Forecasting Municipal Solid Waste Generation in Thailand with Grey Modelling

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ABSTRACT

Forecasting municipal solid waste generation is crucial in planning for effective and sustainable waste management. Where data on waste are limited, the grey model (GM) has proven to be a useful tool for forecasting. This study applied GM for forecasting municipal solid waste generation in Thailand up to 2030, based on a dataset from 2011-2018. Both univariate models and multivariate models with four influencing factors (population density, gross domestic product per capita, household expenditure, and household size) were tested. The GM (1,1)-0.1 and GM (1,3) provided the lowest prediction errors among all models. Based on these models, waste generation in 2030 was projected to be 84,070-95,728 tonnes/day (1.23-1.40 kg/capita/day), an approximately 10-25% increase compared to 2018. In a business-as-usual scenario, there would be 6,404,848 tonnes of improperly treated waste by 2030, resulting in greenhouse gas emissions from its disposal of up to 2,600 $GgCO_2e$. This amount of waste is equivalent to 380 MWe of electricity; therefore, it should receive more attention. Results show that the improved management of improperly treated waste would help Thailand reach its waste-to-energy production target of 500 MW by 2036. Furthermore, diverting this portion of waste from open dump sites would directly reduce greenhouse gas emissions from the waste sector more than the set target of Thailand's Nationally Determined Contribution Roadmap on Mitigation 2021-2030 (1,300 $GgCO_2e$).

1. INTRODUCTION

Thailand's municipal solid waste (MSW) generation has grown continuously in the last decade. In contrast, waste collection, transportation services, and sanitary facilities are still limited, leading to illegal waste dumping, open burning, and MSW leakage into the environment (Wichai-utcha and Chavalparit, 2019). Other critical issues related to MSW management in Thailand include the lack of MSW statistics required for effective waste management planning, insufficient budget for operation and maintenance, inefficient waste treatment technology, limitations of laws and regulations, and poor cooperation between local government and private sectors. Thailand is challenged to move forward to zero waste management and achieve sustainable development goals (SDGs) and a circular economy. Forecasting can assist decision-makers and policymakers in projecting future needs and selecting appropriate MSW treatment technologies. A reliable forecast of MSW generation (MSWG) should be made available to create a sustainable solid waste management plan at the city or country level. For example, Johnson et al. (2017) employed a gradient-boosting regression model to predict MSWG across New York City and applied a spatiotemporal model. The models helped improve waste collection and the distribution of waste collecting vehicles and develop waste reduction strategies. An MSWG forecasting model and scenario analysis were applied to investigate the effect of current waste policies up to 2050 in the Balearic Islands. The forecasted and

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scenario results identified that the optimistic scenario decreased the amount of MSW sent to landfills by 40% and increased selective collection by 30% (Estay-Ossandon and Mena-Nieto, 2018). Di-Foggia and Beccarello (2021) used an econometric method based on a regression model to estimate the costs of waste facilities in Italy. The results from the model suggest that Italy could reduce landfill use and raise waste-to-energy capacity leading to a more positive cost-saving impact on waste management.

The selection of an appropriate prediction model depends on the purposes, the duration of prediction (short-, medium-, or long-term), and data availability. Linear regression analysis is a fundamental approach that is helpful in MSW forecasting (Ghinea et al., 2016). However, it requires many input data to produce steady and trustworthy results (Armstrong, 2001). Another model widely used to forecast MSW is the artificial neural network (ANN). ANN is a mathematically based nonlinear model. It has been used to estimate weekly and monthly waste generation and provides good performance and better results than the principal component regression analysis. (Noori et al., 2009). Nevertheless, the ANN model needs many months of waste generation data for long-term forecasting (Ali-Abdoli et al., 2012). Both regression analysis and ANN have limited utility if there is insufficient input information. When using limited data, available forecasting models include system dynamics (SD), grey model (GM), and fuzzy logic.

The SD model provides a viable alternative when there is limited data availability. It has been used for simulating MSWG and evaluating source separation, the capacity of waste treatment, and cost management (Sukholthaman and Sharp, 2016). SD modeling can be beneficial for policymakers and sanitation managers to project a broad view of waste management. However, it is relatively complex and requires advanced software processing (Xiao et al., 2020).

One widely used mathematical model for environmental projection is the GM of grey system theory, introduced by Deng (1982). The advantage of GM is its ability to work with limited data (at least four data points required). Chhay et al. (2018) used the univariate GM with 16 annual datasets to predict MSWG for the next 15 years. Zhang et al. (2019) also used multivariate GM to forecast MSWG for the next five years using nine annual datasets.

