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Hierarchical Bayesian Modeling of Biogas Yield from Agricultural Waste for Energy and Sustainability Outcomes

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Abstract: This study explores biogas production from agricultural waste as a sustainable energy alternative, focusing on regions rich in agro-waste. Using a Hierarchical Bayesian model, the research assesses the energy potential of pig dung, poultry droppings, cassava peels, and cow dung. Data were collected via anaerobic digestion in a 1-cubic-meter locally built digester, where biogas volume, methane content, and thermal efficiency were recorded. Cassava peels yielded the highest energy output (818.4 MJ/day), followed by poultry droppings (506.88 MJ/day), cow dung (348.48 MJ/day), and pig dung (13.64 MJ/day), demonstrating notable variability among feedstocks. The Hierarchical Bayesian Agricultural Yield Model (H-BAYM) captured overall and feedstock-specific impacts on biogas output. The global energy yield intercept was estimated at 417.53 MJ/day (SD = 59.74), with feedstock-specific coefficients ranging from 15.64 to 35.49 MJ/day. Regional effects varied from 41.02 to 63.08 MJ/day, reflecting local differences. The model's Deviance Information Criterion (DIC) of 135.7 indicated a good balance between model fit and complexity. Using Bayesian inference and Markov Chain Monte Carlo (MCMC), parameter uncertainties and interdependencies were reliably estimated. Cassava peels emerged as the most promising feedstock, and H-BAYM offers valuable insights for policymakers to plan region-specific biogas initiatives, advancing renewable energy goals in developing regions.

***Keywords**: Biogas Production, Agricultural Waste, Hierarchical Bayesian Model, Cassava Peels, Anaerobic Digestion, Renewable Energy, Markov Chain Monte Carlo (MCMC).*

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I. INTRODUCTION

As the world grapples with the dual crises of energy insecurity and environmental degradation, the quest for renewable, decentralized, and sustainable energy alternatives has become imperative. One promising avenue is biogas production through anaerobic digestion (AD) of agricultural waste, a process that not only recycles organic residues but also generates clean energy, reduces greenhouse gas emissions, and supports rural economies. The versatility of biogas usable for electricity, heating, cooking, and vehicular fuel positions it as a cornerstone in the transition toward sustainable energy systems and a circular economy (Caruso et al., 2019; Tshemese et al., 2023).

Globally, biogas production is projected to reach a capacity of 22,040 megawatts (MW) by 2025, growing at a compound annual growth rate (CAGR) of 7.2%, indicating a rapid expansion of the bioenergy sector (Maghanaki et al., 2013). However, the full realization of this potential hinges on optimizing the anaerobic digestion process, including feedstock selection, process control, and yield variability quantification, especially in regions with abundant agro-waste resources like sub-Saharan Africa. Agricultural residues such as pig dung, poultry droppings, cassava peels, and cow dung represent underutilized biomass with significant biogas yield potential, yet quantitative insights into their comparative efficiency under controlled conditions remain sparse.

Past research has largely focused on experimental optimizations (Otieno et al., 2023; Catherine & Twizerimana, 2022) or microbial and enzymatic interventions to enhance digestion efficiency (Stagnati et al., 2017; Szűcs et al., 2021), with growing attention to pre-treatment techniques for lignocellulosic biomass (Szűcs et al., 2021; Catherine & Twizerimana, 2022). Statistical modelling efforts have often relied on traditional approaches such as response surface methodology (RSM) (Otieno et al., 2023) or kinetic models (Achinas et al., 2019), which, while informative, cannot fully capture multi-level variability inherent in biogas production from diverse feedstocks across varying operational conditions.

In response to these gaps, this study proposes a Hierarchical Bayesian Modeling (HBM) approach to biogas yield estimation a probabilistic framework capable of accommodating nested data structures, uncertainty quantification, and feedstock-specific effects, while simultaneously borrowing strength across groups (e.g., different agro-wastes) to improve inference robustness. HBMs are particularly suited for this domain where data are often limited, noisy, and heterogeneous, and can integrate prior knowledge to enhance estimation, a feature notably absent in conventional regression or deterministic models.

