Production of Biofuel by Pyrolysis of Sugarcane Bagasse and Cassava Rhizome in a Free Fall Reactor: Experimental and Modelling Approaches

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Abstract
Agricultural residues are being explored as sustainable energy sources to mitigate global warming and reduce greenhouse gas emissions. This study investigates biofuel production from a free-fall reactor using sugarcane bagasse (SCB) and cassava rhizome (CR) as feedstocks, employing both experimental and modelling approaches. Pyrolysis was conducted with varying SCB-CR blend ratios, from 400 to 650 °C, with a 30 min residence time, to analyse yields of biochar, bio-oil and biogas. Ultimate and proximate analyses were performed on feedstocks and biofuels, to determine their properties. Mathematical models for biofuel yields were developed using multi-expression programming (MEP), and validated against multilinear regression (MLR). Optimal 50:50 SCB-CR composition produced the highest bio-oil yield of 36.2%, with a heating value of 23.6 MJ/kg, at 550 °C, alongside with 16.2% biochar and 47.6% biogas. MEP models demonstrated superior accuracy, with R^2 values of 0.974, 0.917 and 0.774, for biochar, bio-oil and biogas, respectively, outperforming MLR models. Results indicate that co-pyrolysis of SCB and CR enhanced biofuel yield and quality, due to synergistic effects. Integration of experimental data with modelling provides a pathway in optimizing process parameters for large-scale biofuel production.

Keywords: biofuel; CR; modelling; MEP; pyrolysis; SCB.

Introduction•

The energy crisis around the globe has deepened, due to an over-reliance on fossil fuels for energy generation. Escalating demand for energy, driven by rapid population growth, enhanced living standards and technological progress, has led to a rise in costs associated with fossil fuels [1]. Unfortunately, usage of fossil fuels has contributed significantly to environmental degradation, manifesting in the form of greenhouse gas emissions and global warming [2]. To overcome these

•The abbreviations list is in page 197.

challenges, there has been an increased emphasis on renewable energy sources like biomass, wind, hydrothermal and solar energy [3]. Thus, there is an urgent need to explore alternative and sustainable energy sources such as biomass [4]. Biomass can be a low-cost, clean and eco-friendly energy source. Hemicellulose, cellulose and lignin are its three main constituents [5]. Conventional biomass is generally categorized into two main types: terrestrial and aquatic. Main conversion feedstocks are wood and energy crops, although their availability is seasonal and heterogeneous [6].

Sugarcane bagasse (SCB) is a fibrous residue material derived from the extraction of juice in the plant's stalk. It contains cellulose, hemicellulose and lignin, making it an excellent option for generation of renewable energy and bio-based compounds [7]. Moreover, SCB has found applications in heat and electricity generation within sugar mills, paper production, cattle feed and manufacturing of disposable food containers, due to its high calorific value [3]. Cassava is one of Nigeria's most commonly grown and economically staple crops. Nigeria is one of the major cassava producers in 2021, with approximately 63 million tons. Cassava rhizome (CR), peels, leaves and stalks are often considered residues [8]. Cassava residues are inexpensive, plentiful and renewable feedstock that can be transformed into biofuel with a high hydrocarbon content [9]. Regrettably, these residues are frequently burned in fields, wasting potential energy resources. Notably, CR can be converted into biochar, bio-oil and biogas through pyrolysis [10]. SCB and CR are high-potential biofuel feedstocks, due to their superior availability in tropical agricultural economies and relatively high heating values (16–18 MJ/kg), surpassing those of rice husk, corn stover and wood residues. Their status as low-cost agro-wastes further enhances their economic attractiveness, supporting sustainable waste valorisation and bioeconomy development [3, 8].

SCB and CR are ideal lignocellulosic feedstocks for pyrolysis, due to their high cellulose and hemicellulose content, which enhances bio-oil production. SCB's lower ash content (1-6%) compared to CR, particularly in nutrient-rich soils, makes it more efficient in pyrolysis [7, 8]. Lignin in both feedstocks contributes to increased char production and energy density [5]. In contrast to traditional biofuel feedstocks, such as wood biomass, algae and municipal waste, SCB and CR offer significant advantages. Wood biomass has stable energy yields, but is scarce in tropical regions, while algae-based biofuels require costly cultivation and harvesting [11-12]. Waste-derived biofuels are highly variable in composition and difficult to process. SCB and CR, abundant in tropical regions like Nigeria, Brazil and Thailand, provide reliable and low-cost alternatives for biofuel production without competing with food crops [3, 8].

Pyrolysis is a thermochemical process for biomass conversion in the absence of oxygen, and at temperatures ranging from 300 to 700°C. In the process of pyrolysis, thermal breakdown of biomass takes place within the reactor [13]. Thermal efficiency of pyrolysis reactors is based on design, feedstock and operating conditions. Various types of reactors have specific configurations and operating modes. Some of the commonly used reactor types include fixed and fluidized beds, vacuum, ablative systems, solar pyrolytic, plasma reactors, microwave and free-fall reactors [14, 18]. Free-fall reactors efficiently process large feedstocks, reduce residence time and ensure uniform thermal exposure, potentially boosting yields. However, they have lower heat recovery potential [19]. In contrast, although fluidized bed reactors provide better heat control and offer up to 75% efficiency, due to excellent heat and mass transfer and uniform temperature distribution [21], they use biomass with the same small particle size as feedstock. Fixed bed reactors have the simplest and robust design, but they may be inefficient with large volumes [15, 22], usually 30-50%, due to slower heat transfer and batch operation. Microwave reactors deliver quick heating, but are prone to hot spots and scaling issues [18].

Since free-fall reactors have moderate to high efficiency, ranging from 40-65%, due to rapid heating and short residence time [20], they are suitable for fast pyrolysis applications. This comparison highlights free-fall reactors as a suitable option for fast pyrolysis, where simplicity and ease of operation are prioritized, despite its lower efficiency compared to fluidized-bed systems.

Temperatures of reactors generally vary from 250 to 600 ºC, depending on biomass feedstock and envisioned output distribution (solid, liquid and gaseous products). During pyrolysis process, the biomass is transformed into pyrolytic oil (bio-oil), biochar and biogas [23]. Pyrolysis factors like temperature, heating rate and residence time affect product distribution yields in the process, which is usually carried out at atmospheric or slightly higher pressure. Pyrolysis may be classified as slow, moderate, fast, ultra-quick or flash, based on differences in temperature, heating rate, residence time and end products [24]. Efficient heat distribution enhances bio-oil yield, by enabling fast pyrolysis and minimizing secondary reactions. However, free-fall reactors often suffer from limited residence time, resulting in uneven heating and variable product quality [19].

The choice of heat source in pyrolysis significantly affects both energy efficiency and environmental impact. Although fossil fuel heating offers consistent thermal performance, it contributes heavily to greenhouse gas emissions. Solar-assisted systems are cleaner, but limited by irradiance variability, hindering continuous reactor operation [13]. Biomass-based heating supports carbon neutrality and energy self-sufficiency. However, it is constrained by feedstock inconsistency and heat recovery challenges. Electric heating enhances pyrolysis performance by ensuring rapid and uniform heating, although its sustainability is directly influenced by the source of electricity used [25].

