Global J. Environ. Sci. Manage. 9(2): 227-240, Spring 2023, Serial #34

Global Journal of Environmental Science and Management
(GJESM)

Homepage: https://www.gjesm.net/

Podcasts

ORIGINAL RESEARCH ARTICLE

Municipal solid wastes quantification and model forecasting

Y.M. Teshome[1,*], N.G. Habtu[2], M.B. Molla[3], M.D. Ulsido[4]

[1]Climate Change and Bioenergy Development, Wondo Genet College of Forestry and Natural Resources, Hawassa University, Ethiopia

[2]Chemical, Environmental and Process Engineering, Institute of Technology, Bahir Dar University, Ethiopia

[3]GIS-Remote Sensing and Environmental Management, Wondo Genet College of Forestry and Natural Resources, Hawassa University, Ethiopia

[4]Water Supply and Environmental Engineering, Institute of Technology, Hawassa University, Ethiopia

ARTICLE INFO

Article History:
Received 12 April 2022
Revised 17 June 2022
Accepted 25 August 2022

Keywords:
Income levels
Model development
Socioeconomic factors
Solid waste
Waste composition

DOI: 10.22034/gjesm.2023.02.04

ABSTRACT

BACKGROUND AND OBJECTIVES: The amount of solid waste produced and its impact on communities and the environment are becoming a global concern. This study aims to assess the amount, composition, and prediction models of solid waste generation in the study area.

METHODS: Solid waste data were collected from both residential and non-residential areas using stratified and systematic sampling approaches. Interviews and field measurements were used to obtain socioeconomic and solid waste data from 90 households and 69 samples from non-residential areas.

FINDINGS: The research area's mean household solid waste generation rate is 0.39kilograms per capita per day. Organic waste accounted for the majority of the waste generated in the study area (71.28 percent), followed by other waste (9.77 percent), paper (6.71 percent), and plastic waste (6.41 percent). The solid waste generation rate demonstrated a positive relationship ($p<0.05$) with monthly household income and educational level. However, there was a negative association between family size and age ($p > 0.05$). Based on a high regression coefficient determination value (0.72), low mean absolute error (0.094), sum square error (1.28), and standard error of the estimate (0.908), Model 4 was chosen as the best-fit model among the proposed models.

CONCLUSION: The developed models met multiple linear regression assumptions and could be used to estimate the rate of household solid waste generation. This study generated large amounts of organic waste present in municipal solid waste sources that can contaminate the environment and have an impact on human health while also having a massive energy recovery capability.

NUMBER OF REFERENCES
51

NUMBER OF FIGURES
5

NUMBER OF TABLES
8

*Corresponding Author:
Email: *yirdawmeride@gmail.com*
Phone: +2510581141231
ORCID: 0000-0002-4598-5179

Note: Discussion period for this manuscript open until July 1, 2023 on GJESM website at the "Show Article".

INTRODUCTION

The population of the universe has rapidly expanded, from 3.1 billion in 1960 to almost 7 billion in 2010. By 2050, 9.3 billion people are projected to exist on Earth (Malav *et al.*, 2020). Municipal solid waste (MSW) production worldwide is reportedly between 1.7 and 1.9 billion metric tons per year (Wilson *et al.*, 2016). Also, solid waste generation will increase from 1.3 billion to 2.5 billion metric tons per year by 2025, with developing countries accounting for the majority of the growth (Pandey *et al.*, 2015). The amount of solid waste produced has increased over time due to population growth and urbanization worldwide. However, there are fewer rooms accessible to keep waste (Eboh *et al.,* 2016). Owing to the differences in population growth, geography, climate, and living standards, solid waste generation trends fluctuate from area to area, country to country, and city to city (Noufal *et al*., 2020). Developed countries can produce more solid waste than developing countries, but because of institutional competency, access to technology, and sufficient costs for sustainable solid waste treatment, most developed countries are effective in regulating waste (Shahzad *et al*., 2013). Since solid waste managementhas an impact on both the environment and human health, as well as having the potential to considerably increase resource conservation, it is becoming a concern for both national and municipal governments (Ghinea *et al*., 2016). An effort is being made in Africa for a range of waste streams to develop and put into effect rules, regulations, and policies that facilitate the management and collection of urban solid waste, including recycling, recovery, and environmentally sound disposal (Mukwana *et al*., 2014). To manage waste effectively, it is important to gather a lot of data from several sources, including accurate estimates of the quantity of waste that will be produced in the future as well as data on the factors that will affect that generation of waste (Grazhdani, 2016). The development of current waste management infrastructures as well as their continued sustainable development and optimization are based on future projections of the generation of MSW (Abasi and El Hanandeh, 2016). For proper decision-making about the management of solid waste in urban areas, it is crucial to know the amountand kind of waste produced (Intharathirat *et al*., 2015). MSW is diverse in both quantity and composition. The changes in the seasons and household income levels affect it differently (Monavari *et al*., 2012). Investigators have conducted studies on the factors that influence the rate of waste formation. The studies' findings demonstrate that factors such as educational level, age, family size, and income have a substantial impact on the amount of household waste generated (Zulkifli *et al*., 2019; Noufal*et al*., 2020). The categorization and measurement of waste quantity and composition are made more challengingdue tothis fluctuation. Domestic solid waste generation and composition in various regions of the world have been evaluated by severalstudies (Noufal *et al*., 2020). The studies revealed that analyzing the characteristics of MSW is critical for a variety of reasons, including determining the potential of waste resources for recycling, reuse, and recovery processes; estimating solid waste generation sources; and designing simple treatment facilities. However, solid waste generated in households varies greatly and is largely dependent on socioeconomic status (Amaya *et al*., 2019). Forecasts of solid waste from mathematical prediction models are regarded as a crucial tool for decision-makers, policy-makers, and stakeholders in creating the best and most comprehensive solid waste management policies (Abbasi and El Hanandeh, 2016). To estimate the solid waste generation rate, several multiple regression models have been built for various cities around the world (Verma *et al*., 2019). Unfortunately, the social, economic, and geographic heterogeneity of the various regions of the world makes it difficult to draw conclusions or make projections with the suggested models. It is necessary to adapt models and their variables to the circumstances in other places, often with varying degrees of success. Some of the difficulties associated with adapting these models, according to Kumar and Samandder (2017), are related withinadequate or unavailable information in databases from other countries. The majority of the work put into creating models for estimating the generation of solid waste is based on the data that is only available for one country, which makes it unrepresentative of the elements of Ethiopian MSW. There is littlecurrent, trustworthy data on the composition and quantity of solid waste in Ethiopia, including thestudy location. Because there are so few solid wastecharacteristic data points, the Yirgalem town Administration appears to struggle to create effective site-specific SWM programs and initiatives. Similar to other Ethiopian towns, Yirgalem rarely has access to accurate waste statistics about the rates and types of solid waste that are generated, the effectiveness of solid waste collection, and the quantity of recycled and disposed solid waste. Due to the absence of accurate waste statistics, the rate of generation of solid waste must be anticipated by using predictive techniques based onthe limited amount of available data.When modeling genuine MSW, it iscritical that you employ the right preparation method. Therefore, the study aims to identify the quantity and composition of solid waste, as well as correlate waste quantity with relevant socioeconomic parameters of households, and develop a model for forecasting solid waste generation. The study was carried out in Yirgalem town, in Ethiopia, using information from the two seasons' variations in 2021.

