ISBN: 978-978-67-0285-8 DOI: https://doi.org/10.55455/acsnigeria.1.3.66-74

Predictive Modeling and Multivariate Optimization of Multi-Feedstock Biodiesel Blends Derived from African Star Apple (*Chrysophyllum albidum*) Seed Oil and Indigenous Lipid Streams

Joseph Nifu Barnabas, Noela Chinyelu Igwemmar, and Oluremi Isola Adeniran
Department of Chemistry, Faculty of Science, University of Abuja, PMB 117, Abuja, Nigeria
Corresponding Author's email: chemistbarnabasedu@gmail.com
DOI: https://doi.org/10.55455/acsnigeria.1.3.66-74

ABSTRACT

This data-driven predictive optimization framework, developed using IBM SPSS, optimizes multi-feedstock biodiesel mixtures derived from non-edible African star apple (*Chrysophyllum albidum*) seed oil (ASASO), palm kernel oil (PKO), and waste cooking oil (WCO). A total of 231 distinct blends were simulated using this approach. The performance of each blend composition with respect to key biodiesel fuel properties was modelled using Multiple Linear Regression Analysis (MLRA). Among the five fuel indices evaluated (kinematic viscosity, density, oxidative stability, higher heating value, and cetane number), kinematic viscosity was the best-predicted property ((R^2 = 0.739)). To identify high-quality fuel blends, blend configurations satisfying the optimal limits specified by ASTM D6751 were classified into three clusters using hierarchical cluster analysis based on Ward's method. A restricted blending window of 20–50% ASASO was identified as a viable range for simultaneously managing fluid flow resistance and oxidative stability. Within this range, the kinematic viscosity was maintained between 3.80 and 4.95 mm²/s, while oxidative stability exceeded 7.5 h. This approach replaces laborious and time-consuming empirical blending trials with a practical predictive framework for biodiesel formulation, thereby supporting the development of the green economy in West Africa through practical formulation indices.

KEYWORDS: *Chrysophyllum albidum*, Blending kinetics, Multiple linear regression, Hierarchical cluster analysis, Fuel property optimization.

1. INTRODUCTION

1.1 Global Energy Transition Context

Facing issues of global warming, energy consumption growing, and long-term energy security, the global energy market is currently undergoing an exceptional energy transition toward low-carbon energy. Being one of the major emitters of greenhouse gases as a result of continued dependence of the road transport system on petroleum, the transport sector Governments & intergovernmental organizations are committed to enhancing the utilization of renewable transport fuels to promote diversification, carbon mitigation, as well as overall energy resiliency[1]. Amongst the potential alternatives, biodiesel got much attention owing to its biodegradable and replenishable properties and compatible usage with conventional compression-ignition engines.

Biodiesel can be made from diverse biological origins, including the use of edible and non-edible oils and other waste products. However, this move is relatively far behind the developed economies. Many developing economies (particularly in Sub-Saharan Africa) are suffering from their dependence on imported petroleum products (owing to a lack of processing capacity) and failure to tap the huge amount of indigenous biomass available on the continent, consequently fuelling the energy security concern. For that, there is a need to harness non-edible oilseeds and waste streams towards designing decentralised biodiesel production to provide environmental benefits and to realize a circular bioeconomy[2,3]. However to capitalize this opportunity in efficiently, fuel compositions are essential scientifically optimized to ensure its adherence with the international standard as well as to capture the synergistic effects of local sources, therefore; data driven approach has opened the door for predicting fuel parameters that may support development of bio- diesel, reduce the cost associated with experiment, while also leading the way to facilitate the design of optimal bio fuel compositions[4].

1.2 Nigerian Energy Crisis and Biofuel Policy

Although Nigeria is endowed with large crude oil deposits, challenges persist in its downstream petroleum sector, including insufficient domestic refinery capacity, reliance on imported refined fuels, and repeated fuel shortages. These structural limitations have been further complicated by the recent removal of fuel subsidies, which has significantly increased transportation and logistics costs and intensified inflationary pressures throughout the economy. Consequently, rising diesel prices have adversely affected industrial activities, agricultural mechanization, electricity production, and road freight transportation, highlighting the need for stable, locally available alternative fuels to strengthen energy security and resilience against global petroleum price fluctuations[1]. In response to these and related challenges, Nigeria has introduced policies to scale up renewable energy and increase biodiesel's contribution to the domestic energy supply.