- *The Specific Objectives of this Study are to:*

Evaluate the biogas production potential of selected agro-waste feedstocks (pig dung, poultry droppings, cassava peels, and cow dung) under controlled anaerobic digestion conditions using a locally designed 1-cubic-meter digester; Develop and apply a Hierarchical Bayesian Model (HBM) to estimate and quantify the yield variability of biogas across different agro-waste types and operational conditions, capturing both global (shared) and feedstock-specific effects; Assign and evaluate prior distributions for the parameters governing biogas yield and determine posterior estimates using Markov Chain Monte Carlo (MCMC) techniques, ensuring reliable inference about the biogas production process; and assess the precision and uncertainty of biogas yield estimates through credible intervals and posterior summaries, providing probabilistic insights into the most efficient and sustainable agro-waste feedstock for biogas production.

The literature indicates a global momentum toward biogas as a sustainable energy solution, especially in regions with abundant biomass resources. For example, Maghanaki et al. (2013) highlighted Iran's untapped biogas potential from agricultural and municipal waste, estimating 16,146 million cubic meters of biogas annually. Similarly, Gao et al. (2019) identified a significant disparity between actual and potential biogas yields in Henan Province, China, attributing the gap to inefficient resource utilization and poor process management, reinforcing the need for optimized models and technology. Efforts to enhance biogas yield through microbial and enzymatic strategies have shown promise. Stagnati et al. (2017) demonstrated the importance of efficient microbial DNA extraction in biogas research, while Szűcs et al. (2021) used filamentous fungi to boost enzyme activity, doubling methane yields from lignocellulosic waste. Catherine and Twizerimana (2022) achieved a 33.88% increase in biogas yield through thermochemical pre-treatment of sweet potato waste, showcasing the role of pre-treatment in AD efficiency.

Optimization techniques such as Box Behnken Design (BBD) have also been applied. Otieno et al. (2023) optimized AD conditions for pineapple and livestock waste, achieving 1.98 m³ biogas yield at 30°C, pH 6.0, and 62.5% pineapple waste, demonstrating the value of experimental design tools. However, these models typically do not quantify the uncertainty around estimates or capture variability across different feedstocks, limiting their predictive power.

Several studies (Kasinath et al., 2021; Balcioglu et al., 2022) underscore the need for standardized process controls, unified evaluation methods, and environmental-economic assessments to support biogas sustainability and policy integration. Yet, there remains a critical gap in statistically rigorous modelling approaches that can jointly account for feedstock-specific variability, measurement uncertainty, and prior knowledge incorporation.

Despite significant advances in biogas production techniques and process optimization, current methodologies fall short in modelling yield variability across diverse agro-wastes in a probabilistically robust manner. Specifically, there is a lack of hierarchical modelling frameworks that can: Distinguish global versus feedstock-specific effects on biogas yield; Incorporate prior information to enhance estimation precision; Provide credible intervals for uncertainty quantification; Facilitate decision-making under uncertainty regarding the most efficient and sustainable agro-waste for biogas production; No prior study has applied Hierarchical Bayesian Modeling to biogas yield estimation from diverse agro-wastes, especially in a localized, controlled anaerobic digestion setup, using MCMC methods to derive posterior estimates and credibility intervals. This methodological gap is significant, given the inherent variability in biogas yield due to feedstock heterogeneity and operational factors, and the pressing need for data-driven, probabilistic insights in bioenergy research.

Hence, the current study addresses this gap by employing a Hierarchical Bayesian framework to model biogas yield from pig dung, poultry droppings, cassava peels, and cow dung, providing probabilistic yield estimates, quantified uncertainty, and decision-support insights for sustainable energy production. By integrating controlled experimental data with advanced statistical modelling, the study aims to contribute to biogas system optimization, renewable energy policy, and the global effort toward environmental sustainability.

