Energy for Sustainable Development 86 (2025) 101668

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Digesting data: Improving the understanding of biogas use through remote sensing

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A R T I C L E I N F O

Keywords:
Remote monitoring
Machine learning
Biogas
Clean cooking
Sustainable development goals
Sub-Saharan Africa

A B S T R A C T

The use of small-scale biodigesters is gaining traction in Kenya and Uganda as a clean renewable energy solution. In this paper, we explore how remote monitoring through Internet of Things (IoT) technologies can enhance the service quality of biogas digesters in low-resource settings and promote transparency in carbon accounting. Using data from 121 monitored digesters in Uganda and Kenya, we demonstrate how the analysis of real-time pressure and flow data, coupled with machine learning, can provide an understanding of usage patterns, provide behavioural insights, facilitate the early identification of issues requiring intervention, and give insights into relative digester performance. The tools presented offer a powerful means to study behavioural patterns and the adoption dynamics of biogas as a clean cooking fuel, aligning with national and global aims of broader clean cooking interventions.

Introduction

As the United Nations Sustainable Development Goal 7 (SDG7) - clean energy for all by 2030 - falls behind its targets, the Clean Cooking sector faces significant challenges. Despite progress, 2.3 billion people still rely on inefficient and polluting fuels (The World Bank, 2023; International Energy Agency (IEA) et al., 2023), resulting in adverse health outcomes, 3.2 million deaths in 2020 alone (Bobbie Person et al., 2012; Smith et al., 2000; Gordon et al., 2014; Lee et al., 2020; World Health Organization (WHO), 2022), and environmental impacts (Ahrends et al., 2010; Bailis et al., 2015; Food and Agriculture Organization of the United Nations, 2010; Hosonuma et al., 2012; Masera et al., 2015). Improving access to modern, reliable, and sustainable technologies and services for clean cooking has the potential to significantly reduce poverty and enable meaningful pathways to the completion of SDG7 (Reddy et al., 2009; Singh & Inglesi-Lotz, 2021) - although significant challenges remain to meet the SDG7 target.

Biogas digesters, produce biogas, and digestate. Biogas predominantly comprises 40 % - 75 % methane and 25 % - 60 % CO2. The digestate is a nutrient-rich semi-solid liquid fertiliser containing Nitrogen, Phosphorus and Potassium and free of pathogens and odours (Salomon & Silva Lora, 2009; Wang, 2014). At large scale, biogas is mainly used for CHP electricity and heat generation or upgraded to biomethane for vehicles or gas grids (Abanades et al., 2022; Scarlat et al., 2018). At a smaller domestic scale in the global south, biogas digesters offer one potential solution to clean cooking for running appliances such as fridges and grain threshers. Additionally, domestic biogas systems, including the digestate as a fertiliser, offer well-documented environmental, social and health benefits to households and communities (Fulford, 2015; Garfí et al., 2019; Mengistu et al., 2015; Mottaleb & Rahut, 2019; Präger et al., 2019; Rajendran et al., 2012). Domestic-scale market-based biogas implementation has been supported in numerous African and Asian countries by agencies such as SNV (Clemens et al., 2018; SNV, 2022). Scaling up biogas requires overcoming operational challenges, and smart monitoring systems using IoT technology can play a significant role (Bisaga et al., 2017) in improving customer service, system resilience, and optimisation, as demonstrated in other off-grid energy solutions (Ahmad & Zhang, 2021; Ahmed Abdulkadir & Al-Turjman, 2021; Bhattacharyya & Palit, 2016; Finke et al., 2022; Kirchhoff et al., 2016; Salam, 2020; Welsch et al., 2013). This paper demonstrates the value of IoT-enabled remote monitoring of small-scale domestic biogas digesters to provide insights into use patterns, user behaviours, relative performance and support maintenance, user experience, and biogas utilisation.

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https://doi.org/10.1016/j.esd.2025.101668
Received 9 September 2024; Received in revised form 5 February 2025; Accepted 6 February 2025
Available online 31 March 2025
0973-0826/

Challenges with biogas implementation

Biogas adoption faces socio-cultural, technological, environmental, and financial challenges, including stove-stacking, seasonal and cultural beliefs, and social status (Hewitt et al., 2022; Nevzorova & Kutcherov, 2019; Pillarisetti et al., 2014; Ruiz-Mercado & Masera, 2015). Technological issues involve corrosion, digester air tightness, condensation, feedstock ratios, temperature, water availability, and maintenance (Hewitt et al., 2022; Rajendran et al., 2012; Uhunamure et al., 2019). In 2016, 27 % of biodigesters built in Kenya, Tanzania, and Uganda between 2009 and 2013 were inoperative, emphasising these barriers (Clemens et al., 2018).

Measurement methods for clean cooking interventions

To reduce household air pollution, researchers, policymakers, and practitioners must evaluate clean cooking interventions, substantiate health and social benefits, and understand challenges (Quinn et al., 2018). A nuanced understanding of complex cooking needs and behaviours is crucial to linking cleaner technology adoption, traditional stove displacement (Coffey et al., 2021), and meeting cooking needs. Carbon financing initiatives supporting biogas and clean cooking require accurate carbon accounting methodologies, necessitating objective data collection on cookstove usage patterns ("Gold Standard Methodology: Technologies and Practices to Displace Decentralized Thermal Energy Consumption Version 3.1,", 2017).

Researchers have employed various methods to study clean cooking interventions and user behaviours. These include household surveys (Brooks et al., 2016; Piedrahita et al., 2016), semi-structured interviews (Mukhopadhyay et al., 2012; Rhodes et al., 2014), in-person observations (Coffey et al., 2021; Simons et al., 2014), participant cooking diaries (Leary et al., 2018), and sensor-based measurements (Piedrahita et al., 2016; Pillarisetti et al., 2014). Each method has its strengths and limitations. Surveys and interviews provide broad insights but may be subject to self-reporting bias. Observational studies offer direct data but can alter behaviour. Cooking diaries combine self-reported data with energy measurements but face challenges in low-literacy settings. Sensor-based monitoring provides objective data on stove use without influencing behaviour, addressing some limitations of other methods. See Table 3 in Supplementary Materials for more details on these methodologies.

Biogas digester monitoring

Biogas monitoring involves monitoring the biogas produced and consumed and the internal state of the digester and slurry, which affects biogas quality. Commercially monitored parameters on large digesters include pH, temperature, slurry level, biogas consumption, pressure, as well as output gas composition and various offline measurements such as digestate conductivity, Chemical Oxygen Demand (COD), Total Organic Carbon (TOC), Volatile Fatty Acids (VFA) among others (Gupta, 2020; Vanrolleghem, 1995; Wu et al., 2019). Monitoring supports understanding and controlling key parameters for process stabilisation, optimisation, and maximising methane production (Wu et al., 2019).

Despite its establishment for industrial-scale systems (e.g. gasdata, 2024; Jimenez et al., 2022), monitoring has been limited for small household scale domestic digesters due to complexity and high instrumentation cost relative to the cost of a digester and small potential financial returns or savings in low resource settings (Radu et al., 2022; Wu et al., 2019). This is despite potential benefits such as process optimisation, maintenance support, improved customer service, carbon offsetting, insights for potential biogas digester system optimisation, and billing (Ahmed et al., 2015; Gupta, 2020; Radu et al., 2022; Robinson et al., 2023; Xu & Wang, 2019). Studies to date have included no more than two digesters and are often run for small monitoring periods (Dieudonne & Shima, 2018; Gupta, 2020; Radu et al., 2022; Teixeira et al., 2017), with limited longitudinal studies on biogas digester usage behaviour.

Remote IoT data and machine learning in low resource settings

Off-grid energy providers have leveraged remote monitoring technologies with machine learning to improve service provision and create new scalable energy access business models in sub-Saharan Africa, such as in smart grids, mini-grids, and solar home systems (Ahmad & Zhang, 2021; Ahmed Abdulkadir & Al-Turjman, 2021; Bhattacharyya & Palit, 2016; Finke et al., 2022; Kirchhoff et al., 2016; Salam, 2020; Welsch et al., 2013). These technologies have been used to detect light degradation of solar streetlights and plan their service and maintenance (Kama et al., 2017), reveal energy usage patterns, disaggregate loads, infer degraded batteries, and identify dusty solar panels (Bisaga et al., 2017), optimising customer service. Beyond energy, monitoring and analytics have been used in water kiosks and smart handpumps (Colchester et al., 2017; Koehler et al., 2015; Papastylianou et al., 2014), for instance, through machine learning, using accelerometer vibration patterns recorded while pumping, it was found groundwater depth could be estimated (Colchester et al., 2017).

For biogas energy provision, efforts to develop practical monitoring systems for low-resource settings often focus on measuring multiple internal digester parameters to study the digestion process and performance (Dong et al., 2019). However, many sensor-based solutions face challenges for long-term affordable monitoring of small-scale biogas digester systems. For example, Teixeira et al. (2017) developed a low-cost remote monitoring system for a digester measuring temperature, pressure, pH, and methane, but due to budget constraints, the selected methane sensor had insufficient measurement range and was prone to corrosion (Iswanto et al., 2021; Zhengzhou Winsen Electronics Technology Co., Ltd., 2014). Furthermore, pH electrodes degrade over time and require regular cleaning and calibration for reliable long-term monitoring (Vanrolleghem, 1995; Munro et al., 1996). Radu et al. (2022) proposed a promising solution using an off-the-shelf landfill gas monitoring system. Still, its high upfront and yearly servicing costs put it out of reach for most household-scale digesters. Affordable, robust, long-term monitoring remains a challenge.

Objectives

Innovative systems using real-time data for monitoring can significantly contribute to scaling up energy access by improving customer service, enhancing system resilience, and providing insights for system optimisation (Bisaga et al., 2017). However, limited research has focused on data-driven enabled biogas digesters in low-resource settings.

This paper has two key objectives:

- Gain insights into the use patterns and user behaviour of domestic biogas digesters in Sub-Saharan Africa to demonstrate the value of IoT technology on a household scale.
- To illustrate the use of IoT data to enable relative performance evaluation of biodigesters.

The study involved 121 monitored digesters across two programmes in Uganda and Kenya, part of the Smart Biogas 2 and 3 project (Smart Biogas II, 2022, Smart Biogas III, 2025). The developed tools can enhance user experience, support biogas-as-a-service delivery models, and provide greater transparency for carbon accounting (Robinson et al., 2023). Combined with qualitative methods, these tools can be used to study biogas adoption patterns and user behaviours, which is crucial for supporting the transition to cleaner cooking.

Materials and methods

The study utilised "Smart Biogas" - a remote monitoring device developed initially by CREATIVenergie (Charity number SC047910) through an Innovate UK-funded project ("Smart Biogas Network", Grant #132479) and later commercialised by Inclusive Energy. The current work extends this foundation using data from subsequent Inclusive Energy led Innovate UK projects: Smart Biogas II (#105909) and III (#10046103).

The field implementation was conducted in partnership with the Kenya Biogas Program (KBP) and Biogas Solutions Uganda (BSUL), who served as delivery partners for the Africa Biogas Partnership (ABP) East Africa. Smart Biogas meters were installed on household biogas digesters at small farms participating in the Kenya and Uganda biogas programmes. While KBP, BSUL, and Inclusive Energy collected the primary data, this study presents a secondary analysis of the data provided. All participating households provided informed consent and appropriate data privacy agreements for the collection of sensor data from their digesters.

The digesters included in this study were drawn from households who participated in a Performance Fuel Testing (PFT) assessment for carbon monitoring and verification in Kenya and Uganda, as part of a verification process under the Gold Standard methodology ("Gold Standard Methodology: Technologies and Practices to Displace Decentralized Thermal Energy Consumption Version 3.1,", 2017). These were part of approximately 8000 digesters installed across the two programmes at the time of the study. The PFT component of the Kitchen Performance Test (KPT) measures 24–72 h fuel consumption patterns to estimate emission reductions, requiring a 90/30 precision ratio (90 % confidence that measured values fall within ±30 % of actual population values).

From this PFT subset, households were selected via simple random sampling for smart meter installation, with formal stratification not employed. When households had non-functioning digesters or declined participation, replacements were obtained through the same random sampling process. This yielded final samples of 121 households across Kenya and Uganda. Available Smart Biogas hardware and budget constraints primarily determined the sample size. While the random sampling captured the diversity of installed digester sizes and types and provided sufficient data to validate the analytical methods described in subsequent sections, a larger dataset would be required for statistically significant conclusions about the broader Kenya and Uganda digester programmes and to be able to draw meaningful inferences across different digester types.

Meters were fitted to 121 existing digesters across Kenya and Uganda. The study included digesters with designs ranging from $4m^3$ to $15m^3$. Table 1 below summarises the range of digesters considered.

Table 1
Summarises the different digester types on which the Smart Biogas system was fitted.

