Journal of Materials Science Research and Reviews

9(3): 39-49, 2022; Article no.JMSRR.88410

Estimation of Soaked California Bearing Ratio of a Lateritic Soil Using Mathematical Model

Oluwayinka Glory Akinwamide [a*], Ibitoye A. Biliyamin [b] and Joseph Adebayo Ige [c]

[a] *Department of Civil Engineering, School of Engineering, The Federal Polytechnic, Ado Ekiti, Ekiti State, Nigeria.*
[b] *Department of Civil and Environmental Engineering, Faculty of Engineering, Kwara State University, Malete, Kwara State, Nigeria.*
[c] *Department of Civil Engineering, Faculty of Engineering, Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/88410

Original Research Article

Received 08 May 2022
Accepted 12 July 2022
Published 23 July 2022

ABSTRACT

California Bearing Ratio (CBR) test is a common laboratory test, performed to evaluate the shear strength and stiffness modulus of sub grade for the design of pavement. CBR test is a laborious test, therefore it is vital to develop the models for quick assessment of CBR. This study investigates the development of a mathematical model to estimate Soaked California Bearing Ratio of a lateritic soil. This research use Multiple Linear Regression (MLR) with R. studio software with a view to correlate Soaked California Bearing Ratio (SCBR) for the measured index properties. To achieve the objectives of this study, 20 soil samples were obtained with 4 samples representing a Local government. R programming studio Software version has been used to develop a mathematical model for the MLR. The experimental data and predictive models were developed in terms of liquid limit (LL), plasticity index (PI) Maximum Dry Density and percentages of fines, Gravel, and Sand respectively. The results from the index properties characterized the study area as Clayey soils (A-4, A-6 and A-7-5) and Silty or Clayey gravelling soils (A-2-6,A-2-7) according to AASHTO classification system The soil strength assessment indicates that the soils samples from all the Zones fell within the minimum dry density recommended for subgrade materials, stabilization is recommended for its suitability for either sub base or base course material for future

**Corresponding author: Email: akinwamideoluwayinka@gmail.com;*

contractor around this study area, this will savage haulage expenses when material are move from far distance to the site of work. The strengths of the developed Multiple Linear Regression (MLR) models have been examined in terms of regression coefficient of determination (R2). It is found that the correlation give a predictive power of 70%. The residual plotted on histogram curve is symmetrical in nature indicating normality of residual value.

Keywords: Index properties; multiple linear regression; mathematical model; soaked cbr;senatorial zone; coefficient of determination.

1. INTRODUCTION

"The strength of a soil to be used as a sub-grade in pavement is assessed from its California bearing ratio (CBR) value. If the CBR value of soil is low, the thickness of pavement will be high, which will result in high cost of construction and vice-versa. Subgrade is the most important part of a pavement structure, which should have a reasonable stiffness modulus and shear strength" Faisal Iqbal et al , [1]. "CBR (California Bearing Ratio) test is performed to evaluate stiffness modulus and shear strength of subgrade soils. However, CBR test is laborious and time consuming, particularly when soil is discovered to be unsuitable. In order to overcome this limitation, it may be appropriate to correlate CBR value of soils with its index properties like grain size analysis, Consistency limits, and compaction characteristics such as MDD (Maximum Dry Density) and OMC (Optimum Moisture Content)" Faisal Iqbal et al , [1]. "The soil property California Bearing Ratio (CBR) is the most prominently used parameter for estimation of overlay thickness of flexible pavements in India. Civil engineers often encounter problems in establishing the correct engineering property, the CBR of the soil while designing the thickness of Sub-Base and Base – Course layers" [2]. "While designing a new alignment or a green field expressway, where the alignment is passing through open lands and agricultural fields insist a large number of soils are to be collected to establish CBR properties based on which the overlay thickness is designed. But while carrying a pre-feasibility study or detailed project report collection of large samples of CBR data is constrained by time and budget resources. Under such situations, CBR data for the project corridor can be derived through the published correlations between CBR and index properties of the soil as they provide them reasonable and cost-effective solutions" [3].

However, no attempts have been made of recent to estimate any statistical model to evaluate the correlations between CBR value and its index properties. Using MLRA (Multiple Linear Regression) based Models with Liquid limit LL %, Plastic limit PL %, Group index GI, Plastic index PI %, Optimum moisture content OMC (%) and Maximum dry density MDD (kN/m^3) as input variables.

2. METHODOLOGY

2.1 Multiple Linear Regression Analysis (MLRA)

According to Saufie, et al. [4], Alan, [5] and Faesil [6], "multiple linear regression (MLR) is one of the modelling techniques to investigate the relationship between a dependent variable and several independent variables. It is a generalisation of the simple linear regression model. They stated further that in multiple linear regression models, an error term is assumed to be normally distributed with mean and variance (which is a constant)". In the same way, [Pamela,2017 and Pierre, 2017], discussed the risk in Civil engineering, the soil mechanics, and foundation engineering, to identify the soil properties adsorption with statistical analysis and regression step-by-step using Microsoft Excel. A MLRA provides an attempt to develop a correlation between more than two variables. One is the response (dependent variable) and others are explanatory (independent) variables. In this research work, CBR is the dependent variable and all other soils parameters are independent variables. Graph is plotted between CBR and other soil parameters and a suitable trend line is drawn through the plotted points for obtaining the value of coefficient of determination (R^2). The value of R^2 provides a measure of how well the future outcomes are likely to be predicted by the model [7]. Generally, any correlation greater than 0.88 is usually considered as a best fit, CBR value will be the function of all other index properties. Mathematically:

