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ESTIMATING LANDFILL METHANE EMISSIONS BASED ON CLIMATIC CONDITIONS AND MAJOR WASTE COMPONENTS IN SHAH ALAM, SELANGOR, MALAYSIA

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Abstract: The main goal of this study is to evaluate the effects of Shah Alam climatic conditions and waste components on landfill methane emissions. Waste characterisation and simulated landfill reactors were conducted for several waste components at average rainfall rates of 4, 10, and 20 mm/day and ambient temperatures of 25°C and 37°C. The analysis of waste characterisation revealed Cooked Food Waste (CFW) with high moisture and Volatile Solid (VS) content produced more methane, with the ultimate methane generation potential (L_0) value of 328.39 ml CH_4/g VS. In simulated landfill reactors, 100% Paper Waste (PW) produced higher methane, with the total methane output being 43.78 L/kg and 91.27 L/kg at 25°C and 37°C, respectively. Rainfall and ambient temperature showed a considerable impact on methane generation rates. In establishing the prediction equation for methane generation rate (k), backwards elimination in Multiple Linear Regression (MLR) analysis was selected as the best-fit model with an adjusted R^2 of 0.673. Only eight out of 13 Independent Variables (IVs) were significant at α=0.1. The localised L_o and k values obtained are 59.38 m^3/Mg and 0.078 y^{-1}. Incorporating both localised values in estimating landfill methane resulted in lower emissions compared to the emissions that were predicted from Landfill Gas Emissions Model (LandGEM) and Intergovernmental Panel on Climate Change (IPCC) models.

Keywords: Methane generation rate (k), ultimate methane generation potential (L_o), waste components, climatic conditions, methane estimation models.

Introduction

Landfills significantly contribute to global climate change through Landfill Gases (LFGs) emissions. LFGs comprise 50-60% Methane (CH_4), 30-40% Carbon Dioxide (CO_2), less than 1% Volatile Organic Compounds (VOCs), and trace amounts of inorganic chemicals, resulting from the Anaerobic Decomposition (AD) of organic waste (Duan *et al*., 2021). Methane is the second major component of Greenhouse Gases (GHGs). However, it can trap more than 28 times the trapping heat as CO_2 (United States Environmental Protection Agency, 2019). Its half-life is about 12 years by degrading into hydroxyl radicals (Cady, n.d.).

According to Yang *et al*. (2015), 60% of worldwide methane emissions originated from the waste sector. In the United States, GHG emissions from landfills amounted to 115.7 Mt of Carbon Dioxide equivalent (CO_2e) in 2015 (United States Environmental Protection Agency, 2019). Meanwhile, in 2015, the waste sector, including landfills, Wastewater Treatment plants (WWT), and incineration, accounted for 90% of total GHG emissions in Canada, representing 19 megatonnes of CH_4 emissions (Vu *et al*., 2017). Based on data from the Ministry of Energy, Water, and Communications (2004), the total methane emissions from the waste sector in Malaysia are 1.3 Gg/year, which indicates 53% of emissions.

Accurately determining methane emissions from landfills is crucial for effective climate change mitigation. Several models have been developed in recent years to estimate the methane generation rate in landfills. The First-Order Decay (FOD) model is generally acknowledged as the most prevalent approach such as the IPCC model (IPCC 2006) and the United States Environmental Protection Agency Landfill Gas Emissions Model (LandGEM) (Alexander *et al*., 2005). The principal parameters used in FOD models to estimate methane generation are the methane generation rate constant (k value, yr^{-1}) and ultimate methane potential (L_o, g CH_4 kg^{-1} waste). In landfills, the methane generation rate k value represents the time taken by organic matter in waste to decay to half of its initial mass. Meanwhile, L_o denotes the most significant quantity of CH_4 that can be generated from a specific unit mass of waste under idealised anaerobic conditions.

Although widely used, more researchers claimed this approach is insufficiently accurate and not mutually comparable (Das *et al*., 2016; Berisha & Dimiskovska, 2018; Fallahizadeh *et al*., 2019). The uncertainty of this approach is attributed to the unreliability of the suggested default L_o and k values by developers. These values are significantly influenced by waste components, moisture conditions within a landfill, the availability of nutrients for methane-generating microbes, pH, and temperature (Nwaokorie *et al*., 2018; Araye *et al*., 2023; Rafey & Siddiqui, 2023). For example, the L_o relied on waste composition and its degradable organic content. In contrast, in the measurement of k, all parameters, which are waste composition, moisture, ambient temperature, and pH should be accounted for (Guermoud *et al*., 2009; Mønster *et al*., 2014; Karanjekar *et al*., 2015; Krause *et al*., 2016).

The LandGEM model only represented homogeneous waste, making it inaccurate for determining methane production from various organic content. Furthermore, homogeneous waste implies that L_o remains constant across space and time, disregarding future disposal rates, site closure timelines, and collection efficiencies. Meanwhile, the default k value in the LandGEM model only accounts for moisture content variations due to rainfall and leachate recirculation while ignoring the variations of temperature and waste composition. Besides that, default k and L_o values from this model were developed based on the United States landfills' conditions, which represent lower organic content and arid conditions (Usman, 2022). Hence, not accounting for waste composition and ambient temperature will oversimplify methane emissions in landfills. Meanwhile, developing this model based on historical data from developed countries makes it inaccurate for use in tropical countries (Ramprasad *et al*., 2023).

The Intergovernmental Panel on Climate Change (IPCC) model uses waste composition and degradable organic content to determine a landfill's ultimate methane generation potential (L_o). Based on the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, the waste composition for this model does not represent the composition of developing and undeveloped countries. However, in the 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, incorporating new half-life data from some developing countries makes this model more conventional for tropical countries (Intergovernmental Panel on Climate Change, 2019). However, this new amendment still does not include specific waste composition and climatic condition data that are practical for landfills in Malaysia.

Besides that, LandGEM and IPCC typically focus on organic waste decomposition. Incorporating inorganic waste into these models requires adjustments to account for its impact on waste density, moisture content, and overall landfill conditions, especially for tropical climate countries that generally dispose of their inorganic waste at landfills. Accurate data on waste composition, including the proportion of inorganic materials is crucial for reliable methane emission estimates. Note that inaccurate assumptions about waste composition can lead to overestimation or underestimation of methane production (Boongla *et al*., 2025).

The existing models are too sensitive to the necessary inputs: L_o and k. An increased k value correlates with a more rapid methane generation in the waste. Consequently, a smaller k value results in prolonged methane generation from the landfill even after its closure, indicating an extended time of post-closure care and prolonged carbon storage (Aghdam *et al*., 2018; Nwaokorie *et al*., 2018; Toha & Rahman, 2023; Wang *et al*., 2023).

The new model, Capturing Landfill Emission for Energy Needs (CLEEN) was developed by the University of Texas at Arlington. This model aims to provide an improved model in the quantification of CH_4 emissions by allowing users to use specific variations of temperature and moisture content of landfill conditions, as well as waste composition. A study by Karanjekar *et al*. (2015) proved that CH_4 estimation using the CLEEN model was closest to field-measurement data, compared to the estimation obtained from the LandGEM and IPCC models.

Although it is now well established, L_o and k values from that study remain unreliable for developing countries due to the composition of different waste streams and climatic conditions. Thus, this study was conducted to estimate Shah Alam landfill methane emissions by incorporating localised k and L_o values. The present study is significant in providing regional and national GHG inventory data. It looks at the potential economic benefits of harnessing CH_4 for sustainable Municipal Solid Waste (MSW) management. It is beneficial as guidance in establishing the new policy of reducing regional and global GHG emissions, subsequently assisting Malaysia in achieving Sustainable Development Goals (SDGs) by 2030.

Materials and Methods

Waste Characterisation Analysis

The initial moisture content of the waste components was obtained on a wet weight basis, following the standard methods of APHA 2540B (AWWA-APHA, 2005). Samples from moisture analysis were further conducted to determine their Volatile Solid (VS) content according to Standard Method APHA 2540-E. Biochemical Methane Potential (BMP) analysis was performed using 125 mL and 250 mL serum bottles for homogenous and heterogeneous waste components, respectively, with 70% working volume. All serum bottles were incubated at 37°C for 30-40 days until the daily methane generation was less than 1% over three consecutive days (Jingura & Kamusoko, 2017). Methane gas was analysed using an Agilent 7890A Gas Chromatography-Flame Ionisation Detector (GC-FID) instrument by extracting the gas from serum bottles with a 25 µl syringe. The measurement was conducted three times per week.

Experimental Design

Waste Composition: Waste components considered in this study are based on the percentage of MSW produced in Shah Alam. Data from Majlis Bandaraya Shah Alam (MBSA) revealed that seven waste categories were produced annually: Food, paper, yard, plastic, diaper, textile, and inorganic. This study expanded food waste types, including fruit, vegetable, cooked, and uncooked waste to improve existing methane estimation models.

Annual Rainfall Rate: To ascertain that annual rainfall influences the methane emission rate in the landfill, the minimum, average, and maximum rainfall rates used are 4, 10, and 20 mm/day, corresponding to 120, 300, and 600 mm/month, respectively. These precipitation rates were obtained from the Malaysian Meteorological Department, which includes two catchment stations: Subang Jaya and Petaling Jaya.

Annual Ambient Temperature: The ambient temperature rates measured were 25°C and 37°C. These values were selected based on data from the Malaysian Meteorological Department, representing an annual minimum and maximum ambient temperature occurrence in Malaysia.

Experimental Design: A balanced incomplete block design was used to reduce experimental error, increase precision, and compare treatments under more uniform conditions (Karanjekar *et al*., 2015). Due to limited space and time, the number of reactors developed in this study is limited to 30. To study the effects of waste composition on methane generation rates, 12 combinations of waste compositions were selected. The waste mixture ranges from 0-100% for biodegradable waste and 0-40% for non-biodegradable waste. The total mixture of waste components in reactors must be 100%. Table 1 summarises all waste combinations that were applied in this study.

Statistical Analysis System (SAS) software was used to construct an experimental design for setting up the reactors. Correspondingly, the matrix with treatments and block combinations was obtained, as tabulated in Table 2.

