Kufa Journal of Engineering
Vol. 13, No. 2, April 2022, P.P. 73-83
Article history: Received 5 February 2022, accepted 6 March 2022

PREDICTING SOIL COMPRESSIVE STRENGTH OF SULAIMANI GOVERNORATE, IRAQ

Nihad B. Salih[1] and Yaseen A. Hamaamin[2]

1 Department of Water Resources Engineering, College of Engineering, University of Sulaimani, Sulaimani City, Northern Iraq. Email: nihad.salih@univsul.edu.iq.

2 Civil Engineering Department, College of Engineering, University of Sulaimani, Sulaimani City, Northern Iraq. Email: yassen.amin@univsul.edu.iq

HTTPS://DOI.ORG/10.30572/2018/KJE/130206

ABSTRACT

Soils shear strength is one of the significant properties for geotechnical engineering purposes. Shear strength components, cohesion and angle of internal friction, are used in soil's bearing capacity determination, which is the key factor in construction developments. Unconfined compression test is a common type of soil shear testing to obtain the unconfined compressive strength (UCS) and cohesion (C). UCS is a widely used soil's geotechnical characteristics for design and practice of soil foundation of construction projects. The laboratory determination of UCS is tiresome, which requires very-accurately prepared field sample and in some way a time-consuming, the purpose of this study is established. This study aims to establish a predictive model for Sulaimani soil UCS determination using multiple linear regression methods. Models were created from undisturbed fine-grained soil samples collected from three different locations in Sulaimani Governorate in the Kurdistan Region of Iraq. The accuracy of the established equations is tested by utilizing three different versions of coefficient of determinations namely R^2, adjusted-R^2 and predicted-R^2. Box-Cox statistical transformation of data enhanced the performance of the regression models. The results showed a reliability of the transformed-data regression model to predict UCS with R^2 of 0.80, $R^2_{-adjusted}$ of 0.80 and $R^2_{-predicted}$ of 0.77.

KEYWORDS

Unconfined compressive strength, Prediction models, Fine-grained soil, Sulaimani soil.

Article information: This manuscript was handled by Abbas Al-Hdabi, Managing Editor.

1. INTRODUCTION

Commonly, unconfined compression test is the most well-known experimental method for soil's shear strength determination. This is due to its suitable way of testing to determine soil's shear strength (Fattah et al., 2007; Fattah and Dawood, 2016; Rashed et al., 2017). This test is mainly used for saturated, cohesive soils obtained from thin-walled soil sampling tubes (ASTM, D2166). Hence, it consists of the UCS determination of fine-grained soil in specific conditions, namely; intact, remolded, or compacted, using the application of the axial load with distance-controlled (ASTM, D2166; Abdalla, 2017; Sharma and Singh, 2018; Salih, 2020; Abdalqadir et al., 2021).

The importance of soil's unconfined compressive strength is in the obtained maximum capability of tested soil samples in terms of axial strength in addition to soil's bearing capacity. Soil's real capability achievement in terms of bearing capacity is significant to discover the suitable type of construction projects for the tested ground location (ASTM, D2166).

For soil's geotechnical engineering characteristics, unconfined compression test plays a notable role. It is important in the obtained useful geotechnical soil shear properties, the soil's cohesion from the maximum obtained axial stress applied on the prepared soil samples for testing. Soil's cohesion is one of the important geotechnical properties to measure the soil foundation bearing capacity, which is imposed for most of the construction projects. More on the unconfined compressive strength, it is considered as a significant construction parameters for roads in addition to earthwork projects (Yarbasi et al., 2007). Also, to assess the required geotechnical properties of construction materials, UCS is important (Sharma et al., 2017; Singh et al., 2016; Umrao et al., 2017).

The best precise measurement technique is the direct determination of soils UCS; however, this technique needs accurate laboratory work, which can be in somewhat expensive and time consuming. This is according to some difficulty in sample preparation and testing accuracy, the laboratory determination of UCS value is in some way expensive and tiresome, which requires an accurate sample size in order to obtain accurate magnitude (Sharma et al., 2017; Singh et al., 2005).

