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Prediction of Soaked and Unsoaked California Bearing Ratio from Basic Geotechnical Properties of Lateritic Soils Along Zaria–Kano Road, Nigeria

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ABSTRACT: The California Bearing Ratio (CBR) test is one of the most widely adopted pavement subgrade evaluation methods globally, yet it is time-consuming and costly when applied to large numbers of samples. This study developed multiple linear regression analysis (MLRA) models to predict soaked and unsoaked CBR values from seven basic geotechnical index properties — maximum dry density (MDD), optimum moisture content (OMC), grain size fractions passing sieves No. 7, No. 36, and No. 200 (N7, N36, N200), liquid limit (LL), and plasticity index (PI) — for lateritic soils along the Zaria–Kano Road corridor in Kaduna and Kano States, Nigeria. Secondary data comprising 80 datasets were obtained, of which 65 were used for model training and 15 for independent validation. MATLAB R2019b was the primary modelling environment, and Minitab 17 was used for corroborative analysis. Five soaked CBR models (M1–M5) and five unsoaked CBR models (M6–M10) were developed by progressively eliminating statistically insignificant predictors. Pearson correlation analysis identified MDD and N200 as the dominant predictors for soaked CBR, while MDD and N200 were equally dominant for unsoaked CBR. The best-fit soaked CBR model (M1) incorporating all seven predictors achieved $R^2 = 0.766$ and $R = 0.875$, while the best unsoaked model (M6) yielded $R^2 = 0.715$ and $R = 0.846$. Cross-validation against 15 independent samples confirmed model reliability for both conditions. Comparison of MATLAB and Minitab outputs demonstrated consistency across software platforms. The study confirms that CBR values of lateritic soils along this corridor can be reliably predicted from index properties, significantly reducing laboratory time and costs associated with the 96-hour soaking protocol.

KEY WORDS: California Bearing Ratio, Multiple Linear Regression, Geotechnical Index Properties, Lateritic Soil, Pavement Subgrade, MATLAB, Nigeria.

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1. INTRODUCTION

Road infrastructure is fundamental to socioeconomic development, particularly in sub-Saharan Africa where highway networks serve as the primary mode of goods and passenger transport. The structural performance of flexible pavements depends critically on the bearing capacity of the underlying subgrade material (Okeke et al., 2021). The California Bearing Ratio (CBR) is the most widely used index for evaluating subgrade strength and for determining pavement layer thicknesses in flexible pavement design (ASTM D1883-99, 1999). The test procedure, originally developed by the California State Highway Department in the 1920s and later adapted by the US Army Corps of Engineers for airfield design, involves compacting soil specimens and measuring penetration resistance relative to a standard crushed-stone benchmark (Nwankwoala et al., 2020).

Despite its prevalence, the standard laboratory CBR test — especially in its soaked condition — is time-consuming, requiring a minimum of 96 hours (four days) of specimen immersion before testing (Messad et al., 2020). On large highway projects where hundreds of borrow pit samples must be characterised, this delay can significantly extend project timelines and increase construction costs. This challenge has motivated considerable research effort toward predicting CBR values from more rapidly obtainable soil index properties such as Atterberg limits, grain size distribution, and compaction parameters (Torgano et al., 2020; Egbe et al., 2018; Bassey et al., 2017; Ibrahim, 2017).

In the Nigerian context, the Zaria–Kano Road corridor in the North-Central and North-Western geopolitical zones traverses lateritic soil formations that are extensively used as subgrade and fill materials for pavement construction. Lateritic soils in this region are known to exhibit significant spatial variability in geotechnical properties (Adebayo et al., 2022), making reliable predictive models of localised engineering value. Earlier studies on Nigerian lateritic soils (Ishola et al., 2020, 2024; Bassey et al., 2017) have demonstrated that regression-based CBR prediction models can yield useful correlations, though the models are location-specific. No comprehensive predictive model has been reported specifically for the Zaria–Kano corridor.