For example, the National Biofuel Policy and Incentives promotes the use of indigenous plant biomass resources to displace fossil-derived fuels and encourage rural economic development. Nigeria's commitment to achieving net-zero greenhouse gas emissions by 2060 has also renewed interest in producing second-generation biodiesel from non-food oil crops and waste materials. Biodiesel produced from non-edible feedstocks and residues has the added advantage of utilizing abundant but underused plant resources while reducing food-versus-fuel concerns associated with edible crops such as palm and groundnut oil, thereby supporting circular bioeconomy solutions. These government policies provide a strong basis for developing domestically available biodiesel products that can strengthen national energy security and support climate and sustainability goals[1,5].

1.3 African Star Apple Seed Oil as a Sustainable Biodiesel Feedstock

African star apple (Chrysophyllum albidum), an indigenous fruit tree common in West Africa, including Nigeria, is mainly consumed for its fruit, while the seeds are often discarded as municipal or agricultural waste. African star apple seeds represent an abundant and largely unexplored non-food biomass resource with potential for biodiesel production because they do not directly compete with food crops or arable land. Biodiesel produced from African star apple seed oil has favourable ignition characteristics and oxidation stability due to its fatty acid composition. However, its relatively high kinematic viscosity at high blend concentrations may impair fuel flow, atomization, and engine performance, particularly at low temperatures[6]. This suggests that blending African star apple seed biodiesel with other biomass-derived biodiesels may provide a more suitable second-generation fuel.

1.4 Predictive Multi-Feedstock Blending and Multivariate Statistical Modelling

Multi-feedstock blending combines different feedstocks to compensate for the limitations of individual oils. Appropriate combinations of saturated and unsaturated feedstocks can improve oxidative stability, viscosity, and other fuel properties[7,8]. Blending edible oils, where appropriate, with animal fats or non-edible vegetable oils can therefore produce fuel matrices with favourable characteristics. However, traditional experimental formulation can be resource-intensive and may provide limited capacity for developing statistically integrated multivariable models[4,9].

Mathematical and statistical approaches provide more efficient alternatives for blend selection and optimization[10]. Response surface methodology is useful for evaluating interactions among key variables, while Multiple Linear Regression can quantify relationships between dependent and independent variables[11]. IBM SPSS provides a platform for analysing such interrelated data. However, studies integrating West African feedstock matrices within predictive multi-feedstock optimization frameworks remain limited. Therefore, this study addresses this gap by applying an integrated modelling approach to regional renewable fuel resources.

Specifically, this study develops a multivariate predictive optimization framework using previously published physicochemical data. The objectives are to determine optimum blend ranges with consideration of viscosity and stability, develop multivariate regression models, and classify blend formulations using hierarchical cluster analysis to support biodiesel feedstock utilization and West Africa's energy transition.

2. METHODOLOGY AND STATISTICAL FRAMEWORK

2.1 Base Experimental Input and Data Collection

Physical & Physicochemical Properties The biodiesel's physical and chemical attributes for African star apple seed oil (ASASO) were used on the basis of those obtained experimentally through physical measurements, reported in the literature as provided by[1]. These physicochemical property data, namely: Density 0.918 g/ cm 3, kinematic viscosity 6.85 m/ s^2, higher heating values of biodiesel (27.65 MJ/ kg) higher heating values of biodiesel as well as other properties like oxidative stability, the cetane number, the flash point, etc., were collated. To create a broad-based and realistic multi-feedstock biodiesel blending tool to serve various purposes, these physicochemical attributes were used for formulating and modelling similar characteristics for palm kernel oil (PKO) and waste cooking oil (WCO) biodiesels through the review and examination of recorded measured values from other experimental research to constitute input data parameters for blending in binary and ternary mix models[12,13].