Therefore, modeling approaches to assess soil's UCS can be used as a suitable balance for the UCS's cost and accuracy and can be applied for a huge number and types of natural soils, such as regression techniques, which is easy and not expensive. For this reason, several studies have carried out some work to predict the compressive strength of soil, however most of them used distorted soil samples, and therefore available literatures on the subject are limited. Hence, multiple regression models have been developed by Akan et al. (2015). These models have used for UCS prediction of jet-grouted columns. Independent variables have selected and utilized such as pressure of grouting, speed of rotation-lifting, water/cement ratio and flow rate of water. Those variables have been utilized with various input collection. In addition, Shahbazi et al. (2016) founded a 2nd order equation of polynomial regression for swelling percent, swelling pressure, and UCS prediction, which used for expansive soil stabilization by steel slag and carpet waste fibers. Surface methodology has been utilized for employing response.

The main objectives of the present study are to investigate, compare and check the performance modeling method of multi-linear regression using three versions of R^2 to estimate soil materials UCS in Sulaimani city, Northern Iraq. Importantly, the current study is in effort to improve modeling techniques in geotechnical engineering field via using statistical improvements with cost-effective modeling approaches to estimate UCS with lesser time and efforts for future simulations and UCS estimations by geotechnical designers.

2. THE STUDY METHODOLOGY

2.1. Sampling locations and natural properties determination

In this study, sixty-three undisturbed fine-grained soil samples have been selected and collected from Sulaimani city surface soils from various sites, namely Barika, Arbat and Hwana districts (Fig. 1). The most realistic and useful tectonic subdivision for the northern part of Iraq (Buday, 1980) shown in Fig. 2 that is selected to collect the samples of the current study, Alluvium sediment and soil cover most part of Iraq consist of the boulder, gravel, and sand silt and clay deposits. The locations (Latitude and Longitude) of all the three fields are described in Table 1. The samples were collected from shallow depths of the natural ground level (1.0 m – 2.0 m). Undisturbed soil samples were collected by a small diameter thin-walled tube (38.0 mm in diameter), which is suitable for unconfined compression test conduction. In order to avoid disturbance and changes in cross-section or loss of moisture, the collected soil samples were waxed at both ends and handled carefully. Then, the collected soil samples were used for the laboratory testing experiments, which are field density (ranged between 16.85 kN/m^2 - 20.0 kN/m^2), natural moisture content (ranged between 12.81% - 26.07%) and unconfined compression tests (ASTM, D 2166). Commonly, the UCS sample's height/diameter ratio can between 2.0 to 3.0 with diameters of 38.0 mm. Therefore, hence the field soil samples were compacted and prepared in the size of 3.8 cm (diameter), and 7.6 cm (length) by using the available tube for soils unconfined compression test. Then, the soil samples were placed in the uniaxial loading device so that they are centered on the bottom plate. After that, loading platen is lowered at 0.5 mm/min extension speed.

Fig. 1. Location of soil bore holes, A-Sulaimani governorate location in Iraq, B-The cities of Sulaimani Governorate, consists of the place of collected soil samples (Iraq Maps, 2021 from www.google.iq).

Table 1. Latitude and Attitude data for the selected places of soil samples in Sulaimani city.

Location	Latitude	Attitude
Barika	35.393755	45.595097
Arbat	35.425511	45.580990
Hwana	35.504690	45.431129