In a developing country such as Thailand, publicly available data on MSWG are limited and inconsistent. Intharathirat et al. (2015) applied multivariate GM to forecast Thai MSWG to 2030 using 13 annual datasets from 2000 to 2012, and the results were highly accurate for 18 years. Unfortunately, the methodology for estimating MSWG in national statistics has changed since 2010. Hence, the most recent and continuous dataset on MSWG in Thailand contains only eight annual datasets (2011-2018). The monthly statistics for MSWG of the whole country were not available publicly. As a result, GM is a feasible model for MSWG forecasting, providing solutions that can benefit sustainable MSW management. This study provides updated forecasts of MSWG in Thailand based on GM and presents the estimates for energy potential and GHG emissions from improperly treated waste (impW). The results will aid policymakers and local authorities in planning waste and GHG management policies.

2. METHODOLOGY

2.1 Input data for the models

2.1.1 MSW generation and management in Thailand

The key government offices responsible for analyzing and reporting the waste situation in Thailand are the Pollution Control Department (PCD) and the Department of Local Administration (DLA). The annual MSWG data during 1993-2018 is available publicly on the state report of pollution and solid waste in the country by the PCD (PCD, 2022a) and online database (PCD, 2022b). However, the MSWG data is inconsistent due to the data collection system and estimation method leading to limited available MSWG data for the forecast. Details of MSWG during 1993-2018 are shown in Supplementary data: Supplement S1-S2.

The PCD also reports on various types of waste disposal and waste utilization. To estimate the energy potential and GHG emissions, this study focused on the collected waste that is improperly treated; this includes open dumping (OD), controlled dumping (CD) of waste of more than 50 tonnes/day, incineration (IN) without proper pollution control, and open burning (OB). When this study was conducted, the most recent year for which information was available was 2017. MSW data of 2,441 municipalities were analyzed by Phongphiphat et al. (2019) and found that proportions of OD, IN, CD, and OB were 16.4%, 0.6%, 0.9%, and 0.4%, respectively. This study used these proportions to estimate GHG emissions and energy potential for impW in all future years.

2.1.2 Factors influencing MSWG

Selected current studies on MSWG forecasting are summarized in Table 1. Social and economic factors are frequently used in forecasting models, particularly population and GDP. This study considered the potential drivers by focusing on data availability, statistical significance, and the relationship between drivers and waste quantity at the national level. Four drivers, including population density, household size, gross domestic product (GDP) per capita, and household expenditure were selected for the model. Population density represents urban morphology and it is beneficial when one needs to compare countries or cities (Oribe-Garcia et al., 2015). Household size is the number of people per household, which is related to household solid waste in an econometric model (Beigl et al., 2004). GDP/capita was trained and tested in a regression model and provided high coefficient of determination (R^2) results (Ceylan, 2020). Household expenditure represents the potential for goods consumption by a household. According to Weng et al. (2010), there is a statistically significant and positive association between consumption expenditure and the amount of garbage discarded.

The data sources of selected drivers were as follows: the number of registered populations, number of houses, and country area were from DOPA (2018), the GDP statistics were from NESDB (2018), and the average household expenditures were from NSO (2018). The population density, household size, and GDP/capita were calculated. The 2019-2030 population projections were from NESDB (2013). Other future values were from the projections calculated using GM (1,1). These drivers were used as independent variables in the multivariate GM.

2.1.3 Dataset selected for model training and testing

The annual data for MSWG in tonnes/day and the selected factors during 2011-2018 were used for model training and testing with the GM models. This study used an ex-pose forecast. The model was built using the training data, while the test data were preserved to estimate forecast accuracy. Hyndman and Athanasopoulos (2018) suggested that the test data typically comprise about 20% of the total data. However, due to the limited data availability, only the last two values of the MSW sequence (data from 2017 and 2018) were used for model testing. The preceding values in the sequence stood for model training.

2.2 Forecasting using the grey model

After data collection, six steps of work were carried out to forecast MSWG: (1) preliminary analysis of collected data; (2) analysis of variable correlations by using Pearson correlation (R) and GRA; (3) training of the data in univariate and multivariate GM models; (4) model validation by using four error measures (described in section 2.3) to select a suitable model for MSWG forecast; (5) using the selected model to forecast; and (6) analysis of the prediction interval to evaluate the uncertainty of forecasting.

GM models are mathematical approaches operating based on two sequences, including a sequence of raw data and its accumulation-generated sequence. The univariate GM models, such as GM (1,1) and GM (1,1)-α, are first-order grey differential equations with one variable and without influencing factors forms (Sifeng and Yi, 2010). The multivariate GM models or GM (1,n) include influencing factors that relate to waste quantity, where n-1 equals the influencing factors number. Both differential equations in GM (1,1) and GM (1,n) can be estimated by the least square method to generate the forecasted data. All GM equations used for forecasting in this study are explained in Supporting Information 2.

2.3 Model validation and prediction intervals

To validate and compare the forecasts, four error measures, including the mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), were calculated. Their equations were explained in Chhay et al. (2018), Kannangara et al. (2018), and Zhang et al. (2019).

The best-fit model was used to forecast MSWG from 2019 to 2030 with the prediction interval (PI) of 95%, assuming that the forecast errors were normally distributed. Details and the equation were explained by Intharathirat et al. (2015).

