Improving CPT-Based Earthquake Liquefaction Hazard Assessment at Challenging Soil Sites

Kaleigh M. Yost

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Civil Engineering

Russell A. Green, Chair
Alba Yerro-Colom
Eileen R. Martin
Adrian Rodriguez-Marek

October 21, 2022
Blacksburg, VA

Keywords: Liquefaction, multiple thin-layer effects, material point method, cone penetrometer test

Copyright © 2022, Kaleigh Yost
Improving CPT-Based Earthquake Liquefaction Hazard Assessment at Challenging Soil Sites

Kaleigh M. Yost

Academic Abstract

Earthquake-induced soil liquefaction is a phenomenon in which saturated, sandy soil loses its strength and stiffness during earthquake shaking. Liquefaction can be extremely costly and damaging to infrastructure. The commonly used “simplified” stress-based liquefaction triggering framework is correlated with metrics computed from in-situ tests like the Cone Penetration Test (CPT). While CPT-based procedures have been shown to accurately predict liquefaction occurrence in homogenous, sandy soil profiles, they tend to over-predict the occurrence of liquefaction in challenging, highly interlayered soil profiles. One contributing factor to the over-prediction is multiple thin-layer effects in CPT data, a phenomenon in which data in interlayered zones is blurred or averaged, making it difficult to identify specific layer boundaries and associated CPT parameters like tip resistance. Multiple thin-layer correction procedures have been proposed to convert the measured tip resistance in an interlayered profile ($q^m$) to the “true” or characteristic tip resistance ($q^t$) that would be measured without the influence of multiple thin-layer effects.

In this dissertation, the efficacy of existing multiple thin-layer correction procedures is assessed. It is shown that existing procedures are not effective for layer thicknesses equal to or less than about 1.6 times the diameter of the cone. Two new multiple thin-layer correction procedures are proposed. Furthermore, a framework for numerically simulating CPTs in interlayered soil profiles using the Material Point Method (MPM) is developed. A framework for linking uncertainties associated with the numerical analyses and the laboratory CPT calibration chamber tests used to calibrate the numerical analyses is also proposed. Finally, a database of laboratory and numerically-generated CPT data is presented. It is shown how this database can be used to improve existing, and develop new, multiple thin-layer correction procedures. Ultimately, the work detailed in this dissertation will improve the characterization of highly interlayered soil profiles using CPTs to support more accurate liquefaction hazard assessment at challenging soil sites.
Earthquake-induced soil liquefaction is a phenomenon in which saturated, sandy soil loses its strength and stiffness during earthquake shaking. Liquefaction can be extremely costly and damaging to infrastructure. Existing procedures used to assess liquefaction hazard were developed specifically for homogenous, sandy soil profiles. These procedures do not perform well in challenging, highly interlayered soil profiles. One reason for this is the inadequate characterization of the soil profile by the chosen in-situ test method. For example, the cone penetration test (CPT) consists of hydraulically advancing a steel probe with a conical shaped tip (“cone”) into the ground. Typically, the penetrometer is about 3.6 to 4.4 cm in diameter, and data are recorded at 1 to 5 cm depth intervals. However, data recorded at a specific depth are representative of soil that falls within a zone several times the diameter of the penetrometer ahead of and behind the tip of the cone. In a highly interlayered soil profile, this means the CPT records blurred or averaged data within interlayered zones.

Typical liquefaction analyses compute a factor of safety against liquefaction at every depth in the soil profile where CPT data are recorded. Hence, having data that are blurred can result in an inaccurate factor of safety against liquefaction. To account for this blurring (called multiple thin-layer effects), correction procedures have been proposed. This dissertation evaluates the effectiveness of those procedures and develops new procedures. Additionally, a numerical simulation tool is shown to be capable of simulating CPTs in layered soil profiles. This reduces the need for costly laboratory testing to further evaluate multiple thin-layer effects. Finally, a combined laboratory and numerically-generated CPT database is developed to support the improvement of, and development of new, multiple thin-layer correction procedures. The broader impacts of this work support more accurate liquefaction evaluations in challenging soil profiles worldwide, like those in Christchurch, New Zealand, and the Groningen region of the Netherlands.
Acknowledgements

I would like to express my gratitude for the guidance and support of my advisors and committee members, Dr. Russell Green, Dr. Alba Yerro-Colom, Dr. Eileen Martin, and Dr. Adrian Rodriguez-Marek throughout my time pursuing my PhD. Their mentorship has been essential to my success. I am also very grateful for the support of the entire geotechnical faculty at Virginia Tech who have provided me with an exemplary educational experience over the past four years.

I would like to thank Dr. Mario Martinelli, Dirk de Lange, and all the folks in the geotechnical unit at Deltares for the insightful discussions, research collaborations, and supporting me during my stay in the Netherlands.

I am deeply thankful for the mentoring I have received throughout my academic career from my undergraduate advisor, Dr. Alexandros Taflanidis, and my graduate advisor during my master’s work, Dr. Brady Cox.

I am very grateful for the scholarship and friendship of many of my peers currently or formerly at Virginia Tech, especially Luis Zambrano-Cruzatty, Mohsen Zaker Esteghamati, Tat Shing Thum, Abdel Alsardi, Kristin Ulmer, Sneha Upadhyaya, and Tyler Quick. I am also grateful for my friends from the University of Texas, especially to Andrew Stolte and Andrew Keene, who helped me make the decision to pursue a Ph.D. in the first place.

Finally, I would like to thank my husband, AJ, and my parents, without whose support this would not have been possible.
# Table of Contents

Academic Abstract ........................................................................................................... ii
General Audience Abstract ............................................................................................... iii
Acknowledgements ............................................................................................................ iv
Table of Contents ............................................................................................................... v
List of Figures ..................................................................................................................... viii
List of Tables ....................................................................................................................... xiv

## Chapter 1: Introduction .................................................................................................. 16
1.1. Problem Statement ...................................................................................................... 16
1.2. Background: Cone Penetration Testing in Challenging Soil Profiles ...................... 18
1.3. Dissertation Structure and Contents ........................................................................ 22
References .......................................................................................................................... 24

## Chapter 2: Assessment of the Efficacies of Correction Procedures for Multiple Thin Layer Effects on Cone Penetration Tests .......................................................... 28
2.1. Abstract ...................................................................................................................... 30
2.2. Introduction ............................................................................................................... 30
2.3. Overview of Calibration Chamber Tests ................................................................... 33
2.4. Thin-Layer Correction Procedures .......................................................................... 35
2.5. Application of the Thin-Layer Correction Procedures to the Calibration Chamber Data .................................................................................................................. 41
2.6. Application of the Thin-Layer Correction Procedures to the CES and Valentine’s Day Earthquake Data ...................................................................................... 44
2.7. Discussion and Conclusions .................................................................................... 47
2.8. Acknowledgements ................................................................................................... 50
References .......................................................................................................................... 50

## Chapter 3: Correcting Measured CPT Tip Resistance for Multiple Thin-Layer Effects ......................................................................................................................... 64
3.1. Abstract ...................................................................................................................... 66
3.2. Introduction ............................................................................................................... 66
3.3. Assessing Existing Procedure Efficacy ................................................................... 67
3.4. Proposed alternative inverse procedure ................................................................... 70
3.5. Discussion and Conclusions .................................................................................... 73
References .......................................................................................................................... 74

## Chapter 4: MPM Modeling of Cone Penetrometer Testing for Multiple Thin-Layer Effects in Complex Soil Stratigraphy ................................................................. 79
4.1. Abstract ...................................................................................................................... 81
4.2. Introduction ............................................................................................................... 81
4.3. Previous Numerical Studies of Cone Penetrometer Tests ....................................... 83
4.4. The Material Point Method ..................................................................................... 86
4.5. Physical Calibration Chamber Tests ....................................................................... 87
4.6. MPM Model .............................................................................................................. 89
4.7. Calibration and Validation of CPT models ............................................................... 94
4.8. Applications .............................................................................................................. 95
Appendix C: Data Repository Information for Chapter 6 ................................................................. 258

Appendix D: Harnessing Numerical Tools to Study the Limitations of CPTs for Characterizing Complex Soil Stratigraphies for Liquefaction Assessment..... 261

Appendix E: Bench-Scale Testing of Grouts for Geoslice Peels ................................................. 272
List of Figures

Figure 1.1  Evaluation of liquefaction response of a soil profile.  

Figure 1.2 Zone of influence around the tip of the cone penetrometer.  

Figure 1.3 Schematic of multiple thin-layer effects in CPT data. Tip resistance from CPTs performed in homogenous clay and sand profiles can be considered characteristic or “true” tip resistances, \( q'_{\text{clay}} \) (labeled 1) and \( q'_{\text{sand}} \) (labeled 2). Measured tip resistance (\( q'' \)) from a CPT performed in a layered sand-clay profile is affected by multiple thin-layer effects (labeled 3a). True tip resistance of the layered profile (\( q' \), labeled 3b) can be constructed using \( q'_{\text{sand}}, q'_{\text{clay}}, \) and the known layer geometry. 

Figure 2.1  Schematic of thin-layer effect for a sand layer of varying thickness embedded in a clay layer (Idriss and Boulanger 2008; reprinted with permission from EERI).  

Figure 2.2  Stratigraphy, relative density (\( D_R \)), and thin layer thickness to cone diameter ratio (\( H/d_{\text{cone}} \)) of each of the De Lange (2018) calibration chamber soil models. The white and gray areas represent the layers of Baskarp B15 sand and Vingerling K147 clay, respectively.  

Figure 2.3  Thin-layer factors for sand layers derived from the Boulanger and DeJong (2018) inversion procedure (BD18) with and without smoothing and filtering (designated as \( K_{H,\text{net}} \) and \( K_H \), respectively) (Boulanger and DeJong 2018; used under CC-BY-NC-ND). 

Figure 2.4  Normalized cone penetration filter, \( w_c/\left(w_c\right)_{z'=0} \), vs. normalized depth, \( z' \), from the cone tip (Boulanger and DeJong 2018; used under CC-BY-NC-ND).  

Figure 2.5 (a) Unstable results after removal of smoothing procedure from the BD18 procedure as applied to CPT data from the De Lange (2018) dataset; and (b) Error plot after removal of the smoothing procedure during inversion. Solution does not converge after 500 steps with \( err < 10^{-6} \).  

Figure 2.6  Thin-layer correction factors (\( K_H \)) derived from laboratory test results (shown as points) and numerical simulations using the Koppejan method (shown as curves) (from De Lange (2018)).  

Figure 2.7  Relationship between normalized thin layer thickness (\( H/d_{\text{cone}} \)) and the curve fitting parameter \( m \).  

Figure 2.8  Thin-layer correction factor (\( K_H \)) curves for several normalized thin layer thicknesses (\( H/d_{\text{cone}} \)) shown as lines and \( K_H \) values derived from the calibration chamber tests shown as points.  

Figure 2.9  Results from thin-layer correction procedures applied to: (a) Soil Model 1 (reference soil model - no thin clay layers); (b) Soil Model 4 with 40-mm-thick clay layers represented by the shaded areas; (c) Soil Model 8 with 20-mm-thick clay layers represented by the shaded areas; and (d) Soil Model 10 with 20-mm-thick clay layers represented by the shaded areas, where \( q'' \) is measured tip resistance, \( q'_{\text{inv}} \) is the inverted tip resistance per the Boulanger and DeJong (BD18) procedure, \( q'_{\text{invmod}} \) is the inverted tip resistance per the modified BD18 procedure (BD18MOD), \( q'_{\text{corr}} \) is the corrected tip resistance from the Deltares procedure, and \( q' \) is the true tip resistance (as measured in reference sand model).
Figure 2.10 Conceptual illustration of ROC analyses: (a) frequency distributions of liquefaction manifestation and no liquefaction manifestation observations as a function of $LPI$; (b) corresponding ROC curve, where the area under the ROC curve ($AUC$) is used to assess the efficiency of a diagnostic test (after Maurer et al. 2015a, b).

Figure 3.1 Thin-layer correction factor ($K_H$) values derived from the De Lange (2018) calibration chamber tests (shown as points) were used to define $K_H$ curves for several normalized thin-layer thicknesses ($H/d_{cone}$) for the Deltares procedure (Yost et al. 2021a).

Figure 3.2 Results from application of multiple-thin-layer correction procedures to De Lange (2018) calibration chamber data for: (a) Soil Model 4 with 40-mm-thick clay layers; and (b) Soil Model 8 with 20-mm-thick-clay layers (Yost et al. 2021a).

Figure 3.3 Comparison between Cea22 inverse procedure using the standard misfit function and the logarithmic function on data from Soil Model 9 CPT 3 from De Lange (2018) (modified from Cooper et al. 2022).

Figure 3.4 Cea22 inverse approach to correct for multiple-thin-layer effects in CPT tip resistance (modified from Cooper et al. 2022).

Figure 4.1 Schematic of thin-layer and transition-zone effects for a stiff sand layer embedded in a softer clay (Idriss and Boulanger 2008; reprinted with permission from EERI).

Figure 4.2 Configurations of two- and three-layered soil profiles used in previous numerical studies to quantify transition-zone and thin-layer effects on measured tip resistance.

Figure 4.3 Illustration of the material point method.

Figure 4.4 Calibration chamber setup (De Lange 2018).

Figure 4.5 Variation of Baskarp B15 sand strength parameters with relative density, $D_R$, and confining pressure, $\sigma_3$ based on data from CD triaxial tests (Data from Ibsen and Bødker 1994; Borup and Hedegaard 1995).

Figure 4.6 Cone penetration test MPM model configuration.

Figure 4.7 Downdrag of material from overlying into underlying layers in calibration chamber tests and MPM models (De Lange 2018).

Figure 4.8 Sensitivity analysis of soil-cone contact properties on numerical tip resistance for Soil Model 4 CPT 2. Cases 1 through 5 are described in detail in Table 3.6.

Figure 4.9 Calibration of shape factor, $y$, using finite element method (FEM) triaxial simulations and experimental CD triaxial tests from Ibsen and Bødker (1994) and Borup and Hedegaard (1995).

Figure 4.10 Comparison of experimental and numerical $q_m$ in the uniform sand profiles from the De Lange (2018) calibration chamber tests.

Figure 4.11 Comparison of experimental and numerical $q_m$ with numerical $q_t$ in layered soil profiles from the De Lange (2018) calibration chamber tests.

Figure 4.12 Transition-zone effects demonstrated using MPM simulation of CPT for: (a) Case 1, soft clay overlying stiffer sand; and (b) Case 2, stiffer sand overlying soft clay.
Figure 4.13 Thin-layer effects demonstrated using MPM simulation of CPT for: (a) Case 3, stiff sand embedded in softer clay; (b) Case 4, soft clay embedded in stiffer sand.

Figure 4.14 Comparison of thin-layer correction factors computed from this study with those suggested by Boulanger and DeJong (2018).

Figure 4.15 Multiple thin-layer effects demonstrated using MPM simulation of CPT in layered soil profiles.

Figure 5.1 Mapping experimental uncertainties to numerical parameters (see Notation for parameter definitions).

Figure 5.2 Calibration chamber setup: (a) profile view, and (b) cross-sectional view.

Figure 5.3 Variability in experimental tip resistance ($q_c$) for CPTs performed in homogenous sand profiles during the De Lange (2018) study: (a) Three CPTs performed at $\sigma'_{v0}=100$ kPa with $D_R=60\%$, and (b) One CPT performed at $\sigma'_{v0}=50$ kPa and one at $\sigma'_{v0}=100$ kPa with $D_R=36\%$.

Figure 5.4 (a) Geometry and mesh of 2D axisymmetric model, and (b) boundary conditions.

Figure 5.5 Critical state line for Baskarp B15 sand based on 14 CD triaxial tests performed on loose specimens with $D_R=1\%$. All triaxial data are from Ibsen and Bødker (1994).

Figure 5.6 Comparison of numerical and experimental triaxial data from Ibsen and Bødker (1994). (a-c) Dense specimens; (d-f) Medium dense specimens; (g-i) Loose specimens.

Figure 5.7 Calibration of hardening modulus, $H$

Figure 5.8 Baseline tip resistance ($q_c$) realizations from MPM simulations compared with experimental data, and determination of average tip resistance ($\bar{q}_c$) for (a) homogenous sand profile and (b) layered sand-clay profile. Insets indicate depth ranges over which $\bar{q}_c$ was computed.

Figure 5.9 All realizations from the sensitivity analysis compared to the baseline realization and experimental data for three soil profiles: (a) homogenous sand, (b) homogenous clay, and (c) layered sand-clay, where gray zones represent clay layers.

Figure 5.10 Range of average tip resistance ($\bar{q}_c$) values obtained by varying a single parameter from the upper to lower bound value indicated on either side of the bar (a) Homogeneous sand profile, (b) Homogeneous clay profile, (c) Embedded sand layer in layered profile, and (d) Embedded clay layer in layered profile.

Figure 5.11 Comparison of sensitivity index for all soil profiles: (a) Homogeneous sand profile, (b) Homogeneous clay profile, (c) Embedded sand layer in layered profile, and (d) Embedded clay layer in layered profile. Greyed zones indicate parameters that are not used in the analysis for that particular profile. Noise levels are indicated with a dashed line at the level of SI$_{noise}$.

Figure 5.12 (a) Position of three material points (9122, 70418, and 11654) along the rigid boundary in a homogenous sand profile whose stress history is shown in (b) and (c); (b) Evolution of effective vertical and horizontal stresses, $\sigma'_v$ and $\sigma'_h$, along the rigid boundary (fixed in x-direction) during CPT
penetration; (c) Evolution of $\sigma'_{\|}/\sigma'_{v}$ along the rigid boundary during CPT penetration.

Figure 5.13  (a) Comparison of $q_c$ using varying boundary conditions and initial stress states in homogenous sand profile; (b) Impact of increasing $\sigma'_{\|}/\sigma'_{v}$ on $q_c$ when using rigid radial boundary conditions.

Figure 5.14  (a) Void ratio ($e$) after 0.64 m of penetration for a homogenous sand profile with $D_R=60\%$; (b) Impact of increasing $D_R$ from 60% to 65% on $q_c$.

Figure 6.1  Schematic of multiple thin-layer effects in CPT data. Tip resistance from CPTs performed in homogenous clay and sand profiles can be considered characteristic or “true” tip resistances, $q^{clay}$ (labeled 1) and $q^{sand}$ (labeled 2). Measured tip resistance ($q^m$) from a CPT performed in a layered sand-clay profile is affected by multiple thin-layer effects (labeled 3a). True tip resistance of the layered profile ($q'$, labeled 3b) can be constructed using $q^{sand}$, $q^{clay}$, and the known layer geometry.

Figure 6.2  Flow chart describing multiple thin-layer correction procedures.

Figure 6.3  Layered soil profile geometries from the De Lange (2018) calibration chamber experiments. Gray areas represent clay layers and white areas represent sand layers. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.

Figure 6.4  Comparison of tip resistance ($q_c$) measured in laboratory cone penetration tests in homogenous sand profiles and $q_c$ computed using Equation 6.2.

Figure 6.5  Comparison of tip resistance ($q_c$) measured in clay layers during laboratory cone penetration tests and $q_c$ computed using Equation 6.3.

Figure 6.6a  Pairs of $q^m$ and $q'$ generated from laboratory data. Clay layers are indicated in gray. Lab Database CPT Index is shown above each plot. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.

Figure 6.6b  Pairs of $q^m$ and $q'$ generated from laboratory data. Clay layers are indicated in gray. Lab Database CPT Index is shown above each plot. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.

Figure 6.7  MPM geometry (modified from Yost et al. 2022c).

Figure 6.8  15 soil profiles generated for MPM simulations. Gray zones represent clay layers, white zones represent sand layers. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.

Figure 6.9a  Pairs of $q^m$ and $q'$ generated from MPM data – CPTs 1 through 10. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.

Figure 6.9b  Pairs of $q^m$ and $q'$ generated from MPM data – CPTs 11 through 20. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.

Figure 6.9c  Pairs of $q^m$ and $q'$ generated from MPM data – CPTs 21 through 30. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.

Figure 6.10  (a) Chi-squared blurring filter; (b) Comparison of $q^m$, $q'$, and $q^{m,sim}$ generated by convolving the chi-squared blurring filter shown in (a) with $q'$.
Figure 6.11  Efficacy of multiple thin-layer correction procedures on MPM CPT 6 from this database: (a) Boulanger and DeJong (2018) [BD18] (b) Cooper et al. (2022) [CEA22] and (c) Yost et al. (2021) “Deltares” [DEL21].

Figure A.1 Results from thin layer correction procedures applied to each of the Deltares Soil Models with sand layers represented by the white areas and clay layers represented by the shaded areas, where $q^m$ is measured tip resistance, $q^{inv}$ is the inverted tip resistance per the Boulanger and DeJong (2018) [BD18] procedure, $q^{invmod}$ is the inverted tip resistance per the modified BD18 procedure (BD18MOD), $q^{corr}$ is the corrected tip resistance from the Deltares procedure, and $q'$ is true tip resistance (as measured in reference sand model).

Figure A.2 (a) Measured (black solid line) and inverted (blue dashed line) cone tip resistance versus depth after the first pass of the BD18 inversion procedure is performed (Step 1.2) (b) Measured (black solid line) and inverted (blue dashed line) cone tip resistance versus depth after the second high-frequency pass is performed (Step 1.3). (c) Measured (solid black line) and inverted after interface removal (blue dashed line) cone tip resistance versus depth (Step 3.4).

Figure A.3 Define the maximum measured tip resistance in the thin layer, $q^{m,max}$, as the peak $q^m$ measured in the thin layer.

Figure A.4 Define the beginning of transition into stiffer material (into the thin layer) as the depth of the first trough above the peak and the end of the transition into the softer layer (out of the thin layer) as the depth of the first trough below the peak.

Figure A.5 Define the top of the thin layer as half the distance between the beginning of the transition into the stiffer material (of the thin layer) and the maximum $q^m$. Define the bottom of the thin layer as half the distance between the maximum $q^m$ and the end of the transition (out of the thin layer) into the softer material.

Figure A.6 The thin layer correction factor is applied to $q^{m,max}$ in the thin layer, and then the resulting $q^{corr}$ is applied across the entire thin layer. The $q^m$ values identified at the start and end of the transition zones are applied across the entire respective transition zone.

Figure A.7 Measured tip resistance, $q^m$ (solid black) and corrected tip resistance, $q^{corr}$ (blue dashed) versus depth.

Figure B.1 Determination of $G_{ref}$ and $e_{min}^*$ for NorSand elasticity model by matching curve to reported curve from Bodker (1996).

Figure B.2 Calibration of dilatancy parameters with assumed critical state line $e_{cs} = 0.90 - 0.012(p'/p_a)^{0.7}$: (a) Stress ratio, $\eta$, versus plastic dilatancy, $D^p$, to obtain maximum dilatancy, $D_{max}$, and corresponding stress ratio, $\eta_{max}$ (b) $D_{max}$ versus state parameter $\psi$ at $D_{max}$ to determine $\xi$; (c) $\eta_{max}$ versus $D_{max}$ to determine $N$. Data plotted in gray was not included in the regression and corresponds to tests performed with confining pressures less than 100 kPa.

Figure B.3 Calibration of hardening modulus $H$, with initial image state parameter, $\psi_{i,0}$
Figure B.4 Comparison of experimental and numerical cone penetrometer test tip resistance ($q_c$) in sand computed using NorSand with a constant $H$ and with $H$ modeled dynamically as a function of $\psi_i$.  

Figure B.5 Key to interpreting data tables in Appendix B.2.  

Figure B.6 Tracked material point locations at the beginning (a) and end (b) of cone penetration. Material point size is enlarged in the inset.  

Figure B.7 Comparison of mean effective stress between rigid and flexible boundary conditions for (a) $\sigma_{h0}^\prime=90$ kPa and (b) $\sigma_{h0}^\prime=50$ kPa.  

Figure B.8 Comparison of volumetric strain between rigid and flexible boundary conditions for (a) $\sigma_{h0}^\prime=90$ kPa and (b) $\sigma_{h0}^\prime=50$ kPa.  

Figure B.9 Comparison of stress paths between rigid and flexible boundary conditions for (a) $\sigma_{h0}^\prime=90$ kPa and (b) $\sigma_{h0}^\prime=50$ kPa.  

Figure D.1 MPM model geometry and discretization (Yost et al. 2022).  

Figure D.2 Multiple thin-layer effects on tip resistance for profiles with varying layer thickness (modified from Yost et al. 2022).  

Figure E.1 a) Bench-scale geoslicer with front panel removed. b) Bench-scale geoslicer with front panel clamped in place.  

Figure E.2 Grain size distributions of the poorly graded sand and its coarser and finer portions used to create the soil samples.  

Figure E.3 Open-weave cotton cloth used as reinforcement for the geo-slice peels.  

Figure E.4 (a) Geo-slice sample divided into six 4”×8” sections. (b) Corresponding peels created using MG Gel Foam [MG-1, MG-2], Flex Seal Liquid [FS-1, FS-2], and DirtGlue Dry [DG-1, DG-2].  

Figure E.5 Results of unassisted bending tests for peels created with (a) MG Gel Foam [MG-2], (b) Flex Seal Liquid [FS-1], and (c) DirtGlue Dry [DG-2].
List of Tables

Table 2.1 Summary of the results from the ROC analyses obtained using the uncorrected and corrected CPT data using the BD18, BD18MOD, and Deltarees procedures for all the case histories and for bins of cases histories having $I_{c10} < 2.05$ and $I_{c10} \geq 2.05$ (highest values of $AUC$ within an $I_{c10}$ bin are bolded and italicized) 57

Table 4.1 Transition-zone effects quantified in numerical studies of two-layered profiles 104
Table 4.2 Thin-layer effects quantified in numerical studies of three-layered soil profiles 105
Table 4.3 Summary of De Lange (2018) calibration chamber tests 105
Table 4.4 Index properties of Baskarp B15 sand and Vingerling K147 clay 106
Table 4.5 Undrained shear strength of Vingerling K147 clay 106
Table 4.6 Sensitivity analysis of soil-cone contact parameters on numerical tip resistance for Soil Model 4 CPT 2 106
Table 4.7 Material parameters used for MPM simulations of CPT in layered profiles…. 107
Table 4.8 Comparison of Sensing and Development Distances (S and D) and Minimum Thin Layer Thickness (T) observed in this study with existing literature 107
Table 5.1 Index properties soil used in CC tests 146
Table 5.2 Estimated Constitutive Parameters of Baskarp B15 Sand 146
Table 5.3 Estimated Constitutive Parameters of Vingerling K147 Clay 146
Table 6.1 Summary of laboratory CPTs performed in homogenous sand profiles (used as reference models) 180
Table 6.2 Summary of laboratory CPTs performed in layered sand-clay profiles (used in database) 181
Table 6.3 Comparison of sand $q_c$ from lab data and Schmertmann (1978) fitted relationship 182
Table 6.4 Comparison of clay tip resistance ($q_c$) from lab data and the fitted relationship in Equation 6.3 182
Table 6.5 Constitutive parameters for sand and clay layers in MPM models 182
Table A.1 Listing of calibration chamber tests performed by Deltarees (De Lange 2018). 200
Table B.1 NorSand constitutive modeling parameters 236
Table B.2 Summary of triaxial tests used to calibrate hardening modulus, $H$ 241
Table B.3a Input parameters used for numerical sensitivity analysis in sand (Part 1/3) 246
Table B.3b Input parameters used for numerical sensitivity analysis in sand (Part 2/3) 247
Table B.3c Input parameters used for numerical sensitivity analysis in sand (Part 3/3) 248
Table B.4a Input parameters used for numerical sensitivity analysis in clay (Part 1/2) 249
Table B.4b Input parameters used for numerical sensitivity analysis in clay (Part 2/2) 249
Table B.5a Input parameters used for numerical sensitivity analysis in layered soil (Part 1/4) 250
Table B.5b Input parameters used for numerical sensitivity analysis in layered soil (Part 2/4) 251
<table>
<thead>
<tr>
<th>Table B.5c</th>
<th>Input parameters used for numerical sensitivity analysis in layered soil (Part 3/4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table B.5d</td>
<td>Input parameters used for numerical sensitivity analysis in layered soil (Part 4/4)</td>
</tr>
<tr>
<td>Table E.1</td>
<td>Summary of Tested Adhesives and Recommended Treatments</td>
</tr>
<tr>
<td>Table E.2</td>
<td>Geo-slice Peel Evaluation Criteria for Phase 2 of Testing</td>
</tr>
<tr>
<td>Table E.3</td>
<td>Results of Phase One Feasibility Testing of Geo-slice Peels</td>
</tr>
<tr>
<td>Table E.4</td>
<td>Results of Phase Two Testing of Geo-slice Peels</td>
</tr>
<tr>
<td>Table E.5</td>
<td>Geo-slice Peel Evaluation</td>
</tr>
</tbody>
</table>
Chapter 1: Introduction

1.1. Problem Statement

Soil liquefaction is a phenomenon in which soil loses its strength and stiffness during earthquake shaking. Liquefaction can cause excessive damage to the built environment, including cracking of foundations, severe and irregular building settlements, breaking of utility lines, and loss of embankment stability, among many other adverse consequences. The liquefaction response of a soil profile to a given level of earthquake shaking is evaluated by first computing the liquefaction triggering potential at any point in the soil profile using information about the soil profile and the earthquake of interest. Liquefaction triggering models output a factor of safety against liquefaction triggering or the probability that liquefaction will trigger at any point in a soil profile. Then, liquefaction triggering predictions are translated into damage metrics such as Liquefaction Potential Index (LPI; Iwasaki 1978), Liquefaction Severity Number (LSN; Tonkin & Taylor, van Ballegooy et al. 2014) using liquefaction manifestation models. Damage metrics like LPI are indicators of the severity of surficial liquefaction manifestation (or liquefaction damage potential). The overall process of evaluating liquefaction response of a profile is shown in Figure 1.1.

Figure 1.1. Evaluation of liquefaction response of a soil profile.

Extensive research efforts to develop methods for evaluating liquefaction triggering have resulted in significant advances in the state-of-practice (e.g., Whitman 1971; Seed and Idriss 1971; Dobry et al. 1982; Seed et al. 1985; Stark and Olson 1995; Robertson and Wride 1998; Kayen and Mitchell 1997; Youd et al. 2001; Andrus et al. 2004; Cetin et al. 2004; Moss et al. 2006; Kramer
and Mayfield 2007; Idriss and Boulanger 2006; Idriss and Boulanger 2008; Kayen et al. 2013; Boulanger and Idriss 2014; Green et al. 2019, 2020; among others). The primary focus of these prior efforts was to evaluate the liquefaction triggering potential of cohesionless, free-draining soil deposits (i.e., clean sand deposits). In contrast, liquefaction response of highly interlayered soil deposits containing layers of varying soil type, drainage condition, and liquefaction potential (i.e., “challenging” soil profiles) has not been comprehensively addressed.

Major limitations of existing liquefaction triggering and/or manifestation models in their application to challenging soil profiles was highlighted by the dissonance between the predictions of liquefaction damage and the observed liquefaction damage after the 2010-2011 Canterbury Earthquake Sequence (CES) in New Zealand. It was found that while the existing models did a good job of predicting the manifestation of liquefaction for case history sites that had uniform sandy soil profiles, they greatly over-predicted the severity of liquefaction at sites that had challenging soil profiles (e.g., Beyzaei et al. 2015, 2018; Cox et al. 2017; McLaughlin 2017; Yost et al. 2019). However, the exact cause of these over-predictions was not immediately apparent. A remaining, overarching question is whether the shortcomings in the current liquefaction models are related to the prediction of liquefaction triggering at depth (i.e., did the soil layer predicted to liquefy actually liquefy?), or, the prediction of liquefaction response of the entire profile (i.e., given that liquefaction occurred somewhere in the profile, will it manifest at the ground surface?).

This dissertation addresses the first part of the question, specifically, by developing ways to overcome the shortcomings in the site characterization techniques used to predict liquefaction triggering. Cone penetration tests (CPTs), one of the preferred soil characterization techniques for liquefaction assessment, have deficiencies in their ability to properly characterize highly interlayered (challenging) soil sites. The inability to properly identify the location and stiffness of individual thin soil layers in a highly interlayered profile results in inaccurate input data to liquefaction triggering (and subsequently, manifestation) models and contributes to the over-prediction of liquefaction severity. The objective of this research is to improve CPT-based characterization of highly interlayered soil profiles to advance the state of knowledge and practice in liquefaction hazard assessment at challenging soil sites. This will have global implications for regions where the cost of mitigating liquefaction at challenging soil sites would be extremely high, for example, Christchurch, New Zealand and the Groningen region of the Netherlands.
1.2. Background: Cone Penetration Testing in Challenging Soil Profiles

The CPT is a preferred in-situ test method for characterizing soil profiles for liquefaction triggering evaluation because it provides “nearly continuous” data with depth. The test consists of hydraulically advancing a steel rod (typically 10 to 15 cm in diameter) with a conical shaped tip into the ground at a constant rate (typically 2 cm/sec). The cone penetrometer (or “cone”) typically collects data at 1 to 5 cm depth increments. In its most basic form, the CPT collects tip resistance \( q_c \) and sleeve friction \( f_s \) measurements. Tip resistance is proportional to the vertical force imparted on the conical shaped face of the cone by the surrounding soil. Sleeve friction is the frictional force imparted on the perimeter of the cone shaft.

Despite its robustness, the CPT has significant limitations in characterizing challenging soil profiles that contain many thin, interbedded soil layers. This is because measurements of \( q_c \) and \( f_s \) at a given depth in a profile are influenced by soil both above and below the cone tip. The “zone of influence” (Figure 1.2) tends to be larger when the cone is in denser soils and smaller when the cone is in looser soils. Consequently, the measured values of \( q_c \) and \( f_s \) represent contributions from all of the soil within the zone of influence and do not necessarily represent “true” values for the soil at the tip of the cone where the measurement is being reported. In that sense, the measured data can be thought of as a “blurred” version of the true data. In a uniform soil profile, this is not particularly consequential. However, in a layered soil profile, this can result in inaccurate identification of soil layer stiffness and thickness. Three related phenomena can result in the “blurring” of the measured tip resistance: thin-layer, transition-zone, and multiple thin-layer effects. More details about these phenomena and their distinctions will be presented subsequently.
In keeping with the notation used in prior literature (e.g., Boulanger and DeJong 2018, Yost et al. 2021), the following definitions are utilized in this work:

- \( q_m \) - the "measured" or "blurred" tip resistance recorded during a CPT in a soil profile of any number of layers
- \( q_t \) - the "true" or fully developed tip resistance that would be recorded in a soil layer of infinite thickness, absent of any influence of other layers

Figure 1.3 illustrates the thin-layer and transition-zone effects by comparing the tip resistance for three soil profiles, one of homogenous clay, one of homogenous sand, and one of clay with a thin embedded sand layer. Two related phenomena are evident:

1. The maximum \( q_m \) in the thin sand layer is an underestimate of the \( q'_t \) of the sand layer (\( q'_{sand} \)) because it is also being influenced by the \( q'_t \) of the overlying and underlying clay (\( q'_{clay} \)). This phenomenon is typically referred to as the **thin-layer effect**. Note that as the thin sand layer decreases in thickness, the maximum \( q_m \) would also decrease (i.e., thin-layer effects become more significant as layer thickness decreases).

2. \( q_m \) does not transition abruptly at the layer boundary, but rather, it is influenced by the material both above and below the boundary such that a smooth transition zone exists where
\( q^m \) is neither representative of the fully developed \( q' \) of the sand or clay alone but reflects a combination of both. This phenomenon is typically referred to as the **transition-zone effect**.

Although not illustrated in Figure 1.3, multiple thin soil layers occurring in sequence in a profile can make the interpretation of \( q^m \) even more ambiguous because both thin-layer and transition-zone effects can overlap several times over. This is henceforth referred to as **multiple thin-layer effects**.

**Figure 1.3.** Schematic of thin-layer and transition zone effects in CPT data. Tip resistance from CPTs performed in homogenous clay and sand profiles can be considered characteristic or “true” tip resistances, \( q'_{\text{clay}} \) (labeled 1) and \( q'_{\text{sand}} \) (labeled 2). Measured tip resistance (\( q^m \)) from a CPT performed in a layered sand-clay profile is affected by multiple thin-layer effects (labeled 3a). True tip resistance of the layered profile (\( q' \), labeled 3b) can be constructed using \( q'_{\text{sand}} \), \( q'_{\text{clay}} \), and the known layer geometry.

Many studies have discussed the potential contribution of thin-layer, transition-zone, and multiple thin-layer effects to the over-prediction of liquefaction severity at sites with complex stratigraphy in Christchurch, New Zealand (e.g., Beyzaei et al. 2015; Beyzaei et al. 2018; Cox et al. 2017; McLaughlin 2017; Yost et al. 2019). Several procedures to correct for transition-zone, thin-layer, and multiple thin-layer effects have been proposed. Thin-layer effects have often been addressed by applying a thin-layer correction factor (\( K_H \)) to the peak \( q^m \) in a given thin layer to obtain the "true" tip resistance (\( q' \)) (Youd et al. 2001; Ahmadi and Robertson 2005; Mo et al. 2017). Other
procedures incorporate thin-layer correction factors and layer interface detection such that \( K_H \) is applied not just to the peak \( q^m \) in a given layer but across the entire thickness of the layer (de Greef and Lengkeek 2018; Yost et al. 2021). Recently proposed procedures use an inverse problem approach to "deblur" \( q^m \) and provide a best-estimate of \( q' \) without having to manually apply correction factors (Boulanger and DeJong 2018; Cooper et al. 2021), though \( K_H \) can be computed using these methods for purposes of comparison. These methods assume an underlying “blurring” model that describes the influence of soil stiffness away from the tip of the cone on the \( q^m \) reported at a given depth. The procedure first guesses a \( q^{inv} \) that is meant to be an estimate of \( q' \). Then, the blurring model is applied to \( q' \) to obtain a simulated measured tip resistance, \( q^{m,sim} \). This \( q^{m,sim} \) is compared to the actual measured tip resistance, \( q^m \). If the misfit between the two is small enough, \( q^{inv} \) is output as the final estimate of \( q' \). If the misfit is too large, the procedure iterates. Despite the availability of multiple thin-layer correction procedures, existing procedure efficacy is limited; this is demonstrated and discussed in this dissertation.

One of the challenges of developing and validating multiple thin-layer correction procedures is the lack of available datasets that contain both \( q^m \) and \( q' \) for a given soil profile. For example, field CPT data alone only provide \( q^m \). To obtain \( q' \), the geometry and properties of each layer in the soil profile must be known. Laboratory calibration chamber studies, such as those performed by De Lange (2018), can provide both \( q^m \) and \( q' \) by performing CPTs in both single-layer and multi-layered soil profiles prepared under similar conditions. However, few calibration chamber studies of CPT in layered soil profiles exist and many uncertainties must be understood and overcome in the laboratory testing process. Furthermore, laboratory tests are costly and expensive. Numerical tools show promise in being able to supplement limited available laboratory data and are explored in this thesis.

1.3. Research Tasks
In support of the overall objective to improve liquefaction hazard analysis at challenging soil sites by improving characterization of challenging soil profiles with the CPT, the following tasks were performed:

1. The efficacy of current multiple thin-layer correction procedures was assessed.
2. New, more effective multiple thin-layer correction procedures were developed.
3. A numerical framework for simulating CPTs in challenging soil profiles using the Material Point Method was established.

4. A CPT database of \( q^m - q' \) pairs in challenging soil profiles was created to support the improvement of existing, and development of new, multiple thin-layer correction procedures.

1.4. Dissertation Structure and Contents

This thesis is organized as a series of manuscripts presented that have either already been published in peer-reviewed geotechnical journals or conference proceedings or will be submitted shortly after this thesis is published. Together, they accomplish the research tasks presented in Section 1.3. Five appendices follow the primary chapters.

In Chapter 2, a new multiple thin-layer correction procedure is developed (the “Deltares” procedure) and its efficacy is assessed along with an existing correction procedure (from Boulanger and DeJong 2018) using direct and indirect methods. The direct assessment utilizes laboratory calibration chamber test data conducted at Deltares by De Lange (2018). The indirect method compares liquefaction hazard predictions made using uncorrected and corrected CPT data from a large CPT case history database in Christchurch, New Zealand. Results show that neither of the multiple thin-layer correction procedures explored (1) perform adequately in direct assessments for profiles with layer thicknesses less than ~1.6 times the diameter of the cone, which typical challenging Christchurch profiles have or (2) improve liquefaction hazard predictions across the large CPT database. These results indicate that development of better multiple thin-layer correction methods is required to improve liquefaction hazard assessment.

In Chapter 3, the Cooper et al. (2022) inverse multiple thin-layer correction procedure is proposed as an alternative to the Boulanger and DeJong (2018) and Deltares procedures. The Cooper et al. (2022) procedure searches for a \( q' \) profile comprising a finite number of layers each with a constant \( q' \), eliminating the need for a transition-zone correction step like the one implemented in the Boulanger and DeJong (2018) procedure. The Cooper et al. (2022) procedure is shown to perform well on a soil profile with layer thicknesses 0.8 times the diameter of the cone when using \( q^{m, \text{sim}} \) derived from the known \( q' \) profile. To improve the Cooper et al. (2022) procedure so that it can reliably estimate \( q' \) without using a known \( q' \) profile in the artificial blurring process, a better
blurring model that mimics multiple thin-layer effects in CPT data is required. In order to develop a better model, more \( q'' - q' \) data is required from either laboratory or numerical CPT tests.

Chapter 4 details the development of a numerical framework to simulate CPTs in homogenous and layered soil profiles using the Material Point Method (MPM). The goal of this exercise was twofold: (1) better understand the important mechanisms contributing to multiple thin-layer effects and (2) demonstrate the feasibility of creating pairs of \( q'' \) and \( q' \) in layered soil profiles to develop and validate multiple thin-layer correction procedures. The framework to simulate CPTs using MPM was validated with laboratory data and shown to be effective.

In Chapter 5, the numerical framework described in Chapter 4 is extended to include more advanced constitutive models and a better description of soil-cone contact. A thorough assessment of how uncertainties in laboratory experiments are propagated through the numerical model was performed and recommendations for reducing uncertainty in laboratory and numerical CPT calibration chamber studies are provided. The outcomes have implications for understanding the limitations of using experimental and numerical data in developing multiple thin-layer correction procedures.

Chapter 6 describes the creation of a \( q'' - q' \) database using experimental and numerical CPT data. 49 \( q'' - q' \) pairs for highly interlayered soil profiles are curated in an open-source database complete with Jupyter notebook to perform initial data processing. In particular, this database is constructed with the intent of using statistical learning tools to (1) develop new multiple thin-layer correction procedures and (2) develop a new blurring method to better represent multiple thin-layer effects, ultimately to be implemented in new or existing inverse-style multiple thin-layer correction procedures. Uses of this dataset are demonstrated through several examples.

Chapter 7 contains conclusions and recommendations for future work.

Appendix A contains supplemental material for Chapter 2, including flow charts describing the implementation of the Boulanger and DeJong (2018) and Deltas multiple thin-layer correction procedures, and a Matlab script to perform the Deltas procedure.
Appendix B contains supplemental material for Chapter 5, including a detailed explanation of constitutive modeling calibration procedures, tables detailing the numerical input parameters for the sensitivity analyses, and a discussion of the variation in stress behavior when using different radial boundary conditions.

Appendix C details how to access the data repository containing the $q^m$-$q^t$ database generated in Chapter 6.

Appendix D is a peer reviewed conference paper included in the proceedings of the 12th National Conference on Earthquake Engineering (12NCEE). This paper is included as an appendix because its main findings are presented in Chapter 4 of this thesis.

Appendix E is a peer reviewed conference paper included in the proceedings of the International Foundations Congress and Equipment Expo (IFCEE 2021). This paper is included as an appendix because the study discussed in this paper is supportive but ancillary to the primary discussion of this thesis.

References


Chapter 2: Assessment of the Efficacies of Correction Procedures for Multiple Thin Layer Effects on Cone Penetration Tests

The contributions of the authors to the composition of this manuscript are delineated as follows:

**Kaleigh M. Yost:**
- Performed literature review; performed all analyses; prepared figures and tables; co-wrote the draft manuscript.
- Developed new multiple thin-layer correction procedure using laboratory data from Deltares.
- Created software used in this study.
- Addressed coauthor comments in manuscript revisions.
- Addressed reviewer comments and prepared the final version of the manuscript.

**Dr. Russell A. Green:**
- Lead primary investigator of this study.
- Proposed idea of developing a new multiple thin-layer correction procedure using laboratory data from Deltares.
- Provided valuable feedback throughout the study.
- Co-wrote the draft manuscript.
- Reviewed and edited the draft and final manuscripts.

**Dr. Sneha Upadhyaya**
- Curated data used in this study.
- Created software used in this study.
- Performed analyses used to inform this study.
- Reviewed and edited the draft and final manuscripts.

**Dr. Brett W. Maurer**
- Curated data used in this study.
- Created software used in this study.
- Performed analyses used to inform this study.
- Reviewed and edited the draft and final manuscripts.

**Dr. Alba Yerro-Colom**
- Provided valuable feedback throughout the study.
- Reviewed and edited the draft and final manuscripts.

**Dr. Eileen R. Martin**
- Provided valuable feedback throughout the study.
- Reviewed and edited the draft and final manuscripts.

**Jon Cooper**
- Performed analyses used to inform this study.
Assessment of the Efficacies of Correction Procedures for Multiple Thin Layer Effects on Cone Penetration Tests

Kaleigh M. Yost¹, Russell A. Green², Sneha Upadhyaya³, Brett W. Maurer⁴, Alba Yerro-Colom⁵, Eileen R. Martin⁶, and Jon Cooper⁷

¹Graduate Student, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Professor, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)
³Graduate Student, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: usneha@vt.edu)
⁴Assistant Professor, Dept. of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195 (email: bwmaurer@uw.edu)
⁵Assistant Professor, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: aayerro@vt.edu)
⁶Assistant Professor, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: ermartin@vt.edu)
⁷Graduate Student, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: jonc7@vt.edu)

Submitted to Soil Dynamics and Earthquake Engineering
Submitted on: 4 January 2021
Accepted for Publication: 16 February 2021
Published Online: 1 March 2021

Reference:
2.1. **Abstract**

Multiple interbedded fine-grained layers in a sand deposit have a “smoothing” effect on the measured Cone Penetration Test (CPT) tip resistance ($q_c$), resulting in a significant underestimation of the predicted liquefaction resistance of the sand layers. Trends identified by De Lange (2018) through calibration chamber tests on stratified sand-clay profiles are used herein to develop a new thin-layer correction procedure for $q_c$ (the “Deltares” procedure). The efficacies of the Deltares and the independently-developed Boulanger and DeJong (2018) procedures are both directly assessed using CPT data from calibration chamber tests and indirectly inferred from CPT-based liquefaction case histories in Christchurch, New Zealand. The results highlight limitations of the assessed thin-layer CPT $q_c$ correction procedures for layers less than 40 mm thick. Multiple, interbedded thin layers also influence the measured CPT sleeve friction ($f_s$), but in a more complex way than they influence $q_c$. To-date, no procedures have been proposed to address all the thin-layer-effects phenomena on the measured $f_s$, with errors in properly characterizing the $f_s$ of a layer inherently influencing the accuracy of predicting the liquefaction susceptibility and potential of the layer. In totality, the thin-layer-effects correction procedures proposed to-date generally result in slightly less accurate predictions of the observed liquefaction severity for cases having highly stratified profiles, opposite of what would be expected and desired.

2.2. **Introduction**

For over forty years, extensive research efforts have focused on developing procedures for evaluating liquefaction triggering, resulting in significant advances in the state-of-practice (e.g., Whitman 1971; Seed and Idriss 1971; Seed et al. 1985; Stark and Olson 1995; Robertson and Wride 1998; Youd et al. 2001; Andrus et al. 2004; Cetin et al. 2004; Moss et al. 2006; Idriss and Boulanger 2006 and 2008; Kayen et al. 2013; Boulanger and Idriss 2014; Green et al. 2019; Green et al. 2020; among others). The success of these efforts is highlighted by the relatively high accuracy of several currently-used liquefaction models (e.g., Green et al. 2014, 2015). However, the primary focus of past research was on liquefaction triggering of cohesionless, free-draining soil deposits and not on predicting the liquefaction response of soil profiles with complex stratigraphy, such as sand profiles with multiple interbedded silt and/or clay layers (Beyzaei et al. 2017). Comparison of predicted versus observed severity of surficial liquefaction manifestations at sites comprised of sand with interbedded silt and clay during the 2010-2011 Canterbury, New Zealand, earthquake sequence (CES) highlighted significant limitations in the predictive
capabilities of current liquefaction triggering and/or manifestation models (e.g., Maurer et al. 2015b). In general, current methods accurately predicted liquefaction severity in eastern Christchurch, but significantly over-predicted liquefaction severity in western Christchurch, particularly in southwest Christchurch.

In an effort to understand the reason for these trends in the geo-spatial prediction accuracy, Maurer et al. (2015a) computed the average Cone Penetration Test (CPT) Soil Behavior Type Index \( I_c \) (Robertson 1990) for the upper 10 meters \( I_{c,10} \) of profiles across Christchurch, where \( I_c \) is commonly used as a proxy for soil type and fines content (FC). Maurer et al. (2015a) observed that the deposits in eastern Christchurch predominantly have an \( I_{c,10} < 2.05 \) and those in western Christchurch predominantly have an \( I_{c,10} > 2.05 \), which is a direct result of the depositional environments of the respective deposits. Note that \( I_c = 2.05 \) separates “Sands” (i.e., clean sands to silty sands) from “Sand Mixtures” (i.e., silty sand to sandy silt) (Robertson and Wride 1998).

Upon more detailed studies of the geologic, geomorphic, and geotechnical characteristics of the profiles that have an \( I_{c,10} > 2.05 \), the profiles were shown to be highly stratified and composed of multiple thin soil layers (e.g., Beyzaei et al. 2015; Stringer et al. 2015; van Ballegooy et al. 2014b; McLaughlin 2017; Beyzaei et al. 2017; Cox et al. 2017; among others). Boulanger et al. (2016) noted the limitation of the CPT, as well as other in-situ tests commonly used to predict liquefaction triggering, to identify and characterize thin layers, which may significantly influence the liquefaction response of a soil profile. Specifically, multiple interbedded layers have a “smoothing” effect on the measured CPT tip resistance (e.g., van der Linden 2016), generally resulting in a significant underestimation of the density of the sand layers and an overestimation of the stiffness of the fine-grained layers.

CPT tip resistance \( (q_c) \) measurements are made as a function of depth, usually in depth increments of one to two centimeters, and sometimes up to five centimeters. However, \( q_c \) is influenced by soil \( \sim 10-30 \) cone diameters ahead of the cone tip, with the zone of influence being smaller for looser/softer soils and larger for denser/stiffer soils (Ahmadi and Robertson 2005). As a result of this “stress-bulb-influence-zone” phenomenon, measured values of \( q_c \) reflect average values for the soils in the zone of influence and do not represent the “true” values for the soil at a given depth.
This is conceptually illustrated in Figure 2.1 which shows the influence of a sand layer of varying thickness on the measured tip resistance in a profile composed of both clay and sand strata. As shown, the measured $q_c$ is influenced by the stiffer sand layer while the depth of the CPT tip is still in the overlying clay layer. Similarly, the measured $q_c$ is also influenced by the underlying softer clay layer while the CPT tip is in the overlying sand layer. Also, the measured $q_c$ for the sand layer is increasingly biased to be less than the fully developed or “true” $q_c$ for the layer as the layer gets thinner. These phenomena are referred to as transition and thin-layer effects (e.g., Ahmadi and Robertson 2005). Deltares performed a series of calibration chamber tests on soil profiles consisting of thinly interlayered soft clay and sand of varying layer thicknesses and densities (De Lange 2018) that experimentally confirm these phenomena. The results showed that the measured $q_c$ in the interbedded sand layers is less than the “true” $q_c$ for the layers by a factor of 1.5 to 6, where the “true” $q_c$ for the sand layers was determined by testing reference soil models consisting solely of sand of similar density.

