Soil Unit Weight Estimation Using the Cone Penetration Test and Machine Learning

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ABSTRACT
Soil unit weight is an essential soil parameter for assessing total and effective stresses in geotechnical engineering. Several empirical correlations have been developed to estimate the soil unit weight from piezocone penetration tests (CPTu). This paper investigates the potential of a data-driven approach for the estimation of soil unit weight from CPTu data. A compiled database of paired CPTu readings and laboratory measured unit weights from different field test sites with a variety of soil types, geological environments, and stress histories was used to explore and develop a machine learning algorithm directly estimating unit weights from piezocone data. The random forest algorithm was employed to calibrate the CPTu readings to the soil unit weights. The results outperformed the existing widely used CPT-based relationships to estimate the soil unit weight.

RÉSUMÉ
Le poids volumique des sols est un paramètre de sol essentiel pour évaluer les contraintes totales et effectives en géotechnique. Plusieurs corrélations empiriques ont été développées pour estimer le poids volumique des sols à partir des tests de pénétration piézocône (CPTu). Cet article étudie le potentiel d'une approche basée sur les données pour l'estimation du poids volumique des sols à partir des données CPTu. Une base de données compilée à partir de couples de valeurs de CPTu et de poids volumiques mesurés en laboratoire à partir de différents sites d'essai sur le terrain avec une variété de types de sols, d'environnements géologiques et d'historiques de contraintes a été utilisée pour explorer et développer un algorithme d'apprentissage automatique estimant directement les poids volumiques à partir des données de piézocône. L'algorithme random forest a été utilisé pour calibrer les valeurs de CPTu aux poids volumiques des sols. Les résultats ont été comparés à certaines des relations basées sur le CPT largement utilisées pour estimer le poids volumique des sols.

1 INTRODUCTION

Soil characterization is an essential task in civil and geotechnical engineering. Different soil properties such as soil type, unit weight, particle size distribution, permeability, Atterberg limits, strength, and other variables have an influence in the analysis and design of geotechnical projects. Soil unit weight is an essential soil parameter for assessing in-situ stress conditions. A reliable estimate of the unit weight profile is therefore considered an initial step towards the accurate evaluation of total and effective overburden stresses (σ_{vo} and σ'_{vo}) in a soil profile.

Soil unit weight can be measured through laboratory measurements of mass and volume of undisturbed soil samples. However, drilling and collecting undisturbed samples from individual soil layers can be a difficult, costly, and a time-consuming process, particularly when dealing with layered soils. Alternatively, and for lower risk geotechnical projects, in-situ methods can be used to provide an empirical estimate of unit weight.

Methodologies have been proposed for the estimation of unit weight through electrical resistivity (Nelissen 1988), gamma radiation (Sully & Eschesuria 1988), radioactive isotope (Mimura et al. 1995), and dielectric measurements (Shinn, et al. 1998). Although these methods can provide immediate estimates of soil unit weight, their use may not be cost-effective and they require specialized equipment.

There are several methods to estimate soil unit weight from piezocone penetration tests (CPTu) and seismic piezocone penetration tests (SCPTu) (e.g. Larsson and Mulabdić 1991, Lunne et al. 1997, Mayne 2007, Mayne et al. 2010, Robertson and Cabal 2010, Mayne 2014, Lengkeek et al. 2018). In CPTu test analysis, accurate estimation of unit weight is necessary for the determination of overburden stresses and to compute normalized CPTu interpretation values such as normalized tip resistance (Q_t, Q_{tn}), friction ratio (F), and porewater pressure (B_q). In fact, most geotechnical parameters derived from CPTu require an estimate of the soil unit weight profile. Direct CPTu based estimates of the continuous soil unit weight profile is much more efficient than undisturbed sampling and laboratory analysis.

