Chapter

Multivariate Assessment of California Bearing Ratio with Contrasted Geotechnical Properties of Soils in Ilorin-Lokoja Highway

Attah Fakeye, Olusegun Ige and Olufemi Ogunsanwo

Abstract

California Bearing Ratio (CBR) is an important parameter used in designing pavement layers in road construction but testing this parameter requires time, labor, and huge cost. The study therefore applies multivariate approach to evaluate CBR based on contrasted geotechnical parameters along Ilorin-Lokoja highway. The results obtained showed that the migmatite-gneiss-derived soils are slightly more fines (< 0.075 mm; 7.4–59.6%), more plastic (PI; 1.6–39%), and have low strength (MDD = 1.8 mg/m^3; CBR = 29.0%) than the metasediments (11–57.7%, 2.0–30%, 1.6 mg/m^3, 23.6%) and older granite soils (8.2–32.7%, 2.6–13.4%, 1.7 mg/m^3, 27.8%), respectively. The principal component analysis (PCA) revealed three major components (eigenvalues >1) which accounted for 83.8% of the total variance at the rate of 33.4, 14.7, and 11.4%. Major contributing variables for the components were fines (R = 0.87), plasticity index (R = 0.7), and coarse sand (R = 0.67%). Spatial distribution of these groups established interplay of sediment-gradation and moisture-connection evident in hierarchical cluster analysis that revealed patterns of homogeneity and soil relationships. Regression analysis established five models from predictor variables such as fines, activity, free swell, liquid and plastic limits, weighted plasticity index, optimum moisture content, and maximum dry density with the coefficient of determination (R^2 = 0.33) and root mean square error (RMSE) of 7.80.

Keywords: multivariate, principal component analysis, regression, hierarchical analysis, geotechnical properties

1. Introduction

Identification and quantitative characterization of soils are of dire importance in geotechnical assessment despite the difficulties experienced using conventional approach. Index properties are important parameters in the analysis of geotechnical engineering problems, particularly to estimate strength of the soil material. Conversely, laboratory test takes 2–4 days to measure compaction and California Bearing Ratio (CBR) values for pavement design. As a result, they are expensive and time-consuming.

Also due to lack of specialized personnel, these tests are oftentimes avoided in many soil investigation programs. Thus, the need to incorporate statistical approach in predicting soil properties becomes inevitable.

Several authors have applied this approach in relating and predicting soil properties. One to one relationship was presented among soil properties [1] such as liquid limit (LL), plastic limit (PL), plasticity index (PI), optimum moisture content (OMC), and maximum dry density (MDD). Furthermore, Carter and Bentley explained that soil type, density, moisture content play an important role in soil relationship [2] and correlated soil expansion index and plasticity index, fine fraction and weighted plasticity index (i.e., product of PI and percentage passing 0.425 mm). Apart from index properties, some researchers like Owoseni et al. [3] and Yildrin and Gunaydin [4] observed that California Bearing Ratio depends on other factors such as type of soils, permeability of soil, maximum dry density and optimum moisture content. To correct overlapping problem and uncertainty in prediction, Yitagesu et al. applied multiple regressions to improve the ability of predicting soil properties, and better model the extent of their relationship [5].

This paper attempts to identify geotechnical characteristics of soils developed on different rocks and establish relationships among various properties in order to estimate soil strength capability in three lithological units. Multivariate approach using principal component analysis (PCA) and hierarchical classification methods are used to identify patterns, detect and classify new parameters into groups; and further propose regression models to determine CBR values in view of huge cost and labor.

2. Methodology

Soil samples (130 samples) were collected along the Ilorin-Lokoja highway (>300 km length) which spans across latitude 7°25′N-8°40′N and longitude 4°30′E-6°45′E. Simultaneously, Garmin GPS was used to record coordinates of sample locations. The topography ranges from a relatively flat to hilly, undulating terrain with elevation ranging between 100 and 700 m above sea level. The highway is overlying the Precambrian Basement rock of South Western Nigeria (**Figure 1**) and cut across three geologic units: the migmatite-gneiss complex (denoted by PCB), the metasediments/volcanic series (PCM) and the older granite series (PCG) [6].

Majority of the rock is the migmatite—gneiss essentially made up of migmatite and banded gneiss. Others are flaggy quartzite with biotite gneiss, undifferentiated schist, porphyritic granite (porphyroblastic), and medium-coarse grained biotite and hornblende granite. Temperature ranges from 25 to 35°C. Climate is dry to wet, with a mean annual rainfall of 1200 mm. Due to heavy rainfall, considerable moisture change occur in the soils which dries up at prolonged dry season. This induces soils susceptibility to volume changes.

