Fragility Functions for Liquefaction-Induced Ground Failure

Mertcan Geyin, S.M.ASCE[1] and Brett W. Maurer, M.ASCE[2]

Abstract: The predicted severity of liquefaction manifested at the ground surface is a popular and pragmatic proxy of damage potential for infrastructure. Towards this end, the Liquefaction Potential Index (*LPI*) and similar models are commonly used, and often codified, to predict surface manifestations on level ground. These predictions typically use deterministic thresholds from the literature - obtained via calibration on case-history data - to classify the expected manifestation. While widely adopted, such thresholds obscure the uncertainty of expected outcomes and are incompatible with probabilistic frameworks. Proposed thresholds are also intimately tied to the liquefaction analytics used to compute them and to the methodology used to select them, each of which can conflict with forward applications, leading to erroneous predictions. Accordingly, using 15,223 case histories from 24 earthquakes, this study develops fragility functions that probabilistically predict surficial manifestations of liquefaction using triggering and manifestation models popular in practice. Deterministic workflows are easily extended by selecting appropriate fragility coefficients; options are provided for six CPT-based triggering models, one CPT-inversion filter, three manifestation models, and three manifestation severities. Model application is demonstrated by predicting: (i) liquefaction manifestations in Christchurch, NZ, resulting from an Alpine Fault earthquake, wherein a logic-tree is used to ensemble predictions from 18 models; and (ii) the return period of liquefaction manifestations in the SODO district of Seattle, USA, wherein predictions are compared to historical observations.

[1]Graduate Research Asst., Civil & Environmental Eng, University of Washington, Seattle, WA (mgeyin@uw.edu)
[2]Asst. Professor, Civil & Environmental Eng, University of Washington, Seattle, WA (bwmaurer@uw.edu)

Introduction

Proposed herein are fragility functions for probabilistically predicting the occurrence and severity of liquefaction-induced land damage on level ground. These functions are developed as extensions to deterministic liquefaction triggering and manifestation models popular in practice, such that users need only select fragility coefficients, presented in Tables 4 and 5, corresponding to the models of choice. Following development and analysis of the fragility functions, application is demonstrated via (i) a scenario earthquake simulation, and (ii) within a probabilistic seismic-hazard analysis.

The severity of soil liquefaction manifested at the ground surface is a pragmatic proxy of damage potential for many types of infrastructure (e.g., shallow foundations and lifelines). The greater the severity of surface manifestation, the greater the likelihood of damage. By way of this proxy, manifestation models have been proposed to link the computed factor of safety against liquefaction triggering (FS_{liq}) at-depth within a profile to damage potential at the surface. Iwasaki et al. (1978) proposed what may be the first manifestation model – the Liquefaction Potential Index (*LPI*) – which has been used in countless studies worldwide (e.g., among many, Luna and Frost 2000; Rix and Romero 2001; Holzer et al. 2006; Lenz and Baise 2007; Hayati and Andrus 2008, Chen et al. 2016; Boulanger et al. 2018). Other manifestation models also in current use include, but are not limited to, the Liquefaction Severity Number (*LSN*) (van Ballegooy et al. 2014a) and a modified version of *LPI* termed LPI_{ISH} (Maurer et al. 2015a).

Central to the typical use of these and similar models, which will be defined subsequently, are proposed index thresholds for classifying the expected risk or severity of manifestation. For example, Iwasaki et al. (1984) proposed that risk of manifestation is "low" at sites where $LPI \leq 5$, "high" where $5 < LPI \leq 15$, and "very high" where $LPI > 15$. Some, but not all, evaluations of *LPI* following more recent earthquakes (e.g., Toprak and Holzer 2003; Holzer et al. 2005; Maurer et al. 2014a) have supported the Iwasaki et al. (1984) classification thresholds. In similar fashion, Tokin and Taylor (2013) proposed that manifestations should be "little to none" at sites where *LSN* < 10; "minor" where 10 < *LSN* < 20; "moderate to severe" where 20 < *LSN* < 40; and "major" where *LSN* > 40. Thus, an *LPI* of 5 and an *LSN* of 10 to 20 may correspond to similar expected outcomes. While manifestation models are widely employed in this manner – using deterministic classification thresholds - it is often unappreciated that such thresholds have innate limitations. Namely, they (i) are unique to the liquefaction analytics used to compute them; (ii) are tied to the method used to select them, and by corollary, to the relative consequences of misprediction assumed therein; and (iii) inherently conceal the probabilities of possible outcomes. These limitations are elaborated as follows.

First, many liquefaction triggering models are available to predict FS_{liq}, an input to *LPI*, LPI_{ISH}, *LSN*, and other manifestation models. These models typically yield different FS_{liq} values for the same soil profile and seismic loading, and thus different manifestation model predictions (Lee et al. 2003; Maurer et al. 2015b). For example, using data from the 2010-2011 Canterbury, New Zealand, earthquakes, Maurer et al. (2015b) found that the relationship between expected manifestation severity and computed *LPI* was unique to the adopted triggering model. That is, each had different optimal classification thresholds. Other procedural variants, such as differences in CPT data processing, correction, or filtering (e.g., Boulanger and DeJong 2018) could systematically alter FS_{liq} values, further biasing proposed thresholds.