The existing empirical relationships and expressions to estimate the unit weight from CPTu data have been mostly developed using statistical modelling. This paper investigates the potential of a data-driven machine learning approach for the estimation of soil unit weight from CPTu data. A compiled database of paired CPTu readings and laboratory measured unit weights is used to explore and develop a machine learning algorithm directly estimating unit weights from raw piezocone data. The database includes CPTu and laboratory results from different field test sites with a variety of soil types, geological environments, and stress histories. A random forest algorithm is employed to calibrate the CPTu readings to the soil unit weights. The performance of the developed model is compared with some of the proposed expressions in the literature.

2 BACKGROUND

2.1 Piezocone Penetration Testing (CPTu)

The CPTu is a highly instrumented direct push probe used as an efficient, accurate, and repeatable means to collect subsurface geotechnical data in soils. The CPTu has a wide variety of applications throughout geotechnical practice.

The CPTu is typically advanced at a standard rate of 2 cm/s through the soil and all measurements are made near continuously with depth. The CPTu measures cone tip resistance (q_c), sleeve friction (f_s), dynamic pore pressure (u_2), inclination, and temperature. End area effect corrections are required to calculate the corrected or total tip resistance (q_t). The CPTu can be equipped with other modules to collect additional in-situ soil variables and enhance CPTu data. For instance, measurements of shear wave velocity (V_s) and natural gamma activity of a soil can be performed using Seismic CPTu (SCPTu) and Gamma CPTu (GCPTu), respectively.

2.2 Existing CPT Relationships to Estimate Unit Weight

Several relationships have been proposed to directly estimate soil unit weight from CPTu and SCPTu measurements. Larsson and Mulabdić (1991) developed a method to assign unit weights for Swedish clays based on a chart of net cone resistance (q_{net}) and normalized pore water pressure (B_q). Lunne et al. (1997) suggested a table of assigned unit weights based on soil types determined using the soil behaviour type (SBT) chart established by Robertson et al. (1986).

When SCPTu is available, Burns and Mayne (1996) proposed a relationship between the unit weight and shear wave velocity (V_s), while incorporating effective stress (σ'_{vo}). Alternatively, Mayne (2001) suggested an expression using shear wave measurements and depth (z) in lieu of effective stress. Later, Mayne (2007) developed a correlation between the unit weight and normalized shear wave velocity (V_{s1}), where $V_{s1} = V_s/(\sigma'_{vo}/\sigma_{atm})^{0.25}$.

Robertson and Cabal (2010) proposed an equation where the unit weight is a function of the cone tip resistance (q_t) and the friction ratio (R_f). Mayne et al. (2010) developed a relationship where tip resistance (q_t), sleeve friction (f_s), and depth (z) are the input variables. They also suggested a correlation can be established between unit weight and sleeve friction and effective stress. Mayne (2014) later suggested a relationship solely dependent on the sleeve friction. To include organic soils, Lengkeek et al. (2018) also proposed an expression where unit weight is calculated using tip resistance (q_t) and sleeve friction (f_s).

It should be noted that some of the proposed expressions require an initial estimate of unit weight in order to calculate the effective stress and start the process, and are thus iterative in nature.

3 PROPOSED DATA-DRIVEN APPROACH

3.1 Dataset Description

A compiled database of 1228 paired CPTu readings and laboratory measured unit weights was used to explore and assess the potential of a data-driven approach in developing an empirical correlation between CPTu data and soil unit weight measured in laboratory. This data set is the same as used by Mayne (2014), updated with new data as they became available. The database includes CPTu and laboratory results from 114 different field test sites from a variety of soil types, geological environments, and stress histories. The soil types include peat, clay, silt, sand, till, etc. The laboratory measured unit weights range from 10 to 24 kN/m^3, with a mean of 16.8 kN/m^3. The CPTu parameters paired with sample unit weights include corrected tip resistance (q_t), dynamic porewater pressure (u_2), and sleeve friction (f_s). The hydrostatic porewater pressure (u_o) and the effective overburden stress (σ'_{vo}) is calculated and paired with the measured unit weight values. These five parameters and depth (z) were used as input features in model development.

