RESEARCH

SHIFTING SANDS: Predicting and Mitigating Soil Liquefaction through Explainable Models

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Abstract

Soil liquefaction, a phenomenon in which the strength and stiffness of soil are significantly reduced by earthquake shaking, poses a formidable threat to public safety around the world, causing extensive property damage and loss of life, particularly in seismic areas. In order to mitigate the potential risk, we developed a machine learning model that predicts whether particular soils will undergo liquefaction in response to specific seismic parameters by utilizing information obtained from soil investigation. The XGBoost Classifier achieved the highest mean test accuracy for different train test splits, and with a mean accuracy of 84.69% against 83% which is the mean accuracy on the same train test splits of the empirical procedure proposed by Idriss and Boulanger in their 2014 paper[1]. Results show that the main drivers of predictions are the SPT N-Value(corrected), peak ground acceleration, fines content, and earthquake magnitude, which all corresponds to geotechnical theory. This model is also able to suggest the extent of soil improvement needed by providing the optimal amount of change in the N-value of the soil for it to be classified as non liquefiable.

Keywords: soil liquefaction; geotechnical; prediction

HIGHLIGHTS

- XGBoost Classifier got a mean accuracy of 84.69% in comparison to 83% by the empirical method.
- SPT-N value (N_{1-60}), peak ground acceleration (a), and fines content ($FC\%$) were the main drivers of predictions.
- Counterfactuals can propose alterations in soil characteristics to reverse a forecast from being liquefiable to non-liquefiable.

1 Introduction

On the 17th of October 1989, the Loma Prieta earthquake, a devastating seismic event that struck the heart of California, underscored the catastrophic potential of soil liquefaction in urban settings. This magnitude 6.9 earthquake not only claimed lives and caused widespread structural damage but also served as a stark reminder of an earthquake's capacity to compromise the integrity of soil, transforming solid ground into a fluid-like state with alarming speed and consequences. Soil liquefaction, where the strength and stiffness of soil are significantly reduced due to the stress and shaking during an earthquake, emerged as a critical factor in the destruction, particularly in areas with loose, water-saturated sediments. This event is one of the few soil liquefaction events with an estimated amount of damage attributed to soil liquefaction, and not due to the earthquake as a whole. Soil liquefaction caused \$99.2 million of the total earthquake loss of \$5.9 billion. The damage of the earthquake itself was mostly on above ground structures like flyovers and buildings meanwhile, much of the devastation soil liquefaction brought was on underground assets. Approximately 13.6 km of gas-distribution lines were replaced, and more than 20% of the wastewater collection lines were repaired or replaced.[2]

Over at the Pacific Ring of Fire, the Philippines, particularly the island of Luzon, experienced a magnitude 7.5 earthquake in 1990 that devastated the country. The earthquake called the *"Great Luzon Earthquake of 1990"*, triggered soil liquefaction events all over Luzon. Numerous structures at liquefaction sites experienced settlement or tilting, and one bridge collapsed as a result of liquefaction-induced lateral spread. The extensive damage of the earthquake as a whole, urged the government to enforce stricter building codes and spark the creation of the National Structural Code of the Philippines[3]. More recently on the 28th of September 2018, an earthquake of 7.5 magnitude hit the Central Sulawesi province of Indonesia. Resulting soil liquefaction buried the suburb of Balaroa and Petobo village 3 metres (9.8 ft) deep in mud. The government of Indonesia is considering designating the two neighborhoods of Balaroa and Petobo, that have been totally buried under mud, as mass graves.

Investigating the intricacies of soil liquefaction is highly motivated in the geotechnical community due to the severe damage that can result from such occurrences. Determining the factors that contribute to this occurrence and devising preventative measures has been an active area of research. To contribute to this effort we developed a machine learning model that predicts if certain soils would liquefy given its soil properties and earthquake parameters. Soil properties are obtainable through soil investigation, particularly the Standard Penetration Test, since one of the features used, the *N-value*, is a product of that test. Earthquake parameters on the other hand are usually available in the form of *design earthquakes*. These are earthquake parameters that are prescribed by various design codes depending on the country or region.

2 Related Works

The inherent danger of soil liquefaction has been recognized since 1971, when the term was first coined. Given soil liquefaction's extensive impact on infrastructure and safety in earthquake-prone regions, this critical issue has been extensively studied over the decades. In this section, we will cover previous studies that are aimed at assessing liquefaction potential of soils, both by traditional techniques based on geotechnical concepts and machine learning models.

