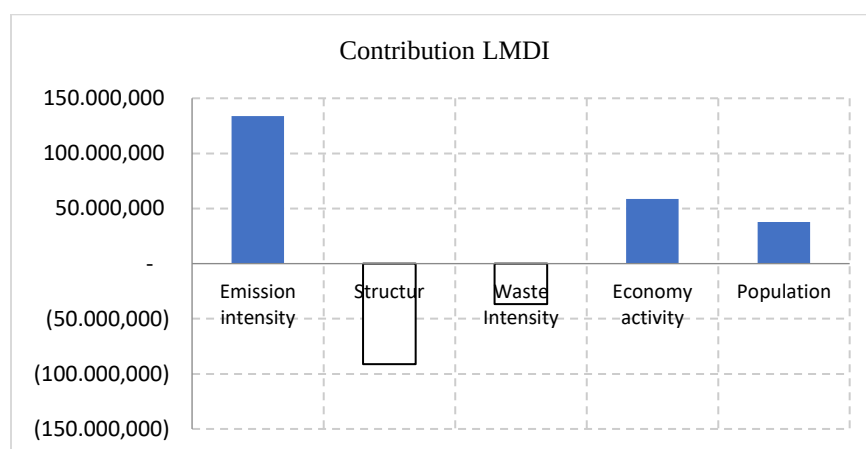


Figure 5. Contribution of GHG emissions by driving factor, 2019–2024

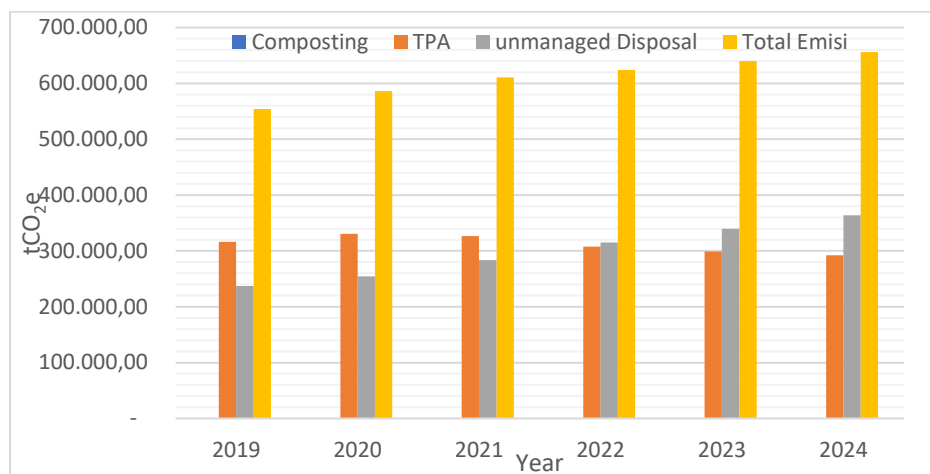


Figure 6. GHG emission trends in Tangerang Regency, 2019–2024

Percentage contributions are calculated relative to the net change in emissions. Because some factors produce large positive effects while others provide negative offsets, the relative contribution of a factor can exceed 100%. This does not represent a share of total emissions, but rather a contribution to the net change. The additive nature of LMDI ensures that the sum of all factor effects remains identical to the actual change in emissions.

The dominance of the emission-intensity effect reflects not only current waste-management conditions but also the delayed CH₄ generation from waste disposed of in previous years. Under the FOD approach, DOC continues to decay over time, producing a legacy methane effect that carries historical disposal into current-year emissions (Intergovernmental Panel on Climate Change., 2019b). Therefore, the LMDI emission intensity effect in this study is interpreted as a composite temporal effect combining current emission characteristics and inherited methane-generation potential from historical disposal.

The negative treatment structure effect indicates that changes in the distribution of management pathways have generally contributed to mitigation. However, improvement remains suboptimal because the decline in waste sent to landfill was accompanied by high unmanaged disposal, represented in the model as open dumping. Structural transformation therefore requires more than reducing landfill disposal; waste flows must instead be redirected toward source reduction, recycling, composting, biological treatment, and controlled residual-waste treatment.