3.2 Machine Learning Modelling

Machine Learning is a subfield of artificial intelligence and computer science which deals with the development of algorithms that enable computers to perform a specific task, without the need of rule-based programming. A machine learning model acquires information from existing data and allows the computers to discover the patterns and predictive rules. Statistical modelling, on the other hand, is a subfield of mathematics and employs computational equations to formulate the relationships between variables in the data.

One of the major differences between machine learning and statistical modelling is that in the latter, all the assumptions must be satisfied and the uncertainty estimates (e.g. confidence intervals) need to be identified, determined, and analyzed. For example, to develop a linear regression model, one needs to ensure that there is little or no multicollinearity, errors are normally distributed, etc. In contrast, machine learning requires little or no priori assumptions to be considered and thus are far more flexible than statistical models. In addition, statistical models are usually not applicable on large data sets with many variables and are suited for low dimensional data sets. Machine learning models, on the other hand, are data-hungry and need large data sets in order to be trained and can continuously adapt as more data become available. In general, as more data are available, the more accurate and robust the prediction becomes. Machine learning models can be applied on high dimensional data sets with numerous variables and observations.

Empirical relationships are frequently used in geotechnical engineering to estimate various soil properties and geotechnical parameters. The machine learning approach can better deal with uncertainties and complexities in geotechnical engineering problems, leading to more robust predictive models compared to traditional statistical modelling (Shahin et al. 2008, Puri et al. 2018). Machine Learning modelling has gained substantial interest in the geotechnical engineering community and has gradually become an alternative solution for geotechnical problems. Example applications of machine learning modelling for geotechnical problems can be found in Goh (1995), Zhou et al. (2016, 2019), Zhang et al. (2015, 2016, 2020), Li et al. (2018), Puri et al. (2018), Entezari et al. (2020, 2021), Erharter et al. (2021).

There exist various machine learning algorithms such as artificial neural network (ANN), Bayesian network (BN), support vector machine (SVM), and random forest (RF). For this study, the random forest algorithm was employed to calibrate CPTu data to soil unit weight measured in laboratory.

3.3 Random Forest Algorithm

Random forest technique was first introduced by Ho (1995) and further extended by Breiman (2001). It is one of the widely used machine learning algorithms for classification and regression tasks. Individual decision trees are prone to overfitting. Random forest is an ensemble of several decision trees trained using the Bagging learning (Breiman 1996) as well as random subspace method (Ho 1995).

In Bagging learning, several predictive models are trained using several randomly generated training datasets from the original training dataset. The random subspace method is similar to bagging in a sense that a random subset of features selected from the feature space is employed to train each predictive model in the ensemble. In both bagging and random subspace methods, replacement is allowed, meaning observations in the training sets and features in the feature subspace can occur several times. Ultimately, the random forest algorithm, as an aggregated predictor, makes estimations on new data by averaging the predictions made by individual trees in the ensemble. This results in reducing the effects of overfitting and improving the predictive performance and generalization of the model compared to individual decision trees (Breiman 2001). It has been shown that the random forest algorithm is powerful in modelling problems with a large number of input features and when nonlinear relationships exist between input and output variables (Strobl et al. 2009, Biau 2012).

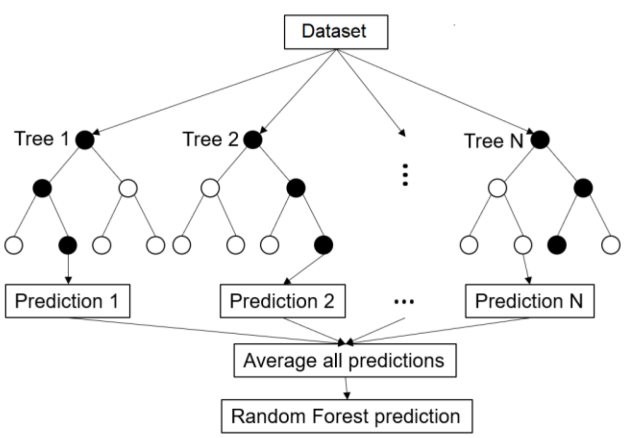

Figure 1. Random forest algorithm.

