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TOWARDS AUTOMATIC DETECTION OF QUICK CLAY USING FIELD TESTING

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The identification of quick clay is of paramount importance for proper landslide hazard and risk assessments in regions of Scandinavia and North America. Field investigation methods, such as rotary pressure sounding and total sounding, are effective and robust methods used in Norway to identify the presence of quick clay. However, their interpretation usually relies on visual inspection.Theinterpretation of soil layers based onthese methods bear uncertainties and must be supplemented with laboratory tests to be able to predict quick clay presence accurately. This study focuses on developing and employing an algorithm to automate quick clay detection from field tests such as rotary pressure sounding and total sounding and to quantify the uncertainties associated with these predictions.Data from three different sites, Tiller-Flotten, Buvika, and Kvithammer-Åsen in mid Norway, are used to test the algorithm. The algorithm predicts the presence of quick clay by utilizing predefined thresholdson field data and laboratory data. Confusion matrix performance parameters, such as True Positive Rate (TPR), False Positive Rate (FPR), the accuracy, and the precision are computed to evaluate effectiveness of the algorithms. The results indicate that the selection of threshold values is important in the detection of the quick clay presence.

Keywords: Quick clay, detection, total sounding, rotary pressure sounding, python, receiver operating characteristics, optimum operation point.

1. Introduction

Sensitive marine clay deposits cover large parts of the land in Norway, Sweden and eastern Canada. These clays are leached marine clays that may change from a relatively stiff and brittle material to a viscous liquid when remolded (Rosenqvist 1953). Landslides in sensitive clays can initiatequickly and expand over large areas retrogressively due to the low remolded strength of the clays. L'Heureux et al. (2018) reported that quick clay landslides with an extent greater than 50,000 m^3have occurredapproximately once per year since 1950. Some of the well-known quick clay landslides in Norway, among many others, are Rissa (Gregersen 1981) and Gjerdrum (Ryan et al. 2021).

In Norway, approximately 80% of the population lives below the marine limit where quick clays occur. Substantial efforts are needed to develop effective and reliable methods for quick clay detection. Geotechnical field tests, namely total sounding, rotary pressure sounding, and cone penetration tests, are widely performed together with laboratory testingfor identifyingsoil types and possible quick clay presence.However, the only certain method for detection of quick clay is to test a sample in its remolded state in the laboratory.The fall cone test is usually employed for this matter. In Norway, a clay is defined as quick when the remolded shear strength is less than 0.5 kPa (NGF 2011). In the current study however, a relaxed criterion of remolded shear strength of2 kPa, $c_{ur}\leq 2$ kPa, is considered for identifying aquick clay.This is in line with the Norwegian guidelines and NVE (2020) definition of brittle clay.

Due to laboratory testing being time demanding and expensive, field investigation methods are widely utilized to predict quick clay presence in Norway. Such predictions based on field tests data, i.e., soundings,are mostly based on engineering judgement. The uncertainties associated withsuch interpretationsarise fromthe limited number of sounding and laboratory tests, as well as test procedure and equipment. In the study of Papaioannou et al. (2023, 2024), a Bayesian-based approach is utilized for quantification of uncertainties of quick clay presence using rotary pressure sounding over space.A threshold-based methodology is opted for the prediction of quickclay using rotary pressure sounding, and certain thresholds are reported for quick clay identifications.

The aim of this study is todevelop and enhanceapython-based automated algorithm to interpret both rotary pressure sounding and total sounding data for the identification of quick clay. The novelty of the current paper arises from extending the methodology in Papaioannou et al. (2024) for total sounding and testing the method on a larger database. A threshold-based methodology is used for the prediction of quick clay by analyzing the statistical characteristics of the sounding data. Dataset from three sites, namely Tiller-Flotten, Buvika, and Kvithammer-Åsen, in mid Norway are used to assess the prediction performance of the algorithm, and to report the calibrated thresholds values.

