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Author(s)	JIANG, Yazhou
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Deterministic and stochastic study on long-term subsidence of soft clay due to the Niigataken Chuetsu-oki Earthquake in 2007

by

Jiang Yazhou

A thesis submitted for the degree of Doctor of Philosophy

Examination Committee:

Prof. Koichi ISOBE

Prof. Yoichi WATABE

Prof. Yasunori MIYAMORI

Prof. Satoshi NISHIMURA

Thesis No.

Division of Field Engineering For Environment

Graduate School of Engineering, Hokkaido University

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ABSTRACT

During the 2007 Niigataken Chuetsu-oki Earthquake, ground liquefaction was prominent at the foot of sand dunes and old river channels, whereas clayey grounds exhibited no significant immediate failures. However, long-term settlement was observed at Shinbashi in Kashiwazaki City, where cumulative ground subsidence of 71 mm was recorded over 14 years from the surface to a depth of 23 m.

To investigate the mechanisms of both seismic deformation and long-term post-earthquake settlement, extensive ground investigations, boring surveys, and laboratory tests were conducted. Results revealed that the clay at the site was highly structured, strongly compressible, and extremely soft. Finite element (FE) simulations were performed using the Transformation Stress-Cyclic Mobility (TS-CM) constitutive model, incorporating subloading and superloading concepts. Model parameters were calibrated based on laboratory tests, and soil-water coupling elasto-plastic FE analysis was used to simulate ground subsidence. The simulations closely matched field observations, enabling forward predictions of post-earthquake subsidence. Findings indicated that the highly structured clay exhibited greater long-term consolidation potential than lower-structured clay due to significant excess pore water pressure generation during seismic loading and subsequent consolidation. This conclusion was further validated through laboratory consolidation tests.

Despite the agreement between deterministic FE simulations and field measurements, uncertainty in geotechnical parameters necessitates a stochastic analysis framework for more reliable long-term settlement predictions. To address this, the stochastic finite element analysis (SFEA) software JRiveruncertainty was developed. The software supports parallel computing, integrates predefined finite element solvers with custom computational models, and incorporates multiple sampling methods (e.g., direct Monte Carlo, Latin Hypercube Sampling, Sobol sequence). It also accommodates various probability distributions (e.g., normal, lognormal, exponential, Poisson) and features sensitivity analysis, spatial variability analysis (random field generation), and the stochastic response surface method (SRSM), such as Polynomial Chaos Expansion (PCE).

Stochastic analysis was applied to quantify the influence of uncertain parameters on subsidence behavior. Sobol global sensitivity analysis identified permeability coefficient, initial soil structure, and critical state stress ratio as the three most influential parameters affecting soil deformation and long-

term subsidence. Monte Carlo simulations with varying sample sizes and distributions assessed settlement reliability, revealing that:

- For an allowable settlement of 100 mm, the Reliability of the subsidence no more than 100 mm in 20 years is 79% (corresponding to a failure probability of 21%) and the Reliability of the subsidence no more than 100 mm in 25 years is 44% (corresponding to a failure probability of 56%), highlighting long-term risks in soft clay consolidation.

- The model factor for settlements remained stable across different sampling techniques and sample sizes, simultaneously with the uncertainty propagation analysis both demonstrating robustness in numerical predictions.

- Latin Hypercube Sampling (LHS) significantly reduced computational costs while maintaining accuracy, with LHS using 1000 samples achieving similar precision to the Sobol sequence with 5120 samples.

- As for Stochastic Response Surface Method (SRS), it allows us to obtain reliable uncertainty quantification results with significantly reduced computational cost with proper sample selection and regression modelling.

These findings underscore the importance of incorporating uncertainty quantification in geotechnical engineering, particularly in seismic risk assessment and long-term resilience planning. By integrating stochastic analysis with traditional deterministic models, this research provides a more reliable and computationally efficient approach for evaluating subsidence risks in soft clay, aiding informed engineering design and decision-making in earthquake-prone regions.

PREFACE

The research work, presented in this thesis was conducted at the University of Hokkaido in the laboratory of Analytical Geomechanics of the Division of Field Engineering For Environment of Graduate School of Engineering during the period April 2022 to June 2025.

This work was performed under the supervision of Associate Professor Koichi ISOBE. This thesis is presented in the form of a thesis by publications, based on the publications listed below.

(1) International conferences

1. Jiang, Y., Isobe, K., Ohtsuka, S. and Takahara, T., 2024. Sensitivity analysis on long-term subsidence of soft clay due to The Niigataken Chuetsu-oki Earthquake in 2007. 8th International Conference on Earthquake Geotechnical Engineering (Japanese Geotechnical Society Special Publication), 10(44), pp.1635-1640.

DOI: <https://doi.org/10.3208/jgssp.v10.OS-33-01>

(2) International journals

1. Jiang, Y., Isobe, K., Ohtsuka, S. and Takahara, T., 2025. Study on long-term subsidence of soft clay due to Niigata-ken Chuetsu-oki earthquake of 2007. Soils and Foundations, 65(1), 101536.

DOI: <https://doi.org/10.1016/j.sandf.2024.101536>

CHAPTER 1 - BACKGROUND & GENERAL INTRODUCTION

1.1 Background

The Niigataken Chuetsu-oki Earthquake in 2007 that hit Japan on July 16th, killed 11 people and damaged more than 1,000 houses. The quake registered 6.8 on the magnitude scale of the Japan Meteorological Agency (JMA), and a Kyoshin Net (K-NET) accelerograph measured a maximum value of 680 gal. A maximum seismic intensity of 6 upper was measured in Kashiwazaki city (See Figure 1-1).

Many houses were damaged (See Figure 1-2), and ground deformation types such as liquefaction were observed in Kashiwazaki City in Figure 1-3 (Isobe et al., 2014a) and Kariwa Village. In the Hashiba district of Kashiwazaki City and in Kariwa Village, foundation damage to timber houses and ground deformation were extensively observed. Therefore, a lot of attention was paid to house damage due to liquefaction on the foot of sand dune or the old river channels in the temblor. Conversely, it was thought that house damage on the Kashiwazaki Plane which consists of alluvial soft clay was relatively less than that due to liquefaction. However, it was clarified from the results of ground subsidence measured by Niigata Prefecture at the Shinbashi district in Kashiwazaki City that ground subsidence continues over a lengthy period after the quake (Ohtsuka et al., 2021).

The same phenomena have been observed in the 1957 Mexico earthquake, the 1978 Miyagiken-oki Earthquake, the 1985 Mexico Earthquake, the 1995 Hyogo-ken Nanbu Earthquake and the 2011 off the Pacific coast of Tohoku earthquake which are reported by Zeevaert (1973), Suzuki (1984), Jaime et al. (1987), Matsuda (1997), Yasuhara et al. (1982), Nigorikawa et al. (2015) and Sento (2020), especially in the classic example of the Mexican earthquake that the post-earthquake settlement of the soft soil layer which is relatively far from the epicenter is very significant (Ovando-Shelley et al., 2013; Avilés et al., 2010; Albano et al., 2016).

Occurrences of such similar cases are often associated with the deposition of a thick layer of soft alluvial clay. This research holds significance because this phenomenon will greatly impact the maintenance and management of various buried pipes and pile foundations.

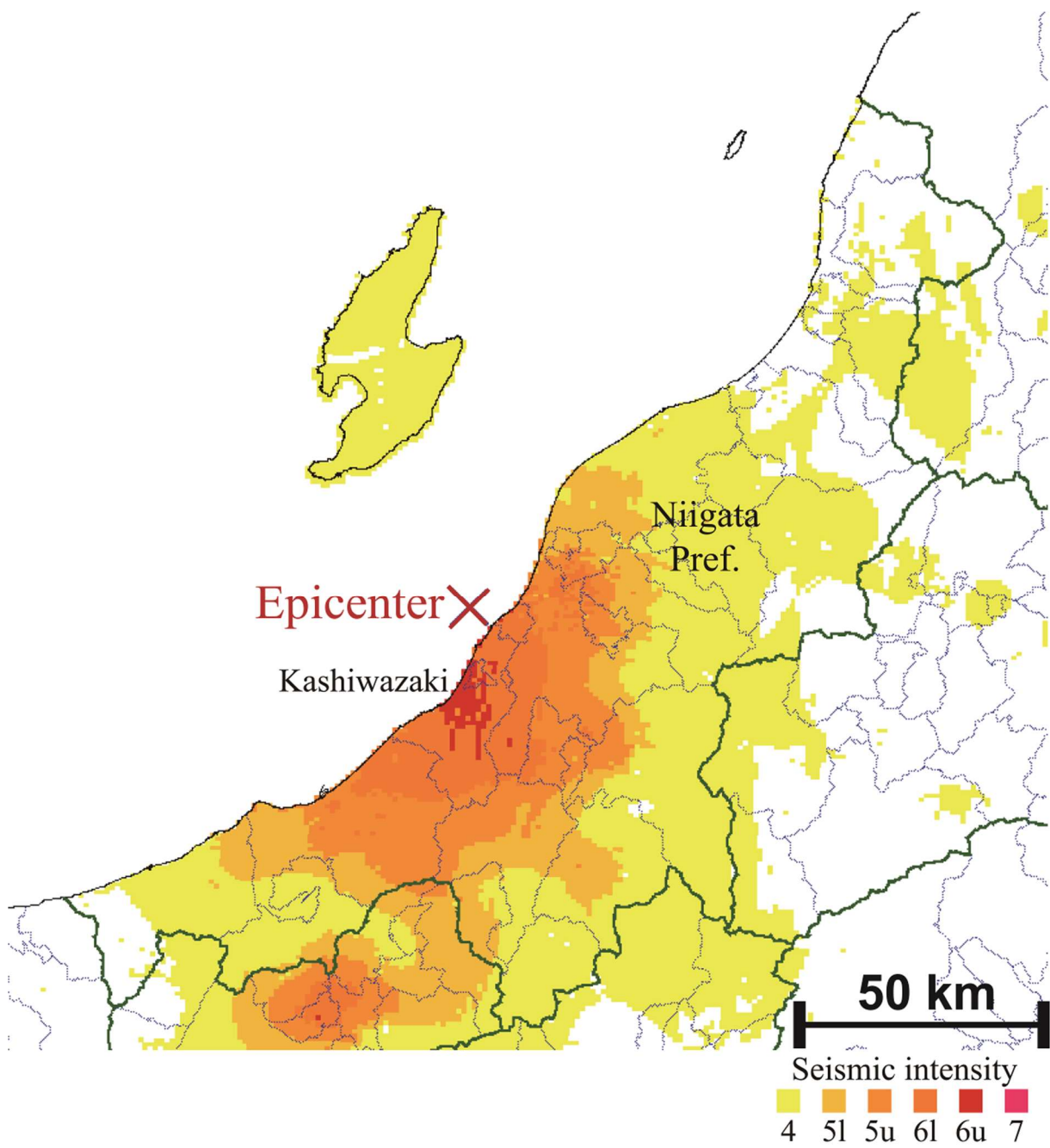


Fig. 1-1 Seismic intensity distribution map of the 2007 Niigataken Chuetsu-oki Earthquake

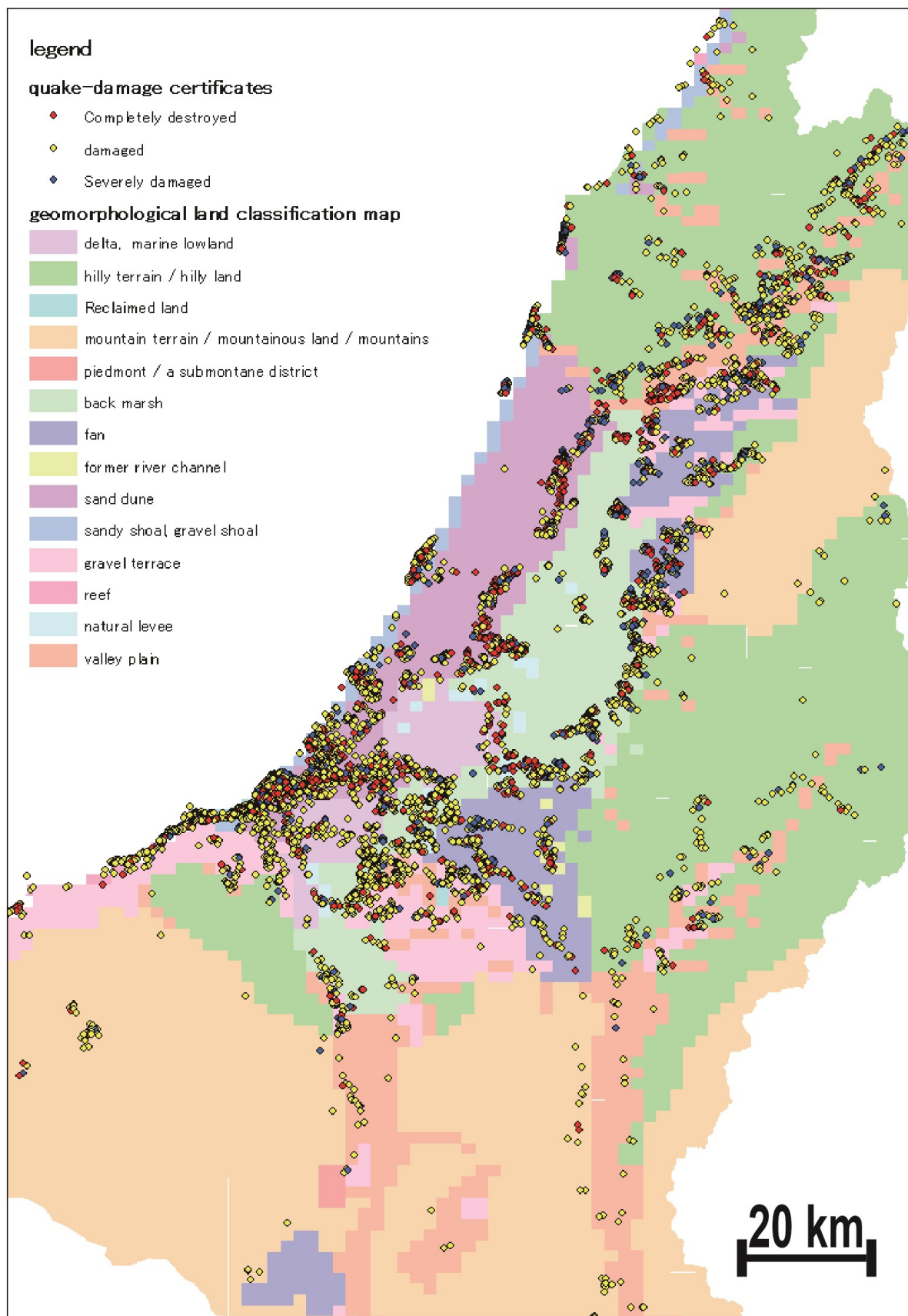


Figure 1-2 Distribution map of residential damage in Kashiwazaki city and Kariwa village due to the 2007 Niigataken Chuetsu-oki Earthquake and their geomorphological land classification map



(a) the severest damaged house



(b) damaged houses due to ground crack



(c) sand boiling

Figure 1-3 Earthquake damage in Matsunami district of Kashiwazaki city (Isobe et al., 2014a)

1.2 Introduction of Geotechnical Uncertainty

Compared to structural engineering, research on geotechnical uncertainty has lagged behind due to the complexity and variability of soil properties. Unlike engineered materials such as steel and concrete, soil is a naturally occurring material with significant spatial variability, making it difficult to characterize with precise mathematical models. Additionally, the challenges in obtaining representative soil samples and the limitations of current laboratory and in-situ testing methods further increase uncertainty. However, understanding and quantifying geotechnical uncertainty is essential for improving design reliability, optimizing risk management, and ensuring the safety and cost-effectiveness of geotechnical projects. With the advancement of probabilistic methods, numerical simulations, and data-driven techniques, research in geotechnical uncertainty is rapidly evolving and gaining importance in modern geotechnical engineering.

Geotechnical uncertainty arises due to natural variability in soil properties, measurement errors, and modeling approximations. Morgenstern (2018) categorizes uncertainties in geotechnical analysis into three types: human uncertainty, model uncertainty, and parameter uncertainty. Christian (1993) further divide parameter uncertainty into two components: data dispersion and systematic error. Data dispersion consists of spatial variability and random test errors, while systematic errors include statistical errors and deviations in the mean value. Phoon & Kulhawy (1999) propose another classification, dividing soil variability into inherent variability, measurement error, and transformation uncertainty.

Duncan & Michael (2000) discuss the uncertainties in parameters used in geotechnical calculations, emphasizing the influence of variability on the factor of safety and reliability. ISSMGE-TC304 (Ching et al., 2021) provides reference coefficient of variation (CV) values for different soil properties, while Kim (2012) and Tan (2003) provides extra CV values of clay. Fan (2021) conduct parameter sensitivity analysis in predicting ground movement adjacent to an excavation based on elastic displacement theory. Einstein (1996) in geotechnical field (who is the relative of the most famous Einstein) also study the variability in the geometrical properties of the structure, boundary conditions, and material parameters. Phoon & Tang (2019) introduce again the concept of "model factor," defined as the ratio of measured to calculated response, classifying it based on conservativeness and variability levels. Tang (2017, 2019) statistically evaluate the model factor for bearing capacity predictions in dense sand overlying clay using

centrifuge test data.

Reliability assessment methods have also been developed to account for geotechnical uncertainty. Hsiao (2008) compare excavation-induced settlement with a tolerable limit of 75 mm and update probability exceedance values as excavation progresses. Nour (2002) analyze the variability of settlement and differential settlement in foundations on heterogeneous soil using stochastic finite element methods. Wang (2020) apply Monte Carlo (MC) simulations to study the uncertain settlement behavior of permafrost subgrades under climate change, while Wang (2015) employ stochastic finite element methods (SFEM) to model soil properties as random fields.

Löfman (2022) quantifies the inherent variability and transformation uncertainty of Finnish clays and investigates their influence on settlement response. His study highlights the importance of considering cross-correlations between model parameters, showing that ignoring these correlations can overestimate settlement uncertainty. The combination of Monte Carlo simulation and copula functions is found to be the most effective approach for capturing settlement uncertainty. To address these challenges, probabilistic methods such as Monte Carlo simulation, reliability analysis, and stochastic response surface methods are widely applied in geotechnical engineering.

(1) Probability Distributions

In stochastic analysis, different probability distributions are used to model the uncertainty of geotechnical parameters. The most commonly used distributions include:

Uniform Distribution: Assumes that all values within a specified range are equally likely, often used when there is limited prior knowledge about the parameter.

Normal Distribution: A bell-shaped distribution found by Gauss where values are more concentrated around the mean. Most parameters in the world follow a normal distribution and its variants.

Lognormal Distribution: Skewed distribution where values are always positive. Many parameters in the engineering field are suitable to be described using this distribution.

Exponential Distribution: Used to model the occurrence of rare events, such as the time until failure or extreme soil properties.

Weibull Distribution: Control distribution shape through shape parameters.

Beta Distribution: Flexible fitting of multiple forms within the [0,1] interval.

Gamma Distribution: Including shape parameters and scale parameters.

Generalized Extreme Value (GEV) distribution: Extreme event modeling is suitable for this

distribution.

Selecting an appropriate distribution is crucial for accurately representing natural variability in geotechnical models.

(2) Sampling Method:

A well-chosen sampling method ensures that the variability of input parameters is properly captured while maintaining computational efficiency. The commonly used methods include:

Direct Monte Carlo Sampling (DMCS): The most fundamental approach, where random values are drawn directly from the specified distributions. While simple and unbiased, it requires a large number of samples for accurate probability estimates.

Latin Hypercube Sampling (LHS): An advanced stratified sampling method that divides the cumulative distribution function (CDF) into equal probability intervals and ensures that each interval is sampled once. This improves the efficiency of capturing parameter variability, especially when dealing with non-uniform distributions. LHS typically has higher accuracy and efficiency compared to Direct MCS (Baecher and Christian 2005; McKay et al. 2000; Startzman and Wattenbarger 1985). In the case of non-uniform distributions, LHS achieves stratification by projecting the sampled uniform values onto the target distribution using inverse transform sampling.

Importance Sampling (IS): A variance reduction technique that focuses sampling efforts on the most critical regions (e.g., failure regions), improving accuracy with fewer samples. Rubinstein (2016), Gong (2018), Ching and Phoon (2009), Zhao (2021) conducted relevant work in the field of IS.

Sobol Sequence Sampling: A quasi-random low-discrepancy sequence that ensures a more uniform spread of samples across the parameter space. This improves convergence speed compared to purely random sampling methods.

(3) Stochastic Response Surface Method (SRSM)

The Stochastic Response Surface Method (SRSM) is a surrogate modeling technique that approximates complex numerical simulations by constructing an explicit mathematical model of the system's response. Instead of performing costly full-scale numerical analyses for every sample, SRSM builds an approximate response surface, significantly reducing computational time while maintaining reasonable accuracy.

SRSM is based on the idea that the relationship between uncertain input parameters and system responses can be approximated using interpolation or regression techniques. The response surface is

built using a limited number of carefully selected simulations, and once established, it allows for efficient uncertainty quantification and sensitivity analysis.

Different kinds of SRSM include:

1) Polynomial Chaos Expansion (PCE): Expresses the random system response as a series of orthogonal polynomials, enabling an efficient representation of uncertainty.

2) Kriging-Based Response Surfaces: Uses spatial correlation functions to construct surrogate models, predicting outputs with an associated uncertainty estimate.

3) Gaussian Process Regression (GPR): A probabilistic machine-learning approach that models uncertainty and provides predictions with confidence intervals.

By replacing full-scale simulations with an efficient approximation, SRSM enables rapid uncertainty propagation and sensitivity analysis, making it especially useful for computationally expensive geotechnical models.

SRSM relies on various interpolation and regression techniques to construct response surfaces. Some commonly used models include Linear Regression, Polynomial Regression, Polynomial Chaos Expansion (PCE), Sparse PCE, Standard Kriging, Active Learning Kriging models.

These interpolation models provide flexible and efficient ways to approximate complex numerical simulations, ensuring that SRSM can effectively balance computational efficiency and accuracy in geotechnical applications.

The Stochastic Response Surface Method (SRSM) is widely applied in geotechnical reliability analysis. Li (2014) develop a non-intrusive SRSM using Hermite polynomial chaos expansion (PCE) to evaluate the reliability of underground caverns. They demonstrate that SRSM achieves comparable accuracy to direct Monte Carlo simulation with fewer samples. Huang (2009) implement a collocation-based SRSM with an Excel add-in, making Hermite polynomial basis functions more accessible to practitioners. Li (2011) extend SRSM by incorporating Nataf transformation to handle correlated non-normal variables. Mollon (2011) apply SRSM to analyze tunnel face stability under compressed-air pressurized shields, considering soil cohesion and friction angle correlation effects. Their findings reveal that variable correlations significantly impact collapse pressure uncertainty, while the non-normality of input distributions has a negligible effect. Bauer and Pula (2000), Rebba (2002), Mao (2012), Phoon (2007) make relative discussion and research on the response surface method too.

(4) Spatial Variation

Soil properties exhibit spatial variability, meaning that key geotechnical parameters such as shear strength, permeability, and compression index change across different locations. Since Vanmarcke (1977)'s most prominent study of spatial variability, this research field has attracted great attention. Unlike simple random variability, spatial variation is correlated, meaning that values at nearby points tend to be more similar than those at distant locations. Meanwhile, spatial variability of soil properties is non-negligible in both the horizontal and vertical directions (Griffiths et al., 2002; Wang et al., 2019). To model spatial variation, the following methods and points are commonly used.

Random Field Theory treats soil properties as spatially correlated random fields, capturing natural variability across a site. In order to describe the random field, it is necessary to add at least two additional modules, Covariance Functions and Fluctuation Scale, in addition to the original random model calculation module.

Covariance Functions describe how soil properties change with distance. A commonly used function is the exponential covariance function, which ensures that closer points are more strongly correlated. Fluctuation Scale define the scale over which soil properties remain similar. Short fluctuation scale indicates rapid variation, while long fluctuation scale suggests smoother transitions. Relative research is conducted by Li (2015), Phoon and Kulhawy (1999), Jiang and Huang (2016), Liu (2017), Cheng (2019).

Understanding and incorporating spatial variability is crucial for geotechnical engineering, particularly in predicting differential settlement, improving foundation design and slope stability performance assessments.

As for Random Field Expansion, in numerical modeling, random fields are often expanded using Karhunen-Loève Expansion (K-L Expansion) which is a mathematical technique that decomposes a random field into orthogonal basis functions, capturing dominant variability patterns, especially in geotechnical problems.

While 1D and 2D random field models are more widely used, extending these approaches to 3D problems introduces additional complexity. This is because of much higher computational cost, much more complexity in correlation structures and much more limited field data for 3 directions of spatial variance.

Despite these challenges, incorporating realistic spatial variability into numerical models is essential for achieving more accurate and reliable predictions of geotechnical behavior.

Abbasov et al. (2024) use Sobol indices to quantify parameter uncertainty in rainfall-induced landslide modeling. Wang et al. (2015) apply stochastic finite element methods (SFEM) to study soil spatial variation in cold regions. Grasmick and Mooney (2017) adopt a probabilistic approach for predicting the ground settlement considering the spatial variability of soil properties. Huang (2017) and Zhang (2023) also study actual projects considering the influence of soil spatial variability.

1.3 Research Objectives

The primary objective of this research is to systematically investigate the mechanisms driving long-term subsidence in soft clay following the Niigataken Chuetsu-oki Earthquake (2007). By integrating geotechnical characterization, advanced numerical modeling, and probabilistic analysis, this study aims to enhance the understanding of post-seismic ground deformation and its implications for geotechnical engineering. Additionally, this research involves the development of a parallel computing-based probabilistic computation software with a graphical user interface (GUI) to improve the efficiency and accessibility of uncertainty quantification in geotechnical modeling. Specifically, the research pursues the following objectives:

(1) Characterization of Soft Clay's Physical and Mechanical Properties

Conduct a comprehensive geotechnical investigation to evaluate the physical, consolidation, and shear strength characteristics of soft clay deposits in Kashiwazaki City. This involves laboratory testing, field observations, and in-situ measurements to derive essential material parameters governing long-term subsidence behaviour.

(2) Development of an Advanced Numerical Model for Post-Earthquake Subsidence Simulation

Establish a finite element-based soil-water coupled elastoplastic model utilizing the Transformation Stress-Cyclic Mobility (TS-CM) constitutive framework. The model will incorporate cyclic loading effects, excess pore water pressure dissipation, and structural degradation, enabling the accurate replication of observed subsidence patterns.

(3) Deterministic Prediction of Long-Term Subsidence

Perform deterministic simulations to quantify the temporal evolution of post-earthquake settlement, providing insights into the governing consolidation mechanisms and their long-term impact on infrastructure stability.

(4) Stochastic Analysis and Reliability Assessment of the Numerical Model

Implement stochastic uncertainty quantification using advanced probabilistic techniques such as Monte Carlo simulations and Sobol sensitivity analysis to assess the influence of key geotechnical parameters on settlement variability. Furthermore, evaluate the predictive accuracy, robustness, and practical applicability of the numerical model by comparing simulated results with field measurements. A reliability-based assessment will be conducted to quantify uncertainty in settlement predictions, offering insights into risk-informed decision-making for infrastructure resilience and mitigation strategies.

(5) Development of a Parallel Computing-Based Non-intrusive stochastic Computation Software

Design and implement a non-intrusive stochastic computation software “JRiver_uncertainty”, which enables non-intrusive stochastic finite element analysis under a CPU-based parallel computing architecture. The software features an intuitive graphical user interface (GUI) for seamless integration with existing numerical models, significantly enhancing computational efficiency and accessibility. Additionally, the software incorporates stochastic response surface methods, including Polynomial Chaos Expansion (PCE) to improve the efficiency of uncertainty propagation and global sensitivity analysis in complex geotechnical systems.

Through these objectives, this research aims to contribute to the advancement of geotechnical earthquake engineering, particularly in the understanding, modeling, and prediction of post-seismic settlement in soft clay sites.

1.4 Methodology

This research employs a comprehensive multi-scale methodological approach that integrates field investigations, laboratory testing, numerical simulations, and probabilistic analyses to systematically investigate the long-term subsidence of soft clay following the Niigataken Chuetsu-oki Earthquake (2007). The methodology consists of the following key components:

(1) Field Investigations

Extensive in-situ geotechnical investigations were conducted to assess the subsurface conditions and mechanical properties of the soft clay deposits in Kashiwazaki City. These investigations included:

Boring surveys to obtain undisturbed soil samples at different depths.

Standard Penetration Tests (SPT) to evaluate the relative density and strength characteristics of the soil layers.

Groundwater level monitoring to assess hydrogeological influences on long-term consolidation behaviour.

(2) Laboratory Tests

A series of controlled laboratory experiments were conducted to determine the physical, mechanical, and consolidation characteristics of the sampled clay, including:

Oedometer tests to evaluate compressibility, consolidation parameters, and permeability coefficients for different soil strata.

Static and cyclic triaxial compression tests to investigate stress-strain behavior, shear strength, and cyclic degradation effects under varying confining pressures.

Index property tests (e.g., grain size distribution, plasticity index, and water content) to classify the soil and correlate its behavior with established geotechnical models.

(3) Numerical Simulations and Stochastic Analyses

Elasto-plastic finite element (FE) analyses was conducted to simulate post-earthquake subsidence and consolidation behaviour. Additionally, stochastic analyses were performed to account for uncertainties in geotechnical parameters

By integrating experimental, numerical, and probabilistic approaches, this research provides a rigorous and systematic framework for analyzing and predicting post-seismic subsidence in soft clay deposits. The findings will contribute to a deeper understanding of long-term settlement mechanisms and support the development of more effective mitigation strategies for geotechnical infrastructure in seismically active regions.

1.5 Thesis Structure

This thesis is structured into six chapters:

Chapter 1 introduces the engineering background, the significance of long-term ground settlement in Niigata's soft clay areas and the research status of geotechnical uncertainty, clarifies research objectives and methodology, and outlines the thesis structure.

Chapter 2 presents comprehensive field investigations and laboratory tests to characterize the

geological features and engineering properties of Kashiwazaki clay, including regional geological conditions, physico-mechanical property tests, static/cyclic triaxial tests, and consolidation tests.

Chapter 3 conducts deterministic finite element analysis, focusing on: 1) establishing the TS-CM constitutive model with calibrated parameters; 2) simulating site response during the 2007 Niigata earthquake; 3) predicting long-term post-earthquake consolidation settlement; 4) analyzing settlement characteristics at different soil depths.

Chapter 4 systematically introduces geotechnical uncertainty quantification methods and a self-developed non-intrusive stochastic computation software “JRiver_uncertainty”, including: 1) parameter uncertainty quantification; 2) sensitivity analysis especially Sobol analysis; 3) model factor evaluation framework; 4) Reliability of allowable settlements; 5) features of the self-developed non-intrusive stochastic computation software.

Chapter 5 performs uncertainty analysis results based on Chapter 4's framework, emphasizing: 1) reliability analysis using different sampling methods; 2) parameter sensitivity ranking via Sobol indices; 3) model factor evaluation; 4) Brief Analysis Results of Stochastic Response Surface Method (SRSR).

Chapter 6 summarizes key findings, discusses implications for soft clay sites, and identifies directions for future research.

CHAPTER 2 - GEOGRAPHICAL CONDITIONS & SOFT CLAY CHARACTERISTICS

2.1 Geographical Conditions in Kashiwazaki City

Figures 2-1 (a) (b), 2-2, 2-3 show the terrain classification, thickness map of alluvial deposits, altitude distribution map and geological cross section map for the city. The area, where the ground subsidence was observed before the earthquake, is mainly located on the land which consists of soft alluvial clay.

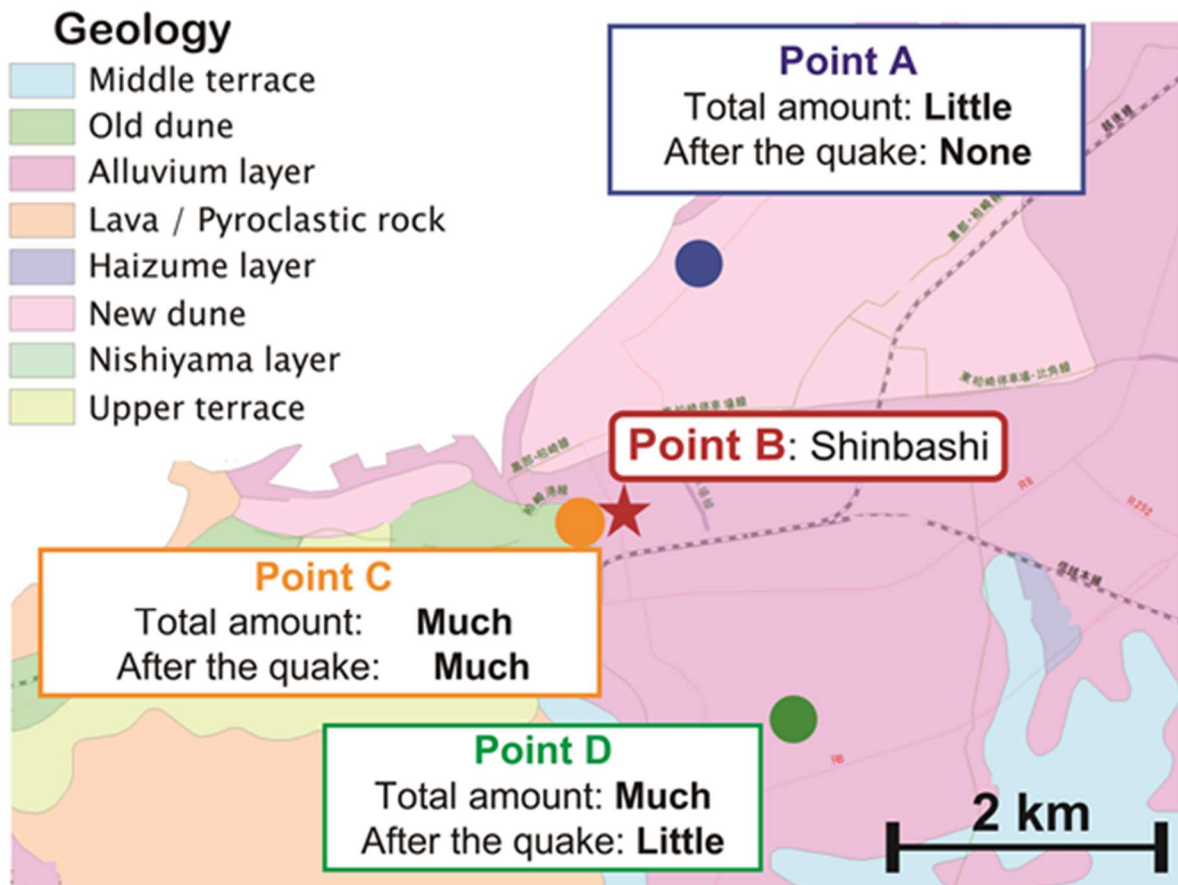


Figure 2-1(a) Terrain classification map for Kashiwazaki City (See Ohtsuka et al., 2021)

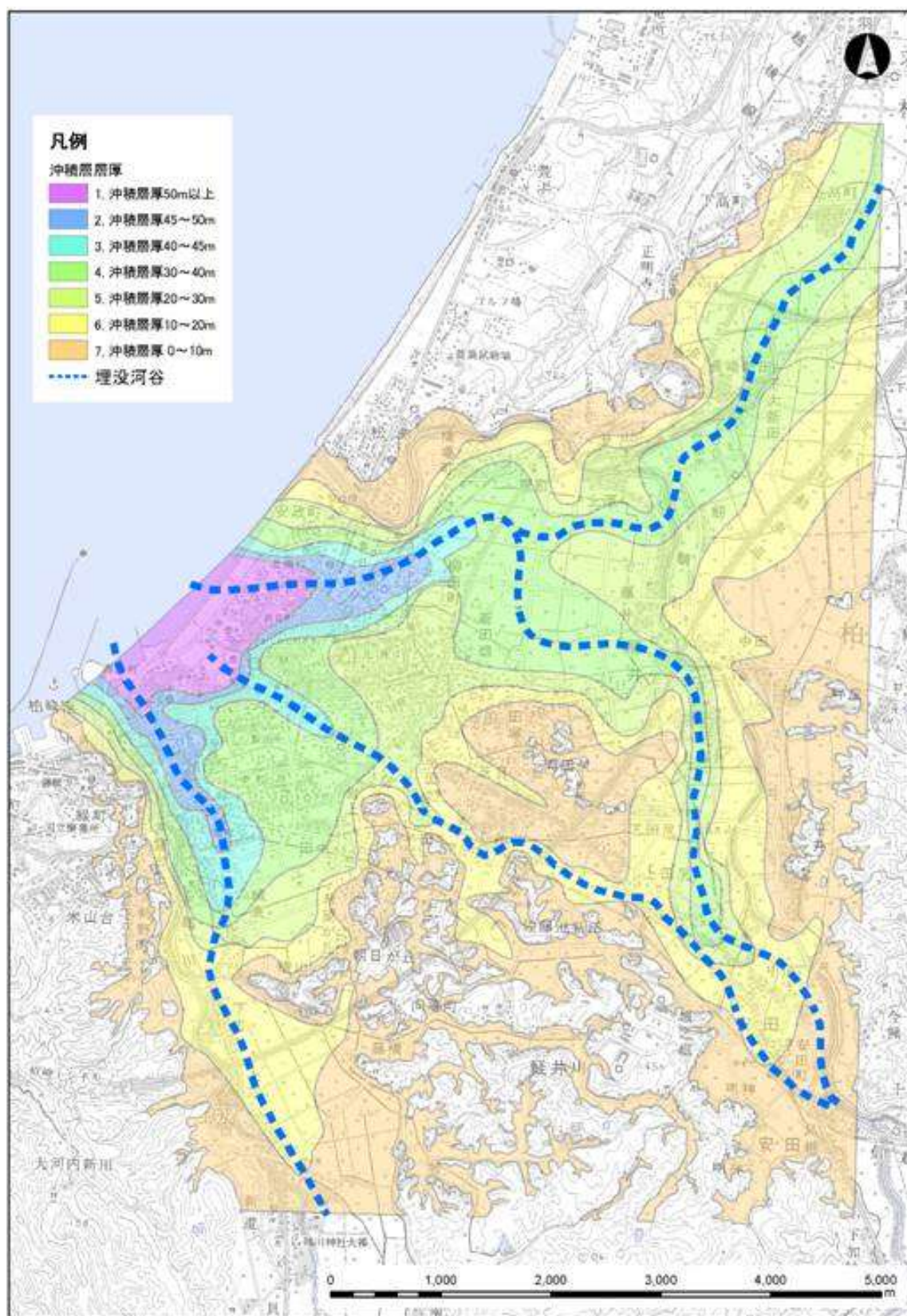


Figure 2-1(b) Thickness map of alluvial deposits

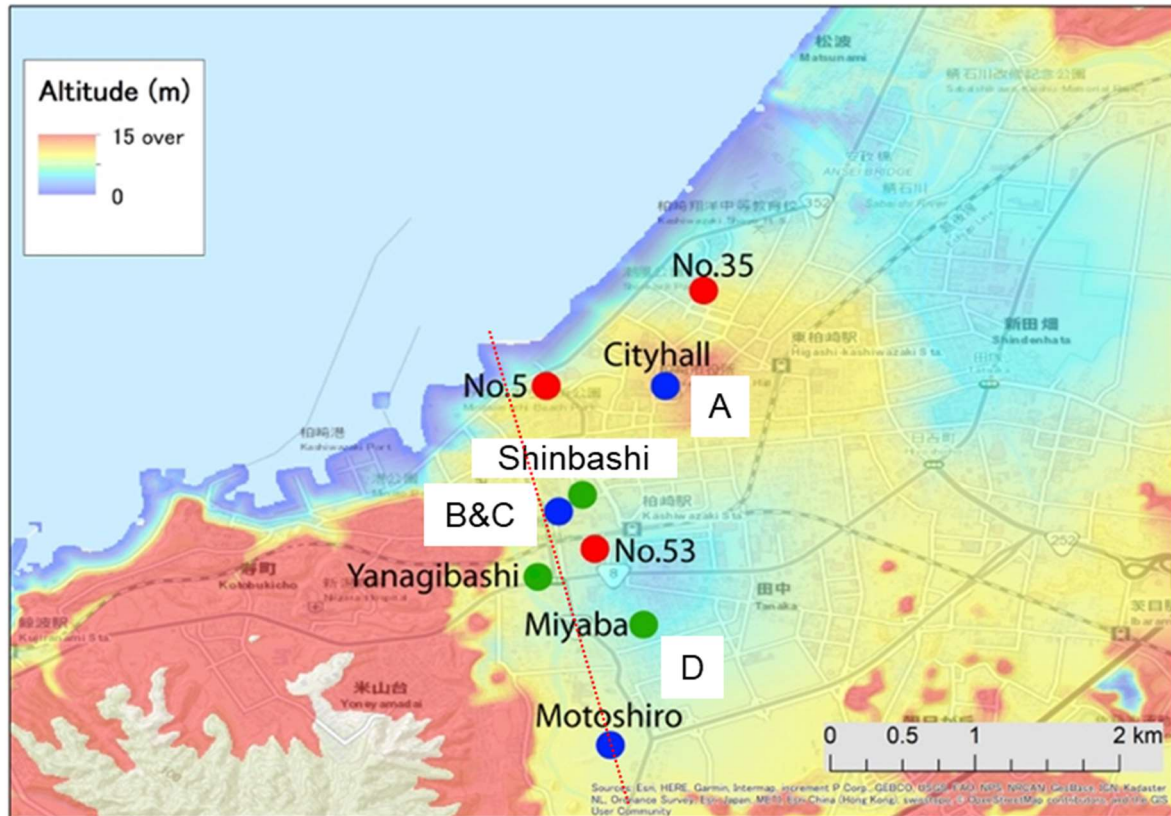


Figure 2-2 Altitude distribution map for Kashiwazaki City (See Ohtsuka et al., 2021)

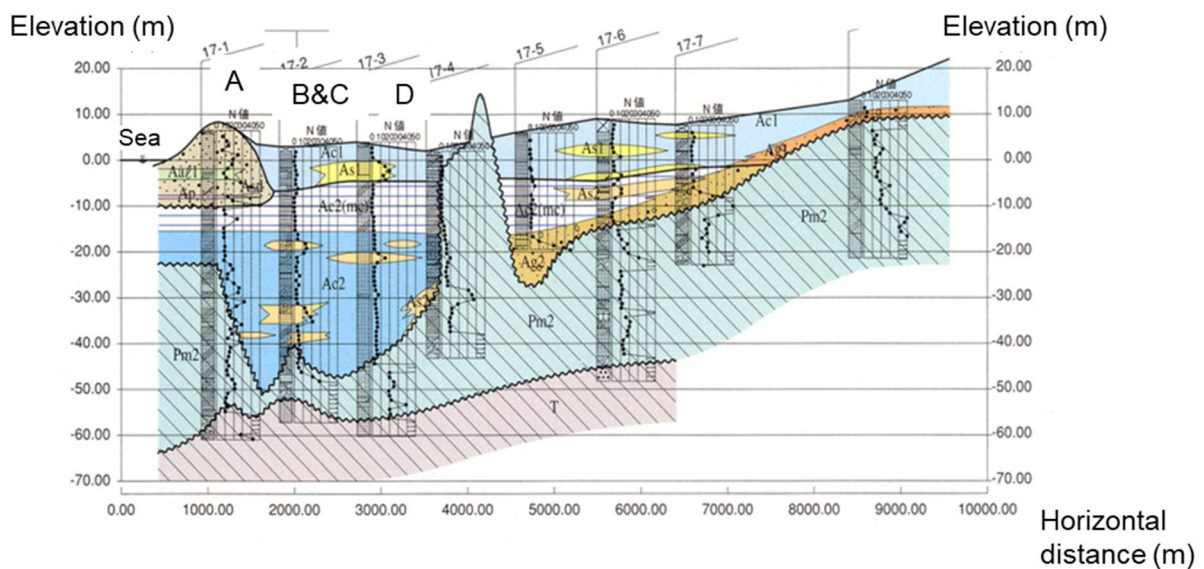


Figure 2-3 Geological cross section map for Kashiwazaki City (See Ohtsuka et al., 2021)

As is shown in Figure 2-1(b), Most of the Kashiwazaki Plain is a floodplain lowland formed by rivers such as the Ugawa, Sabaishi, and Betsuyama, with natural levees distributed along the rivers. The

coastal sand dunes are divided into north and south by the Sabaishi River, and the area around the city has a height of about 10m. In the Kashiwazaki Plain, diluvial deposits that form ancient sand dunes and buried terraces are distributed, filling in the basin-shaped topography of the Neogene layers that form the base of the plain. Furthermore, alluvial deposits have accumulated over this, up to a thickness of over 50m, and are particularly deep along the Ukawa and Sabaishi rivers.