When training a random forest model, the main parameters to determine are the number of trees in the ensemble, the number of features to randomly select for each decision split, and the minimum number of observations in each tree leaf. For this study, the number of trees was set to 1000. The number of randomly selected features for each decision split was set to p/3 where p is the number of all features. The minimum leaf size was set to 5.

3.4 Training the Model and Performance Evaluation

To assess the performance of the random forest algorithm for modelling the relationship between CPTu data and soil unit weight, the dataset was split into training and test sets. This was done so that the performance of the final model could be examined on the test set that is not seen by the random forest during the training phase. Subsequently, 20% of the dataset (246 datapoints) was randomly selected and put aside as the test set. The remaining 80% of the dataset (982 datapoints) was used as the training set for the random forest algorithm. Figure 1 shows the histogram of the unit weight values of the dataset.

For training the random forest algorithm, various models were created with different combinations of input features and the performance of each model was assessed on the test set. This was done as a sensitivity analysis to qualitatively assess the relative importance of the input features in random forest modelling to estimate the soil unit weight.

To evaluate the performance of each random forest model, properties of the cumulative distribution function (CDF) of errors on the test set were quantified. The error was calculated as the discrepancy between the laboratory and model predicted unit weights. The 50^{th} percentile in the CDF is taken as the bias of the prediction. Assuming the error follows a normal distribution, the CDF values at 15.9% and 84.1% correspond to ±1 standard deviation. The overall error is thus calculated as the average of the two CDF values at 15.9% and 84.1%. The other performance measure was the coefficient of determination (R^2) on the test set.

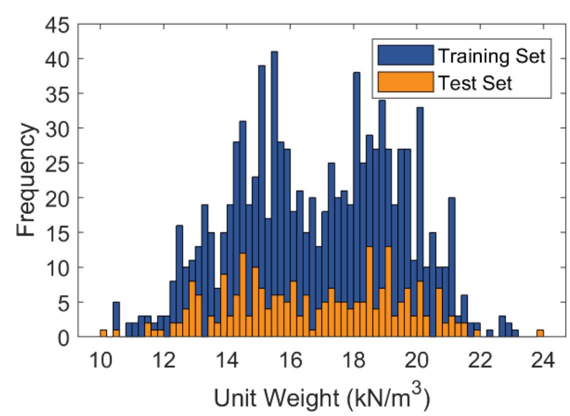

Figure 2. Histogram of the unit weight values for the training and test sets.

4 RESULTS

The relationship between the soil unit weight measured in the laboratory and the estimated unit weight using the random forest model is shown in Figure 3. This relationship is shown for the test set which is the data not used in training the random forest model. The model was trained using all six input features including corrected tip resistance (q_t), the dynamic pore water pressure (u_2), the sleeve friction (f_s), the hydrostatic porewater pressure (u_o), the effective overburden stress (σ'_{vo}) and depth (z). The R^2 of the model was observed to be 0.86. The CDF of errors is also shown in Figure 3. As can be seen, the bias and error of the estimated results are –0.05 kN/m^3 and 0.8 kN/m^3, respectively. The error of 0.8 kN/m^3 means that 68.2% of the estimated unit weights fall within ±0.8 kN/m^3 of the laboratory results.

The developed model uses the effective stress as an input parameter. This means an iteration or initial estimate of unit weight is require to determine the effective stress, which may not be desirable. Also, the information on phreatic surface and thus u_o may not always be available to be consumed by the model. Consequently, a random forest model was trained with only q_t, f_s, u_2, and z as input features. The relationship between the measured unit weight and estimated unit weight from this model as well as the CDF of errors are shown in Figure 4. Eliminating these two variables from the input features caused a slight decrease in performance when compared to the previous model with all six features. As such, R^2 decreased from 0.86 to 0.81 and the error increased from 0.80 to 0.93 kN/m^3. However, the correlation remains strong and the model is effective for the prediction of soil unit weight.

