

UNIVERSITY OF CALIFORNIA

Los Angeles

Effects of Sea Level Rise on Earthquake-Induced Soil Liquefaction in Coastal California

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy in Civil Engineering

by

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2026

ABSTRACT OF THE DISSERTATION

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Doctor of Philosophy in Civil Engineering

University of California, Los Angeles, 2026

Professor Scott J. Brandenburg, Chair

Global sea levels may rise up to five meters by 2150, elevating coastal groundwater and intensifying cascading hazards. Little attention has been given to how changing groundwater interacts with earthquake-induced soil liquefaction. Coastal California's 25 million residents and critical infrastructure sit on loose, liquefiable soils. Because liquefaction occurs primarily in saturated, sand-like soils, groundwater elevation strongly governs the hazard. Yet the standard of practice assumes a fixed groundwater depth observed during a site investigation, an assumption that may not hold where sea level rise (SLR) and tides dynamically control the water table.

The term liquefaction was first used by Hazen in 1919, and earthquake-induced liquefaction became a major focus of geotechnical research after the 1964 Niigata and Alaska earthquakes. Although probabilistic seismic hazard analysis is standard in earthquake engineering, an equivalent treatment has not been widely adopted for liquefaction because few probabilistic liquefaction hazard analysis (PLHA) tools exist. PLHA accounts for uncertainty in ground motion, earthquake load, and soil resistance.

This dissertation presents a PLHA framework, implemented as the open source Python package `ucla_plha`, that incorporates the liquefaction term into the seismic hazard calculation. Traditional stress-based methods cannot assign a return period to a computed factor of safety; by evaluating liquefaction within the hazard integral, the framework deter-

mines the factor of safety associated with a selected return period, which may differ from the corresponding seismic hazard return period. The analysis uses the Uniform California Earthquake Rupture Forecast Version 3 fault source model, four V_{S30} dependent NGA-West2 ground motion models, and five liquefaction triggering models. I contributed to the UCLA Coastal Geotechnical Database, populated with cone penetration tests and borings from the California Geological Survey. Pore pressure outputs from two-dimensional groundwater models were propagated through the PLHA, and liquefaction hazard was evaluated using high performance computing along 150 coastal transects under multiple SLR scenarios. Results were synthesized into maps of Santa Monica and Moss Landing. Analyses show that SLR of up to 2 m can increase the rate of liquefaction up to a factor of ten. These findings support treating groundwater depth as a distribution and evaluating liquefaction probabilistically.

The dissertation of Meera Lakshmi Kota is approved.

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To my parents, Dr. Rajasri Kota and Dr. Prasad Kota, thank you for instilling the importance of learning in me and always supporting me. None of this would have been possible without you.

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Acknowledgments

This research was supported by the University Climate Action Initiative under contract number R02CP7031 with Scott J. Brandenburg serving as the Principal Investigator. The content of this dissertation does not necessarily represent the opinions of the University of California. I have also been generously funded through the Civil and Environmental Engineering department at UCLA through departmental grants and teaching opportunities, for which I am very grateful.

A version of Chapter 4 is Kota, M. L., Maple, M., Brandenburg, S. J., and Gallien, T. (2026). `ucla_plha`: A Python package for probabilistic liquefaction hazard analysis in California. *Earthquake Spectra* (in review). Scott J. Brandenburg directed the research as Principal Investigator; Margit Maple and Timu Gallien of the Coastal Flood Lab at UCLA developed and ran the groundwater simulations used in Chapters 5 and 6.

First and foremost, I would like to sincerely thank my advisor, Scott Brandenburg. I fondly remember our discussions prior to my starting at UCLA and I feel strongly more than ever that I chose the best advisor to steer me on this journey. Our lively weekly meetings, discussing all things technical to political shaped me into a better researcher and person. Thank you for all your guidance, support, trust, and faith in me during the last four years. I hope to be a mentor like you some day.

Next, I would like to thank the rest of my committee members. Timu, thank you for cosigning this project with us many moons ago. Our many meetings taught me not only a lot about coastal engineering but also how to be a more critical thinker. Jon, thank you for always being a supportive committee member and teacher. Your insights, technical and professional, have been very helpful for the completion of this thesis. Idil, thank you for your thoughtful comments and for always being a supportive mentor when I needed it.

I would also like to thank my UCLA Geotechnical community. Specifically my friends over the years: Sera Tirkes, Taylor Nguyen, Steve Zhang, John Stapleton, and Varun Renu-gah. Thank you all for always being open to chatting with me in the office, grabbing a

quick lunch, and being a sounding board for me. I am very grateful and thankful to you all. I'd also like to thank alumni Dr. Ken Hudson, Dr. Tristan Buckreis, Dr. Zehan Liu, and Dr. Pengfei Wang for being supportive to answer all my questions early on in the program. I would also like to thank Margit, who was instrumental in the groundwater modeling for this project. Working with you over the past 4 years and having someone along for the same ride has been fun.

More generally at UCLA CEE, I would like to thank the CEE GSA and its members. As a member it was great to get to know more of the community and staff and I thank you all, especially the admin for your support.

In Los Angeles, I would like to thank all my local friends. Spending time with everyone outside of the program gave me drive to keep moving forward. Whether it was trying a new matcha cafe or a new Bollywood dance class, I am thankful for you all. Christine, Ryan, Coco, Leroi, Sandra, Chris, Daisy, Hana, Tyler, Jenn, Joe, Jessica, Jannette, Sam, Antora, Michael, Alberto, Kim, Aarya, Maddy, and Sonali - thank you!

Outside of LA, I am very thankful to all my friends who checked in on me and reminded me there was life outside the walls of Boelter. Shenelle, Anjana, Nammi, Stephanie, Pin and Ace, Brianna, Hersh, Kate and Aaron, and Meg and Jeet - thank you all for your care and support even from thousands of miles away.

I would also like to thank all the educators who have supported me and reminded me that I belonged in STEM. Starting with the BeWiSE community, who introduced me to civil engineering in middle school and gave me an opportunity to send an experiment to the International Space Station. To Girl Scouts and all my mentors for showing me that girls and women could do it all. To the teachers at Torrey Pines High School, who expected excellence even out of 16 year olds. To my professors at UC Berkeley, especially Professor Kenichi Soga, who introduced me to geotechnical engineering during my junior year and changed my life for the better - thank you!

Next, I would like to thank my sister, Maya. Having a sister like you is a blessing of

a lifetime. Our nightly FaceTime calls where you calmly supported me and talked through things with me, stick with me more than you know. I hope to support you as much on your own doctoral journey and together we can be Dr. Kotas.

To my parents, Dr. Rajasri and Dr. Prasad Kota. Education and learning were always a priority at home and for that I am thankful. Like Amma always says, “Education is not something anyone can take away from you” and that is a sentiment that pushed me through to the end. Thank you both for instilling a curious nature in me and Maya. I love you both very much.

To Vera, our sweet, precious chihuahua. Thank you for always keeping me company, for reminding me when it was time to take a break and take you for a walk, and for the infinite cuddles. Those hours on the couch, writing and coding next to you, while giving you belly rubs, were some of the best moments of this degree.

And lastly, to my amazing husband and partner in life, Dev Chakraborty. This dissertation would have been incomplete without your support. Thank you for being my personal Stack Overflow, from setting up my Anaconda to explaining how GitHub works (for the 10th time). Thank you for calmly listening every time I ran into a problem and asking curious questions about what exactly PLHA was, for bringing joy into the sometimes mundane, sometimes tough daily life of a PhD, and constantly reminding me that I could do this. I am completely indebted to you, and this PhD is as much yours as it is mine.

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Kota, M. L., Maple, M., Brandenburg, S. J., & Gallien, T. (2026). ucla_plha: A Python package for probabilistic liquefaction hazard analysis in California. *Earthquake Spectra* (In Review).

Kota, M. L., Brandenburg, S. J., Maple, M., & Gallien, T. (2025). Sea level rise effects on earthquake-induced soil liquefaction. In Z. Liu, J. Dai, & K. Robinson (Eds.), *Proceedings of the 9th International Symposium on Geotechnical Safety and Risk (ISGSR 2025)*. Research Publishing. https://doi.org/10.3850/GRF-25280825_isgsr-109-P356-cd

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CHAPTER 1

Introduction

1.1 Motivation for Dissertation Research

California's coastline is home to dense urban infrastructure, including ports, highways, and residential communities. Many of these areas are underlain by loose cohesionless soils that are highly susceptible to earthquake-induced liquefaction, as documented in numerous well-characterized case histories, including San Francisco, California ([Lawson et al., 1908](#)), Moss Landing, California ([Boulanger et al., 1997](#)); Niigata, Japan ([Seed and Idriss, 1967](#)); and Christchurch, New Zealand ([Green et al., 2014](#)). Despite this, current practice has two notable limitations: it does not account for dynamic groundwater conditions and usually relies on deterministic rather than probabilistic liquefaction hazard analysis.

In standard of practice liquefaction analysis, geotechnical engineers collect soil strength data in situ, measure groundwater levels at the time of a site investigation, and assume that the groundwater level is hydrostatic. However, in coastal areas, sea level rise, tidal fluctuations, and waves significantly influence groundwater, causing permanent changes in the mean groundwater level over time, while transient oscillations can extend much farther inland. Groundwater elevation is critical to soil liquefaction hazard because only sand-like, saturated soils will liquefy during earthquake shaking. Because many well-documented liquefaction case histories come from coastal locations, and because critical infrastructure is heavily concentrated along the California coast, understanding how sea level rise affects

liquefaction hazard is essential.

Additionally, the current standard of practice pairs probabilistic seismic hazard analysis with deterministic liquefaction analysis. Probabilistic Liquefaction Hazard Analysis (PLHA) addresses this gap but is not widely used, largely because of a lack of computational tools. To fill this gap in research, I have developed a PLHA framework and accompanying code, which enable practitioners to calculate both probabilistic seismic hazard and liquefaction hazard at a site in seconds.

This dissertation presents one of the first frameworks to couple spatially and temporally varying coastal groundwater, simulated under multiple sea level rise scenarios, with a fully probabilistic liquefaction hazard analysis mapped continuously at coastal sites in California. This work helps quantify how sea level rise and tidal forcing impact liquefaction hazard along the California coast, information that is directly relevant to state climate adaptation planning.

1.2 Research Tasks and Scope

This dissertation develops a probabilistic liquefaction hazard framework and applies it to quantify how tides and sea level rise influence liquefaction hazard in coastal California. The specific research tasks that have been completed are as follows:

- Create a robust Python package, which uses UCERF3 ([Field et al., 2013](#)), to efficiently compute probabilistic seismic and liquefaction hazard, with a runtime on the order of seconds per site. The code uses vectorization and various efficiency methods to accomplish this objective. The code incorporates multiple ground motion models and liquefaction triggering models, and is published as an open-source package on GitHub ([Kota and Brandenburg, 2025](#)).
- Validate the code against other open-source probabilistic seismic hazard analysis (PSHA) codes

- Develop the UCLA Coastal Geotechnical Database by compiling geotechnical field borings and cone penetration tests (CPTs) provided by the California Geological Survey (CGS)
- Select five appropriate and representative CPTs for subsequent PLHA
- Incorporate spatially and temporally varying pore pressure outputs from a 2D coastal groundwater model into PLHA input configuration files
- Use high performance computing to calculate liquefaction hazard at about 150 Monitoring and Prediction (MOP) transect lines along the coast, using representative CPTs from the Coastal Geotechnical and Next Generation Liquefaction ([Zimmaro et al., 2019](#)) databases under multiple sea level rise scenarios
- Synthesize results into hazard maps that characterize the influence of tides and sea level rise on liquefaction hazard along the California coastline

1.3 Funding Explanation and Relevant Partners

The work was primarily supported by the UC Climate Action Grant ([University of California Action Initiative, 2023](#)), under grant number R02CP7031. The grant falls under the California Climate Action Initiative, through which the California State Budget Act allocated over \$100 million toward climate change research with measurable real world impacts. As part of the grant, the team at UCLA partnered with specific state and federal entities, including the United States Geological Survey (USGS), CGS, and the California Seismic Safety Commission. The partners were involved to varying degrees over the duration of the grant (from fall 2023 to the end of 2025).

Engagement with USGS primarily involved discussions and coordination with Andrew Makdisi and Alex Grant, whose team is working on a similar probabilistic liquefaction hazard implementation (further discussed in Chapter 4). CGS is a division of the California

Department of Conservation. Through its Essential Facility Review Unit, CGS is responsible for evaluating geologic and seismic hazards for public K–12 schools, community colleges, and hospitals across California prior to construction ([California Geological Survey, 2026](#)); as a result, CGS has access to an extensive amount of subsurface soil data. Specifically, Brian Olson at CGS provided the subsurface soil data (CPT and soil borings) used to create the Coastal Geotechnical Database, as explained in Chapter 3. CGS was briefed on the curation of the database and was provided access. The California Seismic Safety Commission, specifically Jia-Wang Connelly and Annde Ewertse, participated as an interested party and was kept up to date as the project progressed.

1.4 Organization

This dissertation is organized into seven chapters. Chapter 2 provides technical background on the mechanics of liquefaction and associated hazard methods. It also briefly discusses sea level rise and how it affects groundwater levels in California. Chapter 3 describes the creation of the Coastal Geotechnical Database, including data entry, QA/QC, and database access. The chapter closes with a discussion of the cone penetration tests selected from the database for use in later analyses.

Chapter 4 presents the PLHA methodology. It details the decoupled and direct methods and subsequently how the liquefaction hazard is included within the overall hazard integral. This chapter describes the implementation of the UCERF3 fault source model ([Field et al., 2013](#)), the ground motion models, and the liquefaction triggering models within the hazard analysis, along with the organization of the code repository on GitHub. It then presents an example application of the code using a single CPT from Moss Landing. It closes with a Moss Landing regional overview comparing computed return periods against locations where liquefaction was observed during the 1989 Loma Prieta earthquake.

Chapter 5 focuses on the 2D groundwater analysis performed by Margit Maple using

PFLOTRAN ([Hammond et al., 2014](#)). The chapter provides basic background information about the model, forcings used, boundary conditions, and the MOP lines used in the later analyses. The chapter then turns to how outputs from the 2D groundwater model are propagated into the PLHA, which was my primary responsibility.

Chapter 6 presents examples that combine the PLHA methodology with the groundwater model. First, the behavior of the five CPTs is discussed, and hazard results are presented at a single location. The analysis is then extended from individual locations to the 50 Santa Monica and 99 Moss Landing MOP transects, showing how liquefaction hazard varies spatially with SLR.

Chapter 7 presents conclusions and recommendations for future work in the context of the PLHA methodology. Future work includes extending the analysis to the remainder of the California coast once the groundwater model is complete.

CHAPTER 2

Technical Background on Liquefaction Hazard Analysis and Sea Level Rise

This chapter is organized in three parts. The first introduces liquefaction hazard: its consequences, the susceptibility, triggering, and manifestation components of an evaluation, and the models used for each. The second is a primer on probabilistic seismic hazard analysis (PSHA) and probabilistic liquefaction hazard analysis (PLHA). The third discusses sea level rise and groundwater dynamics at the coast.

2.1 Liquefaction Background

Section [2.1](#) first provides a high level introduction to liquefaction hazards, followed by discussions of liquefaction susceptibility, triggering mechanisms, and manifestation.

2.1.1 Liquefaction Overview: Consequences, Hazards, and Mitigation

Liquefaction is the sudden loss of strength and stiffness exhibited by saturated sandy soils. When earthquakes shake saturated, loose sand, high water pressures cause water to flow upward to the surface, often eroding soil particles. Earthquake-induced liquefaction became a significant concern for engineering practitioners following the 1964 Good Friday Alaska and Niigata, Japan earthquakes (Figure [2.1](#)), which occurred within a three-month

period. The liquefaction triggered by these earthquakes caused severe damage to the affected communities, establishing seismically induced liquefaction as a major hazard and an active research area in geotechnical engineering ([Seed et al., 2003](#)).



Figure 2.1: Soil Liquefaction, Niigata 1964 ([Japan National Committee on Earthquake Engineering, 1964](#))

Earthquake-induced soil liquefaction can cause massive infrastructure damage. Soil that was previously strong enough to support buildings, roadways, embankments, rail lines, and other infrastructure may temporarily become very weak, causing buildings to settle, lifelines to be buried, and utilities to break. In densely developed cities, liquefaction events can cause lasting damage to this critical infrastructure and delay post-earthquake reconstruction efforts.

Physical consequences of earthquake-induced soil liquefaction include lateral spreading, sediment ejecta (sand boils), lateral flow, increased passive pressures on retaining structures, uplift of buried infrastructure to the ground surface, differential settlement, and loss of bearing pressure ([Pacific Northwest Seismic Network, 2022](#)).



Figure 2.2: Soil Liquefaction, Christchurch, New Zealand 2011 ([Lincoln, 2011](#))

Ground displacement mechanisms include ground loss due to ejecta, shear-induced deformation (bearing capacity and soil-structure interaction ratcheting), volumetric deformation (partial drainage, sedimentation, and consolidation), lateral spreading, and flow slides as shown in Figure 2.2 from the 2011 Christchurch Earthquake sequence. Building settlement depends on the density and thickness of the liquefiable layer and the thickness of the non-liquefiable crust ([Bray, 2021](#)).

Mitigation of liquefaction consequences is guided by several overarching principles. These include increasing soil density, introducing cementation, adjusting the grain size distribution through soil replacement, lowering the degree of saturation, and increasing the effective stress of the site soil. This is often done in the field through ground improvement (replacement, solidification, displacement, or vibratory densification), or through structural countermeasures ([Huang and Wen, 2015](#); [Bao et al., 2019](#)). Densification methods can include vibratory or dynamic compaction, while cementation methods can include deep soil mixing or permeation grouting. Wick drains can address drainage pathways for excess pore pressure, whereas structural measures such as deep foundations extend through liquefiable layers to bear within competent strata. Emerging ground improvement methods include

bio-mediated soil improvement (DeJong et al., 2010).

2.1.2 Definition and Background of Earthquake-Induced Liquefaction Mechanics

The term “liquefaction” was first used by Hazen (1919) and then by Mogami and Kubo (1953). Since then, liquefaction has taken on many different definitions and has been used generally to describe soil deformations caused by the generation of excess pore pressure under undrained loading conditions (Kramer, 1996). The American Society of Civil Engineers offers an alternative definition: “the sudden large decrease of shearing resistance of a cohesionless soil, caused by a collapse of the structure by shock or strain, and associated with a sudden but temporary increase of the pore fluid pressure” (1958). The term liquefaction is also used to describe the onset of soil failure (triggering) (NASEM, 2021).

This dissertation focuses primarily on liquefaction induced by earthquake ground motions. Earthquake-induced liquefaction occurs when earthquake ground motions induce added stress in saturated or partially saturated granular material that can contract (i.e., shrink in volume). The particles lose contact and are temporarily suspended in pressurized fluid, and the soil then begins to behave in a fluid-like manner. More precisely, liquefaction has been described as “the seismic generation of excess pore water pressures and consequent softening of granular soils” (NASEM, 2021).

The governing term for liquefaction is effective stress σ' . Effective stress is defined as $\sigma - u$, where σ is the total external pressure in a soil column and u is the pore water pressure. Earthquake shaking causes the pore water pressure in soil to increase and the grain-to-grain soil stress and strength decrease as that water pressure increases (Bray, 2021). The soil particles post-liquefaction are shown in the idealized schematic of Figure 2.3. When excess pore pressure u_e generated by earthquake ground motions equals the initial effective stress σ' , liquefaction occurs. Effective stress governs soil strength; soils with higher effective stress generally exhibit greater resistance to seismic loading.

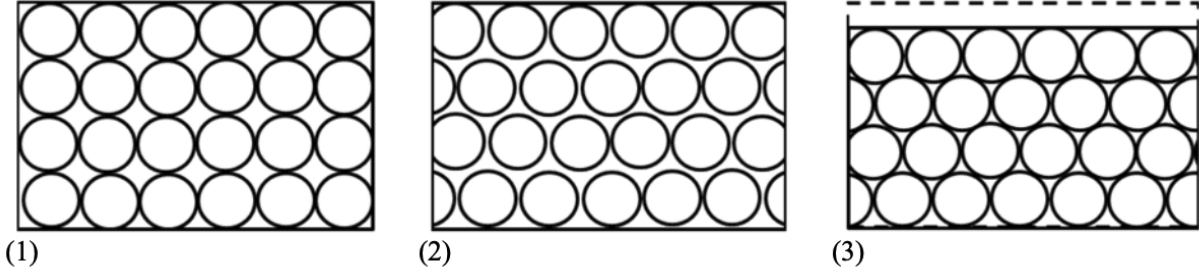


Figure 2.3: Idealized schematic of liquefiable soils ([NASEM, 2021](#))

Liquefaction phenomena can be categorized into two groups: flow liquefaction and cyclic mobility ([Kramer, 1996](#); [Kramer and Stewart, 2024](#)). Flow liquefaction is less common than cyclic mobility, but its consequences can be much more damaging and dramatic. Flow liquefaction occurs when the static shear stress (required for equilibrium) exceeds the shear strength of the liquefied soil. Flow liquefaction usually develops rapidly, and can move soil masses large distances ([Kramer, 1996](#)). Note that flow liquefaction could also be triggered by non-seismic loading ([Kramer and Stewart, 2024](#)).

Conversely, cyclic mobility happens when the static shear stress is lower than the inherent shear strength of the liquefied soil ([Kramer, 1996](#)). Cyclic mobility is described as a “substantial and often rapid reduction in soil stiffness and strength associated with the buildup of very high pore water pressure that occurs in granular soils” ([Kramer and Stewart, 2024](#)). To evaluate liquefaction hazard for a particular site, three factors should be considered: whether the soil is susceptible to liquefaction, whether liquefaction will be triggered in susceptible soil, and whether damage will occur if liquefaction is triggered ([Kramer and Stewart, 2024](#)).

2.1.3 Liquefaction Susceptibility

Liquefaction susceptibility is a property of the soil itself: it describes whether liquefaction could be triggered in some state, not whether it will be triggered in a given earthquake. The latter depends on the in situ condition of the deposit and the ground motion at the soil

site (Kramer and Stewart, 2024). Susceptibility is fundamentally related to mineralogy and composition, with sand-like soils being susceptible to liquefaction and clay-like soils being non-susceptible. Although clay-like soils are not susceptible to liquefaction, they may still undergo cyclic softening which is a progressive buildup of shear strain and loss of strength and stiffness under cyclic loading, and should be evaluated separately (Boulanger and Idriss, 2007). A soil’s susceptibility to liquefaction can be quantified, largely based on its composition, and more specifically the plasticity of the soil. To evaluate susceptibility, historical, geological, and compositional factors of the site soils must be considered. Some susceptibility criteria also include soil state (e.g., water content), but here susceptibility is based solely on soil composition and not state.

Historical evidence can be gleaned from post-earthquake reconnaissance, as liquefaction events often recur in the same places (Youd, 1984). Case histories can therefore be instrumental in assessing the site conditions that cause liquefaction to occur. Post-earthquake reconnaissance has shown that liquefaction sites tend to be located within a radius of a seismic source. The Next Generation Liquefaction (NGL) database contains information about many existing liquefaction case histories, including recent events in Turkey, Japan, and New Zealand (Zimmaro et al., 2019). For these sites (crustal events), the Joyner-Boore source-to-site distance (R_{JB}) was calculated. A histogram of the calculated values is shown in Figure 2.4 (Pretell 2024, personal communication). For the 465 selected sites, the average R_{JB} was 17 km.

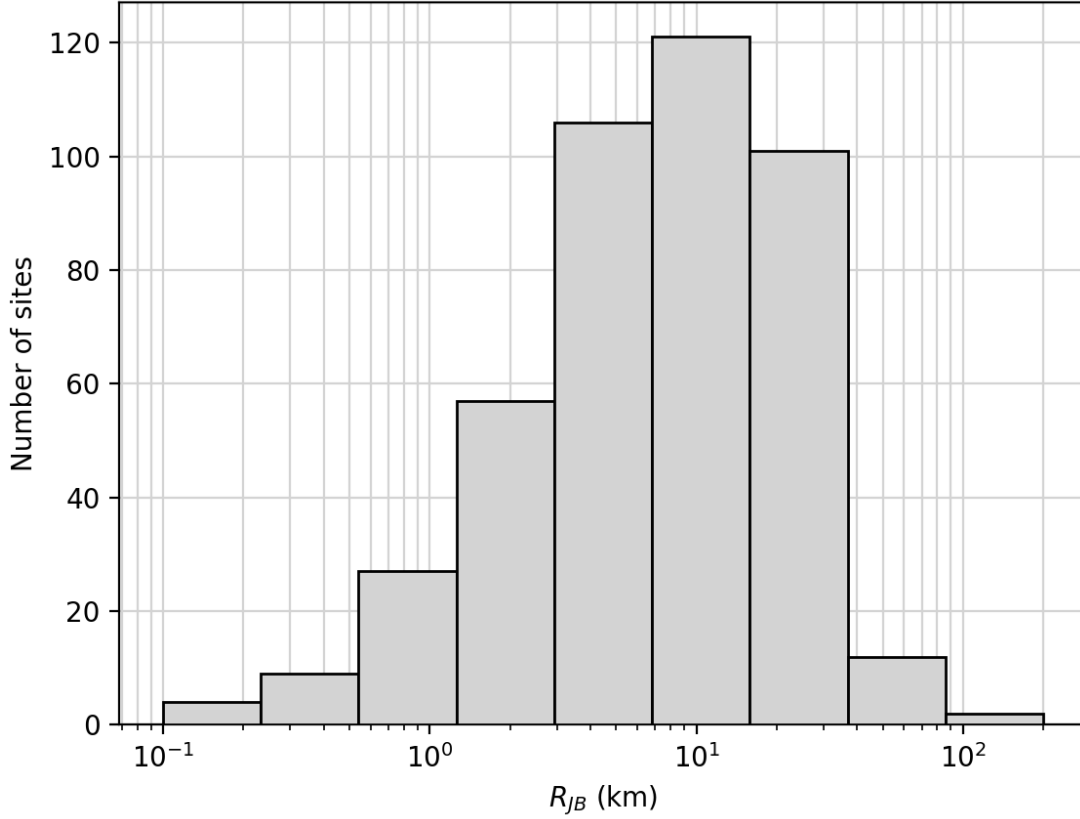


Figure 2.4: Distribution of Active Crustal R_{JB} Distances (Pretell, 2024)

Youd found that liquefaction continues to occur at sites where groundwater and soil “remain unchanged” (1984). From a geological perspective, processes that create loosely deposited uniform grain size distributions tend to create liquefiable soil. This can include saturated colluvial deposits (downslope unconsolidated sediments), artificial fill, and fluvial and aeolian deposits (sediments transported by water and wind, respectively). With regard to age, older soils (Pleistocene, 2.6 million to 11,700 years) are much less likely to liquefy than Holocene soils (11,700 years ago-present day). This is due to the cementation that occurs in older soils (Kramer, 1996). This age effect increases resistance to triggering rather than reducing susceptibility, which is not itself age-dependent (Kramer and Stewart, 2024). Man-made fills that are loosely placed, such as mine tailings dams, or fill in deltaic areas,

are also prone to liquefaction, due to the lack of compaction.

