DEVELOPMENT OF REGRESSION EQUATIONS FOR THE CALIFORNIA BEARING RATIO OF COHESIONLESS SOIL

Md Mahabub Rahman[1], Md Roknuzzaman[2], Jannatul Muntaha[*3], Animesh Ray[4] and Md. Nur Azad[5]

[1] Lecturer, Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, e-mail: mmr.civil@hstu.ac.bd
[2] Associate Professor, Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, e-mail: mrz.civil@hstu.ac.bd
[3] Undergraduate student at Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, e-mail: jannatulmuntaha75@gmail.com
[4] Undergraduate student at Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, e-mail: animeshce18hstu@gmail.com
[5] Graduate student at Department of Civil Engineering, Hajee Mohammad Danesh Science and Technology University, Bangladesh, e-mail: nurazad.hstu@gmail.com

***Corresponding Author**

ABSTRACT

The California Bearing Ratio (CBR) is a crucial factor in the design and construction of flexible pavements. It is used to determine the stiffness of basement soil and its shear modulus. However, calculating California Bearing Ratio (CBR) values can be time-consuming and challenging for civil engineers who need to make prompt decisions. Researchers have developed correlation equations that can determine CBR values based on easily identifiable indices and technical factors to address this issue. This approach aims to reduce the time required for CBR calculations while still considering their significance. However, most of the equations developed so far have limited applicability and success because they rely on single or double variables. This article focuses on evaluating regression equations for sandy soils using nine selected soil parameters. The study used industry-standard software packages, specifically SPSS and Microsoft Excel 2013, to perform linear and non-linear regression analyses. The correlation equations were derived from a single parameter. The coefficient of determination (R2) for single linear and non-linear regression ranged from 0.000007 to 0.604. The study found that correlation equations based on non-linear regression showed higher correlation coefficients than linear regression equations. Three models with higher R2 values were further statistically analyzed. The z-test findings indicate that there are no significant differences between the obtained and predicted CBR for any of the three models (Models 4, 10, and 13). As a result, these models could be used to predict CBR for sandy soil.

Keywords: *Regression, california bearing ratio, cohesionless soil, soil parameters*

1. INTRODUCTION

Roads play a crucial role in economic development and provide societal benefits. In our country, the majority of the highway system consists of flexible pavement. The weight from the pavement surface is ultimately distributed through various layers, including the subgrade, subbase, base course, and surface course. The soil's strength at the site influences the design, effectiveness, and height of flexible pavements (Ramasubbarao & Siva, 2013; Rakaraddi & Gomarsi, 2015). The primary function of the basement is to provide adequate support for the pavement. The subgrade must be robust enough to withstand unfavourable weather and load conditions to accomplish this. Soil behaviour is challenging to predict because of regional variations in soil conditions. A thorough evaluation of soil characteristics at each site is necessary for optimal design. The California Bearing Ratio (CBR) test is now a widely used, comprehensive test in pavement design that assesses the shear quality and stiffness modulus of subgrade material. In modern times, the most popular technique for figuring out the bearing strength of pavement materials is the CBR test, which is essential to pavement design practice in the majority of nations (John et al. 2017; Charman, 1988). In practice, only a small number of CBR tests could be conducted due to the higher cost per test and the fact that it takes a long time. Because of this, it is sometimes challenging to identify specific variances in the CBR values throughout the whole length of roadways. It will be simple to obtain information about the strength of the subgrade along the length of the roads in these situations if the CBR could be estimated based on some tests that are quick, simple, and affordable. This will also be helpful and important to construct the entire length of the road in a short amount of time (Roy et al. 2010). Consequently, to get over the aforementioned challenges, researchers have established empirical correlations between the CBR value and certain soil index properties.

Patel & Desai (2010) determined CBR for alluvial soils in South Gujarat using index characteristics. They observed a statistically significant relationship, indicating that these index characteristics may be utilized to predict CBR values. The study, however, was restricted to alluvial soils and may not be relevant to other soil types. Singh (2011) employed sixteen natural soil specimens from Assam's Nagaon area to correlate soil parameters. LL, PL, MDD, OMC, and PI were associated with the CBR characteristic. Some regression models were developed to determine the relationship between the CBR value and the soil index attributes. Furthermore, Muley and Jain (2013) examined the CBR of the poor soil following its mixing with stone dust. The purpose of the study was to find a link to forecast the soil CBR. Additionally, MLRA models were created to establish connections between CBR and soil index features. According to the findings of Talukdar (2014) and Roy (2010) correlations of CBR with PI, PL, and LL as a single variable were found to be generally negative, indicating that the genuine CBR value could not be attributed to those limitations. As for the prediction of CBR value from MDD, OMC, PI, LL, and PL using a single variable equation Mishra and Tegar (2019), and Priya et al. (2019) were able to get good correlations. However, the study was limited to specific locations and may not be applicable to other contexts. The purpose of this work is to develop significant relationships between the soil's CBR and other cohesionless soil geotechnical properties. The correlations are expressed as linear and non-linear correlation equations, which are then utilized to calculate the CBR of the subgrade soils. This would save time and money by obviating the necessity for comprehensive CBR testing in that region.

