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Non-linear Regression Models for Predicting Biogas Yields from Selected Bio-wastes

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Authors' contributions

This work was carried out in collaboration between both authors. Author AVJ designed the study and performed the statistical analysis. Author CI wrote the protocol, managed the literature searches and the first draft of the manuscript. Both authors read and approved the final manuscript.

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ABSTRACT

The benefits of biogas as alternative energy to other fossil fuel sources, due to its renewability, environmentally friendly nature, health benefits, etc., cannot be overemphasized. There are numerous models for predicting biogas production rate from bio-materials, including the modified Gompertz equation. These models are primarily dependent on specific biomass parameters. When any of these parameters, like the slurry volume, changes, another round of experiments must be conducted and curve fitted before biogas yield predictions can be made. This could be time-consuming and costly. Using experimentally published data, simple empirical models can be developed for predicting biogas yields over a range of input parameters. This will eliminate the need for always performing experiments before biogas yield predictions can be made. In light of this, scarce literature provides explicit models for predicting biogas yield over a range of parameters based on published data. This study developed non-linear regression models using published data on parameters that affect biogas yields, like the slurry volume, carbon-to-nitrogen ratio,

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temperature, total solids, volatile solids, hydraulic retention time, and pH. The data covered seven readily available bio-wastes, including cow dung, cow dung with plant waste, cow dung with poultry dung, poultry dung with grass, pig dung, and plant wastes. On validation of the models, the results showed that the models had a relatively low standard error of estimates, Akaike information criterion, Schwarz criterion, and Hannan-Quinn information criterion. Furthermore, the coefficients of determination, $R^{2,}$ were between 94.62 and 98.93%. The percentage average absolute deviation (% AAD) for each model was less than 7 %. The non-linear models were found to adequately predict the biogas yields within the limits of the available data set.

Keywords: Biogas; non-linear models; bio-wastes; renewable energy.

ABBREVIATIONS

CD : Cow dung
CO : Co-digestion
PD : Poultry dung
FVW : Fruit and vegetable wastes
C/N : Carbon to Nitrogen ratio
T : Temperature (oC)
TS : Total solids (%)
VS : Volatile solids (%)
HRT : Hydraulic retention time in D (days)
BP : Biogas produced in L (litres)

1. INTRODUCTION

Sustainable development has become a global priority. Global prosperity and human development have always been tied to energy. But the health threat imposed by fossil fuel, its non-renewable nature, the environmental pollution from the constant release of carbon dioxide, etc., a cause for global concern, has necessitated the search for alternative renewable and cleaner energies with a less negative effect on the environment. Unfortunately, only about 20 percent of the global energy requirement is met by renewable sources like solar, wind, biomass, etc., of which energy from biomass has gained significant importance due to its waste volume reduction and energy recovery. Consequently, the need for a sustainable supply of clean energy has increased the quest for alternatively cleaner and renewable energy sources that can mitigate climate change effects [1]. To achieve this goal, the contribution of renewable energy to the total energy supply mix must continue to increase significantly and ultimately be the sole energy source in the future. Many developed countries increasingly utilize solar, wind, nuclear, biomass, and geothermal energy sources. Their contribution to the total energy mix in those countries is increasing significantly. However, this is not the case in many developing countries where the primary energy source remains fossil fuels and biomass.

Biomass is a common bio-energy source, especially in many rural communities of developing countries. This is due to its availability, scalability, abundance, and cost-effectiveness in generating clean and renewable bio-energy compared to other renewable energy sources [2]. Another advantage of biomass clean energy sources is that they can valorize plant and animal waste (which could pose environmental and public health issues when not properly disposed of) for effective waste management. Many biomass fuels produce biogas, such as wood, charcoal, agricultural residues, household waste [3], animal waste, and energy crops [4]. Biogas production, one of the most environmentally beneficial technologies for bioenergy production [5], plays an essential role as an energy source capable of increasing the supply stability of gaseous fuels. As a source of renewable natural gas, it has been adopted as one of the best alternatives for fossil fuels after the 1970s world energy crisis. Biogas is a clean and renewable fuel produced through a natural process in which bacteria convert organic materials into a mixture of methane and carbon dioxide gases with traces of ammonia and hydrogen sulfide [6]. It is a colorless, odorless, and flammable gas. It can be collected, with special installations, from landfill sites [7]. Many technologies, such as incineration and refuse-derived fuel (RDF), etc., produce energy from solid wastes. Among them, anaerobic digestion has become a promising technology, particularly for recovering energy from the organic fraction of solid wastes. According to the department of alternative energy development and efficiency [8], one cubic meter (m^3) of biogas comprises 60% methane, with a heating value of around 21 mega-joules, an equivalent of 0.6 liters of diesel oil or 0.67 liters of gasoline, 0.55 liters of fuel oil, 0.46 kg of LPG or 1.2 kWh of electricity. As a result, biogas is used for cooking, heating, and fuel sources for electric generators, automobiles, etc., in many households, farms, and public utility systems.