Compositional factors that affect volume change are important in liquefaction hazard due to the high excess pore pressure developed. Pore pressure generation is not as significant in fine-grained, plastic soils, so it is the plasticity of the soil, rather than grain size alone, that governs this behavior (Kramer and Stewart, 2024). Soils can behave in a sand-like or clay-like manner; this behavior depends on the plasticity of the fines (Boulanger and Idriss, 2006). These behaviors can be mainly correlated with Atterberg Limits (LL , PL , PI).

Non-plastic and low-plasticity silts can liquefy, particularly under undrained loading, when effective stress drops sharply as excess pore pressure rises. Not all fine-grained soils are susceptible; soils that behave in a clay-like manner are generally not considered liquefiable, although they may undergo cyclic softening and strength loss.

The Chinese Criteria (Wang, 1979) were widely used for several decades to assess liquefaction susceptibility. These criteria are:

1. Less than 15% finer than 0.005 mm
2. Liquid Limit less than 35
3. Water content greater than $0.9 \times \text{Liquid Limit}$

Two other commonly used fine-grained susceptibility criteria include Boulanger and Idriss (2006) and Bray and Sancio (2006). Boulanger and Idriss found that fine-grained soils behave in a more sand-like manner if $PI < 7$ (2006). If a soil plots within the CL-ML range, then the criterion is instead $PI < 5$. The Bray and Sancio method does not rely on PI alone. This method demonstrated that PI coupled with w_c/LL ratio can help assess liquefaction susceptibility, although w_c/LL ratio implies a density dependence, which is not inherent to susceptibility. Bray and Sancio found that young non-plastic silts and low-plasticity silts can liquefy at $PI < 12$ and $w_c/LL > 0.85$. For $12 < PI < 18$ and $w_c/LL > 0.8$, soils can also liquefy under a significant number of cycles.

Subsequent laboratory work has found sand-like pore pressure and stress-strain response in silty sands with plasticity indices above the recommended sand-like boundary (Beyzaei et al., 2018; Stuedlein et al., 2023). Because results scatter between materials, Kramer and Stewart (2024) suggest that a PI of roughly 6 to 12 is a reasonable range for the median of a probabilistic susceptibility criterion.

For liquefaction susceptibility, another method for determining clay-like behavior can be through strength normalization. Ladd and Foott proposed a relationship between undrained strength, S_u , and vertical effective stress σ'_v (1974). Their method, Stress History and Normalized Soil Engineering Properties (SHANSEP), helps assess whether a soil is clay or sand-like. If, under monotonic loading (one loading direction), the strength normalizes through the S_u/σ'_{vc} ratio, the soil is considered clay-like, and would therefore not be expected to liquefy.

Liquefaction susceptibility can also be assessed from cone penetration test (CPT) data through the soil behavior type index (I_c). An I_c of 2.6 has been taken as the boundary between sand-like and clay-like materials, with sand-like soils falling below (Robertson and Wride, 1998). The range $2.50 < I_c < 2.70$ is now more commonly treated as a transition rather than a sharp boundary (Robertson, 2009).

The criteria above screen soils into those that should be carried forward into a liquefaction triggering analysis and those that should not, but a soil classified as non-susceptible has not thereby been cleared. Where site soils are judged non-susceptible, the liquefaction hazard evaluation itself may be concluded, but cyclic softening still warrants evaluation (Kramer and Stewart, 2024). Clay-like soils subjected to strong shaking may still soften cyclically, producing ground deformations of comparable engineering consequence. Boulanger and Idriss recommend that such soils be evaluated using procedures rooted in undrained shear strength and stress history.

2.1.4 Liquefaction Triggering

A susceptible soil will not necessarily liquefy; triggering also requires loading of sufficient intensity and duration. Liquefaction triggering occurs when ground shaking is strong enough for the soil to lose strength and there is a sudden increase in excess pore water pressure. A liquefaction hazard analysis should evaluate whether the shaking is significant enough for liquefaction to trigger.

Liquefaction triggering is dependent on the initial state of the soil. Below, monotonic and cyclic loading are introduced in relation to the initial state of a soil. Monotonic loading of a soil column occurs when the shear stress of a soil increases, but there is no change in the direction of the loading conditions (NASEM, 2021). Dry granular sand specimens behave differently when sheared, depending on whether they are loose or dense. Casagrande (1936) ran triaxial tests on loose and dense specimens, the results of which were reproduced by Kramer (1996), as shown in Figure 2.5. The loose soil decreases in void ratio (contracts) and the dense soil increases in void ratio (dilates) (NASEM, 2021). A constant void ratio for both loose and dense soils is reached at high strains (e_c).

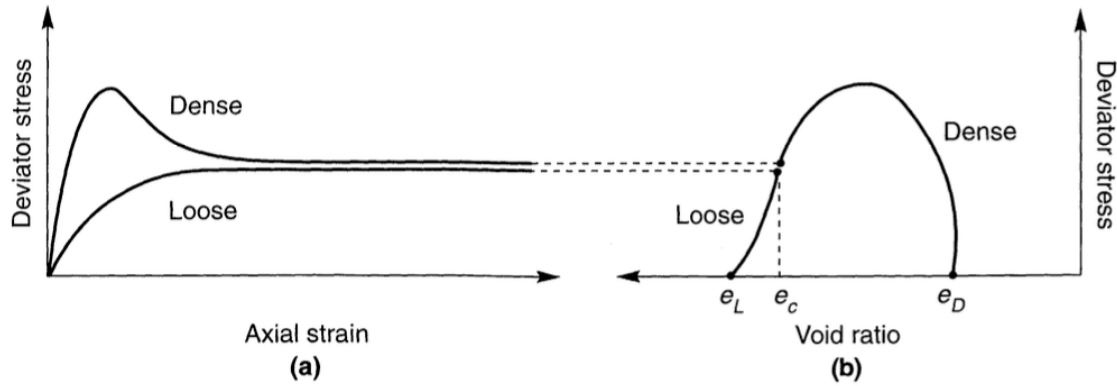


Figure 2.5: Stress-strain and stress-void ratio for dense and loose sands for drained monotonic loading at a constant pressure (Kramer, 1996)

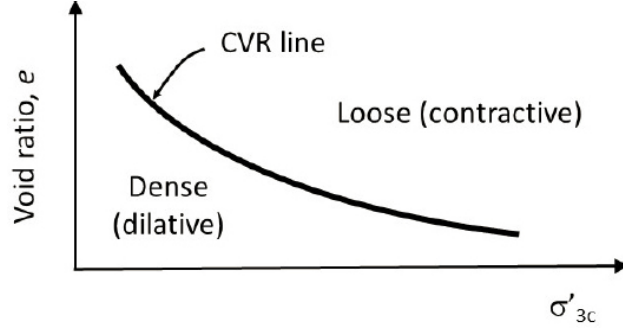


Figure 2.6: Critical Void Ratio/Critical State line separating dilative and contractive soil states ([Kramer, 1996](#))

The critical void ratio (CVR) line or critical state line (CSL) as shown in Figure 2.6 marks the distinct boundary between the two soil states. When dense soil dilates, the void ratio increases to reach the CSL; conversely, when loose soil contracts, the void ratio decreases. When an excessive amount of load is applied to a saturated soil and there is not enough time for the water to drain out of the voids, undrained loading occurs. For dense soils, dilation leads to an increase in effective stress and lower pore water pressure; the opposite is true in loose soils, causing them to lose strength.

Saturated soils that plot above the CSL are contractive and generate high pore pressures. They can also have large shear strains. The state parameter ψ helps determine whether a soil will dilate or contract ([NASEM, 2021](#)). It is defined as $e - e_{SS}$ where e is the void ratio and e_{SS} is the steady state void ratio. Soils above the CSL tend to have positive state parameters and will contract, whereas soils below the CSL have negative state parameters and will dilate. This is shown in Figure 2.7.

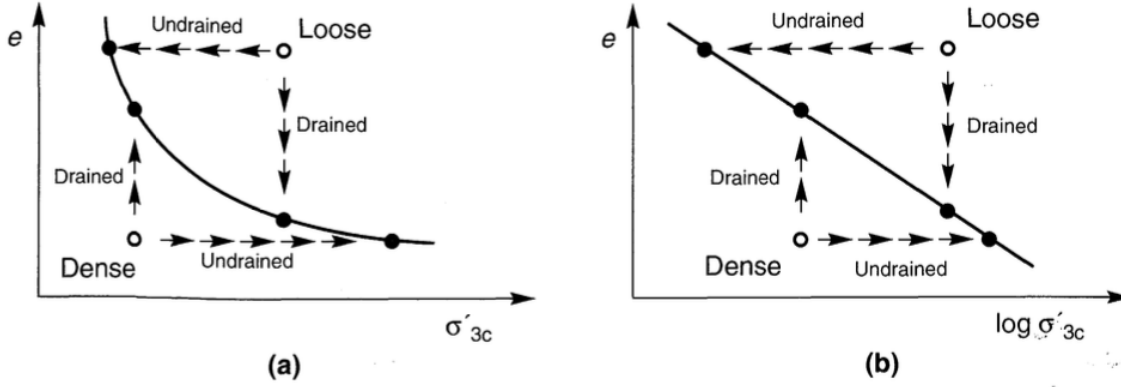


Figure 2.7: a) Loose and Dense Soil specimen behavior under monotonic loading b) SSL/CSL with state parameter examples (Kramer, 1996)

Additionally, cyclic shear stress reversal is common during an earthquake loading event (NASEM, 2021). Under cyclic loading, both loose and dense soils initially generate positive excess pore pressures at low shear strains. As loading increases in dense soils, their dilative tendency causes the effective stress path to move along the failure envelope. Soil stiffness changes (either increasing or decreasing) along the failure envelope as the effective stress changes. The maximum shear strain is minimal until the effective stress is relatively low, after which the strain values increase significantly. Examples of loose liquefiable soils under cyclic loading are shown in Figure 2.8 (NASEM, 2021). Panels 1 and 2 show the stress-strain behavior of a loose soil and the effective stress path of the sample. r_u is the pore pressure ratio (excess pore pressure divided by initial vertical effective stress). Panel 3 illustrates how the shear strain in the sample develops while r_u is near 0. After 22 cycles, r_u reaches 1. Panel 4 shows the effective stress reduction as the number of cycles increases (NASEM, 2021).

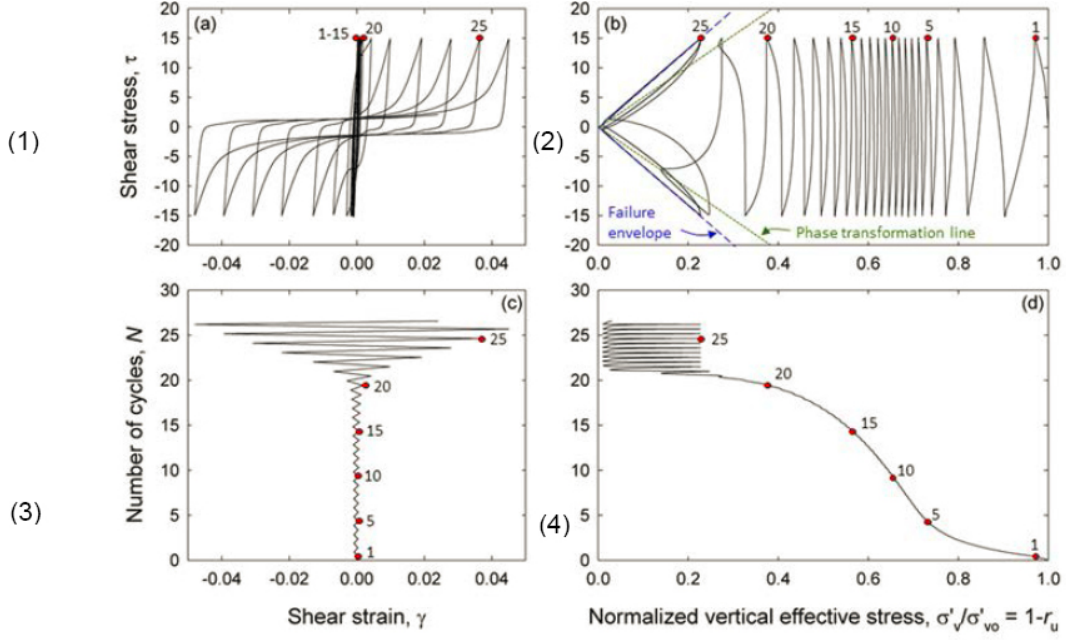


Figure 2.8: Behavior of loose liquefiable soil under cyclic loading, shown through Panels 1-4 (NASEM, 2021)

The commonly used stress-based approach for liquefaction triggering analysis was first introduced by Seed and Idriss (1967). The factor of safety against triggering, FS , is defined as liquefaction resistance divided by seismic demand. The cyclic resistance ratio (CRR) is the liquefaction resistance and the cyclic stress ratio (CSR) is the seismic demand.

CSR is calculated at a specific depth and for an earthquake with a particular magnitude and peak ground acceleration (PGA). It represents the one-dimensional response of vertically propagated shear waves (NASEM, 2021).

$$CSR_{M=m}(z) = \frac{0.65 \cdot \tau_{cyc,max}(z)}{\sigma'_{v0}(z)} = \frac{0.65 \cdot (PGA/g) \cdot \sigma_v(z) \cdot r_d(z)}{\sigma'_{v0}(z)} \quad (2.1)$$

The 0.65 factor reduces the CSR from a peak value to a more representative value during earthquake loading. $\tau_{cyc,max}$ is the maximum cyclic shear stress, σ_{v0} is the initial total vertical stress and σ'_{v0} is the initial effective vertical stress, both at a specified depth. PGA is the peak surface horizontal ground acceleration. r_d is a depth dependent shear stress reduction coefficient. r_d has a maximum of 1 at the surface and decreases with depth.

Liquefaction depends not only on CSR but also on the number of cycles (Ulmer et al., 2024). Therefore, CSR is modified using a magnitude scaling factor, MSF to represent a magnitude 7.5 equivalent earthquake. MSF allows for an adjustment of CSR based on the number of earthquake loading cycles.

$$CSR_{M=7.5}(z) = \frac{CSR_M(z)}{MSF} \quad (2.2)$$

There are well known MSF relationships such as Youd et al. (2001), Cetin et al. (2004), and Boulanger and Idriss (2014).

There is also a variety of CRR relationships. They are dependent on in-situ penetration resistance, fines content, effective stress, magnitude, vertical effective stress, and static shear stress. CRR relationships are referenced to an effective stress of 1 atm, clean sand, and magnitude 7.5. If these references do not represent a given site, adjustments can be made. Common standard penetration test (SPT) or blowcount (N) relationships include Youd et al. (2001), Cetin et al. (2004) and Boulanger and Idriss 2014. CRR relationships have also been developed based on tip resistance, q_t , from CPTs. CPT based CRR relationships include Robertson and Wride (1998), Moss et al. (2006), and Boulanger and Idriss (2016). K_σ is the overburden stress factor and is an effective stress adjustment. K_α modifies CRR for static shear stress (NASEM, 2021). Clean sand adjustments account for the influence of increased fines content.

2.1.5 Liquefaction Manifestation

Liquefaction manifestation refers to the observable expression of subsurface liquefaction at the ground surface, such as sand boils, ground cracking, lateral spreading, settlement, and loss of foundation support (Ulmer et al., 2024; NASEM, 2021). Whether triggering in a subsurface layer produces surface effects depends on the geometry and properties of the soil profile above it, particularly the thickness and strength of the overlying non-liquefiable crust.

Three broad classes of manifestation assessment exist in practice: relative layer thickness criteria, severity index criteria, and hydraulic profile analysis criteria.

Relative Layer Thickness Criteria

The influence of a non-liquefiable capping layer of thickness H_1 on suppressing the surficial manifestation of liquefaction in an underlying liquefiable layer of thickness H_2 was quantified by [Ishihara \(1985\)](#) based on field performance data from the 1976 Tangshan and 1983 Nihonkai-Chubu earthquakes. Ishihara plotted observations of liquefaction surface effects using H_1 and H_2 and proposed boundary curves for predicting liquefaction manifestation as a function of H_1 , H_2 , and PGA as shown in [Figure 2.9](#). A family of curves corresponding to different PGA levels was proposed, indicating that for a given PGA, there is a limiting H_1 beyond which surface manifestation does not form regardless of the thickness of the underlying liquefiable layer ([Ishihara, 1985](#)). This method remains widely used in practice to assess whether a non-liquefiable crust is sufficient to suppress surficial manifestation of liquefaction that triggers at depth ([Ulmer et al., 2024](#)).

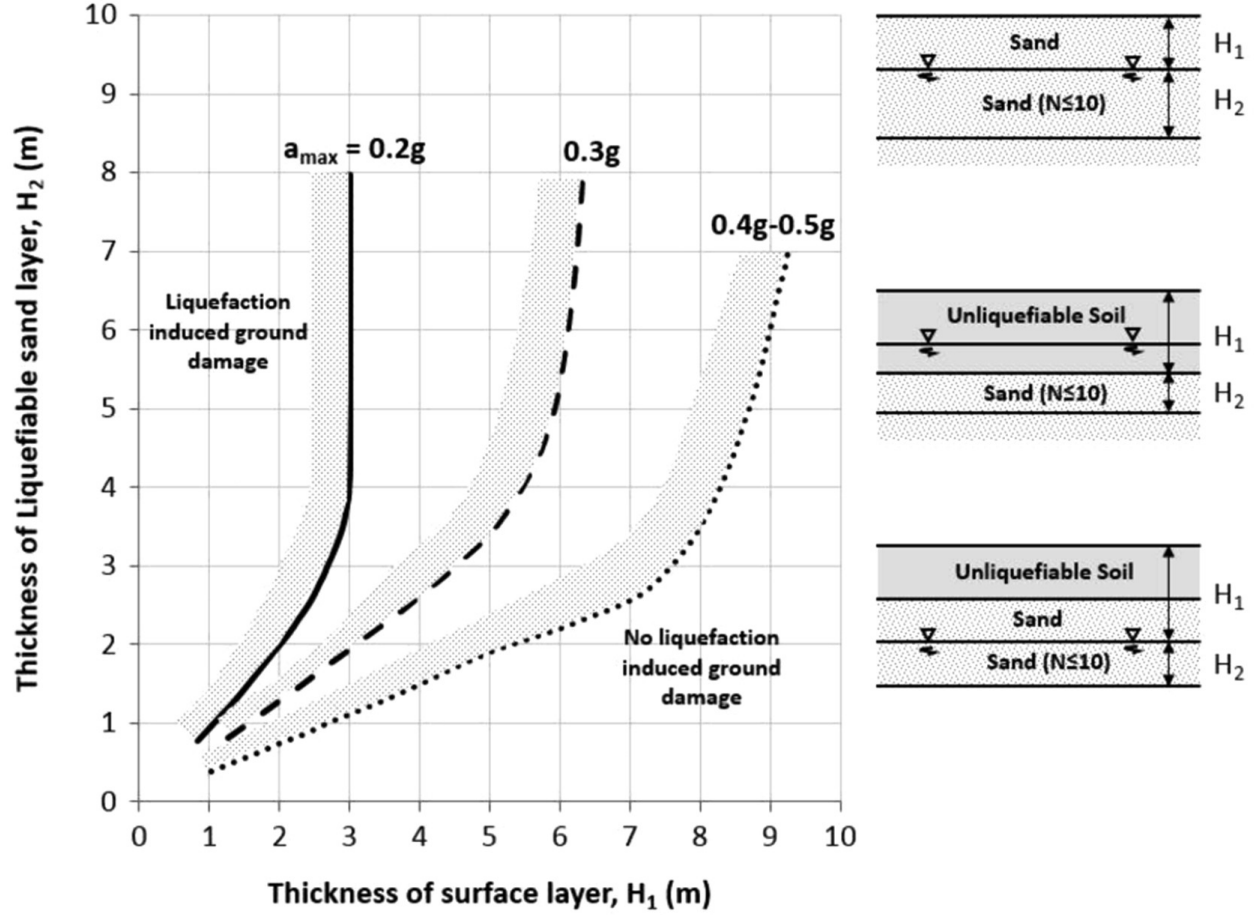


Figure 2.9: Surface Manifestation: Thickness of liquefiable layer versus thickness of overlying layer at sites (Ishihara, 1985)

Severity Index Criteria

Liquefaction severity indices estimate the severity of surface manifestation based on the cumulative liquefaction response of a soil profile, rather than relying on a single critical layer. These profile-integrated metrics are related empirically to observed surface damage, and their use avoids the subjectivity inherent in critical layer identification (Ulmer et al., 2024).

The Liquefaction Potential Index (LPI), introduced by Iwasaki et al. (1978), is the most widely used severity index. LPI integrates liquefaction response within the upper 20 m of a soil profile and ranges from 0 to 100. Iwasaki et al. (1978) established the following severity categories based on field observations from the various earthquakes: low ($LPI \leq 5$), high

($5 < LPI \leq 15$), and very high ($LPI > 15$).

A key limitation of the original LPI formulation is that it does not account for the protective effect of a non-liquefiable surface crust. Maurer et al. (2015) addressed this by deriving a novel Ishihara-inspired index, LPI_{ISH} , which modifies the LPI depth weighting function to incorporate the H_1 – H_2 boundary curves of Ishihara (1985). This modification results in LPI_{ISH} assigning higher weight to shallower layers than standard LPI, and was found to improve predictive capacity and reduce false-positive predictions across numerous case histories from multiple earthquakes in regions outside Japan (Maurer et al., 2015).

The Liquefaction Severity Number (LSN), developed following the 2010–2011 Canterbury, New Zealand earthquake sequence (van Ballegooy et al., 2014), provides an alternative profile-based index using post-earthquake volumetric strain ε_v as the primary variable. ε_v is the post-earthquake volumetric strain at depth z in decimal form, computed as a function of FS_L using the method of Ishihara and Yoshimine (1992) as implemented with CPT data by Zhang et al. (2004). Unlike LPI, LSN includes contributions from all layers with $FS_L < 2$ and employs a power-law depth weighting function. Severity categories are defined as low ($LSN \leq 20$), moderate ($20 < LSN \leq 40$), and high ($LSN > 40$) (Ulmer et al., 2024).

Whereas LPI and LSN are typically applied deterministically, Geyin and Maurer (2020) developed fragility functions relating such indices to the probability of liquefaction manifestation states, from no surface effect to severe ejecta, calibrated on a large global database of CPT case histories. Geyin et al. (2022) later extended this index-based prediction to regional scales using machine learning to estimate manifestation severity from geospatial data where site specific investigations are unavailable.

Hydraulic Profile Analysis Criteria

Hutabarat and Bray (2022) developed an ejecta prediction framework based on a hydraulic analysis of the CPT profile. The method defines two parameters: a liquefaction ejecta demand parameter (LD) that estimates the upward seepage pressure capable of producing

artesian flow due to elevated excess hydraulic head, and a crust resistance parameter (CR) that captures the undrained shear strength and thickness of the non-liquefiable crust layer.

Using 176 field case histories with observations of ejecta severity, [Hutabarat and Bray \(2022\)](#) developed charts relating LD – CR position to ejecta severity categories for both thick sand and stratified soil sites as shown in Figure 2.10.

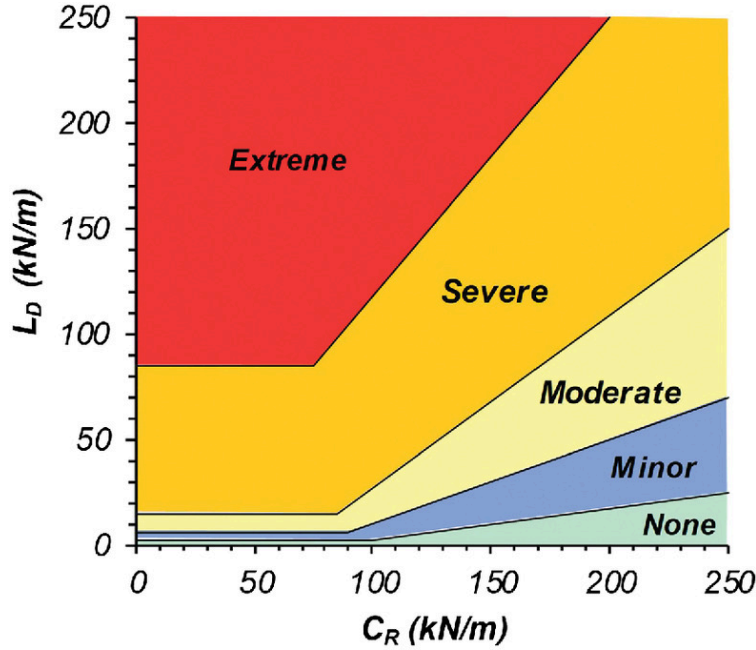


Figure 2.10: Liquefaction-induced ejecta severity chart ([Hutabarat and Bray, 2022](#))

2.1.6 Critical Layer Models

The stress-based framework introduced by [Seed and Idriss \(1967\)](#) and described in Section 2.1.4 forms the foundation for both deterministic and probabilistic approaches to liquefaction triggering evaluation. In a deterministic framework, the factor of safety $FS_L = \frac{CRR}{CSR}$ governs the assessment, with $FS_L < 1$ indicating triggering. The current standard of practice relies mainly on deterministic approaches to analyze liquefaction triggering. These models are primarily based on field case history databases compiled from earthquake reconnaissance, and more specifically on observations of surface liquefaction at the site, which are typically classified as binary *yes*, *no* occurrences, though some models also incorporate *marginal* ob-

servations (Ulmer et al., 2024). Triggering curves were typically drawn to separate yes- and no-liquefaction case histories as a function of an in-situ strength parameter, such as standard penetration test blow counts N or CPT tip resistance q_c .

Probabilistic models extend this framework by expressing the probability of liquefaction, P_L , as a continuous function of demand and resistance, providing more information about the likelihood of triggering than a binary outcome – an advantage particularly relevant for performance-based earthquake engineering applications, such as PLHA (Kramer and Mayfield, 2007).

A number of probabilistic procedures for liquefaction triggering have been developed such as Liao et al. (1988), Toprak et al. (1999), Cetin et al. (2004), Moss et al. (2006), Boulanger and Idriss (2012), Boulanger and Idriss (2016) and Cetin et al. (2018). These procedures provide predictions of liquefaction resistance for a specific site. Additional probabilistic procedures have been developed as more robust case histories and liquefaction site investigations have become available. These triggering methods usually begin by identifying the median input parameters, such as penetration resistance and fines content. The median and standard deviation are also estimated for the earthquake demand parameters, and then lastly a closed form probability of liquefaction, P_L , is used for assessment. An example of the seismic soil liquefaction triggering curves from Cetin et al. (2018) is shown in Figure 2.11.

