Machine Learning in Geotechnical Engineering

Soil Layering by Cone Penetration Test Data

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1. Introduction

Accurate subsurface characterization is essential for foundation and ground improvement design in geotechnical engineering. Given the inherent spatial heterogeneity of soil deposits, soil properties often vary significantly with depth within a site. To support effective and reliable design, geotechnical engineers often segregate subsurface profiles into a finite number of layers, each assumed to be internally homogeneous and assigned representative soil properties. This process – commonly referred to as soil layering - relies on data acquired during subsurface investigations. Typical sources of geotechnical data include standard penetration test (SPT) blow counts, laboratory-based soil classification and index properties, and measurements of tip and sleeve resistances from cone penetration test (CPT), among others.

The SPT is widely employed due to its adaptability across diverse soil types and its ability to retrieve physical samples. However, its sampling intervals – typically 2.5 ft for upper 10 feet soil and 5.0 feet for thereafter – are relatively coarse. This low sampling resolution often leads to insufficient profile accuracy, underrepresentation of thin layers, and unreliable estimates of stiffness. Additionally, SPT blow counts tend to exhibit considerable variability, which can obscure the identification of layer boundaries and transition zones. These limitations motivate the exploration of alternative data sources for soil stratification.

In contrast, CPT involves continuous penetration of an instrumented electronic cone into the ground, during which tip resistance, sleeve friction, and pore water pressure on sleeve are recorded in real time. The CPT offers significantly higher resolution, by which typical data intervals are as small as 0.065 ft (2.0 cm). Furthermore, CPT measurements are generally more continuous and less variable than those from the SPT, making CPT data particularly promising for applications requiring detailed stratigraphic resolution.

The objective of this project is to investigate the feasibility of automating soil layering using unsupervised machine learning techniques applied to CPT data. The outcomes aim to contribute to the broader development of automated geotechnical analysis workflows, with the potential to enhance both the efficiency and consistency of subsurface characterization in practice.

2. Methodology

2.1 Problem statement

Given one or more CPT profiles containing cone resistance and sleeve friction measurements, the objective is to segment the soil subsurface into the smallest number of distinct soil layers that both capture essential geotechnical features and exhibits a high degree of internal homogeneity. This problem can be formulated as a clustering task subject to a continuity constraint. Specifically, data points with similar cone tip resistance and sleeve friction values should be assigned into the same cluster, while maintaining depth-wise contiguity within each cluster. That is, clusters must consist of continuous intervals along the depth axis and cannot be fragmented or overlap with one another.

2.2 Dataset

The primary data source used in this project is Reference 1, which consists of 984 publicly available cone penetration test records collected from various sites across North America. This dataset was selected because of its large volume, uniform formatting, and comprehensive documentation. For the purposes of this study, the No.4 and No.5 datasets (as identified in Reference 2) are used for analysis. As pore water pressure (u_2) measurements are not included in the original datasets, they are assumed to be zero at all depths throughout this analysis.

2.3 Code Implementation

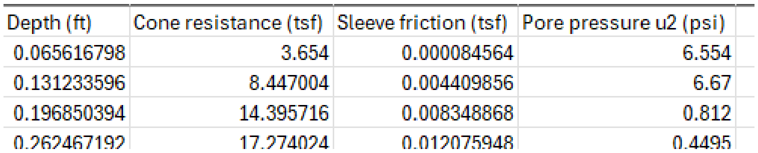
All computation and analyses are conducted in a Jupyter Notebook environment, utilizing Python version 3.9.19 with Visual Studio Code. Key external libraries are Scikit-learn, Numpy, Pandas, Matplotlib, SciPy, and Shapely. The complete source code and reproducibility instructions are available at:

https://github.com/Drzyjiang/ML-in-Geotechnical-Engineering/tree/main/Soil%20Layering%20by%20Cone%20Penetration%20Test%20Data/Code

2.4 Preprocessing

2.4.1 Data extraction

This project utilizes input data in .csv format, structured with column headers including “Depth (ft)”, “Cone resistance (tsf)”, “Sleeve friction (tsf)”, and “Pore pressure u2 (psi)” (Figure 1). Because the original data is distributed in .mat and .pkl formats, a MATLAB script is developed and provided for converting these formats into a standardized .csv file.



Depth (ft)	Cone resistance (tsf)	Sleeve friction (tsf)	Pore pressure u2 (psi)
0.065616798	3.654	0.000084564	6.554
0.131233596	8.447004	0.004409856	6.67
0.196850394	14.395716	0.008348868	0.812
0.262467192	17.274024	0.012075948	0.4495

Figure 1 Preview of standardized .csv format supported by this project

2.4.2 Data filtering

In practical applications, CPT measurements often contain irregular fluctuations, which do not reflect true stratigraphic transitions. To mitigate these effects, a moving average (window) function is applied to smooth the raw cone resistance and sleeve friction profiles. The window length must be carefully selected: one that is too short may fail to suppress noise, while an excessively long window may obscure important stratigraphic features. In this project, a single-pass averaging is applied with a window length as 3.0 ft, which effectively balances noise reduction with signal fidelity.

Although the moving average is effective in suppressing cyclic fluctuations, it is less effective against narrow, high-amplitude spikes. Such spikes often correspond to thin, erratic interbeds that are typically negligible in soil layering with thickness less than 2 ft. A spike removal algorithm was developed to remove these features; However, due to the complexity of overlapping or nested spikes in real-world data, this method remains under development and is not employed in this analysis.

2.4.3 Correct cone resistance

Cone resistance q_c is often corrected to tip resistance q_t by accounting for pore water pressure u_2, using the following equation:

$$q_t = q_c + u_2(1 - a_n)$$

where q_t is corrected tip resistance (tsf);

q_c is measured cone resistance (tsf);

u_2 is pore pressure (tsf);

a_n is cone area ratio.

The raw cone resistance and sleeve friction and the preprocessed profiles are compared in Figure 2.