Due to its numerous applications, the need to accurately predict the amount of biogas obtained from a given mass or volume of a substrate cannot be overemphasized. Predicting biogas yields from the various types of available biomaterials is helpful for the efficient design and construction of biogas digesters and other equipment used for biogas generation. Accurate biogas prediction from different biomaterials helps optimize the production value chain, reducing the associated costs and maximizing biogas yield. Consequently, many scholars have tried to find the best ways to optimize the biogas yield of different substrates. Unbiased decisions in biogas production optimization are guided by the development of models commonly referred to as Decision support tools (DST). Some of these models include the Modified Gompertz model, widely used to study growth rate (i.e., used to fit growth data), and the first-order kinetic model used to model batch Biochemical Methane Potential (BMP) data to obtain valuable interpretation about hydrolysis kinetics. The Logistics model used to predict the methane production potential as a function of time, the 3-D numerical simulation model based on the conservation of mass and energy, and the species transport model that predicts biogas production from plug-flow anaerobic digesters [9]. Also, the Bus well Formula has been used to forecast the BMP of various substrates.

However, these models for biogas prediction have one common limitation. Experimentation must be conducted to furnish the models with the essential information to estimate biogas production yield. This means that for any change in substrate properties like slurry volume and temperature, new sets of experimental analyses must always be performed to generate data for model curve fitting. This will increase the overall costs and time. Furthermore, models for predicting biogas yields without recourse to experimentation, e.g., regression models based on available data, are scarce in the open literature. Therefore, this study aims to develop time and cost-saving regression models from published data for predicting the biogas yields of common substrates found in our everyday lives without regular experimental analysis. The regression models utilize seven parameters that significantly influence biogas yields from various biomaterial substrates. See Fig. 1. They include the slurry volume, temperature, carbon-nitrogen ratio, total solids, volatile solids, pH, and hydraulic retention time.

