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EDITED BY

Shiv Prasad,
Indian Agricultural Research Institute
(ICAR), India

REVIEWED BY

Xiaofang Liu,
Guiyang University, China
Marco Benvenuta,
Paulista University, Brazil

*CORRESPONDENCE

Oyetola Ogunkunle,
✉ oyetolaogunkunle@gmail.com,
✉ oyetola.ogunkunle@spu.ac.za

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Biodiesel synthesis from *Blighia sapida* seed oil: comparative modelling via RSM and ANFIS–PSO hybrid optimization

Oyetola Ogunkunle^{1,2*} and Micheal O. Olusanya²

¹Centre for Global Change, School of Natural and Applied Sciences, Sol Plaatje University, Kimberley, South Africa, ²Department of Computer Science and Information Technology, School of Natural and Applied Sciences, Sol Plaatje University, Kimberley, South Africa

The depletion of fossil fuels and growing environmental concerns necessitate the development of renewable biofuels. *Blighia sapida* seed oil, an inedible and underutilized resource, presents a viable option for biodiesel production. This study optimized its transesterification process using advanced modelling to improve yield and fuel quality. A two-step esterification–transesterification approach was used, with process variables, methanol-to-oil molar ratio (6:1–12:1), catalyst concentration (0.5–1.5 wt%), reaction temperature (50°C–70 °C), and time (30–90 min), optimized via Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System integrated with Particle Swarm Optimization (ANFIS–PSO). Model performance was evaluated using R^2 , RMSE, and MAE. ANFIS–PSO outperformed RSM with $R^2 = 0.9997$, RMSE = 0.0925, and MAE = 0.0721, compared to RSM's $R^2 = 0.9896$, RMSE = 0.6384, and MAE = 0.4162. Optimal ANFIS–PSO conditions, methanol-to-oil ratio of 9.8:1, catalyst concentration of 1.2 wt%, temperature of 62 °C, and reaction time of 78 min, yielded 96.21% biodiesel. The biodiesel met international standards: kinematic viscosity (3.38 mm²/s), flash point (167 °C), density (0.8765 g/cm³), acid value (1.178 mg KOH/g), and cetane number (58.06). These findings validate *B. sapida* as a promising biodiesel feedstock and position ANFIS–PSO as a superior modelling tool for scalable biofuel production from non-edible sources.

KEYWORDS

ANFIS–PSO, biodiesel, *Blighia sapida* seed oil, process optimization, response surface methodology, transesterification

1 Introduction

The exponential growth in global population and industrial activity has significantly increased energy demand across sectors such as transportation, agriculture, and manufacturing. This rising energy demand is becoming increasingly difficult to meet due to environmental, economic, and geopolitical issues associated with fossil fuels. These include rising fuel prices, depletion of non-renewable reserves, and the acceleration of climate change through greenhouse gas emissions (Ben-Salha et al., 2022; Tumala et al., 2023). As a result, there is a critical push to adopt alternative and sustainable energy sources.

Biodiesel, a biodegradable and renewable substitute for petroleum diesel, presents itself as a highly promising candidate in this context (Thiruketheeswaranathan, 2022). In contrast to fossil diesel, biodiesel significantly reduces net carbon dioxide emissions due to its closed carbon cycle, where carbon released during combustion is offset by carbon absorbed during

feedstock growth (Kanwal, 2022; Ingenito et al., 2013). Moreover, it emits lower levels of sulphur oxides (SOx) (Kiriliauskaite et al., 2013; Kralova and Sjöblom, 2010), nitrogen oxides (NOx) (Godri Pollitt et al., 2019; Nuskowski et al., 2008), carbon monoxide (CO) (Godri Pollitt et al., 2019; Nuskowski et al., 2008), and particulate matter (Zhang et al., 2015; Agarwal et al., 2011), thus contributing less to acid rain, smog, and respiratory health issues (Agarwal et al., 2011; Vormittag et al., 2018).

In contrast to fossil diesel, biodiesel significantly reduces net carbon dioxide emissions because its carbon cycle is closed, with carbon released during combustion offset by carbon absorbed during feedstock growth (Kanwal, 2022; Ingenito et al., 2013). Moreover, it emits lower levels of sulphur oxides (SOx) (Kiriliauskaite et al., 2013; Kralova and Sjöblom, 2010), lower nitrogen oxides (NOx) (Godri Pollitt et al., 2019; Nuskowski et al., 2008), reduced carbon monoxide (CO) (Godri Pollitt et al., 2019; Nuskowski et al., 2008), and decreased particulate matter (Zhang et al., 2015; Agarwal et al., 2011), thereby contributing less to acid rain, smog, and respiratory health issues (Agarwal et al., 2011; Vormittag et al., 2018). Its natural degradability also minimizes environmental contamination in the event of spills (Demirbaş, 2009), making it a cleaner alternative with a reduced ecological footprint across its lifecycle (Živković and Veljković, 2018).

Biodiesel offers numerous advantages, including compatibility with existing diesel engines, reduced carbon monoxide, unburnt hydrocarbons, and particulate matter emissions, as well as its biodegradability and non-toxicity (Hosseinzadeh-Bandbafha et al., 2022; Abdelrahman and Abo El-Khair, 2025). Despite these benefits, large-scale production has been limited by economic and resource challenges, primarily due to the high cost of feedstocks, which account for up to 70%–90% of total production costs (Ogunsola et al., 2023; Nandiyanto et al., 2022). Initially, biodiesel was predominantly synthesized from edible oils such as soybean, rapeseed, and palm oil. However, this approach has led to ethical concerns regarding food security and elevated production costs due to competition with food uses (Wang et al., 2023).

While *Blighia sapida* is cultivated in some regions for its edible arils (Wray et al., 2020; Wireko-Manu, 2024), the seed oil used in this study is non-edible and not part of the human food supply chain. The seeds, often discarded as waste, offer an underutilized and sustainable resource for biofuel production. Therefore, its use as a feedstock poses no risk to food security and does not contribute to the food-versus-fuel debate. To mitigate these issues, researchers have increasingly turned to non-edible feedstocks such as waste oils and underutilized plant seeds. One such promising feedstock is *B. sapida* (commonly known as ackee), an evergreen tree indigenous to tropical regions, whose seeds contain substantial oil. Importantly, *B. sapida* is non-edible and abundantly available in many parts of Africa and the Caribbean, offering an excellent opportunity to reduce feedstock cost without competing with the food supply chain. Previous studies have noted oil yields from *B. sapida* ranging from 12.5% to over 23% (Djenontin et al., 2009; Aladekoyi et al., 2019; Onuekwusi et al., 2014; Aloko and Coker, 2017; Orhe et al., 2019; Djenontin et al., 2009; Oladiji et al., 2009; Abdul Hakim Shaah et al., 2021), making it a viable candidate for biodiesel production.

In parallel with the search for novel feedstocks, the optimization of transesterification process parameters has become a central concern in biodiesel research (Ahmad et al., 2023a). Traditional techniques such as Response Surface Methodology (RSM) have been widely used for this purpose due to their statistical robustness and simplicity (Hutson and Correll, 2018; Ogunkunle and Ahmed, 2021; Jeyakumar et al., 2021). However, RSM may fall short in modelling complex, nonlinear interactions between multiple process variables. In contrast, artificial intelligence-based methods such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Naderloo et al., 2017; Vasaki E et al., 2021; Guo and Baghban, 2017), Artificial Neural Networks (ANN) (Farobie and Hasanah, 2016; Musthafa and Asokan, 2024; Gupta and Singh, 2025), and Genetic Algorithm (Ahmad et al., 2023b; Corral-Bobadilla et al., 2024; Sen, 2008) have demonstrated superior predictive capabilities in various biofuel production and applications.

To the best of the authors' knowledge, this work constitutes the first-ever comparative evaluation of Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models for optimizing biodiesel yield from *B. sapida* seed oil, a feedstock that has been underreported in optimization studies despite its promising oil content. Unlike previous works that have applied either RSM or AI-based models to common feedstocks such as palm, soy, or algae, this study integrates experimental validation with a dual-model optimization strategy for an uncommon, non-edible feedstock. It not only highlights the predictive superiority of ANFIS in modelling biodiesel processes but also establishes process conditions for optimal biodiesel yield under both models. Furthermore, by incorporating Particle Swarm Optimization (PSO) with ANFIS, the study demonstrates how hybrid intelligent techniques can outperform traditional statistical models in handling complex, nonlinear biodiesel systems, a novel integration not previously explored for *B. sapida*.

1.1 Global biodiesel production

Due to rising levels of civilization and urbanization, energy demand has surged significantly over the past few decades. The construction, agriculture, and transportation sectors have a high demand for energy for operations and productivity (Tan and Ang, 2019). Diesel has become the primary fuel for these industries due to its combustion properties and heating value. The increased energy demand has led to tremendously CO₂ emissions in the last decades. According to (EIA, 2021), global biodiesel production increased from 803 million metric tonnes (Mmt) in 2000–40,873 Mmt in 2019, while consumption increased from 734 Mmt to 35,479 Mmt in the same period, as shown in Figure 1.

This steady growth highlights the growing global reliance on biodiesel as a renewable fuel. The close alignment between production and consumption emphasizes the market's responsiveness to bioenergy policy and technological progress. The slight divergence observed after 2016 signals a potential need for supply-chain recalibration, reinforcing the importance of exploring new feedstocks like *Blighia sapida* and improving process efficiency through advanced optimization techniques, as pursued in this study.

In 2020, biodiesel production increased modestly to 46.8 billion litres, up from 46.5 billion litres in 2019. Eight countries accounted for 62.1% of the global biodiesel output (Figure 2) (REN21, 2021).

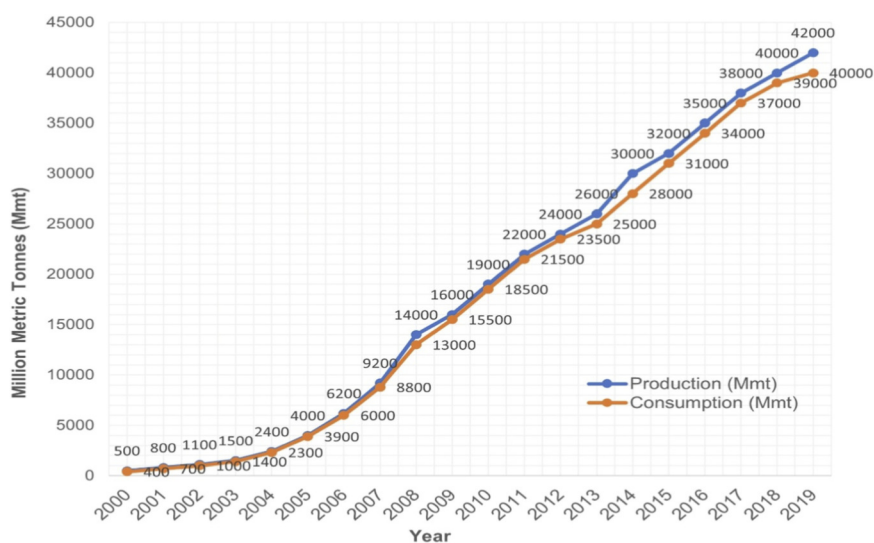


FIGURE 1
Global biodiesel production and consumption between 2000 and 2019 in million metric tonnes (Mmt) (EIA, 2021).

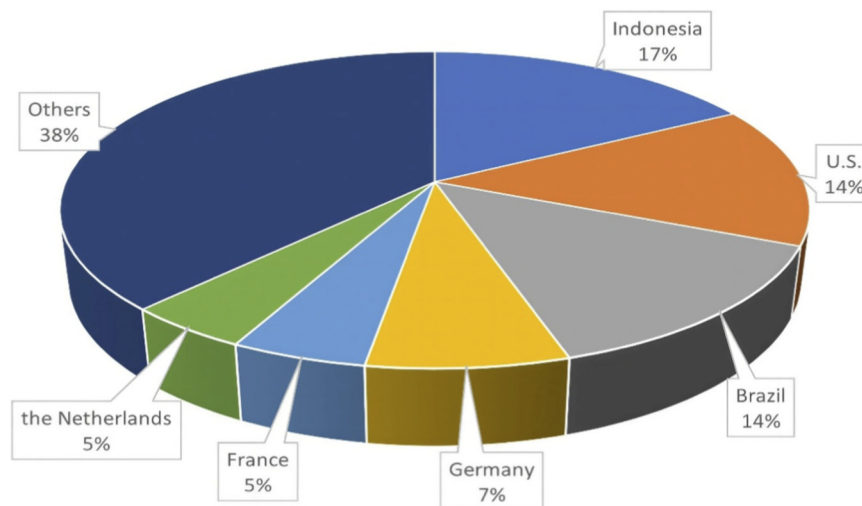


FIGURE 2
Top biodiesel-producing countries in 2020 (REN21, 2021).