Digester Type/ Brand	Description	Country	Size [m^3]	Number in Study
Modified Camartec Design (MCD)	A fixed dome design adopted from Tanzania. Modified to allow used of fresh undiluted cattle dung as a substrate to suit livestock keepers in dry and semi-arid areas.	Uganda	13	2
			12	1
			6	16
			8	1
			9	7
Expanding Plastic Bag		Kenya	9	2
			10	1
Masonry Dome	Similar to the MCD but installed by the Kenya Biogas Programme	Kenya	6	5
			8	16
			10	11
			12	6
			15	1
			unknown	21
BSUL 2015/ 2016	Developed in 2015/2016 by BSUL, SNV and biogas experts in Uganda. Based on the MCD model with features to reduce cost (available in sizes $1m^3$ to $13m^3$).	Uganda	13	4
			9	7
			6	10
			4	1
		Kenya	unknown	1
Flexi/Poly/ Expanding Bag Digester Biogas	Digesters made from a flexible UV resistant geotextile.	Uganda	6	1
			9	1
		Kenya	9	2
		Kenya	10	1
Sistema Biobolsa	A prefabricated module biodigester made from a flexible UV resistant geotextile. Available in a broad range of sizes.	Uganda	30	1
Blue Flame Slurry	A floating dome digester design designed by BSUL in collaboration with Crest Tank Limited.	Uganda	6	2
	Total			121

The Smart Biogas system

The Smart Biogas Meter is installed between the digester and the stove (see Fig. 1). It measures biogas consumption volume and static gauge pressure within the digester - the difference between the atmospheric pressure and the digester pressure, providing high-resolution, non-intrusive, objective data for understanding longitudinal biogas usage (Inclusive Energy, 2023; Robinson et al., 2023). Fig. 1 shows (a) the unit with the web dashboard and (b) the unit installed in a kitchen in line with a biogas stove. The Smart Biogas web platform displays real-time gauge pressure and flow data through an interactive dashboard; it also allows biogas programmes to monitor system usage, process payments, and manage maintenance operations through features like an interactive map view, CRM system, and maintenance tracking tools. Further details are available on the Inclusive Energy Website (https://inclusive.energy/smart-biogas).

The Smart Biogas meters are installed between the digester and stove (see Figs. 1 and 2) and are designed to measure gas static gauge pressure and flow. They are an affordable way to monitor a biogas digester, track gas usage, and spot leaking and venting (Inclusive Energy, 2023). The system can be used with all biogas digesters (e.g., floating drum, fixed dome, and flexible bag digesters).

The pressure monitoring system employs two sensors: an MPX12 series silicon piezoresistive static pressure sensor and a Sensirion SDP800 series differential pressure sensor. The MPX12 measures gauge pressure within a 0–10 kPa range, while the SDP800 measures differential pressure within 0–500 Pa and is calibrated explicitly for flow monitoring using a venturi (see Fig. 2). The sensor was calibrated with a diaphragm gas flow meter before installation on digesters. The flow calculations are done on the device's microcontroller (rather than the server). Storage is provided locally so that this can run 'offline' if the data connection is lost for more than a day, ensuring consumption data is accurate, which would be vital if it were being used for billing or as part of a carbon credit methodology.

The MPX12 series silicon piezoresistive static pressure sensor employs a silicone gel barrier that directly protects its die while allowing accurate pressure transmission. Meanwhile, the Sensirion SDP800 series differential pressure sensor uses a combination of materials, including silicone as a static seal, PBT, and other materials for gas path protection. Both sensors undergo manual calibration for optimal accuracy, and to maintain sensor integrity in the corrosive biogas environment, the gas stream passes through a hydrogen sulphide (H_2S) scrubber and a moisture trap before reaching the sensors. The entire system is protected by an IP65-rated fire-retardant HDPE enclosure, ensuring durability in harsh environments.

The MPX12 sensor requires external temperature compensation, implemented through the STM32L072CZ microcontroller. The sensor's

Fig. 1. (a) The Smartbiogas unit and web dashboard; (b) A SmartBiogas meter installed in a kitchen in-line with the stove.

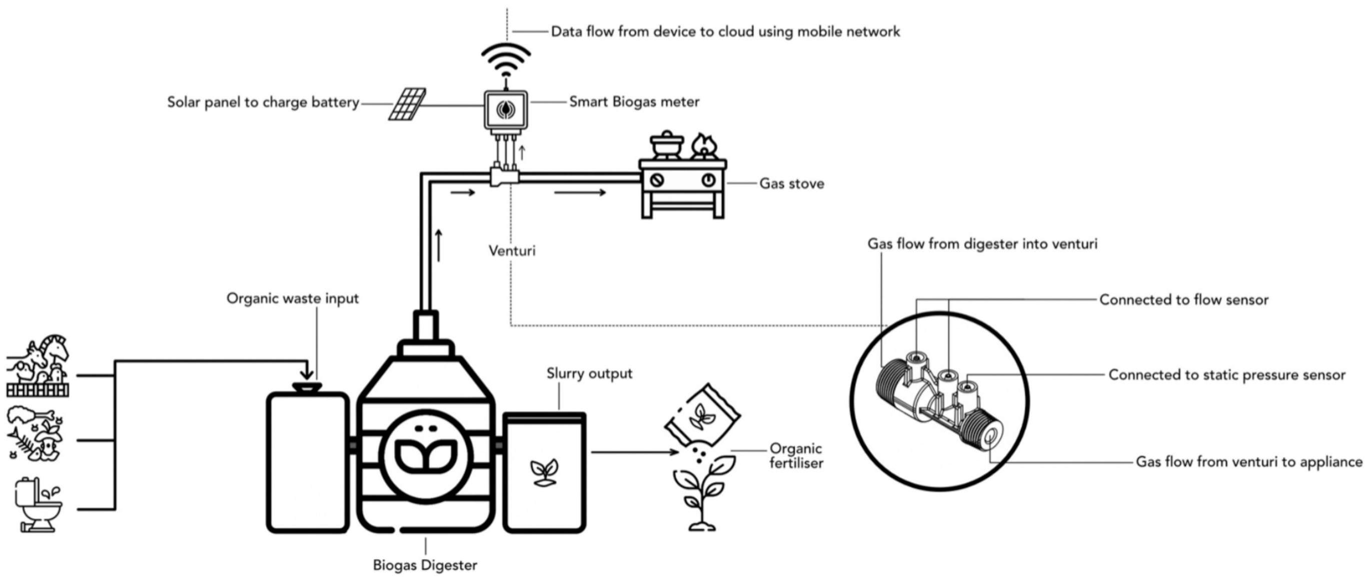

Fig. 2. The Smart Biogas system is installed between the stove and biogas digester and the stove and monitors static pressure and gas flow.

signal conditioning is handled by an MCP6271T operational amplifier, which amplifies and filters the sensor's output signal. This dual approach of temperature compensation and signal conditioning ensures the MPX12 maintains accurate pressure measurements across its operating temperature range of −40 °C to +125 °C.

The SDP800 differential pressure sensor incorporates Sensirion's patented CMOSens® technology, which integrates the sensor element, signal processing, and digital calibration on a single CMOS chip. This integration addresses sensor drift, and the sensor demonstrates excellent repeatability, achieving an offset stability of less than 0.05 Pa/year. The sensor features integrated temperature compensation across −20 °C to +85 °C, achieving a zero-point accuracy of 0.1 Pa and span accuracy of 3 % of a reading. This stability is crucial for biogas applications where long-term reliability is essential. Inclusive Energy have measured the drift after 2 years of field operation and it was found to be negligible. Inclusive Energy offers two system variants: a standard range model for cleaned gas applications with ±5 % accuracy, selected for this installation, and a raw range model designed for high water content and corrosive gases with ±7 % accuracy. Both variants maintain these specifications over their operational lifetime, thanks to the inherent stability of the CMOSens® technology.

Power was provided via small solar panel charging a $LiFePO_4$ battery. The data is sampled for each sensor every 5 milliseconds, and the average for each minute is cached in memory and sent to the Smart Biogas server every hour. The system features 42 days of local data storage capacity, leveraging the STM32L072CZ microcontroller's 192 KB of flash memory and 20 KB of RAM. The storage architecture is optimised to handle both sensor data streams. This microcontroller was chosen for its ultra-low-power design and ability to manage data buffering and transmission efficiently. The microcontroller implements a circular buffer system in flash memory, allowing continuous data collection while maintaining the most recent 42 days of measurements. The system utilises a SIM800L GSM module that supports 2G networks and integrates with the microcontroller via the UART interface. When network connectivity is available, the system transmits data packets through the GSM module while maintaining local storage. This redundant approach ensures no data loss during connectivity interruptions, with the system automatically transmitting stored data once the network connection is restored.

Analysis methodology

This study aims to demonstrate the value of remotely monitoring biogas digesters using simple, low-cost sensors and provide approaches to extract insights related to user behaviour and relative digester performance from the data. Rather than presenting a comprehensive analysis of all aspects and digester types, the study introduces methods and approaches to illustrate the valuable insights that can be obtained by organisations implementing household-scale biogas.

The data analysis focused on two key areas:

1. Approaches for identifying usage patterns of individual household digesters from real-time pressure and flow data that can complement other more qualitative data collection approaches.
2. Examples of combining multi-digester data to make relative comparisons between digesters and gain insights within and across biogas programmes.

Feature extraction

Daily use feature extraction. Data analysis was conducted on a daily basis to align with typical human activity and sleep patterns. Over a year, generation and consumption are affected by numerous factors, such as seasonal feedstock supply shifts, water and feed mixing constraints (Wardle et al., 2021), cooking requirements, and other human factors. Acknowledging these relationships helps contextualise the significant variability observed in daily biogas patterns across households.

Table 2
A summary of the daily features extracted for each day of monitored data.

Day-Centric Features	Description
Peak Pressure	The highest daily gauge pressure reached by the digester, influenced by factors such as feedstock amount, digester temperature, and gas production rate.
Min Pressure	The lowest daily gauge pressure reached by the digester, influenced by factors such as gas consumption, digester temperature, and gas production rate.
Pressure Range	The daily difference between peak and minimum pressure, used as a measure of digester pressure variability.
Standard deviation of Pressure	A measure of the variability in the digester gauge pressure over a 24-h period. A high standard deviation indicates that the gauge pressure is fluctuating more widely.
Total, mean, and median time spent cooking	The total, mean and median time that the digester is used for cooking on a given day. These features can give a measure of the use of the digester.
Shortest time spent cooking	Overall, of the individual meals in the day, what is the one with the minimum cooking duration
Max time spent cooking	Overall, the individual meals in the day, what is the one with the maximum cooking duration.
Total gas consumption	The total amount of biogas consumed on a given day.
Total number of individual cooking events	The total number of times that the digester is used for cooking on a given day.
Mean length of cooking event.	The average length of a cooking event on a given day. Over extended periods, this might be used to identify changes in cooking habits or preferences.
Median length of cooking event	The length of the cooking event that occurs in the middle of the distribution of cooking event lengths on a given day. This can be less sensitive to outliers than the mean length of cooking event.
Filling rate (mean gradient of pressure increase)	The average rate at which the digester is filled with feedstock on a given day. This gives an indication of the rate of production of biogas.
Cooking rate (Mean gradient pressure decrease)	The average rate at which gas is consumed by the cooking appliances on a given day.
Average External Temperature	The average temperature of the environment surrounding the digester on a given day, which influences the temperature of the digestate and the gas production rate.
Biogas Utilisation Effectiveness	A measure of how effectively the biogas is being used. This gives a measure of how much of the produced biogas is being used.
Average Energy per cooking event	The average energy per cooking event

Understanding changes in digester use over extended periods provides valuable data for assessing biogas adoption, potentially helping to evaluate the impact of biogas digesters on carbon mitigation and providing data to help biogas users optimise their digester usage. To understand changes in use patterns over extended periods, informative features were extracted from the minutely sampled points for each digester, seeking to encapsulate daily patterns and reveal underlying trends. Based on domain knowledge, features were selected to represent key characteristics in the data relating to using a biogas digester system over 24 h, as summarised in Table 2. Studying how these features change over extended periods allows us to gain insights into seasonal use patterns.

Fig. 3 shows gauge pressure and flow graph for three days of digester use, displaying digester pressure and consumption flow. The raw gauge pressure and flow data can be noisy, so to extract meaningful features, the data were smoothed using locally weighted scatterplot smoothing (LOWESS) (Cleveland, 1979). LOWESS captures the data's underlying trends and peaks/troughs while reducing noise. Data was first smoothed using this method before calculating the given features for each day of digester data.

Biogas production and consumption in digesters are affected by numerous factors, including feeding rate, type of substrate, dilution rate (with water), temperature (International Renewable Energy Agency (IRENA), 2016), and various human factors. To understand some of these factors, we combined the extracted feature data with historical average daily weather data for each digester location obtained from the Open Meteo API, including precipitation, air temperature, and soil temperature at various depths. By integrating weather data with the digester use data, we aimed to disaggregate the data and identify potential weather-related patterns affecting biogas digester use.

Hourly use patterns. Household digester use will exhibit distinct daily patterns that reflect human household routines. However, usage can fluctuate over a year; for example, it can be affected by numerous interplaying factors such as crop seasons and farming responsibilities, school schedules, or the presence of visitors increasing load. Understanding these temporal dynamics and contextual drivers enables more nuanced insights into real-world digester use and adoption.

Visualising typical usage profiles provides a way to compare behaviour between different digesters and households across time, for example, to understand how usage might change in other seasons of the year. Pairing quantification of usage patterns with qualitative investigation, such as semi-structured interviews, would allow richer insights.