2.1 Laboratory analysis

Geotechnical tests were carried out on air-dried (35–40°C) soil samples at the Soil Geotechnical Laboratory of Nigerian Building and Road Research Institute following the British Standard [7] Part 2: Clause 9.2, 4.5, 5.3, 5.4, and Part 4, Clause 3.3 and 3.4 methods. The soil engineering parameters obtained include natural moisture content, Atterberg limits, particle size distribution, free swell, compaction test and California Bearing Ratio.

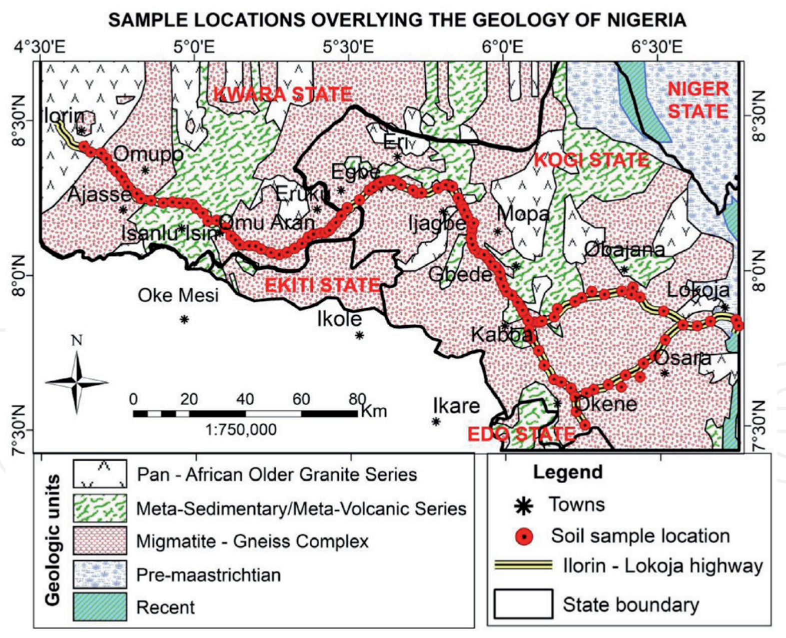

Figure 1.
Geology of Nigeria showing the study highway overlain by sampling points (red dots).

2.2 Statistical analysis

In SPSS statistical software, 20 soil parameters were explored and their relationships examined. Data transformation was applied to ensure equal influence on the model thus, fulfilling the linear model assumptions. The strength and relationship trends on the dataset were examined from Pearson correlation matrix and quantitative measures of linear associations determined. Principal component analysis (PCA) approach was incorporated to reduce the data with many variables, identify clusters, and transform the soil variables into new uncorrelated variables that preserve most of the information [8]. Components with eigenvalues >1 were retained and subjected to varimax rotation to maximize correlation between the factors and measured variables. Thereafter, Agglomerative Hierarchical Cluster (AHC) analysis was computed to identify analogous behavior among different soil characteristics and soil individuals using Ward's method and squared Euclidean distance as a measure of similarity between soils [9].

3. Results and discussions

The statistical summary of the laboratory test is shown in **Table 1**. The soils exhibited wide variations of data clustering around the mean value (1.08–88.6%) and high coefficients of variation (1.7–147%). The median of some parameters was lower than the mean value, indicating a low effect of abnormality on sampling values.

3.1 Particle size characteristics

In the migmatite-gneiss derived soils (PCB), gravel and coarse sand varied with coefficient of variation (CV) from 18.3 to 100% (<23.5%), medium to fine sand was between 8.0 and 86% (>32%) while the percentage of silt and clay were 3.2–50.8% (52.4%) and 0.9–34.6% (58.8%) respectively. However, the percentage of fines (<0.075 mm) ranged between 7.4 and 59.6% (48.0%). This proportion of

