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Summary of work performed on Task 9- Screening Criteria for Liquefaction-induced Lateral Spread as part of Development of Next Generation Liquefaction (NGL) Database for Liquefaction-Induced Lateral Spread

Introduction

Greetings to all UDOT Technical Advisory Members for the NGL Lateral Spread Development Project. Massoud Hosseinali and I would like to forward your review and comments on the approach we have developed regarding Task 9 – Lateral Spread Screening Criteria for the subject contract with the Utah Department of Transportation.

In this study, we sought to develop a probabilistic framework for determining the likelihood of generating liquefaction-induced lateral spread as a function of soil and subsurface conditions from the dataset we have compiled.

Finished Products

1. We have created a probabilistic framework by expanding the conventional probability chain for predicting the amount of lateral spread displacement.
    a. Conventional Approach: $P(D_H > y) = P(L)P(D_H > y|L)$ where $P(L)$ is the probability of triggering liquefaction, and $P(D_H > y|L)$ is the probability the horizontal displacement, D_H, exceeds some threshold value (e.g., 0.1, 0.3 and 1.0 m) given liquefaction.
    b. Revised Approach: $P(D_H > y) = P(L)P(LS|L)P(D_H > y|LS)$. We extended the probability chain above by adding a term to predict the probability of lateral spread susceptibility given liquefaction (i.e., $P(LS|L)$). The probability is essentially a probabilistic approach to develop "screening criteria." It allows a multivariate analysis of the factors that contribute to causing lateral when liquefaction has been triggered and to express the probability of lateral spread given these factors.
    c. We postulated that $P(LS|L)$ could be expanded to: $P[L_s \mid F, PI, SI, T, D, Z, G. R, M_w, X_n]$ where the independent variables in this equation are fines content, F, plasticity index, PI, soil index, SI, layer thickness, T, soil density D, depth of critical layer, Z, relative geological susceptibility, G, seismic source distance, R, and earthquake magnitude, M_w, and represent other possible evaluated as part of the research, X_n.
2. To solve the multivariate problem discussed in 1c, we applied conventional neural networks (CNN).
    a. Because the development of a lateral spread susceptibility model requires spatial context (i.e., continuity and thickness of the critical layer are essential in causing lateral spread), we chose the following scheme to capture these effects. Fig. 1 shows the lateral spread that developed in Heber road during the 1979 Imperial Valley earthquake. This figure shows the location of SPT boreholes and the zone of lateral spread displacement. From examples like this, we classified three types of borehole pairs: (1) pairs with both boreholes found <u>inside</u> the lateral spread zone (e.g., borehole 4 paired with 5 and borehole 5 paired with 6), (2) pairs with both boreholes located <u>outside</u> the lateral spread

zone (e.g., borehole 1 paired with 2), and (3) boundary pairs of boreholes that cross the margin of the lateral spread zone (e.g., borehole 11 paired with 4(,

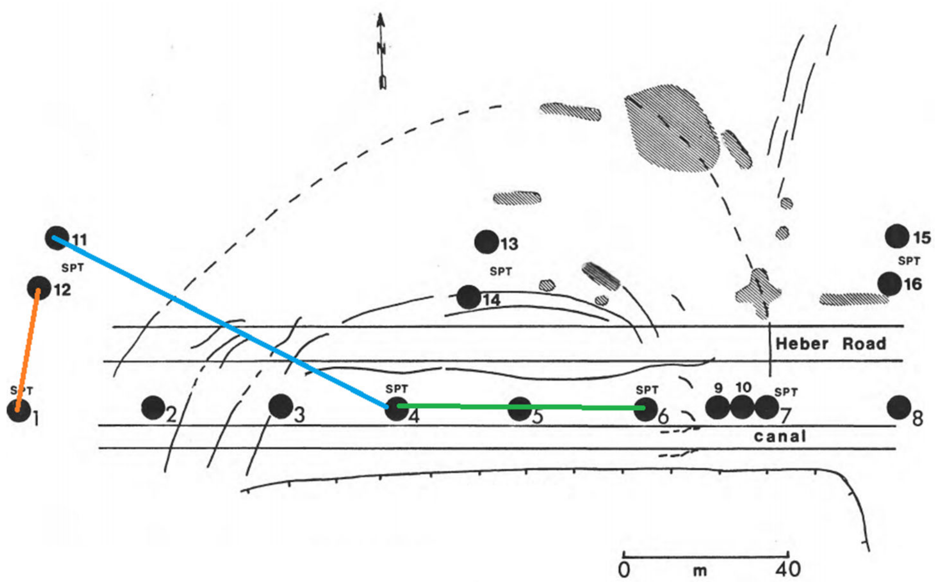

Figure 1 SPT boreholes and lateral spread in Heber road at 1979 Imperial Valley case history