$$CBR = f(\%F, LL, PI, OMC, MDD) \qquad (3.1)$$

Table 1. The derived theoretical model equation for the regression

Model no.	Derivative equation
Model 1	$\alpha + \beta_1(\text{gravel}) + \epsilon$
Model 2	$\alpha + \beta_1(\text{gravel}) + \beta_2(\text{sand}) + \epsilon$
Model 3	$\alpha + \beta_1(\text{gravel}) + \beta_2(\text{sand}) + \beta_3(\text{fine}) + \epsilon$
Model 4	$\alpha + \beta_1(\text{gravel}) + \beta_2(\text{sand}) + \beta_3(\text{fine}) + \beta_4(\text{ll}) + \beta_5(\text{pl}) + \epsilon$
Model 5	$\alpha + \beta_1(\text{gravel}) + \beta_2(\text{sand}) + \beta_3(\text{fine}) + \beta_4(\text{ll}) + \beta_5(\text{pl}) + \beta_6(\text{omc}) + \epsilon$
Model 6	$\alpha + \beta_1(\text{gravel}) + \beta_2(\text{sand}) + \beta_3(\text{fine}) + \beta_4(\text{ll}) + \beta_5(\text{pl}) + \beta_6(\text{omc}) + \beta_7(\text{mdd}) + \epsilon$

The equation will be created as follows:

$$Y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_3x_3 + \ldots\ldots\ b_nx_n \quad (3.2)$$

Where b_o, b_1, b_2, b_3, b_4, b_n are constants, Y is CBR and, x_1, x_2, x_3, x_4, x_n are soil properties considered for analysis.The values of these constants can be obtained by using Data Analysis Tool bar of Microsoft Excel and then putting these values with their corresponding soil properties in order to obtain a suitable equation Rakaraddi, and Gomar si, (2015).

Based on the impact parameter for the model, Table 1 shows the developed theoretical models for the Regression.

2.2 Experimental Program

The soil samples used for this research work were carried out within the five Local Government of Ekiti North Senatorial districts in Ekiti state, Nigeria. A total of twenty (20) sample of soils were obtained at the depth of 1.3m and laboratory tests of Liquid Limits (LL,) Plastic Limits (PL) **,** Plasticity Index (PI),particle size distribution, Optimum Moisture Content (OMC), Maximum Dry Density (MDD) and soaked California Bearing Ratio (CBR) have been performed on these samples at Geotechnical Laboratory, Department of Civil Engineering, The Federal Polytechnic Ado-Ekiti, according to AASHTO and BS 1377 [8] Specifications. The soil classifications of these soil samples have been done according to AASHTO method. The results are given in Table 1 along with % finer passing from #200 sieves for each sample.

3. RESULTS AND DISCUSSION

Table 2 shows the summary of the classification of all the soil samples based on AASHTO soil Classification system. The soils are characterized as Clayey soils (A-4, A-6 and A-7-5) and Clayey gravelling soils (A-2-4, A-2-6,A-2-7).Hence, the soils are describing as clay of high compressibility respectively.

Figs. 1a and 1b showed the result of grain size analysis performed on the soils samples showed that many of the zones had a very high percentage finer than 0.075 fractions that is > 35% varied between 15 and 75 %. These results showed that there exist very fine materials within the study area. This is in agreement with [9].

Consistency Limit Test results for Liquid Limit (LL %), plastic limit (PL%) and plasticity index (PI %) for all the samples varied between 19.90 – 49.02 % for LL; 8.8 – 27.27 % for PL % and 8.63 - 23.57 % for PI % respectively as showed in Table 2 and Figs. 2a and 2b respectively. According to Ola, [10] as sited by Akinwamide et al, [11] asserted that the larger the PI % value the greater the engineering problems associated with using the soil as an engineering material such as foundation support for residential building, roads, subgrades etc.

Table 2 , Figs. 3a and 3b presents the results of Maximum Dry Density (MDD kg/m3), and the Optimum Moisture Content (OMC) performed on the samples ranges between 2035 – 2377 Kg/m^3 and 11.88 – 24.25 % respectively. According to FMW, [12] recommendation, the above analysis indicates that the soils samples from all the study area fell above the minimum dry density recommended for subgrade materials. However, the soils are recommended for sub grade and fill material respectively since their MDD is within the minimum specification for sub grade and earth fill materials.

The results of the soaked California bearing ratio performed on all the samples varied between 1.38 – 9.39 % as showed in Table 2. According to Akinwamide et al, [11] a high reduction in CBR values after soaking indicates that the soil is very sensitive to changes in the moisture content.