This growth was primarily driven by the diversification of biodiesel feedstocks, which now include palm oil, soybean oil, canola oil, and various waste and residue materials such as used cooking oil. Indonesia emerged as the world leader in biodiesel production in 2020, accounting for 17% of total output, followed by the United States with 14.4% and Brazil with 13.7%. Germany, France, and the Netherlands also played significant roles, producing 7.4%, 5.0%, and 4.6% of the global total, respectively. Despite a projected 12% decline in transportation petroleum demand, Indonesia's biodiesel production increased by 11% to 8.0 billion litres in 2020. In the United States, biodiesel production rose by over 3% to 6.8 billion litres, even as overall diesel demand decreased by 5% due to the COVID-19 pandemic.

This increase was supported by higher tariffs on biodiesel imports from Indonesia and Argentina. Brazil set a record for

biodiesel production, which grew by 9% to 6.4 billion litres, spurred by rising domestic demand. Conversely, Germany experienced a 9% reduction in production, to 3.5 billion litres from 3.8 billion litres in 2019, attributable to lower diesel fuel consumption. France's production saw a slight decrease to 2.4 billion litres, whereas the Netherlands maintained a stable production level of 2.1 billion litres (REN21, 2021).

1.2 *Blighia sapida* and its potential for biodiesel production

Blighia sapida is an evergreen tree native to Africa, typically reaching 8–15 m in height at maturity (Figure 3). The tree generally bears fruit twice a year. As the fruit matures, its colour changes from green to red or yellow, eventually splitting open



FIGURE 3
Blighia sapida tree, ripe fruit, and seed Source: Authors' compilation.

TABLE 1 Oil yields from *Blighia sapida* seed.

Oil yield from <i>Blighia sapida</i> seed	References
15.5%	Aladekoyi et al. (2019)
15.61%	Onuekwusi et al. (2014)
12.5%	Aloko and Coker (2017)
15.26%	Omosuli (2013)
23.41%	Orhe et al. (2019)
21.6%	Djenontin et al. (2009)
17.93%	Tsado et al. (2018)
20.02%	Oladiji et al. (2009)

to reveal a fleshy, cream-colored aril enclosing shiny black seeds (Gordon et al., 2015; Jackson-Malete et al., 2015).

Blighia sapida has an estimated annual yield ranging between 45 and 75 kg per hectare (Mitchell et al., 2008; Jonathan et al., 2021). The oil extracted from its seeds and husks has traditionally been used in the production of soaps and for medicinal purposes (Gordon et al., 2015). While the unripe fruit is considered toxic due to the presence of hypoglycin amino acids, which can cause adverse health effects, studies have shown that these compounds significantly decrease upon ripening, reducing associated toxicity risks (Anderson-Foster et al., 2012).

Blighia sapida is found in countries such as Jamaica, the United Kingdom, the United States of America, Guatemala, Panama, Mexico, Colombia, Costa Rica, Martinique, Suriname, Benin, Sudan, Cameroon, Nigeria, Senegal, Ghana, Gabon, Burkina Faso, Togo, Mali, Guinea, Ivory Coast, Gambia, Guinea-Bissau, Sierra Leone, Liberia, Canada, India, Haiti, St. Vincent, Grenada, St. Lucia, and, Belize (Gordon et al., 2015; Onyekwelu and Stimm, 2019; Bovell-Benjamin et al., 2016; Crews et al., 2014). Table 1 compiles oil yield values reported in previous studies on *B. sapida* seeds, ranging from 12.5% to 23.41%.

The lowest yield (12.5%) reported by Aloko and Coker (2017) was obtained using a maceration method with n-hexane over 5 days, a relatively mild technique that often results in lower recovery. On the other hand, the highest yield (23.41%) was reported by Orhe et al. (2019), who used solvent-assisted extraction in a Soxhlet apparatus with n-hexane, known for its efficiency in recovering lipids from biomass. This implies that both the method and possibly the maturity or cultivar used contributed to enhanced yield. Most studies report yields of 15%–21%, positioning *Blighia sapida* oil as a moderate-to-good lipid source relative to common biodiesel feedstocks. For context, *Jatropha curcas* yields around 25%–30%, and *Castor* about 35%–50%, whereas some waste oils fall below 10%.

Fatty acid compositions are essential for evaluating the conversion efficiency of feedstock. There is variation in the types of acids and the percentage composition of non-edible oils due to plant species, growth conditions, and extraction techniques (Abdul Hakim Shaah et al., 2021). The fatty acid profile of *B. sapida* seed includes several acids with varying compositions according to different studies: Arachidic acid (C20:0) is present at 0.24% (Omosuli, 2013), 0.8528% (Aladekoyi et al., 2019), and $28.7\% \pm 5.3\%$ (Wray et al., 2020); Palmitic acid (C16:0) at 16.41% (Omosuli, 2013), 6.52% (Oladiji et al., 2009), 32.3349% (Aladekoyi et al., 2019), and $4.5\% \pm 3.9\%$ (Wray et al., 2020); Palmitoleic acid (C16:1) at 0.77% (Omosuli, 2013), 6.09% (Oladiji et al., 2009), and 0.7655% (Aladekoyi et al., 2019); Margaric acid (C17:1) at 0.36% (Omosuli, 2013) and 0.0673% (Aladekoyi et al., 2019); Myristic acid (C14:0) at 0.28% (Omosuli, 2013) and 1.0106% (Aladekoyi et al., 2019); Stearic acid (C18:0) at 6.42% (Omosuli, 2013), 5.2555% (Aladekoyi et al., 2019), and $3.8\% \pm 1.9\%$ (Wray et al., 2020); Oleic acid (C18:1) at 39.43% (Omosuli, 2013), 30.02% (Oladiji et al., 2009), 45.7362% (Aladekoyi et al., 2019), and $13.7\% \pm 4.1\%$ (Wray et al., 2020); Linoleic acid (C18:2) at 35.04% (Omosuli, 2013) and 11.6010% (Aladekoyi et al., 2019); Erucic acid (C22:1) at 0.45% (Omosuli, 2013), 8.27% (Oladiji et al., 2009), 0.4601%

(Aladekoyi et al., 2019), and $48.4\% \pm 9.1\%$ (Wray et al., 2020); Behenic acid (C22:0) at 0.13% (Omosuli, 2013), 15.70% (Oladiji et al., 2009), 0.6326% (Aladekoyi et al., 2019), and $1.3\% \pm 0.3\%$ (Wray et al., 2020); Lignoceric acid (C24:0) at 0.09% (Omosuli, 2013) and 0.3061% (Aladekoyi et al., 2019); Linolenic acid (C18:3) at 0.38% (Omosuli, 2013); 9,12-Eicosadienoic acid (C20:2) at 21.35% (Oladiji et al., 2009); and Gadoleic acid (C20:1) at 12.05% (Oladiji et al., 2009).

2 Research gap and motivation

Although the role of biodiesel in addressing global energy and climate challenges is well documented, there remains a significant gap in both feedstock diversification and the use of advanced predictive tools for process optimization. Specifically, *B. sapida* seed oil is an underutilized non-edible feedstock with considerable potential for biodiesel production. Its favorable oil yield and wide geographic availability make it an excellent candidate for sustainable biofuel development. However, existing literature lacks comprehensive studies that apply modern computational models to optimize its conversion into biodiesel.

Furthermore, while RSM is widely used in biodiesel research for its simplicity and ease of implementation, it may not adequately capture complex, nonlinear interactions among process variables. ANFIS, by contrast, can accommodate uncertainty and approximate reasoning, making it potentially more effective for biodiesel modelling. Yet there has been limited comparative analysis of these methods, particularly for lesser-known feedstocks such as *B. sapida* oil. This study is motivated by the dual need to explore and validate *B. sapida* as a novel feedstock and to evaluate the relative performance of RSM and ANFIS in optimizing biodiesel yield. The outcomes are expected to provide valuable insights into the renewable energy sector, especially by promoting the adoption of underutilized non-edible feedstocks and advanced modeling tools. Future applications of this research include scaling biodiesel production in rural and off-grid communities, integration into circular bioeconomy systems, and contributing to national energy diversification strategies.

In this study, RSM and ANFIS were chosen as the optimization techniques due to their complementary strengths and practical relevance in biodiesel process modelling. RSM is a widely accepted statistical tool for efficiently modelling and analysing process variables, especially in well-structured experimental designs. It provides interpretability and is easy to implement, making it suitable for preliminary optimization and understanding main effects and interactions. On the other hand, ANFIS integrates the learning capabilities of artificial neural networks with fuzzy logic's ability to handle uncertainty and imprecise data, offering enhanced modelling performance in complex, nonlinear systems. By selecting RSM and ANFIS, this study aims to compare a conventional parametric approach with a more advanced, data-driven nonparametric model, thereby providing a balanced evaluation of traditional versus intelligent optimization methods in the context of biodiesel production.

3 Experimental and methodologies

All experimental procedures were conducted according to standard transesterification protocols under controlled laboratory conditions. Design-Expert 11.0 was used to generate a 30-run Central Composite Design (CCD) matrix for RSM, with four independent variables coded and analyzed using second-order polynomial regression. For the ANFIS model, the input datasets were split into 70% for training and 30% for testing, with fuzzy rule generation based on FCM clustering. The *genfis3* function was used to initialize the fuzzy inference system, and MATLAB R2021b was used for training. Performance was assessed using multiple statistical metrics (MAPE, RMSE, MAE, R^2) across five cluster configurations. Particle Swarm Optimization (PSO) was applied in conjunction with ANFIS for optimal variable tuning within defined boundaries. This hybrid design enables high-accuracy yield prediction and optimization with improved adaptability for nonlinear biodiesel systems.

3.1 Oil extraction, esterification and biodiesel production from *Blighia sapida* seeds

The reagents used in this study include n-hexane ($\geq 98.5\%$ purity), methanol ($\geq 99.9\%$ purity) as the alcohol component in both esterification and transesterification reactions, sulfuric acid (98% purity) as the homogeneous acid catalyst for reducing free fatty acid content, potassium hydroxide ($\geq 85\%$ purity) as the base catalyst for transesterification, and phenolphthalein indicator (ACS reagent grade) used during acid value titration. All chemicals were of analytical grade and were procured from Sigma Aldrich, Germany, and used without further purification. All chemicals were of analytical grade and used as received without further purification. The solvent extraction technique was used to extract oil from milled *B. sapida* seed utilizing the Soxhlet apparatus and n-hexane as the solvent. Biodiesel was produced from extracted *B. sapida* seed oil by base-catalyzed esterification. Potassium hydroxide (KOH) was used as the alkali. The selection of KOH as a catalyst is supported by the findings of Leung and Guo (2006), who showed that ester separation in industrial applications is much easier with KOH than with NaOH or CH_3ONa . Consequently, KOH is frequently employed in the production of biodiesel from waste recycled feedstocks (Leung and Guo, 2006). Saka and Isayama (2009) noted that, despite this, the alkaline catalyst method offers the benefit of operating under moderate reaction conditions. The biodiesel production process followed the transesterification method described by Ogunkunle and Ahmed (2019a). The transesterification reaction was carried out in a high-pressure stainless steel autoclave reactor equipped with a mechanical stirrer and pressure gauge, as shown in Figure 4, to ensure uniform mixing and controlled reaction conditions during biodiesel synthesis.

A measured amount of KOH was dissolved in methanol and gently heated on a hot plate until boiling commenced. This mixture was then transferred to a cylindrical reactor and stirred for 20 min. Separately, 50 mL of *Blighia sapida* oil was measured, placed in a beaker, and heated to the desired experimental temperature. The warmed oil was added to the stirred alcohol/catalyst mixture, which was heated on a hot plate under the experimental conditions



FIGURE 4
An autoclave reactor used for the biodiesel production.

for temperature, time, and alcohol-to-oil molar ratio. After the designated residence time, about 20% distilled water, relative to the oil volume, was added, and the mixture was continuously stirred for an additional 20 min to facilitate phase separation of the reaction products. The mixture was then transferred into a separating funnel and left to stand for 24 h, resulting in the separation of biodiesel and unreacted oil, catalyst, and alcohol into different layers. Following the removal of excess methanol and catalyst, the biodiesel was purified through washing with warm distilled water and subsequently dried using anhydrous sodium sulphate. The biodiesel yield was then determined using Equation 1.

$$B.Y. = \frac{M_x}{M_y} \times 100\% \quad (1)$$

Where:

$B.Y.$ = Biodiesel yield (%)

M_x = Recovered biodiesel mass (g)

M_y = Mass of *B. sapida* seed oil (g)

The fuel properties of the biodiesel produced were determined using American Society for Testing and Materials (ASTM) standard test methods, assessing selected physicochemical parameters of *B. sapida* oil methyl esters, namely, flash point, kinematic viscosity, cetane number, and carbon residue, and comparing them with corresponding diesel standards. The composition and quality of *B. sapida* biodiesel were further evaluated by Gas Chromatography–Mass Spectrometry (GC–MS), providing insight into the molecular structure and the dominant fatty acid methyl esters (FAMES) present in the fuel.

