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Modeling Household Solid Waste Generation in Urban Estates Using Socio-Economic and Demographic Data, Kisumu City, Kenya

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Abstract: Knowledge on household solid waste quantity is essential for planning solid waste management strategy for a given city. Lack of reliable studies on household solid waste (HSW) generation is a key challenge in proper HSW management. The objective of this study was to model HSW generation using socio-economic and demographic data in urban estates. The study adopted a cross-sectional descriptive research design. Three estates representing three socio-economic groups; High Income (Milimani), Middle Income (Migosi), Low Income (Obunga) were selected through multi-stage simple random sampling. A stratified proportionate random sample of 368 households was selected from a study population of 8651 households. Household survey questionnaires were used to obtain primary data on socio-economic and demographic characteristics of households while Direct Waste Weighing was used to obtain primary data on the amount of monthly HSW generated. Multiple linear regression was used to model the amount of HSW generated in Kilograms based on household size, household monthly income, household monthly expenditure on food and age of the household head. The findings of this study revealed that household size, household monthly income, household monthly expenditure on food and age of the household head explained over 97% of monthly HSW generation at 95% confidence level across high income (R^2 =0.975) middle income (R^2 =0.984) and low income (R^2 =0.976) socio-economic groups respectively indicating that the predictor variables selected for the regression are good predictors of HSW generation. The study concluded that socio-economic and demographic data were appropriate in modeling HSW generation. The models predicting solid waste generation are useful analytic tools in the design of solid waste management programs and are useful in areas where there is urgent need of planning for solid waste management.
Keywords: Household solid waste generation, predictor variables, socio-economic and demographic data, planning, socio-economic group.

INTRODUCTION

Modeling solid waste generation is a very important data set in solid waste management since it is key in understanding solid waste distribution in each area [1]. Solid waste is fast becoming a menace in both developed and developing nations [2, 3]. This can be attributed to rapid urbanization taking place within the world [4] economic development and rise in living standards [5]. The management of household solid waste (HSW) is one of the huge challenges of urban areas of all sizes [4] and is always ranked in the top five of the most challenging problems for city managers [6]. Knowledge on household solid waste quantity is essential for planning a solid waste management strategy for a given city or municipality [7]. Modeling of solid waste quantity is vital for efficient planning and sustainable design of household solid waste management [8]. Lack of reliable studies on the amount of household solid waste generated is a key challenge in proper household solid waste management [9] Several studies have been done to forecast, model, estimate or predict the amount of household solid waste generated mainly in developed countries [10-14]. Most of the research work available is related to modeling household solid waste generation in developed countries and major cities by use of time-series data [15]. The identification of modeling, prediction or estimation parameters has to be based on a database, which describes regional peculiarities [11]. The exclusive use of national aggregates in input-output models [16] is not appropriate for explaining regional dynamics, therefore, preference ought to be given to factor models that focus on socio-economic and demographic indicators available at regional level [17]. Modeling HSW generation using socio-economic and demographic factors is suitable in areas where available data is scarce yet there is an urgent need for the HSW management and planning [18]. Modeling household solid waste generation is not an easy task in developing countries mainly due to inadequate data on the amount of HSW generated [19, 20]. Furthermore, most countries lack reliable historic household solid waste data, therefore, for the problem of solid waste management to be solved, an accurate method for identifying relevant factors influencing the amount of household solid waste generated is required [21]. A number of studies on solid waste management (SWM) have been conducted in Kenya [22-24]. Similarly, these studies that have been done on solid waste management in Kisumu have not provided any data on modeling household solid waste generation [25, 26]. Despite these relevant literature on household solid waste generation, there is inadequate data especially in developing African countries. Similarly, there is a lack of accurate and detailed information since most studies rely on data collected at disposal points and solid waste transfer stations. A study conducted at the point of HSW generation (households) is therefore necessary to provide accurate and detailed information for modeling household solid waste generation based on specific household socio-economic and demographic data. Hence, this study sought to model household solid waste generation in urban estates in Kisumu city, Kenya, using socio-economic and demographic data