Table 2. Laboratory test results for soil samples

Sample No	%G	%S	%F	LL (%)	PL (%)	PI (%)	OMC (%)	MDD G/M^3	*SK* CBR(%)	AASHTO CLASS.
1	5	65	30	30.00	14.02	15.98	16.42	2227	2.88	A-2-6
2	8	49	43	43.15	9.00	34.15	19.45	2173	2.63	A-7-5
3	7	57	36	43.01	22.32	20.69	16.43	2267	1.38	A-7-5
4	5	40	55	39.07	21.56	17.51	21.17	2234	1.75	A-2-6
5	9	55	36	49.02	17.01	32.01	21.21	2242	4.15	A-7-5
6	5	63	32	38.31	14.78	23.53	21.67	2197	1.89	A-2-6
7	6	28	62	32.20	8.8	23.4	20.87	2113	2.63	A-2-6
8	10	74	16	40.10	16.27	23.83	24.25	2093	2.51	A-7-5
9	30	50	25	33.80	18.05	15.75	21.11	2215	3.63	A-2-6
10	12	72	16	29.01	7.80	21.21	22.81	2207	4.13	A-2-6
11	13	47	40	45.00	14.80	30.2	17.27	2236	2.83	A-7-5
12	30	42	28	32.00	23.57	8.63	21.67	2266	2.13	A-2-4
13	28	30	42	28.15	16.09	12.06	21.03	2054	3.40	A-2-6
14	37	28	35	32.01	13.64	18	11.88	2377	9.39	A-2-6
15	15	43	42	28.51	18.92	9.59	19.01	2123	3.51	A-2-4
16	5	30	65	41.20	13.93	27.27	17.6	2035	3.51	A-7-5
17	10	37	53	39.07	21.56	17.51	21.17	2234	1.75	A-2-6
18	30	40	27	33.80	18.05	15.75	21.11	2215	3.63	A-2-6
19	31	31	38	19.90	NP	NP	22.52	2060	3.26	A-3
20	15	42	43	28.51	18.92	9.59	19.01	2123	3.51	A-2-4