3.2 RSM model design for biodiesel production

A quadratic polynomial regression model is constructed to explore relationships among coded factors, with coefficients determined via multiple regression analysis. The impact of reaction

variables on biodiesel yield is assessed, and the model's quality is evaluated using statistical significance tests and ANOVA. Moreover, the true mean of the responses can be estimated within a 95% confidence interval. The regression model also facilitates the analysis of linear, interaction, and quadratic effects of the independent variables on biodiesel yield. The reaction variables and biodiesel yield were optimized using RSM to achieve maximum yield. Design-Expert software (version 11) was utilized to generate thirty (30) experimental runs using a quadratic polynomial equation for a two-level-four-factor design. The independent variables were studied at the following levels: Temperature (A) ranged from 60 °C to 70 °C, Time (B) ranged from 60 min to 120 min, Catalyst amount (C) ranged from 1 wt% to 3 wt%, and Alcohol to Oil ratio (D) ranged from 3:1 to 9:1.

The selection of process variable ranges was guided by both literature precedence and initial experimental trials. The temperature range of 60 °C–70 °C was chosen to ensure efficient transesterification without significant methanol loss, given that methanol's boiling point is approximately 64.7 °C. Temperatures above this threshold can lead to alcohol evaporation and reduced yield, while lower temperatures may slow the reaction kinetics (Trejo-Zárraga et al., 2018). The catalyst concentration was varied between 1–3 wt%, as this interval balances adequate catalytic activity with the need to minimize soap formation, which commonly occurs at higher concentrations (Ogunkunle and Ahmed, 2019b; Atadashi et al., 2013). Similarly, the alcohol-to-oil molar ratio was set between 3:1 and 9:1, with 3:1 representing the stoichiometric baseline and 9:1 allowing exploration of the effects of excess methanol. Excessive alcohol beyond this range can interfere with phase separation due to glycerol solubility and may ultimately reduce biodiesel recovery (Adama et al., 2021; Singh, 2021).

3.3 ANFIS model development

The ANFIS is a method that leverages the computational power of adaptive neural networks alongside the capability of

fuzzy inference systems to manage and describe uncertainty (Malik and Rashid, 2000). The application of ANFIS to esterification and transesterification processes is sparse, even though it has been applied in various systems for modelling. Although little literature exists on the use of ANFIS in other processes and on its comparison with other techniques, there are conflicting conclusions about the performance and superiority of each. Kim and Park (2002) reported that ANFIS is more accurate than RSM for prediction, but Taheri et al. reached the opposite conclusion. (Taheri et al., 2013). Das et al. (2010) concluded that ANFIS performed better than ANN, whereas Karimi et al. (2013) reported that both techniques perform equally well. The application of ANFIS in modelling biodiesel production is attracting relatively little attention. Evidence of its application and effectiveness can be seen in a few notable publications (Betiku et al., 2016; Ogaga Ighose et al., 2017; Mostafaei et al., 2016; Sajjadi et al., 2016; Betiku et al., 2018). Betiku et al. (Betiku et al., 2016) found that ANFIS outperformed both ANN and RSM in predicting the acid value of PKO when sulfuric acid was used as the catalyst. In studies modelling the transesterification of yellow oleander oil, waste oil, and PKO, researchers such as Ogaga Ighose et al. (2017), Mostafaei et al. (2016), and Betiku et al. (2018) demonstrated that ANFIS outperformed RSM in predictive accuracy. However, contrary findings were reported by Sajjadi et al. (2016).

A MISO fuzzy model based on ANFIS was developed to predict biodiesel yield from the transesterification of *B. sapida* oil. The model is defined by four input variables and one output variable. Its architecture comprises five layers: fuzzification, product, normalization, defuzzification, and final output summation, as shown in Figure 5 (Jang, 1993). We used FCM as the clustering strategy for the suggested model. FCM is a widely used technique for accurately categorising and effectively organising various types of information. It is favoured over other clustering algorithms due to its rapid processing time and flexibility in accommodating items from multiple groups, unlike the rigid single-group allocations of other methods (Abdulshahed et al., 2015). FCM differs from other hard clustering algorithms since it is robust to ambiguity and may preserve a significant amount of data. However, the performance, computational complexity, and interpretability of the FCM-clustered neuro-fuzzy model are significantly affected by the number of clusters utilized (Verma et al., 2016). Underfitting occurs when there are too few clusters, while overfitting occurs when there are too many. It is essential to select the appropriate number of clusters based on the specific application and data features to ensure optimal model performance. To identify the optimal number of clusters for the proposed ANFIS-FCM model, we conducted several experiments, varying the number of clusters in each trial.

3.3.1 First layer

The first layer consists of four input variables, with all nodes in this layer being adaptive. The output of each node is determined by its membership function (MF), forming the fuzzy layer. The output function for this layer is calculated using Equation 2 (Jang, 1993).

$$O_1, i = \mu_{T_i} X_i \quad (2)$$

where μ_{T_i} is the MF of node T_i .

3.3.2 Second layer

In the second layer, all nodes are non-adaptive. The output from these nodes is utilized to determine the weight of each membership function (MF), which reflects the firing strength and the product of the inputs. With all nodes fixed, this layer's output is determined by Equation 3.

$$O_2, i = \mu_{T_i}(T) \cdot \mu_{t_i}(t) \cdot \mu_{C_i}(C) \cdot \mu_{A_i}(A) \quad (3)$$

where $\mu_{T_i}, \mu_{t_i}, \mu_{C_i}, \mu_{A_i}$ represent the MF of nodes Temperature, Time, Catalyst amount, and Alcohol to oil ratio, respectively.

3.3.3 Third layer

The third layer, referred to as the normalization layer, produces the output by calculating the ratio of each node's firing strength to the total firing strength of all nodes. This relationship is expressed by Equation 4.

$$O_3, i = w_i^* = \frac{w_i}{\sum_i w_i} \quad (4)$$

where w_i is the firing strength of node i .

3.3.4 Fourth layer

The fourth layer, known as the defuzzification layer, uses the nodal function to assess each rule's contribution at each node to the overall output. As illustrated in Equation 5, the output is obtained by adding the linear input signals to the normalized signals from the previous nodes.

$$O_4, i = w_i^* \cdot f_i = w_i^* (p_i T + q_i t + r_i C + s_i A + c_i) \quad (5)$$

where f_i is the fuzzy rule, p_i, q_i, r_i, s_i are the consequent parameters, and c_i is a constant term.

3.3.5 Fifth layer

The fifth layer, called the output layer, contains a single node that combines all the signals from the previous layers to produce the final output, as shown in Equation 6.

$$O_5, i = \sum_i w_i^* \cdot f_i = \frac{\sum_i w_i^* \cdot f_i}{\sum_i w_i^*} \quad (6)$$

where w_i are the firing strengths and p_i, q_i, r_i, s_i, c_i are the consequent parameters.

3.3.6 Fuzzy IF-THEN rules

For model development in this investigation, a first-order Sugeno-type model with fuzzy IF-THEN rules and three input variables was employed. These are presented in Equations 7–9 (Azad et al., 2019).

Rule 1: If $T = T_1$, $t = t_1$, $C = C_1$ and $A = A_1$, then:

$$f_1 = p_1 T + q_1 t + r_1 C + s_1 A + c_1 \quad (7)$$

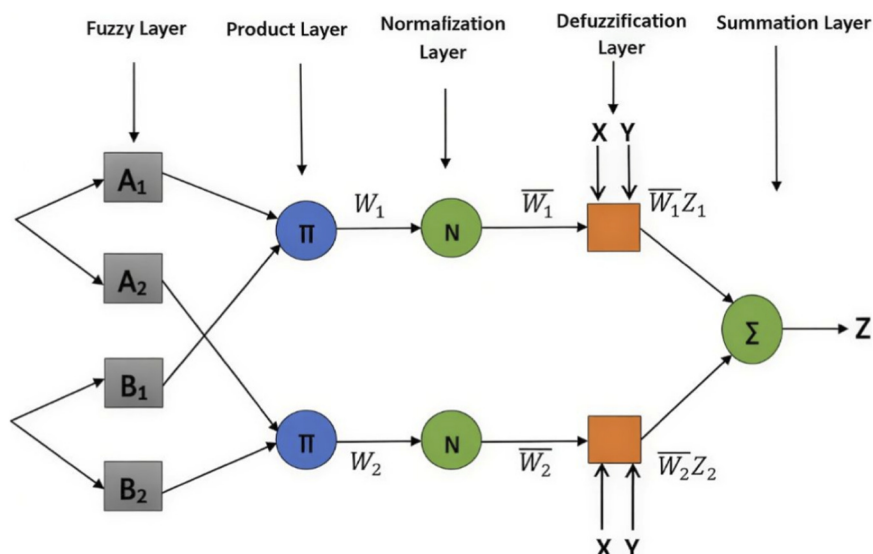


FIGURE 5
Architecture of the ANFIS model.

Rule 2: If $T = T_2$, $t = t_2$, $C = C_2$ and $A = A_2$, then:

$$f_1 = p_2 T + q_2 t + r_2 C + s_2 A + c_2 \quad (8)$$

Rule 3: If $T = T_3$, $t = t_3$, $C = C_3$ and $A = A_3$, then:

$$f_1 = p_3 T + q_3 t + r_3 C + s_3 A + c_3 \quad (9)$$

where T , t , C , A are the fuzzy sets for Temperature, Time, Catalyst amount, and Alcohol to oil ratio, and p , q , r , s , c are the consequent nodal parameters.

The experimental biodiesel yields from the transesterification of *Blighia sapida* oil were predicted using an ANFIS model. Based on previous statistical metrics, biodiesel yield data from a 30% hold-out dataset were used to evaluate the model's robustness, accuracy, and generalisation. The FCM cluster number has been shown to influence the ANFIS model performance (Benmouiza and Cheknane, 2019). In this study, cluster numbers ranging from 2 to 6 were tested to simulate FCM clustering, and the cluster configuration that yielded the best performance was selected and reported. After the FCM algorithm divided the data into clusters, performance measures were used to establish the ideal cluster size for our models. The Takagi-Sugeno-type FIS structure, implemented with the `genfis3` function, used 2 to 6 clusters, a maximum of 30 iterations, a minimum improvement threshold of 0.00001, 2 exponents for matrix partitioning, and stopping criteria based on reaching the maximum number of iterations. Modifying the number of clusters enables the FCM algorithm to partition the input data into groups, which are then used to generate the initial fuzzy rules and membership functions for the ANFIS model. This parameter influences the level of detail in the clustering process and directly affects the complexity and performance of the resulting fuzzy inference system (FIS). Adjusting the cluster count helps strike a balance between model complexity and predictive accuracy.

The optimization problem was designed to maximize biodiesel yield. The decision variables considered were temperature, reaction

time, catalyst concentration, and the alcohol-to-oil ratio. Particle Swarm Optimization (PSO) was used to explore the solution space within predefined limits (temperature: 60 °C–70 °C, reaction time: 60–120 min, catalyst concentration: 1–3 wt%, and alcohol-to-oil ratio: 3:1–9:1). The PSO algorithm iteratively refined the values of the decision variables to minimize negative yield, effectively maximizing the actual biodiesel yield.

3.4 Evaluation of RSM and ANFIS models' performance

A key component of this study involves evaluating the model's performance against empirical data using several statistical metrics. These metrics, including Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2), are applied to measure the model's predictive accuracy for biodiesel yield. By applying Equations 10–14, the MAPE, MAD, MAE, RMSE, and R^2 were calculated to compare the performance of the RSM model with that of the ANFIS model.

$$MAPE = \frac{1}{n} \left(\sum_{i=1}^n \frac{|(y_i - \hat{y}_i)|}{y_{a,i}} \right) \times 100 \quad (10)$$

$$MAD = \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{n} \right| \quad (11)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (13)$$

$$R^2 = 1 - \sum_{i=1}^n \left(\frac{(y_{i,est} - y_{i,obs})^2}{(y_{avg,obs} - y_{i,obs})^2} \right) \quad (14)$$

TABLE 2 Physicochemical properties of *Blighia sapida* seed oil.