		Migmatite-Gneiss (PCB) = 87					Metasediment/Metavolcanic (PCM) = 33					Older Granite (PCG) = 11				
Properties	**Units**	**Min**	**Max**	**Mean**	**SD**	**CV**	**Min**	**Max**	**Mean**	**SD**	**CV**	**Min**	**Max**	**Mean**	**SD**	**CV**
NMC	**%**	2.6	22.7	11.8	4.5	38	3.1	18.4	12.1	4.1	34	2.4	16.2	7.5	4.3	56.8
Gravel		38.6	100	89.3	13.2	14.8	65	100	87	10.5	12.1	45	100	85.8	19.6	22.8
CS		18.3	99.2	80.4	18.9	23.5	43.1	100	74.6	15.3	20.6	19.4	100	77.5	25.8	33.3
MS		13.6	86	51.5	16.6	32.3	21.5	84.2	53.8	15.3	28.5	18.9	92.1	53.9	18.8	34.9
FS		8	79.5	28.9	14.3	49.4	15.2	71.1	36.8	13.3	36.1	14	41	28	7.9	28
Sand		20	87	59.5	14.3	24	25	81	50.1	13.9	27.8	31	81	57.6	17.4	30.2
Silt		3.2	50.8	17.1	9	52.4	6.1	44.3	20.3	8.4	41.2	2.4	24.5	15.5	7.5	48.6
Clay		0.9	34.6	12.3	7.3	58.8	1.8	28.7	15.2	7	46.3	1.2	18.8	10.8	6.6	60.8
Fines		7.4	59.6	23	11	48	11.7	57.7	28.6	10.4	36.5	8.2	32.7	21.8	7.5	34.6
Ac		0.1	8.5	1.1	1.2	110	0.2	7.9	0.9	1.4	147	0.2	5.1	1.2	1.4	123
Fsw		1.8	28.4	6.4	5.7	88.3	2.8	19.6	7.1	5.1	72.2	3.2	4.7	4	0.5	11.6
LL		13.4	69	28.4	11.7	41.1	13.4	48.5	30.3	9.7	32	16.5	32.4	23.2	5.7	24.5
PL		2.2	50	19	9.6	50.5	10.2	31.7	20.3	6.3	31	8.6	26.5	16.6	5.7	34.5
PI		1.6	39	9.4	6.5	68.7	2.1	30.1	10	7.3	72.6	2.6	13.4	6.5	3.4	51.9
wPI		0.3	31.9	5.1	4.6	90.6	0.9	25.3	5.8	5.7	97.8	0.9	7.3	3.5	2.1	60.6
BD	**mg/m^3**	1	2.9	2	0.3	15	1.5	2.2	1.9	0.2	8.5	1.7	2.1	1.9	0.1	5.9
DD		0.8	2.4	1.7	0.2	13.9	1.2	1.9	1.5	0.2	10.8	1.5	1.9	1.6	0.1	8
MDD		0.9	2.6	1.8	0.3	14.4	1.3	2.1	1.6	0.2	11.9	1.6	1.9	1.7	0.1	7.6

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		Migmatite-Gneiss (PCB) = 87					Metasediment/Metavolcanic (PCM) = 33					Older Granite (PCG) = 11				
MC	%	7.6	27	15.9	4.8	29.8	7.6	23.9	16.5	3.8	23	9.1	19.7	14.1	3.6	25.8
OMC		5.7	25	13	4.2	32.2	10.1	22.5	15	2.9	19.6	8.9	18.2	14	2.9	20.8
CBRu		12.5	70	50.8	12.4	24.4	17	75.1	47.7	11.9	25	30.4	58.6	52.5	8	15.3
CBRs		10	56.4	29	9.7	33.4	11.2	45	23.6	7.1	30	12.1	37.2	27.8	6.5	23.3
SP		1.5	15.4	5.5	2.8	51.9	2	11.6	6	3	49.8	2.3	7.9	4.3	1.6	38.4
Dr		0.7	1	0.9	0	4.6	0.9	1	0.9	0	3.2	0.9	1	1	0	1.7
Wr		0.8	2	1.3	0.2	19.7	0.8	1.6	1.1	0.2	20.9	0.6	1.6	1	0.3	26.8
LLr		0.7	6.3	2.7	1.1	42.8	1.3	9.1	2.9	1.7	58.3	2	7.8	3.9	1.9	48.3
PIr		1.1	8.1	1.7	1	56.2	1.1	2.6	1.5	0.4	25.7	1.1	2	1.5	0.3	21.5

Parameter abbreviations are described in the Abbreviations section

Table 1.
Statistical summary of soil properties.

fines is similar to those reported by Ige et al. [10]. In the metasediment derived soils (PCM), content of gravel and coarse sand were higher from 43 to 100% (<20.6%), while medium to fine sand was between 15.2 and 84.2% with 36% CV. Similarly, the percentage of silt and clay ranged between 6.1–44.3% (41.2%) and 1.8–28.7% (46.3%). The proportion of fines (11.7–57.7%; 36.6% CV) is relatively as high as the PCB origin. Similarly, the older granite rock (PCG) exhibited a wide range of gradation with gravel and coarse sand ranging between 19.4 and 100% (<33.3%). Medium to fine sand content was lower (14–92%) (CV = 28–34.9%) while percentage of silt and clay varied between 2.4–24.5% and 1.2–18.8% (CV = 48.6–60.8%), respectively. The amount of fines (8.2–32.7%) and CV (34.6%) are very low in this area.