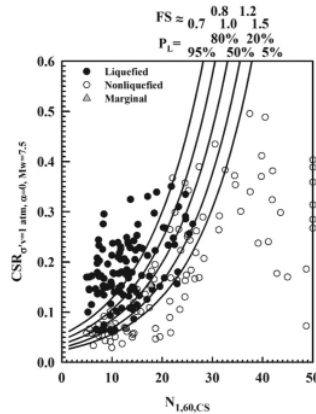


Figure 2.11: Seismic Soil Liquefaction Triggering Curves (Cetin et al., 2018)

All of these legacy models rely on a *critical layer* framework, in which a single layer is identified: the layer that liquefied (or in the case of “no liquefaction” case histories, the layer that would have liquefied first had the shaking been stronger) and was responsible for the “observed consequences” (Kramer and Stewart, 2024). This single layer’s properties are then used as the data point in model development.

Selection of the critical layer is often difficult and can be subjective based on interpretation of the analyzer. This leads to repeatability challenges, as discussed further in Section 3.3.1 of Ulmer et al. (2024) and creates a fundamental disconnect between how models are developed (using a single identified layer per site) and how they are typically applied in practice (using all layers). Despite these limitations, the legacy probabilistic triggering models such as Moss et al., Cetin et al., and Boulanger and Idriss remain widely used in geotechnical practice and provide important benchmarks against which newer frameworks are evaluated.

2.1.7 NGL SMT Manifestation Model

As another alternative to the critical-layer triggering model approach, there has been further research into *profile based models*, where instead of a critical layer, the entire profile is considered and a probability of manifestation can be calculated for an entire CPT sounding.

The Supported Modeling Team (SMT), under the Next Generation Liquefaction (NGL) project, developed an integrated framework for evaluating the probability of liquefaction susceptibility $P[S]$, triggering given susceptibility $P[T | S]$, and surface manifestation $P[M]$ (Ulmer et al., 2024). This dissertation uses the NGL SMT model for the liquefaction triggering component of the PLHA pipeline, making the framework directly relevant to the analyses presented in subsequent chapters. A central motivation for the NGL SMT approach is to overcome the limitations of the critical layer framework used in legacy models. Rather than selecting a single representative layer per site, the SMT model explicitly treats the full CPT profile and separates the problem of triggering from the problem of manifestation (Ulmer et al., 2024). Another reason the SMT model was used for this dissertation analysis was

that groundwater changes may affect the critical layer selection, as shown in Chapter 4. Therefore, it is beneficial to avoid critical layer methods for this reason.

2.1.8 Susceptibility Model, $P[S]$

The susceptibility model evaluates the probability that a given soil layer is capable of experiencing liquefaction. It is based on the soil behavior type index I_c from CPT data, with susceptibility decreasing as I_c increases (as soil behavior becomes more clay-like).

2.1.9 Triggering Model, $P[T | S]$

The triggering model $P[T | S]$ expresses the probability that a susceptible soil layer will liquefy under a given level of seismic demand. The SMT's approach is distinct from legacy models in that it uses laboratory cyclic test data to establish an initial *prior* distribution for CRR, which is then updated using NGL field case history data through Bayesian inference to produce a *posterior* triggering model.

2.1.10 Manifestation Model, $P[M]$

The manifestation model $P[M]$ evaluates the probability that liquefaction triggering in one or more layers will produce observable surface effects. The SMT formulates $P[M]$ as a product of layer-level components. This profile-based manifestation model avoids the need to identify a critical layer and instead integrates contributions from all susceptible layers within the profile.

2.2 Probabilistic Hazard Background

The following sections summarize probabilistic seismic hazard analysis (PSHA) and its advantages over deterministic methods, and Section 2.2.2 broadly reviews probabilistic liquefaction hazard analysis (PLHA).

2.2.1 Probabilistic Seismic Hazard Analysis

Probabilistic Seismic Hazard Analysis (PSHA) is a powerful tool for evaluating earthquake risk at a specific location. This approach comprehensively integrates ground motions from all earthquake sources by considering the slip rate and magnitude distribution for each source, source-to-site distance, site conditions, and ground motion uncertainty. PSHA calculates the annual rate of exceedance of a ground motion intensity measure, such as PGA (McGuire, 1995). PSHA was first formulated by Cornell (1968), and aleatory variability with regard to ground shaking was introduced by Esteva (Esteva, 1969).

Previously, Deterministic Seismic Hazard Assessment (DSHA) served as the primary methodology for evaluating earthquake hazards. DSHA’s appeal lies in its streamlined approach, concentrating on the “maximum credible earthquake” (MCE) scenario originating from nearby faults. However, there are some limitations of a deterministic analysis, and these are rooted in the way this analysis considers uncertainty (Gerstenberger et al., 2020). The selection of earthquake ground motions is often subjective, especially when considering both magnitude and distance. This subjective choice becomes especially important in regions with highly active faults. At a specific site, a closer, low-magnitude earthquake event will generate a spectral acceleration response that differs significantly from that of a high-magnitude event farther away. This difference is particularly pronounced at both shorter and longer periods. Another limitation is the treatment of ground motion uncertainty. Usually, DSHA uses a $+1\sigma$ ground motion, but there is no true justification for this selection. It would be better to integrate the hazard from all sources and select a suitable return period for a particular application.

Figure 2.12 shows an example of a site with two rupture events, one with $M = 6.5$ and $R = 10$ km, and the other with $M = 7.5$ and $R = 20$ km. The closer event has higher spectral accelerations at oscillator periods shorter than about 0.9 seconds, but lower spectral accelerations at longer periods. This illustrates that different events might need to be selected for structures with different natural periods using DSHA (Baker et al., 2021).

The Campbell and Bozorgnia ([Campbell and Bozorgnia, 2014](#)) ground motion model was used in this example.

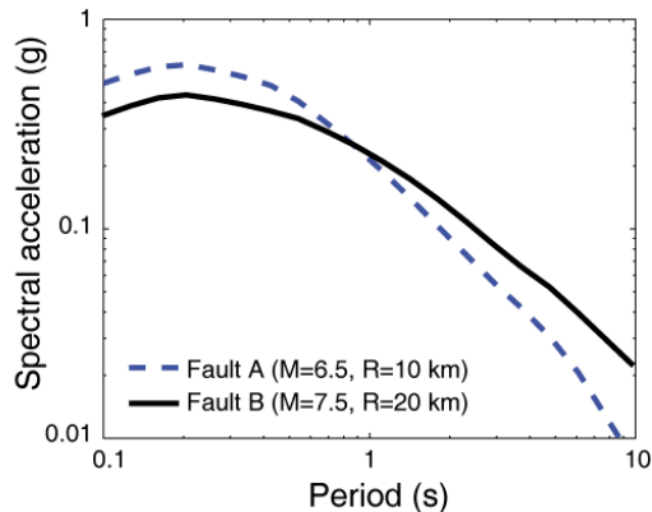


Figure 2.12: Predicted median response of two earthquake events ([Baker et al., 2021](#))

Conversely, identifying a “worst-case” ground motion scenario becomes particularly challenging in regions with less apparent faulting (outside of known highly seismic zones) ([Baker et al., 2021](#)). Reliance on subjective choices of ground motions can compromise the robustness of the analysis. The inherent variability of ground motions and their intensities further complicates the selection of a definitive “worst case” scenario. [Baker et al.](#) states, for example, that during the 1999 Chi-Chi earthquake in Taiwan, PGA values within 10 km of the epicenter ranged from 0.1g to over 1g. Hence, attempting to choose a true maximum, “worst case” ground motion can be a difficult task.

A probabilistic seismic hazard analysis considers all possible earthquake rupture events and also their individual probability over magnitude and time ([Gerstenberger et al., 2020](#)). [Baker et al.](#) define the main steps for a PSHA as:

1. Identify the ground motion intensity measure
2. Identify site properties (e.g., the time-averaged shear wave velocity in the upper 30 m, V_{S30})

3. Compute characteristics such as locations, distances, and occurrence rates of rupture scenarios, and discretize into magnitude bins, with each magnitude having a discrete annual rate of occurrence
4. Consider all ruptures, relevant uncertainty in ground motion intensity, and compute the annual rate of exceedance of the ground motion intensity measure for all events
5. Add together the annual rates of exceedance for all events

The initial PSHA formulation is defined as ([Bazzurro and Cornell, 1999](#); [Kramer, 1996](#); [Baker et al., 2021](#); [Bozorgnia, 2023](#)):

$$P(\text{IM} > im) = \int_{m_{min}}^{m_{max}} \int_{r_{min}}^{r_{max}} P(\text{IM} > im \mid m, r, \xi) f_M(m) f_R(r) dr dm \quad (2.3)$$

In practice, the integrals are discretized and the PSHA formulation becomes:

$$\lambda(\text{IM} > im) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \sum_{j=1}^{N_M} \sum_{k=1}^{N_R} P(\text{IM} > im \mid m_j, r_k, \xi) f_{Mi}(m_j) f_{Ri}(r_k) \Delta r \Delta m \quad (2.4)$$

- IM is a random variable representing the ground motion intensity measure
- im is a specific value of IM
- $\lambda(\text{IM} > im)$ indicates the annual frequency of earthquakes causing IM greater than im
- $n_{sources}$ is the number of seismic sources the assessment is discretized over
- $\lambda(M_i > m_{min})$ is the annual frequency of earthquakes above m_{min} on source i
- N_M is the number of discrete magnitudes m_j
- N_R is the number of discrete distances r_k

- ξ denotes additional site variables on which the ground motion model depends (e.g., V_{S30} , $z_{1.0}$ or $z_{2.5}$)
- $P(\text{IM} > im \mid m_j, r_k, \xi)$ indicates the probability that the chosen intensity measure will exceed im for a given magnitude, distance, and site condition
- $f_{Mi}(m_j)$ is the probability density function of magnitude, from the Gutenberg-Richter truncation model for source i , for example ([Gutenberg and Richter, 1944](#))
- $f_{Ri}(r_k)$ is the probability density function for site-to-source distance over source i ([Bozorgnia, 2023](#))

An important component of a PSHA is the ground motion model (GMM), which quantifies shaking intensity as a random variable conditioned on M , R , and ε . Generally, they are expressed through a log-normal distribution:

$$\mu_{\ln \text{IM}} = f(\text{source, path, site}) \quad (2.5)$$

Another consideration for GMMs is epistemic uncertainty and aleatory variability. Epistemic uncertainty is the lack of knowledge or variability between data models, along with uncertainty in input parameters to those models. Epistemic uncertainty is generally quantified by building logic trees that consider many or all available models. Aleatory variability refers to the inherent randomness in the ground motion system.

The formulation in Equation 2.4 computes the rate of exceedance ([Baker et al., 2021](#)). However, in practice it may be more preferable to calculate the probability of IM greater than im over a specific duration of time, T . This time-dependent distribution is usually assumed to follow a Poisson process, as it allows for mathematical simplicity and often matches observations ([Benjamin and Cornell, 1970](#); [Baker et al., 2021](#)). Events on large earthquake sources, like the San Andreas Fault, are often treated as non-Poisson because after a large-magnitude earthquake has released stresses that accumulated over many years,

there is less likelihood of another large-magnitude event. In those cases, the λ term in Eq. 2.6 can be replaced with an equivalent λ consistent with the exposure duration (Benjamin and Cornell, 1970; Baker et al., 2021).

The PSHA formulation, when considered over a duration of time, T , becomes:

$$P_T(\text{IM} > im) = P[\lambda \text{ over } T \text{ years where } \text{IM} > im] = 1 - e^{-\lambda T} \quad (2.6)$$

λ is the exceedance rate and the return period (RP) is defined as the reciprocal of the rate of exceedance. λ has units of events per year and RP , as its reciprocal, has units of years per event.

$$RP = \frac{1}{\lambda} \quad (2.7)$$

The output of a PSHA is a ground motion hazard curve, which plots corresponding rates of exceedance, λ against an intensity measure. The intensity measure can be PGA, Pseudo-spectral Acceleration (PSA), Arias Intensity (AI), Cumulative Absolute Velocity (CAV), or another. The hazard λ values can be broken down into contributions from each source. The seismic hazard curves for each seismic source can be plotted, and the curves may not be parallel. Plotting these curves together shows which sources are most important.

Disaggregation is an output of PSHA that helps answer the question “Which earthquake rupture event is most likely to cause $IM > x$?” (Baker et al., 2021). The intermediate PSHA calculations can help discern the relative contribution of different earthquake magnitudes and sources. Since seismic hazard is a function of period, the contributions of magnitudes and distances vary at different periods (Bozorgnia, 2023). Using conditional probability, the fraction of earthquakes in specific disaggregation bins that produce $IM > im$ can be found as:

$$\begin{aligned}
& P(m_1 < M < m_2, r_1 < R < r_2, \epsilon_1 < \epsilon < \epsilon_2 \mid \text{IM} > im) \\
& = \frac{\sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_{r_{min}}^{r_{max}} \int_{\epsilon_1}^{\epsilon_2} P(\text{IM} > im \mid m, r, \epsilon) f_{M_i}(m) f_{R_i}(r) dr dm d\epsilon}{\lambda(\text{IM} > im)}
\end{aligned} \tag{2.8}$$

2.2.2 Probabilistic Liquefaction Hazard Analysis

Probabilistic liquefaction hazard analysis (PLHA) can help account for the uncertainty that comes from ground motion, earthquake load, and soil resistance (Hynes, 1999). In traditional practice, liquefaction is evaluated by comparing resistance (CRR) to demand (CSR) for a single ground motion and magnitude, yielding a factor of safety $FS_L = \frac{CRR}{CSR}$ (Section 2.1.4). Because triggering procedures consider only a single ground motion hazard level (Kramer and Mayfield, 2007), the return period associated with the computed factor of safety is unknown, and for a ground motion drawn from a PSHA the true return period is generally longer due to the conservatism built into triggering models. Therefore, as part of the PLHA, the return period of the factor of safety can be quantified directly by integrating liquefaction uncertainty into the hazard calculation.

PLHA convolves a probabilistic liquefaction triggering model with the seismic hazard, analogous to the role of the ground motion model in PSHA. The probabilistic triggering procedures available for this purpose (e.g. Liao et al. (1988), Toprak et al. (1999), Cetin et al. (2004), Moss et al. (2006), Boulanger and Idriss (2012), and Cetin et al. (2018)) are reviewed in Section 2.1.6. Here, the focus is instead on the methods that integrate such a model with PSHA to produce a liquefaction hazard curve.

Performance-based liquefaction assessment was first presented by Yegian and Whitman

(1978). They describe $P[F_L]/\text{yr}$ as

$$\int_R \int_M P[F_L | M, R_i, E \text{ at } i] f(M) dM dR \quad (2.9)$$

where $P[F_L | M, R_i, E \text{ at } i]$ is the conditional probability of liquefaction given that an earthquake of magnitude M and hypocentral distance R occurs at i (Yegian and Whitman, 1978). Atkinson et al. (1984) developed a method that combined the Seed and Idriss (1971) CRR potential liquefaction method with the Cornell (1968) method of seismic hazard. Marrone et al. (2003) provides a “composite liquefaction hazard” and, through disaggregation, a robust probabilistic assessment. This method analyzes distance disaggregation and the spatial distribution of liquefaction through the following formulation:

$$P[L] = \sum_{i,j} P[L | CSR(a_{max}, m_j), (N_1)_{60}] \cdot P[A = a_{max} | m_j] \quad (2.10)$$

where the probability of liquefaction is the joint conditional probability of liquefaction given a seismic event and the annual probability of that event, summed over all events (Marrone et al., 2003). Hwang et al. (2005) similarly developed a fully probabilistic liquefaction method that considers uncertainties in soil strength and ground shaking, using Monte Carlo simulations to generate artificial earthquakes and determine an annual rate of exceedance of liquefaction.

Probabilistic liquefaction hazard assessment finds its foundational elements not only in probabilistic seismic hazard analysis (Section 2.2.1) but also in the performance-based earthquake engineering (PBEE) framework (Kramer and Mayfield, 2007). Using a probabilistic framework, PBEE evaluates risk at a specific site (Kramer and Mayfield, 2007). PBEE was developed by the Pacific Earthquake Engineering Research (PEER) Center to measure different performance objectives (life safety, collapse prevention, dollar loss, and downtime), including their inherent uncertainty (Krawinkler, 2002; Medina and Krawinkler, 2004). The PBEE framework is dependent on Decision Variables (DV), Intensity Measures (IM), En-

gineering Demand Parameters (*EDP*), and Damage Measures (*DM*). Examples of decision variables include economic loss and injuries. Intensity measures include various ground motion parameters, such as ground acceleration. EDPs provide a measure of system response, such as excess pore pressure or the factor of safety against liquefaction. Outcomes of EDPs such as settlement are damage measures (Kramer and Mayfield, 2007). The mean annual rate of exceedance for PBEE is:

$$\begin{aligned} \lambda_{dv} = & \sum_{k=1}^{N_{DM}} \sum_{j=1}^{N_{EDP}} \sum_{i=1}^{N_{IM}} P[DV > dv \mid DM = dm_k] \\ & \times P[DM = dm_k \mid EDP = edp_j] P[EDP = edp_j \mid IM = im_i] \Delta\lambda_{im_i} \end{aligned} \quad (2.11)$$

$P[a \mid b]$ is the conditional probability, and N_{DM} , N_{EDP} , and N_{IM} are the numbers of increments of damage measures, engineering demand parameters, and intensity measures, respectively (Kramer and Mayfield, 2007). To apply this formulation to liquefaction analysis, FS_L can be represented as an EDP. FS_L depends on both magnitude and peak acceleration:

$$\Lambda_{FS_L}^* = \sum_{j=1}^{N_M} \sum_{i=1}^{N_{amax}} P[FS_L < FS_L^* \mid a_{max,i}, m_j] \Delta\lambda_{a_{max,i},m_j} \quad (2.12)$$

$\Lambda_{FS_L}^*$ is the mean annual rate of factor-of-safety non-exceedance, i.e., the rate at which the traditional factor of safety FS_L falls below the threshold FS_L^* . Non-exceedance “represents an undesirable condition” (Kramer and Mayfield, 2007), analogous to exceedance for an intensity measure in PSHA. N_M and N_{amax} are the numbers of magnitude and peak acceleration increments, and $\Delta\lambda_{a_{max,i},m_j}$ is the incremental mean annual rate of exceedance for intensity measure $a_{max,i}$ and magnitude m_j (Kramer and Mayfield, 2007).

Kramer and Mayfield (2007) approached an integrated PLHA by first running the PSHA at a site, then using disaggregation to select a subset of earthquake events for the subsequent PLHA. The benefit of this method is that the PLHA and PSHA are uncoupled; however, it has the disadvantage of not considering all possible earthquakes, and the interpretation

of the disaggregation requires judgment. [Kramer and Mayfield](#) suggest that the PLHA would best be performed inside the hazard integral for these reasons (Kramer, personal communication, 2024). [Kramer and Mayfield \(2007\)](#) also found that a more deterministic, traditional approach to liquefaction hazard analysis produced widely varying return periods, with variation of up to a factor of 2, which highlights the strength of a return-period approach to liquefaction hazard.

[Baker and Faber \(2008\)](#) created a framework to evaluate the spatial distribution of liquefaction occurrence using geostatistical tools. [Franke et al. \(2014\)](#) created an analytical tool for performance-based liquefaction triggering assessment using SPT blow counts. The U.S. Geological Survey (USGS) is also developing a PLHA tool that incorporates uncertainty in susceptibility criteria (Makdisi, personal communication, 2024). This method modifies the traditional PLHA equation by including a probability of susceptibility and a logic-tree framework for computing liquefaction hazard, considering the classical PBEE procedures and convolving a fragility or demand model with the mean hazard curve. The coupled, integral approach adopted in this dissertation, and implemented in the `ucla_plha` package, is described in Chapter 4.

2.3 Sea Level Rise Background

2.3.1 Sea Level Rise Introduction

Anthropogenic sea level rise (SLR) is an ongoing hazard and a severe consequence of climate change. Although the rate of SLR was relatively stable through much of the 20th century ([Williams, 2013](#)), the Intergovernmental Panel on Climate Change (IPCC) states with virtual certainty that “even if the rate remains constant, global mean sea level rise will continue in the 21st century” ([Lee and Romero, 2023](#)). The average rate of SLR over 1901-2018 has been estimated at 1.41 mm/year, with the rate measured by global tide gauges reaching 3.61 mm/year between 2006 and 2018, which is approximately 2.5 times the

previous rate (Fox-Kemper et al., 2021). Looking forward, global sea levels are expected to rise between two and five meters by the year 2150 (Fox-Kemper et al., 2021). SLR is driven by several key factors, including:

- **Thermal Expansion:** Ocean water expands in volume as it absorbs heat from the atmosphere, directly contributing to SLR
- **Melting of Glaciers:** Glaciers worldwide are melting at an alarming rate, contributing to an increase in the volume of the ocean
- **Greenland Ice Sheet:** The Greenland Ice Sheet is experiencing significant melting
- **Antarctic Ice Sheet:** Also experiencing melting, though less than the Greenland Ice Sheet; an increase in the rate of melting could contribute to additional SLR
- **Land-water storage:** Significant changes in land-based water storage such as groundwater depletion can affect SLR (Lee and Romero, 2023)

The primary contributors to SLR are the melting of the aforementioned glaciers as well as seawater expansion as it absorbs heat from rising temperatures (McMichael et al., 2020). However, significant uncertainty surrounds future projections of SLR due to the potential differences in melting rates across these different drivers (Le Bars, 2018). Le Bars describes SLR as a complex sum of time-dependent variables, which makes precise, long-term estimation challenging. Specifically, the long-term contributions of glaciers and land ice are difficult to model (Perrette et al., 2013). As a result, short-term modeling and planning for SLR conditions are considered to be more precise. Additional factors such as tidal forcing and storm surge are often excluded from SLR projections, which can lead to underestimations of effective water level rise, particularly at regional scales (Rasmussen et al., 2018; Calafat et al., 2022).

More recent updated projections from the IPCC Sixth Assessment Report provide scenario-based estimates under Shared Socioeconomic Pathways (SSPs), projecting global

mean SLR of 0.32 - 0.62 m by 2100 under a low-emissions scenario (SSP1-2.6) and 0.63 -1.01 m under a high-emissions scenario (SSP5-8.5), potentially exceeding 2 m (Fox-Kemper et al., 2021). These updated projections surpass earlier estimates and carry important implications for regional infrastructure planning. The compound effect of SLR with tidal forcing and storm surge is particularly consequential in coastal California, where wave setup and tidal amplification can significantly increase water levels (Vitousek et al., 2017; Rasmussen et al., 2018).

2.3.2 Global Sea Level Rise Implications

Rising tides and extreme water levels will impose a variety of coastal hazards. The main impacts include:

- inundation and displacement of wetlands
- erosion of shorelines
- disruption of vulnerable ecosystems
- increased storm flooding and surge
- redistribution of sandy sediments
- increased salinity of freshwater sources (Bijlsma et al., 1996; FitzGerald et al., 2008; Nicholls, 2011)

Rising sea levels and extreme water events will make coastal communities increasingly vulnerable to flooding, storm surge, tsunamis, and other hazards (FitzGerald et al., 2008). Over 600 million people globally live in the low elevation coastal zone (LECZ), land lying less than 10 m above sea level (McGranahan et al., 2007). A significant portion of the LECZ population lives in 17 of the world's 30 largest cities, by population (Small, 2004; FitzGerald et al., 2008). This area includes cities like Mumbai, Jakarta, and Bangkok. Additionally, the severity of SLR impacts varies by community based on geographic factors, such as elevation and the presence of deltas, specifically in low lying deltaic communities. For example, in

densely populated Bangladesh, a 1.5 meter rise in sea level is predicted to affect 22,000 km² of land inhabited by more than 17 million people (FitzGerald et al., 2008). On a global scale, if 2 meters of global mean SLR occurs by the year 2100, up to 187 million people will be forcibly displaced (Nicholls, 2011). Dasgupta et al. found that SLR effects would not be uniform globally; this discrepancy is attributed to factors such as population density, GDP, and vulnerable land mass (2009). Countries in South, Southeast, and East Asia and Africa will be most heavily impacted by SLR (Nicholls et al., 1999; Dasgupta et al., 2009; Nicholls, 2011); these same regions that experience the most significant SLR often exhibit the highest rates of coastal land conversion for urban development (Neumann et al., 2003). This confluence of factors places populations residing in LECZs at heightened risk of devastation due to increasing SLR.

2.3.3 California SLR Hazard

California’s vast coastline, stretching over 1,760 kilometers (Griggs et al., 2019), is the most populated coastline in the continental US, with over 2.68 million residents (NOAA, 2024). The combined GDP of California’s coastal counties would rank among the largest globally were they considered a sovereign nation (NOAA, 2024). This densely populated area is also a critical infrastructure hub that serves not only California but other US states. The state has vital energy and water facilities, transportation centers, shipping ports, and countless homes all under threat from rising sea levels (Heberger et al., 2009). Heberger et al. (2009) found that 1 meter of SLR could inflict economic damage of up to 635 billion US dollars on the state of California. The most recent statewide guidance projects that California will likely experience approximately 0.3 *m* of SLR by 2050, with the range of projections widening substantially thereafter and high-end, low-likelihood scenarios reaching up to roughly 3.7 *m* by 2150 (California Sea Level Rise Science Task Force, 2024).

Befus et al. (2020) modeled sea level rise scenarios across the entire California coastline and found that with about 1 *m* of SLR, groundwater flooding is projected to expand approx-

and found that with about 1 *m* of SLR, groundwater flooding is projected to expand approximately 50 - 130 m inland, with low-lying communities around San Francisco Bay identified as most at risk. Critically, a rise in the water table can substantially alter the cyclic stress ratio and effective stress governing liquefaction triggering in susceptible sandy soils (Grant et al., 2021). Grant et al. (2021) assessed changes in LPI at over 400 CPT soundings around San Francisco Bay under sea levels up to 5 *m* for a hypothetical M 7.0 earthquake scenario, finding that while most sites are insensitive to SLR below 1 m, sites underlain by artificial fill with already-shallow water tables show marked increases in liquefaction severity even under modest SLR.

Mongold and Baker (2024) developed a probabilistic framework for regional liquefaction hazard and loss, which they extended to couple sea level rise to earthquake-induced liquefaction by drawing depth-to-groundwater from the Coastal Storm Modeling System (Barnard et al., 2019), which supplies water-table surfaces for a range of sea level rise scenarios (Mongold and Baker, 2025). In that framework, however, groundwater depths are taken as a ready-made input from this regional model and used to compute LPI at each CPT location, so the water table is assumed rather than modeled and liquefaction enters only as one contributor to an aggregate loss. These findings motivate a probabilistic, more site specific treatment of the SLR and liquefaction interaction across the California coast.

Due to elevation variations, ocean dynamics, and Earth’s uneven gravity field, the concept of relative SLR was established. Relative SLR refers to the way distinct parts of the world will be affected differently by increasing sea levels (NASA, 2024). Relative SLR is influenced in part by the redistribution of water from the melting of global ice sheets, such as from the West Antarctic Ice Sheet. It is also governed by the rates of change for the different drivers detailed in Section 2.3.1, including land-water storage and thermal expansion. For these reasons, California and the broader West Coast of North America are projected to experience relative SLR approximately 1.25 times the global mean (Griggs et al., 2017). Beyond the direct threat of SLR, high coastal wave heights are an additional concern. The

combined effects of extreme wave energy, tidal events, and eroding coastlines all cause the total water level to increase (Cayan et al., 2008).