2.4 Estimation of GHG emissions and energy potential

GHG emissions based on waste disposal activities were estimated following the IPCC guidelines, volume 5 (IPCC, 2006), and applied global warming potentials for CH_4 and N_2O of 28 and 265, respectively (IPCC, 2014). The GHG estimation was conducted from 2017 to 2030. Due to the limited data availability, the shares of impW were assumed to be constant, based on the 2017 data mentioned in section 2.1.1.

Table 1. The literature on the MSW forecasting model including data and driver uses

Modelling methods	Scope	Input data (waste amount)		Forecasting period (year)	Influencing factors			Reference
		Type	No's		Social	Economic	Other	
ANFIS	City	TS-y	41	17	Population, and percentage of urban population	GDP per capita	-	Tiwari et al. (2008)
ANN, RA	City	TS-m	120	22	Population	Household income	Maximum temperature	Ali Abdoli et al. (2012)
ANN	City	TS-y	18	-	Population, number of residents, household, and tourist	Household income	-	Sun and Chungpaibulpatana (2017)
ANN	Municipality	TS-y	13	-	Population, education, owned dwellings, and fraction of one person households	Personal income, employment rate, population worked at usual work place	-	Kannangara et al. (2018)
ANN	Country	TS-y	11	-	Urban population, Human Development Index (HDI), scientists and engineers, life expectancy at birth etc.	GDP, domestic material consumption, health expenditure, etc.	-	Adamović et al. (2018)
ANN, GM	Country	TS-y	16	15	Urban population	GDP, energy consumption	-	Chhay et al. (2018)
EM	City	TS-y	32	-	Population, average household size, population density, infant mortality rate, life expectancy at birth, and overnight stay	GDP, sectoral employment, and unemployment rate	-	Beigl et al. (2004)
FIG-GA-SVR	City	TS-y	21	9	Population	Household income, GDP, and total retail sales of consumer goods	-	Dai et al. (2020)
GM	City	TS-y	9	-	Population	City of GDP, retail sales, consumer spending	-	Zhang (2013)
GM	Country	TS-y	13	18	Population density, urbanization, and household size	Proportion employment, GDP per capita	-	Intharathirat et al. (2015)
GM, RA	City	TS-y	9	5	Population, tourists, and education	Retail sales of social consumer goods, urban per capita consumption expenditure	-	Zhang et al. (2019)
GM	City	TS-y	13	15	Population density	Household income	-	Duman et al. (2019)
RA	City	TS-y	15	-	Population density, average surface of family dwelling, education, etc.	Population employed, total personal income, tourist activity, density of retail outlet, etc.	-	Oribe-Garcia et al. (2015)
RA	City	TS	1	10	Number of residents, population (aged 15-59 years), and urban life expectancy	-	-	Ghinea et al. (2016)
RA	City	TS-w	8	1	Population density, age, education	Earning	Season and weather	Johnson et al. (2017)
RA	City	CS	50	-	Household size, education, occupation	Household income, energy consumption	-	Kumar and Samadder (2017)
RA	City	CS	580	-	Population, education, and culture	Household income and expenditure, energy and fuel structure and industry types	Climate and geography	Han et al. (2018)

Abbreviations: ANFIS=modeling methods include adaptive neuro-fuzzy inference system; ANN=artificial neural network; EM=econometric model; FIG=fuzzy information granulation; GM=grey model; RA=regression analysis; GA-SVR=support vector regression model optimized by genetic algorithm; SD=system dynamic; TSA=time series analysis; TS=time-series data; CS=cross-sectional data; -w=weekly; -m=monthly; -y=yearly

Table 1. The literature on the MSW forecasting model including data and driver uses (cont.)

Modelling methods	Scope	Input Data (waste amount)		Forecasting period (year)	Influencing factors			Reference
		Type	No's		Social	Economic	Other	
RA	Country	TS-y	8	-	Human Development Index	GDP and unemployment rate	Total CO_2 emissions	Namlis and Komilis (2019)
RA	Country	TS-y	24	-	Population	GDP per capita, inflation rate, unemployment rate	-	Ceylan (2020)
SD	Municipality	CS	3	11	Population, average household size,	Household income, and income of municipality	-	Dyson and Chang (2005)
TSA	Region	TS-y	29	29	Population	GDP per capita	-	Chung (2010)
TSA	City	TS-w	417	10	Population, average household size, infant mortality rate, and life expectancy at birth,	Sectoral employment, and GDP per capita	-	Rimaityte et al. (2012)

Abbreviations: ANFIS=modeling methods include adaptive neuro-fuzzy inference system; ANN=artificial neural network; EM=econometric model; FIG=fuzzy information granulation; GM=grey model; RA=regression analysis; GA-SVR=support vector regression model optimized by genetic algorithm; SD=system dynamic; TSA=time series analysis; TS=time-series data; CS=cross-sectional data; -w=weekly; -m=monthly; -y=yearly

Waste composition is an essential part of estimating accurate GHG emissions from impW. This study used created a proxy waste composition (Figure 1) by averaging the results of waste sampling from previous studies conducted by Phongphiphat et al. (2019) and Towprayoon and Phongphiphat (2013) at the MSW landfills of three large municipalities of Thailand, namely, Chiang Mai, Chonburi, and Khon Kaen. The waste sampling and quartering followed the procedures outlined in ASTM (2016). Waste samples were then classified into eleven components according to the IPCC guidelines.

