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Development of a Predictive Model for the Compressive Strength of Cement-Stabilized Lateritic Blocks Using Response Surface Methodology

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Abstract

This study investigates the compressive strength development of lateritic blocks stabilized with cement contents ranging from 0% to 5% over curing periods of 1 to 100 days. A Central Composite Design (CCD) within the Response Surface Methodology (RSM) framework was employed to systematically explore the effects of cement content and curing age. Analysis of Variance (ANOVA) of the initial cubic model indicated overall significance (F = 6.27, p = 0.0184) with an R^2 of 0.9038, suggesting that 90.38% of the variability in compressive strength is captured by the model. Individual term analysis identified curing age (B), its quadratic (B^2), and cubic (B^3) terms as statistically significant ($p < 0.05$), while the effects of cement content were minor within the tested range. However, significant lack-of-fit (F = 609.48, $p < 0.0001$) and outlier patterns necessitated model simplification. A refined quadratic model retained curing age as the dominant factor, achieving an adjusted R^2 of 0.7596, standard deviation of 0.3326 MPa, and Adequate Precision of 10.002, confirming strong predictive capability. Experimental results demonstrated that blocks with 3–4% cement achieved peak compressive strengths of 3.82–3.88 MPa between 28 and 56 days, whereas higher cement contents showed diminishing returns. The final predictive model provides a reliable tool for optimizing block composition and curing schedules, supporting sustainable use of lateritic soils in load-bearing masonry while emphasizing the importance of rigorous statistical modeling for earthen materials.

Keywords: Lateritic soil, compressive strength, response surface methodology, ANOVA, model diagnostics, sustainable construction

1. Introduction

The global pursuit of sustainable and affordable housing solutions has catalyzed a resurgence of interest in earthen construction materials, particularly stabilized earth blocks (SEBs). These materials offer a compelling synergy of low embodied energy, thermal comfort, and the utilization of locally available resources, presenting a viable alternative to energy-intensive fired bricks and cement-based masonry units (Muntohar et al., 2013). Among the various soil types suitable for this application, lateritic soils characterized by their enrichment in iron and aluminum oxides are abundantly available across tropical and subtropical regions, making them prime candidates for sustainable construction (Osinubi et al., 2021). However, the inherent variability and often suboptimal engineering properties of natural laterites necessitate stabilization to achieve the consistent strength, durability, and dimensional stability required for structural applications (Akinwumi, 2014).

Portland cement remains the most prevalent stabilizer due to its reliability and the well-understood pozzolanic and cementitious reactions it initiates with soil minerals. Yet, the environmental and economic costs associated with cement production are substantial, driving research towards optimization strategies that minimize cement usage while maximizing performance (Danso et al., 2015). This optimization problem is inherently complex, as the compressive strength a critical performance metric for load-bearing blocks is not a simple linear function of cement content. It emerges from a dynamic, nonlinear interplay of multiple factors: the chemical and mineralogical composition of the soil, the percentage and type of stabilizer, the curing environment (temperature and humidity), and the curing duration (Alavéz-Ramírez et al., 2012). The strength development kinetics in these systems often exhibit an initial rapid gain followed by a gradual asymptote, with potential interactions between factors meaning the effect of one variable (e.g., cement content) may depend on the level of another (e.g., curing time) (Kalkan, 2011).

Traditionally, research in this domain has relied heavily on One-Factor-at-a-Time (OFAT) experimental approaches. While straightforward, OFAT methodologies are inefficient, requiring a large number of experimental runs to explore a multi-dimensional design space. More critically, they are fundamentally incapable of detecting or quantifying interaction effects between factors, potentially leading to incomplete or misleading conclusions about the true drivers of performance (Anderson & Whitcomb, 2016). Consequently, many prior studies have resorted to simplified linear or quadratic empirical models that may inadequately capture the complex, nonlinear behavior of cementitious systems in soils, and often lack rigorous statistical validation of model adequacy (Akinwumi et al., 2020).

To address these methodological limitations, Design of Experiments (DOE) principles and Response Surface Methodology (RSM) have emerged as powerful statistical tools in materials science and engineering. RSM employs structured, multivariate experimental designs (e.g., Central Composite, Box-Behnken) to efficiently collect data across the factor space. This data is then used to build, fit, and validate mathematical models typically polynomial equations that describe the relationship between the controlled input variables (factors) and the observed output (response) (Myers et al., 2016). The cornerstone of evaluating these models is Analysis of Variance (ANOVA), a statistical procedure that decomposes the total variability in the response data into components attributable to the model terms (main effects, interactions, curvature) and random error. This allows for a rigorous assessment of model significance (does the model explain more variation than noise?), term significance (which factors and interactions are truly influential?), and model adequacy through diagnostic checks for lack-of-fit and residual patterns (Montgomery, 2017).