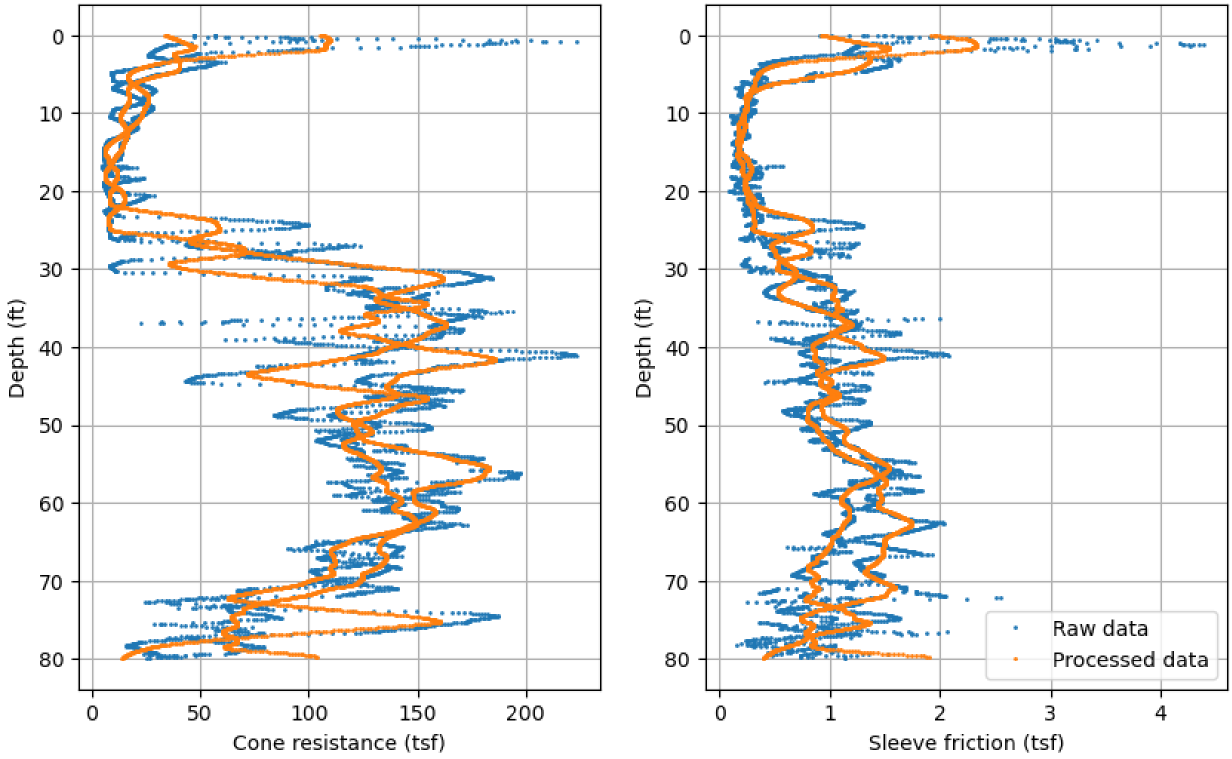


Figure 2 Comparison of raw and preprocessed data

3. Clustering

Prior work (Reference 3) has demonstrated that decision tree and random forest models are effective in clustering one-dimensional geotechnical data, particularly when a continuity constraint on depth is enforced. This study extends that approach to CPT data, evaluating the performance of these models under similar constraints. Depending on whether the soil labels are treated as categorical or numerical, either a classifier or a regressor is employed. For simplicity, the number of soil layers, (i.e., clusters) is specified as four. This value can be refined through sensitivity analysis if needed.

3.1 Decision tree

A decision tree is a hierarchical model that segments data using a series of rule-based splits, forming a tree-like structure. The internal (non-leaf) nodes define the sequence of splitting criteria, while the leaf nodes represent the final clusters – interpreted here as soil layers. With depth as the sole input feature, each split corresponds to a transition depth in the stratigraphy. The splitting rule is selected by optimizing an objective function - such as maximizing information gain (for classification) or minimizing variance (for regression).

A key consideration is the selection of label features for clustering. In this study, three representations are examined:

- Tip resistance and sleeve friction in logarithmic scale;
- Soil behavior type index (I_c);
- Soil behavior type category.

Because depth is the only feature used for tree construction, feature selection randomness does not apply to the decision tree model in this context.

3.1.1 Regression on tip resistance and sleeve friction in logarithmic-scale

A straightforward way is to apply decision tree regression model directly to CPT tip resistance and sleeve friction data. However, domain knowledge suggests that soil type is more closely associated with these parameters when expressed in logarithmic scale. This is consistent with the formulation of the Soil Behavior Type Index (I_c) and the normalized soil behavior type classification chart. Therefore, in this implementation, the preprocessed tip resistance and sleeve friction are transformed to log-scale prior to modeling fitting.

The resulting decision tree regressor identifies three transition depths – rounded to 5.0 ft, 23.0 ft, and 26.0 ft – producing four distinct layers. These results are illustrated in Figure 3. The first layer (0-5 ft) captures a very stiff near-surface stratum, while the second layer (5-23 ft) likely correspond to a cohesive deposit. However, the third layer (23-26 ft) appears trivial and may represent a transitional zone with limited geotechnical significance. Notably, a prominent transition observed at approximately 71 ft is not captured by the model, suggesting limitations in this approach.

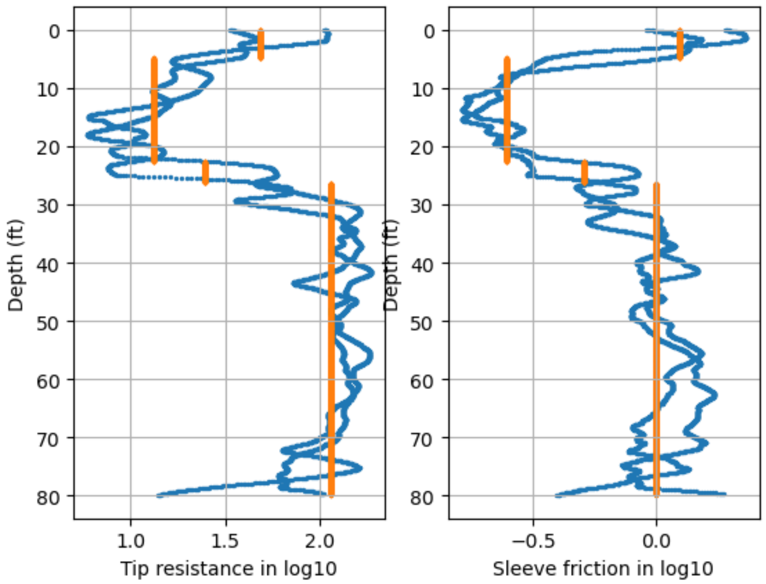


Figure 3 Results (in yellow) of decision tree regression on tip resistance and sleeve friction in log-scale

3.1.2 Regression on soil behavior type index

One of the most widely adopted approaches for soil classification in CPT interpretation is the use of the Soil Behavior Type Index I_c, which is derived from cone tip resistance and sleeve friction data. While raw tip resistance and sleeve friction measurements contain information on range of soil properties, the index I_c offers a transformation grounded in geotechnical domain knowledge that isolates soil behavior characteristics, effectively filtering out unrelated variability.

