Estimation of Soaked California Bearing Ratio using Compaction Characteristics and Liquid Limit for Cohesive Soils in Iraq

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Abstract

Developing reliable models to predict engineering parameters is an effective strategy to reduce the time needed for tests and the overall cost of the project. One of the extensively used parameters in highway construction projects is the California Bearing Ratio (CBR), which is of the significant parameter in road layers. In this study, the goal is to investigate the possibility of predicting CBR values of fine-grained soil from soil index properties for subgrade made from cohesive materials. The simple regression using one variable and multiple regression analysis using multi variable have been investigated to estimate CBR values. Three geotechnical parameters have been utilized in the analysis: Maximum Dry Density (MDD), Optimum Moisture Content (OMC), and Liquid Limit (LL). The results have been validated using Root Mean Square error (RMSE) and Coefficient of determination (R^2). From the simple regression analysis (using only one variable), a useful model was developed to predict CBR value using OMC with R^2 of 0.95 and RMSE of 0.38 %. From the multi-linear regression analysis, a model to predict CBR from LL, OMC and MDD with R^2 of 0.94 and RMSE of 0.4% is also developed. In addition, simple models were developed to estimate the compaction characteristics from the LL index.

Keywords: CBR, Multiple Regression Analysis, LL, MDD, OMC.

1. Introduction

The California Bearing Ratio (CBR) has been utilized over the years as an indicator of the shear strength of the underlying layer of a road. To find this ratio, engineers use a specific penetration test that is originally designed by the California Division of Highways for road construction (Horonjeff and Jones, 1953). Due to its effectiveness and importance for engineering projects, many researchers worked on the ability to predict CBR value from other parameters. In the early years, Black (1962) investigated the prediction of the CBR value of cohesive soil of England due to its relevance to soil-bearing capacity. He studied the relationship between CBR value and both soil moisture content and soil plasticity data. Generally, the estimated CBR values tended to be less than the measured values (Black 1962). Since road safety is dependable on the subgrade layer beneath it, its evaluation is vital to guarantee its safety (Look, 2007). CBR is a widely used index parameter to indicate the stiffness and shear strength of the subgrade layer (Look, 2007).

CBR is used to assess the bearing strength of subgrade, sub-base, and base course materials in road construction. However, due to the critical importance of cost and time in construction, carrying out these tests separately can significantly raise expenses. Thus, establishing a correlation between the CBR values and the soil's index properties can be a valuable tool, helping to save time, effort, and money by reducing the need for comprehensive testing. In this paper, an attempt is made to develop models to predict the CBR value of fine-grained soils. For this purpose, eight samples were collected from Sulaimani region and the following tests were conducted; moisture content, sieve analysis, maximum dry density, liquid limit, plastic limit and $CBR_{(soaked)}$. And then, the effectiveness of predicting the CBR value has been investigated. The analysis incorporates statistical models, specifically simple regression and multiple linear regressions, to quantify the impact of varying moisture levels and maximum dry densities on CBR.

2. Related Works

Taskiran (2010) examined the ability to predict the CBR value of fine-grained soil using Artificial Neural Network (ANN) and Gene Expression Programming (GEP). The research recommended that the MDD is the most effective parameter on CBR among other parameters such as plasticity index (PI), OMC and LL. Moreover, Singh et al. (2011) used 100 samples with varying compaction and moisture levels to develop regression models to estimate the CBR of fine-grained soils. They concluded that moisture content and compaction degree significantly affect CBR values. Rehman et al. (2017) developed models for estimating CBR value using LL, PI, OMC, and MDD for fine-grained soils.

The effect of clay mineralogy on the prediction of CBR has been investigated by Nagaraj and Suresh (2018). They showed that correlations incorporating mineralogy can help better predict CBR and verify laboratory results. Also, a decent correlation between CBR and DCPI (dynamic cone penetration index) has been suggested by Hussein and Alshkane (2018). It has been noticed that CBR value decreased with the increase of moisture content and increased as dry unit weight increased (Hussein and Alshkane 2018). According to Sreelekshmypillai and Vinod (2019), the toughness limit can be used to evaluate the effect of both the LL and PL on the CBR value of fine-grained soils. Essentially, the impact of the toughness limit on the CBR value increases as more compaction energy is applied (Sreelekshmypillai and Vinod, 2019).

Other techniques, such as Artificial Neural Networks (ANN), Genetic Expression Programming and the Kriging Method, have been widely used for CBR prediction. Such as the research by Alam et al. (2020), which has explored CBR prediction of fine-grained soils from index properties and concluded that CBR value could be predicted by these techniques with R greater than 0.99. Moreover, according to their findings, Kriging method can predict the exact amount of CBR value (Alam et al. 2020). In Iraq, Al-Busultan et al. (2020) used ANN to predict CBR value of subbase from other soil data. From a total of 358 subbase samples the ANN model has shown an accepted result for the predicting CBR values. PI is the least important factor, while soluble salts are the most effective factor.

Algorithms such as K-Nearest Neighbors (K-NN), Gaussian Process Regression (GPR), and Kernel Ridge Regression (KRR) have been used lately for analyzing big data on California Bearing Ratio (CBR). Verna et al. (2023) utilized these algorithms to analyze 1011 samples, revealing that these techniques are valued for estimating CBR. The study highlighted that while these algorithms provide significant predictive power, the model's performance is highly dependent on the location of the samples, indicating potential variability in soil characteristics across different regions.