On the other hand, the area where the ground subsidence was rapidly increasing after the quake is located near the seaside, mostly covered by the above-mentioned soft alluvial clay. Local geological characteristic of this area was detailly reported by Ohtsuka et al. (2021). Stratified subsidence and ground water level have been measured by Niigata Prefecture at the Shinbashi district, which is named Point B in Figures 2-1, 2-2, 2-3, from 1989 to 2022.

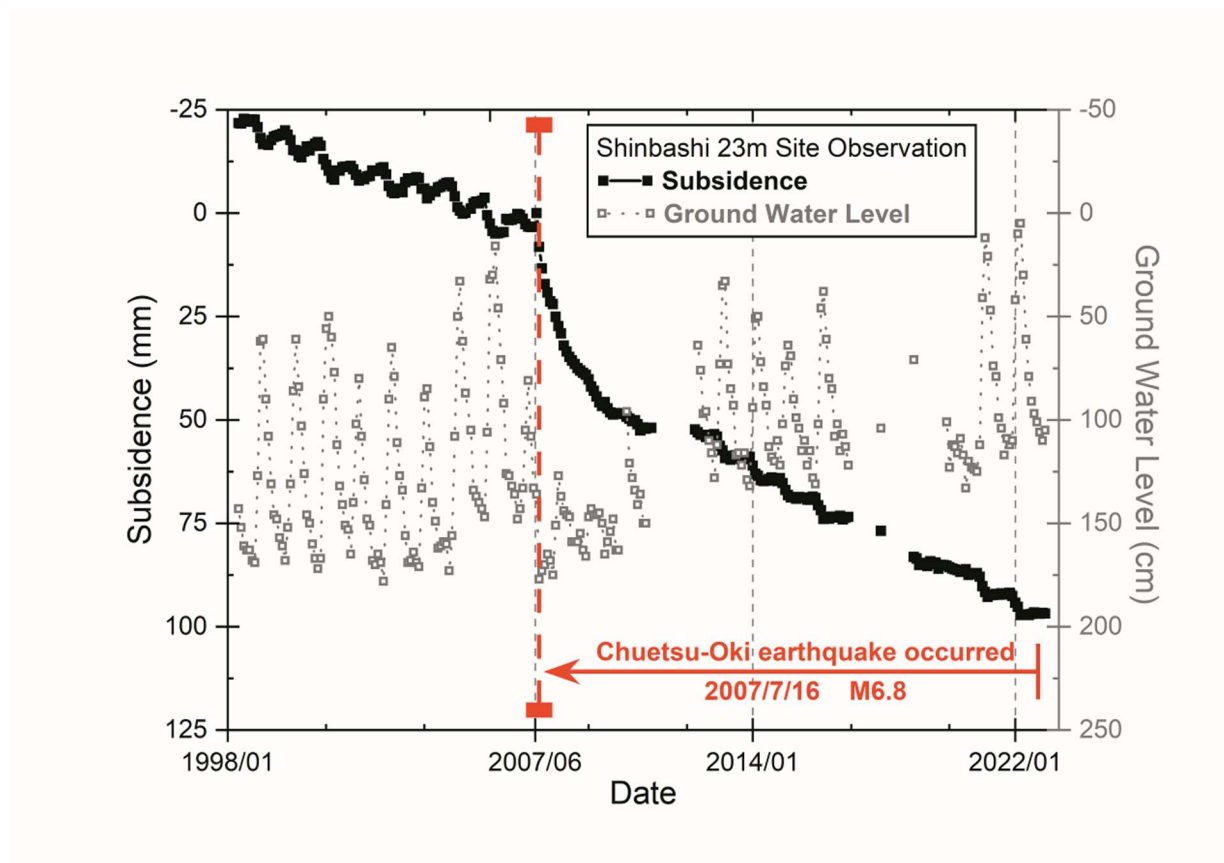


Figure 2-4 Temporal change in ground water level and cumulated subsidence of soil layers up to 23 m deep (from 2005 to 2022)

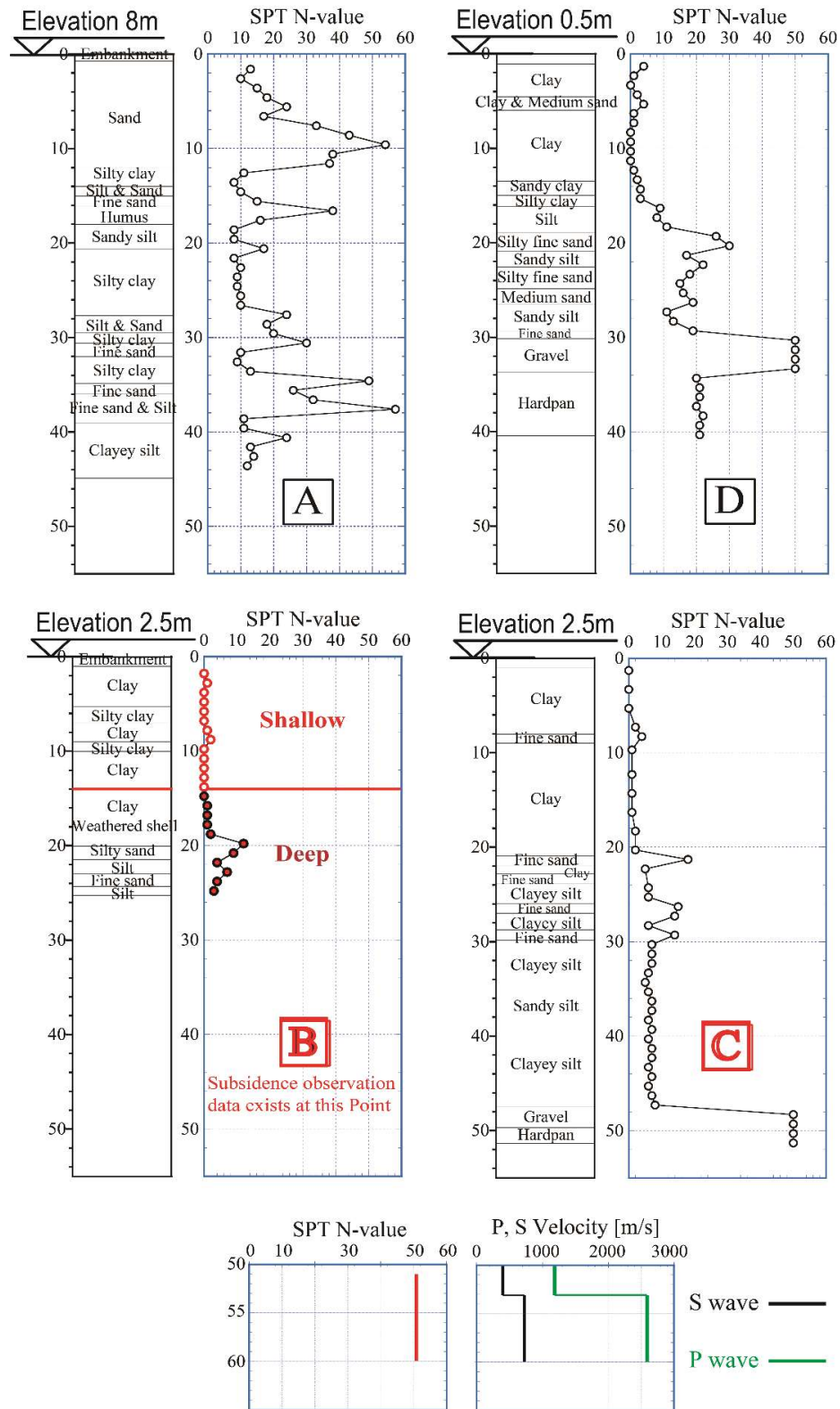


Figure 2-5 Geological column and wave velocity of the Kashiwazaki City obtained from the boring investigation carried out by authors and the database of Hokuriku Geological System (the Points A~D are corresponded to the area on the map shown in Figures 2-1, 2-2, 2-3)

Figure 2-4 shows the temporal change in both the ground water level and the amount of ground subsidence of the soil layers up to 23 m deep. The measurement period of the ground water level and subsidence data in the figure is once a month in most of the years. It was found from the figure that subsidence increases rapidly after the quake of 2007 and continues for a period longer than 10 years. It was not caused by consolidation of soft clay due to the change of ground water level because the drastic change in ground water level at the area was not observed. Both the Niigata Earthquake of 1964 and the Chuetsu Earthquake of 2004 impacted this region historically. However, compared to the Chuetsu-Oki Earthquake of 2007, the epicentre of the 2004 Chuetsu Earthquake was more distant, with a slightly lower recorded seismic intensity. Therefore, following the 2004 Chuetsu Earthquake, no long-term post-earthquake consolidation subsidence was observed in the clay ground. Ground subsidence observation was not conducted around the 1964 Niigata earthquake, creating uncertainty regarding subsequent long-term consolidation subsidence. Hence, studying the long-term settlement phenomenon resulting from the 2007 earthquake is warranted.

In order to investigate the cause, boring investigation involving standard penetration tests (SPT) was carried out near the observation point of ground subsidence and the soft clay was sampled at the area. Figure 2-5 shows the geological column in the city obtained from the boring investigation carried by authors and the database of Hokuriku Geological System. The land of the Shinbashi district mainly consists of very soft clay with the N-value of 0 to 2. Mixing a small piece of weathered shells from the vicinity of 11.0 m depth and its significant contamination from near 14.0 m depth can be confirmed. The soft clay layer exists up to the layer in the 21 m depth and is underlaid by the silt layer with N-value of approximately 10. The silt layer exists up to the layer in the 50 m depth with N-value of more than 50 which is regarded as an engineering foundation ground. In contrast, the thickness of the soft clay layer at the area around the district (Point D) is relatively less than that at the district (Point C). Sand dune with N-value of more than 10 covers the clay and the slit layer at the point A near the seaside. It is clarified that the area, where a lot of subsidence after the quake was observed, is corresponding to the area which consists of the thick alluvial clay layer.

2.2 Physical Property and Consolidation Test Results

Because there is a difference in the amount of contamination in the weathered shells between the

shallow clay layer and the deep clay layer, the intact samples were obtained from the layer between the depth of G.L. -7 m and 21 m at the Shinbashi district of Kashiwazaki City using a small diameter sampler with a two-chambered hydraulic piston developed by Shogaki and Sakamoto (2004) to conduct oedometer tests, static CU tests and cyclic CU tests. In addition, lateral load tests (LLT) were also conducted at the same site. The physical properties, the LLT results and the grain size distribution curve for the deep clay layer in Kashiwazaki City clay are shown in Tables 2-1 and 2-2 and Figure 2-6, respectively. It is clarified that the deep clay has high natural water contents and plasticity index, and consists of more than 50% clay, which exist a greater probability to have a large settlement. It explains why relatively large post-earthquake subsidence occurred at Kashiwazaki area covered with soft clay.

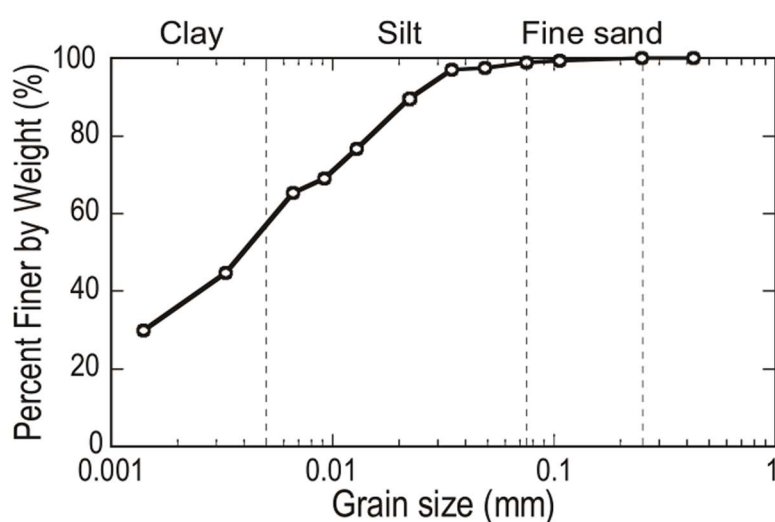


Figure 2-6 Grain size distribution curve for the deep clay layer

Table 2-1 Physical properties of the deep clay sampled in Kashiwazaki city

		Clay
Specific gravity [g/cm ³]	G_s	2.68
Plasticity index [%]	I_p	48.6
Liquid limit [%]	w_l	87.0
Plastic limit [%]	w_p	38.4
Natural water content [%]	w_n	73.5

Table 2-2 Lateral load test results of Point B at the Shinbashi district in Kashiwazaki city

		Shallow layer	Deep layer
Depth [m]	D	9.0	17.0
Earth pressure at rest [kN/m ²]	P_0	24.7	48.5
Yield pressure [kN/m ²]	P_y	56.4	74.0
Destruction pressure [kN/m ²]	P_l	79.3	137.5
Deformation modulus [MN/m ²]	E	0.77	1.10
Subgrade modulus [MN/m ³]	K	14.34	19.98
SPT N-value	N	2	1

Subsequently, some oedometer tests were carried out to clarify the consolidation characteristics of several samples. Two types of specimens were created for the tests as follows: (1) an intact specimen and (2) a reconstituted specimen made from slurry sample plus water after the above tests. Figure 2-7 shows oedometer tests results for the intact and reconstitution samples from the shallow, the deep layers and the thin transitional part. The reason for determining the existence of a transitional part is that the soil at a depth of 16m showed significantly different behavior in the tests compared to other locations, while various tests on deep soil were taken from S-7, S-8, and S-9 samples below a depth of 17m. However, the abnormal behavior of this single depth sample does not affect the overall trend. It implies that the intact samples from each layer have high compression characteristics after applying the consolidation yield pressure (about 80 kPa) comparing with those of the reconstitution samples. According to the reference (Asaoka et al. 2002), the clay obtained from the deep layer are identified as a slightly structured clay. In addition, it is inferred that the layers in the vicinity of the ground surface at the site was overconsolidated since the consolidation yield stress of both samples are around 70-90 kPa. After comparing the 3 intact specimen oedometer lines of the shallow and deep layer clay, it can be seen that the shallow clay has less potential to consolidate than the deep clay, which is also important in subsequent analysis.

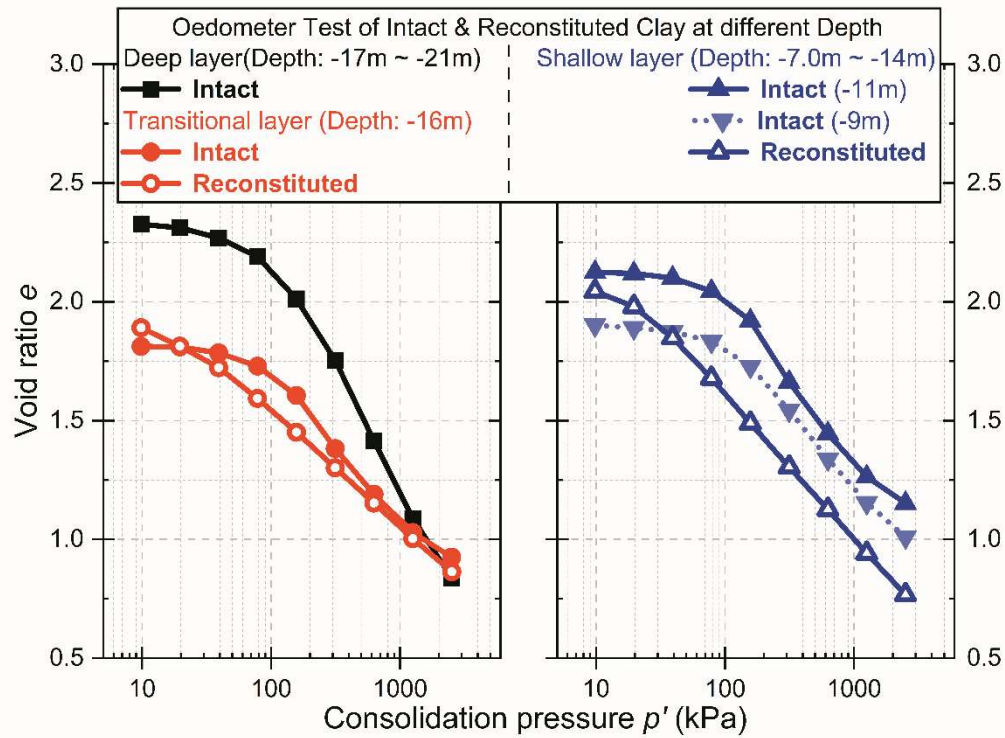


Figure 2-7 Oedometer tests results for the intact and reconstituted samples

2.3 Static and Cyclic Tri-axial Compression Tests

Static and cyclic CU tri-axial tests for the Kashiwazaki clay were carried out to clarify the static and cyclic shear characteristics and its liquefaction strength. In the tri-axial compression tests also, two types of specimens were created for the tests as follows: (1) an intact specimen sampled and (2) a reconstituted specimen formed by slurry sample plus water in the above-mentioned test samples with a pre-consolidation method. The specimens were formed into dimensions of 5 cm in diameter 10 cm in height.

Table 2-3 Testing condition of static and cyclic triaxial compression tests

		Shallow layer		Deep layer	
Sample type		Intact	Reconstitution	Intact	Reconstitution
Preconsolidation method			Iso. consol.		Iso. consol.
Initial void ratio of intact samples	e_0	1.91 ~ 2.13		1.82 ~ 2.34	
Effective confining pressure [kPa]	p'_0	50, 100, 150, 200	50, 100, 150	50, 100, 150	50, 100, 150
Back pressure [kPa]	B.P.	100	100	100	100
Drained condition		Undrained			
Static loading speed [%/min] (Strain control)		0.021			
Dynamic loading frequency [Hz]	f	N/A	N/A	0.01	N/A
Cyclic stress ratio (Stress control)	$\sigma_d / 2\sigma'_0$	N/A	N/A	14.34	N/A

Table 2-3 shows the testing condition of static and cyclic CU tri-axial test cases. The test apparatus consisted of a tri-axial cell, cell-pressure and back-pressure control devices, an axial load control device and a data acquisition/recording system to collect data on the axial load, axial displacement and pore water pressure of the specimens and on volume reduction during consolidation (i.e., water drainage from the specimens). After a self-sustaining specimen had been set up on the pedestal, a cylindrical chamber and cell cover were set up, and the cell was filled with water. To achieve a high degree of saturation, vacuum conditions were applied to both the cell and the sample interior in such a way that the confining stress was constant (20 kPa) during the process. After the final stage of this process was reached (-80 kPa for cell pressure and -100 kPa for the interior sample), deaerated water was circulated into the specimen for about 2 hours, and the pressure of the sample interior and the cell were returned to -20 kPa

and 0 kPa, respectively. The back pressure was then increased gradually to 100 kPa, and pressure of 150 kPa was simultaneously applied to the cell so that the confining stress was held constant at 50 kPa. To ensure specimen saturation, the degree of saturation was evaluated at this stage based on the B-value, defined as the ratio of the pore water pressure increment to the isotropic stress increment under undrained conditions. Using this procedure, the test was continued until the B-value of the specimen was equal to or greater than 0.95. The specimen was isotropic consolidated for 18 hours under a confining pressure of 50 - 200 kPa. The deep clay specimens S-7, S-8 and S-9 are from the depth of 17 m - 19 m while the shallow clay specimens S-1, S-3 and S-5 are from the depth of 7 m - 12 m. In order to examine static shear strength and liquefaction strength, static and cyclic tests were performed by applying deviator stress at a loading rate of 0.021 mm/min and uniform sinusoidal cycles of deviator stress at a frequency of 0.01 Hz with a varying cyclic stress ratio under constant cell pressure. Axial loads were measured using a load cell with a capacity of 5 kN installed between the top cap of the pedestal and the piston in the cell, and axial strain was monitored using a displacement transducer outside the cell. The electrical outputs collected from the load cell, the displacement transducer, the pore water pressure transducer and the gap sensor for the measurement of specimen volume reduction during consolidation were amplified and recorded simultaneously using a computer.

Figures 2-8, 2-9 shows the relationship between deviator stress and axial strain, and the effective stress paths of the static CU tri-axial tests for the intact specimens sampled from both shallow and deep layers. In the case of the deep layer samples under any confining pressure, the mean effective stress p' decreases with the increasing of excess pore water pressure (EPWP), but after then the p' of the sample under the confining pressure of 150 kPa increases a little along the critical state line (C.S.L.), while the p' of the samples under the confining pressure of 50 and 100 kPa continue decreasing along the C.S.L. When the stress path reaches the C.S.L., the deviator stress q of the samples from shallow layer is higher than that for the samples from the deep layer subject to the same confining pressure loading.

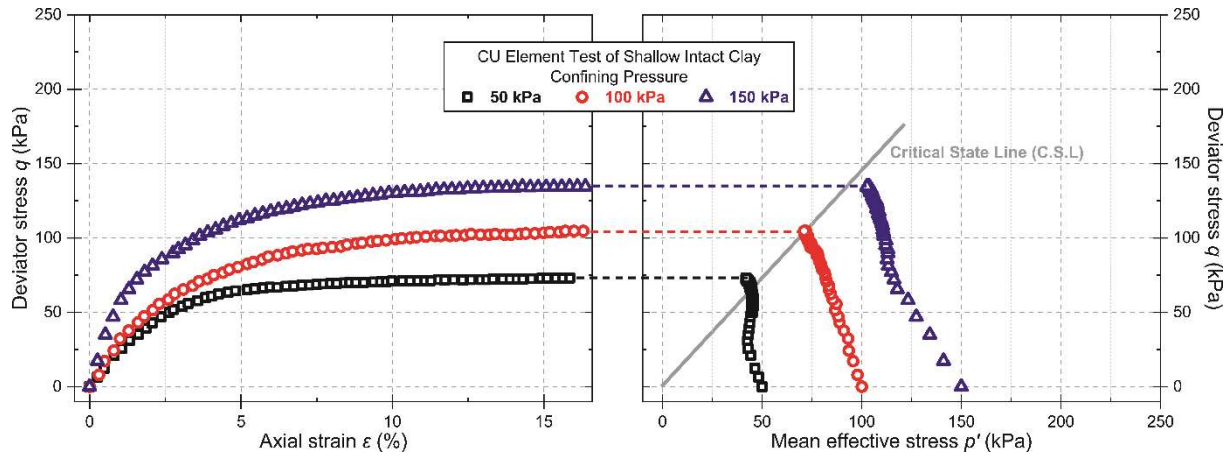


Figure 2-8 Static CU triaxial compression test results for the intact samples from the shallow layer

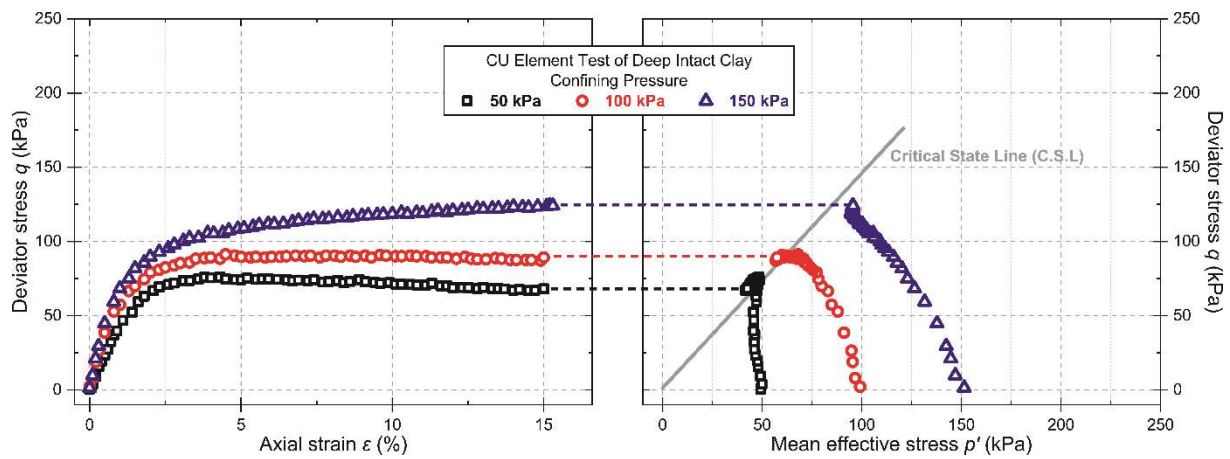


Figure 2-9 Static CU triaxial compression test results for the intact samples from the deep layer

Figures 2-10, 2-11, 2-12 show the relationship between deviator stress and axial strain and the effective stress paths of the cyclic CU tri-axial compression/extension tests for the deep layer when the .
Cyclic Stress Ratio (CSR) are 0.3, 0.4 and 0.5 Figure 2-13 shows the liquefaction strength for the samples from the deep layer. The figures infers that the cyclic shear stress produces the EPWP. The liquefaction strength, which is defined as the cyclic stress ratio by which the double axial strain (DA) reaches 5 % under the cyclic number of 20, for the samples is 0.37. Although the value is greater than that of the typical loose sand, it is natural that the clay layer assumes to be sheared and its EPWP increase during the earthquake.

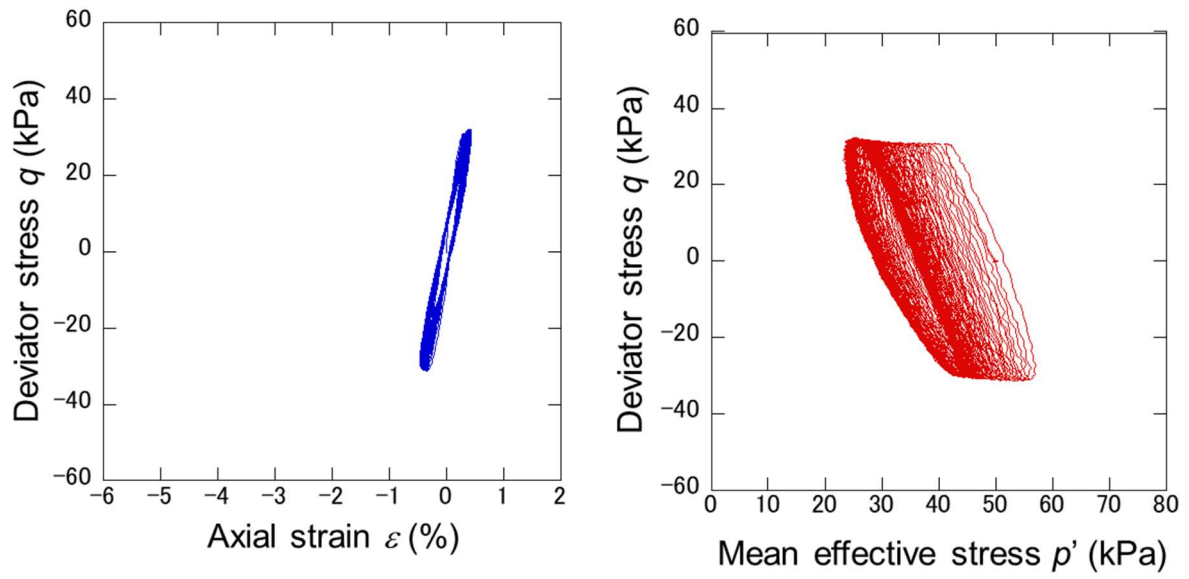


Figure 2-10 Cyclic triaxial test results for intact samples from deep layer (Cyclic Stress Ratio = 0.3)

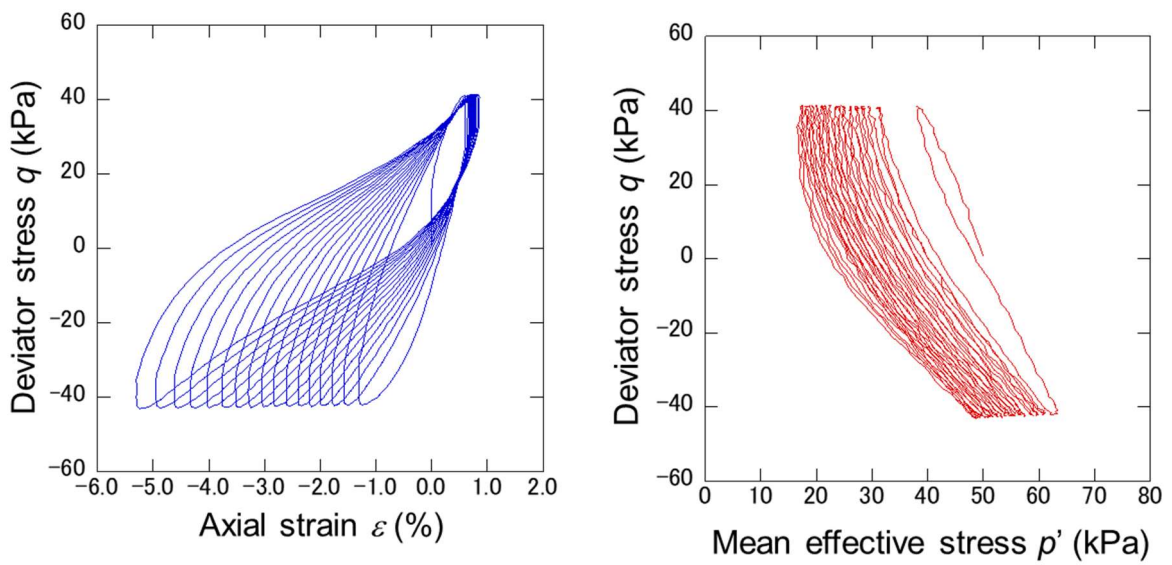


Figure 2-11 Cyclic triaxial test results for intact samples from deep layer (Cyclic Stress Ratio = 0.4)

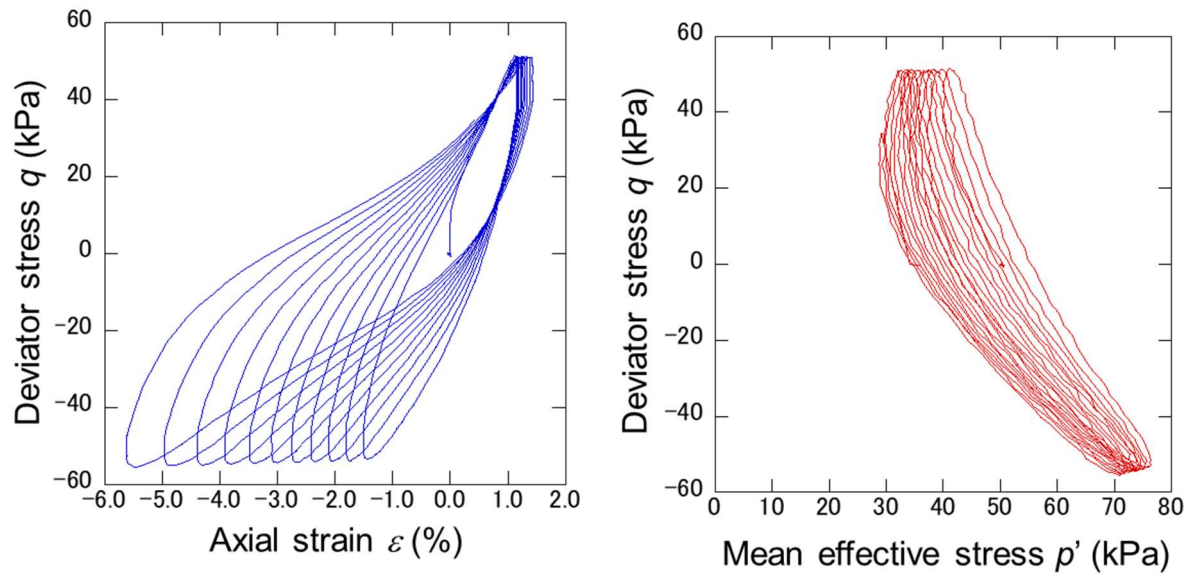


Figure 2-12 Cyclic triaxial test results for intact samples from deep layer (Cyclic Stress Ratio = 0.5)

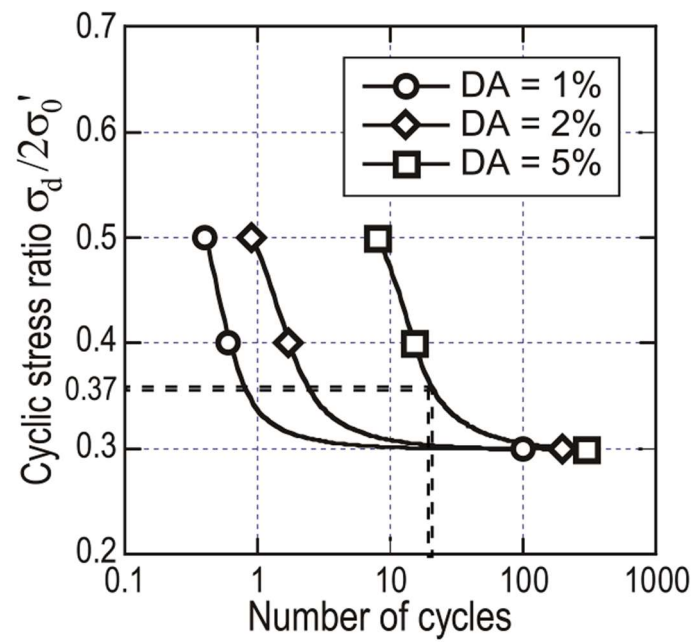


Figure 2-13 Liquefaction strength for the intact samples from the deep layer

CHAPTER 3 - DETERMINISTIC FINITE ELEMENT ANALYSIS

3.1 Abstract

The Transformation Stress-Cyclic Mobility (TS-CM) constitutive model developed by Zhang et al. (2007) is used to simulate the results of indoor element tests, and its parameters are determined based on the test results of the indoor element tests. The TS-CM model contains the concept of subloading described by Hashiguchi (1977) and the concept of superloading described by Asaoka et al. (2002). Therefore, the subsidence behavior of ground is simulated by soil-water coupling elasto-plastic FE analysis using the TS-CM constitutive model and the determined parameters. The FE simulation results are in good agreement with the actual site subsidence observation data. Based on the simulation results, the post-earthquake behavior of the soft clay and its mechanism were discussed and the successive subsidence was predicted forward. According to the simulation results, the relatively high structure-susceptible clay at this site has higher potential in long-term consolidation than relatively low clay due to large excess pore water pressure generation during ground motion and consolidation process after the earthquake. This conclusion can also be verified in consolidation tests of 2 types of clays.