The formulation of I_c is computed as follows (Reference 4):

$$I_c = ((3.47 - logQ_{tn})^2 + (logF_r + 1.22)^2)^{0.5}$$

where Q_{tn} is normalized cone penetration resistance (dimensionless), and F_r is normalized friction ratio (in %), defined as:

$$F_r = \frac{f_s}{q_t - \sigma_{vo}} \cdot 100$$

The normalized resistance Q_{tn} is calculated iteratively by incorporating the initial stress exponent n, as shown below:

$$n = 0.381(I_c) + 0.05\left(\frac{\sigma'_{vo}}{p_a}\right) - 0.15 \leq 1.0$$

$$C_N = (\frac{p_a}{\sigma'_{vo}})^n$$

$$Q_{tn} = \left[\frac{(q_t - \sigma_{vo})}{p_a}\right] \cdot C_N$$

where σ_{vo} and σ'_{vo} are total and effective vertical stress, respectively; p_a is atmospheric pressure; and C_N is a correction factor based on overburden stress.

The computed I_c profile and its corresponding decision tree regression results are illustrated in Figure 4, and its distribution is summarized via a histogram in Figure 5.

Based on the I_c interpretation, the following stratigraphic units are identified:

- From 0-13 ft: a sand mixture layer with gradually increasing silt content;
- From 13-26 ft: a cohesive (clay) layer;
- From 26-70 ft: a sand mixture layer with increasing silt proportion;
- At ~70 ft: a transition into a silt-dominant layer.

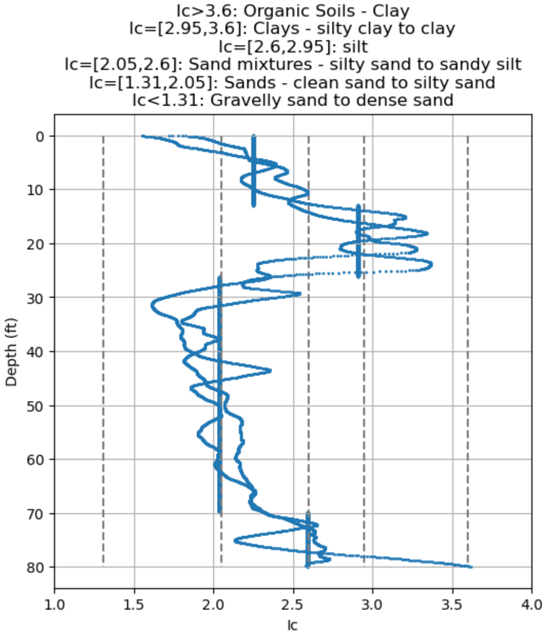


Figure 4 Results of decision tree regressor model trained on I_c

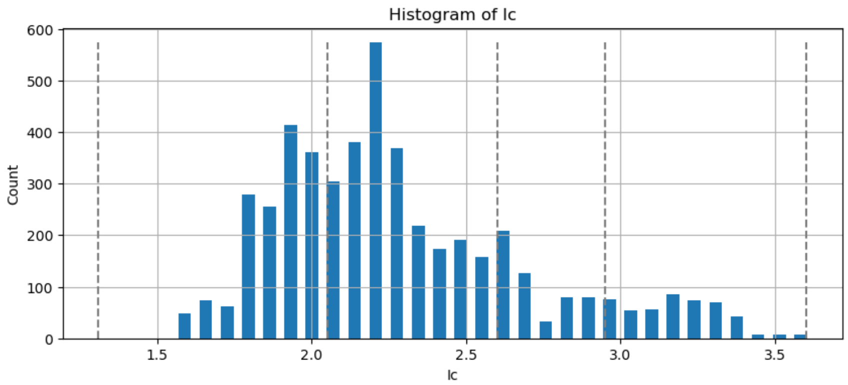


Figure 5 Histogram of soil behavior type index I_c

A decision tree regression model is applied by treating I_c as a continuous variable. The resulting model successfully captures the three major transition depths at 13 ft, 26 ft, and 70 ft, corresponding to significant changes in soil behavior. Importantly, the model avoids overfitting by not assigning separate clusters to trivial or ambiguous transition zones. The predicted stratigraphy is consistent with the known geotechnical behavior reflect in the CPT data.

3.1.3 Classification on simplified soil behavior type

Robertson (2010) proposed an updated the classification system for Normalized Soil Behavior Type (SBTn), which partitions soil into nine zones based on normalized cone penetration parameters. Among these, six zones can be directly associated with specific ranges of the Soil Behavior Type Index I_c. This study adopts a simplified classification scheme that maps I_c values to categorical zone numbers, as summarized in Table 1. It is worth noting that using I_c is a simplification, as the complete SBTn classification typically requires interpretation from the Q_{tn}-F_r chart (Figure 15).

Table 1 Association of soil behavior types with Ic

Zone	**Soil Behavior Type**	**Ic**
1	Sensitive, fine grained	N/A
2	Organic soils – clay	> 3.60
3	Clays – silty clay to clay	2.95 – 3.60
4	Silt mixtures – clayey silt to silt clay	2.60 – 2.95
5	Sandy mixtures – silty sand to sandy silt	2.05 – 2.60
6	Sands – clean sand to silty sand	1.31 – 2.05
7	Gravelly sand to dense sand	< 1.31
8	Very stiff sand to clayey sand	N/A
9	Very stiff, fine grained	N/A

Notes:
1. N/A stands for not applicable.