2.Methodology

A simple methodology is utilized to automate the prediction of the quick clay presence using the rotary pressure and total sounding test data.For these field tests, atwisted tip with a series of rods is rotated and pushed into ground, and corresponding penetration resistanceis recorded with depth (NGF1989 and 1994).Identification of quick clay from these methods is normally done visually based on the inclination and scattering of the penetration resistance profile.The presented methodology for quick clay prediction is an automatedalgorithm based on the shape of the penetration resistance profile. The algorithm is based on the approximation of the nonlinear shape of soundingdata within a sampling window by a linear function($y = mx + b$, where y represents the penetration resistance, m is the slope, x is the distance, and b is the intercept). A window data size, N, is defined for sampling a cluster of N measurements of sounding data.The slope of the linear function, m, and root mean square error, e_{rms}, of linear approximation are estimated using least-squared regression methodand utilized for identification of quick clay.A window size of 61, i.e., N=61, data points is employed in the current analysis, which is considered representative of soil layer thicknesses. Although this window size is found to be effective, the importance of investigating different window sizes to ensure the robustness and accuracy of the results is acknowledged.

The penetration resistance for coarse-grained materials shows greater scatter, whereas soft clays exhibit smoother curves. Consequently, lower e_{rms} values are expected for claytype soils.Besides, a near-constant or negative slope of penetration resistance with depth is associated withthe presence of quick clay. Accordingly, the identification of quick clay from rotary pressure and total sounding is determined by opting for a threshold-based methodology for the values of m and e_{rms}.A clay layer is then identified as quick when the parameters of m and $e_{rms}$are below or equal to the corresponding threshold values, respectively m* and e^*_{rms}.

The thresholds, m* and e^*_{rms}, are obtained by utilizing the optimum operation point(OOP) method in the receiver operating characteristics (ROC) plot. The ROC plot can be used to evaluate the performance of an interpretation by comparing predictionsusing field test data and observations using fall cone test results (see Fawcett, 2006). The ROC plot is constructed using four parameters in confusion matrix, namely true positive(TP),true negative (TN), false positive(FP), and false negative(FN). If a claylayer isidentified as quick clay by sounding data, and the results of fall cone test areconsistent with the sounding prediction, it is aTP prediction. However, it is aFP prediction if the soil layer is not classified as quick clay with fall cone test. If it is not classified as quick clay by both fall cone test and sounding prediction,it is considered asTN prediction. Otherwise, if it is identified as quick clay by fall cone test and the prediction is not consistent with that, it is considered asFN prediction.For the performance assessment, true positive rate (TPR), false positive rate (FPR), accuracy (AC) and precision (PR)can be calculated from the abovementioned confusion matrix parameters. The TPR is the proportion of true positives to total number of truly identified as quick clay by fall cone test and calculated as TPR=TP/(TP+FN). The FPR is the proportion of false positives to total number of truly identified as not quick clay by fall cone test and calculated as FPR=FP/(FP+TN).The AC is the proportion of correctly predicted data to total number data and calculated as AC=(TP+TN)/(TP+TF+FP+FN).The precision is the ratio of correctly classified actual positives to all instancesclassified as positive and calculated as PR=TP/(TP+FP).

The OOPmethod is utilized for determination of the thresholds using on ROC plot. Performance parameters are calculated fora set of pairs of threshold values of m* and e^*_{rms}, and ROC graph is plotted. OOP point is the point on ROC graph which provides the best balance between TPR and FPR, and closest to the upper left corner of the graph where TPR=1 and FPR=0. Thresholds providing the best performance are reported in Section 4.

3. Data

The data used in this study is collected from three different quick clay sites:Buvika, Kvithammer-Åsen, andTiller-Flotten. All three sites are closeto Trondheim, mid Norway.The site at Buvikaconsists of athick marine deposit with quick clays(Solberg et al. 2008).Kvithammer-Åsen is a road construction site (E6 highway)consisting largely of marine clay, some of which are quick clay (Christensen et al. 2021).The Tiller-Flottenquick clay research site was developed through the Norwegian Geotest site (NGTS) project, and it is characterized by more than 50 m thick marine clay deposit (L'Heureux et al. 2019).

Table 2 provides the summary of the dataset utilized in this study.Kvithammer-Åsen site is the only site with total sounding data. Among the fallcone test dataat the Kvithammer-Åsen site (in total 839), 582 test data belong to the total soundings, while the remaining 257 test data are associated with rotary pressure sounding. The quick clay is identified based on the value of remolded shear strength from fall cone test, i.e., $c_{ur} \leq 2$ kPa.