3.2 Constitutive model

Many simulation techniques have recently achieved remarkable development. In particular, research on constitutive models for soils has been developing very quickly. The term initial anisotropy was firstly proposed to describe the phenomenon of anisotropy by Sekiguchi (1977). Then, Hashiguchi and Chen (1988) proposed a rotation tensor to describe stress-induced anisotropy. The concept of subloading was proposed by Hashiguchi and Ueno (1977), Hashiguchi (1978, 1989), which made it possible to describe the over-consolidation of soils easily and efficiently. The concept of superloading, proposed by Asaoka et al. (1994), Asaoka et al. (2000a) and Asaoka et al. (2000b), together with the concept of subloading, makes it possible not only to describe over-consolidation, but also to explain the effect of the soil structure commonly observed in naturally deposited soils. By combining the concepts of subloading and superloading, it is possible for the first time to describe the mechanical behavior of clay and sand with different densities and different structures within the same framework of a

constitutive model. The proposed model is based on the Cam-clay model (Roscoe et al., 1963) and the modified Cam-clay model (Schofield and Worth, 1968). Therefore, the physical meaning of the model is easy to understand and relatively few parameters need to be employed in spite of its ability to deal with different soils using the same model. Kaneda et al. (2003) explained the behavior of delayed compression observed in the land subsidence due to dewatering based on the proposed model and pointed out the importance of compression-softening behavior of naturally deposited soils. Besides, a new approach for describing the stress-induced anisotropy together with a new evolution rule for changes in over-consolidation, by which the mechanical behavior of soils subjected to cyclic loading under undrained conditions, including the cyclic mobility of medium dense sand was proposed based on the aforementioned concepts by Zhang et al. (2007).

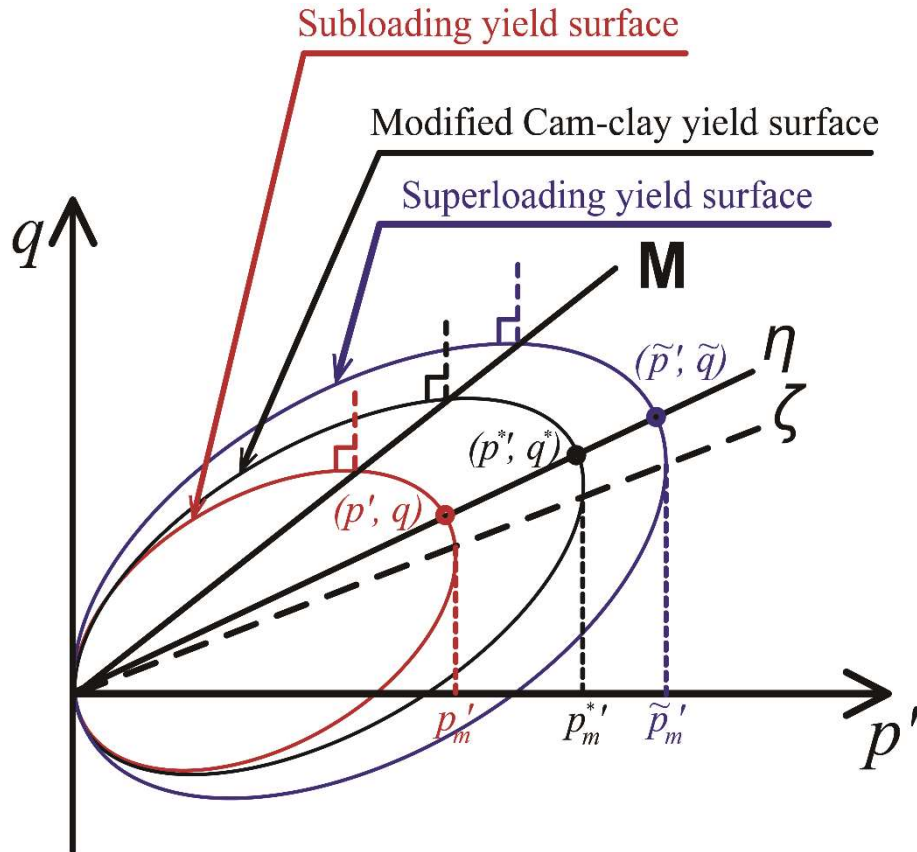


Figure 3-1 Yield surface of Transformation Stress-Cyclic Mobility (TS-CM) model developed by Zhang et al. (2007)

Transformation Stress-Cyclic Mobility (TS-CM) model developed by Zhang et al. (2007), which contains the concept of subloading and superloading as described in the work by Hashiguchi and Ueno

(1977) and Asaoka et al. (2002), is used for the constitutive model in this study. A brief description of the yielding surfaces of TS-CM model is shown in Figure 3-1.

The similarity ratio of the superloading surface to normal yield surface R^* and the similarity ratio of the superloading surface to subloading surface R are the same as those in the work by Asaoka et al. (2002), namely,

$$R^* = \frac{p'^*}{\bar{p}'} = \frac{q^*}{\bar{q}}, \quad 0 < R^* \leq 1 \quad (3-1)$$

$$R = \frac{p'}{\bar{p}'} = \frac{q}{\bar{q}}, \quad 0 < R \leq 1, \quad R = \frac{1}{OCR} \quad (3-2)$$

where, (p', q) , (p^*, q^*) and $(\bar{p}', \bar{q})$ represent the present stress state, the corresponding normally consolidated stress state and the structured stress state at $p' - q$ plane, respectively. The subloading yield surface is given in the following form as:

$$\begin{aligned} & f(p', \eta^*, \zeta) + MD \ln R^* - MD \ln R - \int_0^t J \text{tr} \mathbf{D}^p d\tau \\ & = MD \ln \frac{p'}{p'_0} + MD \ln \frac{M^2 - \zeta^2 + \eta^{*2}}{M^2 - \zeta^2} + MD \ln R^* - MD \ln R - \int_0^t J \text{tr} \mathbf{D}^p d\tau = 0 \end{aligned} \quad (3-3)$$

where, the other variables involved in Equation (1-1), (1-2) and (1-3) are defined as:

$$\begin{aligned} \eta^* &= \sqrt{\frac{3}{2} \hat{\boldsymbol{\eta}} \cdot \hat{\boldsymbol{\eta}}}, \quad \hat{\boldsymbol{\eta}} = \boldsymbol{\eta} - \boldsymbol{\beta}, \quad \boldsymbol{\eta} = \frac{\mathbf{S}}{p'}, \quad \mathbf{S} = \mathbf{T}' + p' \mathbf{I}, \quad p' = -\frac{1}{3} \text{tr} \mathbf{T}', \quad \zeta = \sqrt{\frac{3}{2} \boldsymbol{\beta} \cdot \boldsymbol{\beta}}, \quad \eta = \\ & \sqrt{\frac{3}{2} \boldsymbol{\eta} \cdot \boldsymbol{\eta}} \end{aligned} \quad (3-4)$$

Where, $\mathbf{S}$ is the deviatoric stress tensor; $\boldsymbol{\beta}$ is the anisotropic stress tensor, and $\mathbf{T}'$ is the Cauchy effective stress tensor and is assumed to be positive in tension. J is the Jacobian determination of deformation gradient tensor $\mathbf{F}$ and D is the dilatancy parameter which can be expressed by $\tilde{\lambda}, \tilde{\kappa}$, the compression and the swelling index, respectively, as follows:

$$D = \frac{\tilde{\lambda} - \tilde{\kappa}}{M(1 + e_0)} \quad (3-5)$$

$\mathbf{D}^p$ denotes the plastic component of stretching $\mathbf{D}$ which is assumed to be positive in tension, and is related to the plastic volumetric strain rate in the following form under the condition that the compressive of the volumetric strain is supposed to be positive:

$$\varepsilon_v^p = - \int_0^t J \text{tr} \mathbf{D}^p d\tau \quad (3-6)$$

An associated flow rule is employed in the model, namely,

$$\mathbf{D}^p = \lambda \frac{\partial f}{\partial \mathbf{T}'} \quad (3-7)$$

The consistency equation for the subloading yield surface can then be given as:

$$\frac{\partial f}{\partial \mathbf{T}'} \cdot \dot{\mathbf{T}}' + \frac{\partial f}{\partial \boldsymbol{\beta}} \cdot \dot{\boldsymbol{\beta}} + MD \frac{\dot{R}^*}{R^*} - MD \frac{\dot{R}}{R} - J \text{tr} \mathbf{D}^p = 0 \quad (3-8)$$

In the present model the gradient of the critical state line (C.S.L) is constant and the flat ratio of the elliptical yield surface changes with the value of anisotropy.

The following evolution rule for the anisotropic stress tensor is defined as:

$$\dot{\boldsymbol{\beta}} = \lambda \frac{JM\sqrt{6}b_r(b_l M - \zeta)\hat{\boldsymbol{\eta}}}{(M^2 - \zeta^2 + \eta^{*2})p'} \quad (3-9)$$

where, b_r is an evolution parameter of anisotropy to control a developing rate of stress-induced anisotropy when the soil subjected to shearing or compression, b_l is a limitation parameter in order to avoid the singularity in the Equation (3-3) at the point $\zeta = M$, 0.95 is used for the value of b_l throughout this paper. In the evolution rule the stress-induced anisotropic stress tensor will not exceed the C.S.L.

The following evolution rule for degree of structure R^* is defined as:

$$\dot{R}^* = J \frac{a}{D} R^* (1 - R^*) \sqrt{\frac{2}{3}} \|\mathbf{D}_s^p\| = \lambda \frac{2JMa^* (1 - R^*) \eta^*}{(M^2 - \zeta^2 + \eta^{*2})p'} \quad (3-10)$$

where, $\mathbf{D}_s^p$ is the shear components of plastic stretching tensor, a is the degradation parameter of structure which controls the collapse rate of structure when the soil subjected to shearing or compression. It is the same as in the work by Asaoka et al. (2002).

The following evolution rule for degree of over-consolidation R is controlled by the plastic component of stretching and the increment in anisotropy, and defined as:

$$\begin{aligned} \dot{R} &= -J \frac{m}{D} \left\{ \frac{(p'/p_0')^2}{(p'/p_0')^2 + 1} \right\} \ln R \|\mathbf{D}^p\| + \frac{R}{MD} \frac{\eta}{M} \frac{\partial f}{\partial \boldsymbol{\beta}} \cdot \dot{\boldsymbol{\beta}} \\ &= \lambda \frac{-mJM1}{(M^2 - \zeta^2 + \eta^{*2})p'} \left\{ \frac{\sqrt{6\eta^{*2} + \frac{1}{3}(M^2 - \zeta^2)^2}}{(p'/p_0')^2 + 1} \right\} + \frac{R}{MD} \frac{\eta}{M} \frac{\partial f}{\partial \boldsymbol{\beta}} \cdot \dot{\boldsymbol{\beta}} \end{aligned} \quad (3-11)$$

where, m is the degradation parameter of over-consolidation state which controls the losing rate of over-consolidation when the soil subjected to shearing or compression and p_0' is the reference stress which equals to 98 kPa. Its evolution rule was originally proposed by Zhang et al. (2007) and modified by Morikawa et al. (2012).

Table 3-1 Soil parameters used in the simulation

		Shallow layer	Deep layer	Silt	Gravel
Compression index	λ	0.266	0.440	0.104	
Swelling index	κ	0.050	0.031	0.010	
Stress ratio at critical state $R_f = (2 \cdot M + 3) / (3 - M)$	R_f	4.200	3.800	3.800	
Void ratio ($p' = 98$ kPa on N.C.L.)	N	1.617	1.548	0.920	0.600
Maximum historical preconsolidation pressure	p'_c	70.0	80.0	120.0	
Poisson's ratio	ν	0.370		0.200	0.300
Degradation parameter of overconsolidation state	mR	25.0		2.2	
Degradation parameter of structure	mR^*	0.030	0.450	0.100	
Evolution parameter of anisotropy	br	0.10	0.70	0.10	
Initial mean effective stress [kPa]	p'	8 ~ 73	78~111	117~295	
Initial degree of structure	R_0^*	0.20	0.20	0.10	
Initial degree of overconsolidation - OCR	$1/R_0$	1.3~10.5	1~1.4	2.5	
Initial anisotropy	ζ_0	0.0	0.2	0.0	
Permeability [m/sec]	k	7.0×10^{-10}		1.0×10^{-10}	1.0×10^{-4}
Saturated unit weight [kN/m ³]	γ_{sat}	15.36	15.66	17.00	19.00
Unit weight under water [kN/m ³]	γ'	5.36	5.66	7.00	9.00
Young's modulus [GPa]	E				100.0

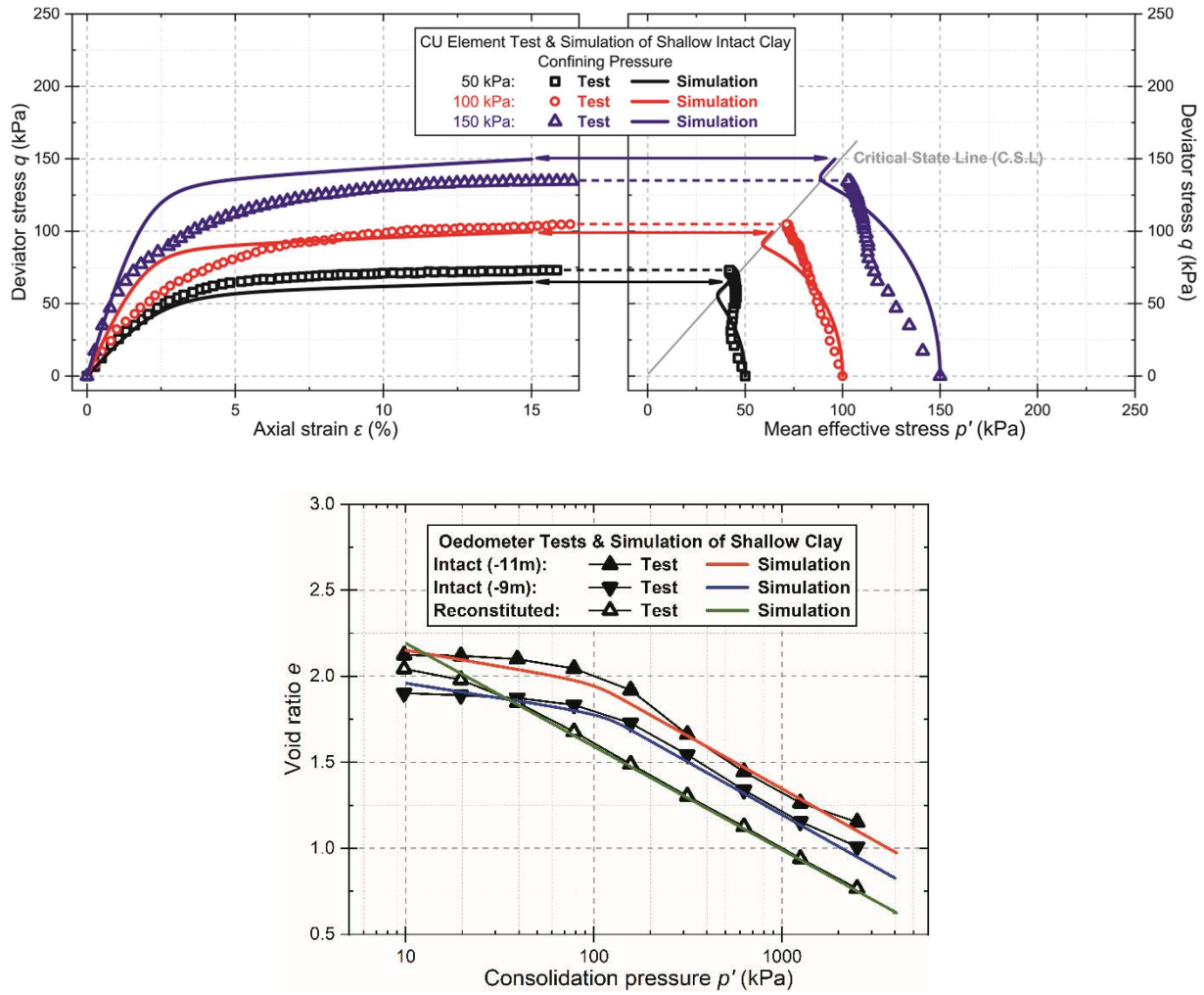


Figure 3-2 Simulation results on static CU triaxial compression test and oedometer test for the intact samples from the shallow layer

Nine parameters are involved in the present model, among which five parameters, M , e_0 , λ , κ and ν are the same as in the Cam-clay model. The other three parameters are the parameter which control the collapse rate of structure, the losing rate of over-consolidation and the developing rate of stress-induced anisotropy. In this paper those parameters are determined to match up precisely with the aforementioned tri-axial compression tests.

The values of material parameters and initial condition used in the simulations are listed in Table 3-1. Figures 3-2 and 3-3 show the performance of the element simulation regarding the behavior of the shallow and deep clay in undrained static compression tests and oedometer tests respectively. Note that the R_f in the table is converted from M . It can be judged from these figures that the simulation results have a good agreement with the experimental results except for the case of very high confining pressure.

Furthermore, as indicated in Table 3-1, deep clay structures demonstrate greater susceptibility to degradation, illustrated by the significantly higher degradation parameter of deep clay (mR^*) compared to shallow clay (0.45 compared to 0.03), despite both types of clay having the same degree of structure ($R_0^* = 0.2$). Figure 3-4 shows the element simulation results of the silt layer. The soil was not sampled from the silt layer in the previous field investigations because the subsidence of the layer was not observed. In this simulation the values of the parameters for the silt layer are assumed to be typical silt such as Fujinomori clay while the parameters of Fujinomori clay are from Nakai and Hinokio (2004) and Isobe et al. (2014b). The boundary value problem (B.V.P.) is executed using the above parameters to investigate the settlement mechanism after the quake and predict the amount of subsidence in the future.

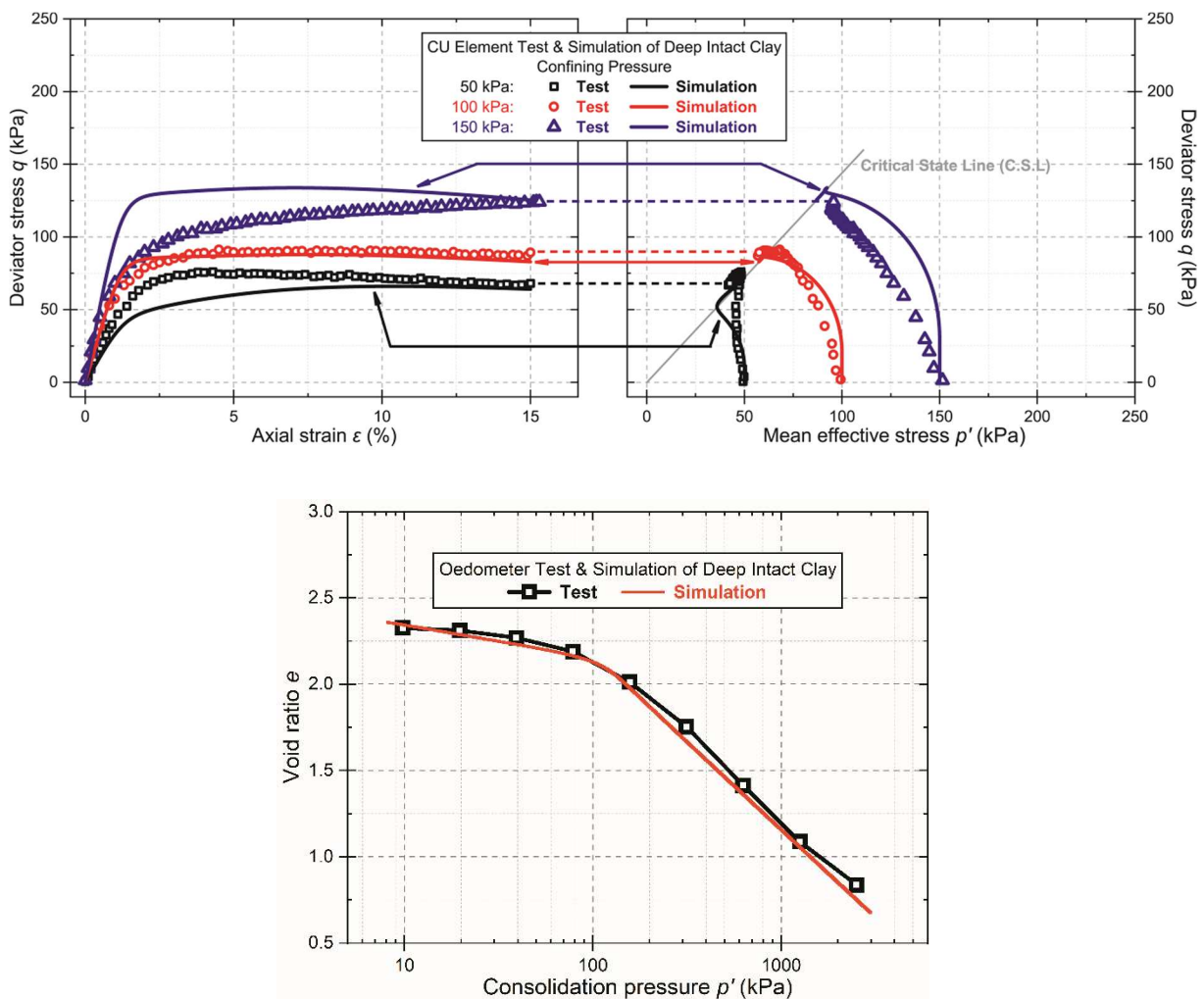


Figure 3-3 Simulation results on static CU triaxial compression test and oedometer test for the intact samples from the deep layer

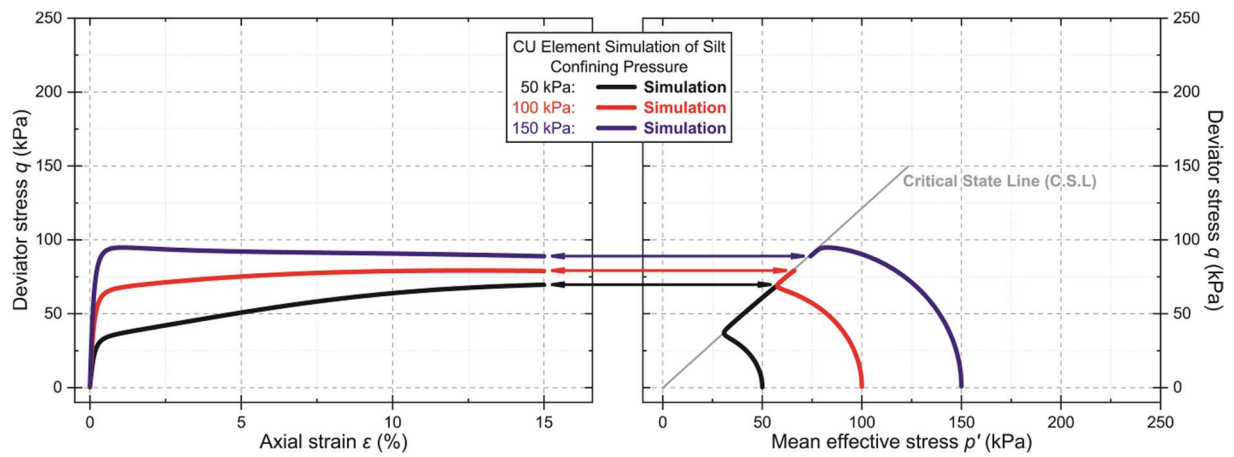


Figure 3-4 Simulation on static CU triaxial compression test for the silt layer

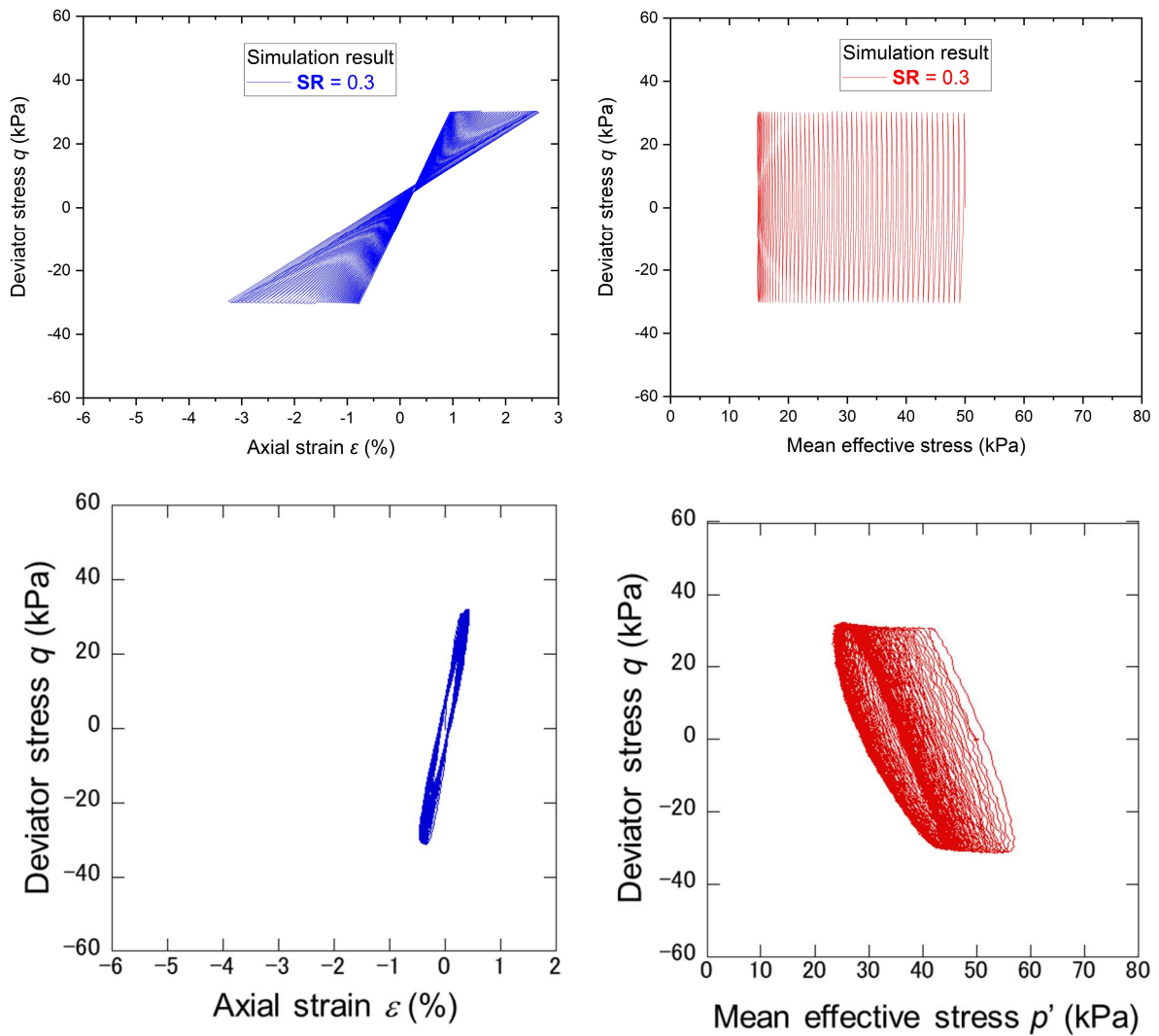


Figure 3-5 Cyclic triaxial test results simulation (Cyclic Stress Ratio = 0.3)

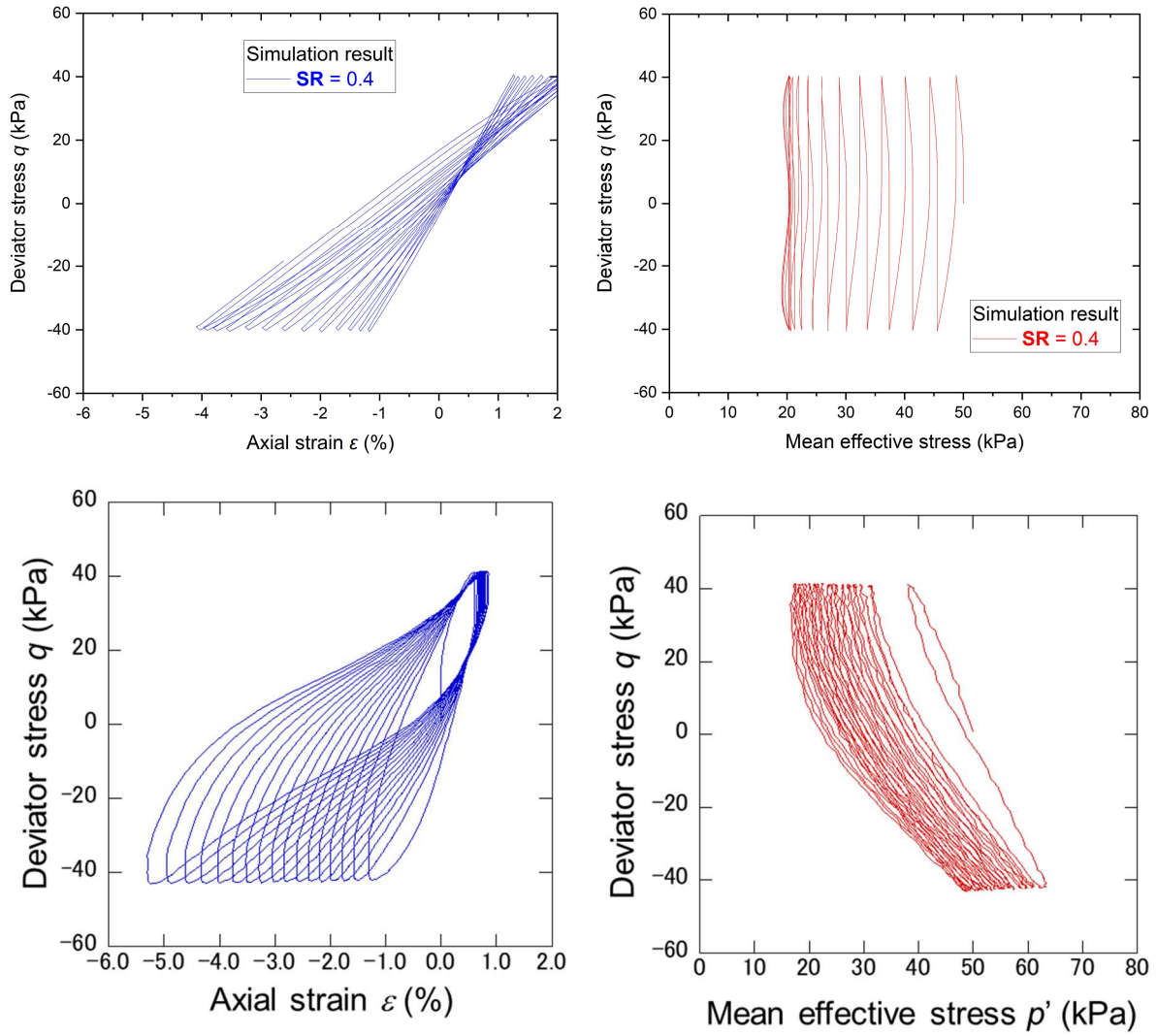


Figure 3-6 Cyclic triaxial test results simulation (Cyclic Stress Ratio = 0.4)

Figure 3-5, 3-6, 3-7 and 3-8 show the cyclic triaxial test results simulation when the cyclic stress ratio is 0.3, 0.4 and 0.5. According to these figures, the cyclic undrained behavior could not be reproduced with perfect accuracy, which may impact the analytical results to some extent. However, the authors believe that the results are reasonably accurate except the situation $SR = 0.3$, given that the parameters used fall within a reasonable range from a physical perspective. Because the discrepancy between the experimental and analytical results for $SR = 0.3$ compared to $SR = 0.4$ or 0.5 is due to a slight underestimation of the initial stiffness in the analytical model under low confining pressure conditions (50 kPa), as shown in Figure 3-3. This underestimation leads to an overestimation of double amplitude axial strain when cyclic shear is applied under the same low confining pressure. The effect is

particularly pronounced for $SR = 0.3$, causing the results to deviate more significantly from the experimental data. However, when examining the excess pore water pressure caused by cyclic shear in Figure 3-8, there is minimal discrepancy between the experimental and analytical results. Since the increase in excess pore water pressure is thought to be the primary cause of long-term settlement in soft clay after an earthquake, and the element simulation is able to reasonably evaluate this increase, the analytical parameters used in this study are considered appropriate and reliable.

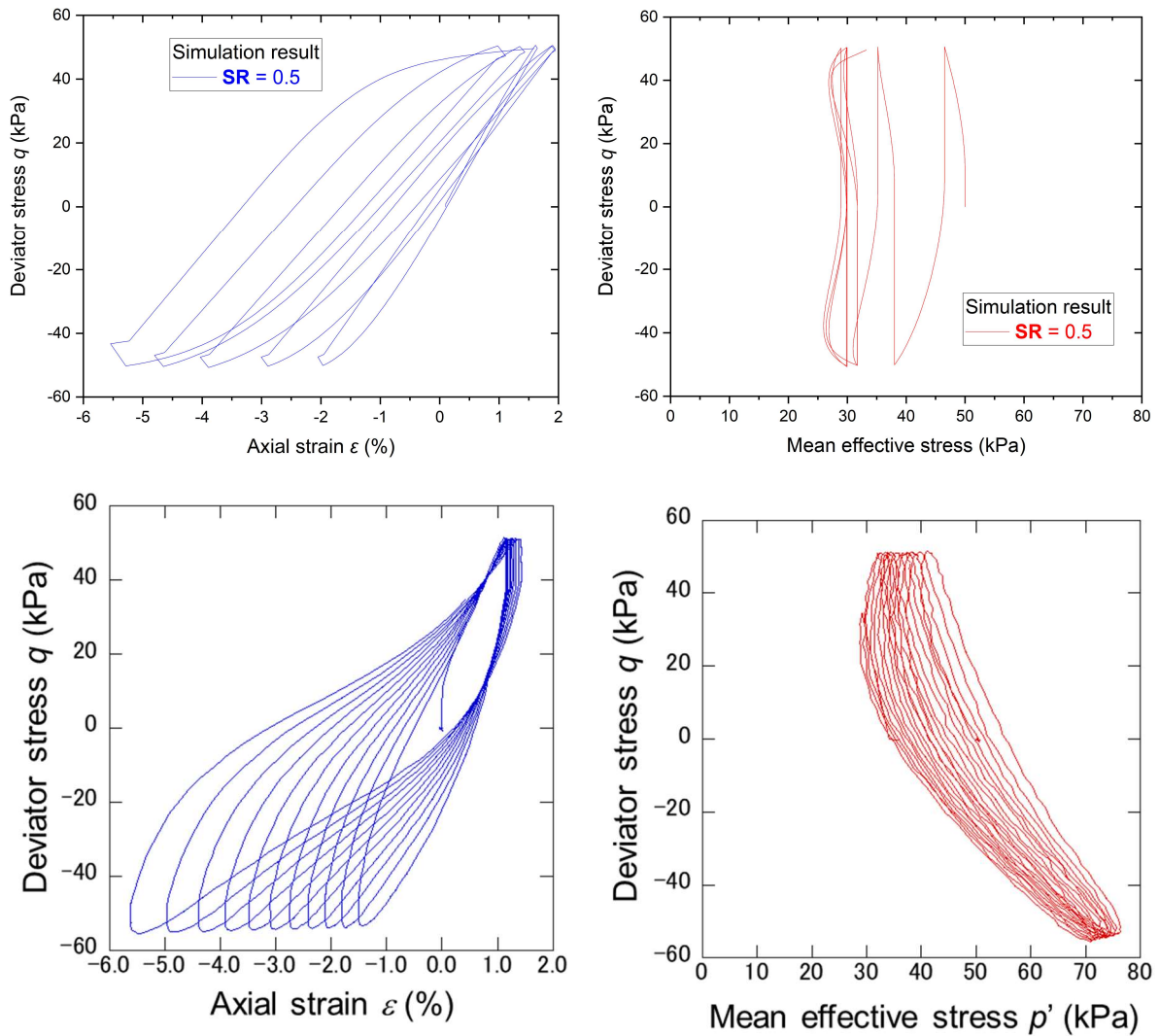


Figure 3-7 Cyclic triaxial test results simulation (Cyclic Stress Ratio = 0.5)

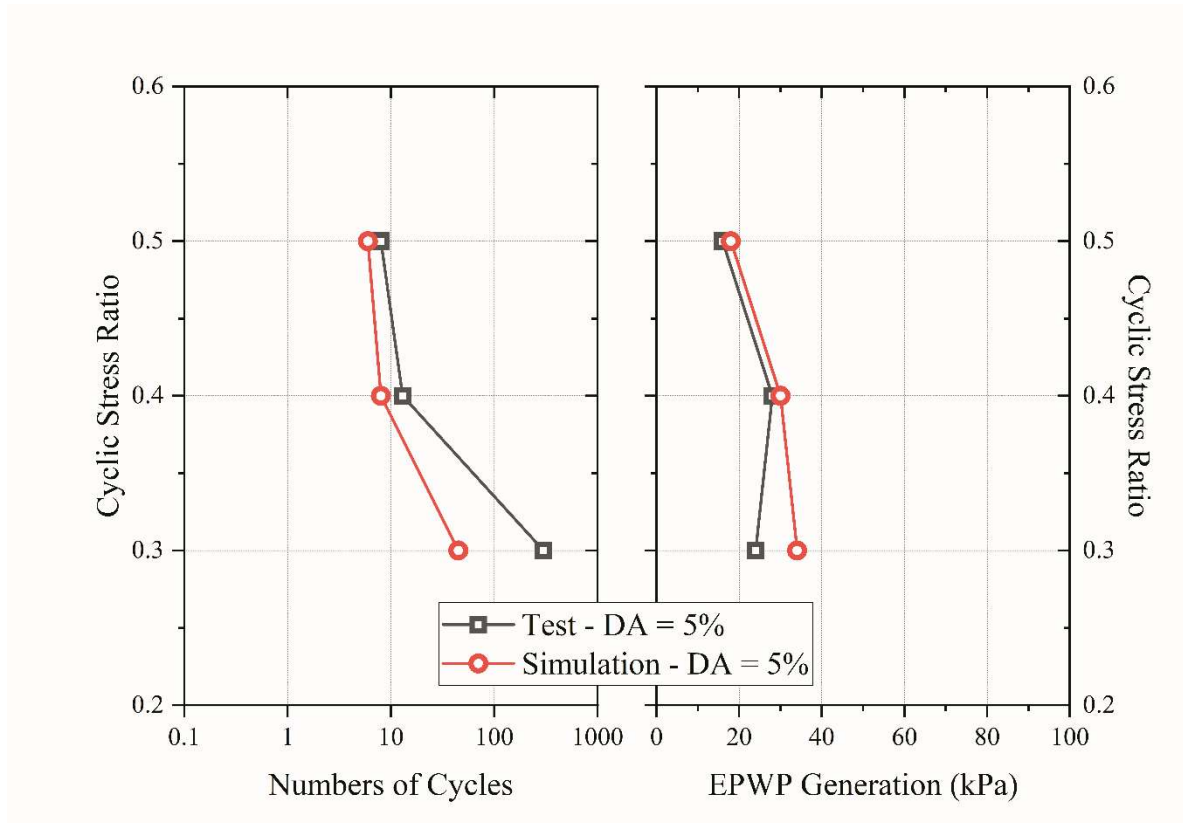


Figure 3-8 Liquefaction strength curve and Excess Pore Water Pressure (EPWP) at DA=5% of the deep layer obtained cyclic triaxial test and simulation

3.3 Analytical condition of Deterministic Finite Element Analysis

The soil - water coupling FE analysis code DBLEAVES (Ye et al., 2007) is used in this simulation. This 2D and 3D FE analysis program is able to solve repeated static and dynamic soil-water coupled B.V.P. by using Oka's two-phase field theory (Oka et al., 1992, 1999) and FE-FD soil-water coupled method. The FE model is simplified to a one-dimensional column of soil elements, whose size is 1 m in width, 1 m in length and 1 m in height, as shown in Figure 3-9. Here it is assumed that the ground is level and the effects of terrain geometric are not taken into account in the simulation. The ground water level is assumed at GL -1.0 m as the groundwater level is slightly lower than the ground surface according to on-site observation data. Excess pore water pressure is not calculated in the surface element (#50) above the groundwater level.