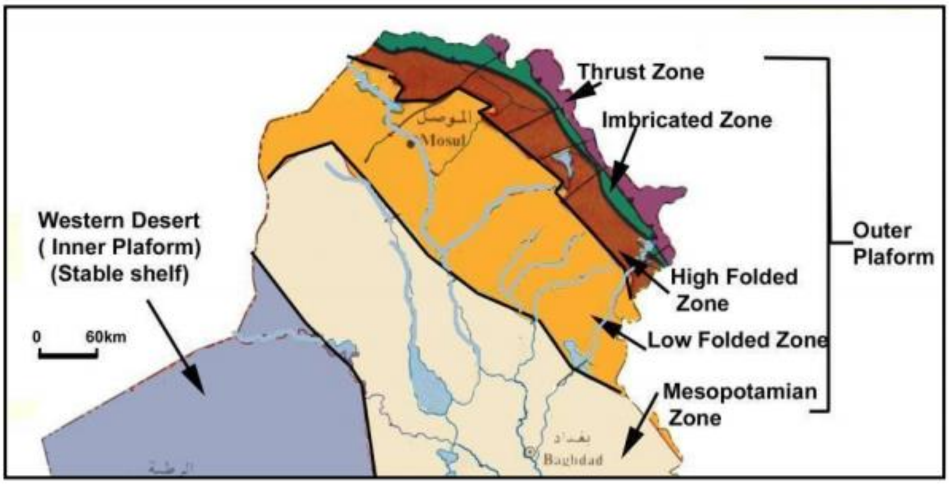

Fig. 2. Northern Iraq map presents the tectonic subdivision (Buday, 1980).

2.2. Regression Methods

For the estimation of complicated system characteristics, data driven equations such as regression models are significant. This is because of these systems are hard to be measured and calculated directly in the fields. UCS of soils, which is one of the geotechnical parameters, required a high level of work and tests to be carried out. Regression techniques can save huge costs and efforts to estimate soil's UCS via using easily calculates physical soil's index properties. In recent years, multiple linear regressions can be considered as widely used statistical techniques in numerous engineering fields. However, one of the most important checks before performing a regression model is the normality of the data provided. Transformation of dataset can be considered as a statistical tool to enhance model prediction using different statistical techniques such as box-cox transformation (Lyman and Longnecker, 2010; Sharma and Singh, 2018).

2.3. Models Assessment Criteria

The regression models predictive accuracy is evaluated using coefficient of determination (R^2), adjusted-R^2 ($R^2_{\text{-adju.}}$), and predicted-R^2 ($R^2_{\text{-pred.}}$)

- Coefficient of determination (R2) is ranging between zero and one. It is the square of the correlation coefficient of Pearson product moment, which presents the degree of relationship between two variables and how they are related, Eq. 1. The prefect performed models will give an R2 close to one (Lyman and Longnecker, 2010). Considering the study of Arnold et al. (2012), R2 > 0.5 exemplifies a satisfactory model rendering.

$$R^2 = \left[\frac{\sum_{i=1}^{n} (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2 (\hat{y}_i - \bar{\hat{y}})^2}} \right]^2 \tag{1}$$

Where: y and $\hat{y}$ are measured and predicted data points respectively with *n* number of data points. $\bar{y}$ and $\bar{\hat{y}}$ are averages of measured and predicted data points respectively.

- Adjusted-R2 (R2-adju.) is a modified version of R2 which can consider the effect of number of variables (Eq. 2). So, the R2-adju. raises only, if the new term modifies the model more than would be predicted by chance. It also reduces when a predictor modifies the model by less expectation than obtained by chance. The deviation of R2-adju from regular R2 relies on the variables number and the size of data points (Cohen et al., 2014).

$$R^2_{adju.} = 1 - \frac{(1-R^2)(1-n)}{(n-k-1)} \tag{2}$$

In each variable, the number of data points is n, and the number of predictor variables is k.

- Predicted-R2 (R2-pred.) is the measure of how well the regression model performing for other data predicting. R2-pred. calculated by testing each single value in the data points technique using the model in order to assess the model prediction capability for the missing observation. All data points in the dataset will be checked via using the mentioned procedure in order to test the robustness of the model against over fitting and predicting random noise (Eq. 3).

$$R^2_{predicted} = 1 - \frac{TSS}{PRESS} = 1 - \frac{\sum_{i=1}^{n}(\hat{y_i} - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

The number of the overall objects in the whole data set is n. The entire sum of squares is *TSS*. *TSS* is the deviation measure from the mean of the data set. So, *PRESS* is the prediction errors squared of the total sum. Consequently, in this procedure for both fitting and testing the model predictive capability in foretelling, all available data are utilized. So, remarking that each *yi* estimate is made, while the data point *yi* is excluded from data set used for model fitting (Consonni et al., 2010).

