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LAND CLAYEY DEPOSITS COMPRESSIBILITY INVESTIGATION USING PRINCIPAL COMPONENT ANALYSIS AND MULTIPLE REGRESSION TOOLS

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Summary

The settlement and compressibility magnitude of the major clayey and marly sediments in Tebessa area (N-E of Algeria) depends on several geotechnical parameters such as compression Cc and recompression Cs indices. The aim of this study was to investigate the parameters related to soil compressibility through tools of statistical analysis, which save time in comparison to multiply repeated laboratory tests. The study also adopted the principal component analysis (PCA) method to eliminate a number of uncorrelated variables that have no influence on the compressibility magnitude, or their impact is insignificant. The highest mean correlation coefficients were obtained for different contributing parameters. Multiple regression analysis has been performed to obtain the best fit model of the output Cc parameter taking into account the best correlation by adding parameters as regressors to reach the highest coefficient of regression R^2. The final obtained model of the present case study gives the best fit model with R^2 of 0.92 which is a better value compared to different published models in the literature (R^2 of 0.7 as maximum). The chosen input parameters using PCA combined with multiple regression analysis allow identifying the most important input parameters that noticeably affect the soil compression index, and provide with the best model for estimating the Cc index.

Keywords

compressibility index • geotechnical parameters • principal component analysis PCA • multiple regression models

1. Introduction

Fine-grained soils in Tebessa valley North-East of Algeria are widespread throughout the province, though the clayey layers and marls present the main geological depositions. Many surface settlements and differential movements occur under increased loadings or can result from the shrinkage swelling phenomenon of the clayey soils [Berrah et al. 2018, Berrah et al. 2021]. As is said in the literature, consolidation settlement occurs in saturated or near-saturated fine-grained soils due to volume change caused by load-induced squeezing out of water from the pore spaces over a relatively long period of time, and is followed by secondary compression [Barron 1948, Duncan 1993, Huang and Zhao 2021, Sivakugan and Ameratunga 2021]. This can be a hazard in semi-arid regions, where large vertical displacements of soil cause damages observed in different structures [Mola Abasi et al. 2016]. Therefore, knowledge of compression index is very important, because it supports designing all shallow foundations, underground structures and deep excavation where the compressibility magnitude may be estimated directly or indirectly using the laboratory tests and empirical equation models. Several equations have been formulated in order to predict the compressibility index and potential using simple geotechnical parameters under sophisticated modeling techniques such as regression analysis, multiple linear regression, artificial neural networks, and Bayesian probabilistic approach [Sousa 2007, Yasser and Hosam 2019, Mandhour 2020]. The empirical relationships and correlations between soil parameters have been used for a long time in geotechnical engineering practice with good reliability.

Several researchers have tended to correlate compression index with various soil parameters and index properties in terms of single and multiple regressions (such as liquid limit, plastic limit, plasticity index, water content, void ratio, etc.), but most of these investigations were specific to regional clays, so due to varying soil properties these correlations are cannot be generalized and have some limitations [Skempton 1944, Nishida 1956, Yamagutshi 1959, Azzouz et al. 1976, Bowles 1989, Solanki et al. 2008, Park and Lee 2011, Kalantary and Afshin 2012, Widodo and Abdelazim 2012, Arpan and Sujit 2012, Sari and Firmansyah 2013, Bryan et al. 2014, McCabe et al. 2014, Nesamatha and Arumairaj 2015, Kumar et al. 2016]. Since the existence of soil differs from place to place due to geological origin, the regional empirical correlations proposed in the literature may be useful for obtaining quick estimations of the compression index.