The efficacy of combining fast and slow pyrolysis techniques to convert different biomass feedstocks such as hybrid poplar, maple, pine and SCB into bio-oil and biochar has been investigated by [19]. This process has used a free-fall reactor integrated with a batch reactor, to optimize product quality and yield. A fluidized-bed reactor was used in the study by [15], conducting fast pyrolysis on palm kernel cake, to investigate process parameters for achieving optimal bio-yield and properties. Pyrolyzed CR has been investigated by [26], employing a counter-rotating twin screw reactor unit with numerous parameters, including pyrolysis temperature, particle size and N flow rate. It has been discovered that a pyrolysis temperature of 550 °C may maximize the yield of bio-oil.

A laboratory-scale free-fall reactor has been used by [14], to pyrolyze agricultural residues from SCB and CR. They have studied the impact of biomass types and pyrolysis parameters on product distribution and their characteristics. Pyrolysis of torrefied *Acacia nilotica* in a tubular fixed-bed reactor with a N atmosphere has been studied by [27]. The authors have optimized the process by combining a central composite design with a response surface approach to maximize pyrolysis oil's yield. Characteristics of bio-oil and char produced by fast pyrolysis of CR have been investigated by [22], in a free-fall reactor, which was catalysed by the addition of several soil conditioners (or improvers). The experimentation's outcome has indicated that yields of char improved, while those of bio-oil and gas decreased.

In the study by [28], thermodynamic models have been developed to examine possibilities for biomass vaporization through pyrolysis and in-line steam reforming methods. In relation to process factors, a rigorous analysis has been conducted on yield, product composition and product selectivity of both methods. A modified vacuum reactor that transforms SCB at low temperatures into gas products has been built by [13]. Experimental approach has considered the effects of pyrolysis duration, temperature and current application as a function of an electromagnetic field. A thermosyphon-fixed bed reactor has also been built by [10], to explore temperature distribution and characteristics of torrefied char in five distinct configurations, using CR as feedstock. The use of thermosyphons in conjunction with a fixed bed reactor enhanced temperature uniformity.

Sweeping gas flow rate, heating rate, process temperature, retention time and particle size have been highlighted, by [21], as key factors influencing product yield and properties such as viscosity, heating value, acidity and chemical composition. Optimizing these parameters holds potential to significantly impact reactor scaling, system economy and efficiency [29].

Many researchers have successfully employed response surface methodology, a versatile statistical tool known for its efficacy, time efficiency and energy savings in optimizing various engineering processes [30]. However, a mathematical model is needed to uncover complex relationships between pyrolysis parameters and biofuel yields. The utilization of machine learning is essential for tackling issues associated with valorisation of agricultural residues, since it is able to handle intricate, nonlinear and multiobjective tasks [31]. It has benefits above traditional statistical models in terms of its capability to learn from historical data, recognize trends and generate accurate forecasts. The utilization of multi-expression programming (MEP) in this study is warranted, due to its ability to build interpretable mathematical expressions that explicitly illustrate the relationship between independent and dependent variables, unlike black-box models (such as artificial neural network, random forest, support vector machine) [32].

The effective utilization of biomass faces challenges due to a lack of appropriate technologies to convert biomass into valuable products, and weak government policies that hinder harnessing potential benefits of these solid residues [33]. To overcome these challenges, it is imperative to develop a pyrolysis reactor that is capable of efficiently converting solid residues into valuable bio-products, which

might consequently address both energy crisis and waste management issues in developing countries.
The motivation for this research stems from the escalating energy demand and incessant rise in fossil fuel costs. Africa produces around 5% of the world's sugarcane, with Sub-Saharan African countries accounting for 30% of the continent’s production. Concurrently, there has been a significant increase in sugarcane cultivation, leading to a surplus of waste material [33]. Addressing the challenges of energy scarcity and waste management constitutes the primary driving force behind this study.
This research aimed to produce biofuels through pyrolysis of SCB and CR in a free-fall reactor. The goals of this study included: assess the impact of varying the ratio of SCB to CR mixtures on the yield of biofuels; characterize biochar, bio-oil and biogas yield under desired conditions, using ASTM D3172; and develop mathematical models for yields of biofuel, using MEP. The comprehensive analysis of this study contributed to existing research by reducing waste from agriculture residues to valuable energy resources, by investigating free-fall reactor systems, to maximize bio-oil output and facilitate effective thermal breakdown. In addition, it facilitates the valorisation of waste, so as to align with circular economy and Sustainable Development Goal 7: Affordable and Clean Energy targets.

Methodology

Sample collection and preparation

CR was collected from TJ International Farm, at Konta Ijabe, Osun State, while SCB was obtained from a farm near Bacita Sugar Company, in Kwara State, Nigeria. Feedstocks were washed with water to remove impurities, and sun-dried for 7 days. Dried materials were grounded and sieved to 1 mm particle size [19]. Proximate and ultimate analyses of raw CR and SCB feedstocks (Table 1) were conducted in accordance with ASTM D3176 and D3172, respectively. SCB and CR have a higher volatile matter content of 77.09 and 72.56% respectively, which indicate greater potential for bio-oil production [14]. Also, CR, with its higher fixed carbon content (13.15%), when compared with SCB, may yield more biochar [34]. Ash content, which is slightly higher in CR (6.37%) than in SCB (5.55%), can affect product quality and reactor performance. Elevated ash levels are known to reduce liquid yields, and complicate reactor operation, due to slagging and fouling [8]. SCB and CR have lower moisture content, which is beneficial, since excessive moisture reduces thermal efficiency [25]. From ultimate analysis, both feedstocks exhibit relatively high C (46.75–48.01%) and H (6.4–6.6%) contents, which are favourable for high-energy yield during pyrolysis [34]. Lower heating value (LHV) of CR (12.5 MJ/kg) and SCB (18.2 MJ/kg) highlights the higher energetic potential from these feedstocks. Although biomass feedstocks have lower energy density than that from conventional fossil fuels, due to lower C and higher O contents, their renewability and carbon neutrality offer significant advantages for sustainable pyrolysis [19].

Table 1: Proximate and ultimate analyses of biomass feedstocks on a dry basis.

Analysis	% wt	CR	SCB
Proximate	Moisture	7.92	5.91
	Fixed carbon	13.15	11.45
	Ash	6.37	5.55
	Volatile matter	72.56	77.09
Ultimate	LHV (MJ/kg)	12.5	18.2
	C	48.01	46.75
	H	6.4	6.6
	N	0.97	0.56
	O	44.62	46.09

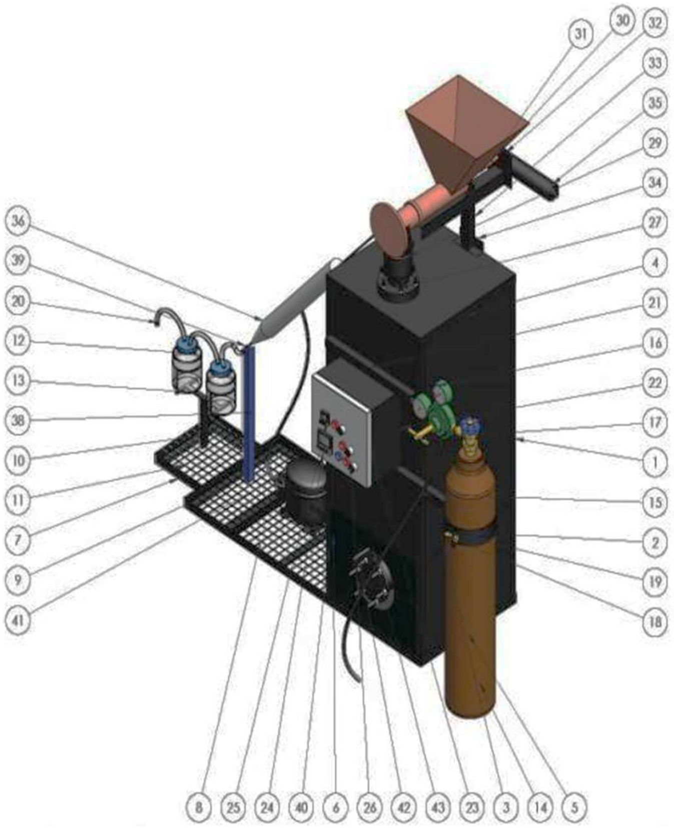
Experimental setup and operational procedures

Biomass feedstocks were converted into biochar, bio-oil and biogas by thermochemical processes, using a locally available free-fall reactor. The reactor operated within a temperature range from 450 to 600 °C, with increments of 50 °C for each experimental run. N gas was supplied at a constant flow rate of 7 g/min throughout experiments [3] Mixed ratios of SCB and CR, along with corresponding temperatures used in the free-fall reactor, are presented in Table 2.