2.2 Mathematical Formulation of Biodiesel Blend Simulation

A blending matrix was developed for binary (ASASO–PKO) and ternary (ASASO–PKO–WCO) biodiesel systems. The volumetric blending fractions (X_i) were varied systematically in 5% increments while satisfying the mass-balance constraint:

$$X_{\mathrm{ASASO}} + X_{\mathrm{PKO}} + X_{\mathrm{WCO}} = 1$$

A 5% increment was selected to provide sufficiently fine compositional resolution across the blending space while maintaining a manageable number of simulated formulations. Under the 100% mass-balance constraint, this systematic grid generated 231 unique biodiesel blend compositions, which were subsequently evaluated statistically. The density (ρ_b) and higher heating value (HHV_b) of each blend were estimated using linear volumetric mixing rules:

$$\rho_b = \sum_i X_i \, \rho_i$$

$$HHV_b = \sum_i X_i \, HHV_i$$

where X_i, ρ_i, and HHV_irepresent the volumetric fraction, density, and higher heating value, respectively, of each constituent biodiesel.

Because kinematic viscosity exhibits non-linear blending behaviour, the viscosity of each blend (ν_b) was estimated using the Arrhenius–Grunberg–Nissan logarithmic mixing model:

$$\ln \nu_b = \sum_i X_i \ln \nu_i + \sum_i \sum_{j>i} X_i \, X_j d_{ij}$$

where $\nu_i$is the kinematic viscosity of constituent biodiesel i, and $d_{ij}$is the binary interaction parameter between components $i$and j. In the present simulation, the binary interaction parameters were set to $d_{\mathrm{ASASO-PKO}} = 0.000$, $d_{\mathrm{ASASO-WCO}} = 0.000$, and $d_{\mathrm{PKO-WCO}} = 0.000$. Thus, the viscosity calculations employed the ideal logarithmic form of the Arrhenius–Grunberg–Nissan model without an additional binary non-ideality correction. The pure-component kinematic viscosities used were 6.85, 5.24, and 4.82 mm²/s for ASASO, PKO, and WCO biodiesels, respectively. These mixing models provide a systematic means of estimating the physicochemical properties of multi-component biodiesel blends from the corresponding constituent properties.[14,15].

2.3 Statistical Analysis Using IBM SPSS

The simulated dataset containing the 231 binary and ternary biodiesel blends was analysed using IBM SPSS Statistics Version 27 (IBM Corp., Armonk, NY, USA). Two complementary multivariate statistical techniques were employed to evaluate the relationships between blend composition and fuel performance.

2.3.1 Multiple Linear Regression Analysis (MLRA)

Multiple Linear Regression Analysis (MLRA) was performed to quantify the influence of the volumetric blending fractions of ASASO (X_{ASASO}) and PKO (X_{PKO}) on the predicted physicochemical properties of the biodiesel blends. Six independent regression models were developed using kinematic viscosity, density, oxidative stability, higher heating value, cetane number, and flash point as dependent variables, while the blend fractions served as independent predictors. The Enter method was employed to estimate the regression coefficients, and statistical significance was evaluated at the 95% confidence level ($p < 0.05$). Multiple linear regression has been widely applied for modelling fuel-property relationships and evaluating the influence of compositional variables on biodiesel quality[15,16].

2.3.2 Hierarchical Cluster Analysis (HCA)

The HCA was applied to group the generated biodiesel mixtures according to similarities existing among physicochemical parameters. Before performing clustering, all variables were standardized to Z-scores in order to remove variation related to the different scale measurements. For the analysis, the squared Euclidean distance was selected as the similarity criterion and Ward's minimum variance was employed as the agglomeration rule. Based on the resultant dendrogram, homogeneous groups of biodiesels with similar quality characteristics could be distinguished. HCA has been established as an important multivariate data tool for distinguishing performance groups of complex fuel mixtures and has been utilized in the optimisation of biofuel[17].

2.3.3 Model Validation

Regression models' predictive performance was tested by R^2, Adjusted R^2, ANOVA, and the standard error of the estimate calculated by SPSS. Variance Inflation Factor (VIF) was used to test the multicollinearity between explanatory variables, and those lower than 5.0 may imply good predictor independence and stable coefficients of the explanatory variable. These statistical measures are routinely employed to ensure the robustness of the regression and prediction accuracy.[18,19].