MATERIALS AND METHODS

Study site description

This study was carried out in Yirgalemtown, Sidama Regional State, Ethiopia. It is located at 6º44´- 6º46´ N latitude and 38º24´ - 38 °26´ E longitudes (Fig. 1). The study area has an elevation of 1600–1960 meter (m). In addition, it is the biggest settlement in the Daleworeda (Yusuf *et al*., 2018). It is situated 311 kilometers (km) south of Addis Ababa and 47 km from Hawassa, the capital of the Southern Nations, Nationalities, and Peoples'and Sidama regions. The total population of Yirgalem town is 64,507, of whom 31,737 are male and 32,770 are female (Yusuf *et al*., 2018). Yirgalem town has a moderate climate, with minimum and maximum annual temperatures of 14 °C and 30 °C, respectively. The study area experienced bimodal rainfall with peaks in April, June, and August, with an annual rainfall of 1138-1690 millimeters (mm) (Yusuf *et al*., 2018).

Hypotheses

The hypotheses are drawnfrom the study's goal. The rates of solid waste generation inhouseholds in Yirgalem town are constant throughout the wet and dry seasons;there is no significant difference between the solid waste generation rate and socioeconomic income levels; the quantity of solid waste produced and socioeconomic characteristics do not significantly correlate with one another.

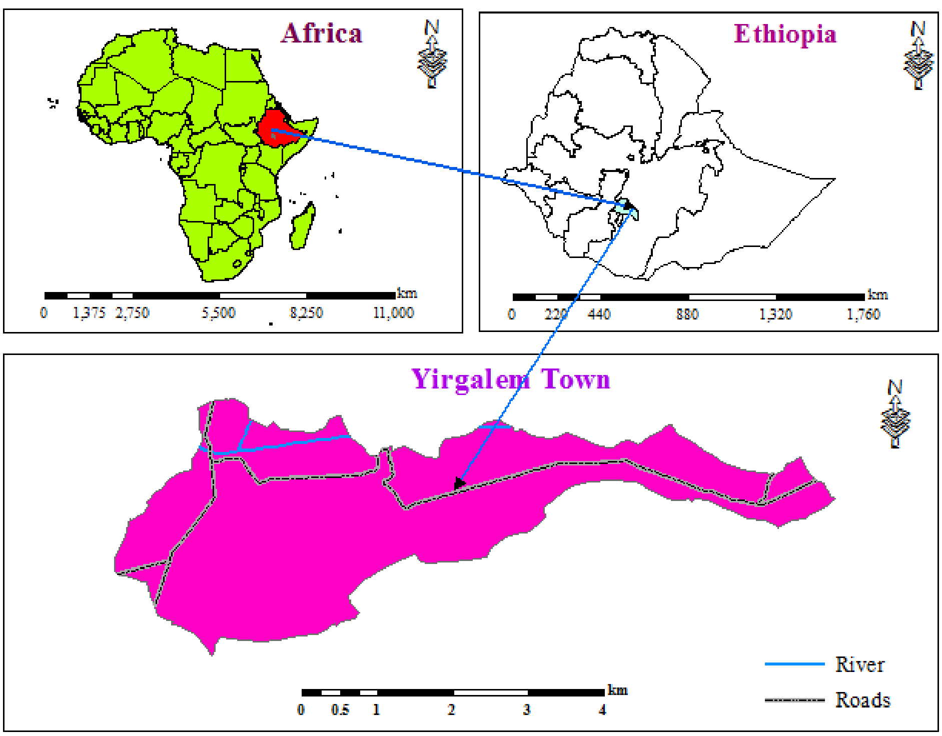

Fig. 1: Geographic location of the study area in Yirgalem town, Sidama Regional State, Ethiopia

Sampling design and techniques

Solid waste data were collected in a longitudinal study.Information on MSW was gathered from both residential and non-residential locations. A stratified sampling technique was used because of the variety of sources used to generate MSW. The municipality was classifiedinto five categories based on the sources of the production of solid waste; residential, commercial areas, institutions, healthcare facilities, and street sweepings (Okey *et al.*, 2013). For each municipal solid waste source, representative samples were gathered using a systematic sampling technique. Household samples were selected based on income, housing types, and the presence of fundamental social services, which serve to divide socioeconomic status into low-, middle-, and high-income categories (Nyankson *et al.*, 2015). The residential zones were divided into three housing types: low-cost landed (low-cost houses), middle-cost landed (living in flats and medium-cost), and high-cost landed (living in high-cost homes) (Yahya *et al.*, 2013). In the study, questionnaires were utilized to collect data on a variety of topics, including the personal and socioeconomic background of the residentials and the overall amount of waste produced.

Sample size determination

According to waste management recommendations, a total of thirty household samples were taken fromeach of the three social-economic groups (low, middle, and high) for a MSW survey (Yahya *et al.*, 2013; Mucyo, 2013). A total of 90 household samples were collected for this study, representing all socioeconomic levels.A previous study (Yahya *et al.*, 2013) that looked intothe generation of solid waste from diverse sources, such as commercial areas, institutions, healthcare facilities, and street sweeping, was the basis for the determination of total samples for non-residential locations. Each waste source was given five sample recommendations. For this investigation, 44 samples from commercial areas, 12 samples from institutions, 9 samples from healthcare facilities, and 7 km of street sweeping were collected twice during the dry and wet seasons.

Solid waste data collection methods

Depending on the amount and type of material generated in the area, MSW was measured at each source using plastic bags with one or more of their daily waste collections. Data on MSW were collected over seven consecutive days (Sachi and Mensah, 2020). To determine the weight of the waste for each solid waste collection location, the collected waste was weighed first. All samples were manually classified into eight waste categories (paper and paper products, plastics, organic (compostable) materials, glass, metals, textiles, wood, and others) at each collectionstationas indicated in Table 1 (Osei-Mensah *et al.*, 2014). To account for seasonal variation, data on solid waste were gathered in two seasons (dry and wet). Dry season data were collected from December 2020 to February 2021, and wet season data were collected from June to August 2021.

