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Modeling unconfined compressive strength of fine-grained soils: Application of pocket penetrometer for predicting soil strength

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ABSTRACT

In recent years, the pocket penetrometer (PPT) test has been used to measure soil compaction and has gained attention due to its simplicity, high speed, and low cost. This study aimed to predict soil strength using a regression relationship between unconfined compressive strength (UCS) and PPT. We collected 45 large soil samples from a forest district in a part of the Hyrcanian Forest. In the laboratory, soil samples were classified according to unified soil classification system. Samples were classified as either silt or clay with a low or high liquid limit. These four soil groups were, brought to four different moisture contents (14%, 25%, 31%, and 36%; $n = 180$ measurements). Samples were then brought to a constant dry unit weight (1.387 kg/m^3). Once the samples were prepared, we measured soil compression strength using a PPT and then determined UCS. We modeled our lab results to determine if PPT could be used as a surrogate for UCS. As soil moisture content increased UCS decreased non-linearly. The behavior of silt and clay with low liquid limit plasticity were similar; likewise, the silt and clay with high liquid limit plasticity produced similar results. According to the values of Eta-squared, soil moisture is more important factor than soil type class in explaining the variance of UCS. In addition, PPT data can accurately predict soil UCS ($R^2 = 0.98$). Therefore, PPT data can be used to predict UCS of fine-grained soils with good accuracy and very low cost.

1. Introduction

Understanding soil mechanical properties is critical for geotechnical analyses and designs to guarantee project success. One of the most important soil properties for construction activities is soil resistance to penetration (a measure of soil strength). There are two principal methods for measuring soil penetrability or penetration resistance: (1) dynamic methods, in which a probe is driven into the soil by a slide hammer or falling weight and (2) static methods, in which a probe with a cone or blunt tip pushed into the soil at a constant velocity (Bradford, 1976). Another important soil physical characteristic is shear strength, which is defined as the magnitude of shear stress that a soil can sustain. Soil shear resistance is a measure of friction and cohesion (i.e. interlocking particles or cementation). Frictional shear strength is a function of gravitational forces and is common in coarse-grained soils; cohesion shear strength is a function of surficial forces common in fine-grained soils (Robertson and Chock, 2017). Soil cohesion is not a constant parameter and is a function of the load transferred by the structure (*e.g.* building, bridge) to the soil and soil moisture content (Tavenas, 1976). Soil cohesion also depends on inter-granular loads and testing method and, when no lateral load is applied to the sample, adhesion is considered to be soil shear strength (Chang and Cho, 2019).

Unconfined compression tests are used to determine adhesive soil strength (Güneyli and Rüşen, 2016). Generally, testing for unconfined compression strength (UCS) measures the adhesive soil strength using a strain-controlled method (Cao, 2018). This test determines the compression strength of a soil cylinder with no lateral load. It is similar to an unconsolidated undrained triaxial test; both are used to determine cohesion in fine-grained soils. In saturated clayey soil samples, soil strength decreases with increased soil moisture content but, in unsaturated soil, when dry weight is fixed, soil strength decreases slightly with increasing saturation. Unconfined compression test has an advantage over a direct shear test, in which stresses and strains are uniformly created in the soil sample and fractures occur in the weakest part of the soil. This soil characteristic is important for calculating safe bearing capacity and soil strength (Patel and Patel, 2012).

Assessing road strength is another phase of construction or maintenance operations (Patel and Patel, 2012) and road traffic

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characteristics depend on the subgrade soil strength. Soil moisture, clay size, and the quantity of clay-sized particles are the main factors that determine soil strength (Dolinar, 2004). Koumoto and Houlsby (2001) examined the relationship between undrained shear strength and soil moisture content in disturbed fine-textured mineral soils and concluded that water holding capacity at the given soil strength depended on soil texture, particle-size distribution and composition, and mineralogical characteristics, especially in the clay fraction. Furthermore, the influence of soil mineralogical characteristics on undrained shear strength depends on inter-granular water content (Trauner et al., 2005; Wood, 1990).

Despite the importance of UCS for geotechnical studies (Schmerimann, 1975), determining this in the laboratory requires considerable time and cost. It is also difficult to collect intact soil cores and preserve sample conditions from the field to the laboratory. This sampling issue leads to differences in UCS between laboratory tests and *in situ* soil conditions (Salgado and Yoon, 2003).