In Table 1, numerous correlations have been presented between CBR and soil index parameters. Bello (2012) presented linear relationships between CBR and other parameters such as LL , PL, and MDD. Ramasubbarao and Sankar (2013) presented moderate to high correlations for soaked CBRs with LL, PL, MDD, and OMC. Additionally, Bhatt et al, (2014) found a moderate correlation between CBR and MDD, while Roy (2016) provided equations with low to high correlations for LL, PL, PI, MDD, and OMC. Araujo and Ruiz (2016) reported moderate correlations for various parameters, and Rehman et al. (2017) detected high correlations for LL and PL but lower for MDD and OMC. Katte et al. (2019) found varying correlations, with MDD showing the strongest relation. Reddy et al. (2019) has also developed a high correlation for CBR prediction from LL, and PI. Finally, Rashed et al. (2021) presented various correlations to predict CBR and the best correlation was with LL. From the literature, it is obvious that there is not an accurate model to estimate the value of CBR for cohesive soils. In addition, there is not sufficient information about the physical and compaction characteristics of cohesive soils. The aim of this study is to develop a simple reliable equation to predict the value of CBR using compaction characteristics and LL as well as to develop a Muli-Linear Model to predict the CBR value.

Table 1 Available correlations in the literature (after Pule and Yendaw, 2024)

Authors	Parameter	Correlation/equation	R/R^2
Bello (2012)	Liquid Limit	CBR = 83.19+0.031 (LL) CBRs = 28.87+0.22 (LL)	N/A
	Plastic Limit	CBR = 65.31+0.8 (PL) CBRs = 13.56+1.04 (PL)	N/A
	Maximum Dry Density	CBR = 65.88+8.66 (MDD) CBRs = -70.22+50.28 (MDD)	N/A
Ramasubbarao And Sankar (2013)	Liquid Limit	CBRs=0.045LL	R=0.82
	Plastic Limit	CBRs = 0. 103PL	R=0.89
	Maximum Dry Density	CBRs = 1.737MDD	R=0.91

	Optimum Moisture Content	CBRs = 0.116OMC	R=0.85
Bhatt et al., (2014)	Maximum Dry Density	CBR = 21.101MDD - 30.56	R^2=0.62
Roy (2016)	Liquid Limit	CBR= -0.070LL + 17.49	R=0.25
	Plastic Limit	CBR = -0.028PL + 17.13	R=0.07
	Plasticity Index	CBR = -0.338PI + 17.73	R=0.48
	Maximum Dry Density	CBR = - 37.65MDD - 51.98	R=0.97
	Optimum Moisture Content	CBR = -1.399OMC + 33.51	R=0.97
Araujo and Ruiz (2016)	Liquid Limit	CBRs = -1.588LL + 73.734	R=0.60
	Plastic Limit	CBRs = -2.796PL + 80.146	R=0.45
	Plasticity Index	CBRs = -1.77811PI + 46.502	R=0.53
	Maximum Dry Density	CBRs = 103.340MDD – 174.71	R=0.74
	Optimum Moisture Content	CBRs = -6.055OMC + 91.368	R=0.81
Rehman et al. (2017)	Liquid Limit	CBRs = -0.4275LL + 20.254	R^2=0.85
	Plasticity Index	CBRs = -0.5746PI + 14.247	R^2=0.89
	Maximum Dry Density	CBRs = 0.476MDD - 45.2	R^2=0.32
	Optimum Moisture Content	CBRs = -2.066OMC + 35.9	R^2=0.54
Katte et al. (2019)	Liquid Limit	CBR = 24.377 + 0.151LL	R=0.19
	Plastic Limit	CBR = 17.632 + 0.425PL	R=0.32
	Plasticity Index	CBR = 35.006 - 0.002 PI	R=0.002
	Maximum Dry Density	CBR = -175.006 + 99.869MDD	R=0.88
	Optimum Moisture Content	CBR = 99.086 - 5.162OMC	R=0.86
Reddy et al. (2019)	Liquid Limit	CBRs = -0.0813LL + 7.2087	R^2=0.93
	Plasticity Index	CBRs = -0.1024PI +6.159 6	R^2 = 0.94
	Maximum Dry Density	CBRs = 12.788MDD- 20.037	R^2=0.91
Rashed et al. (2021)	Liquid Limit	CBRs = -0.4829LL + 24.018	R^2 =0.77
	Plastic Limit	CBRs = -0.5815PL + 20.497	R^2=0.54
	Plasticity Index	CBRs = -0.7331PI + 14.148	R^2=0.52
	Maximum Dry Density	CBRs = 27.094MDD - 43 714	R^2=0.65
	Optimum Moisture Content	CBRs = -0.8079OMC + 17.338	R^2=0.51
Note: CBR: ***Unsoaked CBR*** and CBRs=***Soaked CBR***			

3. Methodology

In this study, we aimed to explore the effectiveness in predicting the CBR value of fine-grained soils using soil index parameters. The samples have been taken from different locations within

Sulaymaniyah region in Iraq as shown in Figure 1. The zone of study was selected based on random selection from cohesive soils since most of the area in this region is covered by a fine-grained soil.