3. RESULTS AND DISCUSSIONS

Unconfined compressive strength of the utilized soil (UCS) is modeled with regression method, using predictor variables of moisture content (%), plastic limit (PL) (%), dry density (γd) (gm/cm^3), compression index (C_c) and compression ratio (C_r). Total of 59 data measured data points is collected from three different locations in Sulaimani city, Northern Iraq (Fig. 1 and 2). The available 59 measured data points is used to create a multilinear regression model (Eq. 4) to predict UCS. Eq. 4 can predict UCS with R^2 of 0.76 and $R^2_{\text{-adjusted}}$ of 0.74 and $R^2_{\text{-predicted}}$ of 0.69, as shown in Table 2. Also, Fig. 2 shows plot of measured UCS vs predicted UCS.

$$UCS\ (\frac{kN}{m2}) = 46 - 22.83WC + 3.35PL + 377\gamma_d - 869Cc + 3041Cr \tag{4}$$

Table 2. Summary of the conducted regression model

R^2	**$R^2_{\text{-adjusted}}$**	**$R^2_{\text{-predicted}}$**
0.76	0.74	0.69

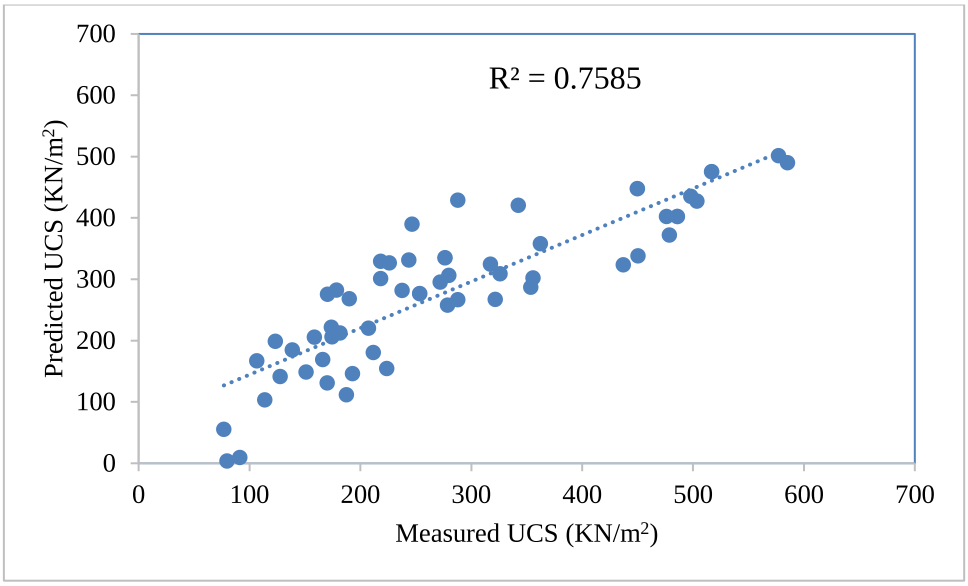

Fig. 2. Measured and predicted UCS from the regression model.

To obtain more robust and better statistical performing model, a box-cox transformation applied on the data set and the transformed regression (Eq. 5) is obtained. Performance of the transformed regression is shown in Table 3, with better performance of R^2 = 0.80, $R^2_{\text{-adjusted}}$ of 0.80 and $R^2_{\text{-predicted}}$ of 0.77 which are all better values compared to the results from regular regression model (Eq. 4).

$$Ln(UCS) = 5.5 - 0.093WC + 0.012PL + 1.07\gamma_d - 3.927Cc + 11.62Cr \qquad (5)$$

Table 3. Summary of the transformed-data regression model.

R^2	$R^2_{\text{-adjusted}}$	$R^2_{\text{-predicted}}$
0.80	0.80	0.77

Fig. 3 shows the plot of the predicted and measured UCS. As can be observed from Fig. 3, the distribution and spread of the transformed data points is better compared to Fig. 2 which is plot of a model from non-transformed data. Therefore, the transformed model (Equation 5) has better performance with higher value of R^2 = 0.8, $R^2_{\text{-adjusted}}$ = 0.8 and $R^2_{\text{-predicted}}$ = 0.77 compared with for the regular model respectively. As the $R^2_{\text{-predicted}}$ from Eq. 5 shows prediction ability of the model compared to the regular non-transformed data model, that confirms higher capability and goodness of the transformed model for UCS prediction.

