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Optimization of Biochar Production from Cassava Peels: An Application of Response Surface Methodology

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Abstract: Pyrolysis of agricultural waste to biochar presents a valorization pathway for wastes in an environmentally friendly way. The study focuses on the optimization of biochar production from cassava peels using response surface methodology. Three most important process parameters were considered for optimization: pyrolysis temperature (350–750 °C), heating rate (5–25 °C/min), and reaction time (20–130 min). For that, a Box-Behnken experimental design has been employed to develop a predictive model for biochar yield and other responses of interest: pH, bulk density, and surface area. The developed empirical models for predicting biochar characteristics with high accuracy were validated through diagnostic plots and experimental trials. It was seen that temperature, heating rate, and reaction time substantially affected the yield of the biochar. The maximization resulted in an overall increase in the physicochemical properties of biochars. This study illustrates scalable applications of biochar and establishes the predictive model for real validation experiments for the application of process flow modeling of biomass pyrolysis. This work emphasizes the optimization of parameters in the production of biochar and gives a real platform for the use of agricultural residues in sustainable waste management and environmental remediation. The predictive model developed can be used as an important tool in designing efficient biomass conversion processes.

Keywords: cassava peel valorization, biochar production optimization, response surface methodology, sustainable waste management

1. Introduction

Increased agricultural and processing activities have increased the production of wastes, which are harmful to the environment if not disposed of or managed properly [1]. The agricultural sector has been noted as one of the leading contributors of biomass, which is mainly obtained from harvested fields [2]. Biomass refers to organic material that can be sourced from a plant or an animal and which can also serve as a renewable source of energy [3–5]. Improper biomass disposal or control can cause environmental degradation, greenhouse gas emissions, and pollution of water bodies and groundwater. Cassava is one of the major staple foods in Nigeria and is massively produced for various industrial uses around the world [6]. However, such agricultural wastes including cassava peel end up being dumped on the ground after harvesting and processing these main root crops.

One of the channels of this waste management is the conversion of the same into biochar. By Ref. [7], biochar is defined as an organic material that is pyrogenous, which constitutes the product of pyrolyzing different types of biomass, including plant or even animal waste [8, 9]. In the process of pyrolysis, organic waste is transformed into a carbon-rich material, known as biochar, which has varied applications in industrial and environmental fields. Its usefulness is wide; it can be used in agriculture, environmental remediation, and energy production [10]. Pyrolysis is known to be one of the most common methods because of its efficient thermal transformation and environmentally friendly technology [2, 10, 11]. This process is a thermochemical reaction that produces biochar, biogas, and bio-oil by applying heat to biomass at controlled temperatures in the absence of oxygen [8].

The properties of the biomass are of utmost importance in considering whether the material is suitable for producing biochar. The properties can be obtained through proximate analysis, which contains physiochemical characteristics such as pH, bulk density, and surface area [7, 8]. The other factors that can affect the production of biochar are temperature, heating rate, and reaction time. Response surface methodology (RSM) allows for studying the interaction among all these variables and optimizes the parameters for better production of biochar [12–14].

The optimization of biochar production from cassava peels holds great promise for the advancement of sustainable energy and environmental remediation efforts [15, 16]. Biochar, a carbon-rich byproduct of biomass pyrolysis, is a multi-functional material whose applications closely align with global sustainability goals. This study aims to investigate the optimization of biochar production from cassava peels using RSM. It aims at the determination of the influence of critical pyrolysis parameters, such

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as temperature, heating rate, and reaction time, on biochar yield and physicochemical properties, and to develop a predictive model for efficient and high-quality biochar production. The need to effectively exploit cassava peels by developing viable and efficient biomass pyrolysis systems has driven the motivations toward this study.

Despite cassava peels being one of the most available agricultural residues, they are still underutilized for high-value applications in the production of biochar [4]. Most of the existing literature focuses on conventional biomass sources, such as wood or rice husks, leaving a wide gap in the exploration of cassava peels as a sustainable feedstock. Moreover, most research on biochar production lacks comprehensive optimization of pyrolysis parameters, which leads to inefficiency in yield and inconsistency in the properties of biochar [8]. Advanced statistical tools, such as RSM, which could address these challenges, have been underutilized in this context. Although biochar yield is often discussed, other critical physicochemical properties, including pH, bulk density, and surface area, are usually not considered, despite their importance for agricultural and environmental applications. Most of the studies are also limited to laboratory-scale experiments, with minimal efforts to develop predictive models that support scalability and integration into industrial systems. This study attempts to fill these knowledge gaps by using RSM for the optimization of pyrolysis parameters of cassava peels, assessing yield and physicochemical properties, and developing a highly accurate predictive model applicable to large-scale operations.

The Box-Behnken design is powerful and efficient in the study of response surfaces, but it also has several limitations. It does not include experiments at the extreme corners of the design space, which might miss critical information about the system's behavior under extreme conditions. BBD is limited to three levels per factor, making it unsuitable for variables requiring more levels. It also becomes less efficient for high-dimensional problems because the number of required runs increases exponentially with the number of factors. The design assumes uniform ranges for factors, complicating its application to variables with irregular or non-symmetric ranges. BBD has limited precision in fitting quadratic models for systems with strong curvature at the edges and is sensitive to missing data, which can compromise the entire model.