Table 2: Composition of feedstocks and their temperatures for pyrolysis.

Run	SCB (%)	CR (%)	Temperature (°C)
1	100	0	450
2	100	0	500
3	100	0	550
4	100	0	600
5	75	25	450
6	75	25	500
7	75	25	550
8	75	25	600
9	50	50	450
10	50	50	500
11	50	50	550
12	50	50	600
13	25	75	450
14	25	75	500
15	25	75	550
16	25	75	600
17	0	100	450
18	0	100	500
19	0	100	550
20	0	100	600

In order to investigate pyrolysis of SCB and CR, and evaluate resulting bio-oil, char and gas yields, a total of 20 experimental runs were carried out. Pyrolysis occurred in the reactor at temperatures ranging from 450 to 600 °C, for 30 min, to generate vapours and solids. Vapours underwent rapid cooling and condensation in a condenser, held at roughly 5 °C, with the aid of an external chiller, and bio-oil was collected in a container. Bio-gas sensors that detect CH4, CO, O2 and CO were attached to the outlet hose of the assembly unit. Bio char and oil were subjected to proximate analysis, following ASTM E 1755-01 standard. C, H, N and S content in char and bio-oil were analysed using a Leco TruSpec Micro CHNS analyser for elemental evaluation. Heating value was determined by an oxygen bomb calorimeter. The free-fall reactor used for experimental runs is shown in Fig. 1.



ITEM NO.	PART NUMBER	QTY.
1	Angle Iron 1750mm H	4
2	1.5mm Thick SS 1110mm(W) x 797mm (H)	4
3	1.5mm Thick SS 797mm(W) x 640mm (H) Side Flange	2
4	1.5mm Thick SS 804mm(W) x 804mm (H) Top Flange	1
5	Base Frame	1
6	1.5mm Thick SS 800mm(H) Angle Iron-Brazing	3
7	Base Frame - Center	1
8	1.5mm Thick SS 1197mm(L) Square Rod	15
9	1.5mm Thick SS 804mm(L) Square Rod	23
10	1.5mm Thick SS 500mm(L) Square Rod	7
11	1.5mm Thick SS 400mm(L) Square Rod	9
12	Bottle Stand	1
13	Assembly of Bio-Products Bottles	2
14	Nitrogen Gas Compartment Full Assembly	1
15	1.5mm Thick SS 500mm(H) Angle Iron	1
16	Nitrogen Gas Cylinder Knob-2	1
17	Nitrogen Gas Cylinder Knob-3	1
18	ISO 7412 - M24 x 65 --- 41-WN	2
19	ISO - 4034 - M24 - N	2
20	ISO - 4034 - M20 - N	6
21	1mm thick-Hose 1	2
22	1.5mm Thick SS 800mm(H) Angle Iron	1
23	1.5mm Thick SS 470mm(W) x 470mm (H) Electrical Panel	1
24	1.5mm Thick SS 470mm(W) x 470mm (H) Electrical Panel - Door	1
25	Electrical Panel Led Screen 1	1
26	Electrical Panel Led Screen 2	1
27	Electrical Panel Knob	3
28	Hollow Top Lid	1
29	ISO 7041-M16-N	6
30	Part Mounted on Hollow Top Lid	1
31	Part Mounted on Hollow Top Lid - 1	1
32	1.5mm Thick SS 600mm(H) Angle Iron - Top Part	1
33	1.5mm Thick SS 200mm(W) x 300mm (H) Base Flange	1
34	1.5mm Thick SS 381mm(H) Flange Iron	1
35	1.5mm Thick SS 200mm(H) Angle Iron	1
36	Exhaust	1
37	Cladding Chamber	1
38	Tab 797mm(L) x 797mm(B)	1
39	Cladding Chamber Holder	1
40	Cladding Chamber Holder Pipe Slot 1	1
41	Condenser	1
42	FR7.5G Compressor	1
43	Part mounted at the front (Close to cylinder)	1
44	Tab 581mm(L) x 581mm(B)	1

Figure 1: Free-fall reactor components.

Mathematical models for biofuel yields using MEP

MEP belongs to the family of evolutionary artificial intelligence algorithms that use genetic strings to encode complex computer programs. It is designed to build mathematical expressions that reflect the specified database [35]. This evolutionary approach evolves numerous solutions in each chromosome, among which the optimal solution is selected. This is characterized as intrinsic parallelism, which is a distinct property of MEP [36].

The population of computer programs is randomly created at the start of an MEP algorithm [37]. Each gene in an MEP program encoded terminal and function sets. In MEP, genes are organized as sequential expressions, and their number is determined by fixed chromosome length, which remains unchanged during computation process [38].

Optimal computer programs for representing chromosomes are chosen by evaluating fitness values of various solutions [39]. A binary tournament approach is applied to select two parents for recombination with an even crossover probability. This recombination results in two individuals. The best individual in existing population replaces the worst one, after mutations occur. Best computer programs are created by repeating these processes iteratively, until the termination requirement is met [40].

Multilinear regression

Multilinear regression (MLR) is a basic statistical approach for predicting dependent variables via its linear association with various independent variables. This approach applies the concept of simple linear regression for models with multiple independent variables [41]. The relationship between multiple independent variables and dependent variables is presented in Eq. (1). MLR was considered in this study, due to its ability to generate mathematical models that show the relationship between dependent and independent variables. However, its weakness lies in its inability to solve complex and nonlinear problems [42].

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1)$$

Herein, MLR model was developed by using MATLAB (R2023b) as programming language to write codes. The training set was learned using '*fitlm*' function. The learned model was applied to the testing set to generalize the model using '*predict*' function.

Results and discussion

Product yields via experimental analysis

Experimental data and corresponding biofuels for each run are presented in Table 3.

Table 3: Experimental data and products yields.