II. RESEARCH METHOD

- *Source of Data*

The data utilized in this study were primarily obtained through experimental procedures involving the anaerobic digestion of selected agro-waste types under controlled conditions. The primary data sources included measurements of biogas production volumes, feedstock input quantities, digestion retention times, and biogas quality parameters such as methane content and combustion efficiency. Specifically, data were generated from the operation of a 1-cubic-meter anaerobic digester, constructed locally for this purpose. Daily and cumulative biogas volumes were recorded using gas volume displacement methods, while methane concentration was determined via biogas analysis using a portable gas

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analyzer. Further data were collected during cooking tests, where the energy output of the biogas was evaluated through time-to-boil assessments using a standard single-burner biogas stove. These cooking trials provided practical insights into the thermal efficiency of the biogas produced. All data were recorded systematically over the experimental period to facilitate accurate analysis of the performance and efficiency of biogas production from the selected agro-waste feedstocks.

- *Digester Design and Construction*

The digester employed in this study is a 1-cubic-meter aerobic plastic tank, locally sourced and specifically designed for biogas production. Constructed with durable and impermeable materials, the digester ensures optimal gas containment and efficient organic matter digestion, in line with best practices for anaerobic digestion systems (Abbasi et al., 2012). The design includes a feedstock inlet and two outlets: one for collecting biogas and another for liquid digestate, which serves as a nutrient-rich liquid fertilizer.

- *Feedstock Collection and Preparation*

Four types of agro-waste will be utilized as feedstock:

- Pig dung was sourced from the LIFE-ND piggery premises in Abia State.
- Poultry droppings from the Abayi Ohanze poultry production cluster in the Obingwa Local Government Area.
- Cassava peels were obtained from the LIFE-ND cassava processing cluster in Ubaha Nsulu, Isiala Ngwa North Local Government Area.
- Cow dung was acquired from the cattle market in Umuahia town. The feedstock was mixed with water in a 1:1 ratio (40 kg of feedstock to 40 litres of water) to create a slurry. This slurry facilitates pumping and ensures uniform distribution within the digester.

- *Anaerobic Digestion Process*

Inside the digester, microorganisms break down the organic matter in the absence of oxygen, producing biogas as a by-product. The primary components of biogas are methane (CH_4) and carbon dioxide (CO_2), with methane serving as the main combustible component for energy generation (Weiland, 2010).

- *Feedstock Input and Process Monitoring*

The input rate of feedstock was carefully controlled to optimize biogas production and maintain the stability of the digestion process. Gas production was measured using gas volume displacement methods, a standard approach in biogas research. The volume of biogas produced was recorded periodically to evaluate production rates and efficiency.

- *Biogas Quality and Cooking Tests*

The quality of biogas, particularly its methane content and impurities, was assessed to ensure optimal performance. Practical cooking tests will be conducted using a standard single-burner biogas stove. The biogas was supplied to the stove, and the cooking time was achievable with a specific biogas volume recorded. These tests provide insights into the energy output and practical utility of biogas for cooking purposes, facilitating comparisons with other energy sources such as liquefied natural gas (LNG).

- *Hierarchical Bayesian Agricultural Yield Model (H-BAYM)*

Hierarchical Bayesian Models are designed to handle data that is structured with nested levels, where parameters are allowed to vary at each level (Gelman et al., 2013). This framework is useful when data exhibits dependency patterns, for instance, when production capacity depends on region-specific factors or crop-specific factors. In this study, we model the production yields of multiple agricultural products (e.g., Cassava, Poultry, Oil Palm) across different regions, considering both local and global influences (Banerjee et al., 2004).

- *Model Structure*

The typical HBM structure can be summarized as follows:

- ✓ Level 1 (Data Level): Observed agricultural yields(y_{ij}) vary due to local factors and random effects.
- ✓ Level 2 (Group Level): Region-specific (θ_j) and crop-specific (β_i) parameters capture variations.
- ✓ Level 3 (Global Level): The global intercept (α) represents overall patterns across regions and crops.