According to DEDE (2020), the target of alternative energy from MSW would increase by 80% from DEDE (2015). Waste-to-energy (WtE) incineration plants are widely encouraged to reduce waste mass with electricity generation. Thus, this study estimated the energy potential in MWe by assuming impW was sent to WtE incineration. The average net calorific value used for unsorted MSW was 7.82 MJ/kg, and the efficiency capacity of the power plant was 20% and 16% of downtime per year (Towpayoon and Phongphiphat, 2013).

3. RESULTS AND DISCUSSION

3.1 Relationship between MSWG and selected drivers

The Pearson correlation coefficient (r) of all variables from 2011 to 2016 was examined as preliminary analysis. Results showed that household size had the strongest inverse relationship with MSWG, at 0.82, followed by population density (r=0.81), GDP/capita (r=0.75), and household expenditure (r=0.70). These results indicated that all drivers were related to waste quantity because the correlation values were higher than 0.70 (Asuero et al., 2006). Moreover, all factors were investigated in GRA, and the results were expressed as a grey relational grade. The grey relational grade's closeness to 1 indicates a higher degree of similarity between the two series' geometric patterns (Wu and Chen, 2005). Results showed that population density (γ=0.71) was the most significant driver, followed by GDP/capita (γ=0.70), household expenditure (γ=0.52), and household size (γ=0.49). Population density was also found to be the most influential factor correlated to MSW quantity from GRA in Intharathirat et al. (2015), though the study was based on a different period of data from Thailand. The relationship between MSWG and household size was opposite that of the Pearson correlation and GRA results. Due to its limitations, GRA only works for the sequences with direct relationships (Javed et al., 2019). Thus, the inverse relationship of household size was the lowest grey relational grade.

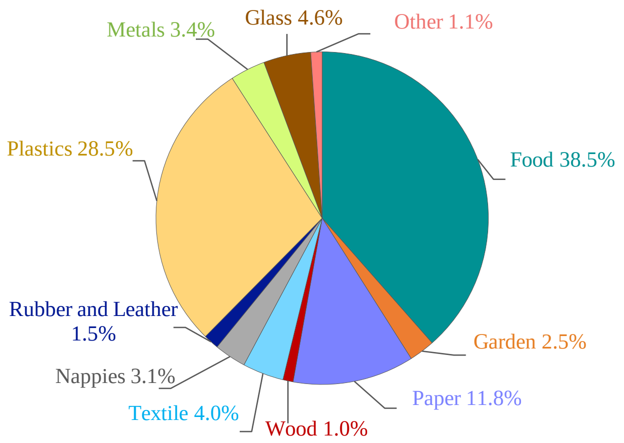

Figure 1. The proxy MSW composition of Thailand for GHG estimation in this study (Adapted by permission from: Springer Nature, Pudcha et al. (2022))

This study used all four factors to train and test the multivariate model. The analysis began with GM (1,5), where all four influencing factors were included. Then, for the following models, the weakest factors from the GRA results were removed one by one. The household size was removed for the GM (1,4). GM (1,3) consisted of two factors, namely population density and household expenditure, and GM (1,2) consisted of only one driver, which was population density.

3.2 Model training and testing

Results from model training using the univariate and multivariate model, based on the data from 2011-2018, are shown in Figures 2(a) and Figure 2(b), respectively. Results from data testing or model validation are shown in Table 2 for Models 1-8. All models yielded MAPE values lower than 10%, indicating a high prediction accuracy (Lewis, 1982). In the univariate models, the forecast errors increased as the α increased. These findings indicated that the old data in the sequence of this study were important to the model. For this reason, predicted values from GM (1,1)-0.1 were closest to the actual values compared to other models, except for one training point in 2013, as shown in Figure 2(a). GM (1,1)-0.5, without preference for old or new data, had the second-best prediction accuracy. Hence, this study used GM (1,1)-0.1 and GM (1,1)-0.5 from the univariate model for further forecasting of MSWG.

The GM (1,n) multivariate models fit the actual data better than the univariate models. The reason was that GM (1,n) models account for multiple factors that influence MSWG; thus, they could capture and predict changes in MSWG better than GM (1,1).

GM (1,3) had the lowest error rate at 0.88%, followed by GM (1,4), GM (1,2), and GM (1,5). It can be concluded that GM (1,3), which was made up of MSWG data, population density, and GDP/capita, provided the best forecasts for existing MSWG data. As seen in Figure 2(b), the trends from GM (1,2) to GM (1,4) increased or slightly increased in their indication of waste projection, while GM (1,5) decreased. GM (1,5) results indicated that conducting the model with a low correlation of influencing factors did not increase the prediction accuracy or yield a reasonable outcome. Moreover, Hyndman and Athanasopoulos (2021) described that the concise time series should be modeled simply because anything with more than one or two parameters will produce poor forecasts due to the estimation error. Therefore, GM (1,5), which had the highest error, was not used to forecast MSWG in this study.