The negative generation-intensity effect indicates that waste generation increased at a slower rate than economic activity, thereby reducing waste generation per unit of GRDP. Meanwhile, the positive economic activity effect indicates that GRDP growth remained an important driver of increasing waste-related emissions. Population growth also contributed positively to emissions, although its effect was smaller than those of economic activity and emission intensity. This finding is consistent with the IPAT/STIRPAT framework, which identifies population, affluence, and technology as major drivers of environmental pressure (York et al., 2003).

The LMDI results provide the diagnostic basis for the subsequent system-dynamics analysis. The dominance of emission intensity, economic activity, and management structure indicates that future mitigation should address both CH₄ formation from disposal pathways and changes in waste allocation among treatment options. Accordingly, the SD model was used to examine how alternative interventions in WTE capacity, CH₄ recovery, recycling, and demographic growth could alter the long-term emission trajectory relative to BAU.

System Dynamics Results

The SD model was developed using Powersim Studio 10 to represent interactions among population, GRDP, waste generation, management structure, and GHG emissions. The model was used to compare BAU with WTE, CH₄ recovery, enhanced recycling, and lower-population-growth scenarios. Before policy simulation, the model underwent behavioral validation, structural verification, dimensional-consistency testing, and an extreme-condition test.

Table 6. Historical comparison between observed and simulated GHG emissions

Year	Observed GHG emissions (tCO ₂ e)	SD Simulation (tCO ₂ e)	Relative difference (%)
2019	541,155.24	496,117.99	- 8.32
2020	574,728.61	520,268.04	- 9.48
2021	601,157.14	544,350.13	- 9.45
2022	615,344.19	568,267.08	- 7.65
2023	631,965.21	591,965.68	- 6.33
2024	648,953.80	615,421.51	- 5.17
means	602,217.36	556,065.07	
STDev	39,311.27	44,661.50	
E ₁			7.66%
E ₂			13.61%

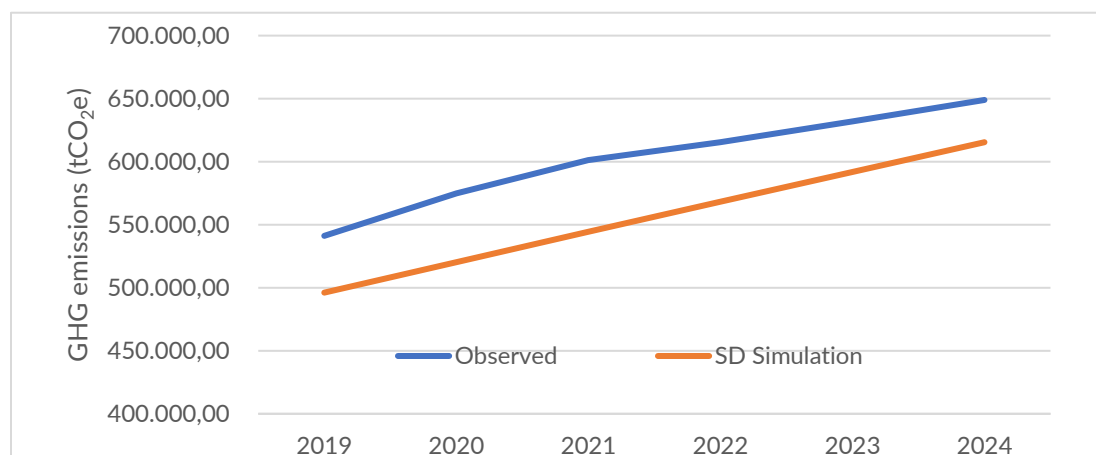


Figure 7. Comparison between observed and simulated GHG emissions during the historical validation period (2019-2024)

Table 7. Extreme-condition validation results

Extreme condition	Expected response	Model response	Evaluation
Population growth rate = 0	Population does not increase	Consistent	Valid
New waste to landfill = 0	CH ₄ declines gradually rather than immediately reaching zero because of legacy methane	Consistent	Valid
New waste generation = 0	New treatment flows = 0	Consistent	Valid
CH ₄ recovery = 100%	CH ₄ emitted reaches a minimum and does not become negative	Consistent	Valid

Behavioral validation showed a close historical fit for population and GRDP, with E₁ values of 0.12% and 2.51%, respectively. Waste generation and GHG emissions exhibited larger mean deviations, with E₁ values of 7.45% and 7.66%, although their E₂ values remained relatively low at 20% and 13.61%, respectively. Thus, the latter two variables exceeded the stricter 5% E₁ criterion commonly applied in system-dynamics behavioral validation but remained within the 30% E₂ criterion.