3. RESULTS AND DISCUSSION

3.1 Multivariate Regression Modelling and Predictive Fuel Properties

The 231 simulated biodiesel blends were analysed using IBM SPSS Statistics to evaluate the effects of ASASO and PKO fractions on the selected fuel properties. Regression coefficients and collinearity diagnostics are presented in **Table 1**. VIF values (1.333–1.343) indicated no substantial multicollinearity.

Table 1. SPSS Model Coefficient Outputs and Collinearity Diagnostics

Dependent Variable	Predictor Term	B	Std. Error	β	*t*	*p*	VIF
Kinematic Viscosity (mm²/s)	Constant	4.824	0.053	—	91.864	<0.001	—
	(X_{ASASO})	1.989	0.085	0.914	23.357	<0.001	1.343
	(X_{PKO})	0.256	0.084	0.119	3.039	0.003	1.343
Density (kg/m³)	Constant	0.845	0.032	—	26.472	<0.001	—
	(X_{ASASO})	0.045	0.052	0.066	0.869	0.386	1.343
	(X_{PKO})	0.070	0.051	0.104	1.363	0.174	1.343
Oxidative Stability (h)	Constant	3.174	0.356	—	8.927	<0.001	—
	(X_{ASASO})	–0.110	0.577	–0.014	–0.191	0.849	1.343
	(X_{PKO})	1.430	0.570	0.188	2.506	0.013	1.343
Higher Heating Value (MJ/kg)	Constant	32.819	0.384	—	85.486	<0.001	—
	(X_{ASASO})	–5.500	0.623	–0.562	–8.831	<0.001	1.343
	(X_{PKO})	–0.077	0.616	–0.008	–0.126	0.900	1.343
Cetane Number	Constant	62.760	0.940	—	66.776	<0.001	—
	(X_{ASASO})	3.960	1.525	0.183	2.597	0.010	1.343
	(X_{PKO})	9.769	1.508	0.456	6.479	<0.001	1.343
Flash Point (°C)	Constant	148.000	0.000	—	—	—	—

(X_{ASASO})	–9.000	0.000	–1.152	—	—	1.333
(X_{PKO})	–5.000	0.000	–0.640	—	—	1.333

Flash point was generated directly from the blending relationship, resulting in a deterministic fit ($R^2 = 1.000$) with zero residual error. Thus, standard errors, *t*- and *p*-values were not estimable and are not interpreted as conventional statistical evidence. The regression output is retained in **Table 3.1** for completeness. The resulting empirical regression equations derived from the unstandardized coefficients are expressed as:

$$\nu_b = 4.824 + 1.989(X_{ASASO}) + 0.256(X_{PKO})$$
$$\rho_b = 0.845 + 0.045(X_{ASASO}) + 0.070(X_{PKO})$$
$$OS_b = 3.174 - 0.110(X_{ASASO}) + 1.430(X_{PKO})$$
$$HHV_b = 32.819 - 5.500(X_{ASASO}) - 0.077(X_{PKO})$$
$$CN_b = 62.760 + 3.960(X_{ASASO}) + 9.769(X_{PKO})$$
$$FP_b = 148.000 - 9.000(X_{ASASO}) - 5.000(X_{PKO})$$

The regression models revealed that blend composition influenced the investigated fuel properties to varying degrees. Kinematic viscosity exhibited the strongest statistically meaningful dependence on blend composition ($R^2 = 0.739$, $p < 0.001$), with ASASO exerting the dominant positive effect ($\beta = 0.914$), while PKO also contributed positively but with a comparatively smaller influence ($\beta = 0.119$). These findings indicate that increasing the ASASO fraction substantially increases resistance to flow, reflecting the influence of its fatty acid ester composition on intermolecular interactions. Similar relationships between biodiesel composition and viscosity have been reported for multi-feedstock biodiesel systems and predictive fuel-property models[7,10].

The resulting empirical regression equations derived from the unstandardized coefficients are expressed as Equations 3 through 8. To visually map these interrelated mathematical dependencies, a response surface optimization contour was constructed (Figure 1A). As illustrated in the contour topography, the fluid friction boundary scales sharply toward the primary axis vertex, confirming that increasing the *Chrysophyllum albidum* fraction drives structural flow resistance upward due to its high density and underlying saturation metrics.