Reactor Setup, Maintenance, and Operation

The laboratory-scale simulated landfill was built using 20-L High-Density Polyethylene (HDPE) wide-mouth plastic buckets that were specifically modified to allow the collection of gas and leachate and the addition of water. Rectors were leak-checked by pressurising sealed reactors with 0.014 Pa of H_2O for 1-2 days. Empty reactors were weighed to obtain a similar condition as an actual landfill, a 10-inch diameter piece of filter fabric (Geotextile) was placed at the bottom of the reactors. Consequently, 10-12% of sludge by weight of waste was added to the reactors after the waste was placed (Karanjekar *et al*., 2015a).Sludge was collected from an anaerobic digester of a domestic WWT located at Setiawangsa, Kuala Lumpur, Malaysia. The sludge was pre-incubated at 35°C for 1-5 days to reduce its methane concentration and lessen

Table 1: Waste components percentage for each waste combination

Waste Component		**Waste Component Percentage**											
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
Food waste	Fruit	100	0	0	0	0	0	0	0	0	0	0	0
	Cooked	0	100	0	0	0	0	0	35	15	60	30	10
	Uncooked	0	0	100	0	0	0	0	1	0	0	0	0
	Vegetable	0	0	0	100	0	0	0	9	0	0	0	0
Paper waste		0	0	0	0	100	0	0	8	14	0	60	0
Textile waste		0	0	0	0	0	100	0	8	14	0	0	60
Garden waste		0	0	0	0	0	0	100	18	15	10	0	0
Diapers		0	0	0	0	0	0	0	8	14	0	10	0
Plastic waste		0	0	0	0	0	0	0	5	14	0	0	30
Inorganic waste		0	0	0	0	0	0	0	8	14	30	0	0

Table 2: Rainfall, temperature, and waste combinations for reactor setup

Rainfall (mm/d)	**Temperature (°C)**	**Waste Combination**											
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**
4	25				7					17	19	21	
	37	1	3			9		13					
10	25		4	5		10	11						
	37								15		20	22	23
20	25	2						14	16				24
	37			6	8		12			18			

its effect in the anaerobic degradation (Filer *et al*., 2019). The sludge characteristics used in this study have been published in Yasim and Buyong (2023).

Tap water was also added in the earlier process of reactor setup so that the waste achieves its near saturation limit to speed up the degradation process. Note that reactors filled with waste were reweighed before operating at the mentioned rainfall–temperature combinations in the experimental design section. Besides that, two control reactors (with seeding but no waste) were prepared to determine methane production from the seed. Figure 1 illustrates the built-up reactors and a schematic diagram of the laboratory-scale landfill reactor setup used in this study.

The rainfall amounts were added daily into reactors to obtain corresponding amounts of rainfall in methane generation, which are 4, 10, and 20 mm/day. Instead of deionised or distilled water, tap water was used as a substitute for rainwater. It is because deionised and distilled water will wash all contaminants from the waste, resulting in higher carbon washout and disturbing methane production.

Meanwhile, reactors with a temperature of 25°C were placed in an air-conditioned room by setting the room temperature to the desired temperature. The rest of the reactors were left outdoors, representing a temperature of 37°C.

The gas produced was pumped into a Tedlar bag using a standard SKC grab air sampler with a flow rate of 1.0 L/min connected to a calibrator. The gas was transferred from the gas collection bag into the GC-FID using a syringe.

Establishing Localised k and L_0

Methane production versus time for each reactor was plotted in graphs. Then, k and L_o values for each reactor were computed using Non-Linear Regression (NLR) in SPSS software.

The comprehensive Multiple Linear Regression (MLR) equation was created by inserting 12 Independent Variables (IDVs), which are temperature, rainfall, and 10 waste components, and k as the Dependent Variable (DV). The steps undertaken for the development of the MLR equation are examining raw data plots by conducting correlation analysis between DV with all IDVs; constructing a preliminary MLR equation and evaluate its assumptions; implementing corrective measures using transformation of DV and IDVs until the model assumptions for regression analysis were satisfied; investigating potential interaction terms; checking outliers; searching the best fitted MLR model using backward elimination, forward selection, and stepwise regression methods. Hence, the best-fitted model was chosen based on the R^2, adjusted R^2, Mallows' Cp, Akaike Information Criterion (AIC), and

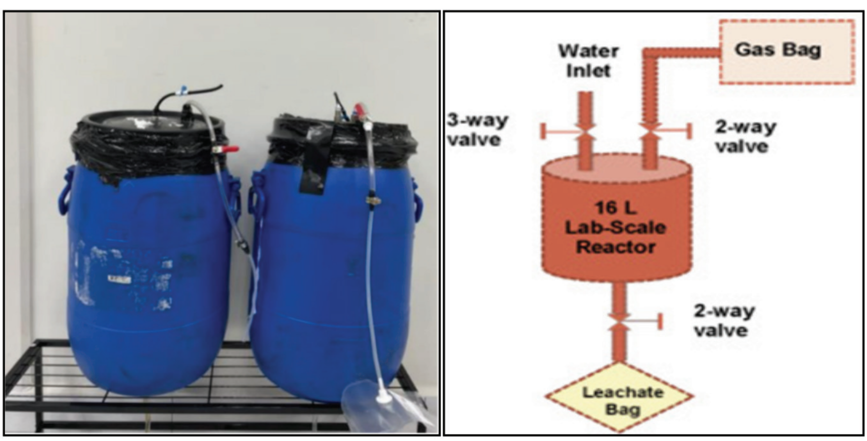


Figure 1: Built-up reactors versus schematic diagram of laboratory-scale landfill reactor setup

Schwarz Criterion Bayesian Criterion (SBC) values. Models with the greatest R^2 and adjusted R^2 values represent a better fit of the model with less redundancy between IDVs.

In determining localised L_o, the values derived from the BMP test were utilised to compute a weighted-average L based on the waste composition data. Subsequently, methane emission was calculated using the CLEEN model by applying localised k and L_o values obtained from this study. For validation, methane emissions from the CLEEN model were compared with field data and estimated emissions from LandGEM and IPCC models.

Results and Discussion

Waste Characterisation

MSW generated in Shah Alam is divided into seven components: Food, paper, yard, plastic, diaper, textile, and inorganic waste. The percentage of waste components is 45% food, 8% paper, 8% textile, 18% garden, 8% diapers, 5% plastic, and 8% inorganic waste. These compositions slightly deviate from the value of other tropical countries like Colombia, Brazil, Bangladesh, Laos, and Myanmar (Glawe *et al*., 2005; Lima *et al*., 2018; Toha & Rahman, 2023; de Santana *et al*., 2024). For example, the percentage of food waste in Laos is 35% lower than in other tropical countries due to the higher agricultural activities.

In contrast, food waste is utilised as animal feed. Conversely, agricultural activities in Myanmar and Nepal exhibit a large proportion of food waste that accounts for more than 50% (Glawe *et al*., 2005). This distinction is due to the differences in lifestyle and culture, population, economic growth, geography, climatic factors, and waste management practices. Furthermore, the percentage of waste generated in each country changes over time due to population growth, expansion of industrial sectors, economic development, and transformation of waste management practices (Ahmad *et al*., 2020).

In this study, inorganic waste was included because it has potential effects on landfill processes and management strategies, as well as the development of methane modelling. Inorganic waste causes physical interference at landfills due to its large size, which will entrap leachate and extend its contact duration with biodegradable waste—unevenly distributing moisture and nutrients needed for methanogens (Meyer-Dombard *et al*., 2020; Mojiri *et al*., 2021).

Meanwhile, chemical interactions occurred due to the high pH of inorganic waste (alkaline substances) that impede acidogenic bacteria for anaerobic digestion (Sarmah *et al*., 2024). Besides that, heavy metal components in inorganic waste can inhibit enzymatic activity and reduce biogas yields by up to 30%. It may also accumulate in leachate and exhibit 40% and 100% removal efficiencies contingent upon treatment methods (Mojiri *et al*., 2021). Therefore, inorganic composition also plays a role in establishing an accurate localised value of L_o and k, especially for tropical climate countries.

The characteristics of waste are profoundly influenced by the emission of methane from landfills, which dictate both modelling methodologies and management strategies. Table 3 represents the results of waste characterisation obtained in this study. The moisture content of reactors A, B, C, and D, which contain Fruit Waste (FW), Cooked Food Waste (CFW), Uncooked Food Waste (UCFW), and Vegetable Waste (VW), respectively, exhibited more than 60% moisture content.

Food waste is one of the organic wastes that naturally contains high moisture content compared to other organic waste. Among all food substrates, VW had the maximum moisture content (85.94%), followed by FW (78.94%), UCFW (69.60%), and CFW (67.88%). Meanwhile, reactors E, F, and G, which are signified as non-food substrates are Paper Waste (PW), Textile Waste (TW), and Garden Waste (GW), respectively and showed low moisture content (less than 20%).

Table 3: Results of all reactors' moisture content, total solids, and volatile solids

Reactor	A	B	C	D	E	F	G	H	I	J	K	L
Moisture content (%)	78.49 ± 1.50	67.88 ± 0.50	69.60 ± 3.93	85.94 ± 0.81	5.10 ± 0.11	6.32 ± 0.02	19.43 ± 1.50	22.32 ± 1.53	9.67 ± 0.13	18.71 ± 1.56	10.78 ± 1.72	11.25 ± 0.27
Total solids (%)	21.51 ± 1.50	32.12 ± 0.50	30.40 ± 3.93	14.06 ± 0.81	94.90 ± 0.11	93.68 ± 0.02	80.57 ± 1.50	77.68 ± 1.53	9.67 ± 0.13	81.29 ± 1.56	89.22 ± 1.72	88.75 ± 0.27
Volatile solids (%)	65.80 ± 3.89	73.72 ± 9.89	71.21 ± 19.69	50.22 ± 13.04	82.55 ± 1.11	70.40 ± 12.42	92.99 ± 0.57	73.60 ± 2.87	24.09 ± 1.39	45.72 ± 2.88	50.18 ± 3.55	67.42 ± 5.39

Shah Alam waste in reactor H showed higher moisture content than other mixture refuses in reactors I, J, K, and L. This is because Shah Alam waste comprises a mixture of seven waste components, which is contributed by higher food waste, about 45%. Moisture content substantially affects methane production dynamics and landfill management strategies. Elevated moisture levels often expedite AD. However, ideal thresholds differ by waste type and necessitate meticulous modelling to balance methane production with emission regulation (Mor *et al*., 2024).

