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Python-Based Process Modelling and Optimisation of Pyrolysis Valorisation of Palm Kernel Shells and Empty Fruit Bunches for Biochar Production: A Circular Economy Assessment

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Abstract

Purpose: Palm kernel shells (PKS) and empty fruit bunches (EFB) are the most abundant agro-industrial residues generated by Ghana's palm oil sector, yet they are mostly open-burned or landfilled, resulting in environmental and economic losses. This study develops and implements a Python-based framework to identify optimal conditions for valorisation of PKS and EFB into biochar within a circular economy context.

Methods: A two-layer multi-component empirical-kinetic model was formulated and validated against published literature data across 300–700 °C. Monte Carlo simulation was used to propagate the feedstock compositional and kinetic parameter uncertainties into biochar yield distributions. Constrained optimisation was performed using Sequential Least Squares Programming, Differential Evolution, and Exhaustive Grid Search. A mill-scale circular economy assessment quantified biochar production, carbon benefit, and economic performance.

Results: The model predicted equilibrium biochar yields within ±2.2 percentage of literature values. Monte Carlo analysis yielded 90% confidence intervals of 27.8–33.1% (PKS) and 23.8–29.3% (EFB) at 500 °C and 30 minutes; lignin content was identified as the dominant uncertainty driver ($|\rho| > 0.70$). All three optimisation methods converged to 393 °C, 50.5 minutes (PKS) and 57.0 minutes (EFB), producing biochar yields of 42.2% and 38.5% respectively. At a representative mill scale (10 t FFB/hr), annual biochar output of 5,567 t, CO_2e benefit of 31,854 t/yr, and net revenues of USD 677,905–3,276,228 are achievable.

Conclusion: The fixed carbon quality constraint is the sole binding optimisation constraint. The framework demonstrates that uncertainty-aware computational modelling can support commercially viable and environmentally beneficial pyrolysis valorisation of palm residues.

Keywords: pyrolysis; biochar; palm kernel shells (PKS); empty fruit bunches (EFB); fresh fruit bunches (FFB); circular economy.

1.0 Introduction

Significant amounts of agricultural residues like palm kernel shells (PKS) and empty fruit bunches (EFB) are produced at every point of the palm oil production process. Ghana, a major palm oil producer in West Africa, processes approximately 2.5 million t/yr of fresh fruit bunches (FFB), producing an equivalent quantity of solid waste [1]. Most of the time, these residues are burned open or left to decompose, resulting in greenhouse gas emissions, poor soil structure and ultimately affecting air quality [2].

Pyrolysis, the thermochemical decomposition of biomass under conditions of no oxygen, is a technically proven and commercially viable process to produce biochar (a solid high in carbon content) which can be utilized for soil amendment, carbon sequestration, industrial adsorption and wastewater treatment [3]. Pyrolysis temperature and residence time are the two operating variables that most strongly govern the yield and quality of the resulting biochar,

since both determine how completely the lignocellulosic structure is thermally decomposed. Identifying the right combination of the two is therefore central to making the process commercially and environmentally viable. Although the economic and environmental benefits of biochar production from palm oil residues have been documented [4], there are site-specific process models which account for the natural variability of feedstock composition and operating conditions that need to be developed before biochar can be widely adopted in sub-Saharan African contexts.

A cheaper way to fill this gap is process modelling and computational optimization, which is being able to find operating conditions that optimize a process and quantify the process' uncertainty without using up too much time and financial resources in the laboratory. Consistent with the current trend in scientific computing, the use of Python-based scientific computing packages such as SciPy, NumPy and Matplotlib is gaining popularity in biomass conversion research, using kinetic modelling [5], stochastic simulation [6] and multi-method optimization [7]. To our knowledge, no study has integrated multi-component kinetics, Monte Carlo uncertainty, and multi-method optimization for PKS/EFB in West Africa.

This research paper fills that gap, in particular, it builds and implements a computational framework for valorisation of PKS/EFB via pyrolysis, which includes: (i) multi-component empirical-kinetic model validated with published literature data; (ii) Monte Carlo simulation to propagate the uncertainties of the feedstock and the kinetics into yield distributions of biochar; (iii) constrained multi-method optimization to find globally optimal operating conditions; and (iv) a circular economy assessment to quantify the biochar production potential, carbon offset and economic value at the palm oil mill scale in Ghana.

The two major solid residues of palm oil milling process are PKS and EFB. The amount of PKS and EFB produced from FFB processing is about 65 kg and 230 kg respectively per tonne of FFB [2]. They have a lignocellulosic structure consisting of cellulose, hemicelluloses, lignin, extractives and ash which dictate their thermochemical reactions during pyrolysis. The lignin content (usually 45 – 55%) in PKS, compared with EFB's more balanced composition with higher cellulose and hemicellulose content [4] gives a structurally distinct thermal decomposition profile. This compositional difference translates immediately to the yield of biochar: lignin is more char-rich than cellulose or hemicellulose, due to its thermally stable aromatic ring structure, and upon pyrolysis yields much more char per unit mass [3]. For PKS, typical yields range from 37% at 300 °C to 18% at 700 °C (residence time ~30 min) and for EFB, typical yields range from 35% at 300 °C to 18% at 700 °C (residence time ~30 min) [8]. These yields are under equilibrium conditions (pyrolysis run to completion) and are the maximum amounts of char that might be recovered at each temperature.

Generally, biomass pyrolysis is modelled as a first-order process; with the decomposition rate of each biomass component being exponentially dependent on the pyrolysis temperature, via the activation energy (E_a) and pre-exponential factor (A) [5]. While single-component models are limited in their predictive ability to an extended range of temperatures, multi-component models that consider cellulose, hemicellulose and lignin as independent parallel reactions provide improved predictive accuracy over broad ranges of temperatures [9]. The reported activation energies for cellulose pyrolysis range from 80 to 130 kJ/mol, hemicellulose 60 to 90 kJ/mol and lignin 40 to 65 kJ/mol, indicating that the activation energy for the pyrolysis of lignin is higher than that of hemicellulose and cellulose [5].

The quality of biochar is evaluated by its fixed carbon (FC) content, which is the carbon fraction that is not easily volatilized. The minimum thresholds for basic and premium grade biochar for the International Biochar Initiative (IBI) and European Biochar Certificate (EBC) differ, being ≥ 50% for the IBI and ≥ 60% for the EBC [10]. High quality biochar can earn higher market value and meet the criteria to claim soil carbon sequestration credits for voluntary carbon markets [3]. The amount of fixed carbon increases with the pyrolysis temperature because volatile matter is gradually removed, and the temperature at which FC content reaches 60% is normally 380–420 °C for lignocellulosic feedstocks [4].

Monte Carlo (MC) simulation is a widely used stochastic technique for propagation of uncertainty in process engineering models [6]. Uncertain inputs in biomass valorisation include feedstock composition, kinetic parameters and operating conditions [7]. In MC studies, commonly used methods involve the ranking of input variables according to their contribution to the uncertainty of the output variables, known as Spearman rank correlation analysis [11].

The circular economy framework is based on the idea that waste is a resource that is fed back into the production process [12]. This includes valorisation of PKS and EFB to biochar, soil amendment applications and carbon credit generation [3] on palm oil mill residues. Economic impact analysis of biochar production from palm residues has shown that biochar can generate net revenues of USD 100–600 per tonne of biochar [4], while voluntary carbon market prices have been found to range between USD 10–80 per tonne of CO_2e [13].

