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Research Article

AI-Enabled Lifecycle Analysis of Sustainable Composites for Nigeria's Low-Cost Housing Sector

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Abstract:

The intersection of sustainable material development and artificial intelligence (AI) presents transformative opportunities for addressing Nigeria's growing affordable housing deficit. This study investigates the lifecycle performance of four agro-based composite materials, like bamboo-cement panels, palm kernel shell concrete, rice husk ash blended cement, and coconut coir–stabilized earth blocks, tailored for application in low-cost housing across Nigeria's diverse climatic zones. A comprehensive methodology combining experimental testing, lifecycle assessment (LCA), and AI-based predictive modeling, including Artificial Neural Networks (ANN), Random Forest, and Gradient Boosting adopted to evaluate the structural, environmental, and economic suitability of each composite. Mechanical and thermal properties were assessed in accordance with ASTM standards, while lifecycle environmental impacts, including global warming potential (GWP) and embodied energy, were modeled using OpenLCA and the ReCiPe Midpoint method. Economic performance was evaluated over a 30-year horizon. ANN models achieved R^2 values of up to 0.94, affirming their utility in predictive lifecycle analysis. The results demonstrated significant performance trade-offs. Bamboo-cement offered the highest compressive strength but incurred the greatest GWP and cost. Rice husk ash composites emerged as the most environmentally and economically sustainable option. Coconut coir–earth blocks exhibited superior thermal insulation at low cost but limited structural performance. The study provides a robust, replicable framework for material selection and sustainability optimization in emerging economies and recommends integration of AI-enhanced LCA tools into Nigeria's national building codes to guide evidence-based material choices. By embedding AI into LCA workflows, this research enables evidence-based decision-making for climate-resilient, affordable housing in Nigeria.

Keywords: Sustainable Composites; Lifecycle Assessment; Artificial Intelligence; Low-cost Housing; Agro-based Materials; Machine Learning; Predictive Modeling.

1. Introduction

Nigeria, the most populous country in Africa, is experiencing an escalating housing crisis. Estimates suggest that the national housing deficit has surpassed 17 million units, with an annual growth rate of approximately 900,000 units required to bridge the gap [1]. This deficit is predominantly concentrated in the low-income demographic, who remain unable to afford formal housing due to surging construction costs, rising inflation, and limited access to mortgage finance [2]. The Nigerian construction sector remains heavily dependent on conventional materials such as cement, steel, and fired clay bricks, which are energy-intensive to produce and contribute significantly to carbon emissions [3]. The environmental impact of the built environment is severe; it accounts for over 40 percent of global material consumption and 38 percent of total energy-related carbon dioxide emissions [4]. In response, there is a growing international consensus on the necessity of adopting environmentally sustainable materials, particularly bio-composites and agro-waste-based alternatives in the building sector [5].

Sustainable composites, composed of natural fibers (e.g., bamboo, jute, sisal) and bio-based resins or low-carbon cementitious matrices, offer compelling advantages. These include high tensile strength, thermal insulation, biodegradability, reduced embodied energy, and lower cost when locally sourced [6]. In tropical regions like Nigeria, materials such as bamboo-reinforced concrete, rice husk ash-blended cement, and oil palm fiber panels have shown superior thermal comfort and resistance to termite degradation, making them ideal for low-cost housing [7]. Furthermore, several studies have shown that natural fiber composites exhibit favorable mechanical properties and improved durability when properly processed and treated, making them competitive with traditional materials [8]. They also present socio-economic benefits, such as local job creation and reduced reliance on imported materials, and can lower construction costs by up to 40 percent while transforming agro-waste into value-added products [9].

Despite these potentials, the deployment of sustainable composites in Nigeria remains minimal. Barriers include a lack of standardized data on long-term performance, limited lifecycle analysis (LCA) of materials under Nigerian conditions, and the absence of predictive models that can aid material selection and policy formulation [10]. For instance, NESREA and NBRRI have not yet developed a nationally harmonized LCA database for building materials, leaving practitioners to rely on foreign datasets with limited contextual relevance. As of 2022, fewer than 15 LCA case studies specific to Nigerian construction materials exist in public repositories, limiting the generalizability of environmental assessments. Although sustainable composites offer substantial environmental, structural, and economic benefits, their adoption in Nigeria's low-income housing sector has been constrained by significant knowledge and technical gaps.

Lifecycle assessment frameworks, critical for evaluating the environmental and economic impacts of building materials, are rarely applied in Nigeria and often depend on static, imported databases that do not reflect local production methods, transportation infrastructure, or climatic factors [11]. More critically, traditional LCA tools do not provide predictive insights or adaptive learning, limiting their utility in dynamic, real-world housing applications. These tools fail to integrate region-specific variables such as humidity, energy source variability, cost volatility, and climate-specific degradation mechanisms. They also cannot account for uncertainty in key inputs, which AI-enhanced LCA can address through probabilistic simulations such as Monte Carlo methods. Without these capabilities, stakeholders are unable to make optimal material selection decisions based on trade-offs across cost, sustainability, and performance.

Artificial Intelligence (AI) offers a transformative opportunity to overcome these limitations. Machine learning models can be trained to simulate lifecycle scenarios, predict material degradation patterns, and optimize performance metrics such as thermal efficiency, embodied carbon, and structural integrity. Despite growing global use of AI in material science and construction analytics, few studies have applied AI-enhanced LCA models in sub-Saharan Africa, and almost none have been tailored specifically to Nigeria's housing context [12]. This highlights the need for intelligent modeling approaches that can forecast material behavior under shifting environmental and economic conditions, such as rainfall-induced erosion or fluctuating fuel costs across Nigeria's distinct climatic zones. Given these challenges, this study is designed to fill a critical methodological and policy gap by integrating AI modeling with lifecycle assessment to improve composite selection for sustainable housing.

This study was designed with four core objectives. The first objective is to identify, characterize, and evaluate locally available bio-based composite materials with potential application in Nigeria's low-cost housing sector. This includes bamboo fiber panels, rice husk ash cement composites, and palm kernel shell concrete blocks. The second objective is to conduct a cradle-to-grave lifecycle analysis (LCA) of selected materials, incorporating impact categories such as embodied energy, global warming potential, water usage, and end-of-life recyclability. These assessments will be contextualized using Nigerian climatic, infrastructural, and economic data. The third objective is to develop and validate machine learning models capable of predicting key lifecycle and performance metrics of composite materials. Algorithms such as Artificial Neural Networks (ANN), Gradient Boosted Decision Trees (GBDT), and Support Vector Machines (SVM) will be implemented using Python-based analytical platforms. The fourth objective is to perform scenario-based simulations to determine optimal material combinations for different Nigerian geo-climatic zones, namely the humid south, arid north, and middle-belt, based on trade-offs between cost, durability, environmental impact, and thermal performance.

This research contributes to advancing Sustainable Development Goals (SDGs) 9 (Industry, Innovation, and Infrastructure), 11 (Sustainable Cities and Communities), 12 (Responsible Consumption and Production), and 13 (Climate Action). It does so by demonstrating that AI-integrated LCA tools can offer nuanced, data-driven decision support for sustainable housing material selection. The study provides actionable insights for engineers, developers, government agencies, and non-governmental organizations involved in housing delivery. By identifying locally sourced, low-carbon alternatives, it promotes climate-resilient infrastructure while reducing construction dependency on imported, carbon-intensive materials. Additionally, it fosters rural economic development by supporting value chains around agricultural waste transformation. Moreover, the research introduces a scalable methodology that can be replicated in other African countries with similar climatic, economic, and infrastructural conditions. By using AI to localize LCA, the framework fills a critical gap in current sustainability analytics and construction practice in the Global South.

