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Prediction and Reliability Analysis of Soil Strength (CBR) Using Multiple Regression Analysis

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Abstract

The California Bearing Ratio (CBR) test is a penetration test used to evaluate the subgrade strength of roads and pavements. Results from the CBR test are used with empirical curves to determine the thickness of pavement layers, and the test remains the most widely used method for the design of flexible pavements. Under normal conditions, obtaining the result of a soaked CBR test takes between four and five days, a duration that can be impractical in emergency situations. During the COVID-19 pandemic, for example, pressure to deliver infrastructure quickly led to the construction of a 1,000-bed Huoshenshan Hospital in Wuhan, China, in ten days (24 January to 2 February 2020); achieving comparable feats depends on faster means of estimating soil strength. This study therefore explores an indirect, regression-based approach to predicting CBR. Geotechnical test results for 84 soil samples were collected, and a multiple regression analysis was carried out with the soaked CBR value as the dependent variable and existing moisture content (EMC), liquid limit (LL), plastic limit (PL), plasticity index (PI), particle size distribution, optimum moisture content (OMC), and maximum dry density (MDD) as independent variables. The analysis produced the relationship $Y = -0.57359169X_1 + 0.677530201X_2 - 0.64691219X_3 - 0.59578021X_4 + 0.004879034X_5 - 0.01717437X_6 + 0.13710102X_7 - 0.266139X_8 - 0.10248341X_9 + 0.118277058X_{10} - 0.10766766X_{11} + 0.25140518X_{12} - 0.16878082X_{13} + 7.543637025X_{14} - 0.20878597X_{15} + 5.381442462X_{16} + 10.18311796$*, where* Y *is the predicted soaked CBR value and* X_1 *through* X_{16} *are the corresponding independent variables. The equation was used to predict CBR values for the remaining samples, achieving an accuracy of approximately 92%. A reliability analysis was subsequently carried out on each independent variable; the percentage passing sieve No. 200 and the maximum dry density returned* R^2 *values of 0.9872 and 0.9691, respectively, against the coefficient of variation.*

Keywords: California Bearing Ratio; soil strength prediction; multiple regression analysis; reliability analysis; pavement subgrade

1. INTRODUCTION

The California Bearing Ratio (CBR) is a measure of the resistance of soil materials to plunger penetration and is widely used as an index of soil strength (Duwa, 2024). CBR values are commonly used for the design of unsealed pavement layers (Duwa, 2024; Chokkerd et al., 2024). In pavement design and materials engineering, CBR has become a standard parameter for determining the strength of granular soils for the design and construction of pavement layers. CBR values are influenced by particle size distribution, particle texture and shape, dry density, and water content (Chokkerd et al., 2024; Eboukou & Manguet, 2022). The CBR is also one of the most important characteristics representing the undrained shear strength of subgrade material in a pavement structure (Chokkerd et al., 2024; Eboukou & Manguet, 2022). Conducting the CBR test requires samples to be transported from the borrow pit, prepared, compacted, and soaked in the laboratory before being penetrated with CBR equipment; consequently, obtaining a realistic CBR value is time-consuming and not readily achievable in the field (Chokkerd et al., 2024; Eboukou & Manguet, 2022; Shadman et al., 2023). Civil engineers are therefore often faced with an urgent need for CBR values within a short time frame, which creates a demand for faster and more economical means of estimating CBR (Eboukou & Manguet, 2022; Shadman et al., 2023; Longtu et al., 2022).

Over the years, several methods of predicting soil strength have been developed (Eyael et al., 2024). In predicting the shear strength of soil, Cone Penetration Test (CPT) data and other soil properties have been combined to estimate soil shear strength parameters (Janibul et al., 2023). Intelligent systems such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) have also been used to predict the shear strength of soil (Besalatpour et al., 2012; Ashish et al., 2019; Muhammad et al., 2025). These studies generally found the ANN model to be more effective at predicting soil shear strength than the ANFIS model, with a root mean square error (RMSE), mean estimation error (MEE), and correlation coefficient (R) between the measured and ANN-estimated soil shear strength of 0.05, 0.01, and 0.86, respectively (Muhammad et al., 2025).

Multiple linear regression (MLR), artificial neural networks (ANN), and fuzzy logic (FL) tools have also previously been used to predict soil strength (Mojtaba, 2012; Aref et al., 2024). For example, Aref et al. (2024) examined variables including the nano-pozzolan content of natural sources (NNP), nano-lime content (NL), median particle size of NNP, active silica content of NNP (SiO_2), and the initial liquid limit (ILL) and initial plastic limit (IPL) of the soils investigated. NNP was added at five percentages (0%, 0.5%, 1%, 1.5%, and 2%), while NL was added at five percentages (0%, 0.3%, 0.6%, 0.9%, and 1.2%), and three median particle sizes (50, 100, and 500 nm) were studied (Mojtaba, 2012; Aref et al., 2024; Radha & Smita, 2025; Arif et al., 2019). Based on the soils and combinations investigated, 120 soil mixtures were prepared and tested, with CBR and plasticity index (PI) examined in particular. CBR tests were conducted under soaked conditions on specimens compacted to maximum dry density (MDD) at the optimum moisture content (OMC), while PI values were obtained from Atterberg limit tests. The results indicated that the CBR and PI of the expansive clayey soils investigated could be effectively predicted using ANN and FL techniques, and that results obtained from MLR were less accurate than those from either ANN or FL; the ANN model was, in turn, found to be slightly more accurate than the FL model for predicting CBR and PI (Aref et al., 2024).

The present study builds on this body of work by developing and testing a multiple-regression-based predictive equation for the soaked CBR of lateritic subgrade soils along a road alignment, using routinely measured index and compaction properties as predictors, and by subjecting the resulting model to a formal reliability analysis.

2. MATERIALS AND METHODS

2.1 Materials

Geo technical test results were obtained from a civil engineering (geotechnical) firm for a road project site in Jahi, Abuja (latitude 9°6′15″ N, longitude 7°26′33″ E). The dataset comprised existing moisture content (EMC), liquid limit (LL), plastic limit (PL), plasticity index (PI), percentage passing BS sieve Nos. 7, 10, 14, 25, 36, 52, 72, 100, and 200, maximum dry density (MDD), optimum moisture content (OMC), specific gravity (Gs), and unsoaked and soaked CBR values for 84 samples collected at 1 km intervals along an 84 km alignment (chainage 0+000 to 84+000). The results are tabulated in Table 1.

Table 1 ***Index Properties, Compaction Characteristics, and CBR Values for 84 Soil Samples (Chainage 0+000–84+000)***