3.3 Forecasts for MSW generation

Five models, GM (1,1)-0.1, GM (1,1)-0.5, GM (1,2), GM (1,3), and GM (1,4), were selected for use in forecasting MSWG to 2030. Figure 3 shows five trend lines for the forecast results. Three of them exhibited an upward trend, while the other two models indicated a downward trend. The results of annual projections are displayed in Table 3.

The projection of MSWG from GM (1,1)-0.5 was the highest among all models. According to GM (1,1)-0.5, MSWG would increase 26% from 2018 to 2030 (PI: 93,922-99,166). The MSWG/capita would increase 23% from 2018 to 2030 (PI: 1.38-1.45). GM (1,1)-0.1 resulted in a slightly lower MSWG forecast, reduced by 0.9% in 2030 compared to GM (1,1)-0.5.

In the case of GM (1,3), the projection of MSWG increased to 10% by 2030 (PI: 83,029-85,110). The projected MSWG/capita increased to 7% by 2030 (PI: 1.22-1.25). The rates of increase in GM (1,3) were lower compared to those of GM (1,1) because although the GDP values increase continuously, Thailand's population will decline slightly (NESDB, 2013). Therefore, GM (1,3) results indicated a balance between the factors influencing MSWG. In addition, GM (1,3) had a narrow PI finding compared to the other models, except for GM (1,4).