2.0 Methodology

2.1 Feedstock Characterization

The compositions of the feedstocks for PKS and EFB were obtained from the published literature, as this study is computational based. The adopted compositions (dry basis) are listed in Table 1, which were taken from [2] and [4].

Table 1 Feedstock composition (dry basis, mass fraction) for PKS and EFB [2, 4].

Component	Cellulose	Hemicellulose	Lignin	Extractives	Ash	Total
PKS	0.26	0.17	0.53	0.01	0.03	1.00
EFB	0.33	0.20	0.35	0.07	0.05	1.00

2.2 Multi-Component Kinetic Model

A two-layer multi-component empirical-kinetic model was developed in Python. In the first layer, where $\gamma i(T)$ is the temperature-dependent char yield fraction of component I at complete conversion:

$$\gamma_i(T) = \gamma_{i,ref} \times exp(-kT_{,i} \times (T - T_{ref})) \quad (1)$$

Equilibrium biochar yield at complete conversion is computed as:

$$Y_{eq}(T) = \Sigma_i [w_i \times \gamma_i(T)] + x_{ash} \quad (2)$$

In the second layer, the kinetic approach to equilibrium over time is described as:

$$Y(T,t) = Y_{eq}(T) + [100 - Y_{eq}(T)] \times exp(-k_{eff}(T) \times t) \quad (3)$$

where $k_{eff}(T) = \Sigma_i[w_i \times A_i \times exp(-Ea_{,i} / RT)]$ is a mass-fraction-weighted effective Arrhenius rate constant. The kinetic parameters for multi-component pyrolysis model are shown in Table 2.

Table 2 Kinetic parameters for multi-component pyrolysis model

Component	y_{ref} (500 °C)	kT (°C⁻¹)	E_a (kJ/mol)	A (s⁻¹)
Cellulose	0.06	0.0030	80	12.5
Hemicellulose	0.12	0.0020	65	2.8
Lignin	0.42	0.0008	45	0.35
Extractives	0.10	0.0025	55	1.5

2.3 Monte Carlo Uncertainty Analysis

Uncertainties in the feedstock compositional and kinetic parameters were propagated through the process model using Monte Carlo simulation (N = 5,000). The component fractions were drawn from a normal distribution (CV = 10%), activation energies were drawn from a normal distribution (CV = 5%) and pre-exponential factors were drawn from a log-normal distribution (CV = 15%). Uncertainties in operating conditions (5°C and 2 minutes) were also

considered. For each uncertain input, the Spearman rank correlation between simulated yield and the input was calculated for sensitivity ranking [11]. The random seed for all simulations was fixed to 42, using Python 3.10, NumPy 1.24, and SciPy 1.11. Convergence of N = 5,000 was verified by comparison with N = 10,000 runs: the mean yield shifted by less than 0.1 percentage points and the 90% confidence interval bounds shifted by less than 0.3 percentage points for both PKS and EFB, confirming using 5,000 simulations is sufficient for stable distributional estimates.

2.4 Constrained Optimisation

The optimisation maximised the biochar yield with negative values subject to the following constraints: (i) $Y \geq 20\%$, (ii) $FC(T) \geq 60\%$ [10], (iii) normalised energy cost $E(T, t) \leq 1.0$, and (iv) conversion progress $\eta \geq 0.85$. The normalized energy cost was estimated as $E(T,T) = (T - T_{amb})/(T_{max} - T_{amb})$. The following methods were used: SLSQP with 20 multi-starts [14], differential evolution [15], and exhaustive grid search over an 80 × 60 temperature-time grid (80 points spanning 300–700 °C; 60 points spanning 10–120 minutes).

2.5 Circular Economy Assessment

The assessment was carried out on a medium scale (10 t FFB/hr, 16 hrs/day, 300 days/yr = 48,000 t/year FFB) of a typical palm oil mill in Ghana. The rates of PKS and EFB generation of 6.5% and 23% of FFB weight were adopted [2]. Carbon sequestration used the IBI methodology (IBI-STD v 2.1): CO_2e = biochar × 0.65 × 0.80 × 3.667 [10]. intergovernmental panel on Climate Change (IPCC) Tier 1 factor of 1.5 kg CO_2e/kg biomass was used for avoided emissions [16]. Biochar prices of USD 200, 400, 600/tonne and carbon credit prices of USD 15, 30, 50 /t CO_2e [13] were used for three market scenarios. An operational processing cost of USD 42/tonne of feedstock was adopted, equivalent to USD 594,720/year at mill scale. The figure is consistent with the lower bound of the USD 20-330/tonne dry feedstock range reported for slow pyrolysis operations in the literature [17], and is appropriate for a mill-integrated Kiln scenario in a sub-Saharan Africa context where feedstocks are generated on-site at negligible transport cost [18].

2.6 Model Assumptions and Limitations

The model assumes isothermal particles, negligible secondary tar cracking, and lumped biomass components (cellulose, hemicellulose, lignin, extractives, and ash treated as independent reactions). Kinetic parameters and feedstock compositions were taken from published literature rather than measured for West African feedstocks, so site-specific variability in composition or particle size was not captured.

The energy cost model employed in this study is a simplified temperature-proportional proxy which does not account for the thermal energy consumed during the residence time holding period or the enthalpy of pyrolysis reactions. As a result, residence time has no influence on the energy constraint in the current optimisation formulation. All code was developed in Python 3.10 using NumPy 1.24 and SciPy 1.11.

3.0 Results and Discussion

3.1 Kinetic Model Validation

The multi-component kinetic model demonstrated good agreement with published literature data across 300–700 °C. In Fig. 1, equilibrium biochar yield curves for PKS and EFB were plotted alongside literature validation points.