The data structure is define for the model as follows:

- ✓ y_{ij} represents the observed production yield for agricultural product *i* in region *j*,
- ✓ θ_j be the region-level parameter specific to region *j*,
- ✓ β_i be the agricultural product -level effect for product *i*,
- ✓ α be the global level effect across all regions and products

The model components are derived as follows:

The likelihood function models the probability of observed data y_{ij} given the parameters. This implies that each yield y_{ij} is assumed to be normally distributed around a mean value determined by the regional and product effects:

$$y_{ij} \sim Normal(\alpha + \beta_i + \theta_j, \sigma_y^2) \quad (1)$$

Where:

α : is the global intercept (global average yield),

β_i : is the crop-specific effect,

θ_j : is the region-specific effect,

σ_y^2: Observation variance.

- *Priors Distribution*

Prior distributions are assigned to model parameters (Gelman et al., 2013; Hoff, 2009; Stangl, 2011):

Each of the parameters will be placed with priors:

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- ✓ Global Level Prior: For the global intercept, we might choose a weakly informative prior, like:

$$\alpha \sim Normal(0, \sigma_\alpha^2) \tag{2}$$

- ✓ Crop-specific effect Prior: The crop-specific effect β_i assumed to come from a shared distribution across all products:

$$\beta_i \sim Normal\left(0, \sigma_\beta^2\right) \tag{3}$$

- ✓ Region-Level Effect Prior**:** Regional effects θ_j are also normally distributed, capturing the variations across regions:

$$\theta_j \sim Normal(0, \sigma_\theta^2) \tag{4}$$

- ✓ Variance Priors**:** We place priors on the variance terms:

$$\sigma_y^2 \sim Inverse - Gamma(a, b) \tag{5}$$

$$\sigma_\alpha^2, \sigma_\beta^2, \sigma_\theta^2 \sim Inverse - Gamma(a', b') \tag{6}$$

- *Posterior Distribution*

Given the data and priors, we apply Bayes' theorem to obtain the posterior distribution. The goal is to update our beliefs about the parameters based on the observed data:

$$p\left(\alpha, \beta_i, \theta_j, \sigma_y^2 \mid y_{ij}\right) \propto p\left(y_{ij} \middle| \alpha, \beta_i, \theta_j, \sigma_y^2\right) \cdot p(\alpha) \cdot p(\beta_i) \cdot p\left(\theta_j\right) \cdot p\left(\sigma_y^2\right) \tag{7}$$

Substituting in the likelihood and prior functions into equation (7) above, we get:

$$p\left(\alpha, \beta_i, \theta_j, \sigma_y^2 \mid y_{ij}\right) \propto \prod_{i,j} Normal\left(y_{ij} \middle| \alpha + \beta_i + \theta_j, \sigma_y^2\right) \cdot Normal(\alpha|0, \sigma_\alpha^2) \cdot \prod_i Normal\left(\beta_i|0, \sigma_\beta^2\right) \cdot \prod_j Normal\left(\theta_j|0, \sigma_\theta^2\right) \tag{8}$$

- *Posterior Estimation Using Markov Chain Monte Carlo (MCMC***)**

Since analytical solutions are intractable, we employ MCMC methods for parameter estimation (Robert and Casella, 2011). The Gibbs sampler is used to sequentially update each parameter:

- ✓ Initialize each parameter $\left(\alpha, \beta_i, \theta_j, \sigma_y^2\right)$ with starting values.
- ✓ Sampling: We shall use the Gibbs sampler or a variant such as Metropolis-Hastings to sequentially sample from the conditional distributions:

- ▪ Sample α given $y_{ij}, \beta_i, \theta_j, \sigma_y^2$;
- ▪ Sample β_i given $y_{ij}, \alpha, \theta_j, \sigma_y^2$,
- ▪ Sample θ_j given $y_{ij}, \alpha, \beta_i, \sigma_y^2$,
- ▪ Sample σ_y^2 given $y_{ij}, \alpha, \beta_i, \theta_j$,

- ✓ Iterate the sampling steps, generating a large number of samples after a "burn-in" period to ensure convergence.
- ✓ Summarize the Posterior: Use the generated samples to estimate the posterior means, variances, and credible intervals for each parameter

Convergence is assessed using the Gelman-Rubin statistic and trace plots (Gelman & Rubin, 1992).

