Framework Development for a Hybrid Geotechnical-Geospatial Liquefaction Assessment Model

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ABSTRACT

Liquefaction assessment can be performed using various bodies of knowledge, each with an associated accuracy based on the data involved. Liquefaction assessment models based on directly measured subsurface geotechnical data, such as SPT and CPT data, are mainly used for site-specific liquefaction assessments and allow for a more accurate and precise liquefaction assessment of a particular site. On the other hand, geospatial-based models are applied at a wider scale using more readily available surface geospatial data as proxies for liquefaction-related parameters including subsurface parameters such as soil density. This study will use logistic regression, which is best suited for developing a hybrid geotechnical-geospatial liquefaction assessment model that classifies sites based on liquefaction occurrence and damage severity. To keep the liquefaction assessment on a per-site basis, the framework includes the simplification of geotechnical data, mainly CPT data, into "representative" values for a site and incorporates these in the development of the hybrid model, along with the widely available geospatial data for an area. Some CPT-derived "representative" values are proposed that may encapsulate the subsurface quantities typically used in stress-based geotechnical approaches. Spatial interpolation of these values will be conducted to effectively expand the coverage of the subsurface geotechnical data.

1 INTRODUCTION

Liquefaction in soil occurs when an earthquake load is applied and pore water pressure builds up sufficiently to counteract the effective stresses in the soil, causing the soil particles to lose contact and essentially float in water. This leads to a loss in strength and stiffness of the soil, and post-liquefaction effects, such as liquefaction ejecta, subsidence, and damage to infrastructure, from the weakening of soil (Idriss and Boulanger, 2008). However, the effects of liquefaction mentioned may not be observed even when liquefaction has occurred due to various reasons (Ministry of Business Innovation & Employment (MBIE) and Ministry for the Environment (MfE), 2017). Due to this, various liquefaction assessment methodologies are concerned not only with the triggering of liquefaction but also with the extent and severity of the damage on the ground surface and structures on or under the site.

Geyin et al. (2020a) classified liquefaction assessment models into 3 tiers – the fully empirical (also referred to as "geospatial" models), semi-mechanistic "simplified stress-based" (also referred to as "geotechnical" models), and the fully mechanistic constitutive models. The geospatial models use easily accessible geospatial data, such as digital elevation models (DEM), geological and geomorphological maps, earthquake intensity measure distribution maps, and groundwater table (GWT) depth maps among others. The semi- and fully mechanistic models use geotechnical data measured directly from the soil itself, with typical on-site subsurface investigations sufficient for use in semi-mechanistic "simplified stress-based" models. Fully mechanistic models generally require more detailed soil testing results as input. The last tier will not be discussed here, and the subsequent discussions will focus only on the first 2 tiers. The omission of the last tier also prevents possible confusion from the usage of the "geotechnical model" as another name for the semi-mechanistic "simplified stress-based" models in the subsequent discussions. Geospatial models benefit from the relative ease of data acquisition and application of the model but lack the ability to incorporate the variations across the depth of the subsurface. Despite this, it has been shown that geospatial models may have performance comparable to that of geotechnical models, depending on the data used to develop the geospatial model (location, quantity, and quality) and where it is subsequently applied (Geyin et al., 2020a). This leads to the objective of this study which is to develop the framework to incorporate measured subsurface geotechnical data in developing geospatial-based liquefaction assessment models. This geospatial-based liquefaction assessment model that utilizes directly-measured subsurface geotechnical data will be called the GTS model/s – an acronym for GeoTechnical and geoSpatial models.