The inability of the CPT to properly characterize highly stratified profiles for predicting liquefaction was highlighted by the CES. However, this shortcoming is of relevance to many other regions of the world, for example, the Flaser beds or tidal flats in the Groningen region of the Netherlands. Similar to the soil profiles in western Christchurch, these complex soil profiles are comprised of multiple thin layers of coarse and fine grained soils. The cost of mispredicting the liquefaction damage potential due to multiple thin-layer effects can be significant if soil improvement schemes are implemented to mitigate the erroneously high predicted liquefaction hazard, such as in the Hawke’s Bay region of New Zealand (El Kortbawi et al. 2019).

Procedures have been proposed to correct $q_c$ for “thin-layer effects” (e.g., Robertson and Fear 1995), but most of these procedures are manually implemented and are not able to correct for multiple thin layers that influence measured $q_c$ at a given depth. However, Boulanger and DeJong (2018) recently proposed an automated procedure to account for multiple thin-layer effects by posing it as an inverse problem, assuming the measured $q_c$ is equal to the “true” $q_c$ convolved with a depth-dependent spatial filter following a simple 1D model.
This paper aims to evaluate the efficacy of thin-layer correction procedures in terms of accuracy (i.e., the ability to estimate “true” $q_c$, as obtained in laboratory calibration chamber test data, from “measured” $q_c$) and the ability to reconcile erroneously high liquefaction predictions, particularly for soil profiles with very thin layers (less than 40-mm-thick). Towards this end, first, an overview of the De Lange (2018) calibration chamber data is presented, followed by an overview of the Boulanger and DeJong (2018) (BD18) inverse filtering procedure. The BD18 procedure is then modified in an attempt to improve its thin-layer correction abilities, with the modified procedure referred to as BD18MOD. A new procedure based on the Koppejan pile capacity method is then proposed, with this procedure referred to herein as “Deltares” procedure because it is derived from work presented in De Lange (2018). The efficacies of BD18, BD18MOD, and Deltares procedures are directly evaluated using the calibration chamber data, as well indirectly inferred from CPT-based liquefaction case history data from the Canterbury, New Zealand, earthquakes.

2.3. **Overview of Calibration Chamber Tests**

As mentioned in the Introduction, Deltares performed a series of calibration chamber tests on pure sand and stratified sand-clay profiles to gain insights into the effect of multiple thin layers on measured $q_c$. Details about the calibration chamber tests are extensively presented in De Lange (2018) and, thus, are only briefly summarized herein. The calibration chamber used was cylindrical in shape, and had an inner diameter of 0.9 m and a height of 0.96 m. The chamber was lined with a flexible rubber membrane, with a porous geotextile placed between the chamber wall and rubber membrane to allow water to flow into the annulus to control lateral pressure applied to the soil sample. Additionally, a water-filled cushion was placed between the top of the soil sample and top of the chamber to control vertical stress on the soil sample. Ports in the top of the calibration chamber and top cushion allowed cone penetrometers to be pushed into the soil sample.

Baskarp B15 sand and Vingerling K147 clay were used to create the soil models. Baskarp B15 sand classifies as a poorly graded sand (SP) per the Unified Soil Classification System (ASTM 2017) and has a median effective particle diameter ($d_{50}$) of 0.136 mm, coefficient of uniformity ($C_u$) of 1.4, coefficient of gradation ($C_c$) of 1.04, specific gravity ($G_s$) of 2.65, and maximum and minimum void ratios ($e_{\text{max}}$ and $e_{\text{min}}$, respectively) of 0.890 and 0.553. Vingerling K147 clay classifies as lean clay (CL) per the Unified Soil Classification System and has liquid limit (LL) of 32.3, plastic limit (PL) of 15.8, and a plasticity index (PI) of 16.5. The Vingerling K147 clay used
to construct the soil models was extruded in a vacuum press, and thus was expected to have a pre-consolidation stress. This was confirmed by the dilative tendencies observed in the stress paths from anisotropic consolidated–undrained (ACU) triaxial compression tests performed on the clay having vertical effective confining stresses of 25 kPa and 50 kPa.

In total, 10 calibration chamber soil models were prepared. Three of these contained pure sand (Models 1, 5, and 6) and serve as reference models and the remainder contained interbedded sand and clay (Models 2, 3, 4, 7, 8, and 10). The model stratigraphies and relevant characteristics are shown in Figure 2.2. A complete listing of models and tests performed on them is provided in Appendix A. For the layered soil models, Vingerling K147 clay layers were formed by placing prefabricated clay bricks of the required dimensions into the chamber. The pure sand models and sand layers in the layered models were prepared by water pluviation with a free water height of 1.5 to 2.5 cm. The density of the sand was closely monitored during the sample preparation by measuring the sample height and weight. The targeted density of the sample was achieved by periodically gently tamping the sand surface during pluviation (van der Linden 2016). Relative densities ($D_R$) of 30% (loose) and 60% (dense) were targeted; however, as seen in Figure 2.2, those target densities were not typically achieved with exact precision during sample preparation. Furthermore, while uncertainty in the reported $D_R$ was reportedly low for the uniform sand models, uncertainty of $D_R$ in the thin interbedded sands in the layered models was reportedly much greater (De Lange 2018). Local variations in sand density within layers were expected but not anticipated to have a significant impact on the results of this study. For the purposes of this work, it is assumed that the reported $D_R$ is consistent throughout all sand layers in a given soil model. It should be noted that the soil models created for the De Lange (2018) study are idealizations of natural soil profiles, with natural soil profiles inherently containing more variability in soil type, soil density/stiffness, layer thickness, etc. and thus even more difficult to characterize.

The vertical and horizontal stresses confining the soil models were applied via the water pressure in the top cushion and in the annulus between the calibration chamber wall and rubber membrane. The stresses were increased smoothly at a rate of 1 kPa/min until the desired stress levels were reached, where the ratio of horizontal to vertical stress for all tests was 0.5. For the models with clay layers, the clay was allowed to fully consolidate before CPTs were performed.
CPTs were performed through ports in the top plate of the calibration chamber. Two different diameter cones were used in the testing, one having a diameter of 25 mm and the other 36 mm. For the tests where the 36-mm-diameter cone was used, only one CPT was performed on the model and it was pushed down through the center of the model. Accordingly, the cone was 450 mm from the sidewall of the calibration chamber. For the tests where the 25-mm-diameter cone was used, three tests were performed on each model, at the vertices of a centrally positioned equilateral triangle having side lengths of 260 mm. Accordingly, the cones were 300 mm from the sidewall of the calibration chamber for each test, and the confining stress was increased between each test (typically tests were performed at vertical effective confining stresses of 25 kPa, 50 kPa, and 100 kPa). The cones were hydraulically pushed at a rate of 4 mm/s in order to obtain one sample every mm, as the maximum sampling frequency of the data acquisition unit is 4 Hz. Both \( q_c \) and sleeve friction \( f_s \) were measured.

### 2.4. Thin-Layer Correction Procedures

Three thin-layer correction procedures are evaluated herein. The first was proposed by Boulanger and DeJong (2018) (BD18) and accounts for multiple thin-layer effects by posing the problem as an inverse problem. BD18 assumed that the measured tip resistance \( (q'_{m}) \) equals the “true” tip resistance \( (q'_{t}) \) convolved with a depth-dependent spatial filter \( (\omega_c) \) following a simple 1D model. Additionally, a modified version of the Boulanger and DeJong (2018) procedure (i.e., BD18MOD) is also evaluated, with the modifications to the BD18 procedure based on comments provided to the authors by Professor Jason DeJong and geared toward improving the BD18 procedure’s thin-layer correction abilities. Finally, a new procedure is proposed herein and is developed by generalizing the trends in the thin-layer effects on \( q''_{m} \) predicted by the Koppejan pile capacity method for a known \( q'_{t} \). Because this latter procedure is based on the calibration chamber tests and analyses of the tests performed by Deltares (De Lange 2018), this procedure is referred to as the “Deltares” procedure, as mentioned in the Introduction, even though it was not formally proposed by Deltares.

The following terminology is used in this section:

- \( q''_{m} \) – measured tip resistance after corrections for unequal area effects have been applied and normalized to atmospheric pressure
• $q^t$ – true tip resistance (i.e., the tip resistance that would be measured in a given soil layer without any influence of multiple thin-layer effects), normalized to atmospheric pressure

• $q^{inv}$ – tip resistance that when convolved with a depth-dependent spatial filter, best predicts the measured tip resistance per the Boulanger and DeJong (2018) inverse procedure (i.e., an estimate of $q^t$, as detailed herein), normalized to atmospheric pressure

• $q^{corr}$ – corrected tip resistance obtained by applying thin-layer corrections via the Deltares procedure to the measured tip resistance (i.e., an estimate of $q^t$, analogous to $q^{inv}$ for the BD18 procedure, as detailed herein)

2.4.1. Overview of the Boulanger and DeJong (BD18) Inverse Filtering Procedure for Thin- and Transition-Layer Effects

As mentioned in the Introduction, BD18 proposed an automated procedure to account for multiple thin-layer effects by posing the problem as an inverse problem. They assumed that the measured tip resistance ($q^m$) equals the “true” tip resistance ($q^t$) convolved with a depth-dependent spatial filter ($w_c$) following a simple 1D model:

$$q^m(z) = q^t(z) \ast w_c(z)$$  \hspace{1cm} (2.1)

where the asterisk indicates convolution of $q^t$ with $w_c$. In this case, the convolution refers to the integral of the point-wise multiplication of $q^t(z)$ and $w_c(z)$, as a function of the amount that one of the functions is shifted relative to the other.

This technique searches for the “inverted” tip resistance ($q^{inv}$), that, when convolved with $w_c$, best predicts $q^m$, where $q^{inv}$ is an estimate of $q^t$. The problem is treated as an optimization problem via an iterative splitting method, which seeks to solve:

$$q^{inv} = \arg\min_{q^t} ||q^m - q^t \ast w_c||_2$$  \hspace{1cm} (2.2)

with added smoothing and filter procedures to dampen fine-scale features that can be detrimental to convergence. Once the optimization procedure is performed, sharp transitions in $q^{inv}$ are identified. A uniform $q^{inv}$ (either the maximum or minimum $q^{inv}$ identified in the transition zone)
is then applied across the entire transition zone. The procedure is described in detail in Appendix A.2.

The thin-layer factors \( K_H \) derived from the procedure are shown in Figure 2.3, where \( K_H \) is defined as:

\[
K_H = \frac{q^t(z)}{q^m(z)}
\]  

(2.3)

where \( q^t(z) \) and \( q^m(z) \) are the true and measured tip resistances, respectively, at a given depth, \( z \).

In Figure 2.3, \( q^t_{\text{strong}} \) and \( q^t_{\text{weak}} \) are the values of \( q^t \) (or the estimated values of \( q^t, q^m \)) in the thin sand and clay layers, respectively, \( H \) is the thickness of the thin sand layer, and \( d_{\text{cone}} \) is the diameter of the cone in the same units as \( H \). As shown in this figure, \( K_H \) increases as the normalized thickness, \( H/d_{\text{cone}} \), of the thin sand layer decreases, consistent with the trends show in Figure 2.1. The thin-layer factor with smoothing and filtering steps included, \( K_{H,\text{net}} \), decreases as \( H/d_{\text{cone}} \) approaches zero. The smoothing and filter models are discussed more next.

2.4.1.1. Cone Penetration Filter Model

The cone penetration filter model, \( w_c(z) \), used by BD18 accounts for the relative influence of soil at a distance from the cone tip (i.e., whether the distant soil is softer or stiffer than the soil immediately adjacent to the cone tip). The cone penetration filter is shown in Figure 2.4, normalized by the \( w_c \) at the cone tip, as a function of normalized depth, \( z' \) (i.e., distance from the cone tip divided by \( d_{\text{cone}} \)). As shown in this figure, the soil above the cone tip has about half the influence on \( q^m \) as compared to the soil below the cone tip, as indicated by the relative areas under the curves. Also, as may be surmised from this figure, if the soil at a given distance from the cone tip is softer than the soil at the cone tip (i.e., \( q^t_{z'}/q^t_{z'=0} < 1 \)), the distant soil will have a larger influence on \( q^m \) than it would otherwise, as indicated by the larger area under the curves for decreasing values of \( q^t_{z'}/q^t_{z'=0} \).
The cone penetration filter model shown in Figure 2.4 has four filter parameters, with baseline values recommended by BD18 for each, which were used in generating Figure 2.4 (i.e., \( z'_{50, \text{ref}} = 4.2, m_{z50} = 0.5, m_z = 3, \) and \( m_q = 2 \)). These parameters can be adjusted to potentially increase or decrease the magnitude of \( K_H \) and the sensing and development distances, which may improve identification of very thin layers, but there is no general procedure for automatically determining these parameters.

2.4.1.2. Smoothing Steps in the BD18 Procedure

The BD18 inversion procedure includes two steps that decrease \( K_H \) as the normalized thin layer thickness \((H/d_{cone})\) decreases:

1. A smoothing step performed after each iteration of the inversion that first prevents \( q^{inv} \) from falling below \( 0.5q^m \) at any given depth, and second computes a moving average of \( q^{inv} \) over a pre-defined smoothing window.

2. The application of a low-pass spatial filter after inversion, which consists of a re-run of the inversion procedure using a limiting \( z'_{50, \text{ref}} \) value equal to the length of the cone tip, instead of the 4.2 that is recommended for the initial inversion.

These steps reportedly improve the performance of the overall procedure and promote convergence of the solution. They also ensure a decrease in \( K_H \) as thin layer thickness approaches zero. As shown in Figure 2.3, removal of the smoothing and filtering steps causes \( K_H \) to approach infinity in very thin layers. However, modifying and removing the smoothing and filtering steps can improve the performance of the inversion procedure in identifying very thin layers, but can also destabilize the solution, resulting in non-convergence as shown in Figure 2.5.

In an attempt to improve the performance of the BD18 procedure on the calibration chamber data from Deltares, and at the suggestion of Professor Jason DeJong, the smoothing and filtering steps were both modified and removed from the procedure. The procedure was then implemented to assess the effects of these changes on \( q^{inv} \). Specifically, the following modifications were made to the BD18 procedure:

- Revise the smoothing window used during inversion to cap at a maximum of three \( q^m \) data points (note that reducing the window below three \( q^m \) data points, or eliminating the
smoothing step altogether, results in a solution that does not converge as shown in Figure 2.5).

- Revise by reducing the limiting $z'_{50,ref}$ value used in the low-pass spatial filter applied after the inversion, and by eliminating the low-pass spatial filter altogether.

- A combination of reducing the smoothing window and eliminating the low-pass spatial filter that is applied after the inversion.

The combination of reducing the smoothing window and eliminating the low pass spatial filter after inversion produced the best results (as will be discussed subsequently), and is referred to henceforth as BD18MOD.

2.4.2. Overview of the Deltares Multiple Thin-Layer Correction Procedure

De Lange (2018) used the Koppejan method, a Dutch bearing capacity prediction method for piles in stratified profiles, to interpret the trends in the Deltares calibration chamber test data. Specifically, the Koppejan pile capacity method allows $q^m$ to be estimated if $q^t$ is known (i.e., opposite of the issue at hand: estimating $q^t$ for a known $q^m$). Accordingly, the authors developed the “Deltares” procedure by generalizing the trends in the thin-layer effects on $q^m$ predicted by the Koppejan method for a known $q^t$.

2.4.2.1. De Lange (2018) $K_H$ Curves

De Lange (2018) fit the Deltares calibration chamber data with curves predicted by the Koppejan method, as shown in Figure 2.6. In this figure, the thin-layer correction factor ($K_H$) is expressed as a function of the normalized stress ratio ($q_{ratio}$), which is defined as:

$$q_{ratio} = \frac{q^m_{max} - \sigma_v}{q^m_{min} - \sigma_v}$$  (2.4)

where $q^m_{max}$ and $q^m_{min}$ are the maximum and minimum measured tip resistances, respectively, in the layered zone, and $\sigma_v$ is the total vertical stress at the depth of interest. Note that De Lange (2018) defined $K_H$ per Equation 2.5, which is slightly different from the BD18 definition.

$$K_H = \frac{q^t - \sigma_v}{q^m_{max} - \sigma_v}$$  (2.5)
The $K_H$ values for the calibration chamber data plotted in this figure were computed as the ratio of tip resistance measured in a reference sand model (i.e., $q'$) and in the sand layers in a stratified model (i.e., $q''$), where the sand in the two models had similar $D_R$ and confining stresses. De Lange (2018) showed that $K_H$ is dependent on the thickness of the thin sand layers ($H$), cone diameter ($d_{cone}$), sand layer density, and confining stress, and ranged between 1.5 and 6. However, no procedure was explicitly outlined by De Lange (2018) on how to calculate thin-layer correction factors for cases where the $q'$ values are unknown, or for profiles having differing values of normalized layer thickness (i.e., $H/d_{cone}$) and confining stresses. Additionally, no guidance was provided on implementing the thin-layer correction factors in tandem with transition zone corrections, other than the recommendation that the corrected tip resistance ($q^{corr}$) be applied over the entire thickness of the thin layer.

The generalization of the trends shown in Figure 2.6 and the development of the “Deltares” thin-layer correction procedure are briefly summarized next, and detailed instructions for implementing the procedure are provided in Appendix C.

### 2.4.2.2. Derivation of Correction Factors

In order to calculate $K_H$ for $H/d_{cone}$ and $q_{ratio}$ values other than those reported in De Lange (2018), it was necessary to generate a set of curves to fit the calibration chamber data presented in Figure 2.6 and to generate additional curves for other $H/d_{cone}$ values. Based on the shape of the Koppejan curves shown in Figure 2.6, it was surmised that a logarithmic curve passing through the point (1,1) would reasonably fit the calibration chamber data.

Understanding that the amount of data is limited, logarithmic curves of the form given by Equation 2.6 were developed to fit the four sets of calibration chamber test data shown in Figure 2.6.

$$K_H = m \cdot \ln(q_{ratio}) + 1 \quad (2.6)$$

A linear regression of $K_H$ versus the natural logarithm of $q_{ratio}$ was used to generate the fitting parameter $m$. This produced a set of curves that have similar shapes to the Koppejan curves shown
in Figure 2.6. Additionally, a relationship between the curve fitting parameter \( m \) and \( H/d_{cone} \) was developed from the calibration chamber data, as shown in Figure 2.7.

A power-law fit was used to approximate the relationship shown in Figure 2.7. The relationship between \( H/d_{cone} \) and the curve fitting parameter \( m \) is thus defined by:

\[
m = 9.0294 \left( \frac{H}{d_{cone}} \right)^{2.865}
\]

Using Equations 2.6 and 2.7, curves defining \( K_H \) could be generated for any combination of \( q_{ratio} \) and \( H/d_{cone} \), as shown in Figure 2.8.

Although Equation 2.6 is an approximation, it can be used to generate \( K_H \) values based on \( q^m \) values for a variety of thin layer thicknesses, cone diameters, and confining stress. Detailed instructions on how to apply the \( K_H \) factors to \( q^m \), in tandem with transition layer corrections, to obtain the “corrected” \( q_c \), or \( q^{corr} \), are provided in Appendix A.3.

2.5. Application of the Thin-Layer Correction Procedures to the Calibration Chamber Data

The BD18, BD18MOD, and Deltares thin-layer correction procedures were applied to the Deltares calibration chamber CPT data to assess their efficacies. However, in comparing the results, it should be remembered that the Deltares procedure was developed and calibrated using the same calibration chamber data that are being used to assess its efficacy, while the BD18 and BD18MOD procedures were calibrated using different data. As a result, the assessment is inherently biased. Select results from the application of the thin-layer correction procedures are shown in Figure 2.9, with the complete results provided in Figure A.1 in Appendix A. In Figure 2.9, the black line represents the \( q^m \) data, the blue solid line represents \( q^{inv} \) from the BD18 procedure, the blue dashed line represents \( q^{inv} \) from the BD18MOD procedure (i.e., \( q^{invmod} \)), the green dashed line represents \( q^{corr} \) from the Deltares procedure, and the red line represents \( q' \) as measured in the corresponding reference sand model (note that \( q^{inv}, q^{invmod}, \) and \( q^{corr} \) are all estimates of \( q' \)). Reference sand models were selected (from the three CPT soundings performed in uniform sand profiles with the 25-mm-diameter cone in the De Lange 2018 dataset) to have a similar \( D_R \) and \( \sigma'_{v} \) to the CPT sounding of interest. Thus, Soil Model 1, CPT 3 (\( D_R = 36\% \) and \( \sigma'_{v} = 100 \) kPa) is compared to itself [Figure 2.9a]; Soil Model 4, CPT 3 (\( D_R = 54\% \) and \( \sigma'_{v} = 100 \) kPa) and Soil Model 8, CPT 3 (\( D_R = 61\% \) and
\( \sigma' = 100 \text{kPa} \) are compared to Soil Model 5, CPT 1 (\( D_R = 60\% \) and \( \sigma' = 100 \text{kPa} \)) [Figures 2.9b and 2.9c]; and Soil Model 10, CPT 3 (\( D_R = 18\% \) and \( \sigma' = 30 \text{kPa} \)) is compared to Soil Model 1, CPT 2 (\( D_R = 36\% \) and \( \sigma' = 50 \text{kPa} \)) [Figure 2.9d]. Since none of the reference sand models served as identical comparisons (in terms of \( \sigma' \) and \( D_R \) of sand) to the layered models, we cannot expect the inverted/corrected results within the sand layers to exactly match the \( q' \) included on the plots in Figure 2.9. However, the \( q' \) provides a point of reference indicating the approximate tip resistance magnitude that should be obtained by the inversion/correction procedure over the entire thickness of the thin sand layers in the layered profiles. Observations from the results presented in Figure 2.9 are as follows:

- None of the methods perform very well on the reference soil models (i.e., pure sand models: Soil Models 1, 5, and 6), exemplified in Figure 2.9a. All procedures erroneously identify and attempt to correct thin layers that were not present. However, the Deltares procedure produces more realistic profiles than the BD18 procedure. The BD18 procedure detects a layer transition if the gradient of \( q'' \) with depth falls below a certain value. On the other hand, the Deltares procedure identifies thin layers by using an algorithm that detects local minima (troughs) and maxima (peaks) in \( q'' \). This algorithm can be tuned to filter out peaks and troughs that do not meet minimum prominence criteria to avoid erroneous peak identification. However, it can be very difficult to identify appropriate criteria if the true layering of the soil profile is unknown (which, absent of additional information, is the case for traditional field CPT data). This highlights a shortcoming of any thin-layer correction procedure, particularly when applied blindly to field data.

- In the soil models with 40-mm-thick clay layers (Soil Models 2 and 4), the Deltares procedure is effective at identifying the interbedded sand layers and correcting \( q'' \), exemplified in Figure 2.9b. In contrast, however, the BD18 procedure actually exacerbates the thin-layer effects, not correcting for them. The modification of BD18 (BD18MOD) results in increased \( q^{inv} \) values (i.e., \( q^{invmod} \) values) in the thin sand layers and decreased values in the thin clay layers, more consistent with the tip resistances of these layers if they were fully developed.

- Neither the BD18 nor the Deltares procedure are effective in correcting for thin-layer effects when the layers are less than 20 mm thick (i.e., Soil Models 8, 9, and 10), although
the Deltares procedure identifies more layers with larger resistance contrasts than the BD18 procedure; refer to Figures 2.9c and 2.9d. The modifications to BD18 (i.e., BD18MOD) do little to improve the efficacy of the procedure in these specific calibration chamber models. None of the three procedures (Deltares, BD18, or BD18MOD) are able to identify all of the thin layers nor identify the correct layer-boundary locations. However, the efficacies of the procedures are likely limited by the ability of the CPT to accurately detect the presence and location of the layers. For example, variations in $q^m$ in the layered zones of Soil Models 8, 9, and 10 are small relative to measurement noise levels and do not line up well with layer boundaries.

- The modifications to the BD18 procedure (i.e., BD18MOD) eliminate some of the smoothing features inherent to the BD18 procedure and seem to improve the performance of the procedure by increasing the contrast in $q^{inv}$ between the clay and sand for the models with the thicker interbedded layers. However, these modifications also tend to de-stabilize the solution (e.g., see large phantom peak between 0.6 and 0.7 m in Figure 2.9b).

It is worthwhile to note that the ratio of stiffness between the sand and clay layers plays a role in the ability of both the CPT and the correction procedures to detect the presence of a thin layer. While De Lange (2018) did not report an expected $q'$ for the clay, a characteristic value of approximately 0.3 MPa can be estimated from Soil Model 9, which had 200-mm-thick clay layers (presumably thick enough for $q'$ of the clay to develop). Very little increase in $q'$ of the clay was observed, whereas a very significant increase in $q'$ of the sand is observed, with increasing confining pressure. In theory, for a given thin-layer thickness, the greater the contrast between the $q'$ of the sand and the clay, the easier the detection of thin layers will be for both the CPT and the correction procedure. This can be observed when examining the soil models with 40-mm-thick layers, in which, as the confining pressure increases (and consequently the magnitude of the stiffness contrast increases), the difference in magnitude of maximum and minimum $q^m$ in the layered zone increases. However, as layers become thinner (e.g., the soil models with 20-mm-thick layers), the thickness may preclude any notable difference in magnitude of maximum and minimum $q^m$, despite an increasing stiffness contrast.
2.6. Application of the Thin-Layer Correction Procedures to the CES and Valentine’s Day Earthquake Data

The BD18, BD18MOD, and Deltares thin-layer correction procedures were applied to field data from the 2010-2011 CES (i.e., 2010 September $M_w$ 7.1 Darfield and 2011 February $M_w$ 6.2 Christchurch earthquakes) and the 2016 February $M_w$ 5.7 Valentine’s Day earthquake that impacted Christchurch, New Zealand. The goal of this effort was to see whether application of the procedures resulted in improved predictions of the actual field liquefaction response. Towards this end, ~3500 CPT soundings from sites where the severity of liquefaction manifestations was well-documented after at least one of the aforementioned earthquakes were compiled, resulting in ~9150 high quality liquefaction case histories. A detailed description of the selection/rejection criteria for the CPT soundings is provided in Maurer et al. (2014, 2015a) and Geyin et al. (2020). The severity of liquefaction manifested at the ground surface was classified in accordance with Green et al. (2014) via post-earthquake ground reconnaissance and using high-resolution aerial and satellite imagery. The CPT soundings and imagery used in this study were extracted from the New Zealand Geotechnical Database (NZGD 2016).

2.6.1. Computation of Predicted Liquefaction Severity

The factor of safety against liquefaction triggering ($FS_{\text{liq}}$) was computed using the CPT-based variant of the simplified procedure proposed by Green et al. (2019) (Gea19), in conjunction with peak ground accelerations ($PGA$) estimated following the Bradley (2013) procedure, which has been used in many prior studies of these earthquakes (e.g., Green et al. 2011, 2014; Maurer et al. 2014, 2015a,b; Carter et al. 2016; among others). However, the case histories associated with the Christchurch earthquake were analyzed using the revised $PGA$s from Upadhyaya et al. (2019), which account for the influence of liquefaction on the ground motions recorded by a few strong motions stations. The depth of ground water table immediately prior to each earthquake was estimated using the event-specific regional ground water models of van Ballegoooy et al. (2014a). An $I_c$ cutoff value of 2.5 was used to distinguish between liquefiable and non-liquefiable soils, where soils with $I_c > 2.5$ were considered to be non-liquefiable (Maurer et al. 2017b, 2019).

The severity of the surficial liquefaction manifestations was predicted using the Liquefaction Potential Index ($LPI$) (Iwasaki et al. 1978). Commonly used $LPI$ thresholds for the predicted severity of surficial liquefaction manifestations are (e.g., Maurer et al. 2014): $LPI < 5$ - Minor-to-
None; $5 \leq LPI < 15$ - Moderate; and $LPI \geq 15$ - Severe. $LPI$ values were computed from the CPT data with and without thin-layer corrections applied, where the “original” and “modified” Boulanger and DeJong (2018) (i.e., BD18 and BD18MOD, respectively) and the Deltares thin-layer correction procedures were used.

In general, the resulting $LPI$ values computed using the corrected CPT data are only slightly different from those computed using the uncorrected CPT data. $LPI$ values across the database, in general, are reduced as a result of the corrections (i.e., less severe surficial liquefaction manifestations are predicted). The decrease is most significant for the BD18MOD procedure, followed by the BD18 and the Deltares procedures, respectively.

2.6.2. ROC Analyses

To assess the efficacies of the thin-layer correction procedures, the case histories were parsed into bins of $I_{c10}$, and receiver-operating-characteristic (ROC) analyses (e.g., Fawcett 2006) were performed on each $I_{c10}$ data bin. ROC analyses are commonly used to evaluate the performance of diagnostic models and have been used extensively in medical diagnostics (e.g., Zou 2007) and to a much lesser degree in geotechnical engineering (e.g., Oommen et al. 2010; Maurer et al. 2015a, 2017a,b,c; Green et al. 2017; Zhu et al. 2017; Upadhyaya et al. 2020). In any ROC analysis application, the distribution of “positives” (e.g., cases of observed surficial liquefaction manifestations) and “negatives” (e.g., cases of no observed surficial liquefaction manifestations) overlap when the frequency of the distributions are expressed as a function of the diagnostic test results (e.g., $LPI$ values). A ROC curve can be drawn by plotting the True Positive Rate ($R_{TP}$) (e.g., liquefaction is predicted and manifestations were observed) versus the False Positive Rate ($R_{FP}$) (e.g., liquefaction is predicted but no manifestations were observed) for varying threshold values (e.g., threshold $LPI$ values). A conceptual illustration of ROC analysis is shown in Figure 2.10, including the relationship among the positive and negative distributions, the threshold $LPI$ values, and the ROC curve.

In ROC-curve space, a random guess is indicated by a 1:1 line through the origin, while a perfect model plots along the left vertical and upper horizontal axes, connecting at point (0,1). A perfect model indicates the existence of a threshold value that perfectly segregates the dataset (e.g., a threshold $LPI$ value below which all the cases are “no manifestation” and above which all the cases
are “manifestation”). The area under the ROC curve \((AUC)\) can be used as an index to evaluate the predictive performance of a diagnostic test (e.g., correlation of computed \(LPI\) values using CPT data with thin layer corrections applied per BD18 to observed severity of surficial liquefaction manifestations) whereby higher \(AUC\) indicates better predictive capabilities. \(AUC\) is statistically equivalent to the probability that sites observed to have liquefaction surface manifestations have higher \(LPI\) values than sites observed to have no surface manifestations (Fawcett 2006). As such, a random guess returns an \(AUC\) of 0.5 whereas a perfect model returns an \(AUC\) of 1, as illustrated in Figure 2.10b. Specific to this study, the efficacies of the thin-layer correction procedures are assessed by comparing the \(AUC\) values corresponding to uncorrected versus corrected CPT data, where the BD18, BD18MOD, and Deltares procedures are used to correct the CPT data for thin-layer effects.

2.6.3. Results
Table 2.1 summarizes the results of the ROC analyses for different severities of surficial liquefaction manifestations for all the cases histories grouped together, and for when the case histories are parsed into bins of \(I_{c,10} < 2.05\) and \(I_{c,10} \geq 2.05\). Recall that the deposits in eastern Christchurch predominantly have an \(I_{c,10} < 2.05\) and those in western Christchurch predominantly have an \(I_{c,10} > 2.05\), where the profiles with an \(I_{c,10} > 2.05\) were shown to be highly stratified. The severity of liquefaction during the CES and Valentine’s Day earthquake was severely-to-excessively over-predicted (i.e., predicted \(LPI\) was 10 to 15 points greater than the expected \(LPI\) for a given liquefaction damage classification, per criteria presented in Maurer et al. 2014) for this latter set of profiles using the uncorrected CPT data (e.g., Maurer et al. 2014; van Ballegooy et al. 2014b; Beyzaei et al. 2015; Stringer et al. 2015; McLaughlin 2017; Beyzaei et al. 2017; Cox et al. 2017; among others). Accordingly, if a thin-layer correction procedure is effective, the \(AUC\) value is expected to increase when the procedure is applied to the CPT data, especially the \(AUC\) value for the case histories that have \(I_{c,10} > 2.05\) (i.e., highly stratified profiles).

From examination of the \(AUC\) values listed in Table 2.1, an increasing trend in \(AUC\) for the corrected CPT data is not observed. Rather, the \(AUC\) values do not vary much for the uncorrected versus corrected CPT data. Moreover, the \(AUC\) values are generally slightly higher for the uncorrected CPT data for case histories having \(I_{c,10} > 2.05\) than when the CPT data is corrected for thin-layer effects (i.e., exactly opposite of what would be expected if the thin-layer corrections
were effective). Because the analysis of the calibration chamber data showed that none of the procedures were able to accurately identify and characterize layers that are 20 to 40 mm thick, the lack of clearly increased AUC after correction is unsurprising.

2.7. Discussion and Conclusions
The BD18/BD18MOD and the Deltares procedures are fundamentally different approaches to correcting data. The Deltares procedure is an algorithm to enhance existing peaks and troughs after smoothing the measured data, and is designed to require outputs to appear as clear layers for easier stratigraphic interpretation of the inverted models. It is not an inverse problem approach, because it does not predict what data would be measured for the proposed $q^{corr}$ model for comparison to the measured data $q^m$ as is done by the BD18 and BD18MOD procedures (which are inverse problem approaches). Because the Deltares procedure was developed based on calibrations of a few laboratory datasets, while the BD18 and BD18MOD include general steps to better model any data acquired, one might expect more general utility of BD18 and BD18MOD across a broader range of stratigraphy scenarios. However, all procedures struggled with detection of fine layers, as noted above. While the basic iterative splitting scheme underlying BD18 and BD18MOD would be expected to converge to a model that minimizes the measured-versus-predicted data misfit when compared to slightly different models, we have no guarantees that this model is a global minimizer of this data misfit over all models. Rather, the resulting model could be a local minimizer, meaning it is simply the best model compared to a small group of similar models, which is a fundamental challenge in inverse problems. Further study is needed to understand the potential for local minimizers in this problem, as well as to use optimization regularization to push the iterative search towards physically realistic stratigraphy that better explains the measured data.

As presented above, calibration chamber data (De Lange 2018) was used to assess the efficacy of the BD18, BD18MOD, and Deltares procedures, although this was not a true test of the Deltares procedure’s efficacy because that procedure was developed and calibrated using these same calibration chamber data. The results of these efforts showed that the BD18 procedure was not able to accurately identify and characterize layers that are 40 mm thick (or less), and actually numerically smoothed the measured CPT data, opposite of its intent. Modifying the BD18 procedure by reducing the smoothing window and eliminating the low pass spatial filter after inversion (BD18MOD) improved the ability of the procedure to identify and characterize layers
that were 40 mm thick, however, the modified procedure was still not able to accurately identify and characterize layers that were 20 mm thick. The Deltares procedure did a good job identifying and characterizing layers that were 40 mm thick, but its efficacy was also not good for 20-mm-thick layers.

The BD18, BD18MOD, and Deltares procedures were used to analyze case histories from the 2010-2011 CES and the 2016 Valentine’s Day earthquake with and without the application of the thin-layer corrections to the CPT data. The results showed that the thin-layer corrections generally resulted in slightly less accurate predictions of the liquefaction severity for cases having highly stratified profiles, opposite of what would be expected and desired. However, limitations in the thin-layer correction procedures may only be one reason for this trend. For example, the applied procedures could be appropriately correcting CPT tip resistance for thin-layer effects, but shortcomings in the liquefaction triggering and manifestation models could still prevent the accurate predictions of cumulative liquefaction response of the profiles. As a result, the observed trends in accuracy of liquefaction severity prediction provide evidence that the thin-layer corrections do not improve predictions using existing liquefaction models, but not direct evidence that the thin-layer corrections are not efficacious unto themselves.

In addition to potential limitations in the triggering and manifestation models, the depth interval for the Canterbury CPT \( q_c \) measurements was 1 and 2 cm; specifically, the interval was 1 cm for 5485 of the case histories analyzed and 2 cm for 3668 of the case histories. These measurement intervals are on par with the thicknesses of the thin layers identified in many of the western Christchurch profiles (Beyzaei et al. 2017). As a result, many of the thin layers in the profiles are only being characterized by one or two \( q_c \) measurements, if at all. Even the most efficacious thin-layer correction procedure may not be effective under these conditions, particularly if no \( q_c \) measurements are made in the thin layer or if the one or two \( q_c \) measurements made in a thin layer are “noisy.” [Note that this was not an issue with the Deltares calibration chamber tests presented above because the \( q_c \) measurements were made using a depth interval of only 1 mm. As a result, approximately 20 \( q_c \) measurements were made in the thinnest layers.]

Finally, per the liquefaction triggering model used (as well as most other CPT-based liquefaction triggering models), the liquefaction susceptibility of a layer is based on the Soil Behavior Type
Index ($I$), which is a function of both the CPT $q_c$ and sleeve friction ($f_s$). The main focus of the study presented herein is on thin-layer effects on $q_c$, but thin-layer effects also affect $f_s$ and in a more complex way than they affect $q_c$. In addition to the stress-bulb-influence-zone phenomenon that influences the measured $q_c$ (i.e., the main focus of the study presented herein), $f_s$ thin-layer effects entail two other phenomena. First is the physical length of the friction sleeve relative to the thickness of the thin layers. Friction sleeves typically have a surface area of 15,000 mm$^2$, and as a result, the length of the friction sleeve will vary depending on the diameter of the cone (e.g., Saussus et al. 2004). Most of the CPT soundings performed in Canterbury had projected cross-sectional areas of 10 or 15 cm$^2$, implying that the friction sleeves were 133.7-mm or 109.3-mm long, respectively. Accordingly, potentially several thin layers were in contact with the friction sleeve for the Canterbury CPT soundings while the cone tip was at any given depth, making the quantification of any given layer’s contribution to the measured $f_s$ difficult to discern. The ambiguity in a thin layer’s contribution to the measured $f_s$ is furthered as a result of the soil in an overlying layer being “dragged down” into the underlying layer by the cone as it advances in depth. This latter phenomenon was clearly noted in the post-test, excavated calibration chamber samples performed by Deltares (van der Linden 2016; De Lange 2018).

Errors in properly characterizing the $f_s$ of a layer inherently influences the accuracy of predicted liquefaction susceptibility and potential of the layer. While the BD18, BD18MOD, and Deltares procedures apply a correction for the stress-bulb-influence-zone phenomenon on the measured $f_s$, they do not correct for the effects of multiple-layer-contact and layer down-drag on the measured $f_s$, which may be significant. [Note that there was no recommendation included in De Lange (2018) for correcting or adjusting the measured $f_s$ for thin layer effects. However, the measured $f_s$ was computed herein as part of the “Deltares” procedure using the same procedure used in the BD18 method (as described in Part 2: Inversion for Sleeve Friction of Appendix B), except that $q^{corr}$ was used instead of $q^{inv}$.] In conclusion, while current procedures for correcting for thin-layer effects are a step in the right direction, they are not sufficient for use with profiles that have layers thinner than 20 to 40 mm, such as the profiles in western Christchurch, New Zealand, the Flaser bed deposits or tidal flats in the Groningen region of the Netherlands, and similar deposits worldwide. In addition to reducing
the depth interval for $q_c$ measurements (i.e., increasing the sampling frequency), one potential way to better identify and characterize thin layers is by using a Vision Cone Penetrometer (VisCPT) (Hryciw et al. 2009). The third generation VisCPT is now under development (Ventola et al. 2020) and will feature enhanced image acquisition. The VisCPT window near the cone tip may allow direct imaging of thin layers and/or the identification of the occurrence and the extent of layer down-drag. This additional information, coupled with more robust inversion algorithms (e.g., Cooper et al. 2020), may lead to a more accurate approach for correcting for thin-layer effects.

2.8. Acknowledgements

This research was partially funded by Nederlandse Aardolie Maatschappij B.V. (NAM) and National Science Foundation (NSF) Grant Numbers CMMI-1825189 and CMMI-1937984. This support is gratefully acknowledged. Additionally, the motivation for this paper came primarily from discussions related to liquefaction hazard that is due to induced earthquakes in the Groningen gas field in the Netherlands. We thank Julian Bommer, Imperial College London, and Jan van Elk, NAM, as well as all the individuals from NAM, Shell, and Deltares for the discussions that both prompted and informed our efforts to investigate thin layer effects. Additionally, particular thanks are due to Peter Robertson, Gregg Drilling & Testing, Inc., for commenting on the paper, and to Jason DeJong, UC Davis, M. Geyin, University of Washington, and Sjoerd van Ballegooy, Tonkin + Tayler, for discussions about the implementation and modification of the BD18 procedure. However, any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NAM or NSF, or those who inspired this work.

References


Table 2.1. Summary of the results from the ROC analyses obtained using the uncorrected and corrected CPT data using the BD18, BD18MOD, and Deltasres procedures for all the case histories and for bins of cases histories having $I_{c10} < 2.05$ and $I_{c10} \geq 2.05$ (highest values of AUC within an $I_{c10}$ bin are bolded and italicized).

<table>
<thead>
<tr>
<th>Manifestation Severity (Green et al. 2014)</th>
<th>Inversion Procedure</th>
<th>$I_{c10}$</th>
<th>( &lt; 2.05 )</th>
<th>( \geq 2.05 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AUC</td>
<td>AUC</td>
<td>AUC</td>
</tr>
<tr>
<td>Any manifestation</td>
<td>Uncorrected</td>
<td>0.8314</td>
<td>0.8594</td>
<td>0.7633</td>
</tr>
<tr>
<td></td>
<td>BD18</td>
<td>0.8325</td>
<td>0.8628</td>
<td>0.7565</td>
</tr>
<tr>
<td></td>
<td>BD18 Mod</td>
<td>\textbf{0.8356}</td>
<td>\textbf{0.8660}</td>
<td>0.7591</td>
</tr>
<tr>
<td></td>
<td>Deltares</td>
<td>0.8295</td>
<td>0.8598</td>
<td>0.7600</td>
</tr>
<tr>
<td>Marginal</td>
<td>Uncorrected</td>
<td>0.7798</td>
<td>0.8013</td>
<td>0.7115</td>
</tr>
<tr>
<td></td>
<td>BD18</td>
<td>0.7827</td>
<td>0.8065</td>
<td>0.7089</td>
</tr>
<tr>
<td></td>
<td>BD18 Mod</td>
<td>\textbf{0.7856}</td>
<td>\textbf{0.8108}</td>
<td>0.7105</td>
</tr>
<tr>
<td></td>
<td>Deltares</td>
<td>0.7780</td>
<td>0.8011</td>
<td>\textbf{0.7116}</td>
</tr>
<tr>
<td>Moderate</td>
<td>Uncorrected</td>
<td>\textbf{0.6577}</td>
<td>0.6880</td>
<td>0.6387</td>
</tr>
<tr>
<td></td>
<td>BD18</td>
<td>0.6524</td>
<td>0.6884</td>
<td>0.6178</td>
</tr>
<tr>
<td></td>
<td>BD18 Mod</td>
<td>0.6554</td>
<td>0.6899</td>
<td>0.6201</td>
</tr>
<tr>
<td></td>
<td>Deltares</td>
<td>0.6530</td>
<td>\textbf{0.6901}</td>
<td>0.6208</td>
</tr>
<tr>
<td>Severe</td>
<td>Uncorrected</td>
<td>0.7100</td>
<td>0.6912</td>
<td>0.7602</td>
</tr>
<tr>
<td></td>
<td>BD18</td>
<td>0.7098</td>
<td>0.6895</td>
<td>0.7665</td>
</tr>
<tr>
<td></td>
<td>BD18 Mod</td>
<td>\textbf{0.7120}</td>
<td>0.6914</td>
<td>\textbf{0.7696}</td>
</tr>
<tr>
<td></td>
<td>Deltares</td>
<td>0.7116</td>
<td>\textbf{0.6932}</td>
<td>0.7614</td>
</tr>
</tbody>
</table>
Figures

**Figure 2.1.** Schematic of thin-layer effect for a sand layer of varying thickness embedded in a clay layer (Idriss and Boulanger 2008; reprinted with permission from EERI).

**Figure 2.2.** Stratigraphy, relative density ($D_R$), and thin layer thickness to cone diameter ratio ($H/d_{cone}$) of each of the De Lange (2018) calibration chamber soil models. The white and gray areas represent the layers of Baskarp B15 sand and Vingerling K147 clay, respectively.
Figure 2.3. Thin-layer factors for sand layers derived from the Boulanger and DeJong (2018) inversion procedure (BD18) with and without smoothing and filtering (designated as $K_{H,\text{net}}$ and $K_H$, respectively) (Boulanger and DeJong 2018; used under CC BY-NC-ND).

Figure 2.4. Normalized cone penetration filter, $w_c/(w_c)_{z'=0}$, vs. normalized depth, $z'$, from the cone tip (Boulanger and DeJong 2018; used under CC BY-NC-ND).
Figure 2.5. (a) Unstable results after removal of smoothing procedure from the BD18 procedure as applied to CPT data from the De Lange (2018) dataset; and (b) Error plot after removal of the smoothing procedure during inversion. Solution does not converge after 500 steps with $err < 10^{-6}$.

Figure 2.6. Thin-layer correction factors ($K_H$) derived from laboratory test results (shown as points) and numerical simulations using the Koppejan method (shown as curves) (after De Lange 2018).
Figure 2.7. Relationship between normalized thin layer thickness ($H/d_{cone}$) and the curve fitting parameter $m$.

Figure 2.8. Thin-layer correction factor ($K_H$) curves for several normalized thin layer thicknesses ($H/d_{cone}$) shown as lines and $K_H$ values derived from the calibration chamber tests shown as points.
Figure 2.9. Results from thin-layer correction procedures applied to: (a) Soil Model 1 (reference soil model - no thin clay layers); (b) Soil Model 4 with 40-mm-thick clay layers represented by the shaded areas; (c) Soil Model 8 with 20-mm-thick clay layers represented by the shaded areas; and (d) Soil Model 10 with 20-mm-thick clay layers represented by the shaded areas, where $q^m$ is measured tip resistance, $q^{inv}$ is the inverted tip resistance per the Boulanger and DeJong (BD18) procedure, $q^{invmad}$ is the inverted tip resistance per the modified BD18 procedure (BD18MOD), $q^{corr}$ is the corrected tip resistance from the Deltares procedure, and $q'$ is the true tip resistance (as measured in reference sand model).
Figure 2.10. Conceptual illustration of ROC analyses: (a) frequency distributions of liquefaction manifestation and no liquefaction manifestation observations as a function of LPI; (b) corresponding ROC curve, where the area under the ROC curve (AUC) is used to assess the efficiency of a diagnostic test (after Maurer et al. 2015a, b).
Chapter 3: Correcting Measured CPT Tip Resistance for Multiple Thin-Layer Effects

The contributions of the authors to the composition of this manuscript are delineated as follows:

**Kaleigh M. Yost**
- Developed scope of the manuscript.
- Developed the Deltares multiple thin-layer correction procedure.
- Performed assessment of efficacy of existing multiple thin-layer correction procedures.
- Prepared the figures and tables.
- Wrote the draft and final manuscripts.

**Jon Cooper**
- Developed the Cooper et al. (2022) multiple thin-layer correction procedure.
- Performed analyses that helped inform the discussions in this manuscript.

**Dr. Russell A. Green**
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

**Dr. Eileen Martin**
- Developed the Cooper et al. (2022) multiple thin-layer correction procedure.
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

**Dr. Alba Yerro**
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft manuscripts.
Correcting Measured CPT Tip Resistance for Multiple Thin-Layer Effects

Kaleigh M. Yost¹, Jon Cooper², Russell A. Green³, Eileen Martin⁴, and Alba Yerro⁵

¹Graduate Student, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Graduate Student, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: jonc7@vt.edu)
³Professor, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)
⁴Assistant Professor, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: ermartin@vt.edu)
⁵Assistant Professor, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: averro@vt.edu)

Published by the CRC Press as a part of the proceedings of the 5th International Symposium on Cone Penetration Testing (CPT’22), 8-10 June 2022, Bologna, Italy

Reference:

3.1. Abstract
Multiple interbedded fine-grained layers in a sand deposit have a “smoothing” effect on the measured tip resistance ($q_c$) from the cone penetrometer test (CPT). This can result in an underestimation of the predicted liquefaction resistance of the sand layers. Herein, the efficacies of two multiple-thin-layer correction procedures are evaluated using published calibration chamber test data. The results highlight limitations of the assessed procedures for profiles with layers less than 40 mm thick. A new approach to estimate the “true” $q_c$ (i.e., values that would be measured in a stratum absent of multiple thin-layer effects) from measured $q_c$ is explored. The proposed numerical optimization algorithm searches for “true” soil profiles with a finite number of layers. We compare two versions of the algorithm that numerically optimize different functions, one of which uses a logarithm to refine fine-scale details, but which requires longer calculation times to yield improved corrected $q_c$ profiles.

3.2. Introduction
Cone penetrometer test (CPT) data (i.e., tip resistance, $q_c$, and sleeve friction, $f_s$) are typically reported at 1 to 2 cm depth increments. However, data measured at a given depth are not representative only of the soil at that discrete depth, but are actually averaged or “blurred” values of the “true” values that fall within a zone of influence above and below the cone tip. For example, this zone of influence can include soils that are as far away as 10 to 30 times the cone diameter ($d_{cone}$) ahead of the cone tip (Ahmadi and Robertson 2005). Thus, the presence of multiple interbedded fine-grained layers in a sand deposit can result in a significant underestimation of the predicted liquefaction resistance of the sand layers. This phenomenon is referred to as multiple thin-layer effects.

Several methods have been proposed to correct CPT data for multiple thin-layer effects. These procedures seek to use the measured CPT data in an interlayered soil profile and estimate the “true” CPT data that would be measured in the profile absent of multiple thin-layer effects (i.e., a true representation of the CPT data at a discrete depth in the profile). In general, approaches to correct for multiple thin-layer effects can be split into two categories: forward procedures and inverse procedures. In both cases, all procedures proposed thus far focus on correcting $q_c$, not $f_s$ (though
some provide methods to retroactively adjust $f_i$ based on the corrected $q_c$; complexities in correcting $f_i$ are briefly discussed in the Discussion and Conclusions of this paper.