To visualise daily biogas usage patterns, we developed a biogas "time-of-use" graph, where we group the data into hourly intervals and calculate the hourly averages for each feature: time spent cooking, total biogas consumed and rate of biogas consumption. The graph depicts three key dimensions:

1. Average Cooking Duration: We calculated the mean duration per cooking event that utilised biogas for each hour of the day over a set period. This represents the typical cooking duration when activity occurs in that hour. This is plotted as bars representing each hour of the day.
2. Cooking Likelihood: the days when cooking occurred during a given hour. This indicates the relative frequency of usage sessions and is plotted using a secondary y-axis.
3. Intensity of Usage: The mean biogas consumption rate during cooking events is shown for each hour. The consumption rate is reflected in the colour shading of the bars. Darker colours indicate heavier gas usage, suggesting more intense cooking.

Plotting these three variables on the same axis provides insights into routine cooking behaviour patterns, indicating when they are most likely to occur, the typical duration of the event, and the intensity of the

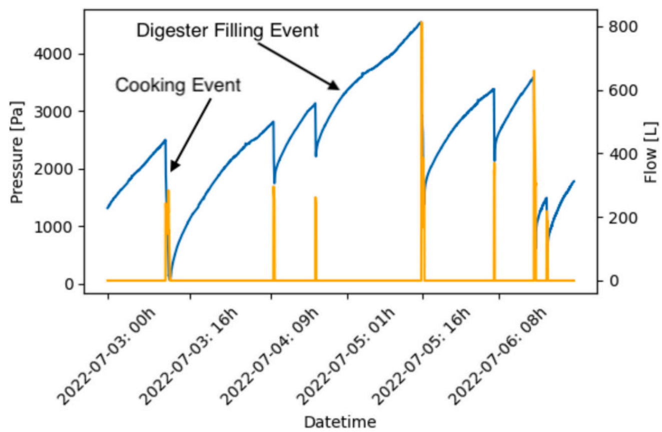

Fig. 3. *An example of three days of digester data. The blue line shows the* gauge *pressure in the digester, and the yellow line shows the biogas flow to the cookstove. The spikes in the flow data correspond to periods of digester use.* (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

usage. Comparing across different periods, such as months, can reveal seasonal shifts in usage profiles.

This condensed graphical format displays key indicators of real-world usage and provides insight into household routine. For example, we can see how people cook, whether they typically cook via long simmers, such as when making a stew, at particular times of the day or using shorter, more intense cooking methods, such as frying, at other times. The results section gives examples of graphs developed using this approach.

Biogas Utilisation Factor (BUF)

As can be seen from Table 1, Biogas Programmes install a range of sizes and types of digesters with varying performance based on local conditions and user behaviour. To enable better comparison of how different households use the available biogas, we introduce the Biogas Utilisation Factor (BUF), a metric that measures the actual biogas use relative to the available biogas, identifying digesters that are effectively utilised or underutilised, potentially venting methane.

The BUF is analogous to production efficiency metrics used in manufacturing (Schreyer, 2001). It measures the effectiveness of converting inputs into desired outputs.

BUF is the relative amount of biogas consumed within a defined period compared to the gas generated in that period. If *u(t)* represents the instantaneous rate of biogas use at time '*t*' (L/h), and *g(t)* represents the instantaneous rate of biogas production at time '*t*' (L/h), *U(T)* is the actual biogas used over a defined period (usually a 24 h day) in litres (L), and *G(T)* is the total biogas generated in the specified period, then BUF is defined as:

$$BUF = \frac{\int_{t1}^{t2} \frac{du}{dt} dt}{\int_{t1}^{t2} \frac{dg}{dt} dt} = \frac{U(T)}{G(T)} \tag{1}$$

BUF helps assess how effectively a consumer uses their biogas digester. While it can be calculated over any duration, calculating it daily (24 h) aligns with digesters' typical usage cycles and patterns.

A higher BUF value indicates more effective utilisation, whereas a lower value suggests biogas loss through venting and/or leaking.

Calculating the BUF. We developed two approaches to calculate the BUF based on digester gauge pressure data (relative to atmospheric pressure) and flow measurements, as biogas generation cannot be measured directly with the current sensor setup.

The first approach combines pressure gradient analysis with flow sensor data to estimate daily biogas generation and usage. It uses the rate of pressure increase when no gas is consumed (typically after cooking events) to assess the baseline biogas production rate, which we assume to be approximately constant over 24 h. During cooking events, the flow sensor directly measures gas consumption (while gas is also generated). We create an adjusted gradient curve by subtracting the estimated constant production rate from the observed pressure changes when consuming gas. This adjusted curve represents the pressure changes due to consumption alone. We can estimate the volume of gas generated over time by integrating under this adjusted curve and using a calibration factor α determined through empirical validation. This calibration factor is established by comparing the calculated gas volume (based on pressure gradient integration) with the actual measured consumption from the flow sensor over multiple days, yielding a linear relationship. Once α is determined, it can be applied to convert the observed pressure gradients into an accurate estimate of biogas generation rate, accounting for system-specific characteristics and non-ideal behavior. This calibration accounts for non-ideal gas behaviour, temperature variations, and other real-world factors. The BUF is then calculated by comparing this estimated generation with the measured consumption.

The second approach estimates the BUF by inference, focusing on venting patterns. It assumes that the pressure change rate tends to zero when the digester vents. We can estimate the time spent venting by identifying these periods of stable pressure at the maximum level. Assuming constant generation, the time spent venting represents the proportion of generated biogas that is not used. The BUF is then calculated as:

$$BUF = 1 - \frac{t_v}{t_T}$$

Where t_T is the interval over which the values are being calculated and t_v is the total venting duration in that interval. For example, this might be applied over a month to estimate the digester's BUF.

Both methods have limitations in accounting for real-system complexities. The first approach is sensitive to pressure fluctuations and relies on the assumption of relatively constant gas production over short periods. The second method is limited to venting days and doesn't provide detailed usage insights. However, they offer complementary perspectives: the first provides a more nuanced view of daily usage patterns, while the second offers a more straightforward estimation of overall utilisation. Together, they provide valuable insights into digester usage patterns, helping identify effective utilisation and potential areas for improvement. More detailed mathematical derivations and explanations of these approaches can be found in the supplementary materials.

Clustering and anomaly detection

One goal of this study was to explore ways of identifying patterns in digester data related to use behaviour. Clustering can be a valuable tool for uncovering these patterns.

Clustering can be defined as identifying the natural subgrouping of a set of data points. Points within the subgroups are similar, whereas data points in different clusters are very different. Clustering algorithms can help identify meaningful structures and patterns of behaviour in time-series data by grouping similar data points.

We explored using k-means clustering to identify patterns in day-based features extracted from digester data and detect anomalies. K-means clustering partitions n observations into k clusters, where each observation belongs to the cluster with the nearest mean (Jain, 2010). The number of clusters can be determined using various methods (Tibshirani et al., 2001).

Exploring patterns in digester data using clustering for individual digesters. Rolling statistics were calculated for selected features to perform k-means clustering and uncover patterns (see Table 2). The rolling window size can be adjusted based on the type of explored pattern, such as a 2- or 3-month window for seasonal patterns or a shorter window for more immediate effects.

For example, to explore patterns relating to cooking duration and precipitation for a given digester, one might cluster the features 'Precipitation Sum' and 'Meantime Spent Cooking' using a short rolling time window. Depending on the explored patterns and relationships, the rolling distribution can consider various statistics, such as mean, median, standard deviation, skewness, kurtosis, and data entropy. Feature scales must be standardised to prevent biases arising from disparate scales.

Combining domain knowledge with methods like the Calinski-Harabasz Index or a dendrogram can indicate the number of clusters. For instance, in the cooking duration/precipitation example, one might start with two clusters to identify district subgroups before trying more clusters. The number of clusters selected can be seen as a parameter for exploring groups in the data.

Once the initial number of clusters was determined, k-means clustering was carried out using the scikit-learn Python library (Pedregosa et al., 2011). In the results section, we provide examples of using this approach to explore patterns in a single digester and reveal patterns across multiple similar digesters, with the potential to extend the analysis to examine patterns across digesters in different countries.

Using clustering to detect anomalies in digester data. The MinClusterDetector algorithm, using K-means clustering, is a straightforward yet practical approach for identifying significant changes in behaviour patterns within multivariate time series data, such as total daily consumption and maximum static digester gauge pressure. The method treats each time step as an independent point in a high-dimensional space, grouping them into clusters based on their proximity to cluster centroids. Time points that belong to minimal outlier clusters are flagged as anomalies. This approach can be trained on historical data containing known anomalies and then applied to predict anomalies in future digester data.

The method may not be effective at detecting subtle, gradual changes (e.g., seasonal trends or temporal dependencies), but it serves as a baseline for comparison against more advanced techniques. For instance, it can be combined with other time-series detection methods, such as STL decomposition for trend and seasonality analysis, ARIMA models for forecasting, or LSTM networks for capturing complex temporal patterns. This work demonstrates its utility in detecting significant operational state changes in biogas digesters, often indicating potential system issues or failures. The method is computationally efficient and scalable to large datasets, making it suitable for real-time monitoring of multiple digesters. Additionally, the results are highly interpretable, as anomalies are identified as small clusters of points that deviate significantly from most of the data. Notably, the method does not rely on assumptions about specific data distributions.

Using K-means as the clustering model, we implemented the MinClusterDetector from the Anomaly Detection Toolkit (ADTK) Python library (Arundo, 2020). The parameters used for clustering included total daily consumption and maximum static digester gauge pressure, which are critical indicators of digester performance. The number of clusters was set to 3 based on initial experimentation, though alternative values were explored. The approach provides a practical method for identifying significant deviations from typical operational behaviour, serving as a foundation for further analysis with more sophisticated methods.

The outcomes of this analysis are presented in the 'Anomaly Detection' subsection in the Results and discussion Section. This approach provides a reliable mechanism for automatically identifying significant deviations from typical observations.

Statistical validation. After identifying clusters, their distributions can be plotted and compared using violin plots. Statistical tests, such as the Mann-Whitney *U* test (McKnight & Najab, 2010), were performed to validate the significance of the differences between the clusters. This non-parametric test is suitable for comparing two independent groups and is robust to outliers.

The following section presents examples of how these methodologies can be applied to the dataset and highlights the insights gained from their use.

Results and discussion

Data cleaning and quality

Smart Biogas monitors collected data for 518 days, from March 1, 2022, to July 31, 2023. During this period, there were digester data points missing due to technical issues, including poor network access and meter malfunctioning or tampering. Two digesters never sent any data and have been excluded from the analysis.

Data was sampled at minute intervals. A single day was considered the minimum unit of temporal analysis, and individual days with more than 5 % missing data were excluded from the study. 115 digesters had data with a minimum of 1 complete day. 61 of these were in Kenya and 54 in Uganda. Kenya had a total of 19,205 complete digester days (60 % of the possible days from the 61 digesters), and 17,163 were available from Uganda (61 % of the potential days from the 54 digesters).

When considering longitudinal analysis, we only included digesters with over 80 % of the data available over the collection period, which enabled the recognition of longitudinal seasonal changes. In Kenya (57 %) and Uganda (56 %), over half the digesters provided more than 80 % of the data. Notably, Kenya had a higher proportion of units with extended periods of complete data: 30 % of digesters exceeded 6 months of complete consecutive days, while 33 % had between 4 and 6 months. Uganda had lower proportions, with 19 % exceeding 6 months and 35 % in the 3–6-month range.

Results of data analysis

The data was analysed on two levels, examining what patterns and trends can be inferred from the real-time gauge pressure and flow data when considering 1) a single individual digester and 2) a comparative analysis of a cluster of digesters.

Individual household digester analysis

This section explores tools that can be used to study the cooking patterns of individual digester users. By monitoring metrics such as a single user's cooking duration and fuel consumption over an extended period, we can gain insights into cooking habits and preferences and how use patterns evolve over time and across seasons. While previous studies have focused on monitoring multiple digester parameters (Wu et al., 2019; Vanrolleghem, 1999), our approach demonstrates that meaningful insights can be gained from simple pressure and flow measurements alone. In alignment with Bisaga et al.'s (2017) findings with solar home systems, essential monitoring of digester parameters could provide improved market intelligence on consumer demand while enabling companies to offer better customer service.

The Features listed in Table 2 were calculated for each complete digester day. We analysed a 6m^3 Ugandan masonry digester (type BSU-2015) with the public node ID 28W2oA as a reference case study. This digester is owned by an agricultural farming family consisting of three males and two females. It is located in the Mpigi state in the Central Region of Uganda and is primarily used for biogas cooking. The results in this section use this digester as a reference to compare against other digesters.