Figure 1: The location of the study region (Google, 2024)

The eight samples were tested in the laboratory to determine their properties. The following laboratory tests have been conducted on the samples:

1. Moisture content (W%) according to ASTM D-2216.
2. Atterberg limits (PL and LL) according to ASTM D-4318.
3. Sieve analysis test according to ASTM D-422.
4. Compaction test (modified) according to ASTM D-1557.
5. CBR according to ASTM D-1883

Then, an analytical approach has been employed to study the effect of optimum moisture content, liquid limit, plastic limit and maximum dry density on CBR. The analysis incorporates statistical models, specifically simple regression and multiple linear regressions, to quantify the impact of these parameters on CBR.

The produced correlations have been validated by means of Root Mean Square Error (RMSE) and the Coefficient of Determination (R^2). RMSE, is a commonly used metric to measure the accuracy of a model's predictions compared to the actual values. It gives you an idea of how well your model is performing. A lower RMSE indicates better accuracy. However, RMSE is sensitive to outliers since it squares the errors, which makes large errors more impactful on the final value.

$$RMSE = \sqrt{\frac{\sum(y_i - y_p)^2}{n}} \quad (1)$$

$$R^2 = 1 - \left(\frac{\sqrt{(y_i - y_p)}}{\sqrt{(y_i - \mu)}}\right)^2 \quad (2)$$

Where: y_i = measured data, y_p = predicted data from the maps, μ= mean of the data, n is the number of data points

4. Results and Discussion

In this study, the results of LL, PI, MDD, OMC and CBR for eight samples of the cohesive soils are presented in Table 2. The aforementioned table additionally displayed the presence of each type of gravel, sand, fines, and soil classification using AASHTO classification system since this system is used in road construction. Table 3 displays the descriptive statistics of the data which illustrates the limit of the soil parameters used in this study.

Table 2 The results of LL, PI, Group Index (GI), MDD, OMC and CBR

Sample No.	Gravel	Sand	Fines Clay) + Silt)	Group classification	LL	PI	GI	MDD gm/cm3	OMC	Soaked CBR
1	0	0	100	A-4	28	10	9	2.08	8.6	7.91
2	5.7	7.1	87.2	A-6	30	11	9	1.981	11.3	4.64

3	8.5	6.9	84.6	A-6	34	15	12	1.966	11.7	4.91
4	5	9	86	A-7-5	45	15	15	1.739	17	2.88
5	6	15	89	A-7-5	45	15	16	1.696	16.4	2.49
6	7	17	76	A-7-5	51	15	14	1.685	17.3	2.79
7	19	16	65	A-7-6	41	12	7	1.765	14.8	3.7
8	26	18	56	A-7-6	43	14	6	1.749	15.6	3.14

Table 3 Descriptive statistics of cohesive soil data

Variable	Gravel	Sand	Fines (Clay + Silt)	LL	PI	GI	MDD gm/cm3	OMC	Soaked CBR
Mean	9.65	11.13	80.48	39.63	13.38	11.00	1.83	14.09	4.06
Range	26	18	44	23	5	10	0.395	8.7	5.42
Minimum	0	0	56	28	10	6	1.685	8.6	2.49
Maximum	26	18	100	51	15	16	2.08	17.3	7.91
Observation	8	8	8	8	8	8	8	8	8

To check the reliability of the equations presented in Table 1, the soil parameters mentioned in Table 2 are used. The results are presented in Table 4. Also, the measured unsoaked CBR results in this study are presented in Table 4 for comparison. As can be seen that some equations produced unrealistic values except the models developed by Reddy et al. (2019) and a model developed by Rashed et al. (2021) for estimated CBRs from PI can give realistic values but generally overestimates the value of CBR for some samples; therefore, the aim of this study is to develop a more reliable equations to predict the soaked CBR for fine-grained soils using high quality samples contain different types of fine-grained soils as presented in Table 2. Several correlation regression models between soil parameters created using the data in Table 2 by means of both simple and multiple regression models.

A correlation matrix analysis was performed to determine the relationships among the laboratory results. This analysis was conducted using Microsoft Excel, and the findings are presented in Table 5. As shown in Table 5, the strongest correlation exists between the CBR and OMC, whereas the weakest correlation is between the CBR and the group index (GI).

Table 4 Predicted CBR by equations from literature using the soil parameters in this study