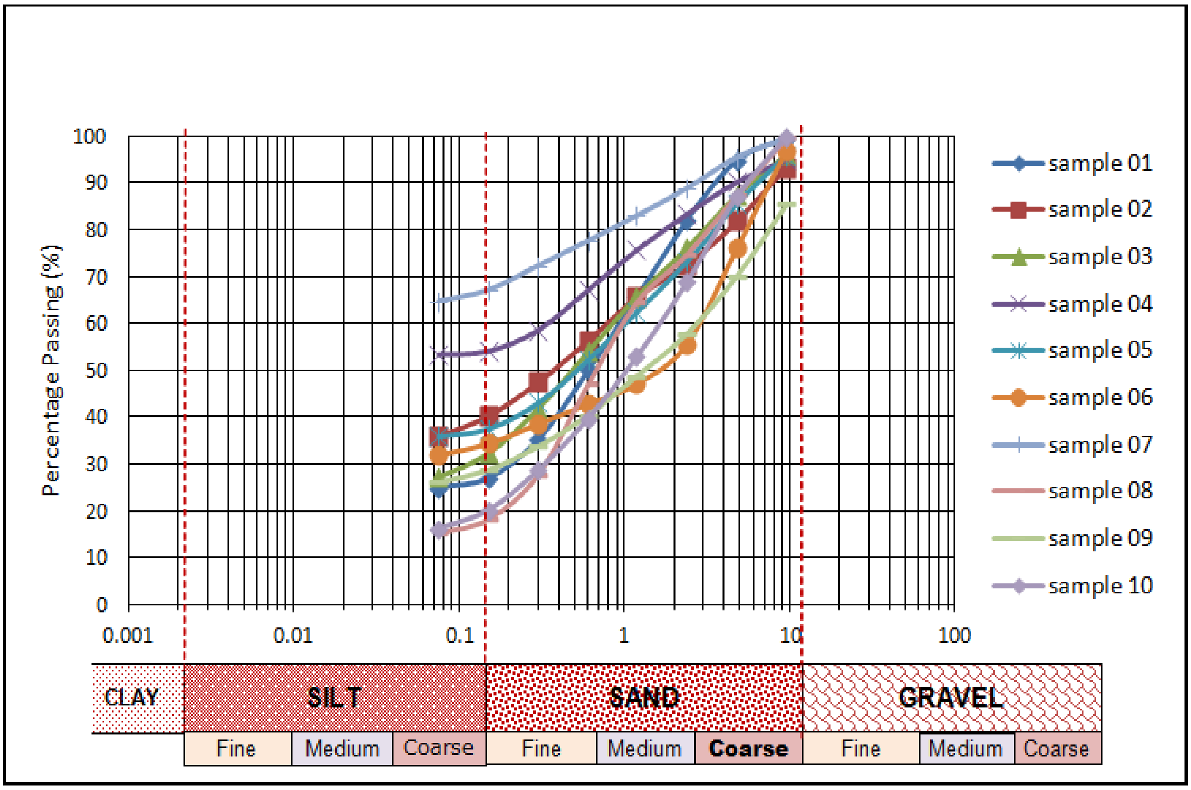

Fig. 1a. Sieve analysis test result sample 1 -10

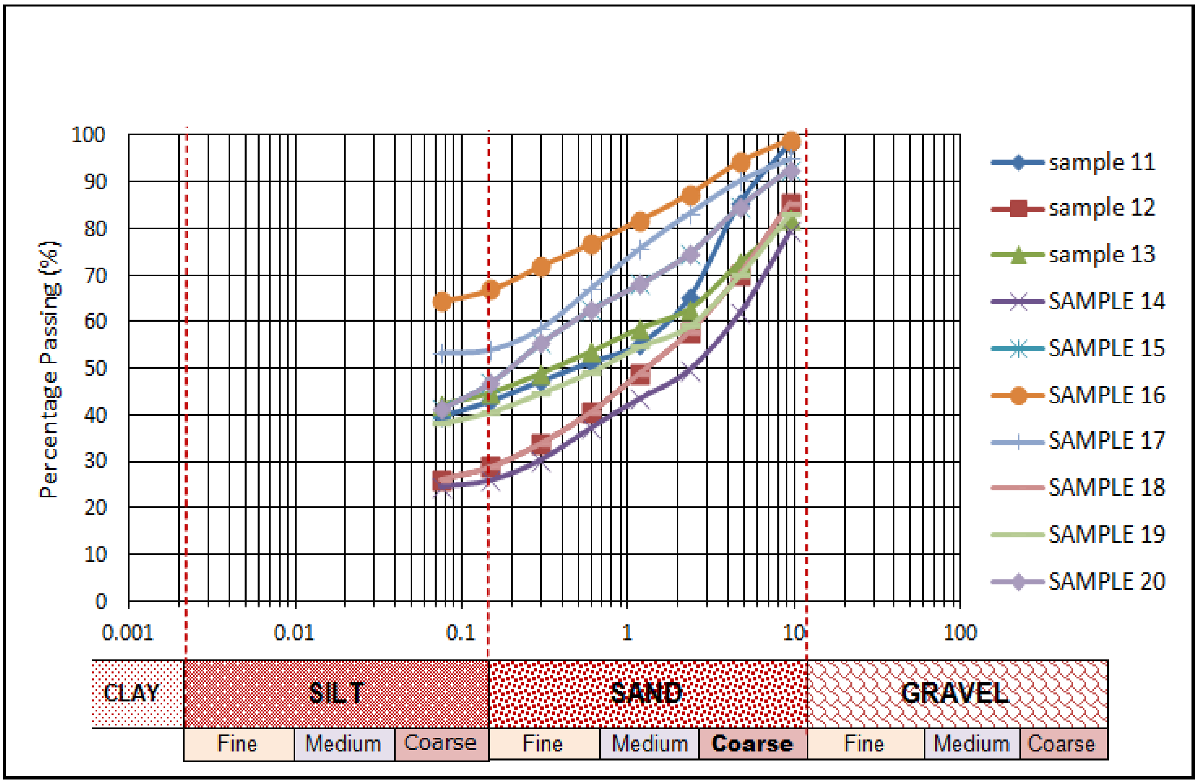

Fig. 1b. Sieve analysis test result sample 11 -20

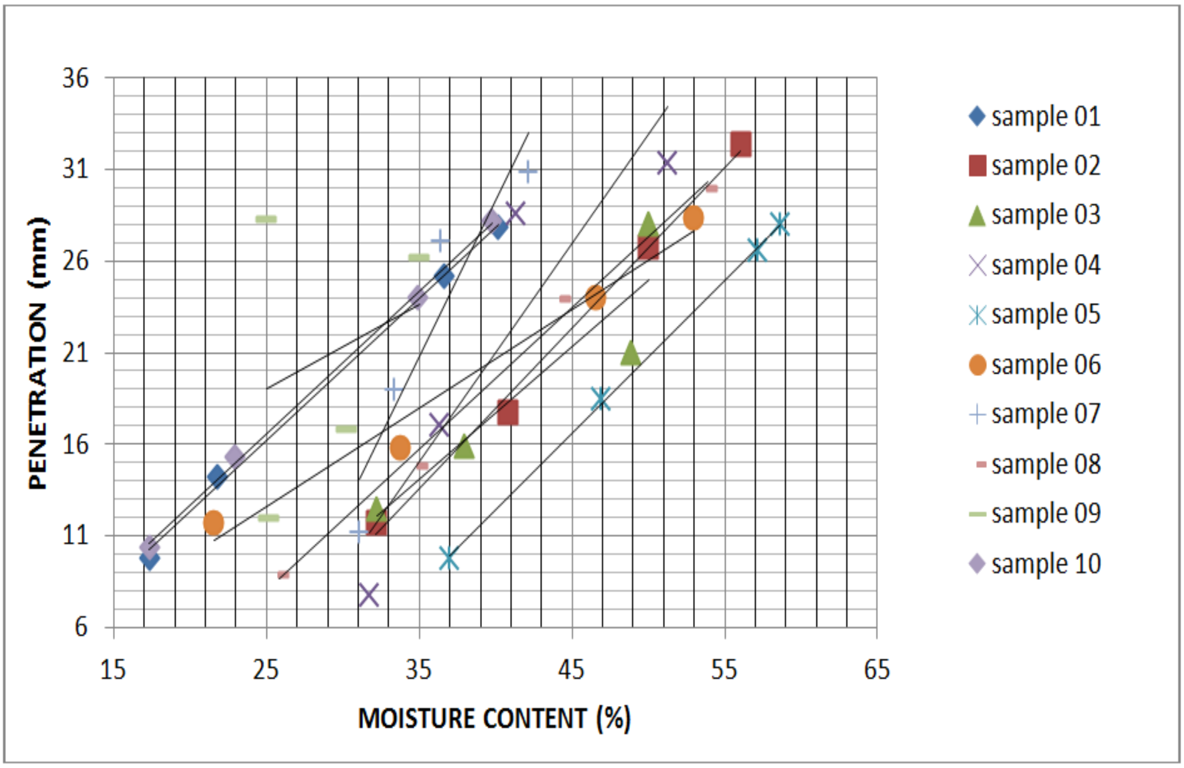

Fig. 2a. Liquid limits test result sample 1-10

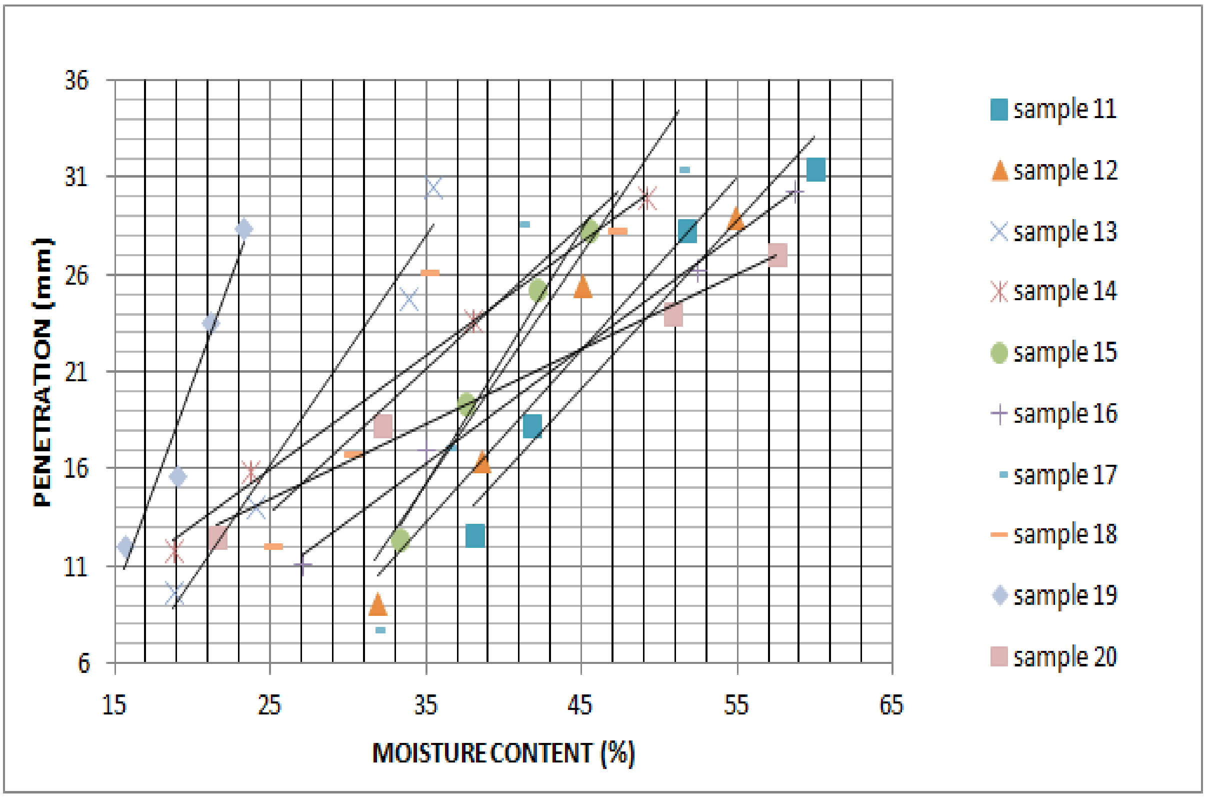