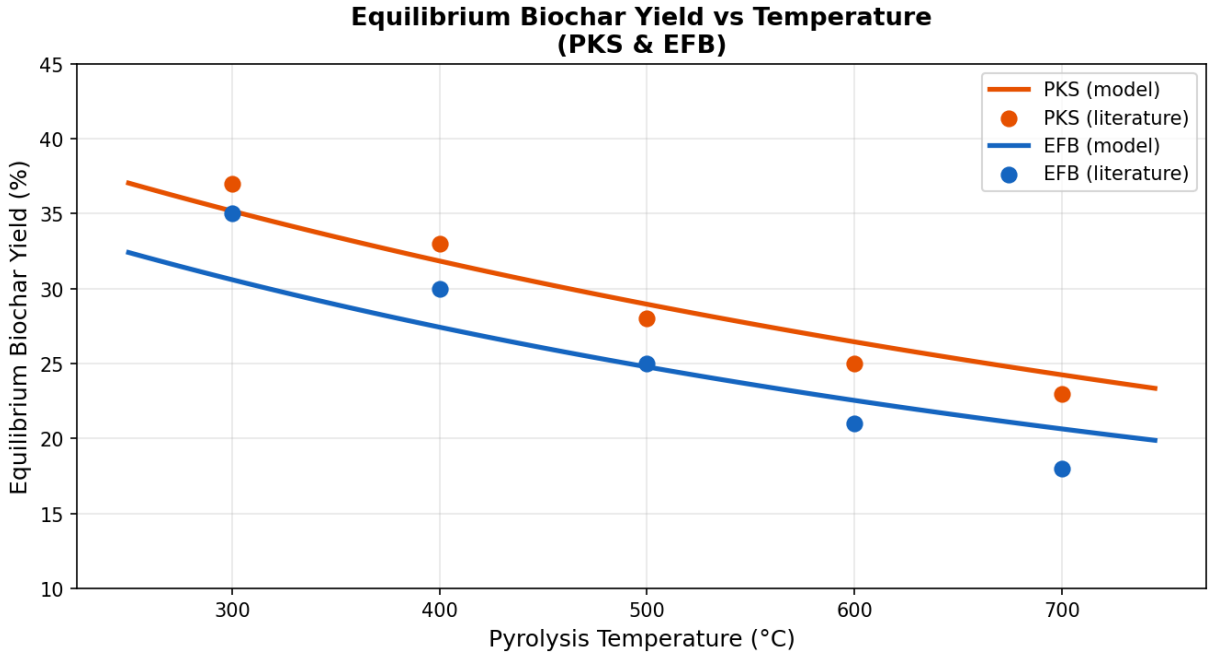


Fig. 1 Equilibrium biochar yield vs. pyrolysis temperature for PKS and EFB

The decreased biochar yield at higher temperatures in both PKS and EFB was due to the increased thermal energy leading to more breakdowns of stable carbon structures to volatile gases and bio-oil, which are not solid char. However, the biochar yield from PKS is always higher than EFB in the whole temperature range (4-6 percentage points more at low and high temperatures). The main reason for this difference is because of the high lignin content in PKS which is 53% whereas EFB is 35%. Lignin is the most heat-resistant biomass component and is more thermally stable than other components, which means that feedstocks with higher lignin content naturally produce more biochar [19, 20, 21, and 22].

Table 3 Model validation: equilibrium biochar yield (%) vs. literature (30 min residence time) [2, 8]

T (°C)	PKS Model	PKS Lit.	EFB Model	EFB Lit.
300	35.2%	37%	30.6%	35%
400	31.8%	33%	27.4%	30%
500	29.0%	28%	24.8%	25%
600	26.5%	25%	22.5%	21%
700	24.3%	23%	20.6%	18%

Table 3 shows how the predicted model deviated from literature values. The deviations were by a root mean square error (RMSE) of 1.39 percentage points for PKS and 2.65 percentage points for EFB across the five validation temperatures (300–700 °C, 30 minutes), but below the target threshold of 3 percentage points and within typical experimental variability of ± 3-5% [9], this confirms that the multi-component kinetic model is correctly calibrated against real experimental data.

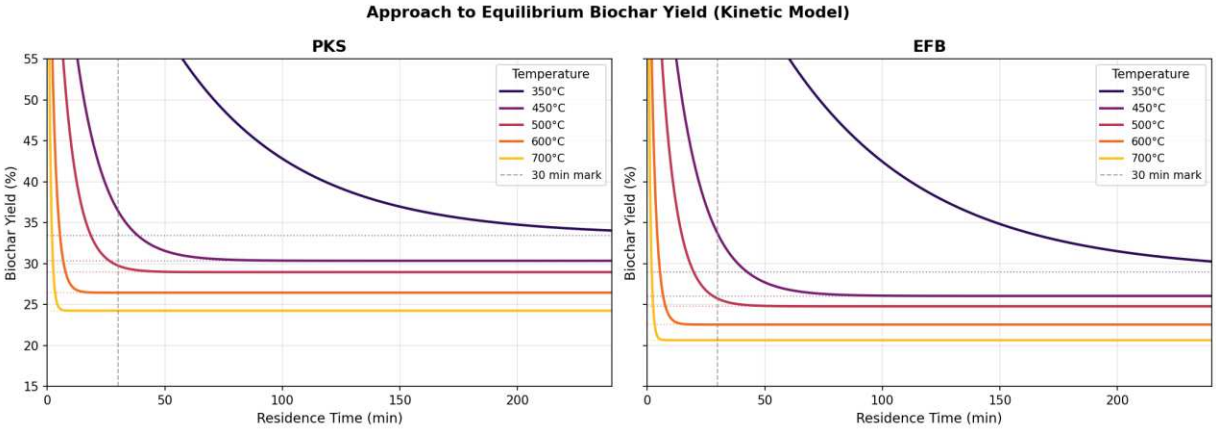


Fig. 2 Biochar yield vs. residence time at selected temperatures for PKS (left) and EFB (right)

The temperature dependence of equilibrium kinetics is illustrated in Fig. 2, demonstrating how higher operating temperatures significantly alter the residence time required to achieve equilibrium. The curves appear to be very steeply at high temperatures (600–700 °C) and they level off almost immediately (5–15 minutes at equilibrium). This implies that at high temperature, pyrolysis is so rapid that more pyrolysis (increasing residence time) does not increase the process. At low temperatures (350 °C), curves are down equally slowly and even after 240 minutes they are not completely flat. The rate of pyrolysis is low at low temperatures. PKS and EFB have very similar shape, but have slightly elevated curves at every temperature due to its higher lignin content.

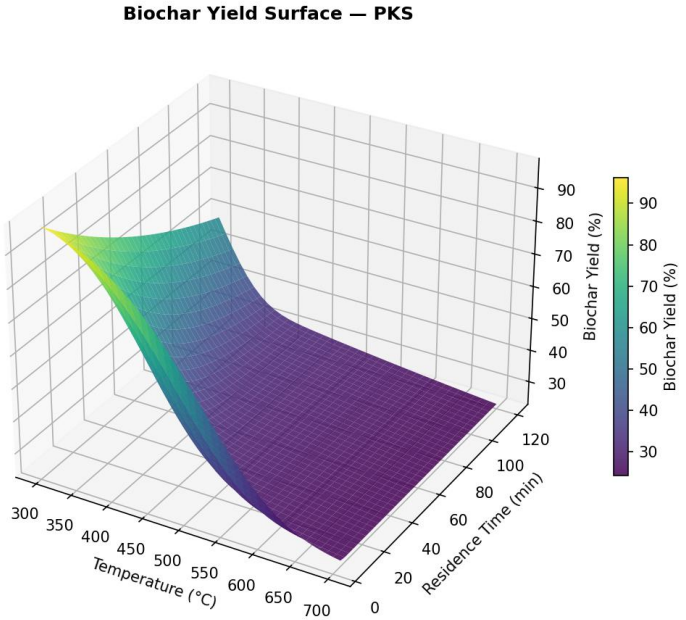


Fig. 3 3D biochar yield surface for PKS as a function of pyrolysis temperature and residence time

The combined response surface for PKS yield as a function of temperature and residence time is presented in 3D in Fig. 3. The maximum yield is at low temperature and short residence time but this is incomplete pyrolysis (does not meet our Fixed Carbon percentage constraint of 60%). The yields decrease with increasing temperature, as there is more thermal cracking of biomass into volatiles. The residence time is observed to have a strong influence on the yield at low temperatures, but a decreasing influence at high temperatures after 15–20 minutes. As the temperature is increased and the residence time is extended, the surface reaches a plateau where an equilibrium char yield is obtained and further

increase in temperature results in little change. The smoothness of the surface implies the mathematical stability of the model and it is suitable for optimization.