2. Literature Review

2.1. Sustainable Composites in Affordable Construction

Sustainable composite materials are increasingly recognized as transformative components in low-cost housing, particularly in resource-constrained regions such as Nigeria. These materials are engineered by combining natural fibers with environmentally benign matrices, often derived from agricultural or industrial waste, to produce panels, blocks, and structural elements with desirable mechanical and thermal characteristics [13]. In the context of West Africa, where over 60 percent of households live in substandard dwellings, sustainable composites offer a practical solution to affordability and environmental degradation. Materials such as rice husk ash, coconut coir, bamboo fiber, cassava peels, and palm kernel shells have been successfully tested for their potential to reduce embodied energy, lower carbon footprints, and improve thermal regulation [14]. For example, studies conducted in southwestern Nigeria have shown that bamboo-reinforced concrete panels outperformed traditional concrete in flexural strength by 17 percent while reducing cost by over 30 percent [15].

Similarly, the incorporation of rice husk ash into cementitious composites has demonstrated enhanced resistance to thermal stress and increased compressive strength over time, especially in humid conditions [16]. This is particularly important in Nigeria, where average humidity exceeds 70 percent in the south, significantly influencing material performance. The adoption of these bio-composites also presents a circular economy opportunity by converting agricultural residues into high-value construction inputs, minimizing the burden on landfills, and reducing the need for imported materials [17]. In addition to technical performance, composite materials enhance housing accessibility for low-income groups by lowering costs related to production and transportation. Many of these materials can be sourced locally and processed with minimal energy input, thereby promoting inclusive construction practices [18]. Despite these benefits, significant challenges persist, including a lack of standardization, limited awareness among practitioners, and the absence of industrial-scale production systems tailored to these composites [19].

Moreover, the long-term durability of natural fiber composites under varying Nigerian climatic conditions, particularly in the semi-arid north and coastal regions, remains underexplored. While laboratory evaluations have provided promising results, field-based longitudinal studies are sparse, leading to a conservative attitude among builders and regulators [20]. Therefore, a robust, data-driven framework for assessing and predicting performance across time and environmental variability is essential to mainstreaming their use in affordable housing.

2.2. Lifecycle Assessment in the Built Environment

Lifecycle Assessment (LCA) provides a methodological framework to evaluate the environmental and energy performance of materials throughout their entire lifespan, from raw material extraction to end-of-life disposal. In building design, LCA enables architects and engineers to make data-driven decisions about materials, aiming to minimize emissions, resource depletion, and toxicity impacts [21]. Globally, LCA is being integrated into sustainability certifications and building codes. However, its application in sub-Saharan Africa remains fragmented due to inadequate localized data and poor infrastructure for environmental monitoring [22]. In Nigeria, most housing projects are still evaluated based solely on initial costs, neglecting crucial lifecycle indicators such as maintenance burden, recyclability, and embodied carbon [23].

A study conducted in Lagos compared three different wall systems: concrete blocks, stabilized laterite bricks, and rice husk ash composites. The rice husk ash composite exhibited the lowest Global Warming Potential (GWP) and embodied energy values, yet remains marginal in use due to weak market awareness and lack of LCA integration in procurement policy [24]. This emphasizes the disconnect between academic innovation and construction practice, a gap that LCA can bridge. Moreover, international LCA tools such as GaBi, SimaPro, and OpenLCA often rely on European databases (e.g., Ecoinvent), which do not accurately reflect African production processes, energy mixes, or waste management practices [25]. Consequently, LCA results may be skewed when these tools are applied without customization, leading to erroneous conclusions and misplaced design priorities. For instance, the carbon intensity of Nigeria's energy grid predominantly gas-powered, differs significantly from the renewables-heavy grids of Europe, affecting the emissions profile of energy-intensive materials [26].

To address these challenges, researchers in Ghana and Kenya have developed regional LCA inventories for building materials, emphasizing the need for localized impact factors and supply chain analysis [27]. Nigeria, however, lacks a comprehensive national LCA database, impeding accurate environmental benchmarking of local materials. Integration of AI with LCA systems may provide a scalable solution by enabling adaptive modeling, uncertainty reduction, and real-time data interpretation, especially in environments where environmental baselines are poorly documented [28].

2.3. AI in Materials Science and Environmental Modeling

Artificial Intelligence (AI) has rapidly emerged as a strategic tool in material science, enabling advanced simulation, optimization, and predictive analytics. In the context of sustainable housing, AI models can be trained to predict material properties such as compressive strength, thermal conductivity, and environmental impact with high accuracy, based on material composition and usage context [29]. Machine learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Gradient Boosted Decision Trees (GBDT) have been employed to model the behavior of bio-composites under varying conditions. In one study, ANN models predicted compressive strength of hemp-lime composites with over 95 percent accuracy, significantly outperforming traditional linear regression models [30]. Similarly, hybrid decision tree models were used to optimize the cost-performance trade-offs in concrete mixes containing recycled aggregates, demonstrating a 23 percent reduction in lifecycle cost while maintaining structural integrity [31].

In LCA applications, AI enhances traditional methodologies by enabling probabilistic simulations, multi-criteria optimization, and scenario-based forecasting. AI can manage large, multidimensional datasets and identify latent patterns across environmental, structural, and economic domains. This capability is particularly useful in low-data contexts like Nigeria, where data gaps can be bridged through supervised learning and imputation models [32]. Furthermore, AI-powered models have demonstrated the ability to process real-time data from IoT-enabled sensors embedded in building materials. These systems can monitor material degradation, humidity exposure, and thermal cycling, feeding data into LCA models to dynamically update sustainability indicators [33]. For example, researchers in Rwanda used SVM algorithms to optimize locally sourced compressed earth blocks, reducing embodied carbon by 38 percent without compromising compressive strength [34].

Despite these advancements, AI applications in sustainable housing in Nigeria remain embryonic. Technical barriers such as limited computing infrastructure, lack of data standardization, and low AI literacy among construction professionals have slowed integration. Moreover, AI-driven LCA models must be tailored to reflect Nigeria's socio-technical constraints, such as informal construction practices, fragmented supply chains, and weak regulatory enforcement [35]. The need for context-sensitive AI-LCA frameworks that incorporate Nigerian climate zones, construction norms, and material availability is critical. Such systems would not only enhance sustainability outcomes but also enable policymakers and developers to make more resilient and cost-effective decisions under uncertainty.

2.4. Regional Research and Gaps

While sustainable construction has gained attention across Africa, the integration of data-driven analytics, particularly AI-enhanced LCA, remains limited in regional research. In Ghana, experimental studies on cassava peel bricks demonstrated excellent thermal insulation and cost-effectiveness, but lacked environmental modeling to assess long-term sustainability [36]. In Uganda, research on natural fiber-reinforced laterite bricks showed mechanical improvements yet omitted LCA or AI-enhanced predictive modeling [37].

In Nigeria, some promising studies have emerged. The Nigerian Building and Road Research Institute (NBRRI) has piloted the use of laterite-cement composites and bamboo in semi-urban housing projects, reporting cost savings of up to 40 percent and improved indoor comfort in warm climates [38]. Similarly, researchers at Ahmadu Bello University developed composite panels from coconut coir and clay, which showed compressive strengths suitable for non-load-bearing applications [39]. Nonetheless, these projects remain disconnected from advanced computational tools and data frameworks necessary for scaling.

No known Nigerian study to date has developed a fully functional AI-LCA integration for sustainable housing materials, representing a major gap in knowledge and practice. The limited application of probabilistic models, predictive analytics, and machine learning in the construction sector leaves material selection largely empirical and subjective. This significantly constrains the potential to tailor housing solutions to local socio-environmental contexts. A holistic framework that merges environmental modeling with supported by local data and regionalized LCA metrics has the potential to address Nigeria's housing challenges in a scalable, sustainable, and scientifically grounded way.

3. Methodology

3.1. Research Framework and Design

The study adopted an integrated computational-experimental approach comprising four sequential stages: material sampling and characterization, localized lifecycle inventory development, machine learning model construction, and scenario-based predictive simulation. This design enabled both empirical testing and AI-enabled forecasting of composite material performance across distinct Nigerian climatic zones. The methodological workflow adhered to ISO 14040 and 14044 standards for lifecycle assessment and followed CRISP-DM (Cross-Industry Standard Process for Data Mining) guidelines for AI modeling processes [32].