2. Material and Methods

The materials used in this study are cassava peel waste and cow dung. Samples of cassava peel waste were picked from a processing factory in Omu-Aran, Kwara State, Nigeria. The cow dung samples were obtained from the Landmark University Teaching and Research farm (Ranch). The cassava peel samples were washed using deionized water and subsequently oven-dried for 4 h at 110 °C. The cassava peel was dried and taken to the Agricultural and Biosystems Engineering Processing Laboratory for size reduction using a hammer mill. The samples were prepared for pyrolysis by incorporating base-sodium hydroxide (NaOH) after size reduction. Solutions of 1000 g NaOH were prepared using 1 mole mixed with 200 g of crushed cassava peel. These mixtures were then put under heating for 2 h on low heat. Then, the samples were prepared for the pyrolysis process in a muffle furnace using 13 runs.

The pyrolysis was carried out at temperatures between 350 °C and 750 °C, with heating rate between 5 °C and 25 °C/mins and reaction time ranging from 20 to 130 min until char was produced. After pyrolysis, the samples were washed back to neutral and then dried in the oven for 24 h at 105 °C. Moreover, sundrying of the cow dung samples was done for 5 h and then oven-dried at 105 °C for 24 h. Size reduction of cow dung samples was done in mortar and pestle. The reduced size cow dung was impregnated with the biochar sample using 5 ml deionized water and then further oven-dried for 3 h. Thereafter, the samples were prepared for physicochemical characterization.

Table 1
Build information for the design

File version	11.1.2.0		
Study Type	Response Surface	Subtype	Randomized
Design Type	Box-Behnken	Runs	13
Design Model	Quadratic	Blocks	No Blocks
Build Time (ms)	1.0000		

3. Experimental Layout

RSM uses statistical and mathematical approaches to determine variable interactions and their respective responses with the minimum number of experimental runs for optimization [12]. Design Expert 13 has been used for the design of the experiments, recording the responses, and analysis of the results. For optimization of biochar production, a BBD was chosen because of its effective statistical methodology for multi-factor optimization and reduction in the number of experimental trials required [17]. The numerical variables included in the experimental design were reaction temperature (°C), heating rate (°C/min), and reaction time (minutes). Thirteen experimental runs were performed. Different parameters such as yield, pH, bulk density, and surface area were analyzed in this study [13, 14].

Mostly, based on the sensitivity of variable factors, optimal factor conditions are suggested by the software depending on desired product yields. Optimization of process parameters requires R^2 value analysis roughly equal to 1 and adjusted R^2 and predicted R^2 values. In suitable models, the difference between the adjusted and predicted R^2 must be less than 0.2 [18]. Precision value greater than 4 is an indication of a good signal-to-noise ratio [4, 19]. Tables 1 and 2 show the design information for the factors and responses, respectively.

4. Results and Discussions

4.1. ANOVA for linear model (response (yield B))

The ANOVA analysis results from Design Expert are presented in Table 4. The *P*-value of the linear model is 0.0037, indicating that the results are statistically significant and that the model is appropriate for predicting the response variable (% biochar yield). Additionally, a model *F*-value of 9.53 implies that the model is truly significant. There is only a 0.37% probability that such a large *F*-value would occur due

Table 2
Design-build information for the response variable

Factor	Name	Units	Type	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
A	Temperature	°C	Numeric	350.00	750.00	−1 ↔ 350.00	+1 ↔ 750.00	550.00	163.30
B	Heating rate	Min/°C	Numeric	5.00	25.00	−1 ↔ 5.00	+1 ↔ 25.00	15.00	8.16
C	Reaction time	Min	Numeric	20.00	130.00	−1 ↔ 20.00	+1 ↔ 130.00	75.00	44.91

Table 3
ANOVA for linear model (RSM for % biochar yield cassava peel (B))

Source	Sum of squares	Df	Mean square	*F*-value	*P*-value	
Model	70.59	3	23.53	9.53	0.0037	Significant
A-Temperature	67.28	1	67.28	27.25	0.0005	
B-Heating rate	3.25	1	3.25	1.32	0.2808	
C-Reaction time	0.0613	1	0.0613	0.0248	0.8783	
Residual	22.22	9	2.47			
Cor Total	92.82	12				

to random fluctuation. In the current situation, A is a crucial model parameter, representing temperature [3].

This study has thus considered that a notable influence of temperature on the production of biochar (B) is already affirmed. Values over 0.1000 indicate that the predictive factors are insignificant [3]. The terms found to be not significant have *P*-values 0.1973 (B) and 0.2808 (C). This shows that there is no interaction between heating rate and reaction time with temperature, but the temperature is important. Importantly, the heating rate and reaction time have no significance on the model (*P*-value = 02808 and 0.8783) respectively.

Also, from the summary of the statistical analysis, it can be stated that the R^2 value is 0.7606, but the predicted R^2 value of 0.4715 is not within proximity to the adjusted R^2 value of 0.6807; in fact, the difference is much greater than 0.2 indicating a severe block effect or problem with either the model or the data. Acceptable accuracy, reflected in the ratio 8.117 which is higher than 4, implies an optimal and adequate signal-to-noise ratio [20]. The average recorded was 3.98%, proving char production takes place during the use of the waste feedstock with a base under the conditions used with an acceptable standard deviation of 1.57 and coefficient of variation (CV %) of 39.44.