For GHG emissions, the observed mean for 2019–2024 was 602,217.34 tCO₂e/year, compared with a simulated mean of 556,065.07 tCO₂e/year. Their standard deviations were 39,311.17 and 44,661.50 tCO₂e/year, respectively, resulting in $E_1 = 7.66\%$ and $E_2 = 13.61\%$. Despite the difference in absolute levels, the simulated trajectory reproduced the observed upward trend, and the relative difference decreased from 8.32% in 2019 to 5.17% in 2024.

This result indicates that the model captures the dominant historical behavior of the waste-emission system, although it should not be interpreted as an exact forecasting model. Consistent with system-dynamics validation principles, the model is therefore used primarily for comparative scenario analysis, in which the direction and relative differences among policy trajectories are more important than point-by-point prediction of historical observations.

The historical validation window was limited to 2019–2024 because consistent observed waste-management and emission data were not available for earlier years. Consequently, the validation should be interpreted as historical behavior reproduction within the available observation period rather than as independent out-of-sample forecasting validation.

Sensitivity analysis was performed to assess the robustness of the SD model under variations in key policy assumptions. Using an OAT approach, WTE capacity, CH₄ recovery efficiency, and recycling rate were varied individually while other model inputs were held constant. Model responses were evaluated from changes in projected GHG emissions in 2030, 2040, and 2050. Three policy parameters were selected for local sensitivity testing: CH₄ recovery efficiency, recycling rate, and WTE treatment capacity. Each parameter was varied by $\pm 20\%$ around its baseline, with all other model inputs maintained at their baseline settings.

Table 8. Parameter ranges used in the OAT sensitivity analysis

Parameter	Unit	Low	Baseline	High	Sensitivity range
CH ₄ recovery efficiency	%	24	30	36	$\pm 20\%$ of baseline
Recycling rate	%	24	30	36	$\pm 20\%$ of baseline
WTE treatment capacity	kt/year	288	360	432	$\pm 20\%$ of baseline

The results of the sensitivity test show how changes in WTE capacity, CH₄ recovery efficiency, and recycling rates affect projected GHG emissions in 2030, 2040, and 2050, providing an indication of the model's robustness presented in table 9.

Table 9. OAT sensitivity analysis of WTE capacity, CH₄ recovery efficiency, and recycling rate

Parameter	Year	Lower (tCO ₂ e)	Base (tCO ₂ e)	Higher (tCO ₂ e)	Lower vs Base (%)	Higher vs Base (%)
WTE capacity	2030	907,279.48	946,257.60	985,235.71	-4.12	+4.12
	2040	961,934.63	960,241.72	942,615.74	+0.18	-1.84
	2050	1,100,836.62	1,078,310.56	1,023,213.42	+2.09	-5.11
CH ₄ recovery efficiency	2030	539,431.25	515,882.83	492,334.41	+4.56	-4.56
	2040	462,649.79	462,649.79	462,649.79	0.00	0.00
	2050	568,756.03	568,756.03	568,756.03	0.00	0.00
Recycling rate	2030	742,285.72	740,551.57	738,866.11	+0.23	-0.23
	2040	912,730.13	909,257.83	905,893.79	+0.38	-0.37
	2050	1,078,040.10	1,075,320.94	1,072,938.73	+0.25	-0.22

The OAT sensitivity analysis showed that WTE capacity produced the strongest response. Higher WTE capacity increased emissions by 4.12% in 2030 but reduced them by 5.11% in 2050, reflecting the shift from immediate combustion emissions to longer-term methane avoidance through waste diversion (Astrup et al., 2015; Istrate et al., 2020). CH₄ recovery changed emissions by $\pm 4.56\%$ in 2030, but the trajectories converged by 2040 after all cases reached the model's maximum recovery limit. Recycling showed low sensitivity, with changes below 0.4%. Overall, the response directions remained consistent with the expected mechanisms, supporting the robustness of the main scenario conclusions. Because OAT does not capture parameter interactions, the results should be interpreted as local sensitivity estimates rather than a global uncertainty assessment (Pianosi et al., 2016; Saltelli & Annoni, 2010).