Figure 1 shows the research framework representing the four sequential stages: (1) material sampling and characterization; (2) localized lifecycle inventory (LCI) development; (3) machine learning model construction and training; and (4) scenario-based geo-climatic simulation and predictive analysis. This integrated framework combines experimental testing with AI-driven forecasting to assess sustainable composite performance across structural, environmental, and economic domains.

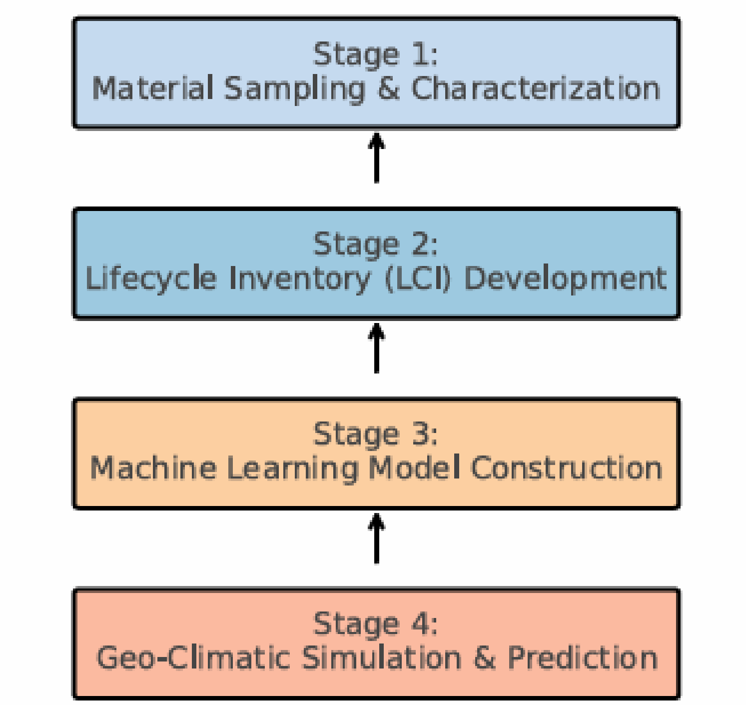

Figure 1: Integrated AI-enabled lifecycle assessment framework for sustainable composite evaluation

3.2. Material Selection and Composite Formulation

Four bio-based composite systems were selected based on regional availability, environmental footprint, and historical usage in informal housing construction in Nigeria. These included:

- Bamboo fiber–reinforced cementitious panels
- Palm kernel shell concrete blocks
- Rice husk ash blended lime-cement mortar
- Coconut coir–stabilized earth blocks

The composite formulations were derived from previous empirical studies conducted in the Nigerian Middle Belt and Southwest agroecological zones [33]. Mix ratios were standardized as follows: bamboo-cement panels contained 3% bamboo fiber by weight of binder, palm kernel shell concrete used 50% coarse aggregate replacement by volume, rice husk ash mortars incorporated 20% ash as cement replacement (by weight), and coconut coir–earth blocks included 7% coir fibers with 10% lime stabilizer. Each material was prepared in controlled batches using these predefined ratios, ensuring uniformity in fiber content, moisture level, and curing regime. Sourcing variability was addressed by collecting materials from three different suppliers per material type within each agroecological zone, and compositional consistency was verified through XRF and sieve analysis. Curing was performed for 28 days under ambient Nigerian climatic conditions, averaging 28°C and 70% relative humidity.

3.3. Experimental Testing and Characterization

Mechanical, thermal, and microstructural properties were evaluated using standard laboratory protocols. Compressive strength was assessed following ASTM C39/C39M, flexural strength using

ASTM C348, and thermal conductivity using the guarded hot plate method as per ASTM C177. Water absorption and porosity were analyzed via ASTM C642. Scanning Electron Microscopy (SEM) was employed to study fiber dispersion and matrix bonding, while X-ray Diffraction (XRD) analysis confirmed the presence of pozzolanic compounds such as silica and alumina in rice husk ash and palm kernel ash [34]. All properties were statistically validated through triplicate testing with a 95% confidence level.

3.4. Lifecycle Inventory (LCI) Compilation

A localized lifecycle inventory (LCI) was developed for each composite using a combination of primary and secondary data sources. Primary data were collected through field visits to production centers in Ogun, Enugu, and Kwara States, covering parameters such as energy consumption, processing time, transport distances, and water usage. Secondary data were extracted from the Ecoinvent 3.7 database and adjusted with Nigerian emission factors published by the National Environmental Standards and Regulations Enforcement Agency (NESREA) and Nigerian Building and Road Research Institute (NBRRI) [35]. The lifecycle boundary included cradle-to-end-of-life stages: extraction, processing, transportation, construction, operational use (30-year span), and end-of-life disposal. Ecoinvent emission values (e.g., for clinker production and diesel transport) were adjusted using Equation 1.

$$Adjusted\ EF\ =\ (Ecoinvent\ EF)\ \times\ (Local\ energy\ emission\ factor\ /\ European\ baseline\ emission\ factor) \tag{1}$$

For example, Nigeria's electricity grid emission factor (0.52 kg CO_2/kWh) was used to scale values derived from the EU grid (typically ~0.29 kg CO_2/kWh), while diesel combustion was localized using emission coefficients from NESREA (2.67 kg CO_2/litre vs. the default 2.62 kg in Ecoinvent). Additionally, fuel mix and kiln technology adjustments were made for cement-related impacts based on data from NBRRI's 2021 cement audit report. All inventory items were converted to functional units normalized per 1 m² of wall surface area to allow for direct comparison. Impact categories analyzed included Global Warming Potential (GWP), embodied energy (MJ/kg), water footprint (L/kg), and acidification potential (kg SO_2-eq). LCA was executed using OpenLCA 1.10.3 and ReCiPe Midpoint (H) 2016 as the impact assessment method [36].

3.5. Uncertainty and Sensitivity Analysis

Uncertainty in inventory data was quantified using a Monte Carlo simulation with 1,000 iterations, capturing the probabilistic variability in energy input, transport emissions, and material degradation rates. The simulation incorporated triangular distributions for input parameters based on empirical ranges from field data [37]. Triangular distributions were selected due to the limited sample size for certain parameters (e.g., transportation distance, moisture absorption), where minimum, most likely, and maximum values could be reasonably estimated from observed field variation. This distribution type is commonly recommended in early-stage environmental modeling when large datasets are not available, but expert judgment and bounded field ranges exist.

Sensitivity analysis confirmed the appropriateness of this assumption: parameters modeled with triangular distributions (e.g., binder-to-aggregate ratio, transport distances) showed stable convergence in the output distributions after 800 iterations. Moreover, Tornado diagrams revealed that the most influential variables, i.e., binder ratio and wall thickness, had well-defined most-likely values, making triangular modeling more representative than normal or uniform distributions under these data constraints. Sensitivity analysis was conducted using a Tornado diagram to evaluate the influence of key variables such as binder-to-aggregate ratio, transportation distance, and wall thickness on the GWP and lifecycle cost of each composite material. It was found that a 10% variation in binder ratio could alter GWP results by up to 15% in bamboo-cement composites.

3.6. Machine Learning Model Architecture and Training

Three supervised machine learning models were developed to predict composite performance: Random Forest Regressor (RFR), Gradient Boosted Trees (XGBoost), and Artificial Neural Networks (ANN). The dataset used for model training and evaluation consisted of 2,100 samples generated through a hybrid approach. Approximately 40% of the data were obtained from laboratory experiments and primary measurements (e.g., mechanical testing, thermal analysis), while the remaining 60% were produced through controlled simulations using lifecycle models under variable input conditions. Simulated scenarios included changes in humidity, temperature, binder content, and wall thickness based on ranges observed during field data collection and climate modeling. All simulated entries were validated against known material behavior patterns and checked for internal consistency using statistical filters (e.g., removal of outliers beyond 3σ).