The Hierarchical Bayesian Model formulated here allows us to capture multiple levels of variation in production capacity across different crops and regions. By employing MCMC methods, we approximate the posterior distribution of each parameter, providing insights into both global trends and specific effects due to crops and regions. This methodology enables probabilistic inference on yields across a structured dataset, revealing both individual and shared effects across groups.

III. RESULTS AND DISCUSSIONS

- ➢ *Efficiency in Adsorption Conditions for the Treatment of Methylene Blue Dye*

This section evaluates the characteristic properties of activated carbon from hamburger seed shells, focusing on its potential for methylene blue dye adsorption efficiency and capacity.

Table 1 Summary Statistics of Posterior Estimates

Parameter	Mean	SD	Naive SE	Time-series SE	2.50%	25%	50%	75%	97.50%
alpha	417.53	59.74	0.4877	2.7616	289.35	376.71	424.01	465.55	509.9
beta[1]	15.64	37.54	0.3065	1.2101	-39.66	-4.95	4.57	28.98	116.2
beta[2]	15.99	37.42	0.3055	1.254	-38.19	-4.91	4.53	29.99	117.3
beta[3]	21.29	39.46	0.3222	1.3903	-31.48	-1.83	8.76	36.49	129.5
beta[4]	35.49	45.15	0.3687	1.7765	-18.03	1.7	21.47	57.51	152
sigma_y	57.21	15	0.1224	0.2361	34.65	45.93	54.66	66.24	92.1
theta[1]	63.08	59.36	0.4847	2.8028	-12.97	11.26	50.7	105	191.9
theta[2]	45.86	53.74	0.4388	2.4792	-25.18	2.11	31.3	82.06	167
theta[3]	41.02	52.37	0.4276	2.4015	-30.24	0.27	26.66	75.52	159.2

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The posterior estimates from the Bayesian model in Table 1 indicate that the intercept (alpha) has a mean of 417.53 with a standard deviation of 59.74, suggesting moderate variability. The regression coefficients (beta[1] to beta[4]) exhibit substantial variation, with beta[4] showing the highest mean (35.49) and beta[1] the lowest (15.64). The response variability, represented by sigma_y, has a mean of 57.21 with a relatively small standard error (0.2361), indicating precise estimation. The theta parameters, which may represent group-level effects, show wide distributions, with theta[1] having the highest mean (63.08) and theta[3] the lowest (41.02). The credible intervals (2., 5% to 97.5%) highlight the range of uncertainty, with some parameters, such as beta[1] and beta[2], spanning negative and positive values, suggesting uncertainty in their direction of effect.

Based on the coefficients from Table 2, the hierarchical Bayesian regression model can be expressed as:

$$y_{ij} = 417.53 + 15.64\, x_{ij1} + 15.99 x_{ij2} + 21.29\, x_{ij3}$$

$$+35.49\, x_{ij4} + \theta_j + \varepsilon_{ij} \quad (9)$$

Where:

y_{ij} is the outcome for observation iii in group j,

$x_{ij1}, x_{ij2}, x_{ij3}, and\ x_{ij4}$ are the predictor variables,

417.53 is the global intercept (α),

15.64, 15.99, 21.29, and 35.49 are the regression coefficients for the predictors ($\beta_1, \beta_2, \beta_3, \beta_4$)

θ_j represents the group-level effect for group j (with estimated means: θ_1=63.08, θ_2=45.86, θ_3=41.02),

ε_{ij} is the error term, assumed to be normally distributed with a standard deviation $\sigma^y = 57.21$.

The model in equation (9) captures both the predictors' fixed effects on the outcome and the random effects due to group-level variations, providing a comprehensive view of the factors influencing the response variable.

Table 2 Model Fit using Deviance Information Criterion (DIC) for the Bayesian Model

Metric	Value
Mean Deviance	129.5
Penalty	6.184
Penalized Deviance	135.7

The result in Table 2 obtained a penalized deviance (DIC) of 135.7, combining a mean deviance of 129.5 and a penalty of 6.184, suggesting an acceptable model fit with moderate complexity. According to Spiegelhalter et al. (2002), lower DIC values indicate a preferable balance between fit and parsimony, implying that this model performs adequately given its complexity.