Authors	Parameters	Correlation/equation	Predicted CBR using Equations in Table 1							
			Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample
Bello (2012)	Liquid Limit	**CBR = 83.19+0.031 (LL)**	84.06	84.12	84.24	84.59	84.59	84.77	84.46	84.52
		CBRs = 28.87+0.22 (LL)	35.03	35.47	36.35	38.77	38.77	40.09	37.89	38.33
	Plastic Limit	**CBR = 65.31+0.8 (PL)**	79.71	80.51	80.51	89.31	89.31	94.11	88.51	88.51
		CBRs = 13.56+1.04 (PL)	32.28	33.32	33.32	44.76	44.76	51.00	43.72	43.72
	Maximum Dry Density (Mg/m3)	**CBR = 65.88+8.66 (MDD)**	83.89	83.04	82.91	80.94	80.57	80.47	81.16	81.03
		CBRs = -70.22+50.28 (MDD)	34.36	29.38	28.63	17.22	15.05	14.50	18.52	17.72
Ramasubbarao and Sankar (2013)	Liquid Limit	**CBRs=0.045(LL)**	1.26	1.35	1.53	2.03	2.03	2.30	1.85	1.94
	Plastic Limit	**CBRs = 0. 103(PL)**	1.85	1.96	1.96	3.09	3.09	3.71	2.99	2.99
	Maximum Dry Density (gm/cm3)	**CBRs = 1.737(MDD)**	3.61	3.44	3.41	3.02	2.95	2.93	3.07	3.04
	Optimum Moisture Content	**CBRs = 0.116(OMC)**	1.00	1.31	1.36	1.97	1.90	2.01	1.72	1.81
Bhatt et al., (2014)	Maximum Dry Density (gm/cm3)	**CBR = 21.101(MDD) - 30.56**	13.33	11.24	10.92	6.13	5.23	5.00	6.68	6.35
Roy (2016)	Liquid Limit	**CBRs = -0.070(LL) + 17.49**	15.53	15.39	15.11	14.34	14.34	13.92	14.62	14.48
	Plastic Limit	**CBRs = -0.028(PL) + 17.13**	16.63	16.60	16.60	16.29	16.29	16.12	16.32	16.32
	Plasticity Index	**CBRs = -0.338(PI) + 17.73**	14.35	14.01	12.66	12.66	12.66	12.66	13.67	13.00
	Maximum Dry Density (gm/cm3)	**CBRs = 37.65(MDD) - 51.98**	26.33	22.60	22.04	13.49	11.87	11.46	14.47	13.87
	Optimum Moisture Content	**CBRs = -1.399(OMC) + 33.51**	21.48	17.70	17.14	9.73	10.57	9.31	12.80	11.69
Araujo and Ruiz (2016)	Liquid Limit	**CBRs = -1.588(LL) + 73.734**	29.27	26.09	19.74	2.27	2.27	-7.25	8.63	5.45
	Plastic Limit	**CBRs = -2.796(PL) + 80.146**	29.82	27.02	27.02	-3.73	-3.73	-20.51	-0.94	-0.94
	Plasticity Index	**CBRS = -1.77811PI + 46.502**	28.72	26.94	19.83	19.83	19.83	19.83	25.16	21.61
	Maximum Dry Density (gm/cm3)	**CBRs = 103.340(MDD) – 174.7**	40.24	30.01	28.46	5.00	0.55	-0.58	7.69	6.03
	Optimum Moisture Content	**CBRS = -6.055(OMC) + 91.368**	39.30	22.95	20.52	-11.57	-7.93	-13.38	1.75	-3.09
Rehman et al. (2017)	Liquid Limit	**CBRs = -0.4275(LL)+ 20.254**	8.28	7.43	5.72	1.02	1.02	-1.55	2.73	1.87
	Plasticity Index	**CBRs = -0.5746(PI) + 14.247**	8.50	7.93	5.63	5.63	5.63	5.63	7.35	6.20
	Maximum Dry Density (Ib/ft3)	**CBRs = 0.476(MDD) - 45.2**	16.61	13.67	13.22	6.48	5.20	4.87	7.25	6.77
	Optimum Moisture Content	**CBRs = -2.066(OMC) + 35.9**	18.13	12.55	11.73	0.78	2.02	0.16	5.32	3.67
Katte et al. (2019)	Liquid Limit	**CBR = 24.377 + 0.151(LL)**	28.61	28.91	29.51	31.17	31.17	32.08	30.57	30.87
	Plastic Limit	**CBR = 17.632 + 0.425(PL)**	25.28	25.71	25.71	30.38	30.38	32.93	29.96	29.96
	Plasticity Index	**CBR = 35.006 - 0.002 (PI)**	34.99	34.98	34.98	34.98	34.98	34.98	34.98	34.98
	Maximum Dry Density	**CBR = -175.006 + 99.869(MDD**	32.72	22.83	21.34	-1.33	-5.63	-6.73	1.26	-0.34
	Optimum Moisture Content	**CBR = 99.086 - 5.162(OMC)**	54.69	40.76	38.69	11.33	14.43	9.78	22.69	18.56
Reddy et al. (2019)	Liquid Limit	**CBRs = -0.0813(LL) + 7.2087**	4.93	4.77	4.44	3.55	3.55	3.06	3.88	3.71
	Plasticity Index	**CBRs = -0.1024(PI) +6.1596**	5.14	5.03	4.62	4.62	4.62	4.62	4.93	4.73
	Maximum Dry Density (gm/cm3)	**CBRs = 12.788(MDD)- 20.037**	6.56	5.30	5.10	2.20	1.65	1.51	2.53	2.33
Rashed et al. (2021)	Liquid Limit	**CBRs = -0.4829(LL) + 24.018**	10.50	9.53	7.60	2.29	2.29	-0.61	4.22	3.25
	Plastic Limit	**CBRs = -0.5815(PL) + 20.497**	10.03	9.45	9.45	3.05	3.05	-0.44	3.63	3.63
	Plasticity Index	**CBRs = -0.7331(PI) + 14.148**	6.82	6.08	3.15	3.15	3.15	3.15	5.35	3.88
	Maximum Dry Density (gm/cm3)	**CBRs = 27.094(MDD) - 43.714**	12.64	9.96	9.55	3.40	2.24	1.94	4.11	3.67
	Optimum Moisture Content	**CBRs = -0.8079(OMC) + 17.338**	10.39	8.21	7.89	3.60	4.09	3.36	5.38	4.73
Note: **CBRs** is soaked CBR		**Experimental CBRs**	**7.91**	**4.64**	**4.91**	**2.88**	**2.49**	**2.79**	**3.7**	**3.14**