2. METHODOLOGY

The method used to develop regression equations with California bearing ratio (CBR) and other soil properties for sandy (cohesionless) soils involves many steps. The steps initialize with the collection of data, which is then followed by data analysis, model building, and validation.

2.1 Data Collection

The first step was to collect data on the California Bearing Ratio (CBR) of various types of cohesionless soils. Thirty-two CBR test reports were collected from non-government organizations.

The test reports included variables such as soil type, grain size distribution, maximum dry density, optimum moisture content, and CBR values.

2.2 Data Analysis

The collected data was then analysed using statistical methods to identify trends and relationships between the variables. A simple regression analysis was conducted using SPSS and Microsoft Excel 2013.

2.3 Model Development

Based on the results of the data analysis, correlation equations were developed. These equations correlate the CBR value to the other independent variables (soil index properties). The general form of the simple linear and non-linear correlation equations is:

$$CBR = a * X + \ldots + z \tag{1}$$

$$CBR = a * X^3 + b * X^2 + c * X + \ldots + z \tag{2}$$

where a, b, c, etc. are coefficients to be determined, and X is the variables (e.g., Maximum Dry Density, Optimum Moisture Content, $\%\,sand$, $\%\,Passing\ 75\,\mu m$, D_{60}, D_{10}, D_{30}, C_c and C_u).

2.4 Model Validation

The developed correlation equations were validated using a separate set of data. This involves comparing the predicted CBR values from the equations with the actual CBR values. The accuracy of the equations was assessed using the coefficient of determination (R^2).

2.5 Refinement

The correlation equations were refined based on the validation results. This included modifying the equation's form and testing the model's adequacy and performance using ANOVA and the Hypothesis test.

3. RESULTS AND DISCUSSIONS

3.1 Statistical Information

To develop statistical relationships using collected data from a private organization that conducted a laboratory investigation on 32 cohesionless soil samples to analyze soil characteristics. The parameters examined included soil index properties, maximum dry density, and optimum moisture content. The California Bearing Ratio test was also conducted to measure the potential strength of subgrade, subbase, and base course materials for road and pavement construction. The descriptive statistics of different soil properties were analyzed, and the results are shown in Table 1. The study provides valuable insights into the suitability of soil for various construction purposes. The mean sand content was found to be 86.28% with a standard deviation of 6.72, indicating a moderate variability in the sand content across the samples. The skewness value of -0.98 suggests a slight left skew in the data, while the kurtosis value of 1.35 indicates a relatively flat distribution. The mean percentage of particles passing through a 75μm sieve was 15.52%, with a standard deviation of 6.15, indicating a high variability in the particle size distribution. The data showed a right-skewed distribution with a positive skewness of 1.15 and a kurtosis value of 0.48, indicating a relatively peaked distribution. The mean Optimum Moisture Content (OMC) was 15.98%, indicating moderate variability. The mean Maximum Dry Density (MDD) was 1.73 g/cc, indicating low variability. The MDD ranged from 1.64 g/cc to 2.3 g/cc, with a median value of 1.695 g/cc. The skewness value of 3.52 suggests a strong right skew, while the kurtosis value of 12.60 indicates a highly peaked distribution. The mean values for

D_{60}, D_{30}, and D_{10} were 0.26, 0.19, and 0.13, respectively, with standard deviations of 0.04, 0.03, and 0.03, respectively, indicating low variability in these properties.

Table 1: Descriptive statistics of laboratory test results for thirty two soil samples

Descriptive Statistics	Sand	% PASSING 75μm	OMC (%)	MDD (g/cc)	D_{60}	D_{30}	D_{10}	Cc	Cu	Obtained CBR
Mean	83.57	16.43	15.38	1.69	0.26	0.18	0.12	1.09	2.10	10.68
Standard Error	1.36	1.36	0.13	0.00	0.00	0.00	0.00	0.01	0.06	0.23
Median	86.80	13.21	15.50	1.70	0.25	0.19	0.13	1.09	2.01	10.40
Mode	87.00	13.00	16.10	1.70	0.25	0.19	0.13	0.96	1.90	10.00
Standard Deviation	7.70	7.69	0.72	0.02	0.01	0.01	0.02	0.08	0.34	1.30
Sample Variance	59.25	59.07	0.51	0.00	0.00	0.00	0.00	0.01	0.12	1.68
Kurtosis	0.20	0.20	-0.22	1.61	3.55	-0.55	-0.68	-0.50	0.33	0.25
Skewness	-1.21	1.21	-0.77	-0.76	1.71	-0.31	-0.14	0.05	0.93	0.90
Range	27.38	27.38	2.60	0.10	0.05	0.03	0.06	0.28	1.25	4.60
Minimum	65.00	7.62	13.80	1.64	0.24	0.17	0.09	0.96	1.65	9.00
Maximum	92.38	35.00	16.40	1.74	0.29	0.20	0.15	1.24	2.90	13.60
Sum	2674.11	525.69	492.00	54.19	8.16	5.90	3.95	34.94	67.28	341.80
Count	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00	32.00