3.2 Monte Carlo Uncertainty Analysis

Monte Carlo simulation (N = 5,000) at 500 °C and 30 minutes produced near-normal yield distributions for both feedstocks, consistent with Central Limit Theorem behaviour.

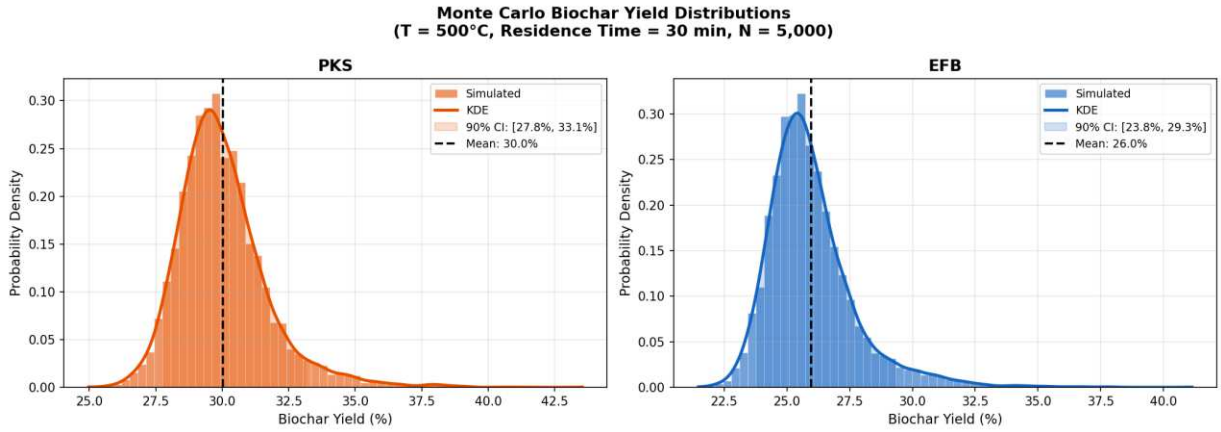


Fig. 4 Monte Carlo biochar yield distributions for PKS (left) and EFB (right) at 500°C and 30 minutes (N = 5,000)

As illustrated in Figure 4, PKS yielded a mean of 30.0% with a 90% confidence level (CL) of 27.8% → 33.1%. This means even under input uncertainty; you can be 90% confident PKS will give between 27.8% and 33.1% biochar at 500 °C. EFB yielded a mean of 26.0% with a 90% CI of 23.8% → 29.3%. Both of them are approximately bell-shaped (near-Normal) as required in the Central Limit Theorem due to a large number of random factors.

Table 4 Monte Carlo simulation results at 500°C, 30 min (N = 5,000)

Statistic	PKS	EFB
Mean yield	30.0%	26.0%
Standard deviation	±1.71%	±1.77%
90% CI (P5–P95)	27.8% – 33.1%	23.8% – 29.3%
Interquartile range (P25–P75)	28.9% – 30.8%	24.9% – 26.7%
Median	29.8%	25.6%

The narrow standard deviations (±1.71% for PKS, ±1.77% for EFB) indicate that the pyrolysis process is relatively robust to input uncertainty at 500 °C as shown in Table 4.

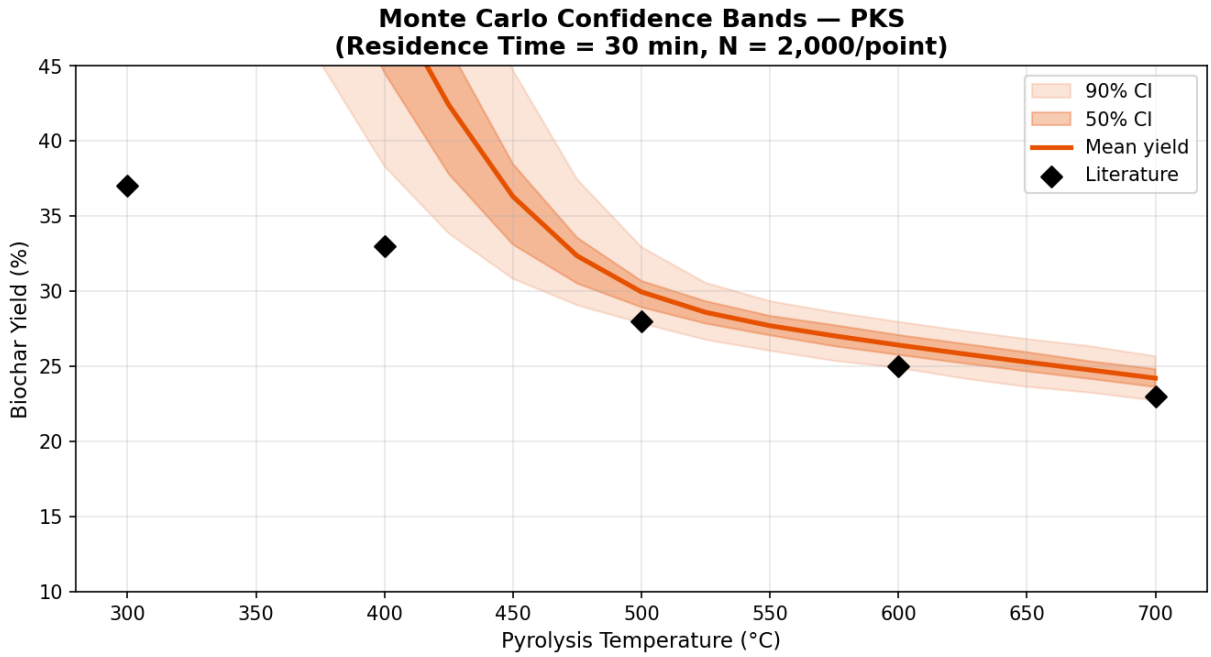


Fig. 5 Monte Carlo confidence bands for PKS biochar yield across 300–700 °C

As shown in Figure 5, the mean yield curve is in good agreement with the literature data, which is a good result, showing successful model calibration and validation over the whole temperature range. The confidence bands are larger at lower temperatures (300–400 °C) because the yield predicted at these temperatures is highly sensitive to small changes and uncertainties in the content of lignin in the biomass. As the temperature rises, however, these bands become much narrower since the yields will tend to approach the equilibrium values, irrespective of the difference in the initial composition. For PKS specifically this does lead to a narrowing of the 90% confidence interval, from around ±4–5% at 300 °C to around ±2-3% at 700 °C. Ultimately, this indicates that the high temperature operations are far more reproducible and stable. The validity of the model predictions is well supported by the fact that all points in the literature are contained within or very near these confidence bands.

Figure 6 presents the Spearman rank correlation sensitivity analysis, identifying the relative influence of each uncertain input on yield variability.