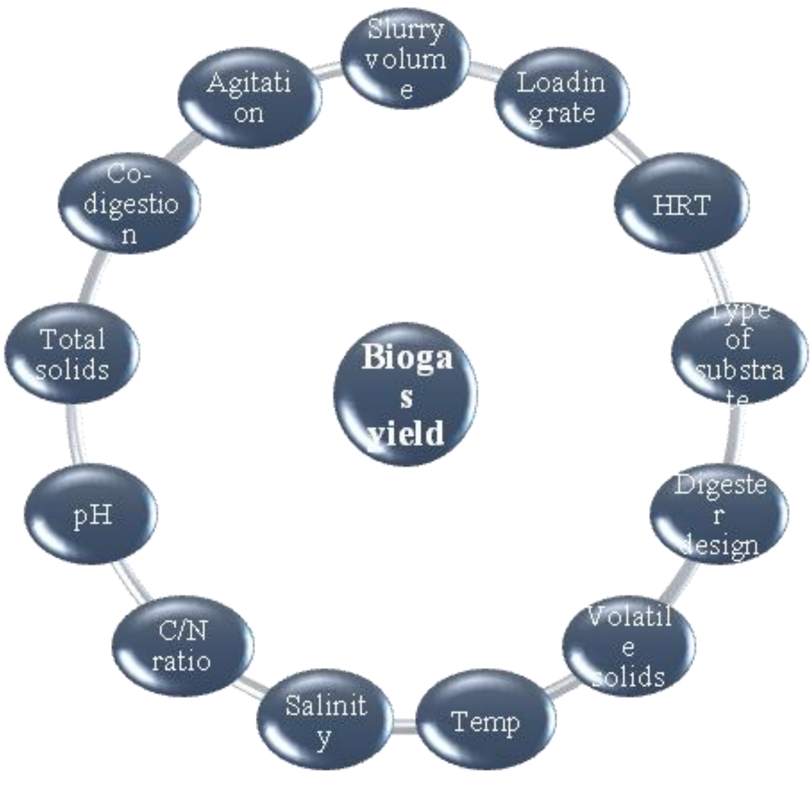

Fig. 1. Factors affecting biogas yield

2. MATERIALS AND METHODS

This study involved the development of non-linear regression models using published biogas data from the open literature (see Appendix A). The biogas data was obtained for seven different substrates, including cow dung, cow dung with fruit vegetable and plant waste, cow dung with poultry dung, poultry dung with grass, grass and fruit vegetable, and plant waste. The input parameters used for the prediction of biogas yield include the volume of slurry (L), volatile solids (%), temperature (^oC), pH, total solid (%), carbon-nitrogen ratio, and hydraulic retention time (days). The developed models were validated using published empirical results different from those used in building the models. The E-view 9 statistical package was used for the analysis.

2.1 Descriptive Statistics of the Input Data

Table 1. Descriptive statistics of the data used in the model development

Substrate		Slurry (L)	C/N	T (^oC)	TS (%)	VS (%)	HRT (days)	pH
Cow dung	Min	0.15	8.10	25.00	1.40	1.10	7.00	6.20
	Max	17.50	24.00	53.00	87.00	78.85	62.00	9.20
	Mean	3.20	15.3	34.90	31.10	46.39	34.38	7.19
Cow dung + Plant waste	Min	0.30	8.50	31.00	5.70	9.50	7.00	5.50
	Max	5.00	40.00	37.00	75.60	91.00	75.00	7.80
	Mean	1.69	16.58	35.00	42.38	58.04	46.38	7.02
Cow dung + Poultry dung	Min	2.00	15.00	32.00	30.00	20.80	30.00	6.50
	Max	15.00	26.30	35.00	95.50	65.70	56.00	8.70
	Mean	4.86	19.44	34.15	63.16	51.24	42.93	7.28
Poultry dung	Min	0.50	3.30	26.00	6.93	14.30	7.00	6.25
	Max	36.70	19.80	38.00	72.80	86.40	63.00	8.40
	Mean	17.77	12.20	31.07	37.10	49.73	34.14	7.12
Poultry dung + Grass	Min	0.13	11.80	28.00	9.10	19.24	20.00	6.30
	Max	5.00	36.54	38.00	78.00	96.35	90.00	8.60
	Mean	1.51	18.04	33.13	37.72	64.87	39.75	7.18
Pig dung	Min	0.20	5.50	28.00	7.80	8.50	14.00	6.20
	Max	17.50	22.00	52.00	91.00	93.00	80.00	8.10
	Mean	6.25	12.85	34.46	27.02	45.80	44.15	6.76
Plant waste	Min	0.02	10.49	30.00	7.70	6.00	12.00	4.00
	Max	4.00	61.17	60.00	81.08	90.29	77.00	8.20
	Mean	1.49	18.79	39.14	18.25	35.07	31.14	5.74

2.2 Model Development

Considering the relationship

$$Y = F(X_1X_2X_3 \dots\dots\dots\dots.) \tag{1}$$

Where Y is the dependent variable and $X_1X_2X_3$….. are independent variables. This expression could be narrowed down to linear and non-linear expressions, as shown below;
For linear expression, we have

$$Y = (a_0 + a_1X_1 + a_2X_2 + a_3X_3 \dots\dots\dots..) \tag{2}$$

While non-linear expression can be polynomial, logarithmic, exponential, or sinusoidal, and the simplest logarithmic form is given as:

$$logY = (a_0 + a_1logX_1 + a_2logX_2 + a_3logX_3 \dots\dots\dots..) \tag{3}$$

The logarithmic function was chosen for this study due to its numerous advantages. The logarithmic function is represented as:

$$logY = a_0 + a_1 logX_1 + a_2 logX_2 + a_3 logX_3 + a_4 logX_4 + a_5 logX_5 + a_6 logX_6 + a_7 logX_7 \quad (4)$$

Where Y is the volume of biogas produced and $X_1 X_2 X_3 X_4 X_5 X_6 X_7$ are volume of slurry (L), carbon/nitrogen ratio (C/N), temperature (T), total solid (TS), volatile solids (VS), hydraulic retention time, and pH, respectively. $a_0, a_1, a_2, a_3, \ldots a_7$ are regression constants.