Using the classification in Table 1, I_c values are converted to discrete zone numbers, which serve as categorical labels for training a decision tree classifier. The trained model is then applied to predict the simplified SBTn zone at each depth. For visualize purposes, each categorical zone is mapped to the midpoint of its corresponding I_c range, and the resulting profile is plotted in Figure 6. The classifier successfully identifies the cohesive layer at approximately 13 ft depth. However, the bottom cohesive layer – observed in other methods – is labeled as sandy, suggesting misclassification. Overall, the decision tree classifier performs reasonably well in capturing major stratigraphic changes. Nevertheless, due to its reliance on fixed I_c thresholds, the model may misclassify gradual transitions where I_c values hover near class boundaries. In such cases, the model assigns different categorical labels to data points with marginal differences, leading to artificial discontinuities in the predicted stratigraphy.

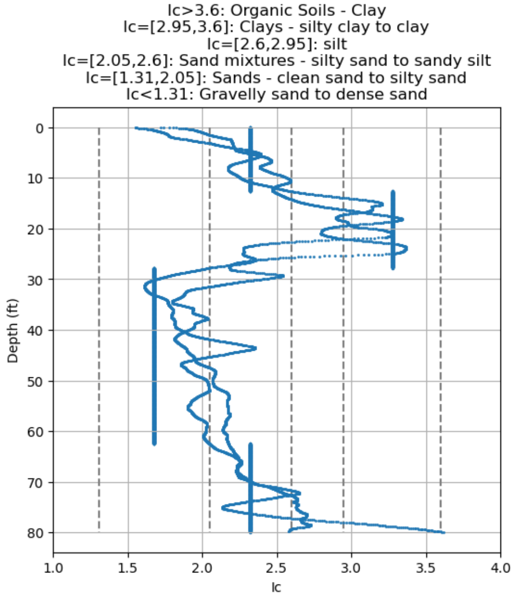


Figure 6 Classification results by decision tree model trained on simplified soil behavior type

3.2 Random forests

Random forests represent an ensemble learning technique that enhances predictive accuracy and model robustness by aggregating the results of multiple decision trees trained on different subsets of the data. These subsets are generated through a process known as bootstrap aggregating, or bagging, which introduces variance among the trees by sampling the training data with replacement. This mechanism effectively reduces overfitting and improves generalization performance. Depending on the nature of the target variable, random forests can be initialized as either classifiers or regressors as needed. In this study, the ensemble consists of 10 trees.

3.2.1 Regression on tip resistance and sleeve friction in log-scale

As an extension of the methodology described in Section 3.1.1, a random forest regressor model is trained on logarithmic values of CPT tip resistance and sleeve friction. The predicted results are superimposed on the original data in Figure 7. The model successfully identifies a cohesionless layer beginning at approximately 5 ft, and a cohesive layer starting near 27 ft. However, instead of clearly delineating the bottom cohesive layer at 71 ft – identified in other models – the random forest emphasizes a narrow transition zone around 25 ft.

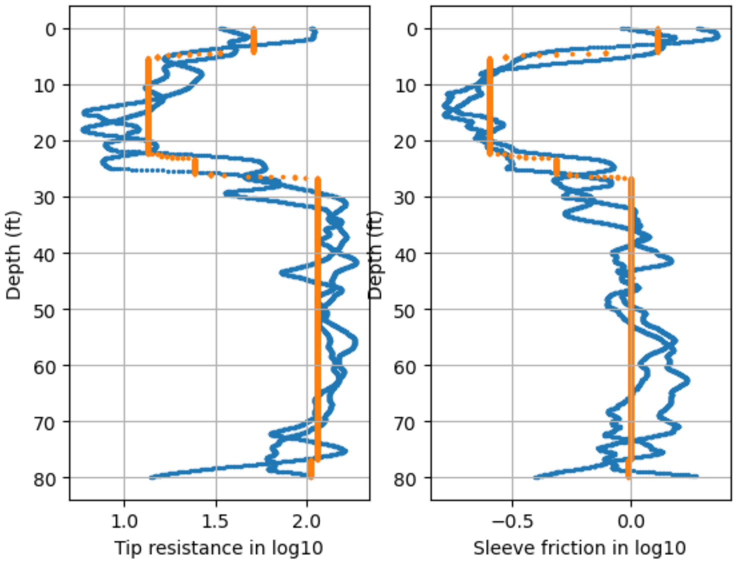


Figure 7 Regression results by random forests on tip resistance and sleeve friction in log-scale

To investigate the decision-making behavior across the ensemble, the splitting thresholds at each non-leaf node are extracted and shown in Figure 8. These thresholds indicate transition depths between neighboring layers. Most trees consistently identify consistent transition depths at approximately 4 ft (Layer 1 to Layer 2), 22 ft (Layer 2 to Layer 3), and 25 ft (Layer 3 to Layer 4). While there is a strong consensus for the first two transitions, the final transition shows greater variability, with some trees identifying it at around 77 ft.

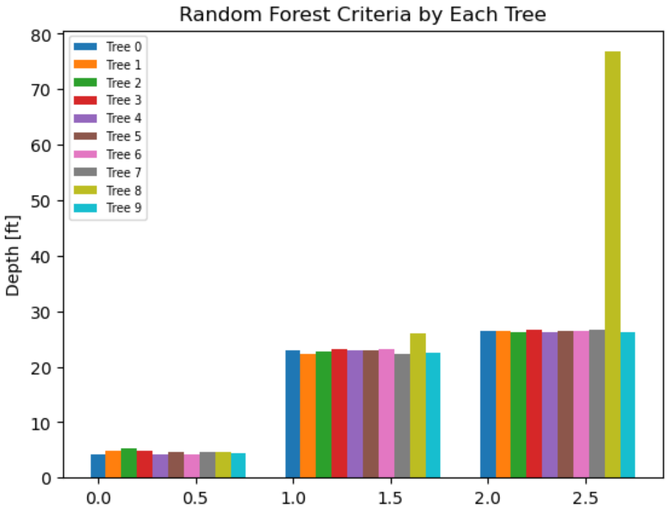


Figure 8 Splitting criteria by each tree in random forests on tip resistance and sleeve friction in log-scale

The performance of decision tree and random forest regressors is evaluated using coefficient of determination R^2:

$$R^2 = 1 - \frac{RSS}{TSS}$$

where RSS is the residual sum of squares:

$$RSS = \sum_I (y_i - f_i)^2$$

TSS is the total sum of squares and computed as,

$$TSS = \sum_I (y_i - \hat{y})^2$$

y_i is observed data; $\hat{y}$ is the mean of observed data; f_i is the predicted data.