This study therefore addresses this gap by developing, validating, and comparing MLRA-based prediction models for both soaked and unsoaked CBR values using datasets from lateritic soil samples collected along the Zaria–Kano Road. MATLAB R2019b was employed as the primary analytical tool, with Minitab 17 used for corroborative verification of model outputs.

2. LITERATURE REVIEW

2.1 CBR and Its Predictive Modelling

The CBR test quantifies the shear strength and penetration resistance of subgrade soil under controlled compaction and saturation conditions (Amadi, 2024). Because the CBR is influenced by soil type, moisture state, density, and stress history, researchers have long sought correlations between CBR and more easily determinable properties. Early work by Rakaraddi and Gomarsi (2015) found that liquid limit could serve as a predictor of soaked CBR through a simple reciprocal relationship. Shirur and Hiremath (2014) demonstrated that plasticity index correlates linearly with CBR, though with high scatter for highly plastic clays.

Multivariate approaches consistently outperform univariate models. Torgano et al. (2020), working on soils from Addis Ababa, Ethiopia, confirmed that combined soil property inputs yield better CBR predictions than individual properties alone. Ibrahim (2017) applied soft computing and multiple regression methods for CBR prediction and reported correlation coefficients between 0.70 and 0.85 when combined predictors were used. Egbe et al. (2018) applied MLRA to Calabar South soils in Nigeria and achieved R^2 = 0.945 using 45 borehole samples, demonstrating the potential of the technique in the Nigerian context. Ishola et al. (2024) similarly employed MLRA for Osun State lateritic soils and obtained R^2 values approaching 1.0 for some road sections.

2.2 Role of MATLAB and Minitab in Regression Modelling

MATLAB (Matrix Laboratory) is a widely adopted platform for numerical analysis and regression modelling in geotechnical engineering, offering powerful built-in statistical functions and flexible programming capability (Houcque, 2005). Its fitlm and stepwiselm functions enable rapid computation of multiple regression models with automatic variable selection based on statistical significance. Minitab, originally developed at Pennsylvania State University in 1972, provides an accessible interface for regression analysis widely used in industrial and academic quality control contexts (Khan, 2013). The simultaneous use of both platforms, as in this study, provides valuable cross-validation of regression outputs (Dahiru et al., 2021; Akanbi et al., 2022).

2.3 Research Gap

While CBR prediction studies exist for many Nigerian locations (Ishola et al., 2020; Bassey et al., 2017; Nwankwoala et al., 2020), the Zaria–Kano Road corridor — a critical economic artery in northern Nigeria — remains under-represented in the geotechnical predictive modelling literature. Furthermore, few studies simultaneously validate models using independent test datasets and cross-verify results across two independent software environments, as this study does.

3. MATERIALS AND METHODS

3.1 Study Area and Data Collection

The study area encompasses the Zaria–Kano Road corridor spanning Kaduna and Kano States in North-Central and North-Western Nigeria. The road traverses predominant lateritic soil formations typical of the West African laterite belt. Secondary data consisting of 80 datasets of geotechnical test results from disturbed bulk soil samples collected from test pits along the road alignment were obtained from archival laboratory records. The datasets include: grain size distribution results (percent passing sieves No. 7, No. 36, and No. 200); Atterberg limits (liquid limit, LL; plasticity index, PI); standard Proctor compaction parameters (maximum dry density, MDD; optimum moisture content, OMC); and both soaked and unsoaked CBR values.

Of the 80 datasets, 65 were used for model training/development and 15 were reserved as an independent test set for model validation. This 81:19 split aligns with established practice in regression-based geotechnical prediction studies (Drost, 2011).