The following research paper aims to use the data set of 118 undisturbed samples collected from Tebessa province and tested in the public laboratory to obtain physical properties such as moist and dry unit weight (γ_d, γ_h), water content (*w*), degree of saturation (*Sr*), fine fraction under 0.08 mm, initial void ration (e_0), liquid limits (*WL*), plasticity index (*IP*), specific gravity (*Gs*), the mechanical properties such as the preconsolidation pressure (*Ps*) and indices of compressibility Cc and Cs measured in oedometer tests. First the matrix data has been analyzed using a combination of statistical tools and approaches proceeding with general statistics, then the principal component analysis PCA was investigated to reduce a large set of variables to a small set that still contains most of the information of the large set. Finally, the significant variables were used with multiple regression analysis to find the best fit models that allow the estimation of engineering compression index Cc of soils. The final model proposed in this research work may save time, as well as money, and serve the public laboratory as a fast tool for predicting the compression index through indirect methods.

2. Methods and materials

2.1. Principal component analysis

The Principal Component Analysis (PCA) is one of the best-known multivariate analysis techniques, also known as eigenvector analysis for removing the adverse effects of collinearity while summarizing the main aspects of the variation in the regressor set [Draper and Smith 1981, Chatterjee and Price 1991, Borůvka et al. 2005, Jolliffe 2016]. Principal components (PC) are uncorrelated and ordered so that the first few retain most of the variation present in all the original variables. The number of the PC is based on the Kaiser's values (variances) higher than 1 [Jolliffe 2002]. The results are represented by circles of correlations which represent the projections of the variables on the first 2 components, a variable that is projected near the circle and close to a principal axis is well represented on it. The PCA has been used in several other soil parameters investigation [Kariuki 2004, Kariuki et al. 2006, Chang et al. 2001], when one has a large number of dimensions. In such cases one needs to have some mathematical means of ascertaining the degree of variation in the multivariate data along different dimensions. This is achieved by looking at the eigenvalues. An eigenvalue can be understood as indicating the length of the axis, while the eigenvector specifies the direction of rotation. With the PCA technique the number of variables can be reduced and the relations among input variables eliminated by developing a set of new variables that are linear functions of the original variables. The number of new variables will not exceed the original number.

Table 1. Summary statistics of 118 analyzed data of the studied soil

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
γd (kN/m^3)	118	0	118	14.100	20.200	16.951	1.273
γh (kN/m^3)	118	0	118	17.300	21.900	19.733	1.022
W %	118	0	118	8.430	32.300	19.292	4.502
FF < 0.08 mm	118	0	118	61.200	98.500	88.297	9.662
WL %	118	0	118	33.000	83.000	52.568	10.304
IP%	118	0	118	16.000	60.000	33.686	8.079
e0	118	0	118	0.355	1.066	0.653	0.144
Cs	118	0	118	0.005	0.184	0.065	0.039
Cc	118	0	118	0.012	0.427	0.194	0.103
Pc (KPA)	118	0	118	12.000	360.000	178.292	53.330
Gs	118	0	118	2.657	2.790	2.709	0.024
Sr %	118	0	118	52.000	100.000	81.669	11.493

Descriptive analysis of all data sets collected from Tebessa area was performed by classical statistics, determining the minimum and maximum values, and calculating the values of mean and the standard deviation presented in Table 1.

In this first step statistical tests were carried out to give a general overview and present as many as possible parameters that are known to have any relationships with the compression index Cc of any clayey soil samples of the studied area. These variables are chosen as independent variables such as preconsolidation pressure (*Pc*), degree of saturation (*Sr*), the specific gravity (*Gs*), dry and wet unit weights ($\gamma_{d,} \gamma_h$), water content (*w*), plasticity index (*IP*), liquid limit (*WL*), the fine fraction (*Ff*) in % < 80μm, initial void ration (e_0) and the recompression index (*Cs*).

2.2. Application of published empirical model

From all models published in the literature, the best fit model that can describe the goodness of fit of the compressibility index of the studied soil region is the model of Azzouz et al (1976) and Al-khafadji et al. [1992] with an R^2 of 0.7 where equations used to predict the Cc are based on the initial water content *w*, initial void ration e_0 and the liquidity limit *WL*.