The mean values for the coefficient of curvature (Cc) and coefficient of uniformity (Cu) were 1.21 and 2.11, respectively, with standard deviations of 0.38 and 0.36, respectively, indicating moderate variability in these properties. The mean California Bearing Ratio (CBR) was 11.15 with a standard deviation of 2.08, indicating moderate variability in the bearing capacity of the soil. The CBR ranged from 9 to 18, with a median value of 10.65. The skewness value of 2.08 suggests a strong right skew in the data, while the kurtosis value of 4.45 indicates a highly peaked distribution.

Figure 1 presents the Pearson correlation coefficients between different soil properties. The Pearson correlation coefficient is a measure of the linear correlation between two variables, ranging from -1 to 1. A value of 1 implies a perfect positive correlation, -1 a perfect negative correlation, and 0 indicates no correlation.

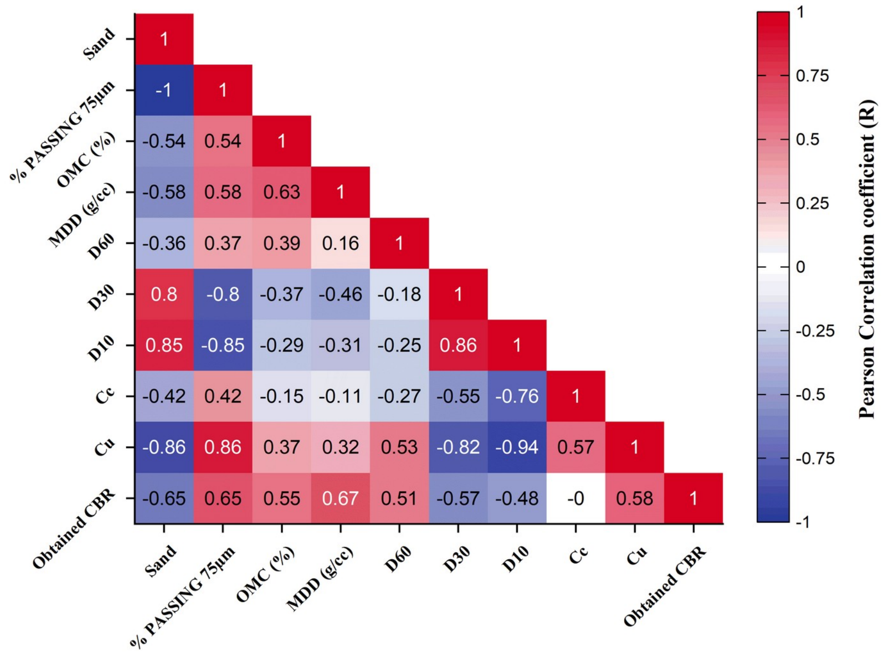

Figure 1: Pearson correlation matrix

The correlation between sand and % passing 75µm is -0.6058, indicating a moderately negative correlation. This suggests that as the sand content increases, the % passing 75µm decreases, and vice versa. The correlation between OMC (%) and MDD (g/cc) is 0.82776, indicating a strong positive correlation. According to this, the MDD (g/cc) rises along with the OMC (%). There is a high positive association (r = 0.87608) between D_{60} and D_{30}. This implies that there is a positive correlation between the D_{60} and the D_{30}. There is a substantial positive association (r = 0.82492) between D_{10} and sand. This indicates that an increase in D_{10} corresponds with an increase in sand content. A substantial positive correlation of 0.76647 is found between C_c and C_u. This implies that when the C_c rises, so does the C_u. A Strongly positive (0.86411) correlation is found between the obtained CBR and C_c. This suggests that as the obtained CBR increases, the Cc also increases. Overall, the correlation matrix provides valuable insights into the relationships between different soil properties. These correlations can be used to predict one soil property based on the value of another, which can be useful in various soil-related research and applications.

3.2 Simple Regression Analysis (SRA)

The variations in CBR value, which was considered as a dependent variable, with OMC, MDD, $\%\,sand$, $\%\,Passing\,75\,\mu m$, D_{60}, D_{10}, D_{30}, C_c and C_u value which were considered independent variables are presented in Figures 2-19. Linear and non-linear SRA were carried out using the data analysis toolbar of Microsoft Excel in order to derive the relationship statistically.