Run	SCB (%)	CR (%)	T (°C)	BC yield (%)	BO yield (%)	BG yield (%)
1	100	0	450	25.1	28.2	46.7
2	100	0	500	22.2	34.4	43.4
3	100	0	550	18.6	28.7	52.7
4	100	0	600	16.7	23.5	59.8
5	75	25	450	22.6	31.2	46.2
6	75	25	500	20.3	31.2	48.5
7	75	25	550	17.6	33.3	49.1
8	75	25	600	16.2	26.7	57.1
9	50	50	450	20.1	32.8	47.1
10	50	50	500	18.7	35.3	46
11	50	50	550	16.2	36.2	47.6
12	50	50	600	14.4	34.3	51.3
13	25	75	450	20.6	27.4	52
14	25	75	500	17.1	29.9	53
15	25	75	550	15.9	29.9	54.2
16	25	75	600	15.2	32.1	52.7
17	0	100	450	15.2	34.2	50.6
18	0	100	500	15.1	35.7	49.2
19	0	100	550	14.5	34.8	50.7
20	0	100	600	13.7	33.7	52.6

Optimum yield of resulting bio-oil, at Run 11, was 36.2%. Corresponding yields of biochar and biogas, at 550 ºC, were 16.2 and 47.6%, respectively. Thus, a 50:50 blend ratio of SCB and CR was most favourable for bio-oil production, at a temperature of 550 ºC, due to its higher yield.

Minimum, maximum, range, mean, median, standard deviation (SD), coefficient of variation (COV), kurtosis and skewness are presented in Table 4, for statistical analysis of data obtained during experimental runs.

Table 4: Statistical analysis of data from experimental runs.

Variables	SCB	CR	Temperature	BC yield	BO yield	BG yield
Minimum	0.00	0.00	450.00	13.70	23.50	43.40
Maximum	100.00	100.00	600.00	25.10	36.20	59.80
Range	100.00	100.00	150.00	11.40	12.70	16.40
Mean	50.00	50.00	525.00	17.80	31.68	50.53
Median	50.00	50.00	525.00	16.90	32.45	50.65
SD	36.27	36.27	57.35	3.14	3.45	3.96
COV	0.73	0.73	0.11	0.18	0.11	0.08
Kurtosis	-1.32	-1.32	-1.40	-0.12	-0.08	0.38
Skewness	0.00	0.00	0.00	0.73	-0.69	0.44

Proximate and ultimate analyses of biochar and bio-oils for base feedstocks, and proportion of feedstock (50:50) with higher yields of bio-oil are presented in Table 5. Elemental composition of bio-oils reveals that previous research [14, 19] values for C (53-65%), H (3.9-6.5%), N (0.4-0.8%) and O (32-38%) are consistent with the results of this study. Elemental compositions of biochar found in the studies of [16, 19, 36]. were C (45-65%), H (2-7%), N (0.3-2.0%) and O (4-35%), which were compatible with the findings of the present study. It is evident from results that O/C and H/C ratios of bio-oil are comparable, varying within 0.5 from 0.7, for O/C and from 0.06 to 0.2, for H/C. Bio-oil derived from feedstocks with a composition of 50:50 exhibits the lowest O/C ratio, and the highest heating value of 23.6 MJ/kg among other bio-oils. This lower O/C ratio indicates reduced O content, which improves bio-oil's calorific value or energy content [19]. Consequently, additional processing and refining, such as catalytic cracking and hydrodeoxygenation, are necessary to make the bio-oil suitable for use as a transportation fuel in conventional combustion engines.

Table 5: Proximate and ultimate analysis of biofuel samples for composition with higher bio-oil yield, at 0:100 and 100:0 compositions.

Composition of feedstock (SCB:CR) (%)	Biofuel	Proximate analysis AC (%)	FC (%)	VM (%)	Ultimate analysis C (%)	H (%)	N (%)	O (%)	O/C	H/C	HHV (MJ/kg)
50-50	Biochar	9.34	21.06	67.52	62.83	4.04	1.30	31.53	0.50	0.064	20.7
	Bio-oil	1.85	10.51	67.87	57.82	5.02	1.01	33.05	0.57	0.087	23.6
0-100	Biochar	7.77	15.07	4.77	59.01	5.45	1.70	33.84	0.57	0.107	18.3
	Bio-oil	1.28	7.17	4.77	55.98	6.32	1.72	35.98	0.64	0.113	22.4
100-0	Biochar	11.62	18.45	65.11	57.57	5.40	1.18	34.49	0.60	0.009	19.5
	Bio-oil	0.22	8.86	65.62	52.45	6.74	1.94	35.45	0.67	0.129	21.3

Effect of reactor temperature on the product yields

The reactor temperature during pyrolysis process is a critical parameter that significantly influences product distribution of biochar, bio-oil and biogas. By varying pyrolysis temperature, experimental runs aimed to explore effects on product yields and identify optimal temperature range for maximizing bio-oil production. Fig. 1 shows the relationship between product yields and temperature of each biomass composition.

In Fig. 2(a), the effect of temperature on bio-oil yield, when using 100% SCB as feedstock, demonstrates that, as pyrolysis temperature increased, bio-oil yield exhibited a non-linear trend. At lower temperatures, bio-oil yield was relatively low, but it gradually increased with higher temperatures. Bio-oil yield reached its peak from 450 to 550 °C. Beyond this range, it started to decline, due to secondary reactions that favour production of char and gas. Also, there was an intriguing relationship between reactor temperature and biochar yield. As temperature increased, char yield displayed a declining trend. Higher temperatures promoted more extensive thermal breakdown of SCB components, leading to a reduction in the proportion of solid residue remaining as char. Moreover, as temperature increased, bio-gas yield revealed a consistent upward trend. Enhanced thermal decomposition of SCB components at higher temperatures resulted in higher biogas yield.

The effect of temperature on bio-oil yield, for a blend of 75% SCB and 25% CR as feedstock, is illustrated in Fig. 2(b). The plot shows a similar trend as in Fig. 2(a), with an increasing bio-oil yield as the temperature rises. The presence of CR in the blend probably enhances overall bio-oil yield compared to 100% SCB alone. Thermal decomposition of SCB and CR components at elevated temperatures resulted in reduced char formation. As the reactor temperature increased, biogas yields also showed a gradual rise.

The impact of temperature on bio-oil yield, for a blend of 50% each SCB and CR as feedstock, is depicted in Fig. 2(c). Bio-oil yield follows a similar pattern as seen in previous graphs, but its optimal value of 36.2%, at 550 °C, was observed during pyrolysis process. Biochar yield decreased as temperature increased from 450 to 600 °C, due to gradual disintegration of organic matter. Also, as temperature increased, biogas yield showed a significant increase, due to secondary cracking of char and pyrolysis vapour [43].

Fig. 2(d) shows the effect of temperature on biofuel yield, for a blend of 25% SCB and 75% CR as feedstock. Bio-oil yield shows an increasing trend with rising temperature, reaching its peak at 600 °C. Biochar yield decreased with increasing reactor temperature. Data suggest that CR, with its unique chemical composition, significantly influenced char production, even at lower temperatures. Biogas yield increased with rising reactor temperature, until it reached a saturation point, resulting in a stable yield. In the case of 100% CR as feedstock, biochar and biogas yield decreased and increased, respectively, as the reactor's temperature increased (Fig. 2(e)). This behaviour can be attributed to the specific chemical composition of CR, where certain components might undergo different thermal degradation mechanisms, leading to variations in char formation.