3. Results and discussion

3.1. Statistical analysis of data samples

The first result that should be considered here is the correlation matrix. It can be observed right away that γ_d has an important regression with γ_h (R^2 = 0.84). Also, both indices are negatively correlated with some parameters, such as water content w, the limit of liquidity *WL*, plasticity index *IP*, void ratio e_0, swelling index C_s, and compression index C_c, but also a noticeably low correlation with the remaining parameters (P_c, G_s, S_r). These variables could be removed without any effect on the quality of the results (Table 2). In this work, the first eigenvalue equals 5.88, and represents 48.99% of the total variability. This means that if the data is represented only on one axis, it will be still able to see the percent of the total variability of the data. Each eigenvalue corresponds to one factor, and each factor to one dimension. However, the factor is a linear combination of initial variables, and all the factors are uncorrelated (R = 0). The eigenvalues and the corresponding factors are sorted by descending order of percentage of the initial variability.

Ideally, the first two or three eigenvalues will correspond to a high percent of the variance, ensuring that the maps based on the first two or three factors are a good quality projection of the initial multi-dimensional Table 1. In this part of the research the first two factors allow representing 56% to 63% of the initial variability of the data. This is a good result, but still one has to be careful while mapping the interpretation as some information might be hidden in the following factors.

Table 2. PCA correlation matrix

Variables	γ_d (kN/m³)	γ_h (kN/m³)	*W* %	*Ff* % < 80 µm	*WL*%	IP%	e_0	Cs	Cc	Pc (kPa)	Gs	Sr
γ_d (kN/m³)	1	0.8489	−0.786	−0.3718	−0.483	−0.468	−0.871	−0.648	−0.711	0.0765	0.1683	0.0128
γ_h (kN/m³)	0.8489	1	−0.584	−0.2581	−0.379	−0.352	−0.803	−0.618	−0.685	0.0811	0.1531	0.3012
W %	−0.7866	−0.5846	1	0.4297	0.4600	0.4756	0.8341	0.6603	0.6751	0.0758	−0.039	0.4807
***Ff* < 0.08 mm**	−0.3718	−0.2581	0.4297	1	0.3665	0.5025	0.3993	0.4778	0.5418	0.1203	0.1416	0.1793
***WL* %**	−0.4835	−0.3795	0.4600	0.3665	1	0.9381	0.4541	0.6702	0.5957	0.0902	0.0775	0.1561
***IP* %**	−0.4682	−0.3523	0.4756	0.5025	0.9381	1	0.4588	0.7026	0.6541	0.1841	0.0902	0.1920
e_0	−0.8717	−0.8036	0.8341	0.3993	0.4541	0.4588	1	0.6886	0.8123	−0.0229	−0.049	0.0117
Cs	−0.6480	−0.6185	0.6603	0.4778	0.6702	0.7026	0.6886	1	0.8453	0.0214	−0.0766	0.0997
Cc	−0.7113	−0.6850	0.6751	0.5418	0.5957	0.6541	0.8123	0.8453	1	0.1011	−0.054	0.0145
***Pc* (kPa)**	0.0765	0.0811	0.0758	0.1203	0.0902	0.1841	−0.022	0.0214	0.1011	1	−0.055	0.2152
Gs	0.1683	0.1531	−0.039	0.1416	0.0775	0.0902	−0.049	−0.076	−0.054	−0.0558	1	0.0795
Sr	0.0128	0.3012	0.4807	0.1793	0.1561	0.1920	0.0117	0.0997	0.0145	0.2152	0.0795	1

According to Factor Loadings Correlations between variables and factors, and the Eigenvalue vectors, the variables with negative contribution are the factors F1, F2 respectively (γ_d, γ_h, e_0, C_c, G_s), the other factors represented by (*w*, *Ff* (%) < 0,08 mm, W_L, *IP*, C_s, P_c, S_r) have a positive contribution in this analysis. It is important to notice the high and strong correlation between the parameter W_L and I_P, also the good correlation between C_c and (e_0, C_s, *IP*). The reason for this is that neither the position of points in space, nor the degrees of similarity between the parameters are taken into account by this method.

The first map is called the correlation circle (below on axes F1 and F2). It shows a projection of the initial variables in the factors space. When two variables are far from the center: if they are close to each other, they are significantly positively correlated (R close to 1); if they are orthogonal, they are not correlated (R close to 0); if they are on the opposite side of the center, they are significantly negatively correlated (R close to –1).