3.2.1 Correlation Matrix Simple Linear Regression Analysis (SLR)

Nine simple linear regression models have been developed based on Pearson's correlation analysis. Simple linear regression analysis was performed on thirty-two samples, in which nine independent variables were correlated with the dependent variable CBR. The resulting simple linear models are shown in figures 2–10 and Table 2. Model 1: $CBR\ vs\,\%\,sand$, Model 2: $CBR\ vs\,\%\,Passing\,75\,\mu m$, Model 3: $CBR\ vs\,OMC$, Model 4: $CBR\ vs\,MDD$, Model 5: $CBR\ vs\,D_{60}$, Model 6: $CBR\ vs\,D_{30}$, Model 7: $CBR\ vs\,D_{10}$, Model 8: $CBR\ vs\,C_c$ and Model 9: $CBR\ vs\,C_u$.

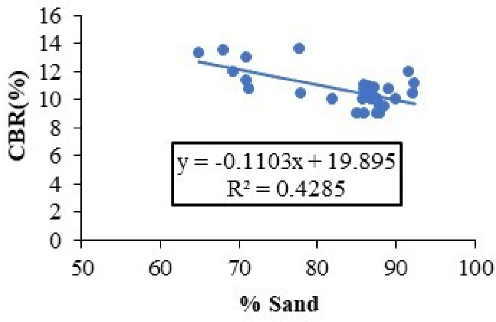

Figure 2: Linear regression model between CBR and %Sand (Model 1)

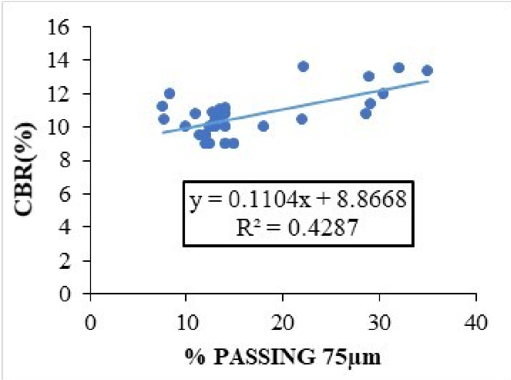

Figure 3: Linear regression model between CBR and % PASSING 75µm (Model 2)

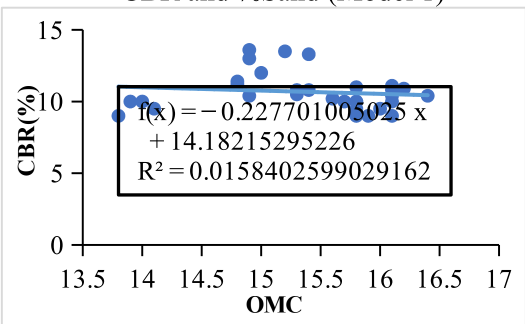

Figure 4: Linear regression model between CBR and OMC (Model 3)

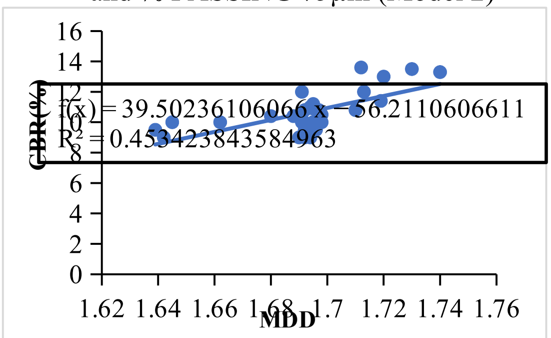

Figure 5: Linear regression model between CBR and MDD (Model 4)

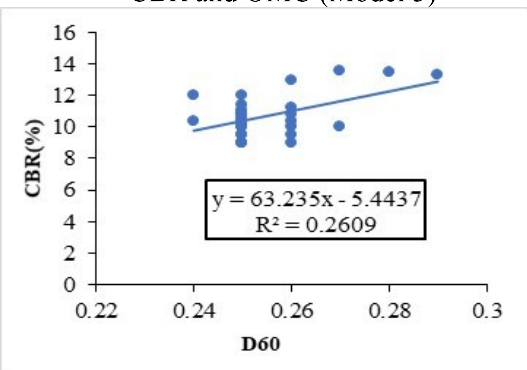

Figure 6: Linear regression model between CBR and D_{60} (Model 5)

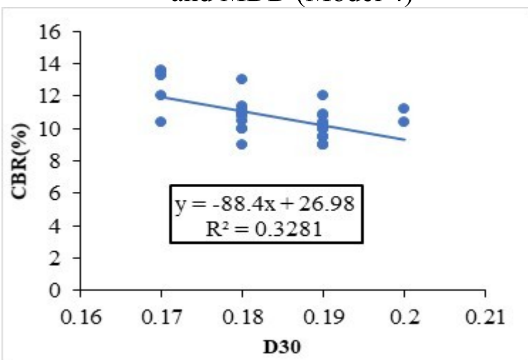

Figure 7: Linear regression model between CBR and D_{30} (Model 6)