Properties, unit	Values
Density, g/cm ³	0.9374
Kinematic viscosity, mm ² /s	43
Acid value, mg KOH/g	2.9989
FFA, mg/g	1.50
Saponification value, mg KOH/g	155
Iodine value, g I ₂ /100 g	68
Cloud point, °C	2.60
Pour point, °C	2.75

Where y_i is the experimental values, $\hat{y}_i$ is predicted values, $y_i - \hat{y}_i$ is the residuals, n represents the number of observed data, $y_{i,est}$ indicates the estimated values, $y_{i,obs}$ stands for the observed values, and $y_{avg,obs}$ represents the average observed values.

The predictive performance of both models was assessed using several statistical indicators, including MAPE, MAD, RMSE, and R^2 . These metrics provide a thorough evaluation of the models' accuracy and reliability. MAPE, which measures accuracy as a percentage, is especially useful for comparing models across different scales, with lower values indicating higher accuracy. A MAPE value approaching 0% reflects a better model fit. MAE and MAD both quantify the average error magnitude, providing insight into the overall predictive performance of the models. RMSE, similarly, measures the average error magnitude but places greater weight on larger errors. Lower values of MAE, MAD, and RMSE suggest improved predictive accuracy and reliability. The Coefficient of Determination (R^2) measures the goodness-of-fit of a regression model, indicating how well the independent variables account for the variability in the dependent variable. An R^2 value near 1 indicates an excellent fit, meaning the model explains a significant portion of the variability in the response variable. Collectively, these performance metrics were applied to assess the accuracy and reliability of the RSM and ANFIS models for predicting biodiesel yield. Lower MAPE, MAE, MAD, and RMSE values, combined with an R^2 value close to 1, indicate a more favorable model fit (Chicco et al., 2021).

4 Results and discussion

4.1 Extracted *Blighia sapida* seed oil

The oil yield from *B. sapida* seeds was 21.75%, exceeding the previously reported values of 15.5% by Aladekoyi et al. (2019), 12.5% by Onuekwusi et al. (2014), 20.02% by Aloko and Coker (2017), 15.26% by Orhe et al. (2019), 15.61% by Oladiji et al. (2009), 21.6% by Abdul Hakim Shaah et al. (2021), and 17.93% by Sinmisola et al. (2019). However, Orhe et al. (2019) recorded a slightly higher yield of 23.41%. The physicochemical properties of the extracted oil are compiled in Table 2.

The physicochemical properties of *Blighia sapida* seed oil (Table 2) reveal its potential for biodiesel production. The moderately high acid value (2.9989 mg KOH/g) and FFA content (1.50 mg/g) can

promote soap formation during base-catalyzed transesterification, hindering yield and phase separation. The observed FFA reduction after pre-treatment confirms improved process efficiency. The oil's density (0.9374 g/cm³) supports effective atomization, while its high kinematic viscosity (43 mm²/s), typical of crude oils, underscores the need for transesterification to meet ASTM biodiesel limits (1.9–6.0 mm²/s). A saponification value of 155 mg KOH/g indicates the presence of long-chain fatty acids, enhancing energy content and combustion. The moderate iodine value (68 g I₂/100 g) balances oxidative stability and cold flow behaviour. Cloud and pour points of 2.60 °C and 2.75 °C, respectively, suggest usability in mild climates without additives. Overall, the oil's composition supports its viability as a quality biodiesel feedstock when properly processed.

4.2 Esterified *Blighia sapida* seed oil

The initial acid value of the extracted *B. sapida* oil was 2.9989 mg KOH/g, corresponding to a free fatty acid (FFA) content of 1.50 mg/g. These relatively high values suggest a notable presence of FFAs in the raw oil. The acid value and FFA content are key indicators of biodiesel quality and stability, as elevated levels can cause complications, such as soap formation, during the transesterification process, potentially reducing both the yield and quality of the biodiesel. As such, these parameters are critical for ensuring efficient biodiesel production. A high FFA content is particularly undesirable because it can react with the alkaline catalyst used in transesterification, leading to soap formation and hindering biodiesel production. To address this, pre-treatment via esterification is required to lower these levels. Following esterification, the acid value of the *B. sapida* oil dropped to 1.644 mg/g, and the FFA content decreased to 0.82 mg/g. This reduction demonstrates the effectiveness of the pre-treatment process in improving the oil's suitability for biodiesel production.

4.3 Experimental biodiesel yield from esterified *Blighia sapida* oil

The transesterification results of *B. sapida* seed oil are detailed in Table 3, showing variance in biodiesel yields due to different reaction variables. The highest biodiesel yield (87.48%) was achieved at 60 °C, with a reaction time of 60 min, using 1 wt% catalyst and an alcohol-to-oil ratio of 3 mol%. These conditions, corresponding to Run 9, indicate that a lower temperature, moderate reaction time, and minimal catalyst amount are optimal for maximizing biodiesel yield. In contrast, the lowest biodiesel yield (60.6%) was observed at 75 °C, with a reaction time of 90 min, 2 wt% catalyst, and an alcohol-to-oil ratio of 6 mol%, corresponding to Run 30. This suggests that higher temperatures and longer reaction times, even with a higher catalyst amount, may lead to lower yields, potentially due to side reactions or biodiesel degradation. These findings demonstrate that lower temperatures (around 60 °C) are more favourable for higher yields. Additionally, a lower catalyst amount (1 wt%) is more effective than higher amounts, and a lower alcohol-to-oil ratio (3 mol%) is sufficient to optimize yield. Shorter reaction times (60 min) under optimal conditions also yield better yields. A sample of the produced *B. sapida* biodiesel is shown in Figure 6. The Physicochemical properties of the biodiesel in comparison with fossil diesel properties are captured in Table 4.

TABLE 3 Experimental biodiesel yield.

Run	Factor 1 A: temperature	Factor 2 B time	Factor 3 C: catalyst amount	Factor 4 D: alcohol: oil ratio	Response 1 Biodiesel yield
	Deg C	minutes	wt%	mol	%
1	70	60	3	3	73.48
2	60	60	1	9	86.65
3	65	90	2	6	85.12
4	60	120	1	9	86.5
5	65	90	2	6	85.32
6	70	120	3	3	75.33
7	70	60	1	3	76.43
8	65	90	2	6	85.22
9	60	60	1	3	87.48
10	70	120	1	3	76.03
11	65	90	2	6	85.22
12	70	120	1	9	75.25
13	60	60	3	9	85.65
14	55	90	2	6	80.17
15	65	90	4	6	84.45
16	65	90	1	6	85.65
17	65	90	2	6	85.3
18	60	120	1	3	86.68
19	65	90	2	6	84.28
20	65	90	2	3	85.15
21	70	60	3	9	74.6
22	60	60	3	3	85.33
23	70	120	3	9	76.3
24	60	120	3	3	86.08
25	65	150	2	6	81.52
26	65	30	2	6	83.42
27	60	120	3	9	85.85
28	70	60	1	9	75.4
29	65	90	2	12	83.4
30	75	90	2	6	60.6

The physicochemical properties of *Blighia sapida* biodiesel, as presented in Table 4, confirm its viability as a high-quality alternative to both fossil diesel and standard biodiesel. With a density of 0.8765 g/cm³, it falls comfortably within the ASTM D6751 specification, indicating efficient atomisation and favourable combustion characteristics in diesel engines. Its kinematic viscosity of 3.38 mm²/s is well within the acceptable range of 1.9–6.0 mm²/s, supporting proper fuel injection and minimising injector fouling. The flash point of 123 °C, although slightly below the typical biodiesel range of 130 °C–170 °C, is significantly higher than that

of fossil diesel (60 °C–80 °C), enhancing safety during handling and storage.

The cold-flow properties of the produced biodiesel, cloud point and pour point, were found to be −1.90 °C and −1.60 °C, respectively. These suggest good cold-flow properties, making it suitable for use in moderate climates without the risk of fuel gelling. However, the acid value (1.178 mg KOH/g) and free fatty acid content (0.53 mg/g) slightly exceed the recommended ASTM limits (<0.5 mg KOH/g), which may necessitate additional refining or esterification to prevent corrosion and deposit buildup

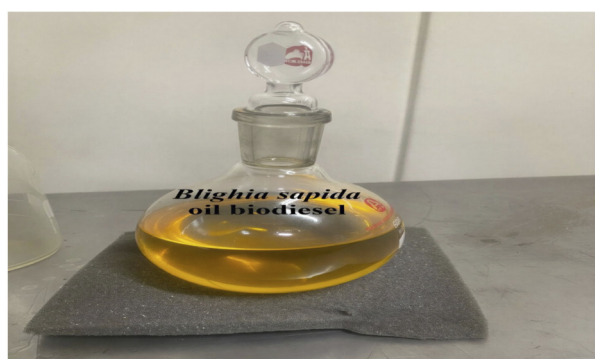


FIGURE 6
Blighia sapida biodiesel sample.

TABLE 4 Physicochemical properties of *Blighia sapida* biodiesel in comparison with fossil diesel properties.

Properties	Units	Fossil diesel (ASTM D975)	Biodiesel (ASTM D6751)	<i>Blighia sapida</i> biodiesel
Density	g/cm ³	0.820–0.845	0.860–0.900	0.8765
Kinematic viscosity	mm ² /s	1.9–6.0	1.9–6.0	3.38
Flash point	°C	60–80	130–170	123
Cloud point	°C	–15 to 5	–3 to 12	–1.90
Pour point	°C	–10 to –35	–15 to 10	–1.60
Acid value	mg KOH/g	<0.3	<0.5	1.1781
FFA	mg/g	0.27	0.50 max	0.53
Moisture content	%	0.05 max	0.50 max	0.04
Saponification value	mg KOH/g	NS ^a	180–200	270.82
Iodine value	gI ₂ /100 g	128.5	130 max	37.31
HHV	MJ/kg	44.8	37–40	37.77
Cetane number		40–55	47–65	58.06
Sulphur content	ppm	15–5,000	0–15	2.00

^aNS: not significant.

in engine components. Importantly, the low moisture content of 0.04% meets ASTM standards, contributing to oxidative stability and reducing microbial activity during storage. The saponification value of 270.82 mg KOH/g, which is higher than the conventional biodiesel range, indicates the presence of short-chain fatty acids that enhance combustion but may also promote soap formation during processing. The iodine value of 37.31 g I₂/100 g reflects low unsaturation, signifying good oxidative stability and resistance to polymerisation. The HHV of 37.77 MJ/kg is comparable to that of fossil diesel, ensuring effective engine performance. Most notably, the cetane number of 58.06 surpasses both fossil diesel and