Table 1: Waste categories of MSW

Waste categories	Waste description
Organic materials	All biodegradable materials like food waste, yard trimming, grass including *Khat*, agricultural crop residues, manures, and other organic
Paper and paper products	Office paper, computer paper, magazines, glossy paper, waxed paper, and newsprint
Plastics	All plastic materials like polyethylene terephthalate (PET) bottles, high-density polyethylene (HDPE), film plastic, plastic bag,
Glass	All glass materials like windows and mirror glass as well as broken bottles and other containers
Metal	The waste originating from Ferrous (Iron, steel, tin cans, and bi-metal cans), aluminum, and non-ferrous non-aluminum metals
textiles	Waste of clothes, carpets, pillows
wood	The waste which includes sawn timber, wooden boards, furniture
others	Dust, ash, e-wastes, stone

Solidwaste generation and composition calculations

Solid waste generation rate

Household solid waste generation (HSWG) kilogram per capita per day (Kg/c/day) was determined as per the mixed or total waste collected in a day and the separated fractions using Eq. 1 (Miezahet *al*., 2015).

$$\mathrm{HSWG}\left(\frac{\frac{\mathrm{kg}}{\mathrm{c}}}{\mathrm{day}}\right)=\frac{\begin{array}{c}\textit{Total weight of HSW}\\ \textit{generated within 7 days}\end{array}}{\begin{array}{c}\textit{a total number of families in the}\\ \textit{household X number of the day}\end{array}} \quad (1)$$

The total amount of household solid waste (HSW) produced by all houses in a town was calculated using Eq. 2 (Miezah *et al*., 2015).

$$\text{Total HSW}\left(\frac{\mathrm{kg}}{\mathrm{day}}\right)= \text{Number of population in the town X}\frac{\mathrm{HSWG}\frac{\mathrm{Kg}}{\mathrm{c}}}{\mathrm{day}} \quad (2)$$

Composition of solid waste

The total weight of all constituents in the sample was combined to compute the weight of the entire sample. The percentage composition of each componentis calculated using Eq. 3 (Miezahet *al*., 2015).

$$\text{Percentage composition waste fraction} = \frac{\text{weight of separated waste}}{\text{the total mixed weight sample}}\text{X100} \quad (3)$$

Methods of model development

A solid waste generation forecasting model was built based on socioeconomic characteristics, such as household size, monthly income, age of the household head, gender, job status,marital status,andeducational level. All these most common traits have an impact on HSWG rates integrated with other variables (Popliet *al*., 2021). Multiple linear regression was used to develop solid waste generation models. Multiple linear regression assumptions, such as linear relationshipsbetween dependent and independent variables, normality of the tested data, multicollinearity test, and homoscedasticity, were evaluated before the data were analyzed (Tabachnicket *al*., 2019). Bivariate Pearson correlation coefficient (r) and a statistical significance test were used to ensure that the dependent and independent variables had a linearrelationship. To make sure the data was normal, a graphic representation of the P-P plot, histograms, and the Kolmogorov-Smirnov test were also utilized. Additionally, the multicollinearity of independent variables was examined using the variance inflation factor (VIF) to identify multivariate correlations and the Pearson correlation coefficient (r) to identify bivariate associations.An illustration of a scatter plot was used to study the homoscedasticity of the standardized residual and predictive values.Four fundamental criteria—the mean absolute error (MAE), the sum of square error (SSE), standard error of the estimate (SEE), and coefficient of multiple determination—were used to select the best-fit model (R^2) (Kulisz and Kujawska, 2020). The average absolute error is expressed using Eq. 4 (Chhay *et al*., 2018).

$$\mathrm{MAE}=\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left|\mathrm{SWG}-\mathrm{SWGp}\right| \quad (4)$$

Where, *SWG* and *SWGp* denote the actual solid waste generation data and the predicted values, respectively. where n represents the number of observations.

The sum of square error can be given using Eq. 5 (Wang *et al*., 2021).

$$SSE=\sum_{i=1}^{n}\left(SWG-SWGp\right)2 \quad (5)$$

The standard error of the estimate can be shown as Eq. 6 (Wang *et al*., 2021).

$$SEE=\sqrt{\frac{\sum_{i=1}^{n}\left(SWG-SWGp\right)2}{n-p}} \quad (6)$$

Where, *p*is the number of parameters in the regression model.

The coefficient of multiple determinations can be expressed using Eq. 7 (Chhay *et al*., 2018).

$$\mathrm{R}^2=\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}}\left(\mathrm{SWGp}-\overline{\mathrm{SWG}}\right)2}{\sum_{\mathrm{i}=1}^{\mathrm{n}}\left(\mathrm{SWG}-\overline{\mathrm{SWG}}\right)2} \quad (7)$$

Where, $\overline{\mathrm{SWG}}$ is the arithmetic mean of the observed data.

Statistical analysis

The association between the amount of waste produced and socioeconomic factors such as household size, monthly income, age of the household head, gender, employment status, marital status, and educational attainment was assessed using correlation analysis. One-way analysis of variance (ANOVA) was used to examine the statistically significant variations in waste generation rates based on income class, and the Student's t-test was used to examine seasonal change.Version 25.0 of SPSS statistics for Windows was used to conduct all statistical analyses. The Tukey test was applied to compare statistical differences and means.There is a p-value < 0.05 for each analysis presented in this study.

RESULTS AND DISCUSSION

Solidwaste generation rate

Table 2 displays the average solid waste generation for the three income levels and two seasonal variations. Based on a statistical analysis of variance, it was discovered that there was a significant difference ($p < 0.05$) between the socioeconomic income level and the rate of HSWG. A multiple comparison analyses of the solid generation rate (kg/c/day) between low- and middle-income groups showed a significant difference ($p = 0.000$). The rate of solid waste generation between the low and high socioeconomic income levels also showed a statistically significant difference ($p = 0.000$). Between the middle- and high-income categories, there was no discernible difference in the rate of solid waste generation ($p = 0.222$). According to this finding, the high- and middle-income socioeconomic categories generated more solid waste than the low-income group. This is because the activities of higher-income families consume more resources than those of lower-income families. According to Amaya *et al.* (2019) households generate more solid waste as their socioeconomic status improves. This outcome is consistent with the findings reported by other researchers (Heriantoet *al*., 2019). Yirgalemtown's mean HSWG rate is 0.39 kg /c/day, with low-income (0.28), middle-income (0.42), and high-income groups (0.47). The result of the predicted solid waste generation rate aids in the development of effective solid waste management strategies. A similar study was reported in Addis Ababa, Ethiopia (Tassie *et al*., 2019), Shire-Endasilasie, Ethiopia (Zewdu and Mohammedbirhan, 2014), Dhanbad, India (Khan *et al.,* 2016), Ghana cities (Miezah *et al.,* 2015), Thika Municipality, Kenya (Kinyua and Njogu, 2015), and Laga Dadi town, Ethiopia (Assefa and Muktar, 2017). The current solid wastegeneration rate is higher than elsewhere reported for Bahir Dar city (Asmare, 2019), Robetown (Erasu *et al.,* 2018), Chiro town (Umer *et al*., 2019), and Debre Berhan town, Ethiopia (Abera, 2017). Thisstudy is less than the report made in Jima town (Getahun *et al.,* 2012) and Sawla town, Ethiopia (Haile *et al*., 2020). The result found fromthis study is within the range of 0.2-0.8 kg/c/day of solid waste generation for most of Sub-Saharan African countries (Miezah *et al*., 2015) and developing countries within the range of 0.3 to 0.9 kg/c/day (Nadeem and Farhan, 2016). Location, climate, lifestyle, urbanization, and economic development of cities contribute to differences in solid waste generation rates. At $p<0.05$, there was also significant variation in the solid waste generation between the wet and dry seasons. The wet season (0.43) had a higher per capita HSWG rate than did the dry season (0.35 kg/c/day). This is because the wet season produces more vegetables, fruits, *Khat*, grass, and other resources than the dry season does. Several studies (Kamran et al., 2015; Mshelia, 2015; Zia *et al*., 2017), have found that the rate of solid waste generation decreases from the wet season to the dry season. Households generated almost 80% of the solid waste, followed by commercial areas (12.13%) and institutions (4.59%). Previous studies have shown that solid waste generation comes from a variety of sources, including residential areas (50–80%), commercial areas (10–30%), street sweeping, and institutions, all of which have varying proportions (Sachiand Mensah, 2020), which is consistent with the results of this study.