Table 1. The summary of the utilized dataset from the sites.

Site / Number of	Rotary pressure sounding	Total sounding	Boreholes with fall cone test	Fall cone test data*
Buvika	15	0	9	50 (32)
Kvithammer-Åsen	38	78	128	839 (340)
Tiller-Flotten	13	0	3	26 (26)

*Number of fall cone test data with a remolded shear strength less than 2 kPais provided in parentheses.

4. Results and discussion

Various pairs of threshold values for m* and $e^*_{rms}$are used to construct the ROC graph, and OOP point providing the balance between TPR and FPR is reported. This investigation is conducted separately for rotary pressure sounding, total sounding, and the combination of both rotary pressure sounding and total sounding.Fig. 1 shows the ROC plots for different values of threshold parameters m* and e^*_{rms}together with OOP point for (a) rotary pressure sounding, (b) total sounding and (c) both rotary pressure and total sounding.

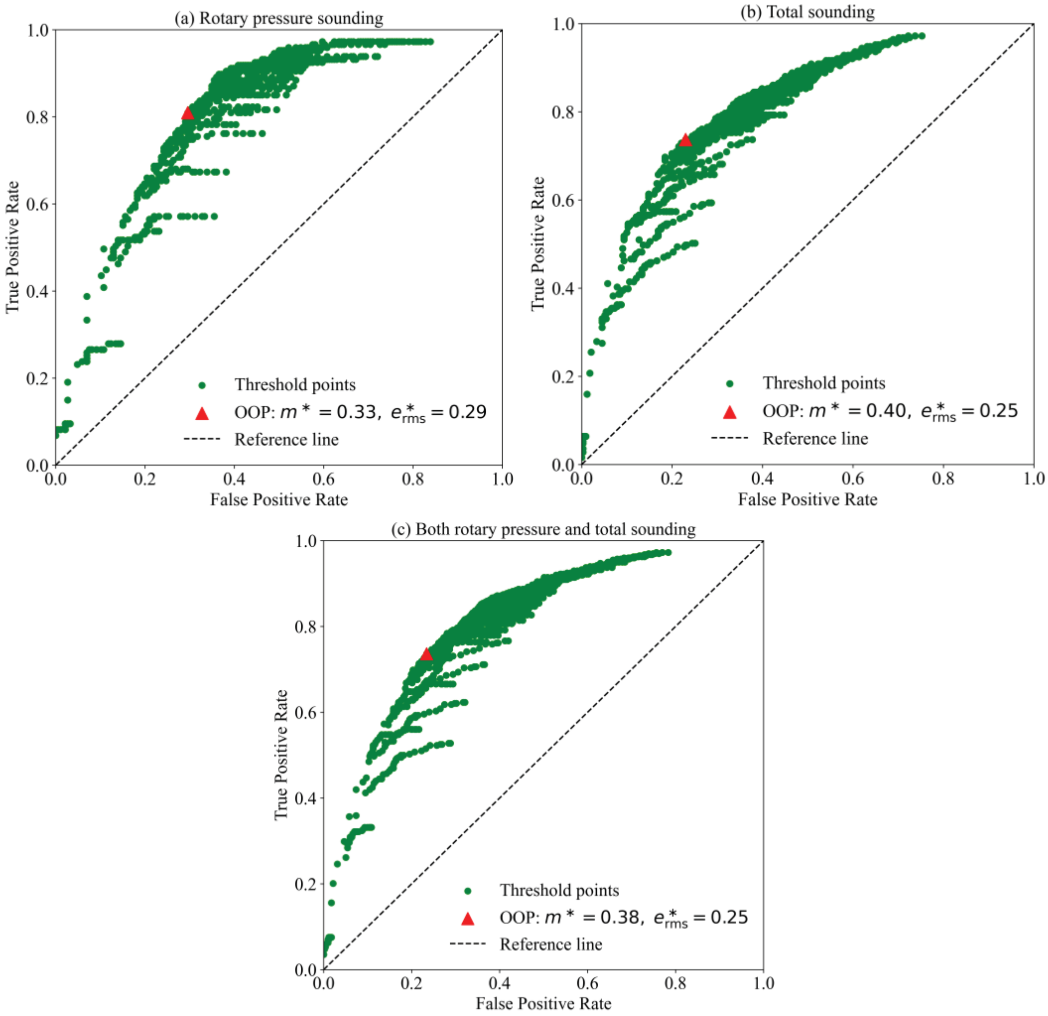

Fig. 1. ROC plotwith different values of threshold parameters m* and $e^*_{rms}$for (a) rotary pressure sounding, (b) total sounding, and (c) the combination of both rotary pressure sounding and total sounding.