2.3.4 Beach Groundwater Dynamics

Relative SLR has an effect on coastal groundwater in California, as groundwater and seawater are directly connected in coastal zones (Habel et al., 2024). Coastal water tables and aquifers are directly influenced by the magnitude of ocean forcing (Nielsen, 1990; Abarca et al., 2013). Coastal groundwater systems respond to SLR with either water tables rising the same amount as sea levels, with unsaturated zones accommodating additional groundwater storage, or water tables rising less than sea levels and instead discharging some of the original storage (Werner and Simmons, 2009; Befus et al., 2020).

The mechanism by which SLR translates to water table rise in coastal unconfined aquifers depends on the balance between the rate of sea level forcing and the hydraulic properties of the subsurface. Werner and Simmons (2009) identify two responses: in aquifers where unsaturated storage capacity is sufficient, the water table rises proportionately with the sea level increase; in aquifers where storage is limited, the water table rise is partially attenuated as excess groundwater discharges to the surface. Shallow sandy beach aquifers typical of coastal California tend to be limited in storage, and their high hydraulic conductivity allows rapid equilibration of the water table to ocean boundary conditions (Befus et al., 2020; Nielsen, 1990).

A beach groundwater system is a “highly dynamic shallow unconfined aquifer” (Horn, 2002). This term is commonly used to refer to any water held in the sand below the beach surface. Sediments in the unconfined aquifer become saturated through tides, waves, and swash (the water layer that washes onto the beach face after a wave break). Sea level fluctuations have been shown to cause the beach groundwater to fluctuate (Nielsen, 1990).

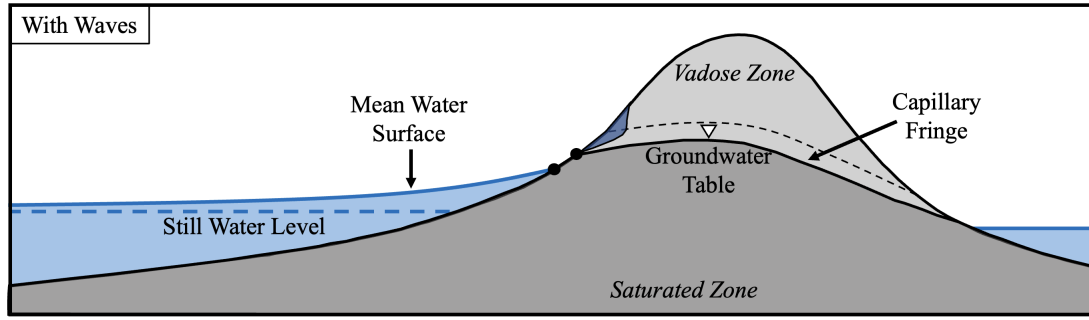


Figure 2.13: Beach Groundwater Schematic (Maple, 2024)

Figure 2.13 shows the beach groundwater dynamics under the influence of waves (Maple, 2024). Understanding the geometry of the beach face and how the ocean affects groundwater dynamics is imperative. The mean water surface is taken to be the mean sea level (MSL) at the shoreline. The location at which the mean water surface and the beach face meet is defined as the shoreline. The still water level is the coastal water level without the influence of seawater run-up (Miller et al., 2019). The vadose (unsaturated) zone sits above the groundwater table. Pore pressure, u , is taken to be zero at the water table (Stephens, 2018). The capillary fringe is a saturated zone above the groundwater table and below the vadose zone (Whitford and Duval, 2020). The saturated, or phreatic, zone underlies the groundwater table, and all pores are assumed to be filled with water. It has been shown that tidal oscillations, estuarine water levels, and wave run-up affect groundwater fluctuations (Levanon et al., 2017). Groundwater measurements from a sand spit in Southern California are shown in Figure 2.14. This sample site in Cardiff, CA, is located between the San Elijo Lagoon and the Pacific Ocean. The beach groundwater here is affected by both ocean and lagoon water levels. The groundwater head measurements were taken from pressure sensors during a December 2015 field investigation. This particular pressure sensor was placed 35 meters inland at a height of 0.6 m MSL. The groundwater head measurements are consistently higher than MSL partly due to groundwater properties, but are dominated by tidal impacts.

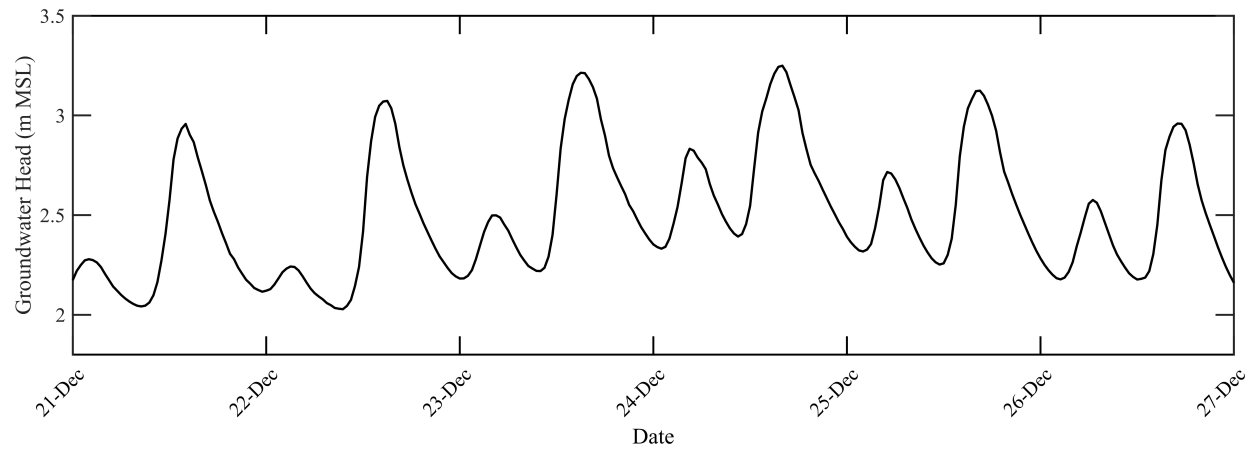


Figure 2.14: In-situ groundwater observations from Cardiff State Beach, courtesy of T. Gallien

This chapter has provided a background on liquefaction hazard as well as sea level rise. This will serve as a basis for the workflow discussed in Chapter 5 and Chapter 6 and how groundwater is imperative to understanding PLHA in coastal California.

CHAPTER 3

Coastal Geotechnical Database

This chapter discusses the creation of the Coastal Geotechnical Database, which is currently housed at the University of California, Los Angeles (UCLA). This includes the schema of the database, the sites chosen for the database, and how the database is used in the dissertation analysis.

3.1 Sites Chosen

As part of the work toward the University of California (UC) Climate Action Seed Grant ([University of California Action Initiative, 2023](#)), the team undertook the task of digitizing existing geotechnical data in coastal areas of California. Liquefaction analysis requires a comprehensive understanding of various site specific parameters, including soil type and density. These parameters can be estimated using in-situ testing methods like soil borings and cone penetration tests (CPTs). The California Geological Survey (CGS), California’s geologic agency, requires geotechnical and sub-surface investigation field data from hospital and school developments to be submitted for review through CGS Note 48 ([California Geological Survey, 2025](#)). This data is therefore considered part of the public archive, maintained by the State. CGS, a partner on the grant, provided numerous soil boring logs and CPT reports. The data requested from CGS included boring logs for school and hospital developments within five to ten kilometers inland of the California coast, which

totaled over 3,000 boring logs. Figure 3.1 shows coastal polygons along the California coast, which serve as areas of interest (AOI) for the project. The AOI was extended inland north of the San Francisco Bay Area to account for the Sacramento Delta.

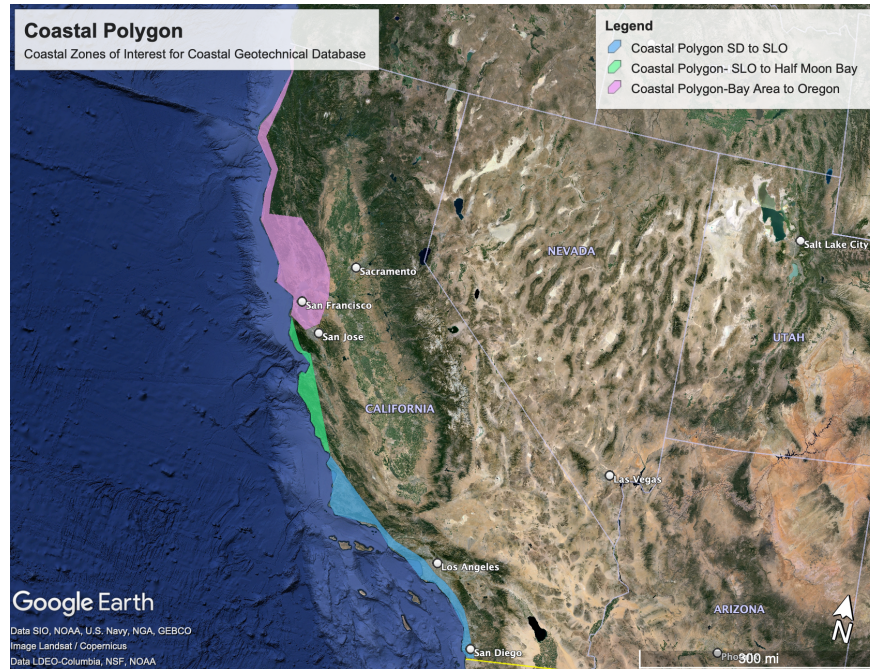


Figure 3.1: Coastal Polygons Containing Areas of Interest for Sites Included in the Database

The majority of the data provided by engineers and consultants to CGS is in Portable Document Format (PDF), which is human readable, but not machine readable. While PDFs are sufficient for human use, they do not lend themselves to easily performing calculations and liquefaction analysis on the underlying data. To rectify this problem, more than 15 undergraduate civil engineering students from UCLA supported an effort to manually digitize boring logs from PDFs. Currently, over 400 of the borings have been entered into the database.

3.2 Database Schema

3.2.1 Soil Boring Schema

The database schema for soil borings contains tables with information necessary for liquefaction analysis. Once a site is added to the database, borings can be added to that site. The number of borings for a site varies, with one site having over 80 boring logs. Information about the drill rig and crew as well as the location of the boring is retained within the database under the “borings” table. Groundwater levels, if recorded, along with the time of recording, are also important information digitized into the “borings” table. The other two tables where data is stored are the “stratigraphies” and “samples” tables. In the “stratigraphies” table, the top and bottom depths of the layer are recorded, as well as any Unified Soil Classification System ([Howard, 1986](#)) classification indicated in the log. Lastly, within the “samples” table, data about each sample in the boring is recorded. This data includes top and bottom depths, sample descriptions, blow counts, and any laboratory results for the sample as provided by the consultants. Tables [3.1](#), [3.2](#), [3.3](#), and [3.4](#) below show the soil boring database schema.

Column	Description/Units
site_name	Human-readable name of site
site_latitude	Decimal degrees
site_longitude	Decimal degrees
site_elevation	NAVD88
vs30	Time-averaged shear wave velocity, up to 30m (m/s)

Table 3.1: Site Table

Column	Description/Units
id	Unique borehole ID
site_id	Human-readable name of site, linked to site table
user_id	Unique ID for user who entered data
boring_latitude	Degrees
boring_longitude	Degrees
groundwater_code	0 = No mention 1 = groundwater not encountered 2 = groundwater reported
groundwater_depth	Meters
groundwater_datetime	If recorded
borehole_type	e.g., Hollow Stem Auger
drill_rig_description	Rig type
borehole_diameter	Diameter in meters
hammer_description	Type and Weight
drilling_crew	Name
drilling_start_datetime	If provided
drilling_end_datetime	If provided

Table 3.2: Borehole Table

Column	Description/Units
site_name	Human-readable name of site and repopulated from site table
borehole_name	Name as assigned in borelog
depth_top	Meters
depth_bottom	Meters
uscs (Howard, 1986)	Classification Symbol, e.g., CL
description	Soil type as described in borelog

Table 3.3: Stratigraphy Table

Column	Description/Units
id	Unique sample ID linked to boring table
site_id	Human-readable name of site, linked to site and boring table
user_id	Unique ID for user who entered data
sampler_description	Options: Standard Penetration Test, Shelby tube, Modified California, Pitcher Barrel, Gel Push, Bulk, Undisturbed, Continuous, and Crandall
sample_name	Unique Sample Name
depth_top	Meters
depth_bottom	Meters
sample_description	As noted in log
sample_diameter	Meters
dry_unit_weight	Unit weight where soil pores are filled with air (kN/m^3)
specific_gravity	Ratio of material density to the density of water
water_content	Percentage (0–100%)
finer_content	Percentage of soil particles smaller than 0.075 mm (No. 200 sieve) (0–100%)
liquid_limit	Water content percentage at which soil transitions from liquid to plastic state (0–100%)
spt_n_value	Number of blows per 12"

Table 3.4: Sample Table

3.2.2 Cone Penetration Tests

Cone penetration tests are also available in the database. At the time of this dissertation, there are 162 CPTs entered into the database. CGS also provided the CPTs, which were performed at hospital and school sites in California. The data included per CPT is stated in Table [3.5](#).

Column	Description/Units
<code>id</code>	Unique CPT ID
<code>site_id</code>	name of site, linked to site table
<code>cgs_app_no</code>	CGS application number (e.g., 03-CGS5345)
<code>user_id</code>	Unique ID for user who entered data
<code>cpt_latitude</code>	Decimal degrees
<code>cpt_longitude</code>	Decimal degrees
<code>elevation</code>	NAVD88 (m)
<code>groundwater_measured</code>	Depth to groundwater as measured in field (m)
<code>groundwater_design</code>	Design groundwater depth used in analysis (m)
<code>cpt_contractor</code>	Contractor that performed the CPT (e.g., ConeTec)
<code>date</code>	Date of CPT sounding
<code>depth</code>	Depth of each reading (m)
<code>data</code>	JSON string storing arrays of per-reading values, with keys: depth – Depth of each reading (m) qc – Tip resistance (MPa) fs – Sleeve friction (MPa) u2 – Pore water pressure measured behind cone tip (MPa)

Table 3.5: Cone Penetration Test Table

3.3 Web Interface, Application Programming Interface (API), and QA/QC

As the input data is public, the database is also publicly available. It is currently published at the following URL: https://uclageo.com/coastal_database/. For over 400 coastal borings, geotechnical practitioners have access to their in-situ soil types and parameters, and detailed information about groundwater. As engineers begin initial site investigations for future developments, they can use this resource and make early decisions regarding possible site hazards. At the time of this dissertation, 82 sites, 433 borings, 2,033 soil layers, and 2,538 samples have been entered into the database. To access the sites, users need to create a log-in and authenticate. Once students have provided their authentication, they can claim a site on the homepage as shown in Figures 3.2 and 3.3.

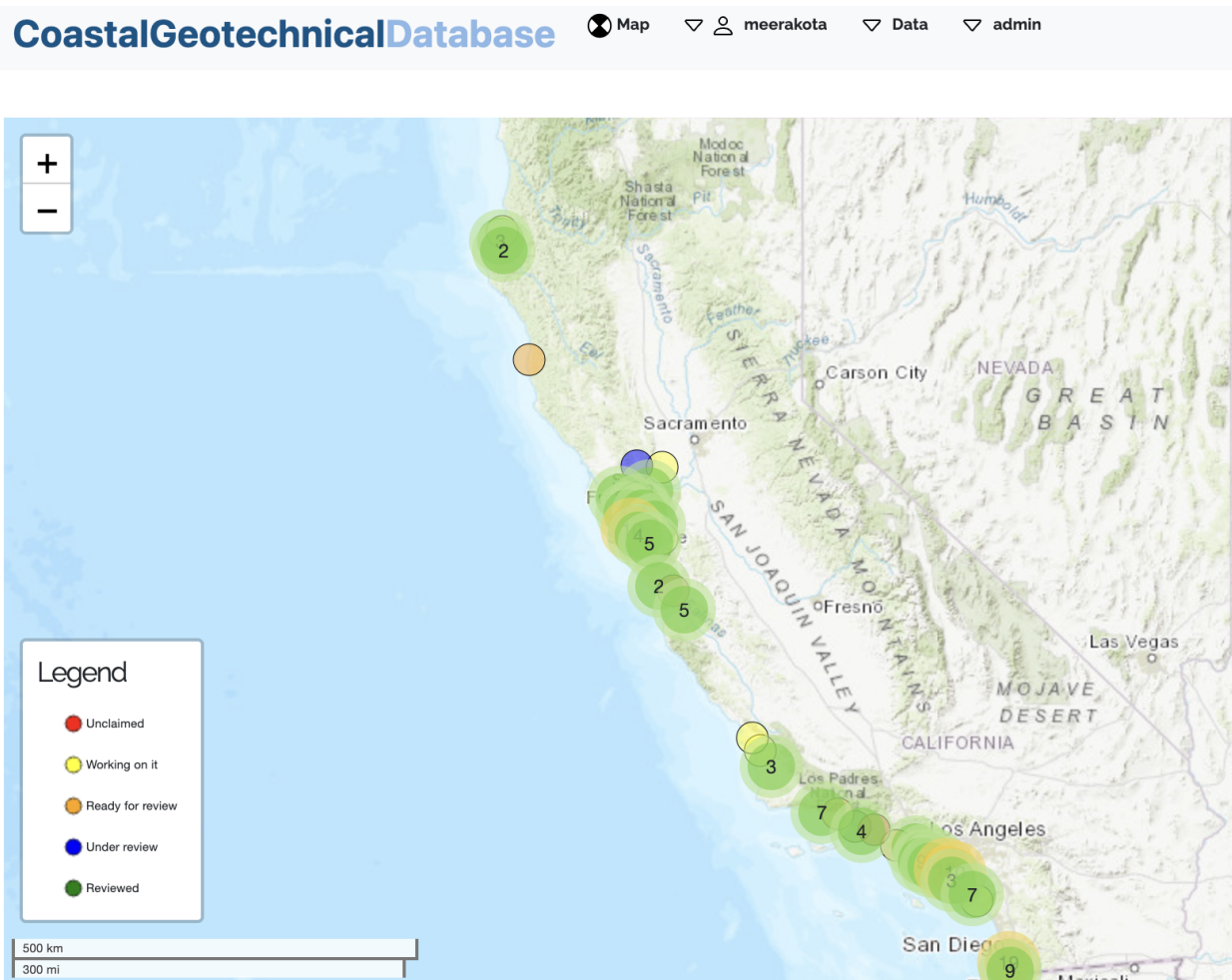


Figure 3.2: Coastal Geotechnical Database – Homepage with Map of Site

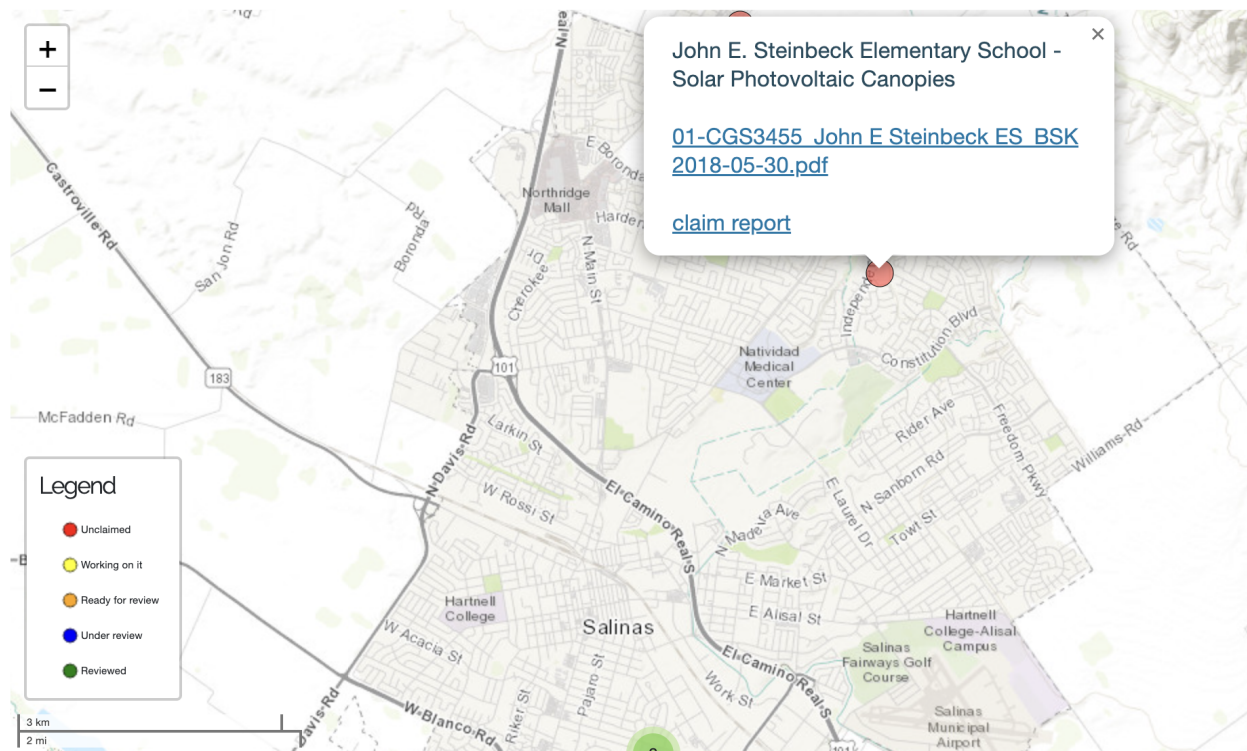


Figure 3.3: Coastal Geotechnical Database – Example Site Pop-Up

Once students claim a site, they can begin to enter information about each borehole. A “form”-like interface becomes available where students enter data, as shown in Figure 3.4.

Actions
[List Boreholes](#)

Units

English

Add Borehole
Site

San Juan Hills High School - Classroom Building

borehole name

borehole latitude, WGS84 (deg)

borehole longitude, WGS84 (deg)

elevation, NAVD88

groundwater code (0 = no mention, 1 = groundwater not encountered, 2 = groundwater specified in boring log)

groundwater depth

Figure 3.4: Coastal Geotechnical Database – Sample Borehole Entry Page

An example of the “samples table” is shown in Figure 3.5.

Samples

Units

English

NEW SAMPLE(S)

Id	Borehole Id	User Id	Name	Top Depth	Bottom Depth	Description	Diameter	Dry Unit Weight	Specific Gravity	Water Content	Fines Content	N
1	1	2	D-1	26.910	43.056	Olive brown to yellow brown silty CLAY / clayey SILT, very moist, very stiff, iron staining	0	130.394		20.5		
2	1	2	D-2	16.404	21.325	@ 5': Dark brown silty CLAY, very moist, very stiff, micaceous, iron staining, trace fine	0	125.394		23.3		

Figure 3.5: Coastal Geotechnical Database – Samples Table Page

Students also have access to a “my data” page which collates all the information they have entered into the database for easy access.

CoastalGeotechnicalDatabase

Map

meerakota

Data

admin

Actions

Edit User

Delete User

List Users

New User

Meera

First Name

Meera

Last Name

Kota

User Name

meerakota

Email

Id

2

Admin

1

Related Sites

Id	User Id	Name	Latitude	Longitude	Elevation	Vs30	Remarks	Actions
2	2	San Juan Hills High School - Classroom Building	33.50000	-117.62280				View Edit Delete

Figure 3.6: Coastal Geotechnical Database – Individual Data Depot

Once students have completed entering the site, boring, stratigraphy, and samples data, they can set their site to be “ready to be reviewed”. Students were paired and reviewed

each other's work. If they found discrepancies, they were encouraged to be in direct contact with the other student and make changes as needed. As part of this review process, Scott Brandenburg developed a boring log viewer using a *Jupyter* notebook. This allowed students to easily access the database and review the boring log data. This tool allows the team to enforce QA/QC standards by ensuring that the data being entered into the database by one person is reviewed by a second person. The viewer is also available on the website for a view of any borehole.

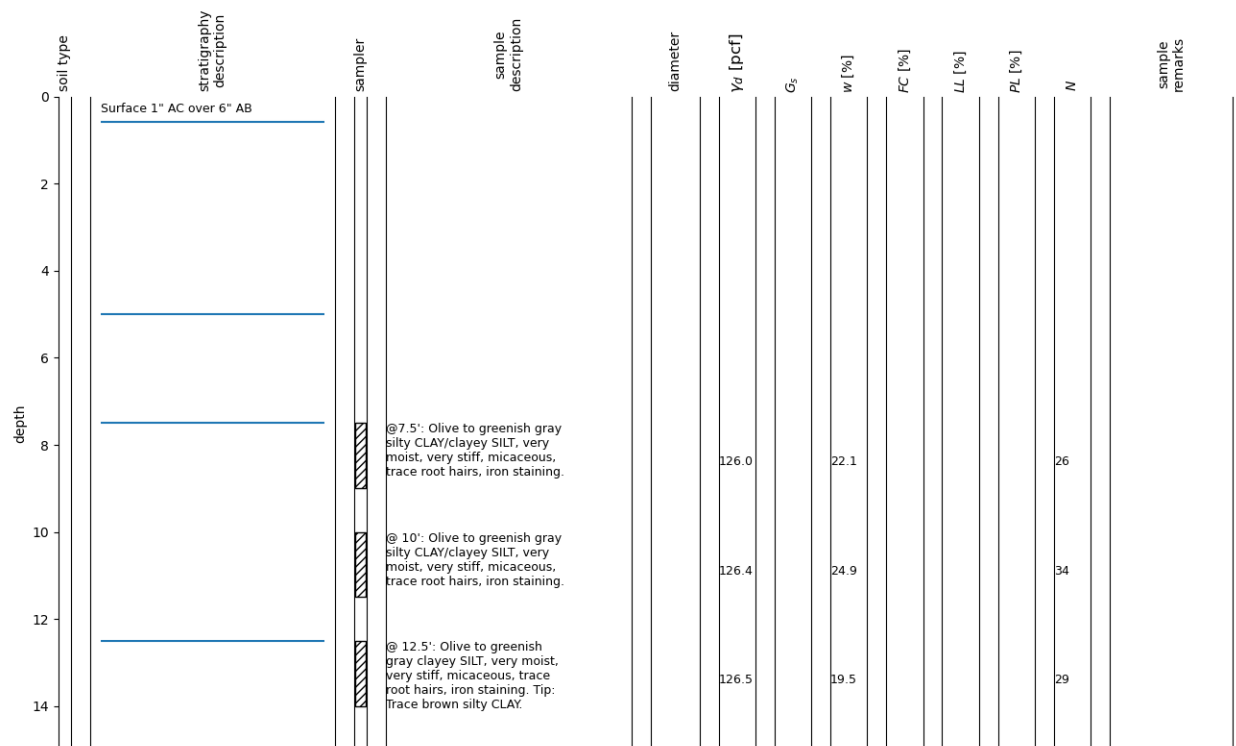


Figure 3.7: Coastal Geotechnical Database – Borehole Log Viewer

3.3.1 Access through Application Programming Interface (API)

The database can be accessed via an Application Programming Interface (API). An API is software that enables communication between two components, usually different computers. The server receives the URL, parses the query string, runs a script to gather requested information, often by querying a relational database, and returns the data to the client in

the requested format such as JSON. The API is a middle layer that allows users to submit a request to the server, but the query itself then originates from the same server that hosts the database (Brandenberg and Kota, 2024).