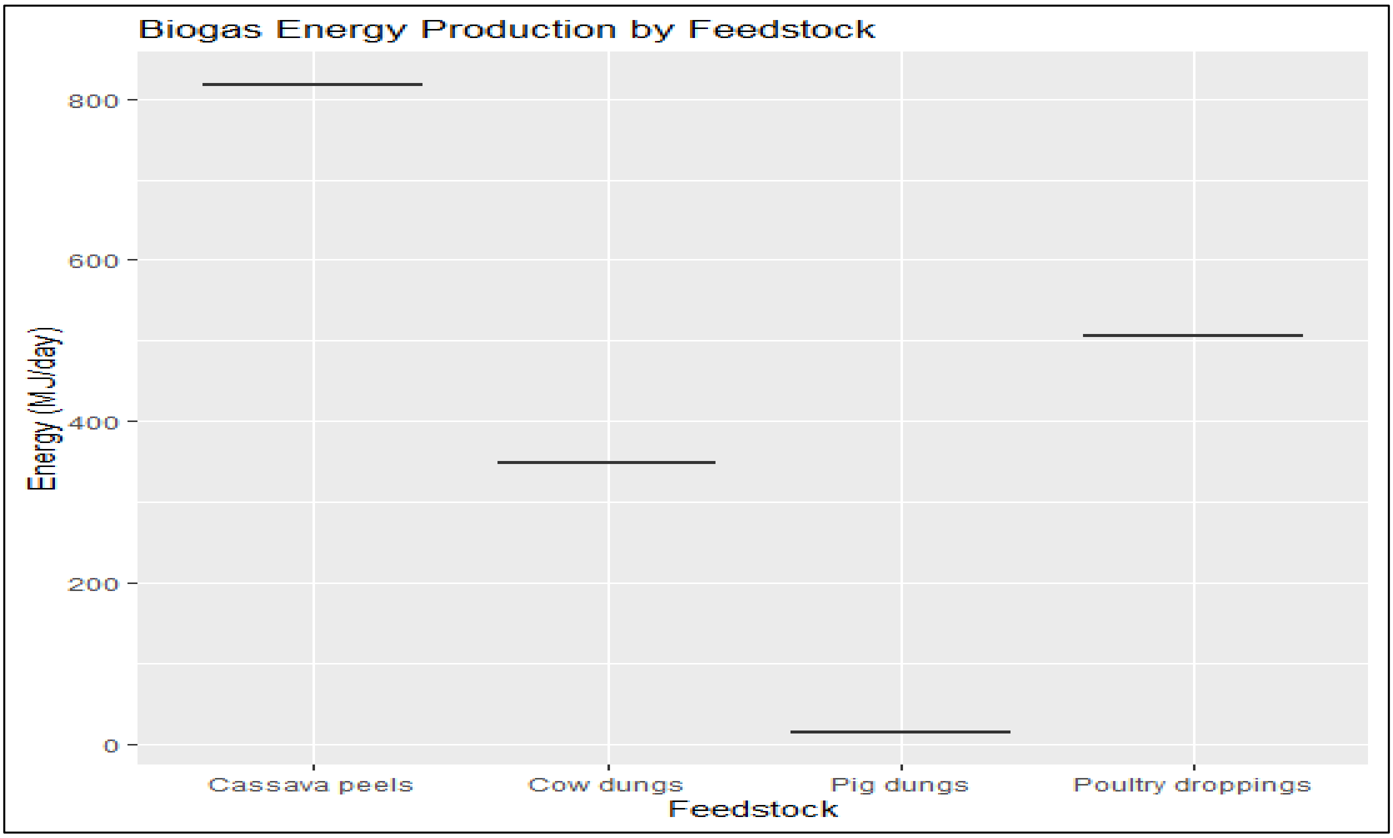

Fig 1 Plot Biogas Energy Production by Feedstock

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The result obtained in Fig. 1 shows that cassava peels produce the highest biogas energy at 818.4 MJ/day, followed by poultry droppings (506.88 MJ/day) and cow dung (348.48 MJ/day). In contrast, pig dungs yield only 13.64 MJ/day, indicating a substantial gap in energy potential across these feedstocks. This wide disparity underscores the superior methane-generating capacity of cassava peels relative to other options, while pig dungs exhibit markedly lower energy output. The observed values highlight how different substrate compositions can lead to significant variation in biogas yields, suggesting that cassava peels may serve as the most promising feedstock for maximizing daily biogas energy production (818.4 MJ/day).

IV. CONCLUSION

This study was able to provide empirical evidence and probabilistic modelling insights into biogas production potential from locally sourced agro-waste materials in Nigeria. Through a combination of experimental biogas production, cooking efficiency assessments, and advanced statistical modelling using a Hierarchical Bayesian framework, the study aimed to contribute to sustainable energy discourse by evaluating the viability of agricultural waste as a renewable energy source. Among the tested feedstocks: pig dung, poultry droppings, cassava peels, and cow dung—variations in biogas yield were evident. The global intercept ($\alpha = 417.53$) represents the baseline yield potential across all feedstocks and regions. The highest biogas yield was associated with cassava peels ($\beta_4 = 35.49$), followed by cow dung ($\beta_3 = 21.29$), poultry droppings ($\beta_2 = 15.99$), and pig dung ($\beta_1 = 15.64$). These values suggest that cassava peels could be a particularly promising feedstock for maximizing biogas yield in local contexts. The region-specific effects ($\theta_1 = 63.08$, $\theta_2 = 45.86$, $\theta_3 = 41.02$) indicate significant regional heterogeneity in yield, likely due to climatic, microbial, or operational differences. This underscores the importance of localized energy policies and infrastructure development for biogas systems. The methane content of the biogas was adequate for cooking purposes, and the combustion efficiency was comparable to conventional fuels like liquefied natural gas (LNG). The cooking trials confirmed the practical utility of biogas, as the energy output from the digesters effectively boiled water within