A sensitivity study is performed to determine the optimal the number of clusters (i.e., leaf nodes) by comparing R^2 between the decision tree and the random forests models. The results, presented in Figure 9, indicate a negligible improvement in prediction accuracy as the number of clusters increases from 2 to 4. Beyond four clusters, the rate of improve improves, and gains become negligible again once the number of clusters exceeds 12. Overall, the random forests model demonstrates slightly superior performance compared to the single decision tree model.

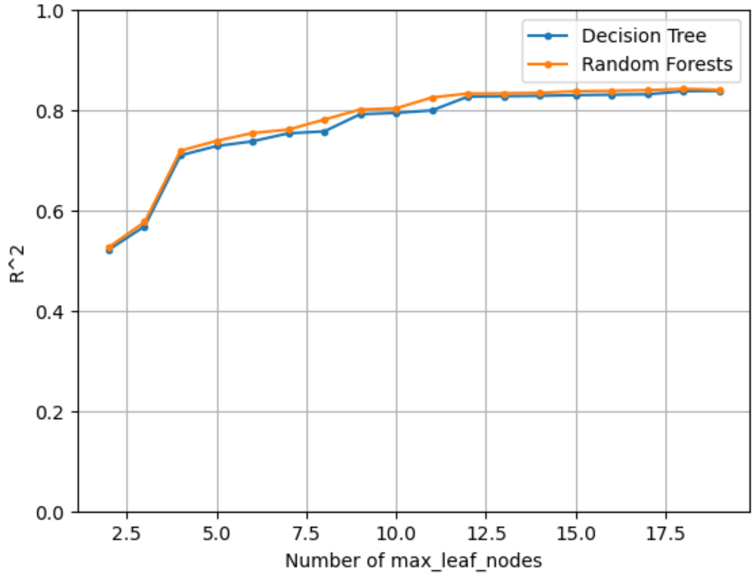


Figure 9 Comparison between decision tree and random forests model trained on tip resistance and sleeve friction

3.2.2 Regression on normalized soil behavior type index

A random forests regressor model is employed to predict the normalized soil behavior type index I_c. The regression results, presented in Figure 10, exhibit strong agreement with the original dataset and reveal four distinctive interbedded layers – two cohesive and two cohesionless. The model successfully captures the major transitions between these layers, with approximate depth changes observed at 13, 26, and 70 ft.

To further investigate the model's internal decision logic, the splitting criteria of individual trees within the random forest ensemble are illustrate in Figure 11. All constituent trees consistently identified the same transition depths, suggesting robust model consensus.

A sensitivity analysis was also conducted to evaluate the influence of the number of layers on model performance. The results of this analysis are summarized in Figure 12, highlighting the advantages of ensemble learning over a single decision tree.

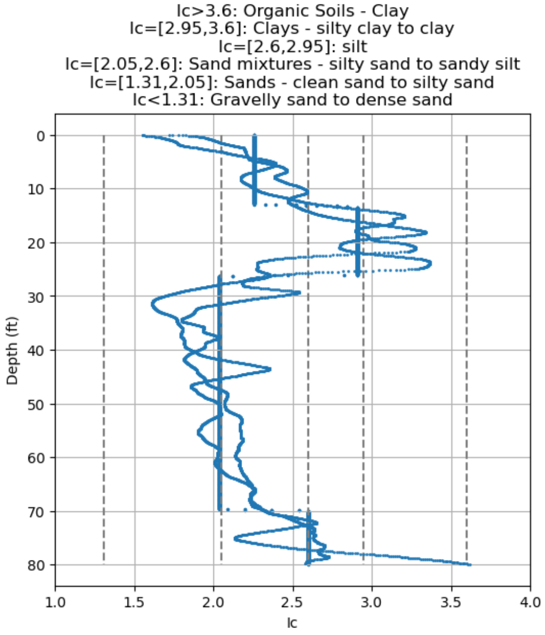


Figure 10 Regression results by random forests model trained on normalized soil behavior type index

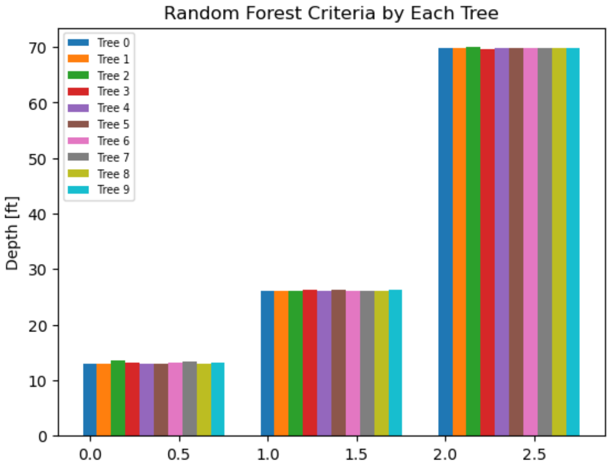


Figure 11 Splitting criteria by each tree in random forests on normalized soil behavior type index

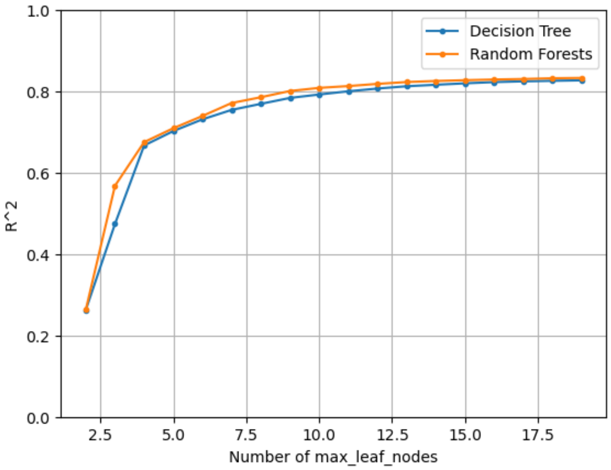


Figure 12 Comparison between decision tree and random forests models trained on soil behavior type index

3.2.3 Classification on Normalized Simplified Soil Behavior Type

To improve classification performance over the single decision tree used in Section 3.1.3, a random forest classifier was implemented to predict the simplified soil behavior type at varying depths. As shown in Figure 13, the model identifies transition depths at approximately 13, 28, and 62 ft. Consistent with the previous decision tree results, the second layer is classified as cohesive, while the remaining layers are classified as cohesionless.