Longitudinal patterns in digester use. Plotting digester features (Table 2) and weather variables (see Feature extraction Section) over time allows for identifying trends, seasonal shifts, and correlations that provide insights into digester performance and user behaviour. For example:

- Fig. 4A and B show biogas generation estimated using Approach 1 (Biogas Utilisation Factor (BUF) Section). Fig. 4A demonstrates a correlation between generation and daily precipitation with generation-lagging rainfall. This is likely because the digester in 4A used rainwater for feeding, so generation depended on water availability; this digester prioritises water use for other applications during drier seasons. In contrast, Fig. 5B shows no such correlation as that digester used tap water from the mains supply.
- Fig. 4C and D plot the maximum cooking gauge pressure against the total daily cooking duration. Fig. 4C shows a positive correlation—higher gauge pressures with associated longer cooking times, indicating effective digester utilisation. However, Fig. 4D shows gradually decreasing gauge pressure over time with minimal use (~15–20 min/day) compared to the digester's potential, suggesting

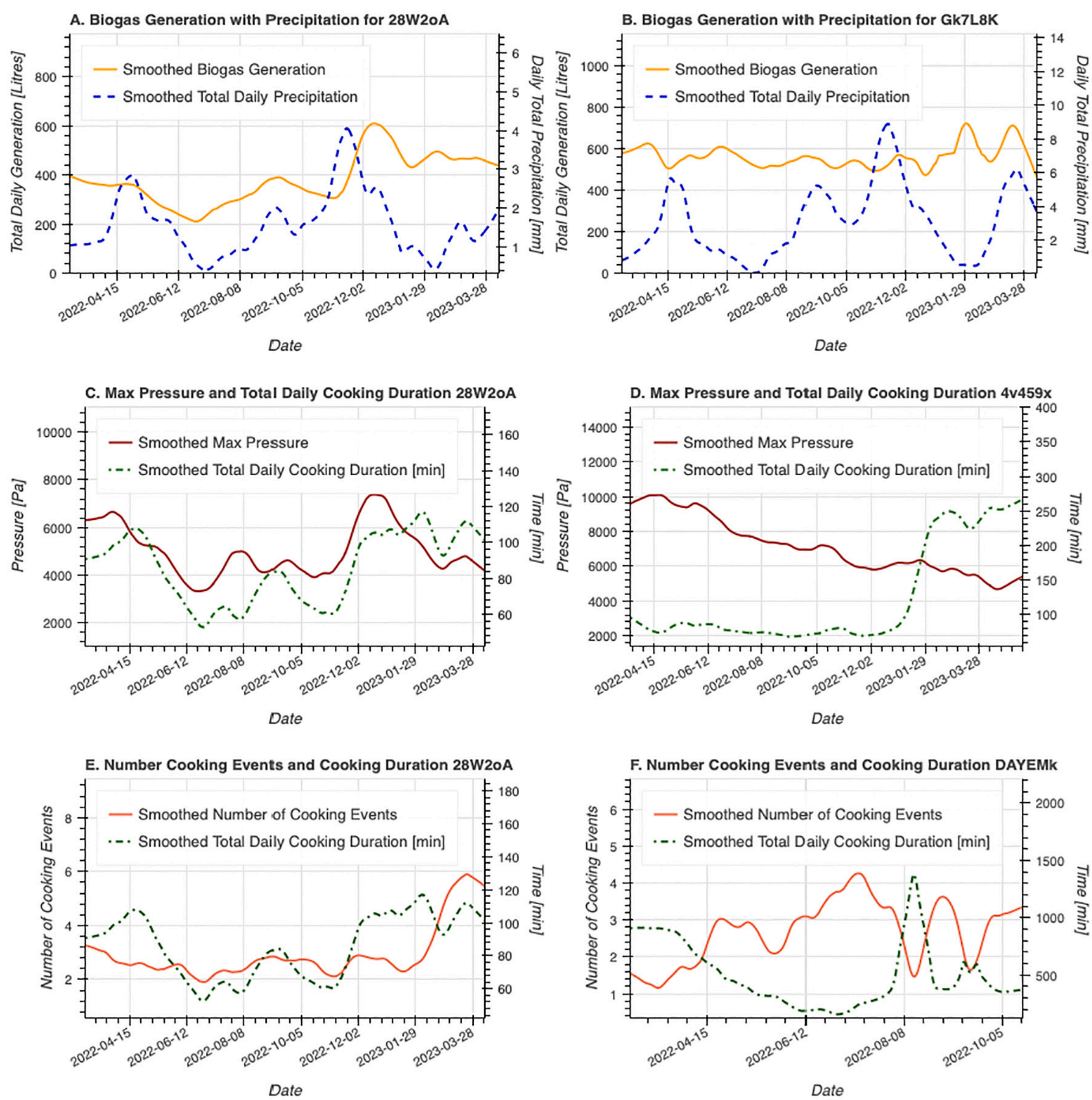

Fig. 4. *Examples of longitudinal plots of features over the monitoring period. Data has been smoothed. (A-B) Biogas generation plotted alongside total daily precipitation; (C—D) Max daily gauge pressure of the digester plotting alongside total daily cooking duration; (E-F) Total number of daily cooking events alongside total daily cooking duration.*

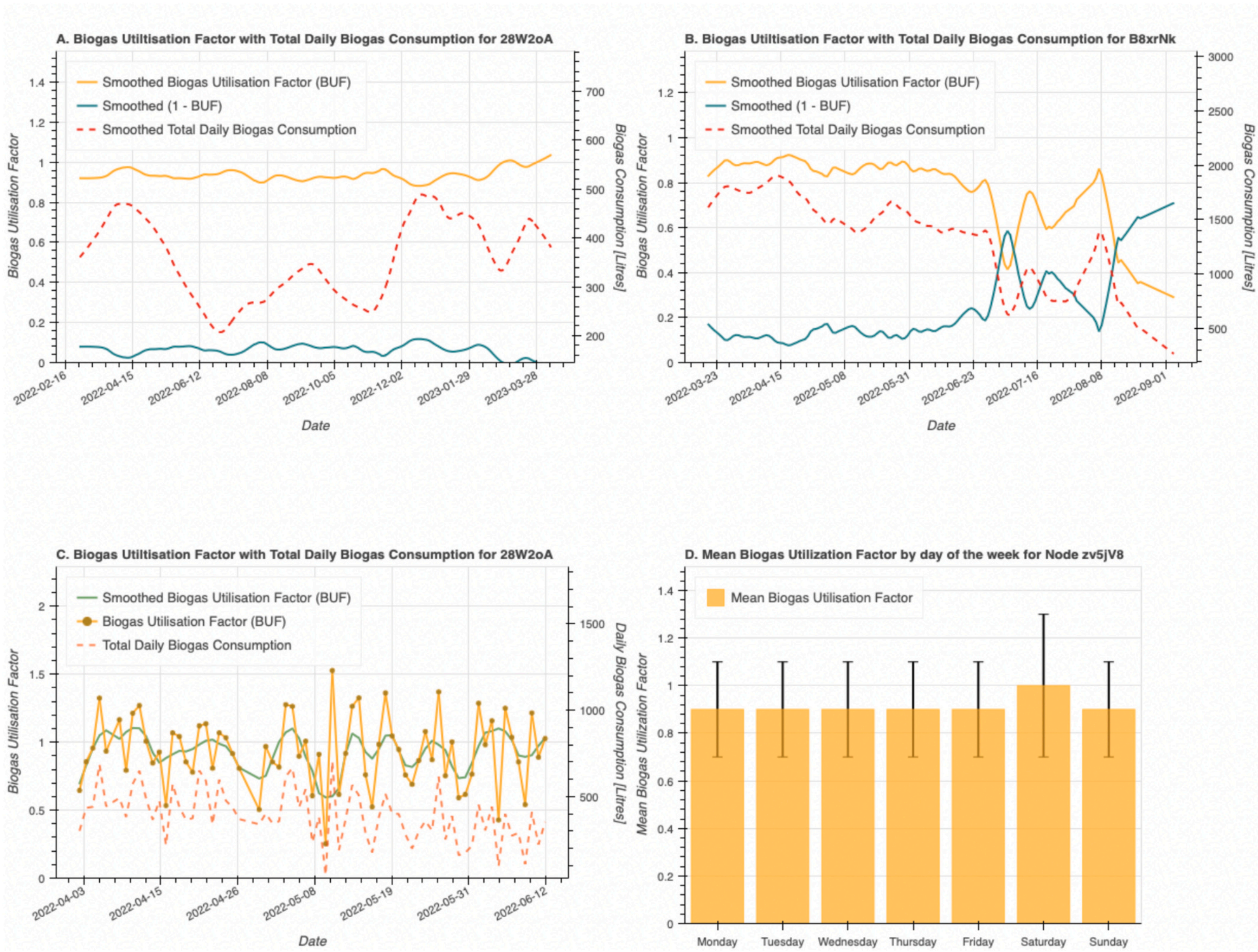

Fig. 5. (A-B) Smoothed Biogas Utilisation Factor (BUF) and (1-BUF) have been plotted alongside total daily biogas consumption on the secondary y-axis; (C) Shows a close-up of the raw Biogas Utilisation and Consumption data; (D) shows an example of the average BUF for each day of the week for a given digester.

underfeeding, though site verification is needed. Interestingly, cooking time increases later.

- Fig. 4E and F show the number and duration of daily cooking events. Fig. 4E initially exhibits relatively stable frequency (~3 events/day on average). Fig. 4F has higher variability, including a period of lower usage around 2022-06-12 with shorter but more frequent events. It also shows a peak in cooking duration but with fewer cooking events.

These examples demonstrate how combining multiple monitored data sources helps reveal patterns in digester performance and user behaviour. Integrating additional contextual data sources, such as crop cycles, festivals, household demographics/routines, and maintenance practices, could enable more profound insights into the observed patterns and user motivations driving their practices.

The Biogas Utilisation Factor (BUF) was calculated for all digesters to quantify gas usage. While previous monitoring systems for household digesters have focused mainly on technical parameters like pH, temperature, and gas composition (Gupta, 2020; Radu et al., 2022), the BUF metric provides a new way to evaluate the relative effective use of a digester, allowing comparison across digesters of different sizes and designs. This addresses a key gap Robinson et al. (2023) identified in understanding how effectively households utilise their biogas systems and provides a standardised way to compare performance across different digester designs. Fig. 5 A shows Digester 28W2oA maintaining a consistently high BUF of nearly 100 % over time, indicating highly effective utilisation. The smoothed BUF determines the average usage across days. At the same time, (1-BUF) estimates the proportion of biogas that goes unused - whether through venting or other losses, which is potentially valuable for biogas programmes to ascertain, for example, helping them identify opportunities for improved gas usage and targeted user support.

Fig. 5C plots the raw daily BUF variability. Some days use more gas than generated (drawing from storage), and others accumulate excess gas (used later or vented). The smoothed line captures longer-term patterns and trends.

Fig. 5D explores potential weekly usage differences, showing slightly higher utilisation on Saturdays. For digesters like 28W2oA, programs could identify opportunities to store weekday surpluses for high-demand Saturdays to minimise venting.

Figs. 5C and 5D demonstrate how quantifying and analysing usage data alongside qualitative information could reveal consumer practices to inform programme improvements.

Clustering to understand patterns in behaviour. To illustrate the clustering methodology described in Biogas Utilisation Factor (BUF) Section on a

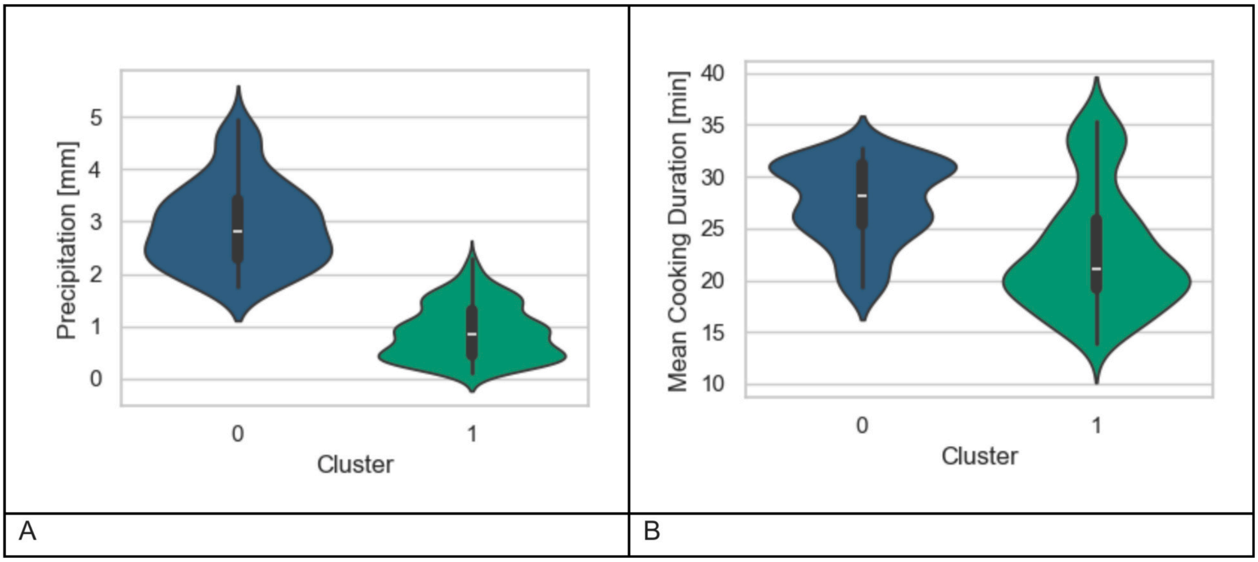

Fig. 6. Violin plots showing the difference in distributions of the two clusters found in the data.