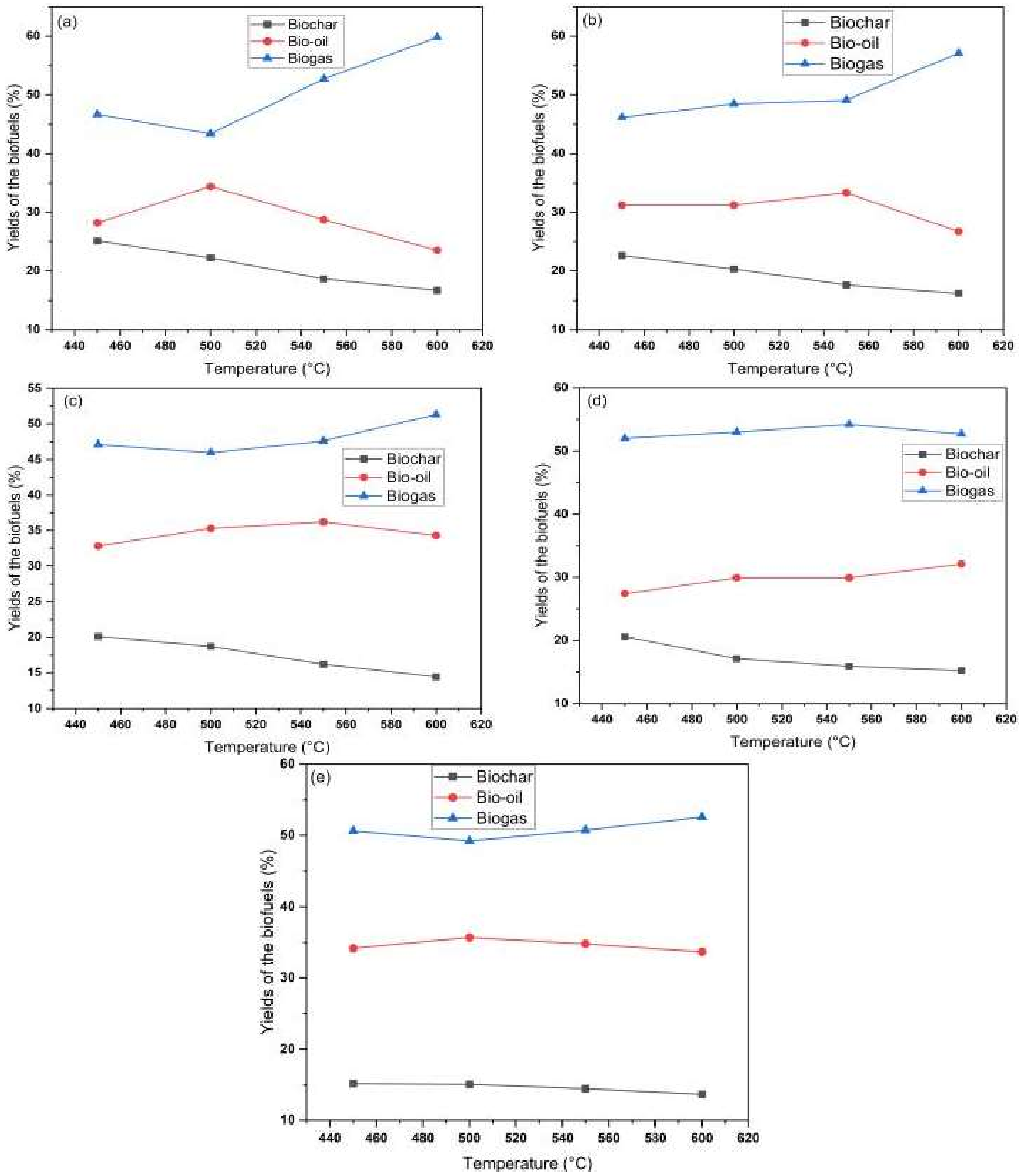


Figure 2: Effects of temperature on the yields of biochar, bio-oil and biogas for SCB and CR, at the ratios of **(a)**100:0, **(b)**75:25, **(c)** 50:50, **(d)** 25:75 and **(e)** 0:100.

Results showed that bio-oil yields from co-pyrolysis of SCB and CR were higher than those obtained from pyrolysis of SCB or CR alone. Lower O/C ratio observed in 50:50 blend of feedstocks indicates reduced O content, which enhances energy content of bio-oil. These findings demonstrate that co-pyrolysis of SCB and CR improves biofuel's yield and quality, due to synergistic effects.

Gas compositions
Changes in biomass composition had a relatively minor impact on percentage of biogas generated during pyrolysis. Across different compositions, biogas yield remained relatively stable, indicating that other factors, such as reactor temperature and heating rate, might play a more substantial role in determining gas production.

It is important to note that the presence of both SCB and CR in the feedstock blend contributed to the gas composition diversity. Varying the chemical composition of the two biomass components can lead to production of different gas species during pyrolysis, including CO, CO_2, CH_4 and other volatile organic compounds. Biogas yield was low, due to incomplete volatilization of biomass at lower temperatures. CO yield for 100:0, 50:50 and 0:100 of SCB and CR was 1.5, 1.2 and 1.4 ppm, respectively. Higher proportions of CH_4 (Fig. 3) were produced, due to thermal decomposition of lignin and secondary tar cracking [44]. The 50:50 blend of SCB and CR yielded the higher composition of CH_4 and the lowest composition of CO_2, which potentially made it more suitable as a fuel [45].

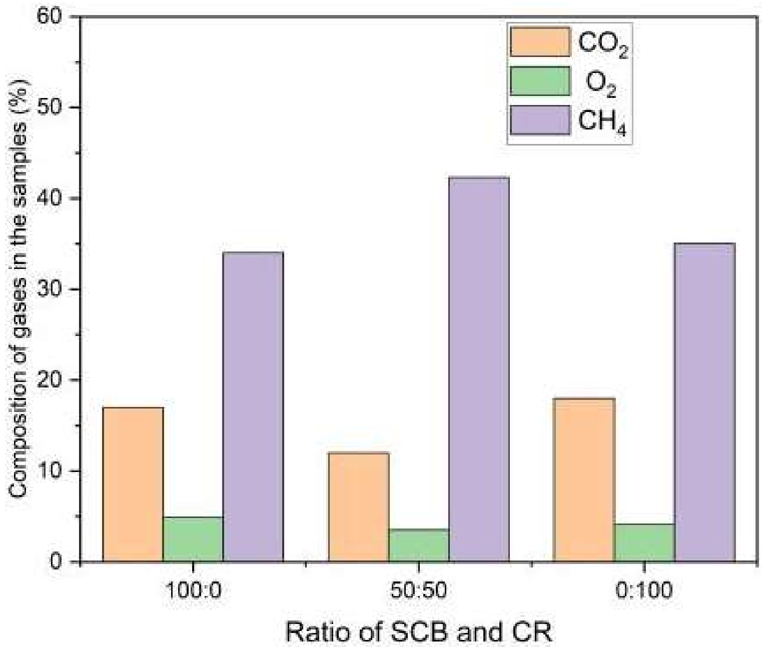


Figure 3: Compositions of biogas for SCB and CR feedstocks at different proportions.

MEP model

In this study, MEPX (an open-source software) was used to develop MEP model that was built using parameters provided in Table 6, which were established by trial and error technique.

Table 6: Parameters used for training MEP model.

Parameters	Values
Function set	$+,-,\times,\div,\wedge$
Terminal set	$x_0, x_1, x_2, rand$
Fitness function	MSE
Generation	2000
Number of subpopulation	10
Subpopulation size	1500
Crossover rate	0.9
Mutation rate	0.01
Tournament size	2
Code length	80

This method was also applied to generate random numbers ranging from -10 to +10. This range was selected to increase diversification and reduce numerical volatility in mathematical modelling, which can cause overflow or underflow during simulation. Experimental data were divided into training and testing sets, at the ratio of 75:25, respectively. This was crucial to minimize overfitting, and ensure that the model effectively generalized to unseen data, as it was tested on data not utilized during training. To ensure better generalization, performance of training and testing datasets was analysed.