Second, researchers have used different methods and justifications – often unstated or nonstandard - to select classification thresholds. For example, Iwasaki et al. (1984) found that among 87 study sites, 80% of sites with manifestations had LPI > 5 and 70% of sites without manifestations had *LPI* < 5; this led to their proposal of *LPI* = 5 as a classification threshold for predicting manifestations. Implicit to this, and any such threshold, is an assumed economy of misprediction. Iwasaki et al. (1984) implicitly treated the costs of false positives (manifestations are expected but not observed) and false negatives (manifestations are observed but not expected) as similar. If Iwasaki et al. (1984) instead assumed that false negatives were significantly more costly than false positives – which is true of many engineering projects – then their proposed threshold would presumably be less than *LPI* = 5. In other words, the threshold would be not that which minimizes the rate of mispredictions, but rather, that which minimizes the cost of mispredictions. Thus, researchers assuming different misprediction economies will invariably propose different classification thresholds. This presents a problem for forward use when the misprediction economy implicit to a proposed threshold either is unknown or differs from that desired in forward analysis.

Due at least partly to the combined effects of the above, proposed thresholds vary significantly for the same manifestation model and what appear to be equivalent expected outcomes. For example, Iwasaki et al. (1984), Toprak and Holzer (2003), Lee et al. (2003), Kang et al. (2014), Papathanassiou et al. (2015), and Maurer et al. (2015b), each calibrating *LPI* on case-history data, proposed *LPI* thresholds of 5, 5, 13, 14, 13.5, and 5, respectively, for binomially classifying the expected occurrence and non-occurrence of surface manifestation. It follows that classification thresholds proposed by one study could be far from optimal (i.e., result in erroneous predictions) when applied to the methods of another. It is reasonable to assume this is true of other manifestation models, such as LPI_{ISH} and *LSN*, though analogous suites of studies are unavailable.

Third, deterministic classifications mask the uncertainty of ground failure and are incompatible with fully probabilistic frameworks, leading to incomplete characterizations of hazard and risk. All existing liquefaction models are imperfect. As a result, and counter to how classification thresholds may be interpreted, multiple outcomes are always possible at a given classifier index value. For example, considering the popular threshold of *LPI* = 5 for predicting manifestations, two sites with respective *LPI* values of 5.01 and 4.99 could be classified differently (e.g., "hazardous" vs. "non-hazardous", "damage likely" vs. "damage unlikely", etc.) even though the probability of liquefaction manifestation is identical. Moreover, because this probability is unknown, many "probabilistic" studies have resigned to compute the probability that some classification threshold will be exceeded – commonly *LPI* = 5 – in lieu of computing the probability of some physical outcome. Various liquefaction hazard assessments in North America have employed *LPI* in this way, computing either the probability or return period of *LPI* exceeding a threshold value (e.g., Cramer et al. 2008, 2017, 2018; Holzer 2008; Gathro et al. 2018; Goda et al. 2011). However, because the probabilistic relationship between *LPI* and liquefaction manifestation is not well defined, the results of these assessments cannot be properly interpreted in the context of hazard and risk. The probability of *LPI* exceeding a classification threshold could be 50% at a site of interest, but what is the probability of liquefaction manifestation? This latter, more meaningful probability is unknown and could be nearly any value between 0 and 100%, depending on the means and methods used to select the threshold.

Accordingly, motivated by these uncertainties and limitations, the objective of this study is to formulate fragility functions that probabilistically predict the occurrence and severity of liquefaction manifestations on free-field level ground. Analyzing 15,223 case histories compiled from 24 earthquakes in 9 countries, fragility functions will be conditioned on the *LPI*, LPI_{ISH}, and *LSN* manifestation models. Given the observed dependence of these models on the procedures used to compute their inputs, functions will be separately proposed using six CPT-based triggering models, each implemented with and without CPT inversion via the Boulanger and DeJong (2018) procedure. This will result in fragility functions for 36 distinct liquefaction models (i.e., 3 manifestation models x 6 triggering models x 2 CPT processing possibilities), allowing users to select fragility coefficients consistent with the models they utilize.

Data

This study analyzes 15,223 case histories, as summarized in Table 1. However, since the majority were compiled from three earthquakes in the Canterbury region of New Zealand, fragility functions will be separately developed and compared for these and the other 21 events, henceforth respectively referred to as the "Canterbury dataset" and "Global dataset."

Canterbury Earthquake Dataset

Earthquakes occurring over the last decade in the Canterbury region of New Zealand have resulted in case-history data of unprecedented quantity and quality. The present study analyzes data compiled from the M_w7.1, 4 Sept. 2010 Darfield earthquake, the M_w6.2, 22 Feb. 2011 Christchurch earthquake, and the M_w5.7, 14 Feb. 2016 Christchurch earthquake. This effort built on a series of successive compilations (Maurer et al. 2014a, 2015c, 2019), augmenting the largest by more than 50% and resulting in a total of 14,948 case histories (following exclusions discussed subsequently). The case histories consist of classifications of liquefaction manifestations, geotechnical and hydrological data, and ground-motion intensity measures.