2.3 Model Validation

The developed models in this study were validated using experimental data from other authors. The validation data set differs from the ones used in developing the models in this study. The statistical error models selected for this study include absolute and average absolute errors. The error models are given as follows:

$$\text{Absolute deviation \%} = \left|\frac{V_{exp} - V_{cal}}{V_{exp}}\right| 100 \quad (5)$$

and

$$\text{Average absolute deviation \%} = \frac{1}{n}\left|\frac{V_{exp} - V_{cal}}{V_{exp}}\right| 100 \quad (6)$$

3. RESULTS AND DISCUSSION

Table 2 shows the correlation coefficients developed for the various substrates in this study using equation 4. Appendix B shows the statistical analysis results for the developed models. The statistical results show that the coefficient of determination for the seven models was between 0.90 and 0.99. The goodness of fit for cow dung, cow dung with plant waste, and cow dung with poultry dung were 0.99. That of poultry with grass, pig dung, and plant waste was 0.95, 0.95, and 0.96, respectively. Poultry dung had the least goodness of fit of 0.9. The goodness of fit indicates how well the model can match the given data. From the results, the regression models for cow dung, cow dung with plant waste, and cow dung with poultry had the best goodness of fit compared to the other models. The fact that the coefficient of determination for all the models was 0.9 and above indicates that the models could predict the biogas yield for 90% and above of the given data. Furthermore, the statistical analysis results showed low values of the standard error of estimate or regression for all the models. The standard error of estimate or regression tells us how wrong or right the regression model is on average [10]. The smaller the values of standard errors of estimate, the better the model. For this study, the standard error of estimate of the regression models for cow dung, cow dung with plant waste, cow dung with poultry dung, poultry dung, poultry dung with grass, pig dung, and plant waste were 0.35, 2.16, 0.18, 1.52, 0.52, 0.34, and 1.62, respectively. These results indicate that the model for cow dung with poultry dung gave a better prediction (least standard error of estimate of 0.18), followed by the pig dung and cow dung models, respectively. The model for the cow dung with plant waste gave the highest standard error of estimate (2.16).

To further ascertain the accuracy and reliability of the developed models, the Akaike information criterion (AIC), the Schwarz criterion (SC), and the Hannan – Quin criterion (HQC) were calculated for each model. See Appendix B. The AIC and HQC allow us to ascertain the model with a better fit. The lower the AIC and HQC, the better the fit. The SC helps screen and select the best model among several models. The lower the SC, the better the model. For this study, the AIC for the models was 1.04 for cow dung, 4.69 for cow dung with plant waste, -0.25 for cow dung with poultry dung, 3.82 for poultry dung, 1.84 for poultry dung with grass, 0.97 for pig dung, and 4.10 for plant waste. Likewise, the HQC for the models was 1.01 for cow dung, 4.71 for cow dung with plant waste, -0.28 for cow dung with poultry dung, 3.80 for poultry dung, 1.87 for poultry dung with grass, 0.99 for pig dung, and 4.12 for plant waste. Also, the SC results for the models were 1.41 for cow dung, 5.07 for cow dung with plant waste, 0.12 for cow dung with poultry dung, 4.12 for poultry dung, 2.24 for poultry dung with grass, 1.35 for pig dung, and 4.49 for plant waste. The AIC, HQC, and SC results show a similar trend with the standard error of estimate results for the models developed in this study. These results indicate that the model for cow dung with poultry dung gave a better prediction (least standard error of estimate, AIC, HQC, and SC), followed by the pig dung and cow dung models, respectively. The model for the cow dung with plant waste gave the highest standard error of estimate AIC, HQC, and SC. The relatively low standard errors of estimate, AIC, HQC, and SC indicate that the developed models in this study are adequate and reliable for predicting biogas yield from the bio-materials considered, given the data set limits from which the models were developed. Fig. 2 shows the SER, AIC, HQC, and SC variation for the various biomaterials materials considered in this study.

