FTL Turkiye2: Capstone Project Data Research
Name: Wisam Elkamali Dafaalla Mohamed 19/05/2024

Title: Machine Learning for Assessing Soil Liquefaction Risk in Seismic Zones

Introduction:

Seismic soil liquefaction is a critical concern in geotechnical engineering, as it can lead to significant ground instability and structural damage during earthquakes. Addressing research questions related to soil liquefaction is essential for developing strategies to mitigate its impacts on infrastructure and communities. A thorough exploration of data is necessary to understand the conditions under which liquefaction occurs, the factors contributing to its likelihood, and the potential severity of its effects. By analyzing relevant data, we aim to enhance predictive models and inform engineering practices that improve resilience against earthquake-induced hazards.

The data available in the literature are mainly based on one of the field tests SPT, CPT, and Vs. In this project the data will be dealt by Calculating the CRR7.5 using (N1)60, qc, and Vs and using it as a common value. The value of CRR7.5 will be calculated upon IS1893-1, 2016.[1]

Data Description:

The data used in this project includes a combination of seismic event records, soil properties, and historical case studies of liquefaction. Key parameters considered

1. Magnitude (Mw): The magnitude of seismic events, reflecting the energy released during an earthquake.
2. Maximum Ground Acceleration (a_max): The peak ground acceleration experienced during an earthquake, influencing the stress on soil layers.
3. Average Depth: The average depth of soil layers studied, providing context for soil behavior under seismic loading.
4. Depth to Groundwater Table: The depth at which the groundwater is located, affecting soil saturation and liquefaction potential.
5. Effective Stress: The stress carried by the soil skeleton, is crucial for determining soil strength and susceptibility to liquefaction.
6. Total Stress: The overall stress, including pore water pressure, acting on the soil.
7. Cyclic Resistance Ratio (CRR7.5): A parameter estimating the soil's resistance to liquefaction under cyclic loading conditions, normalized for a magnitude 7.5 earthquake.

- for SPT:

$$CRR_{7.5}=\frac{1}{34-(N1)60cs}+\frac{(N1)60cs}{135}+\frac{50}{[10(N1)60cs+45]^2}-\frac{1}{200}$$

- for CPT :

$CRR_{7,5} = 0.833\ ((q_{C1N})_{CS}\ /\ 1000) + 0.05$ for $0 < (q_{C1N})_{CS} < 50$

$CRR7.5 = 93\ ((q_{C1N})_{CS}\ /\ 1000)^3 + 0.08$ for $50 \leq (q_{C1N})_{CS} < 160$

- for Vs:

$$CRR7.5 = a\left(\frac{Vs1}{100}\right)^2 + b\left(\frac{1}{Vs1*-Vs1}-\frac{1}{Vs1*}\right)$$

Data sources include geotechnical reports, seismic surveys, and academic research papers. Data formats are primarily tabular datasets and research documents with liquefied and non-liquefied data cases, with data sizes varying based on the specific seismic events and regions analyzed. The selection of this data is due to its relevance in assessing liquefaction potential, providing a comprehensive understanding of the contributing factors: Those data sets include:

- Toprak (1999)[2] : CPT data set, SPT data set
- Moss(2006)[3] : CPT data set
- Hanna (2007)[4]: CPT and Vs data set
- Hanna (2007)[5]:SPT and Vs data set
- Kayen (2013) [6]: Vs data set
- Boulanger(2014)[7] : CPT data set, SPT data set
- Zhao (2022) [8]: CPT data set

Data Analysis and Insights:

Several datasets, including SPT, CPT, and Vs, underwent preprocessing before merging based on calculated CRR7.5 values. While a strong correlation between CRR7.5 and N160cs was expected, the correlation map didn't reflect this relationship, prompting a review of data and calculations. Interestingly, CRR7.5 displayed a direct relationship with q1Ncs and Vs values. In addition, the strong relationship between the total stress and the effective stress; which is calculated by subtracting the pore water pressure has been observed in the correlation map

Figure 1 illustrates correlation coefficients alongside case counts for further analysis while Table 1 presents the distribution of cases across non-liquefied and liquefied conditions, along with corresponding test results for Standard Penetration Test (SPT), Cone Penetration Test (CPT), and Vs (shear wave velocity).