Solid waste composition

The majority of organic wastewas generated by street sweeping (78.79%), followed by institutions (71.26%), commercial areas (69.98%), and residential areas (68.91%) as shown in Table 3. Institutions (22.55%) and commercial areas (5.89%) produced larger amounts of paper waste. As shown in Fig. 2, Yirgalemtown generated a high amount of organic waste (71.28%), followed by miscellaneous waste (9.77%), paper (6.71%), and plastic waste (6.41%). The overall results of the present study indicated that organic (compostable) waste had the highest

Table 2: Analysis of variance of solid waste generation under the three income levels and seasons

Income level	n	solid waste generation (kg/c/day)		f-value	p-value
		Mean*	S.E.**		
Low income	60	0.28^{a}	0.017		
Middle-income level	60	0.42^{b}	0.024	19.77	0.000
High-income Level	60	0.47^{b}	0.023		
Total	180	0.39	0.014		
Seasons					
Wet	90	0.43^{a}	0.020	10.741	0.001
Dry	90	0.35^{b}	0.018		
Total	180	0.39	0.014		

*Means with different superscript letters are significantly different at (α< 0.05)
**Standard error

Table 3: Types of solid wastes under different generated sources

Types of solid waste	Sources of solid waste (%)			
	Residential	Commercial	Institutions	Street sweeping
Organic	68.91	69.98	71.26	78.79
paper	2.15	5.89	22.55	4.84
plastic	5.85	5.57	6.19	7.12
Glass	1.09	1.13	0.00	1.24
Metal	0.59	7.98	0.00	0.00
Textile	5.07	2.01	0.00	1.09
woods	0.21	0.00	0.00	0.00
others	16.14	7.45	0.00	6.92
total	100.00	100.00	100.00	100.00

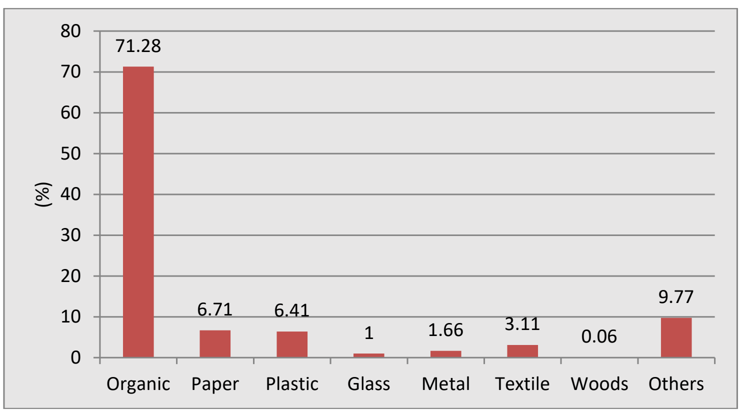

Fig. 2: Overallsolid waste composition in Yirgalem town

percentage. Comparable studies were found in Laga Dadi town, Ethiopia (Assefa and Muktar, 2017), Guayaquil, Ecuador (Amaya *et al*., 2020), Homs City, Syria (Noufal *et al.,* 2020), Thu Dau Mot, Vietnam (Trang *et al.,* 2017), and Sulaimanyah, Iraq (Hamza, 2020). Lower organic waste was found in this study compared to work done by Umer *et al.* (2019) for Chiro town, Ethiopia.

The *relation between HSWGrate and socioeconomic factors*

Table 4 shows the relationship between the rate of HSWG and socioeconomic factors. Household monthly income (r = 0.476, p = 0.000), educational level (r = 0.327,

Table 4: Relation between HSWG rate and socioeconomic factors

	Socioeconomic factors	Pearson correlation (r)	P-value
Solid waste generation rate (kg/c/day)	Gender	0.181	0.087
	Age	-0.053	0.620
	Marital status	0.183	0.084
	Education level	0.327	0.002
	household size	-0.436	0.000
	House ownership	-0.058	0.587
	Job-status	-0.007	0.950
	Monthly income	0.606	0.000

p = 0.002), and solid waste generation rate all showed positive correlations.Solid waste production increases in direct proportion to household prosperity. This is due to the different home consumption habits, which is consistent with a study conducted by Batu *et al*. (2016). Severalstudiesobtained a negative correlation between household monthly income and the solid generation rate per capita each day (Monavari *et al*., 2012; Trang *et al*., 2017). It means that those with a greater income generated a lower rate of solid waste production per capita than lower-income households. There was a negative relationship between household family size and the solid waste generation rate (r =-0.436, p =0.000). In comparison to large families, more people in their homes live together with shared common resources and consume more items, resulting in fewer waste disposals. This study is consistent with reports from other sources (Ogwueleka, 2013). Numerous studies have discovered a positivecorrelation between the size of a household's family and the rate of solid waste produced per capita (Noufal *et al*., 2020). Households with a large number of people generate more solid waste than those with small families. The differences in the outcomes of various studies are related to differences in economic and cultural standing as well as techniques. A higher level of education in the household results in a higher rate of solid waste generation due to increased household income and work prospects. Several academics endorse this study (Getahun *et al*., 2012). Other socioeconomic factors such as job status, marital status, home ownership, and gender had no significant impact on the solid waste generation rate in this study. Similar studies were carried out by earlier researchers (Batu *et al*., 2016).

Model development

The rate of HSWG was not normally distributed when examined using the Kolmogorov–Smirnov method at a significance level of 0.05. To match the data normality, the logarithm data transformation approach for the solid waste generation rate (response variable) was used. For independent variables, Pearson correlation (r) less than 0.3 and VIF less than 5 revealed no multicollinearity issues (Ghinea *et al*., 2016), which meets the current study as shown in Table 6. Normality in terms of error was assessed using normal probability plots and histograms, as shown in Figs. 3 and 4. The homoscedasticity assumption was further tested using a graphical depiction of the scatter plot between the standardized residual and expected response variables, as illustrated in Fig. 5. Using independent variables such as household size, educational level, monthly income, and age of the household head, four types of models were proposed at a significance level of ANOVA analysis (Table 5). Because these independent variables had the greatest impact on the rate of solid waste production at the study site, which is used in the development model. Model 4 (Eq. 9) is the best-fit model, followed by Model 3 (Eq. 8), as described below, based on a high R^2 and low values of mean absolute error (MAE), the sum of square error (SSE), and standard error of the estimate (SEE), as shown in Table 7.