The models' reliability in this study was further ascertained by comparing the estimated biogas yields with published experimental results. The results of the validation are presented in Tables 3 to 9. The results show that the cow dung with plant waste model was more accurate because it had the least % AAD of 0.18.the model for the poultry dung was the least accurate due to the relatively high % AAD of 6.60 compared to the other models. The poultry dung with grass, cow dung, plant waste, cow dung with poultry dung, and pig dung models showed decreasing accuracy with % AADs of 1.13, 1.37, 1.71, 2.10, and 3.05, respectively. From the results, the biogas yield models had average absolute deviations of less than 7 %, indicating that they are relatively accurate, reliable, and adequate for predicting biogas yield from the biomaterials considered in this study.

Modeling biogas yield from various biomass substrates requires a good amount of quality data. The significance of developing such models is the low cost and response time needed to estimate the amount of biogas generated from a particular substrate without recourse to experimental analysis. One limitation of this study is the small volume and range of available data for developing and validating the correlations. This was mainly because experimental works on biogas production considering the slurry volume, carbon to nitrogen ratio, temperature, percentage volatile solid, percentage total solid, hydraulic retention time, and pH in one fell swoop are very limited in the open literature. These factors are known to affect biogas yields and should be included as independent variables for biogas yield modeling. Consequently, researchers should be more inclined to conduct biogas yield experiments incorporating measurable factors like slurry volume, carbon to nitrogen ratio, temperature, percentage volatile solid, percentage total solid, hydraulic retention time, and pH for each biomass used. This will further increase the amount of data output required for building new models and tuning the coefficients of existing ones.

Also, the interdependency of the seven independent variables (slurry volume, carbon to nitrogen ratio, temperature, percentage volatile solid, percentage total solid, hydraulic retention time, and pH) should be investigated. This study is necessary to understand how specific parameters influence biogas production in the presence of others, and as such, the highly influential parameters responsible for biogas production could be identified. Identifying such parameters could help optimize the biogas yield model while reducing the independent variables required for biogas prediction.

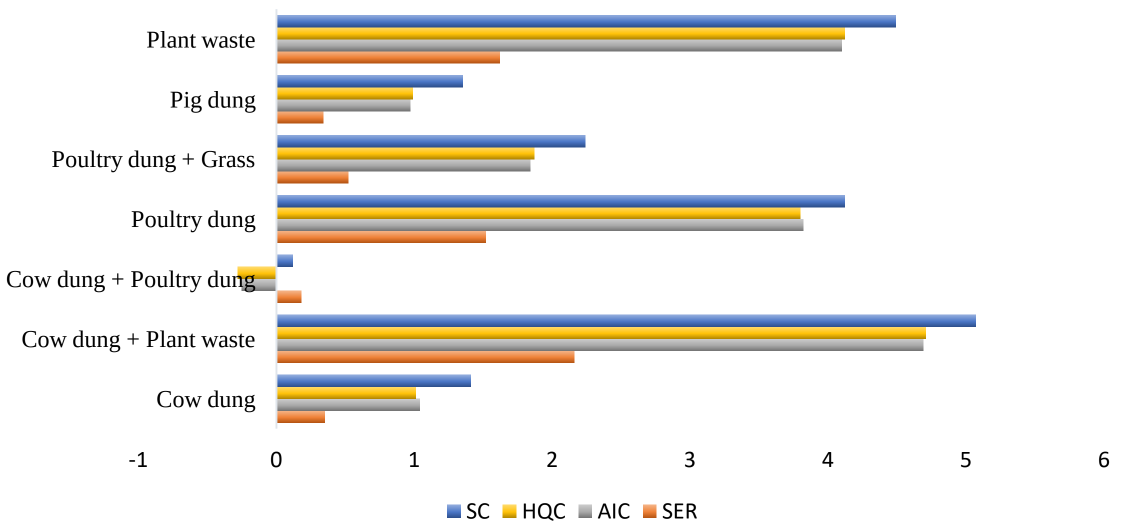

Fig 2. Schwarz criterion (SC), Hannan-Quin criterion (HQC), Akaike information criterion (AIC), and standard error of regression for the various bio-material models