The analysis revealed that TS content for all reactors is above 15% except for reactor D. According to Panjičko *et al*. (2017), the percentage for Total Solid (TS) content needed to ensure the success of the anaerobic digestion process is more than 15%. In this study, it appears that reactor E had the highest TS content (94.90%), followed by reactor F (93.68%) and reactor G (80.57%). The main components of PW are cellulose fibres derived from wood pulp, along with inorganic materials like fillers, coatings, and additives used in paper production. A higher total solid content in PW suggests that the waste contains a larger amount of paper fibres and other non-water materials per unit weight (Barlaz, 2006).

Reactor G has the highest VS content compared to the other reactors, with a value of 92.99%, followed by reactor E, which is 82.55%. It is implied that GW and PW contained more readily biodegradable organic matter. This organic matter serves as the primary food source for the microorganisms involved in anaerobic digestion and with higher VS content, GW can support a more substantial population of methane-producing microorganisms, leading to increased methane production potential. Meanwhile, based on the VS result, reactor I comprised a low amount of biodegradable organic matter, represented by 24.09%. VS features determine methane yield, kinetics, and system design. Effective management relies on minimising VSs in landfills, optimising digestion parameters, and incorporating real-time VSs data into prediction models (Sendilvadivelu *et al*., 2022).

Many studies have confirmed that, besides moisture content, TS and VS are also the crucial parameters in the anaerobic degradation process (Wang *et al*., 2020; Zhao *et al*., 2021). Volatile Solid to Total Solid concentration (VS/TS) indicates organic matter in the substrate that can be digested anaerobically. Besides that, the general activities of anaerobic microbes and the activities of important enzymes linked to hydrolysis, acidification, and methanogenesis stages were found to be involved in the mechanism of VS/TS on anaerobic digestion.

The waste characterisation results obtained in this study are varied from literature, especially for the heterogeneous waste components (Karanjekar *et al*., 2015a; Mboowa *et al*., 2017; Xing *et al*., 2021; Sendilvadivelu *et al*., 2022; Mor *et al*., 2024). However, waste characterisation analysis for some individual waste components found in this study mainly aligns with previous publications (Baawain *et al*., 2017; Parra-Orobio *et al*., 2018a; Mor *et al*., 2024).

In summary, comprehensive waste categorisation is crucial for formulating methane emission modelling and efficient management strategies in Malaysia. It facilitates the customisation of solutions to address the distinct requirements and obstacles of the nation's waste streams, fostering a more sustainable and effective waste management system.

Biochemical Methane Potential (BMP)

The trend of cumulative experimental BMP for all reactors is illustrated in Figure 2. The BMP result was obtained over 37 days and was terminated when the BMP test yielded less than 1% daily production. The graph showed that the acquisition of biodegradable compounds that are readily accessible to microorganisms for the digestion process was determined for all reactors. Among all reactors, Reactor B produced the lowest methane value from the first day of the BMP test until day 17. Consequently, methane generation started to increase rapidly until day 27. After that, methane production achieved a stabilisation stage until day 37.

Simultaneously, the cumulative CH_4 generation trends exhibited distinct curves during the incubation period for Reactors H, I, J, K, and L. It is noticeable that production of CH_4 gas began immediately, with no lag phase. This is due to the presence of co-digestion in all these reactors.

Integrating nutrient-dense waste such as food waste into lignocellulosic materials like paper and TW might supply vital nutrients for microbial proliferation. This can augment microbial activity and expedite the anaerobic degradation (Manyi-Loh & Lues, 2023). Note that incorporating nutrients can modify microbial community dynamics, fostering the proliferation of particular microbes adept at lignocellulose breakdown. Banks *et al*. (2018) stated that nitrogen amendments have been demonstrated to enhance the secretion of enzymes such as xylanases and endoglucanases, essential for lignocellulose degradation. Reactors H and L had the same cumulative CH_4 generation curves, where a rapid increase phase was observed from day 19 until day 27, followed by a stabilisation phase and CH_4 production after day 37 was neglected. However, a rapid increase phase occurred earlier than Reactors H and L at day 9 due to the high percentage of easily biodegradable waste components for Reactors I, J, and K.

From Figure 2, all reactors' stabilisation stage occurred on day 27. Many factors contributed to this stage such as the depletion of substrate, alteration in microbial communities, and environmental conditions. As mentioned by Hu *et al*. (2023), readily degradable substrates

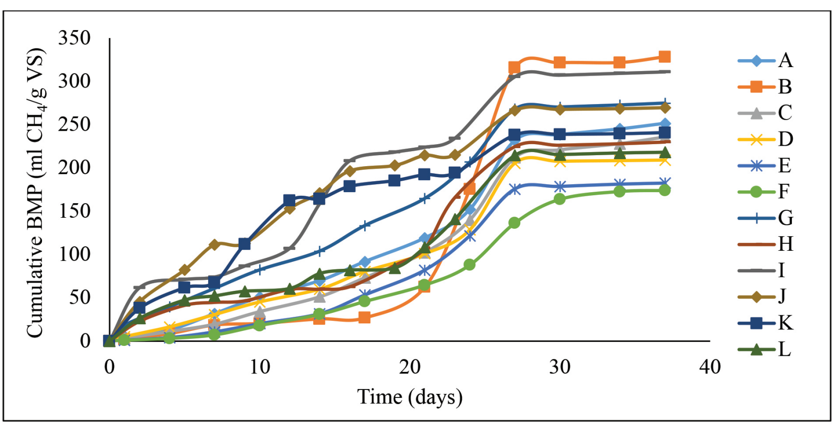


Figure 2: Cumulative BMP of all reactors

such as carbohydrates in food waste facilitate rapid initial methane production. However, these substrates may induce acid stress due to Volatile Fatty Acid (VFA) accumulation under high organic loading, which leads to microbial community shifts by inhibiting acetolastic methanogens. Hydrogenotrophic methanogens predominate in advanced stages or under acidic/nutrient-deficient conditions. This results in diminished methane production due to energetically unfavourable CO_2/H_2 pathways. A transition from acetoclastic to hydrogenotrophic dominance in permafrost thaw systems has reduced methane production by approximately 40%, despite consistent methanogen abundance (Aronson *et al*., 2013).

Reactor B produced the highest BMP compared to the other reactors that contained individual waste components with a value of 328.39 ml CH_4/g VS. This was followed by Reactor G, Reactor A, Reactor C, and Reactor D with values of 274.94 ml CH_4/g VS, 251.64 ml CH_4/g VS, 235.82 ml CH_4/g VS, and 209.12 ml CH_4/g VS, respectively. On the other hand, Reactor E and F yielded less than 200 ml CH_4/g VS. Reactor B contained CFW, which is categorised as a high biodegradable waste component because it is rich with readily biodegradable carbohydrates compared to other waste components such as garden, paper, and TW.

Meanwhile, Reactors E and F are represented by paper and TW, which are classified as the least inert and the least biodegradable waste. The main components of PW are cellulose fibres derived from wood pulp and inorganic materials like fillers, coatings, and additives used in paper production. On the other hand, cellulose, protein, and synthetic fibre are the main components of textile raw materials. The presence of lignin limits the bioavailability of cellulose and hemicellulose, lowering the anaerobic conversion (Zhou *et al*., 2021).

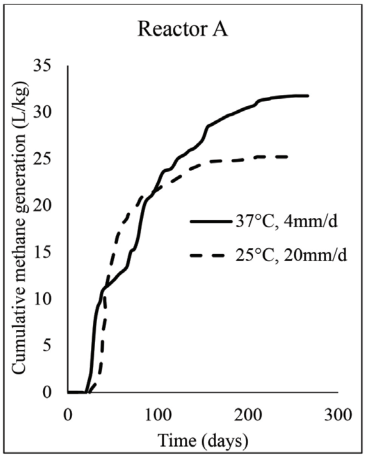
Among reactors that contained a variety of waste components, the highest CH_4 production was noticed in Reactor I with a value of 310.91 ml CH_4/g VS, followed by Reactor J, Reactor K, and Reactor H with cumulative CH_4 production of 269.61 ml CH_4/g VS, 240.85 ml CH_4/g VS, and 229.91 ml CH_4/g VS, respectively. Meanwhile, the lowest one represented by Reactor L with a value of 218.1 ml CH_4/g VS. Reactor L composed of a high percentage of poor biodegradable waste components (60% TW), which is the reason that contributes to the lowest CH_4 production compared to the other mixed waste.

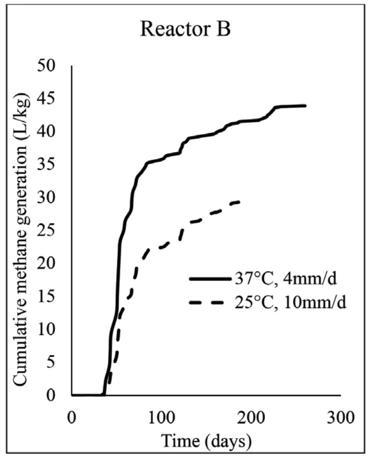
BMP of CFW (Reactor B) that was obtained in this study is slightly consistent with the literature BMP (369 ml CH_4/g VS) obtained by Gu *et al*. (2020) due to the exact composition of food waste that was used, which is 60% rice, 30% vegetable, and 30% chicken/meat. However, BMP of CFW in the presence study is less than BMP value found by Cho *et al*. (2012) with the value is 406 ml CH_4/g VS and study conducted by Zhou *et al*. (2021) with the value of 534 ml CH_4/g VS.

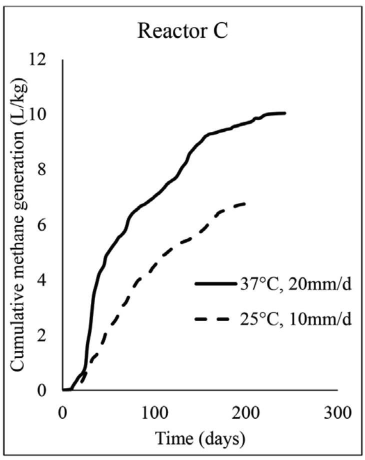
Meanwhile, Parra-Orobio *et al*. (2018) found that BMP of FW in a range of 54-144 ml CH_4/g VS. The contradiction resulted from this study with Cho *et al*. (2012) because of the different experimental setup used. In contrast with Parra-Orobio *et al*. (2018) and Zhou *et al*. (2021), this was due to the different waste composition. Besides that, the BMP value of Shah Alam waste composition (Reactor H), which is 229.91 ml CH_4/g VS is in a range as a result obtained from Sohoo *et al*. (2021b) with a value of 209 ml CH_4/g VS.