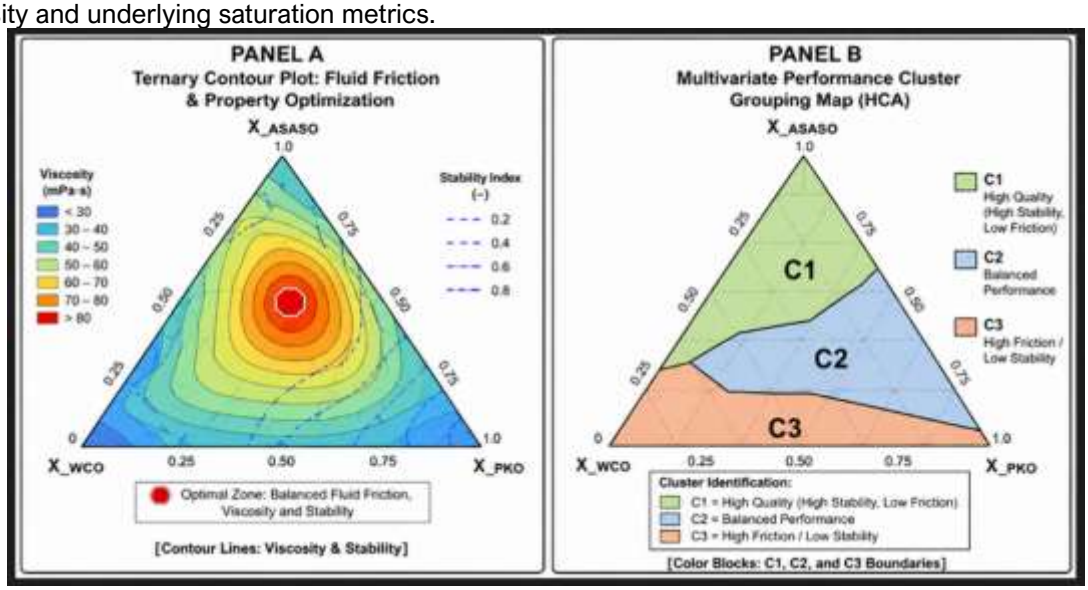

Figure 1: *Multivariate optimization space and hierarchical performance classification mappings for binary and ternary fuel systems: (A) Response surface contour showing the interaction of fluid resistance and oxidative stability parameters across different mixing fractions; (B) Formatted ternary distribution tracking the three distinct homogeneous performance windows isolated via Ward's hierarchical cluster analysis (HCA).*

Density showed only a weak dependence on blend composition, with neither ASASO ($p = 0.386$) nor PKO ($p = 0.174$) exerting a statistically significant effect. The low coefficient of determination ($R^2 = 0.008$) suggests that the constituent biodiesels possess comparable molecular packing characteristics, resulting in only minor variations in blend density.

Oxidative stability also exhibited limited predictive capability ($R^2 = 0.038$); however, PKO significantly improved oxidation resistance ($\beta = 0.188$, $p = 0.013$), whereas ASASO showed no significant contribution ($p = 0.849$). This behaviour indicates that oxidative stability depends not only on

blend ratio but also on intrinsic fuel chemistry, including fatty acid saturation, antioxidant composition and oxidation kinetics[7,8]

The higher heating value model demonstrated moderate predictive performance ($R^2 = 0.311$), with increasing ASASO significantly reducing the energy content of the blends ($\beta = -0.562, p < 0.001$), while PKO exhibited no statistically significant effect. Conversely, both ASASO ($\beta = 0.183$, $p = 0.010$) and PKO ($\beta = 0.456$, $p < 0.001$) significantly increased cetane number, indicating that blend composition can be strategically adjusted to improve ignition quality. Flash point followed a deterministic relationship with blend composition because it was generated directly from the prescribed blending equation; consequently, the regression produced a perfect mathematical fit rather than an independently validated statistical prediction.