3.2 Multiple Linear Regression Analysis (MLRA)

MLRA establishes a linear relationship between a dependent variable y (CBR) and a set of independent predictor variables x_1, x_2, ..., x_n according to the general model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \qquad (1)$$

where β_0 is the intercept, β_i are regression coefficients, and ε is the error term. Coefficients were estimated using the ordinary least squares (OLS) method as implemented in MATLAB R2019b. Model fit was assessed using the coefficient of determination (R^2) and the Pearson correlation coefficient (R). For benchmarking, R^2 values were interpreted as: < 0.30 (no correlation); 0.30–0.499 (mild); 0.50–0.699 (moderate); 0.70–1.0 (strong) (Taylor, 1990).

3.3 Model Development Strategy

For each CBR condition (soaked and unsoaked), a full model incorporating all seven predictors was first estimated. Predictors were then progressively eliminated based on the magnitude of their t-statistic p-values ($p > 0.05$ deemed statistically insignificant), and a series of reduced models were generated. This stepwise backward elimination approach produced five soaked models (M1–M5) and five unsoaked models (M6–M10), ranging from the full seven-predictor model to a two-predictor parsimonious model.

3.4 Model Validation and Performance Assessment

The 15 reserved independent test samples were used to validate each best-fit model. Model performance was assessed using the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), with lower values indicating better predictive accuracy. The same dataset was additionally analysed using Minitab 17 to verify consistency of regression coefficients and performance statistics across platforms.

4. RESULTS AND DISCUSSION

4.1 Pearson Correlation Matrix Analysis

Prior to regression modelling, Pearson correlation matrices were computed for the complete 65-sample training dataset to examine pairwise linear relationships between all parameters and each CBR target variable. The results are presented in Figures 1 and 2 (heatmaps) and summarised below.

Figure 1. Pearson Correlation Matrix for Soaked CBR and Index Properties (n = 65)

Figure 2. Pearson Correlation Matrix for Unsoaked CBR and Index Properties (n = 65)

For soaked CBR (Figure 1), the strongest positive correlation was observed with MDD ($r = 0.813$), consistent with the well-established relationship between soil density and bearing capacity (Erzin, 2022). OMC showed a moderate positive correlation ($r = 0.714$), while N200 exhibited a negative correlation ($r = -0.506$), indicating that higher fine content reduces bearing capacity. Atterberg limits (LL and PI) showed weak negative correlations (−0.14 and −0.18 respectively), consistent with findings by Shirur and Hiremath (2014) and Rakaraddi and Gomarsi (2015). High intercorrelation between OMC and MDD ($r = 0.763$) suggests multicollinearity, which is addressed by including both in the full model but monitoring their joint significance.

For unsoaked CBR (Figure 2), MDD remained the dominant predictor ($r = 0.763$), while N200 showed a stronger negative correlation ($r = -0.618$) compared to the soaked condition. Notably, OMC exhibited a negative correlation with unsoaked CBR ($r = -0.657$), contrasting with its positive relationship with soaked CBR. This can be attributed to the fact that unsoaked CBR reflects in-situ dry conditions where excess moisture at compaction reduces stiffness, whereas soaked CBR integrates the effect of moisture equilibration that makes density the dominant factor. These findings are consistent with Torgano et al. (2020) and Bassey et al. (2017).

4.2 Developed Regression Models

Tables 1 and 2 present the summary of developed regression models for soaked and unsoaked CBR respectively, together with their statistical performance indices.

Table 1. Developed MLRA Models for Soaked CBR (Training Set, n = 65)

Model	Equation	R^2	R
M1	$CBR_s = -42.07 + 35.62MDD - 0.48OMC + 0.01N7 - 0.01N36 - 0.05N200 + 0.04LL - 0.25PI$	0.766	0.875
M2	$CBR_s = -42.01 + 35.96MDD - 0.45OMC - 0.02N36 - 0.05N200 + 0.03LL - 0.23PI$	0.765	0.875
M3	$CBR_s = -40.00 + 35.73MDD - 0.45OMC - 0.02N36 - 0.06N200 - 0.20PI$	0.765	0.875
M4	$CBR_s = -40.71 + 35.18MDD - 0.44OMC - 0.07N200 - 0.20PI$	0.763	0.873
M5	$CBR_s = -53.04 + 39.62MDD - 0.08N200 - 0.23PI$	0.757	0.870