When the variables are close to the center, some information is carried on other axes, so here any interpretation might be risky.

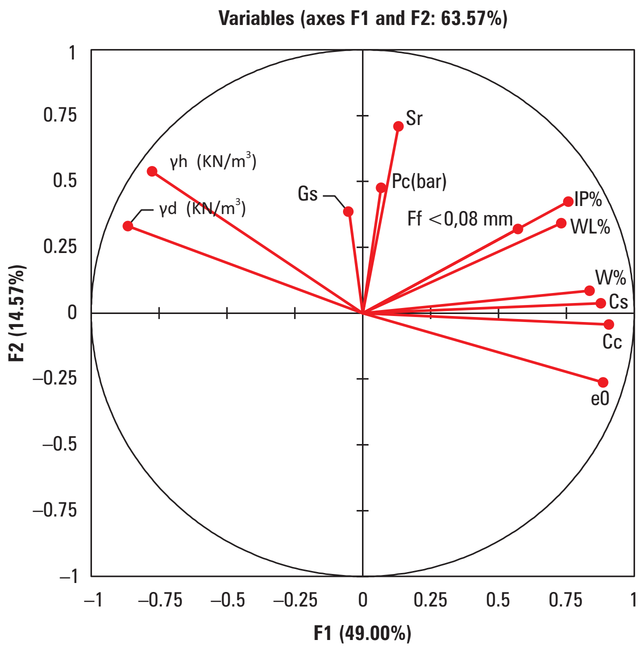

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Fig. 1. Circle of correlation of variables

The first component was negatively correlated with the variable (γ_d (kN/m^3) and γ_h (kN/m^3), slightly negative with the (G_s), and positively correlated with other variables (Fig. 1). Thus, the effect of the variation factor of the variable (γ_d (kN/m^3) led to a reduction of its values, while the values of other variables increased. This component can be interpreted as a response related to the initial soil proprieties, and the standard procedure applied to obtain the compressibility value, according to [Horn and Lebert 1994, Cerato and Lutenegger 2004, Sridharan and Gurtug 2005, Bharat et al. 2020].

3.2. Effects of multicollinearity in the multivariate analysis

The effects of multicollinearity in variables occur if there is a linear relationship between them. It is an extension of the simple case of collinearity between two variables. Multicollinearity creates a problem in regression analysis when independent variables are highly correlated, the relationship between the independent variables and the dependent variables is distorted by a very strong relationship between the independent variables [Montgomery et al. 2021], rendering our interpretation of relationships likely to be incorrect.

By examining the amount of variability in one the independent that is not explained by another independent, the multicollinearity of variables can be detected using tolerance for each independent variable. Tolerance values with less than 0.1 indicate collinearity are used in several methods (linear regression, logistic regression, discriminant factor analysis) as a filter criterion for variables. If collinearity is discovered in the regression output, the interpretation of the relationships should be rejected as false until the issue is resolved. If a variable has a tolerance lower than the fixed threshold, it is calculated by taking into account the variables already used in the model. At the same time, the inverse of the tolerance is used in this study as the variance inflation factor VIF, and it is more responsive towards numerical variables when checking the multicollinearity (Table 3). This issue can be resolved by combining highly correlated variables through principal component analysis, or by omitting a variable in the analysis. The PCA leads to obtaining the six highly correlated parameters as shown in the correlation circle in Figure 2 and in the scree plot in Figure 3 which displays the factor's number retained in factor analysis (FA) as principal components where the first two factors represent 82.80% of the initial variability in the data.

Table 3. Multicollinearity statistics

	γ_d (kN/m^3)	γ_h (kN/m^3)	*W*%	*FF* < 0.08 mm	*WL*%	*IP*%	e_0	*Sr*
Tolerance	0.212	0.155	0.068	0.666	0.157	0.134	0.095	0.234
VIF	4.725	6.458	14.693	1.502	6.353	7.483	10.520	4.276

It can be observed that the contributed parameters are – as mentioned in the circle – divided into three groups (γ_d, γ_h), (*Ff*, *WL*, *IP*), (*Cc*, e_0). Eigenvalues obtained from the matrix represent how variables in a differential equation affect each other.