Fig. 2b. Liquid limits test result sample 11-20

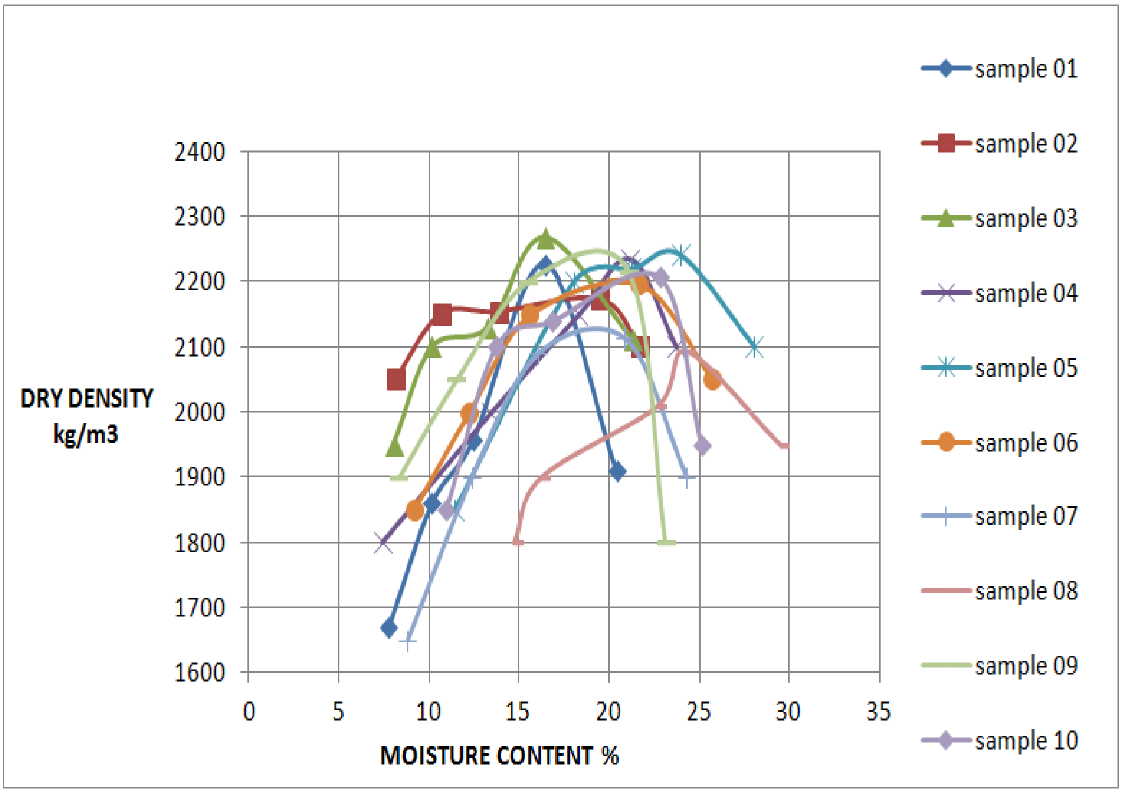

Fig. 3a. Compaction test for sample 1- 10

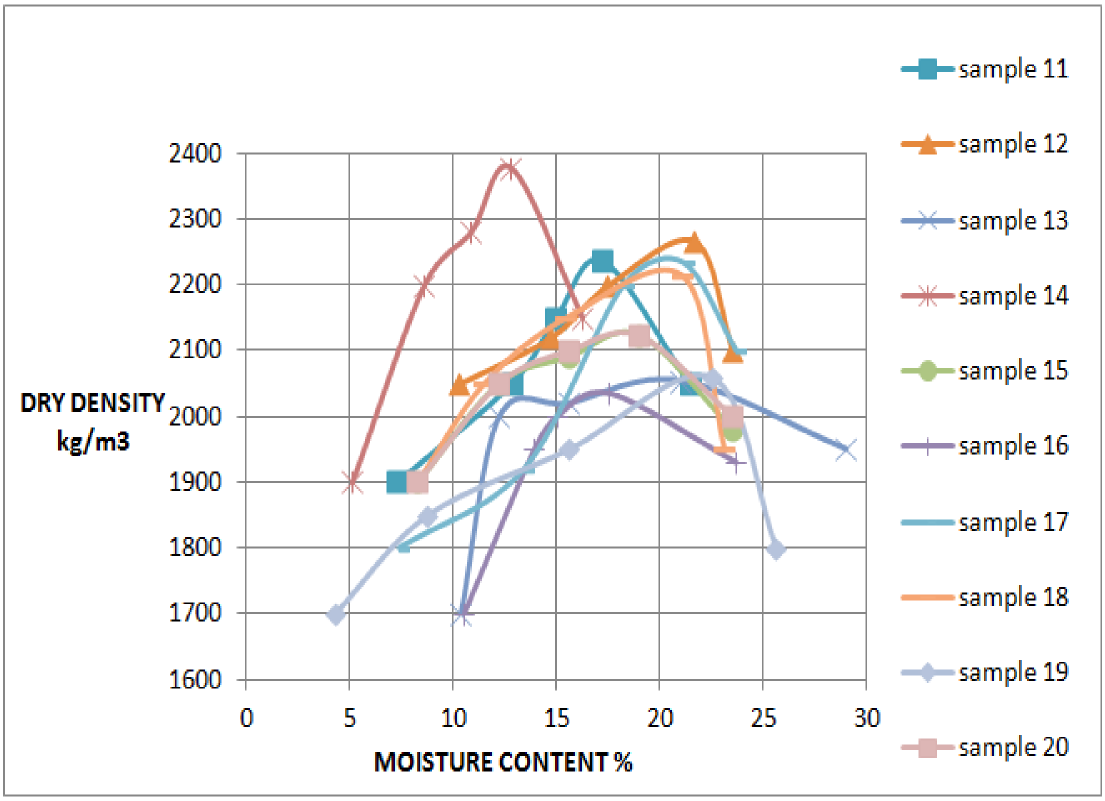

Fig. 3b. Compaction test for sample 11-20

3.1 Correlation by Multiple Linear Regression Analysis

This analysis has been performed by taking CBR as function of more than one independent variables. The equation which has been obtained through MLRA by adopting Microsoft Excel solution are given in Table 2. From the developed model for Soaked CBR, based on the values of coefficient of determination (R^2) and Adjusted Coefficient of Determination (Adj.R^2), it is concluded that model 6 has better correlation.