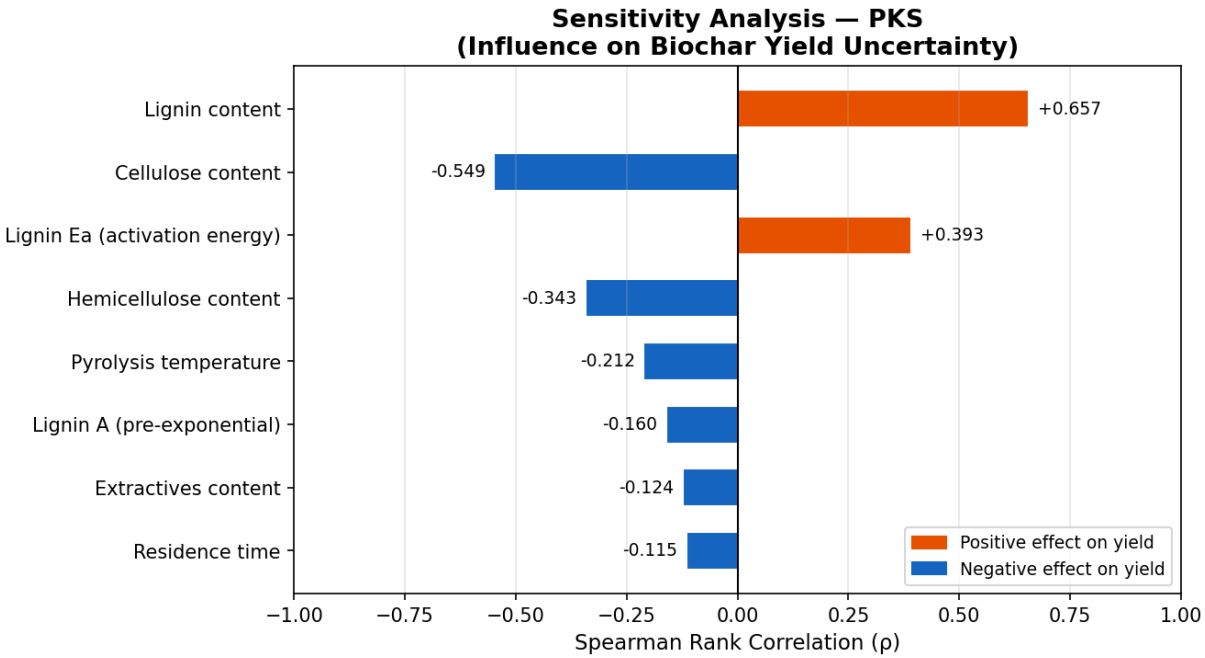


Fig. 6 Sensitivity analysis (Spearman rank correlation) for PKS biochar yield at 500 °C, 30 minutes

Figure 6 presents the Spearman rank correlation sensitivity analysis, identifying the relative influence of each uncertain input on yield variability. Lignin content emerged as the dominant driver of yield uncertainty ($|\rho| > 0.7$), followed by cellulose content (negative effect) and pyrolysis temperature (negative effect). The kinetic parameters and residence time were found to be insensitive at 500 °C, because the equilibrium is achieved almost completely within the 30 minutes residence time at this temperature.

3.3 Constrained Optimisation

All three optimisation methods (SLSQP, Differential Evolution, and grid search) converged to essentially the same solution (Fig. 7), confirming the global nature of the optimum. The feasible operating region seems to be a narrow band in which both yield and biochar quality requirements are met. The biochar does not meet the fixed carbon (FC) quality requirement at low temperatures and the production yield is too low at very high temperatures. Therefore, the optimizer searches for the best yield within this region. The best condition is near 393 °C and 50 minutes, which are at the lower limit of the feasible region. The fixed carbon boundary is the most important constraint for this optimum, with the FC ≥ 60% quality requirement heavily influencing the optimal temperature. This convergence of all three methods to T = 393 °C is physically meaningful, as summarised in Table 5: the fixed carbon quality constraint emerges as the sole binding constraint, pinning the optimal temperature precisely at the point where premium-grade quality is just met.

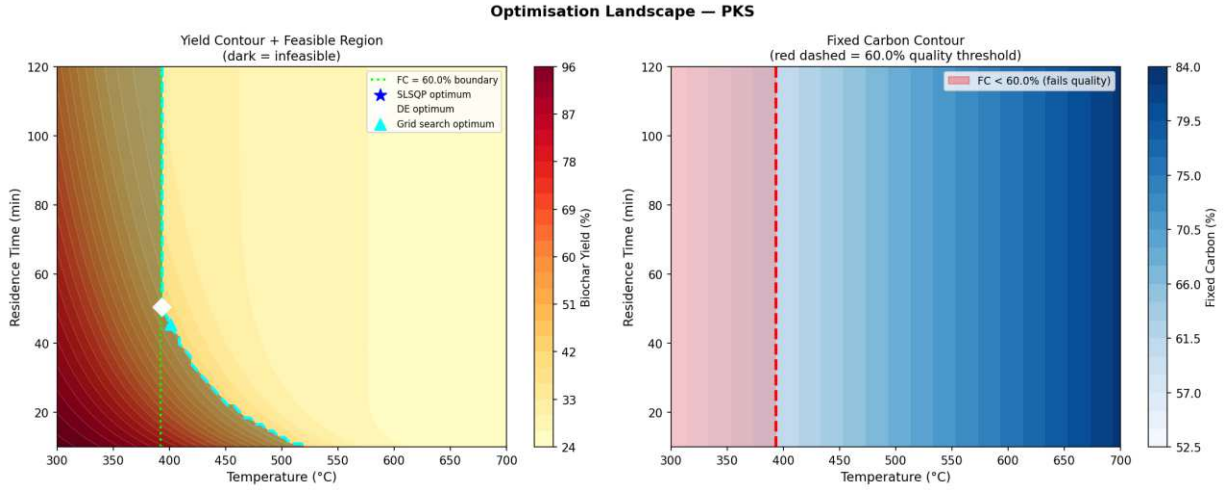


Fig. 7 Optimization landscape for PKS.

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Table 5 Optimal pyrolysis operating conditions and process metrics

Parameter	PKS	EFB
Optimal temperature (°C)	393	393
Optimal residence time (min)	50.5	57.0
Biochar yield (%)	42.2	38.5
Fixed carbon content (%)	60.0	60.0
Normalised energy cost (−)	0.546	0.546
Binding constraint	FC ≥ 60%	FC ≥ 60%

The convergence of all three methods to T = 393 °C is physically meaningful: the fixed carbon quality constraint (FC ≥ 60%) emerges as the sole binding constraint, pinning the optimal temperature precisely at the point where premium-grade quality is just met (Table 5).