Table 2. Model coefficients

Substrate	Model Coefficients							
	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Cow dung	-1.8616	1.2021	-0.7865	0.4741	1.5192	-0.7914	-0.3818	1.1585
Cow dung + Plant waste	-2.0738	3.3394	-0.3048	0.5264	-0.1882	1.5840	0.5149	-2.1537
Cow dung + Poultry dung	-2.4304	1.8770	0.9456	-0.9709	0.1040	1.9646	0.0474	-2.0036
Poultry dung	0.1082	0.4804	-0.5226	0.4332	-0.0716	1.7866	0.0412	-3.4867
Poultry dung + Grass	0.2610	0.5528	1.6154	-0.3107	-0.2084	0.1877	0.8529	-3.5323
Pig dung	0.4208	1.1156	-0.5791	-0.0101	-0.1101	0.3071	-0.0171	-0.3208
Plant waste	8.7733	0.6039	-3.4020	1.2024	-1.4337	-2.2955	1.3134	-5.2441

Furthermore, an artificial intelligence (AI) model can be developed for predicting biogas yield from various biomass waste materials. Presently, literature on AI-based models for predicting biogas yield from multiple substrates is not only limited but is very scarce. AI models are better than regression models and could help deepen the frontiers of biogas prediction modeling. Artificial intelligence can play an essential role in ensuring the efficiency and sustainability of biogas production. The simulation and optimization of the biogas production process improve the understanding of the process parameters for optimal efficiencies and production rates. Artificial intelligence models show that reliability can be improved by modeling complex, non-linear relationships between input and output sets (system responses) and revealing hidden patterns between data sets. AI models have been observed to exhibit human characteristics acquired through learning.

Table 3. Validation of the cow dung model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AAD (%)
[11]	4.5	18.1	35	22.4	46.4	30	9.2	0.73	0.74	**1.37**

Table 4. Validation of the cow dung with plant waste model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AAD (%)
[12]	2.0	16.0	35	62.0	45.0	60	7.2	5.50	5.51	**0.18**

Table 5. Validation of the cow dung with poultry dung model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AD (%)
[13]	3.0	20.0	34	95.4	65	56	7.0	2.24	2.31	3.12
[11]	4.5	22.0	35	83.16	39.2	30	7.0	1.86	1.88	1.08
									% AAD	**2.10**

Table 6. Validation of the poultry dung model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AD (%)
[14]	0.4	9.2	35	28.0	19.0	75	7.2	0.23	0.22	4.35
[15]	4.0	10.1	35	12.0	50.8	35	7.6	2.94	3.20	8.84
									% AAD	**6.60**

Table 7. Validation of the poultry dung with grass model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AD (%)
[16]	0.50	17.7	28	9.1	79.6	52	7.5	1.550	1.549	0.06
[17]	2.50	14.8	30	62.0	85.0	35	6.4	2.280	2.230	2.19
									% AAD	**1.13**

Table 8. Validation of the pig dung model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AAD (%)
[18]	7.0	9.8	35	22.5	28.2	60	6.3	6.22	6.03	**3.05**

Table 9. Validation of the plant waste model

Authors	Slurry (L)	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (days)	pH	Actual (L)	This study (L)	AD (%)
[19]	0.30	14.0	37	11.0	84	50	8.2	0.0093	0.0094	1.08
[20]	0.20	19.1	60	15.0	14	30	7.0	0.2140	0.2090	2.34
									% AAD	**1.71**

4. CONCLUSION

The benefits of biogas as an alternative to fossil fuel due to its renewable sources, environmentally friendly nature, health benefits, etc., cannot be over-emphasized. In this study, seven (7) non-linear regression models for predicting biogas yields from a wide variety of commonly available and abundant waste biomaterials, including cow dung, cow dung with plant waste, cow dung with poultry dung, poultry dung, poultry dung with grass, pig dung, and plant waste were developed. Factors affecting biogas yields like slurry volume, carbon to nitrogen ratio, temperature, percentage of volatile solids, percentage of total solids, hydraulic retention time, and pH were the independent variables for the model development. The relatively low values of the AIC, SC, HQC, and SER statistical criteria for ascertaining the reliability of regression models indicated that the models in this study are adequate. Furthermore, the model validation results showed that all the models had a percentage average absolute deviation (AAD) of less than 7%. The low percentage AAD shows that the models are relatively accurate. However, the developed models are valid for the input data ranges from which they were developed.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX A