Model 3:

$$\log Y = 0.600 + 0.007MI + 0.034Edu - 0.152Hs \quad (8)$$

Model 4:

$$\log Y = 0.687 + 0.007MI + 0.031Edu - 0.153Hs - 0.026 \quad (9)$$

Where, logY is the log-transformed solid waste generation rate (kg/c/day), MI is household monthly income (US dollars), Edu is the educational level of the household head, and Hs is the household size. In the final model, variables (monthly income, family size, educational level, and age) of the household head explained 72% of the solid waste generation

Table 5: Analysis of variance for solid waste prediction model development

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	1.677	1	1.677	51.167	.000[a]
	Residual	2.885	88	.033		
	Total	4.562	89			
2	Regression	2.970	2	1.485	81.183	.000[b]
	Residual	1.592	87	.018		
	Total	4.562	89			
3	Regression	3.211	3	1.070	68.159	.000[c]
	Residual	1.351	86	.016		
	Total	4.562	89			
4	Regression	3.281	4	.820	54.445	.000[d]
	Residual	1.281	85	.015		
	Total	4.562	89			

Table 6: Estimated regression coefficient of independent variables

Model		Unstandardized coefficients		t	Sig.	Collinearitystatistics	
		B	S.E.			Tolerance	VIF
1	(Constant)	.392	.035	11.227	.000		
	Monthly income	.006	.001	7.153	.000	1.000	1.000
2	(Constant)	.669	.042	15.916	.000		
	Monthly income	.007	.001	10.720	.000	.978	1.023
	Household size	-.150	.018	-8.407	.000	.978	1.023
3	(Constant)	.600	.043	14.042	.000		
	Monthly income	.007	.001	10.576	.000	.940	1.064
	Household size	-.152	.017	-9.226	.000	.976	1.024
	Educational level	.034	.009	3.917	.000	.957	1.045
4	(Constant)	.687	.058	11.822	.000		
	Monthly income	.007	.001	11.010	.000	.908	1.101
	Household size	-.153	.016	-9.432	.000	.976	1.024
	Educational level	.031	.009	3.628	.000	.935	1.069
	Age	-.026	.012	-2.155	.034	.953	1.050

Table 7: Selection of best-fitted multiple linear regression model

Model	Regression equation	R^2	MAE	SSE	SEE	Sum rank	Total rank
1	logY=0.392+0.006MI	0.37(4)	0.140(4)	2.902(4)	1.338(4)	16	4
2	logY =0.669+0.007MI - 0.150HS	0.65(3)	0.107(3)	1.597(3)	1.025(3)	12	3
3	logY=0.600+0.007MI+0.034 Edu - 0.152HS	0.70(2)	0.097(2)	1.366(2)	0.937(2)	8	2
4	logY=0.687+0.007MI+0.031 Edu - 0.153HS-0.026Age	0.72(1)	0.094(1)	1.28(1)	0.908(1)	4	1

rate. This research was similar to that of Lebersorger and Beigl (2011), who reported an R^2 of 74.3 percent. The R^2 rarely exceeded 50%, except in studies with a large number of predictors and a small sample size (Lebersorger and Beigl, 2011), which supports the current study. When compared to the findings of the earlier studies (Beitez *et al.,* 2008), the developed models produced lower solid waste per capita. These discrepancies have occurred as a result of differences in the influencing factors of independent variables in

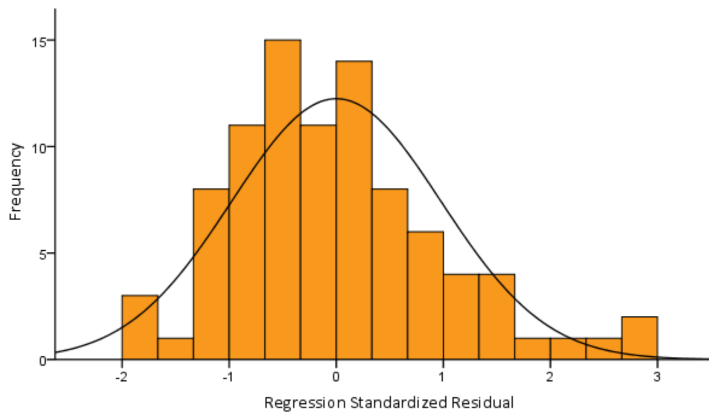

Fig. 3: Residual histogram plots for normality assumption

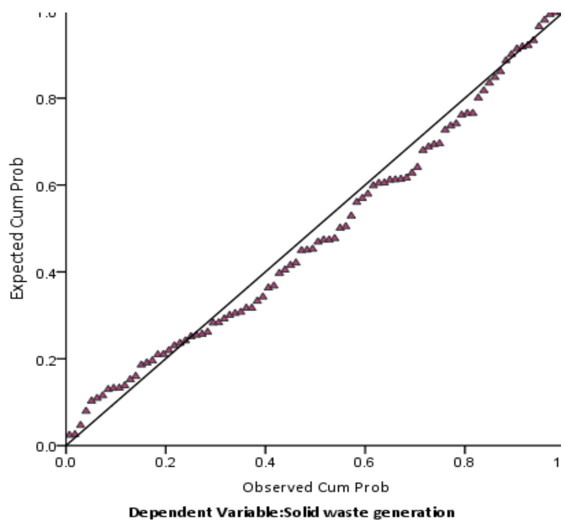

Fig. 4: Residual P-P plots for normality assumption

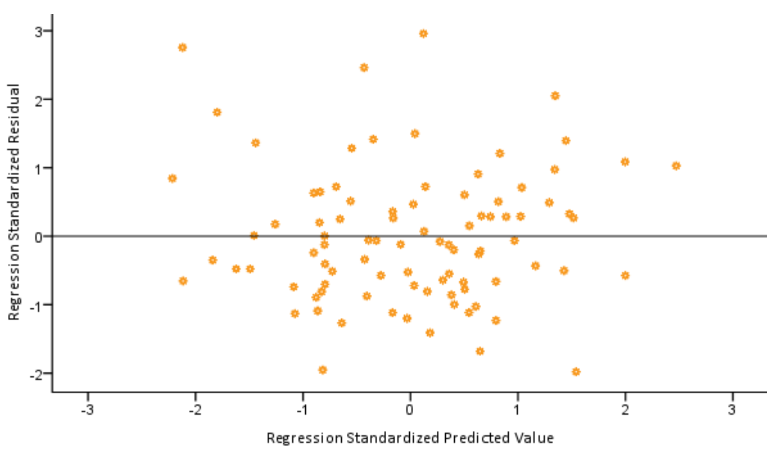

Fig. 5: residual scaterplots for homoscedasticity assumption

Table 8: Comparisons of the observed and predicted value of solid waste generation rate

Models	Paired differences				t	df	Sig.
Model No.	S.D.*	S.E.	95% confidence Interval of the difference				
			Lower	Upper			
Model 3	.12341	.01301	-.01445	.03724	.876	89	.383
Model 4	.12028	.01268	-.02324	.02715	.154	89	.878

*Standard deviation (S.D.)

various locations, nations, cities, and climates. The multiple regression coefficient determination value (R^2 = 0.51) estimated by Beitez *et al.* (2008), which is a minor relative measure of fit compared to this study model (R^2 = 0.72), was also used to explain variances in model prediction values. The different independent variables utilized during the model development caused this difference in coefficient determination (R^2). This way, the study was conductedto close the information gaps that the nation and the study area were encountering.The model established in this study can be used to estimate solid waste generation rates in Yirgalem and other similar towns.

