Mitigation of liquefaction hazard by dynamic compaction - a random field perspective

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Mitigation of liquefaction hazard by dynamic compaction  
- a random field perspective

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Abstract: This paper presents the findings of a case study to quantitatively assess the effect of dynamic compaction (DC) on mitigating liquefaction hazards from a random field perspective. DC is known to increase the density and strength of loose sand deposits, leading to a decrease in liquefaction potentials. Thus, by comparing the liquefaction potentials before and after DC at a given site, the effectiveness of DC in mitigating liquefaction hazards can be quantified. In practice, however, a direct one-to-one comparison is challenging due to limited availability of in situ test data and the fact that the number and location of these data before and after DC are typically different. To overcome these challenges, a random field-based approach is proposed in this study to visualize and quantitatively evaluate the effectiveness of DC across the entire project site. This approach is proven effective in assessing the effects of DC and is validated with liquefaction observations from the 1999 Chi-Chi earthquake.

Keywords: Liquefaction; Dynamic compaction; CPT; Random field models.
1. Introduction

Soil liquefaction and liquefaction-induced damage to buildings, lifeline systems, and port facilities have been widely observed in recent earthquakes including the 1999 Chi-Chi, 2008 Wenchuan, 2010 Chile, 2010-2011 New Zealand and 2011 Tohoku earthquakes. In the 1999 Chi-Chi earthquake, soil liquefaction was one of the main causes to building and infrastructure damage, leading to losses ranging from $20 billion to $30 billion (Uzarski and Arnold 2001). In the 2010-2011 New Zealand earthquakes, approximately half of the $30-billion losses were attributed to soil liquefaction (Cubrinovski et al. 2014). As such, mitigating liquefaction hazards is a significant part of earthquake resistant design (Seed 1981; Seed 1982).

In this paper, the focus is on the coastal reclaimed land created through hydraulic filling, which often consists of saturated layers of loose sand and/or silty sand at shallow depth with a high groundwater level, and is thus very susceptible to liquefaction. In a seismic prone region, such hydraulic filled reclaimed land (HFRL) often has a high liquefaction potential in a great earthquake. To mitigate the risk of liquefaction damage to the buildings and infrastructures in the HFRL, ground improvement methods, such as sand compaction pile (e.g., Akiyoshi et al. 1993; Okamura et al. 2003; Okamura et al. 2006), dynamic compaction (e.g., Chow et al. 1994; Kumar 2001; Shenthan et al. 2004; Michalowski and Nadukuru 2012), vibroflotation (e.g., Haider et al. 1984; Jian et al. 2003), deep soil mixing (e.g., O’Rourke and Goh 1997; Lew et al. 2014), stone column (e.g., Adalier et al. 2003; Adalier and Elgamal 2004; Tang et al. 2015), and blasting (Charlie et al. 1992; Ashford et al. 2004; Rollins et al. 2005), are often used to improve the liquefaction resistance and mitigate the risk of liquefaction.

A suitable ground improvement method is often selected based on such factors as the average thickness of the hydraulic fill, the size of the area to be improved, the cost or budget...
limitation set by the client, the applicability of the method, and local experience. Once a particular method is selected, the associated operating parameters are primarily selected based on local experience and rule of thumbs, and then further refined based on a pilot test in the area to be improved. As is discussed later, the dynamic compaction (DC) was selected and used in a ground improvement project for mitigating the risk of liquefaction at a site in an HFRL, which is the study site of the present paper. Thus, in the presentation that follows, only DC is focused.

Dynamic compaction (DC) has been found to be an effective technique to mitigate liquefaction hazards, as evidenced by the improved ground performance to resisting liquefaction during past earthquakes (Dise et al. 1994; Hausler and Koelling 2004; Hausler and Sitar 2001; Lee et al. 2001). DC reduces the risk of liquefaction hazards by densifying the soil, leading to increased liquefaction resistance.

Regardless of which ground improvement method is used, it is essential to learn from the performance of the improved and unimproved ground in an earthquake. To this end, it is interesting and particularly fitting to note the earlier work by Mitchell and Wentz (1991) on the performance of improved ground during the Loma Prieta Earthquake. Among other studies, Yasuda et al. (1996) observed the effect of soil improvement on ground subsidence due to liquefaction in the 1995 Hyogoken-Nambu earthquake. Hausler et al. (2001) discussed the performance of soil improvement techniques in earthquakes. Wotherspoon et al. (2014) reported the seismic performance of improved ground sites during the 2010–2011 Canterbury earthquake sequence. Although these studies provide a perspective on the reduction of the liquefaction potential by the ground improvement, they represent only one aspect of the present study.

To evaluate the effect of dynamic compaction, in situ tests, such as the cone penetration test (CPT), are usually conducted before and after DC. With CPT data, the liquefaction potential
of soil deposits at a CPT location before and after DC can be evaluated using conventional
deterministic liquefaction models (e.g., Robertson 2009; Robertson and Wride 1998). However,
the locations of CPT before and after DC in a ground improvement project typically differ due to
the local construction practice, project management style, and client requirements. This reduces
the effectiveness of the conventional one-to-one comparison of the factor of safety (FS) or
liquefaction potential values before and after DC at a given CPT location. Furthermore, due to the
complexity of the depositional history and environment, engineering properties of a soil often vary
from one point to another. Consequently, soils in some areas of a project site may be more
susceptible to liquefaction than soils in other areas. Therefore, it is desirable to investigate and
visualize the liquefaction potential of the entire site to aid in the design of DC and to assess the
effectiveness of DC in mitigating the liquefaction hazard. In this regard, random field modeling
provides an effective approach to estimate liquefaction potential of soils at unsampled locations
based on the characterized statistical distribution and spatial variability, thus permitting an
effective mapping of liquefaction hazards over an area of interest. By quantifying and comparing
the liquefaction hazard of the entire project site before and after DC that is enabled through the
random field modeling approach, the effect and benefits of DC in mitigating liquefaction hazards
can be easily demonstrated.