Forward procedures, like the ones proposed by Youd et al. (2001), Ahmadi and Robertson (2005), de Greef and Lengkeek (2018), and others, apply a series of corrections directly to the measured $q_c (q^m)$ to obtain a “corrected” $q_c (q^{corr})$ that is a best estimate of the “true” $q_c$ (i.e., $q_c$ that would be measured in the profile absent of multiple thin-layer effects, $q'$). Inverse procedures (e.g., Boulanger and DeJong 2018; Cooper et al. 2022) start by making a guess of $q' (q^{inv})$ and then apply an artificial blurring model (representative of the blurring effect of the cone in layered soils) to $q^{inv}$ to obtain a “simulated” $q^m (q^{m,sim})$. Then, $q^{m,sim}$ is compared to the actual $q^m$. If the misfit between $q^{m,sim}$ and $q^m$ is too large, an update is automatically applied to provide a new, improved $q^{inv}$ guess. The procedure iterates until the misfit is acceptable, at which point the last guessed $q^{inv}$ is considered to be a best estimate of $q'$.

To develop and validate multiple-thin-layer correction procedures (forward or inverse), one must know both $q^m$ and $q'$ for a given layered soil profile. Typically, we only know $q^m$. CPT calibration chamber tests or numerical simulations can be used to obtain both $q^m$ and $q'$. In the following sections, the efficacy of existing forward and inverse procedures for correcting multiple thin-layer effects is assessed directly using calibration chamber data. Then, an alternate inverse procedure is proposed and assessed using the same calibration chamber data. Finally, a brief discussion of limitations and areas for future procedure improvement is provided.

3.3. Assessing Existing Procedure Efficacy

3.3.1. Overview of Deltares calibration chamber tests

A series of CPT calibration chamber tests performed at Deltares by De Lange (2018) were used to assess the efficacy of existing multiple-thin-layer correction procedures. Several soil profiles were considered in these tests, including layered sand-clay profiles and reference (single layer) sand profiles. The CPTs performed in the reference sand profiles were used to estimate $q'$ for the sand layers in the sand-clay models, where the reference sand profiles had similar relative densities ($D_R$) and overburden pressures ($\sigma^v$) to the sand layers in the layered sand-clay models. No reference clay profiles were constructed, however, $q'$ for the clay could be estimated from one of the sand-
clay models that had clay layers that were thick enough (200 mm, or 8\(d_{cone}\), thick) for \(q'\) to fully develop. Details of how the tests were performed and information about the soils used to create the profiles are excluded for brevity and can be found in De Lange (2018).

3.3.2. **Overview of Deltares forward procedure**

Trends observed by De Lange (2018) using the CPT calibration chamber dataset were used to develop a forward multiple-thin-layer correction procedure, the details of which are discussed thoroughly in Yost et al. (2021). This procedure, termed the Deltares [DEL] procedure, consists of two parts: (1) identification of layer interfaces based on peaks and troughs in \(q^m\), and (2) computation and application of a correction factor \(K_H\) (a function of: layer thickness, \(H\); \(d_{cone}\); and normalized ratio between minimum and maximum \(q^m\) in a layer, \(q_{ratio}\)) that increases tip resistance in thin dense layers. In short, the DEL procedure requires an input of \(q^m\) and outputs a corrected tip resistance (\(q_{corr}\)) that is an estimate of \(q'\). \(K_H\) factors developed for the DEL procedure are provided in Figure 3.1.

3.3.3. **Overview of BD18 inverse procedure**

The Boulanger and DeJong (2018) [BD18] inverse multiple-thin-layer correction procedure proposes that \(q^m\) is equal to \(q'\) convolved with a depth-dependent spatial filter, \(w_c\):

\[
q^m(z) = q'(z) * w_c(z)
\]  

(3.1)

where * represents a convolution, and \(q^m\), \(q'\), and \(w_c\) are all functions of depth (z). The spatial filter \(w_c\) is a discretization of a continuous function that represents the influence of soil above and below the cone tip on \(q_c\) at a particular depth. The BD18 procedure uses an iterative splitting optimization technique to solve the misfit function defined by:

\[
q^{inv} = \arg\min_{q'} \| q^m - q' * w_c \|_2
\]  

(3.2)

The BD18 procedure includes two steps to smooth the results to prevent them from becoming unstable: *first*, a smoothing step performed after each iteration of the inversion that computes a moving average of \(q^{inv}\) over a pre-defined smoothing window, and *second*, a low-pass spatial filtering step performed once the optimization procedure has converged to a solution. After the
optimization procedure is performed, a separate interface correction procedure is applied in which sharp transitions in $q^{inv}$ (which presumably correspond to layer interfaces) are identified. A constant value of $q^{inv}$ (either the maximum or minimum $q^{inv}$ identified in the transition zone) is then applied to the entire transition zone within a layer, effectively setting a single $q^{inv}$ value for each identified soil layer.

A modified version of this procedure, termed BD18MOD, was also explored in this study. For this variant of the procedure, the recommended smoothing and filtering steps that ensure convergence of the solution were adjusted. Specifically, the smoothing window was reduced to a maximum of three $q^m$ data points (the default smoothing window is max[3, ceiling(0.866$d_{cone}$/$\Delta z$)], where $\Delta z$ is the depth interval at which the data were collected), and the low pass spatial filtering step applied after the inversion was eliminated. We found that this improved the performance of the procedure in identifying very thin layers, but also destabilized the solution, resulting in non-convergence for some scenarios.

3.3.4. Assessment of procedures using calibration chamber dataset

Direct assessments of the efficacies of the DEL forward procedure, and the BD18 and BD18MOD inverse procedures were performed using the calibration chamber data from De Lange (2018). Note that this is a biased comparison of the efficacies of the procedures, since the DEL procedure was developed and calibrated using this dataset. Regardless, the DEL and BD18/BD18MOD procedures were applied to the $q^m$ for the layered sand-clay soil profiles reported by De Lange (2018). The resulting $q^{corr}$ (from the DEL procedure), $q^{inv}$ (from the BD18 procedure), and $q^{invmod}$ (from the BD18MOD procedure) were compared with the $q'$ determined from the reference sand profiles. Select results from this exercise are shown in Figure 3.2.

As shown in Figure 3.2a, the DEL procedure was effective at identifying the interbedded sand layers and outputting a $q^{corr}$ that is a good estimate of $q'$ for those layers. Conversely, the BD18 procedure does not identify the interbedded layers, and actually estimates a $q^{inv}$ slightly less than the $q^m$ (and significantly less than $q'$) in the interbedded sand layers. The $q^{inv}$ values estimated using the BD18MOD procedure in the interbedded sand layers are a better estimate of $q'$, but the layer interfaces are not well defined. The performance of these procedures was similar for all soil profiles in this dataset that contained layers that were 40 mm (or 1.6$d_{cone}$) thick.
For the soil profiles in the dataset with interbedded layers less than 40 mm thick, the efficacy of all procedures was poor, as exemplified in Figure 3.2b. None of the procedures were successful at identifying all of the 20-mm-thick layers in this profile or providing a good estimate of $q'$ for those layers, although the DEL procedure did a slightly better job at identifying the layer interfaces compared to the BD18 and BD18MOD procedures.

Several other useful observations were made during this exercise. None of the procedures performed well on the reference sand (single layer) soil models (i.e., all procedures erroneously identified and attempted to correct for thin, interbedded layers that were not present). In general, the BD18MOD procedure performed better than the BD18 procedure on this dataset, however, the modifications to the smoothing steps tended to de-stabilize the solution (e.g., see phantom peak and trough between 0.4 and 0.55 m in Figure 3.2b). Complete results from this analysis are provided in Yost et al. (2021).

3.4. Proposed Alternative Inverse Procedure

Because none of the procedures discussed in the previous section were shown to be especially effective at resolving multiple thin-layer effects for profiles with thin layers less than 40 mm thick, an alternative procedure is desired. The inverse approach proposed by Boulanger and DeJong (2018) is attractive because it is fully automated and incorporates an actual description of the physics behind multiple thin-layer effects (i.e., through the blurring model described by the convolution of $q'$ with the spatial filter $w_c$). Building on this approach, we pose the inverse problem in a new way by assuming that $q'$ is a piecewise constant function, and forcing guesses of $q'$ (i.e., $q^{inv}$) to be a piecewise constant function. Thus, the procedure searches for a finite number of layers in a soil profile, each having a thickness and constant $q^{inv}$. This approach differs from the BD18 approach, which solves for an independent $q^{inv}$ value at every depth, and then subsequently applies a procedure to impose a constant $q^{inv}$ within each identified layer. Reducing the number of degrees of freedom in the problem and eliminating the interface correction step results in a more computationally efficient procedure.

The inverse problem is posed to minimize the misfit function that describes the difference between the actual measured tip resistance profile ($q^m$) and the simulated measured tip resistance profile ($q^{m,sim}$), which is created by applying an artificial blurring filter to the $q^{inv}$ guess. We restrict $q^{inv}$ to
be a piecewise constant function defined by \( N \) layers, each paired with a \( q^{\text{inv}} \) value. Therefore, each proposed \( q^{\text{inv}} \) profile is described by a material property vector, \( m \), that has \( 2N \) components (i.e., thickness and \( q^{\text{inv}} \) for \( N \) layers), where \( N \) can be adjusted throughout the optimization. For any assumed \( m \), we can extract the \( q^{\text{inv}} \) values represented by the piecewise function at every depth of where CPT data were measured. The \( q^{\text{inv}} \) profile resulting from this reconstruction process is denoted by \( q^{\text{inv}}(m) \). The \( q^{\text{inv}} \) profile with the minimized misfit is likely to be a good estimate of the \( q' \) profile, but numerical optimization algorithms may yield different answers depending on the choice of the misfit function. Written as an equation, this algorithm optimizes:

\[
m^{\text{inv}} = \arg\min_{m \in \mathbb{R}^{2N}} \left\| q^m - q^{m,\text{sim}}(q^{\text{inv}}(m)) \right\|_2
\]  

(3.3)

This is not the only way to pose the optimization problem. For applications where both large-scale and fine-scale features contribute to the misfit, a logarithmic misfit function can be more appropriate and is thus proposed as an alternative to Equation 3.3:

\[
m^{\text{inv}} = \arg\min_{m \in \mathbb{R}^{2N}} \log \left( \left\| q^m - q^{m,\text{sim}}(q^{\text{inv}}(m)) \right\|_2 \right)
\]  

(3.4)

This procedure, including both forms of the misfit function, is detailed in Cooper et al. (2022) [Cea22] and is summarized in Figure 3.3.

In addition to posing the optimization problem, it is necessary to select a numerical optimization algorithm to iteratively update the \( q^{\text{inv}} \) guess. Cooper et al. (2022) utilizes a Particle Swarm Optimization (PSO) algorithm that identifies minima of the selected misfit function. PSO was selected because it is able to test many widely varying guesses of \( m \), overcoming the challenges often associated with global versus local minima. Consequently, small adjustments to layer thicknesses or assumed \( q^{\text{inv}} \) only marginally affect \( q^m - q^{m,\text{sim}} \). To optimize the PSO algorithm, two additional computational procedures are proposed. An add-one-in (AOI) algorithm is utilized to automatically add new layers between existing layers to assess whether the addition of that layer reduces the misfit function of the proposed profile. A leave-one-out (LOO) algorithm is utilized to remove insignificant layers from the guessed values of \( q^{\text{inv}} \) that are not physically realistic and contribute to unnecessary additional degrees of freedom.
A key component of this procedure is the application of an artificial blurring filter to the guessed value of $q^{inv}$. The Cea22 procedure adopts the same framework to describe this blurring as proposed by BD18 (i.e., Equation 3.1). However, they propose a blurring filter that is a scaled and truncated chi-squared distribution, selected for its asymmetry, smoothness, and relatively good match with the De Lange (2018) calibration chamber data:

$$q^{m,\text{sim}}(z) = (q^{m,\text{sim}}(q'))(z) = \int_{-\infty}^{\infty} q'(\Delta z)p(z - \Delta z)d\Delta z$$

where $\int_{-\infty}^{\infty} p(z)dz = 1$ and $p(z) \geq 0$ for all $z$. In practice, this integral is only calculated over a finite interval. This blurring function was chosen because it is simple to implement and only requires the use of a matrix convolution function (“conv” in MATLAB). This blurring function results in $q^{m,\text{sim}}$ values that represent a weighted combinations of the $q'$ values of the surrounding soil layers at a given depth. Although this method can quickly compute $q^{m,\text{sim}}$ for any $q^{inv}$ guess, it is a simplification of true physics and could be improved upon in future work. This is exemplified by the difference between the actual observed $q^m$ in the layered soil profile (shown in solid black) and the $q^m$ derived from applying the blurring filter to the known $q'$ (shown in solid blue) in Figure 3.4, and is discussed further in the Discussion and Conclusions.

The Cea22 procedure was applied to the De Lange (2018) calibration chamber data using the $q^m$ derived from applying the blurring filter to $q'$ (i.e., the blue solid line in Figure 3.4), in lieu of using the actual measured $q^m$. It was found that the algorithm with the logarithmic misfit function (i.e., Equation 3.4) was more effective than the standard misfit function (i.e., Equation 3.3) at refining the very thin layers in the calibration chamber test soil profiles; see Figure 3.4. The $q^{inv}$ resulting from the standard misfit function missed several thin layers in $q'$, while the $q^{inv}$ resulting from the logarithmic misfit detects each of the thin layers in the layered zone.

Both algorithms (standard and logarithmic misfit) had $q^{m,\text{sim}}$ closely matching $q^m$ derived from application of the assumed blurring filter to the known $q'$, indicating that the increase in computational rigor provided by the logarithmic misfit algorithm was required to achieve the detailed match between $q^{inv}$ and $q'$ for this profile. Results were similar for other profiles in the De Lange (2018) dataset and are examined in more detail in Cooper et al. (2022).
3.5. Discussion and Conclusions
Multiple thin-layer effects in CPT data can be addressed using forward or inverse procedures. In this paper, a new forward method (DEL procedure) and a new inverse method (Cea22 procedure) are compared to the existing inverse procedure proposed by Boulanger and DeJong (2018) [BD18] using a set of calibration chamber data collected by De Lange (2018). It is shown that neither the DEL nor the BD18 procedure are effective in correcting for multiple thin-layer effects in profiles with soil layers less than 40 mm thick, with the DEL procedure yielding slightly better results than the BD18 procedure. Because this type of profile is of particular interest for liquefaction assessment, it is desirable to improve on these procedures.

The Cea22 procedure poses the inverse problem that was first proposed by Boulanger and DeJong (2018), but in a new way—searching for a finite number of soil layers each with a thickness and constant $q'$. Application of this procedure indicates that this new formulation is better able to identify thin, interbedded layers than the DEL, BD18, or BD18MOD procedures. Furthermore, the restriction on number of degrees of freedom is computationally efficient. It was shown that the logarithmic misfit function is more effective at identifying very thin layers than the standard misfit function. There are tradeoffs in using the standard versus logarithmic misfit function, namely, use of the logarithmic misfit function is significantly more computationally expensive (i.e., 5 to 10 minutes runtime for CPT soundings with several hundred data points, compared to 1 to 2 minutes for the standard misfit function). However, the use of the logarithmic misfit function is anticipated to be worth the extra computational time for highly stratified soil profiles.

Inverse procedures like the BD18 and Cea22 procedure require an artificial “blurring” that mimics multiple thin-layer effects in CPT data. Thus far, simple blurring models have been adopted. For example, the Cea22 procedure uses a convolution of a point spread function derived from the Chi squared probability density function. As shown in Figure 3.4, this method does not capture well the true complexity of the physics involved with cone penetration through layered profiles and can be improved upon. If the $q'$ is known for a profile, a $q''$ derived from applying the blurring filter to $q'$ can be used as input to the multiple-thin-layer correction procedure to assess the efficacy of the procedure itself, without assessing the accuracy of the blurring filter. This is the approach taken in
this paper to assess the Cea22 procedure. Developing a more accurate blurring filter is the focus of ongoing work.

A persistent challenge in developing and validating multiple-thin-layer correction procedures is the lack of available \( q'' \) and \( q' \) pairs for a given layered soil profile. These data can only come from calibration chamber tests (e.g., De Lange 2018) or from numerical simulations. Towards this end, numerical simulations of CPT in layered profiles, like those from Yost et al. (2022), can supplement the limited available calibration chamber data and be used to develop and calibrate these methods. Numerical simulations should be calibrated and validated with laboratory calibration chamber data if possible.

Finally, all the procedures discussed in this paper focus on developing methods to correct CPT \( q_c \) for multiple thin-layer effects. However, CPT \( f_s \) is perhaps even more subject to multiple thin-layer effects owing to the large size of the sleeve friction sensor (typically ~110 to 134 mm in length). As a result, the friction sleeve will likely be in contact with multiple soil layers at once in a highly interlayered profile. Additionally, resolving the \( f_s \) for a given layer is further hampered by soil from overlying layers being dragged down into underlying layers as the cone advances, which has been observed both experimentally (i.e., De Lange 2018) and numerically (i.e., Yost et al. 2022). Since \( f_s \) is required to compute normalized soil behavior type index \( (I_c) \) for liquefaction triggering calculations, it is critical that future work addresses multiple thin-layer effects on \( f_s \).

References


Figures

**Figure 3.1.** Thin-layer correction factor ($K_H$) values derived from the De Lange (2018) calibration chamber tests (shown as points) were used to define $K_H$ curves for several normalized thin-layer thicknesses ($H/d_{cone}$) for the Deltares procedure (Yost et al. 2021a).
Figure 3.2. Results from application of multiple-thin-layer correction procedures to De Lange (2018) calibration chamber data for: (a) Soil Model 4 with 40-mm-thick clay layers; and (b) Soil Model 8 with 20-mm-thick-clay layers (Yost et al. 2021a).

Figure 3.3. Comparison between Cea22 inverse procedure using the standard misfit function and the logarithmic function on data from Soil Model 9 CPT 3 from De Lange (2018) (modified from Cooper et al. 2022).
Figure 3.4. Cea22 inverse approach to correct for multiple-thin-layer effects in CPT tip resistance (modified from Cooper et al. 2022).
Chapter 4: MPM Modeling of Cone Penetrometer Testing for Multiple Thin-Layer Effects in Complex Soil Stratigraphy

The contributions of the authors to the composition of this manuscript are delineated as follows:

Kaleigh M. Yost
- Co-developed scope of the manuscript.
- Performed literature review.
- Performed the numerical simulations presented in this study.
- Prepared the figures and tables.
- Wrote the draft manuscript.
- Addressed coauthor comments in manuscript revisions.
- Addressed reviewer comments and prepared the final version of the manuscript.

Dr. Alba Yerro
- Co-developed scope of the manuscript.
- Reviewed and edited the draft manuscripts.
- Addressed reviewer comments and reviewed final version of the manuscript.

Dr. Russell A. Green
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

Dr. Eileen Martin
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

Jon Cooper
- Performed analyses that helped inform the discussions in this manuscript.
MPM Modeling of Cone Penetrometer Testing for Multiple Thin-Layer Effects in Complex Soil Stratigraphy

Kaleigh M. Yost\textsuperscript{1}, Alba Yerro\textsuperscript{2}, Russell A. Green\textsuperscript{3}, Eileen Martin\textsuperscript{4}, and Jon Cooper\textsuperscript{5}

\textsuperscript{1}Graduate Student, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
\textsuperscript{2}Assistant Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: ayerro@vt.edu)
\textsuperscript{3}Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)
\textsuperscript{4}Assistant Professor, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: ermartin@vt.edu)
\textsuperscript{5}Graduate Student, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: jonc7@vt.edu)

Submitted to Journal of Geotechnical and Geoenvironmental Engineering
Submitted on: 23 March 2021
Accepted for Publication: 7 October 2021
Published Online: 15 December 2021

Used with permission from ASCE

Reference:
4.1. Abstract
Cone penetrometer testing (CPT) is a frequently used soil characterization technique for liquefaction assessment; however, this technique has shortcomings in accurately characterizing very thin soil layers having thicknesses less than two to three times the diameter of the cone. In this study, the material point method (MPM) is used to generate numerical "measured" (or "blurred") CPT tip resistance ($q^m$) in complex soil profiles. Results show that MPM is capable of accurately simulating $q^m$ in soil profiles with layers as thin as 20 mm, even when using basic constitutive models and simplified drainage conditions. It is further shown that MPM simulations are able to replicate the tendency of the CPT to smear the boundaries between very thin, interbedded soil layers in a way that obscures their true thickness and stiffness (typically referred to as thin-layer, transition-zone, or multiple thin-layer effects). While previous numerical studies of CPT have been performed in profiles comprised of two or three layers, this study considers highly interlayered profiles with upwards of 27 soil layers. Difficulties of developing and implementing multiple thin-layer corrections are presented. It is shown that a numerical framework like MPM can generate a larger set of data for the development and validation of multiple thin-layer correction procedures with the aim of improving liquefaction severity predictions in complex soil profiles.

4.2. Introduction
Cone penetrometer testing (CPT) is one of the most frequently used soil characterization techniques for liquefaction triggering assessment. Many CPT-based procedures have been developed to predict liquefaction triggering from cone tip resistance, normalized to reference conditions (e.g., Boulanger and Idriss 2016; Green et al. 2019). While several of the currently used procedures have proven to be highly accurate in predicting the severity of liquefaction of uniform, cohesionless, and free-draining soil deposits (e.g., Green et al. 2014), significant difficulties have arisen in predicting severity of liquefaction in soil deposits with complex stratigraphy (i.e., sand profiles with multiple thin, interbedded silt and/or clay layers). This in part can be attributed to the tendency of the CPT to "blur" the boundaries between very thin, interbedded soil layers in a way that obscures their true thickness and stiffness (Boulanger et al. 2016), often described as thin-layer, transition-zone, or multiple thin-layer effects (the distinction between which will be made clear subsequently). In keeping with the notation used in prior literature (e.g., Boulanger and DeJong 2018; Yost et al. 2021), the following definitions are utilized in this paper:
• $q^m$ - the "measured" or "blurred" tip resistance recorded (either experimentally or numerically) during a CPT in a soil profile of any number of layers

• $q'$ - the "true" or fully developed tip resistance that would be recorded (either experimentally or numerically) in a soil layer of infinite thickness, absent of any influence of other layers

Figure 4.1 illustrates the thin-layer and transition-zone effects on $q^m$ for a series of soil profiles each consisting of an increasingly thin, stiff sand layer (with a known $q'_{sand}$) embedded in softer clay. Two related phenomena are evident:

1. The maximum $q^m$ in the thin sand layer decreases in magnitude as the thickness of the layer decreases. If the sand layer is not thick enough, the maximum $q^m$ in the sand layer may never reach $q'_{sand}$. This phenomenon is typically referred to as the **thin-layer effect**.

2. $q^m$ does not transition abruptly at the layer boundary, but rather, it is influenced by the material both above and below the boundary such that a smooth transition zone exists where $q^m$ is neither representative of the fully developed $q'$ of the sand or clay alone, but reflects a combination of both. This phenomenon is typically referred to as the **transition-zone effect**.

Although not illustrated in Figure 4.1, multiple thin soil layers occurring in sequence in a profile can make interpretation of $q^m$ even more ambiguous, because both thin-layer and transition-zone effects can overlap several times over. This is henceforth referred to as **multiple thin-layer effects**.

Many studies have discussed the potential contribution of thin-layer, transition-zone, and multiple thin-layer effects to the over-prediction of liquefaction severity at sites with complex stratigraphy in Christchurch, New Zealand (e.g., Beyzaei et al. 2015; Cox et al. 2017; McLaughlin 2017; Beyzaei et al. 2018; Yost et al. 2019). Several procedures to correct for transition-zone, thin-layer, and multiple thin-layer effects have been proposed. Thin-layer effects have often been addressed by applying a thin-layer correction factor ($K_H$) to the peak $q^m$ in a given thin layer to obtain the "true" tip resistance ($q'$) (Youd et al. 2001; Ahmadi and Robertson 2005; Mo et al. 2017). Other procedures incorporate thin-layer correction factors and layer interface detection such that $K_H$ is applied not just to the peak $q^m$ in a given layer, but across the entire thickness of the layer (de Greef and Lengkeek 2018; Yost et al. 2021). Recently proposed procedures use an inverse problem approach to "deblur" $q^m$ and provide a best-estimate of $q'$ without having to manually apply correction
factors (Boulanger and DeJong 2018; Cooper et al. 2021), though $K_H$ can be computed using these methods for purposes of comparison. These methods assume an underlying model that describes the influence of soil stiffness away from the tip of the cone on the $q^m$ reported at a given depth. This assumed model, along with $q^m$, is used as input to an iterative optimization procedure that estimates $q'$. 

One of the challenges of developing and validating these correction procedures is the lack of available datasets that contain both $q^m$ and $q'$ for a soil profile. For example, field CPT data alone only provide $q^m$. Laboratory calibration chamber studies, such as those performed by De Lange (2018), can provide both $q^m$ and $q'$ by performing CPTs in both single-layer and multi-layered soil profiles prepared under similar conditions. However, few calibration chamber studies of CPT in layered soil profiles exist. Thus, numerical tools are essential in supplementing the limited available laboratory data to understand thin-layer, transition-zone, and multiple thin-layer effects. Numerical tools can generate both $q^m$ and $q'$ for a single soil profile, where $q^m$ in this context is simply referred as the "measured" or "blurred" tip resistance.

In this paper, the state-of-the-art of numerical modeling of CPTs in layered soil profiles is discussed and the material point method (MPM) is proposed as a particularly appropriate numerical technique for modeling large soil deformations associated with CPTs. Subsequently, a series of laboratory calibration chamber tests in which CPTs were performed in layered soil profiles is summarized. Then, a 2D-axisymmetric MPM framework to simulate a CPT is presented and the calibration chamber tests are used to calibrate and validate this model. It is shown that validated MPM numerical simulations are capable of generating numerical $q^m$ and $q'$ in layered soil profiles. The validated MPM model is then used to study thin-layer, transition-zone, and multiple thin-layer effects for soil profiles consisting of two, three, and upwards of 27 layers.

4.3. Previous Numerical Studies of Cone Penetrometer Tests

4.3.1. Numerical Modeling of CPT in Uniform Soil Profiles

Previous numerical studies of cone penetration can be categorized into two groups: those utilizing either "indirect" or "direct" models, as discussed by Moug et al. (2019). Indirect models use semi-empirical relationships and cavity expansion theory to compute cone tip resistance (e.g.,
Salgado and Prezzi 2007, Mo et al. 2014, Mo et al. 2017; Tehrani and Galavi 2018). Direct models numerically simulate penetration of the cone to compute tip resistance. This section focuses on previous studies in which direct numerical models of CPTs were used.

Successful direct numerical modeling of cone penetration must overcome several challenges including large soil deformations, soil-cone interaction, and complicated drainage conditions. Due to the rotational symmetry of cone penetration, it is often modeled using 2D-axisymmetric numerical formulations - or as a 3D "slice" through the center of the cone - to reduce the computational cost of the analysis. Many direct numerical studies of cone penetration have been performed (the reader is directed to Moug et al. 2019 for an extensive list). The vast majority used some version of the finite element method (FEM) or finite difference method (FDM) and employed re-meshing techniques such as an Arbitrary Lagrangian Eulerian (ALE) algorithm (e.g., van den Berg et al. 1996) or adaptive remeshing (e.g., Susila and Hryciw 2003) to overcome issues that FEM and FDM experience with significant mesh deformation and entanglement when modeling large soil deformations.

More recently, MPM has been used successfully to simulate cone penetration testing and has been shown to be especially capable of overcoming numerical limitations associated with large deformations (e.g., Beuth and Vermeer 2013; Al-Kafaji 2013; Ceccato et al. 2015; Ceccato et al. 2016a; Ceccato et al. 2016b; Martinelli and Galavi 2021; Bisht et al. 2021). For rotationally symmetric problems, the computational cost of MPM can be reduced by using a 2D axisymmetric formulation (e.g., Sulsky and Schreyer 1996, Galavi et al. 2018). Galavi et al. (2018) and Tehrani and Galavi (2018) found excellent agreement between tip resistance obtained from 2D axisymmetric MPM simulations of CPT in uniform sand profiles and those from cylindrical cavity expansion theory from Salgado and Prezzi (2007).

4.3.2. **Numerical Modeling of CPT in Layered Soil Profiles**

Extensive studies have been performed to examine CPT behavior in layered soils, including those using elastic methods (Vreugdenhil et al. 1994; Yue and Yin 1999), cavity expansion theory (Sayed and Hamed 1987; Xu and Lehane 2008; Mo et al. 2017), and experimental studies including calibration chamber tests (Treadwell 1976; Hird et al. 2003; Mlynarek et al. 2012; Tehrani and Galavi 2018) and centrifuge tests (Silva and Bolton 2004, Mo et al. 2015). Of particular interest to
In this study, several direct numerical studies of cone penetration in layered soil profiles using FEM or FDM have been performed (van den Berg et al. 1996; Ahmadi and Robertson 2005; Hryciw et al. 2005; Walker and Yu 2010). To our knowledge, MPM has never been used to study CPT in layered soil profiles. Furthermore, we are not aware of any numerical studies (using FEM, FDM, MPM, or otherwise) that consider CPT in soil profiles with more than three layers. The four aforementioned studies of CPT in layered soils focused on profiles only comprised of two or three layers, configured in four different ways: (1) a soft layer overlying a stiff layer; (2) a stiff layer overlying a soft layer; (3) a stiff layer embedded in softer layers; and (4) a soft layer embedded in stiffer layers. These four cases are shown schematically in Figure 4.2.

The aforementioned studies quantified thin-layer and transition-zone effects using several parameters shown in Figure 4.2 and defined as:

- Sensing distance, $S$, or the distance above the layer interface that $q''$ begins to be influenced by the underlying layer.
- Development distance, $D$, or the distance below the layer interface where $q''$ is no longer influenced by the overlying layer.
- Minimum layer thickness, $T$, required for $q''$ to reach $q'$ (or "fully develop") in a thin layer embedded in another material.

A summary of $S$, $D$, and $T$ values obtained from the studies performed by van den Berg et al. (1996), Ahmadi and Robertson (2005), Hryciw et al. (2005), and Walker and Yu (2010) are provided in Tables 4.1 and 4.2. It is observed from these studies that $S$, $D$, and $T$ depend strongly on the type of soil, the ratio of stiffness between layers, and the effective horizontal stress (Ahmadi and Robertson 2005). Unfortunately, each aforementioned study used different soil types, defined stiffness ratios uniquely, and imposed varying stress conditions on their soil profiles, making direct comparisons difficult. For example, Walker and Yu (2010) only studied layered clay profiles, and varied the stiffness between layers by changing the rigidity index ($I_R$), the ratio between shear modulus and undrained shear strength. Alternatively, Ahmadi et al. (2005) considered layered sand and layered sand-clay profiles, in which they varied stiffness through changing Young’s Modulus ($E$) and Poisson’s ratio ($\nu$). Vertical effective stress ($\sigma'_v$) and at-rest
earth pressure coefficient \((K_0)\) also varied between studies. To the extent possible, details including soil type, soil stiffness parameters \((E, v,\) and \(I_R)\), and stress conditions \((\sigma', K_0)\) that were used in each study are provided for comparison in Tables 4.1 and 4.2. If a particular study did not directly report one or more of the aforementioned parameters, we computed the values based on provided information, if possible.

It is difficult to generalize \(S, D,\) and \(T\) across a broad spectrum of possible soil conditions, but the following can be summarized for the conditions presented in Tables 4.1 and 4.2:

- The greater the stiffness contrast between two layers, the larger \(S\) and \(D\) will be.
- \(S\) and \(D\) are significantly smaller in clay layers (about 2 to 3 times the diameter of the cone, \(d_{cone}\)) than in sand layers (about 10\(d_{cone}\) to 20\(d_{cone}\)).
- \(T\) is greatest for dense sand layers embedded in soft clays (up to about 30\(d_{cone}\)) and is significantly smaller for loose sand layers embedded in soft clays (about 4\(d_{cone}\)).
- \(T\) is only about 2\(d_{cone}\) for soft clay layers embedded in stiffer clays.

This summary highlights that the magnitude of thin-layer and transition-zone effects are highly variable depending on the specific soil conditions and that detailed numerical analysis can be used to quantify \(S, D,\) and \(T\).

4.4. **The Material Point Method**

The material point method (MPM), originally proposed by Sulsky et al. (1994, 1995), is an advanced continuum-based numerical framework that integrates the advantages of point-based (e.g., smoothed-particle hydrodynamics) and mesh-based (e.g., finite element method) procedures. A basic illustration of MPM is shown in Figure 4.3. In MPM, a continuum body is represented by a set of Lagrangian material points (MPs) that carry all the properties associated with the continuum (e.g., mass, state parameters, stresses, strains, velocities, displacements, etc.). The MPs move through a background computational mesh. Constitutive equations and mass balances are solved at the locations of the MPs, and momentum balance equations are solved at the locations of the nodes. Data are mapped between the MPs and nodes using shape functions (linear shape
functions were used in this study). No permanent information is stored at the nodes, which eliminates problems with mesh distortion.

MPM is particularly well suited for large deformation problems (such as modeling CPTs) because it overcomes limitations of extreme mesh distortion. The analyses presented in this paper were performed using a modified version of the open-source Anura3D MPM software (Anura3D 2021). This implementation contains several advancements to the basic MPM implementation to help address common numerical issues associated with MPM. An MPM-mixed integration scheme (Al-Kafaji 2013) was utilized in which Gauss-point integration is used in fully filled elements (elements that contain MPs that cumulatively represent a volume greater than 90% of the element volume [Fern et al. 2019]) to reduce noise caused by cell crossing instabilities (when MPs move across element boundaries) (e.g., Zhou et al. 1999). A strain-smoothening technique and a mass scaling technique were used to reduce issues of volumetric locking and optimize computational time, respectively (Al-Kafaji 2013). Additionally, this analysis used a moving mesh technique to maintain a well-defined contact geometry between the cone and the soil (Al-Kafaji 2013), a contact algorithm to describe the soil-cone interaction (based on Bardenhagen et al. 2001), and a rigid body algorithm for the cone to enforce incompressibility and reduce computational cost (Zambrano-Cruzatty and Yerro 2020); these are further described in the MPM Model section.

4.5. Physical Calibration Chamber Tests
Laboratory data were required to calibrate and validate the MPM model. Towards this end, data were gathered from laboratory calibration chamber tests performed by De Lange (2018). The tests consisted of advancing CPTs through uniform sand and layered sand-clay profiles. Detailed information about these tests is provided in De Lange (2018) and, thus, is only summarized herein.

4.5.1. Experimental Setup
The calibration chamber used by De Lange (2018) consisted of a series of stacked 0.9-meter-diameter cylindrical steel cells lined with a flexible rubber membrane. A 0.96-meter-tall soil sample was prepared within the stacked cells. Vertical confinement was applied via a flexible water-filled cushion placed on top of the soil sample and lateral confinement was applied by pressurizing water in the annular space between the chamber wall and the membrane. After the chamber was pressurized and the clay layers were allowed to consolidate, CPTs were performed by advancing
cones through ports in the top of the chamber and the water-filled cushion and into the soil sample via a hydraulic jacking unit. The cones were advanced at a rate of 4 mm/sec and tip resistance and sleeve friction measurements were taken every 1 mm. A diagram of the calibration chamber set-up is shown in Figure 4.4.

Ten different soil profiles were constructed including uniform sand profiles and layered sand-clay profiles with varying layer thicknesses \((H)\) and sand relative densities \((D_R)\). The uniform sand profiles and the sand layers in the layered profiles were prepared via water pluviation, which ensured a saturated sample. Measured \(D_R\) of the sand layers ranged from 29% to 61%. All sand layers in a given soil profile were prepared to the same \(D_R\). In the layered profiles, preformed clay bricks were placed side by side to create the clay layers. After soil sample preparation, stresses in the chamber were increased linearly at 1 kPa/min until the desired stress state was achieved. Generally, CPTs were performed in each soil profile at vertical stresses of 25, 50, and 100 kPa, where the confining stress was increased with each successive CPT. All tests were performed at \(K_0=0.5\) conditions. Herein, the De Lange (2018) tests will be referred to by their Soil Model (SM) number (indicating the profile stratigraphy and sand layer \(D_R\)) and their CPT number (indicating the stress conditions), as designated in Table 4.3.

4.5.2. Soil Properties

Soil profiles in the De Lange (2018) experiments were prepared using Baskarp B15 sand and Vingerling K147 clay, the index properties of which are summarized in Table 4.4. The strength parameters of the soils vary with \(D_R\) and horizontal confining pressure \((\sigma_3)\) and are discussed in the subsequent sections.

4.5.2.1. Vingerling K147 Clay Strength Parameters

De Lange (2018) provided results from \(K_0\)-Constant Rate of Strain (CRS) consolidation testing and four single-stage undrained anisotropic consolidated triaxial compression (ACU) tests performed on the Vingerling K147 clay. The results indicated that the clay had a preconsolidation stress of approximately 80 kPa. Furthermore, the undrained shear strength \((s_u)\) at various vertical consolidation stresses was reported and is summarized in Table 4.5.
4.5.2.2. Baskarp B15 Sand Strength Parameters

No triaxial tests were performed on the Baskarp B15 sand used in the De Lange (2018) study. Therefore, data from a set of 27 consolidated drained (CD) triaxial tests performed on the same sand, detailed in Ibsen and Bødker (1994) and Borup and Hedegaard (1995), were used to characterize the strength of the Baskarp B15 sand for this study. The CD triaxial tests were performed at $D_R$ of 1%, 51%, and 80%. Therefore, strength parameters derived from these tests at the appropriate confining pressures can be expected to bound the actual strength parameters of the sand used in the calibration chamber tests. The variation of peak friction angle ($\phi'_p$), residual friction angle ($\phi'_r$), peak dilatancy angle ($\psi_p$), and Young’s modulus ($E$) with $D_R$ and $\sigma_3$ is shown in Figure 4.5.

4.6. MPM Model

4.6.1. Geometry and Mesh

A 2D-axisymmetric MPM model was developed to replicate several of the calibration chamber tests described in the previous section using the Anura3D platform. The configuration of the model is shown in Figure 4.6, where the left boundary corresponds to the center of the cone (and axis of symmetry). The bottom and top boundaries of the mesh were fixed in the horizontal and vertical directions. The left and right boundaries were fixed in the horizontal direction. The vertical overburden pressure imparted on the soil by the fluid-filled cushion in the calibration chamber tests was modeled as a single layer of material with a density and height that result in a pressure identical to the overburden pressure applied in the calibration chamber. Stresses were initialized with a $K_0$ procedure with $K_0 = 0.5$ to replicate calibration chamber conditions.

The cone in the MPM model had an apex angle of 60 degrees and diameter ($d_{cone}$) of 25.3 mm, consistent with one of the cones employed in the De Lange (2018) laboratory testing. The tip of the cone was slightly rounded to minimize numerical instabilities. The cone was modeled as a rigid (incompressible) body that was advanced at a prescribed constant velocity into the soil. The rigid body algorithm developed by Zambrano-Cruzatty and Yerro (2020) was employed. The force imparted on the face of the cone was used to compute the tip resistance during the cone penetration. A constant velocity of 10 mm/sec was applied to the cone, in contrast to the 4 mm/sec used in the calibration chamber experiments. It was found that using a larger velocity decreased computational time and did not have an impact on the results.
To reduce computational time, only a portion of the calibration chamber width was included in the domain (the entire vertical height of the calibration chamber was included). The mesh of a typical model is comprised of 5,410 triangular elements and contains 63,753 material points (MPs). The mesh extended about $40d_{cone}$ below the tip of the cone in its initial position, and extended $10d_{cone}$ radially. A refined mesh was used in the region through which the cone penetrates and a higher density of MPs was assigned to the elements in this region to enhance the accuracy of the solution (Figure 4.6). A moving mesh technique (Beuth 2012; Ceccato and Simonini 2019) was employed to ensure the accurate definition of the contact surface between the cone and the soil throughout penetration. As the simulation progressed, the zone of mesh above the cone tip advanced downward at the same velocity as the cone, preserving the shape of the mesh elements and bringing the boundary conditions along with it (i.e., the fixed boundary at the top of mesh in Figure 4.6 moves downward with the mesh at the same velocity as the cone). Simultaneously, the zone of mesh beneath the cone vertically compressed. A local damping factor of 0.05 was implemented to reduce stress oscillations and a mass scaling factor of 10,000 was used to reduce computational time.

4.6.2. Soil-Cone Contact Properties

A contact algorithm after Bardenhagen et al. (2001) was used to describe the interaction between the soil and the cone. The definition of the soil-cone interaction in multi-thin layered profiles is complicated because of the presence of two types of soil (drained sand and undrained clay). Typically, it is appropriate to define the sand-cone interface using a frictional contact law and the clay-cone contact using an adhesion contact law, as described by Ceccato et al. (2017). Contact friction angle between cone and sand ($\delta$) can be expressed as a fraction of the sand’s effective friction angle ($\phi'$) as $\delta = \alpha \phi'$. Durgunoglu and Mitchell (1973) reported values of $\alpha$ ranging from 0.28 (for polished aluminum on sand) to 0.9 (for sanded aluminum on sand). Similarly, adhesion ($\alpha$) at the cone-clay interface can be defined as a fraction (a) of undrained shear strength ($s_u$), where $\alpha = 0$ and $\alpha = 1$ represent a fully smooth and fully rough clay-cone contact, respectively (e.g., van den Berg et al. 1996; Lu et al. 2004; Beuth 2012; Ceccato et al. 2017).

In this context, the nodes along the soil-cone interface (i.e., contact nodes) can be characterized by different contact properties (either the clay-cone or the sand-cone contact properties) depending on what soil type (i.e., clay MPs or sand MPs) is located in the adjacent elements. However, the results
from the experimental calibration chamber test clearly indicate that the cone drags soil from
overlying layers downward as it advances, resulting in a mixture of different soil types in the zone
immediately surrounding the cone (Figure 4.7). Numerically, this means that elements adjacent to
the cone in the layered soil zones can contain both sand and clay MPs (i.e., "mixed" elements).
Ideally, the soil-cone interface in these "mixed" contact nodes should be defined by a combination
of the sand-cone and clay-cone contact properties. For simplification, in the current study, mixed
contact nodes are assigned either clay-cone or sand-cone properties.

In order to examine the effect of this simple strategy, a sensitivity analysis was performed in
reference to the experimental test SM4 CPT2 (Figure 4.8). In the analysis, the contact properties
for sand-cone and clay-cone are varied as well as the prevailing contact properties (either sand-
cone or clay-cone) in the mixed contact nodes. Despite the differences, all the models present
similar trends of the tip resistance profile in the layered zone. A few items can be observed
from the results. (a) Varying δ between a reasonable range of values (Cases 1 to 3, corresponding to
α = 0.3, 0.5, and 0.8) has a relatively minor impact on the tip resistance within the layered zone
between 0.23 and 0.51 meters, and a much more significant impact the tip resistance on the
uppermost and lowermost thick sand layers. In general, α = 0.3 and α = 0.8 underestimates and
overestimates the tip resistance, respectively, while α = 0.5 better fits the experimental results. (b)
When sand-cone contact properties are assigned in mixed contact nodes (Case 1 to 3), the peak
and troughs in tip resistance in the layered zone are slightly offset from the experimental data.
(c) When clay-cone contact properties are assigned in mixed contact nodes (Case 4), the peak and
troughs in tip resistance in the layered zone are more aligned with the experimental data, but the tip
resistance in the layered zone is generally underestimated (even when using fully rough α = 1 clay-
cone contact properties, Case 4). (d) When sand-cone contact properties are assigned in mixed
contact nodes, the use of different contact properties for the clay-cone interface has an insignificant
impact on the results, indicating that clay-cone contact nodes are rare (e.g., Case 2 versus Case 5).
In this context, the contact properties from Case 5 are selected for reference in all the models
presented herein.

Furthermore, in elements that contained more than one material type due to soil downdrag or
movement of the mesh over soil layer boundaries (i.e., mixed elements), the original MPM-MP
scheme is considered in lieu of the MPM-mixed integration scheme (Fern et al. 2019). Thus, stresses were computed at each MP individually using the constitutive model associated with that MP. In general, the MPM-mixed integration scheme is more stable than the original MPM integration scheme because it mitigates stress oscillations caused by MPs crossing element boundaries. Therefore, MPM-mixed integration was used over the majority of the domain. Oscillations in tip resistance in the layered soil profiles were observed to be only slightly larger than those observed in the uniform soil profiles (e.g., numerical $q^m$ from SM1 CPT2 [uniform profile] had oscillations of $\sim 8\%$ while numerical $q^m$ from SM4 CPT2 [layered profile] had oscillations of $\sim 12\%$ in the layered zone). Notably, these oscillations are much smaller than those observed in the experimental $q^m$ (e.g., $\sim 25\%$ variation in experimental $q^m$ is observed for SM1 CPT2). Therefore, for the purposes of this study, problems with stress oscillations due to the use of the original MPM integration scheme in elements with more than one material type are considered to be insignificant.

4.6.3. Constitutive Behavior of Soils

All soil profiles used in the MPM simulations were assumed to be fully saturated. Furthermore, the sand layers were assumed to behave fully drained and the clay layers were assumed to behave fully undrained. While this assumption is a simplification of the actual drainage conditions, it was considered reasonable for the purpose of this study. Below, the constitutive models selected to simulate the behavior of the Vingerling K147 clay and Baskarp B15 sand in the MPM simulations are discussed.

4.6.3.1. Constitutive Behavior of Vingerling K147 Clay

The constitutive behavior of the clay layers was described using a total stress method and the Tresca failure criterion, which utilized the $s_u$ corresponding to the appropriate confining pressure, as reported in Table 4.5. The undrained stiffness parameters $E = 25,000 \text{ kPa}$ and $\nu = 0.49$ were assumed constant regardless of confining pressure.

4.6.3.2. Constitutive Behavior of Baskarp B15 Sand

The constitutive behavior of the sand layers was described using a strain-softening Mohr-Coulomb (SSMC) constitutive model. Results from the Ibsen and Bødker (1994) and Borup and Hedegaard (1995) CD triaxial tests were used to calibrate the SSMC model. Specifically, triaxial
tests performed with confining pressures ranging from 20 to 160 kPa for sand samples prepared at $D_R$ of 1%, 50%, and 80% were examined. This was expected to bound the behavior of the sand in the calibration chamber soil profiles that was prepared at $D_R$ ranging from 29% to 61% and subjected to confining pressures between 25 and 100 kPa.

The SSMC constitutive model (Yerro 2015) was selected based on clear post-peak strength decreases observed in the triaxial force-displacement results for sand prepared at $D_R$ of 50% and 80%, as shown in Figure 4.9. Strain-softening behavior was not observed for the samples prepared at $D_R = 1\%$. Thus, for soil profiles prepared at $D_R$ less than 50%, it was expected that dilatancy and strain-softening effects would diminish in importance, but the degree to which this would occur could not be quantified based on the available data. The variation of strength parameters presented in Figure 4.5 was used to select appropriate strength and stiffness parameters for the sand for each MPM simulation. A $v = 0.33$ was assumed for all simulations.

The SSMC constitutive model required the calibration of a shape factor, $\eta$, used to describe the rate of shear strength decrease with increased deviatoric strain (Yerro 2015). To determine the appropriate $\eta$, the technique described by Zambrano-Cruzatty and Yerro (2020), based on a smeared crack approach from Rots et al. (1985), was employed. A series of FEM numerical simulations was performed using weightless soil specimens one-quarter of the size of the experimental triaxial specimens (which were 71.5 mm by 69.7 mm). The numerical specimens were discretized with an element size of 6.25 mm, equivalent to the size of the elements used adjacent to the cone tip in the MPM CPT model. Then, the force-displacement results were compared with the force-displacement results from the laboratory triaxial tests. Due to the exponential nature of the SSMC model, the exact shape of the force-displacement curve observed in the laboratory triaxial tests cannot be replicated in the numerical simulation. However, an equal area below the numerical and experimental curves indicates that the same amount of energy is dissipated in both the numerical simulation and the laboratory tests, thus calibrating $\eta$. The results of this exercise are shown in Figure 4.9. It should be noted that, as shown in Figure 4.9, at $D_R$ of 1%, no strain softening is observed in the laboratory data and therefore a Mohr-Coulomb (in lieu of SSMC) constitutive model was used in the FEM triaxial simulations. Because area between the curves could not be
equated, it was expected that the MPM CPT simulations would be less accurate for sand layers with $D_R$ less than 50%.

4.7. Calibration and Validation of CPT models

4.7.1. Calibration of MPM Model with Experimental Uniform Soil Profiles
CPTs performed in two uniform sand profiles from the De Lange (2018) calibration chamber tests were used to calibrate the material parameters required for the SSMC constitutive model. Two CPTs were performed in Soil Model 1 ($D_R = 36\%$), one with 50 kPa vertical confining pressure and the other with 100 kPa. Three CPTs were performed in Soil Model 5 ($D_R = 60\%$) at 100 kPa vertical confining pressure. Using Figure 4.5 as a reference, a range of strength parameters was selected to input into MPM simulations corresponding to each experimental CPT. The resulting numerical measured tip resistance ($q^m$) was then compared to the experimental $q^m$. As shown in Figure 4.10, a reasonable fit between numerical $q^m$ and experimental $q^m$ was achieved with a range of strength parameters that are consistent with the triaxial testing (ranges used to achieve the numerical $q^m$ in Figure 4.10 are shown in Figure 4.5 as data bars). With the calibration of the uniform soil profiles complete, layered soil profiles were next examined.

4.7.2. Calibration of MPM Model with Experimental Layered Soil Profiles
Three CPTs performed in three different layered soil profiles from the De Lange (2018) experiments were selected to compare to numerical results from MPM simulations. First, numerical $q^m$ were calibrated with the experimental $q^m$ using the material parameters shown in Table 4.7. Then, numerical $q'_{sand}$ and $q'_{clay}$ were determined by simulating CPTs in uniform profiles of sand and clay, respectively, using the same strength and stiffness parameters used to obtain numerical $q^m$ in the layered profile. Finally, since the layer locations in each soil profile were known, numerical $q'$ for the entire layered profile could be constructed. Each of the aforementioned results for the three CPTs are shown in Figure 4.11.

The results presented in Figure 4.11 show that the calibrated MPM simulations are capable of replicating the experimental $q^m$ measured in the layered zones from the De Lange (2018) calibration chamber tests within an accuracy of about 14%. Numerical $q^m$ fits the experimental $q^m$ better for the denser soil profiles (Soil Model 4, CPT 2 with $D_R=54\%$ and Soil Model 8, CPT 1 with $D_R=61\%$)
compared to the looser soil profile (Soil Model 2, CPT 2 with $D_r=29\%$). This is likely because the SSMC constitutive model more accurately captures the behavior of the denser sand compared to the looser sand. Increased oscillation in numerical $q$ in the lower sand layers is observed for all three models, particularly between 0.5 and 0.6 meters for Soil Model 8. The primary source of this oscillation is unknown. However, the numerical $q$ is considered to be a good fit with the experimental $q$ within the layered zones of all three soil profiles shown in Figure 4.11.

### 4.8. Applications

The following sections demonstrate the application of the validated MPM CPT model to study thin-layer, transition-zone, and multiple thin-layer effects on $q$ data collected by CPTs. Results and their implications are discussed in relation to development and validation of correction procedures for thin-layer, transition-zone, and multiple thin-layer effects.