On one hand, this granularity is similar to the work of Nwaiwu et al. [11] where the lateritic soils are enriched with gravel and sands ranging between 28.2–40% and 42.2–48% resp. However, the high percentage passing through No. 200 (0.075 mm) BS sieve suggests the soil is predominantly of fine materials and classified according to Unified Soils Classification System (USCS) system as clayey sand (SC), silty sand (SM) and silty, clayey sands (SC-SM). Other soil classes obtained include poorly graded sand with silt or clay (SP-SM, SP-SC), poorly graded gravel with clay or silty clayey gravel (GP-GC, GC-GM), silty gravel (GM), sandy lean or fat clay, (CL, CH), and sandy silt or elastic silt (ML, MH) that occurred in low percentage. Similarly, according to American Association of State Highways and Transportation Officials (AASHTO) system, the most dominating classes are A-2 and A-7 soils, hence rated as excellent to good and fair to poor materials for road use.

3.2 Consistency limits

A wide range of plasticity (**Figure 2**) characterized the inorganic silty clayey soils in the area. The liquid limit varied between 13.4 and69% with a lower range experienced in PCG derived soils (<32.4%), while plastic limit and plasticity

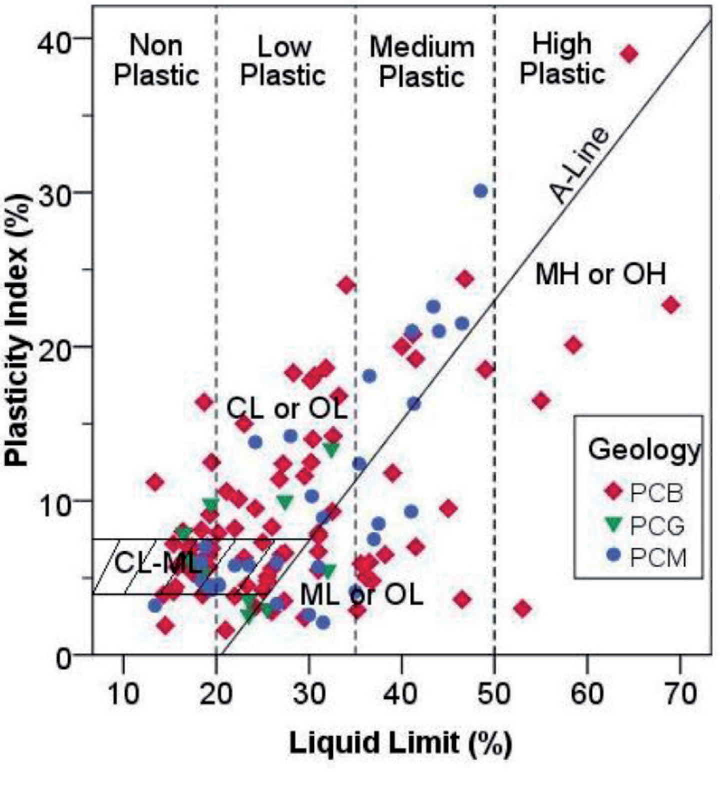

Figure 2.
Casagrande chart of plasticity-liquid limit relationship.

index at the PCB unit ranged between 2.2–50% and 1.62–39%, with mean values of 28.4, 19.0, and 9.4%, respectively (**Table 1**). The Casagrande plasticity chart revealed majority of the soils from the migmatite-gneiss origin placed above the A-line, indicating that they are composed of inorganic clay material and exhibited low to medium plasticity, implying low to medium swelling and compressibility. The moderate plasticity suggests low to medium dry strength, which could easily crumble under load thus leading to pavement failure and possible erosion under climatic threat. The distribution of the soil samples on the chart portrayed the variability in soil plasticity characteristics.

Moreover, free swell (Fsw) varied from 1.8 to 28.4% in PCB, 2.8–19.6% in PCM and 3.2–4.67% in PCG with mean values ranging from 6.4, 7.1, and 4.04%, respectively; while soil activity with mean values oscillated between 0.09–8.5 (1.1), 0.17–7.85 (0.9), and 0.2–5.08 (1.2) within the 3 units. The weighted plasticity index (wPI) value ranged between 0.25–31.9% (5.1%), 0.92–25.3% (5.8%), and 0.87–7.3% (3.5%) with mean from the 3 units. In PCB soils, activity tends to be higher than normal (8.5), high weighted plasticity index (wPI), plasticity ratio (PIr), and swelling potential (SP) indicating that the soils are active. The result of natural moisture content (NMC) (2.6–22.7%) is fairly high, considering the time of sample collection. This indicates the soil potential for water retention, which is a property of fine-grained soils. The high water content also suggests the presence of high water table earlier reported by Adams et al. [12]. These observations correspond with Bayamack et al. [13]. The derived plasticity parameters (wPI, PIr, SP, and LLr) represent the effective contribution of the plasticity of fines to the performance of the entire soil materials, depending on the amount of fines.