The API is useful for accessing and querying the data, specifically for end-to-end workflow; this was how the data was accessed for this dissertation. The code below explains how to access the database via the API using the **requests** library and place the CPT data into a pandas DataFrame.

```
[backgroundcolor=gray!10, linecolor=gray!50, skipabove=10pt, skipbelow=10pt]
```

```
# Code dependencies and packages

import numpy as np
import json
import pandas as pd
import requests
import io

# Pull data from API for Coastal Geotechnical database
def get_data(table):
    url = 'https://uclageo.com/coastal_database/' + table
    headers = {'User-Agent': 'XY', 'Accept': 'application/json'}
    r = requests.get(url, headers=headers)
    df = pd.read_json(io.StringIO(r.text))
    return df

# Put values into dataframe
cpt_df = get_data('conePenetrationTests')
data      = cpt_df['data'].values
groundwater = cpt_df['groundwater_measured'].values
latitude   = cpt_df['latitude'].values
```

```
longitude = cpt_df['longitude'].values
```

3.4 Representative CPTs chosen for PLHA with SLR workflow

Four representative CPTs from the Coastal Geotechnical Database, together with a fifth from the Next Generation Liquefaction database (Ulmer et al., 2023), were chosen for further analysis in this dissertation. These CPTs were used for sea level rise analysis as discussed in Chapter 6. The CPTs were applied at locations along the California coastline, as using site specific data was not feasible everywhere. Although site specific data was not used, it was deemed appropriate to use a subset of the data provided to the team and apply it to the analysis.

To determine which CPTs to choose, the Next Generation Liquefaction Supported Modeling Team (NGL SMT) (Ulmer et al., 2024) model and ngl_tools repository (Hudson et al., 2024) were used to plot the fragility (Probability of profile manifestation) against an array of a_{max} values from $10^{-2}g$ to 10^1g . The CPTs were analyzed using the groundwater at the time of drilling and for a magnitude, $M_w = 7$. A magnitude of 7 was chosen to be representative of the significant fault scenarios in California. Figure 3.8 shows the fragility functions for all CPTs in the Coastal Geotechnical database. The curves exhibit considerable variability in both their limiting values and their shapes. Some profiles reach a probability of manifestation near 1.0 at high a_{max} whereas others plateau well below 1.0; this reflects differences in liquefaction susceptibility and groundwater depth across the sites, as well as the density and thickness of the potentially liquefiable layers. The curves also differ in steepness: profiles whose fragility increases sharply over a narrow range of a_{max} are typically dominated by a single critical layer that triggers at a well-defined acceleration, while flatter curves indicate contributions from multiple layers of differing density and susceptibility that manifest

progressively across a broader range of a_{max} .

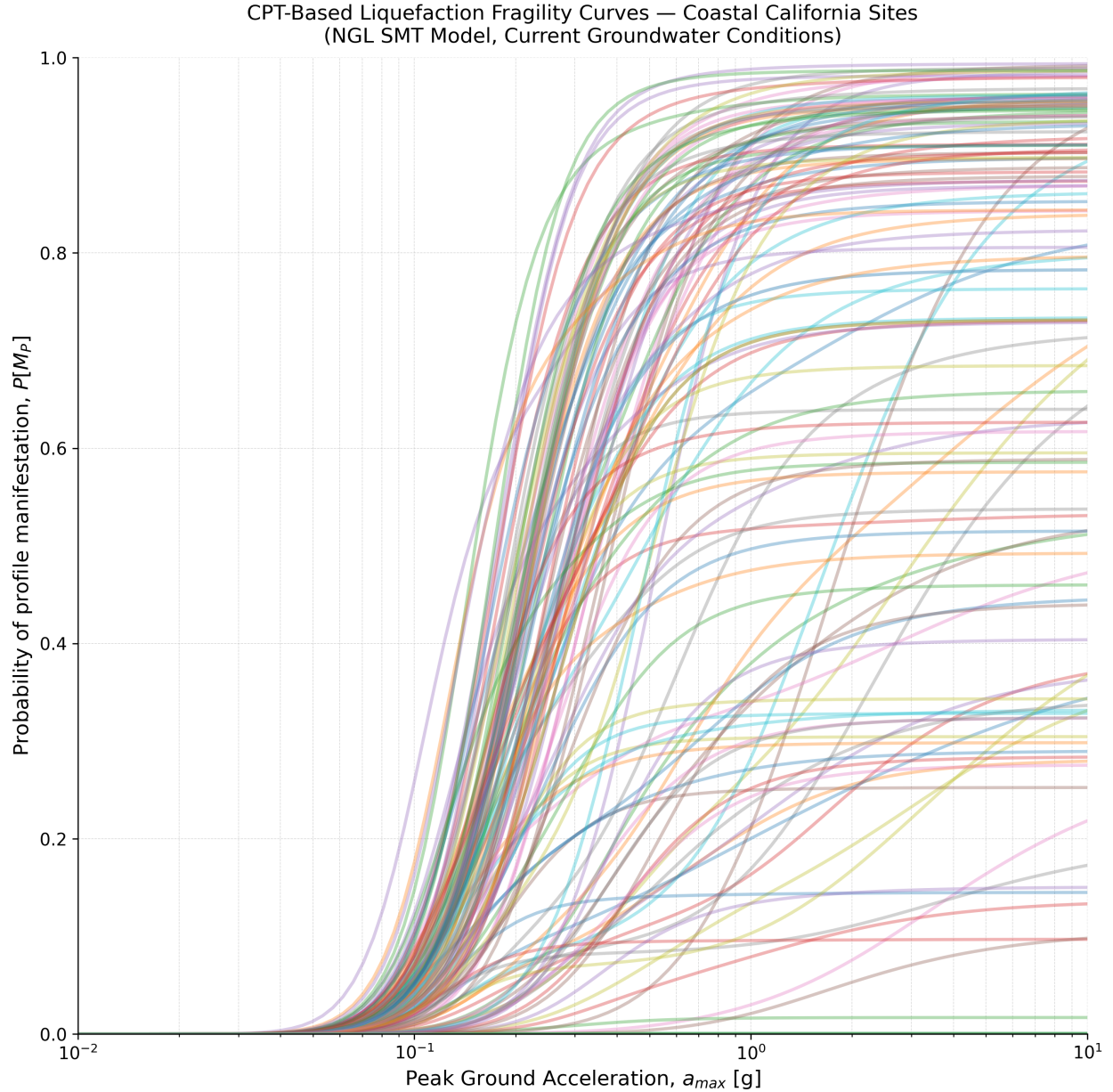


Figure 3.8: Entire Coastal Geotechnical Database Profile Manifestation Fragility Curves

Four CPTs from the Coastal Geotechnical Database were chosen to represent different fragility levels. The four CPTs include 336, 324, 274, and 365, with the number referencing the site ID. One additional CPT was chosen from the Next Generation Liquefaction Database, UC-21, now called CPT 888, from Moss Landing to provide a more “severe” case. Figure 3.9 shows the five CPTs chosen and their manifestation profiles using the NGL SMT

model (Ulmer et al., 2024). CPTs were selected to span the observed range of fragility behavior in terms of the steepness, median, and max probability. This was to help capture the sensitivity of liquefaction hazard to groundwater rise across varying soil conditions. The five CPTs therefore represent various levels of liquefaction susceptibility: 888 reaches the highest level of manifestation for the lowest peak ground acceleration, and 336 reaches the overall highest probability of manifestation (1).

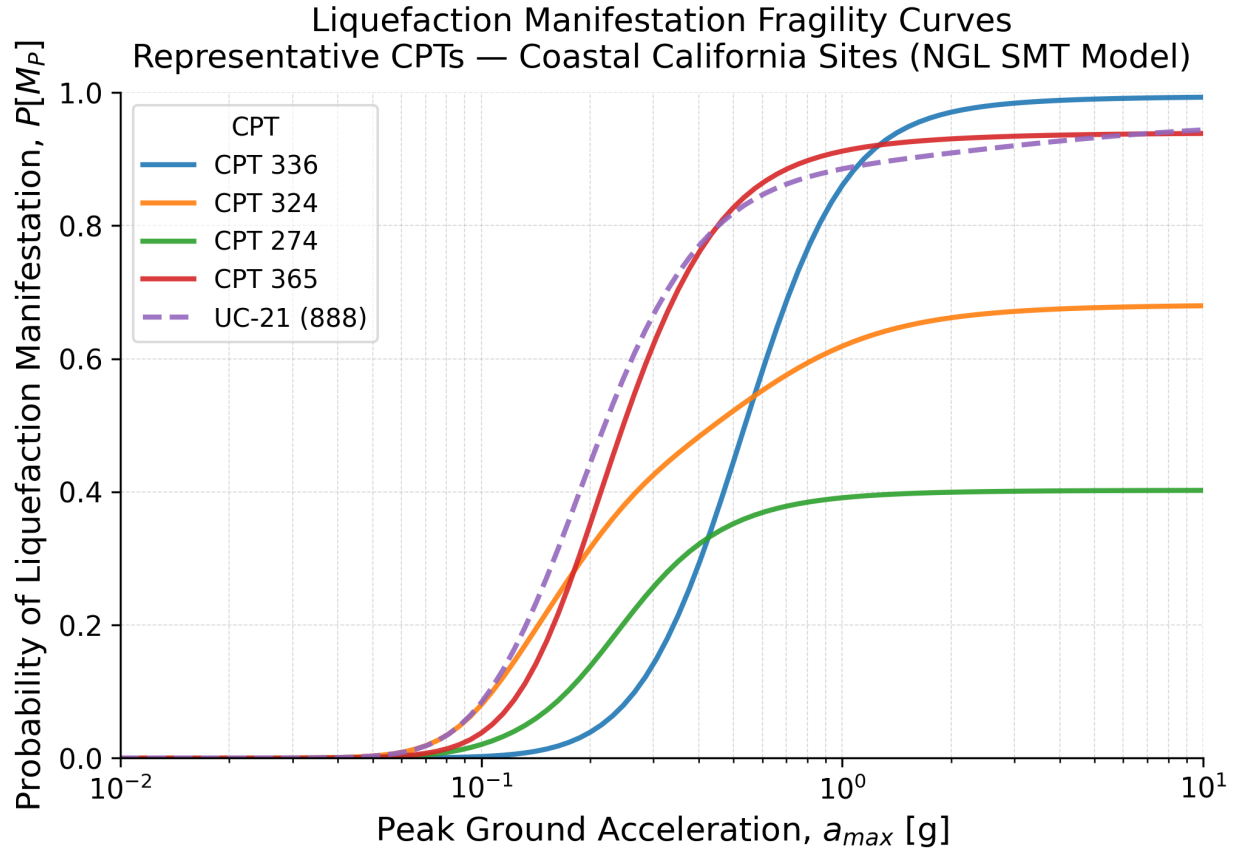


Figure 3.9: Representative Coastal Geotechnical Database Profile Manifestation Fragility Curves

Using the Hudson et al. 2023 inverse layering algorithm, the five cone penetration tests are plotted below. The plots show q_c in MPa, f_s in MPa, I_c [-], and q_{c1Ncs} [-]. Figures 3.10, 3.11, 3.12, 3.13, and 3.14 show plots for the five CPTs.

CPT 274

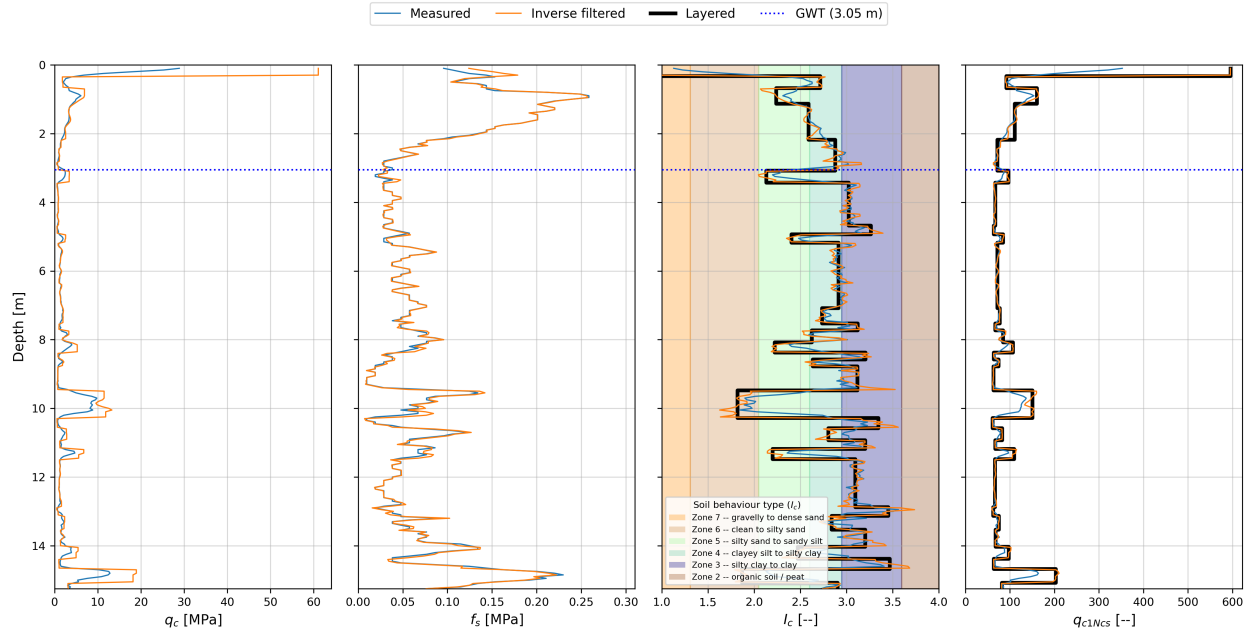


Figure 3.10: Coastal Geotechnical Database CPT 274

CPT 365

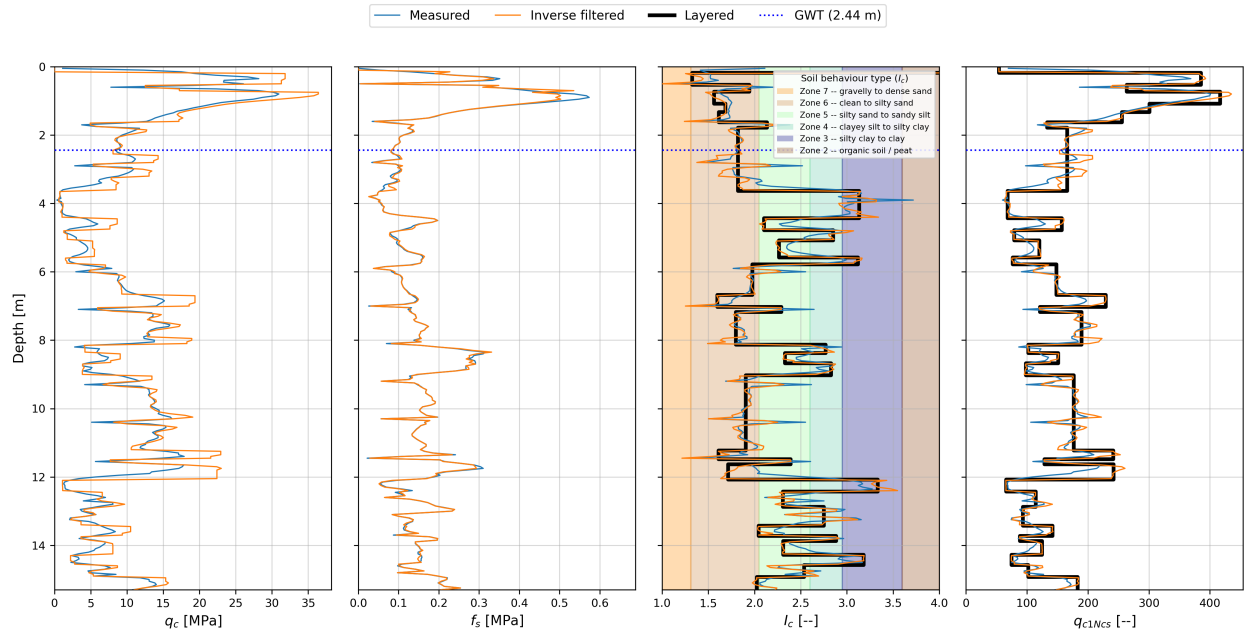


Figure 3.11: Coastal Geotechnical Database CPT 365

CPT 336

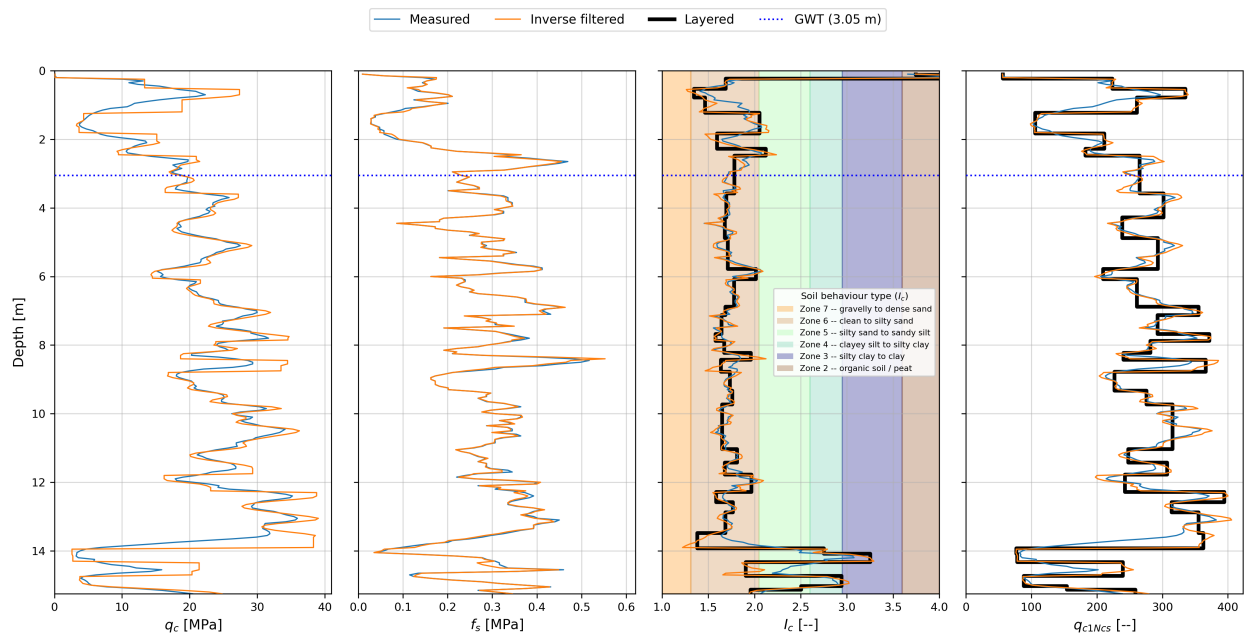


Figure 3.12: Coastal Geotechnical Database CPT 336

CPT 324

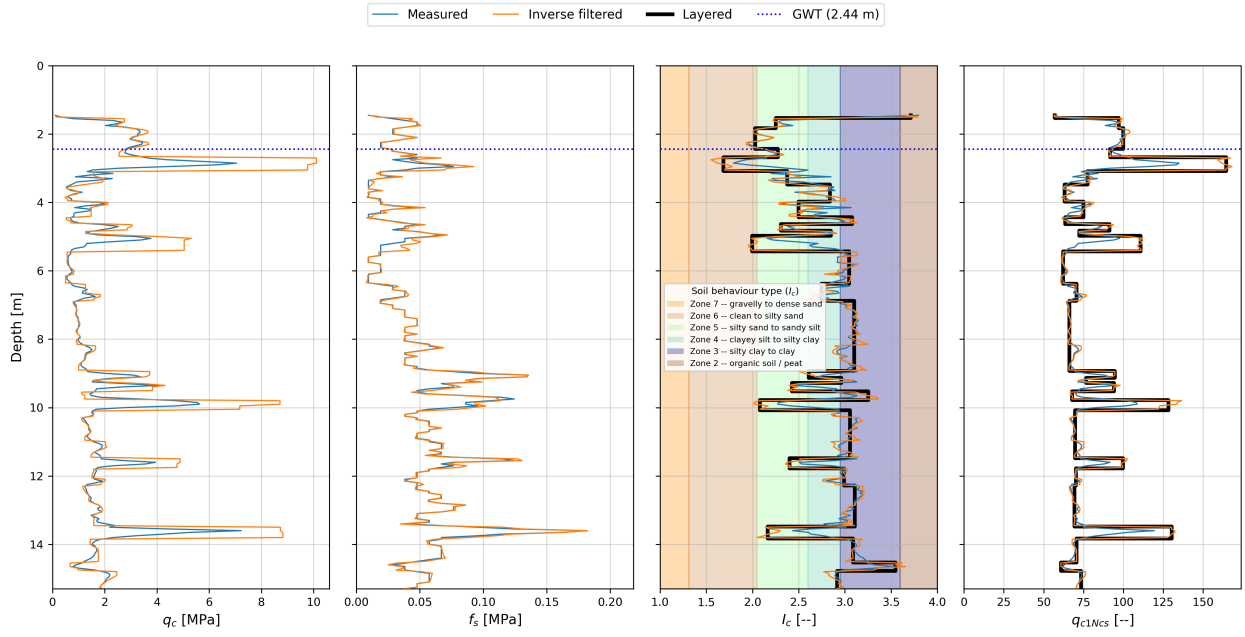


Figure 3.13: Coastal Geotechnical Database CPT 324

CPT 888 (UC-21)

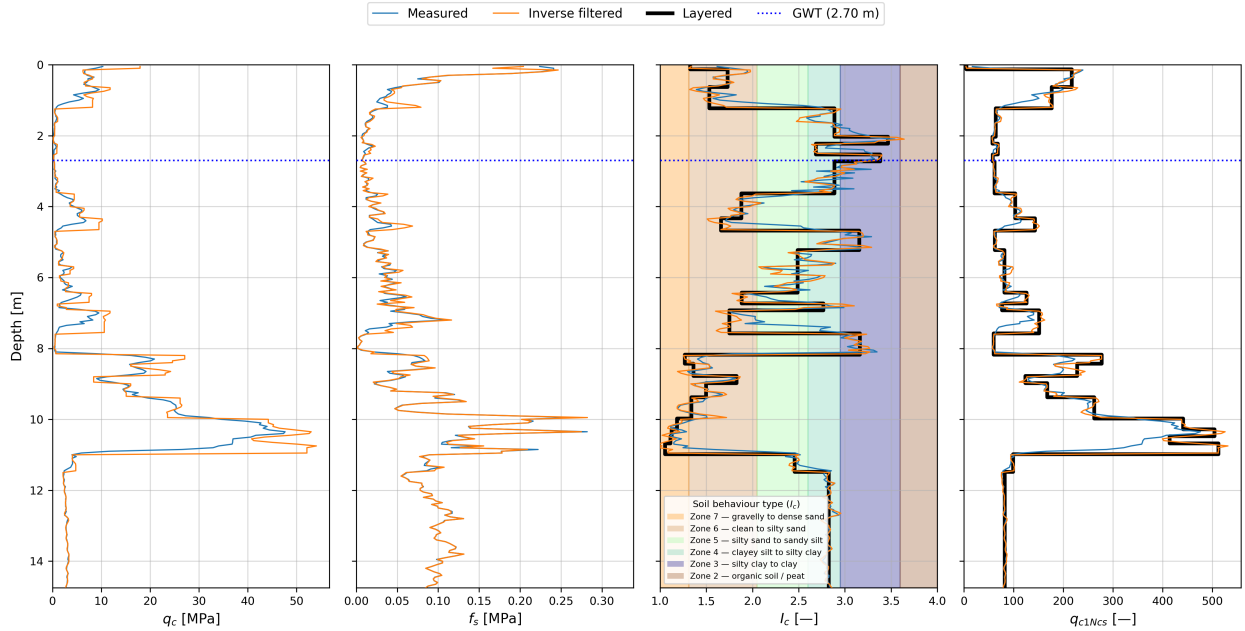


Figure 3.14: NGL Database CPT 888 (UC-21)

As further explored in this dissertation, groundwater can significantly affect liquefaction

resistance and manifestation fragility. Figure 3.15 shows the fragility curves using the original groundwater levels at the time of drilling, and then for groundwater levels of ± 1 m.

It is interesting to note how strongly the CPTs respond to a one meter change in groundwater conditions. Looking at CPT 324, the shallow groundwater table combined with sand-like layers above and below it causes major fluctuations. In contrast, CPT 336 shows little change in fragility for ± 1 m of groundwater change. The remaining three CPTs fall between these extremes: CPT 274 responds primarily through its plateau, which rises noticeably under shallower groundwater and drops by roughly half under deeper groundwater, while CPTs 365 and 888 shift only modestly along the acceleration axis with far less spread than CPT 324.