Validation of developed models

The residual errors' behavior, notably their normal distribution, independence, and homoscedasticity—the gap between the dependent variable's observed and predicted values—determines the validity of the MLR models (Kumar and Samandder, 2017). To ensure the validity and correctness of the findings, the values of R^2 (a relative measure of fit) and performance indicators (an absolute measure of fit), such as mean absolute error (MAE), sum of square error (SSE), and standard error of the estimate (SEE), were computed (Table 7). Using a pair-wise t-test of the anticipated and actual values of a response variable (solid waste generation rate), the superior model was further validated.In Models 3 and 4, there was not a statistically significant difference ($p > 0.05$) between the dependent variable's observed and predicted values. Due to the higher value of $p = 0.878$, model 4 is more precise and accurate in this investigation, as shown in Table 8.

CONCLUSION

The characterization of solid waste is crucial for long-term sustainable planning and development. The analysis of the solid waste in Yirgalem town and its characteristics, along with the Pearson correlation results, show the significant impact of socioeconomic factors on waste generation. The most important aspect in identifying the best alternatives for solid waste treatment and investment is the composition of the waste. Low-income groups generated less solid waste per capita than high- and middle-class groups. In contrast to the dry season, the wet season showed a higher per capita generation rate of household solid waste. The majority of MSW was generated by households, followed by commercial areas and institutions in this study area. The overall results of the current study revealed that organic (compostable) waste received the highest percentage of coverage. The rate of solid waste generation was positively correlated with the monthly household income and educational level. While household size and age of the household headwere negatively associated with the rate of solid waste generation, theresult indicated that households with a large number of people generate more solid waste than those with small families. Other socioeconomic factors such as job status, marital status, home ownership, and genderhad no significant impact on the solid waste generation rate. Four models were developed using the most influential socioeconomic factors such as household monthly income, household size, age, and level of education as predictors and solid waste generation as a response variable. Based on the high regression coefficient determination, least mean absolute error, sum square error, and standard error of the estimate, the last equation (model 4) was selected as the best-fit model among these models. The model developed in this study can be used to estimate solid waste generation rates in the study area and other towns of comparable size. Although, the models generated in this study only consider socioeconomic factors, other researchers should integrate other environmental factors to improve model prediction accuracy.Large amounts of biodegradable (organic) waste present in municipal solid waste sources can contaminate the environment and have an impact on human health, while also having a massive energy recovery capability. MSW composition should be segregated further into sub-categories of solid waste, which is crucial for in-depth analysis. The town administration of Yirgalem should utilise this organic waste as compost for urban agriculture and the manufacture of biogas fuel to decrease the amount of solid waste and energy consumption. This study can serve as a basis for more research in the field as it provides a solid foundation for comparison.

AUTHOR CONTRIBUTIONS

Y.M. Teshome performed the data collection, experimental design, sampling campaigns, solid waste analysis, and prepared the manuscript text. N.G. Habtu performed the literature review and the model configuration and simulations, analyzedand interpreted the data and results, and edited the manuscript. M.B. Mollaorganized the methodology, analyzed, and interpreted the data and results, prepared the manuscript text, and edited the manuscript. M.D. Ulsido organized the methodology, analyzed and interpreted the data and results, prepared the manuscript text, and edited the manuscript.

ACKNOWLEDGMENTS

Hawassa University, Wondo Genet College of Forestry and Natural Resources, University of Gondar, and the German Academic Exchange Service (DAAD) provided financial support [1712874] and educational opportunities. The authors appreciated the invaluable feedback from anonymous reviewers.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

OPEN ACCESS

©2023 The author(s). This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third-party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit: http://creativecommons.org/licenses/by/4.0/

PUBLISHER'S NOTE

GJESM Publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

ABBREVIATIONS

%	Percent
'	Minute
o	Degree
°C	Degree celsius
ANOVA	Analysis of variance
DAAD	German Academic Exchange Service
df	Degree of freedom
E	East
Edu	Educational level
Eq.	Equation
Fig.	Figure
HDPE	High-density polyethylene
Hs	Household size
HSW	Household solid waste
HSWG	Household solid waste generation
Kg/c/day	Kilogram per capita per Day
kg	Kilogram
m	Meter
Km	Kilometer
logY	Logarithm of solid waste generation
MAE	Mean absolute error
MI	Household monthly income
mm	millimeters
MSW	Municipal solid waste
n	Number of samples
N	North
p	Number of regression parameters
PET	Polyethylene terephthalate
r	Pearson correlation coefficient
R^2	Coefficient of multiple determinations
S.D.	Standard deviation
S.E.	Standard error
SEE	Standard error of the estimate
Sig.	Significance value
SPSS	Statistical package for the social sciences

SSE	Sum of square error
Student's t-test	Parametric tests based on the Student's or t-distribution
SWG	Solid waste generation
SWG_p	Solid waste generation prediction value
VIF	Variance inflation factor

REFERENCES

Abbasi, M.; El Hanandeh, A., (2016). Forecasting municipal solid waste generation using artificial intelligence modelling approaches. Waste Manage., 56: 13–22 **(10 pages).**

Abera, K.A., (2017). Household solid waste generation rate and onsite handling practices in Debre Berhan Town, Ethiopia. Sci. J. Public Health. 1(5): 1-9 **(9 pages)**.

Amaya, J.L.; Hidalgo, J.; Jervis, F.; Moreira, C., (2019). Influence of socio-economic factors on household solid waste generation of the city of Guayaquil, Ecuador. in: Proceedings of the 17th LACCEI International Multi-Conference for Engineering, Education, and Technology: "Industry, Innovation, and Infrastructure for Sustainable Cities and Communities". Latin American and Caribbean Consortium of Engineering Institutions.

Asmare, M., (2019). Bahir Dar City municipal solid waste potential assessment for clean Energy. Am. J. Energy Eng., 7(1): 1-8 **(8 pages)**.

Assefa, M.; Muktar, M., (2017). Solid waste generation rate and characterization study for LagaTafo Laga Dadi Town, Oromia, Ethiopia. Int. J. Environ. Prot. Policy. 5(6): 84-93 **(10 pages)**.