Table 5 The results of Correlation coefficient (R) of studied parameters

	Fines (Clay + Silt)	*LL*	*PI*	*GI*	*MDD gm/cm³*	*OMC*	*Soaked CBR*
Fines	1.00						
LL	-0.49	1.00					
PI	-0.26	0.76	1.00				
GI	0.50	0.45	0.64	1.00			
MDD gm/cm³	0.56	-0.97	-0.70	-0.37	1.00		
OMC	-0.52	0.97	0.76	0.44	-0.98	1.00	
Soaked CBR	0.54	-0.87	-0.76	-0.39	0.93	-0.95	1.00

4.1 Correlation between OMC and LL

Figure 2 (a) illustrates the relationship between OMC and LL and shows that OMC and LL are directly proportional. The linear equation (Eq. 3), which is presented in Table 6, has also been produced with an excellent coefficient of determination (R^2) of 0.94 and RMSE of 0.72. The OMC is an essential characteristic for any construction activity, particularly soil work in engineering projects, as it is required for every filling work of soil. This holds significance as predicting OMC from LL leads to saving time, economy, and energy. Figure 2 (b) presents the relationship between the predicted OMC and experimental OMC. This figure and equation model demonstrate that the experimental and predicted OMC values are roughly equal, and the data trend line is closer to the equality line. This indicates that the developed equation (Eq. 3), presented in Table 6, is an excellent equation and can be used to predict OMC from LL.

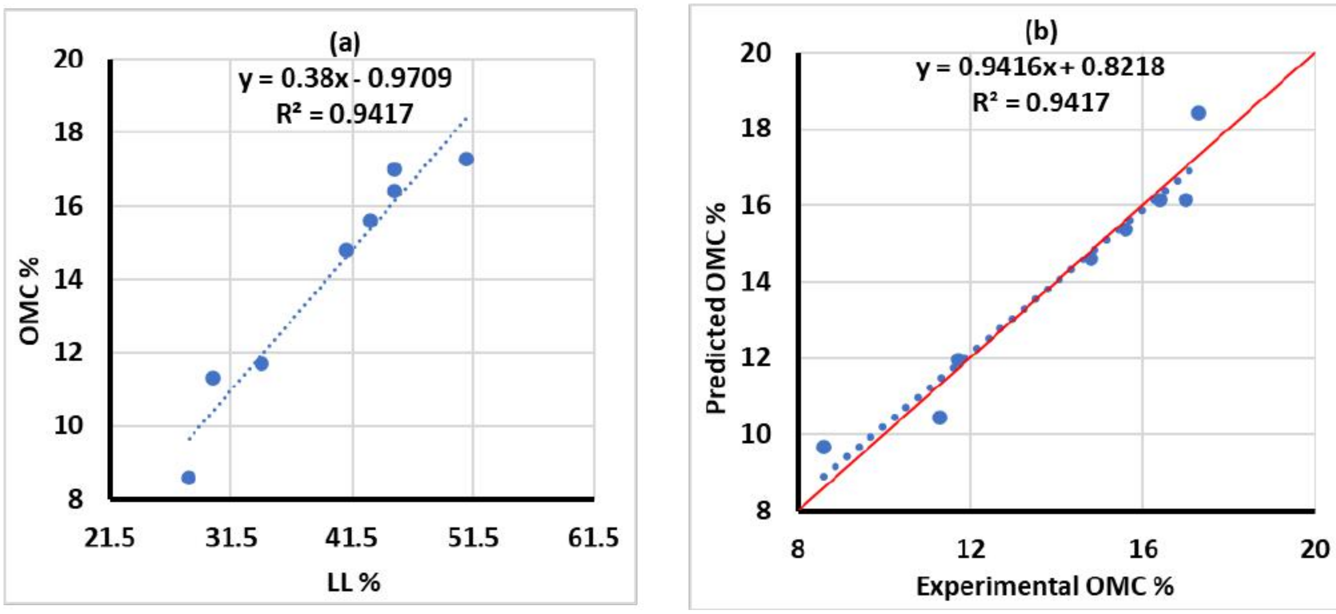

Figure 2: (a) Correlation between OMC and LL and (b) the validation of the predicted OMC as compared to experimental OMC values

4.2 Correlation between MDD and OMC

The relationship between MDD and OMC is illustrated in Figure 3 (a), from which the linear regression equation (Eq. 4 in Table 6) with R^2 of 0.97 and a very low RMSE of 0.02 has been derived, as Table 6 demonstrates. Furthermore, the figure indicates that a drop in OMC results in an increase in MDD. Simultaneously, this regression model plays a significant role in MDD prediction because the direct time and energy requirements of processing MDD make this regression model effective in saving time.

Figure 3 (b) also shows the relationship between the experimental and predicted MDD. This graph shows that an excellent correlation is observed between MDD and OMC. Since the data's equality line and trend line are much closer for each equation, this indicates that Eq. 4 is a reliable equation for estimating of MDD from OMC.