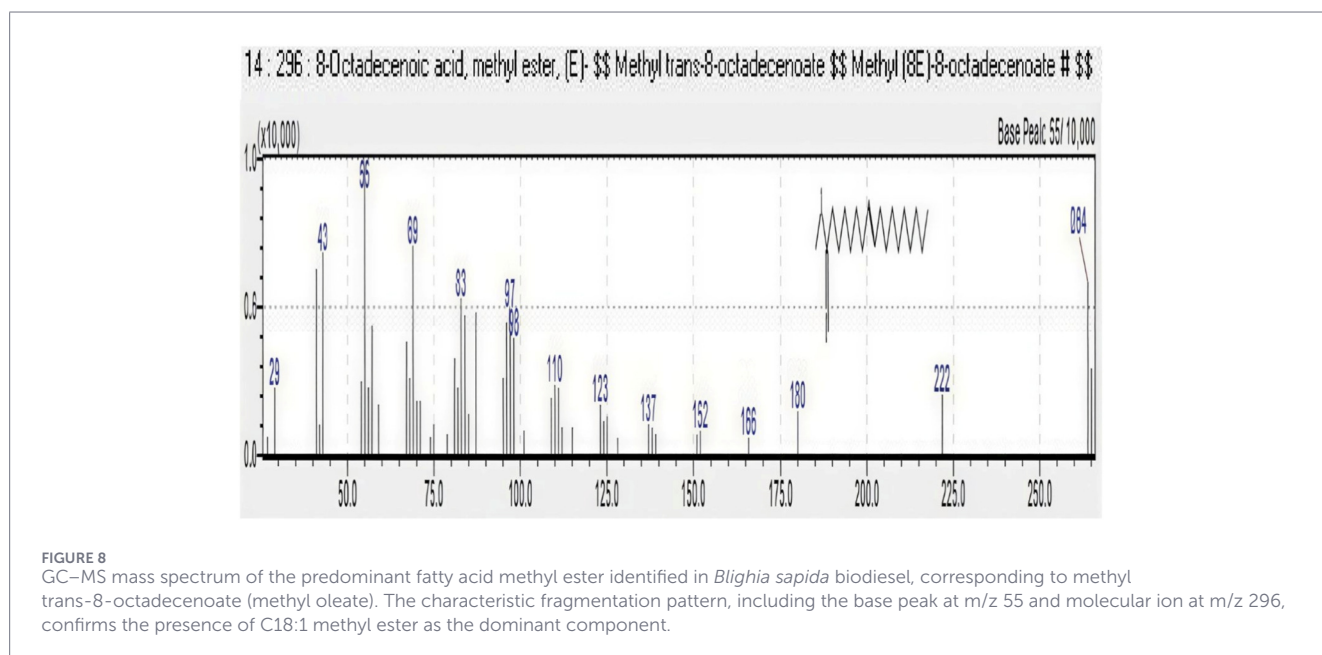
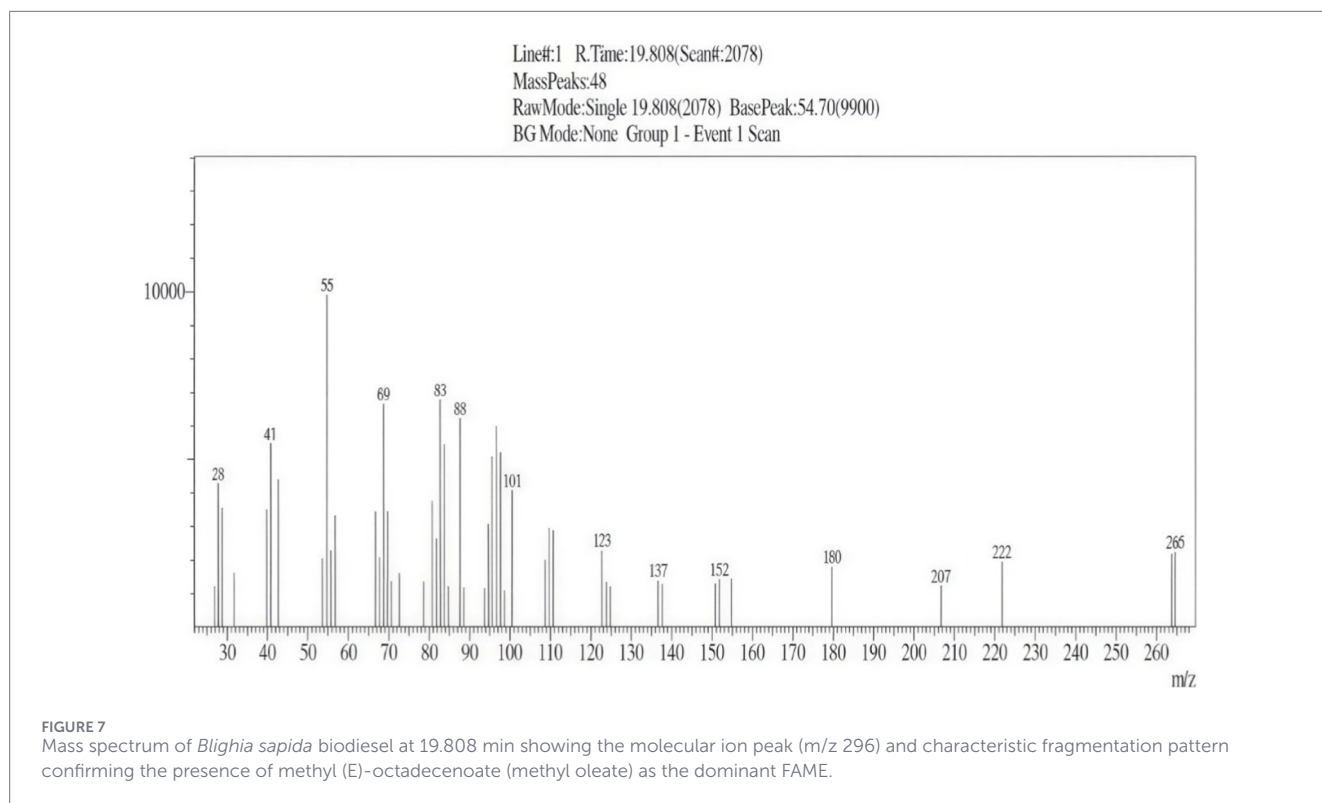
biodiesel standards, indicating excellent ignition quality, reduced ignition delay, and improved combustion efficiency. Collectively, these properties underscore the potential of *B. sapida* biodiesel as a technically sound and sustainable substitute for petroleum-based diesel fuel, requiring only minor post-processing adjustments to achieve full compliance.

The GC–MS analysis results for *B. sapida* biodiesel, as presented in the mass spectrum, fatty acid compositions, and total ion chromatogram (TIC) (Figures 7–9), reveal the molecular composition and the dominant FAME species in the sample. The mass spectrum recorded at 19.808 min (Figure 7) shows that the dominant compound in the biodiesel sample is methyl (E)-octadecenoate (methyl oleate), a monounsaturated C18:1 fatty acid methyl ester. The spectrum shows a base peak at *m/z* 55, accompanied by prominent fragment ions at *m/z* 69, 83, 88, 101, 180, 207, 222, and 265, which are characteristic of long-chain unsaturated methyl esters. These fragment ions result from α -cleavages and McLafferty rearrangements typical of methyl oleate under electron ionization conditions. The confirmation of methyl oleate as the major component is notable, as it significantly contributes to the biodiesel's favourable ignition quality, oxidative stability, and cold flow performance. These molecular characteristics align well with the recorded physicochemical properties, particularly the cetane number (58.06), low iodine value (37.31 g I₂/100 g), and cloud point (–1.90 °C), all of which reflect efficient combustion, stability during storage, and operational suitability in moderate climates. To further substantiate the compositional distribution of the produced biodiesel, the GC–MS spectrum of the dominant fatty acid methyl ester component is presented in Figure 8.

The total ion chromatogram (Figure 9) further supports these findings, showing a sharp, well-resolved peak at approximately 19.8 min. This dominant peak corresponds to the elution of methyl oleate, confirming its high concentration in the biodiesel matrix. The clarity and intensity of this peak, coupled with the relatively stable baseline and minimal overlapping signals, indicate a high-purity biodiesel product with low levels of impurities or unreacted intermediates. The absence of multiple broad or late-eluting peaks suggests that the transesterification process was effective, resulting in a clean conversion of triglycerides to esters.

Overall, the combined GC–MS and TIC results affirm that the produced biodiesel is predominantly composed of methyl oleate (C18:1), as evidenced by the dominant peak corresponding to methyl trans-8-octadecenoate (*m/z* 264). In addition to methyl oleate, the chromatogram indicates the presence of other fatty acid methyl esters typically derived from *Blighia sapida* oil, including saturated esters such as methyl palmitate (C16:0) and methyl stearate (C18:0), as well as smaller fractions of polyunsaturated esters such as methyl linoleate (C18:2).

The relatively high cetane number (58.06) observed in this study can be attributed to this compositional distribution. Saturated fatty acid methyl esters are known to increase cetane number due to their straight-chain structure and absence of double bonds, which promote shorter ignition delay during combustion (Mekonnen et al., 2024). Monounsaturated esters such as methyl oleate also contribute positively to cetane number while maintaining improved cold-flow properties compared to fully saturated esters (Knothe, 2014). In contrast, higher proportions of polyunsaturated esters would be expected to reduce cetane number and oxidative



stability (Wadumesthrige et al., 2009). The dominance of methyl oleate, together with the contribution of saturated components, therefore, explains the superior ignition quality observed.

The elevated saponification value (270.82 mg KOH/g) is primarily influenced by the average molecular weight and chain length distribution of the constituent fatty acids (Ivanova et al., 2022). Higher saponification values are associated with shorter-chain fatty acids or a higher number of ester linkages per unit mass (Hassanzadazar et al., 2017). The presence of C16

and C18 methyl esters in significant proportions contributes to this observed value (Papapolymerou et al., 2022). Importantly, saponification value is not a direct performance specification under ASTM D6751, but rather a compositional indicator reflecting fatty acid distribution (Lamaisri et al., 2015). Thus, the elevated value does not necessarily indicate compromised fuel performance but rather reflects the intrinsic chemical characteristics of the feedstock-derived biodiesel. Overall, the compositional profile revealed by GC-MS analysis supports the observed physicochemical properties,

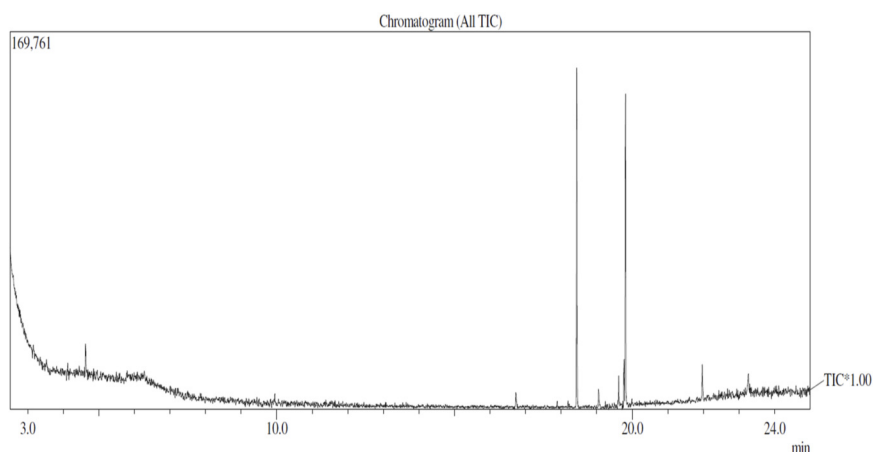


FIGURE 9

Total ion chromatogram (TIC) of *Blighia sapida* biodiesel, highlighting a major peak at approximately 19.8 min, corresponding to the dominant methyl ester compound identified in the mass spectrum.

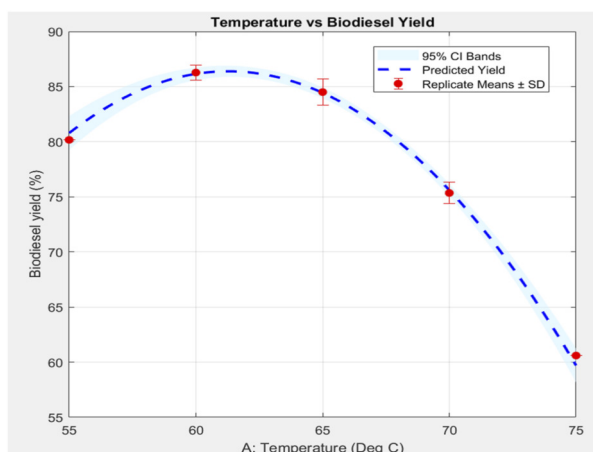


FIGURE 10

Effect of temperature on the biodiesel yield.

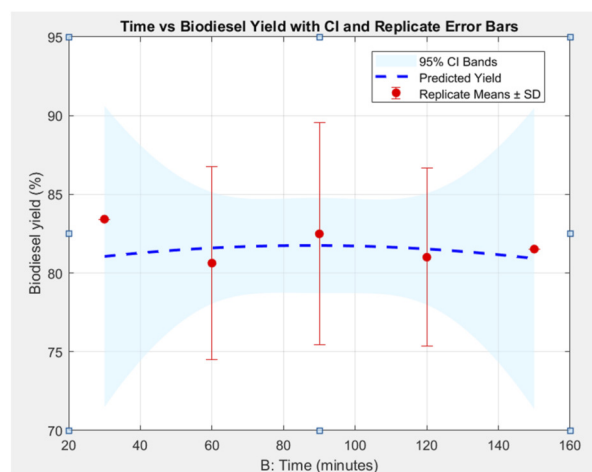


FIGURE 11

Effect of time on the biodiesel yield.