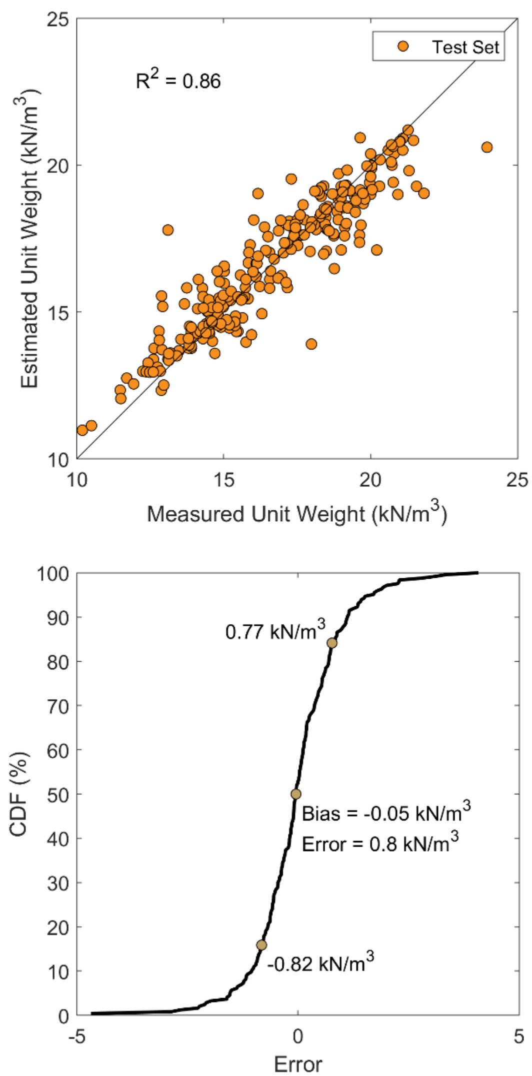

Figure 3. Relationship between laboratory measured and random forest estimated unit weight (top) and the cumulative distribution function (CDF) of errors on the test set (bottom). This model was trained with q_t, f_s, u_2, u_o, σ'_{vo}, and z as input variables.