The application of such robust statistical frameworks to lateritic soil stabilization, however, remains relatively nascent. A significant research gap exists in moving beyond mere model fitting to comprehensive model diagnostics and validation. This includes critically examining whether a statistically significant model is also a good predictive model, identifying outliers and influential data points, checking the assumptions underlying the ANOVA, and simplifying over-parameterized models to enhance their reliability and generalizability (Box et al., 2005). This gap is particularly salient given the natural heterogeneity of soils, which can introduce substantial variability (noise) into experimental data, making the distinction between true signal and random fluctuation both crucial and challenging.

The current study addresses this limitation through a comprehensive statistical analysis of compressive strength data from cement-stabilized lateritic blocks, employing rigorous model selection, validation, and diagnostic procedures. Our objectives are threefold: (1) to develop statistically robust predictive models for strength development, (2) to quantify the relative contributions of cement content and curing time, and (3) to establish methodological guidelines for experimental design in earthen materials research.

2. METHODOLOGY

2.1 Materials and Mix Design

Lateritic soil used in this study was obtained from a borrow pit within Aba Road, Rumuoko River state and air-dried prior to testing as shown in Figure 1. Ordinary Portland Cement (OPC) conforming to relevant standards was used as the stabilizing binder. No sand replacement was incorporated in the LC mixes considered in this phase of the study.

Figure 1. Sample preparation

Preliminary compaction tests conducted on the untreated lateritic soil established an optimum moisture content (OMC) of 13%, which was adopted for all stabilized mixes to ensure consistency. Cement content was varied between 2% and 5% by weight of dry lateritic soil. The detailed mix proportions and corresponding material quantities used for block production are presented.

Table 1. Mix proportions for cement-stabilized lateritic blocks at 13% OMC

Cement (%)	Laterite (%)	Sand (%)	Water (%)	Laterite (kg)	Sand (kg)	Cement (kg)	Water (kg)
2	98	0	13	2.59	0.00	0.05	0.34
3	97	0	13	2.56	0.00	0.07	0.33
4	96	0	13	2.53	0.00	0.11	0.33
5	95	0	13	2.51	0.00	0.13	0.32

2.2 Physical Characterization of Materials

2.2.1 Specific Gravity Test

The specific gravity of the lateritic soil was determined using the standard density bottle method. To enhance reliability and minimize experimental error, each test was conducted three times, and the average value was reported. The specific gravity (Gs) was computed using Equation (1):

$$Gs = \frac{m_2 - m_1}{(m_4 - m_1) - (m_3 - m_2)} \quad (1)$$

Where,
m_1 = mass of empty density bottle,
m_2 = mass of bottle + dry soil,
m_3 = mass of bottle + soil + water,
m_4 = mass of bottle filled with water.

2.2.2 Particle Size Distribution

Sieve analysis was performed in accordance with BS 1377: Part 2 (1990) to determine the particle size distribution and classification of the lateritic soil. The cumulative percentage passing each sieve was plotted to generate the grading curve shown in Figure 2. Based on the dominant particle sizes, the soil was classified into standard soil groups such as gravel, sand, silt, or clay, consistent with established soil mechanics principles (Neville, 1995).