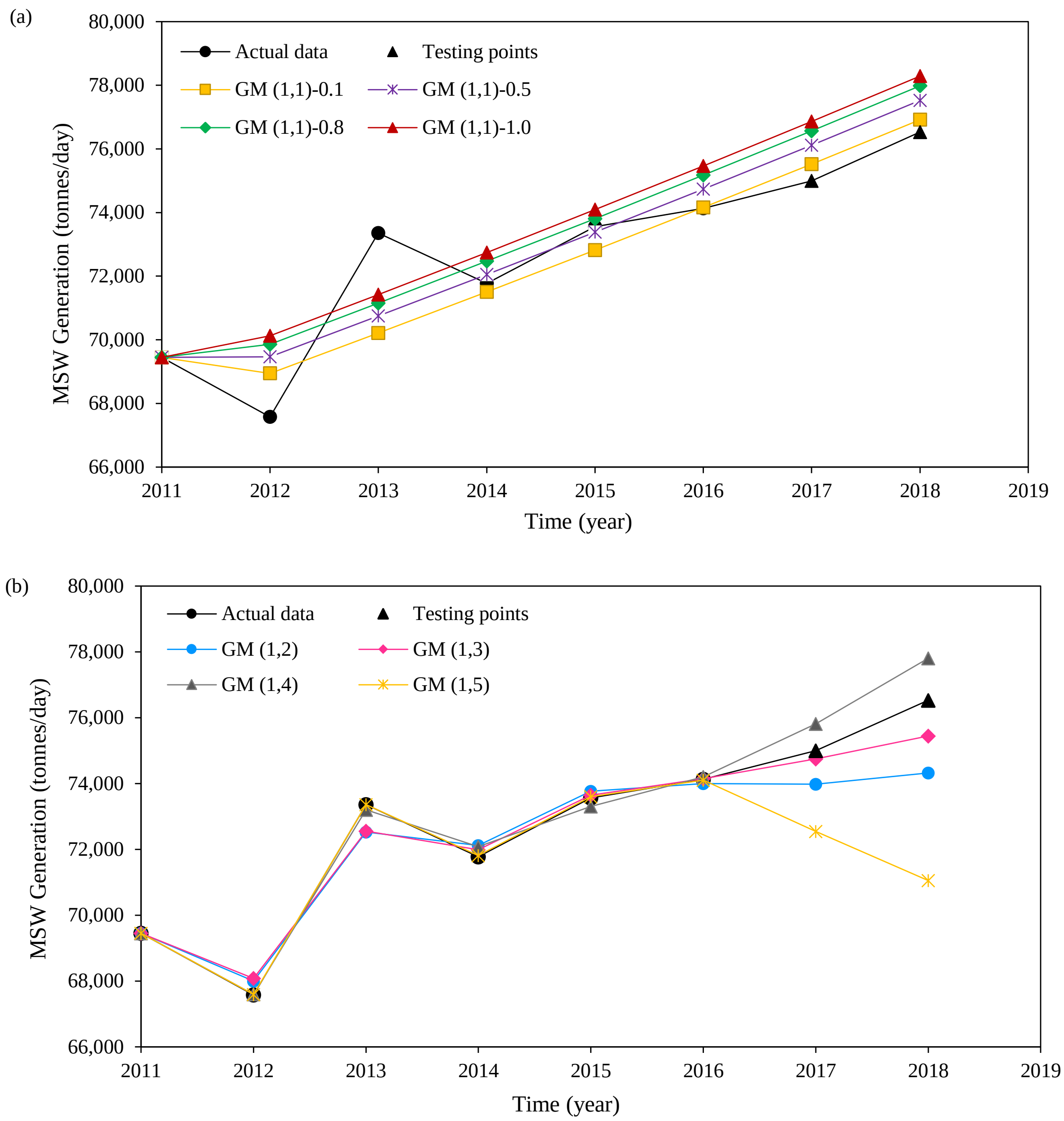

Figure 2. Results of training and testing (a) univariate models, and (b) multivariate models (cont.)

Table 2. Results of model validation using MAPE, MAE, MSE, and RMSE

Classification	No	Model	Average			
			MAPE (%)	MAE	MSE	RMSE
Univariate	1	GM (1,1)-0.1	0.603	456	213,266	462
	2	GM (1,1)-0.5	1.396	1,057	1,120,370	1,058
	3	GM (1,1)-0.8	1.749	1,509	2,279,995	1,510
	4	GM (1,1)-1.0	2.392	1,811	3,283,874	1,812
Multivariate	5	GM (1,2)	2.124	1,615	2,959,891	1,720
	6	GM (1,3)	0.877	669	620,324	788
	7	GM (1,4)	1.378	1,046	1,147,169	1,071
	8	GM (1,5)	5.215	3,966	18,012,534	4,244

Table 3. Forecasts of MSW generation (kt/day), MSW generation rate (kg/capita/day), amount of improperly treated waste (Mt), estimated energy potential (MW), and greenhouse gas emissions ($ktCO_2e$)

Year	MSW generation (kt/day)						Population[a] (Million person)	MSW generation rate (kg/capita/day)						Inappropriately -disposed waste (Mt)		Energy potential (MW)		GHG emissions ($ktCO_{2e}$)	
	Actual data[a]	GM (1,1) -0.1	GM (1,1) -0.5	GM (1,2)	GM (1,3)	GM (1,4)		Actual data[b]	GM (1,1) -0.1	GM (1,1) -0.5	GM (1,2)	GM (1,3)	GM (1,4)	GM (1,1) -0.1	GM (1,3)	GM (1,1) -0.1	GM (1,3)	GM (1,1) -0.1	GM (1,3)
2011	69.450	69.450	69.450	69.450	69.450	69.450	64.076	1.080	1.084	1.084	1.084	1.084	1.084						
2012	67.577	68.944	69.467	68.000	68.079	67.595	64.457	1.050	1.070	1.078	1.055	1.056	1.049						
2013	73.355	70.213	70.749	72.525	72.550	73.202	64.786	1.150	1.084	1.092	1.119	1.120	1.130						
2014	71.779	71.505	72.055	72.119	71.989	72.079	65.125	1.110	1.098	1.106	1.107	1.105	1.107						
2015	73.560	72.820	73.384	73.770	73.646	73.303	65.729	1.130	1.108	1.116	1.122	1.120	1.115						
2016	74.130	74.160	74.738	74.002	74.149	74.203	65.932	1.140	1.125	1.134	1.122	1.125	1.125						
2017	74.998	75.525	76.118	73.976	74.745	75.815	66.189	1.130	1.141	1.150	1.118	1.129	1.145						
2018	76.529	76.915	77.522	74.321	75.444	77.804	66.414	1.150	1.158	1.167	1.119	1.136	1.172						
2019		78.330	78.953	75.963	77.613	75.571	67.990		1.152	1.161	1.117	1.142	1.111	5.241	5.193	311	308	750	749
2020		79.771	80.410	76.246	78.315	75.300	68.128		1.171	1.180	1.119	1.150	1.105	5.337	5.240	317	311	1,039	1,035
2021		81.239	81.894	76.390	78.912	75.182	68.245		1.190	1.200	1.119	1.156	1.102	5.435	5.280	323	313	1,291	1,279
2022		82.734	83.405	76.502	79.499	75.023	68.342		1.211	1.220	1.119	1.163	1.098	5.535	5.319	329	316	1,510	1,488
2023		84.257	84.945	76.588	80.082	74.798	68.417		1.232	1.242	1.119	1.170	1.093	5.637	5.358	335	318	1,704	1,668
2024		85.807	86.512	76.651	80.661	74.501	68.471		1.253	1.263	1.119	1.178	1.088	5.741	5.397	341	320	1,875	1,822
2025		87.386	88.109	76.688	81.237	74.127	68.502		1.276	1.286	1.119	1.186	1.082	5.847	5.435	347	323	2,027	1,956
2026		88.994	89.735	76.700	81.810	73.672	68.511		1.299	1.310	1.120	1.194	1.075	5.954	5.474	353	325	2,164	2,071
2027		90.632	91.391	76.686	82.379	73.130	68.496		1.323	1.334	1.120	1.203	1.068	6.064	5.512	360	327	2,287	2,172
2028		92.300	93.077	76.655	82.954	72.504	68.467		1.348	1.359	1.120	1.212	1.059	6.175	5.550	367	329	2,400	2,259
2029		93.998	94.795	76.578	83.510	71.765	68.394		1.374	1.386	1.120	1.221	1.049	6.289	5.587	373	332	2,504	2,336
2030		95.728	96.544	76.481	84.070	70.928	68.306		1.401	1.413	1.120	1.231	1.038	6.405	5.625	380	334	2,600	2,404