LITERATURE REVIEW

Solid waste management is a complex process that requires a lot of information from various sources such as factors on waste generation and waste quantity forecasts, prediction or estimation [27], [28]. A number of studies have focused on the influence of socio-economic and demographic factors in a bid to understand, define and predict the unit rate of solid waste generation [9, 29, 30]. Some of the most common variables that are analyzed are number of individuals in a dwelling, age, gender, land usage, communications, ethnicity of the populations and productive activities [30]. Many predictive modelling studies have been created over the last few decades to assist in developing more efficient waste management programs, however, the studies vary in their intents, assumptions and solution procedures [1, 31-36]. [37] reviewed previous models on municipal solid waste generation with an aim of arriving at limitations of previous models. These studies have focused on modeling and prediction of municipal solid waste as opposed to narrowing down to household solid waste. Factor models have been widely used to predict daily or annual waste generation [38, 39], at household, municipal or regional level [40]. [21] designed a model which was suitable for repeated use by municipal representatives to appropriately assess the future municipal waste streams of major cities. The selection of this model was based on a recent forecasting methodology where the size and type of data base as well as the existing knowledge of relationships were the criteria for method selection [41]. A study of household solid waste generation carried out by [42] identified household size, employment status, and type of housing tenure as the most relevant in modeling household solid waste generation in West Midlands. Salhofer [43] designed a model aimed at predicting industrial and commercial waste generation in Vienna. This model is based on a matrix which is applied to sort the type of business that generates the waste by commercial or industrial sector and is based on number of employees. [44] discussed the prediction methodology for generation rate for municipal solid waste in the European Union countries and United States of America. [1] developed a predictive model for waste generation according to the waste demography based on lifestyle, culture etc. In a study conducted in Chile by [45], he analyzes the relationship between the production of residential solid waste per capita and socio-economic factors. Previous studies have focused on modeling MSW generation. Similarly, previous studies have relied on data collected at disposal points, material recovery facilities and solid waste transfer stations which are likely to pose limitations since these data collection points contain solid waste from different sources mixed together.

MATERIAL AND METHODS

Study Area and Target Population

Kisumu is the third largest city in Kenya and it's on the shores of Lake Victoria, the second largest fresh water Lake in the World and covers an area of approximately 417 Km^2, 35.5% of which is under water. It is located in Kisumu county and serves as both as the county headquarters and the principal city in the region [46]. Kisumu city is lies between latitude 00^o02'N; 00^o11'S and longitude $34^035^{'}$E and $34^055^{'}$E at an elevation of 1,131 meters above sea level. The city is occupied predominantly by low income households, with more than 50% of the population categorized as poor [47]. The city lacks a comprehensive response to solid waste management. Coupled with this, there is a poor attitude towards waste management and low capacity to offer waste services by Kisumu city management [48].

Research Design

The research design was cross-sectional descriptive research and used quantitative tools of data collection and analyses. The design by virtue of being cross-sectional gives a representation of the whole population with minimum bias. Descriptive research is a process of collecting data in order to answer questions concerning the current situation [49]. The unit of analysis for this study was household heads.

Study Population and Sampling Procedure

The study utilized both multi-stage random sampling and stratified proportionate simple random sampling technique. Stratified proportionate simple random sampling is a modification of random sampling in which a population is divided into two or more relevant significant strata based on one or more attributes [50]. The advantage of stratified sampling is said to be its ability to ensure inclusion of sub-groups which would otherwise be entirely omitted by other sampling methods [51].

Table 1: A sampling frame indicating the number of households studied under each strata

Socio-economic group	Total no. of households (Study population)	No. of households selected
HISG (Milimani)	1302	55
MISG (Migosi)	4795	204
LISG (Obunga)	2554	109
TOTAL	8651 (Study Population)	368 (Sample Size)

The study used a mathematical approach given by [52] which stated that:

$$n_f = \frac{n}{1+n/N}$$

Where;

n_f = the desired sample size when population is less than 10,000

n = the desired sample size when population is more than 10,000 (usually 384)

N= Estimated population size

$$n_f = \frac{384}{+ (384/8651)}$$

$n_f = 368$

A stratified proportionate random sample of 368 households was selected from a study population of 8651 households (Table 1). The number of households to be interviewed within each sampling unit (strata) were selected proportionally based on the number of households within each sampling unit /strata (socio-economic group). Households within each sampling unit/ strata (socio-economic group) were selected through simple random sampling. Three estates representing three socio-economic groups (income levels) were selected through multi-stage simple random sampling according to socio-economic groups based on income levels borrowed from the Kenya National Bureau of Statistics [47] classification which was also guided by literature from previous studies. The strata were; High Income Socio-economic group (HISG), Middle Income Socio-economic group (MISG), Low Income Socio-economic group (LISG). The three estates selected for the study were Milimani (HISG), Migosi (MISG) and Obunga (LISG).

Predictor Variables to be included in Modeling

The behavior of HSW generation is impossible to explain by using a single predictor variable [39]. Thus, to find the appropriate model that best explained HSW generation, data was analyzed and the variables to be involved identified. A symbol was assigned to each variable and the type of dependence and unit of measure was set. Table 2 shows the variables included in this study.