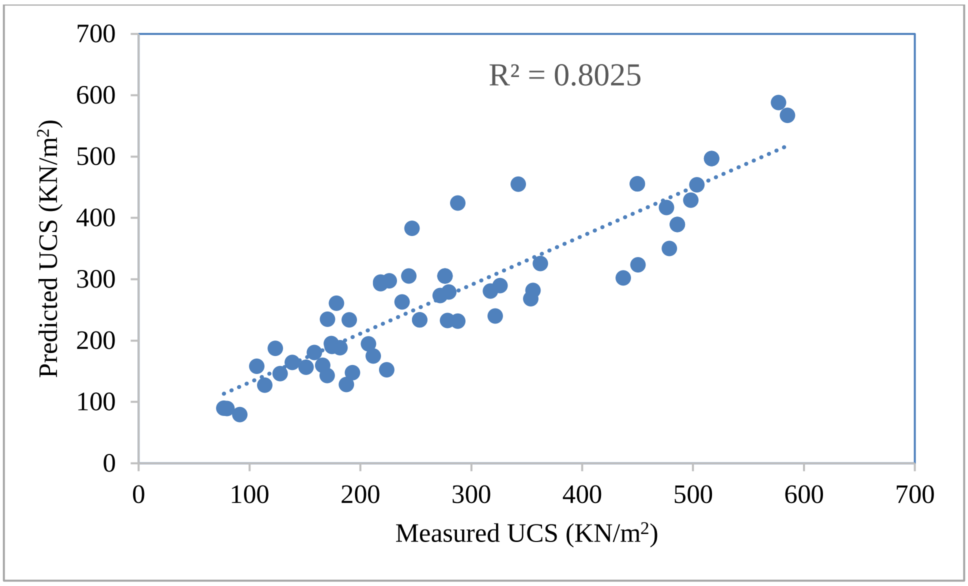

Fig. 3. Measured and predicted UCS from the transformed regression model.

Furthermore, comparing the preference of both transformed and ordinary regression models, box plot of the UCS measured data was plotted against both transformed and ordinary models UCS predicted outputs (Fig. 4).

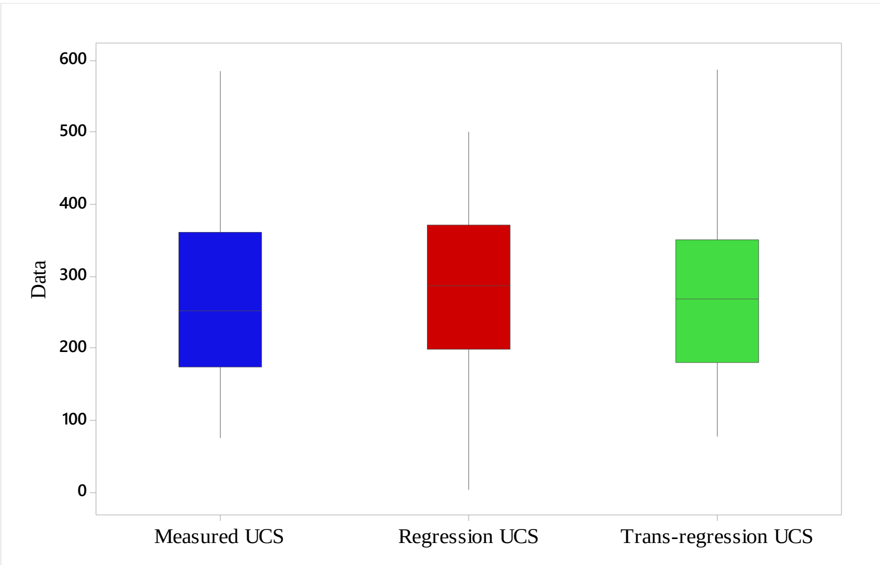

Fig. 4. Box plot of measured data vs regression and the transformed regression outputs.

From Fig. 4, the transformed model has almost the same shape of the measured data with same range of the data (whiskers of the box plots) and the medians of the measured data and the predicted data from the transformed data model are identical with almost same location of data values. While, the regression model output data from non-transformed data points has different range of data (whiskers) and the value of median is more deviated from the median of the measured data. Thus, it can be confirmed that the transformed-data regression model is the better model for predicting UCS with higher values of all evaluation criteria and same shape of the data distribution with the measured data distribution. Finally, all the three data sets plotted in Fig. 5 to show their comparison with each other. As in Fig. 5, the transformed data has almost the same trend and shape of the measured data, while the trend of the ordinary non-transformed data regression predicted values are way off from the measured data in many locations.