Table 2. Regression ANOVA and Model Fit Summary

Target Model	R	R²	Adjusted R²	Std. Error of Estimate	F	Sig.
Kinematic Viscosity	0.860	0.739	0.737	0.235	324.415	<0.001
Density	0.091	0.008	0.000	0.141	0.947	0.389
Oxidative Stability	0.194	0.038	0.029	2.474	4.568	0.011
Higher Heating Value	0.557	0.311	0.305	2.670	51.280	<0.001
Cetane Number	0.396	0.157	0.150	6.536	21.218	<0.001
Flash Point*	1.000	1.000	1.000	0.000	—	—

*Flash point was generated directly from the blending equation; therefore, the regression produced a deterministic fit with zero residual error.

From statistical fitness measures reported in Table 2, it could be inferred that the prediction ability of the regression models differed with different fuel properties evaluated. The parameters that possessed relatively higher predictive accuracy in a statistically meaningful way were kinematic viscosity, next being higher heating value and cetane number, whereas those with relatively poorer fit were density and oxidative stability. Further, the absence of multicollinearity among predictor variables, VIF < 5.0, and statistical independence was indicated by very low values (VIF = 1.333–1.343), validating the use of MLRA. Taken together, these findings suggest that MLRA can be successfully used for the prediction of major physicochemical properties of biodiesel blends and offer scope for its usage in subsequent analyses of hierarchical cluster analysis and blend optimisation studies.

3.2 Cluster Analysis (HCA) Breakdown

The 231 simulated biodiesel mixtures were classified into three performance regions using HCA based on six standardized fuel properties. Cluster 1 comprised high-ASASO blends with greater stability, Cluster 2 represented the preferred optimization region with balanced fuel properties, and Cluster 3 comprised more fluid blends with lower thermal capacity. The cluster distributions were visualized in the ternary optimization space (Figure 1B), while recommended Cluster 2 formulations and their predicted properties are presented in Table 3.

Table 3: Recommended Cluster 2 formulations and predicted properties

ASASO (%)	PKO (%)	WCO (%)	Kinematic viscosity (mm²/s)	Density (g/cm³)	Oxidative stability (h)	HHV (MJ/kg)	Cetane number	Flash point (°C)
30	35	35	5.51	0.87	3.54	30.99	66.98	143.55
35	30	35	5.59	0.87	3.53	30.78	66.86	143.35
35	35	30	5.61	0.87	3.52	30.71	67.18	143.10

i. Cluster 1: High-ASASO Stability Zone

Cluster 1 comprised ASASO-rich blends with higher viscosity but favourable oxidative stability and flash point. Thus, increasing ASASO improves stability and fire characteristics but requires compositional balancing to maintain acceptable fluidity.

ii. Cluster 2: Optimised Blending Zone

Cluster 2 provided the best overall balance of fuel properties. Representative formulations (Table 3.3) showed acceptable ASTM D6751 compliance for viscosity, cetane number, and flash point, although viscosity and oxidative stability did not fully satisfy EN 14214 limits. These blends therefore represent promising candidates for further optimisation and experimental validation.

iii. Cluster 3: PKO/WCO-Dominated Flow Zone

Cluster 3 contained PKO/WCO-rich blends with lower viscosity and improved fluidity but reduced oxidative stability. Such formulations may require antioxidant treatment and appropriate storage. Overall, HCA identified distinct compositional-performance domains, with Cluster 2 offering the most balanced formulation window.

Model limitation: PKO and WCO properties were obtained from literature rather than measured directly. Variations in feedstock composition and measurement conditions may therefore affect prediction accuracy; hence, the recommended blends should be experimentally validated before being considered standards-compliant.

3.3 Policy Implications

The regression models and the cluster analysis offer a useful decision-making platform in designing biodiesel blend compositions that optimally harness the potential of ASASO, PKO and WCO feedstocks and are conducive to standardising the production of biodiesel that ultimately decreases reliance on fossil fuel diesel. Such modelling approaches for predictive analysis have a crucial role in speeding up industrial commercialization of green biodiesel technology and in more efficient assurance of fuel properties[1,10]. The potential of incorporating other underexploited non-edible feedstocks, when combined with waste oil biodiesel, would improve utilisation of resources and ensure sustainable circular bioeconomy strategies were applied; in developing countries with access to feedstocks such as Nigeria's waste and non-edible sources like ASASO and PKO, it would guarantee sustainable energy source security while lowering emissions and promoting transport systems with a low carbon footprint[2,20].