#### 4.8.1. Study of Thin-Layer and Transition Zone Effects

First, two- and three-layered soil profiles were constructed to quantify thin-layer and transition-zone effects to compare to previous studies. Two, two-layered soil profiles consisting of clay overlying sand and sand overlying clay were constructed (Cases 1 and 2, as shown in Figure 4.2) to determine sensing and development distances ($S$ and $D$). Two, three-layered soil profiles consisting of a thin sand layer embedded in clay and a thin clay layer embedded in sand were also constructed (Cases 3 and 4, as shown in Figure 4.2) to determine the required thickness of the thin layer to reach the fully developed tip resistance ($T$). For these analyses, the material parameters associated with Soil Model 4, CPT 2 presented in Table 4.7 were used. A comparison between the numerical $q$ and the numerical $q'$ is shown for the two-layered and three-layered soil profiles to examine transition-zone and thin-layer effects, as shown in Figures 4.12 and 4.13, respectively. The sensing and development distances ($S$ and $D$) and the minimum required thin-layer thickness ($T$) obtained from the simulations shown in Figures 4.12 and 4.13 compare well with those from similar simulations in existing literature, as shown in Table 4.8.

#### 4.8.2. Study of Multiple Thin-Layer Effects

Correction procedures that account for multiple thin-layer effects must overcome even more difficulties than the identification of layer interfaces and determination of $T$ illustrated by simulations in two- and three-layered soil profiles in the previous section. A particular difficulty is that existing
multiple thin-layer correction procedures (e.g., the Boulanger and DeJong 2018 [BD18] procedure, described briefly in the Introduction) do not accurately or reliably account for multiple thin-layer effects caused by soil layers less than about 2 to 3\(d_{cone}\) in thickness (Yost et al. 2021). To illustrate the need for correction procedures that are reliable for these very thin layers, we revisited the \(q''\) and \(q'\) profiles shown in Figure 4.11. Thin-layer correction factors, \(K_H\), for the thin sand layers in these soil profiles were computed using the numerical \(q''\) and \(q'\) of the sand to compare with \(K_H\) derived from the BD18 procedure. Numerical \(q'\) of the sand and clay layers were used as \(q'_{\text{strong}}\) and \(q'_{\text{weak}}\), respectively. The results are shown in Figure 4.14.

As shown in Figure 4.14, the smoothing and filtering steps in the BD18 procedure ensure that \(K_H\) trends toward unity, instead of infinity, as \(H/d_{cone}\) falls below 2 to 3. BD18 imposed this constraint for two reasons: 1) the inversion procedure becomes unstable and tends not to converge if \(K_H\) trends toward infinity, and 2) reliability of measured CPT data decreases as thickness of the thin layer becomes smaller than 2 to 3\(d_{cone}\). The constraint ensures that \(K_H\) is not overestimated in this zone of uncertainty where neither the CPT nor the inversion procedure is providing reliable data. However, as shown from the data points plotted in Figure 4.14 and associated with the numerical CPT results shown in Figure 4.11, actual correction factors in this region should be much higher than those suggested by the BD18 procedure. In fact, the data points from this study align well with the BD18 correction factors without smoothing and filtering, if they were to be extrapolated to smaller \(H/d_{cone}\) values. It is important, however, not to introduce unconservatively large \(K_H\) for very thin layers, which would result in overpredictions of layer stiffness. This is a problem that future correction procedures should attempt to address.

To further illustrate the difficulty in interpreting and correcting \(q''\) for multiple thin-layer effects caused by very thin soil layers, an additional set of numerical analyses was performed. A 0.28-meter-thick layered zone of soil was considered, and normalized layer thickness, \(H/d_{cone}\), was varied among simulations: 1.6, 1.2, 0.8, and 0.4 (significantly smaller than the 2 to 3\(d_{cone}\) limit mentioned previously). For these analyses, the material parameters associated with Soil Model 4, CPT 2 reported in Table 4.7 were used. The results are presented in Figure 4.15.
As shown in Figure 4.15, as \( H/d_{\text{cone}} \) decreases, numerical \( q'' \) is increasingly smoothed in the layered zone, until essentially no distinction between individual thin layers is identifiable. This loss of resolution in \( q'' \) is clearly visible when examining results from the simulations with \( H/d_{\text{cone}} = 0.8 \) and \( 0.4 \). Furthermore, \( q'' \) in the layered zone tends to converge to a particular value, one that is significantly closer to \( q'_{\text{clay}} \) than to \( q'_{\text{sand}} \).

4.9. Discussion and Conclusions

A comparison between numerical and experimental results showed that MPM is capable of accurately simulating CPT tip resistance in soil profiles with layers as thin as 20 mm, even when using basic constitutive models and simplified drainage conditions. A better match between experimental and numerical results may be possible in future work with more advanced constitutive models and more accurate modeling of flow regimes (i.e., performing a hydromechanically coupled analysis). However, "upgrading" these models will come with a significantly greater computational cost.

Even with an "upgraded" numerical model, limitations and artifacts of the physical experiments will not always be possible (or desirable) to replicate numerically. For example, in the calibration chamber dataset used for this study, uncertainty in the prepared \( D_R \) of the 50-mm-thick sand layers was on the order of 0.2\( D_R \) (De Lange et al. 2018). \( D_R \) also tended to increase (up to about 20% plus the original \( D_R \)) between the time of sample preparation to the time of sample excavation (after all CPTs had been performed in the sample, as noted by De Lange 2018). These variations in \( D_R \) were not accounted for in the MPM simulations. Another source of discrepancy between experimental and numerical results presented in this paper is a consequence of the experimental setup itself. In the De Lange (2018) experiments, \( q'' \) in upper region of the calibration chamber was influenced by the protective tube through which CPT was pushed. De Lange et al. (2018) reported that the tube generally moved along with the cone for about 5 cm of penetration, thus producing erroneous peaks in \( q'' \) in this depth range. This artifact is not replicated in the MPM simulations and resulting numerical \( q'' \) profiles.

Another small discrepancy between the experimental and numerical results presented in this paper is a vertical offset of about 1 to 2 cm between the peaks in the experimental and numerical \( q'' \) in the layered zone, observed for all three CPTs presented in Figure 4.11. The peak numerical
$q^m$ occurs at a slightly shallower depth than that of the experimental $q^m$. This is likely caused by limitations in the numerical model’s ability to accurately capture the downdrag behavior, more specifically captures the downdrag behavior, more accurately. While the MPM model qualitatively captures the downdrag behavior, more research is required to improve the accuracy of the contact properties between the cone and the sand-clay soil mixture.

Results from this study highlight that existing multiple thin-layer correction procedures significantly under-correct tip resistance for layers less than 2 to 3 times the diameter of the cone (Figure 4.14), if they can even identify layers this thin to begin with (which they frequently cannot, as shown by Yost et al. 2021). However, over-correcting tip resistance such that the liquefaction resistance of the layer is overestimated would also not be desirable. Without extensive validation efforts, applying any multiple thin-layer correction procedure to $q^m$ may result in under- and/or over-predictions of true tip resistance throughout the entire soil profile, and it is difficult to constrain the results if $q'$ is unknown. Some additional difficulties of developing, validating, and implementing multiple thin-layer correction procedures include the non-uniqueness of $q^m$ (i.e., CPTs performed in various soil stratigraphies can result in the same $q^m$), the loss of resolution in $q^m$ as thickness of layers decreases, and the tendency of $q^m$ in a layered zone to converge to value much closer to the $q'$ of the softer layers than that of the stiffer layer. These findings are consequential because if only $q^m$ is available (i.e., the true stratigraphy and layer stiffnesses in the profile are unknown), the stratigraphy and stiffness of the layered zone could easily be misinterpreted as being a single soft layer, or any number of combinations of interbedded thin layers of varying thickness and stiffness.

When developing and applying multiple thin-layer correction procedures, it is also important to consider limitations of the CPT equipment itself. For instance, the interval of data collection may be too coarse to identify the thin layers of interest. CPT data are typically collected at 1 to 2 cm intervals, and sometimes up to 5 cm intervals. If the thin layers of interest are around the same order of magnitude in thickness, it is likely that there will be too few data points measured in the layer to obtain a representative $q^m$ (and the possibility of missing a thin layer completely is high). Furthermore, although the focus of this study was on CPT tip resistance, CPT sleeve friction
is also an important parameter in liquefaction analyses in that it is used to compute the behavior
type index \( I_C \). Because the length of the friction sleeve on a cone penetrometer is typically 109.3-
mm to 133.7-mm long, depending on the projected cross-sectional area of the cone, in a highly
interlayered soil profile, the sleeve is likely to be in contact with several soil layers at once. The
matter is further complicated when considering the downdrag effect. These difficulties are very
consequential for multiple thin-layer correction procedures, which are typically based on \( q^m \) alone,
and absent of additional constraining information, may not be able accurately identify or correct for
the presence of thin layers in some stratigraphic conditions at all.

In conclusion, multiple thin-layer effects have been shown to be a contributing factor in the
inaccuracy of liquefaction triggering predictions computed using CPT data. It was shown that
MPM simulations of CPTs can be used to generate both measured tip resistance, \( q^m \), and true tip
resistance, \( q' \) (the tip resistance that would be measured in a soil profile absent of multiple thin-layer
effects) for a numerical soil profile. This set of complementary \( q^m \) and \( q' \) data can be used to validate
procedures that correct for multiple thin-layer effects. However, it is noteworthy that application of
multiple thin-layer corrections does not necessarily improve the efficacy of liquefaction predictions
when using existing liquefaction triggering and manifestation models (e.g., Yost et al. 2021).
Limitations of these models may not be resolved by corrections for multiple thin-layer effects
alone. For example, the impact of interlayering on dissipation of pore pressures is not considered
in simplified liquefaction triggering procedures. This and other "system-effects" discussed by
Cubrinovski et al. (2019) may prevent the accurate prediction of liquefaction manifestation at sites
with highly interlayered soil profiles, even if rigorous corrections for multiple thin-layer effects are
implemented.

4.10. Acknowledgements

This research was partially funded by National Science Foundation (NSF) Grant Nos. CMMI-
1825189 and CMMI-1937984. This support is gratefully acknowledged. Additionally, we thank
Julian Bommer, Imperial College London, and Jan van Elk, NAM, as well as all the individuals
from NAM, Shell, and Deltares for the discussions that both prompted and informed our efforts to
investigate thin layer effects. However, any opinions, findings, and conclusions or
recommendations expressed in this material are those of the authors and do not necessarily reflect
the views of NSF, or the others acknowledged.
References
granular materials.” *Computer Methods in Applied Mechanics and Engineering*, Elsevier,
187(3–4), 529–541.
method.” *CMES - Computer Modeling in Engineering and Sciences*, 5(6), 477–495.
Beyzaei, C. Z., Bray, J. D., Cubrinovski, M., Riemer, M., Stringer, M. E., Jacka, M., and Wentz,
F. J. (2015). “Liquefaction resistance of silty soils at the Riccarton Road site, Christchurch,
New Zealand.” *Proc. of the 6th Int. Conf. on Earthquake Geotech. Eng.*, Paper No. 616,
Christchurch, New Zealand.
“Depositional environment effects on observed liquefaction performance in silt swamps
during the Canterbury earthquake sequence.” *Soil Dynamics and Earthquake Engineering*,
Elsevier Ltd, 107, 303–321.
liquefaction and lateral spreading in interbedded sand, silt, and clay deposits using the cone
penetrometer.” *Proc. of the 5th International Conference on Geotechnical and Geophysical
Site Characterisation (ISC’5)*, Queensland, Australia, 81–97.
penetration data for thin-layer and transition effects.” *Proc. of Cone Penetration Testing
2018*, Hicks, Pisano, and Peuchen, eds., CRC Press, Delft, the Netherlands, 25–44.


## Tables

**Table 4.1.** Transition-zone effects quantified in numerical studies of two-layered profiles

<table>
<thead>
<tr>
<th>Case</th>
<th>Reference</th>
<th>Material</th>
<th>Constitutive Model</th>
<th>$I_h$</th>
<th>$E$ (kPa)</th>
<th>$\nu$</th>
<th>$\sigma'$ (kPa)</th>
<th>$K_0$</th>
<th>Sensing distance (S)</th>
<th>Development distance (D)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>van den Berg et al. (1996)</td>
<td>A Clay</td>
<td>Von Mises Criterion</td>
<td>67</td>
<td>2,000</td>
<td>0.49</td>
<td>35</td>
<td>1</td>
<td>$&lt;d_{cone^a}$</td>
<td>1.7$d_{cone^b}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B Sand</td>
<td>Drucker-Prager</td>
<td></td>
<td>2,000</td>
<td>0.30</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Ahmadi and Robertson (2005)</td>
<td>A Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>25,900</td>
<td>0.25</td>
<td>70</td>
<td>0.5</td>
<td>4.2$d_{cone}$</td>
<td>10$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>48,420</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hryciw et al. (2005)</td>
<td>A Sand</td>
<td>Drucker-Prager</td>
<td>-</td>
<td>9,600</td>
<td>0.3</td>
<td>160</td>
<td>0.5</td>
<td>1.7$d_{cone}$</td>
<td>6.7$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B Sand</td>
<td>Drucker-Prager</td>
<td>-</td>
<td>32,700</td>
<td>0.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>van den Berg et al. (1996)</td>
<td>B Sand</td>
<td>Drucker-Prager</td>
<td>-</td>
<td>2,000</td>
<td>0.3</td>
<td>35</td>
<td>1</td>
<td>1.7$d_{cone^b}$</td>
<td>$&lt;d_{cone^a}$</td>
</tr>
<tr>
<td></td>
<td>Ahmadi and Robertson (2005)</td>
<td>A Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>25,900</td>
<td>0.25</td>
<td>70</td>
<td>0.5</td>
<td>10$d_{cone}$</td>
<td>3.5$d_{cone^a}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>32,300</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hryciw et al. (2005)</td>
<td>B Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>32,700</td>
<td>0.3</td>
<td>160</td>
<td>0.5</td>
<td>19.4$d_{cone}$</td>
<td>5.6$d_{cone^a}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A Sand</td>
<td>Drucker-Prager</td>
<td>-</td>
<td>9,600</td>
<td>0.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Walker and Yu (2010)</td>
<td>B Clay</td>
<td>Von Mises Criterion</td>
<td>100</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td>N.R.</td>
<td></td>
<td>2.15$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A Clay</td>
<td>Von Mises Criterion</td>
<td>100</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td>N.R.</td>
<td></td>
<td>2.6$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B Clay</td>
<td>Von Mises Criterion</td>
<td>100</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td>N.R.</td>
<td></td>
<td>2.2$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A Clay</td>
<td>Von Mises Criterion</td>
<td>500</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td>N.R.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: N.R. indicates that value was not reported in the referenced study and could not be estimated by the authors of this study.

*Estimate by authors of this study; value was not reported in referenced study.

bEqual to the height of the cone tip.
Table 4.2. Thin-layer effects quantified in numerical studies of three-layered soil profiles

<table>
<thead>
<tr>
<th>Case</th>
<th>Reference</th>
<th>Layer</th>
<th>Material</th>
<th>Constitutive Model</th>
<th>$I_R$</th>
<th>$E$ (kPa)</th>
<th>$v$</th>
<th>$\sigma'_v$ (kPa)</th>
<th>$K_0$</th>
<th>Required Thickness of T</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>Ahmadi and Robertson (2006)</td>
<td>A</td>
<td>Clay</td>
<td>Tresca</td>
<td>300</td>
<td>17,880</td>
<td>0.49</td>
<td>70</td>
<td>0.5</td>
<td>28$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>48,420</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>Clay</td>
<td>Tresca</td>
<td>300</td>
<td>17,880</td>
<td>0.49</td>
<td></td>
<td>500</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>Sand</td>
<td>Mohr Coulomb</td>
<td>-</td>
<td>25,900</td>
<td>0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>Clay</td>
<td>Von Mises Criterion</td>
<td>100</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>B</td>
<td>Clay</td>
<td>Von Mises Criterion</td>
<td>100</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td>N.R.</td>
<td>N.R.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>Clay</td>
<td>Von Mises Criterion</td>
<td>500</td>
<td>2,980</td>
<td>0.49</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: N.R. indicates that value was not reported in the referenced study and could not be estimated by the authors of this study.

Table 4.3. Summary of De Lange (2018) calibration chamber tests

<table>
<thead>
<tr>
<th>Soil Model</th>
<th>$d_{cone}$ (mm)</th>
<th>$D_R$ (%)</th>
<th>$H/d_{cone}$</th>
<th>$\sigma'_v$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25</td>
<td>36</td>
<td>-</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td>25</td>
<td>29</td>
<td>1.6</td>
<td>25</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>28</td>
<td>0.8</td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>25</td>
<td>54</td>
<td>1.6</td>
<td>25</td>
</tr>
<tr>
<td>5</td>
<td>25</td>
<td>60</td>
<td>-</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>36</td>
<td>41</td>
<td>-</td>
<td>50</td>
</tr>
<tr>
<td>7</td>
<td>36</td>
<td>32</td>
<td>0.56</td>
<td>50</td>
</tr>
<tr>
<td>8</td>
<td>25</td>
<td>61</td>
<td>0.8</td>
<td>25</td>
</tr>
<tr>
<td>9</td>
<td>25</td>
<td>28</td>
<td>0.8</td>
<td>-</td>
</tr>
<tr>
<td>10</td>
<td>25</td>
<td>18</td>
<td>0.8</td>
<td>10</td>
</tr>
</tbody>
</table>
### Table 4.4. Index properties of Baskarp B15 sand and Vingerling K147 clay

<table>
<thead>
<tr>
<th>Soil</th>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baskarp B15 sand</td>
<td>ASTM Classification</td>
<td>Poorly graded sand (SP)</td>
</tr>
<tr>
<td></td>
<td>Median effective particle diameter, $d_{50}$</td>
<td>0.136 mm</td>
</tr>
<tr>
<td></td>
<td>Coefficient of uniformity, $C_u$</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Coefficient of gradation, $C_c$</td>
<td>1.04</td>
</tr>
<tr>
<td></td>
<td>Specific gravity, $G_S$</td>
<td>2.65</td>
</tr>
<tr>
<td></td>
<td>Maximum void ratio, $e_{max}$</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Minimum void ratio, $e_{min}$</td>
<td>0.553</td>
</tr>
<tr>
<td>Vingerling K147 clay</td>
<td>ASTM classification</td>
<td>Lean clay (CL)</td>
</tr>
<tr>
<td></td>
<td>Liquid limit ($LL$)</td>
<td>32.3</td>
</tr>
<tr>
<td></td>
<td>Plastic limit ($PL$)</td>
<td>15.8</td>
</tr>
<tr>
<td></td>
<td>Plasticity index ($PI$)</td>
<td>16.5</td>
</tr>
</tbody>
</table>

Note: Values provided in, or computed from values provided in, De Lange (2018).

### Table 4.5. Undrained shear strength of Vingerling K147 clay

<table>
<thead>
<tr>
<th>$\sigma_v,_{cons}$ (kPa)</th>
<th>$\sigma_h,_{cons}$ (kPa)</th>
<th>$s_u$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>16.25</td>
<td>23.8</td>
</tr>
<tr>
<td>50</td>
<td>32.5</td>
<td>27.9</td>
</tr>
<tr>
<td>100</td>
<td>65</td>
<td>37.9</td>
</tr>
<tr>
<td>200</td>
<td>130</td>
<td>60.4</td>
</tr>
</tbody>
</table>

Source: Data from De Lange (2018).

### Table 4.6. Sensitivity analysis of soil-cone contact parameters on numerical tip resistance for Soil Model 4 CPT 2

<table>
<thead>
<tr>
<th>Case</th>
<th>Sand-cone contact properties</th>
<th>Clay-cone contact properties</th>
<th>Mixed contact node properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\delta=11.4^\circ (\alpha=0.3)$</td>
<td>$a=27$ kPa ($\alpha=1$)</td>
<td>$\delta=11.4^\circ (\alpha=0.3)$</td>
</tr>
<tr>
<td>2</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
<td>$a=27$ kPa ($\alpha=1$)</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
</tr>
<tr>
<td>3</td>
<td>$\delta=30.4^\circ (\alpha=0.8)$</td>
<td>$a=27$ kPa ($\alpha=1$)</td>
<td>$\delta=30.4^\circ (\alpha=0.8)$</td>
</tr>
<tr>
<td>4</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
<td>$a=27$ kPa ($\alpha=1$)</td>
<td>$a=27$ kPa ($\alpha=1$)</td>
</tr>
<tr>
<td>5</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
<td>$\delta=19.0^\circ (\alpha=0.5)$</td>
</tr>
</tbody>
</table>

Note: The strength properties of the sand ($\phi'=38^\circ$) and clay ($s_u=27$ kPa) used in this analysis were based on calibration efforts for this particular calibration chamber test (Soil Model 4 CPT 2) as described in subsequent sections.
Table 4.7. Material parameters used for MPM simulations of CPT in layered profiles

<table>
<thead>
<tr>
<th>Soil</th>
<th>Parameter</th>
<th>Symbol</th>
<th>SM4 CPT2</th>
<th>SM2 CPT2</th>
<th>SM8 CPT1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baskarp B15</td>
<td>Vertical stress</td>
<td>$\sigma_v$ (kPa)</td>
<td>50</td>
<td>50</td>
<td>25</td>
</tr>
<tr>
<td>sand</td>
<td>Relative density of sand</td>
<td>$D_R$ (%)</td>
<td>54</td>
<td>29</td>
<td>61</td>
</tr>
<tr>
<td>Vingerling K147 clay</td>
<td>Layer thickness ratio</td>
<td>$H/d_{cone}$</td>
<td>1.6</td>
<td>1.6</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>Peak friction angle</td>
<td>$\varphi'_p$ (degrees)</td>
<td>38</td>
<td>35</td>
<td>39</td>
</tr>
<tr>
<td></td>
<td>Residual friction angle</td>
<td>$\varphi'_r$ (degrees)</td>
<td>36</td>
<td>34</td>
<td>37</td>
</tr>
<tr>
<td></td>
<td>Peak dilatancy angle</td>
<td>$\psi$ (degrees)</td>
<td>12</td>
<td>7</td>
<td>12.5</td>
</tr>
<tr>
<td></td>
<td>Shape factor</td>
<td>$\eta$</td>
<td>5</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>Young’s modulus</td>
<td>$E$ (kPa)</td>
<td>20,000</td>
<td>7,000</td>
<td>10,000</td>
</tr>
<tr>
<td></td>
<td>Poisson’s ratio</td>
<td>$\nu$</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Undrained shear strength</td>
<td>$s_u$ (kPa)</td>
<td>27</td>
<td>27</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>Young’s modulus</td>
<td>$E$ (kPa)</td>
<td>25,000</td>
<td>25,000</td>
<td>25,000</td>
</tr>
<tr>
<td></td>
<td>Poisson’s ratio</td>
<td>$\nu$</td>
<td>0.49</td>
<td>0.49</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Table 4.8. Comparison of Sensing and Development Distances (S and D) and Minimum Thin Layer Thickness (T) observed in this study with existing literature

<table>
<thead>
<tr>
<th>Case</th>
<th>Value</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>This study</td>
</tr>
<tr>
<td>1</td>
<td>S</td>
<td>&lt;1$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>6.6$d_{cone}$</td>
</tr>
<tr>
<td>2</td>
<td>S</td>
<td>5$d_{cone}$</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>1.2$d_{cone}$</td>
</tr>
<tr>
<td>3</td>
<td>T</td>
<td>12$d_{cone}$</td>
</tr>
<tr>
<td>4</td>
<td>T</td>
<td>2.8$d_{cone}$</td>
</tr>
</tbody>
</table>

$^a$Ranges reported in this column correspond to results from the van den Berg et al. (1996) and Ahmadi and Robertson (2005) numerical studies that used clay and sand material types, but were not completely analogous to the simulations performed in this study. Complete details regarding the parameters used in these reference studies are provided in Tables 3.1 and 3.2.
Figures

Figure 4.1. Schematic of thin-layer and transition-zone effects for a stiff sand layer embedded in a softer clay (Idriss and Boulanger 2008; reprinted with permission from EERI).

Figure 4.2. Configurations of two- and three-layered soil profiles used in previous numerical studies to quantify transition-zone and thin-layer effects on measured tip resistance.
Figure 4.3. Illustration of the material point method.

Figure 4.4. Calibration chamber setup (De Lange 2018).
Figure 4.5. Variation of Baskarp B15 sand strength parameters with relative density, $D_R$, and confining pressure, $\sigma_3$ based on data from CD triaxial tests (Data from Ibsen and Bødker 1994; Borup and Hedegaard 1995).
Figure 4.6. Cone penetration test MPM model configuration.
Figure 4.7. Downdrag of material from overlying into underlying layers in calibration chamber tests and MPM models. (Laboratory images from De Lange 2018).
Figure 4.8. Sensitivity analysis of soil-cone contact properties on numerical tip resistance for Soil Model 4 CPT 2. Cases 1 through 5 are described in detail in Table 3.6.

Figure 4.9. Calibration of shape factor, y, using finite element method (FEM) triaxial simulations and experimental CD triaxial tests from Ibsen and Bødker (1994) and Borup and Hedegaard (1995).
Figure 4.10. Comparison of experimental and numerical $q^m$ in the uniform sand profiles from the De Lange (2018) calibration chamber tests.
Figure 4.11. Comparison of experimental and numerical $q''$ with numerical $q'$ in layered soil profiles from the De Lange (2018) calibration chamber tests.
Figure 4.12. Transition-zone effects demonstrated using MPM simulation of CPT for: (a) Case 1, soft clay overlying stiffer sand; and (b) Case 2, stiffer sand overlying soft clay.

Figure 4.13. Thin-layer effects demonstrated using MPM simulation of CPT for: (a) Case 3, stiff sand embedded in softer clay; (b) Case 4, soft clay embedded in stiffer sand.
Figure 4.14. Comparison of thin-layer correction factors computed from this study with those suggested by Boulanger and DeJong (2018).

Figure 4.15. Multiple thin-layer effects demonstrated using MPM simulation of CPT in layered soil profiles.
Chapter 5: Addressing Complexities in MPM Modeling of Calibration Chamber Cone Penetrometer Tests in Highly Interlayered Soils

The contributions of the authors to the composition of this manuscript are delineated as follows:

**Kaleigh M. Yost:**
- Developed the specific research questions for the study.
- Performed literature review; performed all numerical simulations; prepared figures and tables; wrote the draft and final manuscripts.

**Mario Martinelli:**
- Assisted in developing the specific research questions for the study.
- Supervised and provided feedback on the direction of this study.
- Developed the software used in this study.
- Reviewed and edited the draft and final manuscripts.

**Alba Yerro**
- Provided valuable feedback throughout the course of the study.
- Reviewed and edited the draft and final manuscripts.

**Russell A. Green**
- Provided valuable feedback throughout the course of the study.
- Reviewed and edited the draft and final manuscripts.

**Dirk A. de Lange**
- Provided valuable insights on the details of the experimental tests used in this study.
- Reviewed and edited the draft and final manuscripts.
Addressing Complexities in MPM Modeling of Calibration Chamber Cone Penetrometer Tests in Highly Interlayered Soils

Kaleigh M. Yost¹, Mario Martinelli²,³, Alba Yerro⁴, Russell A. Green⁵, Dirk A. de Lange²

¹Graduate Student, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Geo-Engineering Unit, Deltares, Delft, Netherlands
³Faculty Civil Engineering & Geosciences, Technical University of Delft, Netherlands
⁴Assistant Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: ayerro@vt.edu)
⁵Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)

The authors of the following manuscript intend to submit it to Computers and Geotechnics.
5.1. Abstract
Cone penetrometer tests (CPTs) are used to characterize soil for a variety of geotechnical engineering applications, including earthquake-induced liquefaction assessment. Numerical modeling of CPTs is frequently used to better understand soil behavior, soil-penetrometer interaction, and engineering estimates made from CPT data. However, calibrating and validating numerical CPT simulations with experimental calibration chamber (CC) data can be challenging. Specifically, uncertainties in the interpretation of laboratory strength and compression data compound with uncertainties in the CC testing and the assumptions made when developing the numerical model. This article provides a comprehensive review of uncertainties in the calibration and validation of CPT numerical simulations performed in homogenous sand, homogenous clay, and layered sand-clay soil profiles, comparing numerical results and well-documented experimental calibration chamber tests performed at Deltares. In particular, the Material Point Method (MPM) is used to perform the numerical analyses. A framework is presented to assess how uncertainty in the numerical model output is attributed to each input parameter. It is demonstrated that uncertainty can be accounted for in the numerical simulations. Finally, recommendations for future experimental and numerical studies of CPTs are provided.

5.2. Introduction
Cone penetrometer tests (CPTs) are a popular in-situ method to characterize soil profiles for geotechnical engineering applications like earthquake-induced liquefaction assessment. However, CPTs in highly interlayered soil profiles suffer from multiple thin-layer effects, an averaging or blurring of data associated with layers that fall within the zone of influence around the penetrometer. Multiple thin-layer effects result in the mischaracterization of layer thickness and strength (represented as a proxy by cone tip resistance, \(q_c\)). This has a detrimental effect on the accuracy of engineering predictions made using CPT data. Correction procedures have been proposed to overcome multiple thin-layer effects (e.g., Boulanger and DeJong 2018; Yost et al. 2021; Cooper et al. 2022) but these procedures need improvement for profiles with layers with thicknesses approaching the diameter of the penetrometer (Yost et al. 2021). To develop and validate these correction procedures, large quantities of CPT data are required. Furthermore, an understanding of what the CPT data would look like without multiple thin-layer effects is needed. These data can come from experimental calibration chamber (CC) studies and/or numerical simulations of CPTs.
Numerical simulations for this application are attractive because they can be performed rapidly and at a low cost compared to CC tests. However, simulations must still be calibrated and validated with experimental CC CPT data. Experimental CC tests inherently have a significant amount of uncertainty and attempts to numerically replicate results from experimental tests introduce compounding uncertainties. Simplifying assumptions are typically made about the experimental conditions and methods, complicated soil behavior is reduced to the limitations of the chosen constitutive models, and other potentially significant details from the experimental tests may be smoothed over in the numerical analysis. Advances in numerical capabilities and the desire to simulate more complex soil profiles inevitably come with an increased number of input parameters, assumptions, and associated uncertainties. Furthermore, while a great deal of experimental and numerical work has been done to examine CPTs in homogenous soil profiles (see Section 5.3.1), very few studies have been performed on the highly interlayered soil profiles of particular interest to this study. Thus, a detailed assessment of the uncertainties associated with CC testing and numerical modeling of CC testing in homogenous and layered profiles is warranted. The results will not only provide better data to develop multiple thin-layer correction procedures but will help inform future experimental and numerical studies of CPTs in general.

In this study, we performed numerical simulations of CPTs using the Material Point Method (MPM) on homogenous and layered soil profiles and compared the results to a well-documented experimental CC study conducted at Deltares by De Lange (2018). The objectives of this work are to: (1) demonstrate the complexity of calibrating MPM CPT simulations with CC studies; (2) quantify how uncertainty in the MPM model's output ($q_c$) is attributed to various input parameters; and (3) demonstrate how uncertainty can be accounted for in the MPM simulations. In Section 5.3, we review previous experimental CC tests and MPM simulations of CC tests. The experimental CC tests and MPM model used in this study are detailed in Section 5.4 and Section 5.5, respectively. In Section 5.6, we present a framework to quantify uncertainty in the MPM model input and output. We demonstrate how uncertainty can be addressed in the MPM simulations and discuss how to reduce uncertainty in both experimental and numerical CC tests in Section 5.7. The contents of the article are summarized in Section 5.8.
5.3. Background

5.3.1. Calibration Chamber Tests

The experimental CCs discussed in this paper consist of large (~1 m in height and diameter, or larger), cylindrical vessels into which a soil specimen is prepared, confining stresses are applied, and various types of penetration testing are performed. The first large CCs were developed in the late 1960s and early 1970s and were used to study penetration in dry sands to improve settlement predictions (Chapman 1974; Holden 1991). Over the next ~20 years, several more CCs were constructed, and more complex tests were performed. Furthermore, owing to the expensive and time-consuming nature of CC testing, many researchers began to supplement experimental CC tests with numerical simulations of CC tests. Approximately 40 years of research culminated in the 1st International Symposium on Calibration Chamber Testing in 1991. The proceedings (Huang 1991) highlighted three key attributes of CC tests that are influential to the results of penetration testing (i.e., \(q_c\)) and relevant to the discussion in this study: (1) CC radius, (2) CC boundary conditions, and (3) soil type and profile preparation; each is discussed in further detail subsequently.

1. Much attention has been given to size effects or how the ratio of the CC diameter to penetrometer diameter, \(d_{cone}\), impacts \(q_c\). Since the radial extent of a CC does not replicate free-field conditions, one expects a difference in \(q_c\) obtained in the lab compared to the field. Generally, the larger the CC diameter to \(d_{cone}\) ratio, the less impactful the size effects are (e.g., Mayne and Kulhawy 1991). Furthermore, size effects are generally less apparent (and sometimes not apparent at all) in CPTs performed in looser sands compared to denser sands (e.g., Parkin and Lunne 1982; Ghionna and Jamilolkowski 1991; Schnaid and Houlsby 1991; Fioravante et al. 1991). Salgado et al. (1998) elaborated on this observation, stating that heavily dilatant sands will be more impacted by size effects compared to compressive sands.

2. The type of CC boundary conditions impacts \(q_c\) and can make size effects more or less apparent. Typically, either a constant pressure (flexible) or a zero strain (rigid) radial boundary condition is used in CC testing (some of the most common conditions are described by Salgado et al. 1998). Generally, flexible lateral boundary conditions result in lab \(q_c\) values lower than what they would be in the free-field (e.g., Mayne and Kulhawy 1991). Fioravante et al. (1991) showed that CPTs in very dense Toyoura sand
prepared in a CC with a CC diameter to $d_{cone}$ ratio of ~34 produced a smaller $q_c$ under flexible radial boundary conditions than rigid conditions, noting that increased horizontal stresses during penetration in the latter case resulted in an elevated $q_c$. Although Salgado et al. (1998) predicted that rigid radial boundary conditions would produce $q_c$ values that poorly represent free-field conditions, there is some evidence otherwise. Huang et al. (1991) performed numerical simulations of CC tests and observed that CPTs performed with a rigid radial boundary produced $q_c$ closer to the field condition than CPTs performed with a flexible boundary. Similarly, Butlanska et al. (2010)’s CPT simulations in very dense sand under ~50kPa horizontal confining stresses showed that size effects were observed using a flexible radial boundary but were not observed when using a rigid boundary.

3. The $q_c$ measured in a CC test is influenced by soil type and sample preparation; thus, controlled and repeatable preparation techniques are required to achieve uniformity throughout the sample (e.g., Eid 1987; Ghionna and Jamiolkowski 1991). Different soil types or sample preparation may result in varied impacts on $q_c$ from size effects and boundary conditions.

In summary, $q_c$ obtained from experimental CC tests is dependent on test-specific and soil-specific conditions, which are often intertwined. This makes it difficult to extrapolate expected trends from literature to unique modeling/testing scenarios. Of particular interest to this study is CPT behavior in interlayered soils, which adds additional complexities. There is very little literature on experimental CC tests performed on interlayered soil profiles, with tests performed by De Lange (2018) and, more recently, by Skrede et al. (2022) being the only ones known to the authors. Further exploration of how CPTs perform in interlayered soil profiles in experimental and numerical CCs with different conditions is therefore warranted.

5.3.2. MPM Models of CPTs

Numerical modeling of CPTs must be able to account for large soil deformations and complex contact interactions between the penetrometer and the soil. In this study, MPM is utilized. MPM is a combined mesh- and particle-based numerical method that operates within a continuum framework. MPM was first developed by Sulsky et al. (1994) and has since been used for a variety of different applications involving large deformations. Many researchers have successfully used MPM to simulate cone penetration in clays and sands with increasingly complex conditions. Beuth
and Vermeer (2013) simulated CPTs in undrained clay using MPM. This work was extended for two-phase clay materials under varied drainage conditions by Ceccato et al. (2015, 2016a; b) and Ceccato and Simonini (2017). Since then, Bisht et al. (2021a; b) have simulated CPTs in clay using a two-phase formulation of MPM that incorporates the generalized interpolation material point method (GIMP: Bardenhagen and Kober 2004) to mitigate stress oscillations and a non-linear B-bar method (Simo et al. 1985) to reduce volumetric locking.

MPM simulations of CPTs in sand have received similar attention. Al-Kafaji (2013) modeled pile installation in dry sand utilizing several concepts still used today, like the moving mesh technique. Tehrani and Galavi (2018) performed CPT simulations in dry sand, and Galavi et al. (2018) introduced an axisymmetric formulation that significantly reduced computational costs. Ghasemi et al. (2018) studied CPTs in saturated, one-phase, drained sand using Mohr-Coulomb constitutive relationships. Martinelli and Galavi (2021) used a stress-dependent double-hardening constitutive model to simulate calibration chamber tests in dry, dense sand. Martinelli and Pisano (2022) showed that incorporating advanced, state-dependent constitutive models like NorSand (Jefferies 1993) that model sand behavior over the wide range of stresses experienced during a CPT is possible and desirable. Recently, Martinelli and Galavi (2022) developed a coupled MPM formulation that uses quadrilateral elements and the B-bar method (Hughes 2000) to reduce volumetric locking; this implementation is used in the present study.

These advancements in the numerical algorithms and constitutive capabilities of MPM make it possible to model CPTs accurately. However, they also require more input parameters and assumptions with their associated uncertainties. Furthermore, despite extensive research using MPM to study CPTs in homogenous soil profiles, Yost et al. (2022) is the only study known to the authors that showed the feasibility of using MPM to simulate CPTs in interlayered soil profiles. The inclusion of multiple soil types introduces additional complexities to the analysis and prompted the investigations presented in this paper.

5.4. Calibration Chamber Tests

A series of experimental CC tests performed at Deltares and detailed extensively by De Lange (2018) were used to calibrate and validate the numerical framework presented in Section 5.5. The following paragraphs provide pertinent information regarding the CC tests and also quantify the
uncertainties in the experimental setup, experimental methods, soil profile preparation, and soil properties that guide the development of the numerical model. The experimental uncertainties are mapped to numerical inputs (see Figure 5.1), each of which is assigned a lower bound, upper bound, and baseline values. These values are used later in the Sensitivity Analysis to quantify how the uncertainty in the numerical model’s output ($q_c$) is attributed to its various input parameters.

5.4.1. Experimental Setup

The CC geometry is shown in Figures 5.2a and b. The CC comprised a set of stacked cylindrical steel rings, 0.9 m in inner diameter. A hydraulic jacking unit and reaction frame was used to push a 25.3-mm-diameter penetrometer to a maximum penetration of 0.75 m. Saturated soil profiles 0.96 m in height were prepared within the annular space of the CC. Drainage was allowed through the rigid bottom of the CC via a geotextile and filter plate. A fluid-filled cushion at the top of the chamber applied vertical pressure to the soil. The cushion had several ports that allowed for drainage and for a penetrometer to be advanced through it.

The sides of the chamber were lined with a flexible rubber membrane (~3 mm thick) and a porous geotextile (~2 mm thick) through which water was filled, intending to apply a constant radial pressure and eliminate friction along the wall (i.e., flexible boundary condition). However, due to the thinness and flexibility of the membrane and geotextile, and to the movement of the soil during cone penetration, we suspect that the gap between the rigid CC wall and the soil actually closed, making the radial boundary a rigid one. In the numerical sensitivity study presented herein, we considered both rigid and flexible radial boundaries to see their impact on the results, with the rigid boundary used as the baseline condition.

Typically, a set of three CPTs were performed in each soil profile that was constructed and initial vertical effective stress ($\sigma'_v$) was increased prior to each subsequent CPT. The horizontal effective stress ($\sigma'_h$) was initialized as 0.5$\sigma'_v$. However, there is some uncertainty in the reported initial stresses. For example, the cushion applying pressure to the top of the soil profile was made of foam covered by a relatively thick layer of silicon. The pressure measured in the cushion is not necessarily equal to the pressure acting on the top of the soil profile. To address the possible variation from the reported initial stress conditions, we varied $\sigma'_h$ by $\pm$10 kPa in the sensitivity analyses, with the reported stress as the baseline condition.
5.4.2. Experimental Methods

In the De Lange (2018) experiments, three CPTs were typically performed per soil profile in a triangular pattern, 0.26 m from each other and 0.3 m from the closest edge of the CC; see Figure 5.2b. Ideally, this would be modeled numerically as a 3D problem, but this is prohibitively computationally expensive. We expect the 2D axisymmetric geometry used in this study to reasonably model the conditions, although, the numerical geometry is more difficult to define. Using the true 0.45-m radius of the chamber would not account for the presence of a rigid boundary that, at its closest, would be 0.3 m away from the CPT. Using a 0.3-m radius would underestimate the amount of soil being confined in the CC by about 44%. We decided to consider numerical models with both 0.3-m and 0.45-m radii, with the 0.45-m radius selected as the baseline condition.

The practice of performing more than one CPT per profile also appears to impact results. Based on one set of three tests performed in the same homogenous sand profile at the same applied \( \sigma'_{vo} \), average tip resistance (\( \bar{q}_c \)) computed between 0.1 and 0.7 m tended to increase with each consecutive test, as shown in Figure 5.3a. We will show that the impact of performing multiple CPTs in one soil profile can be accounted for numerically in Section 5.7.2.

5.4.3. Soil Profile Preparation

Both homogenous sand and layered sand-clay profiles were included in the De Lange (2018) study. Clay layers were constructed by placing bricks of trimmed, prefabricated clay side by side on top of a previously placed sand layer. Sand layers were created by pluviating dry sand from a constant height into the CC which was partially filled with water. An as-prepared relative density (\( D_R \)) was reported, but it is representative of the entire sand volume on average and does not capture local variations in density. Spatial variability in \( D_R \) was estimated as \( D_R \pm 10\% \) by De Lange (2018) and is reflected in variations in \( q_c \) of up to \( \sim 20\% \) from \( \bar{q}_c \) in the experimental results; see Figures 5.3a,b. The uncertainty in as-prepared \( D_R \) is even greater for the layered soil profiles because of increased measurement uncertainty in the height of thinner layers. Furthermore, post-test local density measurements indicated increases in density, up to about \( D_R + 20\% \). In the numerical simulations, we considered the reported as-prepared \( D_R \) as the baseline case and established upper and lower bounds as the baseline \( D_R \pm 10\% \).
Another uncertainty in profile preparation is defining the exact depths of the embedded layer interfaces in the layered sand-clay profiles. Measurements of layer interface depths taken at the time of profile preparation and after profile excavation indicate settlement over the course of testing. Thus, neither the initial nor final measurement is precisely representative of the depths of layer interfaces at the time of a particular CPT was performed. Furthermore, there is uncertainty in how the depth readings are “zeroed” because the reference depth (depth at which the CPT enters the soil) may have been affected by the tubes used to protect the cushion from the penetrometer. The potential offset in depth from these factors is small (on the order of millimeters). However, it is enough to potentially explain observed differences in the location of peaks and troughs in $q_c$ when comparing numerical and experimental data, which have previously been thought to be related to limitations in the definition of soil-cone contact properties in the numerical model (i.e., Yost et al. 2022). We did not address this issue in this study, but we acknowledge that small differences in the depths of the peaks and troughs of $q_c$ in the experimental and numerical data can likely be attributed, at least in part, to uncertainty in the actual depths of the layer interfaces.

5.4.4. Soil Properties

The soils used in the experiments were Baskarp B15 sand and Vingerling K147 clay. The sand is uniform and fine. Index properties were determined by De Lange (2018) and are shown in Table 5.1, but no strength tests were performed. The clay is an artificial lean clay produced by Sibelco. De Lange (2018) performed index testing (see Table 5.1), one constant rate of strain consolidation test, and a series of four anisotropically consolidated, undrained (ACU) triaxial tests on the clay. Because the clay was extruded in a vacuum press, it had a preconsolidation pressure of approximately 80 kPa based on the consolidation and ACU test results. After preparing the soil profile in the CC and applying an overburden stress, the clay layers were allowed to consolidate to 90%. In the MPM simulations, the uncertainties associated with the soil properties were addressed through a sensitivity analysis of the constitutive model parameters selected to represent soil behavior. Extensive details regarding the selection and calibration of the constitutive models are provided in Sections 5.5.2 and 5.5.3.
5.5. Numerical Model
A 2D axisymmetric MPM model was created to replicate several CC tests described in Section 5.4. The following sections detail the implementation, geometry, mesh, boundary conditions, and constitutive modeling used in these analyses.

5.5.1. Model Implementation, Geometry, Mesh, and Boundary Conditions
The explicit MPM implementation utilized for this study is detailed extensively in Martinelli and Galavi (2022), and thus, is only briefly summarized herein. The implementation uses linear, 4-noded quadrilateral elements and a Gauss integration scheme to mitigate stress oscillations. To minimize volumetric locking, the B-bar method (Hughes 2000) is implemented, in which only the integration point at the center of an element is used to compute volumetric strains. A mass scaling factor of 10,000 was used to expedite the calculations. A Courant number of 0.95 was used.

The geometry and mesh are shown in Figure 5.4. The height of the model was 2 m, and the bottom 1 m of the domain represented the soil profile. The radial dimension extended either to 0.3 or 0.45 m, depending on the simulation (see Section 5.4.2). The density of the surcharge layer (blue layer in Figure 5.4) was adjusted to get \( \sigma'_{vo} = 50 \text{kPa} \) at the top of the soil to match CC conditions. Contact between the surcharge layer and penetrometer was assumed to be perfectly smooth. Stresses were initialized using an at-rest lateral earth pressure \( (K_0) \) procedure with \( K_0 = 0.5 \). The left boundary was fixed in the x-direction, and the bottom boundary was fixed in the y-direction. The right (radial) boundary was either fixed in the x-direction to represent a rigid boundary (baseline condition) or represented as a thin layer of very soft \( (E = 1 \text{kPa}) \) linear elastic soil that maintained a nearly constant radial stress to represent a flexible boundary (the same technique used by Martinelli and Pisano 2022).

The 25.3-mm-diameter penetrometer with a 60-degree apex angle was “wished into place” at the left boundary (i.e., the axis of symmetry) and embedded 21.91 mm (the height of the conical face) into the soil profile. The cone was modeled as rigid and was advanced at a constant velocity of 40 mm/sec (the experimental CC experiments advanced the cone at 4 mm/sec; however, because the solution is independent of the penetration velocity, a larger value was used for computational speed). The domain was discretized using a moving mesh (Beuth 2012) and compressing mesh to maintain the shape of the soil-cone contact elements throughout the simulation. The compressing
mesh was structured with element widths of about $0.25d_{cone}$ within the penetration zone. The moving mesh was unstructured and finely discretized (widths of ~$0.25d_{cone}$ or less) around the tip of the penetrometer. The discretization was coarser with increasing distance from the penetrometer.

### 5.5.2. Constitutive Modeling of Sand

The constitutive behavior of the saturated Baskarp B15 sand was modeled with the Jefferies and Been (2015) description of NorSand implemented by Martinelli (2019). Since no strength or stiffness testing was performed on the sand as a part of the De Lange (2018) study, consolidated drained (CD) triaxial test data collected by Ibsen and Bødker (1994) on the same sand were used to determine the NorSand model parameters (see Table 5.2). The following paragraphs contain an overview of how these parameters were selected. Complete details are provided in the supplemental materials to this article.

An exponential critical state line (CSL) formulation proposed by Li and Wang (1998) was adopted instead of the log-linear one used by Jefferies and Been (2015). The exponential form has been shown to better capture soil behavior at large mean effective stresses ($p'$) expected during cone penetration (Martinelli and Pisano 2022) and is defined by:

$$e_{cs} = e_{cs,0} - \lambda \left( \frac{p'}{p_a} \right)^m$$  \hspace{1cm} (5.1)

where $e_{cs}$ is the critical state void ratio, $p_a$ is atmospheric pressure in the same units as $p'$, and $e_{cs,0}$, $\lambda$, and $m$ are the CSL parameters defined in Table 5.2. The CSL parameters were determined using CD triaxial tests performed on specimens in very loose states ($D_R = 1\%$) and tested over a wide range of confining stresses. The $e$-$p'$ behavior associated with each test is plotted in Figure 5.5. Instead of drawing a single CSL for this set of tests, a plausible zone where the CSL may fall is defined. To make it easier to assess the uncertainty in CSL location without having to change multiple parameters, two CSL parameters are held constant (namely, $e_{cs,0} = 0.90$ and $m = 0.7$), and the third ($\lambda$) is varied between 0.009 and 0.015 to define the boundaries of the plausible critical state zone (shown in shaded red in Figure 5.5). Those $\lambda$ values are used as the upper and lower bound parameters for the sensitivity analysis.
The elasticity relationship utilized in NorSand is defined as:

\[ G = G_{\text{ref}} \frac{1}{e - e_{\text{min}}^*} p_a \left( \frac{p'}{p_a} \right)^b \]  

(5.2)

where \( G \) is the shear modulus, \( G_{\text{ref}} \), \( b \), and \( e_{\text{min}}^* \) are elasticity parameters defined in Table 5.2, and all other variables are as previously defined. The elasticity parameters were determined based on results from bender element tests performed on Baskarp B15 sand by Bodker (1996). Similar to the approach taken to quantify uncertainty in the CSL, the only elasticity parameter that was modified in subsequent analyses was \( G_{\text{ref}} \), between 700 and 800 (with \( G_{\text{ref}} = 743 \) as the baseline), as shown in Table 5.2. The parameters \( b \) and \( e_{\text{min}}^* \) were held constant.

The CD triaxial tests performed on dense (\( D_R = 80\% \)) and medium dense (\( D_R = 51\% \)) specimens were used to determine the dilatancy parameters \( N \) and \( \chi \), and critical state friction angle \( \phi_{cs} \), using the procedure described by Shuttle and Jefferies (2016). The baseline, upper, and lower bound values for these parameters are provided in Table 5.2. Note that because the baseline \( N \) and \( \chi \) were already on the low end of the typical range for those parameters provided by Shuttle and Jefferies (2016), the lower bounds were selected to be equal to, or very close to, the baseline. The baseline value of Poisson ratio, \( \nu \), was assumed to be 0.2, and the upper and lower bounds of \( \nu \) were set based on typically assumed values.

The remaining parameter \( H \) is a NorSand model parameter that is calibrated by performing numerical single-element tests to replicate results from drained triaxial tests. \( H \) may be assumed constant throughout the simulation or described dynamically as a function of the current state parameter, \( \psi \) (Jefferies and Been 2015). For this analysis, we assumed a constant \( H \) that was a function of the initial state parameter, \( \psi_i \). To calibrate \( H \), we aimed to match the initial stiffness of each considered laboratory triaxial test by varying \( H \) and holding all other parameters constant at baseline values provided in Table 5.2. In total, 12 of the CD triaxial tests were used for this calibration, and the results are shown in Figure 5.6.
In general, we are able to match the experimental deviator stress-axial strain \((q-\varepsilon_a)\) results relatively well for the dense, medium-dense, and loose data sets. The volumetric strain-axial strain \((\varepsilon_v-\varepsilon_a)\) and void ratio-mean effective stress \((e-p')\) results are a good match for the dense data (Figure 5.6 a,b,c), and progressively less so for the medium-dense (Figure 5.6 d,e,f) and loose (Figure 5.6 g,h,i) data. We expect the match to be the worst for the loose data, which have initial states very close to the CSL and thus uncertainty in CSL location has a larger impact on the results. A linear relationship between \(H\) and \(\psi_o\) was defined. However, results showed that \(H\) was also a function of initial mean effective stress \((p'_o)\) as shown in Figure 5.7. To reflect the considerable scatter in the data, a large range of possible \(H\) values was defined for the MPM analyses with a lower bound of 25 and an upper bound of 75, based on the \(\psi_o\) of the sand in the experimental CC tests that were being replicated. The lower bound value of 25 was also used as the baseline because it was observed to produce better matches between the numerical and experimental CPT data.