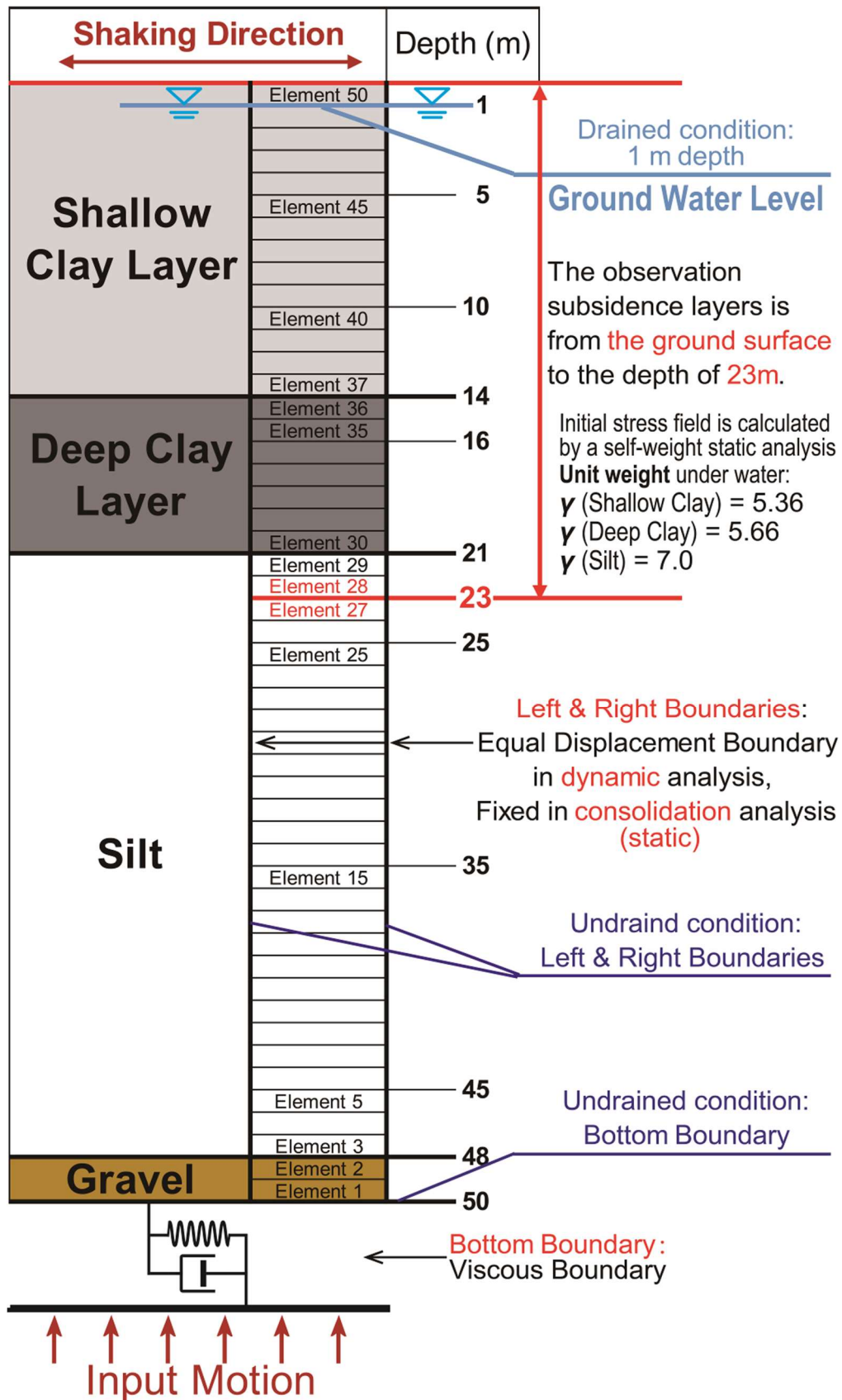


Figure 3-9 Finite element mesh and boundary conditions used in the simulation

The boundary condition is that: (a) the bottom of the ground is viscous boundary (Lysmer and Kuhlemeyer; 1969); (b) in dynamic analysis, an equal-displacement-boundary condition (Yashima et al., 1991) is used between the nodes in two sides of the ground; when the analysis is shifted to consolidation, the boundary condition is then changed to fixed one. (c) 1m depth is set as drainage condition while the other surfaces are impermeable. The V_p and V_s values used for the viscous boundary were estimated from the P, S velocities in the K-NET (Station No. NIG018 near "city hall" or "A" in Figures 2-1, 2-1, 2-3) provided in the reference (Strong-motion Seismograph Networks (K-NET, KiK-net)) shown in Figure 2-5, with V_s and V_p determined as 500 m/s and 1500 m/s, respectively.

In the numerical simulation the process during shaking is simulated by a dynamic soil-water coupled analysis, while the process of dissipation of excess pore water pressure (EPWP) is simulated by a static consolidation analysis. The whole process is a continuous one and therefore it should be simulated in sequential continuously. The simulation is divided into two stages as follows: (a) the dynamic analysis lasts for 280 seconds until shaking stops and (b) the consolidation analysis lasts for 150 years until EPWP dissipates completely. The initial stress field is calculated by a self-weight static analysis in advance and the values of unit weight and the range of the initial stress for each layer is shown in Table 3-1. The value of the initial OCR in the analysis is calculated automatically in the DBLEAVES using the maximum historical pre-consolidation pressure of 70 kPa for shallow layer and 80 kPa for deep layer which is shown in Table 3-1.

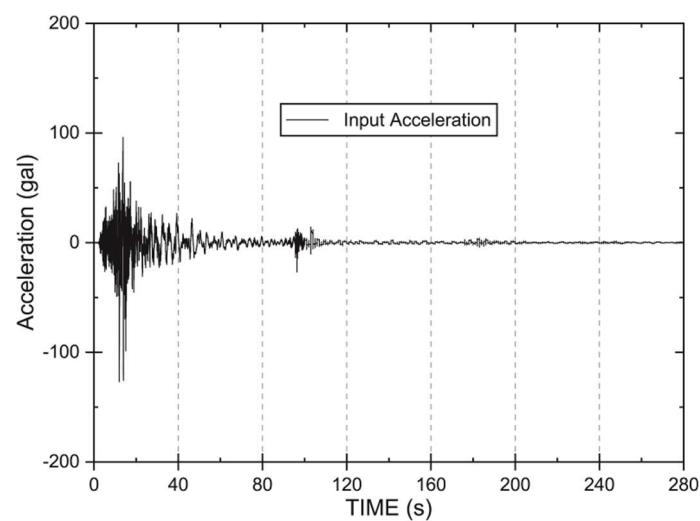


Figure 3-10 Time history of input acceleration used in the simulation

The input motion on base layer of the objective site in the Niigata Chuetsu-oki Earthquake in 2007 was estimated in two steps. Firstly, the peak acceleration on two sites of KiK-net observation station (Kawanishi station and Yunotani station) were predicted by the Shi-Midorikawa attenuation relationship (1999). Secondly, the base acceleration waves for both sites were back analyzed from observed acceleration waves on surface by using one dimensional elastic model with multiple layers. In the calculation, the soil parameters were determined from laboratory tests and PS loggings except for damping ratio. The damping ratio was specified so as to express observed base waves. Then the calculated base waves are separated into ascent and descent waves to compare with estimated peak acceleration. The estimated peak acceleration had the trend of overestimation, then estimated peak accelerations were reduced to 0.7 times. Ultimately the peak acceleration on free surface of engineering foundation at Kashiwazaki city is estimated as 96 gal, and the proportionated acceleration wave on base layer at Yunotani was adopted as the input wave.

Figure 3-10 shows the input acceleration used in the simulation, applied at the bottom of the analytical domain. The stiffness proportional damping with a damping rate of 5% was applied for the damping model, and the Newmark- β method ($\beta = 0.3025$, $\gamma = 0.6$) was used for time integration.

3.4 Compression index induced by dynamic loading C_d

A lot of attention to decrease in effective stress and reconsolidation of saturated clay induced by cyclic shearing have been paid and the research outcomes have been published by Yasuhara et al. (1982), Hyodo et al. (1988), Ohara and Matsuda (1988), Matsuda and Ohara (1990), Yasuhara and Andersen (1991), Hyodo et al. (1992), Matsuda and Nagira (2000) and so on. Generally speaking, the change of the void ratio Δe produced in the soil mass is in proportion to the logarithm of effective stress, the relation between Δe and the logarithm of the increment of effective stress $\Delta \log p'$ or $\Delta \log s_v'$ are shown in Figure 3-11, where C_c and C_s are the compression index, the swelling index obtained by the standard oedometer tests, respectively. In the foregoing references the relationship among both Indices and the compression index induced by dynamic loading C_d are shown as $C_s < C_d < C_c$. Based on the relationship, various experimental estimation methods of post-earthquake settlement of clay layers based have been proposed in these references.

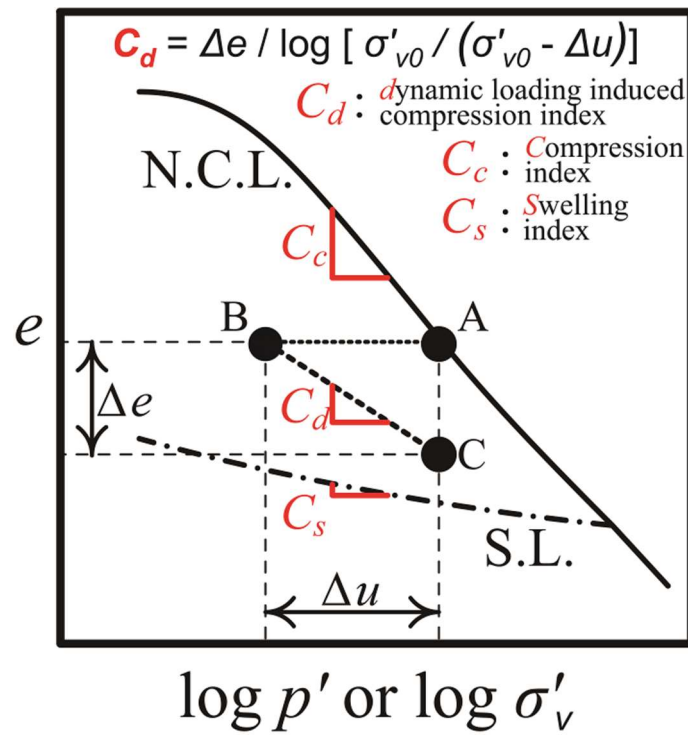


Figure 3-11 Schematic view of C_c , C_s and C_d

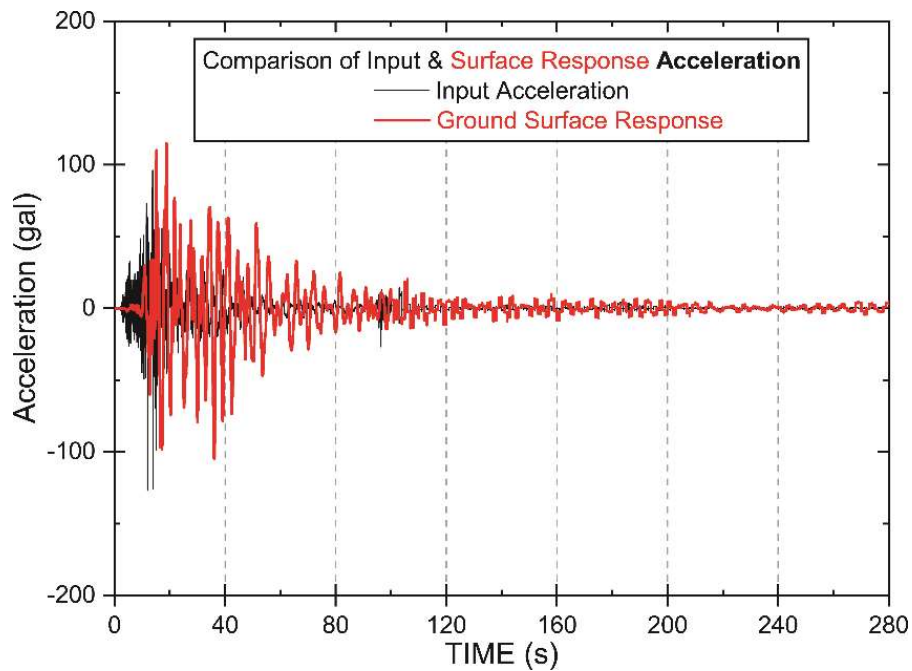


Figure 3-12 Time history of response acceleration on the ground surface and the input acceleration

3.5 Deterministic Finite Element Analysis

Figures 3-12 and 3-13 show the time history of the response acceleration on the ground surface and

the time history comparison between observation and FE analysis of cumulated ground subsidence of soil layers up to 23 m deep. It is obvious from Figure 3-12 that the response acceleration on the ground surface was 116 gal, and the little shaking on the ground surface lasted until 160 sec. The result of subsidence observation included not only the settlement caused by earthquake and consolidation, but also settlement caused by autumn and winter pumping. Therefore, the settlement simulation result of earthquake and consolidation should be slightly smaller than the subsidence observation which included the former.

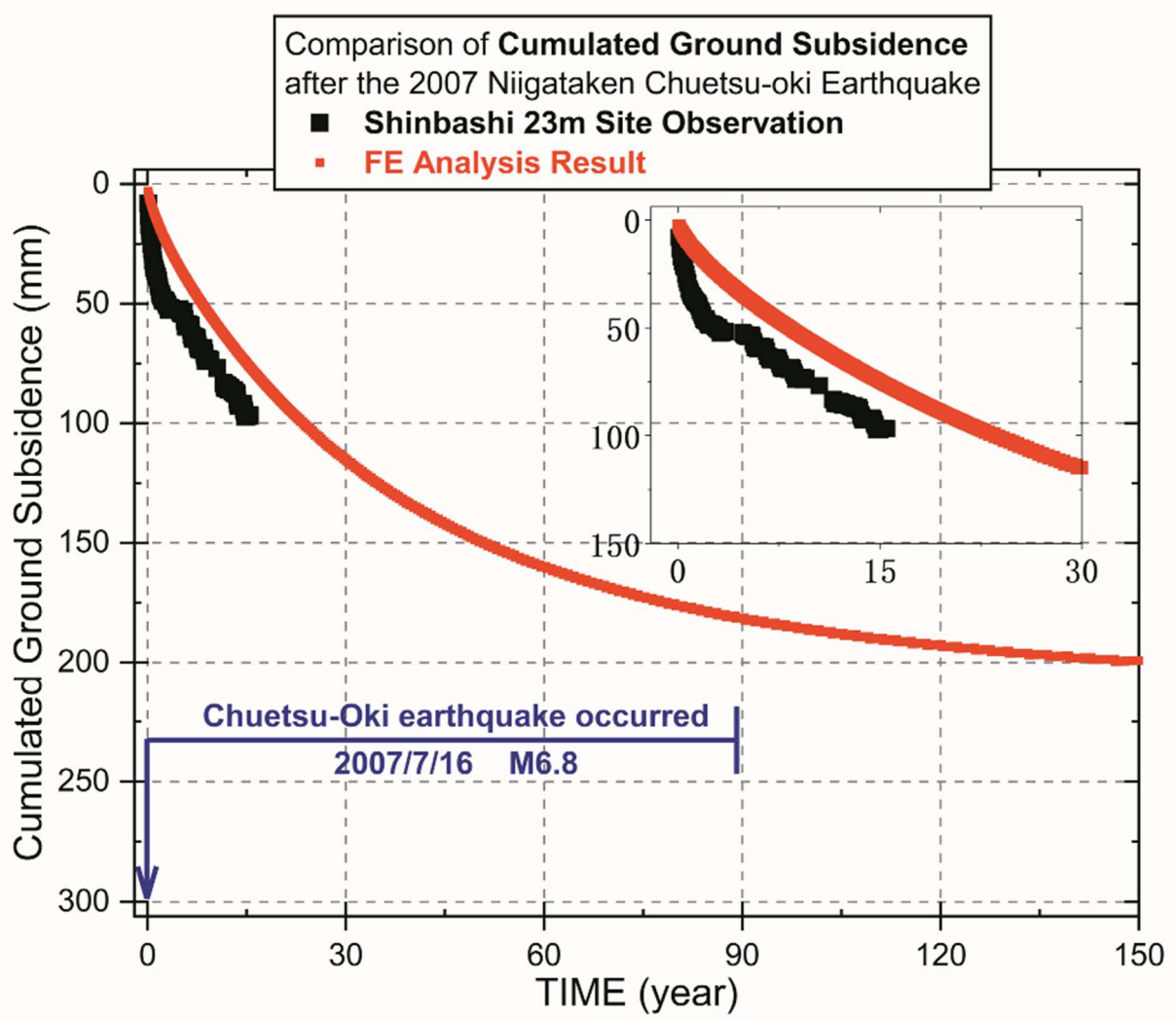


Figure 3-13 Time history comparison between observation and FE analysis of cumulated ground subsidence of soil layers up to 23 m deep

The ground subsidence shown in Figure 3-13 was gradually increasing soon after the shaking,

having a good reasonable agreement with the observation results, and lasted until 150 years later. Its cumulated subsidence finally reached 200 mm. It was caused by the generation of the EPWP in the shallow and deep clayey layers induced by the shaking and its dissipation took a long period of time because of its low permeability. It should be noted that at the beginning stage, the simulated settlement result was a little smaller than the subsidence observation, that is, the settlement calculation result of the first month was 3 mm, and the subsidence observation data of the first month was about 8 mm. The possible reason for this phenomenon was that the observed settlement included immediate subsidence other than consolidation phenomenon, or the other factors such as the difference of drained condition between the actuals and the simulation (one dimensional analysis in the calculation) and the other unknown information.

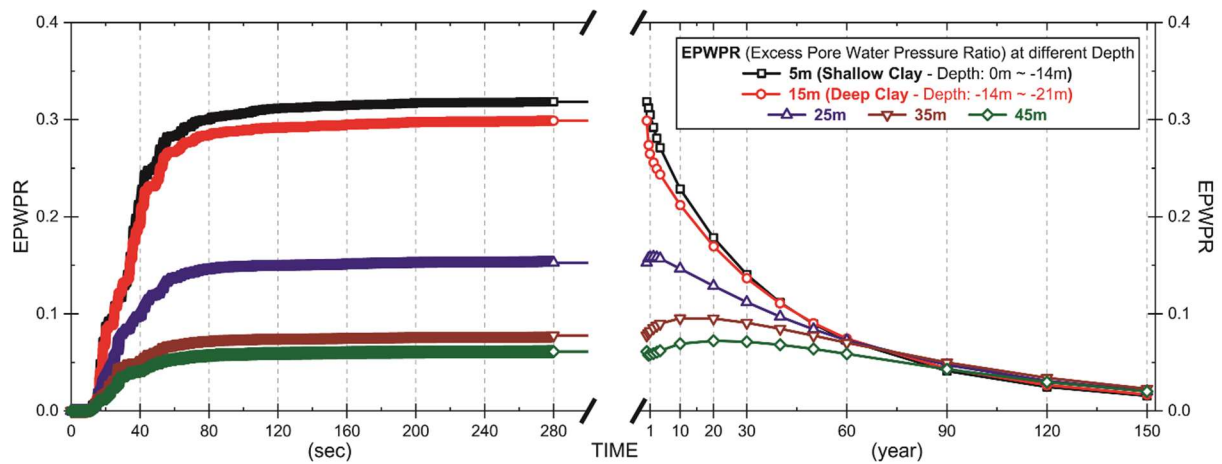


Figure 3-14 Time history of excess pore water pressure ratio (EPWPR) at the different depth

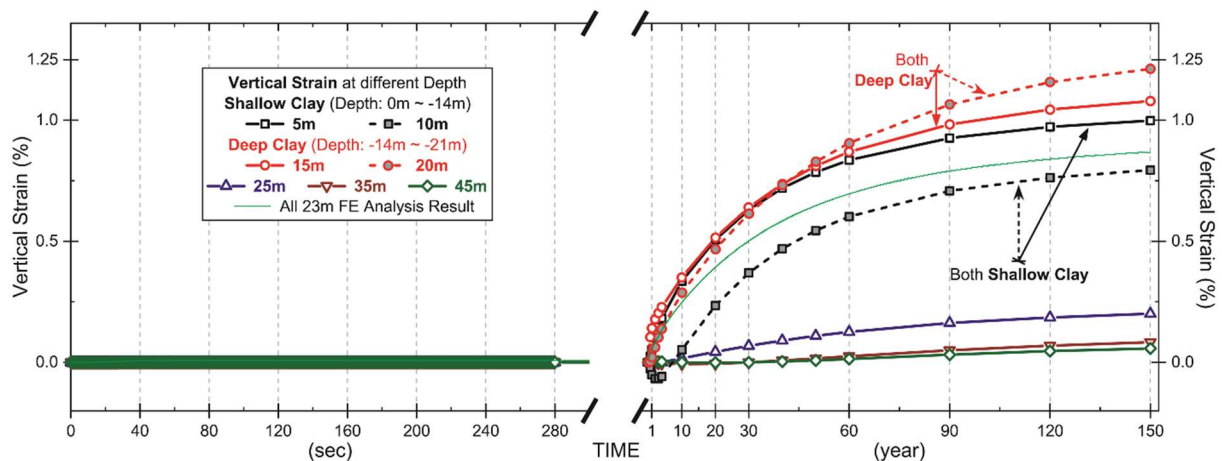


Figure 3-15 Time history of vertical strain at the different depth

Figures 3-14 and 3-15 show the excess pore water pressure ratio (EPWPR) and the vertical strain at several specific depths which have been shown in Figure 3-9, respectively. It is shown in Figure 3-14 that the deeper the soil layer, the smaller the EPWPR after shaking, but the difference in EPWPR between shallow clay and deep clay is not significant. Additionally, the EPWPR of the shallow clay which lays near to the ground surface reach to the maximum value of 0.31. It can be analyzed from this result that the reasons for the relatively large post-earthquake subsidence at Kashiwazaki area covered with soft clay are the generation of the excess pore water pressure in clayey layers due to the 2007 earthquake and its slow dissipation. In Figure 3-15, "All 23m FE Analysis Result" represents the vertical strain of all clay layers including shallow and deep clay layer with a total thickness of 23 m. It should be noted that in Figure 3-15, the vertical strain at the deep clay layer (15 m and 20 m deep represented by solid red line and dashed red line, respectively) is larger than the shallow clay layer (5 m and 10 m deep represented by solid black line and dashed black line, respectively), which verified the conclusion in 3.1 that the deep clay has more potential to consolidate than the shallow clay.

Figures 3-16 and 3-17 show the contour and the isochronous curve of excess pore water pressure (EPWP) or EPWPR distributed in the analytical domain at the specific time (initial, during shaking, soon after shaking, 1, 10, 20 and 30 years later). It can be seen from Figure 3-16 that the horizontal shaking of the soil during the 280s earthquake shaking was not small while the subsidence was small, but there was a relatively large settlement after the earthquake. In addition, it should be noted that the displacement was magnified 10 times in the figure to facilitate readers to feel the deformation. In Figure 3-17, we can see the high EPWPR of the deep and shallow clay in the calculation results, and we can see that the EPWPR gradually decreases with the passage of time after the earthquake. There exists a distinctive feature or depression at the boundary separating the shallow and deep clay layers, owing to the notable disparity in the capacity of deep and shallow clay to generate Excess Pore Water Pressure (EPWP). Following the earthquake, it becomes evident that the EPWP ratio (EPWPR) at this boundary increases abruptly, indicated by the black curve rising to meet the red curve at a depth of 14 meters. This suggests that following the earthquake, before being discharged from the drainage boundary, EPWP and pore water initially propagate and infiltrate from the two peaks of EPWPR in both shallow and deep clay layers towards the depression, which serves as the boundary between the shallow and deep clay layers. Consequently, there is a flattening of the EPWPR curve (transitioning from the black curve to

the red one), with the peak of the deep clay layer notably decreasing from post-earthquake to one year later. The dissipation of EPWPR gradually progresses from the drainage boundary in the subsequent years.

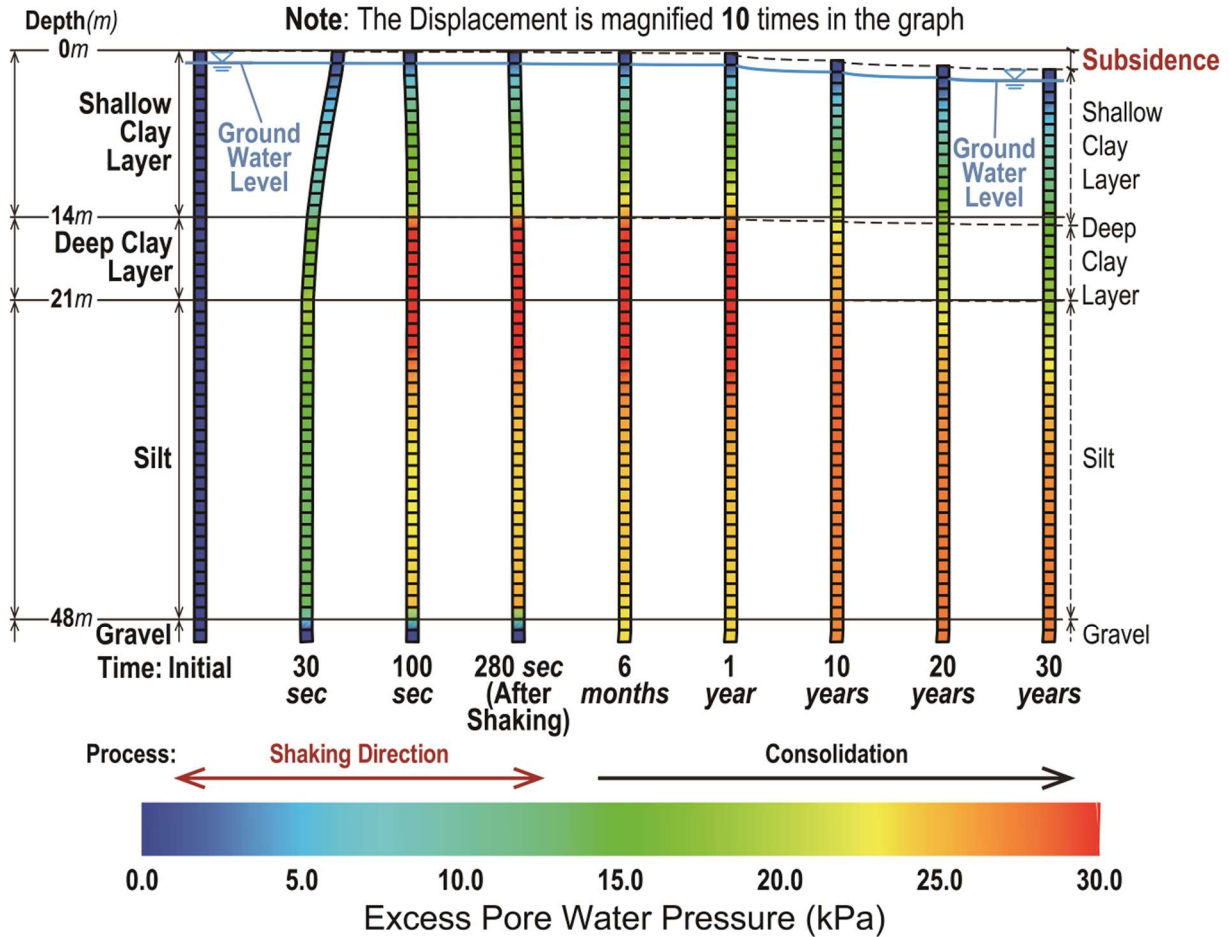


Figure 3-16 Contour of excess pore water pressure during and after the shaking (the displacement was magnified 10 times in the figure)

Figure 3-18 shows the values of C_d (compression index induced by dynamic loading) and Vertical Strain e obtained by FE analysis at the different depth of shallow and deep layer during consolidation. As already mentioned in the introduction, C_d is the ratio of void ratio change Δe during the consolidation process to the logarithm values comparison of effective stress before and after excess pore water pressure dissipation caused by dynamic loads, and it applies to the relationship $C_s < C_d < C_c$ for both shallow and deep clay layer. $C_d^{Shallow}$ is approximately in the range of 0.176 to 0.255 and C_d^{Deep} is approximately in the range of 0.230 to 0.381. It is also

clearly visible that C_d of each layer is not constant along depth and obviously affected by the OCR in the same layer of soil, that is, the parameter R . The OCR gradually increases as the depth becomes shallower in the same soil layer, while the C_d decreases slightly. This phenomenon is consistent with the conclusion of Ohara and Matsuda (1988): " C_{dyn} reduces a little with increase of OCR". Specifically, in the tests of Ohara and Matsuda (1988), C_{dyn} decreased by approximately 26% as OCR increased from 1 to 6, while $C_d^{Shallow}$ decreased by about 30% as OCR increased from 1 to 9.3 in this study. It can be roughly considered that $C_d^{Shallow} < C_d^{Deep}$ while the vertical strain ε of deep layer is also greater than that of shallow ones, which again verified the conclusion in chapter 3.1 and 4.1 that the deep clay has more potential to consolidate and the structure of deep clay is more susceptible to degradation than the shallow clay as the degradation parameter of structure mR^* of deep clay is obviously higher than that of shallow clay (0.45 compared to 0.03).

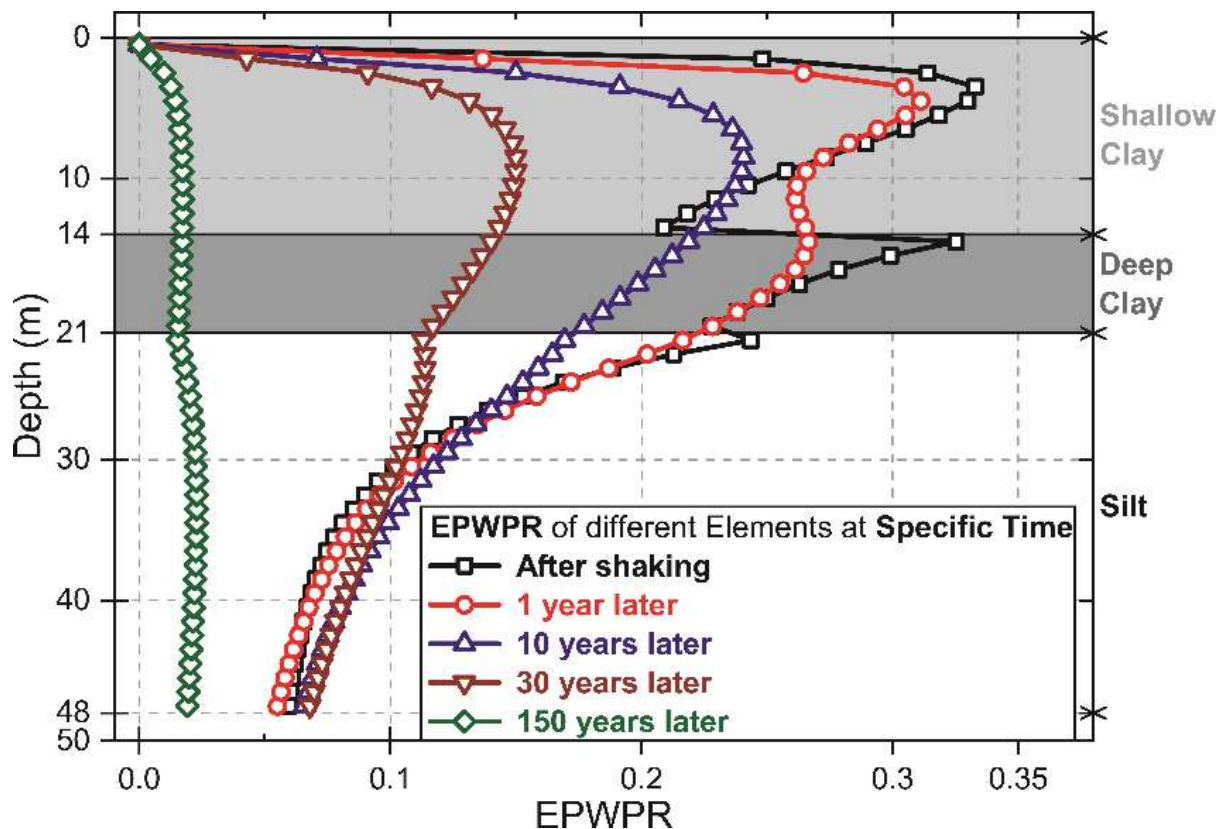


Figure 3-17 Isochronous curve of excess pore water pressure ratio for all elements

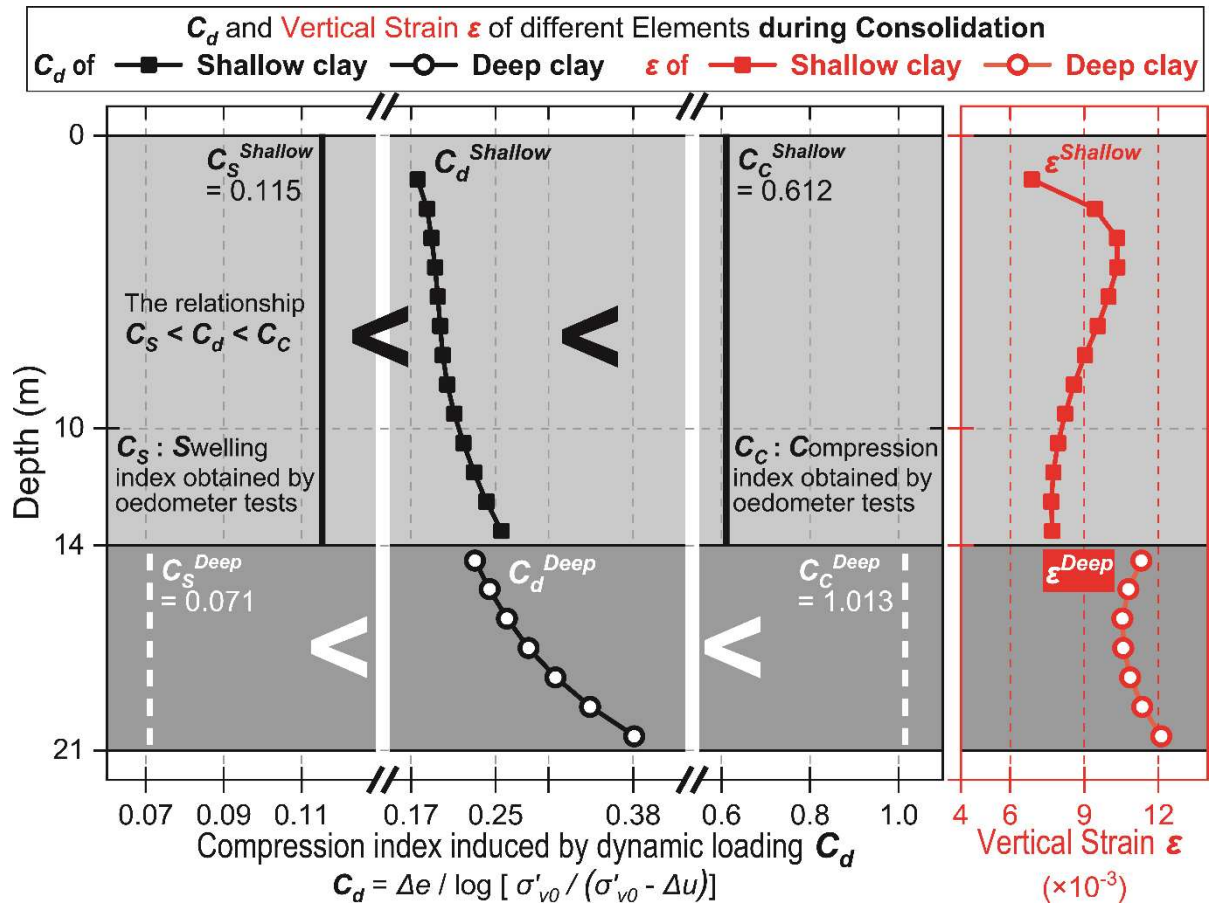


Figure 3-18 The values of C_d (compression index induced by dynamic loading) and Vertical Strain ε obtained by FE analysis at the different depth of shallow and deep layer during consolidation after the earthquake

Although the generation of the EPWP in the silt layer was also observed, the cumulated ground subsidence was less than that of the clayey layer because its value of compression and swelling index and degradation parameter of over-consolidation state were small comparing with those of the clayey layer. It was based on the results of the time history of the over-consolidation state R and degree of structure state R^* shown in Figure 3-19. It was obviously found from the figure that the values of R in all layers were decreasing due to the generation of EPWP during the shaking and it recovered in the procedure of the dissipation of EPWP. The decrease showed especially obvious in the clayey layer while the R of 5 m depth in the shallow clay layer decreased approximately 0.14 and the R of 15 m depth in the deep clay layer decreased about 0.23. This foregoing behavior depended on the value of the parameter of degradation of over-consolidation state mR . Besides, the degrees of structure R^* in the clay layer were increasing during and after the shaking, implying that the collapse of the natural structure in

the clay layer occurred not only under cyclic shearing loading but also during the procedure of consolidation. The soil structure degraded during the consolidation process, and it is thought that it took a long period of time to dissipate the EPWP of the structured clay as pointed out by Kaneda et al. (2003). Another difference should be noted in Figure 3-19 is that the increases of R^* in the deep clay layer (15 m deep in red line) is larger than the shallow clay layer (5 m deep in black line), which once again verified the conclusion that the deep clay has more potential to consolidate than the shallow clay.