Simulations were conducted through 2050 by comparing BAU, WTE, CH₄ recovery, enhanced recycling, and lower-population-growth scenarios. Under BAU, emissions continue to increase to approximately 1,190,940.83 tCO₂e in 2050. This indicates that without intervention, population growth, economic activity, and rising waste generation will sustain the upward GHG trend. Emission values from the SD model represent reproduced system behavior and are not numerically identical to the historical inventory. The historical comparison resulted in $E_1 = 7.66\%$ and $E_2 = 13.61\%$. Although the mean deviation exceeds the stricter 5% E_1 criterion commonly used in applied system-dynamics validation, the model reproduces the observed upward trajectory and comparable temporal variability. Therefore, historical inventory data were used as empirical references for behavioral validation, while scenario interpretation focused on relative changes between simulated trajectories rather than direct prediction of inventory values. Accordingly, historical inventory values were used as empirical references for model validation, whereas scenario interpretation was based on relative differences between simulated trajectories rather than direct substitution for the inventory estimates. Scenario results are therefore used primarily to compare the direction and relative changes among scenarios against BAU.

Table 10. Simulated GHG emissions under different scenarios, 2019–2050 (tCO₂e/year)

Year	BAU	S1-WTE	S2-CH ₄ Recovery	S3-Recycling	S4-Lower Population Growth
2019	496,117.99	496,117.99	496,117.99	496,117.99	496,117.99
2020	520,268.04	520,268.04	520,268.04	520,268.04	520,268.04
2021	544,350.13	544,350.13	544,350.13	544,350.13	544,350.13
2022	568,267.08	568,267.08	568,267.08	568,267.08	568,267.08
2023	591,965.68	591,965.68	591,965.68	591,965.68	591,965.68
2024	615,421.51	615,421.51	615,421.51	615,421.51	615,421.51
2025	638,628.91	638,628.91	638,628.91	638,628.91	638,628.91
2026	661,594.17	661,594.17	661,594.17	666,582.27	661,594.17
2027	684,331.09	684,331.09	587,823.11	685,345.57	684,331.09
2028	706,858.04	706,858.04	573,942.08	703,976.11	706,858.04
2029	729,195.93	729,195.93	557,797.23	722,392.41	729,195.93
2030	751,367.02	946,257.60	539,431.25	740,551.57	751,367.02
2031	773,394.01	911,766.23	518,882.95	758,436.08	773,394.01
2032	795,299.56	891,451.81	496,186.85	776,045.12	795,297.24
2033	817,105.97	880,854.38	490,580.36	793,388.79	816,731.83
2034	838,834.92	876,977.53	483,903.65	810,484.32	837,801.96
2035	860,507.42	916,784.61	476,173.83	827,353.66	858,584.33
2036	882,143.75	909,659.43	467,405.61	844,021.94	879,136.94
2037	903,763.40	907,829.06	478,856.77	860,516.56	899,504.83
2038	925,385.14	909,779.29	490,309.17	876,866.68	919,724.15

2039	947,026.98	914,488.03	501,772.33	893,103.01	939,824.73
2040	968,706.25	960,241.72	513,255.44	909,257.83	959,831.94
2041	990,439.61	957,310.81	524,767.30	925,365.16	979,767.90
2042	1,012,243.08	958,516.42	536,316.41	941,461.06	999,651.26
2043	1,034,132.10	962,742.35	547,910.94	957,584.10	1,019,331.69
2044	1,056,121.57	969,233.03	559,558.78	973,775.93	1,038,864.01
2045	1,078,225.84	1,016,453.37	571,267.52	990,082.03	1,058,289.52
2046	1,100,458.83	1,014,793.27	583,044.53	1,006,552.60	1,077,640.23
2047	1,122,833.98	1,017,153.75	594,896.94	1,023,243.68	1,096,941.72
2048	1,145,364.32	1,022,471.96	606,831.63	1,040,218.63	1,116,215.12
2049	1,168,062.50	1,030,028.01	618,855.32	1,057,549.82	1,135,478.37
2050	1,190,940.83	1,078,310.56	630,974.51	1,075,320.94	1,154,747.13