5.5.3. Constitutive Modeling of Clay

The Tresca constitutive model was used to represent the saturated Vingerling K147 clay behavior. Tests conducted by De Lange (2018) were used to establish the baseline constitutive parameters summarized in Table 5.3.

The initial porosity \((n_o)\) corresponds to the porosity after consolidation occurred in the CC. The undrained shear strength \((s_u)\) and secant shear modulus at 50% of the mobilized strength \((G)\) were determined based on results from an ACU triaxial test performed at a vertical effective consolidation stress \((\sigma'_v,cons)\) equal to 50kPa. Note that the rigidity index \((I_R=G/s_u)\) corresponding to the baseline parameters is 20, considerably lower than the typical range of 50-500 (e.g., Krage et al. 2014). However, because Vingerling clay is an artificial clay and because the tests were performed under relatively low confining pressures, we think this \(I_R\) value is representative. The lower and upper bounds of \(G\) provide a range of \(I_R\) from 15 to 50. The undrained condition of the clay is enforced by including the bulk modulus of water \((k_{water})\). The true \(k_{water}\) is 2.1 GPa; however, we found that we could improve computational speed without impacting results using \(k_{water}\) as low as 200,000 kPa.

5.5.4. Soil-Cone Contact

Contact between the soil and cone is modeled using the Bardenhagen et al. (2001) contact
algorithm with the additions of Al-Kafaji (2013) for adhesive soils. If two different types of soil with different contact properties share the same contact node, then an average contribution is computed (e.g., Talmon et al. 2019). Soil-cone contact properties are typically assumed to be a fraction of the sand’s $\varphi$ or the clay’s $s_u$. In these analyses, the sand-cone contact friction angle ($\varphi_{cont}$) was varied from $0.3\varphi_{cs}$ to $0.9\varphi_{cs}$ based on the range of typical aluminum-sand contact properties reported by Durgunoglu and Mitchell (1973), with the baseline set to $0.5\varphi_{cs}$. The contact adhesion ($a$) was varied from $0.25s_u$ to $0.5s_u$ based on the range of typical steel-clay contact properties reported by Potyondy (1961), with the baseline condition set to $0.5s_u$.

5.6. Sensitivity Analysis

MPM simulations were performed for three soil profiles: one homogenous sand profile prepared at $D_R=36\%$, one homogenous clay profile, and one layered sand-clay profile with 40-mm-thick layers and sand prepared at $D_R=29\%$. Initial stress conditions for each simulation was the same with $\sigma'_{v0}=50$ kPa and $\sigma'_{h0}=25$ kPa. The homogenous sand and layered sand-clay profiles had experimental counterparts from De Lange (2018) to compare to. For each of the three soil profiles, one MPM simulation was performed using the baseline set of input parameters described in Tables 5.2 and 5.3, producing the baseline $q_c$ realization (e.g., as shown in Figure 5.8). Subsequent simulations were performed in which only one input parameter was changed to either its upper or lower bound value, producing additional $q_c$ realizations to compare to the baseline. Note the experimental and numerical data shown in Figure 5.8 match quite well; however, there is some discrepancy, especially at shallow depths. This can be attributed, at least in part, to boundary effects at the top of the chamber and compaction of the sand near the surface caused by placement of the heavy cushion, neither of which are accounted for by the numerical model.

5.6.1. Quantifying Changes in Tip Resistance

A representative $\bar{q}_c$ for each MPM realization was defined over a depth interval dependent on the soil profile type. For the homogenous sand and clay profiles, $\bar{q}_{c,sand}$ or $\bar{q}_{c,clay}$ was computed by averaging $q_c$ values between 0.5054 and 0.5255 m (as shown in Figure 5.8a for the homogenous sand baseline realization). For the layered profile, two $\bar{q}_c$ values were determined within the layered zone: $\bar{q}_{c,embsand}$ associated with the first embedded sand layer ($q_c$ averaged over a 0.0023-m interval centered at the depth of the numerical peak at 0.3082 m) and $\bar{q}_{c,embclay}$ associated with the first embedded clay layer ($q_c$ averaged over a 0.0042-m interval centered at the depth of the
numerical trough at 0.2771 m). This is illustrated in Figure 5.8b for the baseline realization in the layered profile. Note that defining $\bar{q}_{c,\text{embsand}}$ and $\bar{q}_{c,\text{embclay}}$ over small intervals for the embedded layers was necessary because $q_c$ tended to reach a peak/trough value and then immediately start to decrease/increase, never reaching a fully developed value within a given embedded layer.

To compare results between realizations, a sensitivity index (SI; Hoffman and Gardner 1983) was defined as:

$$SI = \frac{(q_{c,\text{upper bound}}-q_{c,\text{lower bound}})}{q_{c,\text{upper bound}}}$$

(5.3)

where $q_{c,\text{upper bound}}$ and $q_{c,\text{lower bound}}$ are the $\bar{q}_c$ values computed from the realizations using the upper and lower bounds of a particular parameter.

Because the numerical simulations are dynamic, there is a level of noisiness, or variation from the mean in the numerical $q_c$, that can make interpreting results difficult. For example, changing one input parameter may produce a slight increase in $\bar{q}_c$; however, that increase may just be due to a slightly different combination of numerical noise. To keep the magnitude of SI in perspective, an SI associated with the noise level (SI\text{noise}) in each baseline realization was computed over the same depth interval used to compute $\bar{q}_c$. For example, in Figure 5.8b, $\bar{q}_{c,\text{embsand}}$ was computed over the depth interval 0.3071 to 0.3094 m. SI\text{noise} for the embedded sand layer was computed as the difference between the maximum and minimum $q_c$ values within that interval divided by the maximum $q_c$ value, or $(1637-1552)/1637 = 0.0519$. Computed in the same way, SI\text{noise} for the embedded clay layer was 0.0325, for the homogenous sand profile was 0.0127, and for the homogenous clay profile was 0.0132. Note that SI\text{noise} was larger for the embedded sand and clay layers, likely a function of having multiple material types in a single numerical element in the layered zone.

5.6.2. Sensitivity Analysis Results

The results from the sensitivity analysis are presented in Figures 5.9 through 5.11. As shown in Figure 5.9a, the realizations for the homogenous sand profile generally fall within a relatively narrow band around the baseline, between about 3280 kPa and 5070 kPa, with the exception of the realization associated with the upper bound $H = 75$, which produces a much larger $\bar{q}_c$ of 8542 kPa. Figures 5.10a and 5.11a indicate that, by far, the parameter dominating the sensitivity in the
homogenous sand simulations is $H$. Other fairly significant contributions are from $D_R$, $\varphi_{conis}$, $\chi$, and the radial boundary condition. SIs associated with $\sigma'_{ho}$, $\lambda$, $\varphi_{cs}$, and CC radius are less significant. Uncertainty in $N$, $G_{ref}$ and $v$ have essentially no impact on $\bar{q}_c$, with SIs falling just at or below $SI_{noise}$ (dashed line in Figure 5.11a).

Two trends observed in Figure 5.10a highlight the differences in soil behavior resulting from a rigid boundary condition (used as the baseline condition in these analyses) and a flexible boundary condition (which tends to dominate in literature): (1) Increasing $\sigma'_{ho}$ resulted in a (very) slight decrease in $\bar{q}_c$, explained by a slightly smaller maximum $p'$ around the tip of the penetrometer (see Appendix B.3 for further details). These results are contrary to literature for chambers with flexible boundary conditions (e.g., Fioravante et al. 1991). The simulation was repeated with a flexible boundary and showed a significant increase in $\bar{q}_c$ with increased $\sigma'_{ho}$. These results are elaborated on further in Section 5.7.2; (2) Decreasing the CC radius resulted in a slight increase in $\bar{q}_c$. Supplemental simulations were performed with a flexible boundary condition and showed the opposite trend (i.e., decreasing CC radius resulted in a decreased $\bar{q}_c$), consistent with observations from literature for a flexible boundary condition (e.g., Ghionna and Jamiolkowski 1991). Both (1) and (2) are explained by the increased confinement and lower allowable deformations in a CC with a rigid radial boundary, and emphasize the importance of not extrapolating expected trends from literature (which is dominated by CCs with flexible boundary conditions) to the rigid boundary conditions used a baseline in this study.

As shown in Figure 5.9b, the realizations for the homogeneous clay profile produced $\bar{q}_c$ values ranging from 230 kPa to 342 kPa compared to the baseline $\bar{q}_c = 264$ kPa. Figure 5.10b and 5.11b show that uncertainty in $G$ and $s_u$ – constitutive parameters of the clay – dominate the uncertainty in $\bar{q}_c$. Contributions from $a$ and $\sigma'_{ho}$ are less significant, but above $SI_{noise}$. SI associated with the radial boundary condition, CC radius and $n_o$ fall just at or below $SI_{noise}$. Notably, increasing $\sigma'_{ho}$ resulted in a slight increase in $\bar{q}_c$, contrary to what was observed for the homogenous sand profile. In the homogenous clay profile with the Tresca constitutive model, the increased $\sigma'_{ho}$ slightly increases $p'$, and $p'$ remains elevated for the duration of penetration resulting in a slightly increased $\bar{q}_c$. 

134
The realizations from the layered profile are shown in Figure 5.9c. For the embedded sand, uncertainty in \( G \) (of the clay) and \( D_R \) (of the sand) resulted in the most uncertainty in \( q_c \) (see Figures 5.10c and 5.11c). Contributions from \( H \), \( \phi_{\text{cont}} \), and radial boundary condition fall above the noise level; all other parameters fall below. In Figure 5.11c, a few of the bars (\( n_o \), \( v \) of sand, \( G_{\text{ref}} \), \( \chi \), and \( \sigma'_{ho} \)) do not touch the baseline value, meaning the realization using the lower bound parameter resulted in a larger \( \overline{q}_c \) than the baseline realization. This is simply a reflection of the significance of the noise level. For the embedded clay layer, SI was largest for \( \phi_{cont} \) and \( H \), \( s_u \), \( G \) (of the clay), and \( D_R \) (of the sand) produced the next largest SIs, followed by \( \chi \) and the boundary condition. All other parameters produced SIs at or below the level of noise.

5.7. Discussion

5.7.1. Sensitivity Analysis Discussion

The sensitivity analysis results showed that \( \overline{q}_c \) of the embedded layers in the layered profile were less sensitive to uncertainties in input parameters than \( \overline{q}_c \) of the homogenous profiles. This is likely because \( q_c \) is unable to fully develop in the embedded layers, so while changes in input parameters significantly affect the fully-developed \( q_c \) in the homogenous profiles, they have less of an impact on the undeveloped \( q_c \) in the layered profile. Furthermore, considering only the layered profile, the \( \overline{q}_c \) of the embedded sand layers was less sensitive to uncertainties in input parameters than the \( \overline{q}_c \) of the embedded clay layers. Similar to the previous explanation, this is likely due to the fact that \( q_c \) in the embedded clay layers is much closer to the fully-developed \( q_c \) of the clay than \( q_c \) in the embedded sand layers is to the fully-developed \( q_c \) of the sand. The impact of changes in input parameters will be reflected more in the layers where \( q_c \) is closer to the fully-developed \( q_c \) (i.e., the clay layers). A final observation is that \( \overline{q}_c \) in the embedded clay layers was more impacted by uncertainties in the sand input parameters than the clay input parameters. This is expected since the range of outputs resulting from changes in sand input parameters was significantly larger than that from the clay in the homogenous profiles, as demonstrated by the difference in ranges of \( q_c \) demonstrated in Figures 5.9a and 5.9b.

5.7.2. Accounting for Multiple CPTs Performed in a Single Profile

Construction of soil profiles for CC tests can be labor intensive and expensive. Therefore, it is advantageous to perform more than one CPT per profile in order to optimize the amount of data obtained. However, this practice may increase uncertainty in the results and make certain
numerical modeling parameters difficult to define. As previously shown in Figure 5.3a, $\bar{q}_c$ tended to increase with additional CPTs performed at the same overburden stress in the De Lange (2018) experiments. This is happening for two primary reasons: (1) the stress state in the CC is significantly altered with each CPT due to the rigid radial boundary condition, and therefore initial stress conditions are not the same for subsequent CPTs, and (2) local densification occurs adjacent to the cone during penetration and extends into the zone of influence of the subsequent CPTs. To demonstrate this, additional MPM simulations were performed to replicate the experimental results from the homogenous sand profile shown in Figure 5.3a.

Figure 5.12 shows the evolution of stresses along the rigid radial boundary over the course of one CPT in the homogenous profile. With increasing penetration, both $\sigma'_v$ and $\sigma'_h$ increase from $\sigma'_{vo}$ and $\sigma'_{ho}$ at all depths along the radial boundary. Vertical stresses increase up to about 20%, and horizontal stresses increase up to about 240%, resulting in $\sigma'_h/\sigma'_v$ much closer to 1.0 than the initial $\sigma'_h/\sigma'_v$ of 0.5. Consequently, the next CPT in this profile will not experience the same initial stress conditions as the previous one, and we should not expect $\bar{q}_c$ to be the same. It was shown in Section 5.6.2 that variations in $\sigma'_{ho}$ did not have a very significant impact on $\bar{q}_c$, and an increased $\sigma'_{ho}$ produced a slightly smaller $\bar{q}_c$ in both the homogenous sand and layered sand-clay profile. This is a result of the rigid radial boundary condition, which limits soil deformations and results in increased confinement. Peak $p'$ adjacent to the penetrometer tip was observed to be slightly smaller for the case of the larger $\sigma'_{ho}$, explaining the slightly smaller $\bar{q}_c$. Overall, however, the stress paths between the two cases ($\sigma'_{ho} = 50$ and 90 kPa) are nearly identical for the rigid boundary condition.

On the contrary, this same simulation performed with a flexible boundary condition indicates an increase in $\bar{q}_c$ with an increased $\sigma'_{ho}$, as shown in Figure 5.13a. With the flexible boundary condition, the soil is less confined and more able to deform. The impact of a varied initial stress condition is more consequential on the results. Furthermore, the deformation and $p'$ for the $\sigma'_{ho} = 90$ kPa case and flexible boundary is quite close to that of the $\sigma'_{ho} = 50$ kPa and 90 kPa rigid boundary cases, explaining why $q_c$ for those three cases seems to converge with depth.

While increasing $\sigma'_{ho}$ alone does not tend to increase $\bar{q}_c$ for the rigid boundary condition, a 20% increase in $\sigma'_{vo}$ to 120 kPa (and accompanied increase in $\sigma'_{ho}$ to 60 kPa) does produce a ~15% increase in $\bar{q}_c$, as shown in Figure 5.13b. This is less than the ~26% increase observed in the lab
CC results between the first and second CPTs. Thus, while the change in the initial stress state does impact the results of subsequent CPTs in the CC, it is probably not the only contributor to the increased $\bar{q}_c$.

The second contributor to the increase in $\bar{q}_c$ with subsequent CPTs is local densification during penetration. As shown in Figure 5.14, by the end of penetration, $e$ was altered primarily within a radius of about 24 cm. Immediately adjacent to the cone is a zone of dilation (shown in red), but the rest of the affected zone indicates compression (shown in blue). Since the CPTs were performed in this profile at locations 26 cm away from each other, it is reasonable to conclude that the zones of influence would overlap. An example of how this could influence the results can be determined by selecting an $e$ in the densest region of the zone of influence at the end of penetration and performing a simulation with a $D_R$ associated with that new $e$ value (and all other conditions held constant). For example, in Figure 5.14a, the darkest blue zone corresponds to an $e \approx 0.669$ or $D_R = 65\%$, compared to the original $D_R = 60\%$. Note that experimental post-test (i.e., after all three CPTs were performed) local density measurements in this profile indicated a $D_R$ of about 70%, making a 5% increase in $D_R$ after one CPT very reasonable. A second simulation performed with an initial $D_R = 65\%$ resulted in a ~10% increase in $\bar{q}_c$, as shown in Figure 5.14b. Combining this ~10% increase in $\bar{q}_c$ from increased density with the ~15% increase from the modified stress conditions, the 26% increase in $\bar{q}_c$ observed in the lab is accounted for quite well.

5.7.3. Reducing Uncertainty in Experimental CC Tests and their Numerical Counterparts

Based on the findings in this study, the following recommendations are provided to reduce uncertainty in both the experimental and numerical aspects of CC testing:

Experimental setup/methods and numerical model geometry/boundary conditions:

- Perform CPTs only at the center of the CC to ensure axisymmetric conditions and to have a well-defined CC radius. Alternatively, quantify the impact of performing a CPT at the center versus an off-center (i.e., closer to the boundary) location by performing a test where multiple CPTs are performed in the same profile without changing $\sigma'_{yo}$.
- Understand the limitations of the CC in applying the desired boundary conditions.
• Perform only one CPT per soil profile to avoid changing initial stress conditions and local densities prior to subsequent CPTs. Alternatively, since preparing calibration chamber samples is extremely labor intensive, show that subsequent CPTs are not impacted by previous ones or quantify the impacts of performing multiple CPTs in one profile experimentally and numerically. Numerical simulations seeking to validate results may choose to use the first experimental CPT performed in a given laboratory calibration chamber soil profile to avoid these concerns.

Soil profile preparation and numerical model initial conditions:
• Minimize and quantify variation in as-prepared $D_R$ of the sand (e.g., by comparing CPTs performed in different locations in the CC and by taking local density measurements).
• Quantify changes in $D_R$ over the course of CC testing. For example, the increase in $D_R$ caused by increased loading may be quantified experimentally by measuring outflowing water during sample pressurization and comparing post-test density measurements with pre-test density measurements. Experimentally quantifying local increases in $D_R$ caused by cone penetration is a more difficult task, but may be done numerically as demonstrated in this article.
• Consider using multiple $D_R$ values in numerical simulations to model even a “homogenous” sand profile (i.e., break the sand profile into layers) if local variations in $D_R$ are significant.
• Measure depth to layer boundaries from a common reference point before and after each CPT, as close to the CPT as possible. Link penetrometer position to true depths in the profile (i.e., ensure the zero depth of the CPT sounding is equal to the zero depth of the soil profile) at the time of the experiment.

Soil properties and constitutive modeling of soil properties:
• Accompany experimental CC tests with a thorough laboratory strength testing program. Ideally, the program should be specifically designed to obtain the parameters needed for constitutive models of interest, so that corresponding numerical models of the CC tests do not need to rely on external literature to estimate constitutive parameters.
- Minimize the contribution of uncertainty from model parameters with no physical significance (e.g., $H$) by performing additional laboratory tests or extending calibration efforts. Further work is needed to quantify how $H$ varies as a function of both $\psi_o$ and $p'_o$, rather than just $\psi_o$.
- Quantify contact properties between the cone and soil through laboratory interface testing. Contact properties are frequently assumed, but they are shown in this study to have a significant impact on the results.

5.8. Conclusions
This study addressed the complexities of numerical modeling (e.g., using MPM) of CPTs performed in CCs in homogenous and interlayered soil profiles. It was shown that significant experimental and numerical uncertainties exist in CC tests but can be accounted for. In this study, uncertainty associated with soil properties and profile preparation, rather than uncertainties associated with the experimental setup (e.g., radial boundary condition, initial stresses, and CC radius), tended to have the most impact on $q_c$. The sensitivity analysis indicated that the parameters that most significantly impact $q_c$ in the homogenous sand and clay profiles are not necessarily the same ones that most significantly impact $q_c$ in the layered soil profile, and in general, the layered soil profile was less sensitive to uncertainties in input parameters than the homogenous soil profiles. Experimental results show that performing multiple CPTs in a single soil profile results in an increased average $q_c$; this observation was explained numerically and attributed to changing stress states and local densities caused by penetration. Finally, recommendations for improving future experimental and numerical CC studies (especially in layered profiles) were provided, suggesting additional data collection is needed to better quantify uncertainty.

5.9. Acknowledgements
This research was partially funded by National Science Foundation (NSF) Grant Nos. CMMI-1825189 and CMMI-1937984 and the Institute for International Education Graduate International Research Experience (IIE-GIRE) program supported by NSF under Grant No. 1829436. This support is gratefully acknowledged. Additionally, we thank Deltares for serving as the host institution for the duration of the IIE-GIRE program, for the use of a version of Anura3D software developed in-house by them, and the discussions regarding the experimental tests used in this
investigation. However, any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NSF or others acknowledged.

5.10. Notation

The following symbols are used in this paper:

- $a =$ adhesion between cone and clay;
- $b =$ exponent of the stiffness relation;
- $C_u =$ coefficient of uniformity;
- $d_{cone} =$ diameter of the cone;
- $D_R =$ relative density;
- $d_{50} =$ mass-median-diameter;
- $E =$ Young’s modulus;
- $e =$ void ratio;
- $e_0 =$ initial void ratio;
- $e_{cs} =$ critical state void ratio;
- $e_{cs,0} =$ critical state void ratio at $p’=0$;
- $e_{\max} =$ maximum void ratio;
- $e_{\min} =$ minimum void ratio;
- $e^{*}_{\min} =$ void ratio at which volumetric strains are negligible (elasticity parameter);
- $G =$ shear modulus;
- $G_{\text{ref}} =$ shear modulus factor;
- $H =$ hardening modulus;
- $I_R =$ rigidity index;
- $k_{\text{water}} =$ bulk modulus of water;
- $K_0 =$ coefficient of at-rest lateral earth pressure;
- $LL =$ liquid limit;
- $m =$ exponent of critical state line;
- $N =$ dilatancy parameter;
- $n =$ porosity;
- $n_0 =$ initial porosity;
$n_{\text{max}} = \text{maximum porosity}$;
$n_{\text{min}} = \text{minimum porosity}$;
$p_a = \text{atmospheric pressure}$;
$p' = \text{mean effective stress}$;
$PL = \text{plastic limit}$;
$q = \text{deviatoric stress}$;
$q_c = \text{tip resistance}$;
$q_c = \text{average tip resistance}$;
$s_u = \text{undrained shear strength}$;
$w = \text{water content}$;
$\varepsilon_a = \text{axial strain}$;
$\lambda = \text{slope of the critical state line}$;
$\nu = \text{Poisson ratio}$;
$\rho_{\text{grains}} = \text{density of particles}$;
$\varphi_{\text{com}} = \text{contact friction angle between cone and sand}$;
$\varphi_{cs} = \text{critical state friction angle}$;
$\sigma'_h = \text{horizontal effective stress}$;
$\sigma'_{ho} = \text{initial horizontal effective stress}$;
$\sigma'_v = \text{vertical effective stress}$;
$\sigma'_{vo} = \text{initial vertical effective stress}$;
$\chi = \text{dilatancy coefficient}$;
$\psi = \text{state parameter}$;
$\psi_o = \text{initial state parameter}$.

**References**


### Tables

#### Table 5.1. Index properties soil used in CC tests

<table>
<thead>
<tr>
<th>Soil</th>
<th>Parameter</th>
<th>Symbol (Unit)</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>Mass-median-diameter</td>
<td>$d_{50}$ (mm)</td>
<td>0.136</td>
</tr>
<tr>
<td></td>
<td>Coefficient of uniformity</td>
<td>$C_u$ (-)</td>
<td>1.4</td>
</tr>
<tr>
<td></td>
<td>Density of particles</td>
<td>$\rho_{\text{grains}}$ (kg/m$^3$)</td>
<td>2650</td>
</tr>
<tr>
<td></td>
<td>Minimum porosity</td>
<td>$n_{\text{min}}$ (%)</td>
<td>35.6</td>
</tr>
<tr>
<td></td>
<td>Maximum porosity</td>
<td>$n_{\text{max}}$ (%)</td>
<td>47.1</td>
</tr>
<tr>
<td></td>
<td>Minimum void ratio</td>
<td>$e_{\text{min}}$ (-)</td>
<td>0.552</td>
</tr>
<tr>
<td></td>
<td>Maximum void ratio</td>
<td>$e_{\text{max}}$ (-)</td>
<td>0.890</td>
</tr>
<tr>
<td>Clay</td>
<td>Water content</td>
<td>$w$ (%)</td>
<td>22.8</td>
</tr>
<tr>
<td></td>
<td>Liquid Limit</td>
<td>$\text{LL}$ (%)</td>
<td>32.3</td>
</tr>
<tr>
<td></td>
<td>Plastic Limit</td>
<td>$\text{PL}$ (%)</td>
<td>15.8</td>
</tr>
</tbody>
</table>

#### Table 5.2. Estimated Constitutive Parameters of Baskarp B15 Sand

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Baseline</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical state void ratio at $p^\prime=0$</td>
<td>$e_{\text{cs},o}$</td>
<td>0.90</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Slope of critical state line</td>
<td>$\lambda$</td>
<td>0.012</td>
<td>0.009</td>
<td>0.015</td>
</tr>
<tr>
<td>Exponent of critical state line</td>
<td>$m$</td>
<td>0.7</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Shear modulus factor</td>
<td>$G_{\text{ref}}$</td>
<td>743</td>
<td>700</td>
<td>800</td>
</tr>
<tr>
<td>Exponent of the stiffness relation</td>
<td>$b$</td>
<td>0.57</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Void ratio at which volumetric strains are negligible</td>
<td>$e_{\text{min}}$</td>
<td>0.051</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Critical state friction angle</td>
<td>$\phi_{\text{cs}}$</td>
<td>30</td>
<td>29</td>
<td>31</td>
</tr>
<tr>
<td>Dilatancy parameter</td>
<td>$N$</td>
<td>0.1</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>Dilatancy coefficient</td>
<td>$\chi$</td>
<td>2.7</td>
<td>2.5</td>
<td>3.5</td>
</tr>
<tr>
<td>Poisson ratio</td>
<td>$\nu$</td>
<td>0.2</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td>Hardening modulus</td>
<td>$H$</td>
<td>25</td>
<td>25</td>
<td>75</td>
</tr>
</tbody>
</table>

#### Table 5.3. Estimated Constitutive Parameters of Vingerling K147 Clay

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol (Unit)</th>
<th>Baseline</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial porosity</td>
<td>$n_o$ (-)</td>
<td>0.362</td>
<td>0.290</td>
<td>0.434</td>
</tr>
<tr>
<td>Undrained shear strength at $\sigma_{\text{v,cons}}=50$ kPa</td>
<td>$s_u$ (kPa)</td>
<td>27.9</td>
<td>22.3</td>
<td>33.5</td>
</tr>
<tr>
<td>Secant Shear Modulus</td>
<td>$G$ (kPa)</td>
<td>552</td>
<td>423</td>
<td>1404</td>
</tr>
</tbody>
</table>
Figures

Figure 5.1. Mapping experimental uncertainties to numerical parameters (see Notation for parameter definitions).

Figure 5.2. Calibration chamber setup: (a) profile view, and (b) cross-sectional view.
Figure 5.3. Variability in experimental tip resistance \( (q_c) \) for CPTs performed in homogenous sand profiles during the De Lange (2018) study: (a) Three CPTs performed at \( \sigma'_{vo} = 100 \text{ kPa} \) with \( D_R = 60\% \), and (b) One CPT performed at \( \sigma'_{vo} = 50 \text{ kPa} \) and one at \( \sigma'_{vo} = 100 \text{ kPa} \) with \( D_R = 36\% \).
Figure 5.4. (a) Geometry and mesh of 2D axisymmetric model, and (b) boundary conditions.

Figure 5.5. Critical state line for Baskarp B15 sand based on 14 CD triaxial tests performed on loose specimens with $D_R = 1\%$. All triaxial data are from Ibsen and Bødker (1994).
**Figure 5.6.** Comparison of numerical and experimental triaxial data from Ibsen and Bødker (1994). (a-c) Dense specimens; (d-f) Medium dense specimens; (g-i) Loose specimens.

**Figure 5.7.** Calibration of hardening modulus, $H$
Figure 5.8. Baseline tip resistance ($q_c$) realizations from MPM simulations compared with experimental data, and determination of average tip resistance ($\bar{q}_c$) for (a) homogenous sand profile and (b) layered sand-clay profile. Insets indicate depth ranges over which $\bar{q}_c$ was computed.
Figure 5.9. All realizations from the sensitivity analysis compared to the baseline realization and experimental data for three soil profiles: (a) homogenous sand, (b) homogenous clay, and (c) layered sand-clay, where gray zones represent clay layers.
Figure 5.10. Range of average tip resistance ($\bar{q}_c$) values obtained by varying a single parameter from the upper to lower bound value indicated on either side of the bar (a) Homogeneous sand profile, (b) Homogeneous clay profile, (c) Embedded sand layer in layered profile, and (d) Embedded clay layer in layered profile.
Figure 5.11. Comparison of sensitivity index for all soil profiles: (a) Homogeneous sand profile, (b) Homogeneous clay profile, (c) Embedded sand layer in layered profile, and (d) Embedded clay layer in layered profile. Greyed zones indicate parameters that are not used in the analysis for that particular profile. Noise levels are indicated with a dashed line at the level of $S_{\text{I}_\text{noise}}$. 
Figure 5.12. (a) Position of three material points (9122, 70418, and 11654) along the rigid boundary in a homogenous sand profile whose stress history is shown in (b) and (c); (b) Evolution of effective vertical and horizontal stresses, $\sigma'_v$ and $\sigma'_h$, along the rigid boundary (fixed in x-direction) during CPT penetration; (c) Evolution of $\sigma'_h/\sigma'_v$ along the rigid boundary during CPT penetration.
Figure 5.13. (a) Comparison of $q_c$ using varying boundary conditions and initial stress states in homogenous sand profile; (b) Impact of increasing $\sigma'_{vo}$ on $q_c$ when using rigid radial boundary conditions.
Figure 5.14. (a) Void ratio (e) after 0.64 m of penetration for a homogenous sand profile with $D_R = 60\%$; (b) Impact of increasing $D_R$ from 60\% to 65\% on $q_c$. 
Chapter 6: A CPT Database for Multiple Thin-Layer Correction Procedure Development

The contributions of the authors to the composition of this manuscript are delineated as follows:

Kaleigh M. Yost
- Developed scope of the manuscript.
- Performed analyses associated with laboratory data.
- Performed the numerical simulations presented in this study.
- Co-authored the Jupyter notebook demonstrating data processing and applications.
- Prepared the figures and tables.
- Wrote the draft manuscript.
- Addressed coauthor comments in manuscript revisions.

Dr. Alba Yerro
- Oversaw creation of MPM portion of the database and provided troubleshooting and feedback.
- Reviewed and edited the draft manuscripts.
- Addressed reviewer comments and reviewed final version of the manuscript.

Dr. Eileen Martin
- Co-authored the Jupyter notebook demonstrating data processing and applications.
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

Dr. Russell A. Green
- Came up with idea for the creation of a CPT database and suggested the use of correlations to generate the laboratory portion of the database.
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.
A CPT Database for Multiple Thin-Layer Correction Procedure Development

Kaleigh M. Yost¹, Alba Yerro², Eileen Martin³, Russell A. Green⁴

¹Graduate Student, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Assistant Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: ayerro@vt.edu)
³Assistant Professor, Dept. of Geophysics and Applied Math and Statistics, Colorado School of Mines, Golden, CO 80401 (email: eileenrmartin@mines.edu)
⁴Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)

The authors of the following manuscript intend to submit it as a data paper to Earthquake Spectra.
6.1. Abstract
Cone penetration tests (CPTs) are a commonly used in-situ method to characterize soil for geotechnical engineering applications like liquefaction evaluation. However, data recorded at a given depth in a CPT sounding is influenced by the properties of all the soil that falls within the zone of influence around the cone tip, rather than only the soil layer at that particular depth. This causes data to be blurred or averaged in layered zones, a phenomenon referred to as multiple thin-layer effects. Multiple thin-layer effects can result in the inaccurate characterization of thin, interbedded layers. Correction procedures have been proposed to adjust CPT tip resistance for multiple thin-layer effects, but many are ineffective for soil layers with thicknesses 1.6 times the diameter of the cone ($d_{cone}$) or less (Yost et al. 2021). To improve these procedures and develop new ones, it is critical to have pairs of measured tip resistance ($q^m$) and true tip resistance ($q'$) data, where $q^m$ is the tip resistance recorded by the CPT in the layered profile and $q'$ represents the tip resistance that would be measured in the profile absent of multiple thin-layer effects. This article presents a database developed from laboratory and numerical CPT data from 49 highly interlayered soil profiles with layer thicknesses ranging from $0.4d_{cone}$ to $3.1d_{cone}$. Each profile has both $q^m$ and $q'$. An accompanying Jupyter notebook is provided to facilitate the use of the data and prepare it for future statistical learning (or other) applications to support multiple thin-layer correction procedure development. Several example uses of this database are outlined, including the evaluation of artificial blurring techniques used in inverse-style multiple thin-layer correction procedures and the direct evaluation of the efficacy of multiple thin-layer correction procedures.

6.2. Introduction
The cone penetration test (CPT) is a widely used in-situ geotechnical method used to characterize soil profiles for a variety of applications, including earthquake-induced soil liquefaction evaluations. Parameters that may be obtained from the CPT include tip resistance ($q_c$), sleeve friction ($f_s$), and pore pressure ($u_2$), each recorded typically at 0.01 to 0.05-cm depth increments. Parameters recorded at a particular depth are affected by the properties of all the soil that falls within the zone of influence around the tip of the cone, not just the properties of the particular soil layer at the current cone depth. Since the zone of influence can be between ~10 to 30 times the diameter of the cone (Ahmadi and Robertson 2005), it is very difficult to identify the exact depths of layer boundaries and accurately characterize the CPT parameters of individual soil layers in highly interlayered soil profiles. This is demonstrated in Figure 6.1, where a CPT performed in a
homogenous clay or sand profile records a characteristic or “true” tip resistance (designated as $q'_{clay}$ or $q'_{sand}$), but a CPT performed in a clay profile with a thin embedded sand layer records a “measured” tip resistance profile (designated as $q''$) that (1) smears the boundaries of the embedded layer and (2) underestimates the tip resistance in the embedded sand layer. When many thin layers occur in sequence in a profile, these effects are amplified and are referred to as “multiple thin-layer effects.” Multiple thin-layer effects have detrimental consequences on engineering predictions that rely on correlations with CPT data. For example, the widespread over-prediction of liquefaction severity in Christchurch, New Zealand, for complex, highly interlayered soil profiles is partially attributed to this phenomenon (e.g., Maurer et al. 2014; Boulanger et al. 2016; Cox et al. 2017; McLaughlin 2017).

Recently, several automated procedures have been proposed to correct for multiple thin-layer effects (e.g., Boulanger and DeJong 2018; de Greef and Lengkeek 2018; Yost et al. 2021; Cooper et al. 2022; Baziw and Verbeek 2022). Generally, these procedures take the recorded or measured tip resistance ($q''$) as an input (e.g., the blue trace labeled 3a in Figure 6.1) and output an estimate of the true tip resistance ($q'$) (e.g., the red trace labeled 3b in Figure 6.1). If the procedure follows a forward model, it directly applies a set of correction factors to $q''$, outputting a “corrected” tip resistance ($q'^{corr}$). If the procedure follows an inverse model, an “inverted” tip resistance ($q'^{inv}$) intending to estimate $q'$ is guessed, a model describing the blurring process of cone penetration is applied to $q'^{inv}$ to obtain a simulated measured tip resistance ($q'^{m,sim}$), and then $q'^{m,sim}$ is compared to the recorded $q''$. If the misfit between $q'^{m,sim}$ and $q''$ is too large, the procedure iterates. A flowchart summarizing the types of procedures is shown in Figure 6.2.

Existing multiple thin-layer correction procedures have several shortcomings, including:

1. Procedures must be calibrated and validated with profiles that include both $q''$ and $q'$. While $q''$ data are readily available, obtaining the corresponding $q'$ is more difficult because soil profile geometry and soil properties for each layer must be known. For example, field CPT data in layered profiles only provide $q''$, not $q'$. To obtain sets of $q''$ and $q'$, laboratory calibration chamber tests, numerical simulations of CPTs, or empirical correlations may be used. However, large sets of $q''$-$q'$ data are not readily available.
(2) Indirect assessment of the efficacy of multiple thin-layer correction procedures can be performed using field data. For example, Yost et al. (2021) (i.e., Chapter 2 of this dissertation) applied multiple thin-layer correction procedures to a CPT database from Christchurch, New Zealand, and compared the accuracy of liquefaction evaluations performed with corrected and uncorrected data. However, they found no improvement in the accuracy of liquefaction evaluations using the corrected data. Furthermore, even if an improvement was observed, it would not necessarily follow that the procedure accurately corrected the data. Direct assessment with $q^m$-$q^t$ pairs is required as a first step in evaluating the efficacy of these procedures.

(3) Many existing procedures become ineffective in soil profiles with layers thicknesses of about $1.6d_{cone}$ or smaller, as shown in Yost et al. (2021, 2022b). As the layers become thinner, their contribution to $q^m$ becomes smaller, and ultimately it may be impossible to visually identify the presence of very thin layers in a $q^m$ profile. Many multiple thin-layer correction procedures rely on the ability to identify peaks and troughs in $q^m$ (e.g., the Deltares procedure from Yost et al. 2021), or use the rate of change in $q^m$ or another CPT parameter (e.g., Boulanger and DeJong 2018), to identify layer boundaries. As the CPT data in layered zones become increasingly smoothed with smaller layer thicknesses, these procedures become less effective. However, many profiles of interest (i.e., the Christchurch profiles) have layers less than $1.6d_{cone}$ thick, and therefore it is necessary to improve existing procedures or develop new procedures that can account for layers of this thickness.

(4) A salient feature of inverse-style correction procedures like Boulanger and DeJong (2018) and Cooper et al. (2022) is that they must define how the CPT blurs or filters $q^t$ to obtain the $q^m$ that is actually recorded. This blurring process is a complex physical procedure that is not well captured by current models (Cooper et al. 2022). Some existing approaches use a blurring filter consisting of a truncated chi-squared distribution with depth-dependent weighting factors (i.e., Boulanger and DeJong 2018), or a simplified version of this distribution (i.e., Cooper et al. 2022). A filter that accurately describes the physics behind multiple thin-layer effects will, when applied to a $q^t$ profile, produce a $q^{m,sim}$ profile that closely matches the actual $q^m$ profile. To develop and assess how well a blurring filter works, pairs of $q^m$-$q^t$ data are required.
Correcting CPT data in highly interlayered profiles with procedures that do not perform well is at best, ineffective, and at worst, not conservative. To overcome the shortcomings of existing procedures described previously, and support the development and validation of new ones, a combined laboratory and numerical database has been constructed containing CPT data from 49 highly interlayered soil profiles with embedded layer thicknesses ranging from 0.01 to 0.08 m (0.4\(d_{cone}\) to 3.1\(d_{cone}\)). Each profile has both \(q_m\) and \(q_t\) data. The data are presented in an array structure that can easily be added to and manipulated as desired by the researcher. The following sections describe the creation of this database. In Section 6.3, the development of the laboratory and numerical parts of the CPT database is discussed. Section 6.4 provides details on how to access, supplement, and utilize the database. Section 6.5 provides examples of how this database can be used to assess blurring filters and the efficacy of existing multiple thin-layer correction procedures. Section 6.6 contains a discussion of the limitations and nuances of this database. Final thoughts are provided in Section 6.7.

6.3. Development of CPT Database

6.3.1. Laboratory Data

A portion of the database presented in this article was generated using curated and processed CPT data originally collected in a series of calibration chamber tests conducted by De Lange (2018). These laboratory tests were also used to calibrate the numerical model used to produce the numerically-generated portion of this database. The following sections provide an overview of the laboratory tests and describe how the data were processed to create the \(q_m-q_t\) profiles provided in this database.

6.3.1.1. Overview

A large CPT calibration chamber study was conducted by De Lange (2018) to study multiple thin-layer effects. The calibration chamber consisted of a series of stacked cylindrical rings with an inner diameter of 0.9 m and a height of approximately 1 m. Homogenous sand and interlayered sand-clay soil profiles were prepared in the chamber. A pressurized, water-filled cushion placed on top of the soil profile provided overburden pressure, and ports within the cushion allowed CPTs to be advanced through the soil profile. Drainage was allowed through a geotextile and filter plate at the bottom of the chamber and through the ports in the cushion at the top of the chamber. The radial boundary was considered to be rigid (Yost et al. 2022a).
Multiple CPTs were performed in homogenous and highly interlayered soil profiles constructed in the chamber. Each profile was designated with a “Soil Model” number. Most of the CPTs were performed with a 25-mm-diameter cone. In two of the soil profiles (Soil Model 6 and Soil Model 7), 36-mm-diameter cones were used. These profiles were excluded from the analyses detailed herein. Two homogenous sand profiles (Soil Model 1 and Soil Model 5) were used as reference models to determine the true tip resistance ($q'$) associated with the sand; their relevant details are provided in Table 6.1. Data from the remaining layered profiles (Soil Models 2 through 4 and 8 through 10), as well as one soil model from the start-up phase of the experiments (Soil Model 4 – Start Up), were used to compile the laboratory portion of the database; see soil profile geometries Figure 6.3. In total, there were 19 CPT soundings performed in layered profiles whose tip resistance data could be used as $q^m$. The relevant information for each of those soundings is summarized in Table 6.2. Note that the tip resistance data from De Lange (2018) were digitized and then resampled at 0.001 m depth increments, consistent with the sampling intervals during the laboratory tests.

The tip resistance recorded from CPTs in the layered profiles from Table 6.2 was considered to be $q^m$. To construct $q'$ profiles that correspond to each of the $q^m$ profiles, both $q'^{\text{sand}}$ and $q'^{\text{clay}}$ were required. To determine $q'^{\text{sand}}$, data from the homogenous sand profiles (i.e., the CPTs in Table 6.1) were used. To determine $q'^{\text{clay}}$, the data collected in the 16-cm-thick clay layers of Soil Model 9 (i.e., Lab Database CPT Indices 12 and 13 from Table 6.2) were used. However, the CPTs performed in these “reference” profiles do not cover all the possible combinations of sand relative density ($D_R$) and applied vertical effective stress ($\sigma'_v$) that were experienced by the CPTs performed in the layered profiles (i.e., the CPTs in Table 6.2). In order to compute $q'^{\text{sand}}$ and $q'^{\text{clay}}$ for any combination of $D_R$ and $\sigma'_v$, well-known empirical correlations for $q_c$ in sands and clays were adopted and calibrated with the reference data. This procedure is summarized in the following sections.

6.3.1.2. Determining Tip Resistance from Overburden Pressure and Density for Sands

The following equation from Schmertmann (1978) can be used to relate $q_c$ to $D_R$ in sands:
where $C_0$, $C_1$, and $C_2$ are coefficients selected to fit the data, $\sigma'$ is assumed to be the initial vertical effective stress ($\sigma'_{vo}$) for normally consolidated sands, $q_c$ and $\sigma'$ are in kPa, and $D_R$ is in decimal form. Because we are interested in estimating $q_c$ from $D_R$, Equation 6.1 can be rewritten as:

$$q_c = C_0 \sigma'_{vo} \exp(C_2 D_R)$$

(6.2)

$C_0$, $C_1$, and $C_2$ were determined from a nonlinear regression analysis (using Matlab function fitnlm) using data from the five CPTs performed in the homogenous sand profiles. For each reference CPT in Table 6.1, average $q_c$ and $\sigma'_{vo}$ were computed between 0.1 and 0.7 m. Since $D_R$ for these profiles was known, the coefficients were computed as $C_0 = 27.7167$, $C_1 = 1.0466$, and $C_2 = 1.9587$. The laboratory and predicted $q_c$ values are compared in Table 6.3 and Figure 6.4. Although the data are limited, the fit is good.

### 6.3.1.3. Determining Tip Resistance from Overburden Pressure and Undrained Shear Strength for Clays

For the undrained conditions expected during cone penetration in the clay layers, $q_c$ can be related to undrained shear strength ($s_u$) by:

$$q_c = N_c s_u + \sigma_{vo}$$

(6.3)

where $N_c$ is the cone factor, $\sigma_{vo}$ is the initial total vertical stress, and all other variables are as previously defined. The two CPTs performed in Soil Model 9 were used to get two data points for a regression analysis; see Table 6.4. Average $q_c$ and $\sigma_{vo}$ were computed between 0.5171 and 0.6171 m, the region where the $q_c$ appears to have reached a characteristic value to define $q_{t,clay}$. The resulting $N_c$ was 6.82, which is low compared to other $N_c$ values reported in the literature for similar clays. For example, Ceccato et al. (2016b) summarize cone factors from nine different numerical studies on soft clays, with values ranging from 9.3 to 11.5. It is difficult to assess whether $N_c=6.82$ is truly appropriate for this study because of the very limited amount of data. However, because $q_{t,clay}$ is so much lower than $q_{t,sand}$, any uncertainties in $q_{t,clay}$ (on the order of
kPa) will be dwarfed by the scale of \( q_{ts,\text{sand}} \) once the data for the layered profiles are combined, the uncertainty in \( N_c \) is likely fairly inconsequential for this application. A comparison of computed and measured \( q_c \) for the clay is shown in Figure 6.5.

6.3.1.4. Normalizing the Laboratory Data

Equations 6.2 and 6.3 were used to compute a \( q_{ts,\text{sand}} \) and \( q_{t,\text{clay}} \) for each CPT listed in Table 6.2. Then, the Idriess and Boulanger (2008) equations were used to normalize all tip resistances (i.e., \( q^m \), \( q_{ts,\text{sand}} \), and \( q_{t,\text{clay}} \)) for overburden pressure:

\[
q_{c1n} = \left( \frac{q_c}{P_a} \right) C_N \tag{6.4}
\]

where \( q_{c1n} \) is normalized cone tip resistance, \( P_a \) is atmospheric pressure, and \( C_N \) is a correction factor defined by:

\[
C_N = \left( \frac{P_a}{\sigma'_v} \right)^m \tag{6.5}
\]

where \( \sigma'_v \) is the effective vertical stress in the same units as \( P_a \), and \( m \) is computed as:

\[
m = 1.338 - 0.249q_{c1n}^{0.264} \tag{6.6}
\]

Note that since \( m \) depends on \( q_{c1n} \), the procedure to compute \( q_{c1n} \) is iterative. From here onward, references to \( q^m \), \( q_{ts,\text{sand}} \), and \( q_{t,\text{clay}} \) are to their normalized \((q_{c1n})\) values.

6.3.1.5. Constructing Measured and True Tip Resistance Profiles

The \( q^m \), \( q_{ts,\text{sand}} \), and \( q_{t,\text{clay}} \) data were truncated between 0.1005 and 0.6005 m to exclude data affected by boundary effects. This eliminated data at the top of the profile where tip resistance is impacted by the upper boundary and not yet fully developed, and at the bottom of the profile where results are impacted by the rigid bottom boundary. For each soil profile, \( q' \) was constructed by assigning \( q_{ts,\text{sand}} \) and \( q_{t,\text{clay}} \) over the depths associated with the sand and clay layers, respectively. Note that although this would ideally result in a piecewise constant profile, it is necessary for there to be only one \( q' \) associated with each depth value in order for the \( q' \) and \( q^m \) profiles to align for further
use. The depths at which the data were sampled (in 0.001-m increments) were realigned (offset by 0.0005 m) such that no data point would fall exactly on a layer boundary. Consequently, the $q'$ profiles resulting from this procedure slightly underestimate the thickness of each layer by up to 1 mm. The resulting $q''$ and $q'$ pairs are shown in Figures 6.6a and 6.6b.

### 6.3.2. Numerically Simulated Data

The bulk of the database proposed in this article comprises numerically-generated CPT data using MPM simulations of cone penetration in layered profiles. Numerical simulations provide a faster and cheaper alternative to performing laboratory calibration chamber tests; for example, one numerical CPT simulation in this dataset takes a few days to perform while a laboratory testing program could take several months. This numerical model was calibrated and validated in previous work by Yost et al. (2022c) using the laboratory data detailed in Section 6.3.1. The following sections provide an overview of the Material Point Method (MPM) and how the MPM simulations were used to generate $q''$-$q'$ pairs for a variety of soil profile geometries.

#### 6.3.2.1. MPM Background

The material point method (MPM) is an advanced numerical modeling technique developed by Sulsky et al. (1994) that combines features of mesh-based and particle-based methods. It is well-suited for large deformation problems because it does not suffer from mesh tangling. MPM has been shown to successfully simulate cone penetration in clays (e.g., Beuth and Vermeer 2013; Ceccato et al. 2015, 2016a; b; Ceccato and Simonini 2017; Bisht et al. 2021a; b), sands (e.g., Tehrani and Galavi 2018; Ghasemi et al. 2018; Martinelli and Galavi 2021; Martinelli and Galavi 2022), and layered sand-clay profiles (e.g., Yost et al. 2022a; Yost et al. 2022c). In this article, the Yost et al. (2022c) framework and geometry are adopted. It was shown by Yost et al. (2022c) that three MPM simulations could generate a $q''$-$q'$ pair for a layered soil profile with two material types. Namely, one simulation performed in the layered profile would provide $q''$, and two additional simulations in homogenous soil profiles using the properties of each soil type in the layered profile would provide $q'$ for each soil type. The entire $q'$ profile can be constructed if the layer geometry is known by assigning the corresponding $q'$ to the depth range associated with its respective soil layer.
The simulations used to generate the numerical portion of this database were performed with a 2D axisymmetric formulation of MPM on the Anura3D platform (Anura3D 2021). Salient features of the MPM implementation include:

- A mixed integration scheme where Gauss-point integration is used in fully-filled elements to reduce cell-crossing error, and material-point integration used otherwise (Al-Kafaji 2013)
- A contact algorithm by Bardenhagen et al. (2001) describing interaction between the penetrometer and the surrounding soil
- A rigid-body algorithm from Zambrano-Cruzatty and Yerro (2020) to enforce incompressibility of the penetrometer and reduce computational time
- A moving mesh technique to maintain contact geometry throughout cone penetration (e.g., Beuth 2012; Al-Kafaji 2013; Ceccato and Simonini 2019)
- A strain-smoothening technique to reduce volumetric locking (Al-Kafaji 2013)
- A mass-scaling technique with a factor of 10,000 to reduce computational time (Al-Kafaji 2013)
- A local damping factor of 0.05 used to reduce stress oscillations

The MPM model and calibration procedure are thoroughly explained in Yost et al. (2022c) and thus is only briefly described here. The simulations were calibrated with the De Lange (2018) laboratory data, and therefore, the geometry, boundary and initial conditions, and soil constitutive models were selected to mimic those experimental tests (see Figure 6.7). The penetrometer had a diameter \( d_{cone} \) equal to 25 mm and an apex angle of 60 degrees. To avoid numerical instabilities, the initial position of the penetrometer was partially embedded in the soil profile and the tip of the penetrometer was slightly rounded. The penetrometer was advanced through the soil profile at a velocity of 0.01 m/sec, and the force imparted on the face of the cone was used to compute \( q_c \). To apply the desired overburden pressure to the soil profile, a layer of material with height and density selected to result in \( \sigma'_{v0} = 50 \text{ kPa} \) at the top of the soil profile was included (i.e., the blue layer shown in Figure 6.7).