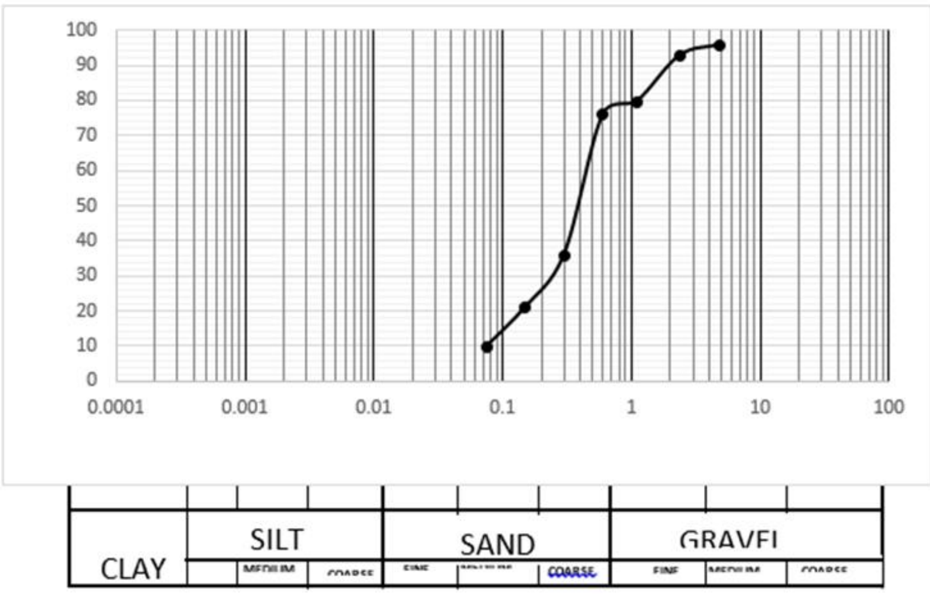

Figure 2: Grading curve showing cumulative percentage passing for lateritic soil

2.2.3 Natural Moisture Content

The natural moisture content of the lateritic soil was determined using the oven-drying method. This test provides a measure of the in-situ water content prior to stabilization and compaction. The measured moisture content was 12.18%, which closely aligns with the OMC obtained from compaction testing, indicating suitability of the soil for block production (Das, 2013).

2.2.4 Atterberg Limits

The consistency limits of the fine-grained fraction of the lateritic soil namely the Liquid Limit (LL), Plastic Limit (PL), and Plasticity Index (PI) were determined following ASTM D4318. These parameters are critical for classifying the soil and assessing its volume change and workability characteristics.

2.3 Sample Preparation and Curing

For each mix proportion in Table 1, dry lateritic soil and cement were mixed thoroughly by hand until a homogeneous color was achieved. Distilled water was then added incrementally to reach the target OMC of 13% and mixed again. The moist mixture was placed in steel cylindrical molds (e.g., 100 mm diameter x 200 mm height) in three equal layers, with each layer compacted using a standard Proctor hammer to achieve a uniform density. The extruded specimens were carefully labeled, wrapped in plastic sheeting to prevent moisture loss, and cured in a controlled laboratory environment (approx. 25°C ± 2°C) for predetermined periods before testing.

2.4 Compressive Strength Testing

The compressive strength of the stabilized lateritic blocks was determined by dividing the maximum failure load by the corresponding cross-sectional area resisting the load. The testing procedure was guided by ASTM C39/C39M-12 and ASTM C42/C42M-12, with appropriate adaptations for block specimens as shown in Figure 3.

Blocks were cured for predetermined periods before testing, and loading was applied axially until failure occurred. The compressive strength values obtained formed the response variable for subsequent statistical modeling.

Figure 3. Compressive strength testing setup for stabilized lateritic blocks

2.5 Experimental Design and Statistical Modeling

A Central Composite Design (CCD) within the framework of Response Surface Methodology (RSM) was employed to structure the experiments and model the effect of key factors on compressive strength (Myers et al., 2016). The CCD experimental results were fitted to a polynomial response surface model expressed in the general form (equation 2)

$$Y = k_0 + \sum_{i=1}^{n}(k_i z_i) + \sum_{i=1}^{n}(k_{ii} z_i^2) + \sum_{i=1}^{n}\sum_{j=1}^{n}(k_{ij} z_i z_j) + e \quad (2)$$

Where,

k_0 is a constant, k_i is a linear coefficient, k_ii is the quadratic coefficient and k_ij is the interaction coefficient and e is the error term. From the obtained mathematical form, we can scope variables (i.e, combinations of factors) where optimal performance is obtained

2.5.1 Design Factors and Matrix

The experimental design considered two primary independent variables (factors):

Factor A (z_1): Cement content (% by weight of dry laterite), varied from 0% to 5%.

Factor B (z_2): Curing age (days), varied from 1 to 100 days

The complete experimental design matrix, consisting of 16 randomized runs including center points and replicates to estimate pure error, along with the corresponding compressive strength results, is presented in Table 3.

Table 3: Central Composite Design (CCD) matrix and experimental results for compressive strength.