The splitting logic used by the individual decision trees in the ensemble is visualized in Figure 14. All trees yield consistent stratigraphic interpretations, supporting the validity and stability of the classification outcome.

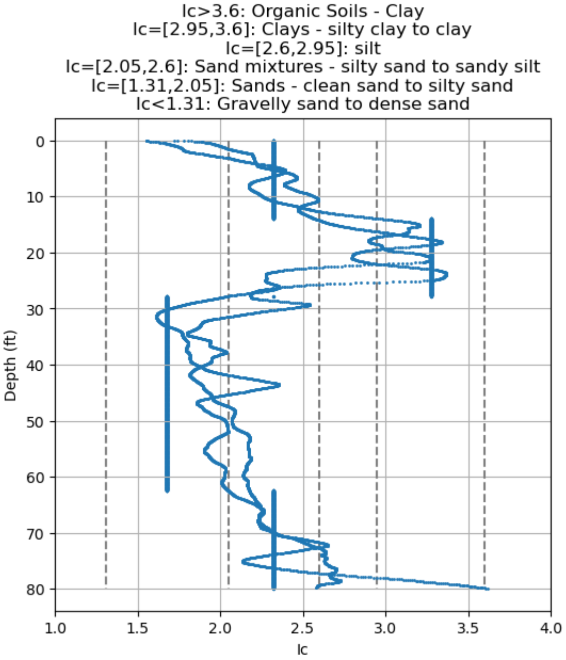


Figure 13 Results of random forests classifier trained on simplified soil behavior type

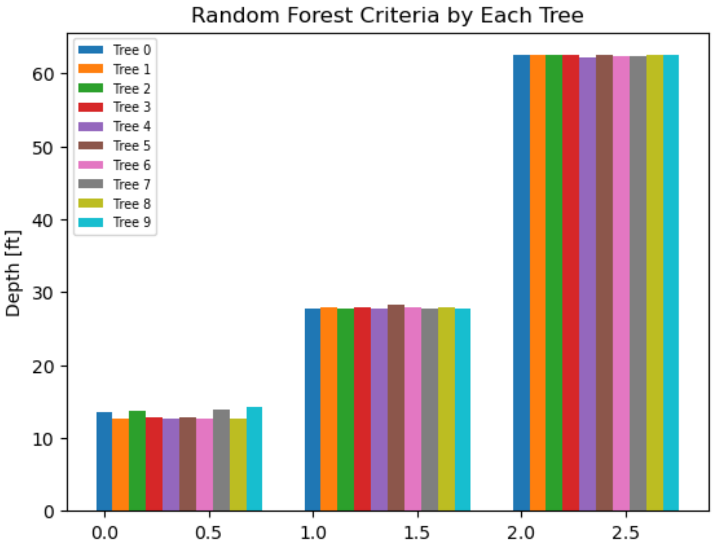


Figure 14 Splitting criteria by each tree in random forests classifier model trained on simplified soil behavior type

3.2.4 Random forests based on soil behavior type

In Section 3.2.3, a random forests classifier model is trained on simplified soil behavior type derived from the normalized soil behavior type index I_c. As an alternative and more rigorous approach, the soil behavior type can be determined using the normalized cone penetration parameters Q_{tn} and F_r, as depicted in Figure 15. Both axes in this chart represent normalized quantities, making it a more robust tool for soil classification.

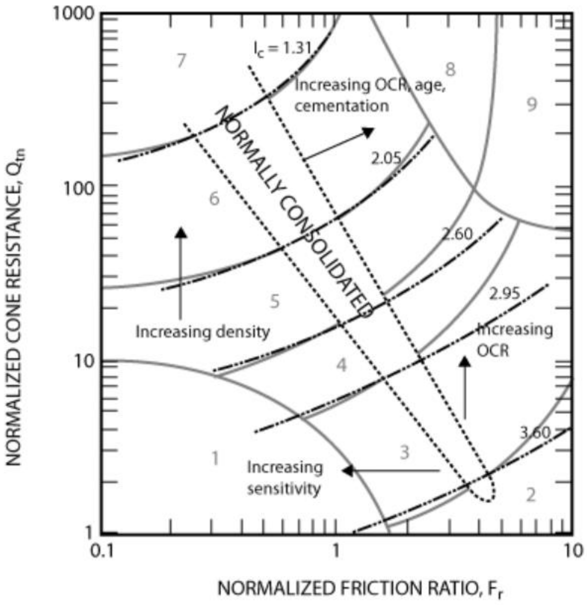


Figure 15 Q_{tn}-F_r chart with soil behavior type zone numbers (Reference 4)

Compared to the soil behavior type index, the Q_{tn}-F_r chart offers several advantages. Notably, it differentiates between soil types that I_c cannot resolve, such as sensitive fine-grained soils (Zone 1), very stiff sand to clayey sand (Zone 8), and very stiff fine-grained soils (Zone 9). The also enhances classification accuracy in transitional soils, including clays (Zone 3), silt mixtures (Zone 4), and stiff fine-grained soils (Zone 9). While the index I_c generally correlates with fine content – high values indicating higher fines – the chart provides a two-dimensional framework. Changes in fines contents are typically observed along the diagonal direction, whereas changes in soil stiffness occur orthogonally.