The UCS is a popular method to measure soil shear strength, but it is not simple to conduct. Therefore, an easier method that uses a pocket penetrometer (PPT) has been proposed. The PPT is used to determine soil compression strength and is a low-cost simple to use method (Yasun, 2018) in both the laboratory and field (Das, 2019). Generally, little research has been conducted for estimating soil UCS using a simple and inexpensive tool, such as PPT (Das, 2019; Texas Department of Transportation, 2006; Yasun, 2018). However, these authors indicate that the PPT could properly estimate soil UCS (Texas Department of Transportation, 2006; Yasun, 2018). Amacher and O'Neill (2004) demonstrated soil compression strength, as measured with the PPT, was significantly higher in compacted trails and areas than in the adjacent undisturbed locations and was noted as an easy tool for use on surface soils, but this work was not correlated with UCS. Similar studies have been conducted to estimate UCS using the dynamic cone penetration test (Aulakh et al., 2017; Enayatpour et al., 2006; Patel and Patel, 2012; Salgado and Yoon, 2003) and jet grout columns (Akan et al., 2015). Furthermore, Dirriba (2017) showed that UCS was correlated with dynamic cone penetration, natural moisture content (NMC), specific gravity (Gs), and liquid limit (LL). Using the PPT to estimate UCS in the field would greatly reduce time and cost to determine this soil property. Consequently, the objective of this paper is to develop an appropriate statistical equation for estimating UCS using the PPT to collect field data.

2. Material and methods

2.1. Study area and sampling

This study was conducted in Namkhaneh District in the Hyrcanian Forest, University of Tehran. The study area was about 750 ha. ArcGIS software was used to develop a sampling plan. A landform map was developed after overlaying map layers of slope, aspect, and elevation originally extracted from a Raster elevation model. The slope layer was classified into six classes (0–5%, 5–12%, 12–25%, 25–40%, 40–65%, above 65%), aspect was classed into classess north, east, south, west, and elevation was classified as 0–1000 m, or above 1000 m. To prepare the final map, soil clay content According to the values of Eta-squared, soil moisture is a more important factor than soil type in explaining the variance of UCS. Mousavi et al 2020 was integrated with the landform (slope, aspect, and elevation) layer. Forty-five soil sample points were randomly selected within homogeneous polygons (Mousavi et al., 2020). Each sample point was located using a Garmin 64S GPS. To collect our samples, the surface organic matter (including mulch, if present) was removed and set aside, then the surface mineral soil was removed to a depth of 30 cm. Samples weighed approximately 5 kg and were placed in double-walled plastic bags, numbered, and transferred to the laboratory (Mousavi et al., 2020). Soil organic matter (OM) content in the samples was measured according to Walkley-Black method (Rankin, 1970). The results of OM content indicated the average of 1.66% for OM in soil samples. The low OM values obtained in this study could be attributed to the point that surface OM layer was removed before collecting the soil samples (0.6–2.92%).

2.2. Sample preparation

Soil samples were classified using the standard practice for classifying the soils (American Society for Testing and Materials D2487-11). We classified the fine-grained soils using the Casagrande plasticity chart. The soil liquid limit was initially determined using the soil testing methods for civil engineering purposes (British Standard, 2016) and the soil plasticity limit was determined using the standard of plastic limit testing (American Society for Testing and Materials (ASTM), 1995). The soil plasticity index was determined as the difference between the liquid limit (LL) and plastic limit (PL). All soil samples were classified as fine-grained soil; 28% of the samples were clay with a high liquid limit (CH), 37% were clay with low liquid limit (CL), 20% were silt with high liquid limit (MH), and 15% were silt with low liquid limit (ML). Each of the four LL categories of samples were prepared considering the dry unit weight of intact soil (1.387 kg/m^3). Each main soil sample was subsampled and brought to four different moisture contents, which were 14%, 25%, 31%, and 36% (dry weight basis). This represents the minimum, maximum, average, and maximum soil moisture contents that would occur during one year of field monitoring (Hayati et al., 2018).