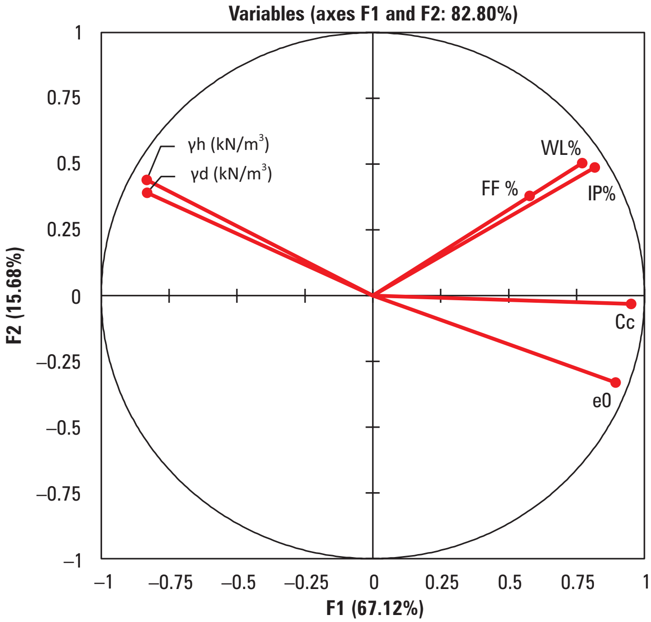

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Fig. 2. Correlation circle

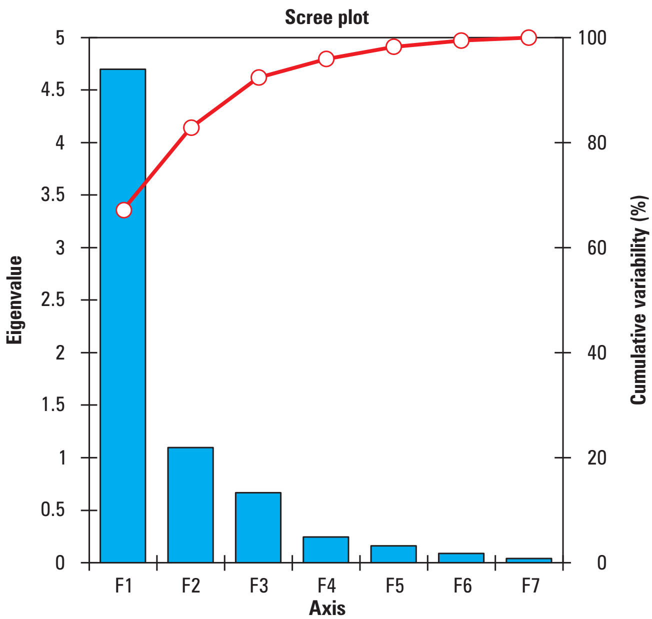

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Fig. 3. Scree plot of data

3.3. Multiple regression analysis and discussion of results

Multiple regression analysis was introduced to derive an equation that can be used to predict the compressibility index from known soil physical properties. It is a very useful tool in reducing the number of variables involved in the compressible soil phenomenon. The variables are reduced to the necessary minimum of factors that can adequately explain the variation in compressibility properties of the studied soils. Tests were carried out to correlate the compressibility index with a combination of variables.

The test of Hypothesis in a linear regression model is used to confirm if the coefficients are significant, Figure 4 shows the negative contribution of variables (γ_h, WL), whereas the other factors (e_0, Ff, IP, γ_d) have a positive contribution in this analysis.

For all statistical models shown in Table 4n single or multiple linear regression models are satisfactorily fulfilled the F-test.