The foundational understanding of liquefaction assessment in the late 20th century was established through the studies conducted by two geotechnical engineers, Raymond Seed and Izzat Idriss, both students of Karl von Terzaghi, widely regarded as the father of geotechnical engineering. The latest iteration of their foundational work is presented in Idriss and Boulanger's 2014 report *CPT and SPT-Based Liquefaction Triggering Procedures.*

Idriss and Boulanger's work uses the same foundational approach Idriss devised with Seed, the stress based framework. The concept compares the earthquake-induced cyclic stress ratios (CSR) with the cyclic resistance ratios (CRR) of the soil. Using this theoretical concept and adapting it based on case histories, they were able to devise a method for prediciting liquefaction triggering. In the latest dataset, updated on 2014, their method was able to predict 83.86% of the case histories correctly.[1]

The probabilistic nature of soil liquefaction, together with the advancement of data science prompted Kumar et. al. to conduct a study on the effectiveness of neural network models in assessing liquefaction probability. They achieved an R^2 value ranging from 0.846 to 0.906, exhibiting great potential for their regressor. One huge caveat to their study is that they are comparing their model to a computed probability, basically comparing their method with another, which is empirical and not exactly the ground truth.[4]

For this study, Idriss and Boulanger's method will serve as the baseline for comparison since it can classify soil layers into liquefiable and non-liquefiable states. It is widely recognized as the most accepted method for liquefaction assessment.

3 Data and Methods

3.1 Data Source

The dataset used in this study are case histories of soil liquefaction events from Idriss and Boulanger's 2010 paper, considering minor additions and corrections from their 2014 paper. The dataset contains 254 data points of various sites where soil investigation data was available before an earthquake event. The ground truth labels of the data points are based on actual observation on site after the earthquake event, classified as having liquefied or not. The available features are composed of physical soil characteristics and calculated features based on theoretical formulas.[1]

3.2 Feature Selection

One of the main goals of this research is to suggest modifications to the features with the intention of changing the resulting prediction, or in the context of data science, generate counterfactuals. To derive value from counterfactuals, it is imperative that the features can be readily manipulated within a real-world context. Furthermore, it is advisable to minimize the use of correlated features, as counterfactuals fail to consider the impact of correlation when manipulating individual features.

Additionally, to reduce reliance on the empirical approach, we refrained from integrating features obtained from the empirical formulas. Some examples of those features are cyclic stress ratio, cyclic resistance ration, magnitude scaling factor, and more.

Table 1 shows the list of features used in training the model. To improve the performance of our model, we also employed feature engineering, generating one additional feature–porewater pressure–derived by subtracting effective vertical stress from total vertical stress.

We were able to arrive with the final list by iterating on which combination of features would yield the best performance. Iteration also involved trying other engineered features based on domain expertise.

Table 1. List of Selected Features

Feature	Data Type	Description
a	numerical	relative peak ground acceleration
M	numerical	magnitude of the earthquake
$Avg\ Depth$	numerical	average deptht to middle of critical layer
$GWT\ Depth$	numerical	groundwater depth
$PorewaterPressure$	numerical	pressure exerted by water at the average depth
N_{1-60}	numerical	corrected SPT-N value, represents soil stiffness
$FC\%$	numerical	percent of fine soil particles present

3.3 Models

Out of the 254 data points, 133 are tagged as liquefiable and 121 are tagged as non-liquefiable, making it a relatively balanced dataset. Consequently, the random chance of predicting correctly is 50.11%, multiplying this by 1.25 gives us the proportional chance criterion of 62.64% for our classifier.

The first step in selecting a model is to gauge the performance of classifiers on training and validation. The training-validation set accounts for 90% of the data, this was used to perform grid search with 10 cross validation splits. The results of eight standard classifier models are detailed in Table 2.

Table 2. Model Train-Validation Performance

Classifier	Train Score	Validation Score
XGBoost	99.95%	86.83%
Gradient Boosting Method	100.00%	85.10%
Suppor Vector Classifier	94.25%	83.70%
Random Forest	98.40%	82.89%
Decision Tree	98.44%	80.63%
L1 Logistic Regression	82.51%	80.26%
L2 Logistic Regression	82.55%	79.85%
KNN	87.48%	79.80%

To minimize computational requirements for the succeeding steps and maximize hypertuning, we selected XGBoost as the model moving forward since it had the highest validation score.

Getting the accuracy of a model on one test split is not enough to statistically prove its advantage over the empirical method. To check the robustness of the methodology itself, and not only a single model, the model was subjected to 30 train test splits. The results on the 30 test splits is summarized on Table 3.

Table 3. XGBoost vs Empirical Method		
Predictor	Mean Train Score	Mean Test Score
XGBoost Classifier	$99.95\% \pm 0.14\%$	$84.69\% \pm 7.48\%$
Idriss and Boulanger (2010)	-	$83.00\% \pm 7.38\%$

The final model that will be used for interpreting SHAP and Dice counterfactuals is an XGBoost Classifier with the following parameters:

- Learning Rate: 0.3
- Max Depth: 4
- n-estimators: 200

Default values were used for parameters not listed above.