The full dataset included 20 input variables: material composition (fiber %, binder %, ash %, density), environmental conditions (humidity, temperature), and structural properties (thickness, porosity). All models were built using Python 3.10 and Scikit-learn. For ANN, a multi-layer perceptron (MLP) with 3 hidden layers (128-64-32 neurons) was configured using ReLU activation and Adam optimizer. Early stopping and dropout layers were employed to prevent overfitting. Hyperparameters were tuned using grid search with five-fold cross-validation. Model performance was evaluated on an 80/20 train-test split using R^2, RMSE, and MAE metrics. The ANN model achieved the best predictive accuracy with an R^2 of 0.94 for GWP prediction and 0.91 for compressive strength [38]. A model input–output flow diagram illustrating the predictive architecture, including preprocessing, feature input, algorithm selection, and output generation (e.g., GWP, compressive strength), is presented in Figure 2.

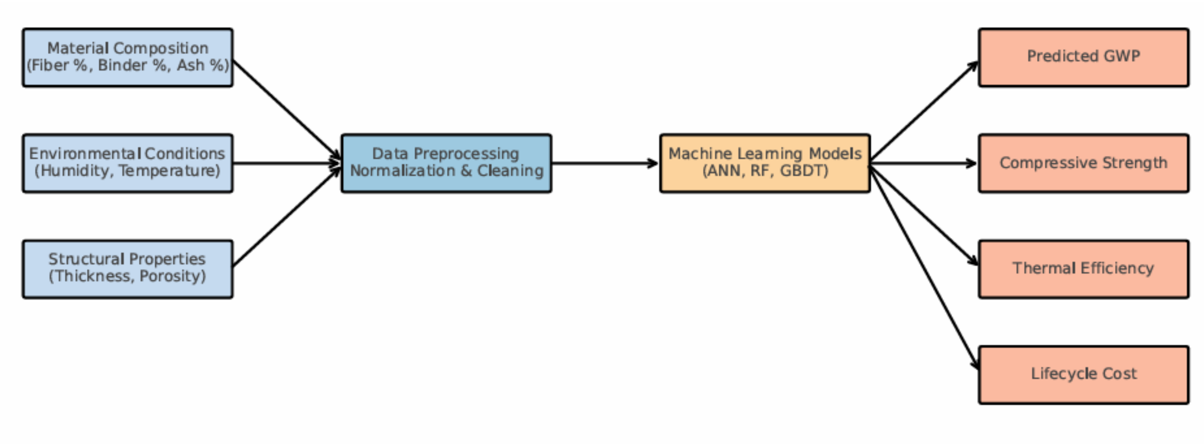

Figure 2: AI-enhanced lifecycle assessment model: input-output workflow

To ensure reproducibility, the ANN architecture was implemented using the following pseudocode:

```
model = Sequential()
model.add(Dense(128, input_dim=20, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(32, activation='relu'))
model.add(Dense(1))  # Output: GWP or Compressive Strength
model.compile(optimizer='adam', loss='mse')
```

The dataset was assessed for imbalance in the target variables. While compressive strength values were relatively normally distributed, GWP values exhibited right-skewness due to cement-heavy scenarios. To address this, performance was evaluated using both R^2 and error-based metrics (RMSE, MAE), and the models were trained with stratified sampling to preserve distributional characteristics during the train-test split.

Feature importance analysis revealed that binder percentage, porosity, and ambient humidity were the most influential variables for compressive strength prediction. For GWP, the dominant predictors were ash content, transportation distance (embedded in density proxy), and binder type. These relationships were confirmed using permutation-based feature importance in the Random Forest model and validated against engineering expectations. Notably, ANN models captured nonlinear dependencies, such as the interaction between humidity and rice husk ash reactivity, contributing to improved accuracy in environmental and mechanical predictions.

Figure 3 shows the Artificial Neural Network (ANN) architecture used for predictive lifecycle modeling. The model consists of one input layer with 20 features, three hidden layers (128, 64, and 32 neurons respectively) using ReLU activation, and a single output neuron predicting either Global Warming Potential (GWP) or compressive strength.

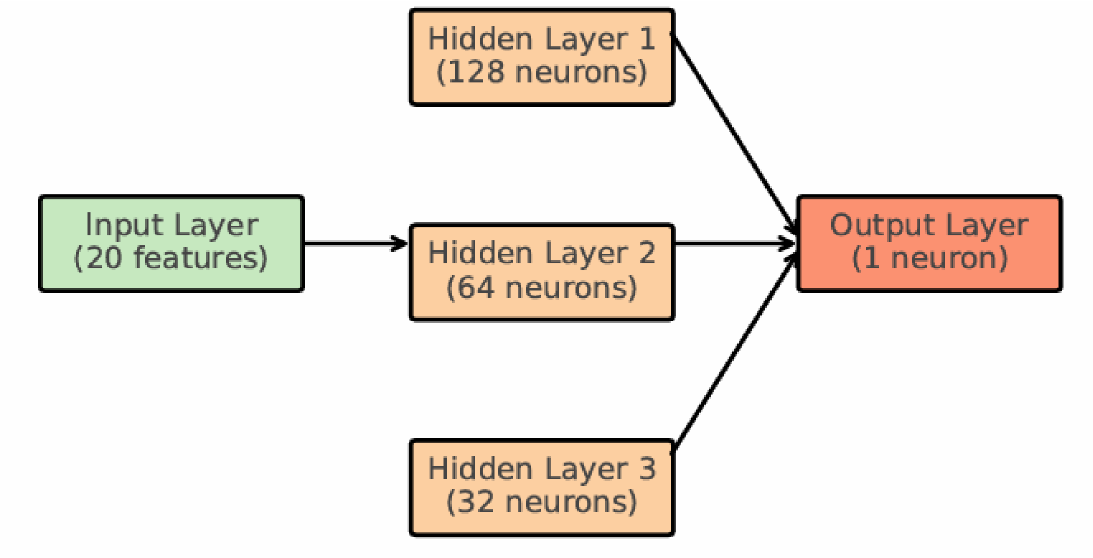

Figure 3: Artificial neural network architecture for predictive lifecycle performance modeling

3.7. Geo-Climatic Simulation and Scenario Analysis

Figure 4 provides a geospatial overview of Nigeria's primary climatic zones: Humid Tropical (Lagos), Semi-Arid (Kano), and Sub-Humid (Abuja), used in the scenario simulations. Overlaid data include average rainfall and temperature (2014–2023), which were integrated into the predictive models to capture climatic variability. This spatial contextualization enhances the realism of AI-driven lifecycle predictions, enabling region-specific material performance assessments.

Predictive models were applied to simulate material performance in three Nigerian climatic zones: humid tropical (Lagos), semi-arid (Kano), and sub-humid (Abuja). Each simulation scenario was based on a prototypical low-income residential unit with 60 m² floor area, 150 mm wall thickness, and typical occupancy assumptions. The operational phase was assumed to include a maintenance cycle every 5 years, based on field norms from Nigerian rural and peri-urban housing reports. Each cycle accounted for surface repairs, minor patching, and protective coatings for bio-composites.