Table 4. Different models proposed for the prediction of the compressibility index by the use of multiple regression analysis

	Goodness of fit statistics										
Models Equation	**ANOVA**										
1 variable	R^2	Ad. R^2	Se	F	P v	VIF					
$Cc = -0.187 + 0.575 \cdot e_0$	**0.81**	0.81	0.017	508.07	< 0.0001						
2 variables											
$Cc = -0.069 - 0.005 \cdot \gamma_h + 0.55 \cdot e_0$	**0.81**	0.81	0.073	253.4	< 0.0001	3.33	3.33				
$Cc = -0.19 + 0.00017 \cdot \gamma_d + 0.58 \cdot e_0$	**0.81**	0.81	0.064	251.85	< 0.0001	2.91	2.91				
$Cc = -0.36 + 0.0025 \cdot Ff + 0.50 \cdot e_0$	**0.87**	0.86	0.036	388.79	< 0.0001	1.20	1.20				
$Cc = -0.25 + 0.002 \cdot WL + 0.49 \cdot e_0$	**0.86**	0.86	0.039	376.15	< 0.0001	1.34	1.34				
$Cc = -0.24 + 0.004 \cdot IP + 0.45 \cdot e_0$	**0.90**	0.89	0.035	519.91	< 0.0001	1.41	1.41				
6 variables											
$Cc = -0.3 - 0.01 \cdot \gamma_h + 0.01 \cdot \gamma_d + 0.002 \cdot Ff - 0.001 \cdot WL + 0.004 \cdot IP + 0.4 \cdot e_0$	**0.92**	0.92	0.07	226.58	< 0.0001	4.19	3.71	1.49	6.24	7.34	4.35

Notations:
Cc: compressibility index , γ_d: dry unit weight in kN/m³, γ_h: wet unit weight in kN/m³, W: water content in %, Ff(%) < 0.08 mm: fraction fine in %, WL: liquidity limit in %, IP: plasticity index in %, e_0: void ratio

The coefficient of determination (R^2) has been used as a global statistic to assess the fit of the model. However, this value will increase when factors are added as regressors. The R^2 for the obtained model is 0.92, and the equation can be formulated as following:

$$Cc = -0.28 - 0.01\,\gamma_h + 0.01\,\gamma_d + 0.002\,Ff - 0.001\,WL + 0.004\,IP + 0.4\,e_0 \quad (1)$$

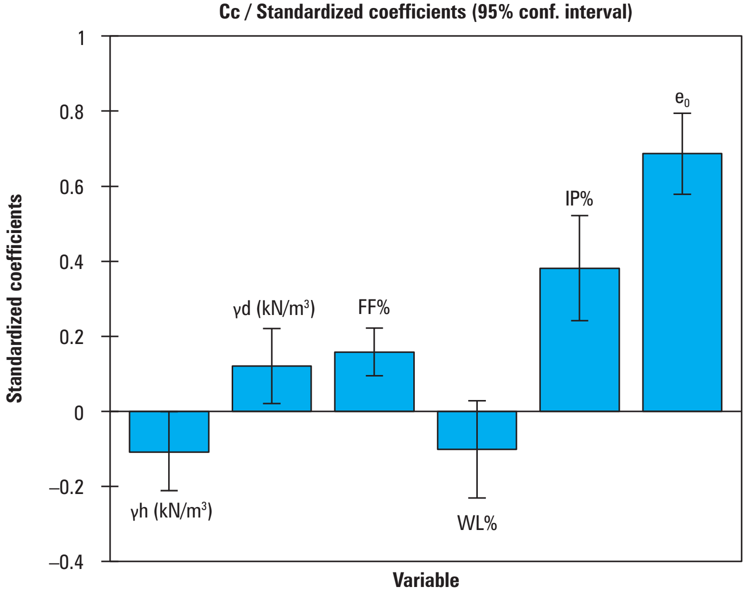

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Fig. 4. Standardized coefficients (Cc)