A triangular mesh with a more refined region near the zone of penetration was used. The mesh extended vertically ~1 m below the tip of the cone and horizontally ~0.225 m. The radial dimension is slightly smaller than what was used in the laboratory experiments, but, for these particular
simulations the radial dimension was shown to play a relatively insignificant role in tip resistance sensitivity in layered zones by Yost et al. (2022a). Material points (MPs) were more concentrated in the zone of penetration. The moving mesh extended from the top of the domain to ~0.06 m below the tip of the cone. The compressing mesh began where the moving mesh ended and extended to the bottom boundary. The left and right boundaries were fixed in the horizontal direction, and the top and bottom boundaries were fixed in the horizontal and vertical directions. The boundary conditions replicate the conditions in the laboratory calibration chamber; namely, a rigid radial boundary.

6.3.2.2. **Overview of MPM Simulations**

To generate the numerical portion of this database, ten highly interlayered soil profiles were created. Each profile consisted of a 0.1-m-thick sand layer overlying a 0.4-m-thick zone of alternating clay and sand layers overlying a 0.5-m-thick sand layer. The stratigraphy of the layered zone was created by randomly selecting a number of layers (up to 40) and randomly selecting layer thicknesses from an exponential distribution with minimum layer thickness of 0.01 m (0.4\(d_{cone}\)) and mean layer thickness of 0.03 m (1.2\(d_{cone}\)). The geometry of each profile is shown in Figure 6.8.

In total, 30 MPM CPT simulations were performed resulting from two iterations on each of the 15 soil profiles shown in Figure 6.8. The first 15 simulations assumed the sand layers were medium dense (\(D_R = 54\%\)) and the second 15 assumed the sand layers were loose (\(D_R = 36\%\)). The sand behavior was represented as completely drained using a strain softening Mohr-Coulomb model and the clay behavior was represented as completely undrained using the Tresca model. The constitutive parameters used for the dense and loose sands and clay layers are summarized in Table 6.5 and were selected based on calibration with the De Lange (2018) laboratory calibration chamber test data and triaxial data on the sand used in the calibration chamber tests from Ibsen and Bødker (1994) and Borup and Hedegaard (1995). Detailed calibration procedures are provided in Yost et al. (2022c) and are not further elaborated on here.

The interface friction coefficient for the sand-cone interface was assumed to be \(\tan(0.5\phi'_{p})\). The interface friction coefficient of the clay was selected to be equal to the interface friction coefficient of the sand used in the analysis. In this implementation of Anura3D, it is not possible to define
average contact properties for elements containing both sand and clay MPs – only one set of contact properties can be used. A sensitivity analysis performed by Yost et al. (2022c) supported using the contact properties associated with the sand to represent contact throughout the layered zones, where the elements immediately adjacent to the cone contain both sand and clay MPs.

6.3.2.3. Determining Tip Resistance from MPM Simulations

The tip resistance profiles obtained from each of the 30 MPM CPT simulations in the layered soil profiles shown in Figure 6.8 are considered to be \( q^m \). The true tip resistance associated with the sand and the clay layers (\( q^{t,sand} \) and \( q^{t,clay} \)) were determined from three supplemental simulations performed in homogenous sand and clay profiles using the constitutive properties provided in Table 6.5. In other words, to determine all the \( q^t \) profiles needed for this database, one simulation was performed for a homogenous sand at \( D_R = 36\% \), one for a homogenous sand at \( D_R = 54\% \), and one for a homogenous clay. Based on the \( D_R \) of the sand in the layered profiles, each \( q^m \) was then grouped with an appropriate \( q^{t,sand} \) and \( q^{t,clay} \).

The \( q^m \), \( q^{t,sand} \), and \( q^{t,clay} \) profiles were truncated between 0.1005 and 0.5005 m – the interlayered zone – and smoothed (averaged) over 0.001-m increments. The smoothing is required because the MPM simulations produce tip resistance values at very small-scale, inconsistent depth increments. The 0.001-m increments were chosen to match the depth interval used in the laboratory data, as described in Section 6.3.1. All tip resistances were then normalized to \( q_{c,ln} \) values per the procedure described in Section 6.3.1.4. Finally, coupled with the known layer geometries shown in Figure 6.5, the \( q^t \) profiles were constructed by selecting either the \( q^{t,sand} \) or \( q^{t,clay} \) at a given depth associated with the appropriate layer, following the same procedure outlined in Section 6.3.1.5. The resulting \( q^m-q^t \) pairs are shown in Figure 6.9a-c.

6.4. Compilation and Structure of Database

The lab data and MPM data were compiled into two .csv files, one containing \( q^m \) data and one containing \( q^t \) data. The first row of each .csv file contains the depths at which the data were sampled (i.e., 0.1005 m to 0.6005 m at 0.001-m increments). Both lab and MPM data were sampled at the same depth increments, but the total depth of the lab profiles was larger. Therefore, the MPM data were padded with zeros on the end to match the depth dimension of the lab data. Each subsequent
row represents one CPT. Rows 2 through 20 contain the tip resistances from each of the lab CPTs. Rows 21 through 50 contain the tip resistances from each of the MPM CPTs.

The first column of each .csv file contains a “profile category” number. Profiles that had the same layer geometry were grouped together. For example, lab CPTs 3 through 5 were assigned the same profile category number. Similarly, MPM CPTs 1 and 16 were assigned the same profile category number. The intent of grouping similar profiles is to improve potential statistical learning applications of this dataset. When training statistical learning algorithms, data are parsed into training and test datasets. By assigning the same profile category number to similar profiles, it is possible to ensure that all profiles that fall within that group are assigned to either the training or test dataset, and not split between the two. This avoids potential problems with the statistical learning algorithm, which could potentially “memorize” a pattern already seen in the training data and apply it to a similar profile in the test data, without truly learning the relationship between $q^m$ and $q^l$.

6.5. How to Access, Supplement, and Use the Database

The database is available on the Virginia Tech data repository, VTechData (Yost 2022d). Two .csv files are provided, one containing $q^m$ data and one containing $q^l$ data, as described in Section 6.4. A Jupyter notebook (created in the Google Colab environment) is also provided to read the data and perform initial processing. Contents of the notebook include:

- A script to read data in and initialize depth, $q^m$, $q^l$, and profile category variables
- A script to visualize the contents of the database
- A framework to parse the database into separate training and test datasets, grouping profiles with same profile category number together
- A script to visualize the parsed training and testing data
- An example of how to manipulate data with subsampling and filtering to change the size of the depth interval
- An example of “chunking” profiles to generate more data to use in training and test datasets
- A framework for how to add data to the existing database
- An example of using a profile from the database to assess a simple blurring filter
6.6. Example Uses

Two potential uses of this database to develop better multiple thin-layer correction procedures are (1) to assess existing blurring filters and develop better ones through statistical learning methods and (2) to directly assess performance of procedures (i.e., assess how well $q^\text{inv}$ or $q^\text{corr}$ matches $q'$). Those applications are demonstrated in the following two sections.

6.6.1. Assessing a CPT Blurring Filter

Selection of a filter that adequately captures the blurring effect of the CPT passing through interlayered soil is critical to the success of inverse-style multiple thin-layer correction procedures. The Jupyter notebook provides an example of how to visually assess the performance of such a filter on $q^m$-$q'$ data from a single profile. A simple triangular distribution and a chi-squared distribution are provided as filter options. Any other filter could easily be implemented into the notebook by the user. The convolution of the filter (e.g., the chi-squared filter shown in Figure 6.10a) with $q'$ generates a $q^m_{\text{sim}}$ that can be compared to $q^m$ (e.g., Figure 6.10b). As shown in Figure 6.10, since the mismatch between $q^m$ and $q^m_{\text{sim}}$ is large, the chosen filter is not a good representation of the physics of multiple thin-layer effects.

This database has been structured to support the development of better blurring filters using statistical learning tools. For example, a neural network could be trained to predict $q^m$ given $q'$ using the parsed training and test data provided in the database. Once trained, the neural network could be inserted within the framework of an existing inverse-style multiple thin-layer correction procedure (like Cooper et al. 2022) to describe the blurring process.

6.6.2. Assessing Efficacy of Multiple Thin-Layer Correction Procedures

The database can also be used to assess the efficacy of multiple thin-layer correction procedures. Using $q^m$ as the input to the procedure, the output ($q^\text{corr}$ or $q^\text{inv}$) is computed and compared directly to $q'$. For example, in Figure 6.11 the performance of the following multiple thin-layer correction procedures are compared: Boulanger and DeJong (2018) inverse procedure [BD18], Cooper et al. (2022) inverse procedure [CEA22], and Yost et al. (2021) forward “Deltares” procedure [DEL21].
None of the procedures shown in Figure 6.11 perform well – no $q^{corr}$ or $q^{inv}$ is a good estimation of $q'$. This is not surprising and has been shown in previous studies for other soil profiles with layer thicknesses on the order of $1.6d_{cone}$ thick or thinner (e.g., Yost et al. 2021, Yost et al. 2022b). This highlights the need to improve these procedures, or develop new techniques to extract $q'$ from $q''$. This database has been structured to aid in the development of new multiple thin-layer correction procedures, using statistical learning tools in particular. For example, a neural network could be developed using the parsed training and test data provided in this dataset to predict $q'$ from a given $q''$. A potential pitfall of this is that the neural network would serve as a black box method to extract $q''$. In other words, no greater understanding of the physics of multiple thin-layer effects would be achieved, there is little control of what $q''$ could potentially look like, and it may be difficult to implement known physical constraints. Furthermore, the performance of the procedure would have to be carefully evaluated if used on profiles that were very different from the profiles used to train and test the procedure.

6.7. Nuances and Limitations

The use of any database comes with limitations. This section discusses some of the relevant nuances and limitations of this database.

6.7.1. Limitations of the Numerical Model

It is important to acknowledge that any numerical technique has inherent limitations on how well it can represent soil behavior. MPM is a continuum method, meaning micro-scale phenomena like particle crushing and breakage are not directly accounted for. At the high mean effective stresses experienced by the soil during cone penetration, particle breakage is possible. Furthermore, simple soil constitutive models were used for the simulations in this article; more advanced critical state constitutive models may be useful in better describing soil behavior over large ranges of stresses. However, the use of more advanced constitutive models also introduces more uncertainties and may not produce better results (e.g., as discussed by Yost et al. 2022a).

Many assumptions and simplifications are made when developing a numerical model to replicate a real-world scenario with respect to the geometry, boundary conditions, drainage conditions of the soil, soil properties, soil-cone contact properties, and other parameters (Yost et al. 2022a). The MPM simulations used to generate the numerically simulated data in this database have been
extensively calibrated with laboratory data. In that sense, some of the uncertainties associated with those assumptions have been reduced, and the MPM results presented in this paper can be considered a direct extension of the laboratory results in which new geometries have been introduced. However, the profile geometries used for the MPM simulations have not been replicated with laboratory testing. It would be useful to perform additional laboratory CPT testing with irregular soil layering and layers as thin as $0.4d_{cone}$, like the profiles used for the MPM simulations, to further validate the MPM results. Another way to indirectly assess the validity of the MPM data could be to use laboratory data only to train a multiple thin-layer correction procedure, and then test it on the MPM data (or vice versa).

6.7.2. Sensitivity to CPT Sampling Interval
Typical CPTs record data at 0.01 to 0.05-m depth intervals. The depth intervals for both the lab and MPM data in this database are 0.001 m. When using this database, there may be a desire to more coarsely sample (subsample) the data to better represent typical CPT sampling intervals. Two example techniques of how to do this include: standard subsampling (i.e., selecting data at a regular depth interval) and subsampling with interpolation (i.e., linearly interpolating the data to the depth interval you select). An example of each is included in the Jupyter notebook provided as supplemental materials to this article. However, there are potential pitfalls of more coarsely sampling the data. While coarser sampling more accurately represents how a typical CPT records $q''$, it may not result in a good representation of $q'$. For example, since most of the profiles in this database have layers on the order of 1 cm thick, sampling at a 2-cm interval may result in very thin layers delineated in $q'$ being missed completely, or only one data point may be sampled in a particular layer. This could prove to be problematic when using this more coarsely sampled data to develop or train multiple thin-layer correction procedures. Thus, it will be important for research using this database to include sensitivity analyses considering different subsampling techniques and intervals.

6.7.3. Limitations of Statistical Learning Applications with this Database
Statistical learning techniques require training data. While data augmentation techniques may be used (such as the data chunking method presented as an example in the Jupyter notebook), the database presented herein is likely too small to robustly train, for example, a neural network. Each
soil profile contained in this database is less than 0.6 m deep: a function of limited laboratory calibration chamber depths and the computational cost of numerically simulating CPTs. This inherently limits the amount of data within a single CPT profile. Furthermore, this database only contains 49 soil profiles. The addition of more data would be largely beneficial for the potential statistical learning applications of this database.

The more variety in the training and testing data, the better because there would be less extrapolation to unseen conditions. That means the addition of \( q^m-q' \) data with varied profile geometries and soil properties would be better than performing additional simulations with the 15 geometries used to generate the existing database. Furthermore, the existing database contains only bimodal \( q' \) data: in other words, the profiles contain only two material types. Ideally, additional simulations would be performed in profiles generated with randomly assigned geometries and randomly assigned material properties for each layer. This would result in more irregular \( q' \) distributions that may better mimic real-world conditions. Currently, the Anura3D platform used to generate the database requires the manual generation of profile geometries in the GiD preprocessor. This process would need to be automated in order to realistically facilitate large-scale testing of more randomly generated profiles.

6.8. Conclusions and Future Research Directions

In this article, a cone penetration test (CPT) database developed from laboratory and numerically simulated data was presented. Measured and true tip resistance (\( q^m \) and \( q' \)) pairs for 49 different highly interlayered soil profiles were generated and compiled into a publicly available dataset. A companion Jupyter notebook was created to facilitate the use of this data; in particular, to train statistical learning techniques to either predict \( q' \) from \( q^m \), or to develop a better blurring model of how the CPT translates \( q' \) to \( q^m \) through the phenomenon referred to as multiple thin-layer effects. Examples of how to use this database to assess existing blurring models and multiple thin-layer correction procedures were provided. Several nuances and limitations of the database were discussed, and the need for more data was highlighted. Future work from the authors aims to contribute more data to the database within the framework presented in this article from the results of new laboratory calibration chamber studies being conducted at Virginia Tech. Additionally, the authors intend to use the database to improve the blurring model used in the Cooper et al. (2022)
multiple thin-layer correction procedure. Contributions to the database from other researchers are encouraged in order to develop a more robust set of data needed for statistical learning techniques and help standardize the way the efficacy of multiple thin-layer correction procedures is assessed.

6.9. Acknowledgements

This research was partially funded by National Science Foundation (NSF) Grant Nos. CMMI-1825189 and CMMI-1937984. Their support is gratefully acknowledged. However, any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NSF or others acknowledged.

References


Canada.


Tables

**Table 6.1.** Summary of laboratory CPTs performed in homogenous sand profiles (used as reference models)

<table>
<thead>
<tr>
<th>Reference CPT Index</th>
<th>De Lange (2018) Soil Model Number</th>
<th>Relative Density, $D_R$, of Sand Layers (%)</th>
<th>Applied Overburden Stress, $\sigma'$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>36</td>
<td>50</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>60</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>100</td>
</tr>
</tbody>
</table>
### Table 6.2. Summary of laboratory CPTs performed in layered sand-clay profiles (used in database)

<table>
<thead>
<tr>
<th>Lab Database CPT Index</th>
<th>De Lange (2018) Soil Model Number</th>
<th>Relative Density, $D_R$, of Sand Layers (%)</th>
<th>Applied Overburden Stress, $\sigma'$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>29</td>
<td>25</td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
<td>50</td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>28</td>
<td>50</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td></td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>7</td>
<td>4</td>
<td>54</td>
<td>50</td>
</tr>
<tr>
<td>8</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>10</td>
<td>8</td>
<td>61</td>
<td>50</td>
</tr>
<tr>
<td>11</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>12</td>
<td>9</td>
<td>28</td>
<td>50</td>
</tr>
<tr>
<td>13</td>
<td></td>
<td></td>
<td>100</td>
</tr>
<tr>
<td>14</td>
<td></td>
<td></td>
<td>10</td>
</tr>
<tr>
<td>15</td>
<td>10</td>
<td>18</td>
<td>20</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td></td>
<td>30</td>
</tr>
<tr>
<td>17</td>
<td></td>
<td></td>
<td>25</td>
</tr>
<tr>
<td>18</td>
<td>4 – Start Up</td>
<td>41</td>
<td>50</td>
</tr>
<tr>
<td>19</td>
<td></td>
<td></td>
<td>200</td>
</tr>
</tbody>
</table>
Table 6.3. Comparison of sand $q_c$ from lab data and Schmertmann (1978) fitted relationship

<table>
<thead>
<tr>
<th>Reference CPT Index</th>
<th>Relative Density, $D_r$ (%)</th>
<th>Initial Vertical Effective Stress, $\sigma_v^e$ (kPa)</th>
<th>$q_c$ from De Lange (2018) Lab Tests (MPa)</th>
<th>$q_c$ predicted from Schmertmann (1978) fit (MPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>36</td>
<td>57.5</td>
<td>3.88</td>
<td>3.90</td>
</tr>
<tr>
<td>2</td>
<td>36</td>
<td>108.1</td>
<td>7.55</td>
<td>7.54</td>
</tr>
<tr>
<td>3</td>
<td>60</td>
<td>107.8</td>
<td>10.0</td>
<td>12.0</td>
</tr>
<tr>
<td>4</td>
<td>60</td>
<td>107.5</td>
<td>12.6</td>
<td>12.0</td>
</tr>
<tr>
<td>5</td>
<td>60</td>
<td>107.7</td>
<td>13.5</td>
<td>12.0</td>
</tr>
</tbody>
</table>

Table 6.4. Comparison of clay tip resistance ($q_c$) from lab data and the fitted relationship in Equation 6.3

<table>
<thead>
<tr>
<th>Lab Database CPT Index</th>
<th>Undrained Shear Strength, $s_u$ (kPa)</th>
<th>Initial Total Vertical Stress, $\sigma_v$ (kPa)</th>
<th>$q_c$ from De Lange (2018) Lab Tests (kPa)</th>
<th>$q_c$ predicted from fit (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>27.9</td>
<td>68.2</td>
<td>295</td>
<td>258</td>
</tr>
<tr>
<td>13</td>
<td>37.9</td>
<td>117.3</td>
<td>349</td>
<td>376</td>
</tr>
</tbody>
</table>

Table 6.5. Constitutive parameters for sand and clay layers in MPM models

<table>
<thead>
<tr>
<th>Sand Layers</th>
<th>Sand Relative Density, $D_r$ (%)</th>
<th>36</th>
<th>54</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Porosity, $n$</td>
<td>0.435</td>
<td>0.415</td>
</tr>
<tr>
<td></td>
<td>Peak friction angle, $\phi'_p$ (deg)</td>
<td>37</td>
<td>38</td>
</tr>
<tr>
<td></td>
<td>Residual friction angle, $\phi'_r$ (deg)</td>
<td>35.5</td>
<td>36</td>
</tr>
<tr>
<td></td>
<td>Dilatancy, $\psi$ (deg)</td>
<td>9.5</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>Young’s Modulus, $E$ (kPa)</td>
<td>10,000</td>
<td>20,000</td>
</tr>
<tr>
<td></td>
<td>Shape factor, $\eta$</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Interface friction coefficient</td>
<td>0.335</td>
<td>0.344</td>
</tr>
<tr>
<td></td>
<td>Poisson ratio, $\nu$</td>
<td>0.33</td>
<td>0.33</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Clay Layers</th>
<th>Young’s Modulus, $E$ (kPa)</th>
<th>25,000</th>
<th>25,000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Undrained shear strength, $s_u$ (kPa)</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td></td>
<td>Poisson ratio, $\nu$</td>
<td>0.49</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>Porosity, $n$</td>
<td>0.3458</td>
<td>0.3458</td>
</tr>
<tr>
<td></td>
<td>Interface friction coefficient</td>
<td>0.335</td>
<td>0.344</td>
</tr>
</tbody>
</table>

182
Figures

Figure 6.1. Schematic of multiple thin-layer effects in CPT data. Tip resistance from CPTs performed in homogenous clay and sand profiles can be considered characteristic or “true” tip resistances, $q'_{\text{clay}}$ (labeled 1) and $q'_{\text{sand}}$ (labeled 2). Measured tip resistance ($q''$) from a CPT performed in a layered sand-clay profile is affected by multiple thin-layer effects (labeled 3a). True tip resistance of the layered profile ($q'$, labeled 3b) can be constructed using $q'_{\text{sand}}, q'_{\text{clay}},$ and the known layer geometry.
Figure 6.2. Flow chart describing multiple thin-layer correction procedures.

Figure 6.3. Layered soil profile geometries from the De Lange (2018) calibration chamber experiments. Gray areas represent clay layers and white areas represent sand layers. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.
Figure 6.4. Comparison of tip resistance ($q_c$) measured in laboratory cone penetration tests in homogenous sand profiles and $q_c$ computed using Equation 6.2.

Figure 6.5. Comparison of tip resistance ($q_c$) measured in clay layers during laboratory cone penetration tests and $q_c$ computed using Equation 6.3.
Figure 6.6a. Pairs of $q^m$ and $q'$ generated from laboratory data. Clay layers are indicated in gray. Lab Database CPT Index is shown above each plot. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.
Figure 6.6b. Pairs of $q^m$ and $q^l$ generated from laboratory data. Clay layers are indicated in gray. Lab Database CPT Index is shown above each plot. Note that soil profiles extend to ~1 m but only the interlayered zones are shown here.

Figure 6.7. MPM geometry (modified from Yost et al. 2022c).
Figure 6.8. 15 soil profiles generated for MPM simulations. Gray zones represent clay layers, white zones represent sand layers. Note that soil profiles extend to ~1 m but only the interlayered zones are shown in this figure.
Figure 6.9a. Pairs of $q^m$ and $q'$ generated from MPM data – CPTs 1 through 10. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.

Figure 6.9b. Pairs of $q^m$ and $q'$ generated from MPM data – CPTs 11 through 20. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.
Figure 6.9c. Pairs of $q_m$ and $q_t$ generated from MPM data – CPTs 21 through 30. Clay layers are indicated in gray. MPM Database CPT Index is shown above each plot.

Figure 6.10. (a) Chi-squared blurring filter; (b) Comparison of $q_m$, $q_t$, and $q_{m,sim}$ generated by convolving the chi-squared blurring filter shown in (a) with $q_t$. 

190
Figure 6.11. Efficacy of multiple thin-layer correction procedures on MPM CPT 6 from this database: (a) Boulanger and DeJong (2018) [BD18] (b) Cooper et al. (2022) [CEA22] and (c) Yost et al. (2021) “Deltares” [DEL21].
Chapter 7: Conclusions and Future Work

7.1. Summary and Contributions

The goal of this dissertation was to advance the state of knowledge and practice in liquefaction hazard assessment at challenging soil sites by improving CPT-based characterization of highly interlayered soil profiles. Because data recorded at a given depth in a CPT are influenced by surrounding soils, not just the soil at that particular depth, tip resistance (for example) collected in highly interlayered soil profiles is blurred or averaged. This phenomenon, referred to as multiple thin-layer effects, can result in the incorrect characterization of thin soil layer location and stiffness, which ultimately impacts engineering calculations made using these data. Of particular interest to this dissertation is that underestimation of tip resistance in thin, dense sand layers contributes to the over-prediction of liquefaction severity at challenging soil sites.

Multiple thin-layer correction procedures can convert measured tip resistance ($q''$) to true tip resistance ($q'$), the tip resistance that would be measured if the CPT recordings were only representative of the soil at a particular depth. However, the efficacy of existing procedures is limited, and training and testing data for such procedures are not readily available. Towards that end, the following major contributions towards improving CPT-based characterization of challenging soil profiles have been made in this dissertation:

- Existing correction procedures for multiple thin-layer effects were shown to be ineffective at correcting tip resistance in soil profiles with layers 1.6 times the diameter of the cone or smaller. This is significant because (1) many soil profiles of interest, like the ones in Christchurch, New Zealand, have layers of this thickness, and (2) as layers get thinner, multiple thin-layer effects are amplified, and the need for correction increases. Furthermore, existing procedures were shown to be ineffective at improving liquefaction hazard assessment across a large CPT case history database.

- A new forward multiple thin-layer correction procedure (the “Deltares” procedure) was proposed and shown to be effective for soil layers 1.6 times the diameter of the cone, but not effective for layers 0.8 times the diameter of the cone. However, the application of the procedure to a large CPT case history database resulted in no improvement in the accuracy of liquefaction prediction.
- A new inverse multiple thin-layer correction procedure (the Cooper et al. 2022 procedure) was presented and shown to be effective in soil profiles with layers 0.8 times the diameter of the cone. However, this procedure requires a priori knowledge of $q'$ because it uses a simplified blurring model that does not well capture the physics of how the cone blurs the data in interlayered zones. The need to develop a better blurring filter was highlighted.

- A numerical framework to simulate CPTs in highly interlayered profiles using the Material Point Method (MPM) was developed and was shown to be capable of producing both $q''$ and $q'$ data for a given soil profile. This was the first study known to the author that used MPM to simulate cone penetration through more than one material type. Furthermore, while previous numerical studies of CPTs have considered profiles of two or three layers, this study considered profiles containing upwards of 27 layers - much closer to the reality of geologies observed in the field.

- A framework was proposed to link uncertainties in numerical simulations of CPTs and uncertainties in the laboratory calibration chamber CPTs used to calibrate the numerical simulations. It was shown that many laboratory uncertainties exist, but they can be accounted for numerically. It was also shown that tip resistance computed from numerical simulations of CPTs in highly interlayered soil profiles is generally less sensitive to uncertainties in input parameters than the tip resistance in homogenous profiles, because the tip resistance in highly interlayered zones never reaches a fully developed (true) value.

- An open-source database containing $q''-q'$ pairs for 49 highly interlayered soil profiles was created using laboratory and numerical CPT data. A framework was developed to parse the data into training and test datasets for future statistical learning applications intending to (1) develop new multiple thin-layer correction procedures and (2) develop better blurring models to implement in existing inverse-style multiple thin-layer correction procedures. The framework and examples were documented in a Jupyter notebook that is available with the database.

The manuscripts presented in Chapters 2 through 6 detailed the efforts to make those contributions. Major conclusions from each chapter are summarized subsequently.
In Chapter 2, the “Deltares” [DEL21] procedure was developed as an alternative multiple thin-layer correction procedure to the Boulanger and DeJong (2018) [BD18] procedure. The efficacy of both procedures, and a third, modified version of the BD18 procedure was assessed directly using laboratory calibration chamber test data and indirectly using a large liquefaction case history database from Christchurch, New Zealand. Results showed that none of the procedures could adequately estimate true tip resistance \( q_t \) from measured tip resistance \( q_m \) in soil profiles with layers less than 40 mm thick (~1.6 times the diameter of the cone. It was also shown that application of the procedures to CPT data from the Christchurch database did not improve liquefaction hazard predictions, and in some cases, made predictions less accurate.

In Chapter 3, the Cooper et al. (2022) [Cea22] inverse multiple thin-layer correction procedure was proposed as an alternative to the BD18 and DEL21 procedures. The Cea22 procedure was shown to perform well on a soil profile with 20 mm thick layers (~1.3 times the diameter of the cone), but required \( q' \) to be known a priori. The blurring filter adopted in the Cea22 procedure that simulates multiple thin-layer effects (i.e., estimates \( q_{m,sim} \) from \( q' \)) must be improved before the procedure can be used without prior information about \( q' \). This chapter highlights the need for more \( q_m-q_t \) data in order to further improve multiple thin-layer correction procedures.

In response to the need for more \( q_m-q_t \) data raised in Chapter 3, Chapter 4 presented a numerical framework to simulate CPTs using the Material Point Method (MPM). This framework was validated using laboratory calibration chamber test data and was shown to be effective for simulating CPTs in both homogenous and layered soil profiles. This chapter showed that existing multiple thin-layer correction procedures significantly under-correct tip resistance in soil layers less than two to three times the diameter of the cone. However, it is also shown that the CPT struggles to identify soil layers on that order of thickness, making it extremely difficult to identify the presence of these layers and correct for them based on \( q_m \) alone.

The numerical framework developed in Chapter 4 was extended in Chapter 5. The MPM simulations performed in this chapter entailed the use of more advanced constitutive models and a better description of soil-cone contact, but they did not necessarily produce better results than those presented in Chapter 4. Additional uncertainties were introduced into the model due to a
more complex description of soil behavior. An in-depth assessment of how numerical and laboratory uncertainties are coupled was performed. It was shown that tip resistance in highly interlayered soil profiles is less sensitive to uncertainties in input parameters than in homogenous profiles. It was also shown that uncertainties in laboratory experiments can be accounted for in numerical simulations if enough documentation is provided.

Chapter 6 built on the lessons from Chapters 4 and 5 and described the creation of a $q^m$-$q'$ database for improving multiple thin-layer correction procedures. In total, 49 $q^m$-$q'$ pairs from laboratory and numerical tests in highly interlayered soil profiles are generated and organized into an open-source database. Example applications of this database are detailed, including an assessment of blurring filters for simulating $q^m$ from $q'$ and a direct assessment of procedure efficacy (i.e., applying the procedure to $q^m$ and comparing the corrected data to $q'$).

7.2. Final Remarks and Future Research Directions

The work detailed in this dissertation helped improve the characterization of challenging soil profiles using the CPT, with the ultimate goal of improving CPT-based soil liquefaction evaluations. More work must be done to continue to develop multiple thin-layer correction procedures that are effective and accurate. Additional data in highly interlayered profiles from laboratory calibration chamber tests and numerical simulations should be collected. The development of an extensive $q^m$-$q'$ database, building on the framework presented in Chapter 6 of this dissertation, will help researchers continue to advance multiple thin-layer correction procedures.

It is important to consider that even a perfect characterization of a challenging soil profile may not result in an improved liquefaction evaluation. In other words, correcting CPT data for multiple thin-layer effects is only one piece of a very complex puzzle. The limitations of the simplified liquefaction triggering procedures (e.g., the procedures used in Chapter 2 of this dissertation) should be seriously considered when studying challenging soil profiles. These simplified triggering procedures are unable to capture many mechanisms that may be critical to understanding soil behavior during earthquake shaking in challenging profiles. For example, water flow through interlayered zones, overlying layers preventing liquefied material from manifesting at the ground surface, or how liquefaction of one layer may reduce seismic demand on another layer are not
accounted for. Many of these limitations are discussed in Boulanger et al. (2016) and Cubrinovski et al. (2019). It is likely required to move beyond 1D analyses that operate within a total stress framework to gain a complete understanding of liquefaction at challenging soil sites. For example, 2D fully-coupled nonlinear dynamic analyses (NDAs) have been shown to be useful in understanding the nuances of liquefaction in challenging soil profiles (e.g., Bassal and Boulanger 2021). However, if CPT data are used as input to these 2D analyses, multiple thin-layer correction is still a necessary step.

While 2D NDAs are a useful research tool, they may be inaccessible to practitioners who still rely on 1D methods and liquefaction severity parameters to assess liquefaction hazard. Therefore, there is value in better calibrating threshold values of 1D liquefaction severity parameters with geologic settings. For example, the threshold value of LPI delineating negative and positive observations of liquefaction manifestation should likely be lower for clean sand profiles compared to the challenging soil profiles discussed in this dissertation. Future work should be done to develop a framework for this.

Verification of liquefaction occurring at depth is also an important step in understanding liquefaction in highly interlayered soil profiles. Novel in-situ sampling techniques such as geo-slicing (e.g., Takada and Atwater 2004; Yost 2021) would allow researchers to identify liquefied layers at depth in a soil profile, even if no liquefaction manifestation occurred at the ground surface. This would allow for the identification of geomorphological features that may impact how liquefaction triggers and manifests in highly interlayered profiles.

This dissertation has shown that there are serious limitations in the CPT’s ability to detect soil layers with thicknesses approaching the diameter of the cone and smaller. Consequently, it can be virtually impossible to identify layers from the tip resistance sounding alone. Many multiple thin-layer correction procedures depend on some level of variation in tip resistance, or other CPT parameter, in order to identify thin layers and correct for multiple thin-layer effects. If little to no variation exists, the procedures will be rendered essentially useless. There are several potential ways to address this problem. First, the CPT itself could be improved. For example, a smaller diameter cone would help in identifying thinner layers because the zone of influence would
inherently be smaller. However, multiple thin-layer effects would not be eliminated. The addition of a vision component to the CPT (e.g., the VisCPT; Hryciw 2009) would allow for the visual identification of layer boundaries, providing additional constraining information for multiple thin-layer correction procedures. Second, multiple thin-layer correction procedures could be developed to use other CPT parameters, like pore pressure, to help identify layer boundaries. Pore pressure measurements should not be affected by nearby soils like tip resistance is, and will only be representative of the soil at the particular depth where the pore pressure sensor is located. Therefore, pore pressure may provide a better indication of layer boundaries. Third, multiple thin-layer correction procedures can be developed that do not rely on variation in CPT parameters to identify layer boundaries. The Cooper et al. (2022) procedure is an example of this, but further advancement in this area is required.

A related discussion is that there are plenty of reasons why CPT parameters may fluctuate that do not necessarily have to do with multiple thin-layer effects. For example, natural fining sequences in the soil or zones of varied relative density can result in a CPT sounding that looks like there may be distinct layering when in fact, there is not, and a more gradual transition in tip resistance is actually appropriate. It would be very difficult for existing multiple thin-layer correction procedures to be able to distinguish these conditions from the conditions of an interlayered profile without additional constraining information about the geology of the site. Generally, multiple thin-layer correction procedures seek to increase the tip resistance in layers identified as thinner and stiffer than the surrounding materials. Some procedures also decrease the tip resistance in layers identified as softer than the surrounding materials. It is possible for multiple thin-layer correction procedures to overcorrect the data and result in an assessment of layer thickness, strength, and stiffness that is not conservative. More work should be done to compare corrected field data with actual samples in the field to assess whether the procedures are doing a good job of identifying layers and if the corrected tip resistances are reasonable based on the geology.

Even if the limitation of identifying very thin layers in CPT data is overcome, consideration should be given to whether it is appropriate to consider layers individually in subsequent engineering analyses. Depending on the application, it may be more accurate to describe the behavior of the
entire layered zone as a whole, because the interaction between layers may be impossible to
decouple. This seems particularly likely if the very thin layers are spatially discontinuous.

Finally, the work presented in dissertation has application outside of the world of earthquake
engineering. Anytime that CPT data are used, consideration should be given to whether multiple
thin-layer effects are impacting the data and if correction is required. For example, in back-analysis
of a slope stability failure, examination of CPT data may find that the tip resistance in the critical
layer is artificially increased due to overlying and underlying stiffer layers, and that the critical
layer is thicker than initially understood. Application of a multiple thin-layer correction procedure,
supplemented with reliable geologic sampling, could help explain the failure.

References
Spatially Preferential Liquefaction Manifestations.” Journal of Geotechnical and
Geoenvironmental Engineering, 147(12), 1–23.
liquefaction and lateral spreading in interbedded sand, silt, and clay deposits using the cone
penetrometer.” Proc. of the 5th International Conference on Geotechnical and Geophysical
Site Characterisation (ISC’5), Queensland, Australia, 81–97.
penetration data for thin-layer and transition effects.” Proc. of Cone Penetration Testing
2018, Hicks, Pisano, and Peuchen, eds., CRC Press, Delft, the Netherlands, 25–44.
and characterization of thin soil layers in cone penetration data by piecewise layer
optimization.” Computers and Geotechnics, 141(104404), 104404.
liquefiable deposits.” Soil Dynamics and Earthquake Engineering, 124, 212–229.
and FEM simulations.” Proceedings of the 17th International Conference on Soil Mechanics
and Geotechnical Engineering: The Academia and Practice of Geotechnical Engineering,

## Appendix A: Supplemental Materials for Chapter 2

### A.1. Deltares Calibration Chamber Tests and Results

**Table A.1.** Listing of calibration chamber tests performed by Deltares (data from De Lange 2018).

<table>
<thead>
<tr>
<th>Soil Model</th>
<th>$d_{cone}$ (mm)</th>
<th>Targeted $D_R$ (%)</th>
<th>Actual $D_R$ (%)</th>
<th>$H^*$ (mm)</th>
<th>$H/d_{cone}$</th>
<th>No. of CPTs</th>
<th>$\sigma'_{v:CPT1}$ (kPa)</th>
<th>$\sigma'_{v:CPT2}$ (kPa)</th>
<th>$\sigma'_{v:CPT3}$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>25</td>
<td>30</td>
<td>36</td>
<td>NA</td>
<td>NA</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>25</td>
<td>30</td>
<td>29</td>
<td>40</td>
<td>1.60</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>25</td>
<td>30</td>
<td>28</td>
<td>20</td>
<td>0.80</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>4</td>
<td>25</td>
<td>60</td>
<td>54</td>
<td>40</td>
<td>1.60</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>5</td>
<td>25</td>
<td>60</td>
<td>60</td>
<td>NA</td>
<td>NA</td>
<td>3</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>6</td>
<td>36</td>
<td>30</td>
<td>41</td>
<td>NA</td>
<td>NA</td>
<td>1</td>
<td>50</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>7</td>
<td>36</td>
<td>30</td>
<td>32</td>
<td>20</td>
<td>0.56</td>
<td>1</td>
<td>50</td>
<td>NA</td>
<td>NA</td>
</tr>
<tr>
<td>8</td>
<td>25</td>
<td>60</td>
<td>61</td>
<td>20</td>
<td>0.80</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>9</td>
<td>25</td>
<td>30</td>
<td>28</td>
<td>20</td>
<td>0.80</td>
<td>3</td>
<td>25</td>
<td>50</td>
<td>100</td>
</tr>
<tr>
<td>10</td>
<td>25</td>
<td>&lt; 30</td>
<td>18</td>
<td>20</td>
<td>0.80</td>
<td>3</td>
<td>10</td>
<td>20</td>
<td>30</td>
</tr>
</tbody>
</table>

*Models 1, 5, and 6 were reference sand models that did not have clay layers

$d_{cone}$ = diameter of the cone penetrometer

$D_R$ = relative density of the sand

$H$ = thickness of the interbedded sand and clay layers

$\sigma'_{v:CPTx}$ = the vertical stress applied to the calibration chamber; all tests were performed with a ratio of horizontal to vertical confining stress of 0.5.
Soil Model 4 CPT 2 ($\sigma'_v = 50 \text{ kPa, } D_R = 54\%$)

Soil Model 4 CPT 3 ($\sigma'_v = 100 \text{ kPa, } D_R = 54\%$)

Soil Model 5 CPT 1 ($\sigma'_v = 100 \text{ kPa, } D_R = 60\%$)

Soil Model 5 CPT 2 ($\sigma'_v = 100 \text{ kPa, } D_R = 60\%$)
Figure A.1. Results from thin layer correction procedures applied to each of the Deltares Soil Models with sand layers represented by the white areas and clay layers represented by the shaded areas, where $q^m$ is measured tip resistance, $q^{inv}$ is the inverted tip resistance per the Boulanger and DeJong (2018) [BD18] procedure, $q^{invmod}$ is the inverted tip resistance per the modified BD18 procedure (BD18MOD), $q^{corr}$ is the corrected tip resistance from the Deltares procedure, and $q'$ is true tip resistance (as measured in reference sand model).

The Boulanger and DeJong (2018) [BD18] inverse procedure for multiple thin layer corrections is detailed in the following.

**Definitions:**
- \( d_{\text{cone}} \) – diameter of the cone
- \( z \) – a vector of depths at which the CPT measurements were recorded
- \( q^m \) – a vector of measured CPT tip resistance, after correction for unequal area effects have been applied and normalized to atmospheric pressure
- \( q^t \) – a vector of true tip resistance (i.e., the tip resistance that would be measured in a given soil layer without any influence of multiple thin layer effects), normalized to atmospheric pressure
- \( q^{\text{inv}} \) – a vector of tip resistance that when convolved with a depth-dependent spatial filter, best predicts the measured tip resistance per the Boulanger and DeJong (2018) inverse procedure (i.e., an estimate of \( q^t \), as detailed herein), normalized to atmospheric pressure
- \( f_{\text{s}m} \) – a vector of measured CPT sleeve friction, normalized to atmospheric pressure
- \( f_{\text{s}t} \) – a vector of true CPT sleeve friction (i.e., the sleeve friction that would be measured in a given soil layer without any influence of multiple thin layer effects), normalized to atmospheric pressure
- \( f_{\text{s}^{\text{inv}}} \) – a vector of inverted CPT sleeve friction, which is an estimate of \( f_{\text{s}t} \) per the BD18 procedure, normalized to atmospheric pressure

**Basis:**
- The relationship between \( q^t \) and \( q^m \) is described by a cone penetration filter model (\( w_c \)):
  \[
  q^m = q^t * w_c \quad (A.1)
  \]
  where the asterisk represents the convolution of \( q^t \) with \( w_c \). Note that ultimately, \( q^t \) is the unknown that is being solved for. Thus, when implementing the solution procedure, \( q^t \) in Equation A.1 is set equal to \( q^{\text{inv}} \) of the previous iteration step. However, in describing the cone penetration filter model, it is more appropriate to define the equations in terms of \( q^t \). The summary of implementation of the solution procedure describes how \( q^{\text{inv}} \) is implemented as an estimate of \( q^t \).
• The filter model, \( w_c \), is defined as:
\[
W_c = \frac{w_1w_2}{\sum w_1w_2}
\]
\[(A.2)\]
where both \( w_1 \) and \( w_2 \) are functions of \( z' \), which is depth relative to the cone tip and defined as:
\[
z' = \frac{z-z_{tip}}{d_{cone}}
\]
\[(A.3)\]
where \( z \) is depth, \( z_{tip} \) is the current depth of the cone tip, and \( d_{cone} \) is the diameter of the cone.

• The first primary component of the filter model is described by:
\[
w_1 = \frac{C_1}{1 + (\frac{z'}{z'_{50,ref}})^{m_50}}
\]
\[(A.4)\]
where \( m_50 \) is a filter parameter set to 3.0, \( C_1 \) is described by Equation A.4a, and \( z'_{50} \) is described by Equation A.4b:
\[
C_1 = \begin{cases} 
1 & \text{for } z' \geq 0 \\
1 + \frac{z'}{8} & \text{for } -4 \leq z' < 0 \\
0.5 & \text{for } z' < 4
\end{cases}
\]
\[(A.4a)\]
\[
z'_{50} = 1 + 2(C_2 \cdot z'_{50,ref} - 1) \left[ 1 - \frac{1}{1 + (\frac{q_{z_t=0}^{t}}{q_{z_t}^{t}})^{m_{50}}} \right]
\]
\[(A.4b)\]
where:
- \( C_2 \) is a filter parameter equal to 0 for points below the cone tip and 0.8 for points above the cone tip.
- \( z'_{50,ref} \) is a filter parameter equal to 4.2.
- \( q_{z_t=0}^{t} \) is the true tip resistance at the depth of the cone tip.
- \( q_{z_t}^{t} \) is the true tip resistance at some depth relative to the cone tip.
- \( m_{50} \) is a filter parameter equal to 0.5.

• The second primary component of the filter model is described by:
\[ w_2 = \sqrt{\frac{2}{1 + \left( \frac{q_{z'}^2}{q_{z'=0}^2} \right)^{m_q}}} \]  

where \( m_q \) is a filter parameter equal to 2.0 and all other variables are as previously defined.

- The true tip resistance, \( q' \), is unknown and must be solved for iteratively using Equation A.6.

\[ q^t = q^m + (q^t - q^t \cdot w_c) \]  

and since \( q^{inv} \) is an estimate of \( q' \), Equation A.6 can be rewritten as

\[ q_{i+1}^{inv} = q^m + (q_i^{inv} - q_i^{inv} \cdot w_c) \]  

where the index \( i \) represents the \( i^{th} \) iteration of the inversion and all other variables are as previously defined. Note that the resulting \( q_{i+1}^{inv} \) is then used as \( q_i^{inv} \) (representing an estimate of \( q^t \)) for the next iteration of the inversion.

- The iteration continues until the error \( (err) \) criteria per Equation A.8 is achieved.

\[ err = \frac{\sum_{l=1}^{\text{length}(z)} (q_{i+1}^{inv} - q_i^{inv})}{\sum_{l=1}^{\text{length}(z)} q_i^m} < 10^{-6} \]  

where the index \( i \) represents the \( i^{th} \) iteration of the inversion and both the numerator and denominator are summations over index \( l \), representing an increment of depth.

**Implementation of BD18 Procedure:**

The BD18 procedure is implemented in three parts: 1) Inversion for tip resistance, 2) Inversion for sleeve friction, and 3) Interface correction.

**Part 1: Inversion for tip resistance**

**Step 1.1 - Inputs**

- Obtain required inputs \( (z, q^m, d_{cone}) \) and define filter and smoothing parameters.

**Step 1.2 – Inversion and Convolution**

- Begin first iteration of the inversion. Let \( q_{i=1}^{inv} = q^m \).
  - Begin convolution procedure. Loop over each depth in \( z \) and:
    - Center and normalize all depths on the current depth of the cone tip (e.g. the current \( z \)) using Equation B.3 to obtain a vector of \( z' \).
    - Truncate \( z' \) and \( q^{inv} \) vectors based on a pre-defined smoothing window.
• Compute \( q'_{z=0} \) as an average \( q^{\text{inv}} \) within ±0.05 of the current \( z \).
• Loop over each value in \( z' \) and:
  o Compute a vector of \( z'_{50} \) values using Equation A.4b.
  o Compute a vector of \( w_1 \) values using Equation A.4.
  o Compute a vector of \( w_2 \) values using Equation A.5.
  o Compute a vector of \( w_c \) values using Equation A.2.
• Compute \( q^t \ast w_c \) for current depth \( q'_{z=0} \) by summing the point-wise multiplication of each value in the truncated \( q^{\text{inv}} \) and \( w_c \) vectors.
  o Compute \( q^{\text{inv}}_{i+1} \) via Equation A.7.
• A smoothing step is implemented after the completion of each inversion iteration. Smooth \( q^{\text{inv}}_{i+1} \) over a pre-defined smoothing span.
• Compute \( err \) via Equation A.8.
  o If \( err > 10^{-6} \), then re-enter iteration loop with \( i = i + 1 \).

Step 1.3 – Smoothing step to remove high-frequency noise

• After a converged \( q^{\text{inv}} \) is obtained, a second smoothing step is performed to remove high-frequency noise. The convolution loop is re-entered for a single iteration with the converged \( q^{\text{inv}} \) and \( z'_{50,\text{ref}} = z'_{50,\text{ref,min}} \).
• After this second high-frequency pass is complete, no further iterations are performed.

Part 2: Inversion for Sleeve Friction

Step 2.1 - Inputs

• Obtain required inputs (\( z, q^m, q^{\text{inv}}, f_s^m \)).

Step 2.2 – Iterative procedure to solve for \( l_c^m \) using equations from Robertson (2009)

• Compute \( Q_{mn}^C \) according to:

\[
Q_{tn}^C = \left( \frac{q^x - \sigma_v}{p_a} \right) \left( \frac{p_a}{\sigma_v} \right)^{n^x} \tag{A.9}
\]

where

\[
q^x = \begin{cases} 
q^m & \text{for } Q_{tn}^C \\
q^{\text{inv}} & \text{for } Q_{tn}^{\text{inv}}
\end{cases}
\]

and \( n^x = 1 \) for the first iteration.
• Compute $F_r^m$ according to:

$$F_r^m = (\frac{f_m}{q_{m-\alpha}}) \cdot 100\% \quad (A.10)$$

• Compute $I_c^m$ according to:

$$I_c^x = [(3.47 - \log(Q_{tn}^x))]^2 + [\log(F_r^x) + 1.22]^2)^{0.5} \quad (A.11)$$

where

$$Q_{tn}^x = \begin{cases} Q_{tn}^m \text{ for } I_c^m \\ Q_{tn}^{inv} \text{ for } I_c^{inv} \end{cases}$$

and

$$F_r^x = \begin{cases} F_r^m \text{ for } I_c^m \\ F_r^{inv} \text{ for } I_c^{inv} \end{cases}$$

• Compute $n^m$ according to:

$$n^x = 0.381 \cdot I_c^x + 0.05 \cdot \frac{\sigma_v}{p_a} - 0.15 \leq 1 \quad (A.12)$$

where

$$I_c^x = \begin{cases} I_c^m \text{ for } n^m \\ I_c^{inv} \text{ for } n^{inv} \end{cases}$$

• If $n^m \approx n^m$ from previous iteration, move on to Step 2.3.

**Step 2.3 – Iterative procedure to solve for $f_s^{inv}$**

• Compute $Q_{m}^{inv}$ according to Equation A.9.

• Compute $F_r^{inv}$ according to:

$$F_r^{inv} = 10^{\left(\frac{3.47-\log(Q_{tn}^{inv})}{3.47-\log(Q_{tn}^m)}\right)(1.22+\log(F_r^m)-1.22)} \quad (A.13)$$

• Compute $I_c^{inv}$ according to Equation A.11.

• Compute $n^{inv}$ according to Equation A.12.

• If $n^{inv} \approx n^{inv}$ from previous iteration, then compute $f_s^{inv}$ according to:

$$f_s^{inv} = F_r^{inv} \cdot \frac{q_{inv-\alpha}}{100\%} \quad (A.14)$$

**Part 3: Interface correction**
Step 3.1: Inputs

- Obtain required inputs \((z, q_{\text{inv}}, f_{s\text{ inv}}, d_{\text{cone}})\).

Step 3.2: Identify sharp transitions in \(q_{\text{inv}}\)

- Calculate the rate of change between each data point in \(q_{\text{inv}}\) using Equation A.15.

\[
m_i = \frac{\ln(q_{i+1}^{\text{inv}}) - \ln(q_i^{\text{inv}})}{z_{i+1} - z_i} \tag{A.15}
\]

where the index \(i\) represents an increment of depth.

- If the value of \(m_i\) calculated in Equation A.15 exceeds a specified maximum, \(m_t\), then a sharp interface is identified. In this procedure, \(m_t = 0.1\) is used as a baseline.

Step 3.3: Identify transition zones

- A transition zone is defined as a range of contiguous points where \(m_i\) is greater than \(m_t / 5\).
  - If the transition zone is less than \(3 \times d_{\text{cone}}\), then it is screened out and not considered to be a transition zone.
  - If the transition zone thickness is greater than \(12 \times d_{\text{cone}}\) and \(q_{\text{inv}}\) is increasing, then the transition zone is truncated to be \(12 \times d_{\text{cone}}\).
  - If the transition zone thickness is greater than \(18 \times d_{\text{cone}}\) and \(q_{\text{inv}}\) is decreasing, then the transition zone is truncated to be \(18 \times d_{\text{cone}}\).

Step 3.4: Perform interface correction

- For transitions from softer to stiffer layers (\(q_{\text{inv}}\) increasing with increasing \(z\)):
  - The \(q_{\text{inv}}\) and \(f_{s\text{ inv}}\) values at the top of the transition zone are assigned to all points in the upper 40% of the transition zone.
  - The \(q_{\text{inv}}\) and \(f_{s\text{ inv}}\) values at the bottom of the transition zone are assigned to all points in the lower 60% of the transition zone.

- For transitions from stiffer to softer layers (\(q_{\text{inv}}\) decreasing with increasing \(z\)):
  - The \(q_{\text{inv}}\) and \(f_{s\text{ inv}}\) values at the top of the transition zone are assigned to all points in the upper 60% of the transition zone.
The $q^{inv}$ and $f_r^{inv}$ values at the bottom of the transition zone are assigned to all points in the lower 40% of the transition zone.