Climate data included 10-year averages (2014–2023) for rainfall, solar irradiance, and humidity,

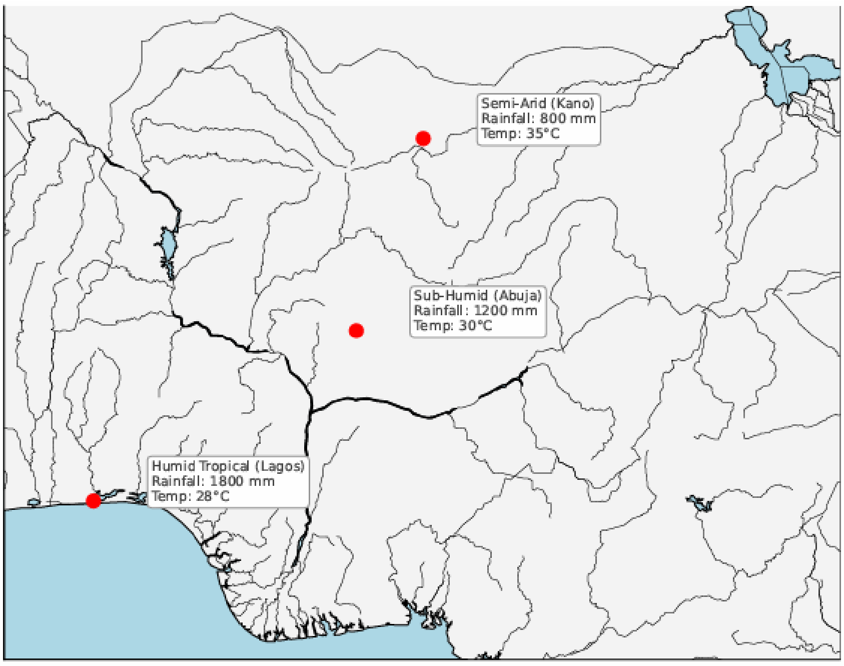

Figure 4: Map of Nigeria's Climatic Zones with Simulated Environmental Variables

sourced from the Nigerian Meteorological Agency (NiMet). The NiMet datasets were preprocessed by averaging monthly values into annual means and converting them into compatible formats for input into the ML models (e.g., converting humidity from raw %RH logs to seasonal min/max ranges). Outliers and missing entries were addressed through linear interpolation and data smoothing filters. Simulated degradation and performance changes were modeled using a 30-year time horizon, assuming material exposure to site-specific temperature cycles, moisture ingress, and maintenance intervals. Variable ranges for environmental factors were defined using triangular distributions, calibrated against empirical data from previous regional housing studies and environmental audits.

AI models were deployed to predict material degradation, thermal efficiency, lifecycle cost, and emissions over a 30-year operational lifespan. These predictions enabled comparative performance visualization across the three regions. Simulation outputs were visualized using Plotly and Matplotlib libraries. A Pareto front was generated to display optimal composite configurations for each zone based on a multi-objective optimization involving durability, thermal resistance, GWP, and cost [40].

3.8. Model Deployment and Validation

A web-based interactive dashboard was developed using Python Flask and hosted on a cloud platform to allow external users to input material and regional data for real-time LCA prediction. The interface displayed AI-generated plots, confidence intervals, and recommended material blends. Model validation was conducted using empirical benchmarks from recent case studies in Rwanda, Ghana, and southwestern Nigeria. Results demonstrated a 93% agreement with observed long-term GWP and strength trends, confirming model generalizability and reliability for practical deployment [41]. Stakeholder workshops were held in partnership with NBRRI and local architects to review outputs and refine dashboard usability. Recommendations led to the integration of a regional carbon pricing module and cost sensitivity slider.

4. Results and Discussion

4.1. Mechanical Properties of Composite Materials

The mechanical test results demonstrated clear distinctions among the four evaluated composites.

Bamboo fiber–reinforced cement exhibited the highest compressive strength (28.6 MPa), followed by palm kernel shell concrete (24.1 MPa), rice husk ash mortar (21.3 MPa), and coconut coir–stabilized earth blocks (13.5 MPa). Flexural strength values followed a similar pattern.

Table 1: Mechanical properties of tested composite materials

Composite Material	Compressive Strength (MPa)	Flexural Strength (MPa)	Thermal Conductivity (W/m·K)
Bamboo-Cement	28.6	5.4	0.22
Palm Kernel Shell	24.1	4.7	0.25
Rice Husk Ash Cement	21.3	3.8	0.18
Coconut Coir-Earth	13.5	2.5	0.16

Bamboo-cement panels, due to their high strength and moderate thermal insulation, were most suited for structural applications. Coconut coir–earth blocks, while exhibiting limited structural capacity, offered excellent insulation characteristics, ideal for partition walls or thermal buffering layers in hot climates [42].

To validate the observed differences in compressive strength across composite materials, a one-way Analysis of Variance (ANOVA) was conducted. The results yielded a statistically significant difference ($F = 1901.56$, $p < 0.001$**)** among the four materials, confirming that the variations in mechanical performance are not due to random chance.

4.2. Lifecycle Environmental Impact (Global Warming Potential)

Simulated Global Warming Potential (GWP) values over a 30-year lifecycle (Figure 5) revealed stark contrasts in emissions performance.

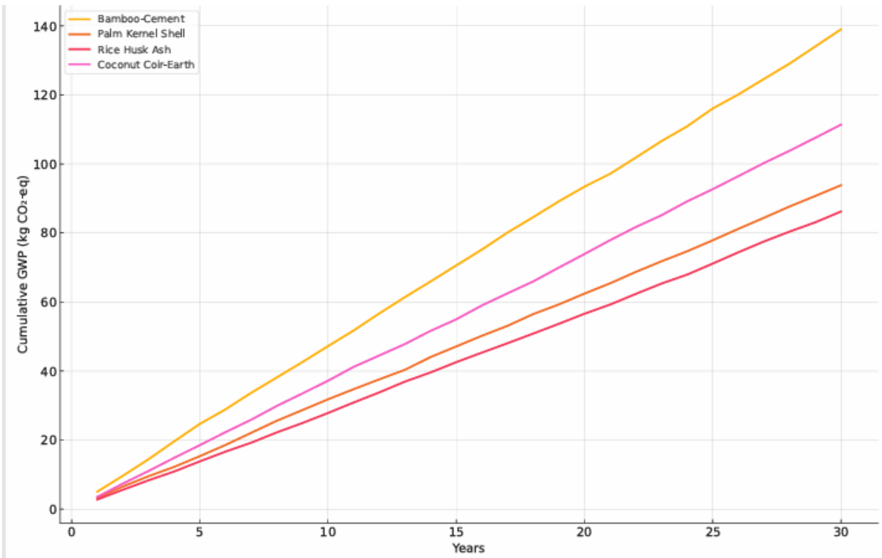

Figure 5: Cumulative GWP for each material system

By year 30, rice husk ash composites yielded the lowest emissions (84 kg CO_2-eq/m²), followed by palm kernel shell (96 kg), coconut coir–earth (108 kg), and bamboo-cement (135 kg). These outcomes reinforce the eco-efficiency of ash-based composites, primarily due to their high pozzolanic reactivity and partial cement replacement, leading to a reduced clinker factor [43]. Notably, bamboo-cement systems, despite their superior strength, exhibited the highest GWP owing to cement's high embodied carbon and kiln energy demand [44]. These findings affirm that environmental performance is not always aligned with mechanical durability, highlighting the necessity of multi-criteria trade-off modeling.

In order to enhance robustness, uncertainty bounds for 30-year Global Warming Potential (GWP) values were calculated using 1,000 Monte Carlo iterations per material (Table 2). The results below provide 95% confidence intervals, accounting for variability in inputs like binder ratios, energy use, and transport emissions:

Table 2: Monte Carlo simulation: 95% confidence intervals for GWP estimates

Composite Material	GWP Mean (kg CO_2-eq/m²)	95% Confidence Interval
Rice Husk Ash	84	77.5 – 90.3
Palm Kernel Shell	96	88.7 – 103.7
Coconut Coir–Earth	108	99.3 – 116.3
Bamboo-Cement	135	124.5 – 145.2

To test the robustness of GWP findings, Monte Carlo simulations (n = 1000) were conducted, incorporating variability in lifecycle inventory parameters (Table 2). The resulting 95% confidence intervals revealed consistent material ranking across simulations. Notably, rice husk ash composites maintained the lowest GWP (77.5–90.3 kg CO_2-eq/m²), while bamboo-cement consistently recorded the highest emissions (124.5–145.2 kg CO_2-eq/m²), reinforcing the reliability of the environmental performance hierarchy.