Results of developed MEP model for estimating biofuel yields, which includes three input variables are presented in Eqs. (2-4). Built MEP models illustrate the correlation between input factors (temperature (x_0) and proportion of SCB $(x1)$ and CR $(x1)$ and output variables (biochar, bio-oil and biogas yields). Developed MEP models revealed interpretable mathematical expressions that explicitly illustrate the relationship between input and output variables. These models can be used to predict biofuel yields for an environmentally sustainable and economically circular economy, resulting in cost and resource savings. The mathematical model for estimating biochar yields is presented in Eq. (2). Table 7 reveals error differences between experimental and MEP predicted data of biofuel yields. These values are in good agreement with experimental data.

Table 7: Experimental data *vs.* MEP predicted data of biofuel yields.

Biochar yield (%)			Bio-oil yield (%)			Biogas yield (%)		
Actual	**Predicted**	**Error**	**Actual**	**Predicted**	**Error**	**Actual**	**Predicted**	**Error**
25.1	25.114	-0.014	28.2	28.180	0.020	46.7	46.673	0.027
22.2	22.208	-0.008	34.4	34.477	-0.077	43.4	48.445	-5.045
18.6	18.906	-0.306	28.7	28.691	0.009	52.7	50.682	2.018
16.7	16.658	0.042	23.5	23.409	0.091	59.8	59.802	-0.002
22.6	22.018	0.582	31.2	31.288	-0.088	46.2	46.430	-0.230
20.3	20.302	-0.002	31.2	31.206	-0.006	48.5	48.204	0.296
17.6	17.600	0.000	33.3	33.304	-0.004	49.1	50.432	-1.332
16.2	16.193	0.007	26.7	27.048	-0.348	57.1	57.101	-0.001
20.1	20.100	0.000	32.8	33.732	-0.932	47.1	44.943	2.157
18.7	17.907	0.793	35.3	33.795	1.505	46.0	46.417	-0.417
16.2	16.051	0.149	36.2	33.912	2.288	47.6	48.072	-0.472
14.4	14.399	0.001	34.3	34.189	0.111	51.3	51.300	0.000
20.6	20.609	-0.009	27.4	27.529	-0.129	52.0	52.000	0.000
15.9	16.005	-0.105	29.9	29.808	0.092	53.0	52.629	0.371
15.2	15.213	-0.013	29.9	30.481	-0.581	54.2	53.636	0.564
15.2	16.197	-0.997	32.1	32.071	0.029	52.7	55.359	-2.659
15.1	15.094	0.006	34.2	34.246	-0.046	50.6	47.759	2.841
14.5	14.455	0.045	35.7	34.348	1.352	49.2	49.218	-0.018
17.1	17.097	0.003	34.8	34.430	0.370	50.7	50.698	0.002
13.7	13.743	-0.043	33.7	34.495	-0.795	52.6	52.264	0.336

$$BC = f + e - \left(\frac{{x_2}^2 - 18735.6112 + 2x_0 + 9.83806x_2}{9367.8056x_2 - \left(b\left(ax_2 + 2(x_1 - x_0)(9367.8056 - x_0 - 9.83806x_2)\right)\right)}\right) + \left(\frac{x_1x_2 - 86.9494x_2 + {x_2}^2 - 18735.6112 + 2x_0}{9367.8056x_2}\right) \quad (2)$$

where

$$a = \frac{(x_1 - x_0)(9367.8056 - x_0 - 9.83806x_2) - x_1x_2 - x_2{}^2 + 9367.8056 - x_0 - 9.83806x_2}{x_2} \quad (2.1)$$

$$b = \frac{2(x_1 - x_0)(9367.8056 - x_0 - 9.83806x_2)^2}{x_2(x_0x_1x_2 + 9464.593x_2 - 9.83806x_2{}^2)} \quad (2.2)$$

$$c = \frac{x_2{}^2(x_0 + x_0x_1 + 96.7874)}{6.90283(9357.96754 - x_0)(9357.96754 - x_0 - 9.83806x_2)} + \frac{b\big(ax_2 + 2(x_1 - x_o)(9367.8056 - x_0 - 9.83806x_2)\big)}{x_2} \quad (2.3)$$

$$d = \frac{9367.8056 - x_0 - bx_2}{x_2} - \frac{x_0x_1x_2}{6.90283x_2 - x_2{}^2 - 2(x_1 - x_0)(9367.8056 - x_0 - 9.83806x_2)} \quad (2.4)$$

$$e = \frac{\frac{2x_0x_2 + a(9367.8056 - x_0 - bx_2)}{ax_2} + dx_2}{bx_2 + (x_1 - x_0)(9367.8056 - x_0 - 9.83806x_2) + x_2{}^2 + 9.83806x_2 + x_2(x_1 - x_0)} \quad (2.5)$$

$$f = \frac{x_2{}^2 - 9367.8056 + x_0 + 9.83806x_2 + 2(x_1 - x_0)(9367.805 - x_0 - 9.83806x_2)}{(c - x_1)(x_2(x_1 - x_0) + 9367.8056 - x_0)} \quad (2.6)$$

Bio-oil yield, as developed from MEP model, is formulated as presented in Eq. (3).

$$BO = -2.953869^{x_0} + 31.9866 - 0.79365^{x_1}(a_1) + \frac{2x_1 + 69.6289}{4.48861(11.31134x_0 + 2x_1 - x_2)} + \frac{31.9866 - x_0}{b_1} + \frac{4.48861 + x_1 + a_1(0.79365^{x_1})}{c_1} \quad (3)$$

where

$$a_1 = \frac{31.9866 + x_2}{x_0{}^{d_1} + 6.65567x_0 - x_2 + 2x_1} + \frac{2x_1 + 69.6289}{11.31134x_0 + 2x_1 - x_2} \quad (3.1)$$

$$b_1 = 4.65567x_0 - x_2 - 2x_1 - \frac{x_1(31.9866 + x_2)}{x_0{}^{d_1} + 6.65567x_0 - x_2 + 2x_1} \quad (3.2)$$

$$c_1 = 13.31134x_0 + 4x_1 - x_2 + \frac{x_1(31.9866 + x_2)}{x_0{}^{d_1} + 6.65567x_0 - x_2 + 2x_1} \quad (3.3)$$

$$d_1 = \frac{5.65567x_0 - x_2}{31.9866 - x_1} \quad (3.4)$$

The mathematical model for biogas yields, as formulated from MEP model, is provided in Eq. (4).

$$BG = \frac{36.2993x_2}{(x_1 - b_2)(x_2 - 2.88776)} + 33.3566 + \frac{x_2 - 8.91265}{33.3566} - \frac{a_2}{36.2993b_2} - \frac{22.1021x_0 + 133.4266 + 23.1021a_2}{23.1021(-6.02489x_1 + x_2 - 5.77552x_0 - 33.3566)} \quad (4)$$

where

$$a_2 = \left(\frac{x_0x_1(x_2 - 2.88776)}{66.7133x_2}\right)^{0.015x_0} \quad (4.1)$$

$$b_2 = 47.71303 - \frac{x_2 - 8.91265}{33.3566} + \frac{36.2993x_2}{x_2 - 2.88776} \quad (4.2)$$

Performance of MEP and MLR models

MEP model was validated via comparative analysis with MLR, in terms of evaluation metrics. MLR model developed three different mathematical equations for biochar, bio-oil and biogas yields, as presented in Eqs. (5-7).

$$BC = 0.41874x_1 + 0.36845x_2 - 0.040511x_3 \tag{5}$$

$$BO = 0.34085x_1 + 0.38856x_2 - 0.0092189x_3 \tag{6}$$

$$BG = 0.24041x_1 + 0.243x_2 + 0.04973x_3 \tag{7}$$

The performance of developed models for biofuel is determined in terms of accuracy and effectiveness using root mean square error (RMSE- Eq. 8), mean absolute error (MAE- Eq. 9) and mean absolute percentage error (MAPE) (Eq. 10). Performance of developed MEP models is presented in Table 8.