To enable classification, each zone on the Q_{tn}-F_r chart was digitized into a polygon defined by a finite set of boundary points. Care was taken to ensure no voids or overlaps between adjacent zones by requiring that shared vertices lie on common boundaries. Using the Shapely library, each data point was effectively assigned a zone number by checking its inclusion within the appropriate polygon. For visual classification, data points were color-coded by zone and overlaid onto the original chart, as shown in Figure 16.

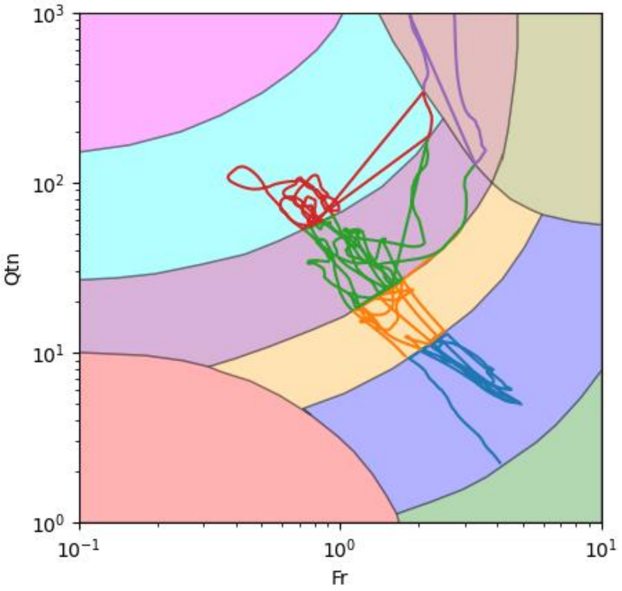


Figure 16 Verification of zone numbers of each data point

Subsequently, a random forests classifier was trained using depth as the sole input feature and the assigned zone number as the target label. The classification results are presented in Figure 17. Points from Layer 0 predominantly reside in Zone 8, transitioning through Zone 5 (sandy mixture) and 4 (silt mixture). Layer 1 includes points spanning Zone 5 and 6 (sands), while Layer 2 is primary in Zone 5. Data in Layer 3 also mainly within Zone 5 and 4. These results suggest that certain layers span over across multiple zones, revealing that it is hard to enforce a unique zone number for each layer.

The splitting criteria for individual trees within the random forest model are displayed in Figure 18. Most trees consistently identify transition depths at approximately 28, 61, and 71 ft. However, some variation exists. For example, Tree 3 and Tree 9 identify 12 ft as the first transition depth - a reasonable outcome given the cohesionless-to-cohesive soil transition at that depth. Conversely, the transition between 61 and 71 ft is less significant, as neither tip resistance, sleeve friction, nor I_c values show pronounced variations in that interval.

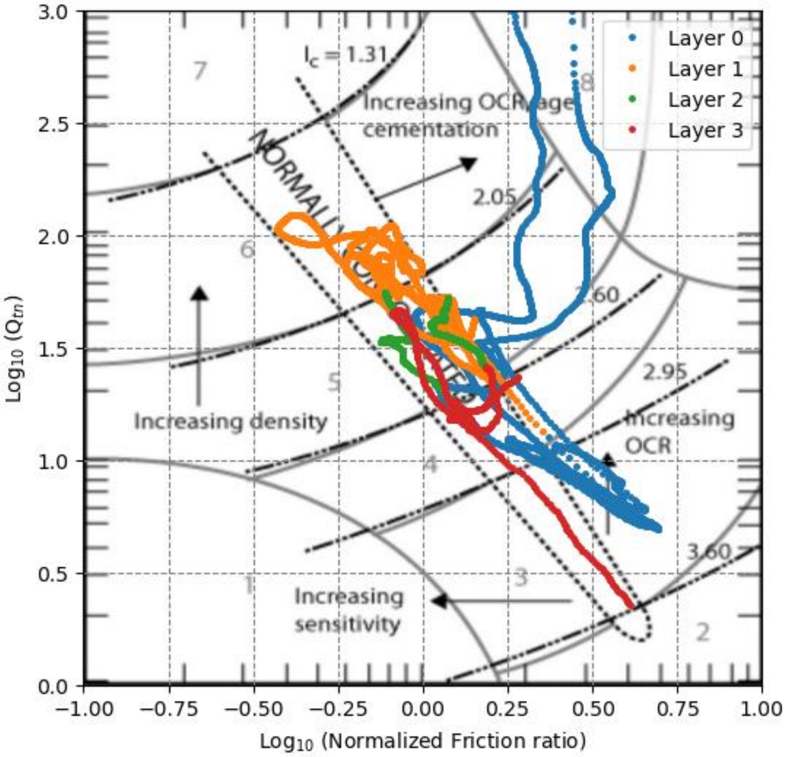


Figure 17 Results of random forests classifier trained on soil behavior type

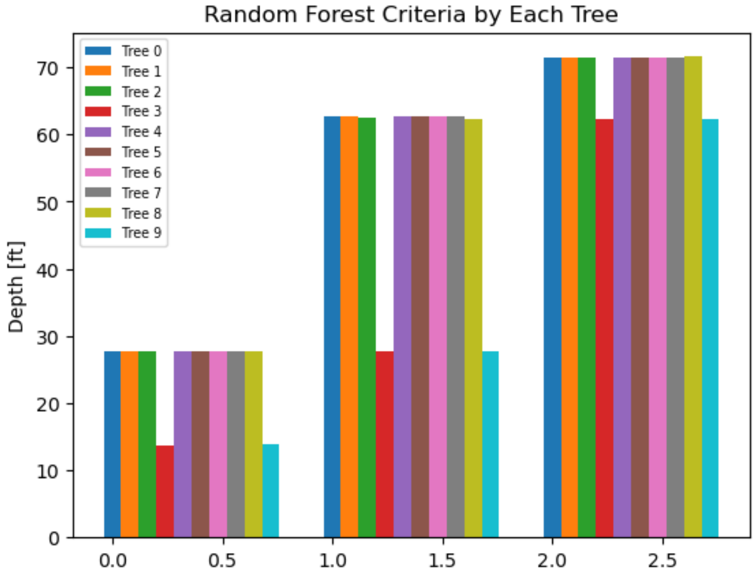


Figure 18 Splitting criteria by each tree in random forests classifier model trained on soil behavior type

3.3 Reduction of random forests splitting criteria

In practice, individual trees within a random forests model may produce divergent splitting criteria, complicating the interpretation of stratigraphic boundaries. This variability is expected, given the heterogeneity inherent in real-world subsurface data. Consequently, a post-processing reduction procedure is required to derive a consistent and interpretable soil layering scheme. In this study, two complementary reduction methods are developed and employed in tandem.