Location (km)	EMC (%)	LL (%)	PL (%)	PI (%)	#7 (3.35mm)	#10 (2mm)	#14 (1.18mm)	#25 (600µm)	#36 (425µm)	#52 (300µm)	#72 (212µm)	#100 (150µm)	#200 (63µm)	MDD (g/cm³)	OMC (%)	Gs	Unsoaked CBR (%)	Soaked CBR (%)
0+000	18	27	19	8	99.13	98.8	98.3	96.97	95.5	91.97	90.57	83.53	83.23	2.14	11.39	2.65	48	15
1+000	20	28	16	12	99.26	98.3	97.60	96.39	94.00	90.89	87.63	80.38	76.86	2.18	11	2.69	31	13
2+000	12	0	0	0	99.07	98.67	98.23	97.57	96.57	94.10	92.67	78.33	27.83	2.21	7.46	2.60	62	26
3+000	22	26	19	7	98.94	97.83	96.48	95.94	93.69	92.3	90.83	81.49	78.39	2.06	14.96	2.68	28	10
4+000	18	29	18	11	99.48	98.49	97.23	96.11	94.89	89.68	87.48	83.68	74.86	2.04	15.06	2.7	30	12
5+000	20	28	18	10	99.06	97.86	94.74	89.96	86.49	75.0	72.86	70.40	69.79	2.16	12.4	2.68	32	13
6+000	14	21	11	10	98.2	97.73	97.4	96.93	96.57	95.6	95	90.40	90.07	2.15	11.63	2.69	50	16
7+000	12	0	0	0	98.39	96.8	94.46	83.10	75.5	49.8	43.9	33.6	26.19	1.64	12.86	2.57	64	14
8+000	16	31	20	11	98.14	97.4	95.4	87.96	84.40	80.6	76.7	74.96	69.38	1.96	14.9	2.68	49	20
9+000	15	29	15	14	0	98.34	96.19	92.86	90.11	86.57	83.60	77.84	72.80	2.09	15.5	2.71	44	18
10+000	14	0	0	0	0	0	98.96	96.4	72.69	68.54	46.89	36.8	29.8	1.57	11.4	2.62	34	14
11+000	10	0	0	0	0	99.84	96.49	93.86	81.5	69.91	49.19	33.39	27.44	1.59	11.9	2.61	30	12
12+000	11	0	0	0	0	0	99.10	97.86	89.68	73.59	60.49	39.86	30.49	1.49	10.89	2.57	30	12
13+000	8	0	0	0	0	99.76	97.48	96.39	79.8	68.1	49.69	38.36	28.84	1.54	13.7	2.61	29	13
14+000	9	0	0	0	99.69	96.86	94.4	90.49	81.81	60.36	54.16	30.8	19.89	1.5	11.86	2.54	40	12
15+000	10	0	0	0	99.17	97.49	93.18	89.39	83.27	64.74	44.18	26.89	20.44	1.52	12.89	2.56	40	14
16+000	11	26	10	0	89.69	81.43	79.83	76.34	70.96	67.49	66.49	53.89	44.86	1.98	16.86	2.67	69	30
17+000	14	0	0	0	0	99.9	97.19	89.85	70.7	54.94	39.9	30.48	19.38	1.49	11.4	2.59	39	10
18+000	16	0	0	0	0	99.6	89.68	74.39	56.86	34.60	29.86	24.36	14.74	1.51	10.33	2.54	29	14
19+000	14	0	0	0	0	99.44	86.57	73.86	64.86	29.8	26.4	19.5	16.38	1.53	11.2	2.53	26	10
20+000	12	0	0	0	0	0	99.38	90.08	79.89	56.69	48.6	30.89	24.89	1.5	11.48	2.6	26	12
21+000	18	0	0	0	0	99.5	94.17	73.6	52.73	28.8	24.2	15.03	14.77	1.56	12.8	2.56	29	13
22+000	9	0	0	0	0	0	99.06	88.73	72.8	51.49	46.8	25.10	24.73	1.54	11.39	2.54	30	14
23+000	11	0	0	0	0	0	99.86	89.49	74.5	54.48	47.3	30.69	26.86	1.52	10.87	2.52	28	11
24+000	12	0	0	0	0	0	98.38	87.49	76.9	64.86	59.38	26.41	13.86	1.55	12.3	2.53	29	12
25+000	8	0	0	0	0	0	99.06	88.96	72.79	51.49	46.9	16.86	10.64	1.54	11.74	2.51	30	14
26+000	12	0	0	0	0	99.73	98.40	84.63	72.4	56.53	53.3	42.53	42.27	1.59	10.9	2.59	28	13
27+000	12	0	0	0	0	99.49	98.36	87.5	74.49	56.69	47.75	42.28	39.86	1.52	8.69	2.6	30	14
28+000	12	0	0	0	0	0	99.40	89.83	73.8	44.83	39.2	18.7	12.89	1.54	11.47	2.60	26	12
29+000	10	0	0	0	0	0	98.69	89.84	69.49	54.1	47.4	30.9	28.39	1.51	11.3	2.56	29	14
30+000	8	0	0	0	0	99.64	97.80	94.4	74.9	53.89	40.2	33.96	19.86	1.55	10.86	2.53	30	14
31+000	10	0	0	0	0	99.69	97.49	93.86	68.87	52.88	49.89	30.69	19.68	1.55	10.24	2.57	28	12
32+000	12	0	0	0	0	99.38	96.80	94.6	69.9	49.29	44.30	29.84	20.86	1.53	9.69	2.60	27	14
33+000	14	0	0	0	0	0	99.59	92.49	74.9	60.89	54.8	44.89	39.68	1.52	10.9	2.58	28	12
34+000	11	0	0	0	0	0	98.48	96.4	86.39	69.48	57.49	35.49	20.86	1.53	12.86	2.57	28	12
35+000	12	0	0	0	0	0	99.89	87.96	84.49	64.48	54.4	33.86	29.49	1.56	14.86	2.55	29	13
36+000	14	0	0	0	0	0	99.09	86.76	74.96	59.9	49.87	31.89	26.89	1.53	10.86	2.54	28	12
37+000	10	0	0	0	0	99.79	96.89	96.8	67.48	51.48	44.86	26.69	21.49	1.49	7.96	2.51	26	10
38+000	10	0	0	0	0	0	99.57	91.69	76.89	51.28	47.8	26.89	24.86	1.54	11.84	2.54	28	12
39+000	12	0	0	0	0	0	99.43	96.49	89.68	74.49	63.38	39.48	29.68	1.50	10.18	2.61	29	12
40+000	14	0	0	0	0	0	99.38	95.54	79.86	69.86	51.5	34.49	27.48	1.52	11.49	2.51	30	14
41+000	12	0	0	0	0	0	99.53	94.43	87.3	73.6	68.3	36.9	35.83	1.49	9.9	2.53	28	12
42+000	11	0	0	0	0	0	99.68	96.69	83.69	70.5	57.78	32.86	24.48	1.54	12.86	2.54	25	13
43+000	10	0	0	0	0	0	99.37	91.9	81.8	65.60	60.73	42.10	41.73	1.53	11.14	2.60	31	14
44+000	10	0	0	0	0	0	98.9	94.49	83.86	69.86	64.49	46.86	38.49	1.52	10.8	2.54	28	13
45+000	12	0	0	0	0	0	99.89	87.79	76.7	54.28	46.89	30.69	22.84	1.54	11.86	2.54	30	14
46+000	6	0	0	0	0	0	99.50	94.53	87.23	67.7	60.5	31.17	30.63	1.51	10.48	2.60	30	14
47+000	12	0	0	0	0	0	98.49	96.34	87.4	49.26	49.9	31.49	24.38	1.51	11.4	2.55	26	11
48+000	11	0	0	0	0	0	99.86	87.71	69.86	54.49	47.39	31.86	29.68	1.5	11.06	2.59	34	14
49+000	11	0	0	0	0	0	98.57	87.49	68.86	54.96	48.86	31.49	28.69	1.50	10.26	2.51	31	14
50+000	15	0	0	0	0	0	98.17	83.63	67.33	46.90	42.73	28.70	28.37	1.52	10.89	2.54	26	14
51+000	9	0	0	0	0	0	99.09	86.79	74.86	54.38	47.96	30.49	24.73	1.51	12.06	2.56	36	16
52+000	11	0	0	0	0	99.5	94.53	87.23	67.7	60.2	31.67	30.89	29.65	1.51	11.40	2.54	36	14
53+000	10	0	0	0	0	99.68	86.99	84.44	73.69	57.49	46.86	30.86	27.70	1.54	10.68	2.57	30	12
54+000	13	0	0	0	0	0	99.57	90.43	76.77	59.17	55.10	41.1	40.43	1.54	10.39	2.60	29	11
55+000	8	0	0	0	0	0	99.89	96.66	80.69	64.8	59.96	42.86	36.86	1.50	11.96	2.54	34	17