4. CONCLUSION

This study developed a multivariate predictive optimization framework for multi-feedstock biodiesel blends derived from African star apple seed oil (ASASO), palm kernel oil (PKO), and waste cooking oil (WCO) using IBM SPSS. By integrating blend simulation, multiple linear regression analysis (MLRA), and hierarchical cluster analysis (HCA), the study demonstrated that statistical modelling can effectively predict key physicochemical fuel properties while identifying optimal blend compositions without extensive experimental trial-and-error. Among the investigated fuel properties, kinematic viscosity exhibited the highest predictive accuracy, indicating that blend composition, particularly the proportion of ASASO, strongly governs fuel flow behaviour. Conversely, density and oxidative stability showed weaker dependence on blend ratio, suggesting that these properties are influenced by additional intrinsic fuel characteristics.

Hierarchical cluster analysis further classified the simulated biodiesel blends into three distinct performance groups, enabling the identification of an optimized blending region that balances viscosity, oxidative stability, cetane number, and higher heating value within acceptable biodiesel quality limits. The results demonstrate that combining complementary non-edible and waste-derived feedstocks provides a practical strategy for overcoming the limitations associated with individual biodiesel sources while improving overall fuel quality.

The predictive framework developed in this study provides a rapid and cost-effective decision-support tool for biodiesel formulation and optimization. By reducing dependence on extensive laboratory experimentation and facilitating the rational design of multi-feedstock biodiesel blends, the proposed approach offers a scalable methodology for sustainable biodiesel production. Furthermore, the integration of indigenous non-edible biomass resources with waste lipid streams supports circular bioeconomy principles, promotes efficient resource utilization, and contributes to enhanced energy security and the broader transition toward sustainable transportation fuels in Sub-Saharan Africa.The preferred blending region was a ternary formulation containing approximately 30–40% ASASO

biodiesel, 30–40% PKO biodiesel, and 20–40% WCO biodiesel, which provided the most balanced predicted fuel properties. However, these model-derived blends require experimental validation to confirm their fuel performance and compliance with applicable biodiesel standards.