Table 3 displays the model's statistical properties, including the total squares owing to the components and the mean square values. Based on the prediction model's favorable statistical results, the Design Expert Software gives additional diagnostic tools for further investigation using the model and experimental data. Figure 1 depicts each of the four approaches examined:

Figure 1
(a) pH, (B) Predicted vs Actual; (b) link between heating rate and temperature in relation to pH; (c) correlation plot of heating rate and temperature in relation to pH. (B) Interaction; (d) perturbation plot demonstrating the link between A, B, and C pH (B). (e) Three-dimensional interaction of heating rate, temperature, and pH (B)

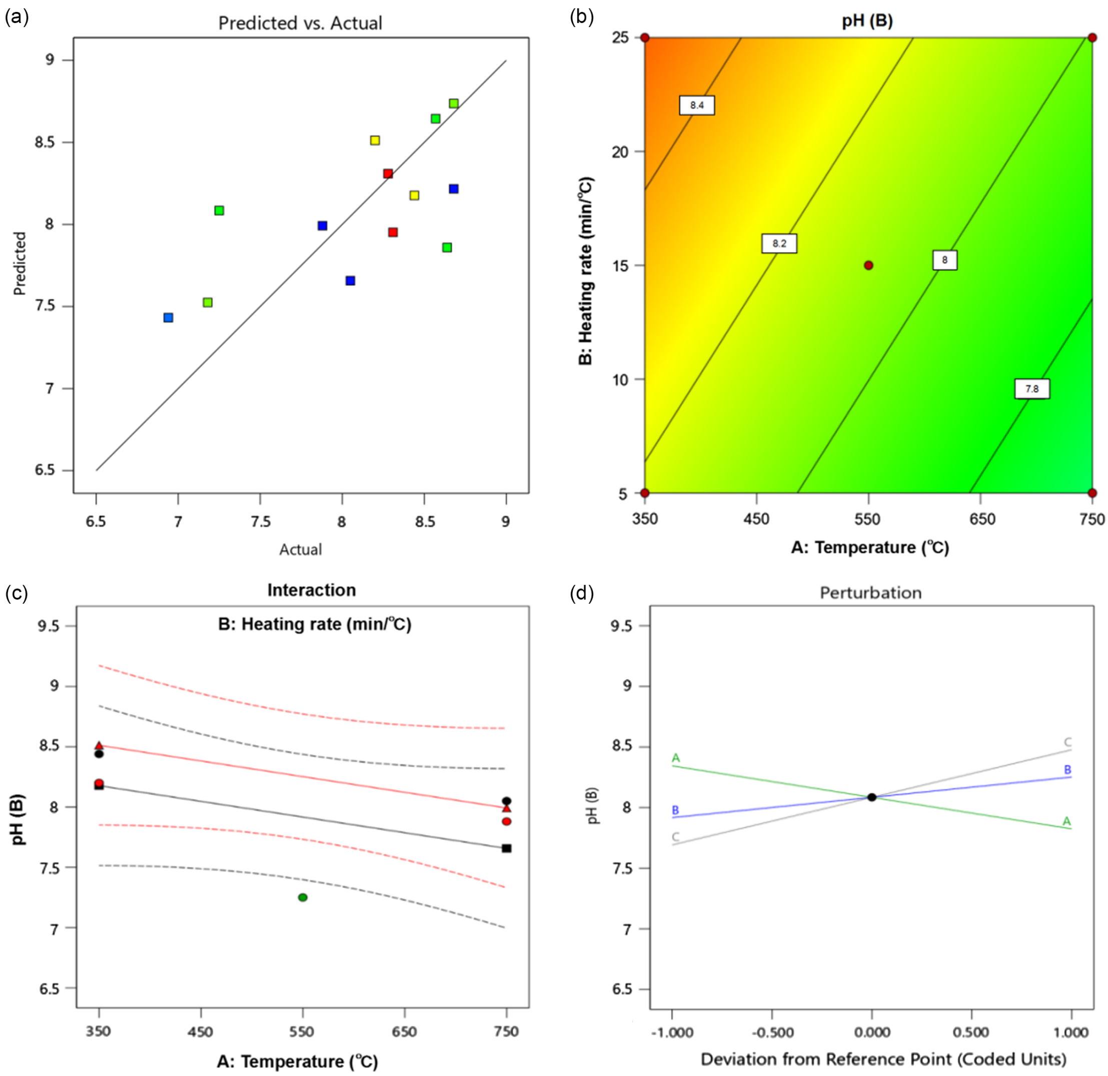
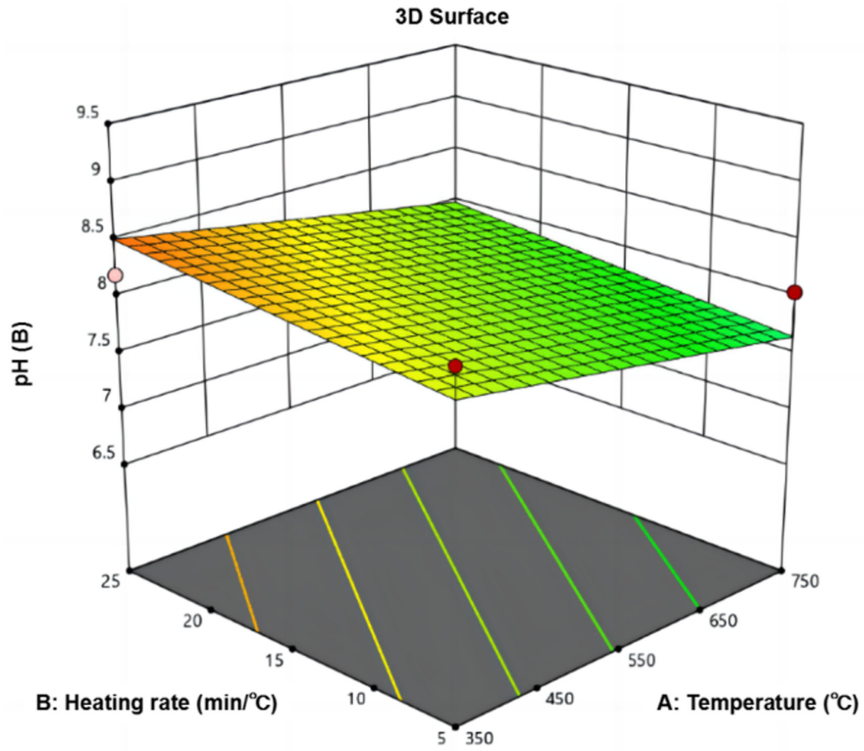


Figure 2
3D interaction between heating rate, temperature, and PH (B)



expected vs actual outcomes, contour map, interaction plot, and perturbation analysis. Equation (1) describes the link regarding yield (B) and classified variables.