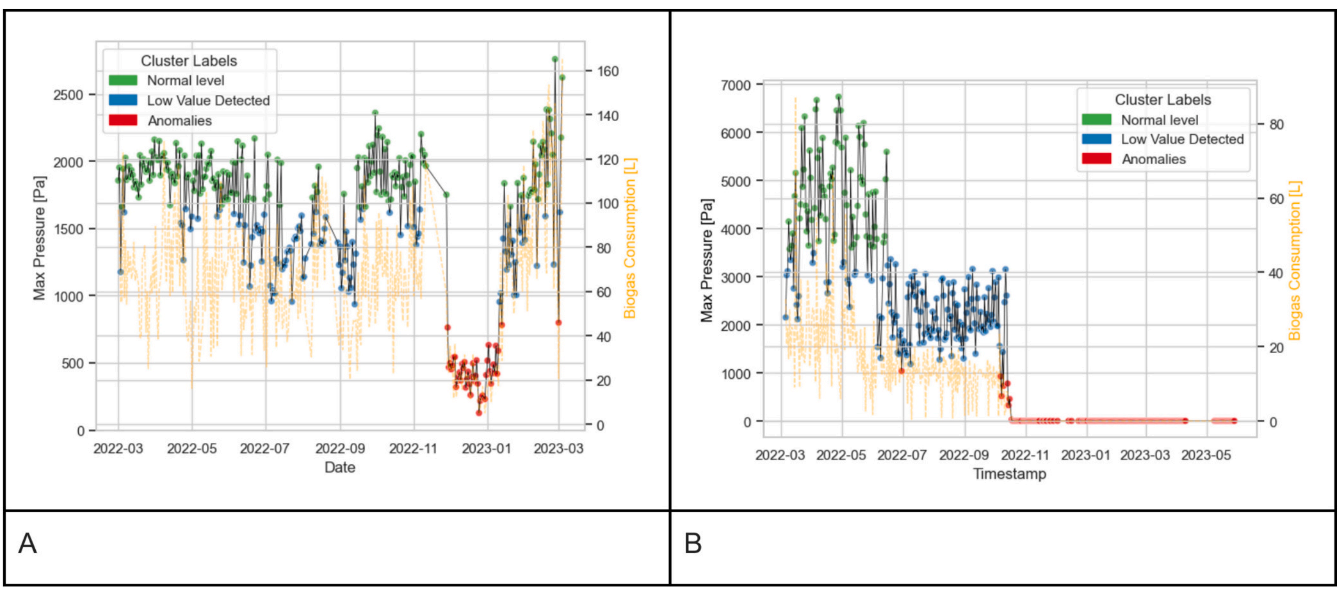

Fig. 7. Examples of the Anomaly detection algorithm in practice, with Max daily gauge pressure plotted alongside Biogas consumption. (A) shows a sudden drop in Max gauge pressure and Total Daily Consumption, which does not go to zero but is a significant deviation from the average behaviour. (B) shows two drops - a significant drop followed by a drop to 0, perhaps caused by a digester leak.

single digester, we explored the relationship between precipitation and mean daily cooking duration. We clustered the features “precipitation sum” and “Mean Cooking Duration” into k = 2 clusters using a 7-day rolling window and the k-means algorithm. The features were standardised using a robust scaler to avoid different variable scales, biasing the clustering results. The resulting cluster distributions were visualised using violin plots (Fig. 6).

Mann-Whitney *U* tests were conducted to assess whether there were statistically significant differences in the selected features between the identified clusters. The results indicated significant differences between the clusters for both precipitation (*p*-value: 1.02e-46) and cooking duration (p-value: 8.21e-13). Therefore, the observed precipitation and cooking duration variations between clusters are statistically significant. The results indicate a tendency to cook longer during high precipitation (cluster 1) and shorter cooking duration at times of less precipitation.

This example highlights how clustering analysis can serve as a valuable tool for uncovering patterns in time series data, such as the relationship between weather conditions and cooking behaviour.

This ability to identify and quantify behavioural dependencies through clustering analysis offers a practical tool for supporting studies like Wardle et al. (2021) by providing quantitative evidence to complement their qualitative findings on how water availability impacts digester operation throughout the year. Monitoring networks of digesters could help biogas programmes study and assess viability across different contexts, develop a more robust understanding of user behaviour under varying conditions, and design targeted interventions to support the year-round operation of digesters.

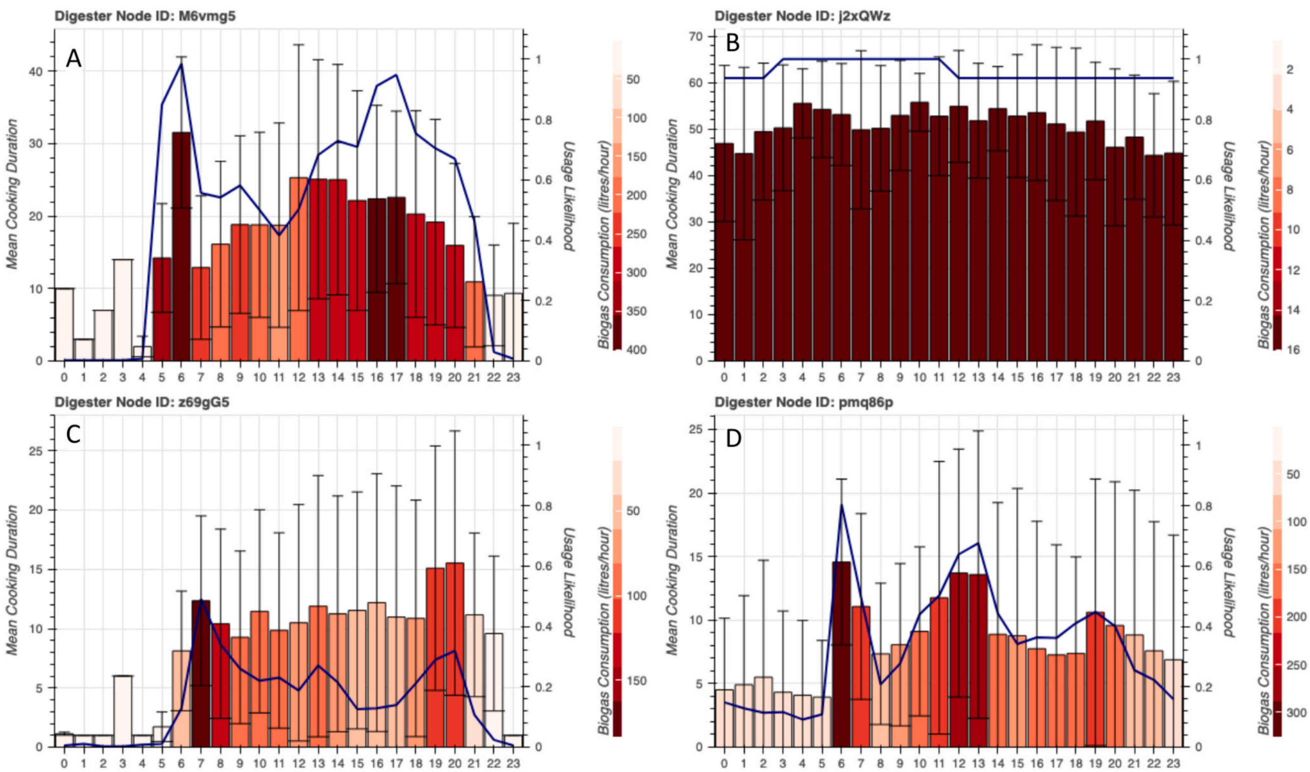

Fig. 8. Time of use biogas graph for different digesters. (A) A 9m^3 BSU 2015 digester at an elevation of 1151 m in Kampala, Central region of Uganda. It was recorded that four males and six females lived in this household. (B) A 30m^3 Sistema Biobolsa digester at 1146 m in Nakaseke, Central Region Uganda. Six males and two females (C) 6m^3 BSU 2015 digester at 1125 m in Bugweri, in the Eastern region of Uganda. Four males and two females were reported to live in this household (D) 6m^3 BSU 2015 digester at 1197 m in Sironko, in the Eastern region of Uganda. There are three male and three female people reported in this household.

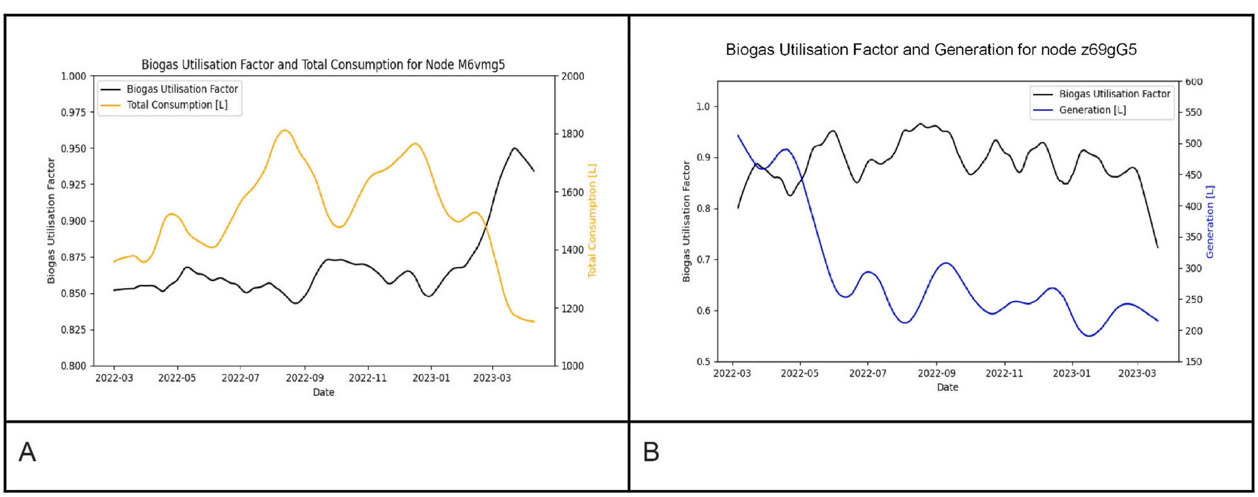

Fig. 9. (A) Biogas Utilisation Factor (BUF) plotted alongside Consumption for node M6vmg5, the same node represented in Fig. 10. (B) Biogas Utilisation Factor (BUF) plotted alongside Generation for node z69gG5, represented in Fig. 9C.

Anomaly detection. The k-means anomaly detection algorithm (Biogas Utilisation Factor (BUF) Section) was applied to two key operational metrics: maximum gauge pressure and biogas consumption. Using data from digesters with known anomalies, the algorithm categorised observations into three distinct operational states: 'normal level,' 'low values,' and 'anomalies.' These categories represent different pressure and consumption regimes, allowing the method to identify when a digester's behaviour deviates significantly from established standard patterns.

The effectiveness of this approach is demonstrated in Fig. 7, which illustrates how the multivariant analysis successfully detects both gradual degradation and sudden changes in digester performance. For example, Fig. 7B shows the algorithm identifying an extended period of low values, which preceded an eventual system failure. This early detection capability could have enabled preventive maintenance before complete system failure occurred. By training on datasets with known anomalies, this method can detect behavioural deviations on other digesters, potentially enabling biogas digester programs to identify issues with digesters and improve customer service remotely.

While treating each time point as an independent observation, the MinClusterDetector algorithm may struggle to identify temporal patterns. Despite this, it effectively identifies operationally significant deviations that necessitate intervention. This approach offers biogas programmes a computationally efficient tool for automated monitoring and early problem detection. By detecting system failures early and, even better, identifying issues before they escalate to system failures (e.g. when values become a 'low level' in this example), programmes can enhance maintenance response times and improve overall service quality.

Further work is needed to explore other time series algorithms that better consider seasonality and temporal dependencies. These algorithms could enhance anomaly detection accuracy in multivariate time series data. These more sophisticated methods might also provide deeper insights into subtle trends and seasonal patterns, thereby improving the robustness of early warning systems for biogas digester operations.

Daily cooking habits: Time of day analysis. The Analysis methodology Section discussed how visualising average usage patterns over 24 h can provide deeper insights into a household's daily routine. The "time-of-use" graphs illustrate households' daily biogas usage behaviours. Fig. 8 shows four households with distinct biogas consumption patterns. The time-of-use visualisation approach builds on methods developed for cookstove monitoring by Ruiz-Mercado et al. (2013) but adapts them specifically for biogas systems. As Pillarisetti et al. (2014) work with cookstove sensors, our findings reveal daily usage patterns that the survey alone cannot capture.

Fig. 8A represents a 9m^3 digester that is regularly used. The family reports using other fuels only when biogas runs low. However, the biogas utilisation factor (Fig. 9A) indicates untapped potential. The time-of-use graph shows that this household cooks regularly around 6 a.m. for approximately 30 min and again from 4 to 5 p.m., among other times.