Sample results shown after different stages of the BD18 procedure are shown for $q^{inv}$ in Figure A.2.

(a) Measured (black solid line) and inverted (blue dashed line) cone tip resistance versus depth after the first pass of the BD18 inversion procedure is performed (Step 1.2) (b) Measured (black solid line) and inverted (blue dashed line) cone tip resistance versus depth after the second high-frequency pass is performed (Step 1.3). (c) Measured (solid black line) and inverted after interface removal (blue dashed line) cone tip resistance versus depth (Step 3.4).

Figure A.2.
Flow Chart for Implementation of BD18 Procedure

Part 1:
Inversion for Tip Resistance

\[ z, q^m, d_{cone} \]

\[ m_{z,50} = 0.5 \]
\[ m_z = 3.0 \]
\[ m_q = 2.0 \]
\[ z'_{50,ref} = 4.2 \]

Filter Parameters

\[ \Delta z = \frac{\text{max}(z) - \text{min}(z)}{\text{length}(z) - 1} \]
\[ z'_{50,ref,min} = 0.866 \]
\[ f_{win} = \text{ceiling}(60 \cdot d_{cone}/\Delta z) \]
\[ s_{win} = \text{max}(3, \text{ceiling}(0.866 \cdot d_{cone}/\Delta z)) \]

\[ q_{i=1}^{inv} = q^m \]

Begin inversion loop

\[ \text{for } i = 1 \text{ to (max # iterations)} \]

Begin convolution loop

\[ \text{for } j = 1 \text{ to length}(z) \]

Center and normalize all depths on cone tip
\( (z'_{i,j} = 0 \text{ at cone tip}) \)

\[ z'_{i,j} = \frac{z - z_{i,j}}{d_{cone}} \]

Define filter window

\[ f_{win,max} = \text{max}(1, j - f_{win}) \]
\[ f_{win,min} = \text{min}(j + f_{win}, \text{length}(z)) \]
\[ q_{win;i,j} = q_{i}^{inv} [f_{win,min} : f_{win,max}] \]
\[ z'_{win;i,j} = z'_{i,j} [f_{win,min} : f_{win,max}] \]
Begin filter Loop #1

- Begin
  - count = 0
  - \( q_{tip} = 0 \)
  - for \( k = 1 \) to length(\( q_{win;j} \))

- \(-0.05 \leq z'_{win;j,k} \leq 0.05\)
  - No \( \rightarrow k = k + 1 \)
  - Yes
    - \( count = count + 1 \)
    - \( q_{tip} = q_{tip} + q_{win;j,k} \)

- \( k = \text{length}(q_{win;j})\)
  - No \( \rightarrow \) End
  - Yes
    - \( q_{z' = 0;f}^{t} = \frac{q_{tip}}{count} \)

Begin filter Loop #2

- Begin
  - for \( k = 1 \) to length(\( q_{win;j} \))

- End

\[ z'_{50: i, j, k} = 1 + 2 \cdot (C_2 \cdot z'_{50, \text{ref}} - 1) \left[ 1 - \frac{1}{1 + \left( \frac{q_{z'_{50: i, j}}}{q_{\text{win}: i, j, k}} \right)^{m_{z}} \right] \]

\[ C_2 = \begin{cases} 
1 & \text{for } z'_{\text{win}: i, j, k} \geq 0 \\
0.8 & \text{for } z'_{\text{win}: i, j, k} < 0 
\end{cases} \]

\[ z'_{50, \text{ref}} = \begin{cases} 
z'_{50, \text{ref}} & \text{for inversion iterations} \\
z'_{50, \text{ref}, \text{min}} & \text{for high frequency pass} 
\end{cases} \]

\[ w_{1: i, j, k} = \frac{C_1}{1 + \left( \frac{z'_{\text{win}: i, j, k}}{z'_{50: i, j, k}} \right)^{m_z}} \]

\[ C_1 = \begin{cases} 
1 & \text{for } z'_{\text{win}: i, j, k} \geq 1 \\
1 + \frac{z'_{\text{win}: i, j, k}}{8} & \text{for } -4 \leq z'_{\text{win}: i, j, k} < 0 \\
0.5 & \text{for } z'_{\text{win}: i, j, k} < -4 
\end{cases} \]
\[ w_{2; i, j, k} = \sqrt{\frac{2}{1 + \left( \frac{q_{z_i = 0; i, j}}{q_{win; i, j, k}} \right)^{m_a}}} \]

Flowchart:

1. Begin filter Loop #3
2. \( q_{i, j}^{conv} = 0 \) for \( k = 1 \) to \( \text{length}(q_{win; i, j}) \)
3. \( q_{i, j}^{conv} = q_{i, j}^{conv} + (q_{win; i, j, k} \cdot w_{c; i, j, k}) \)
4. \( k = k + 1 \)
5. \( k = \text{length}(q_{win; i, j}) \)
6. \( j = j + 1 \)
7. Back to convolution loop for \( j = \text{length}(z) \)
8. End of process
\[ q_{i+1}^{\text{inv}} = q^m + (q_i^{\text{inv}} - q_i^{\text{inv}} \cdot w_c) \]

\[ q_i^{\text{conv}} = q_i^{\text{inv}} \cdot w_c \]

**Back to inversion loop**

**High frequency pass?**

\[ q_{i+1}^{\text{inv}} = \text{max}(0.5 \cdot q^m, q_i^{\text{inv}}) \]

\[ q_i^{\text{inv}} = \text{smooth}(q_i^{\text{inv}}, s_{\text{win}}) \]

\[ \text{err} = \frac{\sum_{l=1}^{\text{length}(z)} |q_{i+1,l}^{\text{inv}} - q_i^{\text{inv}}|}{\sum_{l=1}^{\text{length}(z)} q_l^m} \]

**Yes**

**High frequency pass**

\[ q_i^{\text{inv}} = q_i^{\text{inv}} \]

**Yes**

**Re-enter convolution with converged \( q_i^{\text{inv}} \)**

\[ i = i + 1 \]

**No**
Part 2: Inversion for Sleeve Friction

For \( j = 1 \) to length(\( z \))

Iterate to compute measured parameters first

\( k = 1 \)

\( n_{j,k=1}^x = 1 \)

\[
Q_{tn,j,k}^x = \left( \frac{q_j^x - \sigma_{v,j}}{P_a} \right) \left( \frac{P_a}{\sigma_{v,j}^l} \right)^{n_{j,k}^x}
\]

\[
q_j^x = \begin{cases} 
q_j^m & \text{for } Q_{tn,j,k}^m \\
q_j^{inv} & \text{for } Q_{tn,j,k}^{inv}
\end{cases}
\]

\[
F_{r,j}^m = \left( \frac{f_j^m}{q_j^m - \sigma_{v,j}} \right) \cdot 100\%
\]

\[
F_{r,j}^{inv} = 10 \left[ \left( \frac{1.22 + \log(F_{r,j}^m)}{3.47 - \log(Q_{tn,j,k}^m)} \right) \left( \frac{3.47 - \log(Q_{tn,j,k}^m)}{3.47 - \log(Q_{tn,j,k}^{inv})} \right)^{n_{j,k}^x} \right]
\]
\[ I_{c;j,k}^x = \left[ 3.47 - \log(Q_{\text{inv}}^x_{m;j,k}) \right]^2 + \left[ \log(F_{r;j,k}^m \text{ or } F_{r;j,k}^{\text{inv}}) + 1.22 \right]^2 \]^{0.5} \]

\[ n_{j,k}^x = 0.381 \cdot I_{c;j,k}^x + 0.05 \cdot \frac{\sigma_{v,j}}{p_a} - 0.15 \leq 1 \]

\[ n_{j,k}^x \approx n_{j,k-1}^x \]

- **Yes**
  - **Iteration for measured?**
    - **No**
      - \[ f_{s,j}^{\text{inv}} = F_{r,j}^{\text{inv}} \cdot \frac{q_j^{\text{inv}} - \sigma_{v,j}}{100\%} \]
    - **j = length(z)**
      - **No**
        - \[ f_{s}^{\text{inv}} \]
      - **Yes**
        - \[ j = j+1 \]

- **No**
  - **k = k+1**
  - **Repeat iteration for inverted parameters**
Part 3: Interface Correction

\[ \Delta z' = \frac{\max(z/d_{cone}) - \min(z/d_{cone})}{\text{length}(z)} \]

For \( j = 1 \) to \( \text{length}(z) - 1 \)

\[ m_j = \frac{\ln(q_{j+1}^{\text{inv}}) - \ln(q_j^{\text{inv}})}{\Delta z'} \]

\( j = j + 1 \)

\( j = \text{length}(z) - 1 \)

Yes

\( m_t = 0.1 \)

\[ m_j > \frac{m_t}{5} \text{ for a consecutive range of } z > 3 \cdot d_{cone} \]

No

not a transition zone

Yes

\( q^{\text{inv}} \) increasing with increasing \( z \)

upper limit of transition zone thickness:

- 12 \( \cdot \) \( d_{cone} \)  
  \[ \text{a} \]

No

upper limit of transition zone thickness:

- 18 \( \cdot \) \( d_{cone} \)  
  \[ \text{b} \]
• set $q^{inv}$ and $f_s^{inv}$ of the upper 40% of the transition zone equal to the $q^{mv}$ and $f_s^{mv}$ values at the top of the transition zone.
• set $q^{mv}$ and $f_s^{inv}$ of the lower 60% of the transition zone equal to the $q^{mv}$ and $f_s^{mv}$ values at the bottom of the transition zone.

• set $q^{inv}$ and $f_s^{inv}$ of the upper 60% of the transition zone equal to the $q^{inv}$ and $f_s^{inv}$ values at the top of the transition zone.
• set $q^{inv}$ and $f_s^{inv}$ of the lower 40% of the transition zone equal to the $q^{inv}$ and $f_s^{inv}$ values at the bottom of the transition zone.
A.3. **Deltares Multiple Thin Layer Correction Procedure**

The basis of the “Deltares” multiple thin layer correction procedure based on trends observed in calibration chamber data by De Lange (2018) was described in the text. In this appendix, the application of the Deltares correction procedure is provided in detail.

**Definitions:**

- $d_{cone}$ – diameter of the cone
- $z$ – a vector of depths at which the CPT measurements were recorded
- $\sigma_v$ – a vector of total stress corresponding to $z$
- $q^m$ – a vector of measured tip resistance after any correction for unequal area effects have been applied
- $q'$ – a vector of true tip resistance (i.e., the tip resistance that would be measured in a given soil layer without any influence of multiple thin layer effects)
- $q^{corr}$ – a vector of corrected tip resistance obtained by applying correction factors to the measured tip resistance via the Deltares procedure (i.e., an estimate of $q'$, analogous to $q^{inv}$ for the BD18 procedure)

**Implementation of Deltares Procedure:**

**Step 1 - Inputs**

- Obtain required inputs ($z$, $q^m$, $d_{cone}$, $\sigma_v$) and define filter and smoothing parameters.

**Step 2 – Smooth the $q^m$ data to eliminate erroneous data**

- A moving-average filter (e.g. “smooth” function in Matlab) is used with a default smoothing interval set to 5 $q^m$ data points.

**Step 3 - Identify and process local minimums and maximums in $q^m$**

- Identify all local minima and maxima (peaks and troughs) in $q^m$. An automated peak selection algorithm may be implemented (e.g. “findpeaks” in Matlab), however, input parameters should be adjusted to avoid erroneous peak identification, e.g.:
  - To set a minimum prominence (how much peak stands out due to its height relative to other peaks nearby) for peak identification, a “minimum peak prominence” parameter can be implemented.
To ignore peaks that are very close to one another, a “minimum peak distance” parameter can be implemented.

Both parameters are available in the Matlab signal processing toolbox.

- For computational purposes, it is necessary to have a trough on either side of each identified peak. Therefore:
  - If the first peak is identified before the first trough is identified, add a trough at or near first $q^m$ value.
  - If the last trough is identified before the last peak is identified, add a trough at or near the last $q^m$ value.

**Step 4 - Define transition zones boundaries:**

For each identified peak in $q^m$:

- Define the maximum measured tip resistance in the thin layer, $q^{m,\text{max}}$, as the peak $q^m$ as shown in Figure A.3.

- Define the minimum measured tip resistance in the thin layer, $q^{m,\text{min}}$, as the smaller of the two $q^m$ associated with the preceding or following troughs adjacent to $q^{m,\text{max}}$ as shown in Figure A.3.

![Figure A.3](image_url)

**Figure A.3.** Define the maximum measured tip resistance in the thin layer, $q^{m,\text{max}}$, as the peak $q^m$ measured in the thin layer.
- Define the beginning of the transition into stiffer material (into the thin layer) as the depth of the first trough above the peak and the end of the transition into the softer layer (out of the thin layer) as the depth of the first trough below the peak as shown in Figure A.4.

**Figure A.4.** Define the beginning of transition into stiffer material (into the thin layer) as the depth of the first trough above the peak and the end of the transition into the softer layer (out of the thin layer) as the depth of the first trough below the peak.

*Step 5 – Determine thin layer boundaries (as shown in Figure A.5)*

- Define the top of the thin layer as half the distance between the beginning of the transition into the stiffer material and $q''_{\text{max}}$.

- Define the bottom of the thin layer as half the distance between the $q''_{\text{max}}$ and the end of the transition into the softer material.

- Define the thickness of the thin layer, $H$, as the distance between the top and bottom of the thin layer.
Figure A.5. Define the top of the thin layer as half the distance between the beginning of the transition into the stiffer material (of the thin layer) and the maximum $q^m$. Define the bottom of the thin layer as half the distance between the maximum $q^m$ and the end of the transition (out of the thin layer) into the softer material.

Step 5 - Implement transition zone corrections

- From the beginning of the transition to the start of the thin layer, set $q^{corr} = q^m$ at the beginning (top) of the transition zone.
- From the bottom of the thin layer to the end of the transition into softer material, set $q^{corr} = q^m$ at the end (bottom) of the transition zone.

Step 6 – Implement thin-layer corrections

- Compute the normalized stress ratio, $q_{ratio}$, according to:
  
  $$q_{ratio} = \frac{q_{max} - \sigma_v}{q_{min} - \sigma_v}$$  

  \hspace{1cm} (A.16)

- Compute the thin-layer correction factor, $K_H$ as:
  
  $$K_H = m \cdot \ln(q_{ratio}) + 1$$

  \hspace{1cm} (A.17)

  where:

  $$m = 9.0294(H/d_{cone})^{-2.865}$$

  \hspace{1cm} (A.18)

- Then, compute the corrected tip resistance, $q^{corr}$:

  $$q^{corr} = K_H \cdot (q_{max} - \sigma_v) + \sigma_v$$

  \hspace{1cm} (A.19)
• From the beginning of the thin layer to the end of the thin layer, assign $q^{corr}$ as computed by Equation A.19, as shown in Figure A.6.

![Figure A.6](image)

**Figure A.6.** The thin layer correction factor is applied to $q_{m,\max}$ in the thin layer, and then the resulting $q^{corr}$ is applied across the entire thin layer. The $q^m$ values identified at the start and end of the transition zones are applied across the entire respective transition zone.

After application of the thin layer and transition zone corrections to each identified thin layer, $q^{corr}$ versus depth can be plotted. The $q^m$ and $q^{corr}$ profiles for a single thin stiff layer are shown in Figure A.7.

![Figure A.7](image)

**Figure A.7.** Measured tip resistance, $q^m$ (solid black) and corrected tip resistance, $q^{corr}$ (blue dashed) versus depth.
Limitations of Deltares Procedure:

- There is no recommendation included in De Lange (2018) for correcting or adjusting the measured $f_s$ versus depth profile. However, since $f_s$ is a required input of the liquefaction triggering analyses performed in this study, $f_s^{corr}$ was computed by implementing the same procedure used in the BD18 method (as described in Part 2: Inversion for Sleeve Friction of Section A.2), except that $q^{corr}$ was used instead of $q^{inv}$.

- Correction factors to reduce tip resistance in thin, softer layers embedded in stiffer layers were proposed by De Lange (2018) but only in relation to a known $q'$ profile. Therefore, these cannot be generalized to apply in situations where only $q^m$ is known. However, the transition zone corrections proposed in the Deltares procedure do result in a partial reduction to tip resistance in softer layers by setting $q^{corr}$ across the transition zones equal to the minimum $q^m$ in the transition zone.

- The $K_H$ values reported in De Lange (2018) fell between 1.5 and 6. By using logarithmic curves to represent the relationship between $K_H$ and $q_{ratio}$, it is possible to get much larger values of $K_H$. If a cap is not placed on the maximum likely $K_H$ value, there can be scenarios that result in unrealistically large values of $K_H$. 
Flow Chart for Implementation of Deltares Procedure

1. $z, q^m, d_{conr}, \sigma_v$
   - Remove spurious values of $q^m$ by applying a smoothing window of 5 $q^m$ values in width

2. Identify local minimums (i.e. troughs) and maximums (i.e., peaks) in $q^m$ and their corresponding depths.
   - Notes:
     - If the first peak occurs before the first trough, set $q^m$ as the first trough
     - If the last peak occurs after the last trough, set the last value of $q^m$ as the last trough

3. Determine transition zone boundaries for layers:
   - The start of the transition zone from a softer to a stiffer layer is the trough that immediately precedes the peak.
   - The end of the transition zone from a stiffer to a softer layer is the trough that immediately follows the peak.

4. Determine layer boundaries:
   - The upper boundary of a stiffer layer is the depth corresponding to half the thickness of upper transition zone for the layer.
   - The lower boundary of the stiffer layer is depth corresponding to half the thickness of the lower transition zone for the layer.
Determine $q^{corr}$ for the portions of the soft layers in the transition zone:

- For the portion of the soft layer that is above the stiff layer, $q^{corr}$ is set equal to $q^m$ at the start of the transition zone.
- For the portion of the soft layer that is below the stiff layer, $q^{corr}$ is set equal to $q^m$ at the end of the transition zone.

Determine $q^{corr}$ for the stiff layers:

- Set $q_{min}^m$ equal to the smaller of the $q^m$ values for the trough immediately preceding and following a peak.
- Set $q_{max}^m$ equal to the $q^m$ value for the peak.
- Compute $q_{ratio}$: $q_{ratio} = \frac{q_{max}^m}{q_{min}^m} - \sigma_v$
- Compute $K_H$:
  - $m = 9.0294 \cdot \left( \frac{H}{d_{cone}} \right)^{-2.865}$
  - $K_H = m \cdot \ln(q_{ratio}) + 1$
- $q^{corr} = K_H \cdot (q_{max}^m - \sigma_v) + \sigma_v$
A.4. Deltares Procedure Matlab Scripts

```matlab
%% ThinLayer_Deltares:
% This function performs the Deltares (DEL) thin layer correction procedure 
% References:
% Yost KM, Green RA, Upadhyaya S, Maurer BW, Yerro-Colom A, Martin ER, 
% Cooper J (2021). "Assessment of the efficacies of correction procedures 
% for multiple thin layer effects on Cone Penetration Tests". Soil Dyn Earthq 
% Eng. 144 (May):106677.
% van Elk, J. and Doornhof, D.
% Boulanger, R. and DeJong, J. (2018). Inverse filtering procedure to 
% correct % cone penetration data for thin-layer and transition effects. In 
% Cone Penetration Testing 2018, CRC Press, 2018: 25-44.
% Written by: Kaleigh Yost
% Date: February 2019
% Updated: October 2020
% Note! Several functions in this code require Matlab signal processing 
% toolbox.

% - The inputs are:
% + dCPT - depth(m)
% + qc - tip resistance (MPa)
% + fs - sleeve friction (MPa)
% + tot_stress - total stress (kPa)
% + eff_stress - effective stress (kPa)
% + cone_d - cone diameter(m)
% + minpeakprom (unitless)
% + minpeakdist (unitless)
% - The outputs are:
% + qc_corr - corrected tip resistance(MPa)
% + fs_corr - corrected sleeve friction(MPa)
% + Kh - thin layer correction factors (unitless)
% + x - qratio, equal to max qc minus total stress divided by min qc 
% minus total stress (unitless)
% + layer_thickness - identified thin layer thickness (m)
% + hoverd - ratio of layer thickness to cone diameter (unitless)
% + Ic - soil behavior type index (unitless)
% + Ic_corr - corrected soil behavior type index (unitless)

function [qc_corr, fs_corr, Kh, x, layer_thickness, hoverd, Ic, Ic_corr] = 
ThinLayer_Deltares( dCPT, qc, fs, tot_stress, eff_stress, cone_d, 
minpeakprom, minpeakdist)

% Initialize and Smooth -----------------------------------------------
Patm = 101.3/1000; %Atmospheric Pressure (MPa)
len = length(dCPT);
dz=(max(dCPT)-min(dCPT))/(length(dCPT)-1);
qc=smooth(qc,5);
```

dCPT=round(dCPT,4);
qc_corr=qc;
tot_stress=tot_stress/1000; %[MPa]
eff_stress=eff_stress/1000; %[MPa]

% Find local mins and maxes -----------------------------------------------%
[pks, pkslocs] = findpeaks(qc,dCPT,'MinPeakProminence',minpeakprom,'MinPeakDistance',minpeakdist);
[trghs, trghslocs] = findpeaks(-qc,dCPT,'MinPeakProminence',minpeakprom,'MinPeakDistance',minpeakdist);

% Process mins and maxes ----------------------------------------------------%
trghs=-1*trghs;
if pkslocs(1)<trghslocs(1)
    trghslocs=[dCPT(1); trghslocs];
    trghs=[qc(1);trghs];
end
if pkslocs(length(pkslocs))>trghslocs(length(trghslocs))
    trghslocs=[trghslocs; dCPT(length(dCPT)-5)];
    trghs=[trghs;qc(length(qc)-5)];
end

%% Define thin layers -------------------------------------------------------%
for i=1:length(pkslocs)
    threshold = pkslocs(i);
    ix   = find(trghslocs<threshold,1,'last');
    iy   = find(trghslocs>threshold,1);
    trans_start(i) = trghslocs(ix);
    trans_end(i)   = trghslocs(iy);
    layer_start(i) = round(trans_start(i)+0.5*(pkslocs(i)-trans_start(i)),2);
    layer_end(i)   = round(trans_end(i)-0.5*(trans_end(i)-pkslocs(i)),2);
    [x, layer_start_index(i)] = min(abs(layer_start(i)-dCPT));
    [x, layer_end_index(i)] = min(abs(layer_end(i)-dCPT));
    [x, trans_start_index(i)] = min(abs(trans_start(i)-dCPT));
    [x, trans_end_index(i)] = min(abs(trans_end(i)-dCPT));
    [x, peaks_index(i)] = min(abs(pkslocs(i)-dCPT));
end

%% Calculate layer thicknesses and correction factors ------------------------%
layer_thickness = layer_end-layer_start;
hoverd= layer_thickness/cone_d;
m=9.0294.*(hoverd.^-2.865);
qcmlayermax=pks;
for i=1:length(hoverd)
    qcmlayermin(i)=min(qc(trans_start_index(i)),qc(trans_end_index(i)));
    tot_stress_peak(i)=tot_stress(peaks_index(i));
    x(i)=(qcmlayermax(i)-tot_stress_peak(i))/(qcmlayermin(i)-tot_stress_peak(i));
    if x(i)<1
x(i)=1;
end
Kh(i)=m(i).*log(x(i))+1;
i=i+1;
end
Kh(Kh<1)=1;

% Apply Thin Layer Correction Factors  -------------------------------
for i=1:length(hoverd)
    if Kh(i)>1 && dCPT(layer_start_index(i))>0.1
        dummy1 = layer_start_index(i)-trans_start_index(i)+1;
        dummy2 = layer_end_index(i)-layer_start_index(i);
        dummy3 = trans_end_index(i)-layer_end_index(i)+1;
        if dummy1*dz>0.01
            qc_corr(trans_start_index(i):layer_start_index(i)-1) =
            qc(trans_start_index(i))*ones(length(dummy1));
        end
        if dummy2*dz>0.01
            qc_corr(layer_start_index(i):layer_end_index(i)) =
            (Kh(i)*(qcmlayermax(i)-tot_stress(peaks_index(i)))+tot_stress(peaks_index(i)))*ones(length(dummy2));
        end
        if dummy3*dz>0.01
            qc_corr(layer_end_index(i)+1:trans_end_index(i)) =
            qc(trans_end_index(i))*ones(length(dummy3));
        end
    end
end

% Only report values for thin layers that are being corrected:
for j=1:length(hoverd)
    if Kh(j)>1 && dCPT(layer_start_index(j))>0.1
        test(j)=1;
    else
        test(j)=0;
    end
end
test=find(test>0);
Kh = Kh(test);
layer_thickness = layer_thickness(test);
x = x(test);
hoverd = hoverd(test);

% Perform fs correction as BD18  ----------------------------------------
qn = qc-tot_stress;  % [MPa]
qnm(qn<0)=0.1;      % [MPa]
fs(fs<0)=0.01;      % [MPa]
Fr=100.*fs./qn;    % [dimensionless]

% First get Ic using Robertson's 1999 Ic-nexp relationship
n=ones(len,1);
CN_lim = (Patm./eff_stress).^n;
CN_lim(CN_lim>1.7)=1.7;
qcn_lim = (qn./Patm).*CN_lim;
error = ones(len,1);
while sum(error>0.00001)>0
    Ic=((3.47-log10(qcn_lim)).^2+(1.22+log10(Fr)).^2).^0.5;
    nold=n;
    n=(0.381.*Ic+0.05.*(eff_stress./Patm)-0.15);
    n(n>1)=1;
    error=100.*abs((n-nold))./n;
    CN_limit=(Patm./eff_stress).^n;
    CN_limit(CN_limit>1.7)=1.7;
    qcn_lim=(qn./Patm).*CN_limit;
end

% Back out fs_inv and Ic_corr
qn_inv = qc_corr-tot_stress;  % [MPa]
qn_inv(qn_inv<=0)=0.1;       % [MPa]
n=ones(len,1);
CN_lim_inv = (Patm./eff_stress).^n;
CN_lim_inv(CN_lim_inv>1.7)=1.7;
qcn_lim_inv = (qn_inv./Patm).*CN_lim;
error = ones(len,1);
iterCount = 0;
while sum(error>0.00001)>0 && iterCount<20
    qcn_lim_inv = (qn_inv./Patm).*CN_lim_inv;
    logFinv = (3.47-log10(qcn_lim_inv))./(3.47-log10(qcn_lim));
    logFinv = logFinv.*(1.22+log10(Fr))-1.22;
    Finv = 10.^logFinv;
    Ic_inv = ((3.47-log10(qcn_lim_inv)).^2+(1.22+log10(Finv)).^2).^0.5;
    n=(0.381.*Ic_inv+0.05.*(eff_stress./Patm)-0.15);
    n(n>1)=1;
    error=100.*abs((n-nold))./n;
    CN_lim_inv=(Patm./eff_stress).^n;
    CN_lim_inv(CN_lim_inv>1.7)=1.7;
    nold=n;
    iterCount = iterCount+1;
end
fs_corr = Finv.*(qc_corr-tot_stress)/100;
Ic_corr = Ic_inv;

References


Appendix B: Supplemental Materials for Chapter 5

B.1. Supplemental Materials on Constitutive Modeling of Sand

The NorSand constitutive model used to describe the behavior of the Baskarp B15 sand required the calibration of a number of parameters described in Chapter 5 and summarized in Table B.1 for clarity.

Table B.1. NorSand constitutive modeling parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical state void ratio at $p'=0$</td>
<td>$e_{cs,0}$</td>
</tr>
<tr>
<td>Slope of critical state line</td>
<td>$\lambda$</td>
</tr>
<tr>
<td>Exponent of critical state line</td>
<td>$m$</td>
</tr>
<tr>
<td>Shear modulus factor</td>
<td>$G_{ref}$</td>
</tr>
<tr>
<td>Exponent of the stiffness relation</td>
<td>$b$</td>
</tr>
<tr>
<td>Void ratio at which volumetric strains are negligible</td>
<td>$e^*_{min}$</td>
</tr>
<tr>
<td>Critical state friction angle</td>
<td>$\phi_{cs}$</td>
</tr>
<tr>
<td>Dilatancy parameter</td>
<td>$N$</td>
</tr>
<tr>
<td>Dilatancy coefficient</td>
<td>$\chi$</td>
</tr>
<tr>
<td>Poisson ratio</td>
<td>$\nu$</td>
</tr>
<tr>
<td>Hardening modulus</td>
<td>$H$</td>
</tr>
</tbody>
</table>

An overview of the calibration of each of these parameters was described in Chapter 5, however, complete details were left out for brevity and warrant further description in this Appendix. The calibration of the critical state line parameters $e_{cs,0}$, $\lambda$, and $m$ is detailed thoroughly in Chapter 5 and thus not expanded upon here. Furthermore, selection of $\nu$ does not require further comment. The following sections expand on the procedure used to calibrate the elasticity parameters ($G_{ref}$, $b$, and $e^*_{min}$), the dilatancy parameters ($N$ and $\chi$), the critical state friction angle ($\phi_{cs}$), and the hardening modulus ($H$).

Calibration of elasticity parameters $G_{ref}$, $b$, and $e^*_{min}$:

The elasticity parameters were calibrated using Bender element tests conducted on Baskarp B15 sand by Bødker (1996). Bødker (1996) fit the Bender element results to the following equation by Viggiani and Atkinson (1995):

\[
G = AF(e)p_a^{1-n_1-n_2}(\sigma'_1)^{n_1}(\sigma'_3)^{n_2} \tag{B.1}
\]

where $A$, $n_1$, and $n_2$ must be fitted to the soil behavior, $F(e) = 1/(0.3+0.7e^2)$ from Hardin and Blandford (1989), $e$ is the void ratio, $p_a$ is the atmospheric pressure, and $\sigma'_1$ and $\sigma'_3$ are the major
and minor principal effective stresses, respectively (in the same units as \( p_a \)). Bødker (1996) found \( A=740, \ n_1=0.31, \) and \( n_2=0.26 \) for the Baskarp B15 sand. We can relate this relationship to the corresponding one for NorSand as follows. The relationship between shear modulus, \( G \), and mean effective stress, \( p' \), in NorSand is described as:

\[
G = G_{ref} F_e p_a \left( \frac{p'}{p_a} \right)^b \quad (B.2)
\]

Where \( G_{ref} \) and \( b \) must be fitted to the soil behavior, \( F_e = 1/(e-e_{\text{min}}^*) \), \( e_{\text{min}}^* \) is the minimum void ratio where volumetric strains are negligible (a fitting parameter), and \( p_a \) is the atmospheric pressure. \( G_{ref} \) and \( b \) can be obtained by setting Equations B.1 and B.2 equal:

\[
AF(e)p_a^{1-n_1-n_2}(\sigma'_1)^{n_1}(\sigma'_3)^{n_2} = G_{ref} F_e p_a \left( \frac{p'}{p_a} \right)^b \quad (B.3)
\]

Note that if isotropic conditions are assumed, and therefore \( p' = \sigma'_1 = \sigma'_3 \), then Equation B.3 can be re-written as:

\[
AF(e)p_a^{n_1+n_2} = G_{ref} F_e p_a \left( \frac{p'}{p_a} \right)^b \quad (B.4)
\]

Plugging in the fitting parameters from Bødker (1996), it can easily be seen that the NorSand parameter \( b \) should be equal to 0.57.

\[
740 F(e)p_a \left( \frac{p'}{p_a} \right)^{0.57} = G_{ref} F_e p_a \left( \frac{p'}{p_a} \right)^b \quad (B.5)
\]

Then, the stresses can be eliminated from both sides of the equation, and the respective equations for \( F(e) \) and \( F_e \) can be plugged in:

\[
740 \frac{1}{0.3 + 0.7 e^*} = G_{ref} \frac{1}{e - e_{\text{min}}^*} \quad (B.6)
\]

A parametric nonlinear regression model was used (using Matlab function \textit{fitnlm}) to estimate \( G_{ref} \) and \( e_{\text{min}}^* \) for the NorSand model over a range of \( e \) from 0.60 to 0.85 (because we are most interested
in modeling the sand in looser states). The results of the regression are shown in Figure B.1, where \( G_{ref} = 743 \) and \( e^*_{min} = 0.051 \) were found to be the optimal parameters.

![Figure B.1. Determination of \( G_{ref} \) and \( e^*_{min} \) for NorSand elasticity model by matching curve to reported curve from Bødker (1996).](image.png)

Calibration of \( N, \chi, \) and \( M_{tc} \):

The CD triaxial tests performed on dense \((D_R=80\%)\) and medium dense \((D_R=51\%)\) specimens by Ibsen and Bødker (1994) were used to determine the dilatancy parameters \( N \) and \( \chi \). As shown in Figure B.2, the triaxial tests performed with confining pressures less than 100 kPa tended to produce results that did not fall in line with the results from the other tests. Consequently, the results from those low confining pressure tests were not used to determine the parameters described subsequently, and are represented in gray in Figure B.2.

For each test, stress ratio was computed as \( \eta = q/p' \) and plastic dilatancy was computed as \( D^p = \varepsilon^p_v/\varepsilon^p_q \), where \( \varepsilon^p_v \) is the volumetric strain rate and \( \varepsilon^p_q \) is the deviatoric strain rate. Using a central difference approach per Ghafghazi and Shuttle (2006), \( D^p \) can be computed as:

\[
D^p = \frac{(\varepsilon_{v,j+1} - \varepsilon_{v,j-1}) - (p'_{j+1} - p'_{j-1})/K}{(\varepsilon_{q,j+1} - \varepsilon_{q,j-1}) - (q_{j+1} - q_{j-1})/3G} \quad \text{(B.7)}
\]
where the subscript \( j \) corresponds to the \( j \)th data point, \( K \) is the elastic bulk modulus, and \( G \) is the elastic shear modulus. \( G \) was computed using Equation B.2, and \( K \) was computed as:

\[
K = \frac{2(1 + \nu)}{3(1 - 2\nu)} G \tag{B.8}
\]

Note that deviatoric strain, \( \varepsilon_q \), was computed from the reported axial \( (\varepsilon_a) \) and volumetric \( (\varepsilon_v) \) strains using:

\[
\varepsilon_q = \frac{2}{3}(\varepsilon_a - \varepsilon_r) \tag{B.9}
\]

where \( \varepsilon_r \) is radial strain computed as:

\[
\varepsilon_r = \frac{\varepsilon_v - \varepsilon_a}{2} \tag{B.10}
\]

\( \eta \) was plotted versus \( D^p \) as shown in Figure B.2a. Note the sign convention: negative represents dilation. The maximum (most negative) value of \( D^p \) and corresponding \( \eta \) for each test is recorded as \( D_{max} \) and \( \eta_{max} \). To determine \( \chi \), \( D_{max} \) is plotted versus its corresponding state parameter, \( \psi \), where \( \psi = \varepsilon_c - \varepsilon_{cs} \). The slope of a linear regression through these points is \( \chi \). As shown in Figure B.2b, \( \chi = 2.7 \) was found to be the best fit parameter for this dataset. Note that because \( \psi \) is required to determine \( \chi \), \( \chi \) is inherently affected by the critical state line (CSL). In Chapter 5, three different CSLs were considered (a baseline, upper bound, and lower bound). For each case, the corresponding \( \psi \) was determined. In the remainder of this Appendix, only the case where the baseline CSL \( [\varepsilon_{cs} = 0.90 - 0.012(p'/p_a)^{0.7}] \) was used will be discussed.

To determine \( N \), \( \eta_{max} \) is plotted versus \( D_{max} \). A linear regression through these data provides a slope equal to \( 1 - N \). As shown in Figure B.2c, \( N = 0.1 \) was determined to be the best fit parameter for this dataset. Furthermore, the y-intercept can be interpreted as the critical stress ratio, \( M_{tc} \). In this case, \( M_{tc} = 1.2 \).
Figure B.2. Calibration of dilatancy parameters with assumed critical state line $e_{cs} = 0.90 - 0.012(p'/p_a)^{0.7}$: (a) Stress ratio, $\eta$, versus plastic dilatancy, $D^p$, to obtain maximum dilatancy, $D_{max}$, and corresponding stress ratio, $\eta_{max}$ (b) $D_{max}$ versus state parameter $\psi$ at $D_{max}$ to determine $\chi$; (c) $\eta_{max}$ versus $D_{max}$ to determine $N$. Data plotted in gray was not included in the regression and corresponds to tests performed with confining pressures less than 100 kPa.

Critical state friction angle, $\phi_{cs}$, can be computed from $M_{tc}$ as:

$$M_{tc} = \frac{6\sin\phi_{cs}}{3 - \sin\phi_{cs}}$$  \hspace{1cm} (B.11)
Therefore, \( \phi_{cs} \) is computed as 30 degrees from these data. Note that this value is approximately equal to the \( \phi_{cs} \) reported from other literature on this sand. Anaraki (2008) reported a \( \phi_{cs} \) of about 30 degrees, and Phuong et al. (2016) used 31 degrees.

**Calibration of hardening modulus, \( H \)**

\( H \) is a NorSand model parameter calibrated by performing numerical single-element tests to replicate results from drained triaxial tests. In the analyses presented in Chapter 5, \( H \) was assumed to be a function of the initial state parameter, \( \psi_0 \), and constant throughout a given simulation. There are different approaches to calibrate \( H \). Jefferies and Been (2015) utilize an iterative forward modeling technique in which several parameters in addition to \( H \) are modified in the numerical element tests in an attempt to match the behavior of the laboratory triaxial data over a large range of soil behavior. In this study, a more straightforward approach was adopted in which we calibrated \( H \) alone (i.e., held all other parameters constant) with the goal of matching the initial stiffness of each considered laboratory triaxial test. 12 consolidated drained triaxial tests on Baskarp B15 sand from Ibsen and Bødker (1994) were used for this calibration that had stress conditions similar to those expected in the calibration chamber. The test data corresponding to the results presented in Figure 5.6 and Figure 5.7 from Chapter 5 are summarized in Table B.2. All other numerical input parameters used were consistent with the baseline parameters provided in Table 5.2.

### Table B.2. Summary of triaxial tests used to calibrate hardening modulus, \( H \)

<table>
<thead>
<tr>
<th>Test ID</th>
<th>Relative Density, ( D_r ) (%)</th>
<th>Initial Void Ratio, ( e_0 ) (-)</th>
<th>Initial Mean Effective Stress, ( p' ) (kPa)</th>
<th>Initial State Parameter, ( \psi_0 ) (-)</th>
<th>Initial Image State Parameter, ( \psi_{i0} ) (-)</th>
<th>Plastic hardening modulus, ( H ) (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>9301.15</td>
<td>1</td>
<td>0.853</td>
<td>160</td>
<td>-0.030</td>
<td>-0.039</td>
<td>50</td>
</tr>
<tr>
<td>9301.18</td>
<td>1</td>
<td>0.854</td>
<td>320</td>
<td>-0.019</td>
<td>-0.033</td>
<td>45</td>
</tr>
<tr>
<td>9301.30</td>
<td>1</td>
<td>0.856</td>
<td>640</td>
<td>0.000</td>
<td>-0.022</td>
<td>40</td>
</tr>
<tr>
<td>9301.31</td>
<td>1</td>
<td>0.846</td>
<td>800</td>
<td>-0.003</td>
<td>-0.028</td>
<td>35</td>
</tr>
<tr>
<td>9301.21</td>
<td>1</td>
<td>0.695</td>
<td>160</td>
<td>-0.188</td>
<td>-0.197</td>
<td>75</td>
</tr>
<tr>
<td>9301.27</td>
<td>51</td>
<td>0.698</td>
<td>320</td>
<td>-0.175</td>
<td>-0.189</td>
<td>100</td>
</tr>
<tr>
<td>9301.28</td>
<td>1</td>
<td>0.698</td>
<td>640</td>
<td>-0.158</td>
<td>-0.180</td>
<td>50</td>
</tr>
<tr>
<td>9301.29</td>
<td>1</td>
<td>0.699</td>
<td>800</td>
<td>-0.150</td>
<td>-0.175</td>
<td>35</td>
</tr>
<tr>
<td>9301.03</td>
<td>1</td>
<td>0.612</td>
<td>160</td>
<td>-0.271</td>
<td>-0.280</td>
<td>115</td>
</tr>
<tr>
<td>9301.07</td>
<td>80</td>
<td>0.616</td>
<td>320</td>
<td>-0.257</td>
<td>-0.271</td>
<td>100</td>
</tr>
<tr>
<td>9301.08</td>
<td>1</td>
<td>0.617</td>
<td>640</td>
<td>-0.239</td>
<td>-0.261</td>
<td>60</td>
</tr>
<tr>
<td>9301.32</td>
<td>1</td>
<td>0.614</td>
<td>800</td>
<td>-0.235</td>
<td>-0.260</td>
<td>50</td>
</tr>
</tbody>
</table>

\( H \) may also be described dynamically as a function of the current state parameter, \( \psi \) (Jefferies and Been 2015). This approach was considered for these analyses, but ultimately not adopted. To test
it out, we added the ability to vary $H$ with the image state parameter, $\psi_i$, into the NorSand implementation to see the impact on the results for the homogenous sand model. The blue best-fit line from Figure B.3 was used ($H=39-250\psi_i$), to allow for larger potential changes in $H$ with changing state parameter (note that Figure B.3 is analogous to Figure 5.7, the only difference is the use of $\psi_{i,0}$ instead of $\psi_0$). To compare to the implementation with a constant $H$, $\psi_{i,0}$ for the homogenous sand profile was used to compute an $H=71$ based on the selected best-fit line. The comparison is shown in Figure B.4.

**Figure B.3.** Calibration of hardening modulus $H$, with initial image state parameter, $\psi_{i,0}$
Figure B.4. Comparison of experimental and numerical cone penetrometer test tip resistance ($q_c$) in sand computed using NorSand with a constant $H$ and with $H$ modeled dynamically as a function of $\psi$.

As seen in Figure B.4, there is little difference in the results when using the constant $H$ versus the $H$ varied dynamically with state parameter throughout the simulation. This is likely explained by the state parameter of the soil only changing significantly in the area immediately adjacent to the cone, while the tip resistance ($q_c$) is being computed based on stresses formed in a much larger zone of soil. Thus, although for some applications is may be beneficial to model $H$ dynamically, it is simpler to model the CPT penetration using a constant $H$ (as done in this study) and almost the same result can be obtained.

A final note on $H$ is that the stress paths experienced by the soil near the advancing cone are not replicated by the triaxial tests used to calibrate $H$. With all the other NorSand parameters already established, perhaps it can be appropriate to calibrate $H$ by matching the numerical $q_c$ with the experimental $q_c$, in lieu of trying to match the triaxial data. The results in this study seem to suggest as much, since an $H=25$ gives a much better fit with the data for both the homogenous sand and layered sand-clay profiles than the larger values of $H$ suggested by the triaxial calibration.
References


### B.2. Numerical Simulation Parameters for Sensitivity Analysis

Section 5.6 of this thesis describes results from around 60 numerical simulations performed to identify which input parameters the output tip resistance is most affected by. The following tables document exactly which parameters were used for each simulation. Figure B.5 is provided as a key to describe the layout of the tables.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>LB</th>
<th>UB</th>
<th>Simulation ID</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
<td>50</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-100 BASE</strong></td>
<td>25</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2 DR</strong></td>
<td>33.3</td>
<td>33.3</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2-DR</strong></td>
<td>36</td>
<td>46</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2-DR</strong></td>
<td>0.768</td>
<td>0.735</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2-DR</strong></td>
<td>0.434</td>
<td>0.423</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2-DR</strong></td>
<td>0.45</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td><strong>SAND-C2-DR</strong></td>
<td>fixed x</td>
<td>fixed x</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th>LB</th>
<th>UB</th>
<th>Simulation ID</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>σ_y (kPa)</strong></td>
<td>50</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td><strong>σ_y (kPa)</strong></td>
<td>25</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td><strong>ρ</strong></td>
<td>33.3</td>
<td>33.3</td>
<td></td>
</tr>
<tr>
<td><strong>D_r (%)</strong></td>
<td>36</td>
<td>46</td>
<td></td>
</tr>
<tr>
<td><strong>η</strong></td>
<td>0.768</td>
<td>0.735</td>
<td></td>
</tr>
<tr>
<td><strong>n_o</strong></td>
<td>0.434</td>
<td>0.423</td>
<td></td>
</tr>
<tr>
<td><strong>CC Radius (m)</strong></td>
<td>0.45</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td><strong>Simulation ID</strong></td>
<td>fixed x</td>
<td>fixed x</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sand</th>
<th>LB</th>
<th>UB</th>
<th>Simulation ID</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ψ_o</strong></td>
<td>0.126</td>
<td>-0.092</td>
<td>-0.160</td>
</tr>
<tr>
<td><strong>e_o,0</strong></td>
<td>0.9</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td><strong>λ</strong></td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td><strong>m</strong></td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>φ_{cc} (deg)</strong></td>
<td>30</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>0.1</td>
<td>0.1</td>
<td></td>
</tr>
<tr>
<td><strong>χ</strong></td>
<td>2.7</td>
<td>2.7</td>
<td></td>
</tr>
<tr>
<td><strong>G_{ref}</strong></td>
<td>743</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td><strong>a</strong></td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td><strong>ε_{smax}</strong></td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td><strong>ν</strong></td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>H</strong></td>
<td>25</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td><strong>φ_{cc} (deg)</strong></td>
<td>15</td>
<td>15</td>
<td></td>
</tr>
</tbody>
</table>

**Figure B.5.** Key to interpreting data tables in Appendix B.2.
Table B.3a. Input parameters used for numerical sensitivity analysis in sand (Part 1/3)

<table>
<thead>
<tr>
<th>Lab</th>
<th>$\sigma'_v$ (kPa)</th>
<th>$\sigma'_h$ (kPa)</th>
<th>$p'$</th>
<th>D$_R$ (%)</th>
<th>$\varepsilon_0$</th>
<th>$n_0$</th>
<th>CC Radius (m)</th>
<th>Boundary Condition</th>
<th>$\sigma'_h$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_0$</td>
<td>-0.126</td>
<td>0.9</td>
<td>0.012</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$c_{cs,0}$</td>
<td>0.9</td>
<td>0.9</td>
<td>0.012</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$m$</td>
<td>0.7</td>
<td>0.7</td>
<td>0.012</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$\phi_{cs}$</td>
<td></td>
<td></td>
<td></td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$N$</td>
<td>0.1</td>
<td>0.1</td>
<td>0.012</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$\chi$</td>
<td>2.7</td>
<td>2.7</td>
<td>0.012</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$G_{ref}$</td>
<td>743</td>
<td>743</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$a$</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$c_{min}$</td>
<td>0.051</td>
<td>0.051</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.2</td>
<td>0.2</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$H$</td>
<td>25</td>
<td>25</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
<tr>
<td>$\phi_{cont}$</td>
<td>15</td>
<td>15</td>
<td>0.57</td>
<td>30</td>
<td>0.126</td>
<td>0.126</td>
<td>-0.126</td>
<td>fixed x</td>
<td>-0.126</td>
</tr>
</tbody>
</table>
Table B.3b. Input parameters used for numerical sensitivity analysis in sand (Part 2/3)

<table>
<thead>
<tr>
<th></th>
<th>Lab</th>
<th>Sand</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \lambda )</td>
<td>( \phi_{cs} )</td>
</tr>
<tr>
<td></td>
<td>( \text{LB} )</td>
<td>( \text{UB} )</td>
</tr>
<tr>
<td>( \sigma'_v ) (kPa)</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>( \sigma'_h ) (kPa)</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>( p' )</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td>( D_R ) (%)</td>
<td>36</td>
<td>36</td>
</tr>
<tr>
<td>( e_0 )</td>
<td>0.768</td>
<td>0.768</td>
</tr>
<tr>
<td>( n_0 )</td>
<td>0.434</td>
<td>0.434</td>
</tr>
<tr>
<td>CC Radius (m)</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>Boundary Condition</td>
<td>fixed x</td>
<td>fixed x</td>
</tr>
<tr>
<td>( \psi_0 )</td>
<td>-0.128</td>
<td>-0.125</td>
</tr>
<tr>
<td>( e_{cs,0} )</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>0.009</td>
<td>0.015</td>
</tr>
<tr>
<td>( m )</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>( \phi_{cs} ) (deg)</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td>( N )</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>( \chi )</td>
<td>2.5</td>
<td>3</td>
</tr>
<tr>
<td>( G_{ref} )</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td>( a )</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td>( e_{min}^* )</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>( \phi_{cont} ) (deg)</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>
### Table B.3c. Input parameters used for numerical sensitivity analysis in sand (Part 3/3)

<table>
<thead>
<tr>
<th></th>
<th>$G_{\text{ref}}$</th>
<th>$\nu$</th>
<th>$H$</th>
<th>$\phi_{\text{cont}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LB</td>
<td>UB</td>
<td>LB</td>
<td>UB</td>
</tr>
<tr>
<td>SAND-15-GREF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-16-GREF</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-17-POIS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-18-POIS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-01-BASE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-19-H</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-20-CONT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAND-21-CONT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Lab</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>σ'_v (kPa)</strong></td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td><strong>σ'_h (kPa)</strong></td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td><strong>p'</strong></td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td><strong>Dr (%)</strong></td>
<td>36</td>
<td>36</td>
<td>36</td>
<td>36</td>
</tr>
<tr>
<td><strong>e_0</strong></td>
<td>0.76</td>
<td>0.76</td>
<td>0.76</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>n_0</strong></td>
<td>0.434</td>
<td>0.434</td>
<td>0.434</td>
<td>0.434</td>
</tr>
<tr>
<td><strong>CC Radius (m)</strong></td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td><strong>Boundary Condition</strong></td>
<td>fixed x</td>
<td>fixed x</td>
<td>fixed x</td>
<td>fixed x</td>
</tr>
<tr>
<td><strong>Sand</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>ψ_0</strong></td>
<td>-0.126</td>
<td>-0.126</td>
<td>-0.126</td>
<td>-0.126</td>
</tr>
<tr>
<td><strong>e_{cs,0}</strong></td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td><strong>λ</strong></td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td><strong>m</strong></td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td><strong>φ_{cs} (deg)</strong></td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td><strong>χ</strong></td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td><strong>G_{\text{ref}}</strong></td>
<td>700</td>
<td>800</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td><strong>a</strong></td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td><strong>e_{\text{min}}</strong></td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td><strong>ν</strong></td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td><strong>H</strong></td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td><strong>φ_{\text{cont}} (deg)</strong></td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
</tbody>
</table>
Table B.4a. Input parameters used for numerical sensitivity analysis in clay (Part 1/2)

<table>
<thead>
<tr>
<th>Lab</th>
<th>( \sigma'_v ) (kPa)</th>
<th>( \sigma'_h ) (kPa)</th>
<th>CC Radius (m)</th>
<th>Boundary Condition</th>
<th>( S_u ) (kPa)</th>
<th>G (kPa)</th>
<th>n_0</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>( \sigma'_v )</td>
<td>( \sigma'_h )</td>
<td>CC Radius</td>
<td>Boundary</td>
<td>( S_u )</td>
<td>G</td>
<td>n_0</td>
<td>a</td>
</tr>
<tr>
<td>CLAY-01-BASE</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-02-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-03-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-04-RAD</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-05-BOUND</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
</tbody>
</table>

Table B.4b. Input parameters used for numerical sensitivity analysis in clay (Part 2/2)