4 Results and Discussion

4.1 Model Performance

The initial training and validation scores indicate overfitting for the majority of the models, with the exception of the two Logistic Regression models that incorporated regularization. This is the consequence of small datasets and their inability to achieve optimal randomization for both the training and test data. The 30 train-test split was conducted to evaluate the performance of the resulting models on unseen data by performing multiple splits.

The XGBoost Classifier's mean test score indicates a 1.69% increase from the empirical method proposed by Idriss and Boulanger, and to prove its statistical significance, we conducted a t-test. The test yielded a p-value of 0.03, indicating that the observed improvement in test accuracy by the XGBoost model is statistically significant, given a 5% level of significance.

4.2 Prediction Explanation

Explaining predictions of machine learning models can give users insights on what are the main drivers of predictions, and in the real world setting this can help machine learning models get the validation they need specially from domain experts. Making sense of the prediction is always an added value for any machine learning model, that is why for this study, we implemented SHAP to be able to explain the predictions.

According to the Beeswarm plot from Figure 1, the higher the N_{1-60}, the lower the probability of the soil liquefying. This is because N_{1-60} represents the soil's relative density and stiffness. The variables M and a both refer to ground shaking intensity, suggesting that lower values correspond to a lower probability for the soil to liquefy. Finally, $FC\%$, which refers to the amount of silts and clays in the soil, indicates that soil with more silts and clays is more resistant to liquefaction. This observation is consistent with the understanding that clay can provide cohesion when it is saturated.

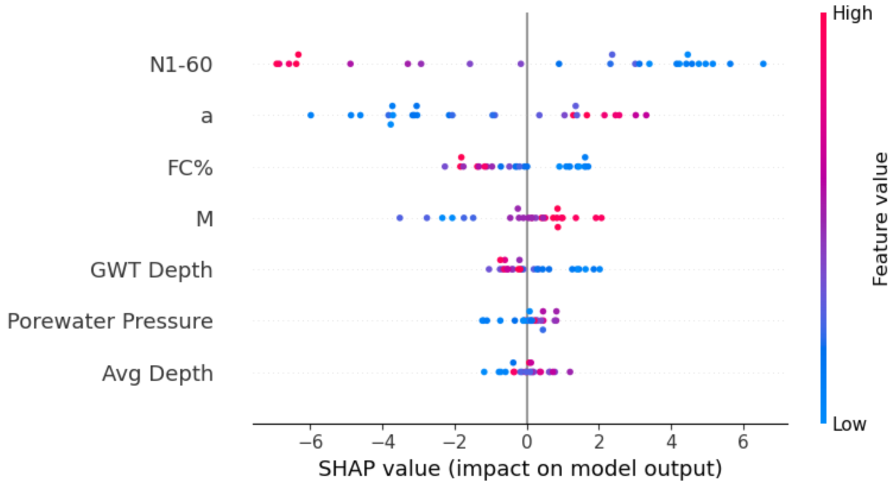

Figure 1 Beeswarm Plot from SHAP implementation

We can also visualize one instance of prediction using a waterfall plot. Figure 2, represents data point from one borehole in Loma Prieta, one that is erroneously predicted by the empirical method as non-liquefiable. However, we can see from Figure 2 that it was correctly predicted as liquefiable by our model, by a very small margin past zero. The waterfall plot also explains what drives the prediction, and what it tells us is that even if it has a significant amount of fine grained soils, and the peak ground acceleration is relatively low, the fact that the soil is very loose (given its N-value) is enough to overturn the prediction into being liquefiable.