Fig. 8B shows a 30 m3 digester. While there appears to be consistent

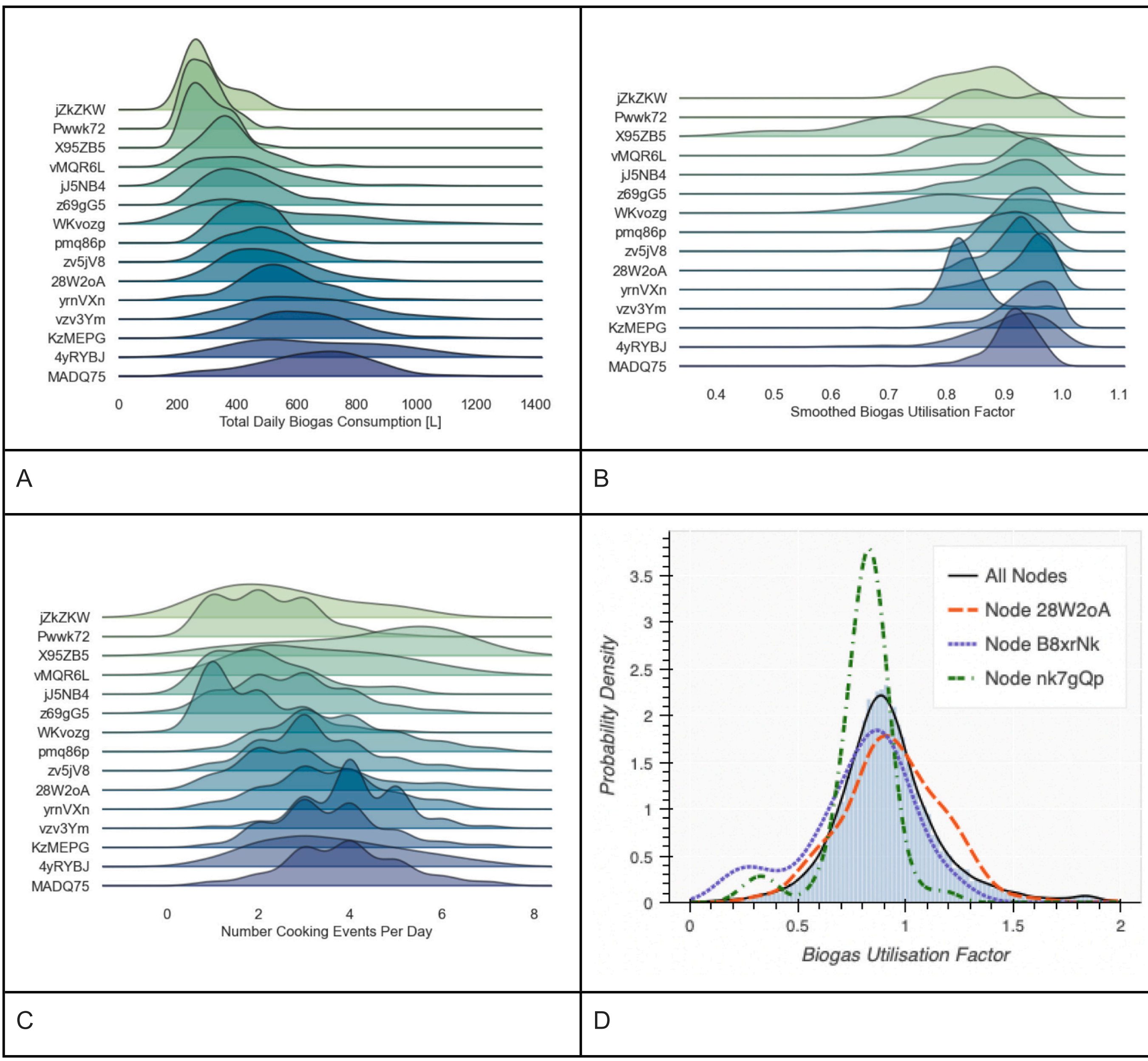

Fig. 10. Ridgeline plots comparing the statistical distributions of features for 6m^3 digesters in Uganda. (A) Total daily biogas consumption measured with the Inclusive Energy calibrated flow meter - ordered by median value (B) The same digesters as in A, but the distribution of the smoothed biogas utilisation factor. (C) Distribution of the number of cooking events per day for the same set of digesters. (D) The distribution of the biogas utilisation factor for three digesters.

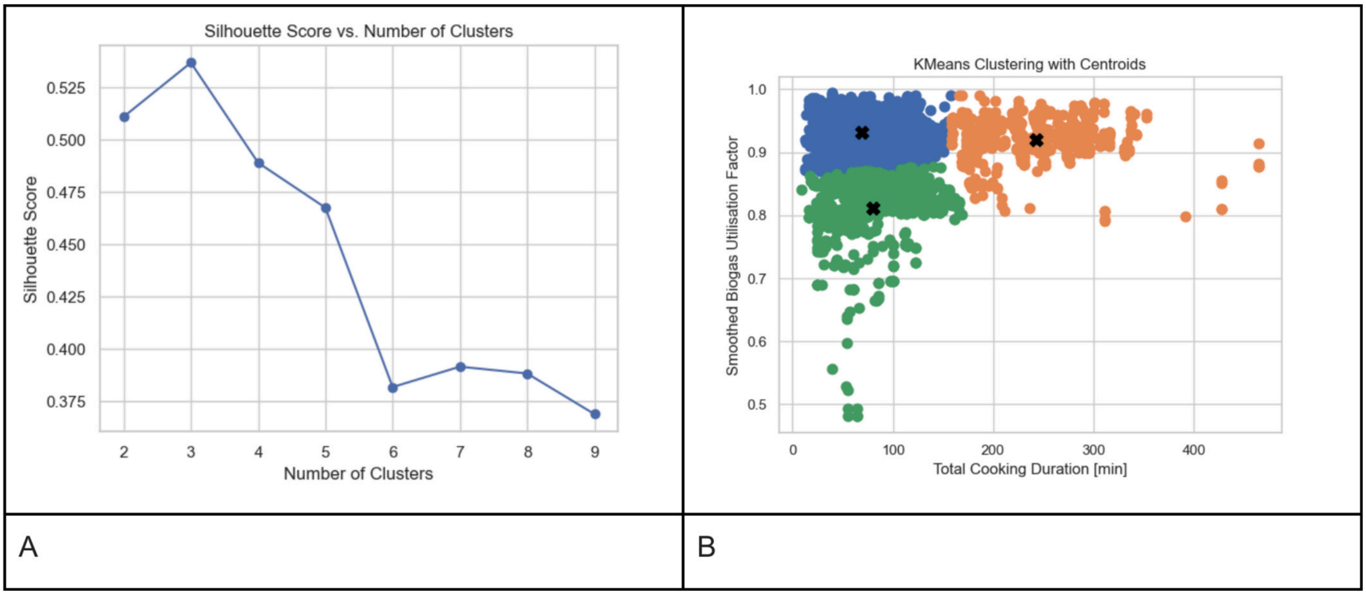

Fig. 11. Carrying out k-mean clustering on rolling distributions of smoothed biogas utilisation and total cooking duration on 6m^3 masonry digesters in Uganda.

usage throughout the day (blue line showing high usage likelihood), the actual biogas consumption rate is extremely low - only around 16 l/h (as indicated by the shading of the bars). This is far below the expected consumption rate for cooking on a biogas stove, which typically requires 150–400 l/h. The continuous low flow rate may indicate continuous leakage through the gas stove (where the meter is generally located), which is common in biogas systems with poor-quality stoves.

Fig. 8C shows relatively brief, irregular cooking compared to 8A. Fig. 9B indicates a decline in biogas generation over the year. Despite this, the biogas produced remains underutilised.

Finally, Fig. 8D illustrates a digester primarily used in the morning and midday hours. Despite the shorter cooking durations, this digester has a median utilisation factor of 0.9. Records show this client did not provide enough feedstock to meet digester feeding requirements, indicating an underfed—and therefore underperforming—system.

These visualisations provide valuable insights into individual digester use patterns. Combining them with collected qualitative methodologies could give rich insights into digester use behaviour.

Collection of similar digesters

It is valuable to compare how digesters are being used relative to one another - this can help biogas programmes identify which digesters are being used well and which are not being used to their full potential. Combining data insights with a qualitative understanding of behaviours could provide valuable insights to inform the use of training and coaching to support those not getting the best out of their digesters. In this section, we consider how comparing the statistical distribution of data features over a specified period provides a valuable approach to understanding the relative behaviour of collections of digesters compared to one another. Following this, we show how, for a given sampling period, we can use the described features to cluster digesters into meaningful groups describing the type of use behaviours.

Comparing statistical distributions. Ridgeline plots effectively display multiple distributions on one graph. Fig. 10A shows 6 m^3 digesters in Uganda with identical construction but distinctly different usage patterns. Fig. 10B presents the smoothed biogas utilisation factor distributions for the same digesters. Smoothing averages the biogas usage factor over time (note this is different from the median or most frequent biogas utilisation factor). Some digesters, like X95ZB5, have a broad spread, while others have a sharper peak. An observable pattern is the relationship between value spread and total consumption - the collection of digesters with lower median biogas production tends to have more variable smoothed utilisation than those with higher median biogas production. Compared to the cooking event frequency distribution in Fig. 10C, digesters with higher consumption generally cook more often. Broadly, more utilisation correlates with more frequent use. However, detailed statistical analysis is needed to verify these observations.

This approach could identify relatively underperforming and underutilised digesters. Combined with this, time-of-use graphs could help households understand and get better use out of their biogas digesters. If programmes adopt such techniques, they may spot struggling digesters versus well-functioning peers and guide households toward better utilisation.

We have shown that concurrently visualising multiple digesters' entire distributions—not just relying on central tendencies—yields deeper behavioural understanding than summary metrics alone. In the final section, we consider how k-mean clustering, as detailed previously, is a valuable tool for helping identify digesters whose owners might need support.

Clustering multiple digesters to uncover patterns. K-means clustering was used to analyse the 7-day window rolling median of 'Total Daily Cooking Duration' and 'Biogas Utilisation Factor' for the Ugandan digesters, as shown in the ridgeline plot. The data was normalised using the robust scaler (de Amorim et al., 2023), which seeks to mitigate the effects of outliers by centring the data around the median and scaling it according to the interquartile range. Based on the Silhouette score (Fig. 11A), it was determined that 3 clusters were a reasonable choice.

Fig. 11B displays the clustering results and centroid values selected by the algorithm. Fig. 12 shows the cluster distributions, revealing the following patterns:

- Cluster 0—*underperforming*—Despite its high BUF, the cooking duration is low compared to other digesters of comparable size, indicating that it is not performing as well as it could during these periods.
- Cluster 1 - *Well-used and effectively operating*, with high biogas utilisation and consumption.

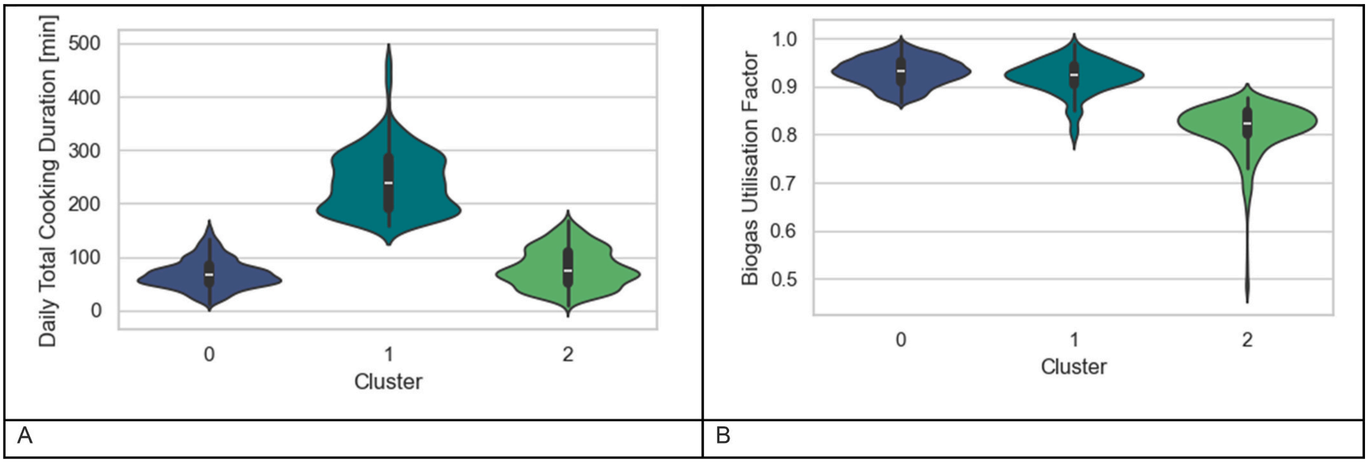

Fig. 12. Clusters resulting from k-mean clustering on the rolling distribution of smoothed biogas utilisation and total cooking duration on the 6m^3 masonry digesters in Uganda.

- Cluster 2 - *Underutilised* - a lower BUF, indicating periods when users do not get the full potential from their digester.

Many additional factors warrant further investigation. However, the key objective was demonstrating clustering's power to uncover behavioural patterns to help implementers better support customers in optimising digester use. Though further analysis is possible, even this simple demonstration identified distinct usage profiles: fully functional digesters, digesters underusing existing capacity, and digesters with sub-optimal gas production. By clustering biogas digesters into categories such as these, biogas programmes can provide targeted guidance to households.

Overall, clustering has the potential to uncover actionable behavioural insights from pressure and flow data features. The patterns revealed can help identify utilisation or performance gaps at the individual digester level, guiding interventions without requiring detailed on-site assessments.