The fragility functions to be developed herein will predict manifestations of liquefaction on free-field level ground – specifically the occurrence and severity of liquefaction ejecta – rather than any other metric of land damage. Sites with lateral spreading were expressly removed from the dataset because the *LPI*, LPI_{ISH}, and *LSN* manifestation models do not fully account for the factors which cause lateral spreading and thus may predict it poorly (e.g., Maurer et al. 2015b;

Rashidian and Gillins 2018). Observations of liquefaction ejecta were compiled by the authors and classified as "none," "minor," "moderate," and "severe" using criteria modified from Green et al. (2014) and given in Table 2. This was accomplished using high-resolution satellite imagery and reconnaissance reports available in the New Zealand Geotechnical Database (NZGD, 2019). Cases for which surface manifestations could not be reliably classified are not included in the dataset. Of the resulting 14,948 cases compiled from Canterbury, 65% are classified as "none" and 35% are cases in which manifestations were observed and classified in accordance with Table 2.

CPT data was compiled from the New Zealand Geotechnical Database at sites where liquefaction manifestations were classified as described above. In compiling case-histories, CPTs were rejected: (1) if the depth of "pre-drill" significantly exceeded the depth to ground water; and (2) if inferred from geospatial autocorrelation analysis (Anselin 1995) to have prematurely terminated (e.g., due to impedance from gravel) at a depth beneath which liquefiable soil could be present. Additional coverage of the CPT data and autocorrelation analyses is provided in Maurer et al. (2014a, 2015b); further processing and use of the CPT data are discussed subsequently. Ground water depths at CPT locations were obtained from the time-dependent regional models of van Ballegooy et al. (2014b), which were derived, in part, using monitoring data from ~1000 piezometers. Peak Ground Accelerations (*PGA*s) were estimated via the Bradley (2013) method, which has previously been used in Canterbury research (e.g., Maurer et al. 2014b; van Ballegooy et al. 2015) and which geostatistically coalesces instrumentally-recorded *PGA*s with *PGA*s from ground-motion prediction equations.

Global Dataset

To compare fragility functions in Canterbury with regions worldwide, 274 case histories were compiled from 21 global earthquakes in nine countries. These cases were obtained from the existing literature, including CPT soundings, observations of liquefaction, and estimations of ground water depth and *PGA*, as generally reported by original investigators. When available, refinements were adopted from more recent literature. Whereas liquefaction in Canterbury was intensively cataloged via reconnaissance and remote sensing, the case histories in the global dataset are typically documented in less detail, often with scant information about the nature or severity of manifestation. Since most global cases do not support use of the Green et al. (2014) classification criteria, a binomial "Manifestation" or "No Manifestation" classification was adopted instead. The implications of using two classification schemes will be discussed later. Of the 274 cases compiled, 58% are "Manifestation" and 42% are "No Manifestation." To properly recognize all sources of data used to compile the global dataset, data and references are provided in Table S1 (electronic supplement) for each case history. In this regard, the data assemblages of Moss (2003) and Boulanger and Idriss (2014) greatly assisted the present effort.

Methodology

Fragility functions will be conditioned on three liquefaction manifestation models, each computed using six CPT-based liquefaction triggering models, implemented with and without CPT inverse filtering. These models, and the symbology henceforth used to identify them, are summarized in Table 3. The methodologies underlying the CPT processing, liquefaction modeling, and fragility function development are detailed as follows. In addition, all calculations performed herein can be carried out via the open-source software program *Horizon* (Geyin and Maurer, 2020).

CPT Processing Methodology

The CPT offers advantages among in-situ tests used to predict liquefaction (NRC 2016). Yet, as a penetration test, the CPT is still potentially limited by the volume of soil mobilized around the cone, which acts as a physical low-pass filter on the true soil stratigraphy. This filter removes information from the high spatial frequencies, such as the data defining a thin soil stratum or the interface between two disparate soils. These smoothing effects, which are commonly referred to as “thin layer” and “transition” effects, have long been recognized and studied (e.g., Treadwell 1976; Lunne et al. 1997; Ahmadi and Robertson 2005; Robertson 2011; van der Linden 2016). While chart-based methods exist for manually correcting these effects on CPT data, Boulanger and DeJong (2018) proposed the first programmable procedure. This methodology, referred to as an “inverse filtering and interface detection” procedure, predicts the “true” CPT profile from measured CPT values. Since these measured values reflect a filtered view of reality, their correction would improve subsurface characterization. As a demonstration of the methodology, CPT data is shown in Fig. 1, both with and without correction.