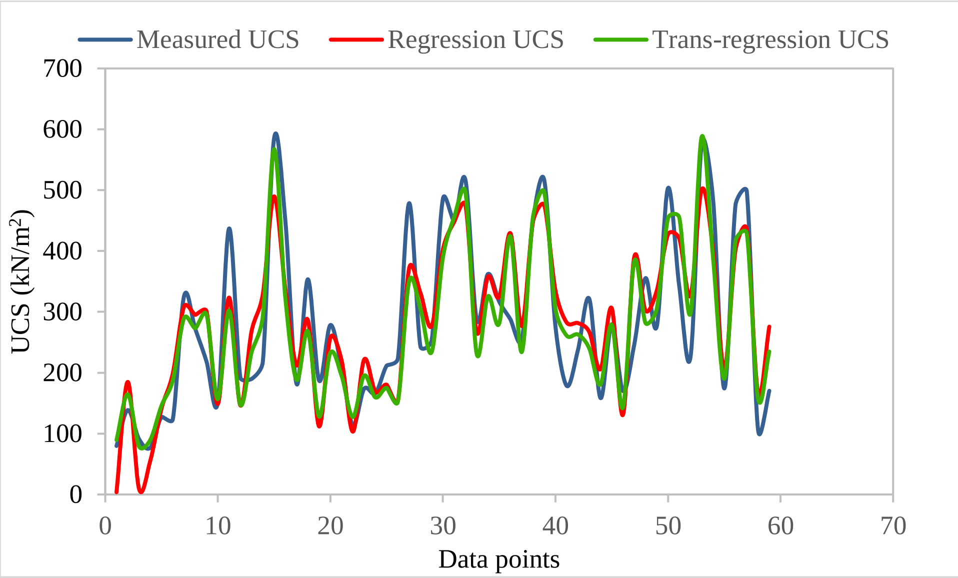

Fig. 5. Trend of the measured and the predicted UCS from the ordinary and the transformed regression models.

4. CONCLUSIONS

It is essential to have an efficient and non-cost model to foresee the time of balancing computation and accuracy prediction in order to estimate UCS for any soil location, such as locations in Sulaimani city, Northern Iraq. Modeling techniques such as regression can save money of cost, time of testing, and efforts for calculation.

In this study, UCS is modeled for soil using regression model. It can be concluded that a transformed data in regression modeling can enhance the prediction ability of ordinary regression models. While, R^2 alone is not a powerful modeling performance measurement, using adjusted-R^2 and predicted R^2 can be considered as better performance evaluation techniques to measure model performances. Notably, the transformed regression model can predict UCS with R^2 of 0.80, $R^2_{\text{-adjusted}}$ of 0.80 and $R^2_{\text{-predicted}}$ of 0.77. While, the $R^2_{\text{-predicted}}$ of 0.77 is a relatively high value, therefore it can be concluded that the model can predict UCS without over fitting.

5. REFERENCES

Abdalla, T. A. (2017) Empirical prediction of geotechnical properties for fine grained soils in Sulaimani City, MSc Thesis: University of Sulaimani, Iraq.

Abdalqadir, Z. K., Salih, N. B. and Salih, S. J. (2021) ‘The improvement of the geotechnical properties of low-plasticity clay (CL) using steel slag in Sulaimani City/Iraq’, Geomechanics and Geoengineering, available: 10.1080/17486025.2021.1903087 [accessed 12 December 2021].

Akan, R., Keskin, S. N., and Uzundurukan, S. (2015) ‘Multiple regression model for the prediction of unconfined compressive strength of Jet grout columns’, Proc Earth Planet Sci, 15, 299-303.

Arnold, J. G., Fong, J. C., and Guss, M. I. (2014) ‘Display screen with transitional graphical user interface’, United States design patent, US D673, 169 S.