Table 2 presents the thresholds at OOP separately for rotary pressure sounding, total sounding, and the combination of both rotary pressure sounding and total sounding.The results indicate that the thresholds determined using the OOP method vary depending on the dataset used. However, the values of m* and $e^*_{rms}$are consistently found to be in the range of 0.33–0.40 and 0.25–0.29, respectively.Additionally, it is observed that the determination of thresholds is highly influenced by the total sounding dataset due to its larger number of fall cone test data.

Table 2.OOP threshold parameters m* and e^*_{rms}, separately for rotary pressure sounding, total sounding, and the combination of both rotary pressure sounding and total sounding.

	m*	e^*_{rms}	TPR	FPR	Accuracy	Precision
Rotary pressure sounding	0.33	0.29	0.81	0.30	0.75	0.68
Total sounding	0.40	0.25	0.74	0.23	0.76	0.71
Both rotary pressure and total sounding	0.38	0.25	0.74	0.23	0.75	0.71

The same threshold-based method for quick clay identification is opted for in Papaioannou et al. (2024) where only rotary pressure sounding data with its 324 fall cone data points are utilized for determination of the values of thresholds.Among the 324 fall cone data points, 127 test data are reported as ground truth, i.e., quick clay. For N=61, Papaioannou et al. (2023) reported thresholds, m* and e^*_{rms}, at OOP as 0.28 and 0.29 respectively. In the current study, a slightly larger number of fall cone data points, 333 data among which 147 tests show quick clay presence are utilized, and m* and e^*_{rms}arefound to be 0.33 and 0.29 respectively. The difference in m* between the current study and Papaioannou et al. (2023) is attributed to the difference in the number of fall cone test data.

This study expands the analysis by incorporating total sounding data in finding optimum thresholds for quick clay identification. Among the 582 fall cone test data points for total soundings, 251 correspond to ground truth values indicating the presence of quick clay. The values of m* and e^*_{rms}at OOP are found to be different when only total sounding data is accounted for (see Table 2).When both rotary pressure sounding and total sounding data are utilized, the values of m* and e^*_{rms} fall between the thresholds obtained from separately analyzing the rotary pressure and total sounding data. However, they are somewhat dominated by the total sounding dataset due to its larger size.

Such thresholds for quick clay identification should be used cautiously as preliminary assessment of the quick clay presence. Laboratory fall cone tests must be performed in case the risk associated with a quick clay landslide is high. Besides, thresholds can be assessed through a risk-based criterion associated with quick clay presence, rather than OOP (see Papaioannou et al. 2024). In case of high societal risk due to quick clay presence, thresholds leading to a higher TPR can be used for the conservative identification of quick clay presence. In addition, the sensitivity of thresholds based on sites, type of field tests, window size, andcalibration methods, such as OOP method or a risk-based optimization method,should be further studied using larger datasets.

5. Conclusions

Thisstudy presents a python-based automated algorithm to interpret both rotary pressure sounding and total sounding data for the identification of quick clay, and the results of a data analysis for threshold identification.These thresholds are related to the slope, m, and root mean square error, e_{rms}, obtained from the penetration resistance in field tests.Uncertainty metrics associated with quick clay detection, such as TPR and FPR, are evaluated by comparing field data with laboratory fall cone test data. The OOP method is utilized for assessing the optimal thresholds, m* and e^*_{rms}.

The optimum values of the threshold parameters m* and $e^*_{rms}$are found to be in the range of 0.33–0.40 and 0.25–0.29, respectively. The study demonstrated that the proposed statistical-based methodology, which combines field and laboratory data, is a robust and reliable method for detecting quick clay.

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