2.3. Measuring PPT

The PPT was used to measure soil compression strength (Fig. 1) in the laboratory and is capable of measuring undrained shear strength of cohesive soils in the range of 0–5 kg/cm^2 (Yasun, 2018). The PPT penetrates directly into the soil and UCS is measured by a calibrated spring with constant stiffness (Das, 2019). Because it is easy to use it is possible to increase the number of test iterations on each soil sample at each moisture content. Laboratory tests in 2016 indicated that this method could be used to approximate UCS of cohesive soil samples (Yasun, 2018).

The PPT has a spring-loaded piston which was pushed into the soil surface after each soil sample was brought to the required moisture content and before UCS testing. The PPT rod was placed perpendicular to the soil surface and was gently and uniformly pressed into the flat surface until the rod progressed to the indicator on the device. When the rod reached the indicator, the compression strength was read.

2.4. Measuring UCS

The UCS was determined on the samples at all four soil moisture contents and at a soil bulk density dry unit weight of 1.387 kg/m^3 using ASTM-D1633 standard on the collected soil cores (four moisture contents × 45 soil samples = 180). Each soil sample (100 mm height and 50 mm diameter) for each moisture content was placed in the unconfined compression apparatus, as shown in Fig. 2. The test load was applied at the rate of 1 mm/min, which corresponded to the strain rate

Fig. 1. PPT.

Fig. 2. Soil sample in an unconfined compression device.

Fig. 3. Sampling template and fractured sample.

of 0.5% per minute for a sample. The stress readings were taken in 5 mm intervals and loading continued until the complete fracture of the sample. A compaction mold was employed to prepare the sample and fractured sample after loading on the unconfined device. In order to reduce measurement error two replicates of each sample were analysed (see Fig. 3).

2.5. Statistical method

Descriptive statistics were used to summarize the collected data. Based on the results of descriptive statistics as well as quantitative evaluation criteria, two different regression models were developed to predict UCS. The first regression model estimated the UCS based on soil type (including ML.CL and MH.CH) and soil moisture content (Eq. (1)).

$$\mathrm{UCS} = \beta_0 + \beta_1 \times (\mathrm{moisture})^2 + \beta_3 \times \mathrm{ML.CL} \quad (1)$$

Soil type is a binary variable of 0 and 1. When the soil type is ML or CL (soil with low LL), the ML.CL factor value in the model is equal to 1. When the soil has a high LL (MH or CH), the ML.CL factor value in the model was assumed to be 0.

In a second regression model, the strength variable of PPT was inserted in the model and other independent variables, including moisture and soil type, were insignificant. Therefore, the final regression model was formed only using the PPT variable (Eq. (2)).

$$\mathrm{UCS} = \beta_0 + \beta_1 \times \mathrm{PPT} + \beta_2 \times (\mathrm{PPT})^2 + \beta_3 \times (\mathrm{PPT})^3 \quad (2)$$

The possibility of removing independent variables was evaluated by a likelihood ratio test. In this study, p-values ≤ 0.05 were considered significant. All the statistical analyses and model fitting were performed in R statistical software.

Final model performance was evaluated using R^2. The efficiency criteria of the model are reliable when they are based on data not used during model fitting. In this study, the regression model was validated using 10-fold cross-validation (Zhang, 1993) in which the data are divided into 10 random folds (subsamples). In each regression stage a fold was excluded as a testing set to evaluate model efficiency. Afterwards, model fitting was conducted using other folds as the training dataset and the fitted model was used to predict an excluded fold. This was repeated for all the folds and the predicted values for all folds were obtained when they were not used in model fitting.

Sensitivity analysis was performed to determine those parameters that mostly influenced model output. In models with a large number of input variables, sensitivity analysis is an essential part of model building and is critical for reducing the number of parameters required in the final mode (Wesseling et al., 2020; Xu et al., 2016). Eta-squared (also called the squared correlation ratio) and standardized regression coefficients (SRC) were employed to determine the most influencing parameters in Model 1 and Model 2, respectively (Chan et al., 1997; Norouzian and Plonsky, 2018; Saltelli et al., 2004). Moreover, an explorative analysis was performed to compare the variation of UCS versus soil type and moisture contents in the first model.