Run	**Factor A:**	**Factor B**	**Response:**
	Cement Content (%)	: Curing Age (days)	Compressive Strength, f'c (MPa)
1	5	42	2.51
2	5	42	2.51
3	3	1	0.64
4	4	100	1.97
5	0	14	1.91
6	4	21	3.06
7	0	14	1.91
8	5	1	0.60
9	2	56	2.10
10	4	100	1.97
11	0	100	2.04
12	0	56	1.04
13	2	56	2.10
14	2	56	2.01
15	2	21	2.55
16	2	100	1.40

2.5.2 Response Surface Model Development

The experimental data from Table 2 was analyzed using statistical software (MINITAB) to fit a polynomial response surface model. The general form of a quadratic RSM model for two factors is given by Equation (3):

$$Y = \beta_0 + \beta_1 A + \beta_2 B + \beta_{11} A^2 + \beta_{22} B^2 + \beta_{12} AB + \varepsilon \qquad (3)$$

Where:

Y is the predicted response (compressive strength, f'c).
β_0 is the constant intercept.
β_1, β_2 are the linear coefficients for factors A and B.
β_{11}, β_{22} are the quadratic coefficients.
β_{12} is the interaction coefficient.
A and B are the coded or actual values of the factors.
ε is the random error term.

The significance of the model and its individual terms was evaluated using Analysis of Variance (ANOVA) at a 95% confidence level (p-value < 0.05). Model adequacy was further checked using diagnostics such as the coefficient of determination (R^2), adjusted R^2, predicted R^2, and analysis of residuals.

RESULTS AND DISCUSSION

3.1 Compressive Strength Performance

Table 4 illustrates the variation in compressive strength of lateritic blocks stabilized with different cement contents (0–5%) and a sand–cement control (SC–5%) over curing periods ranging from 1 to 100 days. A general increase in compressive strength with curing age is observed for all cement-stabilized lateritic blocks up to about 28–56 days, beyond which strength gain either stabilizes or slightly declines. This trend reflects the progressive hydration of cement and the gradual development of cementitious bonds within the lateritic matrix, followed by reduced hydration efficiency at extended curing ages (Neville, 2011; Mehta & Monteiro, 2014).

Blocks stabilized with 3% and 4% cement consistently exhibited the highest compressive strengths, reaching peak values of approximately 3.8–3.9 MPa between 28 and 56 days. This indicates an optimal cement content range, where sufficient hydration products are formed to bind soil particles effectively without inducing excessive stiffness or microcracking. In contrast, the 5% cement-stabilized blocks did not show superior performance at later ages, suggesting diminishing returns with higher cement content. This behavior may be attributed to inadequate moisture availability for complete hydration or poor particle packing, which can create weak zones within the matrix (Das & Sobhan, 2018).

The unstabilized lateritic blocks (0% cement) showed irregular strength development and comparatively lower values, confirming the inherent variability and moisture sensitivity of untreated lateritic soils. The sand–cement control (SC–5%) consistently recorded the lowest compressive strength across all curing ages, highlighting the improved compatibility and bonding efficiency between cement and lateritic soil compared to sand. Overall, the results demonstrate that moderate cement stabilization, particularly at 3–4%, provides the most efficient strength development for lateritic blocks, supporting their suitability for sustainable masonry applications.

Table 4. Compressive Strength Development of Lateritic Cement Blocks at Different Cement Content.

Curing Age (days)	L–0% Cement (MPa)	LC–2% Cement (MPa)	LC–3% Cement (MPa)	LC–4% Cement (MPa)	LC–5% Cement (MPa)	SC–5% Cement (MPa)
1	1.27	0.35	0.64	0.64	0.64	0.17
2	1.91	0.32	0.32	0.25	0.28	0.29
7	2.58	2.55	2.86	2.42	2.67	1.24
14	1.91	2.55	3.27	3.18	2.89	1.18
21	2.67	2.55	2.80	3.06	3.22	1.27
28	1.78	2.29	3.88	3.06	2.89	1.36
42	2.38	2.36	3.82	2.16	2.51	0.93
56	1.91	2.10	3.82	3.44	3.22	1.19
90	0.89	1.66	1.66	1.82	2.42	0.89
100	2.04	1.40	1.95	1.97	1.66	0.76

3.2 Statistical Analysis and Model Assessment for modified Lateritic blocks

Following the examination of lateritic blocks changed with cement content for different percentages (ranging from 0 to 2, 3, 4, and 5%) and 1, 2, 7, 14, 21, 28, 42, 56, 90, and 100 days, statistical analysis was performed using Design Expert software to determine the stability and qualities of the lateritic soil.