<table>
<thead>
<tr>
<th>Lab</th>
<th>( \sigma'_v ) (kPa)</th>
<th>( \sigma'_h ) (kPa)</th>
<th>CC Radius (m)</th>
<th>Boundary Condition</th>
<th>( S_u ) (kPa)</th>
<th>G (kPa)</th>
<th>n_0</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>( \sigma'_v )</td>
<td>( \sigma'_h )</td>
<td>CC Radius</td>
<td>Boundary</td>
<td>( S_u )</td>
<td>G</td>
<td>n_0</td>
<td>a</td>
</tr>
<tr>
<td>CLAY-01-BASE</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-02-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-03-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-04-RAD</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-05-BOUND</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Lab</th>
<th>( \sigma'_v ) (kPa)</th>
<th>( \sigma'_h ) (kPa)</th>
<th>CC Radius (m)</th>
<th>Boundary Condition</th>
<th>( S_u ) (kPa)</th>
<th>G (kPa)</th>
<th>n_0</th>
<th>a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>( \sigma'_v )</td>
<td>( \sigma'_h )</td>
<td>CC Radius</td>
<td>Boundary</td>
<td>( S_u )</td>
<td>G</td>
<td>n_0</td>
<td>a</td>
</tr>
<tr>
<td>CLAY-01-BASE</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-02-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-03-SIGH</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-04-RAD</td>
<td>50</td>
<td>50</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
<tr>
<td>CLAY-05-BOUND</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>50</td>
<td>50</td>
<td>27.9</td>
</tr>
</tbody>
</table>
### Table B.5a. Input parameters used for numerical sensitivity analysis in layered soil (Part 1/4)

<table>
<thead>
<tr>
<th>Lab</th>
<th>(\sigma'_v) (kPa)</th>
<th>50</th>
<th>50</th>
<th>50</th>
<th>50</th>
<th>50</th>
<th>50</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\sigma'_h) (kPa)</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>(p')</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td></td>
<td>(D_R) (%)</td>
<td>29</td>
<td>19</td>
<td>39</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>(e_0)</td>
<td>0.792</td>
<td>0.826</td>
<td>0.758</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
</tr>
<tr>
<td></td>
<td>(n_0)</td>
<td>0.442</td>
<td>0.452</td>
<td>0.431</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
</tr>
<tr>
<td>CC Radius (m)</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.3</td>
<td>0.45</td>
<td>0.45</td>
<td></td>
</tr>
<tr>
<td>Boundary Condition</td>
<td>fixed x</td>
<td>fixed x</td>
<td>fixed x</td>
<td>fixed x</td>
<td>pressure</td>
<td>fixed x</td>
<td></td>
</tr>
<tr>
<td>Sand</td>
<td>(\psi_0)</td>
<td>-0.102</td>
<td>-0.069</td>
<td>-0.136</td>
<td>-0.102</td>
<td>-0.102</td>
<td>-0.102</td>
</tr>
<tr>
<td></td>
<td>(e_{cs,0})</td>
<td>0.7</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>(\lambda)</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(m)</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>(\phi_{cs}) (deg)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>(N)</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td>(\chi)</td>
<td>2.75</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>(G_{ref})</td>
<td>743</td>
<td>743</td>
<td>743</td>
<td>743</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td></td>
<td>(a)</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>(c'_{min})</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>(\nu)</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>(H)</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>(\phi_{cys}) (deg)</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>Clay</td>
<td>(s_u) (kPa)</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
</tr>
<tr>
<td></td>
<td>(G) (kPa)</td>
<td>552</td>
<td>552</td>
<td>552</td>
<td>552</td>
<td>552</td>
<td>552</td>
</tr>
<tr>
<td></td>
<td>(n_0)</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>(a)</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
</tr>
</tbody>
</table>
Table B.5b. Input parameters used for numerical sensitivity analysis in layered soil (Part 2/4)

<table>
<thead>
<tr>
<th>Boundary</th>
<th>Soil Type</th>
<th>( \sigma'_b ) (kPa)</th>
<th>( \lambda )</th>
<th>( \varphi_{cs} ) (deg)</th>
<th>( N )</th>
<th>( \chi )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LAY-06-SIGH</td>
<td>Lab</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>LAY-08-LAM</td>
<td></td>
<td>30.0</td>
<td>36.7</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td>LAY-09-LAM</td>
<td></td>
<td>29</td>
<td>29</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>LAY-10-PHICS</td>
<td></td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
</tr>
<tr>
<td>LAY-11-PHICS</td>
<td></td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
</tr>
<tr>
<td>LAY-01-BASE</td>
<td></td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>LAY-12-N</td>
<td></td>
<td>0.051</td>
<td>0.012</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>LAY-13-CHI</td>
<td></td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Clay

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>( s_o ) (kPa)</th>
<th>( G ) (kPa)</th>
<th>( n_0 )</th>
<th>( a )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>27.9</td>
<td>552</td>
<td>0.362</td>
<td>13.5</td>
</tr>
</tbody>
</table>

251
Table B.5c. Input parameters used for numerical sensitivity analysis in layered soil (Part 3/4)

<table>
<thead>
<tr>
<th>Layer</th>
<th>$G_{\text{ref}}$ (kPa)</th>
<th>$\nu$</th>
<th>$H$ (m)</th>
<th>$\phi_{\text{cont}}$ (deg)</th>
<th>$S_u$ (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LB</td>
<td>UB</td>
<td>LB</td>
<td>UB</td>
<td>LB</td>
<td>UB</td>
</tr>
<tr>
<td>LAY-16-GREF</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td>LAY-17-POIS</td>
<td>29</td>
<td>29</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>LAY-18-POIS</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
</tr>
<tr>
<td>LAY-01-BASE</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
</tr>
<tr>
<td>LAY-02-CONT</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>LAY-01-SU</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>LAY-02-SU</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td>Lab</td>
<td>$\sigma'_v$ (kPa)</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>$\sigma'_h$ (kPa)</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>$p'$</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>$D_R$ (%)</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>$e_0$</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>$n_0$</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>CC Radius (m)</td>
<td>70</td>
<td>70</td>
<td>70</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Boundary Condition</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Sand</td>
<td>$\psi_0$</td>
<td>-0.12</td>
<td>-0.12</td>
<td>-0.12</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>$\psi_{\text{cs},0}$</td>
<td>9</td>
<td>9</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>$\lambda$</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>$m$</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>$\phi_{\text{cs}}$ (deg)</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>$\chi$</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>$G_{\text{ref}}$</td>
<td>700</td>
<td>800</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>$\epsilon_{\text{min}}$</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>Clay</td>
<td>$s_0$ (kPa)</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
<td>27.9</td>
</tr>
<tr>
<td></td>
<td>$G$ (kPa)</td>
<td>552</td>
<td>552</td>
<td>552</td>
<td>552</td>
</tr>
<tr>
<td></td>
<td>$n_0$</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
<td>13.5</td>
</tr>
</tbody>
</table>
Table B.5d. Input parameters used for numerical sensitivity analysis in layered soil (Part 4/4)

<table>
<thead>
<tr>
<th></th>
<th>Lab</th>
<th>Sand</th>
<th>Clay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$G$</td>
<td>$n_0$</td>
<td>$a$</td>
</tr>
<tr>
<td></td>
<td>LB</td>
<td>UB</td>
<td>LB</td>
</tr>
<tr>
<td>$\sigma'_v$ (kPa)</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>$\sigma'_h$ (kPa)</td>
<td>25</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>$p'$</td>
<td>33.3</td>
<td>33.3</td>
<td>33.3</td>
</tr>
<tr>
<td>$D_R$ (%)</td>
<td>29</td>
<td>29</td>
<td>29</td>
</tr>
<tr>
<td>$\varepsilon_0$</td>
<td>0.792</td>
<td>0.792</td>
<td>0.792</td>
</tr>
<tr>
<td>$n_0$</td>
<td>0.442</td>
<td>0.442</td>
<td>0.442</td>
</tr>
<tr>
<td>CC Radius (m)</td>
<td>0.45</td>
<td>0.45</td>
<td>0.45</td>
</tr>
<tr>
<td>Boundary Condition</td>
<td>fixed</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>Sand</td>
<td>$\psi_0$</td>
<td>-0.102</td>
<td>-0.102</td>
</tr>
<tr>
<td></td>
<td>$e_{cs,0}$</td>
<td>0.9</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>$\lambda$</td>
<td>0.012</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>$m$</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>$\varphi_{cs}$ (deg)</td>
<td>30</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>$N$</td>
<td>0.1</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>$\chi$</td>
<td>2.7</td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>$G_{ref}$</td>
<td>743</td>
<td>743</td>
</tr>
<tr>
<td></td>
<td>$\alpha$</td>
<td>0.57</td>
<td>0.57</td>
</tr>
<tr>
<td></td>
<td>$e^{*}_{min}$</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>$\nu$</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>$H$</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>$\varphi_{cont}$ (deg)</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>Clay</td>
<td>$s_u$ (kPa)</td>
<td>27.9</td>
<td>27.9</td>
</tr>
<tr>
<td></td>
<td>$G$ (kPa)</td>
<td>423</td>
<td>1404</td>
</tr>
<tr>
<td></td>
<td>$n_0$</td>
<td>0.362</td>
<td>0.362</td>
</tr>
<tr>
<td></td>
<td>$a$</td>
<td>13.5</td>
<td>13.5</td>
</tr>
</tbody>
</table>

253
B.3. Stress Conditions under Differing Radial Boundary Conditions

This appendix investigates the trends in tip resistance \( q_c \), mean effective stress \( p' \), and volumetric strain \( \varepsilon_v \) resulting from changing initial stress conditions and radial boundary conditions. Four simulations were performed:

- Rigid radial boundary condition and initial horizontal effective stress \( \sigma'_{h0} = 50 \text{ kPa} \)
- Rigid radial boundary condition and initial horizontal effective stress \( \sigma'_{h0} = 90 \text{ kPa} \)
- Flexible radial boundary condition and initial horizontal effective stress \( \sigma'_{h0} = 50 \text{ kPa} \)
- Flexible radial boundary condition and initial horizontal effective stress \( \sigma'_{h0} = 90 \text{ kPa} \)

All simulations were performed in a homogenous sand profile with \( D_R = 60\% \) and initial effective vertical stress \( \sigma'_{v0} = 100 \text{ kPa} \). The NorSand constitutive model was used to describe sand behavior using the parameters defined in Table 5.2. The following trends, observed in Figure 5.13a, prompted the investigations detailed herein:

1. Rigid radial boundary conditions produce larger \( q_c \) than flexible boundary conditions, regardless of \( \sigma'_{h0} \).
2. With rigid radial boundary conditions, \( q_c \) is very similar regardless of \( \sigma'_{h0} \), and actually tended to be slightly larger with a smaller \( \sigma'_{h0} \). The opposite trend was observed with the flexible boundary conditions, where \( q_c \) was much smaller for smaller \( \sigma'_{h0} \).
3. The difference between \( q_c \) from the rigid and flexible boundary conditions is smaller when \( \sigma'_{h0} \) is larger.

For each of the four simulations, stresses and strains were tracked at three material points (MPs), each at about 0.5 m deep in the soil profile. The first was one times the radius of the cone \( r_{cone} = 0.0253 \text{ m} \) away from the axis of symmetry (left boundary), the second was \( 2r_{cone} \) away, and the third \( 3r_{cone} \) away. The MP locations are shown in Figure B.6.
Several plots were prepared to compare $p'$, $\varepsilon_v$, and stress paths for the four simulations; see Figures B.7 through B.9. In general, a higher $q_c$ was accompanied by a higher $p'$ and a less dilative (less negative) $\varepsilon_v$ at MPs close to the cone. The following can be noted:

- Figure B.7 shows that maximum $p'$ is larger for the rigid boundary condition regardless of $\sigma '\_h0$, and, the difference in maximum $p'$ between the rigid and flexible boundary conditions is smaller for the larger $\sigma '\_h0$. This is consistent with observations (1) and (3) because we expect a larger $p'$ to result in a larger $q_c$.

- Figure B.8 shows that more dilation is allowed to occur with the flexible boundary condition than with the rigid boundary condition because deformations are allowed at the boundary. However, with a larger $\sigma '\_h0$, the amount of dilation for the flexible boundary condition reduces and is almost the same as the amount of dilation observed for the rigid boundary condition. This is intuitive because the increased confinement has a similar effect as the rigid boundary condition. This is also consistent with observation (3).

- For the rigid boundary condition, essentially the same amount of dilation occurs regardless of $\sigma '\_h0$ (Figure B.8). At the closest MP to the cone, there is very slightly less dilation for
the $\sigma'_{h0} = 50$ kPa case, and the corresponding $q_c$ and $p'$ are slightly larger, compared to the $\sigma'_{h0} = 90$ kPa case. This helps explain observation (2).

- The stress paths for both rigid and flexible boundary conditions are nearly identical for the $\sigma'_{h0} = 90$ kPa case (Figure B.9a), while for the $\sigma'_{h0} = 50$ kPa condition, there is more initial contraction in the simulation with the rigid boundary condition (Figure B.9b). This also supports observation (3).

![Comparison of mean effective stress between rigid and flexible boundary conditions for (a) $\sigma'_{h0}=90$ kPa and (b) $\sigma'_{h0}=50$ kPa.](image)

**Figure B.7.** Comparison of mean effective stress between rigid and flexible boundary conditions for (a) $\sigma'_{h0}=90$ kPa and (b) $\sigma'_{h0}=50$ kPa.
Figure B.8. Comparison of volumetric strain between rigid and flexible boundary conditions for (a) $\sigma_{h0}'=90$ kPa and (b) $\sigma_{h0}'=50$ kPa.

Figure B.9. Comparison of stress paths between rigid and flexible boundary conditions for (a) $\sigma_{h0}'=90$ kPa and (b) $\sigma_{h0}'=50$ kPa.
Appendix C: Data Repository Information for Chapter 6

This appendix details information associated with accessing the CPT database and Jupyter notebook described in Chapter 6. The database and notebook are available in the Virginia Tech Data Repository at https://doi.org/10.7294/21408450. The database citation is:


The contents of the readme file accompanying the dataset are provided below.

**Title of Dataset:** Data Associated with A CPT Database for Multiple Thin-Layer Correction Procedure Development

**Author(s):** Kaleigh Yost, Alba Yerro Colom, Eileen Martin, Russell Green

**Categories:** Civil Geotechnical Engineering

**Group:** Civil and Environmental Engineering

**Item Type:** Dataset

**Keywords:** Cone Penetration Test (CPT), Multiple Thin-Layer Effects, Statistical Learning, Material Point Method, Laboratory Calibration Chamber Tests, Challenging Soil Profiles, Interlayered Soil Profiles, Thin Layer Effects, Transition Zone Effects

**Description:**

CONTENTS AND METHODOLOGY

**CPT Database**

This cone penetrometer test (CPT) dataset comprises laboratory-based and numerically-generated data collected in highly interlayered soil profiles. Both the measured tip resistance in the interlayered profile and the true tip resistance (that would be measured in the profile absent of multiple thin-layer effects) are provided for 49 CPT profiles. All tip resistance values have been normalized for overburden pressure and represent $q_{ctn}$ values.

The CPT data is presented in two .csv files. The file "qt.csv" contains true tip resistance, qt,
associated with each of the 49 profiles. The file "qm.csv" contains the measured tip resistance, $q^m$, associated with each of the 49 profiles.

Each .csv file contains 50 rows. The first column of each file contains a "profile category” number. This identifies CPTs with the same soil profile geometry (i.e., CPTs with the same soil profile geometry are assigned the same profile category number). The first row of each file contains the depths associated with each tip resistance value. The first cell in the first row is "NAN" so that depths align with tip resistance values in the underlying rows.

Rows 2 through 20 contain laboratory data. The laboratory data are derived from a series of calibration chamber tests performed at Deltares (details of the experiments are described in De Lange 2018). Details about how the laboratory data were processed to create the $q^m$-$q^l$ profiles in this dataset are provided in Yost et al. (2022) and Yost (2022).

Rows 21 through 50 contain numerical data. The numerical data were generated using a 2D axisymmetric implementation of the Material Point Method with a slightly modified version of the open source software Anura3D (anura3d.com). Complete details regarding the calibration and validation of the numerical model used to generate this data are provided in Yost et al. (2022) and Yost (2022).

**Jupyter Notebook**

The Jupyter notebook "CPT-database-companion-notebook.ipynb" reads the data and performs several operations intended to prepare the data for statistical learning applications, including:

- A script to read data in and initialize depth, $q^m$, $q^l$, and profile category variables
- A script to visualize the contents of the database
- A framework to parse the database into separate training and test datasets, grouping profiles with same profile category number together
- A script to visualize the parsed training and testing data
- An example of how to manipulate data with subsampling and filtering to change the size of the depth interval
- An example of “chunking” profiles to generate more data to use in training and test datasets
- A framework for how to add data to the existing database
- An example of using a profile from the database to assess a simple blurring filter

MANUSCRIPTS ACCOMPANYING THIS DATASET


REFERENCES


License: CC0 1.0 Universal (CC0 1.0) Public Domain Dedication
Publisher: University Libraries, Virginia Tech
Corresponding Author Name: Kaleigh Yost
Corresponding Author E-mail Address: kmyost@vt.edu
Files/Folders in Dataset and Description of Files
qm.csv - this file contains the "measured" tip resistance (qm) data for all 49 soil profiles
qt.csv - this file contains the "true" tip resistance (qt) data for all 49 soil profiles
CPT-database-companion-notebook.ipynb - this notebook, developed in Google Colab, reads in the qm.csv and qt.csv files and performs operations on the data
Appendix D: Harnessing Numerical Tools to Study the Limitations of CPTs for Characterizing Complex Soil Stratigraphies for Liquefaction Assessment

The contributions of the authors to the composition of this manuscript are delineated as follows:

Kaleigh M. Yost
- Developed scope of the manuscript.
- Performed numerical analyses presented in manuscript.
- Prepared the figures.
- Wrote the draft and final manuscripts.

Dr. Alba Yerro
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft manuscripts.

Dr. Russell A. Green
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

Dr. Eileen Martin
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.
Harnessing Numerical Tools to Study the Limitations of CPTs for Characterizing Complex Soil Stratigraphies for Liquefaction Assessment

Kaleigh M. Yost¹, Alba Yerro², Russell A. Green³, Eileen Martin⁴

¹Graduate Student, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)
³Assistant Professor, Dept. of Civil and & Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: ayearro@vt.edu)
⁴Assistant Professor, Dept. of Mathematics, Virginia Tech, Blacksburg, VA 24061 (email: ermartin@vt.edu)

Published by the Earthquake Engineering Research Institute (EERI) as a part of the proceedings of the 12th National Conference in Earthquake Engineering (12NCEE), 27 June to 1 July, 2022, Salt Lake City, Utah

Reference:

Abstract

This paper describes the use of the Material Point Method (MPM) to simulate cone penetrometer testing (CPT) in complex soil profiles. CPT-based liquefaction evaluation procedures have been shown to be inaccurate in highly interlayered soil stratigraphies. One contributing factor to this inaccuracy is that CPT measurements at discrete depths reflect the properties of all soils that fall within a zone of influence around the cone tip, not just the properties of the soil at a particular depth. Consequently, the CPT loses resolution in soil profiles with many thin, interbedded soil layers (multiple thin-layer effects) and provides inaccurate input data to liquefaction analyses. While several procedures have been proposed to correct for multiple thin-layer effects, they tend to decrease in efficacy as the thickness of soil layers decreases. Results from the MPM analyses detailed in this paper highlight limitations of (1) the CPT in characterizing complex soil stratigraphies and (2) procedures proposed to correct for multiple thin-layer effects in CPT data.

Introduction

Cone penetrometer tests (CPTs) are a preferred method for in-situ soil characterization for liquefaction assessment because they collect data at very small depth increments (typically 1 to 2 cm), providing nearly continuous profiles of the subsurface. Standard-of-practice CPT-based liquefaction severity procedures (i.e., stress-based liquefaction triggering models coupled with manifestation models) have been shown to work well for relatively uniform, sandy soil profiles (e.g., Green et al. 2014). However, for complex soil profiles comprising many interbedded layers of potentially liquefiable and non-liquefiable soils, the procedures tend to overestimate the severity of liquefaction manifestation (e.g., Beyzaei et al. 2017; McLaughlin 2017).

One contributor to this overestimation is multiple thin-layer effects, in which data collected in layered profiles by the CPT is “smoothed” (Boulanger et al. 2016). This occurs because CPT data (i.e., tip resistance, \( q_c \), and sleeve friction, \( f_s \)) recorded at discrete depths are reflective of the soil that falls within a zone of influence around the tip of the cone, not just of the soil at a given depth. The zone of influence varies in size depending on the diameter of the cone \( d_{cone} \) and properties of the soils in the profile and can extend between 10 to 30 times \( d_{cone} \) below the cone tip (Ahmadi and Robertson 2005), for example. Several researchers have proposed procedures to correct for multiple thin-layer effects in CPT data (e.g., Boulanger and DeJong 2018; Yost et al. 2021; Cooper
et al. 2022). However, existing procedures have decreasing efficacy as the thickness of interbedded layers decreases, particularly when the layer thickness is less than 2 to 3\(d_{cone}\) (Yost et al. 2021). To develop, validate, and assess the efficacy of multiple-thin-layer correction procedures, it is necessary to have sets of “true” data (i.e., data that would be recorded by the CPT absent of multiple thin-layer effects) and “measured” data (i.e., data actually recorded by the CPT) for the same layered soil profiles. The availability of these data is relatively scarce, as it can only come from calibration chamber tests or numerical analyses; note that field CPT data only provide “measured” data. To this end, this paper shows how advanced numerical tools such as the Material Point Method (MPM) can be used to numerically simulate CPTs in layered soil profiles to better understand the limitations of (1) the CPT in characterizing complex soil profiles for liquefaction assessment and (2) the procedures proposed to correct for multiple thin-layer effects in CPT data.

**Background**

Previous numerical studies of CPTs in layered soils performed using the Finite Element or Finite Difference Methods (FEM or FDM, e.g. Ahmadi and Robertson 2005; van den Berg et al. 1996; Walker and Yu 2010) have shown that the size of the zone of influence around the cone tip is strongly influenced by the type of soil, the stiffness ratio between soil layers, and the effective horizontal stress. However, none of these studies examined what happens when more than two or three soil layers are present in sequence in a profile. Furthermore, FEM and FDM require adaptive re-meshing techniques to accommodate the large soil deformations associated with cone penetration. We propose MPM as an alternative procedure for this application.

MPM, originally proposed by Sulsky et al. (1994), is a continuum-based numerical framework that adopts features both of point-based and mesh-based numerical methods. In MPM, the continuum is discretized into a set of material points (MPs) that carry material data and move through a background computational mesh. The momentum balance equations are solved at the locations of the mesh nodes, but the constitutive equations and the mass balance equations are solved at the locations of the MPs. No permanent data are stored at the nodes. Data are mapped from the MPs to the nodes and vice versa at each time step using shape functions. This avoids problems with mesh distortion and makes MPM particularly suited for problems with large soil deformations, like cone penetration.
Methods

The analyses discussed herein were performed using a modified version of the open-source Anura3D MPM software (Anura3D 2021). This MPM formulation incorporates several advancements to the standard MPM formulation, all of which are detailed in Yost et al. (2022). The MPM CPT model used for this study was first calibrated and validated with a set of CPT calibration chamber test data collected by De Lange (2018). De Lange (2018) performed CPTs in layered sand-clay profiles as well as “reference” single-layer sand profiles with similar confining pressure and sand relative density ($D_R$) as the layered models. The former tests provided “measured” $q_c$ in the layered profiles, or $q''_m$, which was impacted by multiple thin-layer effects. The latter tests provided “true” $q_c$ for the sand layers in the layered profiles, or $q'_{sand}$, in the sense that the $q_c$ recorded by the CPT in the reference sand profile would be the $q_c$ recorded by the CPT in the sand layers of the layered profile absent of multiple thin-layer effects.

A 2D-axisymmetric MPM model was created, mimicking the geometry from De Lange (2018). The model geometry and discretization are shown in Figure D.1. The left boundary is the axis of symmetry and represents the center of the cone. The cone has an apex angle of 60° and $d_{cone} = 25.3$ mm. The left and right boundaries of the model were fixed in the horizontal direction, and the top and bottom boundaries were fixed in the horizontal and vertical directions. The entire vertical height of the calibration chamber (i.e., ~1 m of soil, or ~40$d_{cone}$) was included in the MPM model, but to minimize the computational time, the radial dimension was reduced to 10$d_{cone}$ from the axis of symmetry.

Triangular mesh elements were assigned. A refined mesh was used in the region immediately adjacent to the cone, and more MPs were assigned per element in this area as well. A moving mesh technique (Al-Kafaji 2013) was used, allowing the portion of mesh above the cone tip to advance downward at the same velocity as the cone while the portion of mesh below the cone tip compresses. In this way, the cone-soil interface remains well defined throughout the calculation, which is essential for the accuracy of the contact formulation and the model’s overall performance (Bardenhagen et al. 2001). The forces imparted on the conical face of the penetrometer by the soil were computed and converted to stress using the known cone tip area. This stress is equivalent to the $q_c$ measured by the CPTs in the lab.
All soils in the MPM model were assumed to be saturated. Clay layers were assumed to behave undrained and were modeled using a total stress method and the Tresca failure criterion. Sand layers were assumed to behave drained and were modeled using a strain-softening Mohr-Coulomb constitutive model (Yerro 2015). During the calibration and validation phase, the calibration chamber tests (De Lange 2018) were replicated using the MPM model, and laboratory and numerical results were compared. Appropriate material parameters for each simulation were identified based on available laboratory data (see Yost et al. 2022 for details). The MPM model was shown to be capable of adequately replicating $q_c$ in both reference sand and layered sand-clay soil profiles, despite the use of the simplified drainage conditions and basic constitutive models described previously. Complete details regarding the calibration and validation of the model can be found in Yost et al. (2022).

**Results and Discussion**

After the MPM model was calibrated and validated, it was used to study multiple thin-layer effects for a variety of soil profile geometries. A set of simulations was performed using four soil profiles with 0.28-meter-thick zones of alternating sand and clay layers. The four profiles had different layer thickness to cone diameter ratios ($H/d_{cone}$): 1.6, 1.2, 0.8, and 0.4. The resulting $q_c$ profiles were considered to be $q^m$ for the layered profiles. In order to compare $q^m$ determined for each profile to the true $q_c$ that would be expected in the sand and clay layers ($q_{sand}^l$ and $q_{clay}^l$), two additional CPT simulations were performed considering a single layer of sand and clay. All simulations considered a vertical overburden pressure of 50 kPa, $K_0 = 0.5$ conditions, and sand $D_R = 54\%$ (if sand were present in the profile). The results are shown in Figure D.2.

Several observations can be made from this exercise. First, $q^m$ in the thin sand layers is significantly smaller than the $q_{sand}^l$. $q^m$ in the thin clay layers is slightly larger than $q_{clay}^l$. In other words, $q_c$ in thin, dense layers is significantly underestimated, and slightly overestimated in thin, soft layers. As $H/d_{cone}$ decreases, both of these effects are magnified. Furthermore, boundaries between sand and clay layers are increasingly blurred as $H/d_{cone}$ decreases, to the point where identification of the presence and location of thin layers from $q^m$ data alone is nearly impossible for $H/d_{cone} < 0.8$. Finally, as $H/d_{cone}$ decreases, $q^m$ in the layered zone tends to converge to a single value that is much closer to $q_{clay}^l$ than to $q_{sand}^l$. 

266
The results of these simulations highlight the difficulties in attempting to correct CPT data for multiple thin-layer effects. Many correction procedures (e.g., Boulanger and DeJong 2018) require the detection of layer interfaces in $q''$ data. But if the variation in $q''$ is so small that no distinction between individual layers can be made (i.e., the CPT is not detecting the layer interface at all), the correction procedures will not work. For example, the entire layered zone in Figure D.2 with $H/d_{cone} = 0.4$ may be mistaken for a 0.28-meter-thick uniform layer of soil. The results also highlight the non-uniqueness of $q''$; namely, soil stratigraphies with different layer thicknesses and stiffnesses can have essentially the same $q''$. Consequently, procedures that attempt to extract $q'$ from $q''$ must be used with caution and should include techniques to reduce the uncertainty of the solution, e.g., by incorporating physically realistic constraints on what the $q'$ profile can look like. The efficacy of correction procedures may be increased by using large sets of numerically-developed $q''$ and $q'$ as training data, as suggested by Yost et al. (2022).

Finally, most research has focused on addressing multiple thin-layer effects on $q_c$. However, the impact of multiple thin-layer effects on $f_s$ is even more complicated. The relatively long length of the friction sleeve results in it being in contact with multiple thin layers at once. Also, there is a downdrag effect in which the advancing cone drags soil from overlying layers down into underlying layers, creating a zone of material immediately adjacent to the cone that is not representative of a given layer (shown physically by De Lange 2018 and numerically by Yost et al. 2022). Both $q_c$ and $f_s$ are required for most CPT-based liquefaction evaluation procedures, and their accuracy impacts the accuracy of the predicted liquefaction response. Future work should address multiple thin-layer effects on $f_s$, in addition to $q_c$, in order to obtain accurate liquefaction evaluations.

**Conclusions**

In this paper, MPM is used to numerically simulate CPTs in highly stratified soil profiles. The results highlight the limitations of the CPT in characterizing complex soil stratigraphies for liquefaction assessment, as well as the limitations of the correction procedures developed to overcome the limitations of the CPT. The CPT loses its ability to detect the presence of very thin soil layers as the ratio of layer thickness to cone diameter gets smaller, a phenomenon referred to
as multiple thin-layer effects. The efficacy of multiple-thin-layer correction procedures that rely on the cone’s ability to detect layer interfaces is poor for profiles that have very thin soil layers relative to the diameter of the cone. Furthermore, correction procedures must be used with caution due to the non-uniqueness of measured $q_c$ and should include physically realistic constraints to reduce uncertainty in their solutions. Finally, the impact of multiple thin-layer effects on CPT sleeve friction should also be considered in future work because both $q_c$ and $f_s$ are required for CPT-based liquefaction evaluation.

Acknowledgements

This research was partially funded by National Science Foundation (NSF) Grant Numbers CMMI-1825189 and CMMI-1937984. This support is gratefully acknowledged. We thank Julian Bommer, Imperial College London, and Jan van Elk, NAM, as well as all the individuals from NAM, Shell, and Deltares for the discussions that prompted and informed our investigation of thin-layer effects. However, any opinions, findings, and conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NSF or the others acknowledged.

References


Zealand.” Proc. 3rd Intern. Conf. on Performance-Based Design in Earthquake Geotechnical Engineering (PBDIII), Vancouver, Canada, 16-19 July.


Figures

Figure D.1. MPM model geometry and discretization (Yost et al. 2022).

Figure D.2. Multiple thin-layer effects on tip resistance for profiles with varying layer thickness (modified from Yost et al. 2022).
Appendix E: Bench-Scale Testing of Grouts for Geoslice Peels

The contributions of the authors to the composition of this manuscript are delineated as follows:

Kaleigh M. Yost
- Performed laboratory experiments detailed in this manuscript.
- Prepared the figures and tables.
- Wrote the draft and final manuscripts.

Dr. Russell A. Green
- Developed idea for this manuscript.
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.

Eric Herwitz
- Performed laboratory experiments detailed in this manuscript.

Liam Wotherspoon
- Provided valuable feedback throughout this study.
- Reviewed and edited the draft and final manuscripts.
Bench-Scale Testing of Grouts for Geoslice Peels

Kaleigh M. Yost¹, Russell A. Green², Eric Herwitz³, and Liam Wotherspoon⁴

¹Graduate Student, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: kmyost@vt.edu)
²Professor, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: rugreen@vt.edu)
³Undergraduate Student, Dept. of Civil and Environmental Engineering, Virginia Tech, Blacksburg, VA 24061 (email: eherwitz@vt.edu)
⁴Associate Professor, Dept. of Civil and Environmental Engineering, University of Auckland, New Zealand (email: l.wotherspoon@auckland.ac.nz)

Published by the American Society of Civil Engineers (ASCE) as a part of the proceedings of the International Foundations Congress and Equipment Expo (IFCEE), 10-14 May, 2021, Dallas, Texas

Used with permission from ASCE

Reference:

Abstract

Geo-slicing is a novel in-situ sampling technique developed in Japan to identify evidence of paleoseismicity in soil deposits not conducive to trenching. To preserve and enhance the stratigraphic features of the geo-slice sample, a “peel” is created from the vertical slice of the soil profile by laying a reinforcing cloth and a grout or adhesive over the slice. After the adhesive dries, the cloth is removed from the slice. A thin layer of soil remains attached to the cloth, creating the peel. The peel can then be examined for paleoliquefaction features such as dikes and sills of sand that are generally devoid of bedding structures. Previous geo-slicing studies used a highly toxic Japanese grout. To conform to modern environmental regulations, it is necessary to identify a less-hazardous grout that still produces a satisfactory peel. A bench-scale study of multiple adhesives for creating geo-slice peels was performed. Adhesives are evaluated for their efficacy in creating a relief that enhances the bedding structures of the soil slice, and for other properties such as flexibility and hazard level. Of the eleven adhesives evaluated herein, Flex Seal Liquid was identified as most suitable for creating geo-slice peels.

Introduction

Paleoliquefaction evidence serves as a geologic record of earthquakes that occurred during the Holocene and late Pleistocene periods. For earthquakes that were not instrumentally recorded, paleoliquefaction evidence can inform back-analyses used to determine magnitude, ground accelerations, and location of rupture associated with these earthquakes. This is particularly useful to assess seismic hazard in continental settings where large earthquakes are infrequent, such as the New Madrid Seismic Zone and the Wabash Valley region (Obermeier et al. 2001). For more recent earthquakes where magnitude and ground accelerations are well-defined, techniques used to identify paleoliquefaction features in the subsurface can be used to evaluate the accuracy of liquefaction triggering procedures and provide insights into possible geomorphologic controls on liquefaction manifestation (e.g. the presence of a thick, non-liquefiable cap soil layer). Evidence of liquefaction can manifest at the ground surface (e.g. as a sand boil) or in the subsurface (e.g. as a dike or sill of fluidized sand preserved in a cohesive layer). Paleoliquefaction features are typically identified during extensive field surveys consisting of visual inspection of stream or river banks (e.g. Green et al. 2005; Olson et al. 2005; Obermeier et al. 2005), or by trenching (e.g. Bastin
et al. 2016; Maurer et al. 2019). Both techniques are limited by the depth to the groundwater table and therefore typically result in relatively shallow observations of paleoliquefaction evidence.

Following the 1995 Kobe earthquake, Nakata and Shimazaki (1997) invented a new soil sampling technique called geo-slicing to search for evidence of liquefaction in the subsurface without needing to trench. Geo-slicing has since been popularized in Japan, but has only been used in the US once (Takada and Atwater 2004). As implemented in the study by Takada and Atwater (2004), the geo-slicer consists of two primary parts: a 0.55-meter-wide × 9.14-meter-long × 0.08-meter-thick trapezoidal steel sheet pile and a flat rectangular cover or “shutter” plate that slides along the open face of the sheet pile. The sheet pile and shutter plate are sequentially driven into the ground with a vibratory hammer. The geo-slicer is then extracted as a single element, with a soil sample encased in the annular space. Once the geo-slicer is extracted, it is laid horizontally on the ground. The shutter plate is removed and the disturbed soil on the surface is scraped clean to reveal detailed soil stratigraphy. To enhance and preserve the bedding features in the sample, a “peel” is created by covering the soil sample with a reinforcing cloth and pouring permeation grout over the surface. Once the grout cures, the peel is removed from the sample. Because the grout permeates more deeply into coarser-grained soils, the resulting peel shows a relief of the soil bedding in more detail than the soil sample itself. Examining the peel allows for highly detailed cataloguing of stratigraphy and subsurface liquefaction features.

One of the difficulties in implementing the geo-slicing method outside of Japan is importation and use of the grout to make the peels due to environmental regulations. Takada and Atwater (2004) used a toxic Japanese grout, Hycel SAC-100 (also referred to as OH-1), comprised of a prepolymer, methyl ethyl ketone, and toluene di-isocyanate. The grout cures within an hour, producing a flexible peel that can be removed from the sample and rolled up for storage. The aim of this study was to identify an alternative grout that conforms to current environmental regulations, but retains the desirable properties of the Hycel SAC-100. The ultimate goal is to implement the geo-slicing technique in the field to search for evidence of liquefaction in the subsurface at a suite of sites in New Zealand. In addition to cataloguing subsurface liquefaction evidence, strata identified in the geo-slices will be characterized in terms of soil classification, grain size distribution, and Atterberg limits to complement existing site characterization data at
the sites. Other more detailed tests, such as the cyclic triaxial test, may be performed on select samples. In the following, the materials and methodology of this bench-scale study are discussed and recommendations for grout selection for field-scale implementation are provided.

**Materials and Methods**

To perform this study, a “bench-scale geo-slicer” was constructed, which is a bench-scale apparatus to prepare simulated vertical slices of soil profiles for evaluating adhesives for creating geo-slice peels. Sand was water-pluviated into the bench-scale geo-slicer to simulate the natural bedding structure of a soil deposit. After the sample was created, a weight was placed on top of the sample, and the sample was allowed to consolidate for 24 hours. After the consolidation phase, the bench-scale geo-slicer was laid horizontally and the front panel was removed, revealing the soil sample. The surface of the sample was scraped clean with a spatula. Peels of the sample were then created. The following describes the materials used to perform this procedure.

*Bench-scale geo-slicer*

The bench-scale geo-slicer was constructed out of a wooden frame. The front panel of the bench-scale geo-slicer is removable and must be clamped into place during sample formation. The seams of the bench-scale geo-slicer were waterproofed with sealant and a drainage hole was drilled near the bottom of the frame. The hole was plugged during deposition of the soil, and was unplugged to allow for drainage during the consolidation phase. A piece of geosynthetic was placed over the drainage hole to act as a filter. Prior to pluviation, the geo-slicer was filled with water. A consolidation block was placed directly on top of the sample after pluviation and a weight was placed on top to increase the overburden pressure and to induce consolidation. The bench-scale geo-slicer is shown in Figure E.1.

*Soils*

To simulate variation in soil stratigraphy, a poorly graded sand was passed through a #40 sieve to separate the coarser and finer portions. Layered samples were created by water-pluviating the coarser and finer portions into the bench-scale geo-slicer in alternating patterns. The grain size distributions of the three sands are shown in Figure E.2.
Cloth
Takada and Atwater (2004) used a cotton cloth to reinforce their peels. A similar open-weave cotton cloth was selected for this study. The cloth is placed on top of the soil sample once the front panel of the bench-scale geo-slicer is removed and the surface is scraped clean. A sample of the cloth is shown in Figure E.3.

Adhesives
A total of eleven different adhesive products were tested in this study. The products can generally be categorized as either permeation grouts, erosion control products, or liquid rubber products. The permeation grouts discussed herein are either single component (meaning they only require the addition of water to activate), or three-component (meaning they require the addition of an accelerator and a catalyst as well as water). The grout-to-water ratio and the percent by volume of the accelerator and catalyst additives can be adjusted to change the cure time of the grouts. Several time-to-cure tests were performed to obtain appropriate ratios for this application. The adhesive is applied either directly to the soil sample prior to placing the cloth or poured through the cloth after it has been placed, depending on adhesive viscosity. Three of the erosion control products (DirtGlue, DG XX-13, and DG Cool) are liquids that can be diluted with water, but are also effective as undiluted products. Because the time to cure was only lengthened by the addition of water, the tests were primarily performed with undiluted products. The fourth erosion control product (DirtGlue Dry) is a powdered polymer that is activated when water is applied. The liquid rubber products Flex Seal Liquid and Flex Seal Spray are meant to be used undiluted and were applied directly to the sample without the addition of water. A summary of the adhesives and treatments used in this study is provided in Table E.1.

Peel Preparation and Evaluation
Once the adhesive has cured, the peel is removed from the soil sample and laid flat with the soil side facing upwards. Loose soil is removed by gently blowing air on the peel. The peel can then be evaluated.

Two phases of testing were performed. The first phase was a feasibility study, in which all eleven adhesives included in Table E.1 were evaluated for their ability to create an acceptable peel. A
peel was considered acceptable if a layer of soil firmly and uniformly adhered to the reinforcing cloth, and the peel was flexible enough to bend. If an acceptable peel could be created using a given adhesive, that adhesive advanced to the second phase of testing. In the second phase of testing, the grouts and the resulting peels were evaluated based on the characteristics outlined in Table E.2.

To quantify the flexibility of the peels, bending tests were performed on cured peels. The flexibility of the peels was assessed by draping the center of the peel over a 2-cm-diameter metal bar and measuring the angle of bending with horizontal. The flexibility test was performed twice: first in an “unassisted” manner, meaning the angle of bending was measured as the peel folded over the bar due to gravity alone, and second in an “assisted” manner, meaning the angle was measured as the peel was manually folded over the bar.

Results and Discussion

Phase One: Feasibility

In Phase One of testing, eleven adhesive products were evaluated for their ability to create an acceptable peel. Only three adhesives were able to produce a flexible peel that firmly and uniformly adhered the soil to the cloth: MG Gel Foam, DirtGlue Dry, and Flex Seal Liquid. These adhesives advanced to Phase Two. The results of Phase One testing are provided in Table E.3.

Phase Two: Further Evaluation

In Phase Two of testing, six peels were created on the same geo-slice sample using the MG Gel Foam, the DirtGlue Dry, and the Flex Seal Liquid. The sample and the resulting peels are shown in Figures E.4a and E.4b, respectively. Immediately after curing, the six peels were subjected to unassisted bending tests, select results of which are shown in Figure E.5. A summary of the results of the Phase Two tests is presented in Table E.4.

The three adhesives were ranked (with 1 being the most desirable and 3 being the least desirable) with respect to each of the Phase Two evaluation criteria as shown in Table E.5. The DirtGlue Dry peels were the thinnest and most flexible, and the adhesive is the least hazardous. However, the DirtGlue Dry peels took the longest to cure. Furthermore, if the peels were removed prior to being
fully cured, pieces of the soil easily dislodged from the cloth (for example, as observed for peel DG-1 in Figure E.4b). The MG Gel Foam peels were the thickest and least flexible, and the adhesive is the most hazardous. However, the MG Gel Foam peels enhanced the stratification features very well and cured quickly. The Flex Seal Liquid peels had desirable flexibility and a relatively fast time to cure. The Flex Seal Liquid peel met the <2.0 cm thickness requirement presented in Table E.2 and adequately enhanced the stratification features.

Conclusions and Further Work
No adhesive with identical properties to the toxic Hycel SAC-100 grout used by Takada and Atwater (2004) to create geo-slice peels was found during this study. However, the MG Gel Foam, Flex Seal Liquid, and DirtGlue Dry products produced acceptable results. When making a final adhesive selection for field implementation, the thickness and flexibility of the peel, time to cure, enhancement of stratification features, and hazard level of the adhesive should all be considered. For this specific application, the DirtGlue Dry produced the most desirable results, but also took the longest amount of time to cure. Further tests will be performed to determine whether time to cure can be reduced. However, due to this limitation of the DirtGlue Dry, the Flex Seal Liquid is recommended as the preferred adhesive for future implementation in field-scale geo-slicing studies. The characteristics of the Flex Seal Liquid peels are adequate for this application and Flex Seal Liquid is a less hazardous alternative to the Hycel SAC-100 grout used in previous geo-slicing studies. Furthermore, Flex Seal Liquid or other similar liquid rubber products can easily be found in hardware stores and do not present issues with current environmental regulations.

This bench-scale work will be continued prior to field implementation to include durability testing of geo-slice peels as well as the exploration of alternative adhesives, cloths, and adhesive application techniques.

Acknowledgements
This research was funded in part by the National Science Foundation (NSF) Grants CMMI-1825189 and CMMI-1937984. This support is gratefully acknowledged. Additionally, Dr. Brian Atwater (USGS) provided information about the field implementation of geo-slicing and creating peels, and Jim Spiegel (Spetec), Bill Phillips (Mountain Grout), and Chris Rider and Larry
Guilbault (Global Environmental Solutions) provided the grouts tested in this study. However, any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the NSF or others that are acknowledged.

References


### Table E.1. Summary of Tested Adhesives and Recommended Treatments

<table>
<thead>
<tr>
<th>Category</th>
<th>Manufacturer</th>
<th>Product</th>
<th>Description</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Permeation Grouts</td>
<td>Spetec</td>
<td>SP PUR GT500</td>
<td>Single component, low viscosity, flexible hydrophilic polyurethane resin</td>
<td>1:1 grout to water ratio; pour over cloth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SP AG200</td>
<td>Three component, water-swelling hydrogel acrylic</td>
<td>1:1 grout to water ratio &amp; 0.5% additives TEA and SP; pour over cloth</td>
</tr>
<tr>
<td></td>
<td>Mountain Grout</td>
<td>MG Gel Foam</td>
<td>Single component, low viscosity hydrophilic polyurethane resin</td>
<td>1:3 grout to water ratio; pour directly on sample</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MG Acrylate</td>
<td>Three component, fast-reacting, low viscosity acrylate polymer</td>
<td>1:1 grout to water ratio &amp; 0.325% additives TEA and SP; pour over cloth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MG Acrylate Extra Strength +</td>
<td>Three component, fast-reacting, low viscosity acrylate polymer, plus latex</td>
<td>1:1 grout to water ratio &amp; 0.325% additives TEA and SP + Latex; pour over</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Latex</td>
<td>for added strength</td>
<td>cloth</td>
</tr>
<tr>
<td>Erosion Control Products</td>
<td>Global Environmental Solutions</td>
<td>DirtGlue</td>
<td>Single component, hydrophobic acrylic organic-based polymer emulsion</td>
<td>undiluted; pour over cloth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DirtGlue Dry</td>
<td>Acrylate-based fine granulated powdered polymer</td>
<td>spread directly on sample, thoroughly expose to water to activate</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DG XX-13</td>
<td>Single component, hydrophobic acrylic organic-based polymer emulsion</td>
<td>undiluted; pour over cloth</td>
</tr>
<tr>
<td></td>
<td></td>
<td>DG Cool</td>
<td>Single component, hydrophobic acrylic organic-based polymer emulsion</td>
<td>undiluted; pour over cloth</td>
</tr>
<tr>
<td>Liquid Rubber</td>
<td>Swift Response</td>
<td>Flex Seal Liquid</td>
<td>Liquid rubber (clear)</td>
<td>undiluted; pour directly on sample</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Flex Seal Spray</td>
<td>Liquid rubber (clear)</td>
<td>undiluted; spray over cloth</td>
</tr>
</tbody>
</table>

### Table E.2. Geo-slice Peel Evaluation Criteria for Phase 2 of Testing

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thickness of Peel</td>
<td>Less than 2.0 cm</td>
</tr>
<tr>
<td>Flexibility of Peel</td>
<td>Able to roll for storage and transport (as evaluated by bending tests)</td>
</tr>
<tr>
<td>Time to Cure</td>
<td>Less than 24 hours, 1 to 2 hours preferred</td>
</tr>
<tr>
<td>Enhancement of Stratification Features</td>
<td>Grout permeates more deeply in coarser-grained layers than in finer-grained layers</td>
</tr>
<tr>
<td>Hazard Level of Adhesive</td>
<td>Non-toxic, non-hazardous preferred</td>
</tr>
</tbody>
</table>
### Table E.3. Results of Phase One Feasibility Testing of Geo-slice Peels

<table>
<thead>
<tr>
<th>Product</th>
<th>Adheres Soil to Cloth</th>
<th>Uniform Peel</th>
<th>Flexible</th>
<th>Acceptable Peel?</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP PUR GT500</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>SP AG200</td>
<td>No</td>
<td>N/A</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>MG Gel Foam</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>MG Acrylate</td>
<td>No</td>
<td>N/A</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>MG Acrylate Extra Strength + Latex</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>DirtGlue</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>DirtGlue Dry</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>DG XX-13</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>MG Acrylate Extra Strength + Latex</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>DirtGlue</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>DirtGlue Dry</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Flex Seal Liquid</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Flex Seal Spray</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

### Table E.4. Results of Phase Two Testing of Geo-slice Peels

<table>
<thead>
<tr>
<th>Product</th>
<th>Peel ID</th>
<th>Amount of Product Applied</th>
<th>Peel Thickness (cm)</th>
<th>Angle of Bending (deg)</th>
<th>Time to Cure (hrs)</th>
<th>Enhancement of Stratification Features</th>
<th>Globally Harmonized System of Classification and Labeling of Chemicals (GHS) Hazard Classification (Category)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MG Gel Foam (liquid)</td>
<td>MG-1</td>
<td>120 mL</td>
<td>3.8</td>
<td>0.9</td>
<td>7</td>
<td>90</td>
<td>Yes, Acute Toxicity (4), Skin Irritation (2), Eye Irritation (2), Respiratory Sensitization (1), Target organ toxicity single exposure (3), Target organ toxicity repeated exposure (2)</td>
</tr>
<tr>
<td></td>
<td>MG-2</td>
<td></td>
<td>2.9</td>
<td>1.6</td>
<td>17</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>DirtGlue Dry (powder)</td>
<td>DG-1</td>
<td>15 grams</td>
<td>1.0</td>
<td>0.2</td>
<td>90</td>
<td>90</td>
<td>Yes, Non-hazardous</td>
</tr>
<tr>
<td></td>
<td>DG-2</td>
<td></td>
<td>0.4</td>
<td>0.2</td>
<td>90</td>
<td>90</td>
<td></td>
</tr>
<tr>
<td>Flex Seal Liquid (liquid)</td>
<td>FS-1</td>
<td>60 mL</td>
<td>2.0</td>
<td>0.5</td>
<td>16</td>
<td>90</td>
<td>Yes, Skin sensitization (1), Carcinogenicity (2), Reproductive toxicity (2), Flammable liquids (3)</td>
</tr>
<tr>
<td></td>
<td>FS-2</td>
<td></td>
<td>1.6</td>
<td>0.4</td>
<td>43</td>
<td>90</td>
<td></td>
</tr>
</tbody>
</table>
Table E.5. Geo-slice Peel Evaluation

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Adhesive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MG Gel Foam</td>
</tr>
<tr>
<td>Thickness of Peel</td>
<td>3</td>
</tr>
<tr>
<td>Flexibility of Peel</td>
<td>3</td>
</tr>
<tr>
<td>Time to Cure</td>
<td>1</td>
</tr>
<tr>
<td>Enhancement of Stratification Features</td>
<td>1</td>
</tr>
<tr>
<td>Hazard Level of Adhesive</td>
<td>3</td>
</tr>
</tbody>
</table>

Figures

Figure E.1. a) Bench-scale geoslicer with front panel removed. b) Bench-scale geoslicer with front panel clamped in place.
Figure E.2. Grain size distributions of the poorly graded sand and its coarser and finer portions used to create the soil samples.

Figure E.3. Open-weave cotton cloth used as reinforcement for the geo-slice peels.
**Figure E.4.** (a) Geo-slice sample divided into six 4”×8” sections. (b) Corresponding peels created using MG Gel Foam [MG-1, MG-2], Flex Seal Liquid [FS-1, FS-2], and DirtGlue Dry [DG-1, DG-2].

**Figure E.5.** Results of unassisted bending tests for peels created with (a) MG Gel Foam [MG-2], (b) Flex Seal Liquid [FS-1], and (c) DirtGlue Dry [DG-2].