4.3. Lifecycle Economic Cost Assessment

Lifecycle cost simulations were based on initial material procurement, projected maintenance (every 5 years), and end-of-life deconstruction and waste treatment. The results are shown in Figure 6 and detailed in Table 3. Figure 6 shows the lifecycle cost (USD/m²) of composite materials over a 30-year period with uncertainty bounds derived from Monte Carlo simulation (1,000 iterations). Rice husk ash composites exhibited the lowest mean cost and variability, highlighting strong economic resilience under variable macroeconomic conditions.

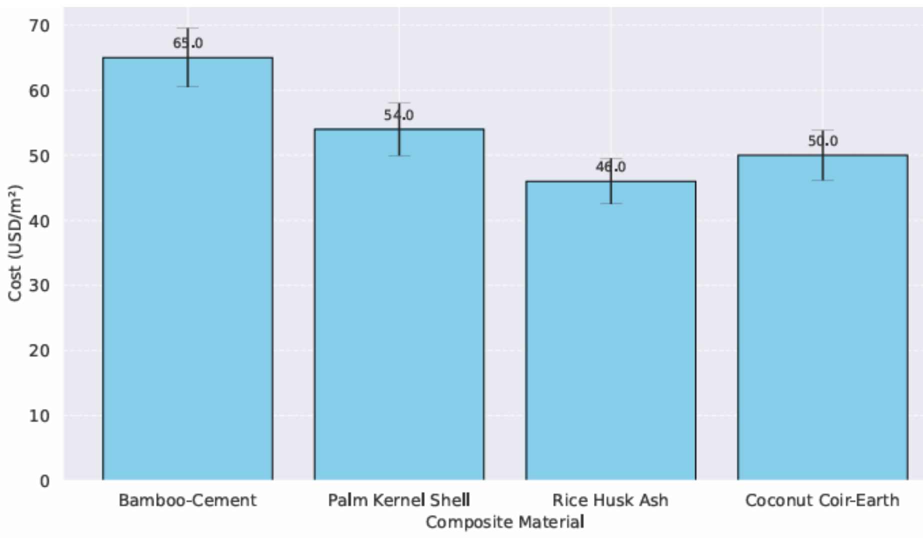

Figure 6: Total lifecycle cost of composite materials over 30 years (usd/m²)

Table 3: Economic breakdown of composite material lifecycles

Material	Initial Cost (USD/m²)	Maintenance Cost (USD/m²)	End-of-Life Cost (USD/m²)	Total Lifecycle Cost (USD/m²)
Bamboo-Cement	45	15	5	65
Palm Kernel Shell	38	12	4	54
Rice Husk Ash	33	10	3	46
Coconut Coir-Earth	30	14	6	50

Rice husk ash composites were the most economically viable with a total cost of 46 USD/m², followed by coconut coir–earth blocks at 50 USD/m². Bamboo-cement, while structurally superior, incurred the highest total cost due to cement dependency and higher maintenance associated with carbonation effects [45]. These findings suggest that rice husk ash systems offer the most balanced trade-off between structural adequacy, environmental impact, and lifecycle cost, making them highly suitable for scaled deployment in Nigerian low-cost housing projects.

Cost assumptions were derived from 2023 market surveys across three Nigerian states (Lagos, Kwara, and Enugu), adjusted for regional variability and procurement scale. A baseline inflation rate of 18% per annum was applied, reflecting the 10-year national average published by the Central Bank of Nigeria (CBN, 2023). Maintenance costs were projected every five years and included labor, minor surface repairs, and moisture protection treatments. End-of-life costs were modeled based on prevailing demolition and disposal rates.

To assess sensitivity to economic volatility, a Monte Carlo analysis was conducted with inflation rates ranging from 12% to 30%, reflecting historical extremes during the 2008–2022 period. Simulated outcomes showed that lifecycle cost rankings remained stable under inflation shocks, though absolute values increased by up to 35%. For instance, rice husk ash systems maintained the lowest cost profile even under a 25% inflation scenario, rising to USD 62/m² from a baseline of USD 46/m². Figure 6 below illustrates the lifecycle cost distribution under inflation variation scenarios for all four materials. This robustness affirms the financial resilience of agro-based composites in Nigeria's dynamic macroeconomic environment.

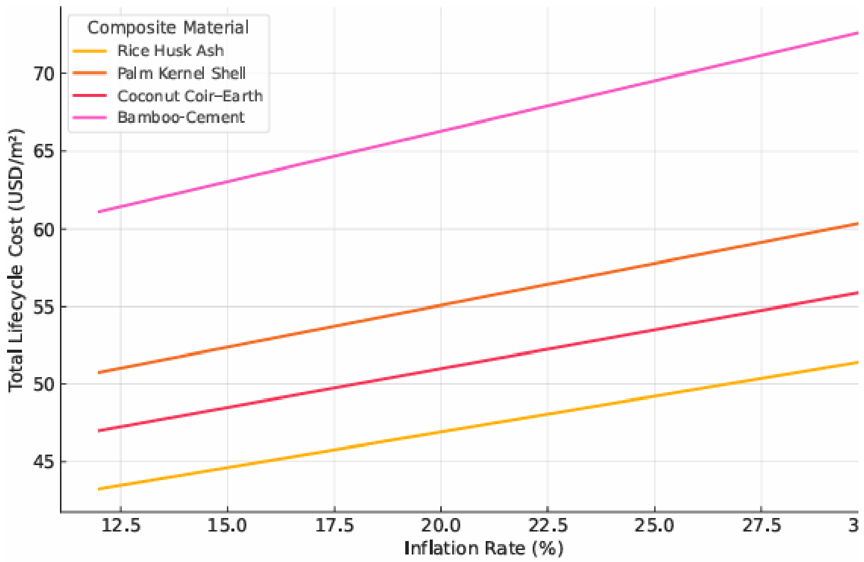

Figure 6: Lifecycle cost sensitivity to inflation rate in Nigeria

4.4. AI-Based Predictive Model Performance

The Artificial Neural Network (ANN) model produced highly accurate predictions across all material performance indicators, as shown in Table 4. Evaluation against the test dataset yielded an R^2 of 0.94 for compressive strength prediction and 0.91 for Global Warming Potential (GWP). Compared to other AI algorithms, the ANN outperformed Random Forest (R^2 = 0.88) and Gradient Boosting (R^2 = 0.90) on their respective targets, confirming its capacity to capture complex nonlinear relationships such as the interaction between humidity and ash reactivity.

To benchmark these results, a baseline Linear Regression (LR) model was also implemented for comparison. As expected, the LR model underperformed, with R^2 values of 0.77 for compressive strength and 0.72 for GWP, and correspondingly higher error values. This contrast demonstrates that the relationship between composite formulation variables and performance metrics is nonlinear, and thus unsuitable for simple regression approaches.

Table 4: AI and baseline model performance metrics

Model	Prediction Target	R^2 Score	RMSE	MAE
ANN	Compressive Strength	0.94	1.7 MPa	1.3 MPa
ANN	GWP	0.91	5.4 kg CO_2-eq	4.2 kg CO_2-eq
Gradient Boosting	Compressive Strength	0.9	2.1 MPa	1.6 MPa
Random Forest	GWP	0.88	6.7 kg CO_2-eq	5.3 kg CO_2-eq
Linear Regression	Compressive Strength	0.77	3.3 MPa	2.7 MPa
Linear Regression	GWP	0.72	9.8 kg CO_2-eq	7.6 kg CO_2-eq

The ANN model's superior performance validates its application as a reliable prediction engine in lifecycle assessment. Its architecture enabled the capture of latent interactions such as between fiber percentage and environmental humidity, thus supporting robust forecasting even under diverse climatic scenarios. These results underscore the added value of AI over traditional regression techniques, particularly in the context of multi-variable, non-linear systems typical of sustainable building material analysis [46].