Location (km)	EMC (%)	LL (%)	PL (%)	PI (%)	#7 (3.35mm)	#10 (2mm)	#14 (1.18mm)	#25 (600μm)	#36 (425μm)	#52 (300μm)	#72 (212μm)	#100 (150μm)	#200 (63μm)	MDD (g/cm³)	OMC (%)	Gs	Unsoaked CBR (%)	Soaked CBR (%)
56+000	13	0	0	0	0	0	99.37	90.07	77.2	55.23	49.7	29.43	29.17	1.52	10.96	2.56	32	13
57+000	10	0	0	0	0	0	99.46	90.67	74.8	58.89	50.6	30.84	26.86	1.54	11.36	2.58	34	15
58+000	14	0	0	0	0	0	99.4	96.84	82.86	69.48	50.68	39.4	26.68	1.55	10.49	2.54	22	10
59+000	14	0	0	0	0	0	99.60	93.86	78.89	64.49	50.68	39.48	24.69	1.52	11.48	2.57	32	14
60+000	14	0	0	0	0	0	96.49	89.38	75.85	63.57	54.21	36.66	24.44	1.53	11.48	2.57	24	11
61+000	10	0	0	0	0	0	98.89	94.56	84.96	74.84	63.86	35.49	22.84	1.52	10.96	2.54	26	12
62+000	9	0	0	0	0	0	99.39	96.69	89.48	76.64	63.40	36.46	28.64	1.52	10.28	2.57	28	12
63+000	12	0	0	0	0	0	99.5	94.53	86.89	69.9	63.89	32.69	30.63	1.50	11.84	2.56	26	13
64+000	14	0	0	0	0	0	99.86	87.71	69.96	54.46	45.34	32.89	26.68	1.59	13.86	2.53	26	12
65+000	12	0	0	0	0	99.68	90.49	84.48	70.86	61.48	39.6	29.48	28.38	1.56	12.86	2.52	29	14
66+000	13	0	0	0	0	98.49	84.4	76.68	63.38	54.86	47.68	36.86	29.68	1.64	12.84	2.53	30	14
67+000	10	0	0	0	0	98.69	94.39	86.4	60.6	49.60	32.66	30.46	24.49	1.57	14.60	2.50	26	13
68+000	12	0	0	0	98.13	97.57	94.6	83.20	72.37	49.23	41.40	21.50	21.10	1.51	10.86	2.50	24	10
69+000	11	0	0	0	0	99.29	90.68	80.67	56.38	50.48	43.89	30.89	27.25	1.54	11.09	2.51	28	13
70+000	9	0	0	0	0	99.38	89.39	86.78	60.89	54.49	49.69	38.86	24.38	1.57	12.06	2.54	29	14
71+000	10	0	0	0	0	99.94	96.49	87.49	83.38	76.69	50.6	34.69	26.86	1.52	11.60	2.50	36	16
72+000	11	0	0	0	0	99.76	97.28	87.76	84.48	70.48	51.68	34.49	28.69	1.56	10.86	2.57	32	16
73+000	18	0	0	0	0	0	99.46	86.69	67.8	62.86	44.0	32.89	27.4	1.58	10.46	2.54	24	10
74+000	16	0	0	0	0	0	99.26	86.69	84.48	54.09	47.36	32.87	26.69	1.56	10.86	2.50	26	11
75+000	10	0	0	0	0	0	99.03	88.70	72.73	51.47	46.1	25.10	24.73	1.61	12.86	2.55	30	14
76+000	12	0	0	0	0	0	99.68	96.69	83.69	62.29	46.86	24.49	22.86	1.58	11.49	2.53	24	11
77+000	10	0	0	0	0	99.90	94.46	87.38	69.89	63.8	49.4	30.63	25.49	1.53	10.16	2.54	29	12
78+000	13	0	0	0	0	0	99.40	89.83	73.77	44.83	39.17	18.73	18.37	1.59	11.46	2.55	29	13
79+000	11	0	0	0	0	0	99.59	86.69	74.49	46.9	40.86	22.86	20.49	1.54	10.86	2.54	30	14
80+000	12	0	0	0	0	0	97.53	83.27	67.73	49.77	44.2	25.77	25.33	1.94	8.16	2.61	36	19
81+000	11	0	0	0	0	0	99.69	92.86	84.4	60.89	53.86	31.69	27.48	1.51	11.38	2.54	32	14
82+000	10	0	0	0	0	0	98.49	96.38	84.40	64.48	50.86	44.69	30.68	1.56	12.60	2.50	30	12
83+000	10	0	0	0	0	0	99.86	94.46	83.89	69.86	44.86	34.69	29.69	1.52	10.89	2.51	27	14
84+000	12	0	0	0	0	0	99.57	92.76	76.7	64.48	56.69	39.49	32.68	1.53	14.06	2.53	28	10

Note. EMC = existing moisture content; LL = liquid limit; PL = plastic limit; PI = plasticity index; #7–#200 = percentage passing the indicated BS sieve; MDD = maximum dry density; OMC = optimum moisture content; Gs = specific gravity. A value of 0 indicates the Atterberg limit test could not be determined (non-plastic material) for that sample.

2.2 Methods

2.2.1 Regression analysis

Multiple regression analysis was carried out on the dataset using the Data Analysis add-in in Microsoft Excel. Fifty of the 84 samples were used to develop the regression model: the independent variables (EMC, LL, PL, PI, percentage passing each sieve size, MDD, OMC, and Gs) were entered in the input X range, and the dependent variable (soaked CBR) was entered in the input Y range, as shown in Fig. 1. The Labels option was selected to retain variable names in the output for ease of interpretation. Following the regression run, a multiple linear equation was obtained and subsequently assessed for reliability.

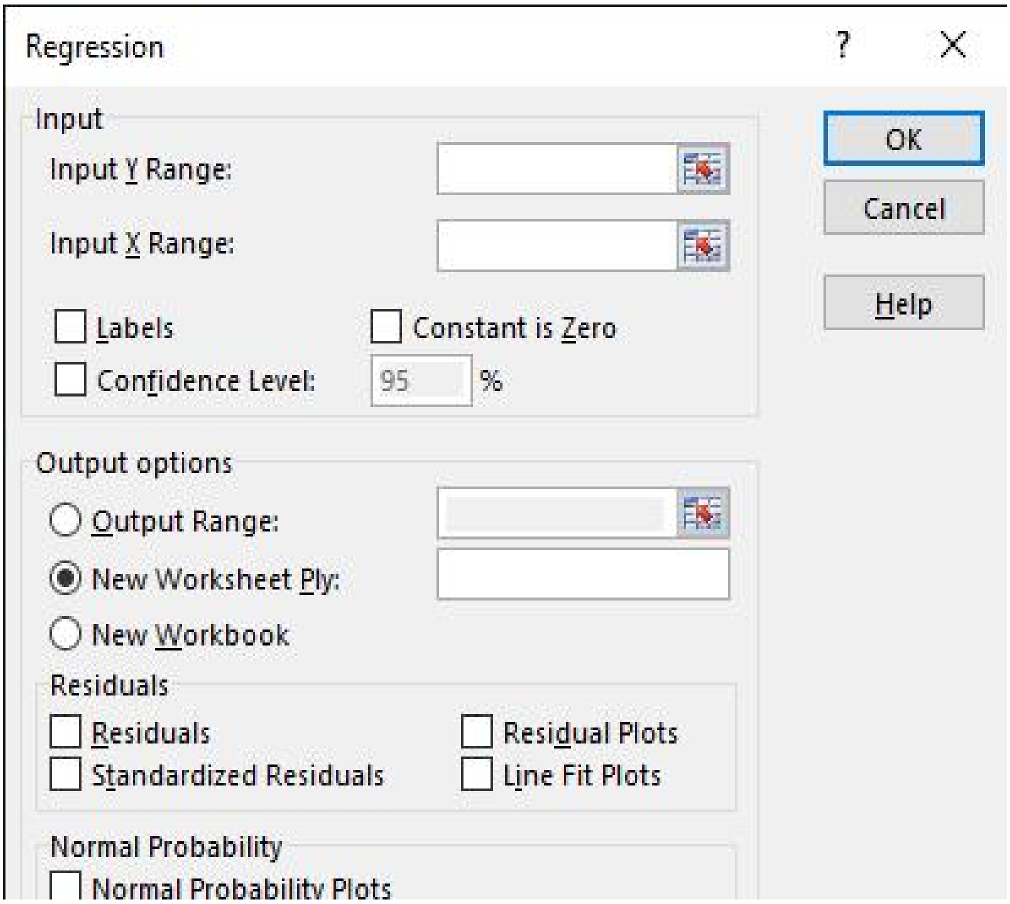

Fig. 1: ***Regression analysis dialog box in Microsoft Excel.***

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2.2.2 Reliability analysis

A reliability analysis of the regression equation was carried out using a First-Order Reliability Method (FORM) program executed from a DOS-based command shell (Fig. 2). The formula obtained from the regression analysis was recalled within the program, as shown in Fig. 3. The coefficient of variation was varied in turn for each of the sixteen independent variables, and the corresponding reliability index was recorded. For each variable, a graph of reliability index (vertical axis) against coefficient of variation (horizontal axis) was then plotted to assess the sensitivity of the predicted soaked CBR to that variable.