2 REVIEW OF RELATED LITERATURE

2.1 Geotechnical and geospatial models

Geotechnical models utilize directly measured subsurface data to determine the liquefaction potential of a site. These geotechnical models are further divided into two kinds: the triggering and the manifestation models. The triggering models determine, on a per-layer basis, whether the soil layer will liquefy or not by computing their factors of safety. Manifestation models use the factor of safety from the triggering models' output to quantify an index representing the risk or vulnerability to liquefaction damage of the site underlain by the analyzed subsurface stratum. Some examples of these indices are the liquefaction potential index (LPI) (Iwasaki et al., 1984), liquefaction severity number (LSN) (van Ballegooy et al., 2013), and modified LPI (LPI_{ISH}) to incorporate Ishihara's (1985) protective crust concept (Maurer et al., 2015). Unlike the geospatial models, the geotechnical models use inputs that apply only to a small area around the site of the subsurface investigation thereby limiting the area where the results can be reasonably applied to. Although it can be argued that most developed areas have been investigated geotechnically, these data are often inaccessible as they are owned by their respective owners and are mostly not shared publicly. And with the complexity of some geotechnical models, it can be argued that a higher level of expertise is required to implement these models compared to the effort required for geospatial models.

Geospatial models have the advantage of using input data that are easily accessible (or derived from easily accessible data) to most users. Youd and Hoose (1977) used geology (the age of the deposit) and geomorphology (the depositional environment) to classify the liquefaction susceptibility of a deposit. More recent geospatial models by Zhu et al. (2015, 2017) take advantage of the accessibility of geospatial data over a wide area, such as digital elevation models (DEM) and earthquake intensity measure distribution maps among others, to serve as proxies (or derive proxies from) for liquefaction-related parameters, which, in turn, they grouped into 3 categories – density, saturation, and load. One of the drawbacks is that some of these inputs are surface-based proxies and may not reflect variations and local nuances across the depth of the site.

This may also raise a question on accuracy – for example, Zhu et al. (2015, 2017) used V_{s30}, or the shear wave velocity for the first 30m of the subsurface, derived from the slope of the area, rather than directly measured values.

Geyin et al. (2020a) found that geospatial models' liquefaction prediction performance ranges from better than guessing to being better than most geotechnical models, depending on the training data used to develop the models and where they are subsequently applied, whereas geotechnical models perform more consistently regardless of the area of application. Geyin et al. (2020a) noted the geospatial models' performance as interesting, given the contrast in the availability, accessibility, and kind of data it needed, while the consistency of the geotechnical models' performance is almost expected, given their usage of subsurface data. Additionally, Lin et al. (2021, 2022) found that using New Zealand-specific data in geospatial models leads to better spatial accuracy when used in said area, as these are specifically for that area and are generally of higher resolution than global data.

2.2 Liquefaction-Induced Ground Damage Classification Systems

There are many kinds of liquefaction-induced ground damage (LIGD), also referred to as surface manifestations in some literature, but the most common ones used in classification systems are liquefaction ejecta, crack dimensions, subsidence, and lateral spreading.

Figure 1 collates and simplifies the classifications from available literature into a single system. The most basic classification found in various literature is the existence or non-existence of LIDG (Level A). Geyin et al. (2020b, 2021) and Russell and van Ballegooy (2015) both use a 6-tier classification system (Level C) that is quite similar but with differences in the thresholds used – with a "parent" 3-tier classification (Level B) in the latter as well. This means a site is considered a liquefaction case if LIGD exists and does not consider the triggering of liquefaction itself. Note that the "3" or "Major" classification is put under both "with" and "without lateral spreading" – this is due to Russell and van Ballegooy (2015) describing it with "limited lateral spreading" and putting it under the "Moderate to Severe" parent category, while Geyin et al. (2020b, 2021) describe "3" as without lateral spreading. However, for the purposes of this study, "3" and "Major" will be treated as equivalent to each other.