While the performance of Boulanger and DeJong’s (2018) procedure has not yet been evaluated in the literature, its use can change a site’s perceived liquefaction hazard, with the direction and magnitude of change dependent on numerous factors. Considering this potential influence, and that the Boulanger and DeJong (2018) procedure could soon become popular, both measured and “true” CPT data will be used to develop fragility functions, thereby providing users with the same option. While the reader is referred to Boulanger and DeJong (2018) for complete details, the procedure’s “baseline” parameters were used to compute “true” CPT data. This was the case both for the methods which invert tip resistance and sleeve friction, and that which detects and corrects stratigraphic interfaces. These defaults can conceivably be calibrated via site-specific study (e.g., from borings adjacent to a CPT), but the information compiled for this study either was insufficient to attempt calibration or provided insufficient statistical support to justify it. However, the sensitivity of results to these parameters will be investigated and discussed later in the paper. As part of the processing methodology, CPT tip- and sleeve-measurements were aligned using cross-correlation (Buck et al. 2002), both for measured and "true" CPT data.

Liquefaction Triggering and Manifestation Model Methodology

Six triggering models, as summarized in Table 3, were used to compute the factor-of-safety against liquefaction (FS_{liq}) vs. depth for each CPT. While the reader is referred to these publications for complete details, two nuances pertinent to this study are as follows. First, prior to using any of the six models, liquefaction susceptibility was inferred using the CPT soil-behavior-type index (I_c) (Robertson and Wride 1998), such that soils with $I_c > 2.50$ were assumed not susceptible. This criterion was developed specifically for the Canterbury dataset using lab and field test data (Maurer et al. 2019). However, because an I_c threshold of 2.50 is within the range of general, commonly used values (e.g., 2.4-2.6) (Youd et al. 2001), this criterion is also adopted in analyses of the global dataset. Ultimately, the results of this study were insensitive to this decision. Second, for liquefaction-susceptible soils, the IB08, BI14, and Gea19 models compute liquefaction resistance as a function of fines-content (FC). Accordingly, FC was estimated for the Canterbury dataset using a Canterbury-specific $I_c – FC$ correlation (Maurer et al. 2019), and for the global dataset using a global $I_c – FC$ correlation (Boulanger and Idriss 2014), with the latter estimating FC to be ~10% less for a given I_c.

Next, the results from triggering analysis were input to the LPI, LSN, and LPI_{ISH} manifestation models, which have been given other general names in the literature, including liquefaction hazard frameworks, vulnerability parameters, and damage indices. Nomenclature aside, these models have the same basic objective - to characterize the system-response of a liquefiable soil profile, thereby linking seismic demand to ground failure.

The Liquefaction Potential Index (LPI) is defined as (Iwasaki et al. 1978):

$$LPI = \int_0^{20\,m} F(FS_{liq}) \cdot w(z)\,\mathrm{d}z \quad (1)$$

where $F(FS_{liq})$ and $w(z)$ are functions that weight the respective influences of FS_{liq} and depth, z, on surface manifestation. Specifically, $F(FS_{liq}) = 1 - FS_{liq}$ for $FS_{liq} \leq 1$ and $F(FS_{liq}) = 0$ otherwise; $w(z) = 10 - 0.5z$. *LPI* thus assumes that surface manifestation depends on the thickness of all liquefied strata in a profile's upper 20 m, their proximity to the ground surface, and the amount by which FS_{liq} in each stratum is less than 1.0. Given this definition, *LPI* can range from zero to 100.

A modified *LPI* was proposed by Maurer et al. (2015a) and inspired by Ishihara (1985), who proposed limit-state curves for predicting manifestations as a function of the "crust" thickness (H_1), among other factors. Using these curves, Maurer et al. (2015a) modified *LPI* to include the observed influence of H_1. Given its provenance, the result was termed LPI_{ISH} and is defined by:

$$LPI_{ISH} = \int_{H_1}^{20\,m} F(FS_{liq}) \cdot w(z)\,\mathrm{d}z \quad (2a)$$

where

$$F(FS_{liq}) = \begin{cases} 1 - FS_{liq} & if\ FS_{liq} \leq 1 \ \cap\ H_1 \cdot m(FS_{liq}) \leq 3 \\ 0 & otherwise \end{cases} \quad (2b)$$

$$m(FS_{liq}) = \exp\left(\frac{5}{25.56(1 - FS_{liq})}\right) - 1 \quad (2c)$$

In Eq. (2a), $F(FS_{liq})$ and $w(z)$ have the same objective as in *LPI*, but are functionally different, such that $F(FS_{liq})$ accounts for the crust thickness through parameter H_1 and $w(z)$ is defined by $w(z) = 25.56 \cdot z^{-1}$. Maurer et al. (2015a) recommended a minimum H_1 of 0.4 m, even if liquefiable soils are present at shallower depths. Provided this constraint, LPI_{ISH} can range from zero to 100.

The Liquefaction Severity Number (*LSN*) is adapted from methods for estimating post-liquefaction volumetric strain (e.g., to predict ground settlement), modified to include a power-law depth weighting function (van Ballegooy et al. 2014a):

$$LSN = \int_0^{20\,m} \varepsilon_v \cdot w(z)\,\mathrm{d}z \quad (3)$$

where ε_v is volumetric strain (%) and $w(z) = 10 \cdot z^{-1}$. While there are many methods to estimate ε_v (e.g., Geyin and Maurer 2019), van Ballegooy et al. (2014a) used that of Zhang et al. (2002), which we also adopt. *LSN* values can surpass 100 if liquefiable soils are near the surface, but typically are between zero and 100. These values are not quantities of predicted settlement, but rather, are index values á la *LPI* and LPI_{ISH} that correlate to the probability of surface manifestation.