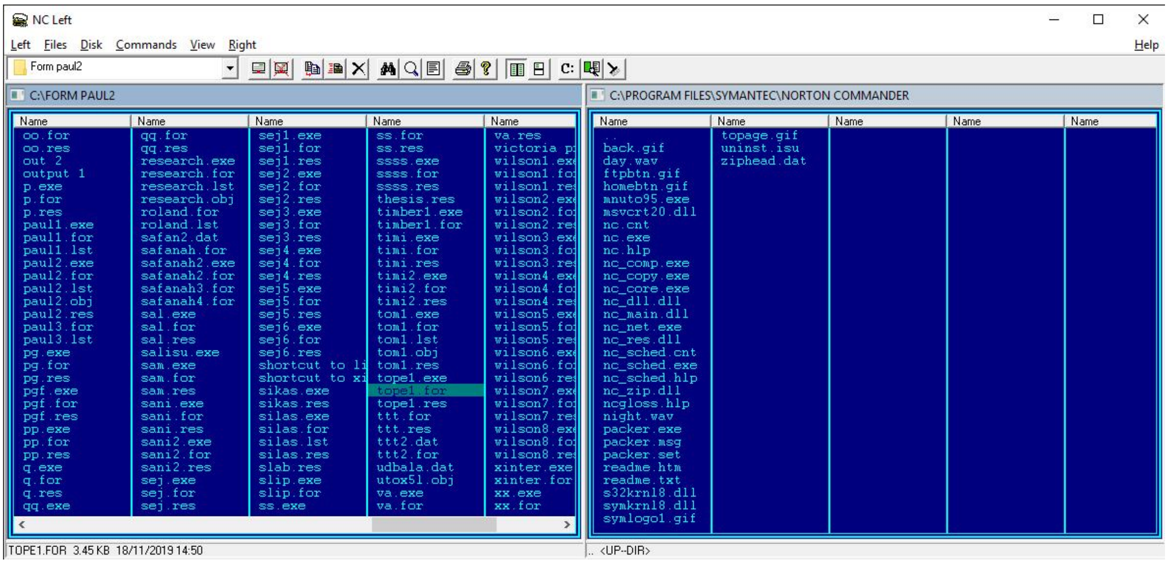
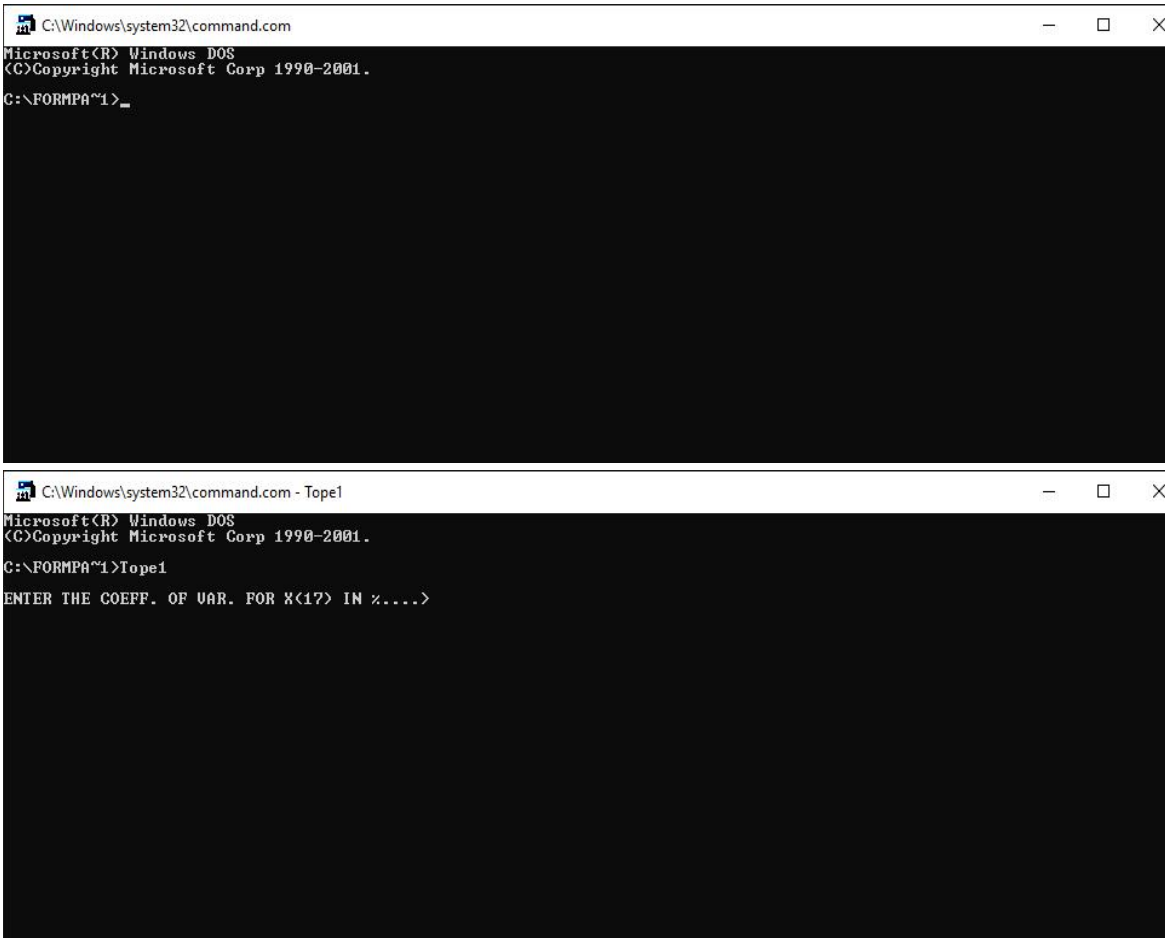


Fig. 2: ***DOS-based interface of the FORM reliability analysis program at launch.***



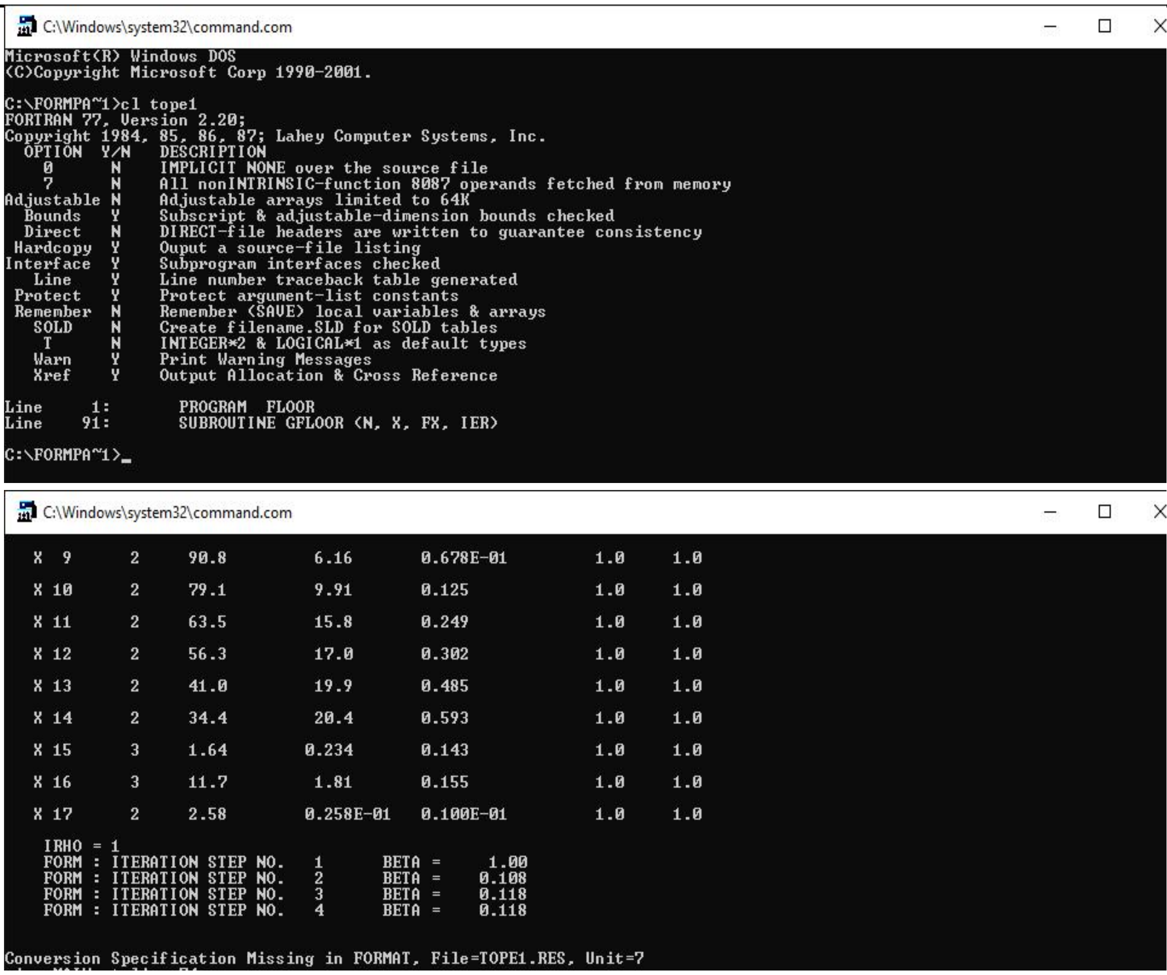


Fig. 3: ***Recall of the regression formula within the reliability analysis program (successive views).***

3. RESULTS AND DISCUSSION

A regression equation was developed using fifty of the eighty-four samples and subsequently used to predict the soaked CBR of the remaining samples. The fit statistics and analysis of variance (ANOVA) for the model are summarised in Table 2, and the regression coefficients for each independent variable are presented in Table 3.