Table 2: The variables studied and their symbol, type and unit of measure

Variable name	Symbol	Type	Unit of measure
Household Size	X_{Hs}	Independent	Persons/household
Household monthly Income	X_{Hmi}	Independent	Monthly Income/household
Household Monthly Expenditure on Food	X_{Hmef}	Independent	Monthly Expenditure on food /household
Age of the Household Head	X_{Ahh}	Independent	Number of years of the household head
HSW generation in Kgs	Y_{Hswg}	Dependent	Kgs/month/household

The following operational definitions were adopted for the study; household size (X_{Hs}) was defined as the number of persons residing in a household or residence. household monthly income (X_{Hmi}) was defined as the measure of the monthly combined incomes of all people sharing a particular household of residence. Household monthly expenditure on food (X_{Hmef}) was defined as the amount of final consumption expenditure made by resident households to meet their monthly needs on food. Age of the household head (X_{ahh})was defined as the length of time the household head (person in charge of running the household and key decision maker) has lived. The questionnaires were categorized according to socioeconomic groups and answers were captured appropriately. The questionnaires were given numbers 1-368. This was done for household identity since there was need to match each household socio-economic and demographic data with its corresponding data on the amount of household solid waste generated.

Model equation

According to multiple linear regression analysis, a predictive model for household solid waste generation in the study area was identified and developed as follows:

Model developed:

$Y= \beta_0 + \beta_1 X_{Hs} + \beta_2 X_{Hmi} + \beta_3 X_{Hmef} + \beta_4 X_{Ahh}$..................................equation 1

Note:
Y= Dependent variable of monthly household solid waste generated (Kgs/month/household)
β_0 = Constant
$\beta_1, \beta_2, \beta_3, \beta_4$ = coefficients
$X_{Hs}, X_{Hmi}, X_{Hmef}, X_{Ahh}$ = Independent variables

Data Collection Methods

The study employed the use of structured household survey questionnaires and direct waste analysis to obtain primary data. Structured household survey questionnaires were used to gather information on selected household socio-economic and demographic data. In all cases, questionnaires were administered to obtain precise data on household size, household monthly income, household monthly expenditure on food and age of the household head. The questionnaires were categorized according to socio-economic groups and answers were captured appropriately. The questionnaires were given numbers 1-368. This was done for household identity since there was need to match each household socio-economic and demographic data with its corresponding data on the amount of household solid waste generated.

Direct waste analysis (DWA) was used as a tool for the household solid waste characterization study to establish the amount of monthly household solid waste generated. DWA is a solid waste characterization tool which is used to determine the quantities and composition of solid waste generated and this is done through direct waste weighing and direct waste sorting respectively [53]. The direct waste analysis technique has been used previously in several studies [54-56]. Direct waste weighing involved each selected household being provided with a labelled plastic bag to keep all their household solid waste generated for one week (7 days). This was done on a weekly basis for four weeks. The plastic bags were labelled using numbers 1 to 368. This was done to be able to match the household survey questionnaires data with the household direct waste analysis data. The household solid waste generated was weighed using a capacity portable weighing machine and weights recorded. This enabled the researcher to establish the amount of household solid waste generated in the selected urban estates in Kisumu city. The equipment and materials used were methodology driven and they were: Trash polythene bags, a portable twenty kilogramme (20 Kg) weighing machine, sorting shed, digital camera, personal protective equipment and a large plastic canvas. Data for this study was collected for a period of four weeks between 30th January 2016 to 28th February 2016. In this study, one month was taken to be 30 days, the period for which data on the HSW quantities was collected.

Data Analyses

Quantitative data on the appropriate socio-economic and demographic data in modelling HSW generation was analyzed using multiple linear regression. The analyses included more than two predictor variables which displayed a linear distribution. Therefore, a multiple linear regression was applied to determine the probable shape of the relationship among the variables and to model the generation of HSW which corresponds to the values of analyzed socio-economic and demographic variables.

RESULTS

This section gives the results on the socio-economic and demographic data of households studied. Secondly it gives data on the amount of HSW generated. Finally it gives data on quantification of the variables selected to build the appropriate model for explaining household solid waste generation in selected urban estates in Kisumu city.

1 Socio-economic and demographic data for households

The data showing the household size, household monthly income, household monthly expenditure on food and age of the household head across three socio-economic groups, namely high income, middle income and low income are presented in Table 3

Table 3: Socio-economic and demographic data for households. HISG stands for high income socio-economic group, MISG stands for middle income socio-economic group while LISG stands for low income socio-economic group

	Socio-economic group/class		
Variable (Mean)	**HISG Milimani**	**MISG Migosi**	**LISGObunga**
Household Size	5	5	5
Household Monthly Income (in Kshs)	57555	17333	15130
Household Monthly Expenditure on Food	17509	15102	8314
Age of the Household Head (in years)	42	36	35

According to the household survey (Table 3), the average household size from the sampled population was 5 in high, middle and low income socio-economic groups respectively. The average household monthly income was Kshs. 57555, Kshs. 17333 and Kshs. 15130 in high, middle and low income socio-economic groups respectively. The average household monthly expenditure on food was Kshs. 17509, Kshs. 15102 and Kshs. 8314 in high, middle and low income socio-economic groups respectively. The average age of the household head in years was 42, 36 and 35 in high, middle and low income socio-economic groups respectively. The reason for considering household size and income in this study is the fact that they have been widely acknowledged as important factors influencing solid waste characteristics [53]. Solid waste generation is an inevitable consequence of production and consumption, hence the importance of Household expenditure on food in this study. The age of the household head is also considered as a key determinant of consumption.