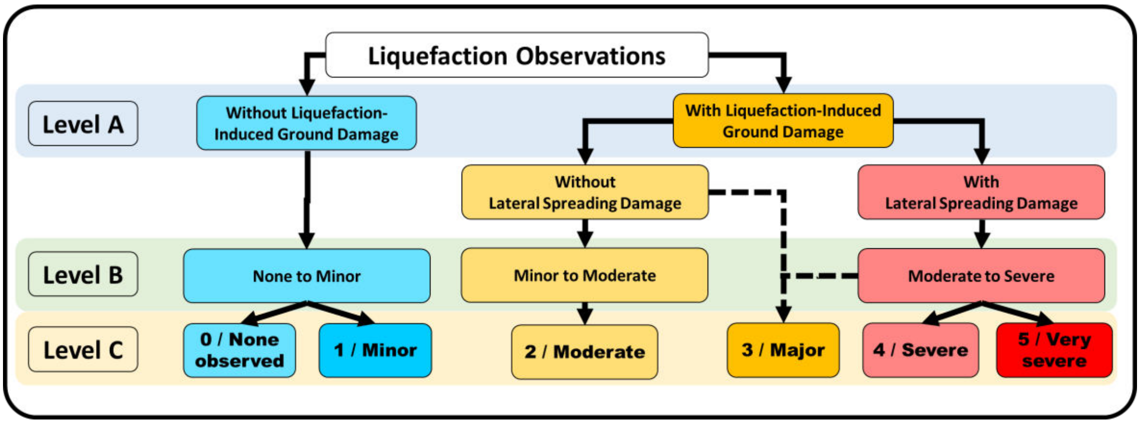

Figure 1: Simplified LIDG classification and levels

2.3 Logistic regression and receiver operating characteristic (ROC) curve

Logistic regression is generally used synonymously with binary logistic regression in literature. It is used to model the relationship between any number of independent variables (X) and dependent variable (Y) that takes on two values only (case or non-case) and uses the logistic function shown in Equation 1 (Kleinbaum and Klein, 2010).

$$P(X) = \frac{1}{1+e^{-z}} = \frac{1}{1+e^{-(\alpha+\beta_1 X_1+\cdots+\beta_N X_N)}} \quad (1)$$

where $P(X)$ = probability of being classified as a case; α, β = coefficients to be fitted; and $X_1 \ldots X_N$ = independent variables.

The variable z represents the value of the risk as determined by the independent variables and is transformed by the logistic function into $P(X)$, restricting its value between 0 and 1 in the process, to facilitate the identification of a threshold separating the cases from the non-cases (Y) (Kleinbaum and Klein, 2010).

The performance of a model can be assessed using the area under the ROC (Receiver Operating Characteristic) curve. The ROC curve is the plot of the true positive rate (TPR) and false positive rate (FPR) for different thresholds used on the model, and the AUC represents the discriminatory ability of the model between cases and non-cases (Kleinbaum and Klein, 2010; Zhu et al., 2015, 2017).

3 PROPOSED FRAMEWORK AND METHODOLOGY

Figure 2 shows the general model development framework incorporating geotechnical and geospatial models to develop the GTS model/s. This framework is very similar to how Zhu et al. (2015, 2017) developed their geospatial models, that is, using logistic regression. This approach will allow the model to have categorical outputs that will correspond to the previously discussed LIGD classifications (or a modified version thereof). Furthermore, sites are considered as liquefaction cases based on the occurrence of LIGD for use in the liquefaction hazard planning, where the LIGD expected at a site is more important than the actual liquefaction triggering. Figure 2 shows the GTS as a model that tries to balance the advantages of the geospatial model in terms of application area, data accessibility and availability, and geotechnical expertise needed, with the geotechnical data as a supplement to provide subsurface detail in the liquefaction assessment. As previously discussed, the extent of the area of application of geospatial and geotechnical models are at the opposite ends of the spectrum; this leaves areas of intermediate size that require more precise and accurate liquefaction assessment needing a model that can take the advantages of both models and combine them into one. This becomes more crucial if we consider areas that have more risk (eg. a city compared to a rural area of the same size). Accuracy in this study refers to how correct the liquefaction assessments are, while precision describes how detailed we can classify the assessment results (ie. Level A-C in section 2.2).