b. We built a “classifier” model using CNNs to compute the newly added probability of lateral spread given liquefaction. Approximately 620 standard penetration testing (SPT) boreholes were collected from 11 earthquakes to train the CNN model (Table 1). The proposed CNN-based screening criteria required a pair of SPT boreholes.

c. The results of the CNN model can be used not only as a binary classifier to predict the probability of lateral spread triggering given liquefaction but also to classify the boreholes pair type as one of within, on the boundary, or outside a potential lateral spread zone. The “out of fold” model accuracy for triggering and multiclass classifiers were 81.4% and 90.5%, respectively. The 81.4% success rate means that a candidate borehole pair during the cross-validation was classified correctly as either inside, outside, or a boundary pair 81.4 percent of the time. The 90.5% success rate that if only inside and outside pairs are considered (i.e., binary classification with marginal pairs dropped), then CNN correctly classifies these pairs 90.5% of the time.

d. The CNN model was trained on independent variables that included: (1) distance between borehole pairs, (2) SPT $N1_{60}$ values versus depth at 0.5-m intervals in borehole, (3) soil index values versus depth in the borehole (Gillins and Bartlett, 2013) (Table 2), and (4) saturation of SPT interval (i.e., was soil below the recorded groundwater table).

Table 1 Count of pair types per earthquake

Earthquake	Boreholes count	Pair type	Pairs count	Reference(s)
1964 Alaska	20	boundary	3	Bartlett and Youd 1992b; Ross et al. 1973
		outside	3	
		within	5	
1964 Niigata, Japan	145	boundary	38	Hamada et al. 1986
		outside	33	
		within	169	
1971 San Fernando, California	39	boundary	12	Bennett 1989; O'Rourke et al. 1992; Youd 1973
		outside	4	
		within	44	
1979 Imperial valley, California	11	boundary	12	Youd and Bennett 1983; Bennett et al. 1984
		outside	2	
		within	6	
1983 Borah peak, Idaho	9	boundary	11	Youd et al. 1985; Andrus 1991; Andrus and Youd 1987
		outside	3	
		within	4	
1983 Noshiro, Japan	187	outside	17	Hamada et al. 1986
		within	8	
1987 Superstition hills, California	2	within	1	Holzier et al. 1989
1989 Loma Prieta, California	15	boundary	15	Robertson et al. 1999
		outside	3	
		within	7	
1990 Luzon, Philippines	13	outside	1	Tokimatsu et al. 1994; Ishihara et al. 1993
		within	1	
1995 Kobe, Japan	156	within	32	Chu et al. 2004
1999 ChiChi, Taiwan	23	boundary	3	
		within	2	

e. The uncertainty associated with a stratified k-fold cross-validation strategy was also studied. The reported accuracy for classification has a normal distribution with a mean of 81.4% and a standard deviation of 1.6%. Finally, as part of this study, a new mathematical representation of soil types was presented. These latent vectors are trained in the context of liquefaction and lateral spread and resulted in 2% boost in model accuracy. Soil type latent vectors could be used in conjunction with or as a substitute for soil index in developing predictive models for liquefaction or its consequences.

Table 2 Soil Index Values used by Gillins and Bartlett, 2013

Typical soil descriptions	**General USCS symbol**	**Soil Index, SI**
Silty gravel with sand, silty gravel, fine gravel	GM	1
Very coarse sand, sand, and gravel, gravelly sand	GM-SP	2
Coarse sand, sand with some gravel	SP	2
Sand, medium to fine sand, sand with some silt	SP-SM	3
Fine sand, sand with silt	SM	4
Very fine sand, silty sand, dirty sand, silty/clayey sand	SM-ML	4
Sandy silt, silt with sand	ML	5
Silty clay, lean clay	CL	6

Implementation

We are seeking feedback on the approach and how to implement it for Departments of Transportation. We propose to develop a webpage graphical user interface (GUI) that can be used by transportation projects to help determine the potential for lateral spread and delineate the potential lateral spread zone.