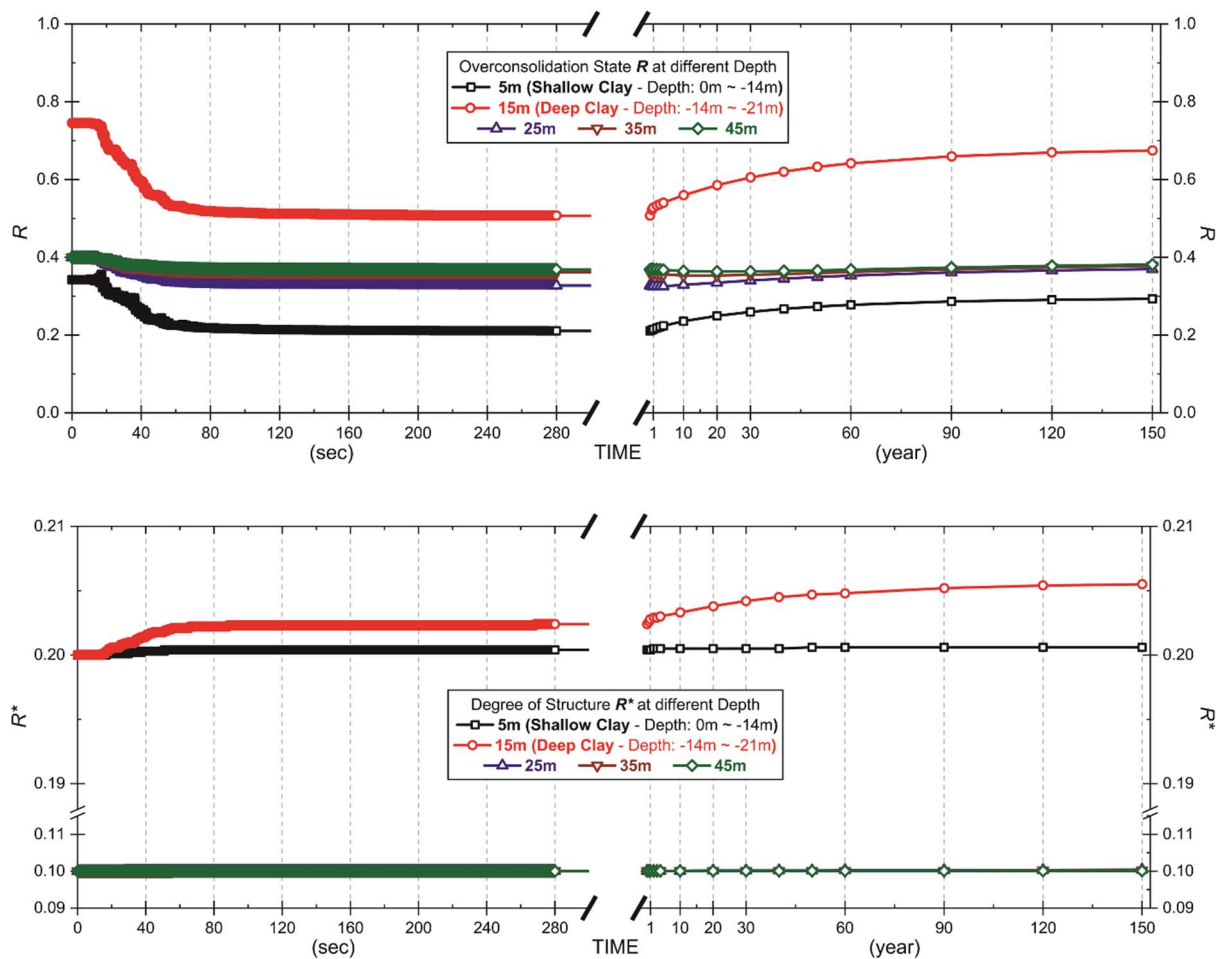


Figure 3-19 Time history of R and R^* at the different depth

Subsequently, one numerical experiment is conducted in order to investigate the difference of the shallow and deep clay layer. In this additional case, the soil parameters in the deep clay layer are replaced by those in the shallow clay layer. Figure 3-20 shows the time history comparison from the observation, original FE analysis and the additional simulation case on cumulated ground subsidence of soil layers up to 23 m deep. It is clearly shown from this figure that the ground subsidence would significantly

decrease if the parameters of the deep clay are replaced by all the shallow clay layer. This enhances the conclusion again that the deep clay has more potential to consolidate and the structure of deep clay is more susceptible to damage than the shallow clay. In addition to the degradation parameter of structure, the difference in shear strain induced by ground motion is behind the difference in the amount of settlement too.

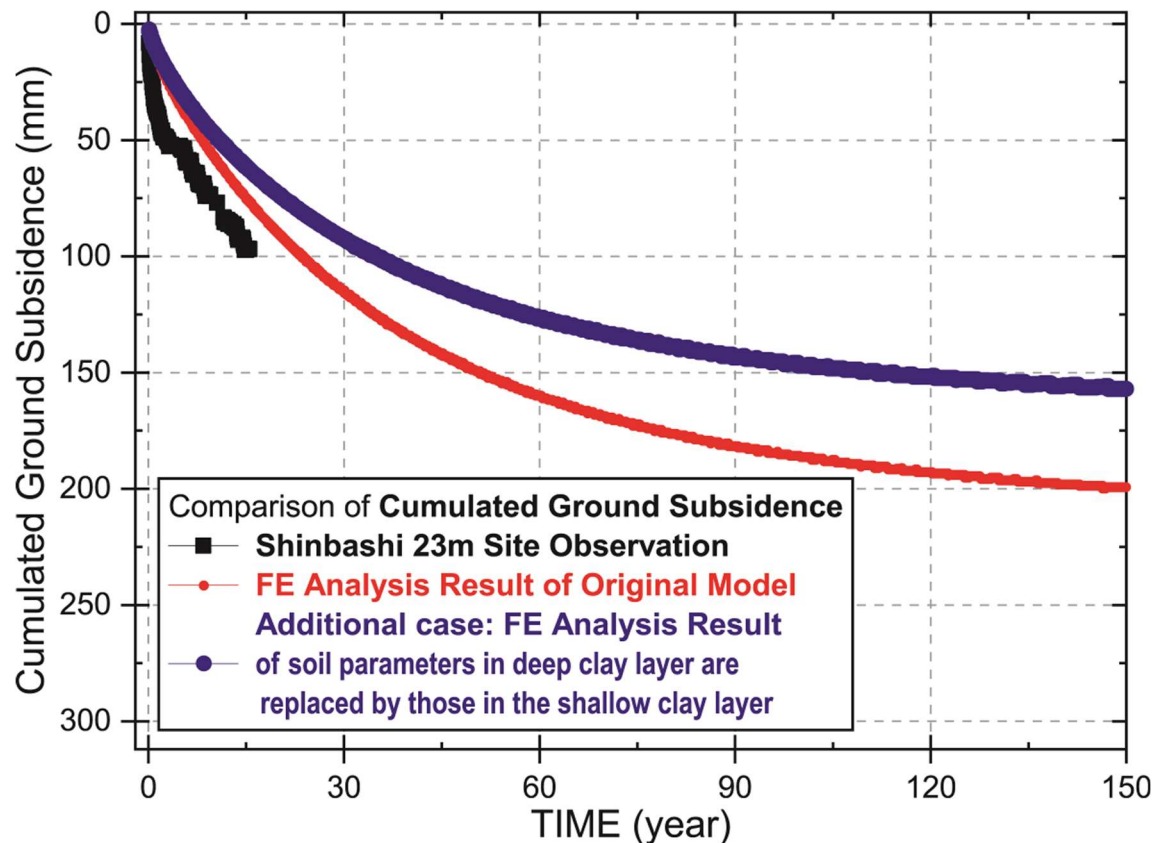


Figure 3-20 Time history comparison between observation, the original FE analysis and the additional simulation case results on the cumulated ground subsidence of soil layers up to 23 m deep

3.6 Summary of Deterministic Finite Element Analysis

The following observations were made:

The structured soft clay with low permeability is widely and deeply in Kashiwazaki City of Niigata Prefecture based on the ground investigation.

Subsidence of ground observed before The Niigataken Chuetsu-oki Earthquake in 2007 was mainly due to groundwater pumping in winter season from the correlation between

fluctuation of ground water table. But the strong correlation between fluctuation of ground water table and post-earthquake subsidence are not observed.

It is confirmed from numerical simulation results based on the ground investigation that highly structured soft clays cause long term post-earthquake subsidence due to (a) the long-term dissipation of excess pore water pressure generated during the large-scale earthquake and (b) the further degradation of the structure of the clay during post-earthquake consolidation process. The characteristics are outstanding for highly structure-susceptible soft clay with weathered seashell presented in deep layer comparing to the less structured soft clay in shallow layer, while meaning the large potential on long term post-earthquake subsidence and high susceptible to damage in structure in the deep layer. Therefore, the deep clay layer will be analyzed detailly in the uncertainty analysis part - Chapter 5.

In addition, it is also found based on the numerical simulation results that the value of C_d (compression index induced by dynamic loading) for the deep layer is greater comparing to the shallow layer. However, it reduces a little with increase of OCR, which is consistent with the conclusion of Ohara and Matsuda (1988).

According to the simulation results using the limited information, it is predicted that the dissipation of the excess pore water pressure and the ground subsidence will last for more than 100 years after the temblor. Although the further investigation is necessary to verify the conclusions because it is influenced by various factors such as topographical distribution, drainage boundary, pumping in winter season and so on, this study clarified the important characteristics of structured soft clay during and after earthquakes.

There are many uncertain factors throughout the entire process of soil mechanics, such as experimental uncertainties, parameter uncertainties, computational model uncertainties, input load uncertainties etc. So, it is necessary to conduct uncertainty analysis in the 2nd important part of the thesis - Uncertainty Analysis.

CHAPTER 4 – UNCERTAINTY QUANTIFICATION METHODS & A NON-INTRUSIVE STOCHASTIC COMPUTATION SOFTWARE

4.1 Abstract

Uncertainty quantification is essential in geotechnical engineering to improve the reliability and accuracy of numerical predictions. This chapter introduces key uncertainty quantification methods, including sensitivity analysis, model factors, and reliability analysis. Sensitivity analysis helps identify influential parameters using techniques such as the Morris method and Sobol analysis. The model factor (M) quantifies deviations between measured and predicted responses, providing insights into the conservatism and accuracy of geotechnical models.

Finally, a non-intrusive stochastic computation software, "JRiver_uncertainty," is developed to enhance uncertainty analysis efficiency using parallel computing. This tool integrates multiple sampling methods, surrogate modeling techniques, and spatial variability analysis, enabling comprehensive geotechnical uncertainty assessment.

4.2 Uncertainty Quantification method - Sensitivity Analysis

Sensitivity analysis is a key technique in uncertainty quantification, helping to determine how input variables influence the output of a model. Common methods include:

(1) Morris Screening Method: A qualitative method that identifies important factors with relatively few simulations. It evaluates the effect of changing one input at a time while considering interactions.

(2) Variance-Based Methods (such as Sobol Analysis): These methods decompose the variance of the output into contributions from individual inputs and their interactions. They provide a more detailed understanding of sensitivity but require more computational effort.

(3) Regression-Based Methods: These methods analyze the relationship between inputs and outputs using statistical models, such as linear regression or machine learning techniques.

(4) Derivative-Based Methods: These methods assess sensitivity based on the derivatives of the output with respect to the inputs, often used in optimization problems.

In addition, from the perspective of single parameter and multi parameter analysis, it can be divided into two types: Local and Global sensitivity analysis. Local Sensitivity Analysis evaluates the effect of

small changes in each parameter while keeping others fixed. Global Sensitivity Analysis examines the contribution of each input variable to the total variance of the output, considering interactions between variables. Among these, Sobol Analysis is one of the most widely used and powerful approaches for both local and global sensitivity analysis.

Sobol Sensitivity Analysis is a variance-based sensitivity analysis method, which quantifies how much of the output variance is caused by each input parameter, both individually and through interactions with other parameters. The core idea of Sobol analysis is to decompose the total variance $\text{Var}(Y)$ of the model output Y into contributions from individual inputs and their interactions. The advantages of Sobol Analysis is that it can capture both individual and interaction effects, while it is applicable to nonlinear models. The Sobol sensitivity indices include:

(1) First-Order Index S_i : Measures the direct contribution of an individual input to the output variance.

(2) Second-Order Index S_{ij} : Captures the interaction effects between two input parameters.

(3) Total Sensitivity Index S_T : Accounts for both direct effects and interactions of a given parameter.

$$S_T = \frac{V_A + V_{AB} + V_{AC} + \dots}{\text{Var}(Y)} \quad (4-1)$$

where:

V_A : The variance caused by input parameter A alone (i.e. first-order effect)

$V_{AB}, V_{AC}, \dots$: The variance (i.e. second-order and third-order interaction terms) generated by the joint action of parameter A and other parameters (such as B, C etc)

$\text{Var}(Y)$: The total variance of the model output Y represents the overall size of all uncertainties.

The Total Sobol Index S_T sums the direct and all interaction effects of an input parameter, reflecting its overall importance:

When calculating, Sobol sequences (a type of quasi-random low-discrepancy sampling) are often used to improve efficiency since Sobol indices rely on variance decomposition and require a large number of model evaluations.

4.3 Uncertainty Quantification method - Model factor M

Model factor is an important approach in uncertainty quantification, used to assess the accuracy and conservatism of numerical predictions by comparing measured and calculated responses.

Geotechnical engineering problems are typically classified into two categories: elastic (deformation) problems and stability problems (Terzaghi, 1943; Terzaghi et al., 1996; Chen, 2007). Elastic (deformation) problems focus on stress distribution and displacement in soil without reaching failure. Typical examples include stress beneath foundations, retaining wall deformations, tunnel settlements, and overall soil consolidation behavior. On the other hand, stability problems involve determining the critical conditions under which soil fails, such as slope failures, bearing capacity failures, and soil liquefaction. Many design codes classify stability-related failures under the ultimate limit state (ULS) framework, while deformation considerations typically fall under the serviceability limit state (SLS) framework.

Due to the natural variability of soil properties, simplifications in numerical models, and construction-induced uncertainties, predicted geotechnical responses often differ from actual measurements. To quantify these deviations, a model factor is introduced by ISO 2015, Phoon and Tang (2019).

However, its definition and focus differ between ULS and SLS analyses. In ULS analysis, the model factor is defined as the ratio of actual load-bearing capacity to predicted load-bearing capacity, reflecting uncertainties related to stability and strength parameters. In SLS analysis, the model factor is defined as the ratio of measured deformation to predicted deformation, primarily accounting for uncertainties in parameters affecting serviceability and deformation performance.

As noted in Annex D of the 4th edition of ISO 2394 (ISO, 2015), the characterization of model uncertainty is a critical component in the geotechnical reliability-based design (RBD) process (Dithinde et al., 2016; Phoon et al., 2016). The model factor can be expressed as the ratio between the measured response ($X_{measured}$) and the calculated response ($X_{calculated}$) in the context of geotechnical uncertainty. For example in the case of ultimate bearing capacity, the larger the model factor ($= X_{measured} / X_{calculated}$), the more conservative is the calculated response.

But in the case of settlement, the situation is exactly the opposite, the larger the calculated value, the more conservative it is. So, the author gave a new definition of Model Factor M:

$$M(t) = \frac{X_{calculated}(t)}{X_{measured}(t)} \quad (4-2)$$

t : time after the earthquake, $0 \leq t \leq 186$ months (latest observation data time is 15.5 years)

$X_{calculated}$: the calculated response, results of Monte-Carlo method at the same time in this study

$X_{measured}$: the measured response, site observation data of subsidence in 15.5 years in this study

The Model Factor M defined in this way has the same trend as the original definition, that is, the larger the value of Model Factor M , the more conservative the calculated value is. Under each sample $Sample_i$ ($i = 1, 2, \dots, n$), there exists a series of time points, and each time point t_i corresponds to a calculated response and a measured response, i.e. a Model Factor $M(t_i)$. A series of time points under a sample $Sample_i$ ($i = 1, 2, \dots, n$) yield a series of Model Factor $M(t_i)$, from which a Mean value and a CV value can be obtained. The larger the Mean value of a series of Model Factor $M(t_i)$ under a sample $Sample_i$, the more averagely conservative the calculated response is throughout the entire time process of one sample. The smaller the CV value of a series of Model Factor $M(t_i)$ under a sample $Sample_i$, the closer the calculated response is to the measured response on average throughout the entire time process of a sample.

Each sample can obtain the Mean and CV values of a series of M values throughout the entire time process under this sample, which are represented as a point on the horizontal and vertical axes in the classification graph of Figure 4-1. All samples form a series of points, and the conservative and dispersion of M can be determined by the classification region where the sample point group is located.

Understanding and correctly applying model factors help engineers improve design safety, optimize probabilistic assessments, and ensure reliable geotechnical performance in both ULS and SLS designs.

The model factor M quantifies both the accuracy and conservatism of geotechnical models. The mean value of M provides engineers with insight into the inherent safety margin, indicating whether the calculation method is generally conservative (mean > 1) or unconservative (mean < 1). However, M is a random variable, and its value can vary depending on the calibration dataset. Thus, even though a method might appear conservative on average, it may not be so for certain datasets or specific conditions. Therefore, in addition to the mean, it is important to consider the dispersion of M , ensuring that the probability of the measured value falling below the calculated value remains within acceptable limits.

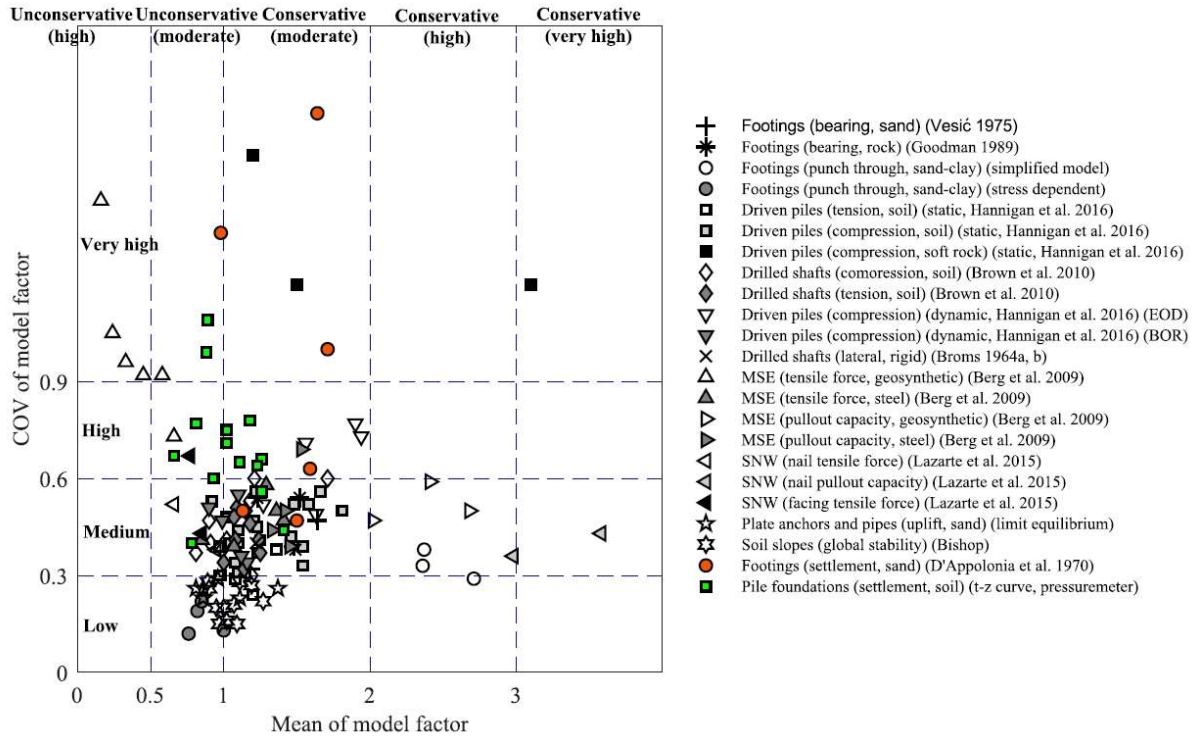
Figure 4-1, sourced from Phoon (2019) and an exceptionally informative manual, presents the mean and coefficient of variation (CV) of data groups corresponding to the same geotechnical structure, limit state, and geomaterial, along with the number of tests (N). They classified model factors based on the mean and coefficient of variation (CV). Specifically, the model factor can be classified as:

- (1) moderately conservative ($1 \leq \text{mean} < 2$),
- (2) highly conservative ($2 \leq \text{mean} < 3$),

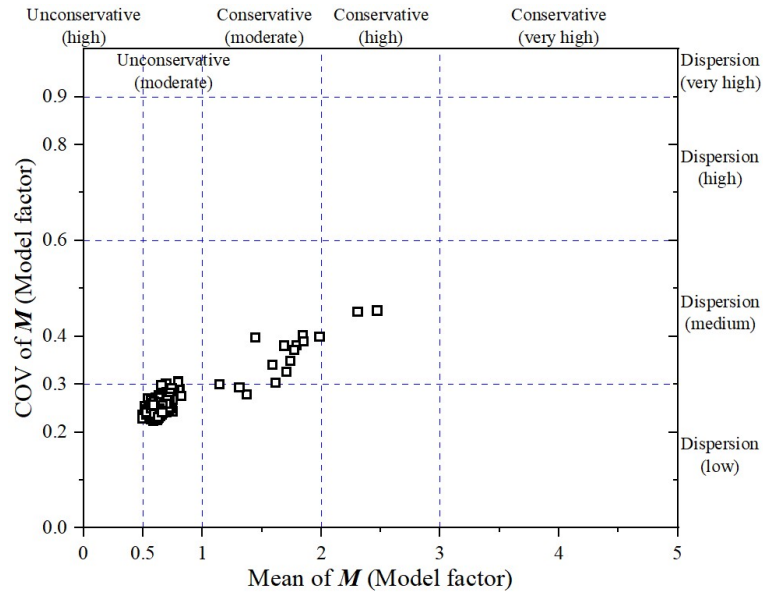
(3) very highly conservative (mean ≥ 3).

For the uncertainty associated with the model, they categorized it into four levels of dispersion:

- (1) low dispersion ($CV < 0.3$),
- (2) medium dispersion ($0.3 \leq CV < 0.6$),
- (3) high dispersion ($0.6 \leq CV < 0.9$),
- (4) very high dispersion ($CV \geq 0.9$).



(a) Classification figure of Model factor (Phoon, K.K. and Tang, C., 2019)



(b) Classification figure of Model factor (Phoon, K.K. and Tang, C., 2019)

Figure 4-1 Classification of Model factor based on the mean (bias) and COV (dispersion) of M

Multiple studies highlight the importance of model factors in calibrating and validating numerical models. In this study, the classification and interpretation of M and its associated uncertainty help improve understanding of the simulation's reliability and conservatism.

4.4 Uncertainty Quantification Application method - Reliability of allowable settlement

Reliability analysis is a crucial application of uncertainty quantification, helping to evaluate the probability that a geotechnical system meets performance requirements.

(1) Allowable Settlement

The allowable settlement in geotechnical engineering can vary depending on several factors, including the type of structure, the foundation design, and the soil conditions. Many buildings can handle some settlement without damage. In clay soils, typical allowable settlement ranges from 25-130 mm. According to Bjerrum (1963), a maximum settlement of 11 cm (110 mm) was given. Skempton and MacDonald's classic study (1956) found that frame structures on isolated footings generally remain undamaged with settlements under 3 inches (76.2 mm), and this can extend to 3 - 5 inches (76.2 mm - 127 mm) on rafts footings. For raft foundations, Tomlinson (1995) noted that settlements of 50-100 mm

are often acceptable.

In this study, we use 100 mm as the tolerable (allowable) settlements.

(2) Reliability

In geotechnical engineering, the reliability of soil settlement is typically evaluated based on allowable settlement limits. Allowable settlement refers to the maximum settlement a structure can tolerate without experiencing significant functional or structural damage. To assess settlement reliability, the observed or predicted settlement values are compared against these thresholds, and the probability of staying within the acceptable limit is quantified to ensure structural performance and safety.

Previous studies, such as Wang (2015), have widely applied Monte Carlo Simulation (MCS) and Reliability Index Approaches to estimate the probability of excessive settlement, thus quantifying failure risks. In this study, Monte Carlo simulations are used to model the reliability of settlement predictions, where key parameters such as soil stiffness and load conditions are treated as random variables with specified probability distributions. The simulation results are compared against the allowable settlement limits, and the reliability index is calculated following the framework proposed by Baecher (2005) and Christian (1993).

The reliability function can be formally expressed as:

$$\beta = P\{g_X(X_1, X_2, \dots, X_n) - S \leq 0\} = \frac{M}{N} \quad (4-3)$$

where:

β : Reliability index or probability of satisfactory performance.

$g_X(X_1, X_2, \dots, X_n)$: Performance function (limit state function) depending on random variables $X_1, X_2, \dots, X_n$.

S : Threshold or safety limit, in the study it is the allowable value of settlement.

N : Total number of states.

M : Number of successful states. According to the law of large numbers, the ratio of M/N is closed to the probability when N is large enough.

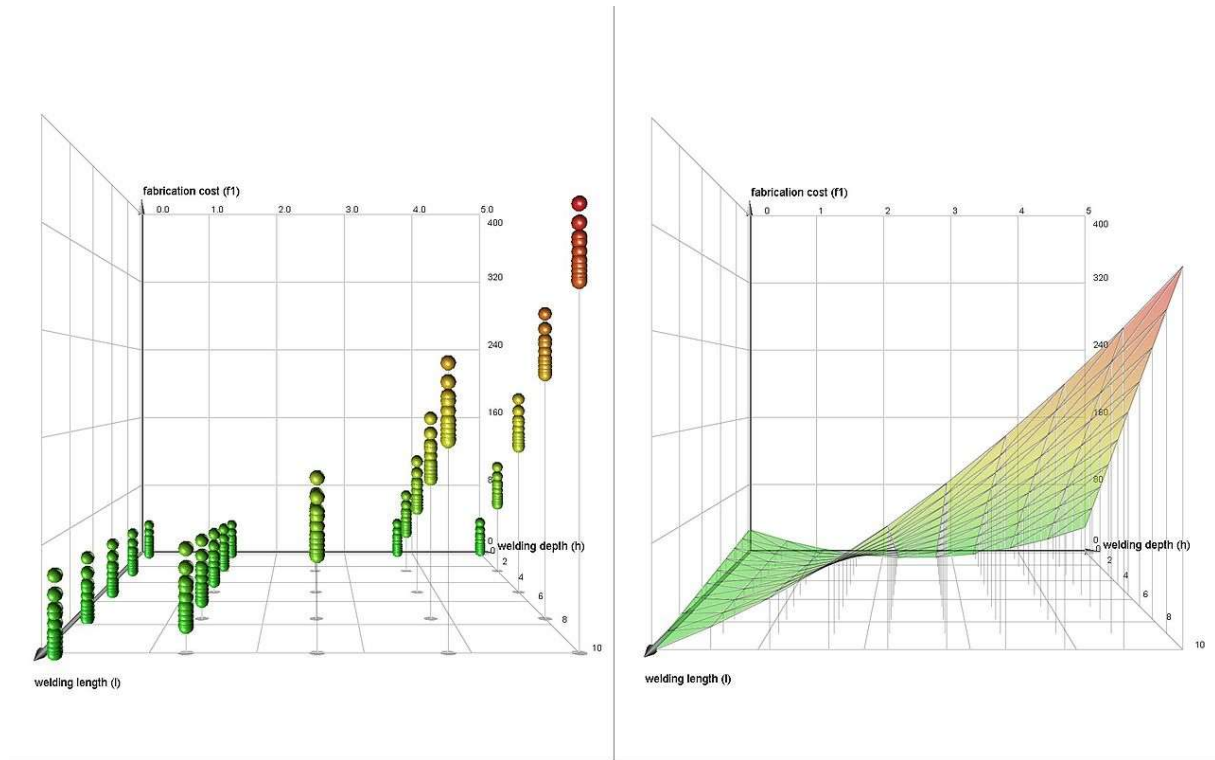
This reliability-based approach allows for a comprehensive consideration of uncertainties in soil properties and loading conditions, leading to more realistic settlement predictions. For projects involving significant loading or soft ground conditions, this method helps ensure that the design maintains an adequate safety margin, mitigating risks associated with excessive settlement.

4.5 Surrogate Model - Stochastic Response Surface Method (SRSM)

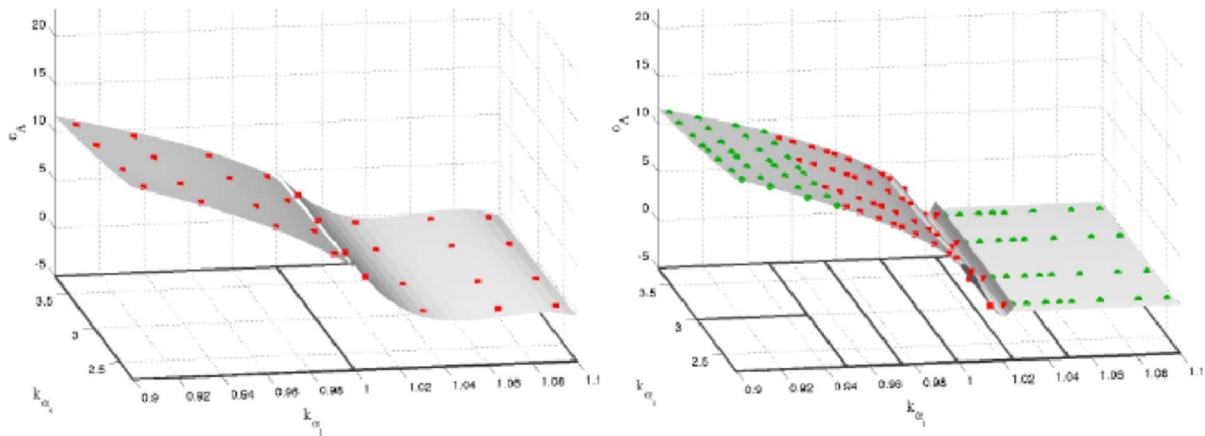
(1) Concept and Principle

Response Surface is a mathematical approximation that establishes an explicit relationship between input parameters and system outputs. This technique can be used to approximate the input-output relationship of complex numerical models using a simplified mathematical surface called a "response surface." The purpose is to replace the expensive model evaluations with a surrogate that can quickly predict output values, which is especially useful for uncertainty quantification, sensitivity analysis, and reliability assessment. In geotechnical uncertainty analysis, it replaces computationally expensive numerical models such as finite element simulations by fitting an explicit function using limited sample points. The key idea is to approximate the input-output behaviour of a black-box model with an analytical function, enabling efficient stochastic analysis (such as Monte Carlo simulation) on the surrogate model. Response Surface and limited sample points can be seen in the conceptual diagram Figure 4-2.

Stochastic Response Surface Method (SRSM) builds on this concept by incorporating the uncertainty in the input variables. SRSM treats the inputs as random variables, generates sample points accordingly, and uses the resulting model responses to fit a surrogate model that captures the probabilistic behavior of the system.



(a) Sample points and Response Surface (From Wikipedia, Response_surface_metodology)



(b) Response Surface with sample points (Le Meitour et al., 2010)

Figure 4-2 Conceptual diagram of Response Surface and limited sample points

(2) General steps of SRSM

1st step - Experimental Design: Generate representative input samples in the parameter space using an appropriate method such as Latin Hypercube Sampling (LHS) or Sobol sequences, and use the numerical model to compute the corresponding representative output points.

2nd step - Response Surface built by fitting model: Fit a response surface model using an interpolation method (such as polynomial regression, Polynomial Chaos Expansion, Kriging model) based on the representative points.

3rd step - Validation: Accuracy of the Stochastic Response Surface is evaluated via independent test sets, residual analysis, or Monte Carlo validation.

4th step - New samples generation and analysis: Larger scale sampling on the validated Stochastic Response Surface can compute failure probabilities or reliability and other uncertainty characteristics.

(3) Response Surface fitting model

SRSM relies on various interpolation and regression techniques to construct response surfaces. Some commonly used models include:

- 1) Simple Linear Regression: The most basic approach, fitting a straight line to the data.
- 2) Polynomial Regression: Uses higher-order polynomials to improve approximation accuracy.
- 3) Polynomial Chaos Expansion (PCE): Extends polynomial regression using orthogonal polynomials to represent stochastic behaviour.
- 4) Sparse PCE: A modified version of PCE that selects only the most significant terms to improve efficiency.
- 5) Simple Kriging: A fundamental Kriging method using a spatial correlation model to make predictions.
- 6) Standard Kriging: A more general form of Kriging that adapts to different correlation structures.
- 7) Active Learning Kriging (without machine learning functions): A strategy that adaptively selects new sample points to improve the response surface.
- 8) Machine Learning-Assisted Active Learning Kriging: Combines machine learning techniques with active learning strategies to enhance Kriging model performance.

These interpolation models provide flexible and efficient ways to approximate complex numerical simulations, ensuring that SRSM can effectively balance computational efficiency and accuracy in geotechnical applications.

In the exploratory study of Section 5.8, Polynomial Regression is used because it is a commonly used SRSM fitting model. It fits a first- or second-order or higher polynomial using least squares, which allows the model to capture nonlinear effects and variable interactions. For example, a second-order model includes squared terms and cross-product terms, providing better flexibility in approximating

complex response patterns. Polynomial regression of second-order can be expressed as follows:

$$y = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \sum_{j=1}^n \beta_{ij} x_i x_j + \epsilon \quad (4-4)$$

where:

y : Model output (response value)

x_i : The i input variables

$\beta_0, \beta_i, \beta_j$: Regression coefficient (to be fitted)

ϵ : Error term

(4) Validation Method

The method commonly used by the author is Independent Test Set Validation. Independent test set validation randomly splits data into training and test sets. The model is trained on the training data and then evaluated on the test data to estimate prediction errors via Mean Squared Error (MSE) and Coefficient of Determination R^2 on the test set.

(5) Advanced Methods and Future Prospects

Polynomial Chaos Expansion (PCE) and Kriging are currently among the most advanced techniques in geotechnical reliability analysis using stochastic response surface modeling (SRSM). They are particularly powerful in handling complex and nonlinear systems under uncertainty. In recent years, the integration of machine learning approaches—such as support vector regression and neural networks—into SRSM frameworks has also gained popularity, especially in areas like adaptive sampling and active learning, aiming to improve both accuracy and computational efficiency. In future work, the author plans to further develop and validate the implementation of PCE and Kriging models to enhance the efficiency and generalization of surrogate models. This effort is expected to contribute to more robust and efficient tools for uncertainty quantification and reliability assessment in practical geotechnical applications.

4.6 A Non-Intrusive Stochastic Computation Software

(1) Introduction of the Software

Based on the deterministic simulation, A non-intrusive Stochastic Finite Element Analysis (SFEA) software based on parallel computing was made and the Monte-Carlo method is used to analyze the parameter and model uncertainty.

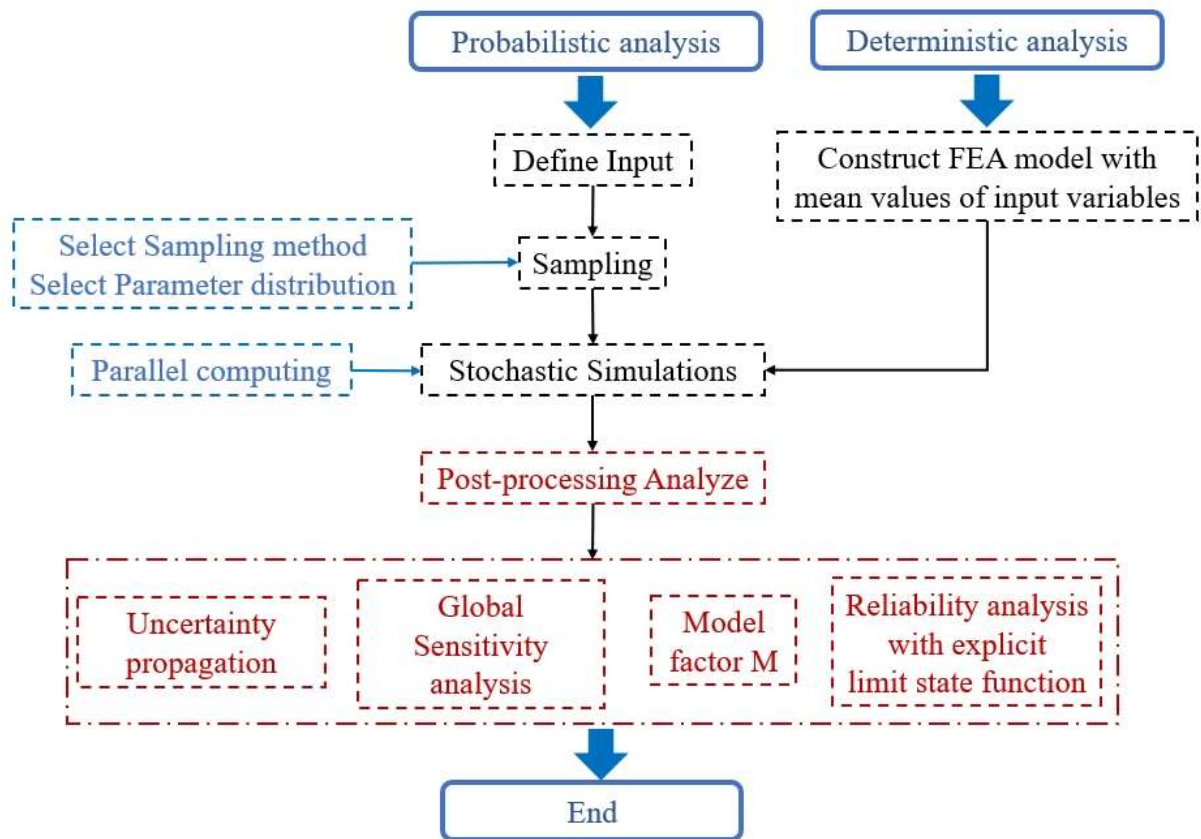


Figure 4-3 Workflow of the non-intrusive SFEA

This section presents the development of a non-intrusive Stochastic Finite Element Analysis (SFEA), named “JRiver_uncertainty”, specifically designed for addressing large-scale uncertainty problems in complex geotechnical engineering applications. Built upon parallel computing technique, the software enables efficient handling of computationally demanding problems, with the details of its parallel performance enhancement discussed in the subsequent section. Its non-intrusive framework enables users to perform stochastic simulations without modifying existing deterministic finite element codes, thereby significantly enhancing computational efficiency. The workflow of the non-intrusive SFEA can be seen in Figure 4-3.

(a) Main menu

(b) Customizing numerical models selecting menu

Figure 4-4 The GUI of the software

As is shown in Figure 4-4 (a) which is the GUI of the software, the software allows users to perform probabilistic analysis using an existing executable program (.exe) such as a FE program. Additionally, users can specify the number of parallel processing threads. Besides, Users can choose to perform Sobol sensitivity analysis and must specify whether to include spatial variability and stochastic response surface analysis on this page.

In addition to finite element model computations, the software also supports users in customizing numerical models such as nonlinear algebraic equations for uncertainty analysis through either a plain text file or the graphical user interface (GUI) which is shown in Figure 4-4 (b).

The screenshot shows the 'Model Uncertainty' module GUI. It has four tabs: 'Program Selection', 'Model Uncertainty' (selected), 'Spatial Variation', and 'Stochastic Response Surface Method'. The 'Parameter selecting' section on the left includes a 'Total parameters number' dropdown set to 2, and fields for 'Parameter Name', 'Parameter ID', 'Parameter location in datafile', 'Row', 'Start column', and 'End column'. The 'Sampling selecting' section on the right includes a 'Sampling Number' field, a 'Sampling Method' dropdown set to 'Latin Hypercube', a 'Distribution' dropdown set to 'Gaussian', a 'Burn-in' checkbox, and an 'A-D Norm. test Stat. Up limit' field set to 0.15.

(a) The GUI of Model Uncertainty module

This screenshot shows the 'Sampling selecting' section with the 'Sampling Method' dropdown menu open. The menu lists four options: 'Step Increment' (selected), 'Direct Monte-Carlo', 'Latin Hypercube', and 'Sobol'.