Figure 1a compares actual and expected values for biochar yield (B). The results show that the linear model of the reaction is appropriate for the experimental data and produces a strong prediction of the models. Figure 1d depicts the perturbation graph, indicating the yield's modification susceptibility.

The temperature gradient shows a trend of increased yield with increasing deviation, while the heating rate displays a decrease in biochar yield with increasing deviation. In contrast, the reaction time indicates a fairly constant yield across changes in deviation. Figure 2 highlights the relationship between temperature, heating rate, and biochar production (B) in a 3-D surface plot. The plot indicates that the temperature increases with a decrease in yield, meaning that increased temperature does not favor increased biochar yield. It also showed that low moderate temperatures of about 350 °C–450 °C maintain a relatively high biochar yield, especially at a heating rate between 10 and 20 min/°C, but as the heating rate rises beyond 20 min/°C, the yield drops drastically irrespective of the temperature [21].

$$Yield\,(B) = +3.98 - 2.90A - 0.6375B - 0.0875C \qquad (1)$$

where A, B, and C represent the codified values of temperature (°C), reaction time (min), and heating rate (°C/min).

4.2. ANOVA for linear model (response pH (B))

Table 4 displays the ANOVA result obtained from the Design expert. The *P*-value for the linear model is 0.1211, indicating that the results are inconsequential; the model is not appropriate for predicting the response (pH). The model's *F*-value of 2.55 indicates that it is not significant, implying that there are no important model terms. Values above 0.1000 imply that the model terms are insignificant. Jeffery et al [22] state that a large number of unimportant model variables indicate a lack of interaction between heating rate and temperature reaction time.

Table 4
Linear model (RSM for biochar pH (B))

Source	Sum of squares	Df	Mean square	*F*-value	*P*-value	
Model	2.00	3	0.6659	2.55	0.1211	not significant
A-Temperature	0.5408	1	0.5408	2.07	0.1841	
B-Heating rate	0.2244	1	0.2244	0.8589	0.3782	
C-Reaction time	1.23	1	1.23	4.72	0.0580	
Residual	2.35	9	0.2613			
Cor Total	4.35	12				

Table 5
Quadratic model (RSM for B. Density (B))

Source	Sum of squares	Df	Mean square	*F*-value	*P*-value	
Model	0.0563	3	0.0188	3.42	0.0660	Not significant
A-Temperature	0.0512	1	0.0512	9.34	0.0137	
B-Heating rate	0.0045	1	0.0045	0.8229	0.3880	
C-Reaction time	0.0006	1	0.0006	0.1117	0.7459	
Residual	0.0494	9	0.0055			
Cor Total	0.1057	12				

Additionally, the statistical fitting yields a R^2 value of 0.4593 and a predicted R^2 of -0.0280, which are consistent with the Adjusted R^2 of 0.2790.

A suitable signal is indicated by a sufficient accuracy ratio that exceeds the threshold of 4 [23]. In this case, the adequate precision value is 4.602 which implies a desirable signal. The coefficient of variation (CV %) is 6.32, and the standard deviation is 0.5112, resulting in a mean of 8.08% for the model. Table 5 presents the model's descriptive statistics and diagnostic tools from Design Expert Software for additional analysis. Predicted versus actual values, contour maps, interaction plots, and perturbation plots are shown in Figure 3.

Figure 3
(a) pH, (b) Predicted versus Actual. (b) Relationship between heating rate and temperature in relation to pH, (c) interaction plot of heating rate and temperature in relation to pH. (B) Interaction. (d) Perturbation plot demonstrating the link between A, B, and C pH (B). (e) Three-dimensional interaction of heating rate, temperature, and pH (B)