The spatial variability of soil properties has long been recognized in geotechnical
engineering (e.g., Popescu et al. 1997; Fenton and Vanmarcke 1998; Vanmarcke 2010; Stuedlein
et al. 2012; Onyejekwe et al. 2016). Many past studies have considered the spatial variation of soil
properties in the liquefaction assessment and mapping. For example, Fenton and Vanmarcke (1991)
perhaps first discussed spatial variation in liquefaction risk assessment. Popescu et al. (1995)
performed numerical simulations of liquefaction considering stochastic input variables. Fenton
and Vanmarcke (1998) further addressed the issue of spatial variation in liquefaction risk. Basie et al. (2006) considered the statistical and spatial characterization of susceptible geologic units in the liquefaction hazard mapping. Lenz and Baise (2007) discussed the spatial variability of liquefaction potential in regional mapping using CPT and SPT data. Baker and Faber (2008) applied geostatistics to account for soil spatial variability in the assessment of liquefaction risk. Chen et al. (2016a) conducted a CPT-based evaluation of liquefaction potential that accounts for soil spatial variability at multiple scales, which was later extended by Wang and Chen (2018) to incorporate both geologic and geotechnical data. Chen et al. (2016b) further performed the probabilistic and spatial assessment of liquefaction-induced settlements through multiscale random field models. Stuedlein and Bong (2017) discussed the effect of spatial variability on static and liquefaction-induced differential settlements. Bong and Stuedlein (2018) further discussed the effect of cone penetration conditioning on random field model parameters and the impact of spatial variability on the liquefaction-induced differential settlements. It is interesting to note the aforementioned studies, again, represent only one aspect of the present study.

In this study, a dynamic compaction (DC) project with before and after CPT investigations for a reclaimed ground in Taiwan is adopted as an example to demonstrate the effectiveness of the proposed random field-based evaluation procedure. The location-specific liquefaction potential analysis using the deterministic (i.e., FS-based) approach is firstly performed. Then, the areal liquefaction is assessed in terms of liquefaction potential index (LPI), followed by the random field modeling of LPI and the creation of the liquefaction hazard map of the study site. The effectiveness of DC in the mitigation of liquefaction hazard is demonstrated through visualization of this hazard at different ground shaking levels for both before and after DC.
While the use of the ground improvement methods to reduce the liquefaction potential and the use of random field theory to aid in the liquefaction potential assessment considering the soil spatial variation are not entirely new, the combined use of the available tools in an areal liquefaction potential analysis using in situ test data before and after ground improvement in a real project setting, which is the focus of this study, is quite rare. The results presented in this paper should be useful to the engineers who are working on the ground improvement projects for the purpose of mitigating the risk of liquefaction-induced damages to buildings and infrastructures.

2. Liquefaction potential: from location-specific to areal analysis

2.1 Factor of safety (FS) against liquefaction

Among methods for soil liquefaction potential evaluation, simplified methods based on in situ tests, such as standard penetration test (SPT), cone penetration test (CPT), and shear wave velocity \( V_s \) test, are preferred in geotechnical engineering practices (Andrus and Stokoe 2000; Robertson and Wride 1998; Seed and Idriss 1971; Youd et al. 2001). With the simplified methods, the factor of safety (FS) against liquefaction is calculated and is defined as the ratio of cyclic resistance ratio (CRR) over the cyclic stress ratio (CSR) as shown in Eq. (1). The soil is said to be liquefied if \( FS \leq 1 \) and be non-liquefied if \( FS > 1 \).

\[
FS = \frac{CRR}{CSR} \quad (1)
\]

The liquefaction resistance CRR is typically computed using the in situ test data. The CPT-based liquefaction model proposed by Robertson and Wride (1998) and subsequently updated by Robertson (2009) is adopted in this study to calculate the CRR, which is summarized in Eq. (2). The CRR is a function of the clean-sand equivalence of the normalized cone tip resistance, denoted
as $q_{1N,cs}$. The reader is referred to (Robertson 2009; Robertson and Wride 1998) for details regarding the evaluation of $q_{1N,cs}$.

$$CRR = \begin{cases} 
0.833 [q_{1N,cs} / 1000] + 0.05 & \text{if } q_{1N,cs} < 50 \\
93 [q_{1N,cs} / 1000]^3 + 0.08 & \text{if } 50 \leq q_{1N,cs} < 160 
\end{cases}$$

(2)

It should be noted that Eq. (2) is generally applicable to soils with a soil behavior type index, denoted as $I_c$, of 2.5 or less. For soils with $I_c > 2.7$, it is generally considered too clay-rich to liquefy (see Robertson 2009) and the CRR might be evaluated using a clay-based equation. For soils with $2.5 < I_c < 2.7$, the soil behavior is believed to transition from sand-like to clay-like (Robertson 2009). A recent study by Ku et al. (2010) proposed $I_c = 2.67$ as an approximation for distinguishing sand-like and clay-like behaviors. When applying Eq. (2), CRR may be set to a high value (e.g., 1.0), indicating no liquefaction under known seismic loading, if $q_{1N,cs} \geq 160$.

The CSR represents the earthquake loading as applied to soil in the context of liquefaction, and the following adjusted form is adopted (Juang et al. 2006; Youd et al. 2001):

$$CSR = 0.65 \left( \frac{a_{\max}}{g} \right) \left( \frac{\sigma_{vo}}{\sigma'_{vo}} \right) (r_d) \left( \frac{1}{MSF} \right) \left( \frac{1}{K_\sigma} \right)$$

(3)

where $a_{\max}$ is the maximum horizontal acceleration at the ground surface; $g$ is the gravitational acceleration and is equal to 9.81 m/s$^2$; $\sigma_{vo}$ and $\sigma'_{vo}$ are the total and effective vertical overburden stresses, respectively; $r_d$ is the stress reduction factor; MSF is the magnitude scaling factor and $K_\sigma$ is the overburden correction factor.