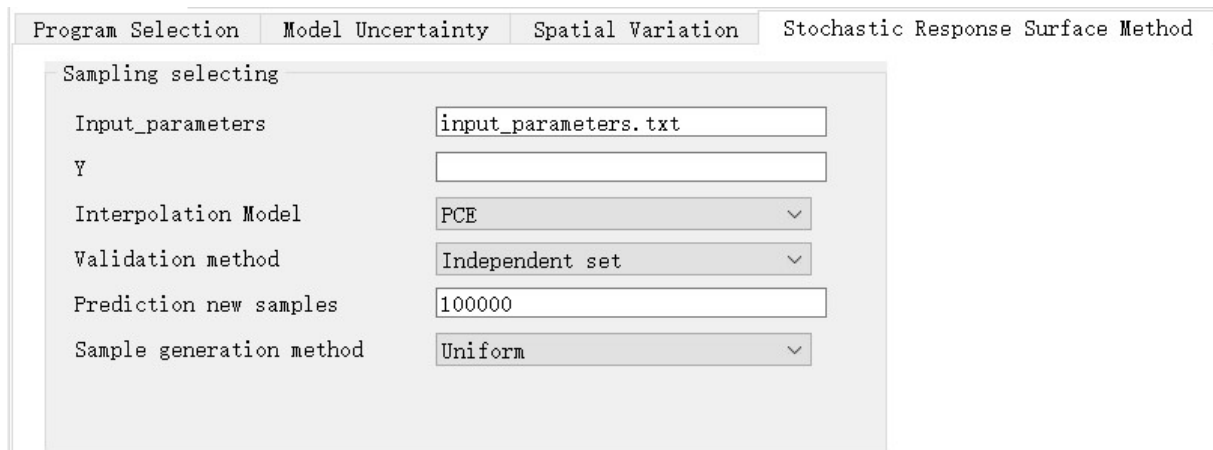
(b) Sampling Method menu

This screenshot shows the 'Sampling selecting' section with the 'Distribution' dropdown menu open. The menu lists six options: 'Linear(for Step-increment)' (selected), 'Linear(for Step-increment)', 'Gaussian', 'Log-Gaussian', 'Expotional', and 'Poison'.

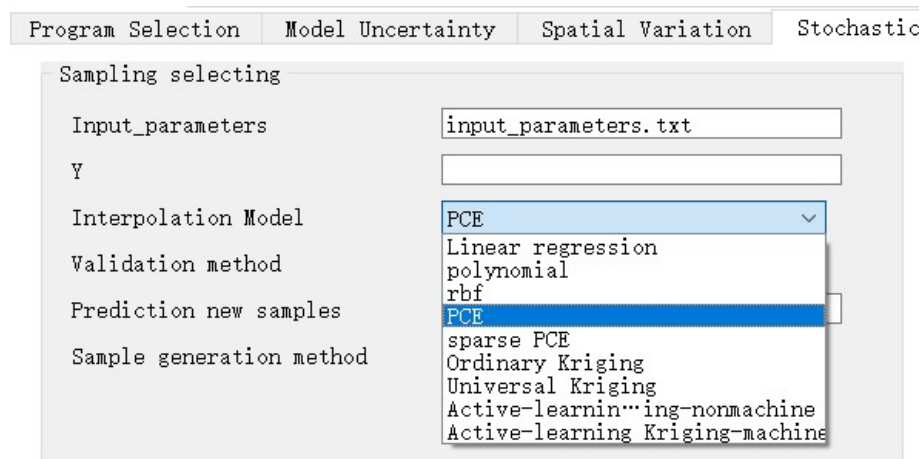
(c) Distribution type menu

Figure 4-5 Model Uncertainty module

In terms of stochastic simulation input capabilities, the software integrates a diverse array of sophisticated probabilistic sampling methods. Figure 4-5 shows the Model Uncertainty module. In the model uncertainty analysis, users can choose between single-parameter or multi-parameter analysis, select a sampling method (linear increment, Direct Monte-Carlo sampling, Latin Hypercube Sampling, or Sobol sequence), and define a probability distribution type (linear increment, normal, lognormal, exponential, or Poisson distribution). Notably, for single-parameter sampling, the software offers a burn-in process option and implements adaptive sampling through the specification of an upper limit for the Anderson-Darling test statistic, substantially improving sampling efficiency and accuracy.



(a) The GUI of SRSM module



(b) Interpolation Model menu

Figure 4-6 Stochastic Response Surface Methods (SRSM) module

As is shown in Figure 4-6, users can perform surrogate modeling through stochastic response surface methods (SRSM). Available interpolation models include simple linear regression, polynomial regression, Polynomial Chaos Expansion (PCE), sparse PCE, simple Kriging, standard Kriging, active learning Kriging (without machine learning functions), and machine learning-assisted active learning Kriging models. Multiple validation methods are available, including independent test sets, residual analysis, and Monte Carlo validation. However, this part of the algorithm is still being refined and tested.

Program Selection Model Uncertainty **Spatial Variation** Stochastic Response Surface Method

Parameter selecting

Total parameters number 2

Parameter Name Parameter ID

Parameter location in datafile

Row Start column End column

Distribution para 1 Distribution para 2

Distribution para 3 Distribution para 4

Add Parameter

Spatial parameters

X - Total distance (m)

Y - Total distance (m)

X - Grid_spacing (m)

Y - Grid_spacing (m)

Mean value μ

Coefficient of Variance

X - Fluctuation Scale (m)

Y - Fluctuation Scale (m)

Covariance function Exponential Squared

Distribution Log-Gaussian

Sampling selecting

Sampling Number

Sampling Method Latin Hypercube

Distribution Gaussian

☐ Burn-in

A-D Norm.test Stat.Up limit 0.15

Statistic Value Allowing Up limit

(a) The GUI of Spatial variation module

Spatial parameters

X - Total distance (m)

Y - Total distance (m)

X - Grid_spacing (m)

Y - Grid_spacing (m)

Mean value μ

Coefficient of Variance

X - Fluctuation Scale (m)

Y - Fluctuation Scale (m)

Covariance function Exponential Squared

Distribution

Exponential Squared

Gaussian Kernel

Exponential

Spherical

Exponential Squared

(b) Covariance function menu

Figure 4-7 Spatial variation module

As is shown in Figure 4-7, users can perform spatial variability analysis in geotechnical engineering, currently limited to 2D random field generation based on generalized Karhunen–Loève (K-L) expansion. 4 different covariance functions can be selected and fluctuation scale is needed for spatial correlation

modeling. 3D random field generation which is quite complex cannot be achieved temporarily.

In conclusion, “JRiver_uncertainty” provides engineers and researchers with a robust and flexible computational platform that significantly augments the capacity for efficient and accurate stochastic finite element analysis. This not only advances reliability analysis and risk assessment in geotechnical engineering but also offers a valuable tool for uncertainty quantification research across various engineering disciplines.

(2) Parallel computing

"JRiver_uncertainty" adopts CPU parallel computing rather than GPU computing, as its computational tasks primarily rely on CPU processing power rather than GPU's high-throughput capabilities. Given that these simulation tasks are not heavily dependent on I/O operations, multiprocessing was chosen over multithreading. Multiprocessing helps overcome the Global Interpreter Lock (GIL) limitation, ensuring each process operates within its own memory space, which enhances system stability and simplifies error handling. This approach is particularly suitable for large-scale, compute-intensive stochastic finite element simulations.

Although multiprocessing introduces some inter-process communication overhead, this overhead is negligible compared to the total computation time. Performance tests indicate that with a 12-core CPU, computational speed improves by approximately fourfold, while with a 24-core CPU, performance increases by a factor of 4 to 5 (see Figure 4-8). These results demonstrate that adding more CPU cores significantly enhances computational efficiency, especially in large-scale geotechnical simulations.

The reason why the actual growth in analysis speed is not as high as the number of threads increases is that: (1) The matrix processing part of the FE software used is based on the Intel MKL library, which consumes a lot of memory when running complex geotechnical models. The memory performance limits parallel efficiency more than the upper limit of CPU cores. But the author did not use a computer with particularly high-performance memory for performance testing. (2) Thread competition, when multiple threads simultaneously access shared resources such as memory or CPU cache, can trigger competition.

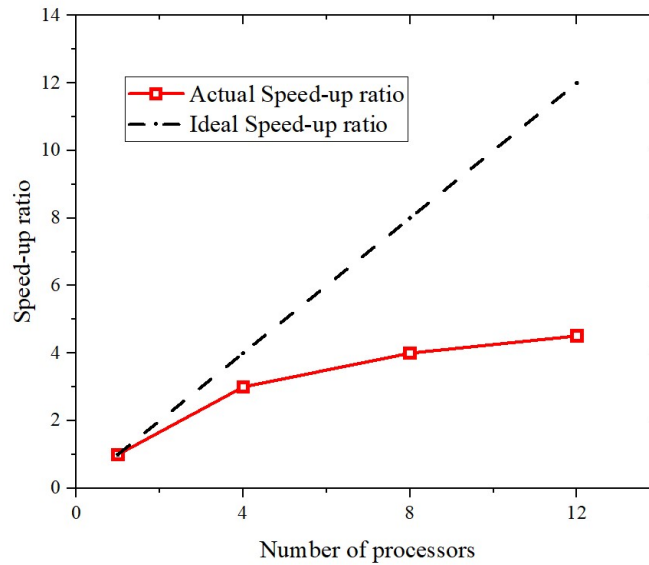


Figure 4-8 CPU parallel computing performance tests

Furthermore, parallel computing is highly scalable, making it particularly effective when handling a large number of random samples. As sample size increases, multi-core CPUs distribute computational tasks efficiently, reducing overall computation time. This approach allows users to adjust resource allocation based on specific hardware configurations or computing clusters, ensuring optimal performance.

Looking forward, we aim to further optimize parallel computing algorithms and explore hybrid CPU-GPU computing and distributed computing to enhance computational efficiency and support larger-scale engineering applications.

CHAPTER 5 – STOCHASTIC ANALYSIS RESULTS

5.1 Abstract

This chapter examines the variability of input parameters of deep clay and their impact on settlement predictions and reliability assessments. The coefficient of variation (CV) for each parameter of deep clay is determined based on well-established literature, ensuring realistic uncertainty representation. Monte Carlo simulations and Taylor expansion are applied to transform parameters like R^*_o and R_f , confirming that Monte Carlo provides more accurate estimates for high CV values. To evaluate the influence of sampling methods and sample sizes, four different cases were considered in this study: (1) LHS with normal distribution, 1000 samples, (2) LHS with uniform distribution, 1000 samples, (3) LHS with uniform distribution, 2000 samples, (4) Sobol sequence, 5120 samples.

Sobol sensitivity analysis reveals that for the Deep clay parameters, the most influential parameters ranking is: initial soil structure R^*_o and permeability k , strength-related parameter Stress ratio at critical state R_f , saturated unit weight γ_{sat} , maximum historical pre-consolidation pressure (p'_c). Among the 8 input parameters of Deep clay, the first 3 influential parameters (k , R^*_o , R_f) of Deep clay are dominant which contribute around 60% to both the settlement of Deep clay layer and All layers, and the first 5 parameters contributed 80 - 85%. These findings highlight the importance of accurate soil characterization and permeability estimation in geotechnical design.

As for Uncertainty Propagation analysis, the computation model shows Propagation Robustness and Inherent Model Security.

The model factor M results show that minimal influence occurs from sampling methods (LHS, Sobol) and probability distributions (uniform, normal), confirming model robustness. The settlement calculation exhibits "moderately conservative to moderately unconservative" characteristics with "medium to low dispersion".

Reliability analysis shows that the Reliability of the subsidence no more than 100 mm in 20 years is 79% (corresponding to a failure probability of 21%) and the Reliability of the subsidence no more than 100 mm in 25 years is 44% (corresponding to a failure probability of 56%). LHS with a uniform distribution provides a good balance between accuracy and computational efficiency, while normal distribution sampling introduces larger errors.

As for Stochastic Response Surface Method, it allows reliable uncertainty quantification results with significantly reduced computational cost with proper sample selection and regression modelling.

These results emphasize the need for reliable soil property measurements, long-term monitoring, and careful selection of probability distributions in geotechnical risk assessments. The findings provide useful insights for optimizing foundation design and minimizing settlement risks in practice.

5.2 Input coefficient of variation (CV) of Deep clay

The input parameters follow a Gaussian distribution, uniform distribution, or Sobol sequence, with their uncertainty quantified by the coefficient of variation (CV). The CV values of deep clay are primarily derived from statistical data provided in well-known literature, including the classic studies of Duncan (2000) and Phoon (1999), as well as the latest report by Ching et al. (2021). Additionally, studies by Kim (2012), Tan (2007), and Wang (2015) are referenced to supplement the data and for cross-validation.

This study considers eight uncertain parameters of deep clay, namely N , λ , κ , p'_c , γ_{sat} , k , R^*_0 and R_f . The first six parameters have their CV values directly sourced from the above literature. However, R^*_0 and R_f require further transformation and processing to derive appropriate CV values for analysis.

For R^*_0 of deep clay, which represents the inverse of clay sensitivity ($R^*_0 = 1/\text{sensitivity}$), the transformation is relatively straightforward. We utilized Monte Carlo simulations (100,000,000 samples) and higher-order Taylor expansion for comparison and validation. Theoretically, Taylor expansion is less suitable for high CV values, which is confirmed by our results showing that Monte Carlo methods yield more reasonable estimates. The corresponding Python code is provided in the appendix.

For R_f of deep clay, it can be derived from the friction angle ϕ using the following Equations (5-1) (5-2). We applied Monte Carlo simulations (100,000,000 samples) to transform the results, yielding CV (R_f) values ranging from 0.046 to 0.18.

$$M = \frac{6\sin(\phi)}{3 - \sin(\phi)} \quad (5-1)$$

$$R_f = \frac{2M+3}{3-M} \quad (5-2)$$

Furthermore, the selection of these parameters is well justified, as they significantly impact foundation settlement and seepage calculations and exhibit substantial variability in real-world engineering projects. The final CV values align well with prior studies and engineering experience,

reinforcing the reliability of the analysis.

An error analysis is also crucial in the CV calculation process. While the Taylor expansion method provides quick estimates in some cases, it can introduce significant errors when CV values are large. In this study, Monte Carlo simulations were chosen for higher computational accuracy, reducing transformation-induced errors.

The role of CV in subsequent analysis is particularly important in stochastic modeling, including Sobol sensitivity analysis and reliability assessments. Properly selected CV values directly influence the accuracy of the final results. Therefore, in foundation design, settlement prediction, and risk evaluation, careful determination of parameter variability is essential, and field test data should be used for validation.

The final CV values of Deep clay used in the stochastic analysis are shown in Table 5-1.

Table 5-1 CV of Deep clay used in the Stochastic analysis

		Coefficient of Variation (CV)	
		Single parameter CV	Global CV
Compression index	λ	0.1 - 0.2 - 0.37	0.235
Swelling index	κ	0.1 - 0.2 - 0.37	0.235
Maximum historical preconsolidation pressure	p'_c	0.1 - 0.2 - 0.35	0.225
Void ratio ($p' = 98$ kPa on N.C.L.)	N	0.07 - 0.2 - 0.3	0.185
Saturated unit weight [kN/m ³]	γ_{sat}	0.01 - 0.1	0.050
Permeability [m/sec]	k	0.68 - 0.8 - 0.9	0.800
Initial degree of structure	R_0^*	0.1 - 0.34 - 0.58	0.350
Stress ratio at critical state	R_f	0.05 - 0.12 - 0.2	0.200

5.3 Number of Samples

In Monte Carlo simulations, determining an appropriate sample size is a key challenge, especially when dealing with computationally expensive geotechnical models. The sample size directly affects both the accuracy of probability estimates and the computational cost.

To begin with, the author conducts the analysis of the sample size requirement in the case of single

parameter calculation.

According to Yusuke Honjo and other researchers, estimates based on Chebyshev's inequality tend to be overly conservative. Chebyshev's inequality is given as Equation (5-3):

$$N \geq \frac{P_f(1-P_f)}{(1-\alpha)\delta^2 P_f^2} = \frac{(1/P_f)-1}{(1-\alpha)\delta^2} \approx \frac{1}{(1-\alpha)\delta^2 P_f} \quad (5-3)$$

where:

N : Minimum required sample size

α : Confidence level

δ : Allowable error

P_f : Probability of Failure

For example, to estimate a $P_f = 1\%$ with a $\delta = \pm 10\%$ at a 95% confidence level, Chebyshev's inequality suggests that more than 200,000 samples are needed. However, such a large sample size is impractical for complex numerical models due to excessive computational demands.

A more practical estimate comes from the Broding's inequality (1964), which suggests that for $P_f = 1\%$, a much lower sample size of approximately 300 is sufficient, making Monte Carlo simulations feasible for most geotechnical applications. Furthermore, if we slightly relax the accuracy requirement for P_f , the required sample size can be further reduced. Broding inequality is given as Equation (5-4):

$$M \geq \frac{-\ln(1-C)}{1-R_0} \quad (5-4)$$

where:

M : Minimum required sample size

C : Confidence level

R_0 : Target reliability

$1 - R_0$: P_f - Probability of Failure

Griffiths & Fenton (2008) provide another useful guideline, shown in Equation (5-5) particularly for risk assessment in geotechnical engineering in their famous book: if the confidence level is lowered to 90%, the required sample size can drop below 100 in certain cases.

$$n \cong \left(\frac{z_{\alpha/2} \sigma_g}{e} \right)^2 \quad (5-5)$$

where:

n : Minimum required sample size

$z_{\alpha/2}$: Quantile of standard normal distribution

σ_g : Estimated value of sample standard deviation

e : Maximum allowable estimation error

These findings highlight the need to carefully select an appropriate probabilistic framework when applying Monte Carlo methods. A good balance between computational efficiency and statistical reliability is crucial. The above situation mainly involves estimating the sample size required for single parameter analysis. When considering multi parameter calculations, the sample size requirement will not simply increase exponentially with the number of parameters. Because there is often coupling correlation between parameters, the importance and influence of different parameters vary, and advanced sampling methods can be used. Each specific analysis condition is different, and the required sample size is often estimated through practical approximation methods.

To evaluate the influence of sampling methods and sample sizes, four different cases were considered in this study:

- (1) LHS with normal distribution, 1000 samples
- (2) LHS with uniform distribution, 1000 samples
- (3) LHS with uniform distribution, 2000 samples
- (4) Sobol sequence, 5120 samples

These cases were selected to compare the effects of different distributions, sample sizes, and low-discrepancy sequences on the reliability assessment of geotechnical models. By analyzing these cases, we aim to determine the optimal sampling strategy that provides accurate probability estimates while keeping computational costs manageable.

5.4 Results of Reliability

The reliability analysis results of deep clay for 100 mm allowable settlement values are shown in Figure 5-1. When using Sobol Sequence with 5120 samples or Latin Hypercube Sampling (LHS) with a uniform distribution (2000 samples), the Reliability of the subsidence no more than 100 mm in 20 years is 79% (corresponding to a failure probability of 21%) and the Reliability of the subsidence no more than 100 mm in 25 years is 44% (corresponding to a failure probability of 56%).

A Sobol Sequence with 5120 samples implies higher computational accuracy. It can be seen that under the uniform distribution of LHS sampling, the reliability is close to high-precision results for both

1000 and 2000 samples. However, under Gaussian distribution sampling, there are significant errors. The analysis shows that LHS with a uniform distribution provides results close to those obtained with the Sobol sequence method, which is more accurate but computationally more demanding. This suggests that even with fewer samples, LHS with a uniform distribution can still deliver reasonable accuracy. This is because when LHS adopts a uniform distribution, its sample distribution characteristics are closer to Sobol sequences. However, when using a normal distribution in LHS, the results show larger deviations. This highlights that while advanced sampling techniques can improve computational efficiency, the choice of probability distribution has a significant impact on result accuracy.

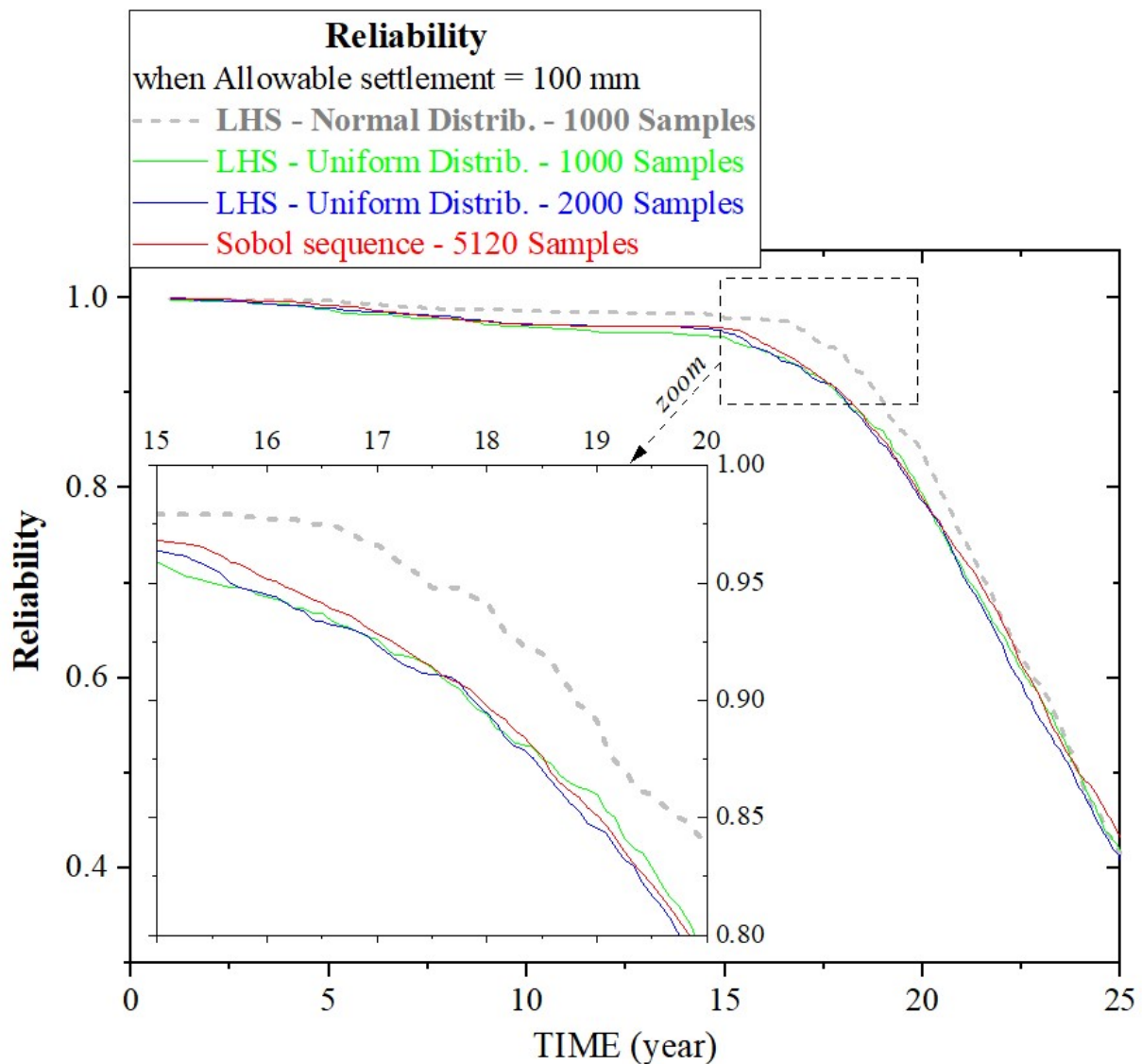


Figure 5-1 Reliability when allowable settlement = 100 mm

As for engineering significance, the results indicate that the probability of exceeding settlement thresholds (100mm) is not negligible over a long period. For soft clay foundations, this suggests that long-term monitoring and preventive measures should be considered during the design phase to reduce the risk of excessive settlement. Although Sobol sequences provide high accuracy, the study shows that LHS with uniform distribution offers a good balance between accuracy and computational efficiency. This is particularly valuable in large-scale engineering projects where computational resources are limited. The significant deviation observed when using a normal distribution highlights the need to carefully select an appropriate probability distribution for settlement analysis. Over-reliance on standard distributions without validation can lead to inaccurate risk assessments, affecting engineering decisions.

As for practical recommendations, for soft clay foundations, using LHS with a uniform distribution is a practical and efficient choice when computational resources are limited. Engineering teams should validate the assumed probability distribution with field data to ensure accurate predictions.

This section emphasizes that the sampling method and probability distribution choice significantly impact settlement reliability analysis. While LHS with a uniform distribution is computationally efficient, Sobol sequences provide higher accuracy. For engineering applications, a balanced approach considering both computational cost and result reliability is essential. Additionally, validating probability distributions with real-world data can help improve prediction accuracy and guide better decision-making.

5.5 Results of Global Sensitivity analysis of 8 Deep clay Parameters

(1) Output: Deep clay layer's subsidence

Firstly, when the output is the subsidence of Deep clay layer, the results will be discussed.

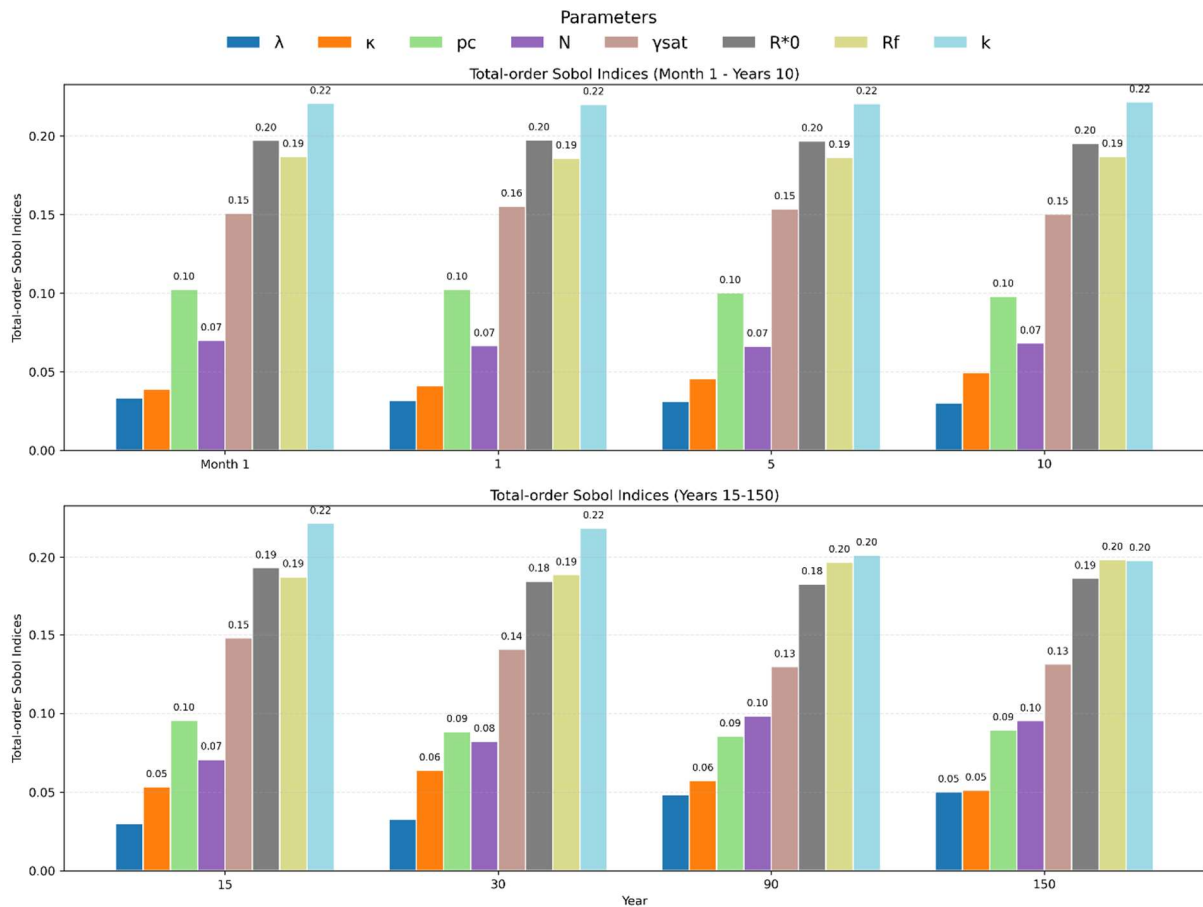
The 8 Deep clay Parameters' influence on the subsidence of Deep clay layer is given below using the Global Sensitivity analysis. The Total Sobol Indices of the 8 Deep clay Parameters are shown in Figure 5-2: (a) all specific years, (b) Month 1 which is approximate to earthquake - induced deformation, (c) year 1, (d) year 5, (e) year 10, (f) year 15, (g) year 30, (h) year 90, (i) year 150.

The figures clearly indicate that k (permeability) and R^*_o (initial soil structure parameter) of Deep clay are the most influential factors on the subsidence of Deep clay layer, consistently showing high total-order indices (around 0.18 - 0.23) across all time periods, and the Sobol index remained very stable

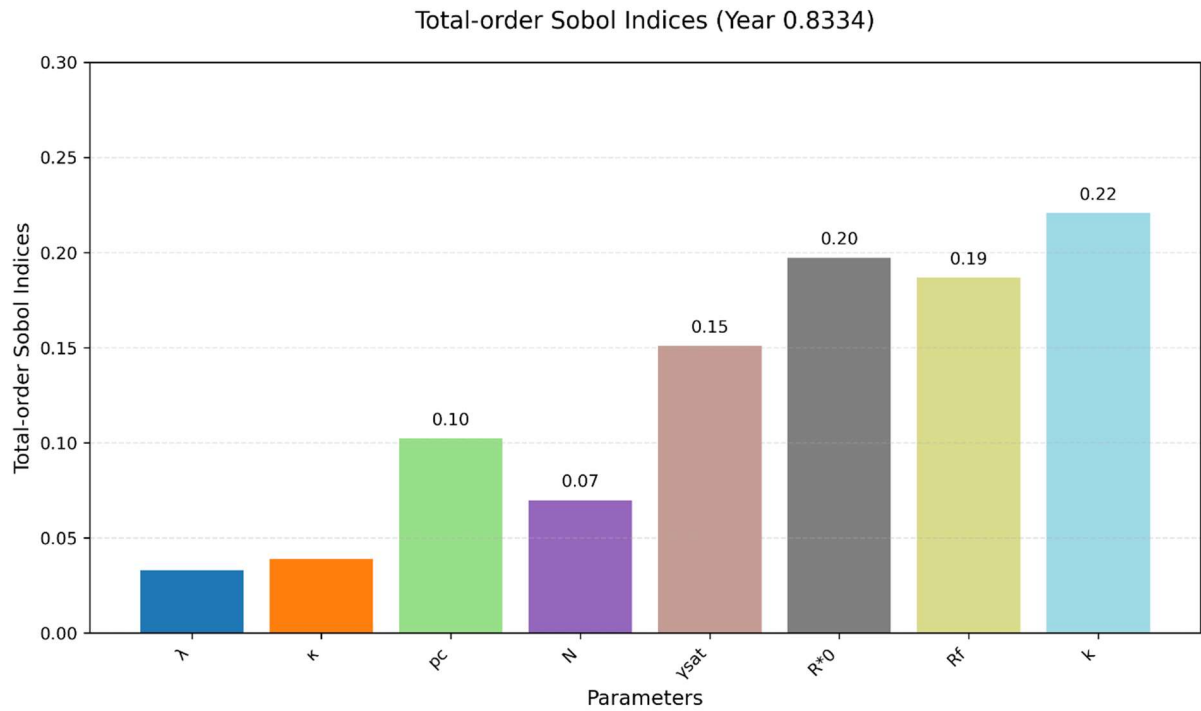
throughout the entire time period. R_f (critical state stress ratio, a strength – related parameter) of Deep clay ranks as the third most influential factor on the subsidence of Deep clay layer, with indices between 0.19 - 0.20, and it became the second most important factor at the end of the timeline, meaning that soil strength also plays a significant role in the model's output variability. Saturated unit weight γ_{sat} and Maximum historical pre-consolidation pressure (p'_c), exhibit relatively lower sensitivities but still contribute to the overall behaviour. The first 3 influential parameters (k , R^*_0 , R_f) of Deep clay contribute over 60% to the settlement of Deep clay layer, and the first 5 parameters contributed 85%, while the impact on the Deep clay layer is relatively stable throughout the entire time process.

Among the remaining three parameters of Deep clay, the ranking of the impact on Deep clay layer settlement is Void ratio N ($p' = 98$ kPa on N.C.L), Swelling index κ , and Compression index λ .

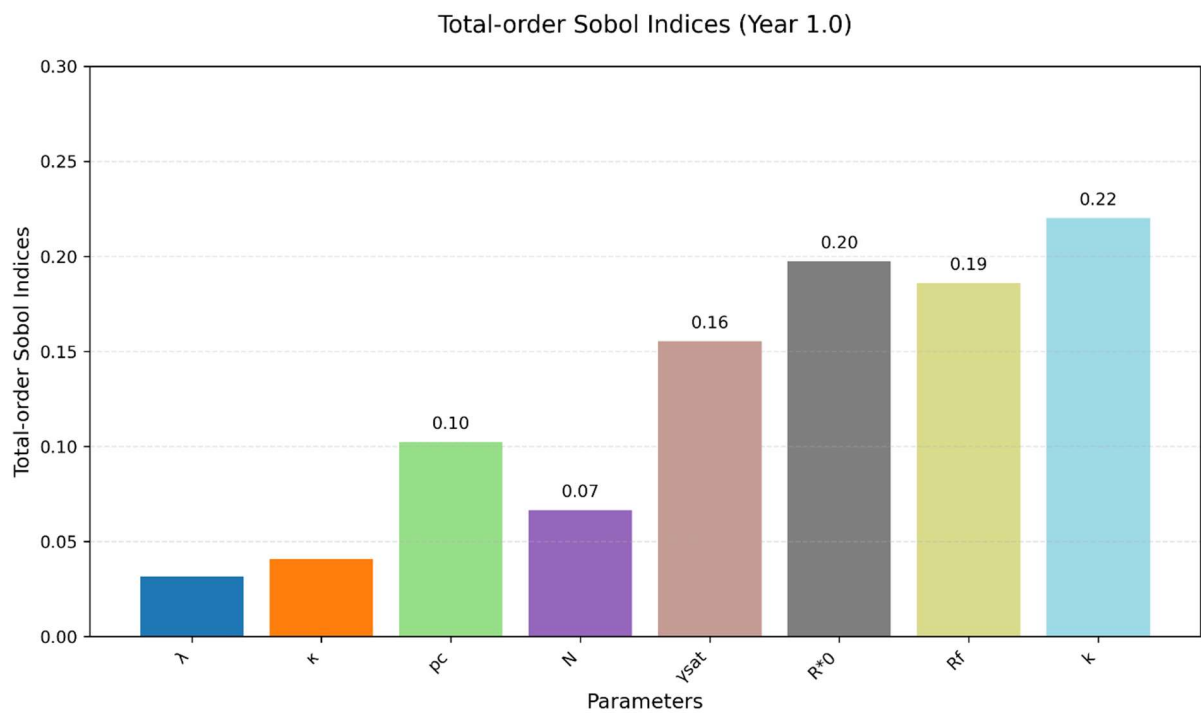
This suggests that initial soil structure and permeability are the key drivers of uncertainty in the system's behaviour, while the strength – related parameter is of approximately same importance.