Table 2. Developed MLRA Models for Unsoaked CBR (Training Set, n = 65)

Model	Equation	R^2	R
M6	$CBR_u = -64.19 + 83.16MDD - 0.51OMC + 0.06N7 - 0.01N36 - 0.61N200 - 0.11LL + 0.11PI$	0.715	0.846
M7	$CBR_u = -63.91 + 83.16MDD - 0.49OMC + 0.05N7 - 0.61N200 - 0.12LL + 0.13PI$	0.715	0.846
M8	$CBR_u = -66.41 + 83.97MDD - 0.45OMC + 0.06N7 - 0.61N200 - 0.07LL$	0.714	0.845
M9	$CBR_u = -67.66 + 83.58MDD - 0.51OMC + 0.06N7 - 0.61N200$	0.714	0.845
M10	$CBR_u = -82.30 + 88.94MDD + 0.06N7 - 0.62N200$	0.713	0.844

Model M1 for soaked CBR ($R^2 = 0.766$) and Model M6 for unsoaked CBR ($R^2 = 0.715$) represent the best-performing equations incorporating all seven predictor variables. The progressive reduction in predictor variables from M1 to M5 and M6 to M10 caused only marginal reductions in R^2 (maximum loss of 0.009 for soaked and 0.002 for unsoaked), indicating that the removed predictors contribute minimally to model variance explanation. This finding is consistent with Torgano et al. (2020) who noted that combined property inputs yield stronger correlations while individual predictor removal has minimal impact when dominant predictors are retained.