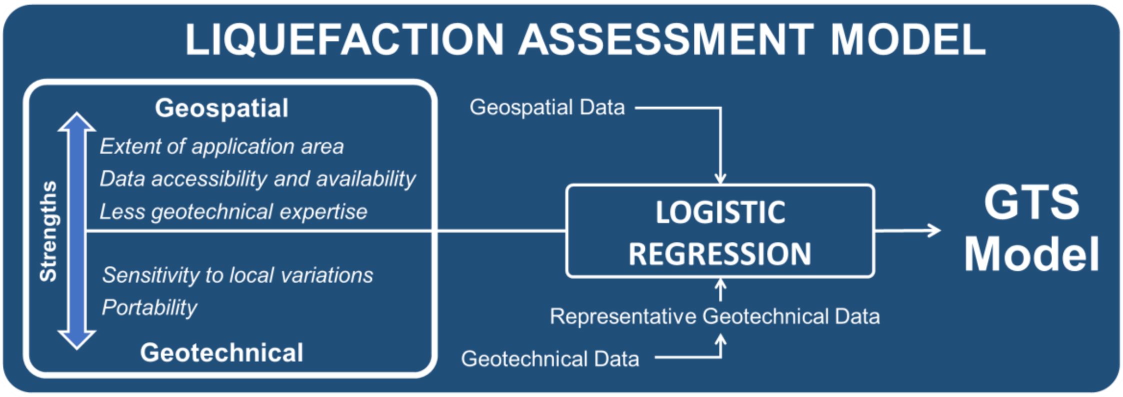

Figure 2: Simplified model development framework

Prior to logistic regression, a dataset consisting of independent variables (geotechnical and geospatial predictors of LIGD) and a dependent variable (LIGD classification) for a particular site on a 2D surface coordinate will be created. Geospatial data can be readily assigned to a site, but geotechnical data often have a third dimension (i.e. depth). To address this, subsurface geotechnical data at a site will be “simplified” into a single value that reflects the variations across the depth. These simplified parameters will be called representative geotechnical data or RGD.

Figure 3 shows the process of the data preparation and model development phases. Once the datasets are prepared, they will be sampled and used to develop the GTS model/s via logistic regression.