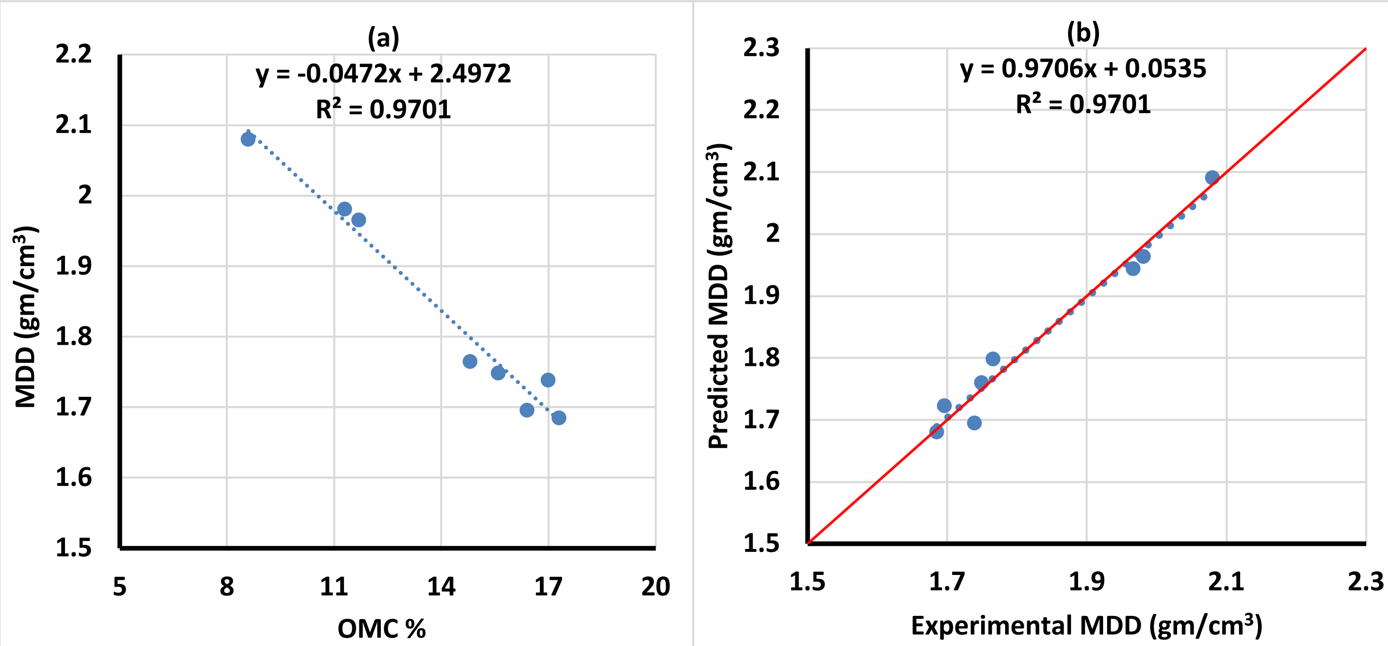

Figure 3: (a) Correlation between MDD and OMC and (b) validation of the predicted MDD as compared to experimental MDD values.

4.3 Correlation between CBR and MDD

An exponential correlation is established between CBR and MDD, as seen in Figure 4 (a); Eq. 5 in Table 6 explains this correlation, which has an R^2 of 0.91 and RMSE of 0.51. This Figure shows that increasing MDD increases CBR and vice versa. The CBR value is a crucial factor in any engineering project involving soil work since it affects road design and determines whether or not it is appropriate for filling. The CBR test requires many days to conduct at a later period. As a result, this regression model is essential for reducing processing time or for immediately determining the value of CBR produced from the CBR test.

Figure 4 (b) illustrates the correlation between the experimental and predicted CBR. This correlation is significant; when comparing the data's trend line to the equality line, the predicted CBR roughly matches the experimental CBR.