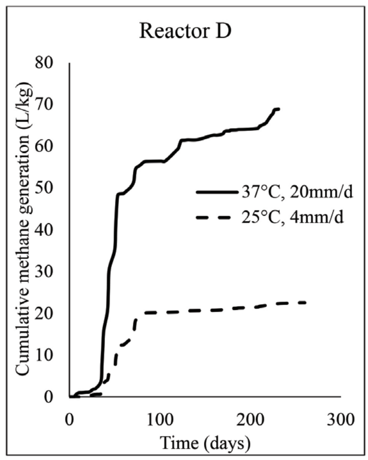
Effects of Climatic Conditions on Methane Generation

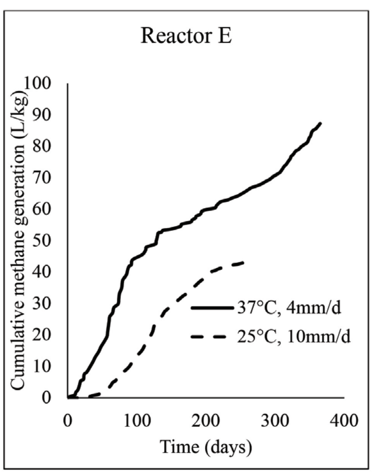
Figure 3 displays the effects of temperature on total methane generation for all reactors. The results revealed an association between climatic conditions (ambient temperature and rainfall) and the decomposition of waste in producing methane gas. The ambient temperature significantly influences the methane generation of all reactors while productivity increases as the temperature rises. The cumulative methane

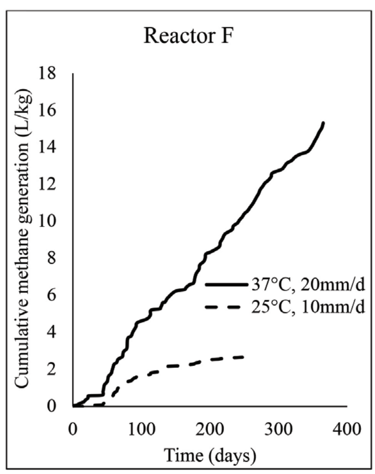

Reactor A
Cumulative methane generation (L/kg)
0 5 10 15 20 25 30 35
0 100 200 300
Time (days)
37°C, 4mm/d
25°C, 20mm/d
(A)


Reactor B
Cumulative methane generation (L/kg)
0 5 10 15 20 25 30 35 40 45 50
0 100 200 300
Time (days)
37°C, 4mm/d
25°C, 10mm/d
(B)


Reactor C
Cumulative methane generation (L/kg)
0 2 4 6 8 10 12
0 100 200 300
Time (days)
37°C, 20mm/d
25°C, 10mm/d
(C)


Reactor D
Cumulative methane generation (L/kg)
0 10 20 30 40 50 60 70 80
0 100 200 300
Time (days)
37°C, 20mm/d
25°C, 4mm/d
(D)


Reactor E
Cumulative methane generation (L/kg)
0 10 20 30 40 50 60 70 80 90 100
0 100 200 300 400
Time (days)
37°C, 4mm/d
25°C, 10mm/d
(E)


Reactor F
Cumulative methane generation (L/kg)
0 2 4 6 8 10 12 14 16 18
0 100 200 300 400
Time (days)
37°C, 20mm/d
25°C, 10mm/d
(F)

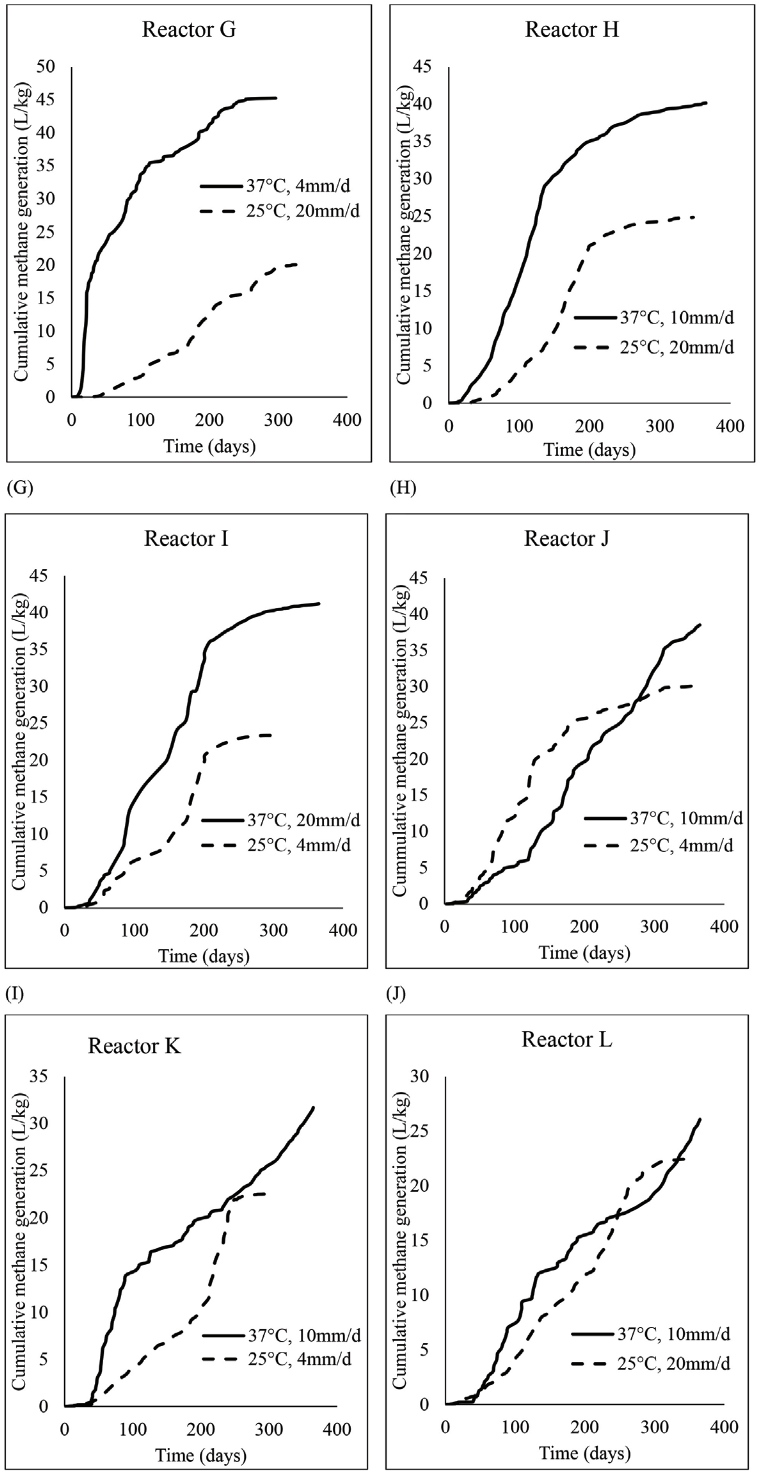


Figure 3: Graphs of cumulative methane generation versus time for all reactors at different temperatures

generation for all reactors at 37°C is in a range of 10.05 L/kg to 91.27 L/kg while the waste decomposition rate at 25°C is half that at 37°C, which is in a range of 2.66 L/kg to 43.78 L/kg.

Microorganisms play an important role in the decomposition process, but these organisms are too sensitive to temperature. Temperature significantly affects acetogenic bacteria and methanogenic archaea in the four-stage anaerobic digestion process (hydrolysis, acidogenesis, acetogenesis, and methanogenesis). In the acetogenesis phase, the digestion of organic acids into acetic acid, CO_2, and hydrogen is influenced by temperature. In contrast, higher temperature enhances their syntrophic interactions with hydrogenotrophic methanogens. Meanwhile, in the methanogenesis stage, elevated temperature accelerates the formation of methane gas from the reaction of CO_2 and hydrogen by hydrogenotrophic methanogens. In addition, acetoclastic methanogens decompose acetate into CH_4 and CO_2 in the methanogenesis phase. This process is less heat-tolerant, predominating at elevated temperatures (Kanong & Sakulrat, 2022).

Furthermore, the anaerobic microbial activities at higher temperatures can expedite and enhance the transition from the acetogenesis to the methanogenesis phase. The quick shift from acidogenesis to methanogenesis leads to the short lag phase. It decreases VFA accumulation, resulting in low Biochemical Oxygen Demand (BOD) and BOD/COD ratios, increasing methane yield (Kanong & Sakulrat, 2022). These reasons can be observed in all reactors.

In contrast, reactors applied with the lowest temperature (25°C) started their AD process later than those at 37°C. The optimal medium for bacterial growth is a mesophilic condition (temperature 35°C to 55°C), as found by many studies. Krause *et al*. (2018) found that waste biodegradation at mesophilic conditions (at a temperature of 35°C) is more stable and necessitates less energy, compared to the thermophilic conditions (at a temperature of 55°C). Karanjekar *et al*. (2015) studied the relationship between temperature (20°C, 30°C, and 37°C) and methane generation rates at a laboratory-scale landfill. The findings indicated that the lag phase is most prolonged for all reactors at a low temperature of 20°C and 30°C in comparison to the temperatures of 37°C, which consequently leads to the higher methane production in a mesophilic condition (at a temperature of 37°C). Acetoclastic methanogens such as Methanosarcina and Methanosaeta flourish at moderate temperatures (30°C-50°C) and predominate in acetate-driven methanogenesis. Their activity diminishes at 55°C-60°C, leading to a decrease in CH_4 generation (Sudiartha *et al*., 2023; Zhang *et al*., 2024). Besides that, the reaction kinetics and yields of the anaerobic degradation process are also enhanced by higher temperature (Filer *et al*., 2019).