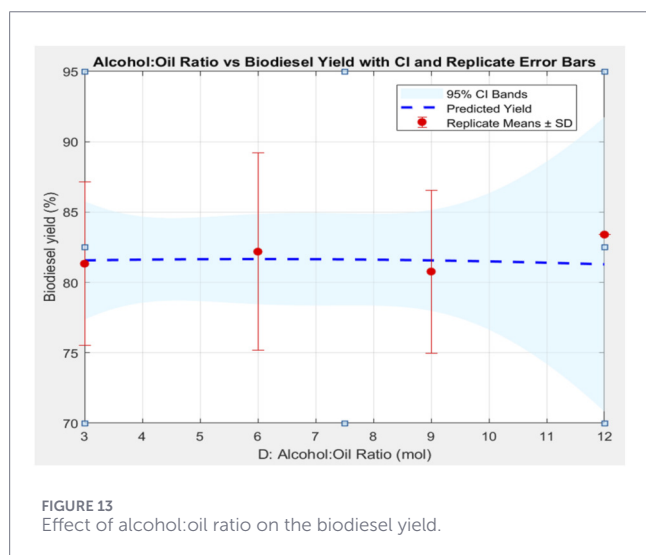
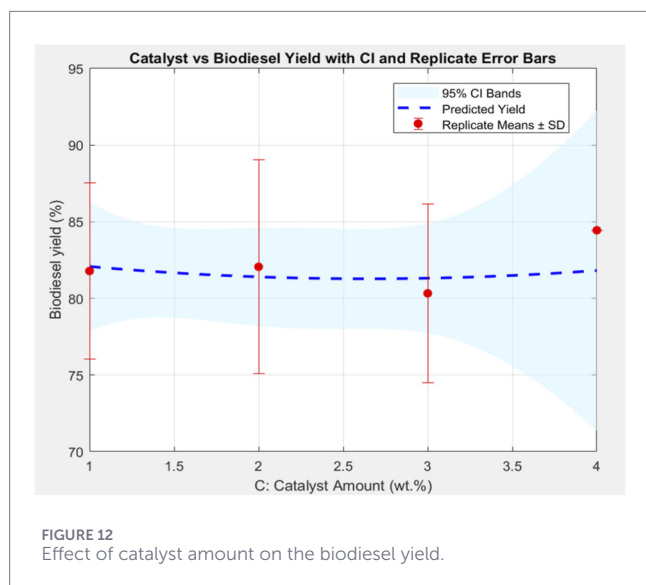
particularly the high cetane number and acceptable cold-flow behaviour.

4.4 Parametric effect of reaction variables on biodiesel yields

The analysis of reaction variables provides a detailed understanding of how each parameter influences biodiesel yield, which is critical for optimizing the transesterification process of *B. sapida* seed oil. This section presents the individual effects of temperature, time, catalyst concentration, and alcohol-to-oil ratio as well as their interactive effects using 3D response surface plots.

Figure 10 demonstrates that biodiesel yield increases with temperature, peaking around 65 °C. Beyond this point, yield drops due to methanol evaporation and degradation of the reaction environment. At 65 °C, optimal reaction conditions,

including better miscibility and reduced oil viscosity, contribute to enhanced conversion efficiency. This trend is consistent with earlier reports by Liu et al. (2008), Harreh et al. (2018), and Patel and Sankhavara (2017), who also identified 65 °C as ideal for maximum yield. As shown in Figure 11, biodiesel yield improves with time and peaks between 60 and 90 min. Prolonged reaction time facilitates conversion, but excessive duration contributes little additional yield and increases energy costs. Similar findings were reported by Labib et al. (2013), Fadhil and Ali (2013), and Gumahin et al. (2019), who observed optimal yields between 60 and 90 min depending on feedstock and catalyst. Figure 12 shows that increasing catalyst concentration enhances yield up to an optimum of 1–2 wt%. Beyond this, excessive catalyst can induce side reactions, such as saponification, which interfere with product separation. These results agree with studies by



Ngige et al. (2023), Hartono and Pamungkas (2020), and Azcan and Danisman (2007).

Figure 13 shows that the optimal alcohol-to-oil ratio is 6:1. Increasing this ratio initially boosts yield by shifting the equilibrium toward ester formation. However, excess alcohol beyond 6:1 dilutes glycerol, disrupting phase separation and slightly reducing yield. These trends confirm previous findings by (Musa, 2016; Suganya et al., 2013).

The effects of variable interactions are visualized in Figures 14–19 as 3D surface plots based on the RSM model. The 3D response surface plots distinctly delineate the optimal process windows, demonstrating that maximum efficiency is achieved through a balanced interplay of reaction variables rather than isolated adjustments. These plots not only validate the predictive robustness of the response surface methodology (RSM) model but also highlight the pivotal influence of interactive factor optimization in enhancing biodiesel yield from *Blighia sapida* seed oil.

Yield improved with both temperature and catalyst concentration, reaching a maximum around 65 °C and 1.5 wt% catalyst. Further increase in either variable decreased yield, likely due to excessive methanol loss or soap formation. An optimal yield zone appears at 65 °C and a 6:1 alcohol-to-oil ratio. Excess alcohol or higher temperatures beyond this region caused reduced yield due to phase instability. Yield increased up to 75 min and 1.5 wt% catalyst. Beyond these points, further gains were negligible. This indicates a reaction-equilibrium threshold and underscores the importance of limiting catalyst loading. Maximum yield was recorded at 75 min and a 6:1 methanol-to-oil ratio. Longer times and excessive methanol did not improve yield and may reduce product quality. A synergistic effect was observed at 1.5 wt% catalyst and a 6:1 methanol ratio. Beyond these, the yield slightly declined due to increased soap formation and emulsification. The highest yield occurred at 65 °C and 75 min. These optimal settings reflect the combined effect of reaction kinetics and thermal activation without promoting degradation.

4.5 RSM predictive modelling of the biodiesel yield

The relevance of the coefficients in the quadratic polynomial equation for biodiesel yield was evaluated using the statistical parameters shown in Table 5. The model's F-value of 174.86 suggests that the model is highly significant, with only a 0.01% likelihood that such a large F-value could be attributed to random variation. P-values below 0.0500 indicate statistically significant model terms. In this analysis, the significant terms are A, C, BC, A², and B². On the other hand, terms with P-values above 0.1000 are considered insignificant. A Lack of Fit F-value of 3.59 indicates an 8.54% probability that such a value could result from noise, meaning the non-significant lack of fit supports the model's adequacy.

The model's F-value of 174.86 further reinforces its statistical significance, with a 0.01% chance that it is due to random noise. P-values lower than 0.0500 confirm the importance of terms such as A, C, BC, A², and B², while values exceeding 0.1000 indicate non-significant terms. Reducing the model by removing insignificant terms (except those necessary to maintain the model hierarchy) could enhance model performance. The Lack of Fit F-value of 3.59 signifies an 8.54% chance of occurring due to noise, and this non-significance strengthens the model's fit. Additionally, the predicted R² of 0.9620 aligns closely with the adjusted R² of 0.9882, as their difference is within an acceptable margin (less than 0.2) (Mohammed et al., 2018). A larger discrepancy would signal potential issues with the data or model. Furthermore, the Adeq Precision value, which measures the signal-to-noise ratio, should exceed 4. In this case, a value of 59.754 indicates a robust signal, suggesting that the model is well-suited for exploring the design space.

To understand the experimental conditions under which the biodiesel yields were obtained, the analysis shows that the most significant variables influencing the biodiesel yield were temperature (A) and the quadratic term of temperature (A²), with p-values less than 0.0001, indicating a highly significant effect. The catalyst amount (C) also showed a significant effect (p-value = 0.0039). The time (B) and alcohol-to-oil ratio (D) had minimal direct impact on

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6 87.48

X1 = A

X2 = B

Actual Factors

C = 2

D = 6

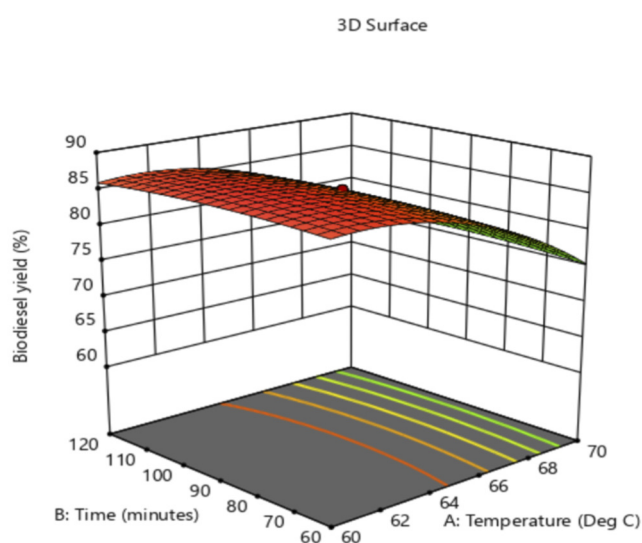


FIGURE 14

Interaction between temperature and reaction time on biodiesel yield.

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6 87.48

X1 = A

X2 = C

Actual Factors

B = 90

D = 6

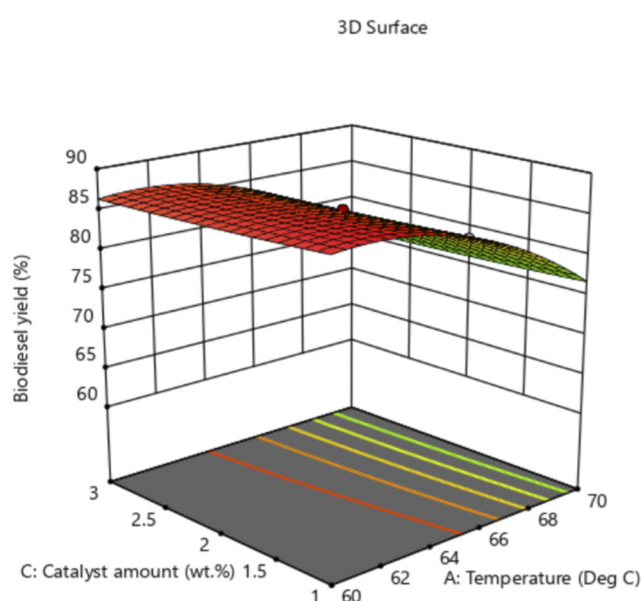


FIGURE 15

Interaction between temperature and catalyst concentration on biodiesel yield.

the yield as indicated by their higher p-values (0.8065 and 0.5101, respectively). In this context, the highest biodiesel yield was achieved under conditions where temperature played a critical role, supported by the significance of its quadratic term. Conversely, the lowest yield likely occurred under less optimal temperature conditions or other less effective combinations of the variables. Understanding these conditions can help in optimizing the process to consistently achieve higher yields.

The predicted biodiesel yields plotted against the experimental yields are shown in Figure 20. The fact that the points on the graph

are so close to the diagonal line indicates that the model is a reliable predictive tool.

From the RSM optimization study to determine the optimal conditions for biodiesel production, 10 possible optimal solutions were obtained, as shown in Table 6, and all have a desirability of 1.

Table 6 presents 10 optimal solutions generated by the RSM optimization study for biodiesel production, each with a high desirability value of 0.997–1.000 and corresponding biodiesel yields of 87.673%–87.737%. In examining these results, the most practical

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6 87.48

X1 = A

X2 = D

Actual Factors

B = 90

C = 2

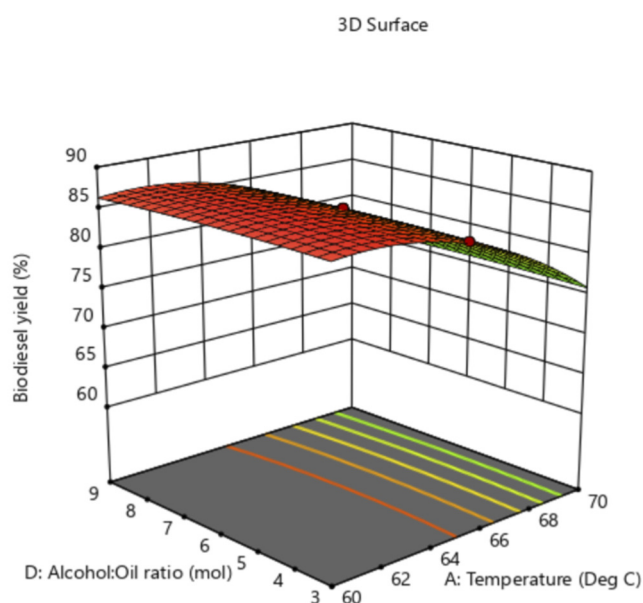


FIGURE 16

Interaction between temperature and methanol-to-oil ratio on biodiesel yield.