Table A1. Data for cow dung with poultry dung as co-substrate correlation

CD	CO	Slurry volume	C/N	T(^{o}C)	TS (%)	VS (%)	HRT(D)	PH	BP (L)	Authors
CD	**PD**									
1	1	4.5	18.60	35	65.3	20.8	30	8.3	0.320	[11]
1	4	4.5	26.30	35	79.7	42.5	30	7.1	2.800	[11]
9	1	4.5	15.20	35	63.2	32.0	30	7.6	0.800	[11]
1	1	3.0	20.00	34	95.5	65.7	50	6.5	2.960	[13]
1	2	3.0	21.00	34	95.0	65.0	56	7.5	2.050	[13]
1	1	3.0	21.00	34	95.0	62.0	56	7.1	2.200	[13]
1	3	2.0	17.00	32	34.0	52.0	50	6.9	0.902	[14]
1	1	2.0	20.88	32	36.0	52.0	53	8.7	0.800	[14]
3	1	2.0	17.00	35	38.0	65.0	50	7.0	0.906	[14]
1	3	2.0	20.88	35	34.0	58.0	50	7.0	0.800	[14]

Table A2. Data for cow dung correlation

Slurry volume	C/N	T(^{o}C)	TS (%)	VS (%)	HRT (Days)	PH	BP (L)	Authors
4.00	15.0	33	37.0	17.0	14	6.2	0.51	[3]
2.00	12.0	35	45.2	73.0	60	6.8	0.42	[12]
2.00	17.0	35	42.0	78.3	60	7.1	0.38	[12]
2.00	17.2	35	87.0	63.3	60	7.5	1.26	[12]
3.00	18.1	34	61.5	75.7	56	7.4	2.07	[13]
0.25	8.2	37	34.1	19.5	14	7.2	0.182	[21]
0.25	8.2	37	34.1	19.5	14	8.5	0.234	[21]
0.80	12.8	30	9.2	71.4	20	6.8	0.167	[22]
0.80	18.2	30	10.9	70.4	20	6.8	0.17	[22]

Table A3. Data for cow dung with fruit/vegetable/plant waste as co-substrate correlation

CD	CO	Slurry volume	C/N	T(^{o}C)	TS (%)	VS (%)	HRT(D)	PH	BP (L)	Authors
CD	**FVW**									
3	1	2.0	13.10	35	65.4	62.2	60	6.2	9.00	[12]
3	1	2.0	8.50	35	63.5	67.3	60	7.1	10.70	[12]
1	1	2.0	13.10	35	75.6	53.0	60	7.3	6.50	[12]
1	1	2.0	16.10	35	67.2	61.2	60	7.2	7.56	[12]
3	1	0.3	16.0	35	62.5	45.0	60	7.5	0.12	[12]
1	3	0.7	11.40	35	26.5	52.1	35	7.4	0.20	[23]
1	6	0.7	18.14	35	25.8	52.3	35	7.6	0.18	[23]
1	9	0.7	15.40	35	24.8	52.1	35	7.6	0.12	[23]
1	12	0.7	12.60	35	26.6	52.2	35	7.2	0.15	[23]
1	1	2.5	40.00	31	28.0	91.0	75	6.5	2.75	[24]

Table A4. Data for poultry dung correlation

Slurry	C/N	T(^{o}C)	TS (%)	VS(%)	HRT(D)	PH	BP (L)	Authors
3	10.3	32	12	54.7	56	7.8	2.6	[13]
4	10.5	35	37	25.2	34	8.4	0.381	[15]
4	10.5	35	37	25.2	34	8.4	0.381	[15]
0.5	15.14	38	24	14.3	21	7.5	0.095	[25]
36.7	15	28	63.8	40.76	21	7.2	9. 95	[26]
36.7	15	26	68.5	55.56	7	7.6	5.69	[26]
36.7	15	28	69.8	62.6	14	7.5	8.89	[26]
36.7	15	28	72.8	65.5	28	7.0	10.86	[26]
4	3.3	32	50.1	38.8	35	6.4	0.21	[27]
15	10.3	28	50.5	64.3	18	6.4	3.7	[28]