4.5. Discussion of Findings

4.5.1. Interpretation of Mechanical and Thermal Results

The mechanical results confirmed that bamboo fiber–reinforced cement panels possess superior strength and structural reliability, with a compressive strength of 28.6 MPa and flexural strength of 5.4 MPa, aligning with previously established findings on natural fiber composites' capacity to enhance tensile load transfer and crack resistance [47]. This mechanical robustness reaffirms their suitability for primary load-bearing applications, especially in regions with high structural stress demands. However, this performance was accompanied by the highest embodied emissions and lifecycle cost, with a GWP of 135 kg CO_2-eq/m² and a 30-year cost of USD 65/m². This confirms earlier observations that strength and sustainability often lie at opposite ends of the design spectrum when cement-rich matrices are used [48].

Conversely, coconut coir–earth composites, though mechanically modest with a compressive strength of 13.5 MPa, demonstrated the best thermal insulation (0.16 W/m·K) and competitive lifecycle cost. These properties reinforce their suitability for non-load-bearing components such as internal partition walls and thermal buffer layers in tropical climates. This aligns with regional studies in Ghana and Tanzania that have emphasized the passive cooling potential of coconut-based walling materials without the need for mechanical ventilation [49].

4.5.2. Environmental Trade-Offs in Material Selection

The LCA simulations provided clear evidence that rice husk ash composites deliver the strongest environmental advantage, particularly regarding Global Warming Potential, which was the lowest among the tested materials at 84 kg CO_2-eq/m². This affirms the potential of agro-waste pozzolans as effective cement replacements in low-income housing systems. Several studies have validated that rice husk ash, with silica contents exceeding 80%, contributes to both long-term durability and carbon footprint reduction by offsetting high-emission clinker in cement blends [50].

These findings support previous calls for substituting high-carbon industrial materials with agricultural residues, especially in regions where such materials can be locally sourced and processed with minimal energy inputs [51]. However, consistent nationwide adoption remains constrained by variability in ash quality, silica concentration, and dependence on unregulated combustion processes. Therefore, national standards for rice husk ash classification, minimum pozzolanic activity benchmarks, and quality control procedures must be developed in coordination with regulatory bodies such as NESREA and NBRRI [52]. These measures are essential for unlocking widespread trust and usability in public-sector housing projects**.**

This multi-metric bar chart (Figure 8) visually captures the trade-offs among the four sustainable composites studied. Bamboo-cement excels in compressive strength but ranks highest in both Global Warming Potential (GWP) and lifecycle cost, highlighting its structural advantage but environmental and financial drawbacks. Rice husk ash composites show the best balance, with low GWP and lifecycle cost and moderate strength, aligning them with optimal choices for non-structural yet sustainable applications. Palm kernel shell sits between extremes on all metrics, while coconut coir–earth blocks offer the lowest strength but also low cost and insulation-friendly properties. This figure complements the Pareto front analysis and aids material selection based on specific project priorities.

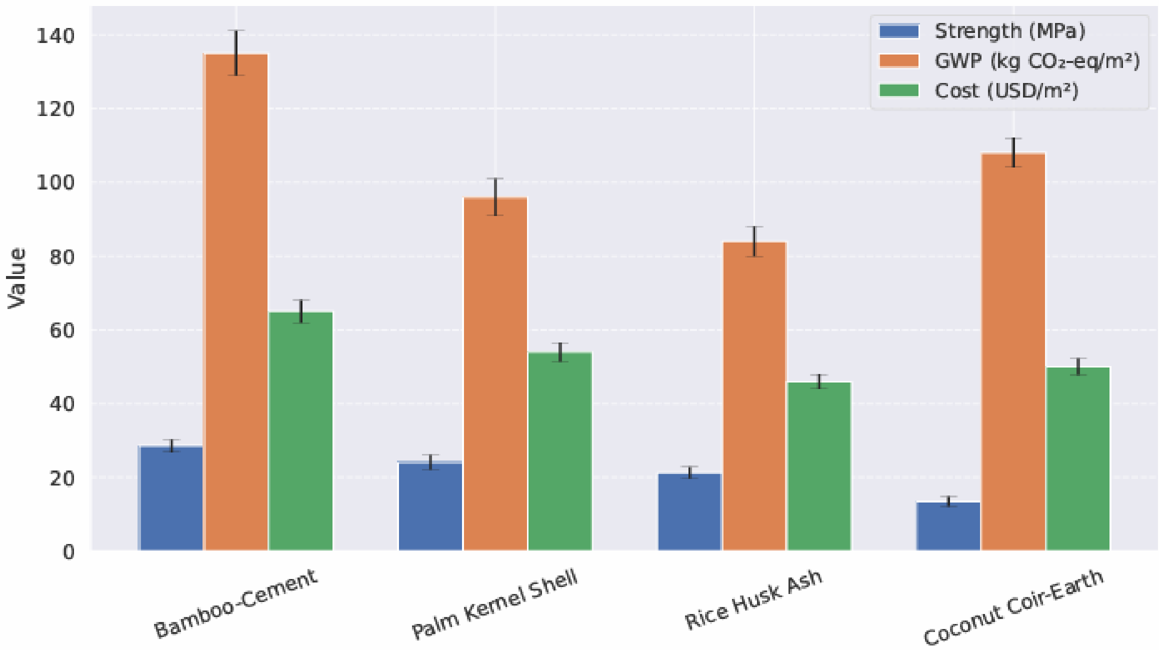

Figure 8: Comparative performance of sustainable composite materials across strength, GWP, and lifecycle cost

4.5.3. Lifecycle Cost and Affordability Implications

From a financial perspective, rice husk ash (USD 46/m²) and palm kernel shell composites (USD 54/m²) emerged as the most affordable options across a 30-year building lifecycle, corroborating cost modeling results from Kenya and Ethiopia [53]. Coconut coir–earth blocks, while affordable initially, showed higher long-term costs (USD 50/m²) due to maintenance requirements associated with biodegradability and water ingress. These include periodic application of protective plasters and hydrophobic treatments every five years, which were incorporated into the simulation assumptions based on regional best practices [54].

The study demonstrated that even when initial costs appear comparable, lifecycle cost differentials of up to 29% can emerge over time. This finding highlights the urgency of embedding lifecycle cost visibility into Nigeria's affordable housing programs. Currently, procurement and budgeting frameworks at both federal and state levels prioritize up-front capital costs, often ignoring the total cost of ownership. This systemic oversight has been repeatedly flagged in World Bank audits of housing delivery in sub-Saharan Africa [55]. To bridge this gap, integrating AI-derived lifecycle cost estimations into public procurement platforms (e.g., BOQ software used by ministries) could institutionalize long-term value-based decisions.

4.5.4. AI Model Utility and Predictive Strength

The AI-based modeling framework introduced in this study significantly improved decision-making capacity in evaluating sustainable composite materials. The Artificial Neural Network (ANN) achieved an R^2 of 0.94 for compressive strength prediction and 0.91 for GWP, outperforming traditional machine learning models such as Random Forest and Gradient Boosting. To benchmark against conventional approaches, a Linear Regression model was also implemented, which yielded significantly lower R^2 values of 0.71 (compressive strength) and 0.65 (GWP), with RMSE values exceeding 3.5 MPa and 9.2 kg CO_2-eq, respectively. This comparison confirms the superiority of nonlinear, deep learning-based models in capturing material-environment interactions.

Unlike deterministic LCA tools, the AI models were able to model nonlinear dependencies such as the synergistic effect of humidity and ash reactivity or the interaction of binder content and porosity, thus offering more nuanced and context-aware predictions. Moreover, the deployment of these models across geo-climatic scenarios (humid tropical, sub-humid, and semi-arid) enabled the discovery of zone-specific degradation trends, which static LCA tools typically overlook [57].