3. Results and discussion

As soil moisture increased, the mean UCS, standard deviation, and coefficient of variation decreased (Table 1). Furthermore, with increasing moisture content, the dispersion of strength data decreased. Thus, when the soil moisture reaches saturation, UCS is highly reduced, which is consistent with the results of Sharma and Singh (2018).

As soil moisture increased in all LL classes the UCS decreased non-

Table 1
Minimum, maximum, mean, standard deviation of USC and coefficient of variation for soil samples at four moisture contents.

Moisture content (%)	UCS (kPa)				
	Min	Max	Mean	Standard deviation	Coefficient of variation
14	118.00	274.80	178.51	41.99	23.52
25	105.22	224.48	145.215	31.51	21.69
31	81.10	185.19	122.02	25.52	20.91
36	69.44	151.00	93.32	17.90	19.18

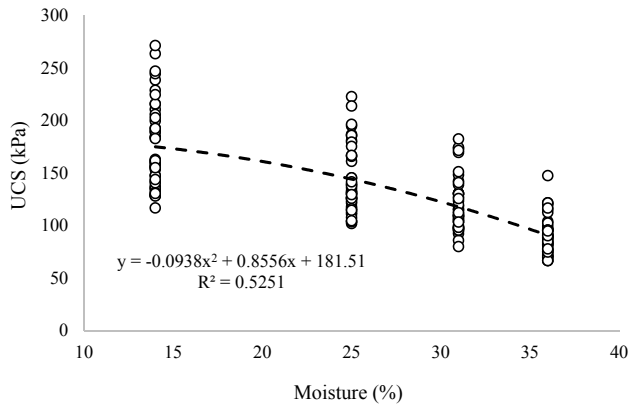

Fig. 4. Relationship between UCS and soil moisture.

linearly, suggesting that decreasing fine-grained soil strength is related to increased moisture content (Fig. 4). This is also consistent with the previous studies (Dahale et al., 2012; Tang et al., 2007). Further, strength loss at the maximum soil moisture (36%) can be due to the development of a double layer of water and decreased electrostatic force between clay particles. In other words, in a dry clay soil there is a surface negative charge that is balanced by exchangeable cations (*e.g.,* calcium, potassium, magnesium, and sodium) which surrounds clay particles and adheres by electrostatic attraction. Adding water forms a double layer around the particle, weakens clay particle attraction, which results in a nonlinear soil strength decrease (Lambe, 1958).

Fig. 5 shows the variability of UCS and PPT data for each soil and four levels of moisture content. Accordingly, the dispersion of PPT data was higher than that of UCS data for different soil types. In addition, the dispersion of PPT data was higher than that of UCS for the moisture contents of 14, 25, and 31%, but was lower than UCS for the moisture content of 36%. Based on this graph, both low and high LL soils have similar medians for UCS. Therefore, in the modeling process, the presence of four separable soil types was not significant. In the final model,

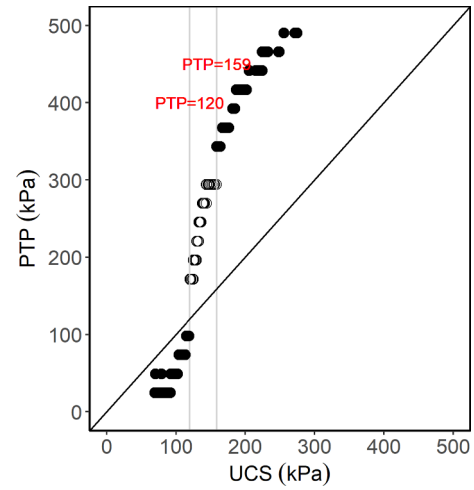

Fig. 6. Relationship between PPT strength and UCS.

ML and CL soils were entered into the model as CL.ML factor and the CH and MH soils were classified and entered into the model as MH.CH factor. Comparing the model performance also indicated a better model fit with the merged soil types than the model that included all the soil types separately.

We used PPT as a quick and easy index of UCS and the model showed that as PPT increased UCS also increased with a nonlinear trend (Fig. 6). Given that the accuracy of the UCS measurement was higher than the PPT measurements, we displayed the UCS on the X axis. As UCS increased, PPT values should also increase; but the increasing rate of PPT for the UCS values of larger than 120 kPa was not in proportion to the increasing rate in UCS. Therefore, the relationship between UCS and PPT was not linear. The relationship of PPT and UCS had a higher curvature when the UCS values were greater than 159 kPa or less than 120 kPa.