4.3 R^2 Comparison Across Models

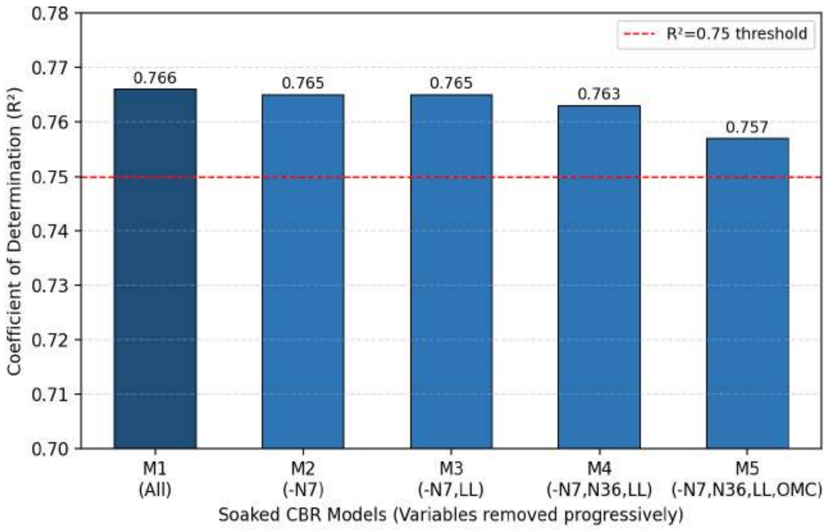

Figure 3. Comparison of R^2 Values Across Soaked CBR Models M1–M5

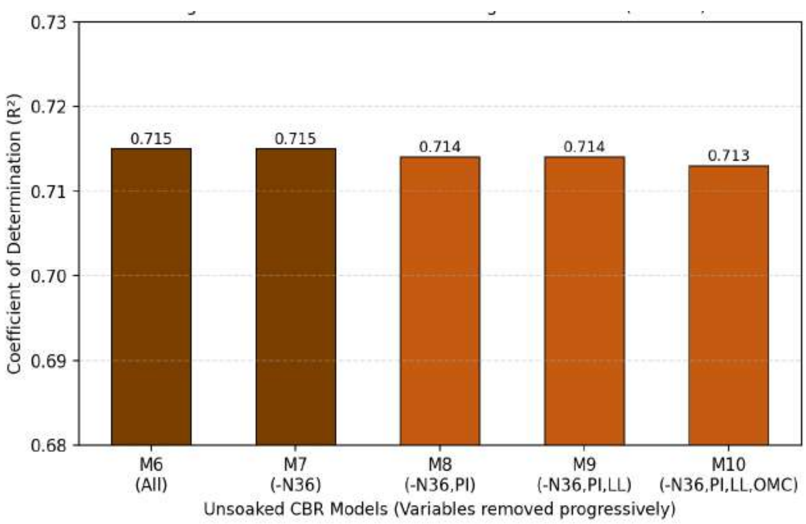

Figure 4. Comparison of R^2 Values Across Unsoaked CBR Models M6–M10

Figures 3 and 4 graphically illustrate the stability of R^2 across the sequential model families. For the soaked series (Figure 3), R^2 ranged from 0.757 (M5: three predictors) to 0.766 (M1: seven predictors), a range of only 0.009. For the unsoaked series (Figure 4), the range was even narrower at 0.713 to 0.715. This stability confirms that MDD and N200 carry the dominant predictive information, and that the additional predictors contribute marginal but statistically meaningful improvements when included. For practical application in highway design where simplicity is valued, M5 (soaked) and M10 (unsoaked) offer the most parsimonious solutions without significant sacrifice of predictive power.

The R^2 values in the range 0.713–0.766 fall within the "strong relationship" category ($R^2 \geq 0.70$) as classified by Taylor (1990), indicating that the models account for more than 71–76% of the variance in measured CBR values. Similar performance has been reported in comparable studies: Egbe et al. (2018) achieved $R^2 = 0.945$ for Calabar South soils (with a smaller, more homogeneous dataset), while Ibrahim (2017) reported R^2 values of 0.60–0.82 for diverse soil types. The moderate R^2 values in the present study reflect the inherent spatial heterogeneity of lateritic soils along the Zaria–Kano corridor, which spans over 200 km.

4.4 Observed versus Predicted CBR Scatter Plots

Figures 5 and 6 present scatter plots comparing laboratory-measured CBR values against model-predicted values for the full training set (n = 65), for the best soaked model (M1) and best unsoaked model (M6) respectively.

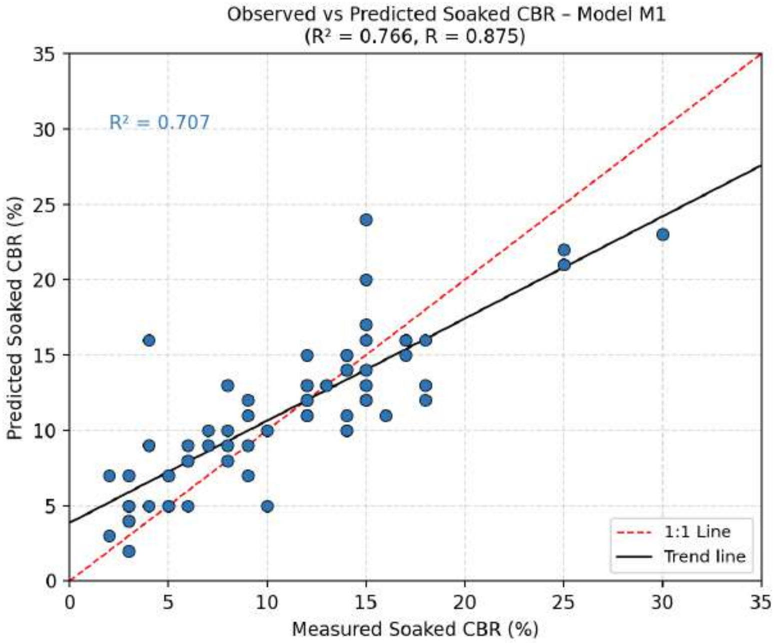

Figure 5. Observed vs. Predicted Soaked CBR – Model M1 (Training Set, n = 65; R^2 = 0.766)