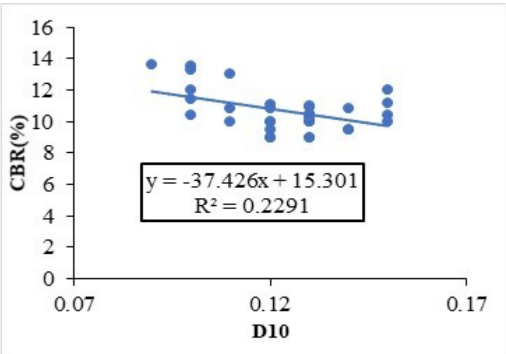

Figure 8: Linear regression model between CBR and D_{10} (Model 7)

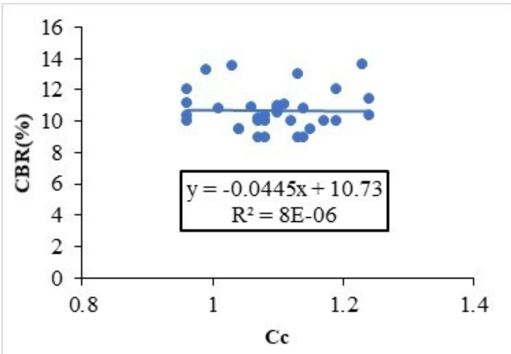

Figure 9: Linear regression model between CBR and C_c (Model 8)

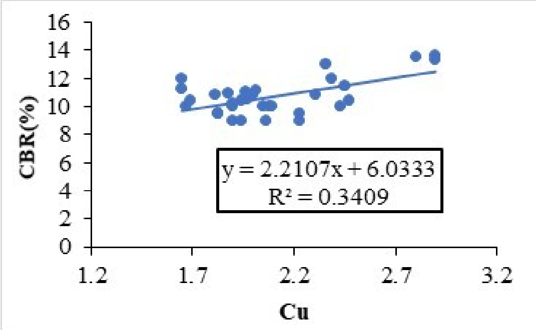

Figure 10: Linear regression model between CBR and C_u (Model 9)

Model (1-9) shows a linear relationship between CBR and other soil properties where sand, % Passing 75µm and MDD show fairly good correlation with CBR, and OMC, D_{60}, D_{30}, D_{10}, C_c, C_u show very weak correlation with CBR. The value of the coefficient of determination of Cc and OMC with CBR is so small and close to 0, so it can be said that there is no linear relationship between the variables. From all the linear relationships, MDD shows a relatively good correlation with CBR compared to other parameters. MDD can describe 45.34% of the variance of CBR.

Table 2: Performance evaluation indicators

Model No.	Correlation Equation	R2
1	$CBR = 19.89 - 0.11 * \%Sand$	0.4285
2	$CBR = 8.867 + 0.11 * \%Passing\ 75\ \mu m$	0.4287
3	$CBR = 14.18 - 0.227 * OMC$	0.015
4	$CBR = -56.21 + 39.5 * MDD$	0.453
5	$CBR = -5.44 + 63.23 * D60$	0.269
6	$CBR = 26.98 - 88.4 * D30$	0.328
7	$CBR = 15.3 - 37.425 * D10$	0.229
8	$CBR = 10.72 - 0.0445 * Cc$	0.000007
9	$CBR = 6.033 + 2.21 * Cu$	0.3409

3.2.2 Simple Non-linear Regression Analysis (SLR)

Some conclusions are drawn from the evaluation, and these are then displayed using a receiver operating characteristic (ROC) curve. Nine non-linear models have also been developed to show the effect of geotechnical properties (MDD, OMC, $\%\,sand$, $\%\,Passing\ 75\,\mu m$, D_{60}, D_{10}, D_{30}, C_c and C_u) on the CBR values of soil. The proposed non-linear models are shown in Figures 10 to 19. Model 10: $CBR\ vs\ MDD$, Model 11: $CBR\ vs\ OMC$, Model 12: $CBR\ vs\ \%\,sand$,, Model 13: $CBR\ vs\ C_u$, Model 14: $CBR\ vs\ \%\,Passing\ 75\,\mu m$, Model 15: $CBR\ vs\ D_{60}$, Model 16: $CBR\ vs\ D_{30}$, Model 17: $CBR\ vs\ D_{10}$, Model 18: $CBR\ vs\ C_c$.