3.3 Compaction and California Bearing Ratio

The maximum dry density (MDD) of the soils from PCB area (**Table 1**) increases with mean to 2.6 mg/m^3 (1.77 mg/m^3) at 25% (13%) optimum moisture contents (OMC). These values are higher than those obtained in metasediment (PCM) and older granite (PCG) units with 2.1 mg/m^3 (1.6 mg/m^3) MDD and 22.5% (15%) OMC. The low density-moisture relationship implies low strength instigated by loose soils that are susceptible to erosion. The interaction of the subgrade with water greatly reduces strength and therefore promotes continuous failure of the overlying pavement. Few examples of soil compaction curves (**Figure 3**) illustrate distinct peak of maximum dry density at optimum moisture content.

The CBR values at 95% OMC after 48 hours of immersion varied between 10 and 56.4% for PCB, 11 and 45% for PCM and 12.1 and 37.2% for PCG soils (**Table 1**). The mean values within the three lithological units varied between 28.8, 23.6, and 27.8%, respectively. For unsoaked condition, the CBR varied in a higher rate from 12.5 to 75.0% within the 3 units. The result showed a reduction in strength due to soaking suggesting a probable drastic reduction in strength by more than half during wet condition and the penetration resistance becomes reduced due to excessive moisture. These values are similar to those found along Ado Ekiti-Akure road (27–100%) by Adams and Adetoro [14]. The low mean CBR value (<30%) suggests that the soils may not withstand ground vibrations when vehicular load is applied and reinforces its susceptibility to erosion. Soil improvement measures are therefore, envisaged for the stability of soils for adequate strength.

3.4 Simple linear regression

High statistically significant correlation (R > 0.70) is recorded among 13 soil attributes pairs (**Table 2**) such as gravel, coarse sand (CS), medium sand (MS), fine

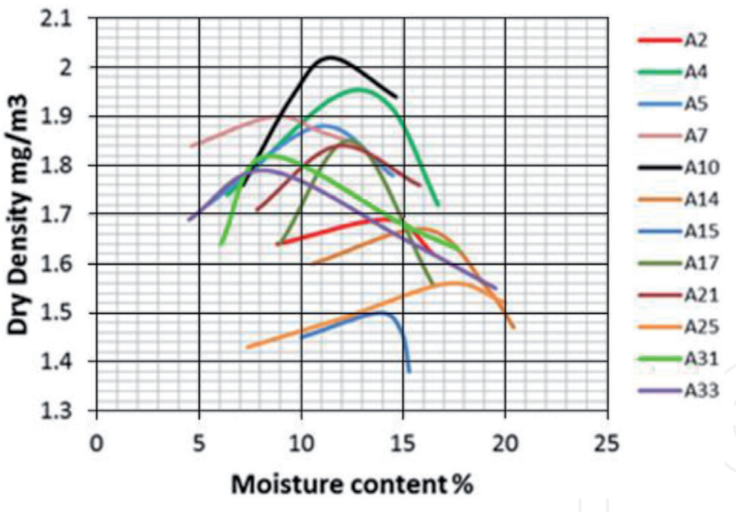

Figure 3.
Compaction curves of selected soil samples.

Properties	R values	Properties	R values
FS and fines	0.97	Fsw and CBRu	−0.62
Gravel and CS	0.96	Fsw and PI	0.61
BD and MDD	0.95	LL and PI	0.61
DD and MDD	0.95	NMC and clay	0.60
Silt and clay	0.94	MS and silt	0.60
Silt and fines	0.92	LL and MC	0.59
BD and DD	0.90	PL and MC	0.56
PI and wPI	0.89	PI and MC	0.56
Clay and fines	0.88	FS and sand	−0.56
Fsw and LL	0.88	NMC and LL	0.56
FS and silt	0.80	MS and clay	0.56
LL and PL	0.80	DD and OMC	−0.55
FS and clay	0.77	MDD and OMC	−0.54
CS and MS	0.75	Gravel and sand	0.52
MC and OMC	0.72	fines and OMC	0.52
Gravel and MS	0.70	FS and LL	0.52
LL and CBRu	−0.70	FS and PL	0.51
MS and FS	0.68	FS and OMC	0.51
MS and fines	0.68	NMC and Fsw	0.51
Fsw and wPI	0.68	Clay and Ac	−0.51
Fsw and PL	0.66	fines and LL	0.51
LL and wPI	0.64	NMC and fines	0.50
PL and CBRu	−0.62	Sand and fines	−0.50

Table 2.
Pearson significant correlation of soil properties.

sand (FS), silt, clay, fines, swelling potential (SP), free swell (Fsw), liquid limit (LL), plasticity index (PI), dry density (DD) and maximum dry density (MDD) which raises the issue of multi-collinearity. However, other parameters exhibit low correlations (R < 0.50) including sand, activity (Ac), plastic limit (PL), moisture content (MC) and optimum moisture content (OMC).