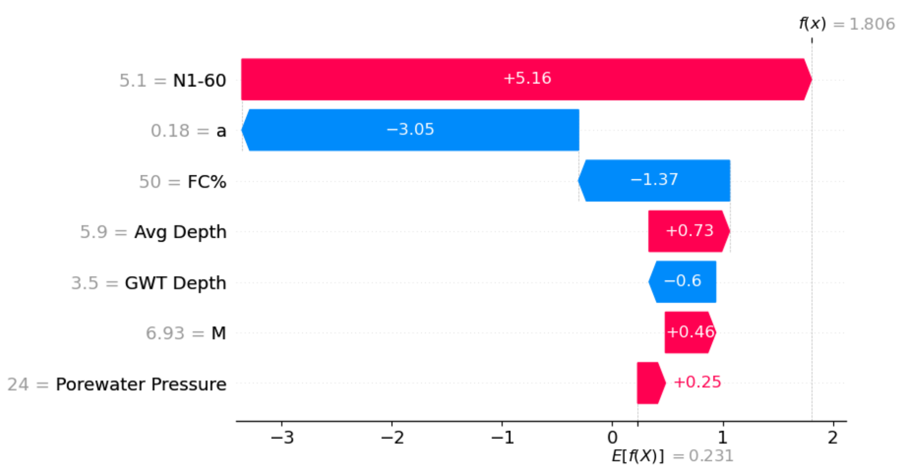

Figure 2 Waterfall Plot from SHAP implementation

4.3 Counterfactuals

The mitigation component of this study was accomplished by utilizing the DICE package in python to generate counterfactual scenarios. In the context of machine learning, counterfactuals refer to scenarios in which a particular data point would have different features, leading to an alternative prediction. Exploring "what-if" scenarios is valuable specifically for soils that are forecasted to undergo liquefaction, as they would offer recommendations on how to mitigate the risk of liquefaction.

For the implementation of DICE counterfactuals we used the same instance, the Loma Prieta site, demonstrated in the waterfall plot (Figure 2). Counterfactuals suggest that by increasing the N-value from 5.1 to 10.3, the soil would be able to resist liquefaction at the same earthquake parameters. This is valuable information since one of the main metrics measured in soil improvement execution is the improvement in N-value.

5 Conclusion

This study successfully developed a machine learning model using XGBoost to predict soil liquefaction occurence, achieving a mean accuracy of 84.69%. This surpasses the mean accuracy of the established empirical method (83.00%) by 1.69%, demonstrating the potential of XGBoost for improved liquefaction prediction.

The explainability analysis using SHAP provided valuable insights into the key factors influencing the model's predictions. Features like N_{1-60} (soil stifness), earthquake magnitude M, peak ground acceleration a, and fine content percentage $FC\%$ were identified as significant contributors to liquefaction risk. The model's credibility is reinforced by the fact that its predictive drivers are consistent with geotechnical theory.

Furthermore, the application of DICE counterfactuals allowed for exploring "what-if" scenarios and identifying actionable steps to mitigate liquefaction risks. In the case of the Loma Prieta site, increasing the N-value emerged as a strategic recommendation, potentially achieved through soil densification techniques like compaction grouting or dynamic compaction. This targeted approach facilitates efficient soil improvement execution and minimizes excessive alterations to the site's geotechnical profile.

The value of this study can be highlighted on the case of one Loma Prieta datapoint. If this study was available before the occurence of the Loma Prieta incident, there could have been an opportunity to implement soil improvement techniques that could have prevented the disaster. Assuming the cost of damage was distributed equally among all 25 boreholes for Loma Prieta, we could have prevented $8.6 million, in present value, worth of structural damage and possibly prevented injuries and loss of life.

6 Recommendation

Our group considered potential topics for further exploration as extensions of this project:

- **Extend the dataset**: The current dataset is limited to 254 datapoints. Increasing the size of the data could help the model arrive at a generalized solution.
- **Explore other Soil Investgation Features**: The feature highlighted in this study is the N-value obtained through Standard Penetration Testing. Other tests such as Cone Penetration test which yields cone resistance and friction values, and crosshole test that provides shear wave velocity, are gaining popularity. It is worthwhile to explore these features as they might produce a better performing model.
- **Neural Network Models**: Neural network models might be able to detect patterns and interaction between features that domain experts could have missed.
- **Cost Sensitive Learning**: The cost the two types of errors are not equal for this case. Usually for cases that involve risk of damage and life a heavier cost is attributed to a false negative prediction. For the case of Loma Prieta, the data point was predicted by the empirical model to be non liquefiable when it was not resulted in extensive damage. The challenge for this topic is on how to create a cost function that would have reasonable cost proportions between false negatives and false positives.

Our group is convinced that implementing these recommendations will significantly enhance the effectiveness and accuracy of soil liquefaction assessments. We believe that these have the potential to help mitigate the risk of soil and the consequences that come with it.

Competing interests
The authors declare that they have no competing interests.

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Author details

References

1. Idriss, Boulanger: Spt based liquefaction trigerring procedures. Univ. of California at Davis (2010)
2. Thomas: The loma prieta, california, earthquake of october 17, 1989: Strong ground motion and ground failure. U.S. Geological Survey (1992)
3. Orense, R.P.: Soil liquefaction during the 2010 darfield and 1990 luzon earthquakes: A comparative study. Proceedings of the Ninth Pacific Conference on Earthquake Engineering Building an Earthquake-Resilient Society (2011)
4. Kumar, et, al.: Liquefaction susceptibility using machine learning based on spt data. Intelligent Systems with Applications **20** (2023)