The first method involves aligning the splitting depths of each tree and computing the median value at each corresponding position in the split sequence. Specifically, the splitting depths from each tree are sorted in ascending order, and for each split index (e.g., first, second, third), the median value among all trees is selected as the representative transition depth. This approach mitigates the influence of outlier and reduces the likelihood of false positive due to errant or extreme splits. However, a key limitation of this method is its sensitivity to offset in the sequence of transition depths across trees. That is, even if a tree incorrectly identifies the first transition depth, its subsequent splits may still correspond meaningfully with other trees.

Take Figure 18 for example, Tree 3 and Tree 9 deviate from the majority by voting for a first transition depth at approximately 13 ft rather than 28 ft. However, upon a closer look, the second and the third transition depths from these two trees align closely with the first and the second transitions identified by the remaining trees. This shift is likely due to bootstrapped variation in training data. Thus, the second and third splits from Tree 3 and Tree 9 should be interpreted as an agreement with other trees, rather than deviations.

To address this sequential offset issue, a second reduction method is applied. Rather than sorting and indexing the splitting depths, all split values across the ensemble are aggregated and subject to agglomerative hierarchical clustering. The number of clusters in the model is set equal to the number of leaves in the original random forest. Through this clustering process, similar transition depths from different trees are grouped, effectively consolidating votes and reducing noise. This method captures repeated patterns in the splitting criteria without relying on strict positional alignment, thereby producing a more robust and coherent representation of the stratigraphy.

4. Verification

The performance of unsupervised machine learning models trained on cone penetration test data is evaluated using two primary metrics: accuracy and simplicity. However, unsupervised learning inherently lacks labeled ground truth, complicating direct validation of soil layering predictions. In this project, verification is ideally performed using supplementary data sources – such as standard penetration test blow counts, laboratory-derived soil classifications, moisture content, plasticity indices, and shear strength parameters – to establish a more rigorous ground truth. Due to the unavailability of these supporting datasets, an alternative approach is adopted.

A professional geotechnical engineer, leveraging domain expertise and empirical experience, provided an expert-based soil profile interpretation. This professional judgement is used as a reference baseline for evaluating the model results. According to this assessment:

- The first transition occurs at approximately 5 ft, indicating a change from clean sand to sandy mixture;
- The second transition is identified at 27 ft, marking a shift from clay to sand;
- The third transition occurs at approximately 70 ft, denoting a boundary between silty and silt;

Table 2 presents a comparative summary of the transition depths identified by each machine learning model alongside the expert interpretation.

Across all models, the second transition near 23-28 ft is consistently identified. Models trained on tip resistance and sleeve friction (in log-scale) successfully detect the first transition at 5 ft, whereas models trained on soil behavior type index (I_c) or simplified soil behavior type tend to identify the first transition around 13 ft, likely reflecting sensitivity to changes in fine content.

The third transition depth exhibits greater variation. Models trained on soil behavior type index and full soil behavior type (Q_{tn}-F_r) correctly place the transition near 70-71 ft, aligning closely with professional judgement. In contrast, models trained on simplified soil behavior type suggest a shallower depth (~62 ft), and those based on tip resistance and sleeve friction overlook this transition altogether, possibly due to scale compression in log-transformed features.

Among the evaluated models, the random forests regressor trained on the soil behavior type index exhibits the best alignment with expert interpretation, followed by the random forests classifier trained on soil behavior type zones. Conversely, models based on simplified soil behavior type exhibit the lowest accuracy. This is attributed to the fixed nature of Ic-based zone thresholds, which as noted in Reference 4, may involve overlapping or ambiguous boundaries and often require regional calibration. Without such tuning, the simplified soil behavior type model, which relies on a single scalar index, becomes susceptible to misclassification.

Table 2 Comparison of machine learning results and professional judgement

Model	**Labels**	**Transition 1 (ft)**	**Transition 2 (ft)**	**Transition 3 (ft)**
Decision tree regressor	Tip resistance and sleeve friction (log-scale)	5.0	23.0	26.0
Decision tree regressor	Soil behavior type index	13.0	26.0	70.0
Decision tree classifier	Simplified soil behavior type	13.0	28.0	62.0
Random forests regressor	Tip resistance and sleeve friction (log-scale)	5.0	23.0	26.0
Random forests regressor	Soil behavior type index	13.0	26.0	70.0
Random forests classifier	Simplified soil behavior type	13.0	28.0	62.0
Random forests classifier	Soil behavior type	25.0	62.0	71.0
Professional judgement	-	5.0	23.0	71.0

In general, model limitations arise from challenges in detecting gradational transitions: some models fail to detect significant changes (false negatives), while others exaggerate minor fluctuations (false positives). There results highlight the importance of incorporating domain expertise and auxiliary data when interpreting machine learning outputs in geotechnical applications.

5. Conclusions

This project investigates the use of unsupervised machine learning models to automate soil stratification based on cone penetration test (CPT) data. A total of seven models – including decision tree and random forests regressor and classifier – were developed and trained using various input features and label representations informed by geotechnical domain knowledge.

Among the evaluated models, the random forests regressor trained on the soil behavior type index (I_c) demonstrated the most consistent and accurate performance in identifying subsurface transition depths. The random forests classifier model trained on soil behavior type zones (Q_{tn}-F_r) followed as the next best-performing approach. Both models show strong alignment with expert-derived stratigraphic interpretations.

The findings highlight the feasibility and effectiveness of applying ensemble-based machine learning techniques, particularly random forests, for data-driven soil profiling in geotechnical engineering. The integration of domain-specific indices and expert-informed labeling schemes is shown to enhance model interpretability and performance. These insights contribute to the growing body of research at the intersection of geotechnical data analytics and artificial intelligence, and lay the groundwork for more robust, automated subsurface characterization frameworks.

6. References

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