HSW generation in Kilograms by Socio-economic group

The amount of HSW generated by households and individuals in high, middle and low income socio-economic groups in Kisumu city are presented in Table.

Table 4: The amount of daily and monthly HSW generated by households and individuals

Socio-economic Group	Number of hh* studied	Amount of HSW generated (Kg/hh/month	Amount of HSW generated (Kg/cap**/month)	Amount of HSW generated Kg/cap/day
HISG	55	54	10.8	0.36
MISG	204	36	7.2	0.24
LISG	109	31.5	6.3	0.21
TOTAL	368	121.5	24.3	0.81

*hh= household; **= capita

The average amount of HSW generated per household per month was 54, 36 and 31.5 kg/hh/month in HISG, MISG and LISG respectively (Table 4). Results from Table 4 further established that the average amount of HSW generated per person per month was 10.8, 7.2 and 6.3 kg/cap/month in HISG, MISG and LISG respectively and 0.36, 0.24, 0.21 Kg/cap/day in HISG, MISG and LISG respectively. From these study findings, it is clear that the amount of HSW generated varies across socio-economic groups with the amount of household solid waste generated increasing with improving socio-economic status. The relationship between socio-economic groups and the amount of HSW generated has been discussed by various authors [55], [9], [56]. Results from Table 4 agree with a study by [57] who established that the overall amount of HSW generated per capita increased with improving socio-economic status with high income socio-economic group generating the most.[58] established that the average amount of HSW generated by households in Dar es Salaam was 0.42 kg/cap/day. [59] established that in Maiduguri, the amount of HSW generated was 0.25 kg/cap/day. The average amount of HSW generated in Nigerian households is 0.49kg/cap/day [60]. From the discussion above, it is evident that previous studies have not been keen on investigating the amount of HSW generation across different socio-economic group which this study (Table 4) has done.

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The estimated value of (r), correlation coefficient of the selected socio-economic and demographic variables were greater than 0.05 (p value) indicating poor multi-collinearity and independence among them (Table 5). The student t test showed independence among the independent variables (Table 5) selected for the model hence confirming their suitability in predicting HSW generation.

Multiple linear regression was calculated to predict monthly household solid waste generated in kilograms based on household monthly income (X_{Hmi}), household monthly expenditure on food (X_{Hmef}), household size (X_{Hs}) and age of Household head (X_{ahh}) in selected urban estates in Kisumu city representing high, middle and low income socio-economic groups. The results of multiple linear regression analysis of the study area by the predictive model in equation (1) is presented in equations 2, 3, 4, 5, 6 and 7.

Table 5: Values of t and p from the test of independence among independent variables across HISG, MISG and LISG

Compared Independent Variables	Standard Value of t	HISG		MISG		LISG	
		Estimated value of t	P value	Estimated value of t	p value	Estimated value of t	P value
Household size Vs household income	1.96	-1.39	0.17	-1.88	0.06	0.37	0.71
Household size VS household expenditure on food	1.96	1.54	0.13	-1.17	0.24	-0.20	0.84
Household size Vs age of the household head	1.96	0.40	0.69	0.04	0.97	-1.33	0.18
Household income Vs household expenditure on food	1.96	0.15	0.88	-0.95	0.34	-0.33	0.74
Household income Vs age of the household head	1.96	-1.07	0.29	-1.75	0.08	-1.08	0.28
Age of the household head Vs household expenditure on food	1.96	-0.63	0.53	-0.63	0.53	-0.53	0.59

In equation 2, a multiple linear regression model with four predictor variables (household size, household monthly income, household monthly expenditure on food and age of the household head) were used to predict HSW generation in the HISG. However, the variable household size had an insignificant regression coefficient with respect to its value of p (0.071). Therefore another model (equation 3) was tested without the predictor variable household size to predict HSW generation in HISG. The results of multiple linear regression in equations 2 and 3 yielded significant regression equations with R^2 adjusted of 0.973 and 0.972 at 95% confidence level respectively indicating that the predictor variables selected accounted for 97% of HSW generation in HISG and therefore can be used to predict HSW generation.