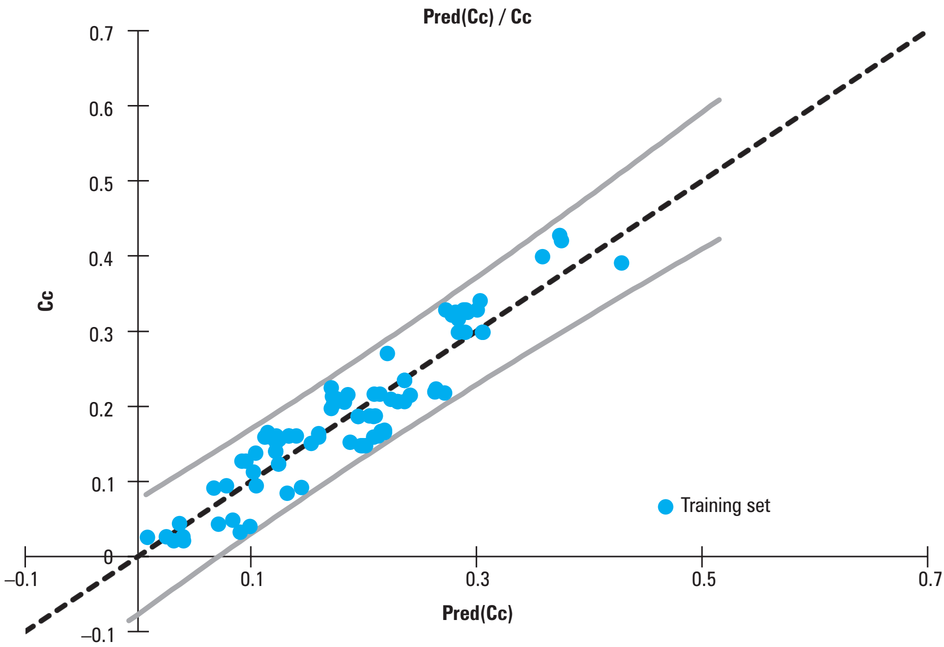

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Fig. 5. Measured C_c vs. predicted C_c

The coefficients of variables lie in the range of 95% confidence level. The overall tests indicated that the variables fulfilled the requirements of the t-test and F-test, A simple routine is needed to effectuate tests that can be performed on disturbed engineered samples to achieve the same purposes.

The empirical models obtained in the present study include 118 data samples compiled from different geotechnical tests for all parameters that appear primarily in relation to the prediction of compressibility coefficient from index properties of soils. In some cases the proposed empirical models cannot be applied appropriately to all soils due to different soil conditions and/or testing procedures. It was hoped that the final model would be acceptable and possible to generalize. Figure 5 shows the best fit correlation between the predicted and measured compression index.

4. Conclusions

The results of principal component analysis using physical soil parameters as input show a strong correlation in the first principal axes, absorbing about 63.57% of the total variance. However, using a multicollinearity study provieds with six highly correlated parameters or principal components, where the first two factors represent 82.80% of the initial variability in the database. PCA allows grouping the best-correlated parameters into three categories; the first group is composed of dry and wet unit weight (γ_d, γ_h), the second consist of Atterberg limits and the percent of fine fraction (*Ff*, *WL*, *IP*), and the last group is represented by compression index and the initial void ratio (Cc, e_0). PCA proved to be useful for the characterization of soils based on their properties. The results obtained from the PCA tools were analyzed using the multiple regression analysis methods to predict and obtain possible correlations between geotechnical soil parameters. The compression index parameter is taken as the output parameter and the other variables proved by the PCA analysis that actually affect the output parameter were taken to be independent and correlated as input parameters. The multiple regression is established for developing empirical models to indicate a reliable assessment of the compressibility of the studied clayey soil in Tebessa area. It indicates the best fit correlation compared to all other empirical published models in the literature, with an R^2 of 0.92, reported from the model of wet unit weight and index of plasticity. In general, the model can be used for all soil conditions. Combining the two considered tools PCA and multiple regression analysis allows to find the best model to predict the compression index parameter from several physical properties, multiple regression analysis can validate the results and conclusions obtained from the application of PCA tool. This methodology of obtaining the model seems to be a useful and powerful tool for estimating engineering properties of compressible soils, and it can be applied to other research in different engineering parametric correlation problems.

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