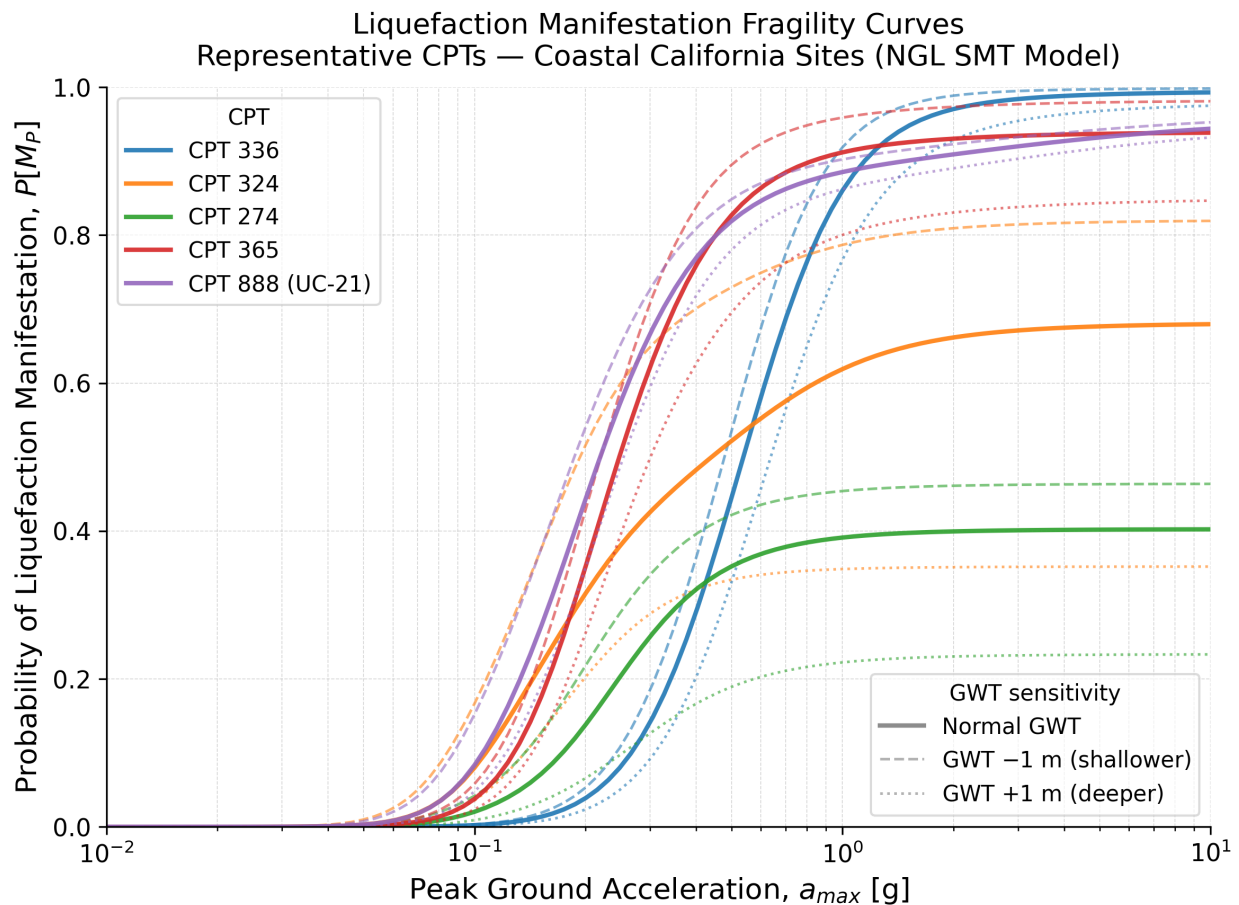


Figure 3.15: Fragility Curve Groundwater Sensitivity

When considering the regional scale of this work, the lack of site specific data was a

concern. However, accessible data was not available for every coastal location at which the hazard calculation would be run. Choosing “representative” CPTs would help show an overall perspective, and these five CPTs span an appropriate range of liquefaction manifestation fragility for use in this scaled-up calculation.

In Chapter 6 these five CPTs will be used to run more than a million analyses at different locations in California to help move toward a regional PLHA map and work product.

CHAPTER 4

ucla_plha: A Python Package for Probabilistic Liquefaction Hazard Analysis in California: Methodology and Example

This chapter presents a Python package called `ucla_plha` that performs PLHA using a coupled method in which the liquefaction hazard is evaluated within the same software package as the PSHA ([Kota and Brandenberg, 2025](#)). The tool is computationally efficient, requiring essentially the same amount of time to perform a PLHA for a single soil layer as a PSHA, and is intended to minimize the computational barriers that have prevented PLHA's routine use in research and practice. Furthermore, as an open source tool, the software is intended to facilitate new contributions for future applications. This chapter first describes the methodology used in the `ucla_plha` code, and explains how it differs from previous PLHA methods. The chapter then goes on to describe the earthquake source models, distance calculation tools, ground motion models, and liquefaction models currently available in the code. Finally, the code is applied and used to compute liquefaction hazard curves and their disaggregations at a site in northern California where liquefaction was observed during the 1989 Loma Prieta earthquake.

4.1 PLHA Introduction

Liquefaction is conventionally evaluated using a simplified procedure (e.g., [Seed and Idriss, 1971](#)) in which the input acceleration corresponds to a single return period from a

PSHA, or to a deterministic earthquake scenario. Because of the uncertainties inherent in liquefaction evaluation (Subsection 2.2.2), the return period for the occurrence of liquefaction computed in this way is not equal to the return period of the ground motion selected from the PSHA. To quantify the return period for liquefaction directly, a probabilistic liquefaction hazard analysis (PLHA) must be performed in which liquefaction is integrated with the PSHA.

Performance-based PLHA methods following the Pacific Earthquake Engineering Research Center (PEER) framework have been available for nearly two decades (e.g., [Kramer and Mayfield \(2007\)](#)) and are reviewed in Chapter 2, yet PLHA is still not routinely performed in research or practice. A key reason is the absence of accessible software. Open source tools such as the National Seismic Hazard Model ([Petersen et al., 2024](#)), OpenQuake ([Pagani et al., 2014](#)), OpenSHA ([Field et al., 2003](#)), and the HAZ repository ([Abrahamson, 2023](#)), as well as proprietary tools such as EZ-FRISK ([McGuire, 2011](#)), make PSHA readily accessible, which has contributed to its widespread adoption in practice. By comparison, similar tools are not currently available for PLHA, which impedes its adoption and motivates the `ucla_plha` package and this dissertation topic.

4.2 Methodology

Building on the PSHA framework reviewed in Section 2.2.1, the annual rate, λ , at which a ground motion intensity measure, IM , exceeds a value, im , at a site is given by Eq. (4.1) ([Cornell, 1968](#)), which provides the basis for the liquefaction extension. Here $n_{sources}$ is the number of seismic sources considered, $P(IM > im | m, r, \xi)$ is the conditional probability that IM exceeds im given magnitude m , distance r , and additional site variables ξ ; f_R and f_M are the distance and magnitude probability density functions, respectively.

$$\lambda(IM > im) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} P(IM > im \mid m, r, \xi) f_R(r) f_M(m) dr dm \quad (4.1)$$

Extending Eq. (4.1) to PLHA requires introducing an additional variable into the hazard integral to represent the probability of liquefaction conditional on im , m , and additional variables χ (e.g., penetration resistance, fines content, shear wave velocity, depth, vertical total stress, and vertical effective stress). The canonical form of the PLHA integral is represented by Eq. (4.2), where Λ represents the annual rate at which the liquefaction factor of safety, FS_L , drops below a specific value, f_{s_l} (i.e., the downcrossing rate, or rate of non-exceedance of f_{s_l}), and $P(FS_L < f_{s_l} \mid im, m, \chi)$ is the probability of liquefaction conditioned on m , im , and χ as represented by a probabilistic liquefaction triggering or consequence model, and this may be considered a liquefaction fragility function. Evaluating Eq. (4.2) for $f_{s_l} = 1.0$ results in the annual rate of liquefaction occurrence. Other thresholds of f_{s_l} may also be relevant for convolving with consequence models, or for satisfying various regulatory requirements; therefore the hazard curves are presented with f_{s_l} as a continuous variable on the horizontal axis.

$$\Lambda(FS_L < f_{s_l}) = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} \int_{-\infty}^{+\infty} P(FS_L < f_{s_l} \mid im, m, \chi) f_{IM}(im \mid m, r, \xi) f_R(r) f_M(m) dim dr dm \quad (4.2)$$

Two strategies may be adopted to solve Eq. (4.2): (1) a decoupled solution strategy that pulls the liquefaction term outside of the integrals over magnitude and distance, and (2) a direct solution strategy in which the liquefaction term remains inside the hazard integral.

4.2.1 Decoupled PLHA Solution Strategy

The decoupled solution strategy is represented by Eq. (4.3), in which the liquefaction term has been pulled out of the integrals over magnitude and distance.

$$\Lambda(FS_L < f_{sl}) = \int_{-\infty}^{+\infty} P(FS_L < f_{sl} | im, m, \chi) \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} f_{IM}(im | m, r, \xi) f_R(r) f_M(m) dr dm dim \quad (4.3)$$

The term in Eq. (4.3) to the right of the liquefaction term is identical to the PSHA integral in Eq. (4.1), except that the cumulative distribution, $P(IM > im | m, r, \xi)$, is replaced by the probability density function $f_{IM}(im | m, r, \xi)$. As a result, Eq. (4.4) represents the gradient of the seismic hazard curve with respect to im .

$$\frac{d\lambda(IM > im)}{dim} = \sum_{i=1}^{n_{sources}} \lambda(M_i > m_{min}) \int_{m_{min}}^{m_{max}} \int_0^{r_{max}} f_{IM}(im | m, r, \xi) f_R(r) f_M(m) dr dm \quad (4.4)$$

Substituting Eq. (4.4) into Eq. (4.3) results in the simplified form for the decoupled approach given by Eq. (4.5) (e.g., Makdisi (2021)).

$$\Lambda(FS_L < f_{sl}) = \int_{-\infty}^{+\infty} P(FS_L < f_{sl} | im, m) d\lambda(IM > im) dim \quad (4.5)$$

The benefit of the decoupled approach is that the PSHA is performed first, and the PLHA is subsequently performed as a separate step. This makes the approach flexible, because any PSHA code can be used, provided that disaggregation data are included in its

output. The downside is that in Eq. (4.2), both IM and FS_L depend on m and im , so separating the integral as indicated by Eq. (4.3) is not mathematically rigorous. Judgment is therefore required to select representative magnitudes and their contribution to hazard when solving Eq. (4.5). The most common approach is to use the PSHA disaggregation at multiple im values (or return periods), and to select a set of magnitudes with weights based on the contribution of each magnitude to the seismic hazard. This approach is represented by Eq. (4.6), where w represents the weights assigned to the selected magnitudes. This numerical integration strategy introduces errors associated with discretization into magnitude bins. Accuracy increases as the number of magnitude bins increases, and in the limiting case where every magnitude from the PSHA is considered, discretization errors are eliminated.

$$\Lambda(FS_L < f_{s_l}) \approx \sum_{i=1}^{n_m} \sum_{j=1}^{n_{im}} w_i P(FS_L < f_{s_l} | im_j, m_i) d\lambda(IM > im_j) \quad (4.6)$$

The decoupled solution strategy is illustrated in Fig. 4.1, where (a) shows the seismic hazard curves for each event and the overall hazard curve, (b) shows the marginal disaggregation for all distances for a single return period, (c) shows liquefaction fragility functions representing the probability of exceedance of FS_L conditioned on PGA , M , and soil properties, and (d) shows the resulting liquefaction hazard curves for each event and the overall hazard curve. The liquefaction hazard curve is computed by weighting the liquefaction fragility curves by their contribution of magnitude to the seismic hazard at a particular return period, then numerically integrating the slope of the hazard curve at that return period with the fragility function. The process is repeated for all desired return periods. The schematic includes only four events for illustrative purposes, whereas actual PSHA / PLHA calculations generally involve hundreds of thousands or millions of events. Numbers are provided on all axes to give an internally consistent representation of the methodology, but they are not intended to represent an accurate hazard calculation; they are merely illustrative.

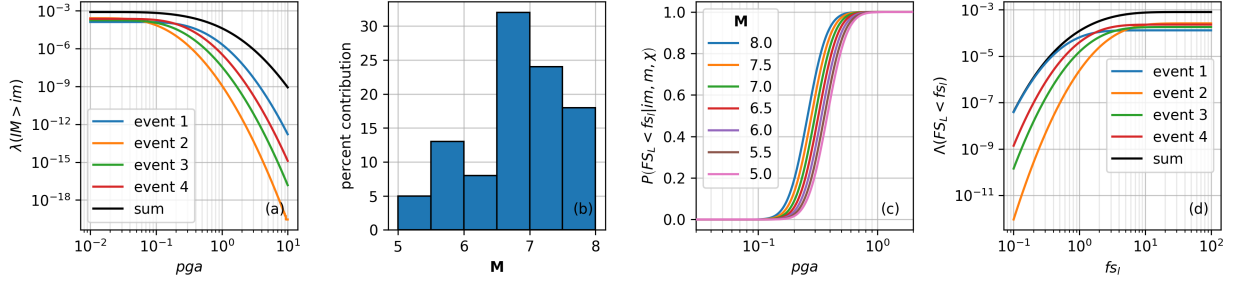


Figure 4.1: Decoupled PLHA Schematic: (a) seismic hazard curves for each event and the total hazard; (b) marginal magnitude disaggregation for a specific return period; (c) liquefaction fragility functions giving the probability of exceeding FS_L conditioned on PGA , M , and soil properties; and (d) the resulting per-event and total liquefaction hazard curves

4.2.2 Direct Solution Strategy

The direct solution strategy leaves the liquefaction term inside the hazard integral, which is mathematically rigorous. This approach requires that the liquefaction evaluation be performed within the same software package as the PSHA, and it therefore lacks the flexibility of the decoupled approach. The triple integral in Eq. (4.2) may appear more computationally demanding than the PSHA double integral in Eq. (4.1). However, in the special case where ground motion demand and liquefaction capacity are lognormally distributed, which is often the case, the triple integral can be reduced to a double integral, thereby rendering the computational demand of a PLHA for a single soil layer essentially equal to that of a PSHA. The computational demand increases when multiple layers are considered.

To reduce the triple integral to a double integral, a general derivation is first presented by defining $FS = C/D$. Here FS is factor of safety, C is capacity, and D is demand. FS , C , and D are random variables rather than scalar quantities. Taking the natural log of both sides gives $\ln(FS) = \ln(C) - \ln(D)$, and substituting $Z = \ln(FS)$, $X = \ln(C)$, and $Y = -\ln(D)$, yields $Z = X + Y$. Assuming X and Y are statistically independent, the probability density function of Z is defined by the convolution integral in (4.7).

$$f_Z(z) = \int_{-\infty}^{+\infty} f_X(z-x)f_Y(x)dx \quad (4.7)$$

If X and Y are normally distributed and uncorrelated, then Z is also normally distributed, with mean and variance defined by (4.8) and (4.9).

$$\mu_Z = \mu_X + \mu_Y \quad (4.8)$$

$$\sigma_Z^2 = \sigma_X^2 + \sigma_Y^2 \quad (4.9)$$

Substituting back for Z , X , and Y , the distribution of the factor of safety can be solved for. Specifically, if C and D are lognormally distributed, then FS is also lognormally distributed with mean and variance given by (4.10) and (4.11). The capacity and demand terms are defined in the next section.

$$\mu_{\ln FS} = \mu_{\ln C} - \mu_{\ln D} \quad (4.10)$$

$$\sigma_{\ln FS}^2 = \sigma_{\ln C}^2 + \sigma_{\ln D}^2 \quad (4.11)$$

Examining Eq. (4.2), and assuming that ground motion demand and liquefaction capacity are lognormally distributed and statistically independent, the innermost integral can now be recognized as the convolution of liquefaction capacity and ground motion intensity. That integral may therefore be replaced by the cumulative distribution function for FS_L , as indicated by Eq. (4.12), where Φ is the standard normal cumulative distribution function. Substituting Eq. (4.12) into (4.2) reduces the triple integral to a double integral.

$$\int_{-\infty}^{+\infty} P(FS_L < f_{sl} | im, m, \chi) f_{IM}(im | m, r, \xi) dim = P(FS_L < f_{sl} | m, r, \xi, \chi) \\ = \Phi\left(\frac{\ln(f_{sl}) - \mu_{\ln FS_L}}{\sigma_{\ln FS_L}}\right) \quad (4.12)$$

4.2.3 Liquefaction Capacity and Ground Motion Demand

Liquefaction hazard is generally evaluated by comparing the cyclic stress ratio, CSR , with the cyclic resistance ratio, CRR . Cyclic stress ratio is defined in Eq. (4.13) in terms of the peak horizontal acceleration a_{max} , acceleration of gravity g , vertical total stress σ_{vo} , vertical effective stress σ'_{vo} , and a depth reduction factor r_d .

$$CSR = 0.65 \frac{a_{max}}{g} \frac{\sigma_{vo}}{\sigma'_{vo}} r_d \quad (4.13)$$

Taking the natural log of both sides of (4.13) results in (4.14).

$$\ln(CSR) = \ln\left(\frac{a_{max}}{g}\right) + \ln\left(0.65 \frac{\sigma_{vo}}{\sigma'_{vo}} r_d\right) \quad (4.14)$$

If a_{max} is lognormally distributed, and σ_{vo} , σ'_{vo} , and r_d are treated as constants, then CSR is also lognormally distributed, with mean and variance given by (4.15) and (4.16).

$$\mu_{\ln CSR} = \mu_{\ln a_{max}} + \ln\left(0.65 \frac{\sigma_{vo}}{\sigma'_{vo}} r_d\right) \quad (4.15)$$

$$\sigma_{\ln CSR}^2 = \sigma_{\ln a_{max}}^2 \quad (4.16)$$

The cyclic resistance ratio is generally represented as a probabilistic function of standard penetration test blow count (e.g., Cetin et al. (2004) and Cetin et al. (2018), Boulanger and Idriss (2012)), cone penetration resistance (e.g., Moss et al. (2006), Boulanger and Idriss

(2016), Ulmer et al. (2024)), or shear wave velocity (e.g., Kayen et al. (2013)). These models all represent CRR as a lognormal distribution function with mean $\mu_{\ln CRR}$ and standard deviation $\sigma_{\ln CRR}$. The factor of safety against liquefaction is therefore also lognormally distributed, with moments indicated by (4.17) and (4.18).

$$\mu_{\ln FS_L} = \mu_{\ln CRR} - \mu_{\ln CSR} \quad (4.17)$$

$$\sigma_{\ln FS_L}^2 = \sigma_{\ln CRR}^2 + \sigma_{\ln CSR}^2 \quad (4.18)$$

The direct solution strategy is illustrated schematically in Fig. 4.2, with part (a) showing probability density functions for CSR and CRR for four different events, part (b) showing probability density functions for FS_L , part (c) showing the cumulative distribution functions for FS_L , and part (d) showing $\Lambda(FS_L < fs_i)$. Note that (d) is computed by multiplying the CDFs in (c) by the discrete rate for each event and summing the results. The direct solution strategy does not use disaggregation information to compute the liquefaction hazard curve because the liquefaction evaluation is performed separately for every event.

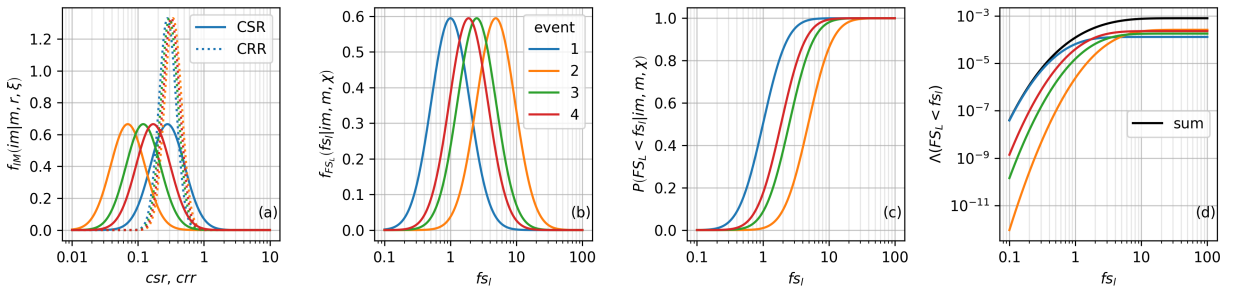


Figure 4.2: Schematic of the Direct Method for Solving the PLHA Integral.

4.3 Inputs

Having defined the relevant equations, the details of the `ucla_plha` code, which is open source and available via GitHub (Kota and Brandenburg, 2025) are now presented. Inputs to the code include information about the site, constraints, fault source models, ground motion models, liquefaction models, and output properties. Inputs are specified in a JavaScript Object Notation (JSON) config file, which is validated using the `jsonschema` Python package (Pezoa et al., 2016) before running the analysis. Example JSON files are provided in the GitHub repository, as is the `ucla_plha_schema.json` file used to validate the input. Required JSON keys are `site`, `source_models`, `ground_motion_models`, and `output`. Optional keys include `liquefaction_models` (omitted if users were to perform a PSHA without an accompanying PLHA), and `constraints`. Users may specify additional keys (e.g., “`project_information`” containing the project ID, company name, etc.). Additional keys will not influence the hazard calculation, but may be useful for record keeping. The following subsections describe the input fields in the config file; documentation for the version of the code released along with this dissertation is also available at https://meerakota.github.io/ucla_plha/.

4.3.1 Site

The location of the site of interest is identified by its latitude, longitude, and elevation in the WGS84 (Malys et al., 1994) reference system. In addition to the site location, V_{S30} , $z_{1.0}$, $z_{2.5}$, and an indicator of whether V_{S30} was measured or inferred can also be specified. V_{S30} is a required input, while the latter three inputs are optional. If unspecified, $z_{1.0}$ and $z_{2.5}$ are assigned the default “centered” values corresponding to the specified V_{S30} for each ground motion model, and V_{S30} is assumed to be inferred rather than measured. Note that not all ground motion models use all input parameters. Information about the soil properties used in the liquefaction models is provided in the liquefaction model section rather than in the

site section, because the inputs differ for each liquefaction model.

4.3.2 Constraints

In the constraints section, users can specify a cutoff distance and a minimum magnitude. Any fault rupture at a distance larger than the cutoff distance, or with a magnitude smaller than the minimum magnitude, is excluded from the analysis. The purpose of the distance cutoff is to improve computational efficiency. The magnitude cutoff also improves computational efficiency, but is additionally present because small magnitude earthquakes generally have durations that are too short to trigger liquefaction, and because magnitude scaling factors are not calibrated for small magnitude events. [Green and Bommer \(2019\)](#) suggest that a minimum magnitude of 5 be used to assess liquefaction at building sites, and that a minimum magnitude of 4.5 may be more appropriate for other types of infrastructure.

4.3.3 Fault Source Models

Seismic hazard calculations require one or more fault source models, in which earthquake sources are organized into a set of events and their annual rates of occurrence that represent, in discrete form, all possible earthquake combinations. The Uniform California Earthquake Rupture Forecast ver. 3 (UCERF3) ([Field et al., 2013](#)) was adopted for this work - specifically, the branch-averaged Fault Model 3.1 (FM3.1) and Fault Model 3.2 (FM3.2), including seismicity on known faults as well as gridded and non-associated background seismicity. Faults are discretized into segments in the UCERF3 model, and events consist of ruptures of one or more segments on one or more faults. Background seismicity is represented at grid points on the Earth's surface, and the grid points are interpreted as epicenters. These data are available in XML and GeoJSON formats through the UCERF3 website (<https://wgcep.org/UCERF3.html>). The native file formats must be parsed and read into NumPy arrays in order to compute source-to-site distances in the `ucla_plha` code, as described in the next section. Rather than repeating this parsing each time the `ucla_plha`

code is executed, the files were preprocessed and saved as NumPy arrays (i.e., using NumPy’s .npz file extension for storing array data in binary format) (Harris et al., 2020). A description of the files used to represent the UCERF3 source model in the code is provided in Table 4.1 for fault source models and in Table 4.2 for background seismicity.

Table 4.1: Description of fault source files.

Filename	Description
<code>ruptures.npz</code>	zipped NumPy array containing rupture index, magnitude, rate, style of faulting, rake angle, dip, and depths to the top and bottom of the fault
<code>ruptures_segments.npz</code>	zipped NumPy array mapping ruptures to segments
<code>fault_id.npy</code>	NumPy array defining fault id corresponding to each triangle
<code>tri_rjb.npy</code>	NumPy array defining Cartesian coordinates of triangles for surface projection of each segment
<code>tri_rrup.npy</code>	NumPy array defining Cartesian coordinates of triangles for each segment
<code>tri_segment_id.npy</code>	NumPy array mapping triangles to segment numbers
<code>rect_rjb.npy</code>	NumPy array defining Cartesian coordinates of rectangles for each segment
<code>rect_segment_id.npy</code>	NumPy array mapping rectangles to segment numbers

Table 4.2: Description of point source files.

Filename	Description
<code>ruptures.npz</code>	zipped NumPy array containing rupture index, magnitude, rate, and style of faulting
<code>node_index.npy</code>	NumPy array containing indices for point sources
<code>points.npy</code>	NumPy array containing Cartesian coordinates of point sources

A weight is assigned to each fault source model within the config file to represent its contribution to the overall hazard and to capture epistemic uncertainty within a logic tree framework. Weights are assigned separately to the fault source and point source portions of the model, so that users can create fault-only or point-source-only hazard curves by setting weights to zero as needed. The specified weights are normalized to sum to unity within the code for convenience, so that users can enter relative weights as they see fit. As described in subsequent sections, weights are also assigned to ground motion models and liquefaction models. These weights are assigned to branches of a logic tree that represent all combinations of the specified source model(s), ground motion model(s), and liquefaction model(s). The

weighted average hazard curve is returned by the `ucla_plha` code. If users wish to compute hazard curves for an individual combination of models, they must create a separate config file containing only the desired models and run a separate analysis.

4.3.4 Source-to-Site Distance

Calculating source-to-site distance is a computationally expensive aspect of PSHA because (1) ground motion models use many different distance metrics to quantify path and near-source effects, (2) source models are often parameterized in a manner that is not conducive to efficient distance calculation, (3) there are generally a large number of fault segments for which to compute source-to-site distance, and (4) each rupture scenario involves many segments, the closest of which defines the source-to-site distance. This section describes how distances are computed in a computationally efficient manner in the `ucla_plha` code.

Required Distance Metrics

The source-to-site distance metrics required by the `ucla_plha` code include the following:

- R_{JB} = Joyner-Boore distance representing the shortest distance between the site and the surface projection of the fault
- R_{RUP} = Rupture distance representing the shortest distance between the site and the fault rupture surface
- R_X = Horizontal distance between the site and the surface projection of the shallowest edge of the rupture surface, measured perpendicular to the strike
- R_{X1} = Horizontal distance between the site and the surface projection of the deepest edge of the rupture surface, measured perpendicular to the strike

- R_{Y0} = Horizontal distance between the site and the surface projection of the rupture surface, measured parallel to the strike

The first two distance parameters are used to model primary source-to-site distance effects, while the latter three are used to model hanging wall effects. R_{JB} , R_{RUP} , and R_X are shown in Figure 4.3 (Kaklamanos et al., 2011).

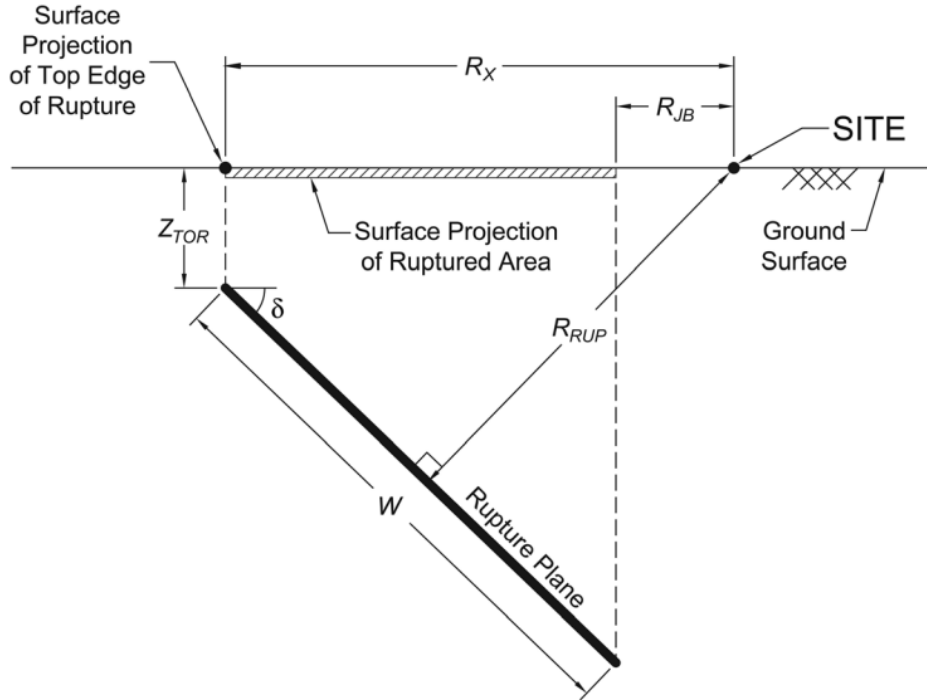


Figure 4.3: Earthquake Source and Relevant source-to-site Distances (Kaklamanos et al., 2011)

Different ground motion models use various combinations of these distance metrics. The inputs required to compute the distance metrics were separated into different files, so that the minimum number of files is opened for a particular set of ground motion models. For example, some ground motion models only use R_{JB} , in which case the data required to compute the other distance metrics do not need to be opened.