Table 2: ***Regression Fit Statistics and Analysis of Variance (ANOVA) for the Predictive Model***

Statistic	Value
Multiple R	0.9312
R^2	0.8672
Adjusted R^2	0.8028
Standard error	1.5503
Observations (n)	50.0000

Source	df	SS	MS	F	Sig. F
Regression	16	517.905	32.369	13.468	3.91136E-10
Residual	33	79.315	2.403		
Total	49	597.220			

Note. df = degrees of freedom; SS = sum of squares; MS = mean square; Sig. F = significance of F.

Table 3: ***Regression Coefficients for Each Independent Variable***

Variable	Coefficients	SE	t	p	LL 95%	UL 95%	LL 95.0%	UL 95.0%
Intercept	10.1831	24.0794	0.4229	0.6751	-38.8067	59.1730	-38.8067	59.1730
EMC (%)	-0.5736	0.1270	-4.5176	0.0001	-0.8319	-0.3153	-0.8319	-0.3153
LL (%)	0.6775	0.2613	2.5929	0.0141	0.1459	1.2091	0.1459	1.2091
PL (%)	-0.6469	0.3283	-1.9705	0.0572	-1.3149	0.0210	-1.3149	0.0210
PI (%)	-0.5958	0.2281	-2.6121	0.0134	-1.0598	-0.1317	-1.0598	-0.1317
#.7 (3.35mm)	0.0049	0.0105	0.4639	0.6458	-0.0165	0.0263	-0.0165	0.0263
#.10 (2mm)	-0.0172	0.0092	-1.8709	0.0702	-0.0359	0.0015	-0.0359	0.0015
#.14 (1.18mm)	0.1371	0.1746	0.7852	0.4379	-0.2181	0.4923	-0.2181	0.4923
#.25 (600mm)	-0.2661	0.0881	-3.0222	0.0048	-0.4453	-0.0870	-0.4453	-0.0870

Variable	Coefficients	SE	t	p	LL 95%	UL 95%	LL 95.0%	UL 95.0%
#.36 (425mm)	-0.1025	0.0684	-1.4988	0.1434	-0.2416	0.0366	-0.2416	0.0366
#.52 (300mm)	0.1183	0.0596	1.9852	0.0555	-0.0029	0.2395	-0.0029	0.2395
#.72 (212mm)	-0.1077	0.0724	-1.4864	0.1467	-0.2550	0.0397	-0.2550	0.0397
#.100 (150mm)	0.2514	0.0707	3.5542	0.0012	0.1075	0.3953	0.1075	0.3953
#.200 (63mm)	-0.1688	0.0475	-3.5535	0.0012	-0.2654	-0.0721	-0.2654	-0.0721
MDD (g/cm3)	7.5436	3.9290	1.9200	0.0635	-0.4500	15.5373	-0.4500	15.5373
OMC (%)	-0.2088	0.2065	-1.0110	0.3194	-0.6289	0.2114	-0.6289	0.2114
Specific Gravity	5.3814	8.6887	0.6194	0.5399	-12.2958	23.0587	-12.2958	23.0587

Note. SE = standard error; LL = lower limit; UL = upper limit. X_1–X_{16} correspond, in order, to EMC, LL, PL, PI, percentage passing BS sieve Nos. 7, 10, 14, 25, 36, 52, 72, 100, and 200, MDD, OMC, and specific gravity.

$$Y = -0.57359169X_1 + 0.677530201X_2 - 0.64691219X_3 - 0.59578021X_4 + 0.004879034X_5 - 0.01717437X_6 + 0.13710102X_7 - 0.266139X_8 - 0.10248341X_9 + 0.118277058X_{10} - 0.10766766X_{11} + 0.25140518X_{12} - 0.16878082X_{13} + 7.543637025X_{14} - 0.20878597X_{15} + 5.381442462X_{16} + 10.18311796$$

where Y is the predicted soaked CBR, and X_1 through X_{16} represent existing moisture content, liquid limit, plastic limit, plasticity index, percentage passing BS sieve Nos. 7, 10, 14, 25, 36, 52, 72, 100, and 200, maximum dry density, optimum moisture content, and specific gravity, respectively (Table 3). As shown in Table 3, the coefficients for EMC, PI, percentage passing sieve No. 25, and percentage passing sieve No. 200 were statistically significant at the 5% level ($p < .05$), as were liquid limit and percentage passing sieve No. 100, indicating that these variables are the strongest individual predictors of soaked CBR within the model.

The predicted CBR values were compared against the corresponding actual (measured) CBR values for all 84 samples, grouped by chainage, in Fig.s 4 through 8. The comparison shows close agreement between the actual and predicted values across the majority of samples, with an average percentage difference of approximately ±7.5%. Using the fifty samples from which the model was developed, the prediction accuracy was approximately 92.5%; when applied to the remaining samples — including ten samples drawn from a different region — the prediction accuracy was approximately 90.8%. This level of agreement suggests that indirect estimation of CBR through regression on routinely measured index and compaction properties can provide a practical, time-saving alternative to the standard four- to five-day soaked CBR procedure, particularly in time-critical construction scenarios.