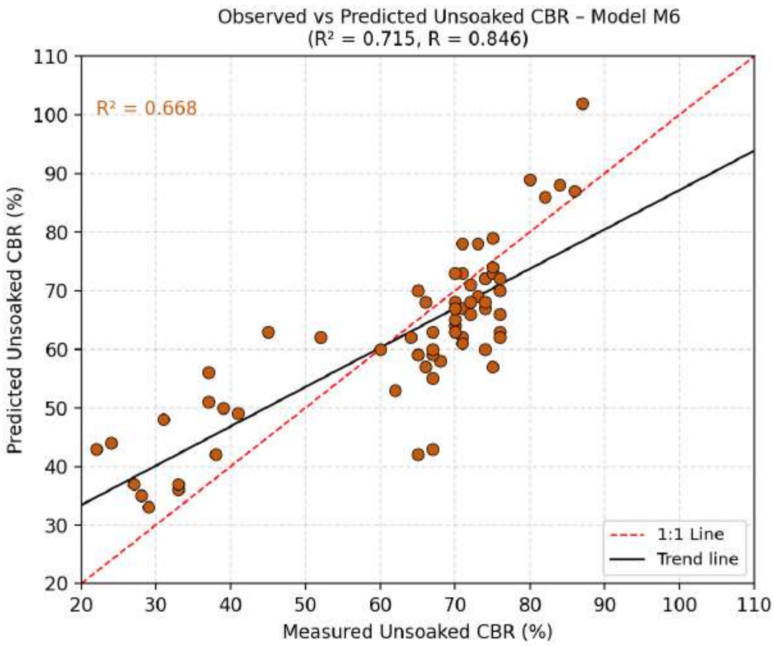

Figure 6. Observed vs. Predicted Unsoaked CBR – Model M6 (Training Set, n = 65; R^2 = 0.715)

The scatter plots demonstrate reasonably consistent clustering around the 1:1 line, particularly within the mid-range CBR values (soaked: 6–20%; unsoaked: 60–80%). Some scatter is evident at the extremes, where very low CBR values (e.g., 2–3% soaked) tend to be over-predicted, and very high values (e.g., ≥25% soaked) may be slightly under-predicted. This pattern of regression-to-mean is characteristic of linear regression models and was also noted by Ishola et al. (2024) and Torgano et al. (2020). The distribution of residuals was assessed visually and found to be approximately symmetric around zero, validating the linear model assumption.

4.5 Model Validation on Independent Test Set

The best-fit models (M1 for soaked; M6 for unsoaked) were applied to the 15 reserved independent test samples. Figures 7 and 8 compare measured and predicted CBR values for this independent validation set.