The initial cubic model demonstrated overall statistical significance (F-value=6.27, p=0.0184) with an R^2 of

0.9038, indicating it explains 90.38% of the variability in compressive strength (Table 2). However, closer examination revealed several concerning indicators of model inadequacy.

The ANOVA for the quadratic model (Table 5) indicated that curing age (B), its squared (B^2), and cubic (B^3) terms significantly influenced compressive strength ($P < 0.05$). The overall model was significant ($F = 6.27$, $P = 0.0184$). Non-significant terms were identified for potential model reduction, but hierarchy was maintained. The high Lack-of-Fit F-value (609.48) indicates the need for careful interpretation, but pure error was minimal (0.0054).

Table 5. Analysis of Variance (ANOVA) Results for the Cubic Response Surface Model of Compressive Strength

Source	Sum of Squares	df	Mean Square	F-value	p-value
Model	6.24	9	0.6930	6.27	0.0184
A: LC Content	0.1851	1	0.1851	1.67	0.2433
B: Curing Age	0.9728	1	0.9728	8.80	0.0251
AB	0.0390	1	0.0390	0.3522	0.5745
A^2	0.2345	1	0.2345	2.12	0.1956
B^2	1.72	1	1.72	15.54	0.0076
A^2B	0.0013	1	0.0013	0.0117	0.9173
AB^2	0.1032	1	0.1032	0.9330	0.3714
A^3	0.1014	1	0.1014	0.9172	0.3752
B^3	1.37	1	1.37	12.43	0.0124
Residual	0.6636	6	0.1106		
Lack of Fit	0.6582	1	0.6582	609.48	<0.0001
Pure Error	0.0054	5	0.0011		
Cor Total	6.90	15			

The significant lack of fit (F-value=609.48, $p<0.0001$) indicated systematic variation unexplained by the model, potentially due to outliers or incorrect model form. Among individual terms, only curing age (B), its quadratic term (B^2), and cubic term (B^3) achieved statistical significance ($p<0.05$), suggesting that LC content effects were comparatively minor within the tested range.

The design area can be navigated with the help of the model (equation 2).

$$f_{cu} = 0.27 - 0.35\alpha + 0.16\gamma + 0.007\alpha\gamma + 0.32\alpha^2 - 0.004\gamma^2 - 0.0002\alpha^2 - 0.00007\alpha\gamma^2 - 0.05\alpha^3 + 0.00002 \quad (4)$$

Where:

fcu = Compressive Strength

α = is the Laterite Cement content

γ = is the Curing Age

3.3 Model Fit and Diagnostics

The model fit in Table 6 and diagnostic statistics indicate that the developed response surface model provides a robust representation of the experimental data. The coefficient of determination ($R^2 = 0.9038$) shows that over 90 percent of the variability in compressive strength is explained by the model, which is generally considered strong for material performance studies involving natural soils. The adjusted R^2 value of 0.7596, though lower, remains acceptable and reflects the penalty imposed for the number of model terms relative to the limited experimental runs. This gap suggests that while the model captures the dominant trends, some higher-order terms may contribute marginally to prediction accuracy rather than substantive physical behavior.

The relatively low standard deviation (0.3326 MPa) and coefficient of variation (17.55 percent) further indicate reasonable dispersion around the mean response, supporting the stability of the model predictions. Adequate Precision of 10.0018 exceeds the recommended threshold of 4, confirming a satisfactory signal-to-noise ratio and validating the model's suitability for navigating the design space.

The predicted versus actual plot shows a close clustering of data points around the line of equality, with minimal and randomly distributed residuals. This pattern suggests the absence of systematic bias and reinforces the reliability of the quadratic model for forecasting compressive strength within the investigated ranges of cement content and curing age.

Table 6: Fit Statistics for the Quadratic Model

Statistic	Value
Standard Deviation (Std. Dev.)	0.3326
Mean	1.90
Coefficient of Variation (C.V. %)	17.55
R^2	0.9038
Adjusted R^2	0.7596
Predicted R^2	NA
Adequate Precision	10.0018