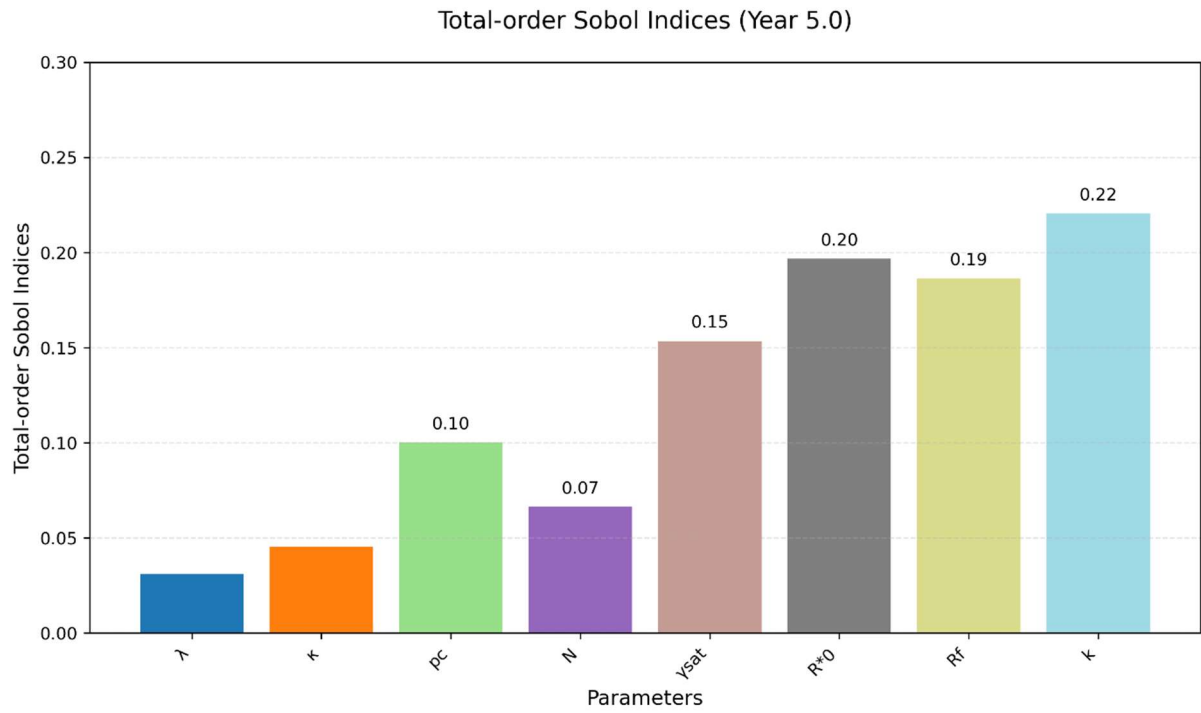
(a) All specific years (Month 1 – Year 150)



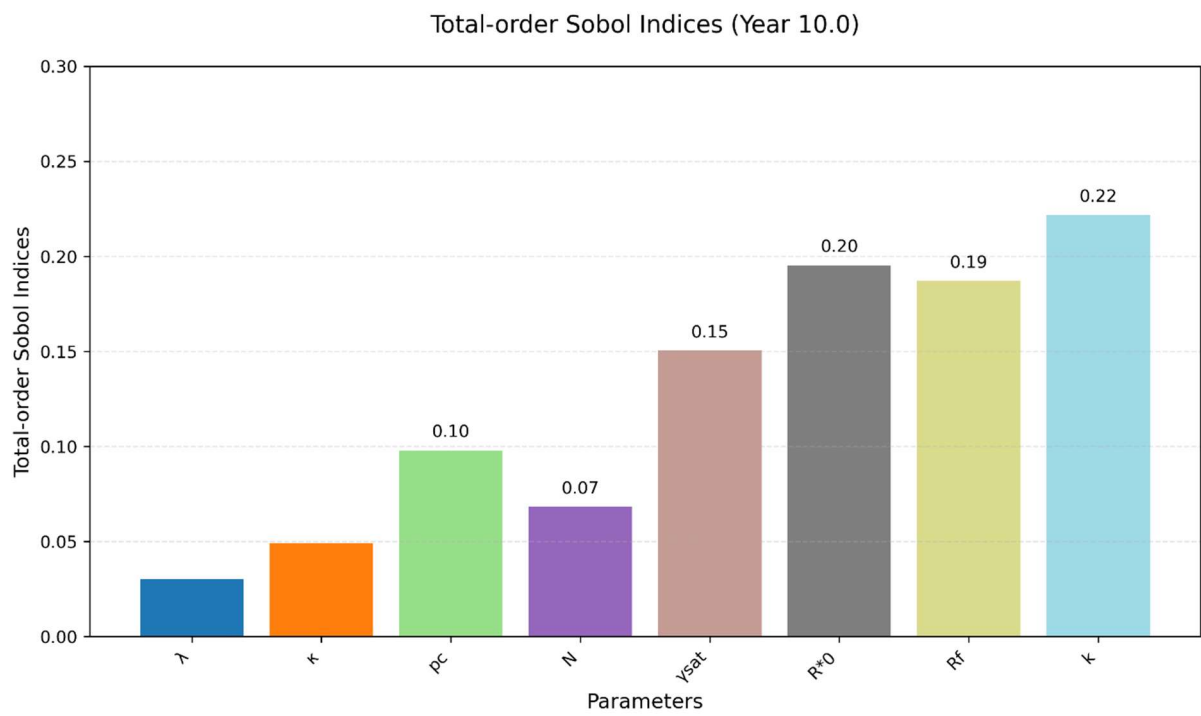
(b) Month 1 which is approximate to earthquake - induced deformation



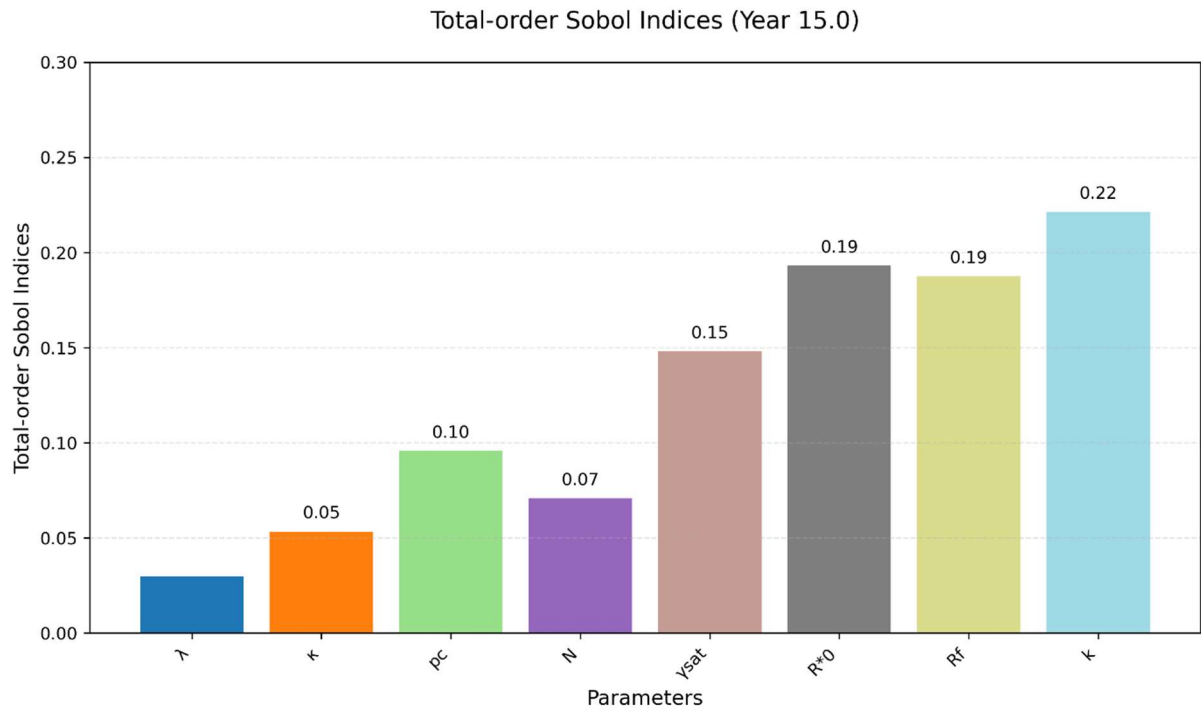
(c) year 1



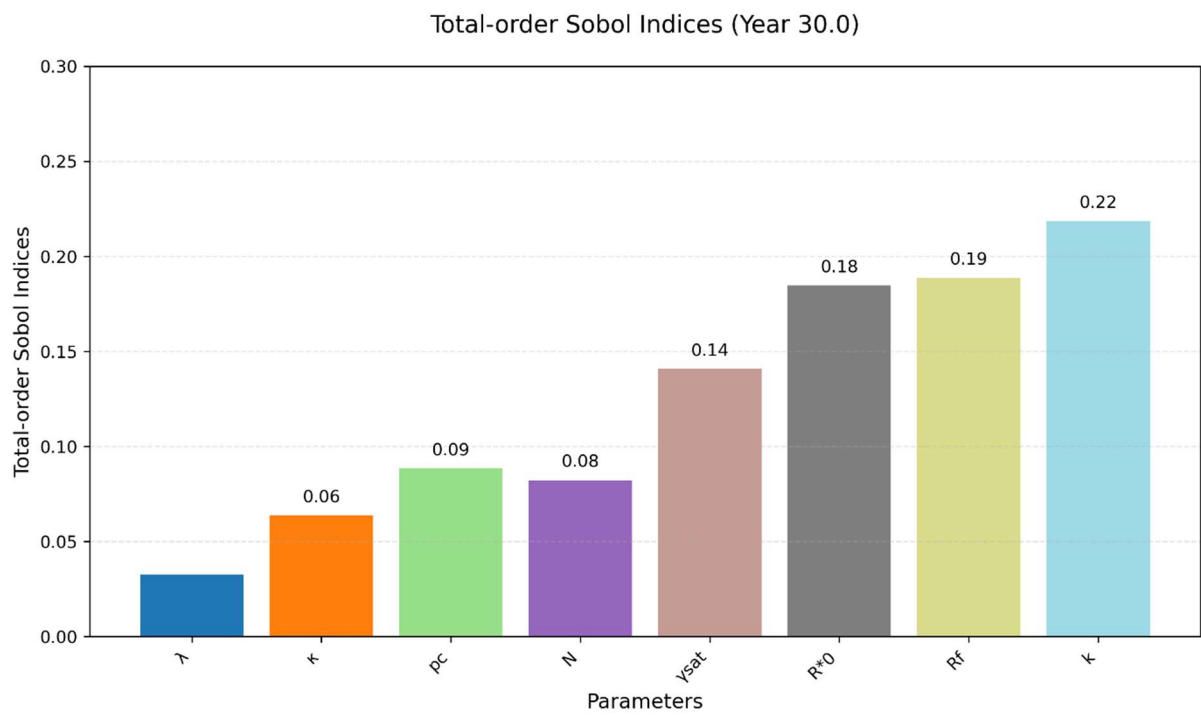
(d) year 5



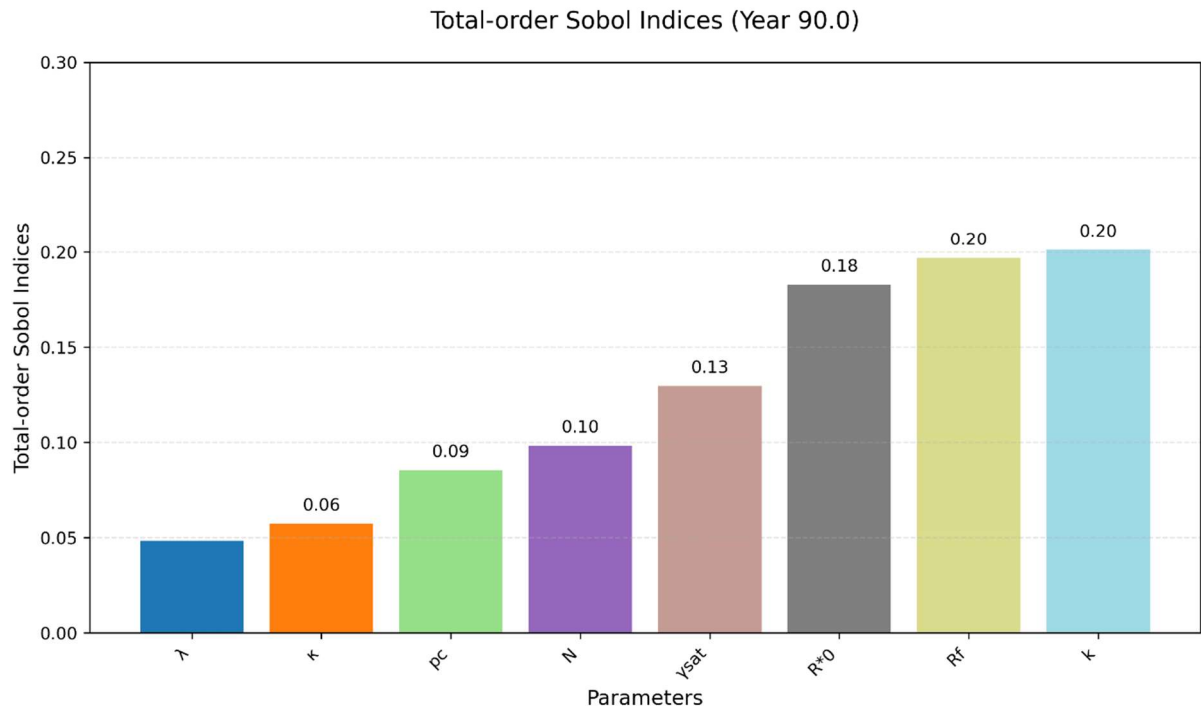
(e) year 10



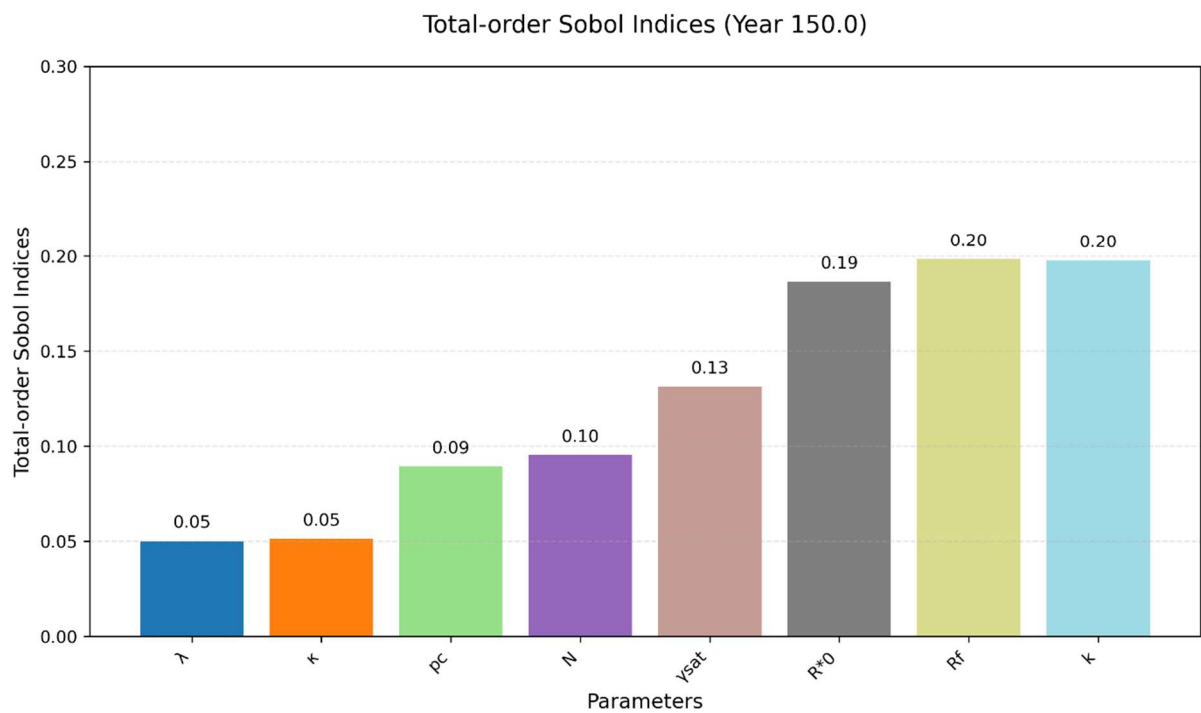
(f) year 15



(g) year 30



(h) year 90



(i) year 150

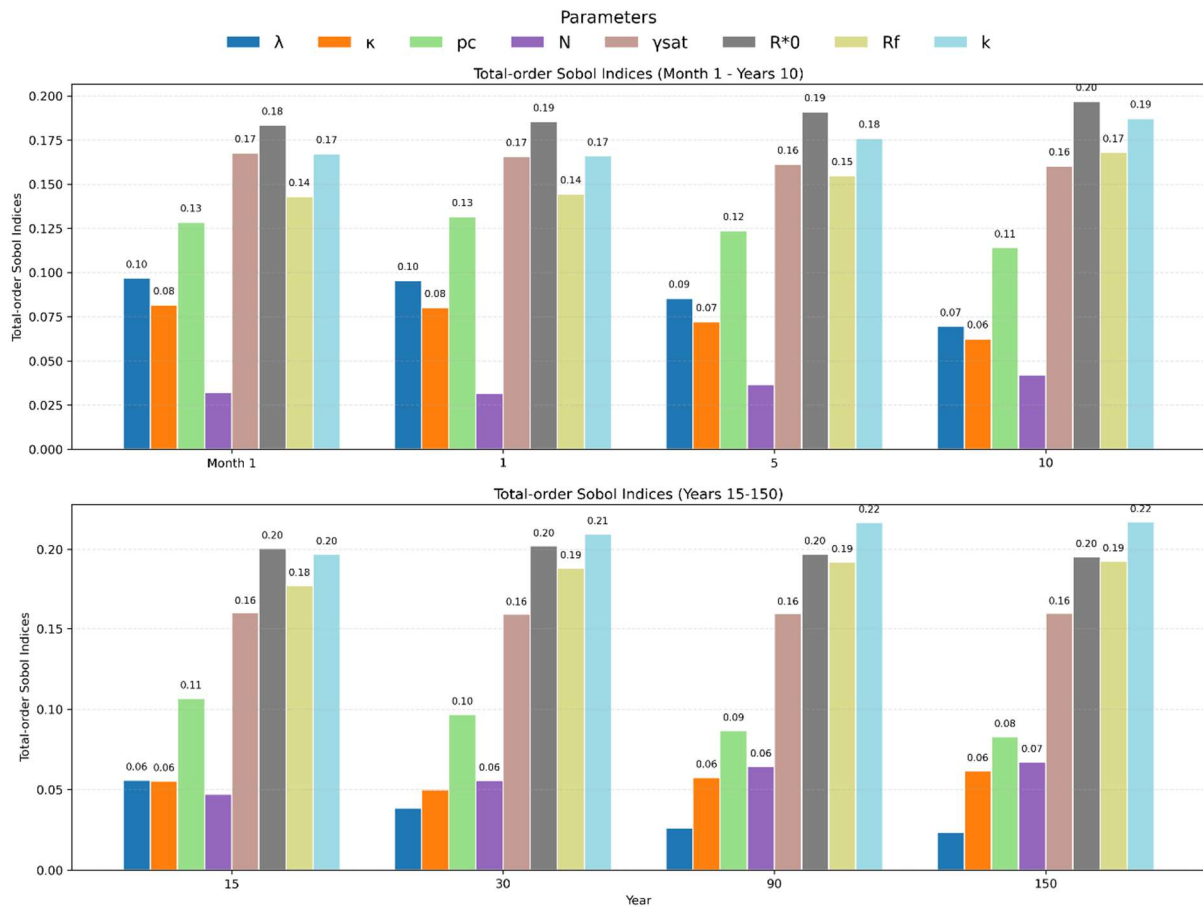
Figure 5-2 The Total Sobol Indices of the 8 Deep clay Parameters ' influence on the subsidence of
Deep clay layer

(2) Output: All layer's subsidence

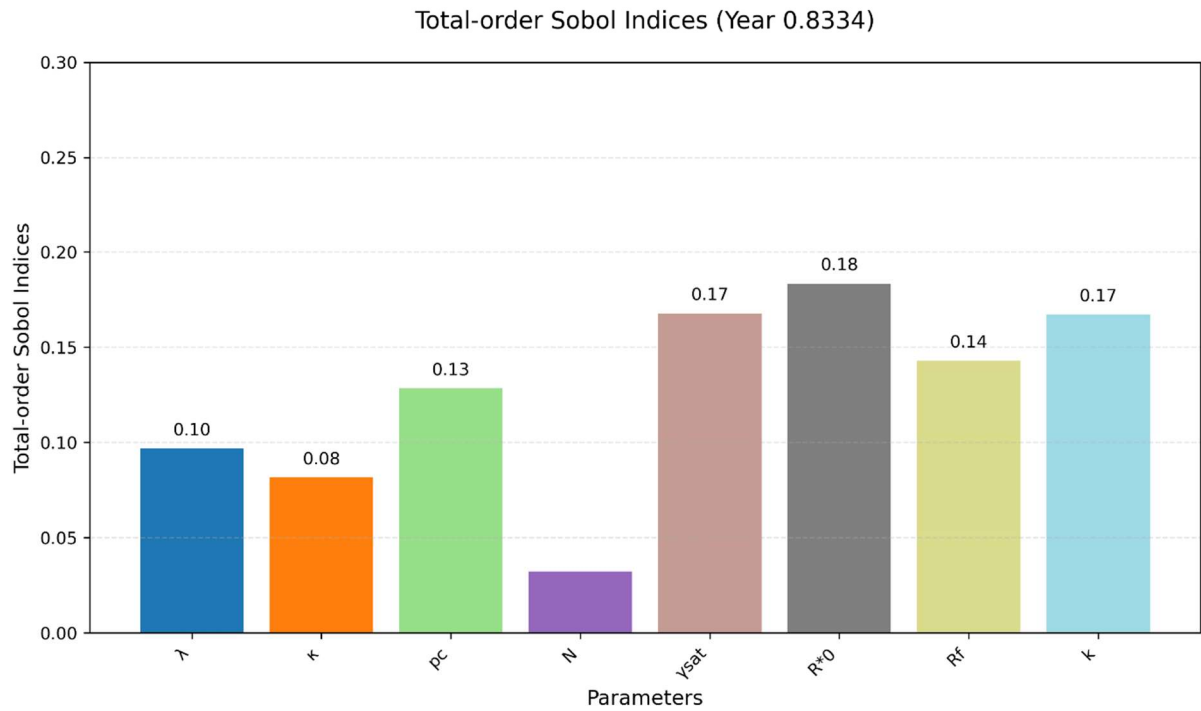
Secondly, when the output is the subsidence of All layers, the results will be discussed.

The 8 Deep clay Parameters' influence on the subsidence of All layers is given below using the Global Sensitivity analysis. The Total Sobol Indices of the 8 Deep clay Parameters are shown in Figure 5-3: (a) all specific years, (b) Month 1 which is approximate to earthquake - induced deformation, (c) year 1, (d) year 5, (e) year 10, (f) year 15, (g) year 30, (h) year 90, (i) year 150.

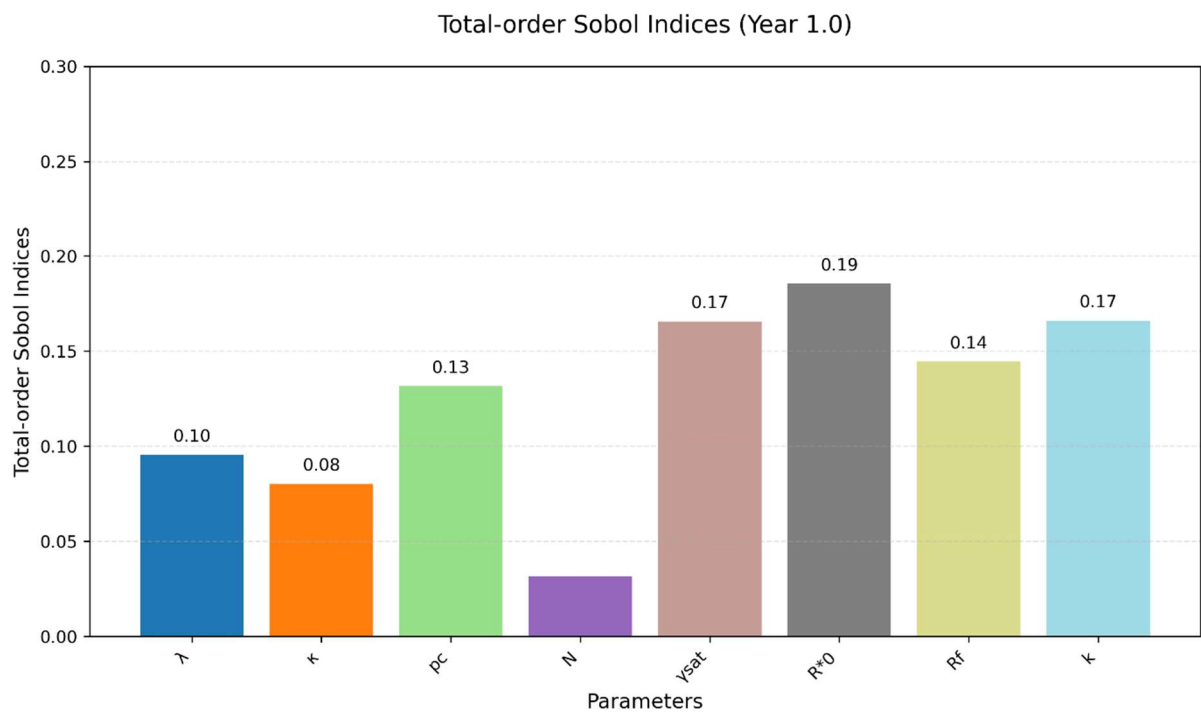
The figures clearly indicate that k (permeability) and R^*_o (initial soil structure parameter) of Deep clay are still the most influential factors on the subsidence of All layers, consistently showing high total-order indices (around 0.17 - 0.22) across all time periods. R_f (critical state stress ratio, a strength – related parameter) of Deep clay still ranks as the third most influential factor on the subsidence of All layers, with indices between 0.14 - 0.19. Saturated unit weight γ_{sat} and Maximum historical pre-consolidation pressure (p'_c), exhibit relatively lower sensitivities but still contribute to the overall behaviour. The first 3 influential parameters (k , R^*_o , R_f) of Deep clay contribute 50% - 60% to the settlement of All layers, and the first 5 parameters contributed 80% - 85%.



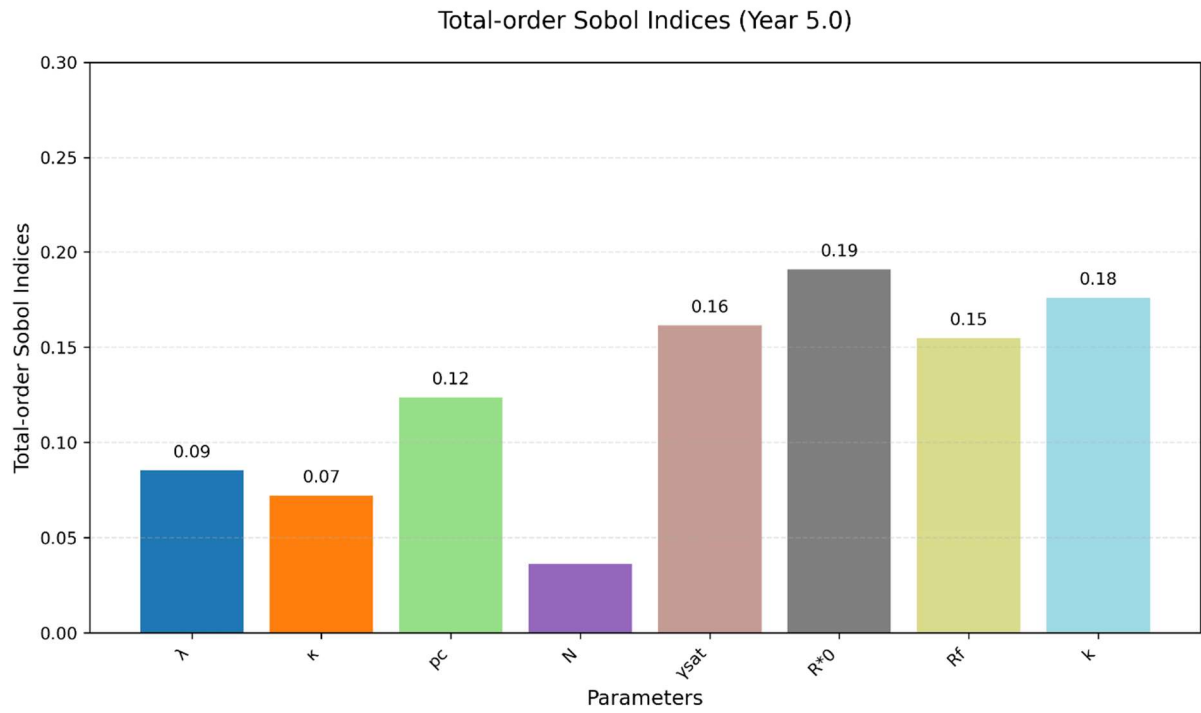
(a) All specific years (Month 1 – Year 150)



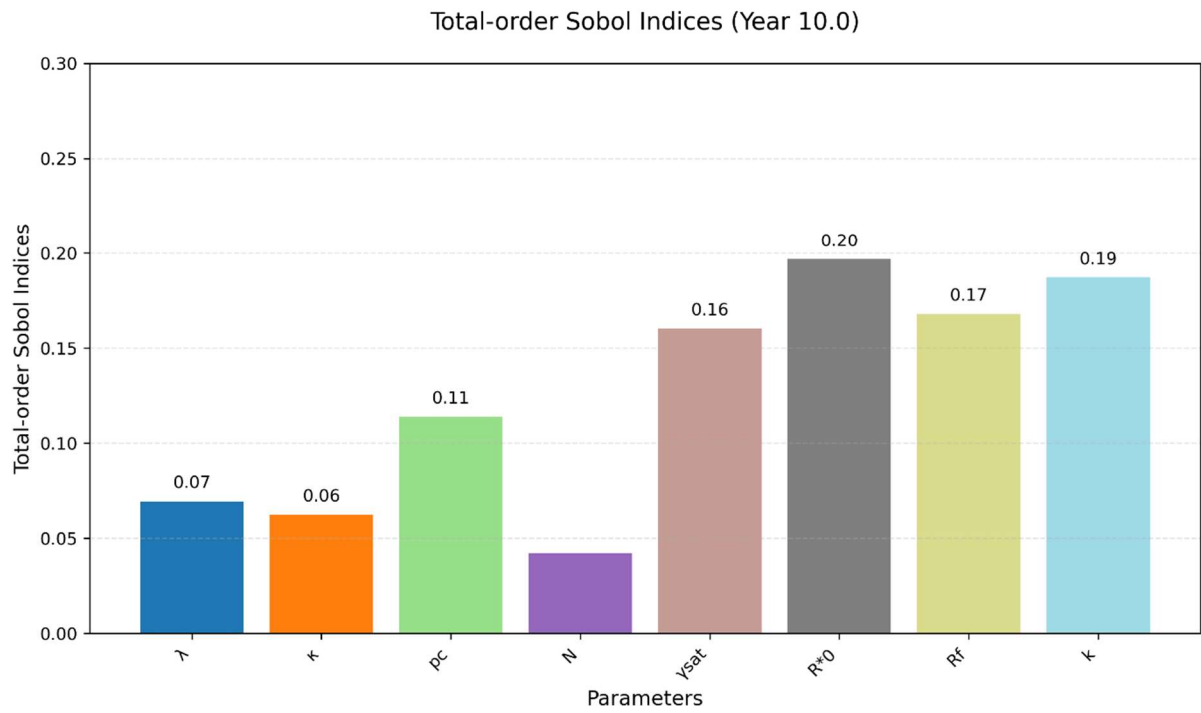
(b) Month 1 which is approximate to earthquake - induced deformation



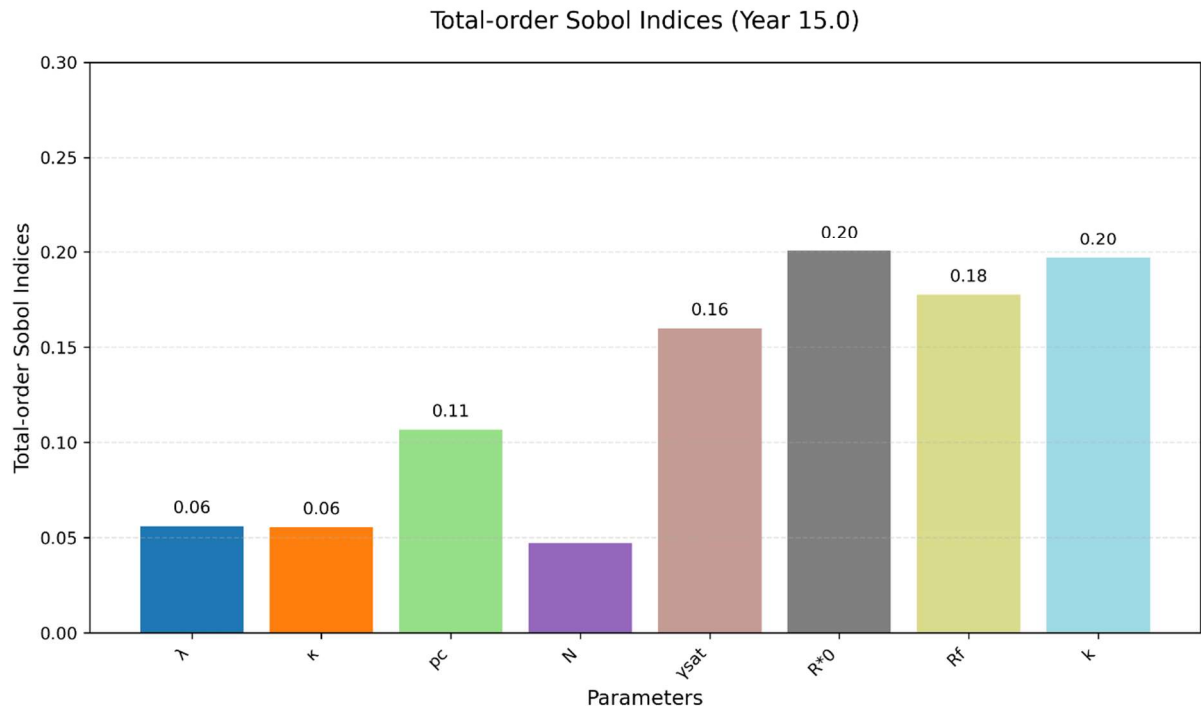
(c) year 1



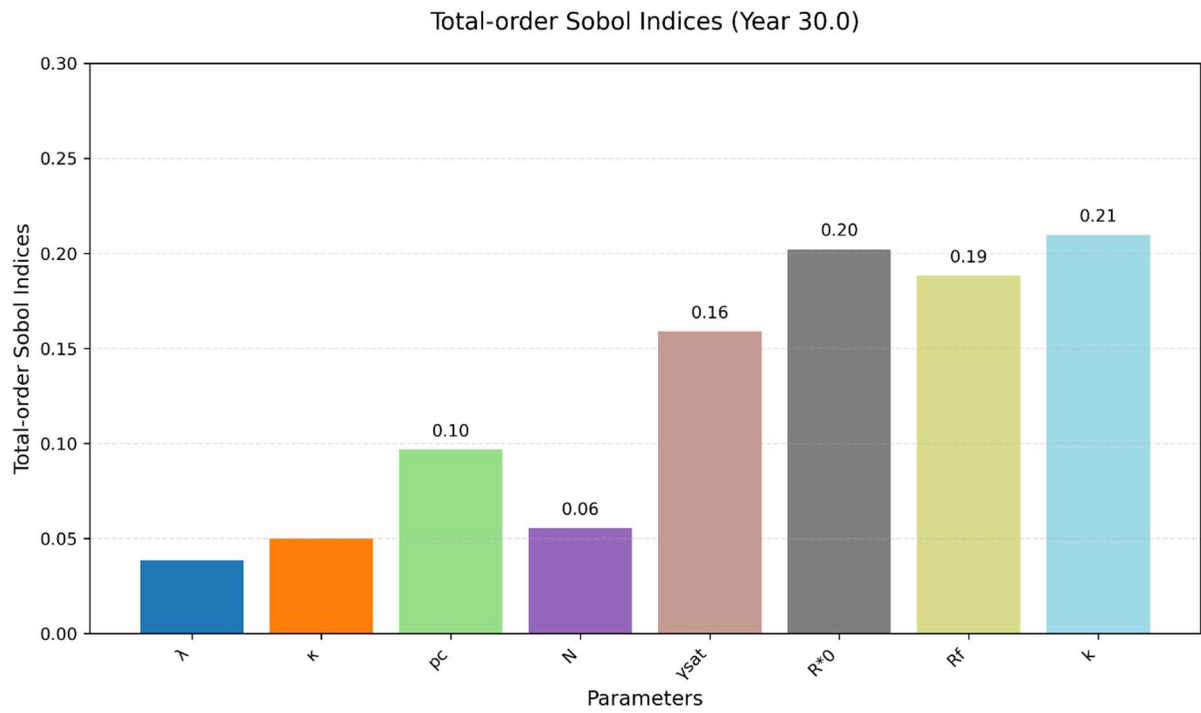
(d) year 5



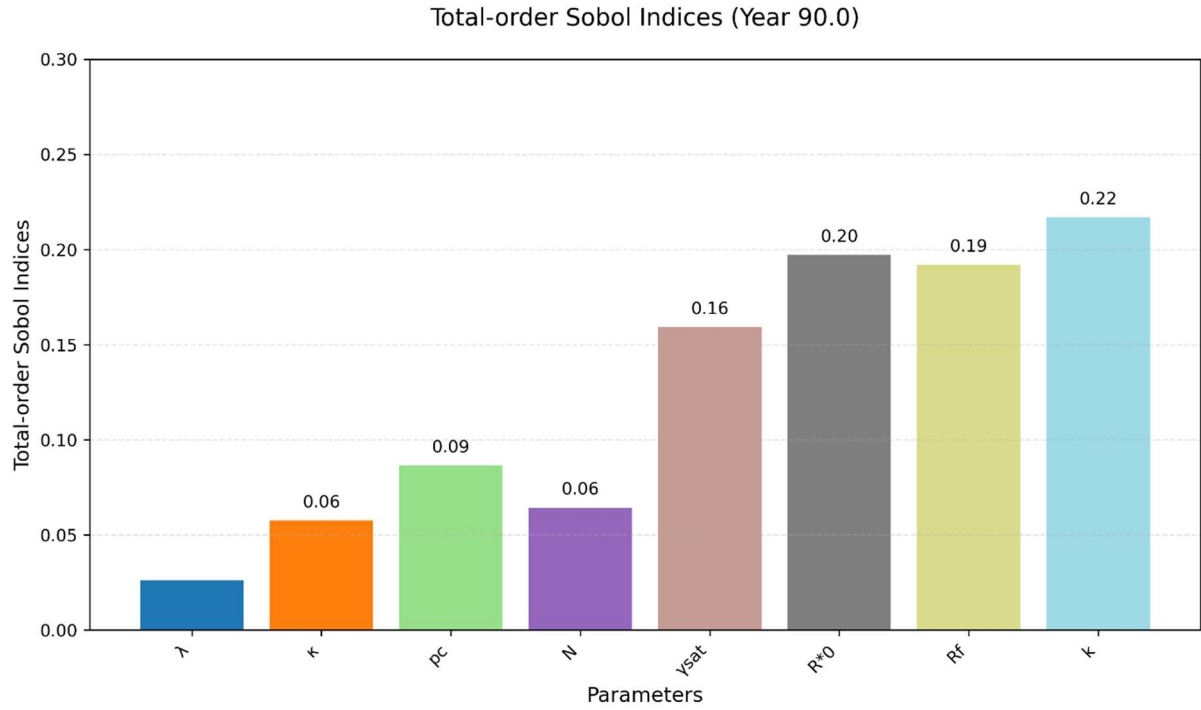
(e) year 10



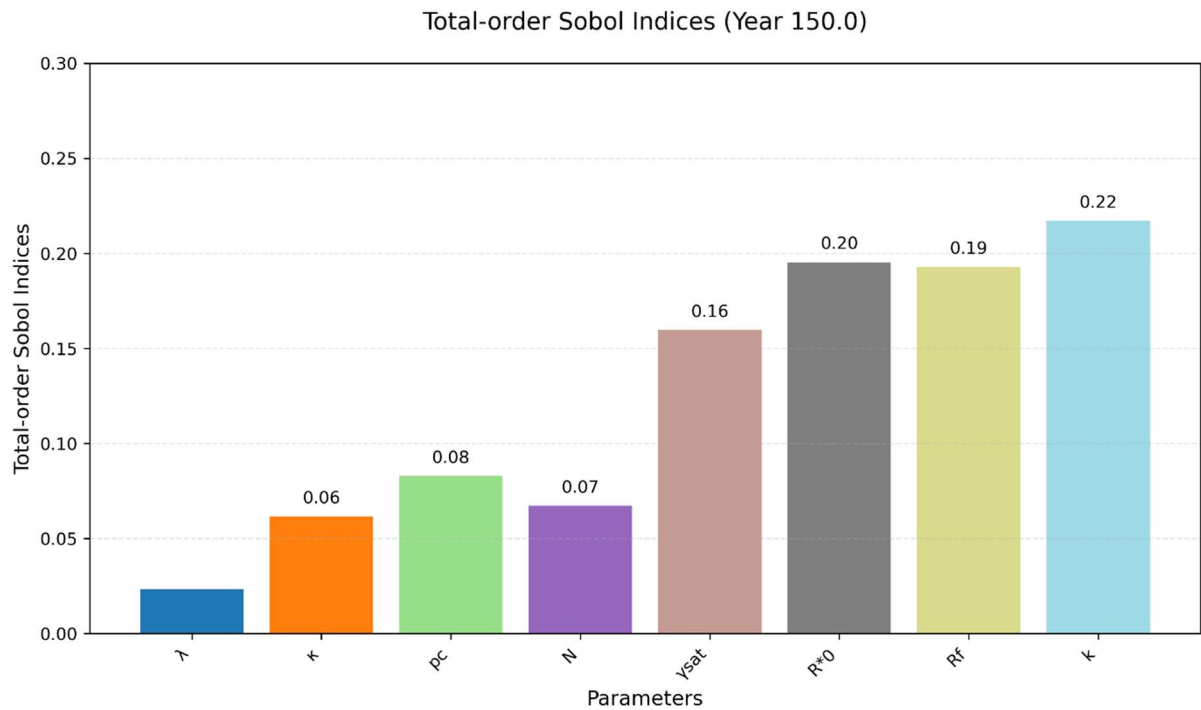
(f) year 15



(g) year 30



(h) year 90



(i) year 150

Figure 5-3 The Total Sobol Indices of the 8 Deep clay Parameters ' influence on the subsidence of **All layers**

Whether it is the Sobol indices on the subsidence of Deep clay layer or All layers, there is no difference in the 5 most important parameters, and the changes are relatively small. But the Sobol indices on the subsidence of All layers is slightly more unstable than the former.

(3) Discussion

This section suggests that the most influential parameters ranking is: initial soil structure R^*_0 and permeability k , strength-related parameter Stress ratio at critical state R_f , saturated unit weight γ_{sat} , maximum historical pre-consolidation pressure (p'_c). The initial soil structure and permeability are the key drivers of uncertainty in the system's behaviour, while the strength – related parameter is of approximately same importance. Among the 8 input parameters of Deep clay, the first 3 influential parameters (k , R^*_0 , R_f) of Deep clay are dominant which contribute around 60% to both the settlement of Deep clay layer and All layers, and the first 5 parameters contributed 80 - 85%.