This could be attributed to the presence of high fine fractions and potential influence from environmental factors. The result corroborates with the observations obtained on gneiss derived laterite in Central Cameroun [15] and reaffirms the views of the earlier scholars that geotechnical properties of laterites depends on the parent materials, climate, vegetation, topography and duration of the laterization phenomenon [16].

3.5 Multivariate analysis of soil properties

3.5.1 Principal component analysis

Among the multivariate analysis techniques, principal component analysis is the most frequently used because it is the starting point in data mining which aims at minimizing the dimensionality of the data. Seven principal components (PCs) were extracted with eigenvalues >1 which accounted for 83.8% of the total variance of data (**Table 3**).

However, the first five PCs accounted for >70% of variability in measured soil properties. While PC1 explained 33.4% of the total variance with fines as the major contributing variable (R = 0.87), PC2 accounted for additional 14.7% of the total variance with plasticity index (PI) as the second major contributing variable (R = 0.70). In PC3, 11.4% was accounted for, with coarse sand (CS) contributing more (R = 0.67). Other components accounted for <15% and as such were removed as they explained less variance than individual variable in the dataset [8].

Based on the communality estimates, the five factors explained more than 90% of variance in MDD, PI, LL, DD, BD, FS, CS, SP, fines and gravel; > 80% in wPI, PL, Fsw, Wr, LLr, NMC, sand, silt and clay; > 70% in MS, MC, CBRu, and Dr.; above 60% in PIr, OMC, and Ac; and 53% in CBRs (**Table 4**). According to Johnson and Wichern [17], a high communality suggests that a high proportion of the variability is explained by the factor with a higher preference over a low communality estimate. By implication, the factors fairly explained the variance in soaked CBR and as such required a regression model to predict the property. The values obtained are similar to those obtained by Shukla et al. [18].

The coefficient of linear correlation between the variables and their factors (**Table 4**) give a meaning to the principal components. The parameters are well represented and explained by the factorial axes on the correlation circle (**Figure 4**).

	Initial eigenvalues		
PCs	**Eigen values**	**% of Variance**	**Cum % of variance**
1	9.0	33.4	33.4
2	3.9	14.7	48.1
3	3.1	11.4	59.5
4	2.5	9.2	68.7
5	1.6	5.8	74.5
6	1.4	5.2	79.6
7	1.1	4.2	83.8

Table 3.
Eigenvalues and proportions of variance explained by PCA.

Soil variables	PC1	PC2	PC3	PC4	PC5	Communalities
SP	0.93	—	—	—	—	0.91
PI	0.87	—	—	—	−0.39	0.95
LL	0.87	—	—	—	0.33	0.94
Fsw	0.86	—	—	—	—	0.85
wPI	0.84	—	—	0.34	—	0.89
CBRu	−0.60	—	—	—	−0.32	0.74
MDD	—	0.96	—	—	—	0.97
DD	—	0.94	—	—	—	0.94
BD	—	0.93	—	—	—	0.91
OMC	0.35	−0.60	—	—	—	0.68
MC	0.43	−0.56	0.32	—	—	0.76
LLr	—	—	−0.78	—	0.39	0.82
Ac	—	—	−0.75	—	—	0.68
C	—	—	0.72	0.39	—	0.85
NMC	0.48	—	0.73	—	—	0.80
S	—	—	0.67	0.42	—	0.86
Fines	0.32	—	0.61	0.43	0.36	0.96
FS	0.36	—	0.53	0.40	0.42	0.91
G	—	—	—	0.94	—	0.94
CS	—	—	—	0.94	—	0.95
MS	—	—	—	0.78	—	0.79
S	—	—	−0.41	0.47	−0.47	0.85
PIr	—	—	—	—	−0.77	0.68
PL	0.43	—	—	—	0.72	0.87
Wr	—	—	—	—	0.89	0.82
Dr	—	—	—	—	0.83	0.74
CBRs	−0.39	0.37	—	—	0.48	0.53

Table 4.
Proportion of variance and communality estimates of soil variables.

This graph shows three groups of variables, suggesting the existence of correlation between them.