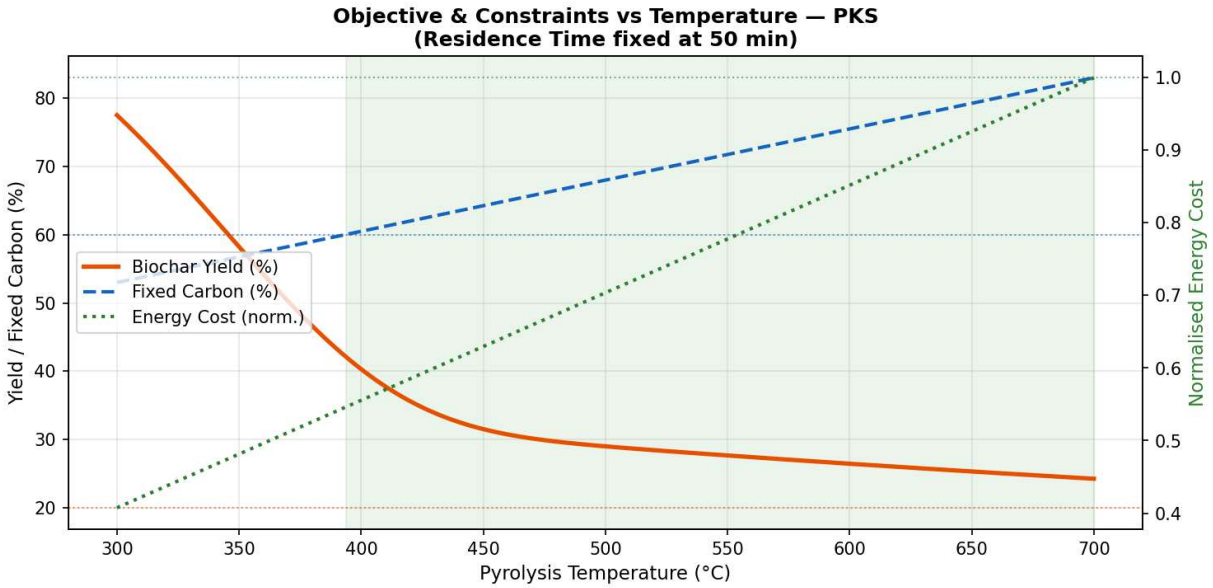


Fig. 8 Biochar yield, fixed carbon content, and normalised energy cost vs. temperature for PKS at optimal residence time of 50.5 min

The basic trade-off in pyrolysis is highly influenced by temperature. From Fig. 8 it was observed that as the yield curve (orange line) is going up, the fixed carbon (FC) curve (blue line) is going down and vice versa, making it impossible to get both a very high yield and a very high FC quality. This limits the operating window to approximately 390–650 °C, with yield being too low for the higher temperatures and FC quality being too low for the lower temperatures. The best operating point is on the left end of this window at 393 °C, where the yield is maximized and the constraint of FC ≥ 60% is just met. Of particular note is that the green energy cost constraint is never binding in this feasible region, indicating that energy cost is not the constraint. Rather, the quality of fixed carbon is the most restrictive factor for the overall process. The yield quality trade-off is clearly visible, where the lower the temperature, the higher the biochar yield and also the higher the temperature, the higher the fixed carbon.

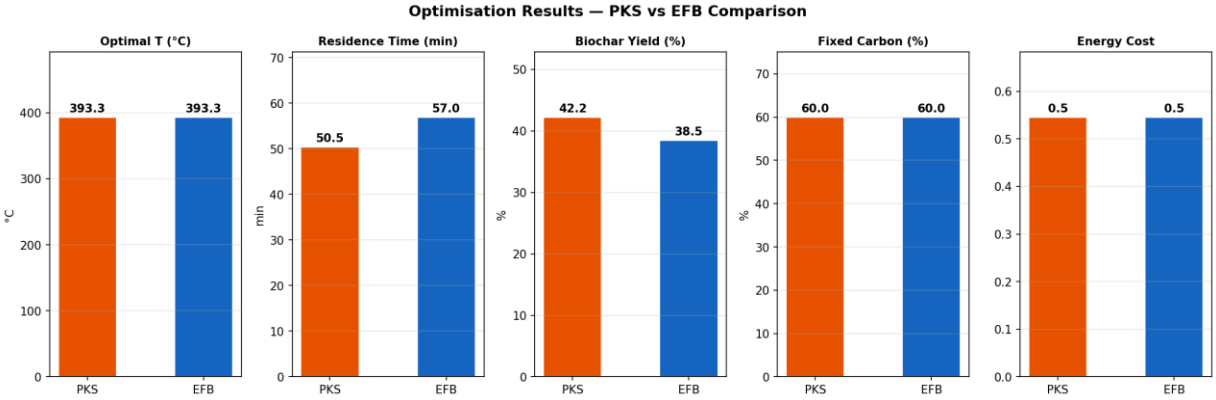


Fig. 9 Comparison of optimisation results for PKS and EFB

Both feed stocks lead to the same optimal temperature (393 °C), validating the fact that the quality driven optimum temperature is a property of the constraint system and not the feedstock. EFB has higher cellulose content, thus has a longer residence time (57.0 vs 50.5 minutes) because of the requirement to approach equilibrium at this lower operating temperature (Figure 9).

3.4 Circular Economy Assessment

At the scale of a medium Ghanaian palm oil mill (10 t/hr FFB, 48,000 t/year FFB), PKS and EFB streams generate 3,120 and 11,040 t/yr respectively.

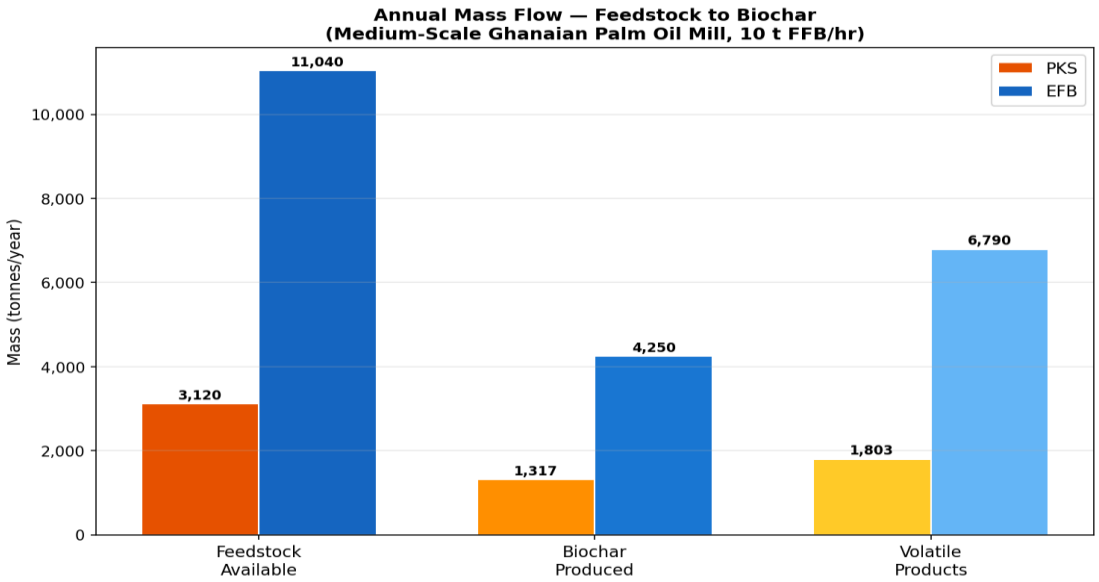


Fig. 10 Annual mass flow for PKS and EFB: feedstock available, biochar produced, and volatile by-products at a 10t FFB/hr Ghanaian palm oil mill.

EFB produces 11,040 t/yr and PKS only 3,120 t/yr from the same mill as shown in Figure 10. This is because EFB accounts for 23% weight of FFB while PKS accounts for 6.5% weight of FFB. This is a clear indicator that EFB is more strategic to valorise at a palm oil mill in Ghana. The yield of PKS is 1,317 tonnes of biochar from 3,120 tonnes of feedstock (42.2%). EFB converts 11,040 tonnes into 4,250 tonnes of biochar (38.5% yield). Even though it produces a slightly higher yield percentage, EFB has a much greater number of units of biochar because of the availability of much more EFB. The mill generates a total of 5,567 tonnes of biochar annually, which is a commercially viable amount. Around 40% of biomass feed is converted to solid biochar and 60% to volatile products (gases and bio-oil) that may offer other energy and revenue streams.