Fragility Function Methodology

The probability of surface manifestations reaching or exceeding a defined manifestation severity (MS_i), given a computed liquefaction manifestation model (*LMM*) value, is herein denoted $F_{MS_i}(LMM)$, where *i* corresponds to the severity of manifestation (e.g., 1 = minor, 2 = moderate, etc.). Adopting the lognormal cumulative distribution function, as is common for fragility functions (e.g., Bradley 2010; Kwak et al. 2016), and which best fit the data relative to other distributions (e.g., beta, chi-squared), $F_{MS_i}(LMM)$ is defined by:

$$F_{MS_i}(LMM) = \Phi\left(\frac{ln(LMM) - ln(\theta)}{\beta}\right) \tag{4}$$

where Φ is the Gaussian cumulative distribution function and θ and β are the distribution's median and logarithmic standard deviation, respectively. In this context, θ is the value of the *LMM* (i.e., *LPI*, LPI_{ISH}, or *LSN*) corresponding to a 50% probability of exceeding a given MS_i .

Several methods exist for fitting fragility functions to empirical data (e.g., Baker 2015; Porter 2019). These include: (1) maximum likelihood estimation; (2) logistic regression; or (3) as utilized in this work, minimizing the squared error term, ε^2 (θ, β), defined as (Porter 2019):

$$\varepsilon^2(\theta, \beta) = \sum_{j=1}^{m} n_j \cdot \left(F_{MS_i} - \frac{f_j}{n_j}\right) \tag{5}$$

where m is the number of bins into which similar *LMM* values are grouped; j is the bin index; and n_j is the total number of cases in each bin, of which f_j are cases for which observed manifestations reached or exceeded a given MS_i. While the adopted approach is attractive considering the large number of compiled case histories (Porter 2019), fragility functions were found to be insensitive to this choice (i.e., very similar model parameters were obtained using each of the methods above). To investigate the uncertainty of fragility functions due to finite case-history data, non-parametric bootstrap sampling (e.g., Diaconis and Efron 1983) was used to generate 10,000 realizations of both the Canterbury and global datasets, with subsamples (i.e., realizations) randomly selected and equal in size to that of the respective, original datasets. By fitting a fragility function to each realization, distributions of possible function parameters are produced, thus quantifying finite-sample uncertainty. All else being equal, this uncertainty should diminish as more case history data is compiled and analyzed. For this study, the 16th, 50th, and 84th percentile fragility-functions will be reported and discussed, though only the 50th percentile (or median) functions will be of interest to most users.

Results and Discussion

Analyzing 15,223 liquefaction case histories, empirical fragility functions conditioned on *LPI*, LPI_{ISH}, and *LSN* were developed, each separately formulated using six triggering models, implemented with and without CPT inverse filtering. All functions are defined by Eq. (4), such that users can easily select fragility coefficients consistent with the analytics of their choosing. In this regard, θ and β values for functions developed using the measured and "true" CPT data (i.e., inverse filtered) are presented in Tables 4 and 5, respectively. As discussed, the Canterbury and global datasets deviate in the classification of manifestations. As a result, analyses of the global dataset result in one function for "any manifestation", whereas analyses of the Canterbury dataset result in three functions for "minor," "moderate," and "severe manifestations." In total, 144 functions are defined in Tables 4 and 5, from which select results will be plotted and discussed.

As demonstrated in Fig. 2a, the functions relate the probability of reaching or exceeding a defined manifestation severity (MS_i) to a computed *LMM* value; in this case, BI14-*LPI* using measured CPT data from Canterbury. As an example, the probabilities of manifestations being *at least* minor, moderate, and severe at *LPI* = 5 are approximately 47%, 16%, and 1%, respectively, per the median functions. Three observations from Fig. 2a, generally true of all *LMMs*, are: (1) BI14-*LPI* is more effective at predicting the presence of *some* manifestation than it is at distinguishing manifestation severity, as evidenced by the flatter functions as MS_i increases; (2) finite-sample uncertainty increases as MS_i increases, as evidenced by the dispersion of bootstrap simulations; and (3) uncertainty also increases as *LPI* increases, principally due to less data at very large *LPI*. Whereas uncertainties in the functions for minor manifestations are relatively inconsequential with respect to computed hazard and risk, those in the functions for severe manifestations should potentially be considered, especially at large *LPI*. With simple arithmetic, the fragility functions can also assess the probability that manifestations will be *in* a severity class (i.e., F_{MS_i} - $F_{MS_{i+1}}$). This is demonstrated in Fig. 2b using the functions from Fig. 2a; for clarity, only median functions are shown. Again using *LPI* = 5 as an example, the probabilities of manifestations being none, minor, moderate, and severe are 53%, 31%, 15%, and 1%, respectively.