The correlation between UCS and PPT was 0.99, which was very

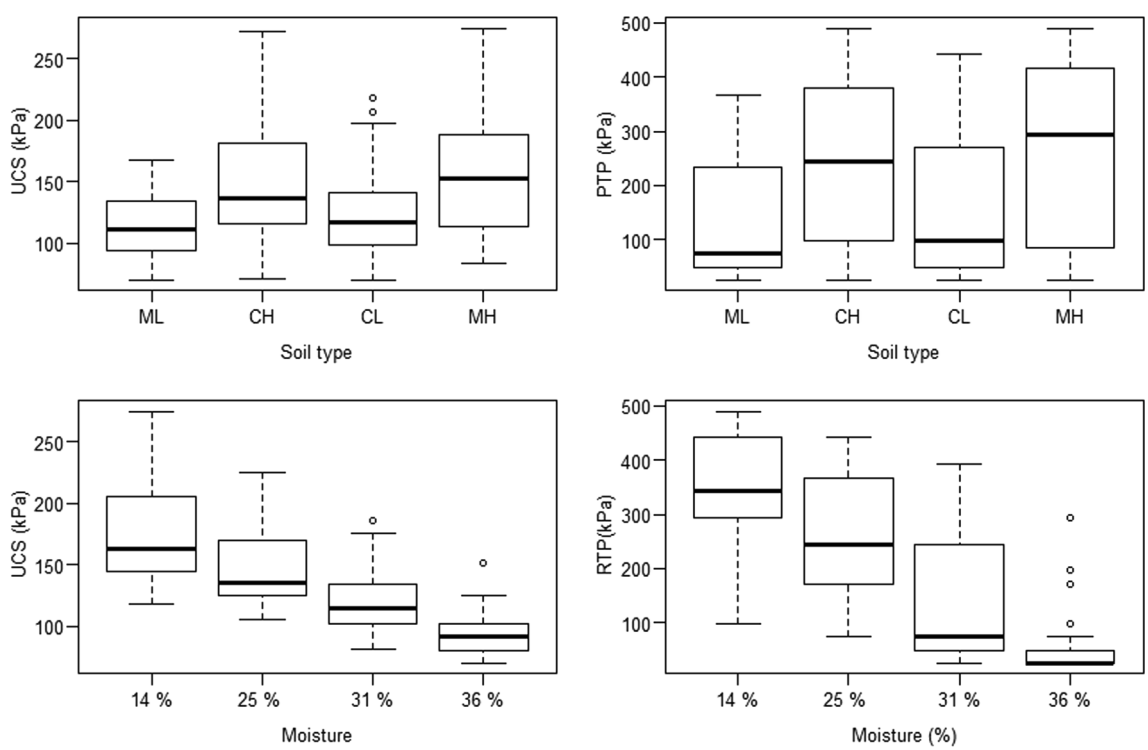

Fig. 5. Distribution of UCS and PPT data for each soil type and four levels of moisture content.

Table 2
Results of Spearman correlation between UCS, PPT, and soil moisture.

Row	Column	R	P-value
UCS	PPT	0.99	< 0.001
UCS	Moisture	−0.77	< 0.001
PPT	Moisture	−0.77	< 0.001

high (Table 2). The correlation between UCS and PPT and also PPT and soil moisture was −0.77, which indicated a negative relationship. Unfortunately, no other studies were found, in which this relationship has been examined, but previous work indicates high correlation between UCS and dynamic cone penetrometer (DCP), (Fitsum, 2014; Patel and Patel, 2012; Salgado and Yoon, 2003). Enayatpour et al. (2006) examined UCS estimation using DCP in stabilized soil, found a high R^2 (0.97 and 0.91), and noted that the DCP method can be a reliable tool for predicting UCS. Furthermore, Dirriba (2017) presented a regression between UCS and other soil characteristics, and R^2 coefficients between UCS and DCP were 0.80–0.83, NMC 0.72, GS 0.62–0.74, and LL 0.63–0.72. Amacher and O'Neill (2004) expressed the main disadvantage of PPT was that many of the compacted soils had compression strength higher than the maximum measurable value of 450 kPa. Despite this limitation, PPT can quickly and easily distinguish between compacted and uncompacted areas.