As for soil mechanics Interpretation, permeability 's dominance stems from direct control over pore pressure dissipation - low permeability dramatically prolongs consolidation. Initial structure of Deep clay represents natural soil's structural strength, where highly structured clays undergo more significant structural collapse and subsequent compression after seismic disturbance. Critical state stress ratio governs the soil's shear strength and its ability to resist deformation, affecting both immediate and long-term settlement. These three parameters collectively govern long-term settlement through three physical mechanisms: seepage field evolution, structural damage, and strength failure. In addition, the author believes that the large structural dissipation parameter mR^* of deep clay is also the reason why the initial structural parameter of deep clay has a significant impact on the settlement. However, since the CV value of the structural dissipation parameter cannot be found (unless the CV value of a structural dissipation parameter is directly assumed), the influence of the structural dissipation parameter in practical significance cannot be analysed.

These findings have direct applications in foundation design, long-term settlement predictions, and geotechnical risk assessment. They provide valuable insights into how soil structure and permeability interact over time, influencing both short-term stability and long-term deformation.

The dominance of soil initial structure and permeability highlights the critical importance of accurate estimation of these parameters. Misjudging these two characteristics can lead to unexpected long-term deformations, potentially compromising the stability of infrastructure such as buildings, embankments, and tunnels. The stable contribution of Critical state stress ratio suggests that soil strength

should not be overlooked, and proper reinforcement strategies should be incorporated to ensure mechanical resilience.

From a risk-based design perspective, the importance of both structural and hydraulic properties suggests that engineers must consider both early-stage mechanical behaviour and long-term hydro-mechanical interactions when designing geotechnical systems. Incorporating uncertainty quantification into foundation design can help mitigate excessive settlement risks and improve infrastructure reliability.

Overall, these findings emphasize the importance of comprehensive site investigations, advanced testing techniques, and long-term monitoring strategies. By understanding how soil structure and permeability influence settlement over different time scales, engineers can develop more resilient, cost-effective, and sustainable geotechnical solutions.

5.6 Brief analysis of Uncertainty Propagation

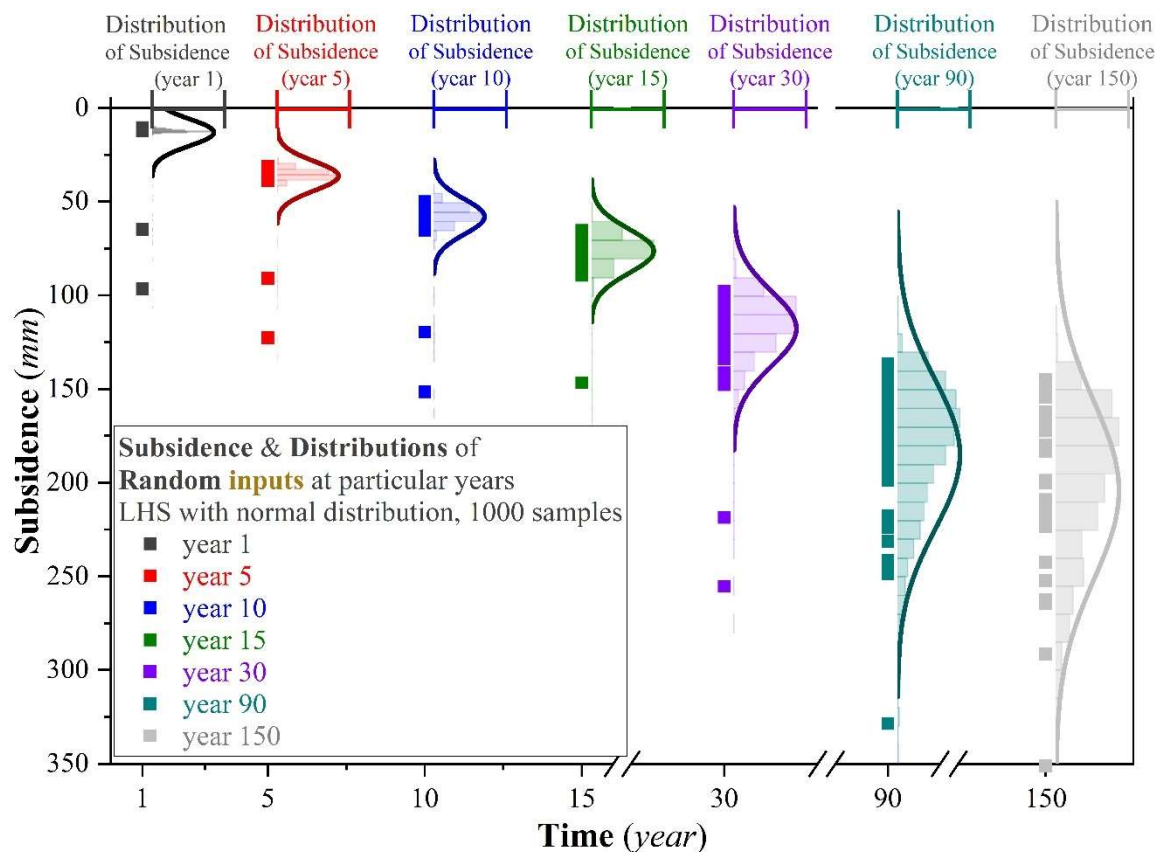


Figure 5-4 Uncertainty Propagation – Subsidence & Distribution of Random inputs at particular years
 - LHS sampling (1000 samples, normal distribution)

The comparison of Uncertainty Propagation between LHS sampling (1000 samples, normal distribution) and Sobol sequence (5120 samples, quasi-uniform distribution) is shown in Figures 5-4 and 5-5. Even considering the soil parameters' variability that are very likely to be overestimated (as CV values are mostly taken from databases of all soil types), it can be seen that the impact on settlement is not extreme, generally around 0.5-2 times of the original value. Therefore, the analysis results in the deterministic part can be considered reasonably reliable.

It reveals that despite completely different sampling methods and input distributions, the output probability distributions consistently exhibit normal or log-normal characteristics. This is largely due to the central limit effect, where complex systems with multiple interacting factors often lead to a Gaussian-like distribution in the results.

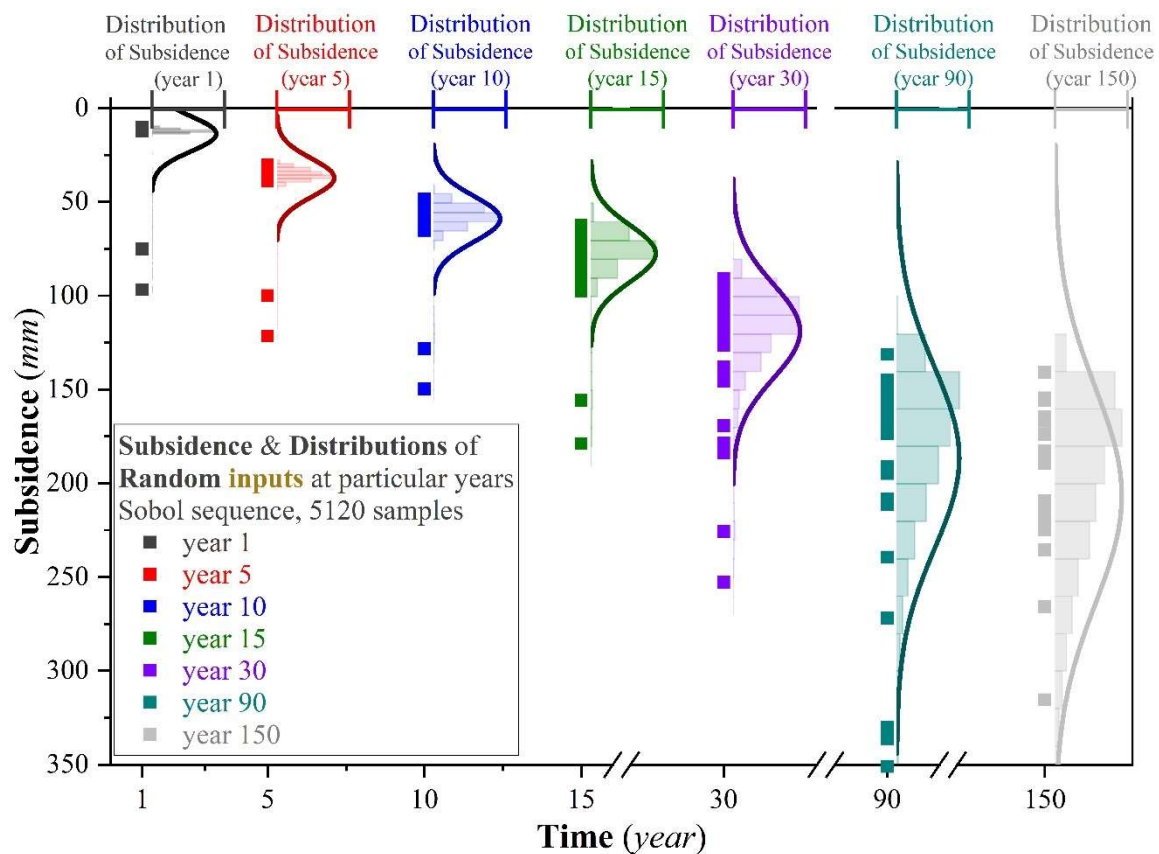


Figure 5-5 Uncertainty Propagation – Subsidence & Distribution of Random inputs at particular years
- Sobol sequence (5120 samples)

This phenomenon shows that the computation model consists of:

(1) Propagation Robustness: The computational model shows "normalization" characteristics in distribution morphology during uncertainty propagation. Regardless of initial input being uniform or normal distribution, the output tends toward bell-shaped distributions, indicating inherent distribution stability of the model.

(2) Inherent Model Security: The normalized output distribution effectively controls the great probability of extreme values. The computation model makes output distributions more concentrated through multi-parameter coupling which is an intrinsic model security advantage.

This characteristic provides benefits that even with different input assumptions, the overall output uncertainty remains predictable in engineering and risk assessment. Meanwhile, it reduces sensitivity to input distribution types, maintaining the referential value when field data is limited.

5.7 Results of Model factor M

The results of Model factor M can be seen in Figures 5-6 (Latin-hypercube Sampling 1000 samples - Joint Gaussian distribution), 5-7 (Latin-hypercube Sampling 1000 samples - Joint Uniform distribution), 5-8 (Sobol Sequence 5120 samples - approximate Joint Uniform distribution).

Despite using different sampling methods (Latin Hypercube, Sobol Sequence) and different probability distributions (Joint Gaussian, Joint Uniform), the overall trend of the model factor remains consistent. This suggests that, in this study, changes in sampling strategy and sample size have minimal influence on the final results, demonstrating the robustness of the model to uncertainty.

The Sobol sequence has a larger sample size (5120 vs. 1000), yet the results remain consistent. While Sobol may improve computational efficiency in some cases, its impact on overall trends is limited.

The choice of distribution does not significantly affect the mean or coefficient of variation of the model factor. This suggests that, in this case, the uncertainty characteristics of input variables have little impact on the final results. This suggests the robustness of the computation model.

As for engineering implications, since different sampling methods, probability distributions, and sample sizes do not significantly alter the results, this indicates that the model is highly stable from the perspective of model uncertainty. For engineering design, this means we can confidently rely on this model for foundation settlement prediction and slope stability analysis without excessive concern over model uncertainties affecting final decisions.

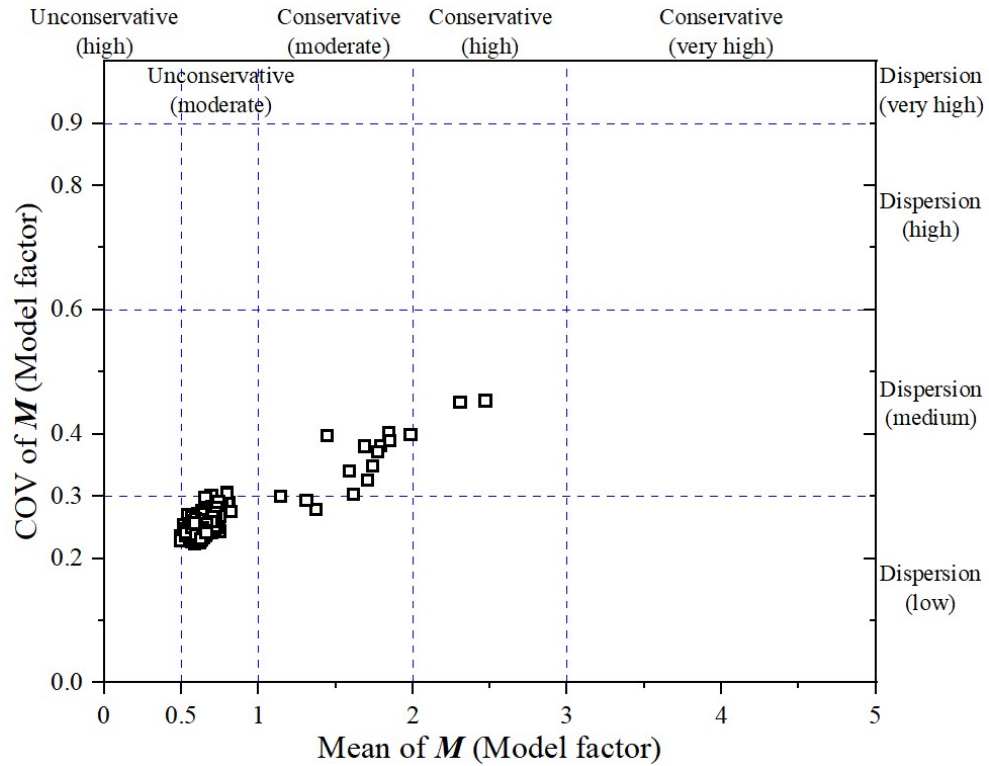


Figure 5-6 Latin-hypercube Sampling 1000 samples - Joint Gaussian distribution

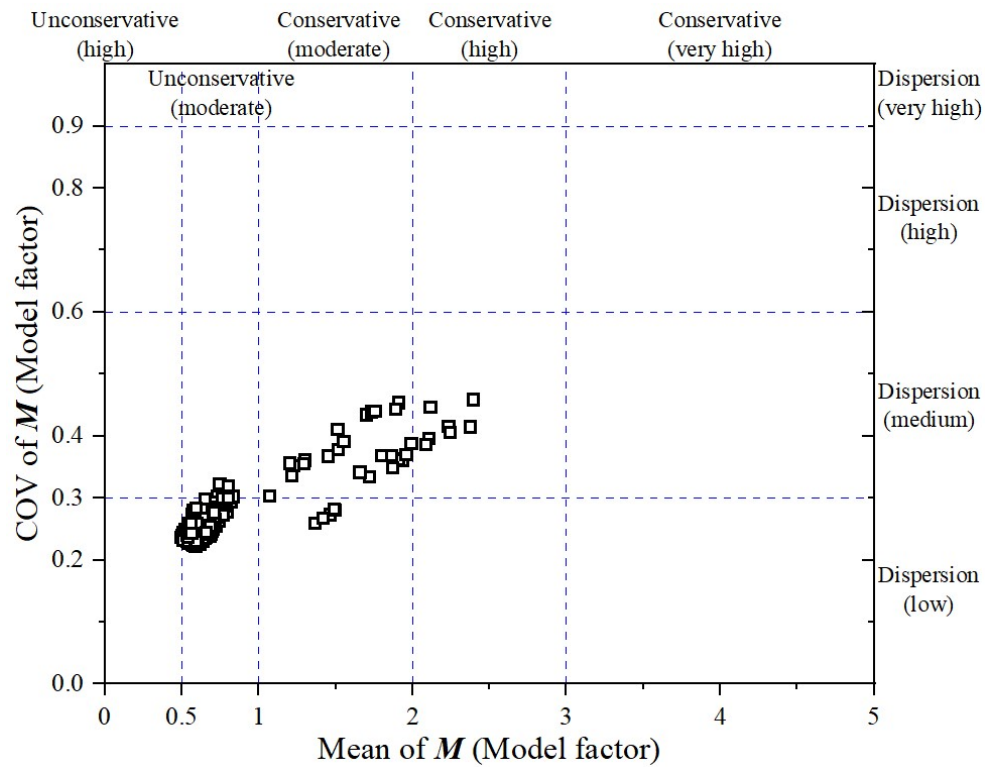


Figure 5-7 Latin-hypercube Sampling 1000 samples - Joint Uniform distribution

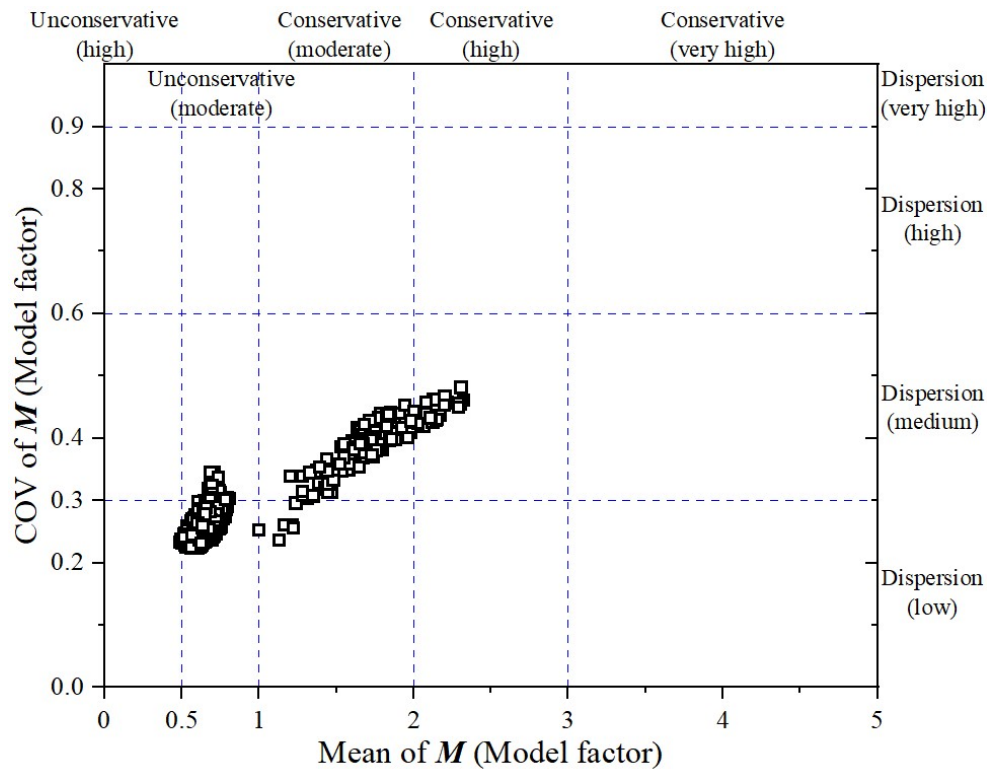


Figure 5-8 Sobol Sequence 5120 samples

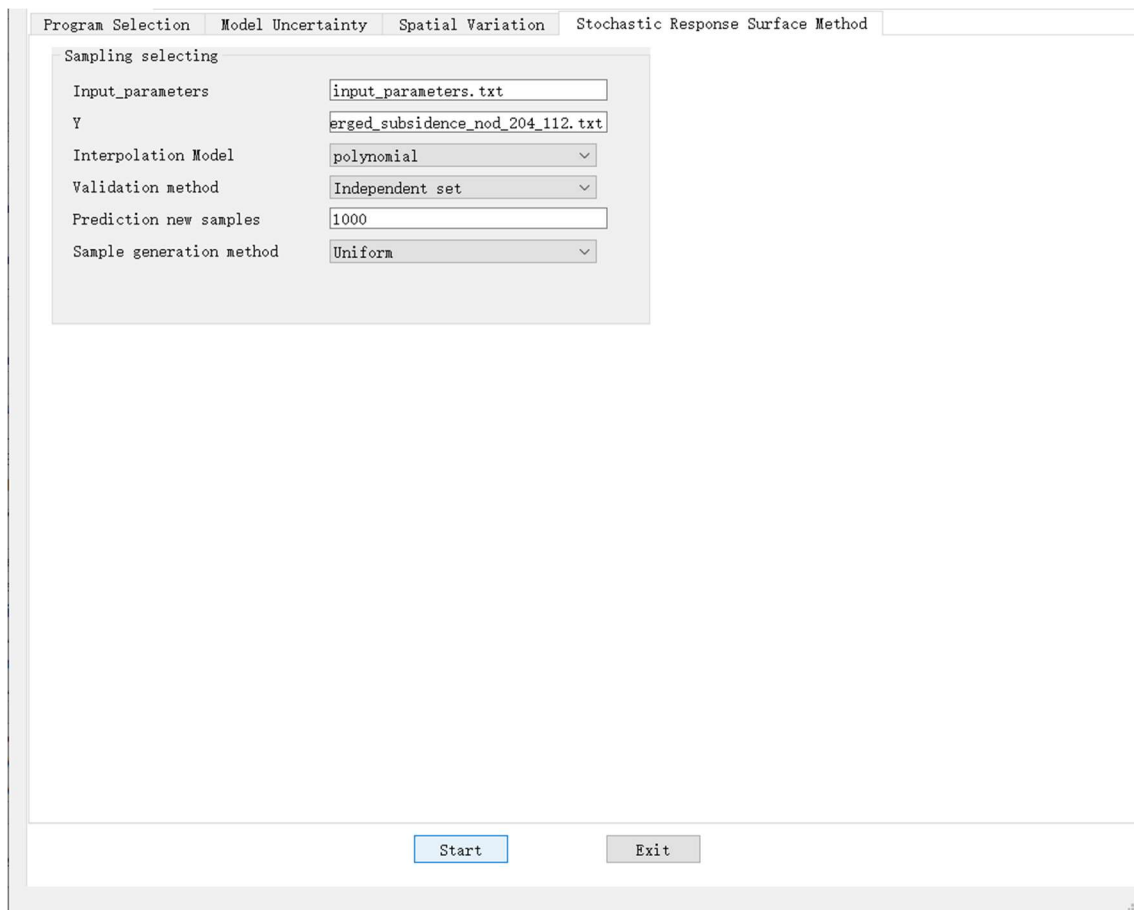
A closer look at the charts shows that the model factor (M) is mainly in the "Moderately Conservative to Moderately Unconservative" region, with its coefficient of variation (CV) mostly within the "Medium to Low Dispersion" range. This indicates that the settlement calculation is generally stable with no significant impact from extreme values, but slightly unconservative. It also means that it is necessary to optimize the calculation results to improve security.

Since the coefficient of variation (CV) remains within the "Medium to Low" dispersion range, this suggests that while the model is reliable, some degree of uncertainty still exists. Therefore, in real-world applications, long-term monitoring such as foundation settlement and seepage changes, is necessary to ensure that model predictions align with reality. In uncertainty management, probabilistic methods such as Monte Carlo simulations can be used to further quantify risks.

The analysis of Model factor M demonstrates minimal influence from sampling methods and probability distributions, confirming model robustness. The settlement calculation exhibits "moderately conservative to moderately unconservative" characteristics with "medium to low dispersion" and long-term monitoring data should be incorporated to enhance prediction reliability.

5.8 Brief Analysis Results of Stochastic Response Surface Method (SRSM)

In this section, a high-order stochastic response surface model (SRSM) was constructed using polynomial regression to approximate the relationship between input parameters and subsidence output at a specific time step. The second-order response surface model, based on least-squares fitting, effectively captured nonlinear trends and interaction effects among the parameters. The validation method uses independent set validation method, and the prediction generation of new sample points uses uniform random sampling method. The predicted sample points are 1000 points. The GUI settings and calculation interface can be seen in Figure 5-9 (a), (b) and (c).



(a) GUI settings of SRSM calculation

```

Number of time steps: 38548
Using default polynomial degree: 2
Performing validation using: independent_set
Starting Independent Set validation loop for 38548 time steps...
Validating time step 500/38548
Validating time step 1000/38548
Validating time step 1500/38548
Validating time step 2000/38548
Validating time step 2500/38548
Validating time step 3000/38548
Validating time step 3500/38548
Validating time step 4000/38548
Validating time step 4500/38548
Validating time step 5000/38548
Validating time step 5500/38548
Validating time step 6000/38548

```

(b) Calculation interface of Validation

```

Generating new samples for prediction...
Starting final prediction loop for 38548 time steps...
Predicting time step 500/38548
Predicting time step 1000/38548
Predicting time step 1500/38548
Predicting time step 2000/38548
Predicting time step 2500/38548
Predicting time step 3000/38548
Predicting time step 3500/38548
Predicting time step 4000/38548
Predicting time step 4500/38548
Predicting time step 5000/38548
Predicting time step 5500/38548
Predicting time step 6000/38548
Predicting time step 6500/38548
Predicting time step 7000/38548

```

(c) Calculation interface of Prediction

Figure 5-9 GUI settings and calculation interface of SRSM

As shown in the reliability curve in Figure 5-10, the dashed gray line represents the result based on only 256 Sobol samples, which shows visible fluctuations and lacks smoothness—this is mainly due to the limited number of samples, causing statistical noise and step-like drops in the reliability values over time. Notably, the blue curve, calculated using a 2nd-order SRSM (Stochastic Response Surface Method) model trained on the same 256 Sobol samples, closely follows the red curve which is the most ideal result.

This comparison highlights that although the original reliability curve with 256 samples has some quality issues due to sample insufficiency, the SRSM method can effectively overcome these limitations

through polynomial regression. It smooths the output, captures the core trend, and gives results that are comparable to those from a much larger sample set.

This demonstrates that with proper sample selection and regression modeling, SRSM allows us to obtain reliable uncertainty quantification results with significantly reduced computational cost—a major advantage when dealing with large-scale or time-consuming numerical models like finite element simulations.

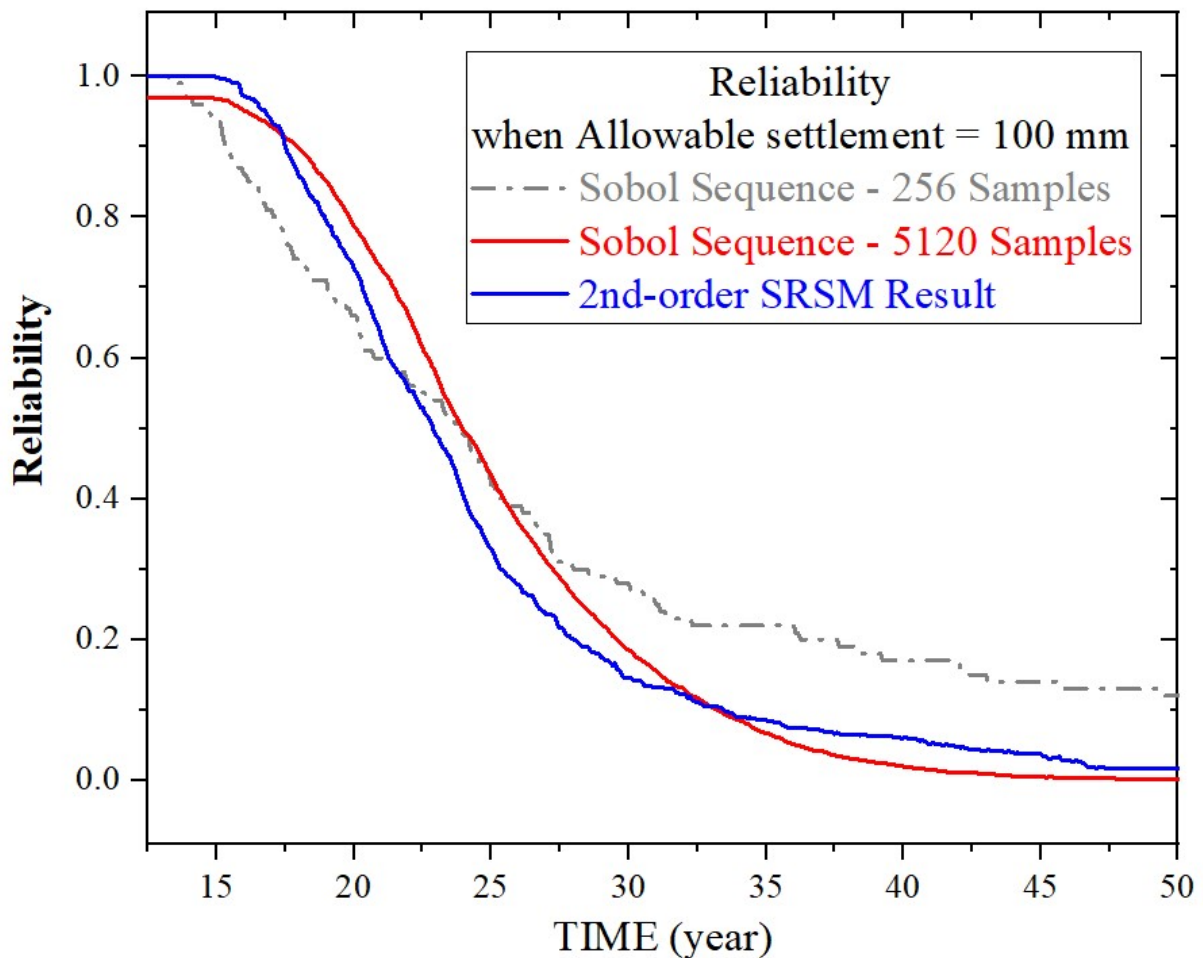


Figure 5-10 SRSM result comparing with original and ideal results

From an engineering perspective, the ability to approximate high-sample results using SRSM opens the possibility for faster decision-making, cost-effective risk assessments, and more iterative design cycles within a reasonable timeframe. It allows engineers to explore uncertainty and sensitivity in design without requiring large-scale computing resources.

In future work, the performance of more advanced SRSM techniques such as Polynomial Chaos

Expansion (PCE) and Kriging-based surrogate modeling will be further evaluated. Meanwhile, active-learning method is quite advanced and worth trying too. These methods, both in theory and in practice, are known to offer improved performance over standard polynomial regression, especially in the field of Uncertainty Quantification (UQ). Their ability to handle complex, nonlinear, and high-dimensional problems makes them promising tools for future geotechnical reliability applications.

5.9 Summary of Stochastic Analysis Results

In terms of reliability analysis, the Reliability of the subsidence no more than 100 mm in 20 years is 79% (corresponding to a failure probability of 21%) and the Reliability of the subsidence no more than 100 mm in 25 years is 44% (corresponding to a failure probability of 56%). LHS with a uniform distribution provides results close to those obtained using the more computationally intensive Sobol sequence method. However, using a normal distribution in LHS introduces larger errors. This underscores the importance of selecting an appropriate probability distribution for reliability assessments.

The stochastic analysis results highlight key factors of deep clay influencing settlement predictions and reliability assessments. Sobol sensitivity analysis reveals that for the deep clay, initial soil structure R^*_0 and permeability k are the most influential factors in settlement predictions. Strength-related parameter Stress ratio at critical state R_f also plays a notable role, while Saturated unit weight γ_{sat} and Maximum historical pre-consolidation pressure (p'_c), exhibit relatively lower sensitivities but still contribute to the overall behaviour. Among the 8 input parameters of Deep clay, the first 3 influential parameters (k , R^*_0 , R_f) of Deep clay contribute around 60% to both the settlement of Deep clay layer and All layers, and the first 5 parameters contributed 85%. These findings highlight the importance of accurate soil characterization and permeability estimation in geotechnical design.

As for Uncertainty Propagation analysis, the computation model shows Propagation Robustness and Inherent Model Security.

For the model factor (M), the results show that minimal influence occurs from sampling methods (LHS, Sobol) and probability distributions (uniform, normal), confirming model robustness. The settlement calculation exhibits "moderately conservative to moderately unconservative" characteristics with "medium to low dispersion". Long-term monitoring data should be incorporated to enhance

prediction reliability and it is necessary to optimize the calculation results to improve security.

For SRSM, it allows us to obtain reliable uncertainty quantification results with significantly reduced computational cost with proper sample selection and regression modelling.

From an engineering perspective, the findings emphasize the need for comprehensive site investigations, accurate soil property measurements, and long-term monitoring. While Sobol sequences provide high accuracy, LHS with a uniform distribution is a practical alternative when computational resources are limited. A balanced approach considering both computational efficiency and accuracy is recommended to optimize foundation design and minimize settlement risks.

CHAPTER 6 – CONCLUSIONS

6.1 Main Findings

As for Deterministic Analysis:

- (1) Ground investigation confirmed that structured soft clay with low permeability is widely distributed throughout Kashiwazaki City in Niigata Prefecture. This geological feature significantly affects the ground behavior in the region.
- (2) Numerical simulations based on field data showed that highly structured soft clays cause long-term post-earthquake subsidence through two mechanisms: slow dissipation of earthquake-generated excess pore water pressure and continued degradation of clay structure during post-consolidation.
- (3) Deep layers containing highly structure-susceptible soft clay with weathered seashell showed greater potential for long-term post-earthquake subsidence compared to less structured clay in shallow layers. This indicates higher susceptibility to structural damage in the deep layers.
- (4) The compression index induced by dynamic loading (C_d) was found to be greater in the deep layer than in the shallow layer. This value slightly decreases with increasing OCR, consistent with findings by Ohara and Matsuda (1988).
- (5) Simulation results predict that excess pore water pressure dissipation and ground subsidence will continue for more than 100 years after the earthquake. While further investigation is needed due to various influencing factors like topography, drainage boundaries, and seasonal pumping, this study has clarified important characteristics of structured soft clay behavior during and after earthquakes.

As for Software Development:

The developed non-intrusive stochastic finite element analysis software "JRiver_uncertainty" successfully integrates parallel computing techniques, enabling efficient handling of large-scale uncertainty problems in geotechnical engineering without modifying existing deterministic finite element codes.

As for Stochastic Analysis Results:

- (1) Latin Hypercube Sampling with uniform distribution provides results comparable to the more computationally intensive Sobol sequence method, offering a practical balance between

accuracy and computational efficiency for engineering applications.

- (2) It is of great importance to select an appropriate probability distribution for reliability assessments because using a normal distribution in LHS introduces larger errors.
- (3) Reliability analysis showed that the Reliability of the subsidence no more than 100 mm in 20 years is 79% (corresponding to a failure probability of 21%) and the Reliability of the subsidence no more than 100 mm in 25 years is 44% (corresponding to a failure probability of 56%), highlighting the significant long-term settlement risks in structured soft clay regions.
- (4) Global sensitivity analysis identified initial soil structure parameter and permeability as the most influential factors affecting settlement behaviour. The strength – related parameter critical state stress ratio ranks as the third most important factor. Among the 8 input parameters of Deep clay, the first 3 influential parameters (k , R^*_o , R_f) of Deep clay contribute around 60% to both the settlement of Deep clay layer and All layers.
- (5) As for Uncertainty Propagation analysis, the computation model shows Propagation Robustness and Inherent Model Security.
- (6) The model factor (M) of settlement calculations exhibits "moderately conservative to moderately unconservative" characteristics with "medium to low dispersion". Long-term monitoring data should be incorporated to enhance prediction reliability and it is necessary to optimize the calculation results to improve security.
- (7) Different sampling methods (Latin Hypercube, Sobol Sequence) and probability distributions showed minimal impact on the model factor, confirming the robustness of the computational approach for practical engineering applications.
- (8) As for Stochastic Response Surface Method (SRS), it allows us to obtain reliable uncertainty quantification results with significantly reduced computational cost with proper sample selection and regression modelling.

6.2 Engineering Implications

For foundation design in structured soft clay regions, special attention should be given to the initial soil structure and long-term permeability changes, as these factors significantly influence settlement behavior.

Engineering designs must account for prolonged settlement periods, especially in post-earthquake scenarios involving structured soft clays.

The moderate conservatism of the model suggests that design based on these predictions provides reasonable safety margins without excessive over-design, balancing safety and economic considerations.

For practical applications, Latin Hypercube Sampling with uniform distribution offers an efficient approach to uncertainty analysis when computational resources are limited, while still providing reliable results.

Regular monitoring of foundation settlement is essential, particularly in areas with structured soft clays, to verify model predictions and implement timely remedial measures if necessary.

6.3 Limitations of the current analysis

There are still some shortcomings in this study.

For deterministic analysis: the constitutive model has deficiencies in calculating the number of dynamic cycles, which lead to calculation errors in the dynamic part.

For uncertainty analysis:

1. The analysis of site spatial variability has not yet been included. In fact, spatial variability usually leads to variance reduction or so-called uncertainty reduction, because the spatial averaging effect - high spots balance low spots so that averaging reduces uncertainty.
2. A larger sample size is needed to obtain more accurate results.
3. The input CV value is highly likely to be overestimated due to being from the database of overall soil types.

6.4 Future Prospects

There are many areas for improvement in this work.

For deterministic analysis, further development of high-precision constitutive models is needed. These models should better represent the complex behavior of structured soft clays, especially during and after earthquakes. Additionally, coupled simulation of hydraulic boundary conditions caused by long-term snowfall and snow melting should be incorporated to better understand seasonal effects on ground behavior.

For uncertainty analysis, the software should continue to be validated for Stochastic Response Surface Method (SRSIM) and spatial variability using random field theory. These methods should be further applied to the analyses in this study to improve reliability assessments.

Based on the parallel computing algorithms developed, a distributed computing platform should be further developed. This would enable the analysis of tens of thousands or even hundreds of thousands of samples using dozens of computing nodes. Such capability would yield extremely high-precision uncertainty analysis results, especially for SOBOL analysis with accurate First-Order Indices, avoiding the curse of dimensionality in multi-parameter analyses.

Bayesian analysis should be incorporated into future work to update parameter distributions based on monitoring data, providing more accurate predictions as more information becomes available.

Finally, analysis of input load uncertainty should be added to the framework. This would account for variability in earthquake magnitudes, duration, and frequency content, providing a more comprehensive assessment of post-earthquake settlement risks.

Appendix

```
def par_monte_carlo_simulation(mean, cv, n_samples=100000000):  
    sigma = cv * mean  
    k = np.random.lognormal(np.log(mean), np.log(1 + cv**2)**0.5, n_samples)  
    inv_k = 1 / k  
    return np.std(inv_k) / np.mean(inv_k)  
  
cv_inv_k1 = par_monte_carlo_simulation(0.2, 0.1)  
cv_inv_k2 = par_monte_carlo_simulation(0.2, 0.6)  
print(f"Monte Carlo: CV(1/k)  $\approx$  {cv_inv_k1:.4f}")  
print(f"Monte Carlo: CV(1/k)  $\approx$  {cv_inv_k2:.4f}")
```

```
def par_monte_carlo_simulation(mean, cv, n_samples=100000000):  
    sigma = cv * mean  
    small_value=1e-6  
    k_degrees = np.random.normal(mean, sigma, n_samples)  
    k_degrees = np.maximum(k_degrees, small_value)  
    sin_k = np.sin(np.radians(k_degrees))  
    M = 6 * sin_k / (3-sin_k)  
    rf = (2 * M + 3) / (3 - M)  
    return np.std(rf) / np.mean(rf)  
  
cv_rf1 = par_monte_carlo_simulation(12.9, 0.1)  
cv_rf2 = par_monte_carlo_simulation(12.9, 0.4)  
print(f"Monte Carlo: CV(rf)  $\approx$  {cv_rf1:.4f}")  
print(f"Monte Carlo: CV(rf)  $\approx$  {cv_rf2:.4f}")
```

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