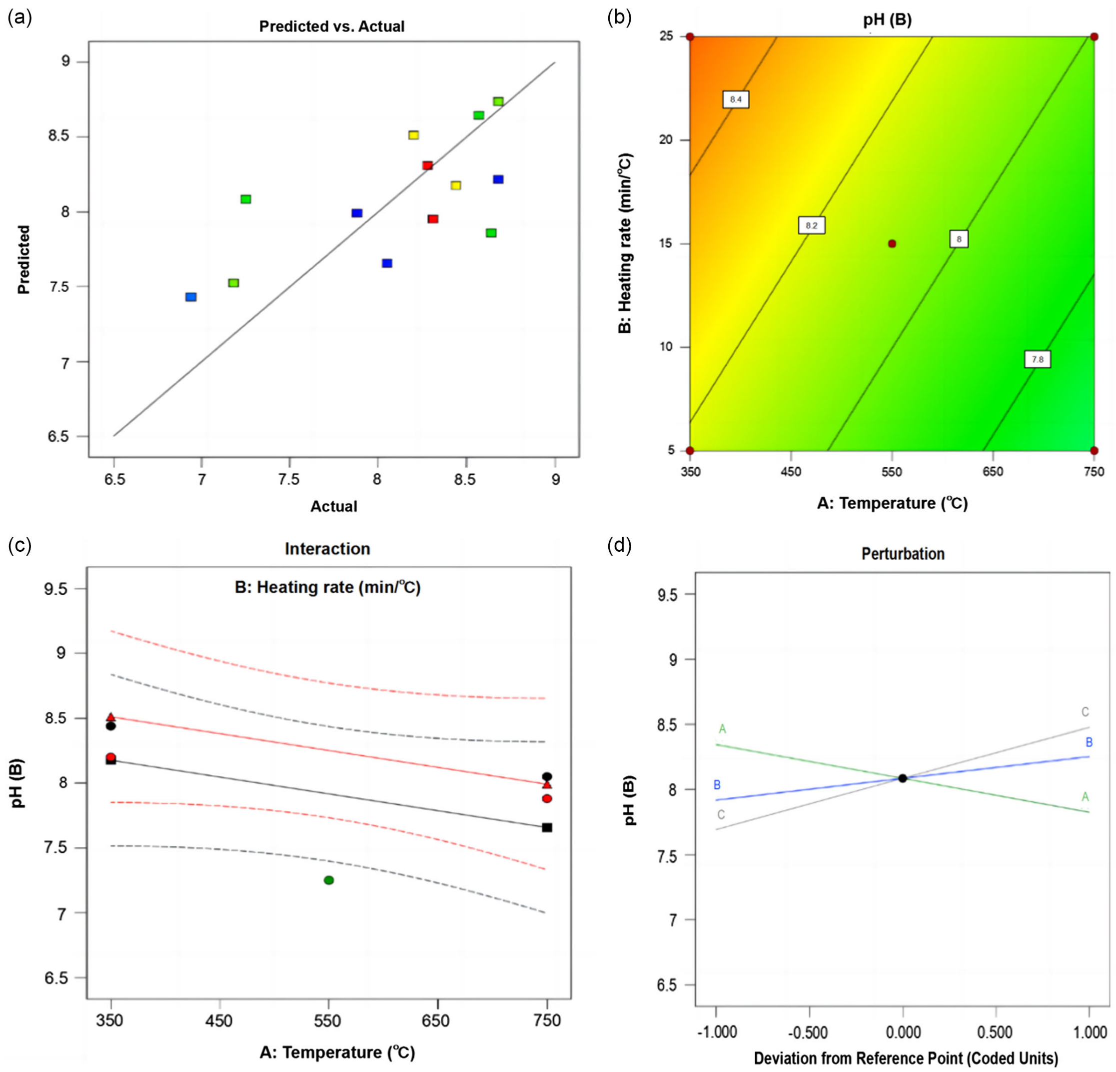
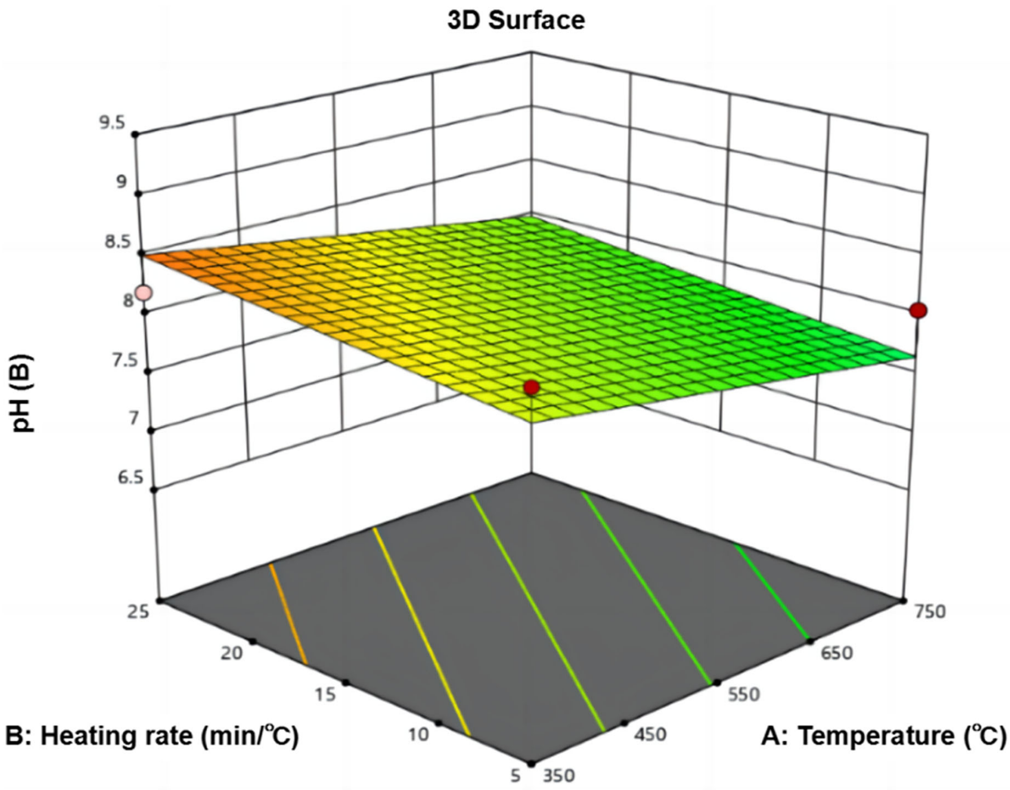


Figure 4
3D interactions between heating rate, temperature, and pH (B)



Equation (2) depicts the link between pH (B) and coded variables. Figure 2a compares the actual and anticipated values for biochar yield, and the points show that the linear model of response fits the experimental data and is a good prediction model. Figure 4 depicts the association between the variables using a three-dimensional surface plot.

$$pH\,(B) = +8.08 - 0.2600A + 0.1675B + 0.3925C \qquad (2)$$

where A, B, and C represent the encoded values of temperature (°C), reaction time (min), and heating rate (°C/min).