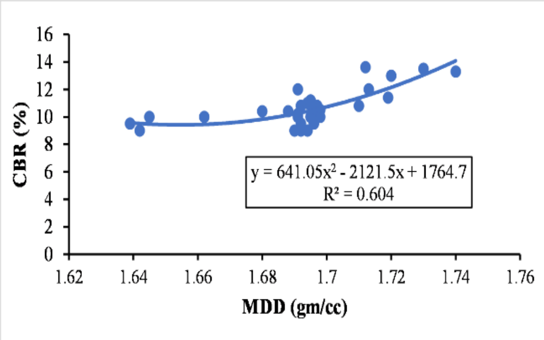

Figure 11: Non-linear regression model between CBR and MDD (Model 10)

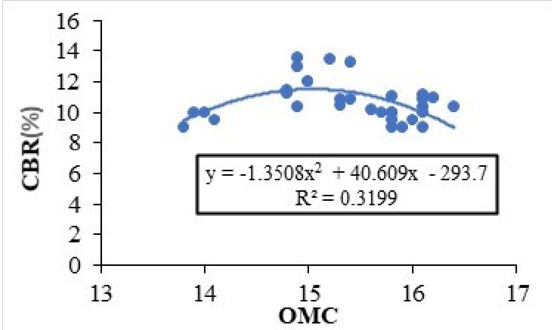

Figure 12: Non-linear regression model between CBR and OMC (Model 11)

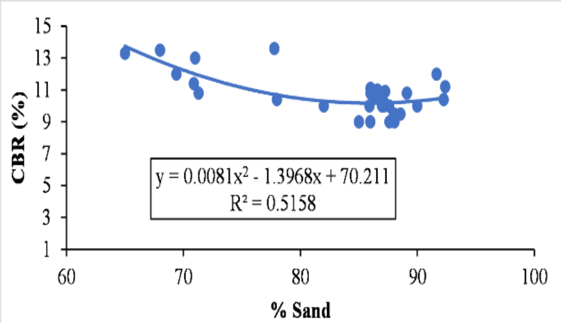

Figure 13: Non-linear regression model between CBR and %Sand (Model 12)

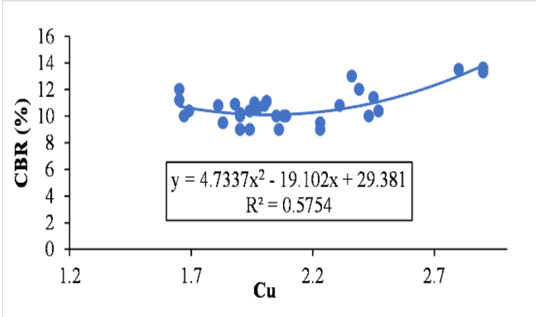

Figure 14: Non-linear regression model between CBR and C_u (Model 13)

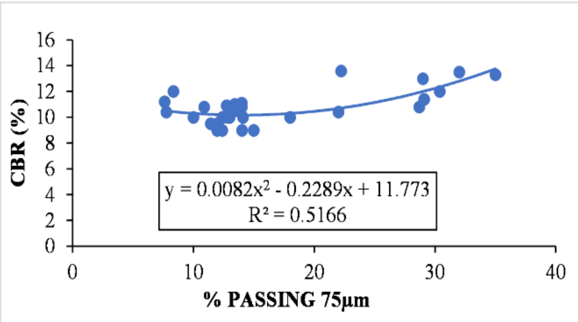

Figure 15: Non-linear regression model between CBR and $\% \, Passing \, 75 \, \mu m$ (Model 14)

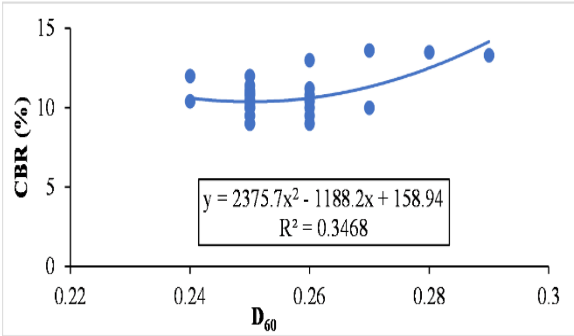

Figure 16: Non-linear regression model between CBR and D_{60} (Model 15)

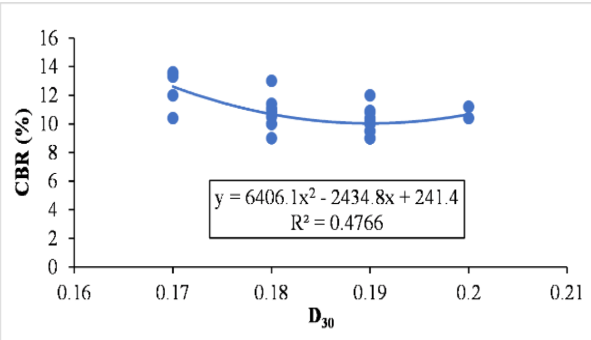

Figure 17: Non-linear regression model between CBR and D_{30} (Model 16)