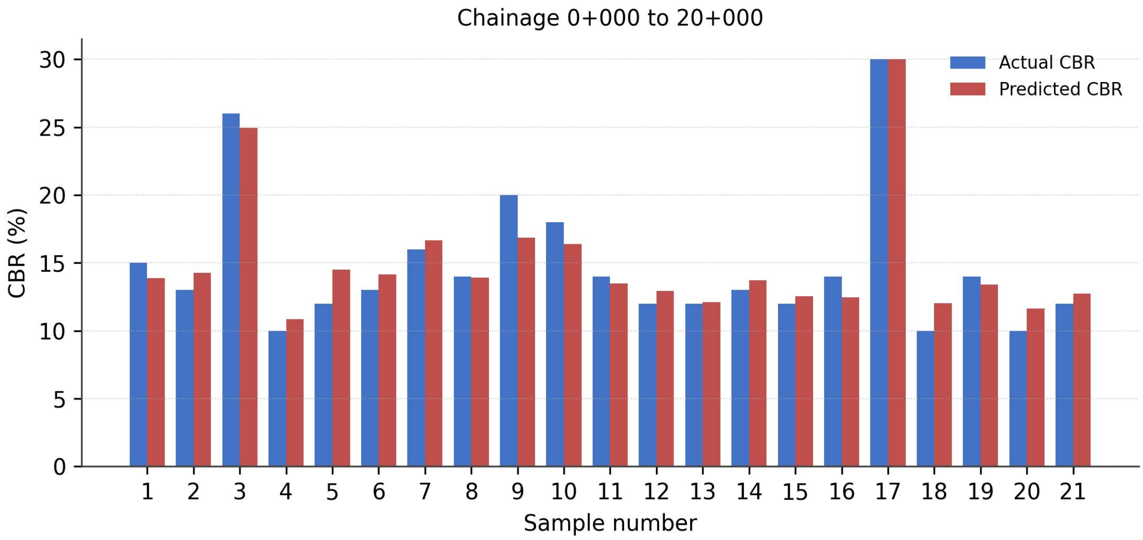


Fig. 4: ***Comparison of actual and predicted CBR, chainage 0+000–20+000.***

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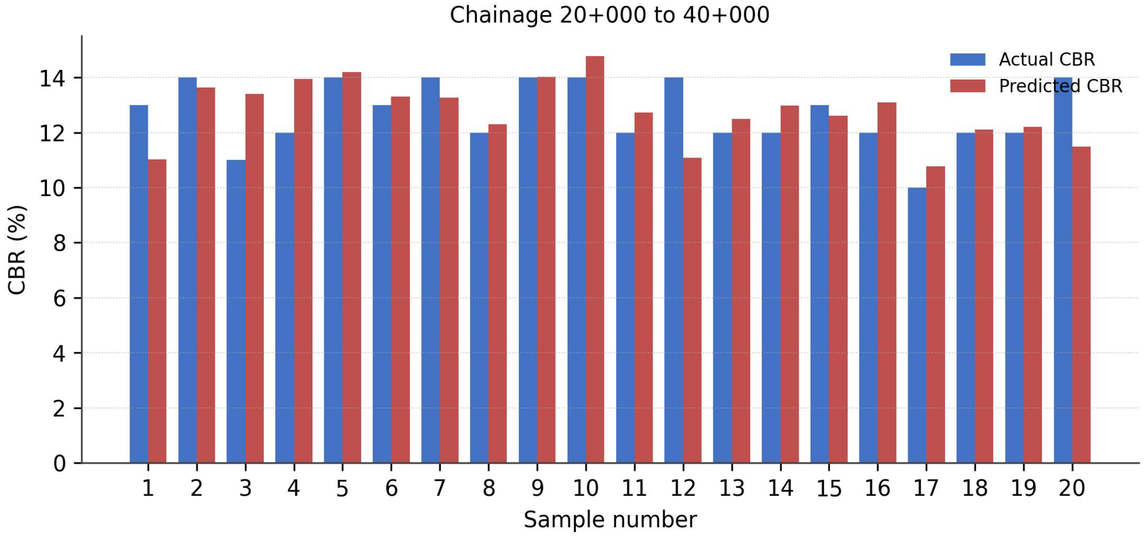

Fig. 5: ***Comparison of actual and predicted CBR, chainage 20+000–40+000.***

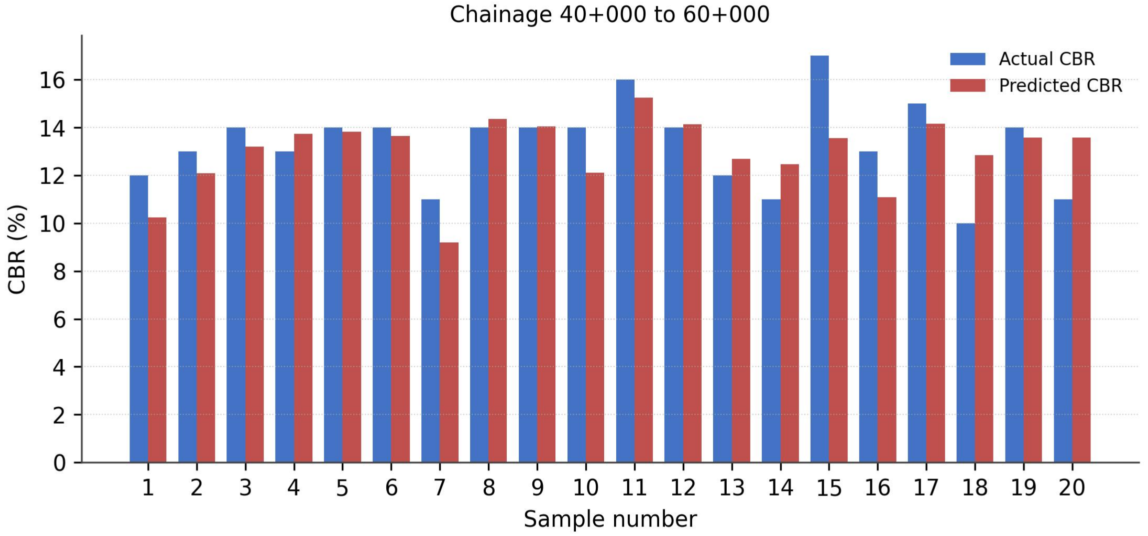

Fig. 6: ***Comparison of actual and predicted CBR, chainage 40+000–60+000.***

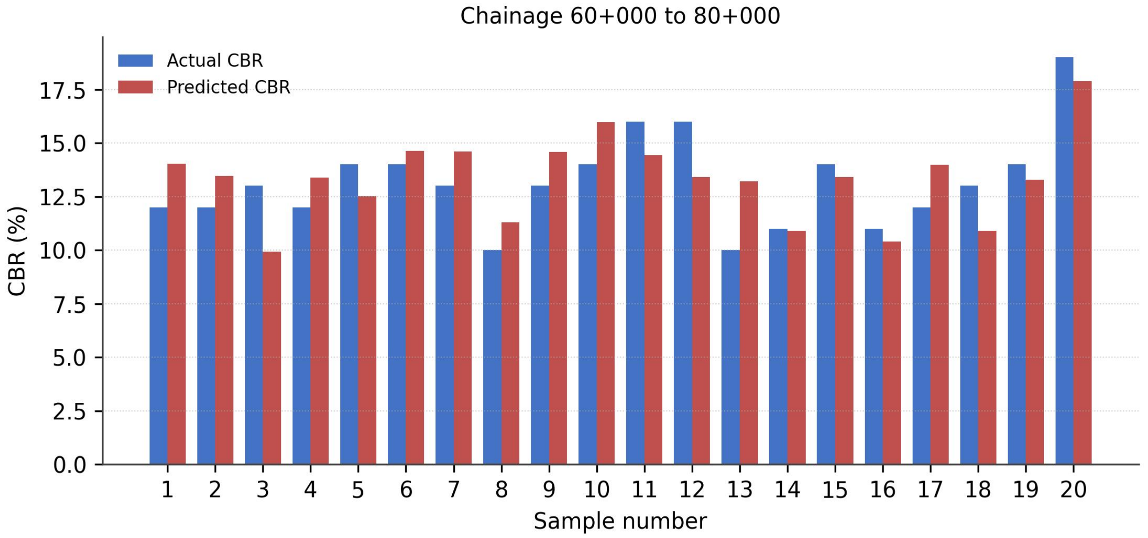

Fig. 7: ***Comparison of actual and predicted CBR, chainage 60+000–80+000.***

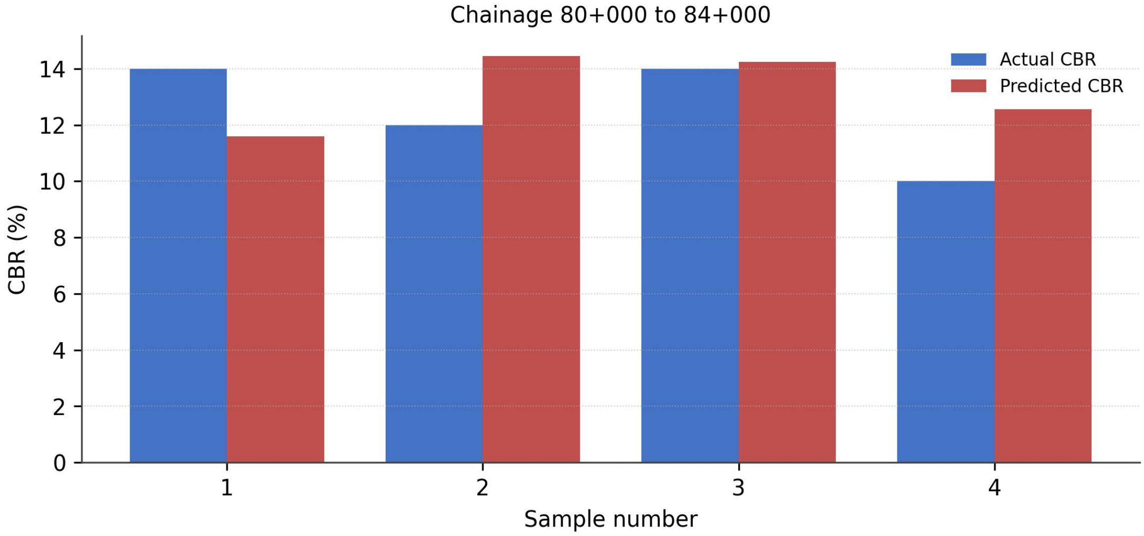

Fig. 8: ***Comparison of actual and predicted CBR, chainage 80+000–84+000.***

3.1 Reliability analysis

A reliability analysis was carried out on the regression equation to assess how reliably it supports prediction, expressed as a reliability index computed for a corresponding coefficient of variation of each variable (X_1 through X_{16}). Fig.s 9 through 12 plot the reliability index (vertical axis) against the coefficient of variation (horizontal axis) for each variable, together with a linear trendline and the coefficient of determination (R^2) for that trendline; together, these plots indicate the sensitivity of the predicted soaked CBR to each variable and identify which variables are most strongly associated with prediction reliability.