The stress reduction factor $r_d$ is a function of depth $z$, defined as (Youd et al. 2001):

$$r_d = \frac{1.000 - 0.4113z^{0.5} + 0.04052z + 0.001753z^{1.5}}{1.000 - 0.4177z^{0.5} + 0.05729z - 0.006205z^{1.5} + 0.001210z^2}$$

(4)

The magnitude scaling factor MSF is related to the moment magnitude $M_w$ as (Youd et al. 2001):
\[ MSF = \frac{10^{2.24}}{M^{2.56}} \]  

(5)

\[ K_\sigma \text{ in Eq. (3) is the overburden correction factor for CSR (Youd et al. 2001). The correction is applied when } \sigma'_{vo} \text{ greater than 100 kPa.} \]

\[ K_\sigma = \left( \frac{\sigma'_{vo}}{P_a} \right)^{(f-1)} \]  

(6)

where \( P_a \) is the atmospheric pressure; \( f \) is an exponent and recommended as \( f = 0.7 \) to 0.8 for relative densities between 40 and 60%; \( f = 0.6 \) to 0.7 for relative densities between 60 and 80%.

2.2 Liquefaction potential index (LPI)

The liquefaction potential index (LPI) defined by Sonmez (2003), which was originated by Iwasaki et al. (1982), is adopted in this study as the index for mapping the liquefaction hazard. The calculation of LPI is based on the assumption that the liquefaction severity is related to the thickness of the potentially liquefiable layers and the factor of safety (FS) against liquefaction. The following integration is used to calculate LPI (Sonmez 2003):

\[ \text{LPI} = \int_0^{20} w(z) F_L \, dz \]  

(7)

where \( z \) is the soil depth in meters (only the top 20 m of the soil profile is considered); \( w(z) \) is a function of soil depth; \( F_L \) is a function of FS against liquefaction (Sonmez 2003)

\[ w(z) = 10 - 0.5z \]  

(8)

\[ F_L = \begin{cases} 
0 & \text{FS} \geq 1.2 \\
1 - \text{FS} & \text{FS} \leq 0.95 \\
2 \times 10^6 e^{-18.427 \text{FS}} & 0.95 < \text{FS} < 1.2 
\end{cases} \]  

(9)

It should be noted that the limiting condition for no liquefaction (and thus no contribution to LPI) was set to \( \text{FS} \geq 1.2 \), in lieu of \( \text{FS} \geq 1 \) as adopted in the original formulation by Iwasaki et
al. (1982). This is to account for the uncertainties of the soil, geological, and seismological parameters. This definition of LPI tends to be more conservative but the entire formulation had been re-calibrated. Based on his re-calibration, Sonmez (2003) provided an updated significance scale, or severity class, for LPI values as shown in Table 1, with which the liquefaction severity at a location can be assessed.

2.3 Liquefaction mapping by random field modeling

As indicated by Toprak and Holzer (2003), LPI provides a convenient tool for risk-based decisions and liquefaction hazard mapping. Focusing on how spatial variability and dependence are considered and incorporated in the liquefaction mapping process, three approaches may be used to generate LPI hazard maps (Juang et al. 2017). They are the averaged index approach, the two-dimensional (2D) local soil property approach, and the three-dimensional (3D) local soil property approach. The averaged index approach is adopted in this paper as it is widely used in current liquefaction hazard mapping studies (e.g., Baise et al. 2006; Bong and Stuedlein 2017; Bong and Stuedlein 2018; Chen et al. 2016a; Lenz and Baise 2007; Wang and Chen 2018; Wang et al. 2017), and it is the most computationally efficient among the three approaches. In the averaged index approach, the probability distribution and the spatial dependence of LPI values at the test locations are characterized and used as inputs for random field modeling. The probability distribution can be easily inferred from test data. The LPI values at the test locations are fitted to a lognormal distribution, thus ln(LPI) will be used in the characterization of spatial dependence and the random field simulation process, which are introduced as follow.
2.3.1 Spatial characterization of LPI

In this study, spatial dependence or spatial variation structure is described using a form of covariance known as the semivariogram $\gamma$, which is equal to one half of the variance of two variables separated by a vector distance $h$:

$$\gamma(h) = \frac{1}{2} \text{Var}[Z(u) - Z(u+h)]$$

where $Z(u)$ and $Z(u+h)$ are the values of the variable (i.e., ln(LPI) in this study) under consideration at locations $u$ and $u+h$, respectively. A scalar form of the vector distance $h$, denoted as $h$, is commonly used to account for both separation distance and orientation (Chen et al. 2012), and therefore can be used to simulate anisotropic random fields:

$$h = \sqrt{\left(\frac{h_x}{a_x}\right)^2 + \left(\frac{h_y}{a_y}\right)^2 + \left(\frac{h_z}{a_z}\right)^2}$$

where $h_x$, $h_y$ and $h_z$ are the scalar components of the vector distance along the principal axes of the field; and $a_x$, $a_y$ and $a_z$ specify how quickly the spatial dependences decrease along the respective axes. The LPI random field studied in this paper is two-dimensional, thus $h_z = 0$. Further, LPI is a scalar index, i.e., there is only one value at each CPT location. For the current case study, there is not sufficient data to favor spatial dependency in either $x$ or $y$ axes. The LPI is therefore assumed to be isotropic in the $x$ and $y$ axes, i.e., $a_x = a_y$. It should be noted that CPT data is highly anisotropic and different scale of fluctuations should be adopted in the vertical and horizontal directions (Ching et al. 2018).