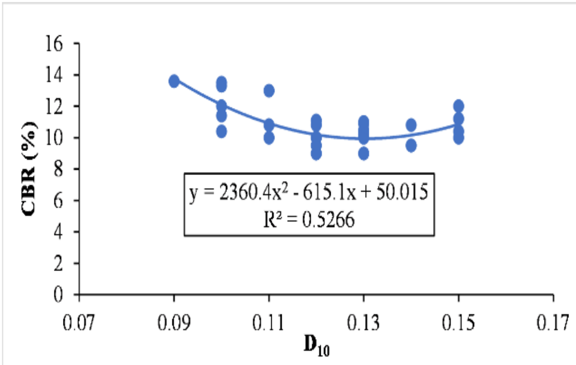

Figure 18: Non-linear regression model between CBR and D_{10} (Model 17)

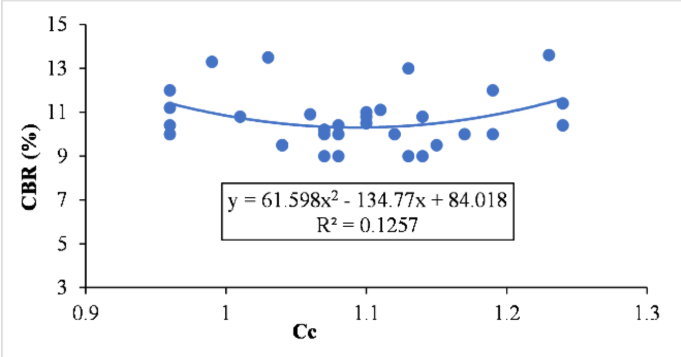

Figure 19: Non-linear regression model between CBR and C_c (Model 18)

The statistical parameters indicate that models 1, 3, 4, 5, and 7 have R-square values (R^2) of 0.604, 0.646, 0.516, 0.575, 0.517, and 0.527, respectively, which are above 50%. This implies that a good relationship exist between the dependent and independent variables of the models. The coefficient of determination for models 6, 8, and 9 is less than 50%; therefore, they have less influence on CBR values. A similar result was reported by Ramasubbarao & Siva (2013). Summary results of non-linear SRA models are presented in Table 3.

Table 3: Model summary of simple nonlinear regression analysis

Model No.	Correlation Equation	R^2
10	$CBR = 641.05 * MDD^{2} - 2121.5 * MDD + 1764.7$	0.604
11	$CBR = -1.3508 * OMC^{2} + 40.609 * OMC - 293.7$	0.3199
12	$CBR = 0.0081 * S^{2} - 1.3968 * S + 70.211$	0.5158
13	$CBR = 4.7337 ¿ Cu^{2} - 19.102 * Cu + 29.381$	0.5754
14	$CBR = 0.0082 * P^{2} - 0.2289 * P + 11.773$	0.5166
15	$CBR = 2375.7 ¿ D_{60}^{2} - 1188.2 ¿ D_{60} + 158.94$	0.3468
16	$CBR = 6406.1 ¿ D_{30}^{2} - 2434.8 * D_{30} + 241.4$	0.4766
17	$CBR = 2360.4 ¿ D_{10}^{2} - 615.1 * D_{10} + 50.015$	0.5266
18	$CBR = 61.598 * Cc^{2} - 134.77 * Cc + 84.018$	0.1257

3.2.3 ANOVA Test

To assess the effectiveness of the suggested model, an analysis of variance (ANOVA) test was performed on the regression models 4, 10, and 13. In this analysis, the null hypothesis is that the CBR is neither related to MDD nor Cu, while the alternative hypothesis is that the CBR is related to MDD and Cu. The results of the ANOVA test are presented in Table 4.

Table 4: ANOVA test results for model 4, 10 and 13

	Source of Variation	SS	df	MS	F	P-value	F crit
Model 4	Between Groups	1292.51	1	1292.51	1537.407	1.79E-45	3.995887
	Within Groups	52.12389	62	0.840708			
	Total	1344.634	63				
Model 10	Between Groups	1292.51	1	1292.51	1537.407	1.79E-45	3.995887
	Within Groups	52.12389	62	0.840708			
	Total	1344.634	63				

Model 13	Between Groups	1177.519	1	1177.519	1309.689	2.1E-43	3.995887
	Within Groups	55.74315	62	0.899083			
	Total	1233.262	63				

SS sum of squares, df degree of freedom, MS mean square, F F-statistic, P value significance of F, F crit F-critical

The null hypothesis is rejected due to the fact that the P value is considerably less than the significance value of 0.05. In other words, the CBR and the proposed variable in model 4, 10, and 13 have a good relationship.

3.2.4 Hypothesis Test

Using the Z-test, the generated model's performance was statistically analyzed. The following assumptions are tested by this test:

- Null hypothesis (H_0): mean measured CBR value = mean predicted CBR value from the suggested SLR model.
- Alternative hypothesis (H_1): mean CBR value measured ≠ mean CBR predicted according to the suggested SLR model.

Hypothesis Test for Models 4, 10, and 13

The significance level for this test was set at 95% (α = 0.05). If the P value is less than 0.05, H_0 is rejected in the Z-test. Table 5 shows the results of the z-test for models 4, 10, and 13.