Computing Distances by Representing UCERF3 Rupture Surfaces as Triangles

The UCERF3 fault segments are represented as triangles in Cartesian space in the `ucla_plha` code, which allows source-to-site distances to be computed with closed-form equations. Each fault section in UCERF3 is stored as latitude and longitude, together with a dip angle, a dip direction, a depth to the top of the rupture, and a depth to the bottom of the rupture. Consecutive pairs of coordinates define the individual segments of a section, and each segment is expanded by projecting its two trace points down dip. Reconstructing the two down dip corners requires placing each corner on the Earth’s surface at a known great-circle distance from its trace point, for which the haversine relation is used ([Robusto, 1957](#); [Sinnott, 1984](#)).

The Earth is treated as an oblate spheroid rather than as a sphere, so the radius that appears in the great-circle relations is a function of latitude. The geocentric radius at latitude ϕ is

$$R(\phi) = \sqrt{\frac{(a^2 \cos \phi)^2 + (b^2 \sin \phi)^2}{(a \cos \phi)^2 + (b \sin \phi)^2}}, \quad (4.19)$$

where $a = 6378.1370$ km and $b = 6356.7523$ km are the equatorial and polar radii of the Earth, respectively. Equation (4.19) is evaluated at each point individually rather than once for the model as a whole, so the radius used to project a trace point differs slightly from the radius used at the resulting down dip corner.

The haversine of the central angle γ are contained at Earth’s center between two points P_1 and P_2 is

$$\text{hav}(\gamma) = \text{hav}(\phi_2 - \phi_1) + \cos(\phi_1) \cos(\phi_2) \text{hav}(\lambda_2 - \lambda_1), \quad (4.20)$$

where

$$\text{hav}(x) = \sin^2\left(\frac{x}{2}\right), \quad (4.21)$$

ϕ_1 and ϕ_2 are the latitudes of P_1 and P_2 , respectively, and λ_1 and λ_2 are their longitudes.

The great-circle distance D follows from the central angle as $D = R\gamma$, so that

$$D = 2R \arcsin\left(\sqrt{\text{hav}(\gamma)}\right). \quad (4.22)$$

Because D and the change in latitude are both known for a projected corner, Eq. (4.20) can be inverted to solve for the unknown change in longitude, as described below.

Calculating the Segment Corners

Figure 4.4 shows two input points from one fault segment in red and illustrates how the dip angle, the depth to the top of the fault, and the depth to the bottom of the fault are used to calculate the down dip width. The dip angle θ of a fault is the angle of inclination measured from the horizontal and varies between 0 and 90 degrees, with vertical faults having a dip angle of 90 degrees (Gonzalez de Vallejo and Ferrer, 2011).

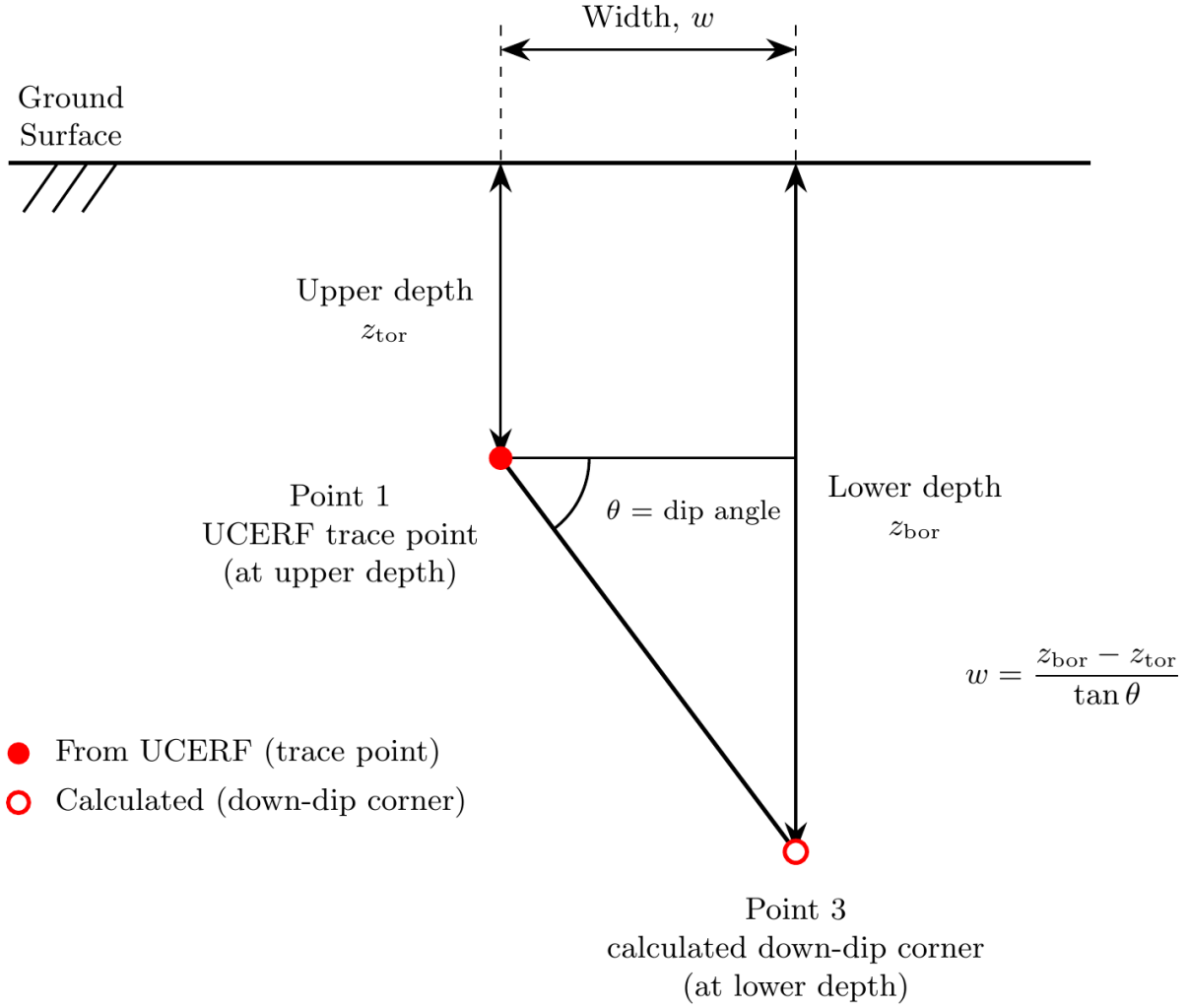


Figure 4.4: UCERF3 Fault Source Model Geometry

For a segment with dip θ , depth to top of rupture z_{tor} , and depth to bottom of rupture z_{bor} , the horizontal (map-view) width of the down-dip projection is

$$w = \frac{z_{\text{bor}} - z_{\text{tor}}}{\tan \theta}. \quad (4.23)$$

Vertical segments therefore have $w = 0$, and their down-dip corners coincide with their trace points in map view.

The dip direction is measured with respect to north and is the direction of maximum gradient along the plane (Gonzalez de Vallejo and Ferrer, 2011). It is shown as α in Figure

4.5. In UCERF3 the dip direction is not unique for each fault section but is instead averaged over all segments of one measured fault, which prevents overlapping points along a single fault. The horizontal offset from each trace point to its corresponding down-dip corner therefore has magnitude w and bearing α , and its northward component is

$$w_y = w \cos \alpha, \quad (4.24)$$

which fixes the latitude of the projected corner. All angles below are in radians; the implementation stores latitude and longitude in degrees and converts as needed. Trace points 1 and 2 project to corners 3 and 4, respectively. A northward arc of length w_y corresponds to a change in latitude of w_y/R , so

$$\Delta\phi_1 = \frac{w_y}{R(\phi_1)}, \quad \Delta\phi_2 = \frac{w_y}{R(\phi_2)}, \quad (4.25)$$

and the projected corner latitudes are $\phi_3 = \phi_1 + \Delta\phi_1$ and $\phi_4 = \phi_2 + \Delta\phi_2$. With w and $\Delta\phi$ known, Eq. (4.20) is inverted for the change in longitude between a trace point and its projected corner:

$$\Delta\lambda_1 = \arccos \left[1 - \frac{2 \sin^2 \left(\frac{w}{2R(\phi_3)} \right) + \cos \Delta\phi_1 - 1}{\cos \phi_1 \cos \phi_3} \right], \quad (4.26)$$

with $\Delta\lambda_2$ following under $1 \rightarrow 2$ and $3 \rightarrow 4$. The projected corner longitudes are $\lambda_3 = \lambda_1 + \Delta\lambda_1$ and $\lambda_4 = \lambda_2 + \Delta\lambda_2$. The radius is evaluated at the trace point in Eq. (4.25) and at the projected corner in Eq. (4.26).

Figure 4.5 shows how the dip direction together with the haversine distance yields the two remaining corners of the segment. Using each consecutive coordinate pair within a fault section, together with the section dip and dip direction, the planar surface is recovered in three-dimensional space with the two trace points (ϕ_1, λ_1) and (ϕ_2, λ_2) at depth z_{tor} and the

two projected points (ϕ_3, λ_3) and (ϕ_4, λ_4) at depth z_{bor} .

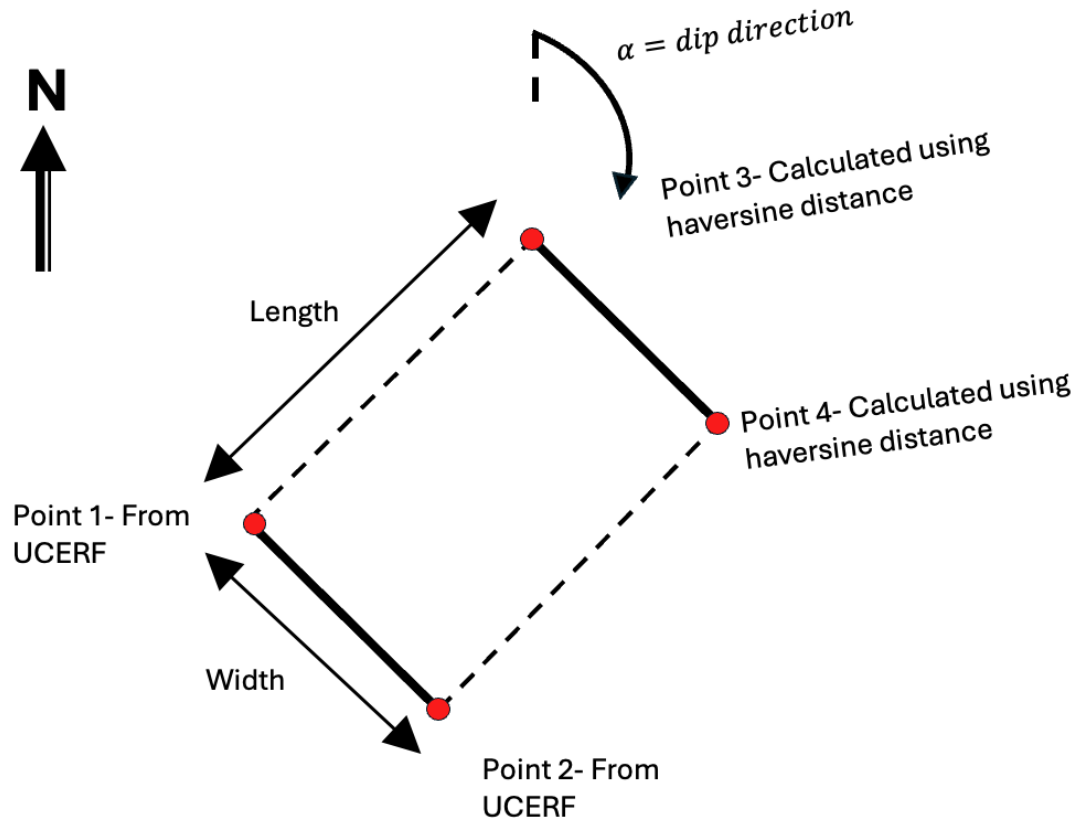


Figure 4.5: UCERF3 Fault Model Geometry and Projected Points calculated using the haversine distance formula

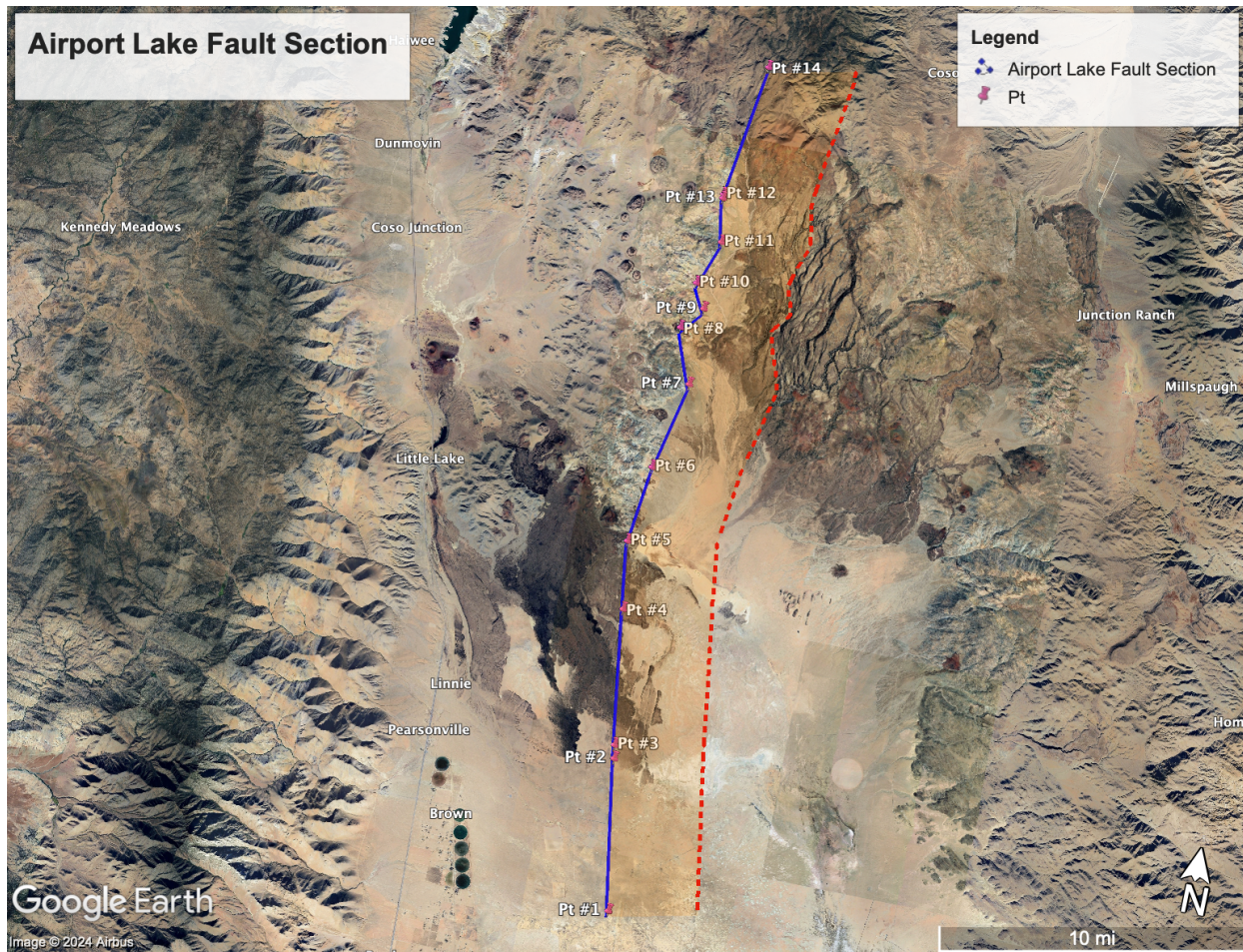


Figure 4.6: Airport Lake Fault Rupture Sections

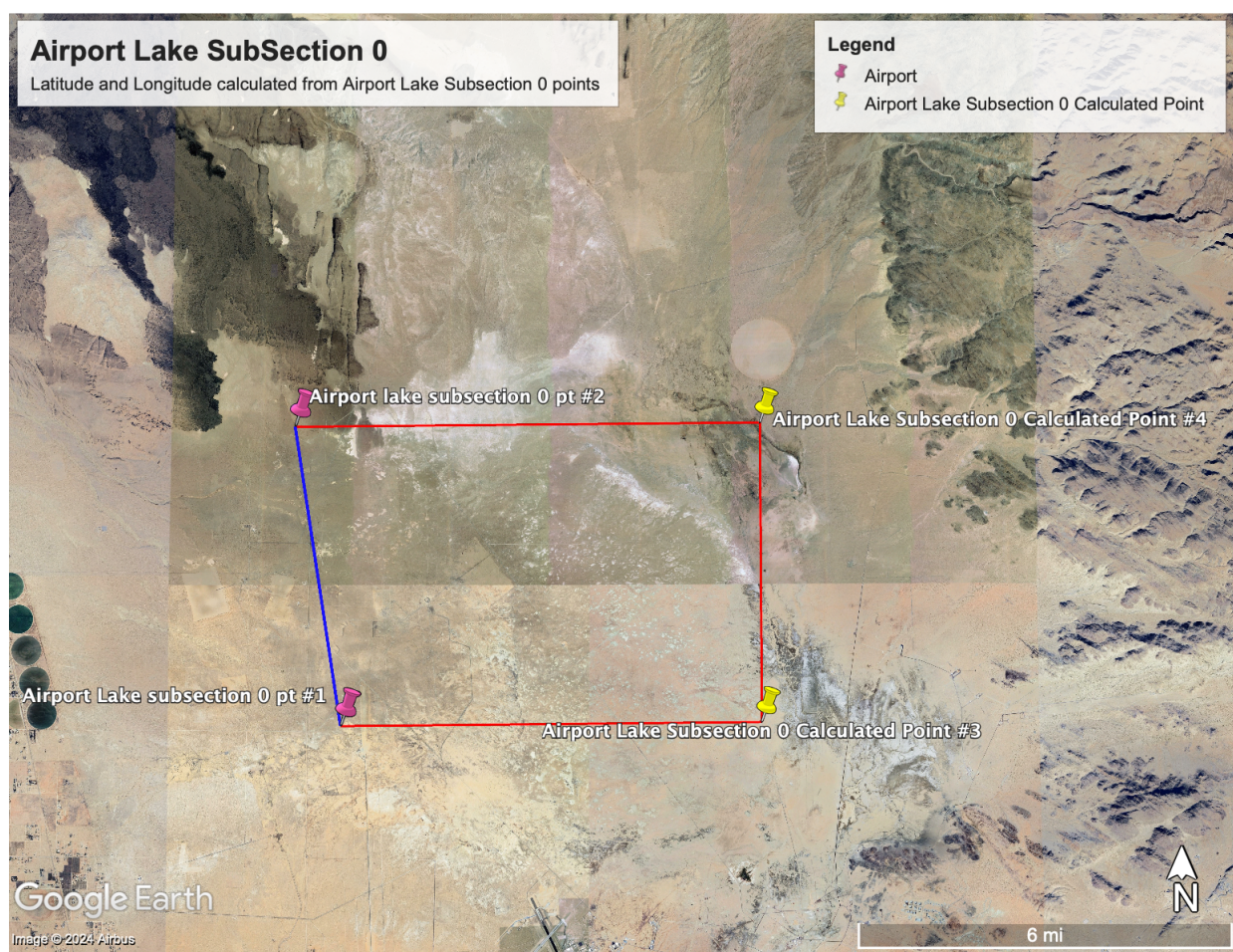


Figure 4.7: Map of Airport Lake Subsection 0 (from UCERF3 and calculated projected points)

Figure 4.6 illustrates all the fault segments for the Airport Lake fault section in UCERF3. Because of the geometry of this fault, using the average dip angle and dip direction results in a continuous rupture surface, whereas segment specific dip and dip direction values would produce gaps and overlaps. Figure 4.7 shows the first fault section in the UCERF3 fault model (Airport Lake Subsection 0), with the pair of points from the fault model in pink and the calculated projected points in yellow.

Conversion to Cartesian Coordinates and Triangulation

Once a rectangle is constructed, it is divided into two triangles using its points 1, 2, 4 and 1, 3, 4, respectively (from Figure 4.5). The latitude and longitude values for each triangle, along with its depth below the surface, are converted from a geographic (latitude, longitude, elevation) coordinate system to a Cartesian coordinate system, allowing distance calculations to be performed more easily. First, the latitude, longitude, and elevation coordinates are converted for the fault rupture segments into Cartesian coordinates with (0,0,0) at the center of the Earth. The x-direction intersects zero latitude and zero longitude, the z-direction intersects the poles, and the y-direction is orthogonal to x and z. The radial term R is the geocentric radius of Eq. 4.19, evaluated at the latitude of each point, so that the conversion follows the ellipsoidal surface rather than a sphere. The site of interest chosen for PSHA calculations is also converted to a Cartesian system. Elevation is measured relative to the Earth's surface, and is positive upward, so depths from UCERF3 are assigned negative values, equal to the negative of the depth. The following equations are used for the conversions:

$$X = (R + elevation) \cdot \cos(latitude) \cdot \cos(longitude) \quad (4.27)$$

$$Y = (R + elevation) \cdot \cos(latitude) \cdot \sin(longitude) \quad (4.28)$$

$$Z = (R + elevation) \cdot \sin(latitude) \quad (4.29)$$

For the over 7000 triangles created by the UCERF3 fault model, the distance between the triangle and the point of interest is calculated. A single fault section can contain up to 7 coordinate pairs. Because a fault section is traced by several coordinate pairs, and each pair of consecutive trace points yields one rectangle and hence two triangles, the distance to a section is taken as the minimum of the point-to-triangle distances over all triangles belonging to that section.

Point-to-Triangle Distance Calculation

The shortest distance between the site and each triangle is then computed using a Python implementation of the closed-form, three-dimensional point-to-triangle algorithm of [Eberly \(1999\)](#). The algorithm computes the minimum distance by determining where a point P projects relative to a triangle in (s, t) , where (s, t) are local coordinates in the plane that contains the triangle. The triangle in Eberly's formulation is defined as:

$$T(s, t) = B + sE_0 + tE_1 \quad (4.30)$$

The distance from P to any point on the triangle is defined as:

$$Q(s, t) = |T(s, t) - P|^2 = as^2 + 2bst + ct^2 + 2ds + 2et + f \quad (4.31)$$

The formulation minimizes $Q(s, t)$ over the triangle domain, D . The s - t plane is split into multiple regions as shown in [Figure 4.8](#). The algorithm determines in which region the point projects and calculates the minimum distance between the point and the triangle. If the point projects into Region 0, for example, the closest point lies inside the triangle.

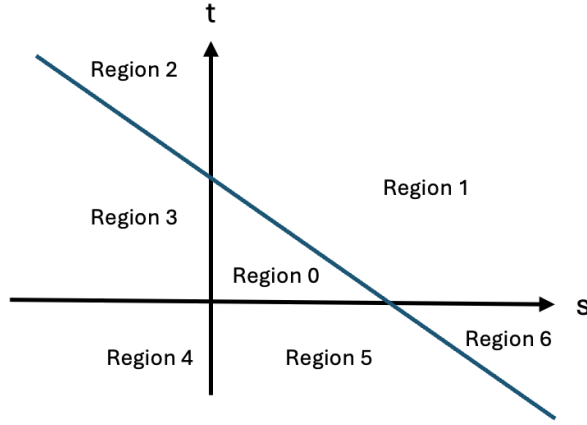


Figure 4.8: Partition of s - t plane over the triangle domain, D for point to triangle 3D distance algorithm (Eberly, 1999)

Rupture and Joyner–Boore Distances

The procedure above yields the rupture distance R_{RUP} when it is applied to the dipping triangles. The Joyner–Boore distance R_{JB} , defined as the shortest horizontal distance to the surface projection of the rupture, is obtained by applying the identical point-to-triangle algorithm to a second set of triangles built from the same corners but with all vertex depths set to zero. Both distances are reduced by taking the minimum over all triangles sharing a segment identifier.

The NGA-West2 ground-motion models additionally require the horizontal distances R_X , R_{X1} , and R_{Y0} , which are measured relative to the surface projection of the rupture rather than to the rupture itself. These are computed from the surface-projected rectangle, whose four corners are the segment corners with their depths set to zero. R_X is the perpendicular distance from the site to the line containing the top edge, and R_{X1} is the corresponding perpendicular distance to the line containing the bottom edge. R_{Y0} is the along-strike distance by which the site lies beyond the ends of the rupture. It is taken as the smaller of the two distances measured from the site to the strike-normal lines through the rupture ends, and is set to zero whenever the site falls between those ends. As with R_{RUP} and R_{JB} , a fault

section in UCERF3 can consist of several geometric objects, so each quantity is obtained by taking the minimum over all objects that share a segment.

Vectorization

The implementation of Eberly’s algorithm presented here is “vectorized”: the triangle and point coordinates are input as NumPy arrays, and NumPy functions perform all operations that would otherwise require Python loops. Python is an interpreted language, and Python loops carry significant runtime overhead and can be orders of magnitude slower than equivalent operations in NumPy (which are primarily written in C) ([van der Walt et al., 2011](#); [McKinney, 2022](#)). The distance algorithm computes only one distance per triangle (two per rectangle). Here is a brief example on vectorization and how that can be implemented in the code.

Below is an example from the BSSA14 ground motion model for a magnitude dependent standard deviation term. Without vectorization, the code requires a loop over all the possible magnitudes.

```
n = len(m)
tau = np.empty(n)
for i in range(n):
    if m[i] <= 4.5:
        tau[i] = tau1
    elif m[i] < 5.5:
        tau[i] = tau1 + (tau2 - tau1) * (m[i] - 4.5)
    else: # m[i] >= 5.5
        tau[i] = tau2
```

Listing 1: Loop-based computation of the magnitude-dependent between-event standard deviation τ .