Table 1 distribution of cases across non-liquefied and liquefied conditions

cases	SPT	CPT	Va
Non -Liquefied	412	511	505
Liquefied	311	175	585

Conclusion:

In conclusion, this study underscores the significance of seismic soil liquefaction in geotechnical engineering and the necessity of robust methodologies for its assessment and mitigation. By leveraging data from various sources and employing the CRR7.5 parameter as a common metric, this research aimed to elucidate the factors influencing liquefaction susceptibility. Despite the expectation of a strong correlation between CRR7.5 and N160cs, discrepancies in the correlation map highlighted the need for thorough data validation and analysis. Nevertheless, intriguing direct relationships between CRR7.5 and q1Ncs and Vs values emerged, suggesting avenues for further investigation. Through rigorous data preprocessing and analysis, this study contributes to advancing predictive models and engineering practices to enhance resilience against earthquake-induced hazards. Continued research in this field is imperative for ensuring the safety and stability of infrastructure and communities in seismic-prone regions.

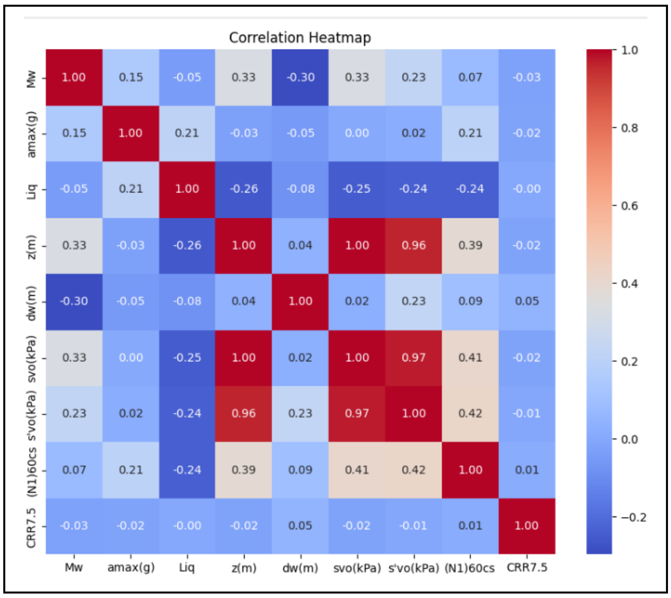
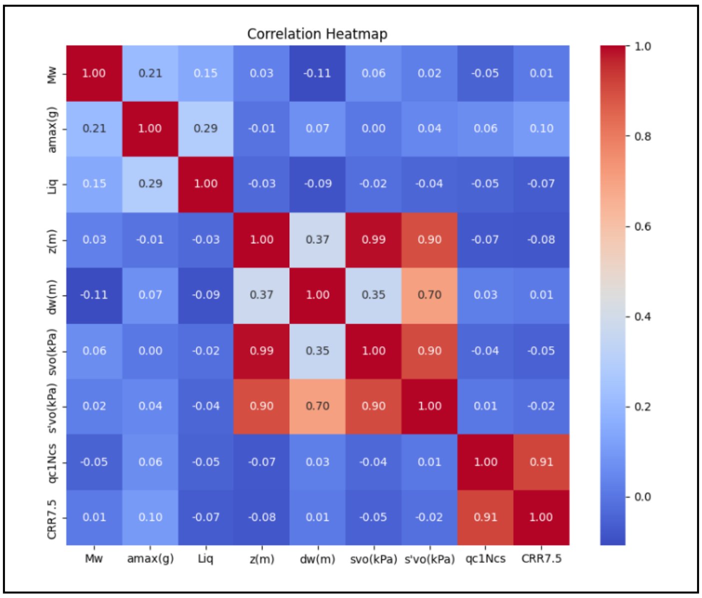
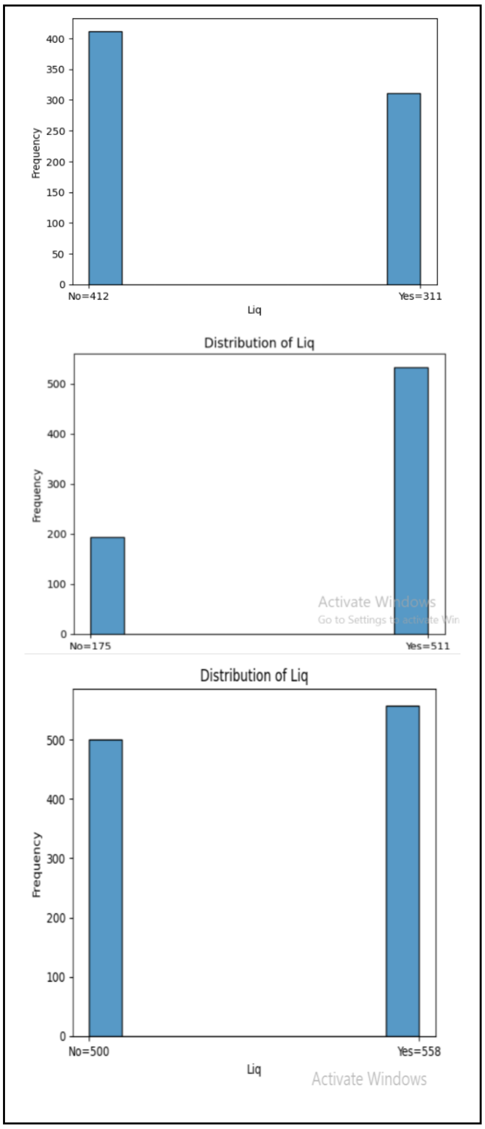
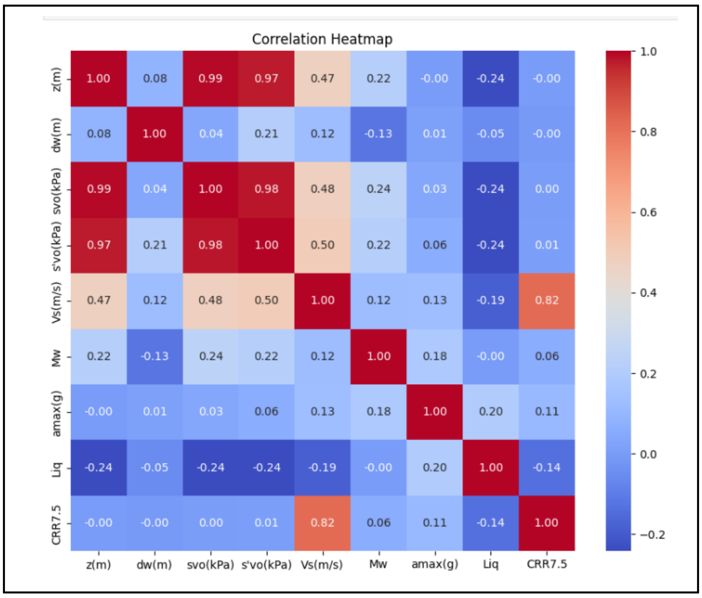