In evaluating the moisture content's impact on the methane production, elevated moisture levels substantially increased methane output. This output was obtained by Reactors C, D, F, I, J, and K. Moisture condition facilitates waste-microbe interactions, helps remove inhibitors, maintains buffer conditions, and restricts oxygen transfer from the atmosphere, which can enhance microbial degradation of organic material (Nwaokorie *et al*., 2018; Purmessur & Surroop, 2019).

However, there are some cases in the reactors. In contrast, the highest moisture content resulted in low methane yield due to the washout of organic matter and anaerobic bacteria. These reasons also resulted in the late start of methane production and shorter AD process in Reactors A, B, E, G, H, and L. This condition has been confirmed by Chai *et al*. (2016). In tropical landfills with high rainfall, excessive precipitation can result in nutrient leaching, diminishing the efficacy of methane-producing bacteria.

The microbial communities in tropical landfills have evolved to high moisture conditions. Nevertheless, excessive rainfall can disrupt this equilibrium by modifying nutrient availability and oxygen levels. This disruption can impact methanogenic and methanotrophic bacteria, affecting methane production and degradation rates (Landfill Gas Primer: An Overview for Environmental Health Professional, 2001).

After disassembling all the reactors, all organic food waste is no longer visible. Nonetheless, other types of garbage such as paper, textiles, garden debris, plastic, diapers, and inorganic waste are still identifiable. Findings in this study are consistent with previous works. In contrast, several researchers have confirmed a direct proportional relationship between the generation rate of CH_4 and moisture content in their experiments (Karanjekar *et al*., 2015; Fei *et al*., 2016; Park *et al*., 2018; Sun *et al*., 2019).

Effects of Waste Compositions on Methane Generation

Figures 4 and 5 illustrate the effect of waste composition on methane generation at both temperatures. PW produced more methane than other types of waste, with a value of 91.27 L/kg and 43.87 L/kg at reactor temperatures of 37°C and 25°C, respectively. Xing *et al*. (2021) stated that PW has a favourable nutrient balance and physical characteristics such as a larger surface area and fibrous structure, which promote microbial activity and enhance constant methane generation. In addition, Kalyoncu and Peşman (2020) also mentioned that the fibrous structure of PW enhances accessibility for microorganisms, allowing for the efficient

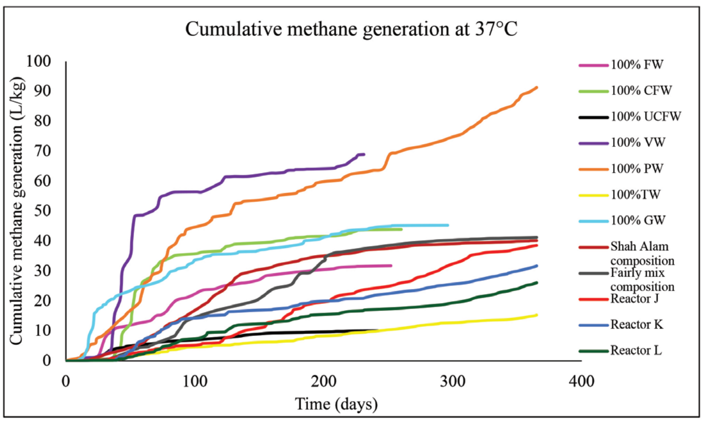


Figure 4: Cumulative methane generation for all waste components at 37°C

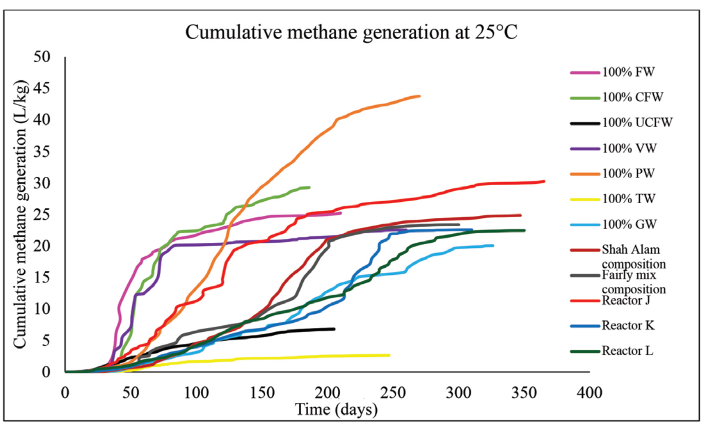


Figure 5: Cumulative methane generation for all waste components at 25°C

utilisation of the available substrate. Thus, the PW used in the study likely contained a favourable balance of carbon, nitrogen, and other essential nutrients required for microbial growth. This inherent nutrient balance in the PW reactor and its high biodegradability and carbon content contributed to the constant and steady methane generation rate.

There is a wide range of definitions of food waste. According to the Food Waste Reduction Alliance (2016), food waste is generated at every stage of the food supply chain, from production to serving, including processing, distribution, storage, sale, preparation, and cooking. Xu *et al*. (2020) and Owamah *et al*. (2021) believed that different compositions of food waste have different methane generation potential. Thus, in this study, four different types of food waste were used in order to identify their methane potential generation rate. Among all these four types of food waste, VW, CFW, and FW have the highest potential in methane generation, with cumulative methane generation within the range of 30-70 L/kg for a temperature of 37°C and 20-30 L/kg for a temperature of 25°C. CFW is a food substrate that yields significant methane because it contains high, easily-degradable carbohydrates, and lipid content. Lipids lead to a balanced nutritional makeup and exhibit slower hydrolysis, carbohydrates and proteins are typically classified as highly degradable organic contents (Owamah *et al*., 2021).

Meanwhile, FW and VW are categorised as food waste containing high lignocellulosic percentage and low lipid content, exhibiting lower methane production. Consequently, UCFW produced the lowest methane generation compared to the other food waste, with a value of 10.85 L/kg and 6.81 L/kg at 37°C and 25°C, respectively. There are many limiting factors in the AD process of food waste, which is why there is an insignificant methane yield from UCFW. One is a high protein level that acts as an inhibitory factor in AD. In contrast, the chicken manure represents UCFW in this study. Another limiting factor is the high level of VFA in the substrate in the early AD stage. As VFA concentration rises during acidogenesis, the pH decreases and can block acetolactic methanogenesis. FD's ideal acetogenesis pH range is between 6.8 and 7.6 (Beodic *et al*., 2020). However, this study found that the initial pH for UCFW is less than 5.

GW resulted in the third-highest methane production at 45.27 L/kg in the reactor at 37°C. In contrast, at a reactor of 25°C, it was placed at the third lowest methane production with a value of 20.05 L/kg. This may be due to lignin, which is difficult to break down and does not contain as much carbon as other compounds such as cellulose (Ghimire *et al*., 2021). Lignin can make it difficult for the anaerobic bacteria to access the other organic materials in the waste, it can also release toxic compounds that can inhibit the bacteria.

According to a study by Olatunji *et al*. (2021), lignin also lowers the pH of the environment, which further inhibits the growth of the bacteria, similar to the findings in this study based on the leachate collection from the reactor. The presence of lignin in GW reactors significantly slows the overall amount of methane produced.

A study by Olatunji *et al*. (2021) determined that in order to improve the overall cumulative methane production from GW, it is suggested to remove or break down the lignin, which pre-treatment methods such as enzymatic hydrolysis or alkaline hydrolysis can do. However, the pre-treatment was not done in this study to maintain similar simulated conditions in all reactors with landfill conditions.

TW is the lowest in methane generation compared to all waste compositions, accounting for 15.31 L.kg and 2.66 L/kg in reactor 37°C and 25°C, respectively. This could be attributed to toxic compounds in the TW. According to Jin *et al*. (2022), TW contains various chemicals, including dyes, pigments, and flame retardants, which can be toxic to anaerobic bacteria and inhibit fermentation. Suppose the TW contains a high concentration of toxic compounds.

In that case, it will take longer for the bacteria to break down the waste, which could lead to multiple peaks in the methane generation curve as seen in this study. Similar results were reported by Kumar *et al*. (2020), where energy and nutrient recovery by anaerobic digestion of textile industry wastes is facing challenges due to the anticipated toxicity, lower pH (6.6), and low nutrients, C:N ratio (12.2). As seen in this study, these factors contribute to the slow degradation of TW in anaerobic digestion.

For all mixture waste compositions such as Shah Alam, a fairly mixed composition, Reactors J, K, and L, methane production resulted in the intermediate range among all waste compositions. This is due to the variable waste composition that acts as a variable nutrient that enhances the methane degradation rate.

It should be noted that the amount of rainfall varied in each example, affecting the duration of the lag phase and the peak intensity. Thus, quantifying the impact of temperature, rainfall, and waste composition on degradation rate requires an MLR equation.

Computed L_{olab} and k_{lab} Value

Lab-scale ultimate methane potential (L_{olab}) and methane generation rate (k_{lab}) were computed using NLR. The results are tabulated in Table 4. The FOD constant (k_{lab}) is the proportionality constant relating the methane generation rate from waste substrates. Several studies have postulated a convergence between the constant relationship of the methane generation rate with waste composition, ambient temperature, and moisture content. Therefore, it is apparent from Table 4 that the methane generation rate for single waste compositions is faster than that for mixed waste compositions. In contrast, the k_{lab} values for this mixed waste are below 1.00 y^{-1}.

In addition, temperature also showed a significant factor in influencing the determination of k_{lab}. In this study, all waste compositions at higher temperature (37°C), except for vegetable, textile, and Reactor J, resulted in a rapid methane generation rate. Elevated temperatures augment microbial activity in anaerobic digestion by expediting enzymatic reactions and metabolic processes. However, the effects differ among microbial populations. Temperature significantly affects acetogenic bacteria and methanogenic archaea in the four-stage anaerobic digestion process (hydrolysis, acidogenesis, acetogenesis, and methanogenesis). Optimal CH_4 production is achieved at temperatures between 35°C-55°C, with acetoclastic routes prevailing below 50°C. Due to microbial stress, methanogenesis diminishes above 65°C (Kanong & Sakulrat, 2022). Mesophilic conditions (37°C) accelerated methane generation for most in this study because bacteria within mesophilic conditions predominate during the initial phases of composting, with breakdown rates escalating up to 40°C (Zhang *et al*., 2024).