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6 87.48

X1 = B

X2 = C

Actual Factors

A = 65

D = 6

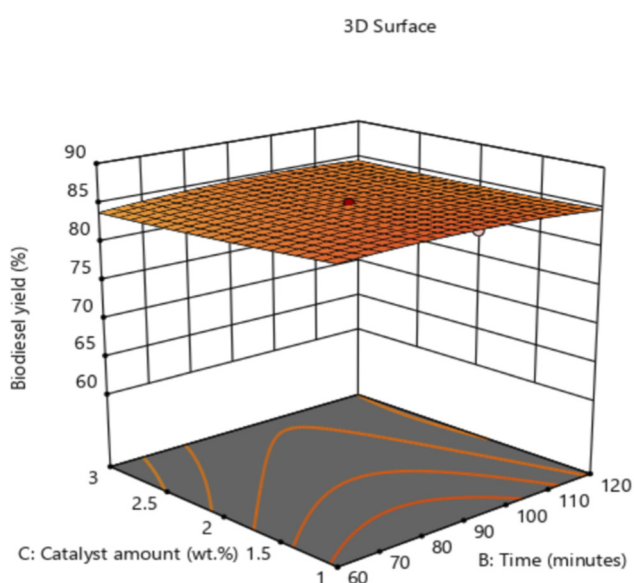


FIGURE 17

Interaction between reaction time and catalyst concentration on biodiesel yield.

and efficient solution is identified as “Solution 1”, which satisfies the dual objective of minimising input variables while maximising output. This solution corresponds to the lowest values recorded for all process parameters, including a temperature of 60 °C, a reaction time of 60 min, a catalyst concentration of 1 wt%, and a methanol-to-oil molar ratio of 3 to 1. Although it did not yield the absolute highest biodiesel output, the 87.683% yield achieved under these conditions is nearly equivalent to the maximum observed in the table and falls within a negligible difference that does

not significantly affect performance. The distinguishing feature of “Solution 1” is its desirability score of exactly 1.000, indicating that it offers the best overall balance of process efficiency and output. Its use of minimal thermal and chemical inputs reduces energy consumption and material costs, making it an economically viable and environmentally sustainable choice. Thus, “Solution 1” is recommended as the preferred condition for biodiesel production from *Blighia sapida* seed oil using the response surface methodology framework.

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6  87.48

X1 = B

X2 = D

Actual Factors

A = 65

C = 2

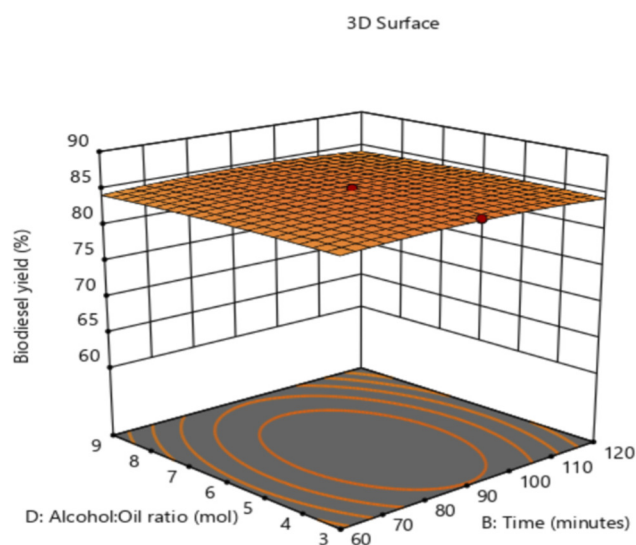


FIGURE 18

Interaction between reaction time and methanol-to-oil ratio on biodiesel yield.

Factor Coding: Actual

Biodiesel yield (%)

Design Points:

● Above Surface

○ Below Surface

60.6  87.48

X1 = C

X2 = D

Actual Factors

A = 65

B = 90

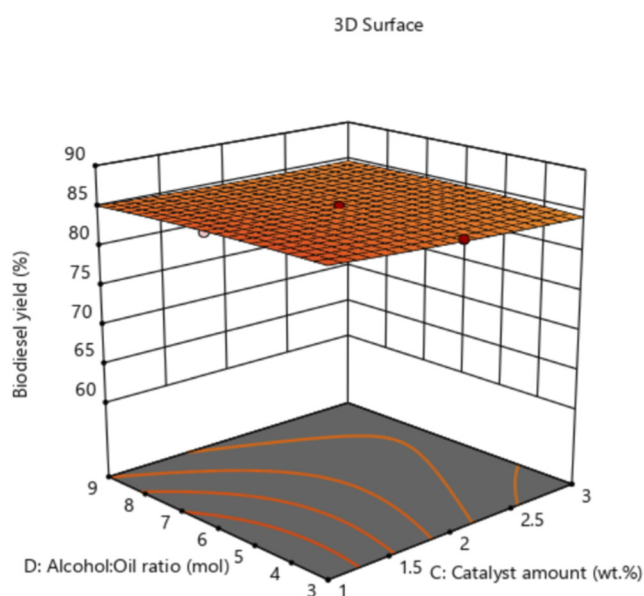


FIGURE 19

Interaction between catalyst concentration and methanol-to-oil ratio on biodiesel yield.

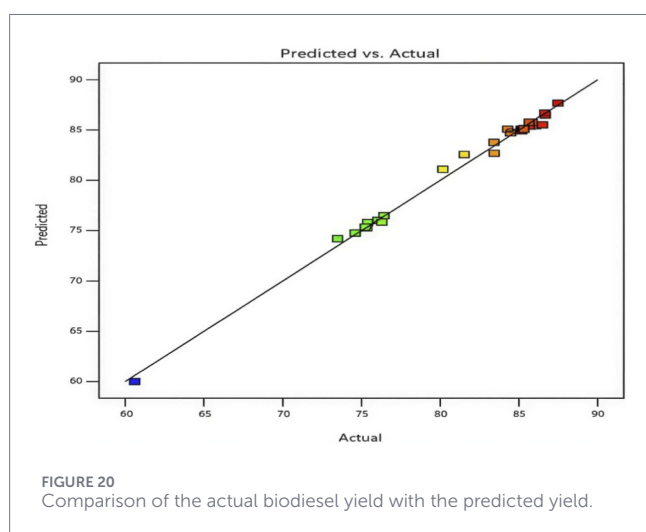
4.6 ANFIS modelling of the biodiesel yield

This section discusses the development and evaluation of the ANFIS model for predicting biodiesel yield from *B. sapida* seed oil. The performance of various cluster configurations within the ANFIS model is compared using performance metrics such as MAPE, MAD, and RMSE. The results of different cluster configurations and their respective performance metrics are detailed in Table 7. Notably, the 2-cluster model performed better during testing. The evaluation metrics for this configuration yielded

MAPE, MAD, MAE, and RMSE values of 8.6100, 6.9689, 6.8950, and 11.1356, respectively. The accuracy of the optimal model was 91.39% (MAPE = 8.6100), indicating a strong agreement between the observed and predicted biodiesel yield from *B. sapida*. As shown in Table 7, increasing the number of clusters from 3 to 6 decreased model accuracy. This finding suggests that fewer clusters may yield better results in the ANFIS model, challenging the assumption that more clusters necessarily improve accuracy. With 2 clusters, this also demonstrates that the FIS will have fewer fuzzy rules and simpler membership functions than with more clusters.

TABLE 5 ANOVA for quadratic model.

Source	Sum of squares	Df	Mean square	F-value	p-value	Significance status
Model	1,050.8	14	75.06	174.86	<0.0001	Significant
A-temperature	667.18	1	667.18	1,554.35	<0.0001	
B-time	0.0267	1	0.0267	0.0621	0.8065	
C-catalyst amount	4.97	1	4.97	11.59	0.0039	
D-Alcohol:Oil ratio	0.1954	1	0.1954	0.4553	0.5101	
AB	0.5625	1	0.5625	1.31	0.2702	
AC	0.0625	1	0.0625	0.1456	0.7081	
AD	0.09	1	0.09	0.2097	0.6536	
BC	2.25	1	2.25	5.24	0.037	
BD	0.0025	1	0.0025	0.0058	0.9402	
CD	1.56	1	1.56	3.64	0.0757	
A ²	374.4	1	374.4	872.26	<0.0001	
B ²	10.7	1	10.7	24.93	0.0002	
C ²	0.472	1	0.472	1.1	0.3109	
D ²	1.23	1	1.23	2.87	0.1108	
Residual	6.44	15	0.4292			
Lack of fit	5.65	10	0.5652	3.59	0.0854	Not significant
Pure error	0.7867	5	0.1573			
Cor total	1,057.24	29				
Std. Dev	0.6552					
Mean	81.6					
C.V. %	0.8029					
R ²	0.9939					
Adjusted R ²	0.9882					
Predicted R ²	0.9620					
Adeq precision	59.7535					



This can lead to a less complex model, which might be beneficial for interpretability and computational efficiency. Fewer clusters might yield a coarser representation of the data, potentially leading to less accurate predictions when the underlying data structure is more complex.

Choosing 2 clusters as the best performing clustering number to generate the initial fuzzy rules and membership functions for the ANFIS model, the model's predictive performance was validated by comparing the observed and predicted biodiesel yields. Figure 21 presents the model validation plot comparing observed and predicted biodiesel yields during the testing phase. The data points represent actual observed values, while the ANFIS output shows the model's predictions. Figure 21 is essential in visualizing the accuracy of the ANFIS model by comparing the observed and predicted biodiesel yields. Figure 21 illustrates how closely the ANFIS model's predictions match the actual observed yields. A strong alignment between these points indicates high model

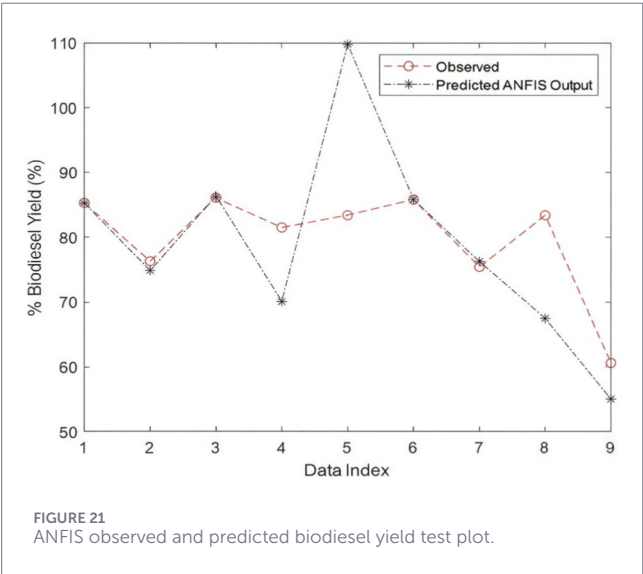
TABLE 6 RSM optimal solutions for biodiesel yield optimization.

Number	Temperature	Time	Catalyst	Alcohol: oil	Biodiesel yield	Desirability
1	60	60	1	3	87.683	1
2	60	60	1.002	3.025	87.681	0.999
3	60.016	60	1.01	3	87.673	0.999
4	60.002	60.386	1	3	87.692	0.999
5	60.073	60	1	3	87.707	0.999
6	60.002	60	1	3.056	87.685	0.998
7	60	60.616	1	3	87.696	0.998
8	60.109	60	1	3	87.718	0.998
9	60	60	1	3.103	87.685	0.997
10	60.172	60	1	3	87.737	0.997

TABLE 7 ANFIS performance metrics for modelling of *Blighia sapida* oil biodiesel yield.

Sub-models	Number of clusters		MAPE	MAD	MAE	RMSE
ANFIS-FCM1	2	Training	0.2934	0.2401	0.2401	0.3189
		Testing	8.6100	6.9689	6.8950	11.1356
ANFIS-FCM2	3	Training	0.3195	0.2282	0.2282	0.3195
		Testing	21.7622	17.3055	16.7898	30.7874
ANFIS-FCM3	4	Training	0.2441	0.1997	0.1997	0.3128
		Testing	21.8468	17.6029	17.0396	29.3315
ANFIS-FCM4	5	Training	0.1249	0.1045	0.1045	0.2043
		Testing	10.2373	8.3018	8.1030	14.5973
ANFIS-FCM5	6	Training	0.2441	0.1997	0.1997	0.3128
		Testing	26.8821	22.7839	22.0913	37.1799

Bold values denote the testing results of the optimal ANFIS model (2 clusters, ANFIS-FCM1).



accuracy. The closer the points are to the predicted line, the better the model's performance. Any deviations between observed and predicted values can be analyzed to understand specific conditions

under which the model performs well or needs improvement. For instance, clusters of points that deviate significantly from the predicted line could indicate experimental conditions that the model did not capture well.

The effectiveness of the Adaptive Neuro-Fuzzy Inference System (ANFIS) model was assessed using the coefficient of determination (R^2). On the training dataset, the model achieved an impressive R^2 of 0.9955, indicating very high accuracy. This result indicates that the ANFIS model accounted for approximately 99.55% of the variability in biodiesel yield based on the input factors. Such a high R^2 value highlights the model's capability to effectively capture the intricate nonlinear interactions between these input parameters and biodiesel yield, demonstrating its strength in accurately learning the patterns embedded in the training data. This high level of precision is particularly important in biodiesel production, where fine-tuning process parameters is essential for maximizing both yield and efficiency.