2.3.2 Sequential simulation process

To generate random field realizations of the variables of interest, a conditional sequential Gaussian simulation method (Baker and Faber 2008; Baker et al. 2011; Goovaerts 1997) is implemented, which has been extensively used by mining scientists and geostatisticians for natural
resource evaluations and spatial predictions of geohazards. In this work, the normal-score mapping method (Goovaerts 1997) is implemented to perform the sequential conditional simulation. In this method, realizations of random variables having non-Gaussian distributions (e.g., the lognormally distributed LPIs) are first generated from the standard Gaussian distribution (zero mean and variance of unity), conditional upon all previously generated values. The needed conditional distribution is easy to compute when the field is Gaussian. The generated Gaussian random field is then transformed to have a specified probability distribution (e.g., lognormal distribution). Previous experience with this method showed that this is a reasonable approximation and the dependence structure will not be significantly affected (Chen et al. 2012; Baker et al. 2011).

Following the sequential simulation method, the simulation process could be briefly described as

\[
(Z_n | Z_p) \sim N(\Sigma_{np} \cdot \Sigma_{pp}^{-1} \cdot Z_p, \sigma_n^2 - \Sigma_{np} \cdot \Sigma_{pp}^{-1} \cdot \Sigma_{pn})
\]  

(12)

in which the unknown value, \(Z_n\), at an unsampled location \(n\) is drawn from the conditional normal distribution with the mean \((\Sigma_{np} \cdot \Sigma_{pp}^{-1} \cdot z)\) and the variance \((\sigma_n^2 - \Sigma_{np} \cdot \Sigma_{pp}^{-1} \cdot \Sigma_{pn})\). It is noted here that \(\Sigma_{np} \cdot \Sigma_{pp}^{-1}\) are essentially the weights assigned in the simple Kriging process (Goovaerts 1997); \(Z_p\) is the vector of known data and previously simulated numerical values; \(\Sigma\) is the covariance matrix of neighboring measurements; the subscriptions \(p\) and \(n\) mean “previous” and “next”, respectively.

For the realization, one value of \(Z_n\) is drawn at random from the posterior univariate normal distribution. Once the unknown value \(Z_n\) is generated, it is inserted into the “previous” vector, i.e., the known data vector \(Z_p\), upon which the “next” unknown value at another un-sampled location will be generated. The detailed process of random field modeling may be found in Chen et al. (2012).

Random field models incorporate the spatial dependence of the measured parameter through the covariance matrix. The covariance of values at two separated locations can be expressed as
\[ \Sigma = \text{cov}[Z_i, Z_j] = \rho_{Z_i, Z_j} \cdot \sigma_{Z_i} \cdot \sigma_{Z_j} \] (13)

where \( \text{COV}[Z_i, Z_j] \) is the covariance of the random variables \( Z_i \) and \( Z_j \), and \( \rho_{Z_i, Z_j} \) is the correlation coefficient between the random variables \( Z_i \) and \( Z_j \) with standard deviations of \( \sigma_{Z_i} \) and \( \sigma_{Z_j} \), respectively. The correlation coefficient \( \rho \) is used to describe the similarity of spatial measurements and is related to the semivariogram \( \gamma \) by

\[ \rho(h) = 1 - \gamma(h) \] (14)

The semivariogram \( \gamma \) can be calculated using Eq. (10), which is termed empirical \( \gamma \) (i.e., experimental semivariogram) herein. Then, the empirical \( \gamma \) is fitted with a theoretical model, such as spherical, exponential, Gaussian or power model (Goovaerts 1997), to determine three model parameters, including nugget effect, sill, and range. The exponential semivariogram model is adopted and expressed as

\[ \gamma(h) = \omega \left[ 1 - \exp\left(\frac{-h}{a}\right) \right] + \tau \] (15)

where \( \tau \) denotes the nugget, i.e., the semivariance when \( h \) equals zero; \( \omega + \tau \) is the sill, namely the constant semivariance when \( h \) is greater than the range; \( a \) is a range parameter and \( 3a \) is the practical range, i.e., the distance at which the exponential semivariogram levels off. It is noted here that the nugget relates to the sampling or measurement error and/or spatial sources of variation at distances smaller than the shortest sampling interval (Goovaerts 1997; Baise et al. 2006).

Once the semivariogram \( \gamma \) is characterized, it will be substituted into the covariance matrix Eq. (13) through Eq. (14). Thus, the unknown value \( Z_n \) (i.e., ln(LPI) in this study) at location \( n \) could be drawn using Eq. (12). The generated value is then assigned to location \( n \) and treated as known data. This process is repeated until all unsampled locations are assigned with values. Each
sequential Gaussian simulation realization varies in space, although it is conditional on observed samples. Thus, Monte Carlo simulations (MCSs) will be used to generate realizations of the \( \ln(\text{LPI}) \) random fields, then the results will be transformed back to lognormal distribution, which will then be used for the probabilistic and spatial assessment of LPI values over the area of interest.

3. Location-specific liquefaction potential analysis

3.1 Site conditions

The location of the study site, the site of the Automotive Research & Testing Center (ARTC), is in the Lukang district of the Chang-Hwa Coastal Industrial Park (CHCIP), as shown in Figure 1. The CHCIP is a large-scale land reclamation project on the west coast of central Taiwan. This land reclamation project was completed by the Sinotech Engineering Consultants for the Industrial Development Bureau of the Ministry of Economic Affairs, Taiwan. The land for the construction of the ARTC, which has the dimension of 2000 m by 800 m (Figure 1) was secured from the CHCIP Authority.