Data-driven insights for enhancing biogas programme effectiveness. This study advances beyond previous monitoring approaches for household digesters (Ahmed et al., 2015; Gupta, 2020; Radu et al., 2022) by demonstrating that relatively simple measurements can provide rich insights into technical performance and user behaviour when combined with appropriate analytics. While earlier biogas sensing work focused mainly on technical parameters like gas pressure, temperature and pH levels (Wu et al., 2019), our integrated approach enables biogas programmes to understand better and support actual household usage patterns. Previous biogas studies like Clemens et al. (2018) relied primarily on periodic surveys to compare digester performance; our continuous monitoring enables a more nuanced understanding of usage patterns. The anomaly and clustering analysis described in the results builds on methodologies developed for other clean energy interventions, such as improved cookstoves (Pillarisetti et al., 2014; Ruiz-Mercado et al., 2013), bringing affordable sensing to biogas digesters in a similar way to Coffey et al. (2021)'s work on biomass cookstove adoption patterns.

Remote monitoring of biogas digesters with simple machine learning analytics provides a practical tool that addresses key challenges in qualitative research, such as digester abandonment in East Africa. Hewitt et al. (2022) highlight how "sub-optimal feeding practices" and "inadequate maintenance issues" contribute significantly to digester failure. While their interview-based methodology reveals the complex social, technical and underlying factors behind these issues, our monitoring and clustering approaches can detect problematic patterns through continuous data analysis, such as common patterns of underutilisation. Furthermore, it offers value to biogas businesses, allowing them to help them "rethink how they deliver training", for example, working out what works and what does not, and providing them with tools to help users understand and optimise their usage and get the most out of their digester, providing a data-driven foundation for targeted interventions. Such insights could help programs optimise their limited resources by focusing interventions where they are most needed and building an evidence base for the most effective intervention strategies.

Conclusions

The study demonstrates the value of remotely monitoring digester gauge pressure and biogas consumption to gain insights into user behaviour and enable relative performance comparisons between digesters. Key findings include:

- Through pressure and flow data analysis, we demonstrate how extracting and clustering key daily features (Table 2) can reveal detailed insights into household cooking behaviours, daily routines, and seasonal usage patterns. Combined with weather data, this approach enables quantitative analysis of factors affecting digester use, such as the impact of water availability on feeding practices. This data-driven methodology complements qualitative research by providing continuous, objective measurements of household usage patterns.
- The Biogas Utilisation Factor (BUF), introduced in the Analysis methodology Section, provides a novel metric for evaluating digester performance. It facilitates relative consumption-to-generation comparisons between various digester sizes and types, identifying underutilised systems. Digesters with an average BUF of less than one will vent methane, making this metric particularly valuable for carbon offsetting programs to quantify relative methane loss and identify opportunities for improved utilisation.
- The time-of-use visualisation approach developed in this study enables a detailed understanding of daily cooking patterns and user behaviour. Combined with BUF analysis, it provides biogas programmes with tools to identify technical and behavioural factors affecting digester performance.
- Based on cookstove monitoring approaches, our anomaly detection and clustering methodologies can effectively identify usage patterns and performance anomalies. They enable prompt issue notification and more rapid resolution to prevent failures. Automating this

process could help biogas companies and programmes offer better customer service and targeted interventions.

- The study demonstrates that relatively simple measurements can provide rich insights into technical performance and user behaviour when combined with appropriate analytics. This advances beyond previous monitoring approaches that relied primarily on periodic surveys or focused solely on technical parameters.

Combining sensor-based approaches with qualitative methods such as semi-structured interviews allows biogas programme to support efforts to sustain adoption and help users get value from their systems. Ultimately, these learnings can enhance access to more reliable biogas energy and sustainable waste treatment for communities worldwide.

CRediT authorship contribution statement

Joel Chaney: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Edward H. Owens:** Validation, Supervision, Funding acquisition. **Benjamin L. Robinson:** Writing – review & editing, Methodology. **Mike J. Clifford:** Writing – review & editing, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used claude.ai to improve clarity and language. After using this tool/service, they thoroughly reviewed and edited the content and took full responsibility for the publication's content.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Joel Chaney has patent #WO2022064223A1 issued to Inclusive Energy. Joel Chaney was a founder and previously employed by Inclusive Energy. The other authors, declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Thank you to Inclusive Energy for providing the dataset used in this study and to Innovate UK Energy Catalyst Project "Smart Biogas 3: Digesting Data" (project reference number 10046103) and JA Hood Trust for funding the research. GCRF and EPSRC funded the initial early stage work on the remote monitoring technology used to gather data for this study within the TAMBA and APAtsCHE project EP/K002708/1 respectively. Further development work was carried out by the charity CREATIVenergie as part of Innovate UK funded "Smart Biogas Network" (project reference number 132479).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esd.2025.101668.

References

Abanades, S., Abbaspour, H., Ahmadi, A., Das, B., Ehyaei, M. A., Esmaeilion, F., El Haj Assad, M., Hajilounezhad, T., Jamali, D. H., Hmida, A., Ozgoli, H. A., Safari, S., AlShabi, M., & Bani-Hani, E. H. (2022). A critical review of biogas production and usage with legislation framework across the globe. *Int J Environ Sci Technol (Tehran), 19*, 3377–3400. https://doi.org/10.1007/s13762-021-03301-6

Ahmad, T., & Zhang, D. (2021). Using the internet of things in smart energy systems and networks. *Sustainable Cities and Society, 68*, Article 102783. https://doi.org/10.1016/j.scs.2021.102783

Ahmed Abdulkadir, A., & Al-Turjman, F. (2021). Smart-grid and solar energy harvesting in the IoT era: An overview. *Concurrency and Computation: Practice and Experience, 33*, Article e4896. https://doi.org/10.1002/cpe.4896

Ahmed, W. A., Aggour, M., & Bennani, F. (2015). *Smart system for biodigester monitoring, in: 2015 3rd International Renewable and Sustainable Energy Conference (IRSEC). Presented at the 2015 3rd International Renewable and Sustainable Energy Conference (IRSEC), pp. 1–4*. https://doi.org/10.1109/IRSEC.2015.7455118

Ahrends, A., Burgess, N. D., Milledge, S. A. H., Bulling, M. T., Fisher, B., Smart, J. C. R., … Lewis, S. L. (2010). Predictable waves of sequential forest degradation and biodiversity loss spreading from an African city. *Proceedings of the National Academy of Sciences of the United States of America, 107*, 14556–14561. https://doi.org/10.1073/pnas.0914471107

Arundo. (2020). *Anomaly Detection Toolkit (ADTK) Version*, 0.6.2.

Bailis, R., Drigo, R., Ghilardi, A., & Masera, O. (2015). The carbon footprint of traditional woodfuels. *Nature Climate Change, 5*, 266–272. https://doi.org/10.1038/nclimate2491

Bhattacharyya, S. C., & Palit, D. (2016). Mini-grid-based off-grid electrification to enhance electricity access in developing countries: What policies may be required? *Energy Policy, 94*, 166–178. https://doi.org/10.1016/j.enpol.2016.04.010

Bisaga, I., Puźniak-Holford, N., Grealish, A., Baker-Brian, C., & Parikh, P. (2017). Scalable off-grid energy services enabled by IoT: A case study of BBOXX SMART Solar. *Energy Policy, 109*, 199–207. https://doi.org/10.1016/j.enpol.2017.07.004

Brooks, N., Bhojvaid, V., Jeuland, M. A., Lewis, J. J., Patange, O., & Pattanayak, S. K. (2016). How much do alternative cookstoves reduce biomass fuel use? Evidence from North India. *Resource and Energy Economics, 43*, 153–171. https://doi.org/10.1016/j.reseneeco.2015.12.001

Clemens, H., Bailis, R., Nyambane, A., & Ndung'u, V. (2018). Africa Biogas Partnership Program: A review of clean cooking implementation through market development in East Africa. *Energy for Sustainable Development, Scaling Up Clean Fuel Cooking Programs, 46*, 23–31. https://doi.org/10.1016/j.esd.2018.05.012

Cleveland, W. S. (1979). Robust locally weighted regression and smoothing scatterplots. *Journal of the American Statistical Association, 74*(368), 829–836.

Coffey, E. R., Mesenbring, E. C., Dalaba, M., Agao, D., Alirigia, R., Begay, T., Moro, A., Oduro, A., Brown, Z., Dickinson, K. L., & Hannigan, M. P. (2021). A glimpse into real-world kitchens: Improving our understanding of cookstove usage through in-field photo-observations and improved cooking event detection (CookED) analytics. *Development Engineering, 6*, Article 100065. https://doi.org/10.1016/j.deveng.2021.100065

Colchester, F. E., Marais, H. G., Thomson, P., Hope, R., & Clifton, D. A. (2017). Accidental infrastructure for groundwater monitoring in Africa. *Environmental Modelling & Software, 91*, 241–250. https://doi.org/10.1016/j.envsoft.2017.01.026

de Amorim, Lucas B. V., Cavalcanti, George D. C., Cruz, Rafael M. O., & The choice of scaling technique matters for classification performance, Applied Soft Computing, Volume 133. (2023). 109924. *ISSN, 1568-4946*. https://doi.org/10.1016/j.asoc.2022.109924

Dieudonne, D., & Shima, H. (2018). Effectiveness of applying IoT to improve biogas digesters in Rwanda, in: 2018 IEEE International Conference on Applied System Invention (ICASI). In *Presented at the 2018 IEEE International Conference on Applied System Invention (ICASI)* (pp. 441–444). https://doi.org/10.1109/ICASI.2018.8394279

Dong, L., Cao, G., Guo, X., Liu, T., Wu, J., & Ren, N. (2019). Efficient biogas production from cattle manure in a plug flow reactor: A large scale long term study. *Bioresource Technology, 278*, 450–455. https://doi.org/10.1016/j.biortech.2019.01.100

Energy, Inclusive (2023). *Who's counting?* London: Exploring whether data pays in biogas carbon projects.

Finke, S., Velenderić, M., Severengiz, S., Pankov, O., & Baum, C. (2022). Transition towards a full self-sufficiency through PV systems integration for sub-Saharan Africa: A technical approach for a smart blockchain-based mini-grid. *Renewable Energy and Environmental Sustainability, 7*, 8. https://doi.org/10.1051/rees/2021054

Food and Agriculture Organization of the United Nations. (2010). What woodfuels can do to mitigate climate change. *FAO Forestry Paper, 162*.

Fulford, D. (2015). Small-scale Rural Biogas Programmes. *PRACTICAL ACTION PUBLISHING.*. https://doi.org/10.3362/9781780448497

Garfí, M., Castro, L., Montero, N., Escalante, H., & Ferrer, I. (2019). Evaluating environmental benefits of low-cost biogas digesters in small-scale farms in Colombia: A life cycle assessment. *Bioresource Technology, 274*, 541–548. https://doi.org/10.1016/j.biortech.2018.12.007

gasdata, 2024, Biogas Analysers | Fixed & Portable Biogas Analysers [WWW Document], URL https://www.gasdata.co.uk/applications/renewable-energy/biogas-monitoring-and-analysis/ (accessed 4.4.24).

Gold Standard. (2017). *Gold Standard Methodology: Technologies and Practices to Displace Decentralized Thermal Energy Consumption Version, 3*(1), 2017.

Gordon, S. B., Bruce, N., Grigg, J., Hibberd, P. L., Kurmi, O., Lam, H., & Martin, W. J. (2014). Respiratory risks from household air pollution in low- and middle-income countries. *The Lancet Respiratory Medicine, 2*(10), 823–860. https://doi.org/10.1016/s2213-2600(14)70168-7

Gupta, A. (2020). Making Biogas SMART using internet of things (IOT), in: 2020 4th International Conference on Electronics, Materials Engineering Nanotechnology (IEMENTech). In *Presented at the 2020 4th International Conference on Electronics, Materials Engineering Nanotechnology (IEMENTech)* (pp. 1–4). https://doi.org/10.1109/IEMENTech51367.2020.9270067

Hewitt, J., Holden, M., Robinson, B. L., Jewitt, S., & Clifford, M. J. (2022). Not quite cooking on gas: Understanding biogas plant failure and abandonment in Northern Tanzania. *Renewable and Sustainable Energy Reviews, 165*, Article 112600. https://doi.org/10.1016/j.rser.2022.112600