In Fig 3., median functions resulting from Canterbury (and shown in Fig. 2a) are compared to results from the Global dataset, for which bootstrap simulations are also plotted. All functions shown are based on BI14-*LPI* and measured CPT data (i.e., without inverse filtering). It can be seen in Fig. 3 that the global function for "any manifestation" has a lesser probability, on average, than the Canterbury function for "minor manifestation." As an example, the *LPI* values corresponding to 50% probability of exceedance, globally and in Canterbury, are respectively 5.5 and 7.5. One possible explanation is that historical criteria for documenting global case histories as "yes" (i.e., some manifestation) tend to fall between the Green et al. (2014) criteria for "minor" and "moderate" manifestations. This is plausible (e.g., given the lack of near-real-time remote sensing for historic case histories) and could result in the noted discrepancy between Canterbury and global results, which exists for most, but not all, of the developed functions. In can also be seen in Fig. 3 that finite-sample uncertainty is relatively larger for the global dataset. This may be attributable to the global data's greater geologic, geomorphic, and seismologic diversity and/or because the global field-data (e.g., CPTs, *PGA*s) were collected over many decades by different investigators. There are also far fewer global case histories; all else being equal, greater finite-sample uncertainty is thus expected. Given (i) the complications of directly comparing (e.g., via hypothesis testing) the Canterbury and global functions; and (ii) the large finite-sample uncertainty of the latter, we heuristically conclude that the functions resulting from the two datasets are consistent. On this basis, use of the Canterbury functions elsewhere appears reasonable, but more global case-history data is ultimately needed to confirm this, or to draw other conclusions.

Median fragility functions for *LPI*, computed using each of the six triggering models, are shown for the Canterbury and global datasets in Figs. 4a and 4b, respectively. As see in Fig. 4, the relationship between expected manifestation severity and computed *LPI* is unique to the adopted triggering model. Using *LPI* = 5 as an example, the probabilities of manifestations being at least minor, using measured CPTs from Canterbury, are 57%, 34%, 49%, 54%, 47%, and 50% for the RW98, AIJ01, MEA06, IB08, BI14, and GEA19 models, respectively. Using measured CPTs from the global dataset, the probabilities of any manifestation are 44%, 29%, 37%, 41%, 38%, and 41% using the same respective models. Therefore, *LPI* values tend to be highest when computed using

AIJ01 and lowest when computed using RW98, both globally and in Canterbury. Clearly, the fragility coefficients obtained with one model should not be used in conjunction with another.

Selecting BI14-*LPI* as a representative example, the effects of CPT inverse-filtering on fragility functions are shown for the Canterbury and global datasets in Figs. 5a and 5b, respectively. In each case, the Boulanger and DeJong (2018) "baseline" parameters were used to compute "true" CPT data. As inferable from Fig. 4a, inverse-filtering has the average tendency to slightly reduce *LPI* values in Canterbury (notably, *LPI* also often increases). Overall, the result is a shift of the formulated functions toward lesser *LPI*. At *LPI* = 5, for example, the probabilities of exceeding minor, moderate, and severe manifestations increase by 4.1%, 4.3%, and 0.25%, respectively, due to inverse filtering. This shift is often less pronounced in the global functions for predicting any manifestation, ranging from 0.7% for BI14-*LPI* (as shown in Fig. 4b) to 6.43% for AIJ01-*LPI*. While some variation exists, these trends generally also apply to all functions based on LPI_{ISH} and *LSN*. While more rigorous analysis of the inverse-filtering procedure is ongoing, it can be inferred from Fig. 4 (and β values in Table 4 vs. 5) that the procedure does not significantly alter model efficacy (i.e., the ability to segregate sites with and without manifestations), either for better or for worse. A limited parametric study was also performed by varying an influential parameter in the procedure: $z'_{50,ref}$, which controls the "aggression" of the inversion, such that changes to CPT data increase as $z'_{50,ref}$ increases. Specifically, the "baseline" $z'_{50,ref}$ value of 4.2 was varied from 3.4 to 5.0. While the reader is referred to Boulanger and DeJong (2018) for a full explanation of $z'_{50,ref}$ (and the complete procedure), the results of this analysis are shown in Fig. 5 using BI14-*LPI* and the Canterbury data. As expected, larger values of $z'_{50,ref}$ tend to further diminish computed *LPI*, shifting the fragility functions in corresponding fashion. In addition, the functions in Fig. 5 do not suggest marked improvement with respect to predictive performance, regardless of the $z'_{50,ref}$ value. However, the intention of this study is not to recommend use or disuse of the Boulanger and DeJong (2018) procedure, nor is it to intensively analyze the procedure's performance. Rather, the intention is to provide users with fragility functions conditioned on an array of liquefaction analytics. In this regard, the study's only recommendation is to employ fragility coefficients in a manner perfectly consistent with their development. As shown in Figs. 4-6, failure to do so would invariably introduce some degree of error.

Demonstration

Fragility-function application will be demonstrated via (i) a scenario earthquake simulation in Christchurch, NZ; and (ii) within a probabilistic seismic-hazard analysis in Seattle, USA.