As described in Lee et al. (2001) and Shen et al. (2018), the CHCIP area is an extension of the recent alluvial plains (Qa) of the Changhua County. The alluvium forms the floodplains and recent terraces of the larger streams that dissect the island. The alluvium also includes coastal sand dunes, recent lacustrine and swamp deposits, and cave deposits in limestone terrain (Ho 1988). The study site was reclaimed by hydraulic filling. The filling material comes from dredged sediments under the waterways and the sea, which consists mainly of silty sand to fine sand. The thickness of the hydraulic fill is approximately 4 to 5 m. A backfill of gravel of approximately 0.2 m is placed over the hydraulic fill. From the soil profiles that were derived through the standard
penetration tests (SPTs), within the top 20 m, the site mainly consists of silty sands (SM or SP–SM) with thin layers of silts (ML) or silty clays (CL).

### 3.2 Dynamic compaction at the site

The study site is located in the seismic zone II according to the seismic design specifications for highway bridges by the Ministry of Communication (1996), which specifies the earthquake seismic loading defined by a maximum horizontal acceleration at the ground surface $a_{\text{max}}$ of 0.23g and a moment magnitude $M_w$ of 7.5 based on a return period of 475 years.

The initial site investigation with SPTs and CPTs, as well as the liquefaction potential analysis at the ARTC site, were performed by Sinotech (Chih-Sheng Ku, personal communication). Based on high liquefaction potential predicted for the ARTC site (as described in Lee et al. 2001), use of the ground improvement to mitigate the risk of liquefaction was recommended by Sinotech. To mitigate the risk of liquefaction, the ARTC contracted with Jianzhong Engineering Co., Ltd. for ground improvement and the subsequent construction work. According to Chih-Sheng Ku (personal communication), the cost and local experience are the two deciding factors in the selection of DC as the ground improvement method for the ARTC project: local experience excluded all ground improvement methods but DC and SCP mentioned previously, and the cost consideration favored DC over SCP.

Thus, a ground improvement project through DC was undertaken at the study site to mitigate the liquefaction hazard (Lee et al. 2001). The reader is referred to the literature (Han 2015; Lukas 1995) for details of the DC technique. In the study area, DC was carried out with a main pounder that weighed 25 tons, which had a base area of 3 m$^2$ and a drop height of 20 m. The sequence of DC with the main pounder is illustrated in Figure 2 with three passes in a subzone of 10 m by 10 m. After the completion of DC with the main pounder, the craters and surrounding
soils were leveled and the surface tamped with a smaller pounder that weighed 12 tons and had a 
base area of 6 m\(^2\) and a drop height of 10 m, which is the ironing pass of the DC.

Before DC, 27 cone penetration tests, denoted as CPT\(_{BC}\), were conducted over the entire 
site to investigate the soil properties. After DC, additional 27 cone penetration tests, denoted as 
CPT\(_{AC}\), were performed again at the locations near the CPT\(_{BC}\) to estimate the effect of dynamic 
compaction. Figure 3 shows the layout of the CPT tests both before and after the compaction. The 
coordinates of the 27 CPT\(_{BC}\) and CPT\(_{AC}\) are listed in Table 2 and Table 3, respectively. It can be 
seen from Figure 3 that the 27 CPT\(_{BC}\) and CPT\(_{AC}\) spread over the study area, which affords the 
evaluation of liquefaction potential for the entire study area. Next, the location-specific 
liquefaction potential analysis is performed to illustrate the use of the traditional deterministic 
method.

3.3 Location-specific liquefaction potential calculations

To calculate the factor of safety (FS) against liquefaction, the following set of input data is 
adopted for the CPT-based liquefaction model: the moist unit weight of the soil \(\gamma_m\) is 16 KN/m\(^3\), 
the saturated unit weight \(\gamma_{sat}\) is 19 KN/m\(^3\), and the groundwater table (GWT) in the study site is 
observed at 2 m below the ground surface. The design earthquake at the study site is adopted as 
the level of seismic loading: \(a_{max} = 0.23 \, g\) and \(M_w = 7.5\).

Figure 4(a) shows the location-specific FS-based liquefaction analysis at location #4 
(marked in the layout in Figure 3). The first subplot of Figure 4(a) is the profiles of \(q_{t,N,cs}\) before 
compaction (BC) and after compaction (AC), which clearly shows the increase in soil strength 
over the depths between 1 m and 8 m. Below the depth of 8 m, there was little change in the 
soil strength. It can be seen that DC tends to disturb and loosen the top layers (top 1 m) even 
though it compacts the deeper layers (up to 8 m). The second subplot of Figure 4(a) shows the
CSR and CRR profiles along the depth for both BC and AC. It can be seen that before DC, the CRR is much smaller than CSR between the depths of 2 m and 5 m, which is the critical layer of soil liquefaction at the location #4. Within the critical layer, there were very thin layers of non-liquefiable clay material, which is reflected by the abrupt change of CRR in these very thin layers. If these noises (exhibited in these very thin layers) are ignored, the critical layer is easily identified. After DC, the CRR is greatly increased, especially in the critical layer. The third subplot of Figure 4(a) shows the FS profiles of BC and AC, and the effect of DC in the increase of FS, especially in the critical layer, is evidenced.

Figure 4(b) shows the location-specific FS-based liquefaction analysis at location #12 (marked in the layout in Figure 3). It can be inferred from the third subplot of Figure 4(b), the critical layer at this location is between the depths of 2 m and 7 m based on the FS profile before DC. After DC, the liquefaction potential at this location has been reduced virtually to zero (as reflected by a FS value of much greater 1) within the first 5 m from the ground surface. However, the dynamic compaction is not effective when the depth is greater than 5 m under the shaking level of the design earthquake. In short, based on the results shown in Figure 4, the liquefaction potential at one location varies from the other due in part to the spatial variation of the natural deposit and the depositional variation of the hydraulic fill.