Other researchers have also agreed upon the impact of moisture content on the k_{lab}. A review of the literature by Sun *et al*. (2019) in evaluating the impact of yearly rainfall on the amount of methane generated at a subset of United States landfills finds that, despite not operating with

Table 4: Results of NLR in computing k and L_o values for all reactors

Reactor at 37°C	**1A**	**3B**	**6C**	**8D**	**9E**	**12F**	**13G**	**15H**	**18I**	**20J**	**22K**	**23L**
L_o (m^3/kg)	3.13	1.30	2.41	7.57	2.44	38.89	0.68	21.79	65.54	84.31	19.79	51.86
K (y^{-1})	1.13	1.30	1.65	0.81	1.07	0.92	1.54	0.81	0.71	0.66	0.98	0.81
Reactor at 25°C	**2A**	**4B**	**5C**	**7D**	**10E**	**11F**	**14G**	**16H**	**17I**	**19J**	**21K**	**24L**
L_o (m^3/kg)	2.98	20.15	16.42	2.14	94.03	14.03	69.98	74.25	56.19	28.59	60.70	49.01
K (y^{-1})	1.15	0.78	1.10	1.36	0.54	1.49	0.61	0.57	0.63	0.82	0.59	0.64

leachate recirculation, wet conditions of landfills exhibit a high decay rate constant in the range of 0.1-0.11 y^{-1}.

Karanjekar *et al*. (2015) study revealed that landfills with higher moisture content can shorten lag times and accelerate methane generation during peaks. Moisture enhances microbial activity in anaerobic digestion by increasing substrate dispersion, assuring nutrient delivery, and excluding oxygen. This creates an optimal environment for anaerobic microbes to flourish. Moisture facilitates a favourable environment for microbial activity by ensuring substrates are accessible to bacteria. In anaerobic digestion, elevated moisture content enhances organic substrates' diffusion, enabling bacteria to access nutrients more effectively. This is especially crucial for decomposing complex organic substances into simpler chemicals that can be utilised by methanogenic bacteria (Łysiak *et al*., 2023).

Moisture also facilitates the transfer of nutrients and metabolic by-products within the anaerobic digestion system. Other than that, it promotes a balanced microbial community by guaranteeing that vital nutrients are dispersed uniformly throughout the reactor. This equilibrium is vital for sustaining optimal circumstances for both acidogenic and methanogenic bacteria, which are required for effective methane generation (Uddin *et al*., 2021). In addition, anaerobic digestion necessitates the absence of oxygen to preserve an anaerobic environment. Elevated moisture levels foster an environment with restricted oxygen, which is crucial for the survival and function of anaerobic microbes. By reducing oxygen infiltration, moisture guarantees the process remains anaerobic, promoting the proliferation of methanogens and other anaerobic microorganisms (Yellezuome *et al*., 2023).

Multiple Linear Regression (MLR)

Multiple Linear Regression (MLR) analysis was used to develop an equation for predicting the methane generation constant (k) as a function of rainfall, temperature, and waste composition. The best MLR equation was obtained through a systematic process. First, raw data plots were examined and correlation analysis was conducted between the Dependent Variable (DV) and all Independent Variables (IDVs). A preliminary MLR equation was then constructed and its assumptions were assessed. When necessary, corrective measures were applied by transforming the DV and IDVs until the regression model assumptions were satisfied. Next, potential interaction terms were explored, outliers were identified, and different MLR techniques were evaluated. Finally, the model that provided the best fit was selected. Table 5 compares SPSS outputs to identify the best MLR model search methods.

The model, consisting of eight IVs chosen by the backwards elimination method had significantly higher R and R^2 values than the one IV model selected through the forward selection regression method. In addition, the C, AIC, and SBC values were lower for a model established by the backwards elimination method. Therefore, the model consisting of eight IVs was chosen as the best-fitted MLR model. The best MLR equation was developed as follows:

$$\log_{10} k = 0.0099\ R + 0.0076\ T + 0.0026\ FW + 0.000002482\ CFW^2 + 0.0036\ UCFW + 0.0022\ VW + 0.0026\ TW + 0.0018\ GW - 2.3964,$$

where k is the first-order constant of methane generation rate (y^{-1}), R is rainfall (mm/d), T is temperature (K), FW, CFW, UCFW, VW, TW, and GW are the percentage of FW, CFW, UCFW, VW, TW, and GW, respectively.

From the MLR equation, climatic parameters show higher coefficient values than the waste composition variables. The reason is that rainfall and temperature positively affect methane production by establishing favourable conditions for microbial activity and the decomposition of organic materials. In contrast, waste predominantly dictates the theoretical methane potential (Krause *et al*., 2023). Field studies conducted by several researchers indicate that rainfall and temperature account for over 50% of the variability in seasonal methane flux while waste composition contributes less than 20% in controlled settings (Karanjekar *et al*., 2015b; Neumann *et al*., 2019; Zhang *et al*., 2021).

On the other hand, UCFW indicates the lowest coefficient value among all variables. Unlike CFW, UCFW lacks the specific microbial community adapted for high methane production. Raw food waste is more complex and less accessible for microbial decomposition than digested waste. This complexity necessitates additional time and energy for hydrolysis, the preliminary phase of anaerobic digestion, potentially impeding methane generation (Dietrich *et al*., 2021).

Besides that, regarding environmental factors, UCFW contains high moisture content and is lower in pH. Anaerobic digestion is highly sensitive to variations in temperature and pH levels (Morales-Polo *et al*., 2018). The ideal circumstances for methane production often exist within a limited range, specifically mesophilic conditions at approximately 35°C and a pH between 6.5 and 7.5. CFW in this study does not inherently offer these circumstances, whereas the initial pH of the reactor is 5.5. Meanwhile, elevated moisture levels in UCFW can accelerate AD. However, if not adequately handled, it may also lead to diminished methane output (Morales-Polo *et al*., 2018).

Table 5 indicates that the IVs explain approximately 67% of the variability in methane generation rate. The remaining unexplained variance of 33% may be influenced by other factors that have not been measured in this study. As Harirchi *et al*. (2022) mentioned, methane production in anaerobic digestion is also affected by complex microbial interactions and inhibitory substances that determine the process's efficiency and stability. The methane generation is contingent upon microbial synergy, substrate availability, and environmental factors. Inhibitors such as VFAs, ammonia, and H_2S adversely impact acetoclastic methanogens, but syntrophic interactions and operational modifications contribute to system stability.

Besides that, this best MLR equation also met all regression model assumptions. Meanwhile, a sigmoidal curve was observed in the standard probability plot, indicating the residuals had a normal distribution. The Pearson correlation and collinearity analysis identified no multicollinearity between IDVs. In checking outlier analysis, no outliers were determined for this best MLR equation. The linearity, homoscedasticity, normality plots, and the results of Pearson correlation, collinearity analysis, and analysis were attached in Appendices.

Thus, this equation is available for estimating the methane generation rate (k) for landfills that accept rainfall in the range of 4 mm/d to 20 mm/d with an annual ambient temperature of 25°C to 37°C. Based on the initial experimental design, this model should be capable of predicting the methane generation rate for 10 types of waste composition. Conversely, only some waste compositions achieved statistical significance at a significance level of $\alpha = 0.05$. Consequently, this final capability of the equation can only be used to predict the methane generation rate produced from fruit, cooked food, uncooked food, vegetables, textile, and GW, only at a percentage of 0-100%.

Table 5: SPSS outputs of MLR model search methods

s	R	R^2	C(p)	AIC	SBC	Independent Variables
Backward elimination	0.820	0.673	5.668	-101.647	-91.044	Rainfall, temperature, FW, UCFW, VW, TW, GW, and standardised CFW^2
Forward selection	0.410	0.168	9.702	-93.222	-90.866	Diapers

CLEEN Model Equation

The CLEEN model is an Excel-based tool that predicts methane generation rates from landfills by applying a simple FOD equation. This model requires several inputs, including the starting year of accepting waste in landfill, annual waste mass, waste composition, average annual ambient temperature, rainfall, and localised k and L_o values. The first decay equation of the CLEEN model is as follows:

$$Q_{CH_4} = \sum_{i=0}^{n} \sum_{j=0}^{12} kL_o \frac{M_i}{12} e^{(-kt_{ij})},$$

where Q is methane recovered from landfills (m^3/yr), M is a mass of waste deposited in the year "i" within the landfill (Mg), k is a FOD constant (yr^{-1}), L_0 is an ultimate methane generation potential (m^3/Mg) ,and t_{ij} is an age of the j^{th} section of waste mass M_i, accepted in the i^{th} year. The CLEEN model proposes utilising $1/12^{th}$ of the mass instead of $1/10^{th}$ as in the LandGEM equation. This model allows users to enter the monthly waste mass and incorporates localised L_o and k values. This will significantly enhance the accuracy of methane emission estimation by accounting for site-specific waste composition, environmental conditions, and operational factors. As a study conducted by Chandra and Ganguly (2023), localised parameters facilitate accurate predictions of peak methane generation, guiding the development of gas wells.

Methane Recovery Oxidation Input

The degradation of waste in landfills produces methane gas that is generally emitted into the ambient air. Meanwhile, methane recovery systems will collect some portions of this gas and bacteria oxidise some in the cover soil. In the CLEEN model, the percentage of methane recovered and oxidised will be accounted for. IPCC 2006 provides a default oxidation percentage value of 10% if the user-specific data is unavailable. However, this study used specific site measurement data obtained by Abushamla *et al*. (2014), which shows that the percentage of methane oxidation at Jeram sanitary landfill is 16.33%. Based on several studies, the amount of methane oxidised depends on the type of cover soil, moisture content, status of landfills (closed or still operating), and type of landfill (sanitary or open dump).

Meanwhile, the percentage of methane recovered from a landfill relies on several parameters such as landfill cover (final, intermediate, daily), gas fluxes, permeability covers, and operating vacuum pressures used to extract gas from landfills. Since there is no reported literature value for the recovery percentage in the Jeram sanitary landfill, IPCC's default value of 10-90% was applied in this study.

Mass of Waste Accepted and Waste Composition Inputs

Jeram sanitary landfill has been operating since 1 January 2007 and is expected to end on 31 December 2031. The available data from the Annual Report of MBSA, as tabulated in Table 6 shows the amount of waste accepted by the Jeram sanitary landfill from 2015 to 2022. Figure 6 illustrates the percentage of waste composition in Shah Alam city, as this data was obtained from the survey on solid waste composition, characteristics, and existing practice of solid waste recycling in Malaysia report.