The results indicate that all variables exhibit some degree of relationship with the reliability index, with the exception of the percentage passing sieve No. 7, which remained essentially constant across the range of coefficient of variation examined (Fig. 10b). Most variables show a negative gradient — that is, the reliability index decreases as the coefficient of variation of the variable increases — indicating an inverse relationship with the reliability of the soaked CBR prediction. Maximum dry density was the only variable to show a positive gradient (Fig. 12c), indicating a direct relationship: an increase in the coefficient of variation of MDD is associated with an increase in the reliability index, and, by extension, an increase in MDD itself is associated with an increase in soaked CBR. This is consistent with well-established geotechnical behaviour, in which better-compacted soils (higher MDD) exhibit greater bearing strength.

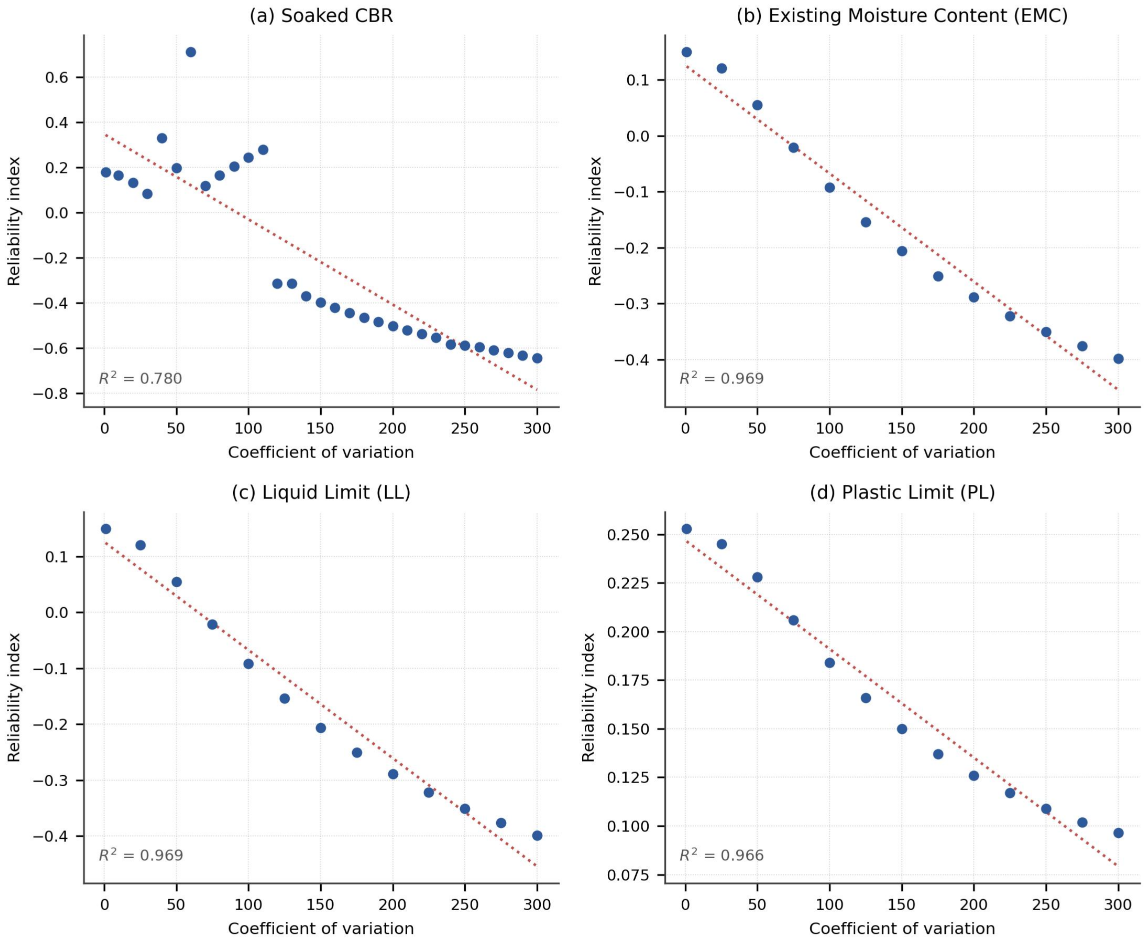

Fig. 9: ***Reliability index versus coefficient of variation for (a) soaked CBR, (b) existing moisture content, (c) liquid limit, and (d) plastic limit.***

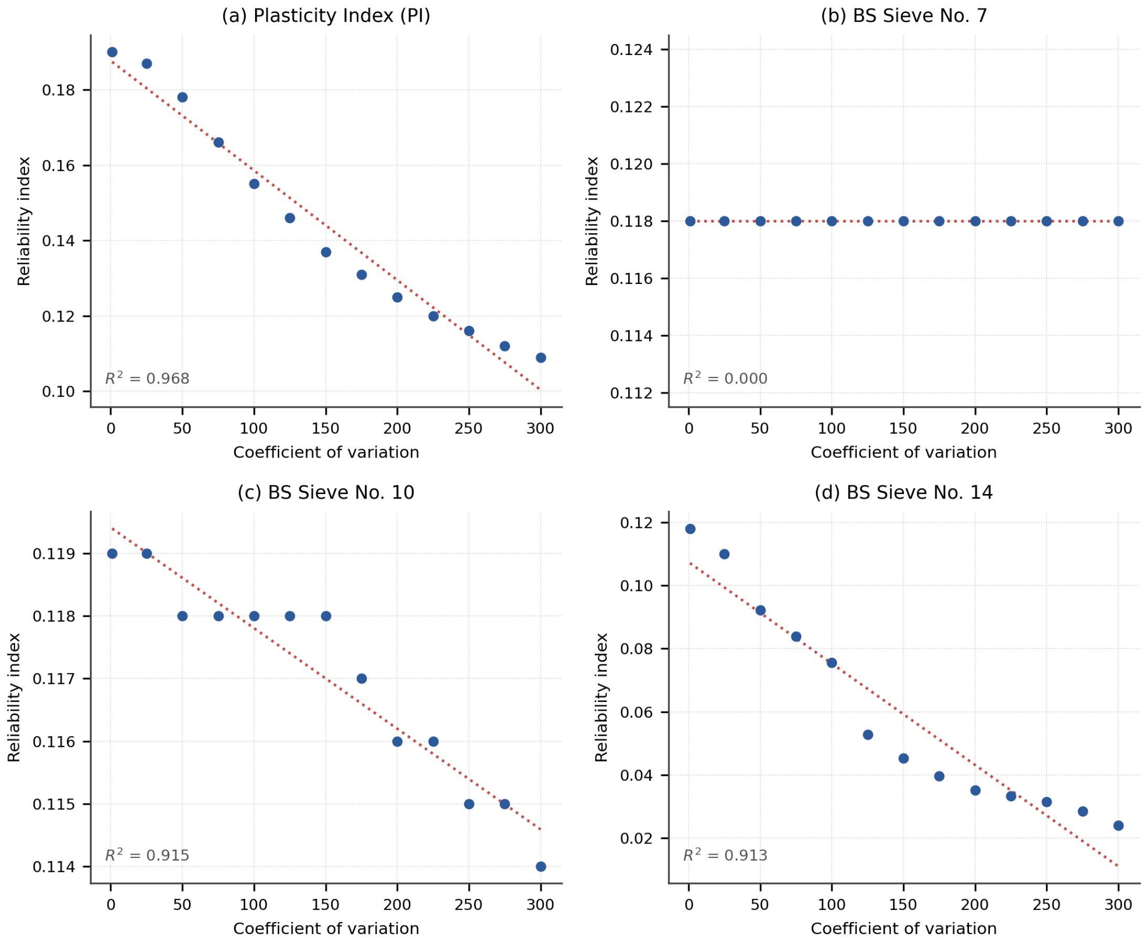

Fig. 10: ***Reliability index versus coefficient of variation for (a) plasticity index, (b) percentage passing sieve No. 7, (c) percentage passing sieve No. 10, and (d) percentage passing sieve No. 14.***