It should be noted that the distances between CPT\textsubscript{BC} and CPT\textsubscript{AC} at both location # 4 and location #12 are approximately 8 m. The distance between CPT\textsubscript{BC} and CPT\textsubscript{AC} can affect the accuracy of before and after comparison at the study site. As can be seen from the data shown in Table 2 and Table 3, the distance between each pair of CPT\textsubscript{BC} and CPT\textsubscript{AC} is in a range of 8 m to 94 m with an average of 37 m. This may lead to an inaccurate evaluation of the effect of DC using the location-specific liquefaction potential analysis as presented previously. This problem may be
overcome by adopting the areal liquefaction potential analysis through the use of random field modeling, which will be introduced in the next section.

4. Areal liquefaction potential analysis

To improve the communication of the effect of DC between engineers, contractors, and clients, the visualization of the liquefaction potential at a project site that covers a significant area is conceptually attractive. To visualize the liquefaction potential in the project area under a given earthquake scenario, random field modeling of the LPI field is performed. In addition, through the generated LPI maps before and after DC, the effect of DC over the entire study site can be evaluated.

4.1 The LPI hazard map generated by random field modeling

The shaking level of the design earthquake at the DC project site is adopted in the liquefaction analysis discussed in this section. Firstly, the LPI values of the 27 CPT samples before compaction, denoted as $\text{LPI}_\text{BC}$, and after compaction, denoted as $\text{LPI}_\text{AC}$, are calculated using the CPT-based liquefaction evaluation method summarized in Section 2.2. The calculated $\text{LPI}_\text{BC}$ and $\text{LPI}_\text{AC}$ values are listed in Table 2 and Table 3, respectively. It can be seen from Table 2 that, before compaction, all of the $\text{LPI}_\text{BC}$ values are in the range between 10.1 and 24.0, corresponding to “high” to “very high” liquefaction severity class (refer to Table 1). This indicates that the study area, in general, has very high liquefaction potentials. After compaction, the $\text{LPI}_\text{AC}$ values are significantly reduced to a range of 0.7 to 11.1.

To characterize the statistical and spatial distributions of the $\text{LPI}_\text{BC}$ and $\text{LPI}_\text{AC}$ values in the study area, the histogram and semivariogram of the LPI values are first constructed. Figure 5(a)
and Figure 5(b) are the histograms of the LPI_{BC} and LPI_{AC} values obtained at the CPT locations. The lognormal distribution is used to fit both histograms. The p-value for the K-S test is 0.68 for before compaction and 0.81 for after compaction. The descriptive statistics including the minimum value, maximum value, mean, standard deviation, and coefficient of variation (COV) of 27 LPI_{BC} and 27 LPI_{AC} values for the design earthquake are provided in Table 4.

As the LPI follows the lognormal distribution, the ln(LPI) is used to characterize semivariogram and generate random fields in the sequential Gaussian simulation. Accordingly, the semivariograms of the ln(LPI_{BC}) and ln(LPI_{AC}) values of the 27 CPT samples are shown in Figure 6(a) and Figure 6(b), respectively. The blue squares are the empirical $\gamma$ calculated from the ln(LPI_{BC}) or ln(LPI_{AC}) values at CPT locations. A weighted least square method by Cressie (1985) is used to fit the empirical $\gamma$. The red lines are the fitted $\gamma$ using the exponential semivariogram model expressed in Eq. (15) and the fitting parameters are marked in the figures. It can be seen that the empirical $\gamma$ of ln(LPI_{AC}) is more scattered than that of ln(LPI_{BC}), and the nugget effect is prominent for the fitted $\gamma$ of ln(LPI_{AC}).

With the histogram and semivariogram as inputs, the random field model can be established and used for generating the liquefaction hazard map. In this case study, the grid size of the random field is set as 10 m, which is the same as the zone size of DC in each pass (see Figure 2). Through a parametric study, it is found that 1000 Monte Carlo Simulations (MCSs) is sufficient to obtain a stable random field, as the COV of the LPI values does not change with the additional increase of MCS number. Each MCS generates one realization of the ln(LPI) field. Then, the LPI field (transformed back to the lognormal distribution) averaged from 1000 MCSs is used to present the liquefaction hazard of the entire site.
Figure 7(a) shows the LPI\textsubscript{BC} map averaged from 1000 MCSs. It can be seen that the project site has very high potential to liquefy under the shaking level of the design earthquake. The associated uncertainty of the outcomes of random field modeling can also be visualized. Figure 7(b) shows the COV of LPI\textsubscript{BC} at each location calculated from 1000 MCSs. It can be seen that the COV become larger at locations further away from the CPT sounding locations, especially at the margins of the study site. The COV map, in this case, offers a means to visualize the accuracy of the random field modeling.

The liquefaction hazard map can also be interpreted with the liquefaction severity class. Using Figure 7(a) and the liquefaction severity classification in Table 1, the liquefaction map based on the severity class can be generated and shown in Figure 8(a). It can be clearly seen that the liquefaction severity of the study area was in Class 4 (high) to Class 5 (very high) before DC.

With the liquefaction hazard map, including the LPI value map in Figure 7(a) and the LPI severity class map in Figure 8(a), the liquefaction risk can be easily visualized. The visualization maps are a useful tool in the design and construction processes of dynamic compaction, especially for communications between engineers, contractors, and clients.

### 4.2 Effectiveness of dynamic compaction based on areal analysis

Following the same procedure presented in Section 4.1, the after-compaction liquefaction hazard map can be obtained through random field modeling and the results are shown in Figure 8(b). The liquefaction hazard maps derived for the scenarios of before DC and after DC, namely Figure 8(a) and Figure 8(b), can be compared and the effectiveness of the DC can be visualized.

Additional quantitative comparison, in terms of LPI\textsubscript{AC} vs. LPI\textsubscript{BC}, using all data from the entire site, is shown in Figure 9(a). For the study area, the effectiveness of DC in reducing LPI...
values is clearly demonstrated. It is noted that some LPI pairs are close to 1:1 line, which means less improvement is achieved with DC at these locations. The simulated data is generally distributed around the field data except an outlier near 1:1 line. It is believed that the simulated data is a reasonable interpolation of the field data.