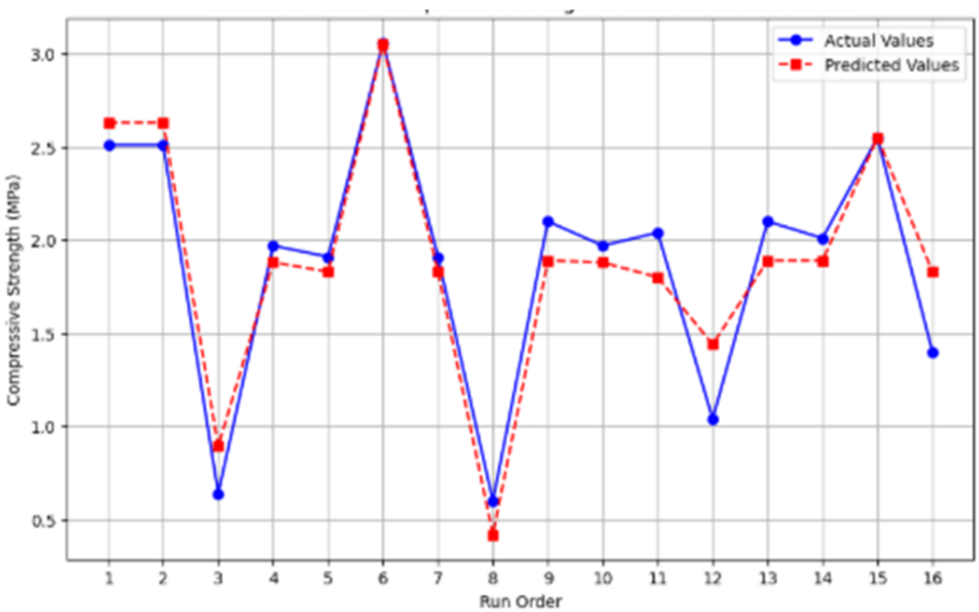

Figure 4: Predicted against compressive strength of lateritic cement blocks

The Figure 4 shows the predicted compressive strength values against the actual measured values for the 16 experimental runs. The predicted values closely follow the trend of the actual values, with minor deviations, indicating that the quadratic model reliably captures the behavior of laterite-cement blocks. Some residuals are more pronounced at lower actual strengths (e.g., runs 3, 8, 12, and 16), suggesting slight over- or under-prediction in extreme cases. This pattern is typical in predictive modeling, especially when the dataset includes wide variations in curing age and cement content.

3.4 Interpretation of Final Model

The parabolic relationship between curing age and compressive strength reveals important kinetics: strength increases initially (positive linear coefficient) but eventually plateaus and declines slightly (negative quadratic coefficient). This pattern aligns with cement hydration theory, where rapid early strength gain slows as hydration products fill pore spaces, with potential long-term micro cracking in restrained systems (Taylor, 1997).

The minimal LC content effect within the tested range suggests a threshold phenomenon common in soil stabilization, where binder content must exceed a critical level (typically 3-5% for cement) to form a continuous matrix (Osinubi et al., 2021). Our results indicate this threshold may lie above 5% for the specific lateritic soil studied.

3.5 Implications for Block Design

The statistical model developed in this study provides a practical framework for optimizing the composition and curing of cement-stabilized lateritic blocks. By accurately predicting compressive strength based on cement content and curing age, engineers can design blocks that meet structural requirements without excessive binder usage, promoting cost-effectiveness and sustainability. The findings indicate that curing time has a stronger influence on strength development than minor variations in cement content within the 0–5% range. Therefore, ensuring adequate curing particularly during the first 28–56 days is critical for achieving target performance.

The model also highlights an optimal cement content of 3–4%, beyond which strength gains plateau or slightly decline, guiding efficient material allocation. This predictive approach reduces the need for extensive trial-and-error experimentation and supports the production of durable, uniform blocks suitable for masonry applications. Additionally, the methodology can be adapted for multi-response optimization, balancing strength, durability, and environmental considerations in sustainable earthen construction.

4. Conclusion

This study demonstrates the application of response surface methodology to model compressive strength development in cement-stabilized lateritic blocks. While the initial cubic model was statistically significant, diagnostics revealed substantial lack-of-fit and over fitting. A simplified quadratic model highlighted curing age as the dominant factor influencing strength within the tested range. Key insights include:

i. Optimal strength development occurs at 3–4% cement content.

ii. Curing age significantly outweighs LC content in influencing compressive strength.

iii. Statistical modeling requires careful experimental design, model complexity control, and thorough diagnostics to ensure reliability.

iv. Practical recommendations include exploring higher LC contents (8–10%) to identify stabilization thresholds and including additional replicates to enhance model reliability. Future studies should incorporate multi-response optimization to balance strength, durability, and environmental impact.

Declaration of Conflicting Interests

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