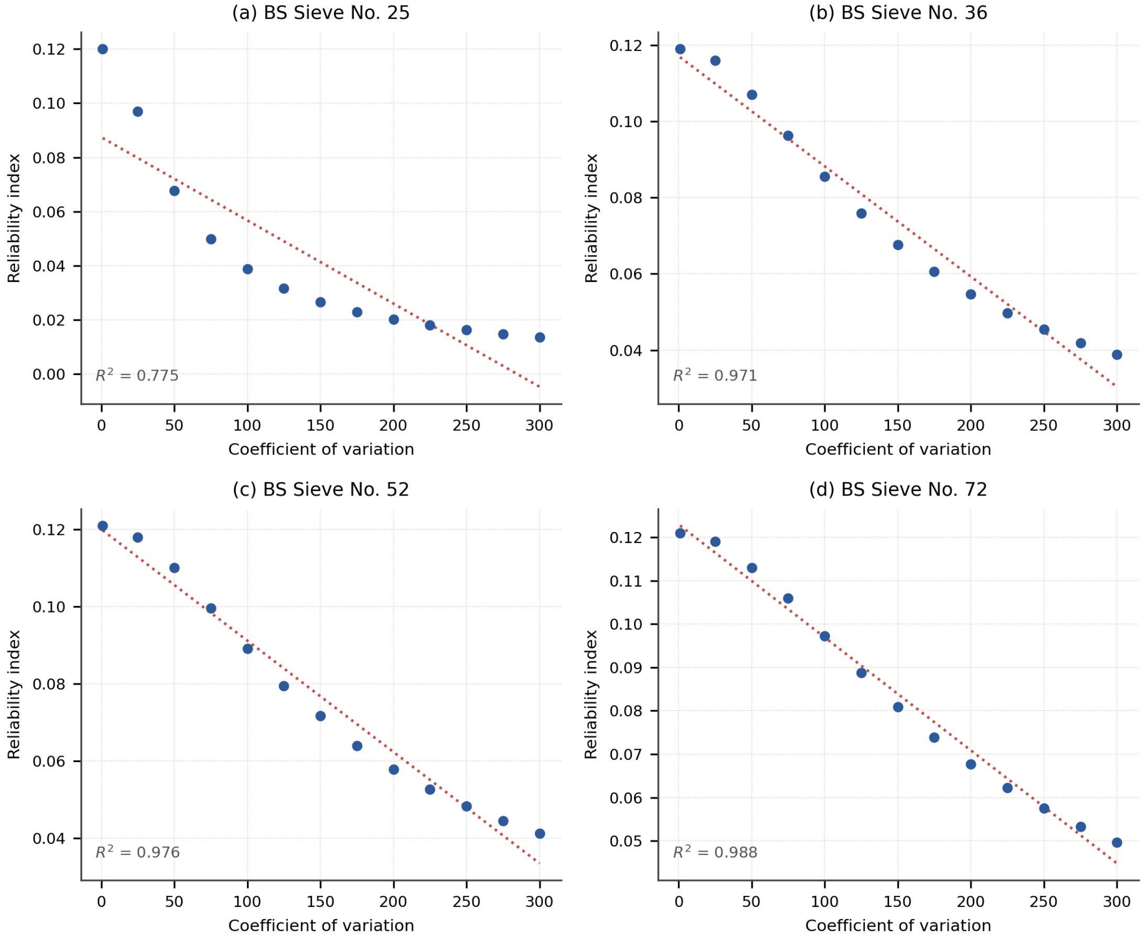

Fig. 11: ***Reliability index versus coefficient of variation for (a) percentage passing sieve No. 25, (b) percentage passing sieve No. 36, (c) percentage passing sieve No. 52, and (d) percentage passing sieve No. 72.***

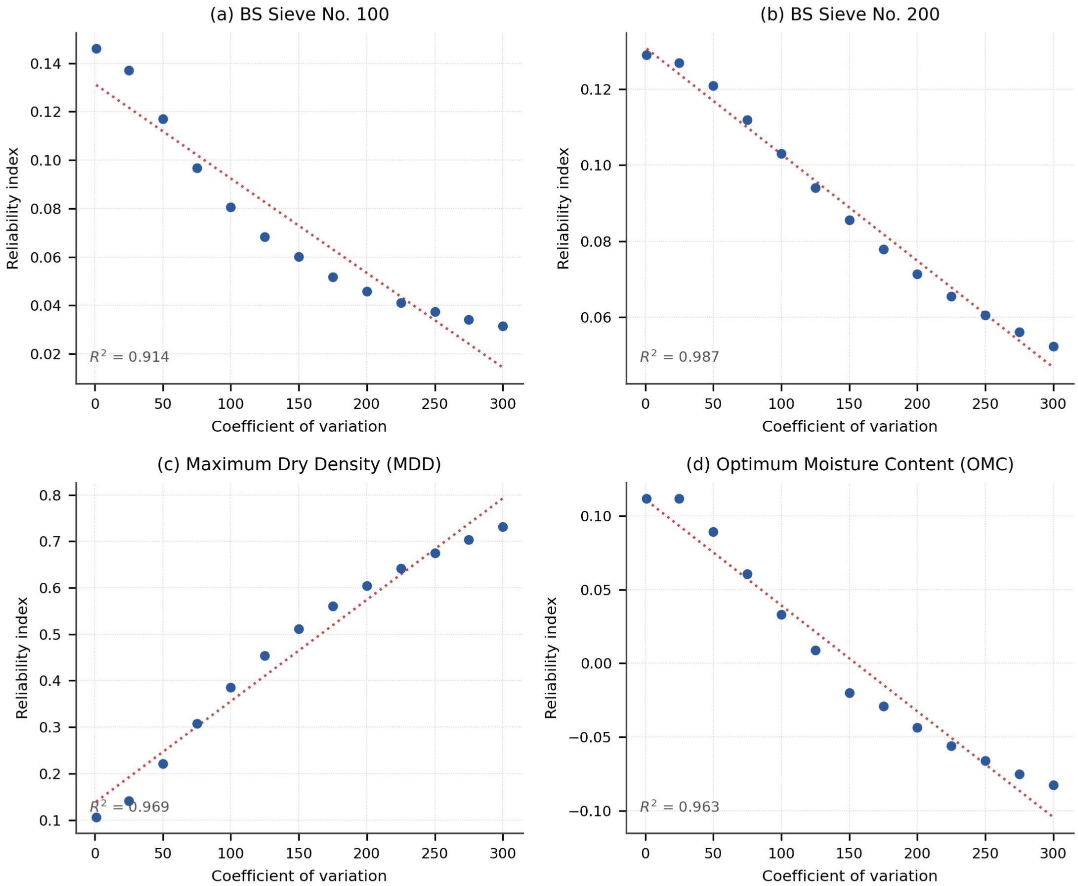

Fig. 12: ***Reliability index versus coefficient of variation for (a) percentage passing sieve No. 100, (b) percentage passing sieve No. 200, (c) maximum dry density, and (d) optimum moisture content.***

This study developed and evaluated a multiple-regression-based approach for the indirect prediction of the soaked California Bearing Ratio (CBR) of subgrade soils, using index and compaction properties routinely measured in geotechnical practice. Based on the analysis of 84 soil samples, the following conclusions are drawn:

1. It is possible to determine the soaked CBR of a soil by an indirect method, with a high degree of accuracy, using multiple regression analysis of routinely measured index and compaction properties.
2. Using 50 of the 84 soil samples collected from the same general location to develop the model, the prediction accuracy achieved was approximately 92.5%.
3. When the model was applied to 10 samples from a different region, the prediction accuracy achieved was approximately 90.8%, suggesting reasonable transferability of the approach beyond the calibration dataset.
4. The reliability analysis showed that maximum dry density is the only independent variable directly proportional to the soaked CBR of the soils studied; all other variables examined were inversely proportional to reliability of the prediction.

These findings support the continued development of indirect, regression-based methods for CBR estimation as a practical complement to conventional laboratory testing, particularly where time constraints make the standard four- to five-day soaked CBR procedure impractical. Future work with a larger and more geographically diverse sample set is recommended to further improve and validate the generalisability of the predictive equation.

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