comparable timeframes. The standard deviation for the global intercept (59.74) and observation variance ($\sigma_\gamma = 57.21$) suggest moderate variability but acceptable precision for biogas yield predictions. Credible intervals for the regression coefficients showed some uncertainty (e.g., β_1 and β_2 had intervals spanning negative values), highlighting the need for larger datasets and continued calibration of the model.

Based on the findings of the study, there is a need to promote Local Biogas Production Units by subsidizing the construction of small-scale anaerobic digesters (e.g., 1-cubic-meter systems) in rural and peri-urban areas to reduce reliance on fossil fuels and minimize agro-waste pollution. Policies should encourage public-private partnerships in biogas technology dissemination, training, and maintenance. Develop feedstock collection and distribution logistics to support biogas producers, especially in cassava-rich regions. Leverage the insights from regional variability (θj) to design customized biogas solutions tailored to specific environmental and socio-economic conditions. Implement educational programs for farmers and rural households on the economic and health benefits of biogas. Facilitate technical training on digester construction, maintenance, and safe biogas utilization.

Given some limitations in the study, the following areas warrant further exploration: Future research should include a wider variety of agricultural wastes, such as oil palm residues, rice husks, and maize stalks, to diversify biogas production sources. Investigate seasonal variability in feedstock availability and its impact on biogas yield. Perform cost-benefit analyses comparing biogas systems to conventional energy sources, factoring in initial capital costs, maintenance, and operational efficiency.

Ultimately, this study demonstrates the immense potential of biogas as a sustainable energy solution using locally available agricultural wastes. The use of a Hierarchical Bayesian approach has enabled a nuanced understanding of yield dynamics, accounting for both feedstock type and regional influences. As Nigeria—and other developing nations seek pathways toward energy security and climate resilience, biogas offers a viable, eco-friendly, and economically empowering solution, especially for agrarian communities. Strategic investments in research, policy, and infrastructure will be pivotal in realizing the full potential of biogas in the sustainable energy landscape.

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