Figure1: The correlation maps and the distribution of liquefaction data sets for the merged data sets SPT, CPT and Vs respectively







References:

[1] IS-1893-Part-1-(2016), “Criteria for Earthquake resistant design of structures, Part 1:General Provisions and buildings,” *Bur. Indian Stand. New Delhi*, vol. 1893, no. December, pp. 1–44, 2016.

[2] S. Toprak, T. L. Holzer, M. J. Bennett, and J. J. Tinsley, “CPT-and SPT-based probabilistic assessment of liquefaction potential,” *7th US–Japan Work. Earthq. Resist. Des. Lifeline Facil. Countermeas. against Liq. Seattle, WA.*, no. August 1999, pp. 69–86, 1999.

[3] R. E. S. Moss, “CPT-based probabilistic assessment of seismic soil liquefaction initiation,” no. April, p. 528, 2003.

[4] A. M. Hanna, D. Ural, and G. Saygili, “Evaluation of liquefaction potential of soil deposits using artificial neural networks,” *Eng. Comput. (Swansea, Wales)*, vol. 24, no. 1, pp. 5–16, 2007.

[5] A. M. Hanna, D. Ural, and G. Saygili, “Neural network model for liquefaction potential in soil deposits using Turkey and Taiwan earthquake data,” *Soil Dyn. Earthq. Eng.*, vol. 27, no. 6, pp. 521–540, 2007.

[6] R. Kayen *et al.*, “Shear-Wave Velocity–Based Probabilistic and Deterministic Assessment of Seismic Soil Liquefaction Potential,” *J. Geotech. Geoenvironmental Eng.*, vol. 139, no. 3, pp. 407–419, 2013.

[7] R. W. Boulanger and I. M. Idriss, “CPT and SPT based liquefaction triggering procedures, Report UCD/CGM-10/2,” *Cent. Geotech. Model.*, no. April, pp. 1–138, 2014.

[8] Z. Zhao, W. Duan, G. Cai, M. Wu, and S. Liu, “CPT-based fully probabilistic seismic liquefaction potential assessment to reduce uncertainty: Integrating XGBoost algorithm with Bayesian theorem,” *Comput. Geotech.*, vol. 149, no. February, p. 104868, 2022.