4.3. ANOVA for quadratic model (B. density (B))

Table 5 shows the ANOVA results derived from the Design expert. The linear model's P-value (0.0660) indicates that it is not significant and so inadequate for predicting the response (B. density). Furthermore, the model's F-value of 3.42 indicates that it is not significant, implying that there are no important model terms. Values over 0.1000 suggest that the model terms are not significant [22]. If there are several negligible model variables, it indicates that there is no interaction between heating rate and reaction time to temperature [23]. The statistical fitting yields a R^2 value of 0.5330, predicted R^2 of −0.0304, and adjusted R^2 of 0.2790. Predicted versus actual values, contour maps, interaction plots, and perturbation plots are shown in Figure 5. Figure 6 depicts the association between the variables using a three-dimensional surface plot.

$$B.density\,(B) = +0.2669 + 0.0800A + 0.0238B + 0.0087C \qquad (3)$$

where A, B, and C represent the codified values of temperature (°C), reaction time (min), and heating rate (°C/min).

The obtained results are in good agreement with the mechanisms of thermal and chemical transformation of biomass during pyrolysis. RSM allows modeling and optimization of multiple variables that interact, providing a robust framework for yield and quality maximization. Results highlight the need to balance the pyrolysis parameters with a view to tailor biochar properties for specific applications, informed by an understanding of the underlying scientific principles.

Figure 5
(a) B. density, (B) Predicted vs. Actual; (b) Relationship between the heating rate and temperature relative to the B. density (B); (c) interaction plot between the heating rate and the temperature relative to the B. Density (B); (d) a perturbation plot depicting the link between A, B, and C, as well as B density (B); (e) a 3D interaction between heating rate, temperature, and B density

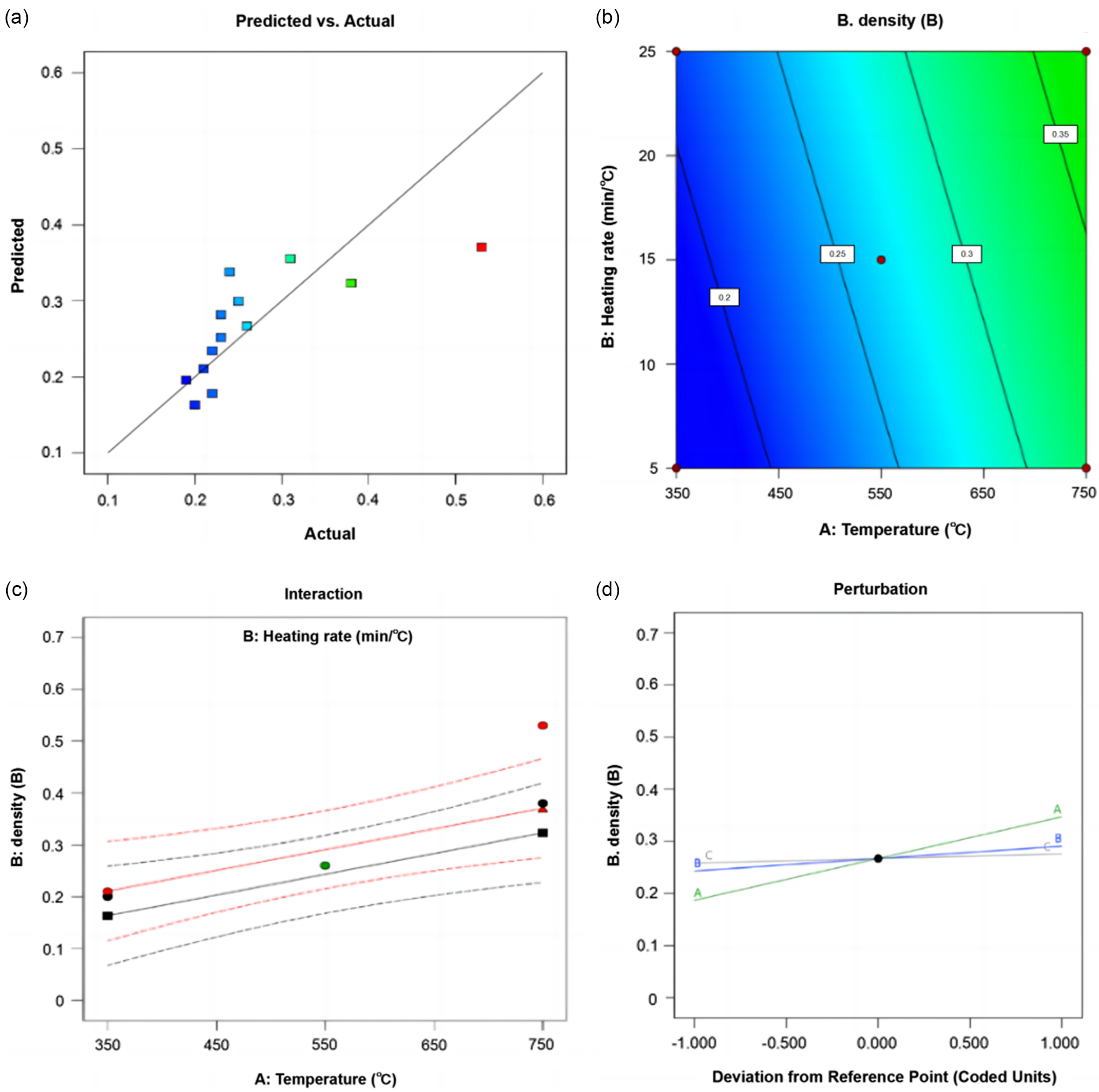
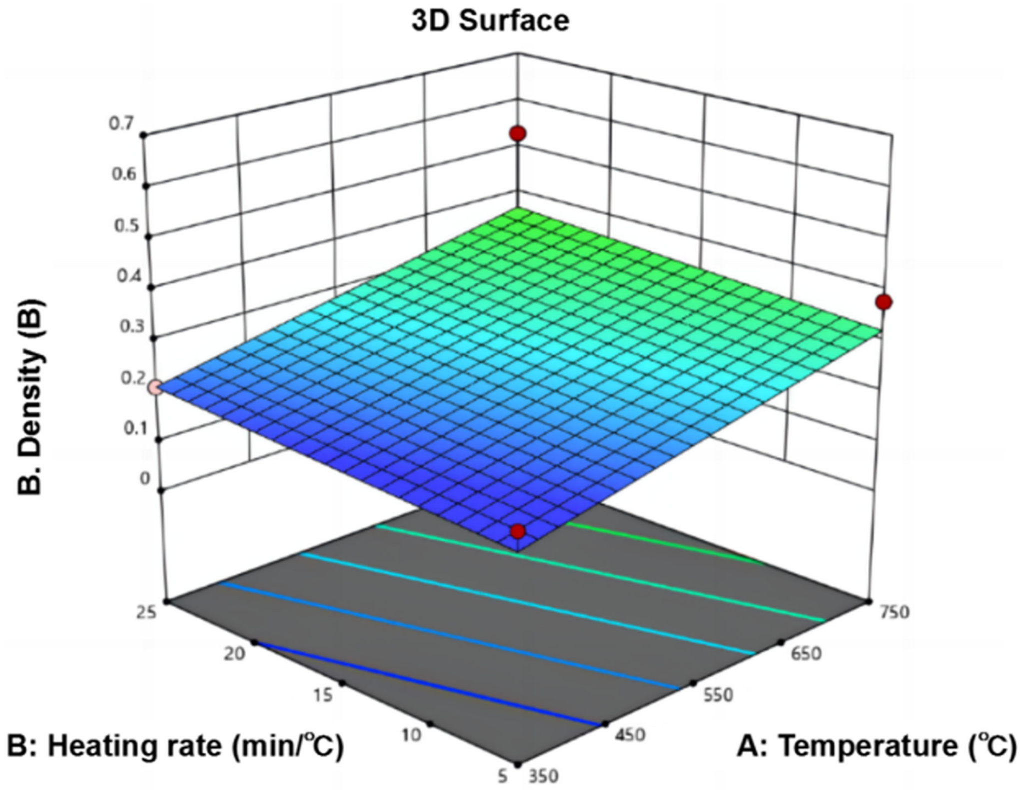