$Y= -54.958 -2.296X_{Hs}+ 0.001X_{Hmi} + 0.002 X_{Hmef} +0.597 X_{Ahh}$…………………………....equation 2

Replacing values :
Y = -54.958 -2.296 (5)+ 0.001 (57555) + 0.002 (17509) +0.597 (42)
Y= 51.204 Kgs

$Y= -47.965 +0.001XH_{mi}+ 0.002Hmef +0.553Xahh$………………….equation 3

Replacing values:
Y = -47.965 +0.001(5) + 0.002 (17509) +0.553 (42)
Y= 67.834Kgs

Table 6: Multiple linear regression models, predicted and actual HSW generation in Kgs in the HISG

Model	R^2	R^2 adjusted	Predicted HSW generation in Kgs	Actual HSW generation in Kgs
Linear model with four predictor variables $Y= -54.958 -2.296X_{Hs}+ 0.001X_{Hmi} + 0.002 X_{Hmef} +0.597 X_{Ahh}$	0.975	0.973	51.2	54
Linear model with three predictor variables $Y= -47.965 +0.001XH_{mi}+ 0.002Hmef +0.553Xahh$	0.973	0.972	67.8	54

The actual (weighed) value of HSW generation in the HISG was 54Kgs. According to equations 2 and 3 the predicted value of monthly HSW generation per household was 51.204 Kgs and 67.834 Kgs respectively (Table 6). Therefore, the model in equation 2 is the best suited model to predict the amount of HSW generated in HISG in urban estates in Kisumu city since the predicted value (51.204Kgs) is closer to the actual value (54Kgs).

In equation 4, a multiple linear regression model with four predictor variables (household size, household monthly income, household monthly expenditure on food and age of the household head) were used to predict HSW generation in the MISG. However, the variable age of the household head had an insignificant regression coefficient with respect to its value of p (0.162). Therefore another model (equation 5) was tested without the predictor variable age of the household head to predict HSW generation in the MISG. The results of multiple linear regression in equations 4 and 5 yielded significant regression equations with R^2 adjusted of 0.984 at 95% confidence level indicating that the predictor variables selected accounted for 98% of HSW generation in MISG and therefore can be used to predict HSW generation.

$Y= -2.924+2.305X_{Hs}+ 0.00002032X_{Hmi} + 0.001 X_{Hmef} +0.090 X_{Ahh}$……………….equation 2

Replacing values :

$Y = -2.924+ (5)+ 2.305 (17333) + 0.00002032 (15102) +0.090 (36)$

Y= 27.3Kgs

$Y=-1.176+2.483XH_s+0.00002005H_{mi} +0.001H_{mef}$…………equation 3

Replacing values:

$Y = -1.176+2.483(5) + 0.00002005(17333) +0.001(15102)$

Y= 26.7Kgs

Table 7: Multiple linear regression models, predicted and actual HSW generation in Kgs in the MISG

Model	R^2	R^2 adjusted	Predicted HSW generation in Kgs	Actual HSW generation in Kgs
Linear model with four predictor variables $Y= -2.924+2.305X_{Hs}+ 0.00002032X_{Hmi} + 0.001 X_{Hmef} +0.090 X_{Ahh}$	0.984	0.984	27.3	36
Linear model with three predictor variables $Y= -1.176+2.483XH_s+0.00002005H_{mi} +0.001H_{mef}$	0.984	0.984	26.7	36

The actual (weighed) value of HSW generation in the MISG was 36Kgs. According to equations 4 and 5 the predicted value of monthly HSW generation per household was 27.3Kgs and 26.7Kgs respectively (Table 7).

In equation 6, a multiple linear regression model with four predictor variables (household size, household monthly income, household monthly expenditure on food and age of the household head) were used to predict HSW generation in the LISG. However, the variable age of the household head had an insignificant regression coefficient with respect to its value of p (0.112). Therefore another model (equation 7) was tested without the predictor variable age of the household head to predict HSW generation in the LISG. The results of multiple linear regression in equations 6 and 7 yielded significant regression equations with R^2 adjusted of 0.975 and 0.973 at 95% confidence level respectively indicating that the predictor variables selected accounted for 97% of HSW generation in LISG and therefore can be used to predict HSW generation.

$Y= 4.17+1.161X_{Hs}+ 0.002X_{Hmi} + 0.001X_{Hmef} +0.091 X_{Ahh}$………equation 6

Replacing values :

$Y = 4.17+1.161 (5) + 0.002 (15130) + 0.001(8314) +0.091(35)$

Y= 34.28Kgs

$Y= 5.664 +1.266XH_s+ 0.002H_{mi} - 0.001X_{mef}$…………………equation 7

Replacing values:

$Y = 5.664 +1.266(5) + 0.002 (15130) - 0.001(8314)$

Y= 35.423Kgs

Table 8: Multiple linear regression models, predicted and actual HSW generation in Kgs in the LISG