ASTM, D2166/D2166M-16 (2016) ‘Standard test method for unconfined compressive strength of cohesive soil’, ASTM International Standards, West Conshohocken.

Buday, T. (1980) Regional geology of Iraq, 1, Stratigraphy: Kassab, I. I. M. and Jassim, S. Z. (Eds) GEOSRVY, Min. Invest. Publ. 445p.

Cohen, P., West, S. G., and Aiken, L. S. (2014) Applied multiple regression/correlation analysis for the behavioral sciences: Psychology Press.

Consonni, V., Ballabio, D., and Todeschini, R. (2010) ‘Evaluation of model predictive ability by external validation techniques’, Journal of chemo-metrics, 24(3-4), 194-201.

Fattah, M. Y., Baqir, H. H., and Al-Rawi, O. F., (2006) ‘Field and laboratory evaluation of a soft clay southern Iraq’, 4th Jordanian Civil Engineering Conference, 28-30 March, Amman-Jordan, 109-116.

Fattah, M. Y., Dawood, B. A., (2016) ‘Collapse potential of gypseous soils from Iraq’, Global Journal of Engineering Science and Research Management, 3(12), 1-12.

Iraq Maps (2021), available: https://www.google.iq/search?q=iraq+maps&source=lnms&tbm=isch&sa=X&ved=2ahUKEwie7v_KmYvoAhWC16YKHYJaA_wQ_AUoAXoECA0QAw&biw=1600&bih=757#imgrc=2rW19Dk_Ej1FQM [accessed 10 December 2021].

Lyman, O. R., and Longnecker, M. (2010) ‘An introduction to statistical methods and data analysis, 6th edition, BROOKS/COLE Cengage Learning.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., and Veith, T. L. (2007) ‘Model evaluations guidelines for systematic quantification of accuracy in watershed simulations’, Transactions of the ASABE, 50(3), 885-900.

Rashed, K. A., Salih, N. B., and Abdalla, T. A. (2017) ‘Correlation of consistency and compressibility properties of soils in Sulaimani city’, Sulaimani Journal for Engineering Sciences, 4(5), 87-95.

Salih, N. B. (2020) ‘Geotechnical characteristics correlations for fine-grained soils’ IOP Conf. Ser.: Mater. Sci. Eng., available:10.1088/1757-899X/737/1/012099.

Shahbazi, M., Rowshanzamir, M., Abtahi, S. M., and Hejazi, S. M. (2016) ‘Optimization of carpet waste fibers and steel slag particles to reinforce expansive soil using response surface methodology’, Appl Clay Sci, 142, 185-192.

Sharma, L. K. and Singh, T. N. (2018) ‘Regression-based models for the prediction of unconfined compressive strength of artificially structured soil, Engineering with Computers, 34(1), 175-186.

Sharma, L. K., Umrao, R. K., Singh, R., Ahmad, M., and Singh, T. N. (2017) ‘Geotechnical characterization of road cut hill slope forming unconsolidated geo-materials: a case study’, Geotech Geol Eng, 35(1), 503-515.

Sharma, L. K., Umrao, R. K., Singh, R., Ahmad, M., and Singh, T. N. (2017) ‘Stability investigation of Hill Cut soil slopes along national highway 222 at Malshej Ghat, Maharashtra’, J Geol Soc India, 89(2), 165-174.

Singh, T. N., Singh, R., Singh, B., Sharma, L. K., Singh, R., and Ansari, M. K. (2016) ‘Investigations and stability analyses of Malin village landslide of Pune district, Maharashtra, India’, Nat Hazards, 81(3), 2019-2030.

Singh, T. N., Verma, A. K., Singh, V., and Sahu, A. (2005) ‘Slake durability study of shaly rock and its predictions’, Environ Geol, 47(2), 246-253.

Umrao, R. K., Singh, R., Sharma, L. K., and Singh, T. N. (2017) ‘Soil slope instability along a strategic road corridor in Meghalaya, northeastern India’, Arabian J Geosci. 10:260.

Yarbasi, N., Kalkan, E., and Akbulut, S. (2007) ‘Modification of the geotechnical properties, as influenced by freeze-thaw, of granular soil with waste additives’, Cold Regions Science and Technology, 48(1), 44-54.