Scenario Earthquake Simulation: Alpine Fault, New Zealand

New Zealand's 600-km long Alpine Fault (AF) represents a major seismic hazard for the South Island. Believed capable of producing M_w8 earthquakes and to have a 29% probability of rupture in the next 50 years (Cochran et al. 2017), the next AF event will undoubtedly be catastrophic for many. Yet, because there is no historic account of any AF earthquake (the last occurred ca. 1717), the potential extent and severity of ground failure is highly uncertain. Accordingly, to provide an example with utility beyond this paper, the fragility functions are first applied in conjunction with simulated ground-motions (Bradley et al. 2017a) from an $M_w7.9$ AF scenario earthquake. Specifically, measured CPTs from Canterbury will be used to predict liquefaction manifestations in the city of Christchurch and its environs. The physics-based simulation of Bradley et al. (2017a), which explicitly models kinematic fault rupture, wave propagation, and the 3D velocity structure of the subsurface, was obtained from the SeisFinder portal (Bradley et al. 2017b). For this demonstration, predictions will be merged from the 18 fragility functions defined in Table 4 and based on the Canterbury dataset. This ensemble approach, in which models are weighted in proportion to their predictive capabilities, is conventional in seismic hazard analysis and has the advantage of avoiding large "swings" as a result of changing a single adopted model. While the 18 functions could be given equal weighting (i.e., 18^{-1}, or 0.055), a scheme derived from receiver-operating-characteristic (ROC) analysis (Geyin et al. 2020) was adopted. Specifically, weights were assigned in proportion to the area under the ROC curve – a measure of diagnostic efficiency – for each of the 18 models on which fragility functions were conditioned. Taking predictive capabilities into account, the functions received weights ranging from 0.049 to 0.059 (the weighting scheme is detailed in Tables S2 and S3). Presented in Fig. 7 are the resulting probabilities of minor, moderate, and severe manifestations. Notably, manifestations were previously shown to be overpredicted by popular liquefaction analytics in areas of Southwest Christchurch during the 2010-2011 Canterbury sequence (Maurer et al. 2014a). The non-trivial probabilities of moderate and severe manifestations in these general areas, as loosely delineated on Fig. 7, should thus be viewed skeptically. Nonetheless, the analyses do suggest at least a small probability of *some* manifestation across much of the study area. These manifestations, in general, would likely have minor severity.

Return Period of Liquefaction Manifestations: Seattle, USA

The return period (T_R) of liquefaction manifestations at a site of interest can be computed using: (i) the fragility functions developed herein; (ii) CPT data from the site; and (iii) the *PGA* hazard curve, which describes the mean annual frequency of *PGA* exceeding a given value at the site's location. Using fragility functions conditioned on *LPI* as an example, T_R is computed as:

$$\lambda_{MS} = {}^{1}/_{T_R} = \int_{LPI=0}^{\infty} F_{MS}(LPI) \cdot \left|\frac{d\lambda_{LPI}}{dLPI}\right| \cdot dLPI \tag{6}$$

where $F_{MS}(LPI)$ is the fragility function for a particular *MS* (e.g., minor, moderate, or severe) and defined by Eq. (4); λ_{MS} is the mean annual exceedance frequency of the *MS* (the reciprocal of which is T_R, in years); and $|d\lambda_{LPI}/dLPI|$ is the absolute value of the derivative of the *LPI* hazard curve, which describes the mean annual frequency of *LPI* exceeding a given value (λ_{LPI}), and which is computed from CPT data and the site-specific *PGA* hazard curve. Specifically, to compute a site's λ_{LPI}, the *PGA* hazard curve must first be deaggregated by earthquake magnitude. This requirement results from use of both *PGA* and magnitude as inputs for predicting liquefaction triggering (true of all six triggering models used in this study). λ_{LPI} is then computed as:

$$\lambda_{LPI} = \sum_{j=1}^{N_{Mw}} \sum_{i=1}^{N_{PGA}} P\left(LPI > lpi \middle| \, pga = pga_i, m = m_j\right) \Delta\lambda_{pga_i, m_j} \tag{7}$$

where N_{Mw} and N_{PGA} are respectively the number of magnitude and *PGA* increments into which the computed seismic hazard is subdivided; $\Delta\lambda_{pgai,mj}$ is the incremental annual-exceedance rate for intensity measure, pga_i, and magnitude, m_j, which follows an established procedure in performance-based liquefaction modeling (Kramer and Mayfield 2007); and $P\left(LPI > lpi \middle| \, pga = pga_i, m = m_j\right)$ is the binomial probability that *LPI* exceeds some threshold value, *lpi*, conditioned on *PGA* and *M*. This overall approach to computing λ_{LPI} is similar to those presented by Goda et al. (2001) and Green et al. (2020).