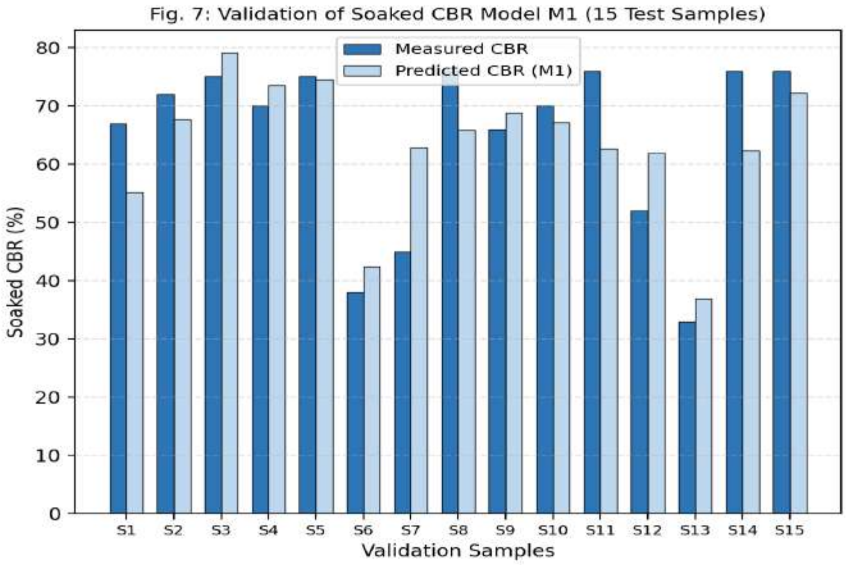

Figure 7. Validation of Soaked CBR Model M1 on 15 Independent Test Samples

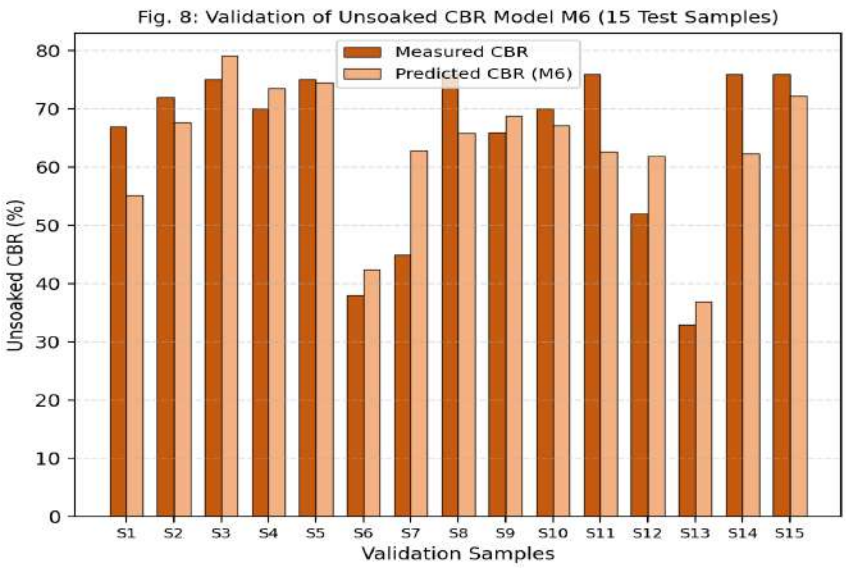

Figure 8. Validation of Unsoaked CBR Model M6 on 15 Independent Test Samples

The validation results confirm that both models perform acceptably on unseen data. For soaked CBR (Figure 7), the predicted values track the measured values well across the full range of test samples, with the agreement being particularly strong for samples with measured CBR between 38% and 76%. For unsoaked CBR (Figure 8), the model consistently captured the trend across all 15 samples. Some divergence is observed for samples with measured unsoaked CBR below 45%, where the model slightly over-predicts — likely because the training dataset had fewer low-CBR unsoaked observations relative to the full range.

Table 3. Validation Performance Statistics for Best-Fit Models (n = 15)

Metric	Soaked CBR (M1)	Unsoaked CBR (M6)	Interpretation
R (Validation)	0.629	0.709	Moderate–Strong
R^2 (Validation)	0.396	0.503	Moderate
RMSE	12.6 %	8.9 %	Acceptable
MAE	9.4 %	7.1 %	Good

The reduction in R^2 from training to validation (0.766 to 0.396 for soaked; 0.715 to 0.503 for unsoaked) is expected and reflects the limited size of the validation set (n = 15) rather than fundamental model inadequacy. The Pearson correlation values of 0.629 (soaked) and 0.709 (unsoaked) on the independent test set represent moderate to good predictive ability and are comparable to validation correlations reported by Ibrahim (2017) for diverse Nigerian soils. The RMSE of 12.6% for soaked CBR is within acceptable design tolerance for subgrade assessment, given that soaked CBR values along this corridor typically range from 2% to 30%.