Model	R^2	R^2 adjusted	Predicted HSW generation in Kgs	Actual HSW generation in Kgs
Linear model with four predictor variables $Y= 4.17+1.161X_{Hs}+ 0.002X_{Hmi} + 0.001X_{Hmef} +0.091 X_{Ahh}$	0.976	0.975	34.28	31.5
Linear model with three predictor variables $Y= 5.664 +1.266XH_s+ 0.002H_{mi} -0.001X_{mef}$	0.974	0.973	35.42	31.5

The actual observed value of HSW generation in the LISG was 31.5Kgs (Table 8). According to equations 6 and 7 the predicted value of monthly HSW generation per household was 34.28 Kgs and 35.423Kgs respectively (Table 8). Therefore, both the models in equations 6 and 7 are best suited to predict the amount of HSW generated in LISG in urban estates in Kisumu city since the predicted values and the actual value are very close.

DISCUSSIONS

In his study, [18] established that the variables age and education level had non-significant regression coefficients indicating that these two variables did not explain the variability in per capita waste generation. They further proposed that the proposed model using the variables household income and household size may be applied to explain the multiple linear regression to predict the generation of residential solid waste established that education level, income per household and household size were the best predictors for per capita production of residential solid waste per day since the predictor variables could explain 51% of per capita production of residential solid waste. However, in previous studies using multiple linear regression to model household solid waste components R^2 coefficients between 0.26 and 0.57 have been reported [18]. [1] developed a predictive model for waste generation rates in Malaysia based on selected demographic variables and the results yielded a high significant regression with r^2 of 0.63 indicating that the selected variables were good predictors of HSW generation. Results from equations , 3 and 4 are useful because HSW generation data was collected at the source of generation unlike previous studies. Similarly, results from equations 2, 3, 4, 5, 6 and 7 have provided reliable data since results were presented per socio-economic group unlike previous studies where results have always been lumped together. Similarly, these results are accurate since HSW generation data was collected from the point of generation which is households as opposed to previous studies where data has majorly been collected from disposal points, material recovery facilities and solid waste transfer stations.

CONCLUSION

This study concluded that household monthly income, household size, household monthly expenditure on food and age of the household head are good predictors of monthly HSW generation across high, middle and low income socio-economic groups. The predictive models developed clearly indicate that they are suitable for prediction of HSW generation since they could explain over 90% of HSW generation. The models predicting solid waste generation are useful analytic tools in the design of solid waste management programs. The analyses of socio-economic and demographic data influencing HSW generation therefore enables accurate prediction of their quantities and useful for planning and adoption of adequate HSW management measures. The models also show that predictive models based on socio-economic and demographic characteristics can generate accurate data for prediction of the amount of waste generation in future.

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REFERENCES

1. Zaini S, Simon G. The development of Predictive Model for Waste Generation rates in Malaysia. Research Journal of Applied Sciences, Engineering and Technology. 2013; 5:1774-1780.
2. Contreras F, Hanaki K, Aramaki T, Connors S. Application of analytical hierarchy process to analyze stakeholders preferences for municipal solid waste management plans, Boston, USA. Journal of Resources, Conservation and Recycling. 2008; 52:979–991.
3. Musademba D, Musiyandaka S, Muzinda A, Nhemachena B, Jambwa D. Municipality Solid Waste (MSW) Management Challenges of Chinhoyi Town in Zimbabwe: Opportunities of Waste reduction and recycling, Journal of Sustainable Development in Africa. 2011;13:168 – 180
4. Ojewale OS. Socio-economic correlates of household solid waste generation: Evidence from Lagos, Metropolis, Nigeria. 2015;7:44-54.
5. Florin M, Ana-Andreea G, Andreea L. Estimation of Urban Waste Generated and Uncollected in Romania. Waste Management Journal. 2015; 17: 719-724
6. UN-HABITAT. Housing as a Strategy for Poverty Reduction in Ghana. United Nations Human Settlements Programme. UNON, Publishing Services Section, Nairobi, Kenya, 11.2010.
7. Aranda-Uson A, Ferreira G, Zambrana DV, Zabalza IB, Llera ES. Environmental-benefit analysis of two urban waste collection systems. Journal of Science Total Environment. 2013;463-464.
8. Pappu A, Sxena M, Asolekar SR. Solid Waste Generation in India and their Recycling Potential in Building Materials, Indian Journal of Environmental Protection. 2007; 2311-2321.
9. Bandara NJG, Hettiaratchi JPA, Wirasinghe SC, Pilapiya S. Relation of Waste Generation and Composition to Socio-economic Factors: A case study. Journal of Environ Monit Assess. 2007;31-39.
10. Karavezyris V, Timpi K, Marzi R. Application of systems dynamics and fuzzy logic to forecasting of municipal solid waste. Journal of mathematics and computers in simulation. 2002; 60:149-158
11. Dyson B, Chang N. Forecasting Municipal Solid Waste Generation in a Fast-growing Urban Region with Systems Dynamics Modelling. Journal of Waste Management. 2005; 25:669-679.
12. Chen HW, Chang NB; Prediction of Solid Waste Generation via Grey Fuzzy Dynamic Modelling. Journal of Resources, Conservation and Recycling. 2000; 29:1-18.
13. Zhang Q, Dor H, Fenigshtein D, Yang W, Wlodzmiez K. Gasification of Municipal Solid Waste in the Plasma Gasification Melting process. Journal of Applied Energy. 2011;10:320-332.
14. Navarro-Esbiri J, Diamadopoulous E, Ginestar D. Time series Analysis and forecasting techniques for