PC1 positively correlates (> 0.84) with SP, PI, LL, Fsw, wPI and MC, NMC, PL, CBRu (**Table 4**) and is termed plasticity parameters. PC2 demonstrated very high positive correlation with soil densities (MDD, DD, BD) (> 0.93) and negatively correlated with moisture contents (MC, OMC) (<−0.6) and is termed moisture-density or compaction parameters since the variables are important functions of soil moisture density. It also showed moderate positive loading from CBRs (0.37) resulting from significant correlation between MDD and OMC. Similarly, PC3 defined as fine gradation parameters showed highest positive correlation (0.72) with clay and NMC; FS, silt and fines (0.53, 0.61, 0.67); and negatively correlated (>0.75) with activity and liquid limit ratio (LLr). These variables are a function of fine soil texture. PC4 and PC5 are positively correlated (>0.70) with coarse materials (gravel, coarse and medium sand), referred to as coarse soil texture.

3.5.2 Agglomerative hierarchical analysis

Agglomerative hierarchical clustering (AHC) of the principal components showed a representation of the soil variables in homogenous classes where soils of same class exhibited similar values. The three major classes distinctively categorized by the AHC are depicted by dendrogram (**Figure 5**) which also displayed the cohesiveness of clusters formed. Class 1 soils were characterized by fines (silt, clay), plasticity and moisture contents (MC, OMC) parameters. Approximately, 47% of these soils were of the migmatite-gneiss derived origin (PCB) with a p-value <0.001.

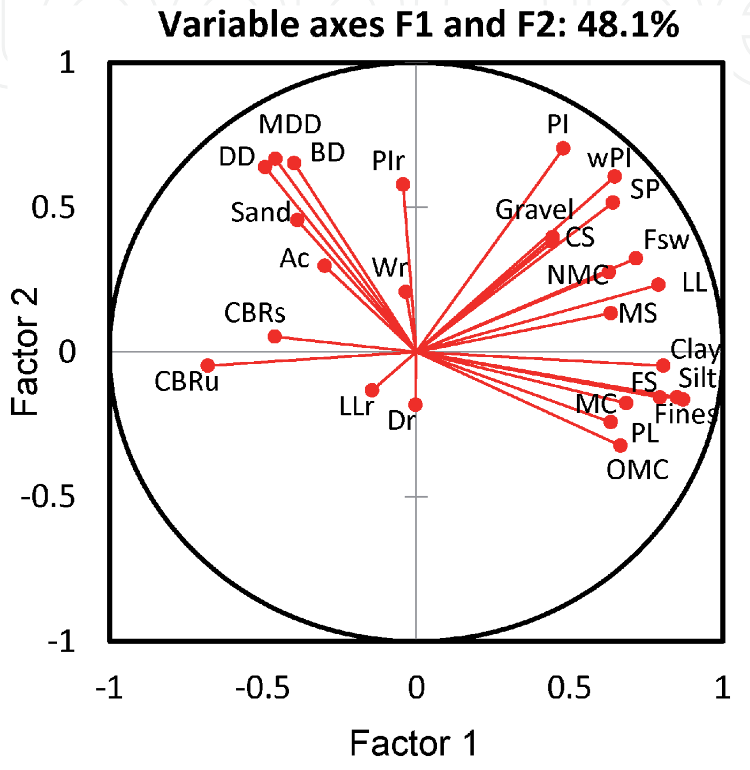

Figure 4.
Score plot and correlation circle obtained with PCA.

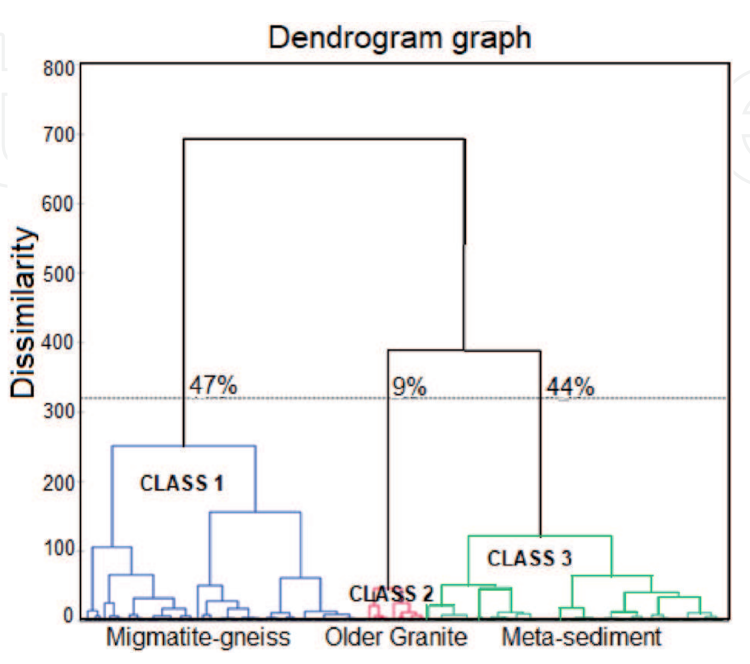

Figure 5.
Dendrogram of the studied soil variables.