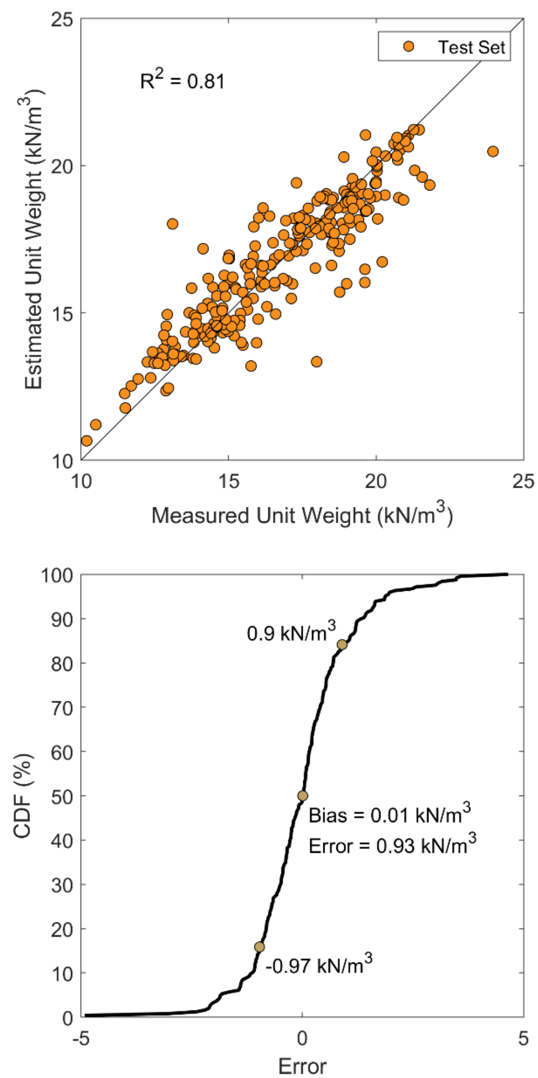

Figure 4. Relationship between laboratory measured and random forest estimated unit weight (top) and the cumulative distribution function (CDF) of errors on the test set (bottom). This model was trained with raw data only (q_t, f_s, u_2, and z) as input variables.

In addition to the two presented models, various random forest models were trained with different combinations of input features. The summary of this subsequent analysis is in Table 1 below, listing the input features used in each trial and the performance measures of each model on the test set. As seen in the table, by comparing models RF1 and RF2, it is evident that effective stress (σ'_{vo}) has a considerable impact on the model performance. The hydrostatic porewater pressure (u_o), on the other hand, appears to have no impact on the performance of the model as models RF2 and RF3 have identical performances. It should be noted that u_o is needed to calculate the effective stress, which appears to be an important feature for unit weight estimation, but its use as an independent input feature does not impact the performance of the models. The depth (z) generally appears to be an effective feature that improves the performance of the models and thus unit weight estimations. Depth could be considered as a proxy for total and effective stress and that can explain why it has a significant impact on the performance of the models.

Table 1. Performance of various random forest models trained using different combinations of input features.

Model	Input Features	R^2	Bias (kN/m^3)	Error (kN/m^3)
RF1	q_t, f_s, u_2, u_o, σ'_{vo}, z	0.86	-0.05	0.80
RF2	q_t, f_s, u_2, u_o, z	0.82	0	0.93
RF3	q_t, f_s, u_2, z	0.81	0.01	0.93
RF4	q_t, f_s, u_2	0.73	0.10	1.08
RF5	q_t, f_s, z	0.77	0.03	1.04
RF6	q_t, f_s	0.70	0.13	1.27

4.1 Comparison to Existing Relationships

In order to compare the performance of the data-driven approach presented in this study to the existing CPT relationships to estimate unit weight, four existing relationships were applied on the test set. These included the expressions proposed by Robertson and Cabal (2010), Mayne et al. (2010), Mayne (2014), and Lengkeek et al. (2018). The performance of these methods was compared to the performance of the random forest models presented in Table 1. According to Robertson and Cabal (2010), Equation 1 based on tip resistance and sleeve friction can be used to estimate unit weight:

$$\gamma/\gamma_w = 0.27[log R_f] + 0.36[\log(q_t/\sigma_{atm})] + 1.236 \quad [1]$$

where γ is soil unit weight, γ_w is unit weight of water in same units as γ, and σ_{atm} is atmospheric pressure in same units as q_t. Equations 2 and 3 are the expressions using sleeve friction alone as suggested by Mayne et al. (2010) and Mayne (2014) to estimate soil unit weight, respectively:

$$\gamma = 1.95\gamma_w(\sigma'_{vo}/\sigma_{atm})^{0.06}.(f_s/\sigma_{atm})^{0.06} \quad [2]$$

$$\gamma = 26 - 14/(1 + [0.5\log(f_s + 1)]^2) \quad [3]$$

where in Eq. 2, σ_{atm} is in same units as f_s and σ'_{vo}, and in Eq. 3, γ is in kN/m^3 and f_s is in kPa. The expression proposed by Lengkeek et al. (2018) to estimate the unit weight is based on tip resistance and sleeve friction:

$$\gamma = \gamma_{ref} - \beta\frac{log(q_{t,ref}/q_t)}{log(R_{f,ref}/R_f)} \quad [4]$$

where values of 19, 5, 30, and 4.12 have been proposed for γ_{ref}, $q_{t,ref}$, $R_{f,ref}$, and β, respectively, and q_t is in MPa.