[a]Statistics of registered population during 2011-2018 from the DOPA and the population projection during 2019-2030 from the NESDB; [b]National statistics from the PCD

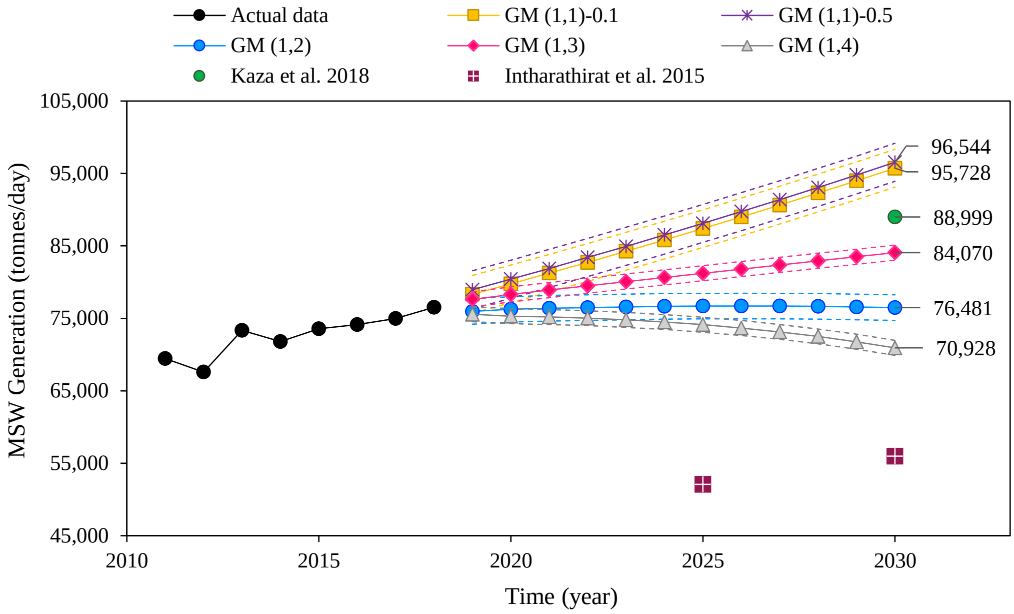

Figure 3. Comparison of forecasts for the MSW generation (tonnes/day) prepared by using five grey models in this study and forecasts conducted by other studies.

GM (1,2) and GM (1,4) showed decreasing trends. The forecasted MSWG for 2030 from GM (1,2) did not differ significantly from 2018 due to the decrease in population. Forecasts from GM (1,4) showed that MSWG would drop by 7% by 2030. Although GM (1,4) had the narrowest PI and the second-highest accuracy from the multivariate model, the downward trend is an unlikely future outcome. Results from these two models indicated that the change of future-influencing factors and model selection had a strong impact on forecasting.

In a previous waste forecast study from Thailand, Kaza et al. (2018) projected waste generation using GDP/capita based on a regression model. Their forecast was in between our results from univariate and multivariate GMs. In another previous study (Intharathirat et al., 2015), the forecasted values for 2025 and 2030 were the lowest (Figure 3) due to the use of a different dataset, as previously mentioned. Kaza et al. (2018) also estimated the average national waste generation rate by region using available data in 2016. The waste generation rate of countries in the East Asia and Pacific region ranged from 0.14 to 3.72 kg/capita/day, with an average of 0.56 kg/capita/day. This study forecasted that the average MSWG/capita for Thais would still be lower than the current rate for East Asia and Pacific countries, even in 2030. Therefore, the forecasting results were reasonable.

Both univariate and multivariate GMs, especially GM (1,1)-0.1 and GM (1,3), performed well although they were modeled with limited data. However, these forecasts are expected to change with the transformation of the population structure, economic factors, consumption trends, and policy and regulation.