The actual values are the value of the experimented soaked CBR in the laboratory. The predicted value is generated by modeling; a residual is a measure of how well a line fits an individual data point. It is the difference between the actual and the predicted values. Fig.5 present the predicted against the observed. Its noteworthy that the residual contains both positive and negative values. The positive residual value predicted values are too slow similarly the negative residual values indicate that the predicted values are too high [13-20].

3.2 Test of Normality of Residual Values using the Histogram

The dome shape or the symmetrical nature of the histogram as showed in Fig. 4 indicates validity of normality of the residuals values.

Table 3. Developed correlations for soaked CBR values

Model number	Model correlation	R^2
1	$\text{CBR} = 1.92 + 0.08(\text{gravel}) + \epsilon$	0.3048
2	$\text{CBR} = 2.25 + 0.08(\text{g}) - 0.01(\text{s}) + \epsilon$	0.3069
3	$\text{CBR} = 5.94 + 0.04(\text{g}) - 0.04(\text{s}) - 0.04(\text{f}) + \epsilon$	0.3081
4	$\text{CBR} = 3.65 + 0.08(\text{g}) - 0.04(\text{s}) - 0.03(\text{f}) + 0.08(\text{ll}) + \epsilon$	0.3081
5	$\text{CBR} = 0.57 + 0.12(\text{g}) + (\text{s}) + 0.01(\text{f}) + 0.08(\text{ll}) - 0.05(\text{pl}) + \epsilon$	0.4618
6	$\text{CBR} = 11.52 + 0.06(\text{g}) - 0.03(\text{s}) - 0.04(\text{f}) + 0.05(\text{ll}) - 0.07(\text{pl}) - 0.30(\text{omc}) + \epsilon$	0.6761
7	$\text{CBR} = 10.06 + 0.06(\text{gravel}) - 0.03(\text{sand}) - 0.04(\text{fine}) + 0.05(\text{ll}) - 0.07(\text{pl}) - 0.29(\text{omc}) + (\text{mdd}) + \epsilon$	0.7032

Table 4. Validation of developed correlation for soaked CBR

S/N	Actual	Predicted	Residuals
1	2.88	3.307938	-0.42794
2	2.63	3.810046	-1.18005
3	1.38	3.067347	-1.68735
4	1.75	1.192242	0.557758
5	4.15	2.809691	1.340309
6	1.89	2.070182	-0.18018
7	2.63	2.588893	0.041107
8	2.51	1.81605	0.69395
9	3.63	3.882851	-0.25285
10	4.13	2.974634	1.155366
11	2.83	2.974634	-1.52033
12	2.13	3.111617	-0.98162
13	3.4	3.5708	-0.1708
14	9.39	7.768478	1.621522
15	3.51	2.640821	0.869179
16	3.51	3.055488	0.454512
17	1.75	1.682204	0.067796
18	3.63	4.106227	-0.47623
19	3.26	4.064017	-0.80402
20	3.51	2.63015	0.87985