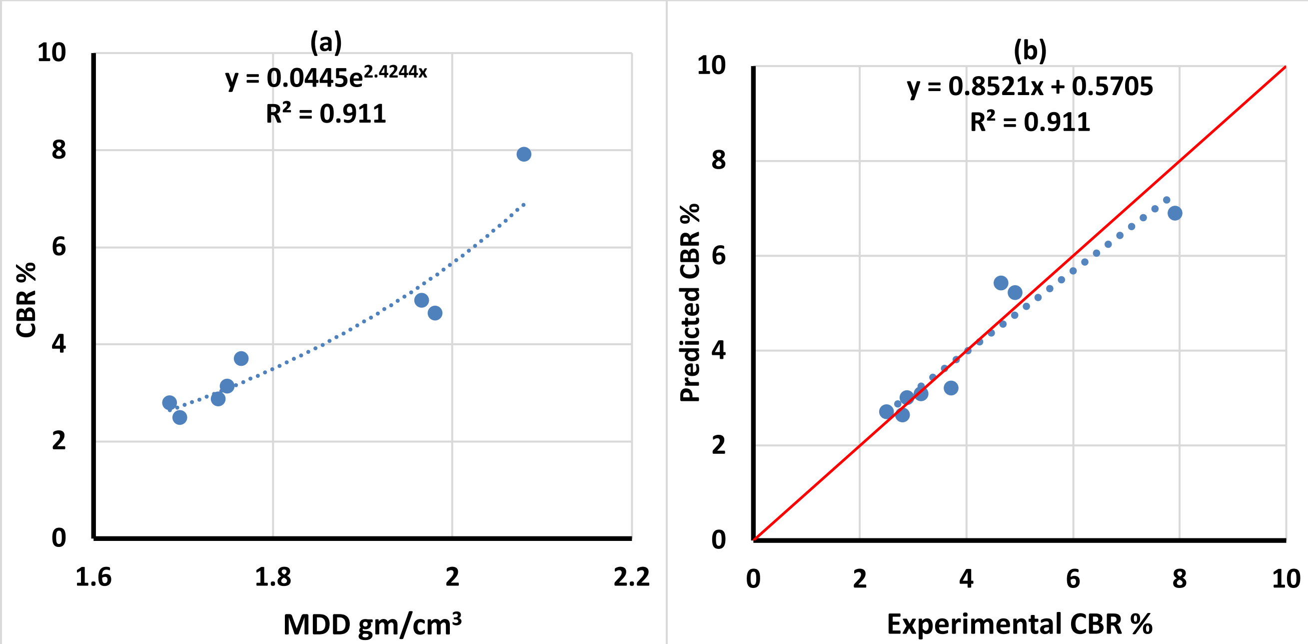

Figure 4: (a) Correlation between CBR and MDD and (b) the validation of predicted CBR as compared to experimental CBR values

4.4 Correlation between CBR and OMC

The correlation between CBR and OMC is presented in Figure 5 (a). It can be noted that the exponential equation (Eq. 6 presented in Table 6) with R^2 of 0.95 and RMSE of 0.38 has been produced for predicting CBR from OMC. This figure and correlation illustrated that CBR decreases with increasing OMC. It had previously been stated how significant the CBR value is; thus, using this regression model to check the CBR value from the CBR test or save time is important.

The relationship between experimental and predicted CBR is shown in Figure 5 (b). It is evident from this figure that the CBR data trend line and the equality line are extremely close, demonstrating the accuracy of Eq. 6.

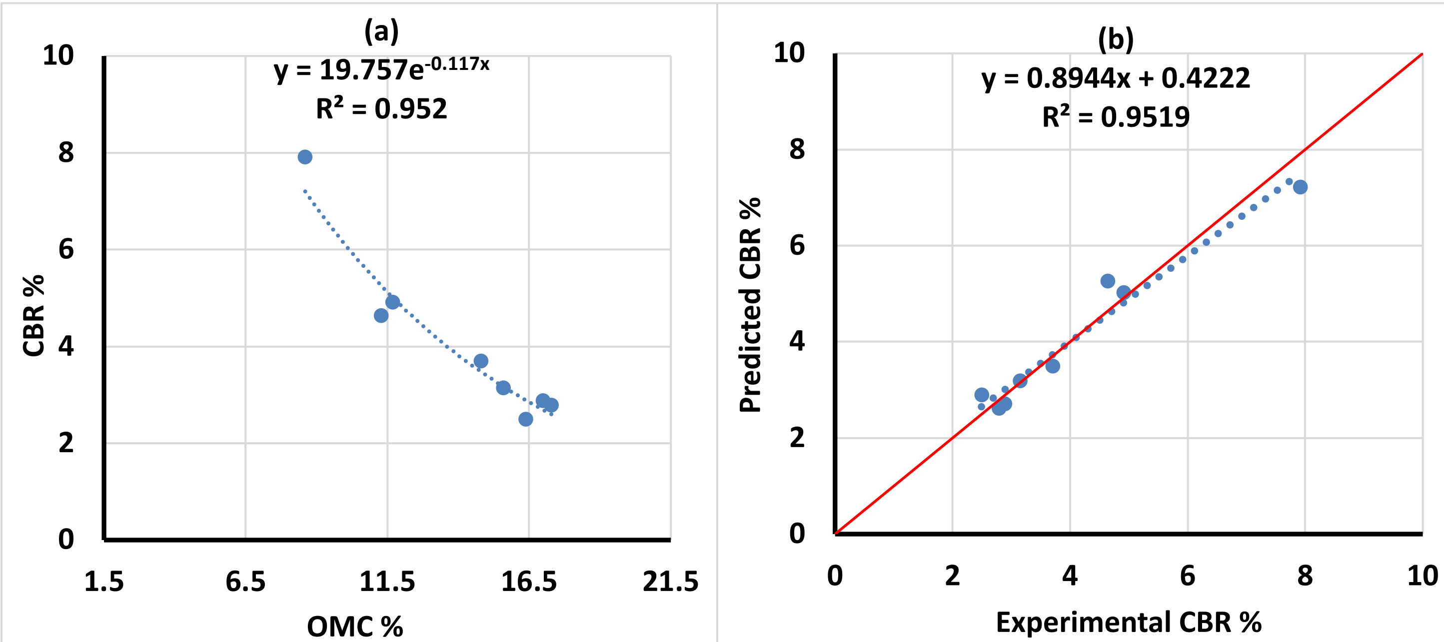

Figure 5: (a) Correlation between CBR and OMC and (b) the validation of predicted CBR as compare to experimental CBR values

4.5 Multiple regressions to predict CBR

As previously mentioned, CBR value is essential for engineering projects including soil work. Thus, the multi regression equation for predicting the CBR value is investigated in this study. For predicting the CBR value as a multi regression equation, the following variables have been used: LL, MDD, and OMC. Equation 7 which is shown in Table 6, has been developed using these parameters in order to increase the CBR value's accuracy. Figure 6 shows the correlation between the experimental and predicted values of CBR. This graph shows that the data's trendline is extremely close to the equality line, indicating that the created equation is of excellent quality and that it can be used to determine the CBR value or to check the CBR value from laboratory. Although, the RMSE of both simple model and multi-variable model are same but one can be more confident to predict CBR using two variables or more.