Figure 9(b) shows the cumulative frequency distributions of simulative LPI\textsubscript{AC} and LPI\textsubscript{BC} values. The cumulative frequency of LPI is defined by the percentage of LPI values equal and greater than a threshold LPI value. For example, after DC, the LPI\textsubscript{AC} values greater than 5 is 18%. In other words, there is only 18% chance that the LPI\textsubscript{AC} values will exceed 5 in this study area after DC. As a comparison, there is 100% chance that the LPI\textsubscript{BC} values will exceed 5 in this study area before DC. Reducing the chance of exceeding LPI = 5, which is a threshold suggested by Toprak and Holzer (2003) for surface manifestations of liquefaction, from 100% before DC to 18% after DC is indeed very significant. Similarly, the chance of exceeding LPI = 15 drops from 54% before DC to zero after DC. As indicated in Table 1 (Sonmez 2003), LPI > 15 indicates a “very high” liquefaction hazard. Such a reduction in the likelihood from 54% to zero is drastic, which again demonstrates the effectiveness of DC at this project site. The effects of DC in the mitigation of liquefaction hazard are effectively visualized through random field modeling, and as such, the latter is demonstrated as a useful tool in geotechnical practice, not just an academic exercise.

Finally, an index called ground improvement ratio ($R_i$) is defined below for the estimation of the effect of dynamic compaction on a relative basis:

$$R_i = \left( \frac{\text{LPI}_{\text{BC}} - \text{LPI}_{\text{AC}}}{\text{LPI}_{\text{BC}}} \right) \times 100\%$$

(16)

Figure 10 shows the improvement ratio ($R_i$) of the entire study area (project site) under the shaking level of the design earthquake. Other than a subzone in the lower left part of the project...
site, identified as location #24 in Figure 3, the entire study area is shown with an improvement ratio ranging approximately from 65% to 90%. To investigate this exception in the effect of DC, the location-specific liquefaction analysis before and after DC is carried out at location #24 and the results are shown in Figure 11. It can be seen that below the depth of 7 m, the $q_{1N,cs}$ values after compaction are smaller than those before compaction, which leads to a decrease in LPI (i.e., $\text{LPI}_{BC} < \text{LPI}_{AC}$) and a lower LPI severity class. This abnormal outcome might be caused by the errors in the CPT soundings, the variation in the DC operation, and the soil variability between the two CPT test locations. Further study is needed to confirm this observation at this local location. Nevertheless, the effectiveness of the random field-based visualization for assessing the effect of DC is further confirmed.

4.3 Performance of the site during the 1999 Chi-Chi earthquake

During the progression of the dynamic compaction (DC) project at the study site, a major earthquake, known as the 21 September 1999 Chi-Chi earthquake ($M_w = 7.6$), struck central Taiwan. The earthquake caused a peak ground surface acceleration of $a_{\text{max}} = 0.12 \, g$ at the study site, and soil liquefaction manifestation was observed in the zone where the DC had not been carried out (Lee et al. 2001). During the 1999 Chi-Chi earthquake, liquefaction was observed in the study site, which provides an opportunity to evaluate the accuracy of the random field modeling. To evaluate the accuracy of the random field modeling, the LPI hazard maps of the study site under the shaking level of the Chi-Chi earthquake ($M_w = 7.6$ and $a_{\text{max}} = 0.12 \, g$) are generated and compared with liquefaction observation.

Similar to the analysis made previously for the design earthquake, the histograms and semivariograms of the $\text{LPI}_{BC}$ and $\text{LPI}_{AC}$ values at CPT sounding locations using the Chi-Chi earthquake ground motion parameters are first characterized. The descriptive statistics of 27 $\text{LPI}_{BC}$
and \( \text{LPI}_{\text{AC}} \) values are shown in Table 4. Following the same procedure as in the previous analysis, the LPI hazard maps (in terms of severity class) before and after DC under the shaking level of the 1999 Chi-Chi earthquake are obtained, as shown in Figs. 12(a) and (b), respectively. It should be noted that at the time of the 1999 Chi-Chi earthquake, the DC had been carried out only in part of the site, as illustrated in Figure 12 where the completed area is marked with dashed lines.

As reported in Lee et al. (2001), there was no observed liquefaction manifestation in the area that the DC work had been completed. This is consistent with the results of random filed modeling shown in Figure 12(b), as the area enclosed by dash lines is assessed with a liquefaction severity of Class 2 (minor). In the unimproved area at this site, however, the evidence of soil liquefaction was found during the 1999 Chi-Chi earthquake. For example, in the vicinity of location #4, where DC had not been carried out, the sand boiling was observed with the ground settlement of 33–45 cm. The field observation is quite consistent with the generated LPI hazard map shown in Figure 12(a), as the liquefaction severity at location #4 was in Class 3 (moderate). Further, in the vicinity of location #7 (Figure 12a), wet surfaces were observed, which is also a sign of liquefaction albeit much less severe. These observations are consistent with the random field modeling that shows liquefaction severity at location #7 as Class 2.