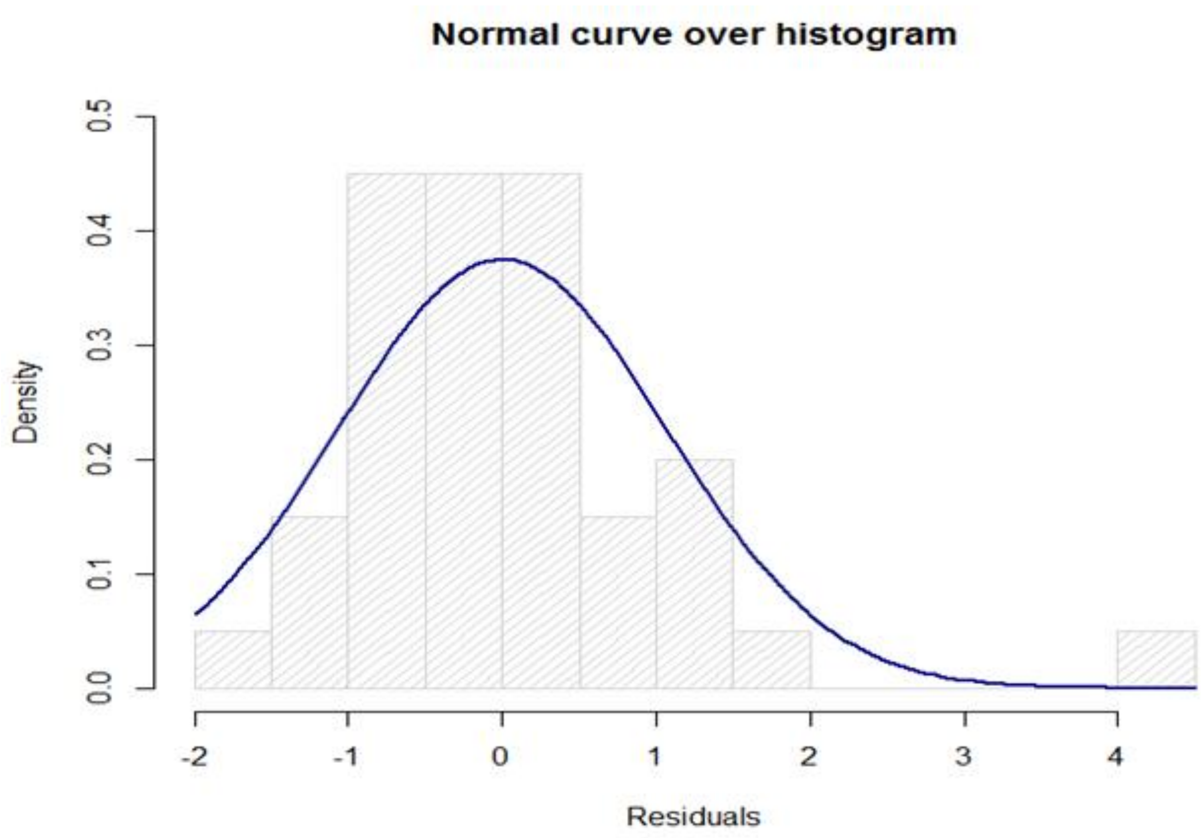

Fig. 4. Histogram showing normality of the residuals

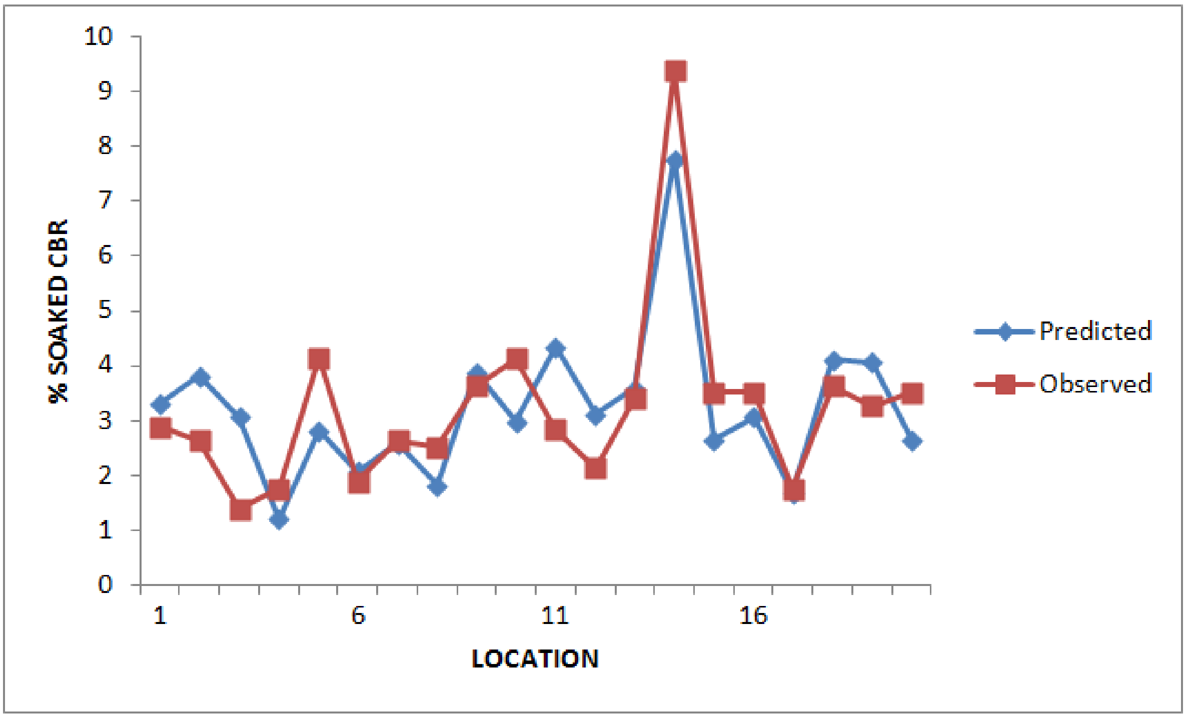

Fig. 5. Graph of predicted against observed CBR

4. CONCLUSION

The soils chosen for the current investigation are primarily from the clay family. Seven soil physical properties are used as independent variables, while CBR is used as the dependent variable, in the development of six multiple linear regression models. The correlation between the observed and the predicted values show that the relationship between observed and the predicted CBR is approximately 70 % strong.

The derived equation is thus written as;

$$\text{Soaked CBR} = 10.06 + 0.06(G) - 0.03(S) - 0.04(F) + 0.05(LL) - 0.07(PI) - 0.29(OMC) + MDD + E.$$

According to the study, there is a significant association between CBR and soil physical characteristics. The equations can be used to forecast soaked CBR in situations where data availability is limited by time and resources. The best model test was adopted to predict soaked CBR, the residual plotted over histogram curve is symmetrical in nature which indicates normality in residuals (error values).

5. RECOMMENDATIONS

1. Laboratory analysis and result should be handled with utmost accuracy to prevent excessive variation between the observed and the predicted.
2. Further work should be done in order to generate more data the regional based data banking Availability of information for the use of geotechnical engineers working in the locality.
3. Prediction can be of great help in the field of Civil Engineering, if individuals are encourage to work more in this field of study.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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