Batu, M.M.; Admasu, E.; Tolosa, F., (2016). Determinants of households' willingness to pay for improved solid waste management in Ethiopia: The case study of Jimma Town. J Environ. Earth Sci., 6(7): 1–14 **(14 pages).**

Benitez, S.O.; Lozano-Olvera, G.; Morelos, R.A.; Vega, C.A., (2008). Mathematical modeling to predict residential solid waste generation. Waste Manage., 28: 7–13 **(7 pages)**.

Chhay, L.; Reyad, M.A.; Suy, R.; Islam, M.R.; Mian, M.M., (2018). Municipal solid waste generation in China: Influncing factors analysis and multi-model forecasting. J. Mater. Cycles Waste Manage., 20(3): 1761-1770 **(10 pages).**

Eboh, F.C.; Ahlstrom, P.; Richards, T., (2016). Estimating the specific chemical exergy of municipal solid waste. Energy Sci. Eng., 4(3): 217–231 **(15 pages)**.

Erasu, D.; Feye, T.; Kiros, A.; Balew, A., (2018). Municipal solid waste generation and disposal in Robe town, Ethiopia. J. Air Waste Manage. Assoc., 68(12): 1391–1397 **(7 pages)**.

Getahun, T.; Mengistie, E.; Haddis, A.; Wasie, F.; Alemayehu, E.; Dadi, D.; Van Gerven, T.; Van der Bruggen, B., (2012). Municipal solid waste generation in growing urban areas in Africa: Current practices and relation to socioeconomic factors in Jimma, Ethiopia. Environ. Monit. Assess., 184(10): 6337–6345 **(9 pages)**.

Ghinea, C.; Dragoi, E.N.; Comanita, E.D.; Gavrilescu, M.; Campean, T.; Curteanu, S.; Gavrilescu, M., (2016). Forecasting municipal solid waste generation using prognostic tools and regression analysis. J. Environ. Manage., 182: 80–93 **(14 pages)**.

Grazhdani, D., (2016). Assessing the variables affecting on the rate of solid waste generation and recycling: An empirical analysis in Prespa Park. Waste Manage., 48: 3–13 **(11 pages)**.

Haile, M.Z.; Mohammed, E.T.; Gebretsadik, F.D., (2020). Physicochemical characterization of municipal solid waste in Sawla town, Gofa Zone, Ethiopia. J. Appl. Sci. Environ. Manage., 23(11): 2023-2029 **(7 pages)**.

Hamza, A.A., (2020). Municipal solid waste quantity, ingredients, and site disposal problems in Pshdar District in Sulaimanyah: Iraqi Kurdistan Region, Iraq. Kufa J. Eng., 11(4): 1–18 **(18 pages)**.

Herianto, H.; Maryono, M.; Budihardjo, M.A., (2019). Factors affecting waste generation: household study in Palangka Raya City, Central Kalimantan. E3S Web of Conference 125: 07007 **(5 pages)**.

Intharathirat, R.; Abdul Salam, P.; Kumar, S.; Untong, A., (2015). Forecasting of municipal solid waste quantity in a developing country using multivariate grey models. Waste Manage., 39: 3–14 **(12 pages)**.

Kamran, A.; Chaudhry, M.N.; Batool, S.A., (2015). Effects of socio-economic status and seasonal variation on municipal solid waste composition: a baseline study for future planning and development. Environ. Sci. Eur., 27(1): 1-16 **(16 pages)**.

Khan, D.; Kumar, A.; Samadder, S.R., (2016). Impact of socioeconomic status on municipal solid waste generation rate. Waste Manage., 49: 15–25 **(11 pages)**.

Kinyua, R.; Njogu, Paul., (2015). An analysis of solid waste generation and characterization in Thika Municipality of Kiambu County, Kenya. J. Environ. Sci. Eng., 4(4): 210-215 **(6 pages)**.

Kulisz, M.; Kujawska, J., (2020). Prediction of municipal waste generation in Poland using neural network modeling. Sustainability. 12(23): 10088 **(16 pages).**

Kumar, A.; Samadder, S.R., (2017). An empirical model for prediction of household solid waste generation rate – A case study of Dhanbad, India. Waste Manage., 68: 3–15 **(13 pages)**.

Lebersorger, S.; Beigl, P., (2011). Municipal solid waste generation in municipalities: Quantifying impacts of household structure, commercial waste and domestic fuel. Waste Manage., 31(9): 1907–1915 **(9 pages)**.

Malav, C.L.; Yadav, K.K.; Gupta, N.; Kumar, S.; Sharma, G.K.; Krishnan, S.; Rezania, S.; Kamyab, H.; Pham, Q.B.; Yadav, S.; Bhattacharyya, S.; Yadav, V.K.; Bach, Q.V., (2020). A review on municipal solid waste as a renewable source for waste-to-energy project in India: Current practices, challenges, and future opportunities. J. Clean. Prod., 277: 123227 **(80 pages)**.

Miezah, K.; Obiri-Danso, K.; Kadar, Z.; Fei-Baffoe, B.; Mensah, M.Y., (2015). Municipal solid waste characterization and quantification as a measure towards effective waste management in Ghana. Waste Manage., 46: 15–27 **(13 pages)**.

Monavari, S.M.; Omrani, G.A.; Karbassi, A.; Raof, F.F., (2012). The effects of socioeconomic parameters on household solid-waste generation and composition in developing countries: A case study Ahvaz, Iran. Environ. Monit. Assess., 184(4): 1841–1846 **(6 pages)**.

Mshelia, A.D., (2015). Seasonal variations of household solid waste generation in Mubi, Nigeria. Int. J. Innovations Educ. Res., 3(5): 115–124 **(10 pages)**.

Mucyo, S., (2013). Analysis of key requirements for effective implementation of biogas technology for municipal solid waste management in Sub-Saharan Africa. A Case Study of Kigali City, Rwanda. Abertay University, Rwanda.

Mukwana, K.C.; Samo, S.R.; Tunio, M.M.; Jakhrani, A.Q.; Luhur, M.R., (2014). Study of energy potential from municipal solid waste of Mirpurkhas city. J. Eng. Sci. Technol., 13(2): 3 **(3 pages).**

Nadeem, K.; Farhan, K., (2016). Waste amount survey and physio-chemical analysis of municipal solid waste generated in Gujranwala-Pakistan. Int. J. Waste Resour., 6(1): 1-8 **(8 pages)**.

Noufal, M.; Yuanyuan, L.; Maalla, Z.; Adipah, S., (2020). Determinants of household solid waste generation and composition in Homs City, Syria. J. Environ. Public Health. 2020: 1–15 **(15 pages)**.

Nyankson, E.A.; Fei-Baffoe, B.; Gorkeh-Miah, J., (2015). Household solid waste generation rate and physical composition analysis: Case of Sekondi-Takoradi Metropolis in the Western Region, Ghana. Int. J. Environ., 4 (2): 1-15 **(15 pages)**.

Ogwueleka, T.C., (2013). Survey of household waste composition and quantities in Abuja, Nigeria. Resour. Conserv. Recycl., 77: 52–60 **(9 pages)**.