In the present study, the first regression model used two variables (soil moisture and soil type) as independent variables. Estimated significant coefficients for each variable in the final model are presented in Table 3. With increasing soil moisture content, the UCS decreased in a second-order nonlinear manner. Regarding soil type, the UCS decreased by 25.43 (i.e. the regression coefficient) when varying soil type from MH.CH to ML.CL.

When PPT was added to the model, only this variable was significant (Table 4) and the other independent variables were not significant. This indicates strong correlation between USC and PPT.

Table 5 presents model validation results based on the 10-fold method and compares Model 1 and Model 2.

In this validation exercise, Model 2 not only had a higher R^2 than Model 1, but also had a lower residual mean square error. Therefore, Model 2 is proposed as a reliable model for estimating UCS using soil resistance to penetration data.

In Model 2, high adjusted R^2 was predictable since PPT and UCS were highly correlated. Soil PPT and UCS evaluated the same soil characteristic (compression strength). Hence, Model 2 showed a higher adjusted R^2 than the first model (Table 5). Measurements of PPT reflected other soil properties (*e.g.* soil moisture and type) that affected UCS. Consequently, these properties were not included in Model 2.

The results of explorative analyses (Fig. 7) indicates that soil moisture causes more variation in UCS than soil type. According to the Eta-squared values, soil moisture explained about 56% of total variance, while soil type explained about 11% of total variance, indicating that soil moisture was a more important factor than soil type in explaining the variance of UCS. According to the results of SRC for Model 2, parameter of RTP had the minimum and squared term of RTP had the maximum effects on UCS variability.

Unfortunately, no direct studies on developing the relationship between UCS and PPT were found in the literature. But, Yasun (2018) showed that the average difference between soil resistance and UCS was between 1.10% and 1.53%, with moisture contents ranging from 14.7% to 27.3%. In general, the results in Model 2, with adjusted R^2 of 98%, showed higher correlation and greater accuracy than studies using other methods for estimating UCS (Enayatpour et al., 2006; Patel and Patel, 2012; Salgado and Yoon, 2003). Based on Model 2, soil penetrometer resistance can be employed to estimate UCS with more accuracy as well as less time and cost.

Table 3
Results of the first model with soil moisture and soil type ML.CL.

Variables	Coefficient	Standard Error	P-value
Constant	203.40	4.74	< 0.001
$(\text{Moisture})^2$	−727.74	42.29	< 0.001
ML.CL	−25.43	3.36	< 0.001

ML.CL is a binary variable of the soil type and accepts values of 0 and 1.

Table 4
Results of the second polynomial model with soil resistance to penetration added.

Variables	Coefficient	Standard Error	P-value
Constant	68.6362	1.5514	< 0.001
PPT	0.6725	0.0335	< 0.001
$(\text{PPT})^2$	−0.0026	0.00016	< 0.001
$(\text{PPT})^3$	0.000004	0.00000022	< 0.001

Table 5
Model validation based on 10-fold method, showing the R-squared (R^2), residual mean square error (RMSE), and mean absolute error (MAE).

Model	R^2	RMSE	MAE
Model 1	62%	27	21
Model 2	98%	5.8	4.5

The results showed the suitability of using PPT for estimating soil resistance to penetration rather than using the more laborious UCS method regarding time and cost. On the other hand, the PPT is a faster and easier way for estimating UCS. The field PPT measurements should be followed by some validation samples of UCS to ensure accurate data. Also, these results indicate the developed models can be used to retrieve the UCS values from the PPT for further applications. Furthermore, the PPT could be applied for efficient soil monitoring in order to predict and monitor soil strength in extensive areas and also used to determine the depth of increased soil strength.

The results of this study should be applied in areas with similar soil types or validated on different soil textural classes and clay content. Although the PPT is a very good indicator of strength, care must be taken in the selection of the equation used to determine the needed strength parameter, as the equations are sensitive to soil characteristics. Therefore, these results are valid for the measured range of soils. However, it may be possible to enhance applicability through further studies on broad diversity of soils from other geographic areas and assay the importance and accuracy of the proposed methodology.