Average Annual Ambient Temperature and Rainfall Inputs

The average annual ambient temperature and rainfall used in the CLEEN model have been obtained from https://climateknowledgeportal.worldbank.org/country/malaysia. The data include mean annual ambient temperature and rainfall in Selangor from 1991 to 2022, where the values are 27.42°C and 6.10 mm/d, respectively. These values are valid for a comprehensive MLR equation as the established equation for the ambient temperature range and rainfall at 25°C to 37°C and 4 mm/d to 20 mm/d, respectively.

Table 6: Waste acceptance in Jeram sanitary landfill from 2015 to 2022

Year	Waste Accepted (metric tons)
2015	110,003.94
2016	62,254.50
2017	127,050.50
2018	178,426.97
2019	169,853.89
2020	104,023.51
2021	114,503.70
2022	112,680.52

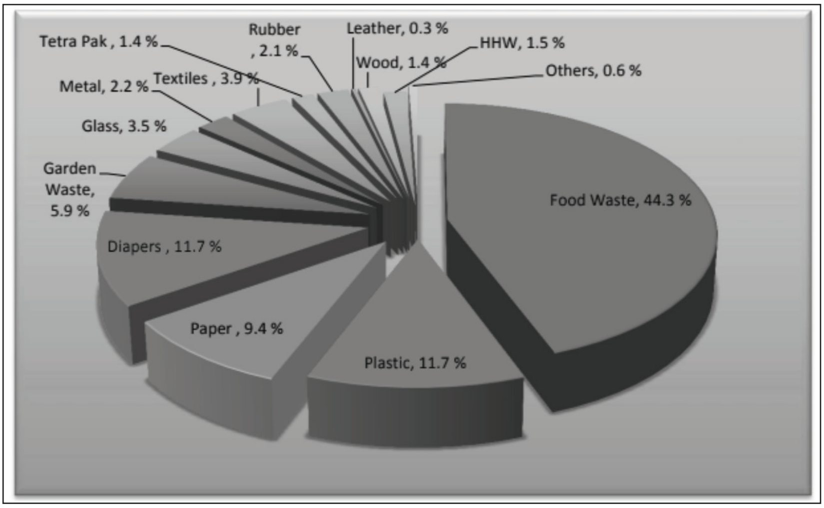


Figure 6: Percentage of waste composition in Shah Alam
Source: Survey on solid waste composition, characteristics, and existing practice of solid waste recycling in Malaysia report

Calculating Localised L_o and k Values

The characterisation of waste data, including BMP, moisture content, and total solids was utilised to calculate localised L_o. This investigation revealed that the BMP levels exceeded the cumulative methane generated in the laboratory-scale reactors. L_o is the maximum quantity of CH_4 that can be generated from a specific unit mass of waste under optimal conditions (anaerobic conditions). Thus, the weighted average of the BMP value per wet waste was utilised. This allows the adjustment of L_0 if there is a change in waste composition variation in the landfill due to the different or improved waste management procedures in the future. Table 7 displays the calculation for the final localised L_o, which is 59.38 m^3/ Mg.

The average annual ambient temperature and rainfall inserted into the MLR equation are 27.42°C and 6.10 mm/d, respectively. Meanwhile, the percentages of FW, CFW, UCFW, VW, TW, and GW are 4%, 34.3%, 1%, 5%, 3.9%, and 5.9%. The calculated k value that was obtained using the MLR equation in

Table 7: Calculation for localised L_o from waste characterisation data

Type of Waste	BMP (m^3/Mg of VS)	VS (%)	BMP (m^3/Mg of Dry Solid)	MC (%)	BMP (m^3/Mg of Wet Waste)	Waste Composition in Shah Alam (%)	Weighted Average of BMP (m^3/Mg of Wet Waste)
FW	251.64	65.80	165.58	78.94	34.87	4	1.39
CFW	328.39	73.72	242.09	67.88	77.76	34.3	26.67
UCFW	235.82	71.21	167.93	69.60	51.05	1	0.51
VW	209.12	50.22	105.02	85.94	14.77	5	0.74
PW	182.54	82.55	150.69	5.10	143.00	9.4	13.44
TW	174.02	70.44	122.58	6.32	114.83.	3.9	4.48
GW	274.94	92.99	255.67	19.43	205.99	5.9	12.15
Total							**59.38**

this study is 1.33 $y^{-1,}$ which is higher than the actual landfill scale data ($k = 0.104\ y^{-1}$, which is the average k value from wet and dry seasons) as has been found in a study conducted by Abushamala *et al*. (2014). Thus, it is needed to alter the present k value using the scale-up factor (f) formula as below:

$$f = k_{field}/k_{calculated,}$$

where k_{field} is the k value obtained from field site measurement (y^{-1}) and $k_{calculated}$ is the k value calculated using the comprehensive MLR equation (y^{-1}). Therefore, the final localised k value is 0.078 y^{-1}.

The k value or methane generation rate constant is a crucial parameter in the FOD model for estimating methane emissions from landfills. This indicates the speed at which organic waste breaks down without oxygen, producing methane. The k value is affected by various factors such as waste composition, moisture content, temperature, and the availability of oxygen (IPCC, 2019). The variability in L_o and k values among various waste types is considerably influenced by multiple factors. These encompass variations in waste composition, experimental methodologies, and landfill conditions. Heterogeneity of waste composition exhibits distinct levels of organic matter, moisture content, and lignin, all of which influence their capacity for degradation and potential for methane generation (Mbugua *et al*., 2023; Llanos-Lizcano *et al*., 2024).

Meanwhile, regarding experimental methodologies, BMP tests, which are frequently employed to assess L_o and k may differ in their configuration and length, resulting in variable outcomes. Slurry-based BMP assays could potentially provide inflated estimates of methane production when compared to solid-phase methods, which more accurately replicate landfill conditions (Casavant *et al*., 2024). Note that landfills vary in temperature, moisture, and waste compaction, affecting methane generation. Models often assume uniform conditions, which may not reflect real-world variability (Araye *et al*., 2023). Therefore, it is essential to incorporate localised L_o and k values in estimating landfill methane emissions accurately.

Comparison of Localised L_0 and k Values with Literature, IPCC, and LandGEM Default Values

The L_0 and k values obtained from this study were compared with the literature value, IPCC, and LandGEM default values as tabulated in Table 8. The result revealed that the L_0 value from the present study is lower than the field-site measurement data reported by Abushamala *et al*. (2014) and the LandGEM default value. L_0 relies significantly on waste composition. In LandGEM, this model assumes that the waste

Table 8: Comparison of k and L_0 value with literature, IPCC, and LandGEM default values

References	Notes	L_0 (m^3/Mg)	k (y^{-1})
IPCC (2006)	Wet tropical default (bulk waste)	-	0.17
LandGEM	CAA conventional landfill	170	0.05
Abushamala *et al*. (2014)	Site-specific measurement at Jeram sanitary landfill	151.7	Wet season = 0.136 Dry season = 0.072
Present study	Lab scale data	59.83	0.078

is homogeneous, making it erroneous to identify methane generated from organic content variables. In addition, default values discretely depend on variations in moisture content but do not explain the variation of waste components.

For the k value comparison, the present study found a lower value than the field-site measurement and IPCC default value, but higher than the LandGEM default value. Ambient temperature and rainfall are two main factors influencing the methane generation rate. In the LandGEM model, these factors are not accounted for in predicting the k value. Meanwhile, in the IPCC model, these two factors are not reflected in the climatic conditions of developing countries. Furthermore, compared with field-site measurement, the waste degradation rate in lab-scale measurement is faster due to the ideal optimum conditions of degradation being applied during the experiment.

Incorporating Localised L_0 and k Values to Estimate Methane Emissions

Estimating landfill methane emissions based on Shah Alam climatic conditions and waste components was quantified by incorporating localised L_0 and k values into the CLEEN model. Consequently, the prediction of methane emissions in Shah Alam landfill was also evaluated using LandGEM and IPCC models. Figure 7 compares predicted methane emissions from this study with those from the LandGEM and IPCC models.

The present study predicted the lowest methane emissions, ranging from 300.20 Mg to 2740.65 Mg from 2015 to 2027. Meanwhile, the LandGEM and IPCC models estimated more than two times higher methane emissions as the CLEEN model. The estimation of the LandGEM model ranged from 553.63 Mg to 5841.96 Mg from 2015 to 2027. The estimation of methane emission using the IPCC model is 740.12 Mg in 2015 and reached a value of 5147.11 Mg in 2027. Many researchers have discovered the

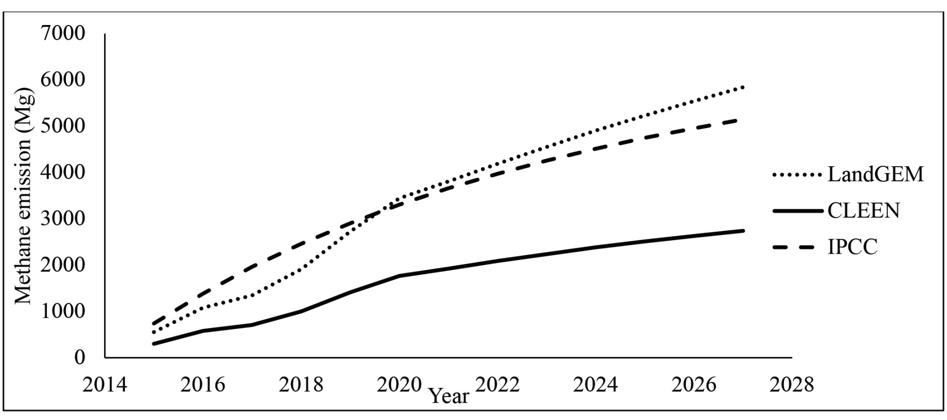


Figure 7: Comparison of methane emission estimation in this study with the LandGEM and IPCC models

same results as in current studies (Kumar *et al*., 2004; Chakraborty *et al*., 2011; Karanjekar *et al*., 2015a; Gollapalli & Kota, 2018; Ghosh *et al*., 2019).