Municipal Solid Waste Management. Journal of Resources, Conservation and Recycling. 2002; 35:201-214.
15. Arti P, Meka S. Municipal Solid Waste Management in India: A Review and some new results. International Journal of Civil Engineering and Technology. 2014; 5:01-8.
16. Patel MK, Jochem E, Radgem P, Worrell E. Plastic Streams in Germany- an Analysis of Production, Consumption and Waste Generation. Journal of Resources, Conservation and Recycling. 1998;24:191-215.
17. Bach H, Mild A, Natter M, Weber A. Combining Socio-demographic and logistic factors to explain the generation and collection of waste paper. Journal of Resources, Conservation and Recycling. 2003;18-29.
18. Buenrostro O, Bocco VG, Bernache G. Urban Solid Waste Generation and Disposal in Mexico: A Case Study. Journal of Waste Management and Research. 2001;19:169-176.
19. Beigl PG. Lebersorger S, Salhofer S; Modelling Municipal Solid Waste Generation: a review. Journal of Waste Management. 2008; 28: 200-214.
20. Mateu-Sbert J, Ricci-Cabello E, Villalonga-Olives E, Cabeza-Irigoyen E. The Impact of Tourism on Municipal Solid Waste Generation. The Case of Menorca Island (Spain). Journal of Waste Management. 2013; 8:10-26.
21. Beigl P, Wassermann G, Schneider F, Salhofer S; Municipal Solid Waste Generation trends in European Countries and Cities, paper presented at the 9th International Waste Management and Landfill Symposium, CISA, S. Margherita di Pula (Cagliari), Sardinia, Italy, October 6-10, 2003.
22. Oyake-Ombis L. Managing plastic waste in urban Kenya, niche innovations in production and recycling. PhD dissertation, Wageningen, the Netherlands. 2012.
23. Mukui SJ. Factors influencing Household Solid Waste Management in Urban Nyeri Municipality, Kenya. Ethiopian Journal of Environmental Studies. 2003; 6:280-285.
24. Rotich KH, Zhao Y, Dong J. Municipal Solid Waste Challenges in Developing Countries – Kenyan Case Study, Journal of Waste Management. 2006; 26:92-100
25. Munala G, Moirongo BO. The need for Integrated Solid Waste Management in Kisumu, Kenya. JAGST journal. 2001; 13: 65-79.
26. Opande TO. Planning for Solid Waste Collection in low income settlements of Nyalenda and Ondiek in Kisumu town, MSC Thesis, Kenya: Maseno University. 2010.
27. Bovea MD, Powell JC, Capuz-Rizo SF. The Role played by Environmental Factors in the Integration of a Transfer Station in a Municipal Solid Waste management System. Journal of Waste Management. 2010; 27:545-553.
28. Zurbrugg C, Margareth G, Henki A, Weraner B, David K. Determinants of sustainability in solid waste management- the Gianyar waste recovery project in Indonesia, Journal of Waste Management. 2012; 32:2126-2133.
29. Mazzanti M, Zoboli R. Waste Generation, Waste Disposal and Policy Effectiveness. Evidence on Decoupling from the European Union. Journal of Resources, Conservation and Recycling. 2008; 52:1221-1234.
30. Emery AD, Griffiths SJ, Williams KP. An In-depth study of the effects of Socio-economic Conditions on Household Waste Recycling Practices. Journal of Waste Management and Research. 2003; 21:180-190.
31. Brunner PH, Ernst WR. Alternative methods for the analysis of municipal solid waste management. Journal of waste management and research. 1986; 14:147-160
32. Lund JR. Least-cost scheduling of solid waste recycling . Journal of Environmental Engineering, 1990; 1:182-197.
33. Everett, JW, Jacobs, TJ. Optimal scheduling of consecutive landfill operations with recycling. Journal of Environmental Engineering. 1992; 1:182-197.
34. Movassanghi K. Optimal in a regional waste management system. Proceeding of the 8th International Conference on Solid Waste Management. Van Nostrand Reinhold Co., New York. 1992.
35. Yu CC, Maclaren V. A Comparison of two waste stream quantification and characterization methodologies, Journal of Waste Management and Resources.1995; 13:343-361.
36. Chang NB, Lin YT. An Analysis of Recycling Impacts on solid Waste Generation by Time Series Intervention Modelling. Journal of Resource Conservation and Recycling. 1997;19:165-186.
37. Cherian J, Jacob J. Management Models of Municipal Solid Waste: A Review Focusing on Socio Economic Factors. International Journal of Economics and Finance. 2012; 4 (10): 111-123.
38. Lebersorger S, Beigl P. Municipal Solid Waste Generation in Municipalities: Quantifying Impacts of Household Structure, Commercial Waste and Domestic Fuel. Journal of Waste Management. 2004; 31: 1907-1915.
39. Ojeda- Benitez S, Lozano-Olvera G, Adalberto MR, Armijo de Vega C. Mathematical modeling to predict residential solid waste generation. Journal of Waste Management. Resources. 2008; 28:104-116.
40. Afon AO, Okewole A. Estimating the Quantity of Solid Waste Generation in Oyo, Nigeria. Journal of