Figures 5 to 8 show the relationships between the measured unit weight and estimated unit weight using these four expressions on the test set. The R^2 values as well as bias and errors associated with the performance of these models are listed in Table 2. Evidently, all the examined existing relationships have similar performance with a slight variation in errors (1.57-1.62 kN/m^3). The Lengkeek et al. (2018) model has the lowest bias (-0.18) while the Mayne et al. (2010) model has the highest R^2 on

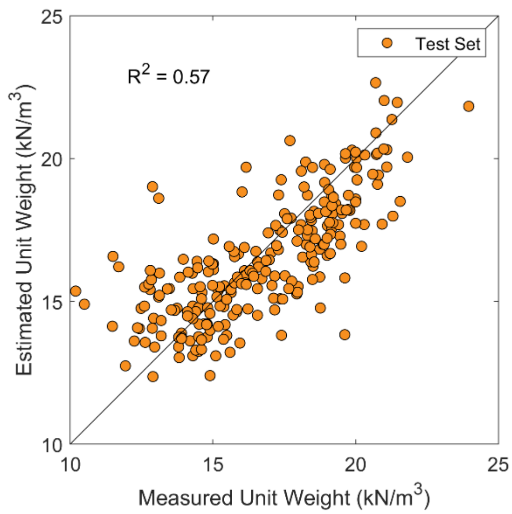

Figure 5. Relationship between measured vs. estimated unit weight using Robertson and Cabal (2010) method.

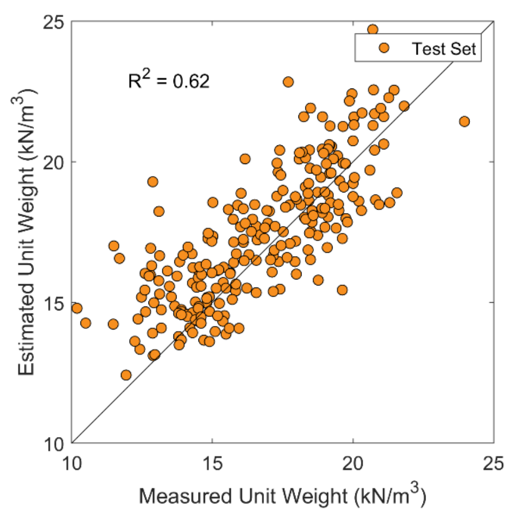

Figure 6. Relationship between measured vs. estimated unit weight using Mayne et al. (2010) method.

the test set. However, by comparing Table 1 and Table 2, it is evident all the random forest models outperform the existing relationships examined here. All the random forest models have an R^2 higher than 0.7, an error of less than 1.27, and a bias near zero.

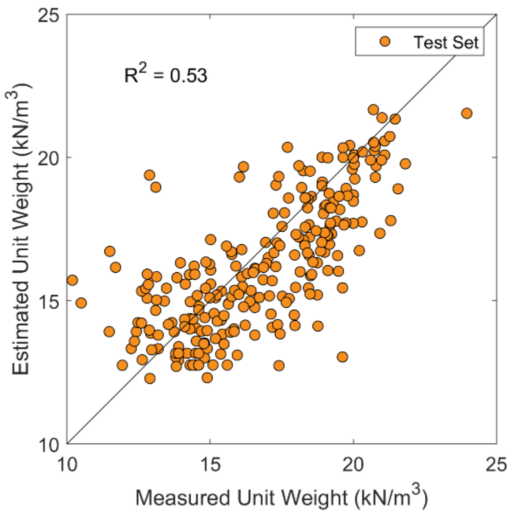

Figure 7. Relationship between measured and estimated unit weight using Mayne (2014) method.