Conclusions

Temperature is directly correlated with methane generation when evaluating the relationship between climatic conditions, waste components, and methane generation rate. For all reactors, a higher temperature, 37°C, accelerated the waste degradation process compared to reactors with a temperature of 25°C. Furthermore, rainfall substantially impacted methane production in some reactors, as higher moisture content yields more methane. However, in certain reactors such as Reactors A, B, E, G, H, and L, the most excellent moisture content resulted in a poor methane output. Regarding the effects of waste components on methane generation, the most striking result to emerge from the data is that PW shows higher methane generation than other types of waste.

The best MLR equation obtained in this study indicated that the waste degradation rate increases with increasing all IVs except for rainfall. Furthermore, this MLR model can be used to estimate methane generation in Malaysian landfills that receive rainfall in the range of 4 to 20 mm/d at ambient temperatures of 25°C to 37°C for fruit, cooked food, uncooked food, vegetables, textile, and GW at 0% to 100%. The localised values of L_o and k values calculated in this study are 59.38 m^3/Mg and 0.078 y^{-1}, respectively.

The estimation of methane emissions using localised L_o and k values from this study was compared with the estimations of the LandGEM and IPCC models. Therefore, implementing localised values led to the lowest estimation of methane emissions compared to those from both the LandGEM and IPCC models.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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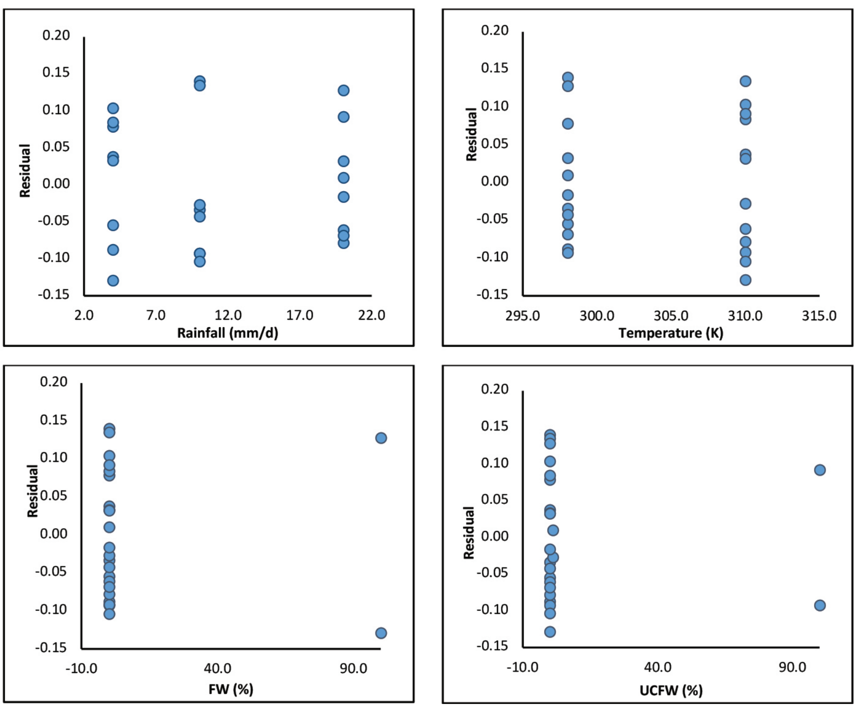
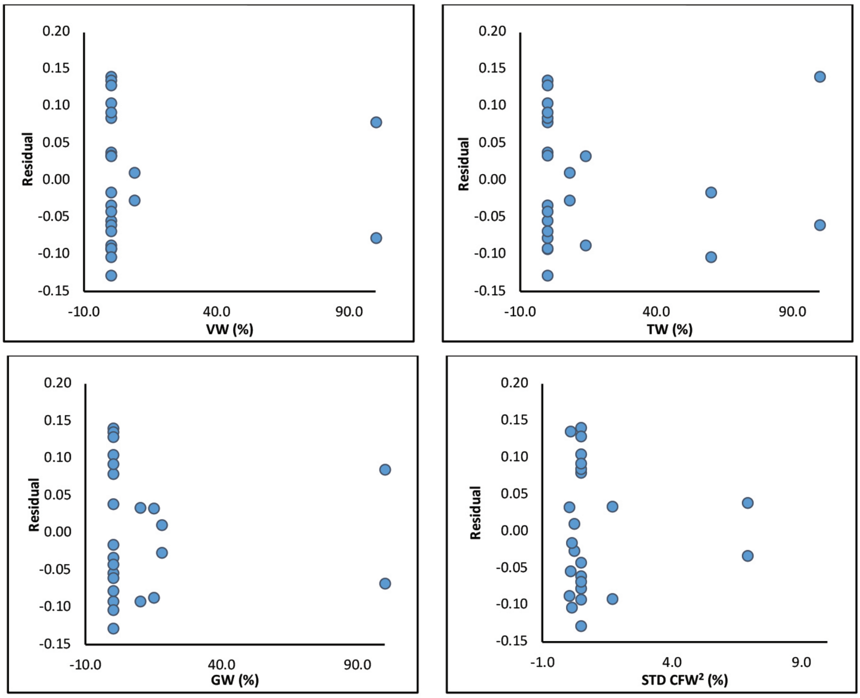
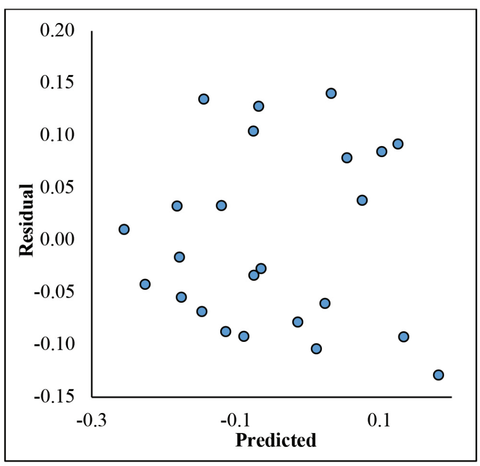
Appendices

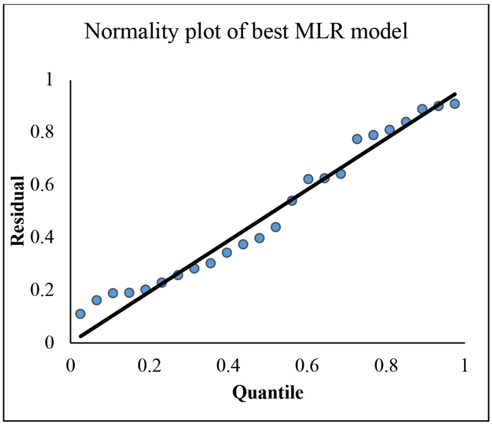




Appendix 1: Plots of residual versus IDVs for best MLR model



Appendix 2: Homoscedasticity plot for the best MLR model



Appendix 3: Normal probability plot of the best MLR model

Appendix 4: Pearson correlation for the best MLR model

	Rainfall	**Temperature**	**%FW**	**%UCFW**	**%VW**	**%TW**	**%GW**	**Std CFW²**	**Log_{10} k**
Rainfall	1	0.000	0.030	0.169	0.046	0.260	0.046	-0.234	-0.216
Temperature	0.000	1	0.000	0.000	0.000	0.000	0.000	0.000	0.313
%FW	0.030	0.000	1	-0.092	-0.100	-0.150	-0.132	-0.085	0.221
%UCFW	0.169	0.000	-0.092	1	-0.100	-0.151	-0.131	-0.087	0.370
%VW	0.046	0.000	-0.100	-0.100	1	-0.157	-0.126	-0.097	0.125
%TW	0.260	0.000	-0.150	-0.151	-0.157	1	-0.182	-0.185	0.066
%GW	0.046	0.000	-0.132	-0.131	-0.126	-0.182	1	-0.122	-0.027
Std CFW²	-0.234	.000	-0.085	-0.087	-0.097	-0.185	-0.122	1	0.120
Log_{10} k	-0.216	0.313	0.221	0.370	0.125	0.066	-.027	.120	1

Appendix 5: Collinearity statistic for the best MLR model

Independent Variables	**VIF**	**T**
Rainfall	1.220	0.820
Temperature	1.000	1.000
%FW	1.189	0.841
%UCFW	1.253	0.798
%VW	1.205	0.830
%TW	1.474	0.679
%GW	1.275	0.784
Standardised %CFW²	1.192	0.839

Appendix 6: Output for checking outliers for best MLR model

Sample	Studentised Residual (t)	Studentised Deleted Residual (t_{ii})	Cook's	Leverage/ Hat-matrix	DFFTIS
1	-1.9836	-2.2312	0.7023	0.5747	-0.2065
2	0.5324	0.5193	0.0350	0.4847	0.0426
3	1.2293	1.2524	0.2746	0.5788	0.1295
4	1.1215	1.1320	0.0356	0.1615	0.0267
5	1.3048	1.3388	0.3006	0.5721	0.1348
6	-0.9183	-0.9132	0.0200	0.1343	-0.0186
7	0.3495	0.3391	0.0025	0.1114	0.0061
8	-0.5858	-0.5726	0.0110	0.1814	-0.0155
9	-0.4669	-0.4544	0.0278	0.4926	-0.0382
10	-1.3469	-1.3879	0.2686	0.5296	-0.1229
11	-0.4442	-0.4319	0.0048	0.1378	-0.0092
12	1.8374	2.0164	0.3258	0.4232	0.1221
13	-0.2707	-0.2622	0.0010	0.0708	-0.0034
14	-0.9403	-0.9364	0.0146	0.0878	-0.0137
15	-1.1018	-1.1103	0.0329	0.1546	-0.0252
16	1.4431	1.5023	0.0569	0.1557	0.0333
17	1.9836	2.2312	0.7023	0.5747	0.2065
18	1.3476	1.3887	0.2678	0.5286	0.1226
19	-1.1838	-1.2011	0.2391	0.5639	-0.1194
20	-0.7634	-0.7522	0.0490	0.3889	-0.0456
21	-1.0050	-1.0054	0.1563	0.5404	-0.0947
22	0.1144	0.1106	0.0004	0.1746	0.0029
23	0.3574	0.3467	0.0042	0.1881	0.0098
24	-0.1717	-0.1661	0.0010	0.1900	-0.0048