To demonstrate this process, a CPT from the South-of-Downtown (SODO) district of Seattle, USA, is analyzed. Deaggregated *PGA* hazard-curve data was obtained for the CPT's location (47.587130, -122.331487), which has D/E seismic site class, from the USGS (2019) Unified Hazard Tool, wherein the 2008 US National Seismic Hazard Model was adopted (Petersen et al., 2008). Using Eqs. 1 and 7, in conjunction with measured CPT data and the Boulanger and Idriss (2014) triggering model, the *LPI* hazard curve was computed and is shown in Fig. 8. This figure, which follows an approach analogous to those demonstrated by Goda et al. (2001) and Green et al. (2020) shows the expected annual rates at which different *LPI* values will be exceeded. Lastly, using this *LPI* hazard curve within Eq. 6, and computing F_{MS} (*LPI*) with appropriate coefficients from Table 4, the computed return periods of minor, moderate, and severe liquefaction manifestations are 60, 127, and 709 years, respectively. Thus, and assuming a Poisson process, the probabilities of minor, moderate, and severe manifestations occurring at least once in the next 100 years are 81%, 54%, and 13%, respectively.

Repeating this process for 43 CPTs from the Washington State Department of Natural Resources (2019), the return period of minor manifestations is mapped in Fig. 9 for a 3 km^2 area of SODO. In the context of hazard mapping, planning, and policy, this information is arguably of much greater value than that derived from "probabilistic" analyses or maps focusing on a classification threshold, the shortcomings of which were previously discussed. Historically, manifestations were observed in the Fig. 9 study area – particularly that with lowest computed return period – following earthquakes in 1949, 1965, and 2001 (Chleborad and Schuster 1990; Bray et al. 2001). These manifestations were generally "minor" per the Green et al. (2014) criteria. Assuming a Poisson process, and adopting (i) the computed return period of 60 years (see above); and (ii) a 170-year exposure window beginning 1850 (ca. Seattle's founding), the probability of three observations is 22% (the only quantity more likely is two, having 23% probability). With respect to the computed return period for severe manifestations (i.e., ~700 years), paleoliquefaction from the nearby Duwamish River (Davis et al. 2019) suggests that "severe" manifestations have occurred at least once, and possibly twice, during the last 1200 years. Assuming a Poisson process, it could similarly be shown that these observations are consonant with the computed return period. While discrepancies between observed and predicted return periods would not necessarily discredit the latter, their close agreement nonetheless gives credence to the developed functions and results.

Conclusions

The severity of liquefaction manifested at the ground surface is a pragmatic proxy of damage potential for infrastructure, making it well-suited for hazard mapping, planning, policy, and preliminary site-assessment. Towards this end, empirical fragility functions were formulated to predict the probability of liquefaction manifestations on free-field level ground. These functions are extensions to popular deterministic liquefaction models, such that users need only select fragility coefficients from Table 4 or 5; options were provided for six CPT-based triggering models, one CPT-inversion filter, and three manifestation models. Fragility functions separately developed from case histories globally and in Canterbury were found to be heuristically consistent. This lends permissibility to the use of Canterbury functions elsewhere, which would allow for manifestation severity to be predicted in higher resolution when desirable, yet additional global case-history data is ultimately needed to confirm this, or to draw other conclusions.

While the proposed functions have a variety of uses, they are not intended to predict lateral spreading, which is a distinct phenomenon influenced by factors not considered in this study, nor can the functions explicitly predict damage to specific infrastructure assets. In this regard, liquefaction could trigger at-depth and damage infrastructure without otherwise manifesting at the surface, or could manifest at the surface without causing asset damage. Asset-specific assessments of liquefaction potential and consequence are thus judicious. Moreover, these functions do not replace the need for improved analytics that more effectively predict the triggering and manifestation of liquefaction. As evident from all fragility functions developed herein, the models on which these functions are conditioned have significant potential for improvement. As one example, interbedded low-permeability soils may complicate prediction of a soil profile's cumulative response by affecting the onset of liquefaction triggering and/or the morphology of manifestation (e.g., Fiegel and Kutter 1994; Brennan and Madabhushi 2005; Özener, et al. 2008).

These affects are not considered by the models utilized herein, which may thus perform less efficiently on profiles with complex stratigraphy (e.g., Juang et al.,2005; Maurer et al. 2015c; Yost et al. 2019; Cubrinovski et al. 2019).

Moreover, the results of this study are tied to the data analyzed, which in effect is the present sum of CPT case histories. The applicability of these results to other case-history data – particularly that with different parameter space (e.g., soils with atypical composition, minerology, age, etc.) – or to other models and procedures, is unknown. In addition, the presented findings should be considered in the context of model regionality and possible bias. Ultimately, additional data will confirm or update the fragility functions developed herein.

Data Availability

Some or all data, models, or code generated during the study are available from the corresponding author, including Tables 4 and 5 as well as all data associated with the Canterbury case-history dataset. Tables S1-S3 are available online in the ASCE library (www.ascelibrary.org) and was compiled from data that may be available in full or part from the Next-Generation Liquefaction Project (Brandenberg et al. 2020). In addition, all calculations demonstrated herein, including CPT processing, may be performed using *Horizon* (Geyin and Maurer, 2020), a freely available open-source program developed by the authors.

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