Okey, E.N.; Umana, E.J.; Markson, A.A.; Okey, P.A., (2013). Municipal solid waste characterization and management in Uyo, AkwaIbom State, Nigeria. WIT Trans. Ecol. Environ., 173: 639–648 **(10 pages)**.

Osei-Mensah, P.; Adjaottor, A.A.; Owusu-Boateng, G., (2014). Characterization of solid waste in the Atwima-Nwabiagya District of the Ashanti Region, Kumasi-Ghana. Int. J. Waste Manage. Technol., 2: 1–14 **(14 pages)**.

Pandey, B.K.; Vyas, S.; Pandey, M.; Gaur, A., (2016). Municipal solid waste to energy conversion methodology as physical, thermal, and biological methods. Curr. Sci. Perspect. 2: 1–6 **(6 pages)**.

Popli, K.; Park, C.; Han, S.M.; Kim, S., (2021). Prediction of solid waste generation rates in urban region of laos using socio-demographic and economic parameters with a multi linear regression approach. Sustainability. 13(6): 3038 **(15 pages)**.

Sachi, P.J.; Mensah, E.A., (2020). Household characteristics and waste generation paradox: What influences solid waste generation in Bolgatanga.Int. J. Environ. Waste Manage., 26(2): 212–233 **(22 pages)**.

Shahzad, S.; Butt, A.; Anwar, S.; Ahmad, S.; Sarwar, T.; Asghar, N., (2017). Municipal solid waste as a renewable source of energy: an overview from the Lahore District in Punjab, Pakistan. Pol. J. Environ. Stud., 26(6): 2721–2729 (**9 pages)**.

Tabachnick, B.G.; Fidell, L.S.; Ullman, J.B., (2019). Using multivariate statistics, Seventh edition. ed. Pearson, N.Y.

Tassie, K.; Endalew, B.; Mulugeta, A., (2019). Composition, generation and management method of municipal solid waste in Addis Ababa City, Central Ethiopia: A Review. Asian J. Environ. Ecol., 9(2): 1–19 **(19 pages)**.

Trang, P.T.; Dong, H.Q.; Toan, D.Q.; Hanh, N.T.; Thu, N.T., (2017). The effects of socio-economic factors on household solid waste generation and composition: A case study in Thu Dau Mot, Vietnam. Energy Procedia., 107: 253–258 **(7 pages)**.

Umer, N.; Shimelis, G.; Ahmed, M.; Sema, T., (2019). Solid waste generation rate and management practices in the case of Chiro Town, West Hararghe Zone, Ethiopia. Am. J. Environ. Prot., 8(4): 87-93 **(7 pages)**.

Verma, A.; Kumar, A.; Singh, N.B., (2019). Application of multi linear model for forecasting municipal solid waste generation in Lucknow City: A case study. Curr. World Environ., 14(3): 421–432 **(12 pages)**.

Wang, D.; Tang, Y.T.; He, J.; Yang, F.; Robinson, D., (2021). Generalized models to predict the lower heating value of municipal solid waste. Energy. 21: 1-29 **(29 pages)**.

Wilson, D.C.; Rodic, L.; Modak, P.; Soos, R.; Rogero, A.C.; Velis, C.; Simonett, O., (2015). Global waste management outlook. United Nations Environment Programme.

Yahya, N.; Mohd, A.B.; Abdullah, P.F.; Hj, N.B., (2013). Survey on solid waste composition, characteristics and existing practice of solid waste recycling in Malaysia.Perumahan Dan Kerajaan Tempatan, Malaysia.

Yusuf, E.; Fiseha, F.; Dulla, D.; Kassahun, G., (2018). Utilization of kangaroo mother care and influencing factors among mothers and care takers of low birth weight babies in Yirgalem Town, Southern, Ethiopia. Divers. Equal. Health Care. 15(2): 87-92 **(6 pages)**.

Zewdu, A.; Mohammedbirhan, M., (2014). Municipal solid waste management and characterization in Aksum and Shire-Endaslassie Towns, North Ethiopia. J. Environ. Earth Sci., 4(13): 1-8 **(8 pages)**.

Zia, A.; Batool, S.; Chauhdry, M.; Munir, S., (2017). Influence of income level and seasons on quantity and composition of municipal solid waste: A case study of the capital City of Pakistan. Sustainability. 9(9): 1568 **(13 pages)**.

Zulkifli, A.A.; MohdYusoff, M.Z.; AbdManaf, L.; Zakaria, M.R.; Roslan, A.M.; Ariffin, H.; Shirai, Y.; Hassan, M.A., (2019). Assessment of municipal solid waste generation in Universiti Putra Malaysia and its potential for green energy production. Sustainability. 11(14): 3909 **(15 pages)**.

AUTHOR (S) BIOSKETCHES

Teshome, Y.M., Ph.D. Candidate, Climate Change and Bioenergy Development, Wondo Genet College of Forestry and Natural Resources, Hawassa University, Ethiopia.

- Email:*yirdawmeride@gmail.com*
- ORCID: 0000-0002-4598-5179
- Web of Science ResearcherID: NA
- Scopus Author ID: NA
- Homepage: https://hu.edu.et/index.php/academics/all-programs/316-all-programs-wcofnr

Habtu, N.G., Ph.D., Associate Professor, Chemical, Environmental and Process Engineering, Institute of Technology, Bahir Dar University, Ethiopia.

- Email: *nigus.gabiye@bdu.edu.et*
- ORCID: 0000-0002-0725-8771
- Web of Science ResearcherID: GPF-8910-2022
- Scopus Author ID: NA
- Homepage: https://bit.bdu.edu.et/fcfe/?q=staffprofile/http://bdu.edu.et/

Molla, M.B., Ph.D., Assisstant Professor, GIS-Remote Sensing and Environmental Management, Wondo Genet College of Forestry and Natural Resources, Hawassa University, Ethiopia.

- Email: *mikiasb@hu.edu.et*
- ORCIDD: 0000-0002-6694-4579
- Web of Science ResearcherID: AAY-1347-2020
- Scopus Author ID: NA
- Homepage: https://hu.edu.et/index.php/academics/all-programs/316-all-programs-wcofnr

Ulsido, M.D., Ph.D., Associate Professor, Water Supply and Environmental Engineering, Institute of Technology, Hawassa University, Ethiopia.

- Email:*mihret@gmail.com*
- ORCID:0000-0002-6961-3193
- Web of Science ResearcherID: NA
- Scopus Author ID: 57190020367
- Homepage: https://www.researchgate.net/profile/Mihret-Ulsido-2

HOW TO CITE THIS ARTICLE

Teshome, M.Y.; Habtu, G.N.; Molla, B.M.; Ulsido, D.M., (2023).Municipal solid waste quantification and model forecasting. Global J. Environ. Sci Manage., 9(2): 227-240.

DOI: 10.22034/gjesm.2023.02.04

url: https://www.gjesm.net/article_254253.html