Figure 11 quantifies the dual-mechanism carbon benefit: direct sequestration in biochar and avoided emissions from eliminated open burning.

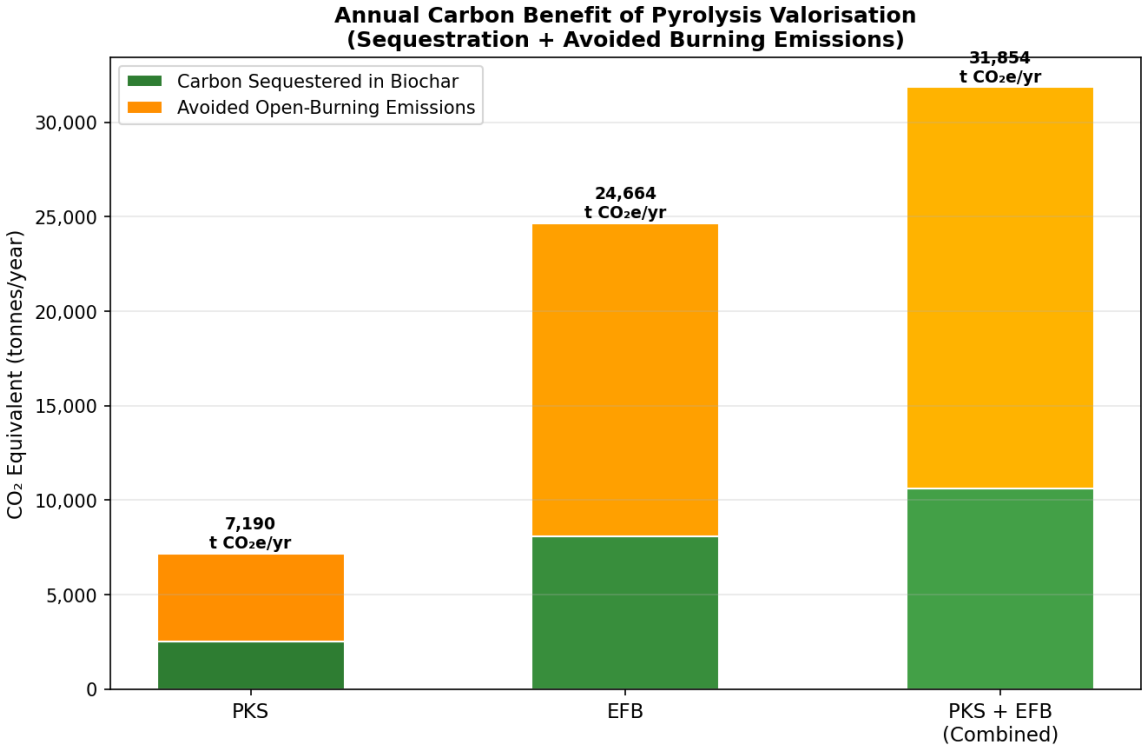


Fig. 11 Annual CO_2e benefit from pyrolysis valorisation

In Table 6, total benefits of EFB are 24,664 tonnes CO_2e while for PKS, it is 7,190 tonnes CO_2e. EFB is much higher in CO_2e reduction as compared to PKS as EFB has more availability of feedstock. The avoided open burning outweighs the effect of carbon sequestration in biochar for both feedstocks, indicating that the primary advantage of biochar over open burning is to stop waste burning and store carbon. Overall, the pyrolysis system can cut CO_2e emissions by approximately 31,854 tonnes per annum for a single palm oil mill in Ghana. The outcomes also point to two important aspects of climate change; the sequestration of carbon in the production of biochar and avoided emissions from the prohibition of open burning.

Table 6 Annual circular economy metrics at mill scale (10 t FFB/hr)

Metric	PKS	EFB	Combined
Feedstock available (t/yr)	3,120	11,040	14,160
Biochar produced (t/yr)	1,317	4,250	5,567
Carbon sequestered (t/yr CO_2e)	2,510	8,104	10,614
Avoided burning emissions (t/yr CO_2e)	4,680	16,560	21,240

Total CO_2e benefit (t/yr CO_2e)	7,190	24,664	31,854
Processing cost (USD/yr)	131,040	463,680	594,720

The combined CO_2e benefit of 31,854 t/year comprises sequestration (10,614 t CO_2e) and avoided burning (21,240 t CO_2e).

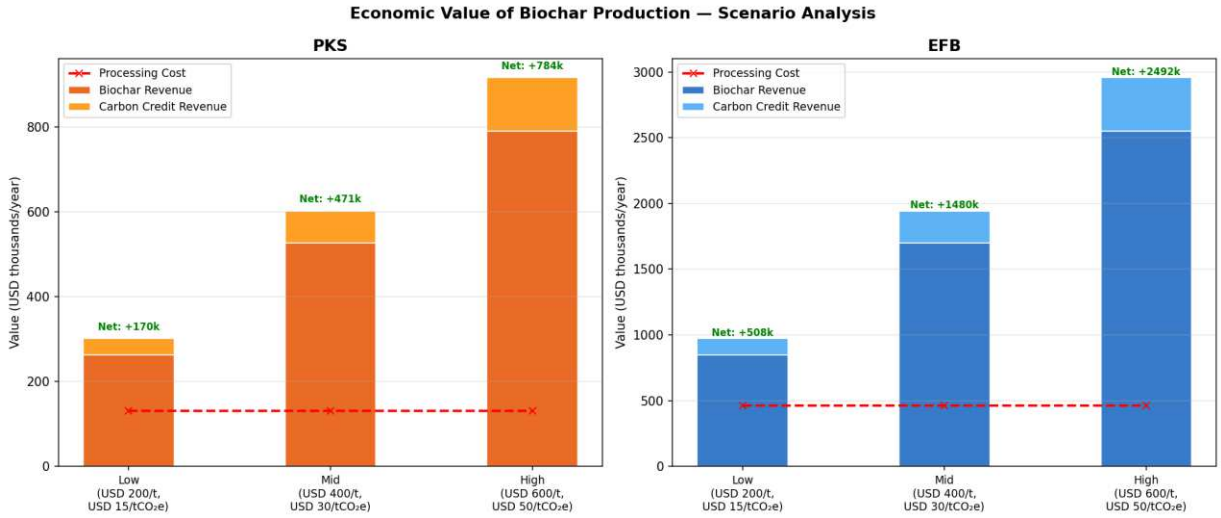


Fig. 12 Economic scenario analysis for PKS (left) and EFB (right)

In every case, the revenue bars sit above the processing cost line as shown in Figure 12. Even under the most conservative assumptions (biochar at USD 200/t, carbon at USD 15/t CO_2e), the net value is positive for both feedstocks as illustrated in Figure 12. For PKS the low-scenario net is +USD 169,944/year; for EFB it is +USD 507,961/year. This means there is no market scenario examined where this investment loses money.

The carbon credit section (lighter upper portion) is noticeably smaller than the biochar section, typically contributing 10–15% of total revenue as shown in Figure 12. This means the business case rests primarily on biochar product value, not carbon markets. EFB generates significantly higher revenues than PKS due to its larger availability, confirming it as the main economic driver of the circular economy system. Although revenues vary substantially between low and high market scenarios, the consistently low processing costs indicate that profitability depends more on market access for biochar and carbon credits than on operational energy expenses.