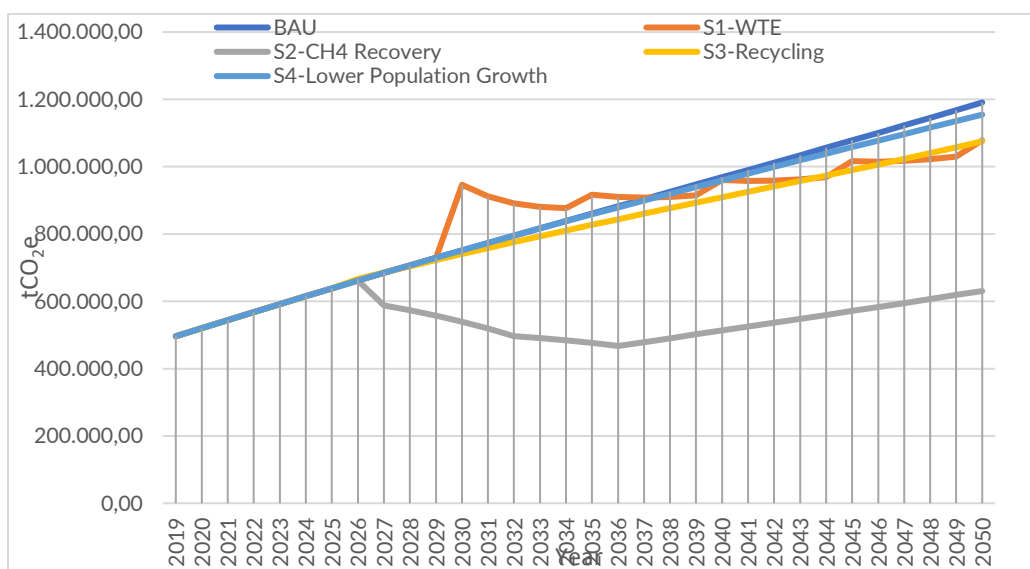


Figure 8. Comparison of GHG emissions under BAU, S1, S2, S3, and S4 scenarios

The WTE scenario shows a different pattern. At the beginning of operation, emissions increase because of direct combustion emissions, particularly fossil CO₂ from plastics and synthetic materials. Under the WTE scenario, total system emissions reach approximately 946,258 tCO₂e in 2030, higher than BAU at approximately 751,367 tCO₂e. Over the long term, diversion of waste from landfill/unmanaged disposal reduces CH₄ formation in disposal pathways, so part of the increase in direct WTE emissions is offset by avoided landfill emissions. By 2050, total emissions under the WTE scenario decline to approximately 1,078,311 tCO₂e, about 9.46% below BAU. WTE emissions include direct combustion emissions, while the benefit of diversion from landfill appears endogenously through reduced waste entering landfill/unmanaged-disposal pathways. Avoided grid electricity and avoided virgin-material production are not included. The initial increase should therefore be interpreted as a transient response associated with the immediate introduction of fossil CO₂ emissions from combustion, whereas the methane-reduction benefit emerges more gradually because FOD-based landfill emissions respond with a time delay.

An increased share of incineration is one intervention that can reduce waste-sector emissions relative to BAU, particularly when incineration replaces landfill disposal and thereby suppresses CH₄ formation from anaerobic degradation (Xiao et al., 2021). Diverting waste from landfill to incineration with energy recovery can provide climate-change benefits by avoiding landfill CH₄ formation. However, the magnitude of the benefit is strongly influenced by waste composition, energy-recovery efficiency, the electricity mix displaced, and the analytical system boundary (Istrate et al., 2020). WTE can reduce total waste-management-system emissions when avoided landfill methane and/or energy

substitution exceed the additional direct fossil emissions from combustion (Astrup et al., 2015). Within the system boundary used in this study, the WTE scenario produces lower emissions than BAU over the long term. Modelled WTE emissions are strongly influenced by waste composition, fossil-carbon fraction, the degree of substitution for landfill/unmanaged disposal, treatment capacity, and the calculation boundary. Scenario comparisons use a sectoral waste-management boundary.