Hosonuma, N., Herold, M., Sy, V. D., Fries, R. S. D., Brockhaus, M., Verchot, L., … Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters, 7*, Article 044009. https://doi.org/10.1088/1748-9326/7/4/044009
International Energy Agency (IEA), International Renewable Energy Agency (IRENA), United Nations Statistics Division (UNSD), World Bank, World Health Organization (WHO), 2023. Chapter 2: Access to Clean Fuels and Technologies for Cooking.
International Renewable Energy Agency (IRENA). (2016). *Measuring small-scale biogas capacity and production*. Abu Dhabi.
Iswanto, I., Ma'arif, A., Kebenaran, B., & Megantoro, P. (2021). Design of gas concentration measurement and monitoring system for biogas power plant. *IJEECS, 22*, 726. https://doi.org/10.11591/ijeecs.v22.i2.pp726-732
Jain, A. K. (2010). Data clustering: 50 years beyond K-means. In *Pattern Recognition letters, Award winning papers from the 19th International Conference on Pattern Recognition (ICPR) 31* (pp. 651–666). https://doi.org/10.1016/j.patrec.2009.09.011
Jimenez, J., Latrille, E., Harmand, J., et al. (2015). Instrumentation and control of anaerobic digestion processes: a review and some research challenges. *Reviews in Environmental Science and Biotechnology, 14*, 615–648. https://doi.org/10.1007/s11157-015-9382-6
Kama, A., Diallo, M., Drame, M. S., Ndiaye, M. L., Ndiaye, A., & Ndiaye, P. A. (2017). *Monitoring the Performance of Solar Street Lights in Sahelian Environment: Case Study of Senegal. 2017 10th International Conference on Developments in eSystems Engineering (DeSE) 56–61*. https://doi.org/10.1109/DeSE.2017.43
Kirchhoff, H., Kebir, N., Neumann, K., Heller, P. W., & Strunz, K. (2016). Developing mutual success factors and their application to swarm electrification: Microgrids with 100% renewable energies in the Global South and Germany. *Journal of Cleaner Production, New approaches for transitions to low fossil carbon societies: promoting opportunities for effective development, diffusion andimplementation of technologies, policies, and strategies, 128*, 190–200. https://doi.org/10.1016/j.jclepro.2016.03.080
Koehler, J., Thomson, P., & Hope, R. (2015). Pump-Priming payments for Sustainable Water Services in Rural Africa. *World Development, 74*, 397–411. https://doi.org/10.1016/j.worlddev.2015.05.020
Leary, J., Batchelor, S., & Scott, N. (2018). *Cooking Diaries Protocols.*. https://doi.org/10.13140/RG.2.2.15851.18728
Lee, K. K., Bing, R., Kiang, J., Bashir, S., Spath, N., Stelzle, D., & Shah, A. (2020). Adverse health effects associated with household air pollution: A systematic review, meta-analysis, and burden estimation study. *The Lancet Global Health, 8*(11), e1427–e1434. https://doi.org/10.1016/s2214-109x(20)30343-0
Masera, O., Bailis, R., Drigo, R., Ghilardi, A., & Ruiz, I. (2015). Environmental Burden of Traditional Bioenergy Use. *Annual Review of Environment and Resources, 40*. https://doi.org/10.1146/annurev-environ-102014-021318
McKnight, P.E., Najab, J., 2010. Mann-Whitney U Test, in: The Corsini Encyclopedia of Psychology. John Wiley & Sons, Ltd, pp. 1–1. doi:https://doi.org/10.1002/9780470479216.corpsy0524.
Mengistu, M. G., Simane, B., Eshete, G., & Workneh, T. (2015). *A review of biogas technology and its contributions to sustainable rural livelihood in Ethiopia.*. https://doi.org/10.1016/J.RSER.2015.04.026
Mottaleb, K. A., & Rahut, D. B. (2019). Biogas adoption and elucidating its impacts in India: Implications for policy. *Biomass and Bioenergy, 123*, 166–174. https://doi.org/10.1016/j.biombioe.2019.01.049
Mukhopadhyay, R., Sambandam, S., Pillarisetti, A., Jack, D., Mukhopadhyay, K., Balakrishnan, K., … Smith, KirkR (2012). Cooking practices, air quality, and the acceptability of advanced cookstoves in Haryana, India: An exploratory study to inform large-scale interventions. *Global Health Action, 5*, 19016. https://doi.org/10.3402/gha.v5i0.19016
Munro, W. A., Thomas, C. L. P., Simpson, I., Shaw, J., & Dodgson, J. (1996). Deterioration of pH electrode response due to biofilm formation on the glass membrane. *Sensors and Actuators B: Chemical, 37*, 187–194. https://doi.org/10.1016/S0925-4005(97)80137-2
Nevzorova, T., & Kutcherov, V. (2019). Barriers to the wider implementation of biogas as a source of energy: A state-of-the-art review. *Energy Strategy Reviews, 26*, Article 100414. https://doi.org/10.1016/j.esr.2019.100414
Papastylianou, T., Behar, J., Guazzi, A., Jorge, J., Laranjeira, S., Maraci, M. A., … Thomson, P. (2014). *Smart handpumps: Technical aspects of a one-year field trial in rural Kenya, in: Appropriate Healthcare Technologies for Low Resource Settings (AHT 2014). Presented at the Appropriate Healthcare Technologies for Low Resource Settings (AHT 2014), pp. 1–4*. https://doi.org/10.1049/cp.2014.0769
Pedregosa, et al. (2011). Scikit-learn: Machine Learning in Python. *JMLR, 12*, 2825–2830.
Person, Bobbie, Loo, Jennifer D., Owuor, Mercy, Ogange, Lorraine, Jefferds, Maria Elena D., & Cohen, Adam L. (2012). "It is good for my Family's Health and Cooks Food in a way that my Heart loves": Qualitative Findings and Implications for Scaling up an improved Cookstove Project in Rural Kenya. *International Journal of Environmental Research and Public Health, 9*, 1566–1580. https://doi.org/10.3390/ijerph9051566
Piedrahita, R., Dickinson, K. L., Kanyomse, E., Coffey, E., Alirigia, R., Hagar, Y., Rivera, I., Oduro, A., Dukic, V., Wiedinmyer, C., & Hannigan, M. (2016). Assessment of cookstove stacking in Northern Ghana using surveys and stove use monitors. *Energy for Sustainable Development, 34*, 67–76. https://doi.org/10.1016/j.esd.2016.07.007
Pillarisetti, A., Vaswani, M., Jack, D., Balakrishnan, K., Bates, M. N., Arora, N. K., & Smith, K. R. (2014). Patterns of Stove Usage after Introduction of an Advanced Cookstove: The Long-Term Application of Household Sensors. *Environmental Science & Technology, 48*, 14525–14533. https://doi.org/10.1021/es504624c
Präger, F., Paczkowski, S., Sailer, G., Derkyi, N. S. A., & Pelz, S. (2019). Biomass sources for a sustainable energy supply in Ghana – A case study for Sunyani. *Renewable and Sustainable Energy Reviews, 107*, 413–424. https://doi.org/10.1016/j.rser.2019.03.016
Quinn, A. K., Bruce, N., Puzzolo, E., Dickinson, K., Sturke, R., Jack, D. W., Mehta, S., Shankar, A., Sherr, K., & Rosenthal, J. P. (2018). An analysis of efforts to scale up clean household energy for cooking around the world. *Energy for Sustainable Development, Scaling Up Clean Fuel Cooking Programs, 46*, 1–10. https://doi.org/10.1016/j.esd.2018.06.011
Radu, T., Smedley, V., Yadav, D., Blanchard, R., Rahaman, S. A., Salam, A., & Visvanathan, C. (2022). The Design, Development and Assessment of a Novel Decentralised IoT-Based Remote monitoring of a Small-Scale Anaerobic Digester Network. *J Energ Power Technol, 04*, 1–17. https://doi.org/10.21926/jept.2204039
Rajendran, K., Aslanzadeh, S., & Taherzadeh, M. J. (2012). Household Biogas Digesters—A Review. *Energies, 5*, 2911–2942. https://doi.org/10.3390/en5082911
Reddy, B. S., Balachandra, P., & Nathan, H. S. K. (2009). Universalisation of access to modern energy services in Indian households—Economic and policy analysis. *Energy Policy, 37*, 4645–4657. https://doi.org/10.1016/j.enpol.2009.06.021
Rhodes, E. L., Dreibelbis, R., Klasen, E., Naithani, N., Baliddawa, J., Menya, D., … Checkley, W. (2014). Behavioural attitudes and Preferences in Cooking Practices with Traditional Open-Fire Stoves in Peru, Nepal, and Kenya: Implications for improved Cookstove Interventions. *International Journal of Environmental Research and Public Health, 11*, 10310–10326. https://doi.org/10.3390/ijerph111010310
Robinson, B. L., Clifford, M. J., & Selby, G. (2023). Towards fair, just, and equitable energy ecosystems through smart monitoring of household-scale biogas plants in Kenya. *Energy Research & Social Science, 98*, Article 103007. https://doi.org/10.1016/j.erss.2023.103007
Ruiz-Mercado, I., Canuz, E., Walker, J. L., & Smith, K. R. (2013). Quantitative metrics of stove adoption using stove Use Monitors (SUMs). *Biomass and Bioenergy, 57*, 136–148. https://doi.org/10.1016/j.biombioe.2013.07.002
Ruiz-Mercado, I., Masera, O., 2015. Patterns of Stove Use in the Context of Fuel–Device Stacking: Rationale and Implications. EcoHealth 12, 42–56. doi:https://doi.org/10.1007/s10393-015-1009-4.
Salam, A. (2020). Internet of things in Sustainable Energy Systems. In A. Salam (Ed.), *Internet of things for Sustainable Community Development: Wireless Communications, Sensing, and Systems, internet of things* (pp. 183–216). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-35291-2_6.
Salomon, K. R., & Silva Lora, E. E. (2009). Estimate of the electric energy generating potential for different sources of biogas in Brazil. *Biomass and Bioenergy, 33*, 1101–1107. https://doi.org/10.1016/j.biombioe.2009.03.001
Scarlat, N., Dallemand, J.-F., & Fahl, F. (2018). Biogas: Developments and perspectives in Europe. *Renewable Energy, 129*, 457–472. https://doi.org/10.1016/j.renene.2018.03.006
Schreyer, P., 2001. Measuring productivity: measurement of aggregate and industry-level productivity growth ; OECD manual, Statistics. OECD, Paris.
Simons, A. M., Beltramo, T., Blalock, G., & Levine, D. I. (2014). Comparing methods for signal analysis of temperature readings from stove use monitors. *Biomass and Bioenergy, 70*, 476–488. https://doi.org/10.1016/j.biombioe.2014.08.008
Singh, K., & Inglesi-Lotz, R. (2021). The Role of Energy Poverty on Economic Growth in Sub-Saharan African Countries. *EEEP, 10*. https://doi.org/10.5547/2160-5890.9.2.ksin
Smart Biogas II – Increasing Wealth from Waste, 2020–2022, Innovate UK funded, project reference: 105909, URL: https://gtr.ukri.org/projects?ref=105909 (last accessed 1st March 2024).
Smart Biogas III: Digesting Data (2023–2025), Innovate UK funded, project reference: 10046103, URL: https://gtr.ukri.org/projects?ref=10046103 (last accessed 1st March 2024).
Smith, K. R., Samet, J. M., Romieu, I., & Bruce, N. (2000). Indoor air pollution in developing countries and acute lower respiratory infections in children. *Thorax, 55*, 518–532. https://doi.org/10.1136/thorax.55.6.518
SNV, 'Household Bio-Digester Installations in Selected Countries in Africa and Asia in 2021', 2022, Status Brief, Energy Sector, URL: https://www.snv.org/update/new-report-saw-household-bio-digester-installation-increase-2021 (accessed April 2024).
Teixeira, P. F. S., Moura, L. F., Lima, S. W. S., Albiero, D., Gondim, F. A., & Alexandria, A. R. D. (2017). Development of a Low-cost Data Acquisition System for Biodigester. *JSBS, 07*, 117–137. https://doi.org/10.4236/jsbs.2017.73009
The World Bank. (2023). *Tracking SDG7: The Energy Progress Report*.
Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the Number of Clusters in a Data Set Via the Gap Statistic. *Journal of the Royal Statistical Society, Series B: Statistical Methodology, 63*, 411–423. https://doi.org/10.1111/1467-9868.00293
Uhunamure, S. E., Nethengwe, N. S., & Tinarwo, D. (2019). Correlating the factors influencing household decisions on adoption and utilisation of biogas technology in South Africa. *Renewable and Sustainable Energy Reviews, 107*, 264–273. https://doi.org/10.1016/j.rser.2019.03.006
Vanrolleghem, A. (1995). *Sensors for Anaerobic Digestion: An Overview, in: Proceedings Workshop monitoring and Control of Anaerobic Digesters, December 6–7, 1995*. France: Narbonne.
Wang, J. (2014). Decentralized Biogas Technology of Anaerobic Digestion and Farm Ecosystem: Opportunities and challenges. *Frontiers in Energy Research, 2*. https://doi.org/10.3389/fenrg.2014.00010
Wardle, J. M., Fischer, A., Tesfaye, Y., & Smith, J. (2021). Seasonal variability of resources: The unexplored adversary of biogas use in rural Ethiopia. *Current Research in Environmental Sustainability, 3*, Article 100072. https://doi.org/10.1016/j.crsust.2021.100072
Welsch, M., Bazilian, M., Howells, M., Divan, D., Elzinga, D., Strbac, G., … Yumkella, K. (2013). Smart and just Grids for sub-Saharan Africa: Exploring options. *Renewable and Sustainable Energy Reviews, 20*, 336–352. https://doi.org/10.1016/j.rser.2012.11.004

World Health Organization (WHO), 2022. Fact Sheets: Household Air Pollution [WWW Document]. URL https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health (accessed 8.23.23).

Wu, D., Li, L., Zhao, X., Peng, Y., Yang, P., & Peng, X. (2019). Anaerobic digestion: A review on process monitoring. *Renewable and Sustainable Energy Reviews, 103*, 1–12. https://doi.org/10.1016/j.rser.2018.12.039

Xu, M., & Wang, C. (2019). Research and Application of the Intelligent Biogas monitoring System based on LoRa Technology, in: 2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM). In *Presented at the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM)* (pp. 277–279). https://doi.org/10.1109/AIAM48774.2019.00062

Zhengzhou Winsen Electronics Technology Co., Ltd, 2014. Flammable Gas Sensor (Model:MQ-4) Manual Version: 1.3.