Table 7 Net annual economic value by market scenario (USD/year)

Feedstock	Low scenario	Mid scenario	High scenario	Assumptions
PKS	+$169,944	+$470,928	+$784,464	Low: $200/t, $15/t CO_2e Mid: $400/t, $30/t CO_2e High: $600/t, $50/t CO_2e
EFB	+$507,961	+$1,479,603	+$2,491,765	
Combine	+$677,9	+$1,950,	+$3,276,	

d	05	531	228	

The venture is profitable under all market scenarios examined. As illustrated in Table 7, EFB drives the majority of economic value due to its greater feedstock availability (11,040 vs. 3,120 t/yr).

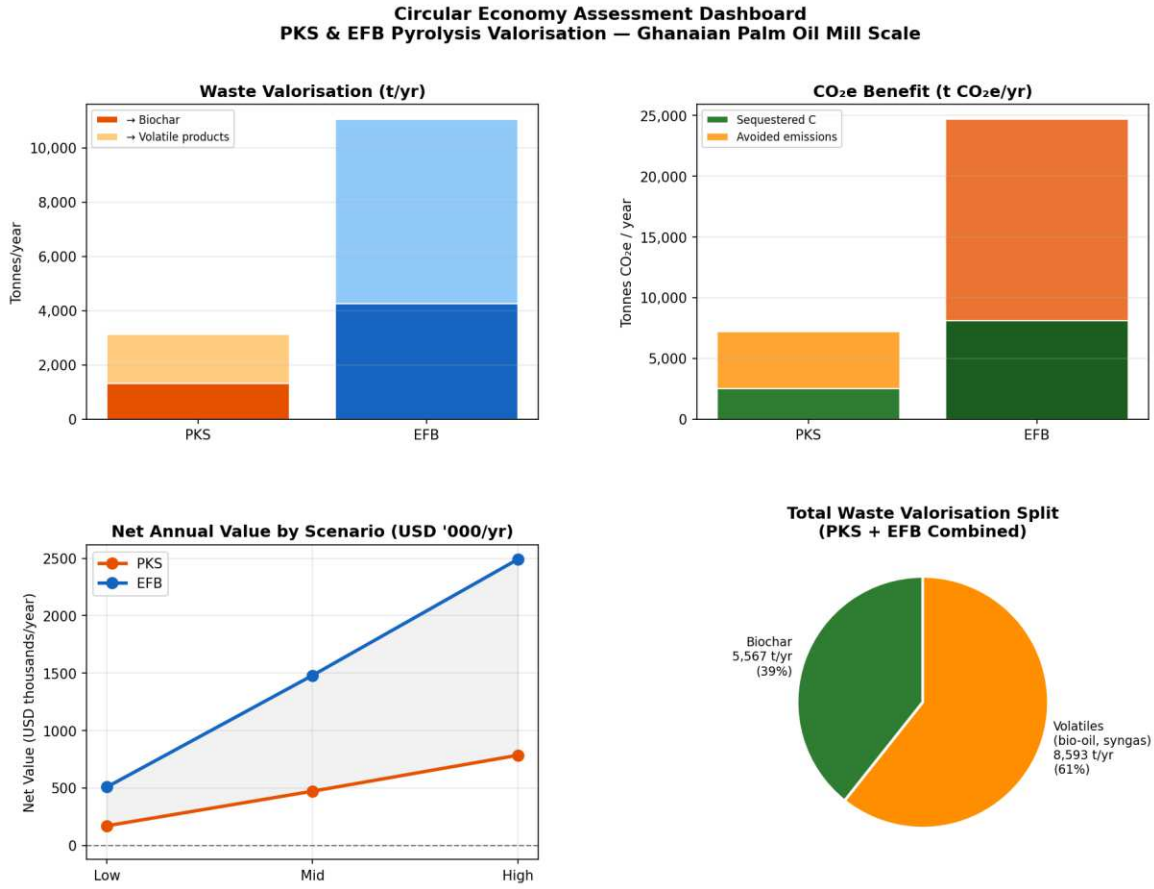


Fig. 13 Circular economy assessment dashboard: waste valorisation mass flow (a), CO_2e benefit (b), net annual value by scenario (bottom-left), and total feedstock valorisation split (bottom-right)

(a) Waste Valorisation (t/yr): A stacked bar showing the proportion of the feedstock that is converted to biochar (darker bar) and volatile products (lighter bar) in the case of the PKS and EFB. This is a shortened version of the mass flow graph, indicating that about 38-42% of both feedstocks are converted to biochar, and the remainder to volatiles.

(b) CO_2e Benefit (t/yr CO_2e): A stacked bar showing sequestered carbon (dark green) and avoided emissions (lighter orange-red) for each feedstock. EFB's bar is visually much taller, immediately communicating its greater influence on climate.

Bottom-Left Panel: Plot of the annual net value across the three market scenarios (Low, Mid, High) for each feedstock, in a line graph rather than bars, in the form of USD '000/yr. Both lines (the orange one and the blue one) run from left to right, both lines are sloping up, and both lines do not go below zero. The grey band partially highlighted between them represents the difference in value between the two feedstocks. The horizontal dashed line at zero is a reference point, and both lines fall nicely above it, reinforcing the profitability for all scenarios.

Bottom-Right Panel: Circular Economy Pie Chart (PKS + EFB Combined). The combined valorisation split for total feedstock processed annually 14,160 tonnes. The green wedge (39%) is biochar which is a valuable solid product that represents 5,567 tonnes of the total input. Volatile products which leave as bio-oil and syngas make up the orange

wedge (61%). This is the circular economy summary in its simplest form: nearly 40% of what was previously burned as waste becomes a premium product, and the remaining 60% carries its own energy recovery potential.

4.0 Conclusions

This research involved the formulation and implementation of a computational model using Python that could be used to optimize the valorisation of PKS and EFB to pyrolysis products. The following conclusions are drawn:

(1) The multi-component kinetic model was able to predict published data of biochar yield within ± 2.2 percentage points in the range of 300–700 °C, eliminating the need for primary laboratory experiments for prediction.

(2) The process robustness was demonstrated using Monte Carlo simulation ($\sigma \approx \pm 1.7\%$) and the influence of the lignin content was found as the main reason for yield uncertainty, which informed the priorities for feedstock characterisation.

(3) The results from constrained optimisation found the global optimum of 393 °C with residence times of 50.5 min (PKS) and 57.0 min (EFB) and biochar yields of 42.2% and 38.5% at the premium-grade fixed carbon (FC) threshold of 60%. The only constraint which was binding was the quality of the fixed carbon.

(4) At palm mill scale, a cost of USD 1,000/t, USD 677,905–3,276,228 of annual net revenues and 31,854 t CO_2e of climate benefit is possible at scale in Ghana, with profitability demonstrated in all market scenarios.

(5) Experimental validation under Ghanaian conditions, techno-economic capital investment analysis and life cycle assessment of the entire value chain should be done in future works. Also, pilot-scale validation under Ghanaian operating conditions is recommended for future work, together with techno-economic capital investment analysis and a full life cycle assessment of the value chain.

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Competing Interest

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Data Availability

The datasets generated during the current study are not publicly available but are available from the corresponding author on request. All model parameters, validation data, optimisation results, and circular economy metrices are fully reported within the manuscript

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