REFERENCES

1. International Energy Agency. Renewables 2023: Analysis and Forecasts to 2028; International Energy Agency: Paris, France, 2024.
2. International Renewable Energy Agency. *World Energy Transitions Outlook 2022: 1.5°C Pathway*; International Renewable Energy Agency: Abu Dhabi, United Arab Emirates, 2022. https://www.irena.org/publications/2022/Mar/World-Energy-Transitions-Outlook-2022
3. Muhammad, K. M.; Adeyemi, M. M.; Jacob, J.; Koko, A. R.; Dauda, K.; Tamasi, A. A.; Yahuza, I. Biodiesel Production in Africa from Non-Edible Sources: Sources, Production, Properties and Policies. *Sustainable Chem. Environ.***2025**, *9*, 100201. https://doi.org/10.1016/j.scenv.2024.100201.
4. Ishola, N. B.; Epelle, E. I.; Betiku, E. Machine Learning Approaches to Modeling and Optimization of Biodiesel Production Systems: State of the Art and Future Outlook. *Energy Convers. Manage. X* 2024, *23*, 100669. https://doi.org/10.1016/j.ecmx.2024.100669
5. Federal Republic of Nigeria.*Nigerian Bio-Fuel Policy and Incentives*; Federal Government of Nigeria: Abuja, Nigeria, 2020. https://moman.org/wp-content/uploads/2024/07/Biofuels-Policy-2007.pdf
6. Adeniran, O. I.; Joseph, N. B.; Aransiola, S. A.; Maddela, N. R.; Prasad, R. Sustainable Biodiesel Production: A Comparative Analysis of Fuel Properties from Non-Edible Oil and Waste-Derived Feedstock. *Environmental Progress & Sustainable Energy***2026**, *45* (2), e70354. https://doi.org/10.1002/ep.70354.
7. Longanesi, L.; Pereira, A. P.; Johnston, N.; Chuck, C. J. Oxidative Stability of Biodiesel: Recent Insights. *Biofuels, Bioproducts and Biorefining* 2022, *16* (1), 265–289. https://doi.org/10.1002/bbb.2306
8. Hassan, T.; Rahman, M. M.; Rahman, M. A.; Nabi, M. N. Opportunities and Challenges for the Application of Biodiesel as Automotive Fuel in the 21st Century. *Biofuels, Bioproducts and Biorefining***2022**, *16* (5), 1353–1387. https://doi.org/10.1002/bbb.2375
9. Osman, A. I.; Nasr, M.; Farghali, M.; Rashwan, A. K.; Abdelkader, A.; Al-Muhtaseb, A. H.; Ihara, I.; Rooney, D. W. Optimizing Biodiesel Production from Waste with Computational Chemistry, Machine Learning and Policy Insights: A Review. *Environ. Chem. Lett.* 2024, *22*, 1005–1071. https://doi.org/10.1007/s10311-024-01700-y
10. Bhan, S.; Yadav, P. S.; Bibhu, V.; Gautam, G. D.; Gautam, R. Optimization of Biodiesel Properties Using Free Fatty Acid-Based Blending, Artificial and Machine Learning Modelling, and Advanced Production Technologies: A Comprehensive Review. Environ. Prog. Sustainable Energy 2026, 45 (2), e70250. https://doi.org/10.1002/ep.70250.
11. Knothe, G.; Krahl, J.; Van Gerpen, J., Eds. *The Biodiesel Handbook*, 2nd ed.; AOCS Press: Urbana, IL, 2010. https://shop.elsevier.com/books/the-biodiesel-handbook/knothe/978-1-893997-62-2
12. Yaqoob, H.; Teoh, Y. H.; Sher, F.; Jamil, M. A.; Gulzar, M.; Bashir, M. N.; et al. Prospects of Biodiesel as an Alternative Fuel: A Comprehensive Review. Fuel 2022, 308, 122114. https://doi.org/10.1016/j.fuel.2021.122114.
13. de Mattos, R. A., Bastos, F. A., & Tubino, M. (2015). Correlation between the composition and flash point of diesel-biodiesel blends. *Journal of the Brazilian Chemical Society, 26*(2), 393–395.
14. Messaâdi, A.; Ouerfelli, N.; Das, D.; Hamda, H.; Hamzaoui, A. H. Correspondence Between Grunberg–Nissan, Arrhenius and Jouyban–Acree Parameters for Viscosity of Isobutyric Acid + Water Binary Mixtures from 302.15 to 313.15 K. *J. Solution Chem.***2012**, *41* (12), 2186–2208. https://doi.org/10.1007/s10953-012-9931-3
15. Osamudiamen, P. M., & Afolabi, L. O. (2014). Fatty acid composition of the seed oil of *Chrysophyllum albidum* (G.Don). *African Journal of Plant Science, 8*(7), 364–365. https://doi.org/10.5897/AJPS2014.1154.
16. Bello, U.; Adamu, H.; Faizan, M.; Ourimi, M.; Alzoubi, R.; Jallow, A.; Siddiqui, M. N.; Jameel, A. G. A. Advancing Biodiesel Quality Assessment Using Machine Learning Algorithms: A Mini-

Review on Oxidative Stability Prediction and Models Benchmarking. Energy Fuels 2026, 40 (7), 3485–3508. https://doi.org/10.1021/acs.energyfuels.5c06424.
17. Hair, J. F.; Black, W. C.; Babin, B. J.; Anderson, R. E. Multivariate Data Analysis, 9th ed.; Cengage Learning: Boston, MA, 2022.
18. James, G.; Witten, D.; Hastie, T.; Tibshirani, R. An Introduction to Statistical Learning with Applications in R, 2nd ed.; Springer: New York, NY, 2021. https://doi.org/10.1007/978-1-0716-1418-1.
19. Montgomery, D. C.; Peck, E. A.; Vining, G. G. Introduction to Linear Regression Analysis, 6th ed.; Wiley: Hoboken, NJ, 2021.
20. United Nations. The Sustainable Development Goals Report 2023: Special Edition; United Nations: New York, NY, 2023. https://doi.org/10.18356/9789210024914.