Similarly, Class 3 showed significant clustering with densities (BD, DD, and MDD) parameters of mainly metasediment origin (PCM). Class 2 soils performed poorly owing to few parameters and p-value >0.05, which might be from the older granite derived origin (PCG).

3.5.3 Multiple regression analysis

Following stepwise regression method, five models were generated in (Eqs. 1–5). The result indicated that between 25 and 33% of the variation in soil properties was explained by the combination of these predictors. In Eq. 5, 70% training dataset accounted for 33% variance with coefficient of determination (R^2 = 0.33) and root mean square error of performance (RMSE = 7.8). Given the p-value <0.001 computed by analysis of variance (ANOVA), the significance level (5%) and the low bias (0.05), the prediction by the explanatory variables is significant.

$$CBRs = 0.008LL - 0.29PL - 0.5wPI - 0.1OMC + 6.87MDD + 25.2 \quad (1)$$

$$CBRs = 6.47MDD - 0.014LL - 0.32PL - 0.59wPI - 0.12OMC + 0.12Fsw + 26.7 \quad (2)$$

$$CBRs = 8.51MDD - 0.1LL - 0.2PL - 0.56wPI - 0.1OMC + 0.11Fsw + 38.1Dr - 0.13Wr - 0.2LLr + 0.88PIr - 14.02 \quad (3)$$

$$CBRs = 0.062LL - 0.51PL - 0.82wPI - 0.28Fsw - 38.06 \quad (4)$$

$$CBRs = 0.31Fines + 1.88Ac + 0.41Fsw - 0.298LL - 0.25PL - 0.73wPI - 0.5OMC + 2.11MDD + 36.03 \quad (5)$$

4. Conclusion

All the variables exhibited a large variation of data clustering around the mean value and high coefficients of variation. The soils within the area are predominantly very fine sands with a high percentage passing through No. 200 (0.075 mm). The natural moisture content and soil activity are moderately high which may be due to soil potential for retaining water. The result of Atterberg limits shows most of the soils classified as inorganic clayey soils under A-2 and A-7 groups. Their variability is locational and between lithology which reflects the influence of parent materials and pedogenic activities. Application of correlation analysis has allowed for the determination of the relationship between index properties, compaction and CBR and for deriving multivariate relationships for the assessment of CBR based on these parameters. Strong correlation existed among index properties but showed weak relationship with CBR under soaked condition. Principal component analysis categorized the measured soil parameters into five major groups for which first three components explained more than half of the total variance. Hierarchical classification validated the clustering of different individuals/variables based on the parent material. Five empirical models were obtained between soaked CBR and index parameters. The coefficient of determination (R^2) and root mean square error (RMSE) revealed that the models obtained were able to predict the target variable to a good degree of accuracy. The pavement challenges witnessed on the highway are attributable to the poor subgrade, the influence of geology and lack of drainage. It is therefore recommended to stabilize the soil with cement or lime in order to improve the strength and provide drainage along the road corridor.

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Conflict of interest

The authors declare no conflict of interest.

Abbreviations

Grain size distribution parameters according to their diameter

G	gravel size (4.0–13.2 mm)
CS	coarse sand size (0.6–2 mm)
MS	medium sand size (0.2–0.425 mm)
FS	fine sand size (0.075–0.2 mm)
S	silt size (0.002 mm)
C	clay size (0.001 mm)

Atterberg limit parameters

LL	liquid limit
PL	plastic limit
PI	plasticity index
wPI	weighted plasticity index [(PI × % passing 0.425 mm)/100]
NMC	natural moisture content
Fsw	free swell

Compaction parameters

MDD	maximum dry density
DD	dry density
BD	bulk density
OMC	optimum moisture content
MC	moisture content
CBRu	unsoaked California Bearing Ratio
CBRs	soaked California Bearing Ratio

Other derived parameters

LLr	liquidity ratio (LL/MC)
PIr	plasticity ratio (LL/PL)
Wr	moisture ratio (MC/OMC)
Dr	density ratio (DD/MDD)

Ac	activity (PI/clay fraction)
SP	swelling potential (PI/PIr)
SD	standard deviation
CV	coefficient of variation [(SD/mean) × 100]
R	correlation coefficient
R^2	coefficient of determination
RMSE	root mean square error

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