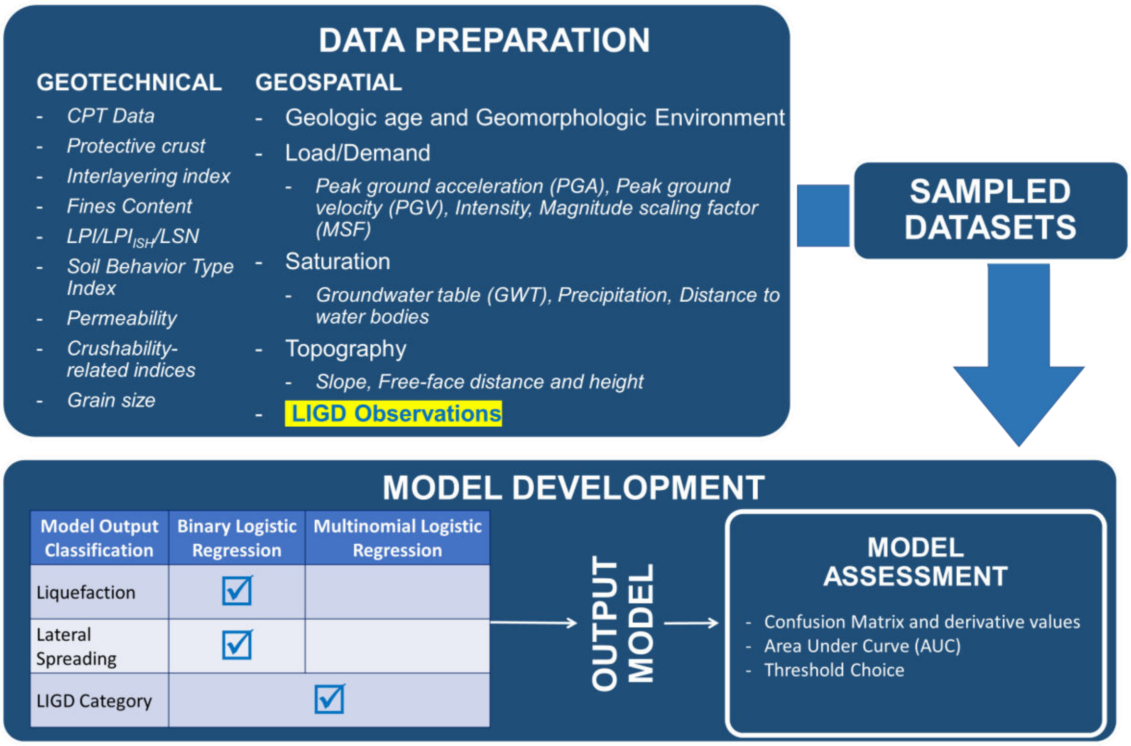

Figure 3: Data preparation and model development process

3.1 Representative geotechnical data (RGD)

Geospatial models characterize the soil's innate resistance to liquefaction via various proxies. In the study by Zhu et al. (2015, 2017), most of the proxies for density are computed from the digital elevation model (DEM) and none are directly measured (or derived from directly measured) subsurface data. This is what the GTS model would add to the existing geospatial models – the inclusion of data derived from directly measured subsurface data or RGD. This intends to include more detail from the subsurface, including the local nuances or variation in an area, resulting in a more accurate and precise liquefaction assessment of a site.

RGD exploration is an essential process in the development of the GTS model/s. RGD being explored in this study include representative subsurface investigation data (e.g. CPT data for the first x meters of the subsurface from a particular reference, representative fines content value, prevalent soil behavior type index), protective crust thickness, and liquefaction manifestation indices, among others. The goal of the RGD is to transform 3D data into a value for a 2D location while reflecting as much of the subsurface variation relevant to liquefaction assessment as possible.

Some of the factors to be investigated in determining the best CPT data representative are the thickness of the subsurface to be considered and the reference where it will start – either from the surface or from the GWT. The use of GWT as the reference line will ensure that the CPT data considered are for layers that may liquefy; however, this also poses a possible complication in the application as different GWT level scenarios will have different CPT data representatives. As such, the sensitivity to the choice of reference and the thickness considered will be investigated. Representative fines content and prevalent soil behavior type index values would quantify the increase in liquefaction resistance related to increased fines content and particular soil types. The liquefaction manifestation indices are also included in the RGD as they already quantify the thickness of liquefied and non-liquefied layers and have weighting functions that account for the layer's depth. Due to the RGD representing only the available subsurface investigation sites, spatial interpolation (via kriging, natural neighbor, etc.) of RGD will be used to complete the datasets.

3.2 Logistic regression for various models

There are 3 kinds of GTS models that are expected to be developed after the execution of the methodology. These are: (I) a model that separates areas with and without LIGD (liquefaction and non-liquefaction cases); (II) a model that separates areas with and without lateral spreading; and (III) a model that classifies the severity of LIGD at a site. The logistic regression needed for each model is also shown in Figure 3. Models I and II can be achieved using binary logistic regression, where the developed model classifies the output into 1 of 2 possible classifications. However, Model III requires classification into one of several LIGD severity classifications (Level B or C in Figure 1, or a modified version thereof) and will require multinomial logistic regression. Given to the nature of the LIGD classifications from Level A to Level C, the multinomial logistic regression can be modelled as a sequential binary logistic regression (Department of Statistics - The Pennsylvania State University, n.d.). To do this, a model separating liquefaction and non-liquefaction cases will be developed first (or the development of Model I) via binary logistic regression. The non-liquefaction cases will be used for another binary logistic regression process to develop a model that separates the sites into either "0/None observed" or "1/Minor". The same process will be applied to the liquefaction cases until classification reaches Level C.

The developed models will be assessed using various performance measures, such as the confusion matrix (and derivative parameters) and area under the curve (AUC) value, among others, to determine the best-performing models in discriminating between classifications.

The developed models' performances will also be compared to the performance of existing liquefaction assessments that are purely geotechnical or geospatial in nature - based on the prediction of liquefaction occurrence and severity of LIGD, whichever is possible, while considering the relative costs of each model as well. The expectation is that the hybrid models will provide better performance compared to the conventional approaches while decreasing the costs to implement the assessment.

4 CONCLUSION

This paper details the framework proposed for a hybrid liquefaction assessment model by incorporating subsurface geotechnical data in the geospatial model development. The general framework and methodology are quite similar to the ones used in some geospatial models in terms of the choice of logistic regression to accommodate classification-based output. The key difference in the proposed framework and methodology was the development of RGD to allow the incorporation of geotechnical data in the development of the model.

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