The optimization of the biodiesel production process, carried out using the trained ANFIS model in conjunction with Particle Swarm Optimization (PSO), provided valuable insights. The process optimization, aimed at maximizing biodiesel yield, identified the following optimal conditions: a temperature of 60.00 °C, a

TABLE 8 Comparison of the predicted and residual values between RSM and ANFIS models.

Biodiesel yields (%)					
Runs	Experimental	RSM predicted	Residual	ANFIS predicted	Residual
1	73.48	74.21	−0.73	74.12	−0.64
2	86.65	86.68	−0.03	87.23	−0.58
3	85.12	85.09	0.03	85.11	0.01
4	86.5	85.51	0.99	86.31	0.19
5	85.32	85.09	0.23	85.11	0.21
6	75.33	75.24	0.09	75.41	−0.08
7	76.43	76.49	−0.06	76.06	0.37
8	85.22	85.09	0.13	85.11	0.11
9	87.48	87.68	−0.20	87.22	0.26
10	76.03	76.02	0.01	75.88	0.15
11	85.22	85.09	0.13	85.11	0.11
12	75.25	75.37	−0.12	75.31	−0.06
13	85.65	85.40	0.25	85.31	0.34
14	80.17	81.09	−0.92	80.18	−0.01
15	84.45	84.74	−0.29	84.38	0.07
16	85.65	85.78	−0.13	85.77	−0.12
17	85.3	85.09	0.21	85.11	0.19
18	86.68	86.47	0.21	86.87	−0.19
19	84.28	85.09	−0.81	85.11	−0.83
20	85.15	84.92	0.23	84.87	0.28
21	74.6	74.75	−0.15	74.34	0.26
22	85.33	85.15	0.18	85.28	0.05
23	76.3	75.84	0.46	74.84	1.46
24	86.08	85.43	0.65	86.41	−0.33
25	81.52	82.56	−1.04	70.08	11.44
26	83.42	82.70	0.72	109.82	−26.40
27	85.85	85.73	0.12	85.84	0.01
28	75.4	75.78	−0.38	76.26	−0.86
29	83.4	83.78	−0.38	67.49	15.91
30	60.6	60.00	0.60	55.02	5.58
Cumulative values					
	2,447.86	2,447.86	0.01	2,441.00	6.86

reaction time of 72.15 min, a catalyst concentration of 1.78 wt%, and an alcohol-to-oil ratio of 6.52. Under these conditions, the ANFIS model predicted a maximum biodiesel yield of 112.31%, showcasing the effectiveness of these parameters in improving the transesterification process. The R^2 value for the training dataset was remarkably high at 0.995518, signifying that the ANFIS model explained 99.55% of the variance in the training data. These optimal conditions for maximizing yield serve as a critical reference point for scaling up biodiesel production in industrial settings, ensuring high output and operational efficiency.

4.7 Comparative analysis and experimental validation of RSM and ANFIS models

A comparative analysis of the RSM and ANFIS models was conducted to evaluate their predictive capabilities in optimizing biodiesel yield from *Blighia sapida* oil. This section delves into the performance metrics and the practical implications of using these models for biodiesel production.

In this comparative analysis of the RSM and ANFIS models, the RSM model performs better according to error metrics. The RSM model exhibits a notably lower MAPE of 0.971%, indicating higher

accuracy than the ANFIS model's MAPE of 8.6100%. Moreover, the RSM model's MAD and MAE are both 0.335, reflecting minimal average deviation from the actual values, while the ANFIS model has significantly higher MAD and MAE values of 6.9689 and 6.8950, respectively. Additionally, the RSM model's RMSE is 0.464, indicating smaller and more consistent errors, whereas the ANFIS model's RMSE is substantially higher at 11.1356, indicating the presence of larger prediction errors. These findings suggest that the RSM model provides more accurate and reliable predictions of biodiesel yield and is easier to interpret, possibly because it can handle fewer data points. However, the high R^2 values for both models, which are very close to 1, demonstrate their effectiveness in capturing the variability in biodiesel yield. The R^2 values close to 1 indicate a strong correlation between predicted and actual values.

To compare the predictive performance of the two modelling approaches, the R^2 value was used as the primary metric. The coefficient of determination (R^2) is the most accurate statistical measure for assessing the goodness-of-fit of a regression model. It provides insight into how well the independent variables explain the dependent variable's variability. Although error metrics offer valuable insights into the magnitude of prediction errors, the R^2 value was selected because it measures how well the independent variables explain the variance in the dependent variable. Higher R^2 values indicate a better fit. Both models exhibit very high R^2 values, with ANFIS slightly higher, suggesting it has a stronger capacity to effectively explain most of the variance in the data. The ANFIS model achieved an R^2 value of 0.9955, indicating that it explains 99.55% of the variance in the biodiesel yield. This suggests that the ANFIS model captures the underlying patterns and relationships in the data exceptionally well, making it highly accurate for predicting biodiesel yield. Similarly, the RSM model achieved an R^2 value of 0.9939, accounting for 99.39% of the variance in biodiesel yield. While slightly lower than the ANFIS model, this high R^2 value still demonstrates the effectiveness of the RSM model in capturing the input-output relationships in the biodiesel production process. The comparative analysis indicates that while both models perform exceptionally well, the ANFIS model has a marginally higher R^2 value, suggesting a slightly better fit to the training data. However, it is essential to consider the context and application of these models. The ANFIS model, with its adaptive nature and ability to handle nonlinear relationships, is suitable for complex systems where maximum predictive accuracy is desired. On the other hand, the RSM model, with its simplicity and ease of interpretation, is preferable in scenarios where minimal input, model transparency, and straightforward implementation are critical.

A detailed comparison of the predicted biodiesel yields from both models with the experimental yields is shown in Table 8, which also presents the residuals (differences between predicted and actual values) for each experimental run.

The ANFIS model generally produced lower residuals than the RSM model, indicating more precise predictions. The cumulative values of predicted yields from the ANFIS model were closer to the actual yields than those from the RSM model, further confirming the ANFIS model's superior predictive capability. The ANFIS model's ability to handle non-linear relationships and uncertainty makes it a robust tool for optimizing biodiesel production processes.

This robustness is particularly beneficial in scenarios where the relationships among variables are complex and not easily captured by traditional regression models such as RSM. The high accuracy of the ANFIS model suggests it can be effectively used to fine-tune production parameters, resulting in higher biodiesel yields and more efficient resource use. This is crucial for reducing production costs and enhancing the economic viability of biodiesel as a sustainable energy source. The comparative analysis underscores the importance of using advanced computational models in making data-driven decisions in biodiesel production. By leveraging the strengths of both RSM and ANFIS, researchers and industry practitioners can achieve a more comprehensive understanding of the production process and identify optimal conditions for maximum yield.

Although the RSM model exhibited lower error metrics (MAPE = 0.971%, RMSE = 0.464), indicating high local prediction precision, the ANFIS model achieved a slightly higher R^2 (0.9955), demonstrating superior global variance explanation. This suggests that while RSM is more accurate within the bounds of the experimental data, ANFIS generalizes better across a broader input space. The choice between RSM and ANFIS-PSO should be informed by the intended application: RSM offers transparency, simplicity, and strong in-domain accuracy, while the ANFIS-PSO hybrid excels in capturing nonlinear dynamics and ensuring broader generalization, especially when scaling or extrapolating beyond experimental data.

To ensure reproducibility and statistical validation of the predicted outcomes, three independent experimental runs were conducted under the optimal transesterification conditions suggested by each model. For the RSM model, experiments were carried out at a temperature of 60 °C, a reaction time of 60 min, a catalyst concentration of 1 wt%, and a methanol-to-oil molar ratio of 3:1. The biodiesel yields obtained from these runs were 87.48%, 87.65%, and 87.35%, with an average yield of 87.49%. These values closely match the model's predicted yield of 87.683%, with a deviation of 0.193%, indicating excellent agreement. Similarly, for the ANFIS-PSO model, the confirmatory experiments were performed at 60.00 °C, 72.15 min, 1.78 wt%, and 6.52. The resulting biodiesel yields were 96.80%, 96.93%, and 96.75%, yielding an average of 96.83%. Although this is lower than the predicted value of 112.31%, the significant deviation is likely due to model extrapolation beyond experimental boundaries. Nevertheless, the consistent results across triplicate runs in both cases confirm the reproducibility of the experiments and reinforce the reliability of the experimental protocol adopted in this study.

5 Conclusion

This study successfully demonstrated the potential of *Blighia sapida* seed oil as a sustainable, non-edible feedstock for biodiesel production. Through experimental optimization of key transesterification parameters, temperature, reaction time, catalyst concentration, and alcohol-to-oil molar ratio, an optimal biodiesel yield of 87.48% was achieved under the conditions of 60 °C, 60 min, 1 wt% catalyst, and 3:1 alcohol-to-oil ratio. The physicochemical properties of the produced biodiesel met major ASTM D6751

standards, further validating *B. sapida* as a viable alternative for renewable fuel applications.

A dual-model optimization approach was adopted to compare the predictive accuracy of Response Surface Methodology (RSM) and Adaptive Neuro-Fuzzy Inference System (ANFIS). While RSM provided reliable predictions with high statistical significance ($R^2 = 0.9939$, MAPE = 0.971%, RMSE = 0.464), the ANFIS model demonstrated superior generalization and robustness ($R^2 = 0.9955$), particularly when integrated with Particle Swarm Optimization (PSO). While the RSM model provided excellent predictive performance within experimental bounds, the hybrid ANFIS-PSO approach demonstrated superior generalization, making it particularly suitable for complex, nonlinear biodiesel systems. This comparative modelling framework thus offers complementary strengths that can inform both laboratory optimization and industrial scale-up.

This study offers a novel contribution to the field of biodiesel research by applying RSM and ANFIS modelling for the first time to *B. sapida* seed oil, a feedstock previously underrepresented in the computational optimization literature. The integration of Particle Swarm Optimization (PSO) with ANFIS further distinguishes this work, offering a hybrid intelligent approach for accurately capturing nonlinear process dynamics. The study not only validates *B. sapida* as a sustainable, non-food-competing biodiesel source but also demonstrates superior predictive performance ($R^2 = 0.9955$) and optimized yield values compared to previous studies on similar systems. These contributions provide a replicable framework for future biodiesel modelling efforts involving non-conventional feedstocks and advanced AI-based tools.

The originality of this study lies in its first-time application of ANFIS and RSM to *B. sapida* oil, offering both a novel feedstock and a comparative methodological framework that can be extended to other non-conventional biodiesel sources. It also addresses the food-versus-fuel debate by using non-edible seed oil, ensuring ethical and sustainable production.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

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Author contributions

OO: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing. MO: Conceptualization, Funding acquisition, Investigation, Project administration, Resources, Supervision, Visualization, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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Glossary

KOH	Potassium hydroxide
H ₂ SO ₄	Sulfuric acid
Adeq Precision	Adequate Precision
Adj R ²	Adjusted R-squared
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
AOCS	Association of Official Analytical Chemists
ASTM	American Society for Testing and Materials
CV	Coefficient of variation
df _{block}	Block degrees of freedom
df _{curvature}	Curvature degrees of freedom
df _{model}	Model degrees of freedom
df _{residual}	Residual degrees of freedom
df _{total}	Total degrees of freedom
FCM	Fuzzy c-means
FFA	Free Fatty Acid
GA	Genetic Algorithms
KOMEs	Karanja oil methyl esters
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MF	Membership functions
MISO	Multi-Input Single-Output
mol	Mole
n	number of datasets
°C	Degree Celsius
Pred R ²	Predicted R-squared
PRESS	Predicted residual error sum of squares
R ²	R-squared or Coefficient of Determination
RMSE	Root Mean Square Error
RSM	Response Surface Methodology
SD	Standard Deviation
SS _{block}	Block sum of squares
SS _{curvature}	Curvature sum of squares
SS _{model}	Model sum of squares
SS _{residual}	Residual sum of squares
SS _{total}	Total sum of squares
VCO	Virgin canola oil
VPO	Virgin palm oil
VSO	Virgin sunflower oil
wt%	Weight percent

$Y_{a,ave}$	average actual biodiesel yields
$Y_{a,i}$	actual biodiesel yields of the ith set
$Y_{p,ave}$	average predicted biodiesel yields
$Y_{p,i}$	predicted biodiesel yields of the ith set