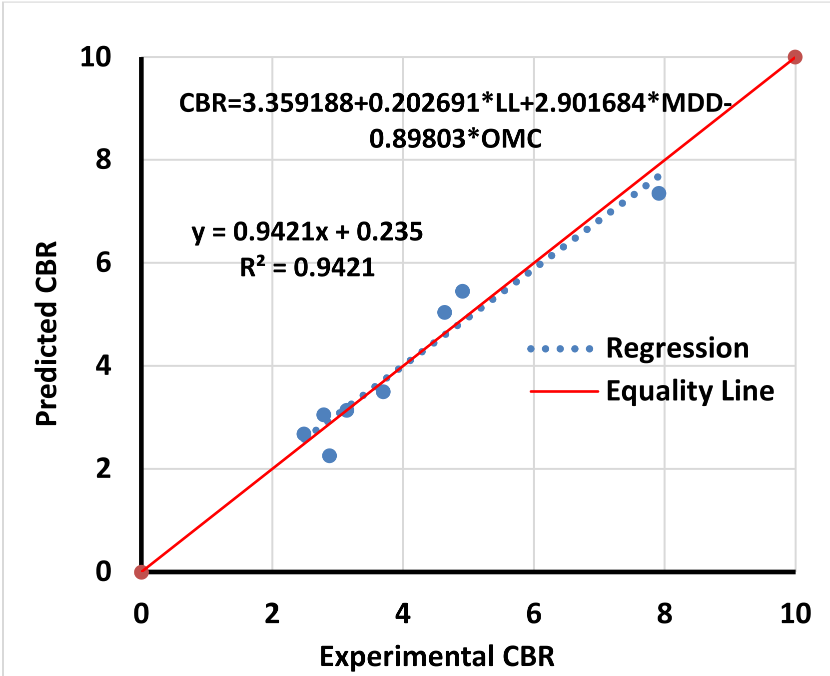

Figure 6: Correlation between experimental and predicted CBR

Table 6: Developed regression models to predict UCS using indirect tests

Eq. No.	Regression Models	RMSE	R^2	R	Description
Single Regression					
3	$OMC = 0.38 * LL - 0.9709$	0.71	0.94	0.97	OMC and LL in %
4	$MDD = 2.4972 - 0.0472 * OMC$	0.02	0.97	0.98	MDD in g/cm³ and OMC is %
5	$CBR = 0.0445 * EXP^{(2.4244*MDD)}$	0.51	0.91	0.95	CBR % and MDD in g/cm³
6	$CBR = 19.757 * EXP^{(-0.117*OMC)}$	0.38	0.95	0.975	CBR % and OMC in %
Multiple Regressions					

7	$CBR = 3.359188 + 0.202691 * LL + 2.901684 * MDD - 0.89803 * OMC$	0.4	0.94	0.97	CBR %, MDD in g/cm^3, LL and OMC in %

4.6 Evaluation of Proposed Equations

Harris and Taylor, 2003, worked on the coefficient of correlation (R) for the evaluation of a developed models. Table 7 provides an explanation of the developed model based on the coefficient of correlation (R). Predicting CBR from geotechnical parameters is the study's primary goal. The best single regression model that has been suggested is Eq. 4 (presented in Table 6), which predicts CBR from OMC. Additionally, Table 7 indicates that every equation suggested for the study is excellent in predicting dependent variables as each equation's R-value is greater than 0.90, which is a good result and can be helpful for establishing independent parameters or confirming the findings of this study.

Table 7: Description of R ranges after Harris and Taylor (2003)

Coefficient of Correlation (R)	Description
0.0-0.2	Very low
0.2-0.4	Low correlation
0.4-0.6	Reasonable Correlation
0.6-0.8	High correlation
0.8-1.0	Very high correlation

5. Conclusions

In conclusion, this research paper provides valuable insights into the relationship between compaction characteristics, liquid limit, and CBR values. Through comprehensive analysis, several key findings have been drawn:

1. Models developed by Reddy et al. (2019) can give realistic values for fine-grained soil in Iraq but generally overestimates the value of CBR and should be used with caution.

2. A model developed by Rashed et al. (2021) predicted CBR from PI may be used to estimate the soaked CBR of fine-grained soils.
3. Simple regression analysis shows a strong correlation between CBR and each of OMC and MDD, with R^2 values of 0.952 and 0.911, respectively, and RMSE values of 0.38 and 0.51, respectively.
4. Multi-regression analysis reveals a strong correlation between CBR and LL, OMC, and MDD, with an R^2 value of 0.9421 and RMSE of 0.4.
5. A predictive model for OMC from LL tests has been developed using simple regression analysis.
6. A strong relationship was observed between OMC and MDD. The R^2 of this relationship is 0.97, and RMSE of 0.02.

These findings greatly enhance geotechnical engineering practices by providing better methodologies for predicting the CBR of subgrades composed of fine-grained soils. It is important to note that while sophisticated methods are not necessary for developing predictive models in geotechnical engineering, having reliable data and straightforward techniques is essential.

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