Table 5: z-test results for model 4, 10 and 13

	Model 4		**Model 10**		**Model 13**	
	Obtained CBR	Predicted CBR	Obtained CBR	Predicted CBR	Obtained CBR	Predicted CBR
Mean	10.68125	10.67831	10.68125	10.73125	10.68125	10.68203
Known Variance	1.68	0.76	1.68	1.015	1.68	0.967
Observations	32	32	32	32	32	32
Hypothesized Mean Difference	0.01		0.05		0.001	
z	-0.02558		-0.34458		-0.00617	
P(Z<=z) one-tail	0.489798		0.365205		0.497537	
z Critical one-tail	1.644854		1.644854		1.644854	
P(Z<=z) two-tail	0.979595		0.730409		0.995075	
z Critical two-tail	1.959964		1.959964		1.959964	

According to Table 5, the calculated z-value for Model 4 is -0.02558. A one-tailed test has a P-value of 0.489798, which is higher than the 0.05 significance limit. We do not, therefore, reject the null hypothesis. The calculated z-value for Model 10 is -0.34458. A one-tailed test has a P-value of 0.365205, which is likewise higher than 0.05. For Model 13, we thus do not reject the null hypothesis. For Model 13, the P-value for a one-tailed test is 0.497537, which is larger than 0.05, and the calculated z-value is -0.00617. For Model 18, we thus do not reject the null hypothesis. According to the z-test results, there are no significant deviations between the obtained and expected CBR for any of the three models (Model 4, Model 10, and Model 13).

4. CONCLUSIONS

The objective of this study was to develop regression equations between the CBR value and getechnical properties of soil, making sure the model generated was cost-effective and less laborious. A clear relationship was developed, with comprehensive models that predict CBR values in terms of

MDD, OMC, $\%\,sand$, $\%\,Passing\,75\,\mu m$, D_{60}, D_{10}, D_{30}, C_c and C_u. The following conclusions were drawn:
:

- The coefficient of determination (R2) indicates that the non-linear regression analysis showed strong correlation between; CBR and (MDD, C_u).
- The linear regression analysis showed a strong correlation between CBR and MDD based on the coefficient.
- It has been also found that the CBR values of the subgrade soil are poorly affected by Cc and D60.
- According to the hypothesis test findings, there is no way to reject the null hypothesis for any of the models. This means that the actual CBR values do not considerably differ from the estimated CBR values for Models 4, 10, and 13. so it is possible to accurately assess CBR using these three models.
- One of the major limitations of this study is that a disturbed soil sample was used here. Along with the number of soil samples, for a better result, a large number of soil samples may be used.

REFERENCES

Ramasubbarao, G.V., & Siva, S.G. (2013). Predicting Soaked CBR Value of Fine-Grained Soils Using Index and Compaction Characteristics. Jordan Journal of Civil Engineering, 7(3): 354-360.

Rakaraddi, P.G., & Gomarsi, V. (2015). Establishing Relationship between CBR with different Soil Properties. International Journal of Research in Engineering and Technology, 4 (2): 182-188.

John, A., Joson, A., Venia, J., Chandran, K., & Chacko, A. (2017). Correlation of CBR Value with Properties of Red Soil. IRJET, 4(3):2042-2044.

Charman, J.H. (1988). Laterite in road pavements. Construction Industry Research and Information Association, London.

Roy, T.K., Chattapadhyay, B., & Roy S.K. (2010). California Bearing Ratio, Evaluation, and Estimation: A Study of Comparison. IGC-IIT, 19-22.

Patel, R.S., & Desai, M.D. (2010). CBR Predicted by Index Properties for Alluvial Soils of South Gujarat. Paper presented to the Indian Geotechnical Conference, 16-18 December, GEO trends, IGS Mumbai Chapter & IIT Bombay, Pp. 79-82.

Singh, D. (2011). Moisture and Compaction Based Statistical Model for Estimating CBR of Fine-Grained Subgrade Soil. International Journal of Earth Sciences and Engineering. 4(6):100-103.

Muley, P., & Jain, P.K. (2013). Betterment and prediction of CBR of Stone Dust Mixed Poor Soils. Proceedings of Indian Geotechnical Conference, December 22-24, IIT Roorkee.

Talukdar, D.K. (2014). A Study of correlation between California Bearing Ratio (CBR) value with other properties of soil. International Journal of Emerging Technology and Advanced Engineering, 4:559 - 562.

Mishra A., & Tegar J.P. (2019). Correlation of CBR with Index Properties of Soil of Kolar Region (Bhopal) using Regression Analysis. International Research of Engineering and technology (IRJET), 6(7):3603-3612.

Priya, G., Arya, K.S., Manjummekudiyil, E.M., Unni, A., & Menon, V.S. (2019). Prediction of CBR Value from Index Properties of Soil. International Research of Engineering and technology (IRJET). 6(4):4029-4033.