Table 8: Evaluation metrics for MEP and MLR models.

Model	Yields	RMSE		MAE		MAPE (%)	
		Training	Testing	Training	Testing	Training	Testing
MEP	Biochar	0.186	1.095	0.112	0.867	0.608	5.256
	Bio-oil	0.645	1.025	0.423	0.505	1.277	1.416
	Biogas	1.626	1.585	0.857	1.186	1.817	2.327
MLR	Biochar	0.875	1.674	0.722	1.249	4.176	7.706
	Bio-oil	3.090	2.583	2.490	1.769	8.327	5.323
	Biogas	3.045	3.091	2.392	2.667	4.680	5.289

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \acute{y}_i)^2} \tag{8}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \acute{y}_i| \tag{9}$$

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \acute{y}_i}{y_i}\right| \tag{10}$$

where ȳ is mean value of the actual values of the biofuel yields, y_i is actual value, `y is predicted value and N is total number of data points. where, $\bar{y}$ is the actual value, y_i is the actual value, $\acute{y}_i$ is the predicted value, and N is the total number of data points. R^2 plots for MEP and MLR models in terms of training and testing set for biochar yields, bio-oil and biogas are presented in Fig. 4. R^2 values for training and testing set of MEP model for biochar yields are 0.997 and 0.974, respectively. R^2 values for training and testing set of MLR model for biochar yields are 0.925 and 0.820, respectively.

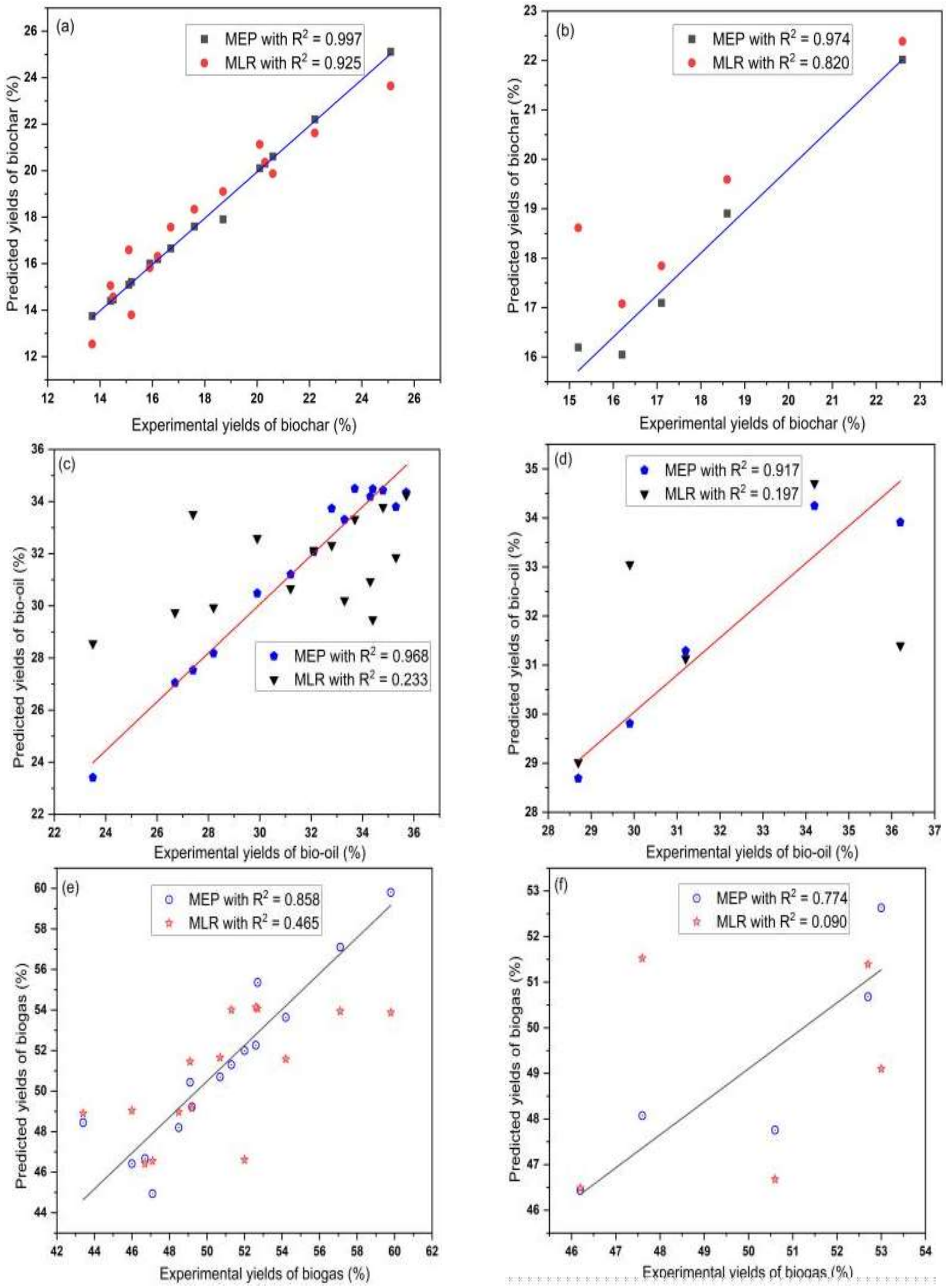


Figure 4: R^2 plots of MEP and MLR models for - **(a)** training set of biochar yield, **(b)** testing set of biochar yield, **(c)** training set of bio-oil yield, **(d)** testing set of bio-oil yield, **(e)** training set of biogas yield and **(f)** testing set of biogas yield.

Parametric and sensitivity analyses

Parametric analysis was conducted in this study to determine the relationship between each input variable and output variables. This was done by varying one of the input variables within its minimum and maximum values, and keeping other input variables constant at their respective average value, as indicated in Table 4. This process was applied to each input variable, and plots that revealed the relationship for each input variable and output variables are presented in Fig. 5. Increasing pyrolysis temperature from 450 to 600 °C results in reduced biochar yield (Fig. 5(a)), due to enhanced thermal degradation of biomass and diminished solid residue formation [24]. In contrast, bio-oil and biogas yields increase as elevated temperatures favour breakdown of cellulose and hemicellulose into condensable volatiles and permanent gases. Lignin, which decomposes over a broader temperature range, contributes more to char formation at lower temperatures [19, 25].