Table A5. Data for poultry dung with grass as co-substrate correlation

CD	CO	Slurry	C/N	T(^{o}C)	TS (%)	VS(%)	HRT(D)	PH	BP (L)	Authors
PD	Grass									
3	2	0.50	15.9	28	9.1	77.10	52	7.3	1.33	[16]
3	2	0.50	14.8	28	9.1	77.60	52	7.5	0.93	[16]
1	1	2.50	17.8	37	50.0	89.00	35	7.1	2.36	[17]
1	2	2.50	22.4	37	78.0	83.00	35	7.6	2.00	[17]
3	1	0.50	18.2	38	23.8	19.24	20	6.8	0.77	[25]
1	1	0.50	15.0	30	25.1	20.50	20	6.3	0.60	[25]
1	3	0.50	11.8	30	25.9	21.13	20	6.6	0.33	[25]
1	2	0.13	12.0	37	56.0	51.00	30	8.6	0.17	[29]
3	1	5.00	36.5	37	33.5	96.35	36	7.0	0.48	[30]
2	1	2.50	19.5	37	71.0	79.00	90	7.4	0.46	[30]

Table A6. Data for pig manure (dung) correlation

Slurry	C/N	T(^{o}C)	TS (%)	VS (%)	HRT(D)	PH	BP (L)	Authors
0.50	22.0	30	9.1	68.0	52	7.0	0.235	[16]
0.50	22.0	30	9.1	64.5	52	6.8	0.240	[16]
7.00	9.8	35	26.3	25.0	40	6.2	7.230	[18]
7.00	9.8	35	26.5	25.0	80	8.1	4.100	[18]
0.25	5.5	37	23.0	20.0	14	6.9	0.250	[21]
0.25	5.5	37	28.0	22.0	14	6.5	0.385	[21]
5.00	8.1	52	7.8	8.5	29	6.5	5.300	[31]
0.20	10.0	36	91.0	93.0	38	6.5	0.125	[32]

Table A7. Data for fruit/vegetable/plant waste substrate correlation

Slurry	C/N	T(^{o}C)	TS (%)	VS (%)	HRT(D)	PH	BP (L)	Authors
4.00	10.49	33	12.0	73.0	14	5.2	0.260	[3]
4.00	14.70	33	7.7	26.4	14	7.1	0.294	[3]
4.00	13.50	37	9.1	26.0	35	5.2	7.240	[15]
4.00	13.00	37	8.0	30.0	35	5.6	4.840	[15]
0.20	17.10	60	15.2	13.8	30	6.9	0.322	[20]
0.25	14.79	37	9.2	18.7	14	5.6	0.443	[21]
0.25	11.30	37	19.7	18.8	14	4.8	0.783	[21]
0.25	12.80	38	19.7	17.0	14	4.5	0.781	[21]
2.50	16.00	30	18.0	20.0	77	5.7	2.690	[24]
0.25	34.00	35	8.3	53.0	42	5.0	0.403	[33]
0.02	11.08	37	21.6	6.0	12	4.0	0.003	[34]

APPENDIX B

Table B1. Statistical parameters for the regression models

	Statistical Analysis Parameters				
Substrate	**R^2**	**Standard Error of Estimate (SER)**	**Akaike Information Criteria (AIC)**	**Schwarz Criterion (SC)**	**Hanna- Quin Criterion (HQC)**
Cow dung	0.99	0.35	1.04	1.41	1.01
Cow dung + Plant waste	0.99	2.16	4.69	5.07	4.71
Cow dung + Poultry dung	0.99	0.18	-0.25	0.12	-0.28
Poultry dung	0.90	1.52	3.82	4.12	3.80
Poultry dung + Grass	0.95	0.52	1.84	2.24	1.87
Pig dung	0.95	0.34	0.97	1.35	0.99
Plant waste	0.96	1.62	4.10	4.49	4.12

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