3.4 Estimation of GHG emissions and energy potential from improperly treated waste

The presence of impW has negative impacts on both human health and the environment. Sustainable management of MSW inevitably includes eliminating impW. Assuming that MSW disposal would be handled as usual with the rates found in 2017, the amount of impW in 2030, based on GM (1,1)-0.1 and GM (1,3), is shown in Table 3. This impW would lead to uncontrolled GHG emissions estimated to be up to 2,600 GgCO_2e in 2030 (Figure 4). OD of MSW is the biggest GHG emission source through the release of CH_4. The estimated shares of GHG emissions from OD, CD, IN, and OB forecasted for 2030 were 88.3%, 10.1%, 0.4%, and 1.2%, respectively. Thailand's Nationally Determined Contribution Roadmap on GHG Mitigation, launched in 2017, set a target for GHG emission reduction from the waste sector at 1,300 GgCO_2e by 2030. The proposed activities for GHG mitigation included waste reduction at source and waste utilization before final disposal (ONEP, 2017). This study's findings suggest that limiting the MSW, especially organic waste going to open dumpsites, could help the nation mitigate a significant amount of GHG and reach the target. In addition, authorities should also be attentive to the controlled dumpsites across the country, as they can be much deeper or taller than open dumpsites and lead to more CH_4 emissions.

A WTE facility is a type of proper waste disposal that aids in the reduction of MSW mass while also providing an alternative fuel source for energy recovery. Besides the WTE facilities, alternative fuel from MSW has been used continuously instead of fossil fuel in cement industries (Hong et al., 2018). In Thailand, the Alternative Energy Development Plan (AEDP) set a target for energy recovery from MSW of 900 MWe by 2037 (DEDE, 2020). As of 2018, there were 273.4 MWe of WTE facilities installed in Thailand, accounting for almost 30% of the AEDP target (DEDE, 2019). The estimated energy potentials of impW in 2030, based on GM (1,1)-0.1 and GM (1,3) in Table 3, could be part of the fuel for the future WTE facilities to reach the AEDP target. Management of impW as an alternative fuel benefits three sectors: waste management, climate change, and alternative energy. However, fossil CO_2 emissions from burning plastic waste cause concern. The application of CO_2-capture technologies could help mitigate GHG emissions from the processes while avoiding GHG emissions from other fossil fuels (Chandel et al., 2012).

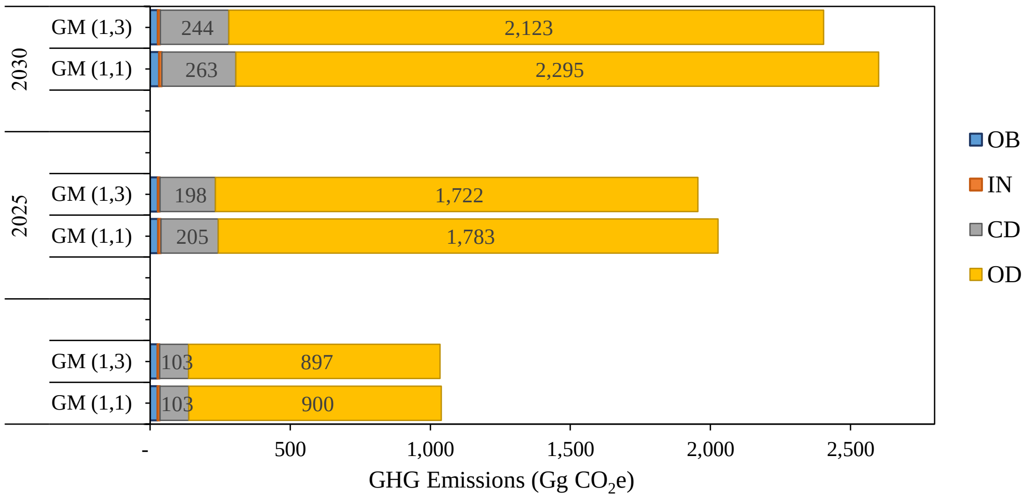

Figure 4. Forecasts of greenhouse gas emissions from improper waste disposal in 2020, 2025, and 2030. (OB=open burning; IN=incineration without pollution prevention; CD=controlled dumping of MSW more than 50 tonnes/day on land; OD=open dumping)

4. CONCLUSION

This study applied univariate and multivariate GMs in forecasting MSWG in Thailand up to 2030, based on the MSW data from 2011-2018. Although GMs can work with limited data, the data stability, the quantity of data, and influencing factors had critical impacts on correlation and forecasting results. The univariate and multivariate models GM (1,1)-0.1 and GM (1,3) offered greater accuracy with a lower error rate than the other six models. As a result, these models were used to forecast MSWG and estimate impW from 2019-2030. Waste generation in 2030 was projected to be 84,070-95,728 tonnes/day (1.23-1.40 kg/capita/day), an approximately 10-25% increase compared to 2018. In a business-as-usual scenario, GHG emission from impW would reach 2,600 GgCO_2e by 2030, with CH_4 emitted from OD accounting for 88.3%. Eliminating dumpsites could help Thailand reach the national GHG mitigation target. The energy potential of impW was projected to be in the range of 334 to 380 MWe. Maximizing the utilization of impW should be prioritized in the future evaluation of national and local policies. In addition, to develop sustainable MSW management in Thailand, it is necessary to increase the efficiency of waste separation at the source and in collection and transportation. Greater attention and further research is needed to investigate the current characteristics of MSW and sorting efficiency, as it affects the design and efficiency of MSW disposal technologies.

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