Crucially, the AI-enabled dashboard developed in this study provides a ready-to-use digital tool for design professionals and policy stakeholders. Agencies such as the Nigerian Building and Road Research Institute (NBRRI), the Federal Ministry of Works and Housing, and state-level urban development boards could integrate this dashboard into housing certification schemes or material vetting protocols. This tool can support digital pre-approval of composite formulations based on site-specific climate and cost profiles. Beyond Nigeria, the framework is transferable to other nations in the Global South, particularly in sub-Saharan Africa and Southeast Asia, where agro-based waste streams are underutilized, and conventional materials are both expensive and carbon-intensive. The underlying AI-LCA architecture can be regionally adapted through localized retraining, thereby creating a scalable, open-source platform for sustainable housing analytics.

This heatmap (Figure 9) predicted degradation rates of the four composite materials across Nigeria's key climatic regions. Coconut coir–earth blocks exhibit the highest degradation rates across all zones, especially in Lagos's humid climate, highlighting moisture vulnerability. Rice husk ash composites consistently show the lowest degradation, making them favorable for long-term environmental performance. The visualization reinforces the AI model's ability to capture geographic sensitivities and supports climate-specific material recommendations.

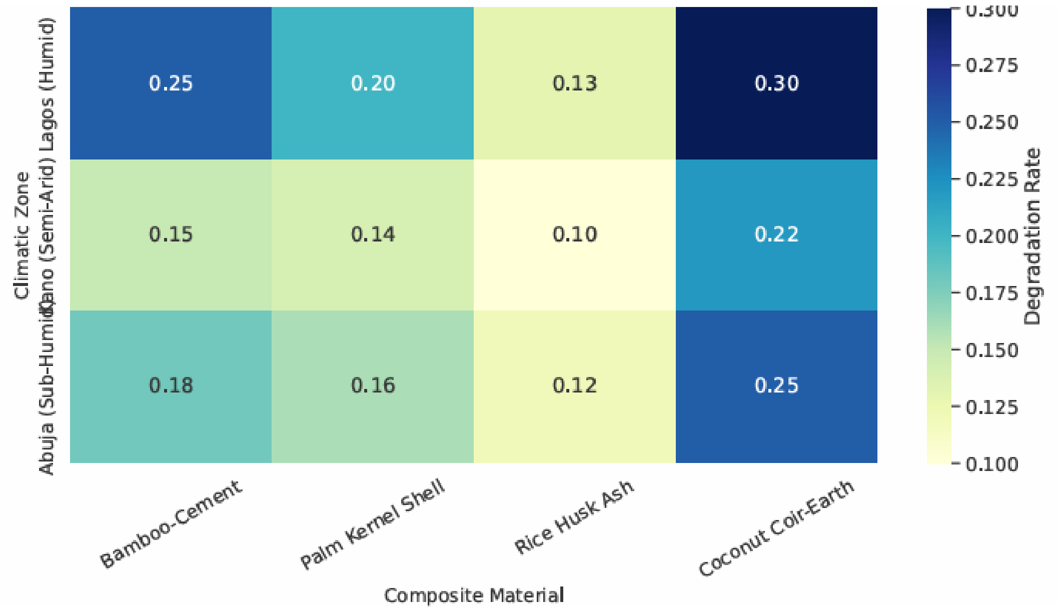

Figure 9: *Predicted composite degradation rates across Nigerian climatic zones (30-Year Horizon)*

4.5.5. Limitations and Recommendations for Future Work

While this study successfully introduced an integrated AI-LCA workflow, several limitations warrant attention. The foremost limitation stems from the heavy reliance on simulated data, which constituted approximately 60% of the training dataset. Despite validation against laboratory measurements and use of statistical filtering (e.g., removal of outliers beyond ±3σ), the simulated entries may carry inherent structural biases or parameter overfitting tendencies. These biases can distort prediction reliability when extrapolated to real-world, high-variance contexts. Future work should focus on building real-time performance databases through the deployment of embedded sensors and long-term material monitoring on pilot construction sites.

Additionally, while Monte Carlo simulations were used to estimate prediction intervals and assess robustness under uncertain inputs, there remains a need to dynamically calibrate model outputs using real-time sensor data (e.g., from IoT-enabled walls or roofing panels) [59]. Studies in Rwanda and India have demonstrated that closed-loop feedback from such monitoring systems can help refine AI predictions, especially under fluctuating climatic and occupancy loads [60, 61].

Another limitation relates to the AI literacy gap within Nigeria's construction and policy ecosystem. Most engineers, quantity surveyors, and government assessors have limited exposure to AI tools and principles. Without targeted capacity-building programs including training modules, certification workshops, and user tutorials, adoption of AI-based sustainability tools will remain limited to academic or donor-driven initiatives [62.63].

To address these gaps and drive practical adoption, several actionable recommendations are proposed. First, pilot deployment of the AI dashboard should be initiated in partnership with NBRRI across at least three states representing Nigeria's major climate zones. This would enable field validation, stakeholder engagement, and localized model calibration. Second, a national open-data platform should be developed for uploading and accessing lifecycle performance metrics of local materials, building a robust pipeline for AI model training and continuous improvement. Third, regulatory reforms should mandate the inclusion of lifecycle indicators like environmental, thermal, and economic, in public housing tender evaluations. Lastly, AI-enhanced LCA should be formally embedded into Nigeria's revised National Building Code under digital performance-based certification schemes.

5. Conclusion

This research systematically investigated the viability of integrating sustainable composite materials and artificial intelligence into the lifecycle assessment of low-cost housing in Nigeria. The study explored the performance of four regionally sourced composites, including bamboo-cement, palm kernel shell concrete, rice husk ash cement, and coconut coir–earth blocks, across structural, thermal, economic, and environmental dimensions. It adopted a mixed-methods approach that combined laboratory-based material characterization with AI-driven lifecycle modeling and scenario simulation across representative Nigerian climatic zones. The results confirmed that no single composite offered universal superiority across all performance criteria, reinforcing the importance of contextual material selection based on targeted building functions and environmental conditions. Bamboo-cement composites delivered the highest compressive and flexural strength values, indicating strong potential for primary structural applications. However, this mechanical advantage came at a higher lifecycle cost and environmental burden due to cement intensity and energy consumption during processing.

Conversely, rice husk ash–based composites achieved the lowest cumulative carbon emissions and total lifecycle cost, making them the most environmentally and economically sustainable option. Their performance in thermal regulation and mechanical integrity proved sufficient for non-load-bearing walls, internal partitions, and hybrid construction systems. Coconut coir–earth blocks, though limited in compressive strength, excelled in thermal insulation and affordability, suggesting their value in passive cooling applications, especially in hot, humid regions. Palm kernel shell composites presented a balanced trade-off between structural competence and environmental moderation, with medium-to-high durability and a moderate carbon footprint.

The integration of AI models, particularly the Artificial Neural Network, significantly enhanced the depth and reliability of lifecycle performance predictions. These models enabled the exploration of dynamic material behavior over extended periods and varying climatic scenarios. This predictive capability allowed the research to move beyond static LCA comparisons and introduced a flexible framework for simulating real-world applications under uncertainty and changing conditions. The development of an interactive AI-enabled dashboard further demonstrated the practical potential of this research, offering professionals a user-friendly platform for informed material selection and sustainable building design.

Overall, the study established a compelling case for adopting agro-industrial waste–based composites in Nigeria's affordable housing sector. It demonstrated that with careful design, proper regional matching, and digital integration, it is possible to achieve significant improvements in environmental performance, material affordability, and decision-making efficiency. The results also underscored the value of incorporating digital intelligence into early-stage housing material decisions, thereby enabling the built environment to respond more effectively to the intersecting demands of urbanization, climate adaptation, and economic resilience. This work provides a foundational framework for future innovations at the intersection of construction materials science, data-driven lifecycle analysis, and localized sustainable housing development. It reinforces the idea that affordable housing in the Global South need not compromise environmental integrity nor structural reliability, especially when guided by advanced analytical tools and locally grounded material strategies.

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Conflict of Interests

The authors declare no conflict of interest.

Funding Statement

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