Figure 6
3D interaction between heating rate, temperature, and B. density



5. Conclusion

The study reports on parametric modeling of some physicochemical properties of Biochar using RSM. From the results, the following conclusions are drawn. The biochar yield, pH, bulk density, and surface area are all significantly influenced by temperature, heating rate, and reaction time. Furthermore, the experimental validation supports the correctness of biochar yield. This model, which is based on physicochemical characterization, operating temperature, heating rate, and reaction time, is simply applicable to further process flow modeling of biomass pyrolysis.

This study presents an opportunity to turn waste into high-value biochar and contributes to resource efficiency and circular economy principles. In this respect, RSM with a Box-Behnken design presents a forceful approach toward the optimization of pyrolysis parameters like temperature, heating rate, and reaction time, which will give a better understanding of their interactions and effects on biochar yield and physicochemical properties. The development of a highly accurate predictive model represents a novel tool for guiding biochar production processes, enabling scalability and integration into industrial systems. This model bridges the gap between laboratory-scale experiments and practical applications, offering a framework for optimizing biomass conversion under varying conditions. In addition, the comprehensive characterization of biochar properties, including pH, bulk density, and surface area, extends its use in soil improvement, pollution remediation, and carbon sequestration.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Timothy Adekanye: Conceptualization, Methodology, Validation, Formal analysis, Writing – review & editing, Supervision, Project administration. **Abiodun Okunola:** Conceptualization, Methodology, Validation, Supervision. **Adeolu Adediran:** Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Writing – review & editing, Supervision. **Afolabi Tokunbo Yemisi:** Resources, Data curation, Project administration. **Aisha Aderibigbe:** Investigation, Writing – original draft, Visualization.

References

[1] Shahzad, H. M. A., Asim, Z., Khan, S. J., Almomani, F., Mahmoud, K. A., Mustafa, M. R. U., & Rasool, K. (2024). Thermochemical and

biochemical conversion of agricultural waste for bioenergy production: An updated review. *Discover Environment*, *2*, 134. https://doi.org/10.1007/s44274-024-00171-w

[2] Te, W. Z., Muhanin, K. N. M., Chu, Y.-M., Selvarajoo, A., Singh, A., Ahmed, S. F., . . . , & Show, P. L. (2021). Optimization of pyrolysis parameters for production of biochar from banana peels: Evaluation of biochar application on the growth of *Ipomoea aquatica*. *Frontiers in Energy Research*, *8*, 637846. https://doi.org/10.3389/fenrg.2020.637846

[3] Atilgan, A., Krakowiak-Bal, A., Ertop, H., Saltuk, B., & Malinowski, M. (2023). The energy potential of waste from banana production: A case study of the Mediterranean region. *Energies*, *16*(14), 5244. https://doi.org/10.3390/en16145244

[4] Odeyemi, S. O., Iwuozor, K. O., Emenike, E. C., Odeyemi, O. T., & Adeniyi, A. G. (2023). Valorization of waste cassava peel into biochar: An alternative to electrically-powered process. *Total Environment Research Themes*, *6*, 100029. https://doi.org/10.1016/j.totert.2023.100029

[5] Antar, M., Lyu, D., Nazari, M., Shah, A., Zhou, X., & Smith, D. L. (2021). Biomass for a sustainable bioeconomy: An overview of world biomass production and utilization. *Renewable and Sustainable Energy Reviews*, *139*, 110691. https://doi.org/10.1016/j.rser.2020.110691

[6] Kolawole, P. O., Agbetoye, L., & Ogunlowo, S. A. (2024). Sustaining world food security with improved cassava processing technology: The Nigeria experience. *Sustainability*, *16*(3), 465–479.