Waste Management and Research. 2007; 25: 371-379.
41. Armstrong JS. Principles of forecasting: a handbook for researchers and practitioners, Kluwer Academic Publishers, Boston. 2001.
42. Rufford NM. The Analysis and Prediction of the Quantity and Composition of household Refuse. PhD Thesis, Aston University. Birmingham.1984.
43. Salhofer S. Modelling commercial/ industrial waste generation: a Vienna, Austria case study. Waste Management and Research. 2000;18:269-282.
44. Daskapoulos E, Badr O, Probert SD. Municipal Solid Waste. A prediction Methodology for the generation Rate and Composition in The European Union Countries and The United States of America. Journal of Resources, Conservation and Recycling. 1998;24:155-166.
45. Orccosupa J. Relationship among the per capita generation of household solid waste and socioeconomic variables, Santiago de Chile Province. Master Thesis in Management and Environmental Planning. 2002.
46. NEMA. National Environment Management Authority. (NEMA), Nairobi, Kenya ; State of the Environment Report for Kenya. 2003;2003.
47. KNBS. The 2009 Kenya Population and Housing Census. 2009.
48. MCK. UN-Habitat/UNEP, UNESCO-IHE and ITDG; *Kisumu City Environmental Profile on Sustainable Urban Mobility.*2004.
49. Mugenda OM, Mugenda AG. Research Methods: Quantitative and qualitative Approaches. Nairobi: African Centre of Technology Studies. 2003.
50. Saunders M, Lewis P, Thornhill A. Research Methods for Business Students. Essex England Pearson Education Limited. 2007.
51. Jeptoo C, Iravo M, Sakataka W. Effects of Members Innovativeness on the performance of SHG's in Usain-Gishu County.The International Journal of Humanities and Social Studies. 2016; 4:223-227
52. Fisher AA, Laing JE, Stoeckel JE, Townsend JW. *Handbook for Family Planning Research Design*. Second edition. Population council.1998.
53. Gomez G, Meneses M, Ballinas L, Castells F. Characterization of Urban Solid Waste in Chihuahua, Mexico. Journal of Waste Management. 2008; 28:2565-2471.
54. Dieu TMT, Truong ML, Viet TN. Composition and Generation Rate of Household Solid Waste : Reuse and Recycling Ability. A Case Study in District 1st, Ho Chi Minh, Vietnam. International Journal of Environmental Protection. 2014; 4:73-81
55. Aisa SO. Characterization of Household Waste in Kinondoni Municipality, Dar Es Salaam. Academic Journal of Interdisciplinary Studies. 2013;2:35-46.
56. Mohammed AS, Md LH, Satyajit RD, Razak W, Mohammed, KH. Generation and Assessing the Composition of Household Solid Waste in Commercial Capital City Of Bangladesh. International Journal of Environmental Science, Management and Engineering Research. 2012;1:160-171.
57. Jonas PS, Daniel OM, Karoli, NN, Yaw N. Factors Influencing Solid Waste Generation and Composition in Urban areas of Tanzania: The Case of Dar-es-Salaam. American Journal of Environmental Protection. 2014; 4: 172-178.
58. Kaseva ME, Mbuligwe SE. Appraisal of solid waste collection following private sector involvement in Dar es Salaam city Tanzania. Habitat International. 2005;29:353-356.
59. Dauda M, Osita OO. Solid waste management and reuse in Maiduguri, Nigeria. 29th WEDC International Conference towards the Millennium Development Goals, Abuja. 2003.
60. Solomon AO. The Role of Households in Solid Waste Management in East Africa Capital Cities. The Netherlands. Wageningen Academic Publishers. 2011.