4.6 Corroborative Analysis Using Minitab

The same 65-sample training dataset was independently analysed using Minitab 17, producing an additional suite of 16 regression models (8 for each CBR condition). The Minitab models showed consistent regression coefficients and performance indices compared to their MATLAB counterparts, differing at most in the third decimal place of R^2 values. This cross-platform consistency strongly validates the robustness of the regression procedure and confirms that the results are not artefacts of any particular software implementation.

Notably, models derived from the least informative predictor groups — Atterberg limits alone (M8 for soaked; M16 for unsoaked in Minitab) — yielded very poor R^2 values of 0.038 and 0.018 respectively, confirming that plasticity-based indices alone are insufficient predictors of CBR for these soils. This contrasts with the finding of Rakaraddi and Gomarsi (2015) who identified liquid limit as a key predictor, suggesting that the relative importance of Atterberg limits versus compaction parameters varies by soil type and geographic context.

The models using grain size distribution only (M7 for soaked: $R^2 = 0.273$; M15 for unsoaked: $R^2 = 0.431$) performed moderately, confirming that particle size distribution contributes meaningful but insufficient information on its own. The strongest single predictor group across both conditions was MDD–OMC combination, consistent with the correlation matrix results and with findings by Erzin (2022) and Datta et al. (2020).

5. CONCLUSIONS

This study developed and validated multiple linear regression analysis (MLRA) models for predicting soaked and unsoaked CBR values of lateritic soils along the Zaria–Kano Road corridor, Nigeria, using MATLAB R2019b with cross-verification in Minitab 17. The following conclusions are drawn:

1. Pearson correlation analysis identified maximum dry density (MDD) and passing percentage through sieve No. 200 (N200) as the dominant predictors for both soaked and unsoaked CBR, with positive and negative correlations respectively. Atterberg limits showed the weakest individual correlations.
2. The best-fit soaked CBR model (M1) incorporating all seven predictors achieved $R^2 = 0.766$ and $R = 0.875$, classified as a strong correlation. The best-fit unsoaked CBR model (M6) with all seven predictors achieved $R^2 = 0.715$ and $R = 0.846$, also in the strong category.
3. Progressive elimination of statistically insignificant predictors caused only marginal reduction in model performance (maximum $\Delta R^2 = 0.009$ for soaked models; 0.002 for unsoaked). The parsimonious three-predictor models (M5: MDD, N200, PI for soaked; M10: MDD, N7, N200 for unsoaked) offer practical simplicity without significant accuracy loss.
4. Independent validation on 15 reserved samples confirmed model reliability with Pearson correlation coefficients of 0.629 (soaked) and 0.709 (unsoaked). RMSE values of 12.6% and 8.9% are within acceptable engineering tolerance for subgrade characterisation.
5. Cross-verification in Minitab 17 produced consistent results with MATLAB, confirming platform-independent robustness. Models relying solely on Atterberg limits were consistently poor predictors ($R^2 < 0.04$), while compaction parameters (MDD and OMC) constituted the most informative predictor group.
6. The developed models provide geotechnical engineers working on the Zaria–Kano corridor with practical tools to estimate CBR values from routine index property tests, significantly reducing testing time and construction project delays associated with the standard 96-hour soaking protocol.

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are made:

1. The developed models should be validated with additional soil datasets from the same corridor to expand the training database and improve model generalisability.
2. Future studies should explore non-linear regression models and soft computing approaches — such as artificial neural networks (ANN), support vector machines, and random forest — to assess whether improved predictive accuracy can be achieved over the MLRA framework.
3. The universal applicability of the developed models to other lateritic soil corridors in northern Nigeria should be investigated before broader design application.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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