[7] Tomczyk, A., Sokołowska, Z., & Boguta, P. (2020). Biochar physicochemical properties: Pyrolysis temperature and feedstock kind effects. *Reviews in Environmental Science and Bio/Technology*, *19*(1), 191–215. https://doi.org/10.1007/s11157-020-09523-3

[8] Afshar, M., & Mofatteh, S. (2024). Biochar for a sustainable future: Environmentally friendly production and diverse applications. *Results in Engineering*, *23*, 102433. https://doi.org/10.1016/j.rineng.2024.102433

[9] Patel, M. R., & Panwar, N. L. (2023). Biochar from agricultural crop residues: Environmental, production, and life cycle assessment overview. *Resources, Conservation & Recycling Advances*, *19*, 200173.

[10] Adekanye, T., Dada, O., & Kolapo, J. (2022). Pyrolysis of maize cob at different temperatures for biochar production: Proximate, ultimate and spectroscopic characterization. *Research in Agricultural Engineering*, *68*(1), 27–34. https://doi.org/10.17221/106/2020-RAE

[11] Qin, L., Wu, Y., Hou, Z., & Jiang, E. (2020). Influence of biomass components, temperature and pressure on the pyrolysis behavior and biochar properties of pine nut shells. *Bioresource Technology*, *313*, 123682. https://doi.org/10.1016/j.biortech.2020.123682

[12] Reji, M., & Kumar, R. (2022). Response surface methodology (RSM): An overview to analyze multivariate data. *Indian Journal of Microbiology Research*, *9*(4), 241–248.

[13] Sulaiman, N. S., Hashim, R., Mohamad Amini, M. H., Danish, M., & Sulaiman, O. (2018). Optimization of activated carbon preparation from cassava stem using response surface methodology on surface area and yield. *Journal of Cleaner Production*, *198*, 1422–1430. https://doi.org/10.1016/j.jclepro.2018.07.061

[14] Mariyam, S., Alherbawi, M., Pradhan, S., Al-Ansari, T., & McKay, G. (2023). Biochar yield prediction using response surface methodology: Effect of fixed carbon and pyrolysis operating conditions. *Biomass Conversion and Biorefinery*, *14*, 28879–28892. https://doi.org/10.1007/s13399-023-03825-6

[15] Chen, Q., & Qi, J. (2023). How much should we trust R2 and adjusted R2: Evidence from regressions in top economics journals and Monte Carlo simulations. *Journal of Applied Economics*, *26*(1), 2207326. https://doi.org/10.1080/15140326.2023.2207326

[16] Bai, S. H., Omidvar, N., Gallart, M., Kämper, W., Tahmasbian, I., Farrar, M. B., . . . , & van Zwieten, L. (2022) Combined effects of biochar and fertilizer applications on yield: A review and meta-analysis. *Science of the Total Environment*, *808*, 152073. https://doi.org/10.1016/j.scitotenv.2021.152073

[17] Mattioli, D., Scarsella, M., & Tuffi, R. (2024). Optimization of pyrolysis parameters by design of experiment for the production of biochar from sewage sludge. *Environments*, *11*(10), 210.

[18] Yang, X., Kang, K., Qiu, L., Zhao, L., & Sun, R. (2020). Effects of carbonization conditions on the yield and fixed carbon content of biochar from pruned apple tree branches. *Renewable Energy*, *146*, 1691–1699. https://doi.org/10.1016/j.renene.2019.07.148

[19] Varma, A. K., & Mondal, P. (2017). Pyrolysis of sugarcane bagasse in semi-batch reactor: Effects of process parameters on product yields and characterization of products. *Industrial Crops and Products*, *95*, 704–717. https://doi.org/10.1016/j.indcrop.2016.11.039

[20] Onokwai, A. O., Owamah, H. I., Ibiwoye, M. O., Ayuba, G. C., & Olayemi, O. A. (2022). Application of response surface methodology (RSM) for the optimization of energy generation from Jebba hydro-power plant, Nigeria. *ISH Journal of Hydraulic Engineering*, *28*(1), 1–9. https://doi.org/10.1080/09715010.2020.1806120

[21] Karuppusamy, S., Kumar, B. S., Kumar, M. R., Guru, K. R., & Rameshbabu, A. M. (2021). Analysis of square threading process by using response surface methodology. *Materials Today: Proceedings*, *37*(Part 2), 3417–3422.

[22] Burks, J. J., Randolph, D. W., & Seida, J. A. (2019). Modeling and interpreting regressions with interactions. *Journal of Accounting Literature*, *42*, 61–79.

[23] Wang, J., Wei, M., He, J., Wang, Y., & Ren, C. (2022). Optimization of repair process parameters for open-arc surfacing welding of grinding rolls based on the response surface method. *Processes*, *10*, 321. https://doi.org/10.3390/pr10020321

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