4. Conclusion

In this study, the behavior of fine-grained soils was investigated using UCS test and PPT on dense soil samples with various moisture contents and the following can be concluded:

- As soil moisture increased, the mean UCS, standard deviation, and coefficient of variation decreased.
- UCS nonlinearly decreased with increasing moisture content.
- Accuracy of PPT predictions decreased when UCS values were greater than 159 kPa or < 120 kPa. An increase in PPT was not in proportion to the UCS and resulted in a nonlinear relationship between UCS and PPT.
- Correlation between UCS and PPT was R^2 0.99.
- Correlation between UCS; PPT and soil moisture was −0.77.
- PPT alone can be used to determine the UCS of fine-grained soils with proper accuracy.

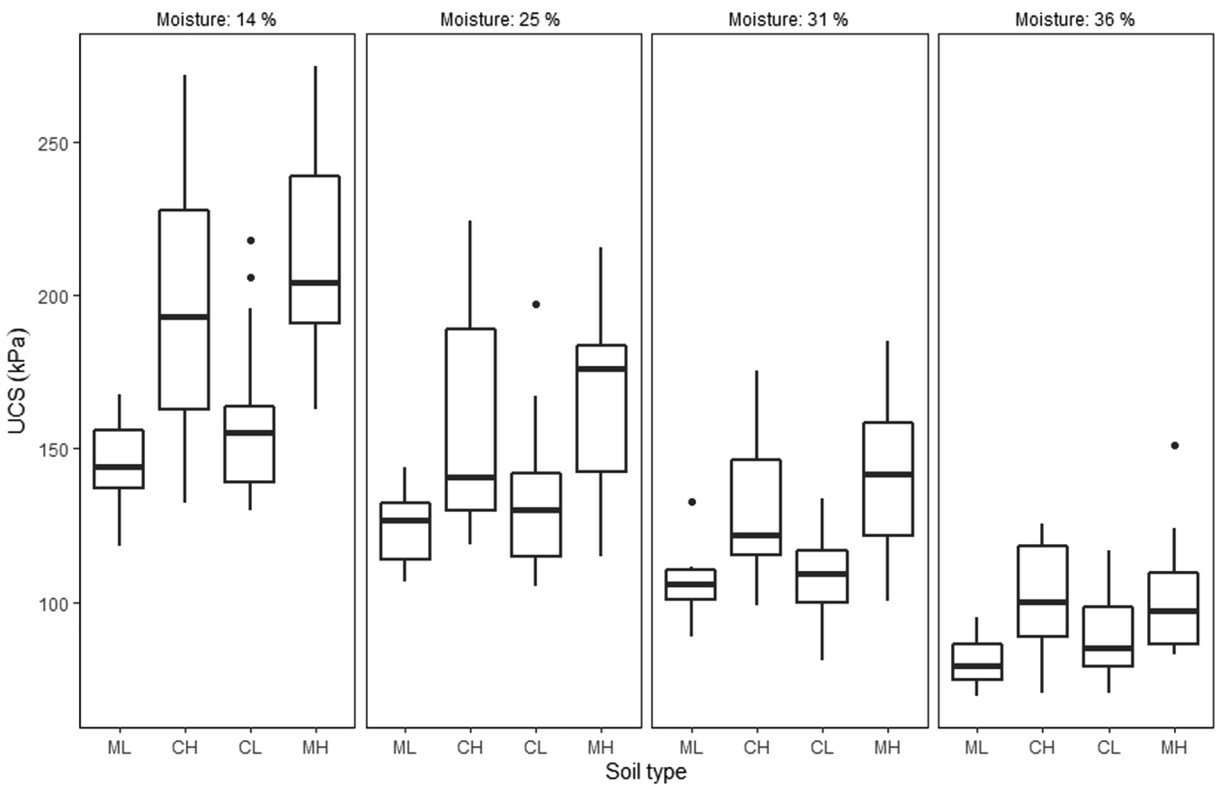

Fig 7. Distribution of UCS versus soil type and soil moisture.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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