The CH₄ recovery scenario produces the largest mitigation effect, with 2050 emissions of 630,974.51 tCO₂e, corresponding to a potential reduction of approximately 47.02% relative to BAU under an assumed CH₄ recovery efficiency of 70%. This effectiveness reflects the high leverage of CH₄ control in a waste-management system where emissions are still dominated by landfill and unmanaged disposal. This finding is consistent with (Xiao et al., 2021), who identified landfill-gas utilization as a major long-term mitigation strategy, and with (Kurniawan et al., 2022), who demonstrated the potential of landfill-gas utilization to reduce emissions while generating energy in Indonesia.

The enhanced-recycling scenario produces emissions 9.71% lower than BAU in 2050. The reduction mainly results from diversion of waste from landfill/unmanaged disposal toward material recovery. This finding is consistent with (Liem et al., 2024) and (Chen, 2016), who showed that increased material recovery can provide GHG mitigation benefits. Because credits for avoided virgin-material production are outside the study system boundary, the recycling mitigation benefit in this model can be viewed as a conservative estimate compared with a life-cycle approach.

Meanwhile, the lower-population-growth scenario produces the smallest mitigation effect, with emissions in 2050 approximately 3.04% below BAU. This indicates that demographic change alone has a relatively limited effect on waste-sector emissions because emissions are also influenced by economic activity, per-capita waste generation, treatment structure, and emission intensity. (Xiao et al., 2021) similarly identified population scale as a positive driver of waste sector GHG emissions. In their Shanghai case study, a population-growth-control scenario reduced emissions by approximately 0.30% relative to BAU in 2050, substantially less than the reductions achieved through landfill-gas utilization, improved waste separation, and increased incineration.

Among the individual interventions assessed, CH₄ recovery achieved the greatest modeled emission reduction compared with the business-as-usual (BAU) scenario. However, this intervention alone does not address the root cause of waste generation. Recycling reduces residual waste, whereas waste-to-energy (WTE) can reduce landfill dependence and generate energy, although it also produces direct emissions. Therefore, an effective low-carbon waste-management strategy requires an integrated approach rather than reliance on a single technology.

The study identifies five key policy priorities: waste reduction at source, expanded recycling and organic waste treatment, elimination of open dumping, CH₄ recovery at landfills, and selective WTE implementation for residues that cannot be recycled or otherwise recovered. These interventions address both waste volumes and the main drivers identified by LMDI, including emission intensity, management structure, waste-generation intensity, and economic activity. By combining LMDI findings with system dynamics (SD) projections, the study provides a more comprehensive basis for formulating a low-carbon waste-management strategy for Tangerang Regency through 2050.

CONCLUSION

GHG emissions from the MSW sector in Tangerang Regency increased from 541,155.24 tCO₂e in 2019 to 648,953.80 tCO₂e in 2024. LMDI decomposition showed that emission intensity, economic activity, and population growth were the main positive drivers, while changes in waste-treatment structure and declining waste-generation intensity partially offset the increase. The emission-intensity effect also reflects the influence of legacy methane generated from waste disposed of in previous years through the FOD mechanism.

SD simulations to 2050 indicate that, relative to BAU, the modeled mitigation potentials are 47.02% for CH₄ recovery (S2), 9.71% for enhanced recycling (S3), 9.46% for WTE (S1), and 3.04% for lower population growth (S4). These percentages represent scenario-based simulation outcomes under the specified assumptions, parameter values, intervention levels, and system boundaries, and should not be interpreted as guaranteed real-world emission reductions.

The results indicate that effective mitigation requires both control of methane emissions and diversion of waste toward controlled treatment pathways. For Tangerang Regency, priority measures include CH₄ recovery, increased recycling and organic-waste diversion, source reduction, and selective use of WTE for residual waste.

A key limitation is that unmanaged waste was represented as unmanaged solid waste disposal because pathway-specific data were unavailable. Therefore, the estimates do not constitute a complete inventory of open burning, littering, informal recovery, and other unmanaged pathways. Future research should extend the present framework by evaluating combined-policy scenarios and incorporating probabilistic uncertainty analysis, economic assessment, and life-cycle analysis.

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