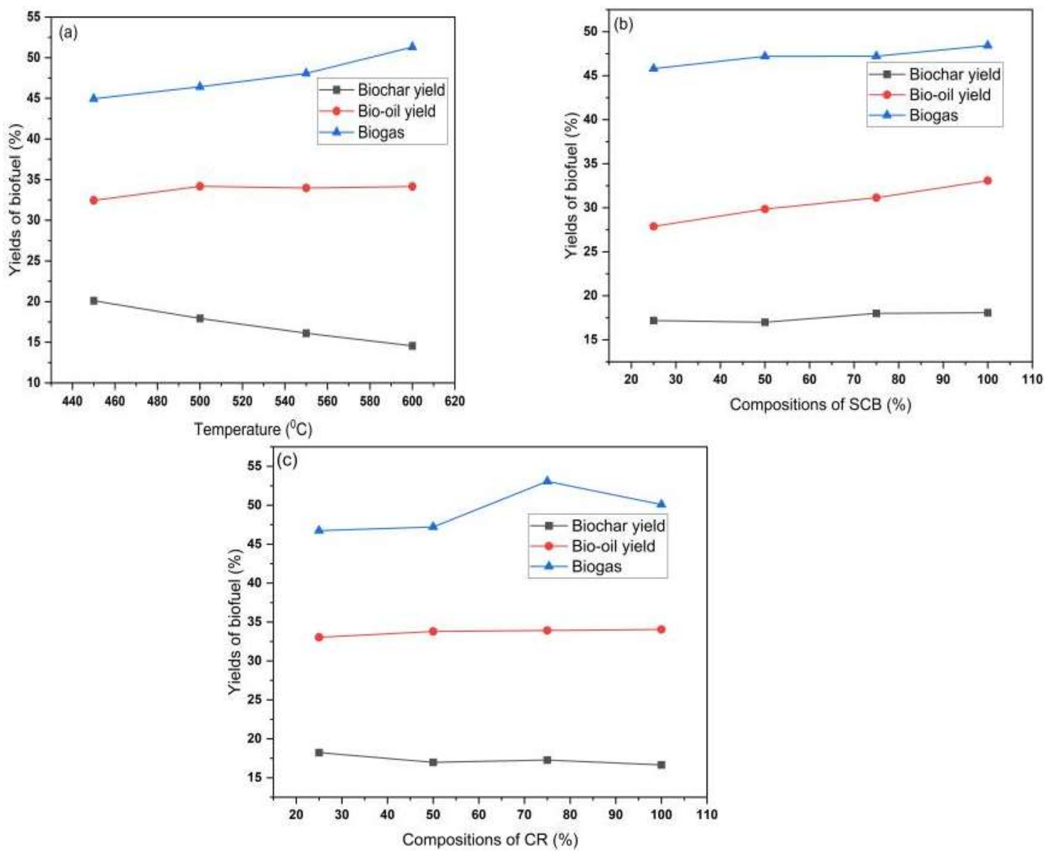


Figure 5: Relationship between biofuel yields and **(a)** pyrolysis temperature, **(b)** composition of SCB and **(c)** content of CR.

Figs. 5b and 5c reveal that increasing SCB proportion enhances bio-oil and biochar yields, attributable to SCB's higher volatile matter and O content, which promote devolatilization and oxygenated species generation. In contrast, CR, with higher C and ash content, favours biochar formation through solid residue stabilization and catalytic ash effects. Observed rise in biogas yield was linked to secondary cracking reactions of pyrolysis vapours and char [43]. Notably, a 50:50 SCB–CR blend yielded optimal bio-oil output, aligning well with experimental data.
A sensitivity analysis was conducted to enhance understanding of how temperature and composition of SCB and CR affect predicted yields of biofuel. Eqs. (11) and (12) are applied to ascertain relative significance and contribution of every input variable in developed MEP model [42].

$$I_i = \frac{n_i}{\sum_{i=1}^{N} n_i} \times 100 \tag{11}$$

$$n_i = f_{max}(x_i) - f_{min}(x_i) \tag{12}$$

where n is number of input variables; $f_{max}(x_i)$ and $f_{min}(x_i)$ are maximum and minimum values of predicted values of biofuel yields for input variable i, respectively; ni was independently calculated for each input variable, when other input variables are constant at their individual average values; Ii is relative significance of each input variable in developed MEP model.
Fig. 6 further confirms that temperature has most significant influence on product distribution, especially for biochar and bio-oil.

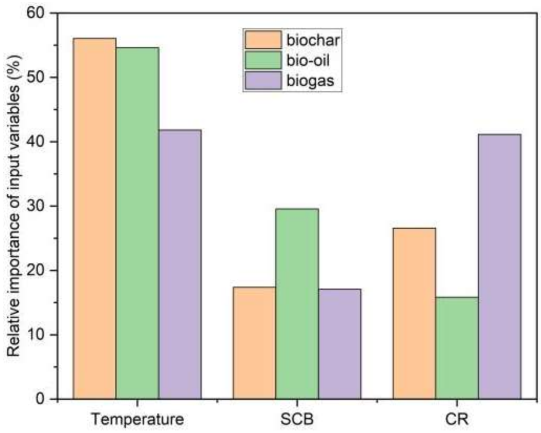


Figure 6: Relative importance of temperature and composition of SCB and CR in developed MEP model.

Relative importance of SCB and CR composition is more distinct for biogas yield, which is influenced by decomposition of light volatiles and non-condensable gases like CO, CO_2 and CH_4 formed during cracking of tars and oxygenates [44]. Co-pyrolysis of SCB and CR also influences biofuel's yield and quality. SCB, with its high lignin and fibre content, provides structural integrity necessary for effective thermal degradation, while CR, which typically contains higher amounts of starch and lower lignin content, can promote rapid devolatilization [7, 9]. Combination of these characteristics facilitates a more uniform heat distribution, and can mitigate issues such as incomplete pyrolysis or excessive char formation that are sometimes observed when processing single feedstock [44]. Consequently, co-pyrolysis of SCB and CR produced bio-oils with a more balanced composition and a higher energy density, as interaction between feedstocks reduced formation of undesirable by-products. Integration of experimental data with modelling approaches underscores the feasibility of optimizing process parameters for large-scale applications.

Conclusions

This study examined biofuel production from SCB and CR in a free-fall reactor. Optimal bio-oil yield of 36.2%, with a heating value of 23.6 MJ/kg, was achieved at a 50:50 SCB-to-CR blend ratio, and with a temperature of 550°C, while corresponding biochar and biogas yields were 16.2% and 47.6%, respectively. MEP model proved highly accurate in predicting biofuel yields, with R^2 values of 0.974, 0.917 and 0.774 for biochar, bio-oil and biogas, respectively, outperforming MLR model, which had much lower R^2 values of 0.820, 0.197 and 0.090. Co-pyrolysis of SCB and CR enhanced biofuel yields and quality, due to synergistic effects and parametric analysis, confirmed that temperature and feedstock composition significantly impact biofuel yields. These results demonstrate the potential of SCB and CR as sustainable biofuel feedstocks, and validate the effectiveness of MEP model for yield prediction.

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Authors' contributions
K. O. Oladosu: conceptualization; methodology; formal analysis; writing original draft; reviewing and editing; supervision; project administration. **K. Mustapha**: methodology; formal analysis; reviewing and editing; project administration. **A. S. Olawore**: methodology; formal analysis; validation; writing original draft; reviewing and editing. **H. A. Ibrahim**: methodology; formal analysis; reviewing and editing. **N. S. Saidu and T. D. Oseni**: formal analysis; reviewing and editing.

Abbreviations
ASTM: American Society for Testing and Materials
CR: cassava rhizome
MAE: mean absolute error
MAPE: mean absolute percentage error
MEP: multi-expression programming
MLR: multilinear regression
R^2: coefficient of determination
RMSE: root mean square error
SCB: sugarcane bagasse

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