Compared to Figure 8(a) and Figure 8(b), the liquefaction potential of the project site (study area) is much smaller due to a smaller level of seismic loading. The effect of the shaking level and the effectiveness of DC may be more obviously observed with Figure 13, which is the box plots of simulated \( \text{LPI}_{\text{BC}} \) and \( \text{LPI}_{\text{AC}} \) values for both the design earthquake level and the Chi-Chi earthquake level of shaking. The dynamic compaction is shown as an effective technique to mitigate liquefaction hazards regardless of the shaking level, although in this case, the effect is more profound at higher ground shaking level.
5. Discussion and limitation

The index LPI has been widely used in mapping the liquefaction hazard over an extended area or a region (e.g., Toprak and Holzer 2003; Holzer et al. 2006; Lenz and Baise 2007; Chen et al. 2016a). It was adopted in this study for its convenience in assessing the effect of dynamic compaction (DC) on the liquefaction hazard under the seismic shaking. However, the LPI is a complex index, affected by many factors (Lee et al. 2004; Li et al. 2006). A careful calibration of LPI is always desirable. In this study, the calibration by Sonmez (2003) was adopted. Although no re-calibration of this LPI was carried out in this study, the use of this LPI is believed to be appropriate, since the focus was to assess the effect of DC (i.e., the relative performance of the ground before and after DC) from the random field perspective. The use of improvement ratio \( R_I \) helps ease the concern of different interpretations of the LPI, as it provides an assessment of the ground improvement for the purpose of mitigating liquefaction hazard by DC on a relative basis.

Another limitation on the use of LPI in this study is the fact that most CPT soundings carried out after DC were limited to a shallower depth (up to the depth of approximately 10 m), as the design of DC in this project was focused on the mitigation of the liquefaction potential of the critical layers, typically at the depths of 2 m to 6 m. The effect of DC at this project site was limited to the depth of approximately 8 m by design. Thus, post-DC tests were limited to this depth accordingly. This is different from the definition of LPI that is extended to the depth of 20 m, although the weights given to the deeper layers (> 10 m) in the LPI are much lower than those at shallower depths.

It should also be noted that there has been an increasing number of studies in recent years that characterize and model the spatial variability of soil properties (e.g., CPT tip resistance and
sleeve friction) or liquefaction indices (e.g., LPI or liquefaction-induced settlements) in liquefaction hazard evaluation. In the current work, the spatial variability of a scalar quantity, i.e., LPI, is explicitly modeled, which is termed the “averaged index approach” by Wang et al. (2017). Alternatively, many studies (e.g., Fenton and Vanmarke 1998; Baker and Faber 2008; Bong and Stuedlein 2018) characterized and modeled the spatial variability of soil properties directly and evaluate liquefaction hazard based on the generated random field of soil properties, which is termed the “local soil property approach” by Wang et al. (2017). A quantitative analysis and comparison of these two types of approaches to account for soil spatial variability have been performed by Wang et al. (2017). In addition, as previously mentioned, the use of random field theory in an areal liquefaction potential analysis using in situ test data before and after ground improvement in a real project setting is quite rare and is a topic less explored. An example is the recent work by Bong and Stuedlein (2017) and Bong and Stuedlein (2018) that investigate the spatial variability of potential liquefiable soils using results of a full-scale field test program of driven timber piles for liquefaction mitigation (Stuedlein et al. 2016; Gianella and Stuedlein 2017).

6. Concluding remarks

In this study, a random field-based visualization procedure is presented to aid the evaluation of the effect of dynamic compaction (DC) using CPT soundings at limited locations at a project site before and after DC. Although it is well known that DC can increase the density and strength of loose deposits, leading to a decrease in the liquefaction potential under a given earthquake scenario, the quantitative evaluation of whether the DC has achieved the intended outcome is usually complicated by different numbers and locations of in situ tests (such as CPT) conducted at the project site before and after DC, preventing an ideal side-by-side and one-to-one
comparisons of liquefaction potential before and after DC. To this end, the liquefaction potential over the study area is generated through a random field modeling approach. At CPT soundings, liquefaction potential index (LPI) values were calculated and used to quantify liquefaction potentials. The random field modeling approach provides a method to map and assess liquefaction hazards for the entire project site given limited CPT soundings. Furthermore, the liquefaction hazard maps before and after DC derived from the random field models removed the need for side-by-side, one-to-one (before DC vs. after DC) CPT tests, which is generally hard to maintain in the construction practice. The random field-based visualization of the liquefaction hazard at the entire project site can greatly facilitate the communications among engineers, contractors, and clients. The outcome of this study clearly demonstrated the effectiveness of random field-based approach for assessing and visualizing the effects of dynamic compaction.

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Table 1 Classification of the liquefaction potential index (adapted from Sonmez 2003).

<table>
<thead>
<tr>
<th>Class</th>
<th>Liquefaction potential index (LPI)</th>
<th>Severity class of liquefaction</th>
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<td>LPI $&gt; 15$</td>
<td>V: Very high</td>
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Table 2 Locations of 27 CPT soundings at the project site before compaction (CPT_{BC}) and their LPI values (LPI_{BC}) under two seismic shaking levels.

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Table 3 Locations of 27 CPT soundings at the project site after compaction (CPT\textsubscript{AC}) and their LPI values (LPI\textsubscript{AC}) under two seismic shaking levels.

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Table 4 Descriptive statistics of the $LPI_{BC}$ and $LPI_{AC}$ values of 27 CPT soundings under two seismic shaking levels.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Design Earthquake</th>
<th>Chi-Chi Earthquake</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$LPI_{BC}$</td>
<td>$LPI_{AC}$</td>
</tr>
<tr>
<td>Minimum</td>
<td>10.1</td>
<td>1.0</td>
</tr>
<tr>
<td>Maximum</td>
<td>24.3</td>
<td>8.0</td>
</tr>
<tr>
<td>Mean</td>
<td>15.8</td>
<td>3.5</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.8</td>
<td>0.7</td>
</tr>
<tr>
<td>COV (%)</td>
<td>11.7</td>
<td>19.9</td>
</tr>
</tbody>
</table>
Exponential model

(a) $a = 116.5\ m$, $\omega = 1.0$, $\tau = 0$

(b) $a = 131.7\ m$, $\omega = 0.61$, $\tau = 0.39$
Fig. 11
Draft

1.5 × IQR

IQR (Interquartile Range)

1.5×IQR

median

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Design Earthquake Chi-Chi Earthquake

LPI values