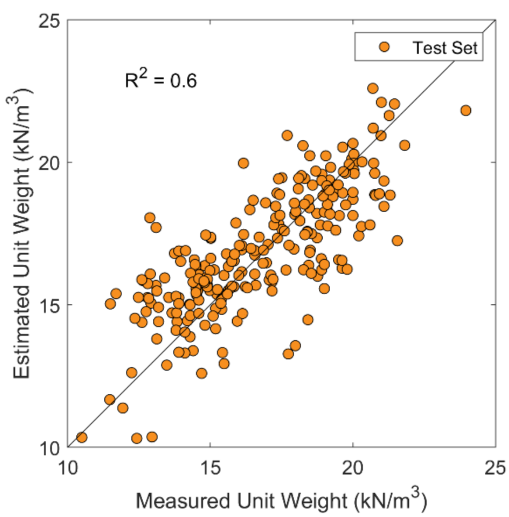

Figure 8. Relationship between measured vs. estimated unit weight using Lengkeek et al. (2018) method.

Table 2. Performance of existing relationships to estimate unit weight.

Model	**R^2**	**Bias (kN/m^3)**	**Error (kN/m^3)**
Robertson & Cabal (2010)	0.57	0.39	1.57
Mayne et al. (2010)	0.62	-0.74	1.61
Mayne (2014)	0.53	0.69	1.62
Lengkeek (2018)	0.60	-0.18	1.59
This Study (RF1)	0.86	-0.05	0.80

5 DISCUSSIONS

The performance of the random forest model was assessed using a test set. Although this could evaluate the generalization and robustness of the model when applied on new data, one can argue the model has seen similar material in the training set and is therefore expected to perform well on the test set. In another words, both training and test sets are from the same test fields with the same soil types and stress history. An evaluation is thus required to examine generalization of the model on data from other sites. Considering that the development dataset included a wide variety of soil types from various test sites around the globe, the developed model should generally have good generalization characteristic but needs to be cross validated using data from test sites other than those used here. Performing a cross validation study is the aim of future work.

As mentioned before, one of the characteristics of machine learning modelling is that they can adapt as more data becomes available and training set expands. Therefore, the performance and robustness of the developed model can be improved as more paired CPTu and laboratory measured unit weight become available. Also, adding other in-situ variables to the input features can potentially enhance the performance of the machine learning model. For example, shear wave velocity (V_s) measurements were not available for this study, but it is a feature that may significantly increase the accuracy of the model. Furthermore, in this study, the random forest algorithm was employed to develop the model. Other machine learning algorithms need to be examined as they may result in better performance compared to the random forest.

One of the disadvantages of data-driven modelling is that with most algorithms, no simple formula can be generated to be published and used by the public. However, the trained model could be shared with other users and made accessible to the public as a module in various software packages. At the time of writing, the authors are exploring methods of making the model described here available to the public such that it may be utilized in practice. If you are interested, please contact info@conetec.com.

6 CONCLUSIONS

With emerging machine learning algorithms and increasing computational power, geotechnical relationships need to be revisited and improved using new data-driven approaches. This paper explored the potential of a data-driven approach to estimate soil unit weight from CPTu data. A compiled database of paired CPTu measurements and laboratory measured unit weights was used to develop a machine learning model to directly estimate unit weight from CPTu data. A random forest algorithm was used as an example of a machine learning algorithm.

Results showed that a random forest model trained with q_t, f_s, u_2, u_o, σ'_{vo}, and z as input features could estimate unit weight with an error of ±0.8 kN/m^3. When only q_t and f_s were used, random forest could predict the unit weight with

±1.27 kN/m^3 error. A comparison performed between the random forest models and existing relationships in literature showed that all the random forest models developed in this study outperform the existing CPT relationships to estimate unit weight.

Although the developed models were trained with a variety of soil types from various test sites, care must be taken when applying them on data from other test sites. A cross validation needs to be performed to assess the performance of the models on data collected from field sites other than those used in this study.

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