In comparison, the vectorized implementation produces the same result without requiring a loop. The array is initialized to the default value, and Boolean masks then select the subset of elements in each magnitude range, to which the corresponding expression is applied

simultaneously.

```
tau = np.full(len(m), tau2)
tau[m <= 4.5] = tau1
band = (4.5 < m) & (m < 5.5)
tau[band] = tau1 + (tau2 - tau1) * (m[band] - 4.5)
```

Listing 2: Vectorized computation of the magnitude-dependent between-event standard deviation τ , with a linear ramp from τ_1 to τ_2 over $4.5 < M < 5.5$.

In the vectorized form the magnitude mask appears on both sides of the equation: the right-hand side, `m[band]`, gathers only the magnitudes within the relevant range, while the left-hand side, `tau[band]`, writes the results back to the same positions. The mask is computed once and reused, which avoids redundant comparisons. Vectorized array operations execute as batched calls over contiguous memory, allowing the use of parallelism. In practice this reduces the overall runtime.

To quantify the vectorization benefit, both forms were run with a time check on an array of five million magnitudes drawn uniformly over $3 \leq M \leq 8$, with an equivalence check confirming that the two implementations return identical results.

```

import time
import numpy as np

tau1, tau2 = 0.40, 0.25

rng = np.random.default_rng(0)
m = rng.uniform(3.0, 8.0, size=5000000)

# Loop implementation
t0 = time.perf_counter()
n = len(m)
tau_loop = np.empty(n)
for i in range(n):
    if m[i] <= 4.5:
        tau_loop[i] = tau1
    elif m[i] < 5.5:
        tau_loop[i] = tau1 + (tau2 - tau1) * (m[i] - 4.5)
    else: # m[i] >= 5.5
        tau_loop[i] = tau2
t_loop = time.perf_counter() - t0

# Vectorized implementation
t0 = time.perf_counter()
tau_vec = np.full(len(m), tau2)
tau_vec[m <= 4.5] = tau1
band = (4.5 < m) & (m < 5.5)
tau_vec[band] = tau1 + (tau2 - tau1) * (m[band] - 4.5)
t_vec = time.perf_counter() - t0

assert np.allclose(tau_loop, tau_vec)
print(f"n elements      : {n:,}")
print(f"loop time         : {t_loop:.4f} s")
print(f"vectorized time    : {t_vec:.4f} s")
print(f"speedup            : {t_loop / t_vec:.1f}x")

```

Listing 3: Comparing the timing of the loop-based and vectorized implementations of τ .

Running this code produces the following output:

```
n elements      : 5,000,000
loop time       : 0.9406 s
vectorized time : 0.0682 s
speedup         : 13.8x
```

On this array, the vectorized implementation runs roughly fourteen times faster than the explicit loop while returning identical values; the precise factor depends on array size and hardware, growing as the per-iteration interpreter overhead of the loop comes to dominate.

This matters especially for PSHA, which uses inherently slow nested loops. Vectorizing the inner dimensions therefore collapses this nesting into a few compiled array operations, yielding speedups substantially larger than the single array.

Pre-processing and Organization

Each rectangular segment has two triangles, and the triangles were saved as two separate NPY files per fault model, with the coordinates stored as 32-bit floats. The `tri_rjb.npy` file contains triangles representing the surface projection of the fault ruptures, while the `tri_rrup.npy` file contains triangles representing the fault planes themselves.

To keep track of the mapping between triangles and fault segments, a separate array of integers corresponding to the rupture index values was created called `fault_id.npy`, such that `fault_id.npy`, `tri_rjb.npy`, and `tri_rrup.npy` all have the same number of rows. Rupture index, magnitude, rate, style of faulting, rake, dip, and depths to the top and bottom of the rupture for each segment were collated from the UCERF3 fault model, and saved in a zipped NumPy array.

Finally, the mapping between ruptures and segments for the UCERF3 model was originally provided in a CSV file with one row per rupture, and a variable number of columns containing the associated segment numbers. This table was flattened into a zipped NumPy array representing the many-to-many relationship between ruptures and segments (i.e., each

segment is associated with many ruptures, and each rupture contains many segments). The array has over 16 million rows, and would be over 100 MB if the indices were stored as 32-bit integers. Zipping these files eases installation of the code, but adds some computational overhead because the files must be opened and unzipped during each execution. Accordingly, a utility that unzips the files in the installation directory is provided. Calling this function once after installation provides a modest reduction in calculation time at the expense of occupying more disk space.

4.3.5 Computing R_{JB} , R_{RUP} , and Background Seismicity

The Eberly procedure described previously is used to compute both R_{RUP} and R_{JB} for both UCERF3 fault models, FM3.1 and FM3.2. The primary difference between the two metrics is that, for R_{JB} , the latitude and longitude points are taken as surface projections and the depth is set to zero when converting from geographic to Cartesian coordinates. Once distances are computed, they are associated with specific rupture scenarios. Because a single rupture scenario may involve many fault sections, the minimum distance over all sections within a rupture is taken as the source-to-site distance for that rupture.

Background seismicity is treated separately. In UCERF3 the background is gridded, and fault ruptures are not explicitly modeled. The background grid locations are interpreted as point sources, and the grid locations are interpreted as epicenters. The remaining distance metrics are calculated from epicentral distance using curve fits to the default methods described by [Thompson and Worden \(2017\)](#).

4.3.6 Ground Motion Models

Ground motion models represent a ground motion intensity measure, IM , as a random variable that contains contributions from source, path, and site effects. The `ucla_plha` code currently implements four ground motion models for shallow crustal earthquakes: [Abrahamson et al. \(2014\)](#), [Boore et al. \(2014\)](#), [Campbell and Bozorgnia \(2014\)](#), and [Chiou and Youngs](#)

(2014) (herein denoted ASK14, BSSA14, CB14, and CY14, respectively). Table 4.3 details the four models and their required inputs, where $\mathbf{M}$ is magnitude, V_{S30} is the time-averaged shear wave velocity in the upper 30 meters, $z_{1.0}$ and $z_{2.5}$ are depths to isosurfaces representing shear wave velocities of 1.0 km/s and 2.5 km/s, respectively, *dip* is the fault dip angle, *fault type* is an integer representing fault slip with reverse = 1, normal = 2, and strike-slip = 3, *measured* V_{S30} is a boolean representing whether V_{S30} is measured or inferred at the site of interest, and z_{tor} and z_{bor} are depths to the top and bottom of the fault rupture, respectively.

Table 4.3: Ground motion models and their required inputs.

Ground Motion Models	Inputs
Abrahamson-Silva-Kamai 2014 (ASK14)	V_{S30} , R_{RUP} , R_{X1} , R_{Y0} , $\mathbf{M}$, <i>dip</i> , <i>fault type</i> , <i>measured</i> V_{S30} , z_{tor} , $z_{1.0}$
Boore-Stewart-Seyhan-Atkinson 2014 (BSSA14)	V_{S30} , R_{JB} , $\mathbf{M}$, <i>fault type</i> , $z_{1.0}$
Campbell-Bozorgnia 2014 (CB14)	V_{S30} , R_{JB} , R_{RUP} , R_X , R_{X1} , $\mathbf{M}$, <i>fault type</i> , z_{tor} , z_{bor} , <i>dip</i> , $z_{2.5}$
Chiou-Youngs 2014 (CY14)	V_{S30} , R_{JB} , R_{RUP} , R_X , $\mathbf{M}$, <i>fault type</i> , <i>measured</i> V_{S30} , z_{tor} , <i>dip</i> , $z_{1.0}$

Currently, these models are implemented only for peak ground acceleration, *PGA*, which is the *IM* used by the liquefaction models implemented in `ucla_plha`. If additional *IMs* (e.g., peak ground velocity, spectral acceleration, cumulative absolute velocity, or Arias intensity) are required for future applications of `ucla_plha`, the required code modifications are relatively straightforward, as they only require the input of new model coefficients. The ground motion models are implemented using vectorized calculations in NumPy, such that the source parameters and distances in Table 4.3 are input as arrays, while site parameters (V_{S30} , $z_{1.0}$, $z_{2.5}$, *measured* V_{S30}) are scalar valued. The ground motion models were validated by plotting model results against the figures provided by the model developers. The ground motion models were also compared with the pygmm package (Kottke et al., 2025). Validation figures for the four ground motion models are shown in Figures 4.9, 4.10, 4.11, 4.12, and 4.13.

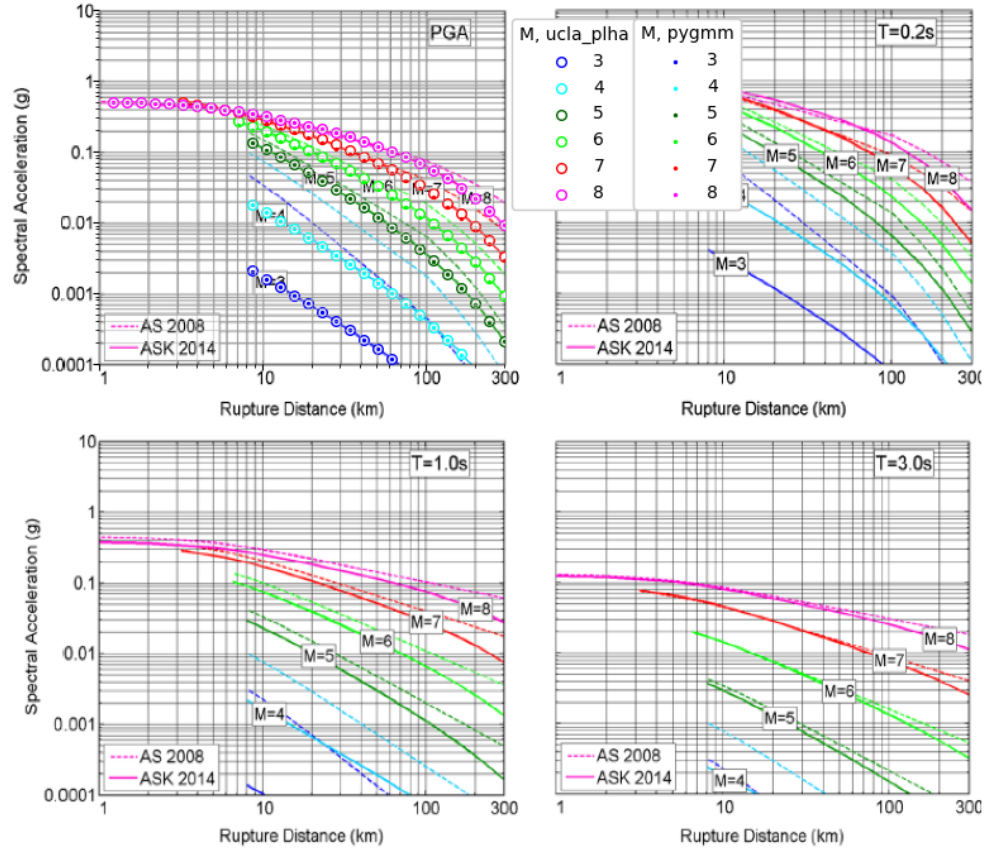


Figure 8. Comparison of the scaling with distance for the current model with the AS08 model for strike-slip earthquakes and rock site conditions ($V_{S30} = 760$ m/s).

Figure 4.9: Verification of the ASK14 ground motion model (Abrahamson et al., 2014) as implemented in `ucla_plha` (open circles) against `pygmm` (dots), shown for PGA and $T = 0.2$, 1.0 , and 3.0 s over M 3–8. Curves reproduce Figure 8 of Abrahamson et al. (2014) (ASK14 solid, AS2008 dashed) for strike-slip earthquakes and rock site conditions ($V_{S30} = 760$ m/s).

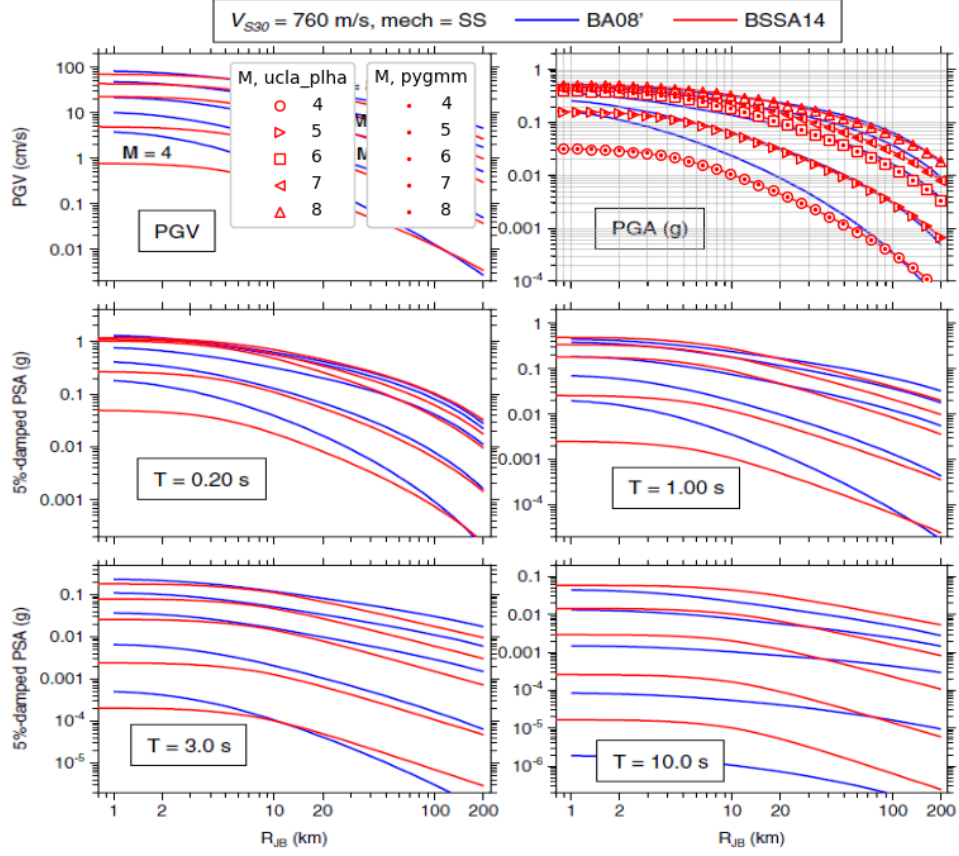


Figure 7. Median trends of proposed GMPEs as compared to BA08', as a function of distance for strike-slip earthquakes and $V_{S30} = 760$ m/s. The BA08' values have been adjusted to RotD50 using the ratios RotD50/GMRot150 in Boore (2010; maximum adjustment of 1.06 for $T = 10$ s).

Figure 4.10: Verification of the BSSA14 ground motion model (Boore et al., 2014) as implemented in ucla_plha (open markers) against pygmm (dots), shown for PGV , PGA , and 5%-damped PSA at $T = 0.20, 1.00, 3.0$, and 10.0 s over M 4–8. Curves reproduce Figure 7 of Boore et al. (2014) (BSSA14 red, BA08' blue) for strike-slip earthquakes and $V_{S30} = 760$ m/s.

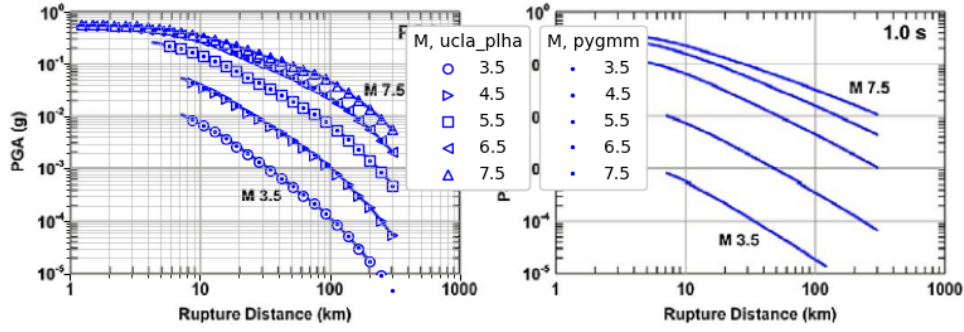


Figure 6. Comparison of CB14 distance-scaling (attenuation) characteristics for $M = 3.5, 4.5, 5.5, 6.5,$ and 7.5 showing how the rate of attenuation of PGA and PSA at $T = 1$ s decrease with magnitude. The GMPE is evaluated for strike-slip faulting, $V_{S30} = 760$ m/s, $Z_{2.5} = 0.6068$ km, and $\delta = 90^\circ$. Default values of Z_{TOR} , Z_{HYP} , and W from Equations 35 to 37 and accompanying text are given in Table C1 of Appendix C in the Electronic Supplement for this manuscript. The curves are truncated at short distances at the default value of Z_{TOR} , the smallest possible value of R_{RUP} .

Figure 4.11: Verification of the CB14 ground motion model (Campbell and Bozorgnia, 2014) as implemented in `ucla_plha` (open markers) against `pygmm` (dots), shown for PGA and PSA at $T = 1.0$ s over $M 3.5$ – 7.5 . Curves reproduce Figure 6 of Campbell and Bozorgnia (2014) for strike-slip faulting with $V_{S30} = 760$ m/s, $Z_{2.5} = 0.6068$ km, and $\delta = 90^\circ$.

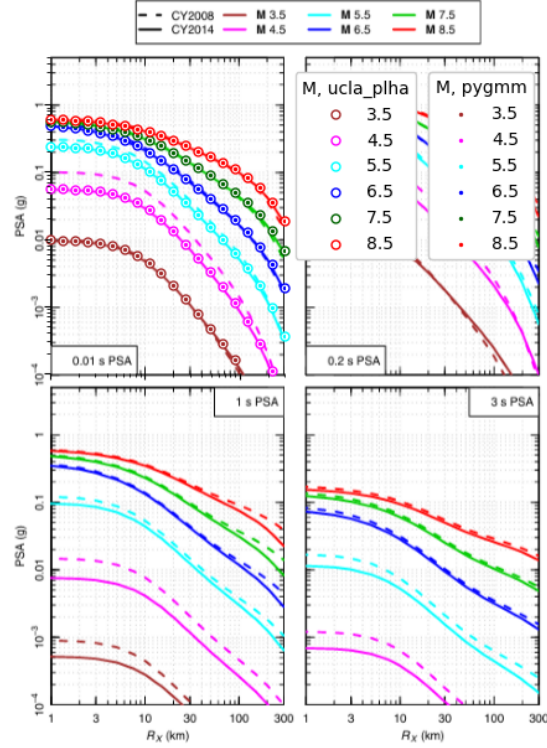


Figure 14. Median amplitude versus R_x predicted by the 2008 Chiou and Youngs NGA model (CY2008) and the updated model (CY2014) for vertical strike slip earthquake, $V_{S30} = 760$ m/s average Z_{TOR} ($\Delta Z_{TOR} = 0$), and $\Delta DPP = 0$.

Figure 4.12: Verification of the CY14 ground motion model (Chiou and Youngs, 2014) as implemented in `ucla_plha` (open circles) against `pygmm` (dots), shown for PSA at $T = 0.01$, 0.2 , 1 , and 3 s over M 3.5–8.5. Curves reproduce Figure 14 of Chiou and Youngs (2014) (CY2014 solid, CY2008 dashed) for a vertical strike-slip earthquake with $V_{S30} = 760$ m/s, $\Delta Z_{TOR} = 0$, and $\Delta DPP = 0$.

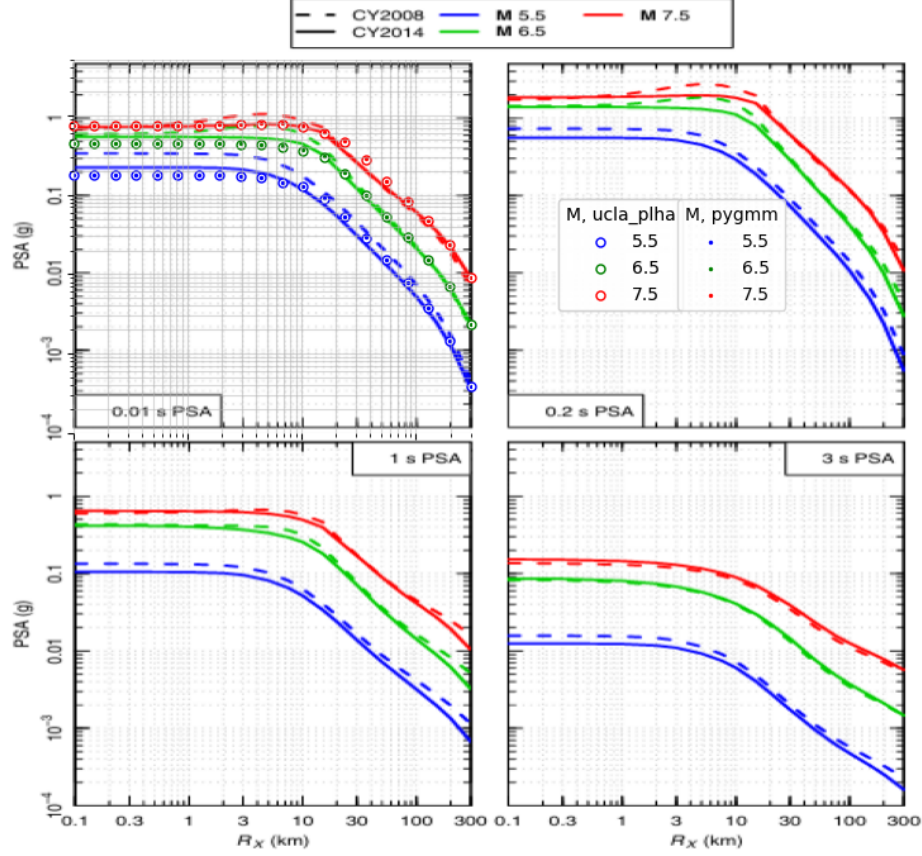


Figure 15. Median amplitude versus R_X predicted by the 2008 Chiou and Youngs NGA model (CY2008) and the updated model (CY2014) for reverse earthquake of 45° dip. Predictions are for average Z_{TOR} ($\Delta Z_{TOR} = 0$), $V_{S30} = 760$ m/s, $\Delta DPP = 0$, and for sites on the hanging wall ($R_{JB} = 0$).

Figure 4.13: Verification of the CY14 ground motion model (Chiou and Youngs, 2014) as implemented in *ucla_plha* (open circles) against *pygmm* (dots), shown for *PSA* at $T = 0.01$, 0.2, 1, and 3 s over M 5.5–7.5. Curves reproduce Figure 15 of Chiou and Youngs (2014) (CY2014 solid, CY2008 dashed) for a reverse earthquake with 45° dip, $V_{S30} = 760$ m/s, $\Delta Z_{TOR} = 0$, $\Delta DPP = 0$, and sites on the hanging wall ($R_{JB} = 0$).

These comparisons are likewise available on the *ucla_plha* GitHub repository and documentation page.

4.3.7 Liquefaction Triggering Models

PLHA requires one or more probabilistic triggering models that represent the probability of liquefaction triggering or its consequences, conditional on one or more ground motion intensity measures. Five liquefaction triggering models are currently implemented in the

`ucla_plha` code, as summarized in Table 4.4. All five models use *PGA* and **M** to quantify shaking intensity. Four of the models use a critical layer approach, and were developed by (i) identifying the layer within the profile that is most likely to trigger or produce surface manifestation, (ii) using one or more geotechnical site investigations to select representative properties for the critical layer, and (iii) defining a boundary separating yes / no cases based on penetration resistance and *CSR*. Probability of triggering for these models is related to the rate of mispredictions. Two of the critical layer models use standard penetration test blow counts (Boulanger and Idriss, 2012; Cetin et al., 2018), and two use cone penetration test tip resistance and sleeve friction (Moss et al., 2006; Boulanger and Idriss, 2016). The remaining model was developed by Ulmer et al. (2024) and uses cone penetration test data to compute the probability of manifestation of the entire profile using all soil layers rather than an individual critical layer.

A number of differences between the critical layer models and the profile-based model warrant discussion with respect to their implementation in `ucla_plha`. The critical layer procedures require scalar-valued inputs for penetration resistance, vertical total and effective stress, depth, etc. because the probability of liquefaction is computed for a single critical layer. In contrast, arrays are input to the profile-based model because it evaluates every layer and computes a probability of manifestation of the profile. It is not recommended to input every data point in the CPT profile as a separate layer, but rather identify major stratigraphic units in the profile and selecting representative properties for each layer. Hudson et al. (2023) developed a clustering algorithm to automate layer identification in an objective and repeatable manner. As a result of analyzing every layer, the profile-based model takes longer to run than the critical layer models. However, it is rare in practice to analyze the properties of only a single critical layer, even though the models were developed in that manner. Rather, the critical layer models are generally used to evaluate every susceptible layer within the profile. Liquefaction hazard curves can be computed for every susceptible layer by running the `ucla_plha` code multiple times using the critical layer models, but

there is no established guidance on how the resulting hazard curves should be combined to represent the overall probability of manifestation of a profile. If this approach is adopted, the computation time will be longer than that of the profile-based model because the PSHA is repeated for each layer in such an analysis, whereas it is performed only once in the profile-based approach.

Inputs to each of the models are summarized in Table 4.4, where $\mu_{ln,pga}$ is the mean of the natural log of the earthquake ground motion intensity measure and $\sigma_{ln,pga}$ is the standard deviation of the natural log of the ground motion intensity measure, σ_v and σ'_v are the total and effective vertical stress, respectively, d is depth, $N_{1,60}$ is overburden- and energy-corrected SPT blow count, q_c is cone tip resistance, q_{c1Ncs} is overburden- and fines-corrected dimensionless cone tip resistance, FC is fines content, V_{S12} is the time-averaged shear wave velocity in the upper 12 m, p_a is atmospheric pressure, z_{top} and z_{bot} are the top and bottom depths of each layer, I_c is the soil behavior type index, and K_{sat} is the saturation factor, generally equal to 1.0 below the water table and 0 above it.

Table 4.4: Triggering models and their required inputs.

Model	Test	Model Type	Inputs
Boulanger and Idriss (2012)	SPT	Critical Layer	$\mu_{ln,pga}$, $\sigma_{ln,pga}$, $\mathbf{M}$, σ_v , σ'_v , d , $N_{1,60}$, FC , p_a
Boulanger and Idriss (2016)	CPT	Critical Layer	$\mu_{ln,pga}$, $\sigma_{ln,pga}$, $\mathbf{M}$, σ_v , σ'_v , d , q_{c1Ncs} , p_a
Cetin et al. (2018)	SPT	Critical Layer	$\mu_{ln,pga}$, $\sigma_{ln,pga}$, $\mathbf{M}$, σ_v , σ'_v , V_{S12} , d , $N_{1,60}$, FC , p_a
Moss et al. (2006)	CPT	Critical Layer	$\mu_{ln,pga}$, $\sigma_{ln,pga}$, $\mathbf{M}$, σ_v , σ'_v , d , q_c , f_s , FC , p_a
Ulmer et al. (2024)	CPT	Profile-Based	$\mu_{ln,pga}$, $\sigma_{ln,pga}$, $\mathbf{M}$, z_{top} , z_{bot} , q_{c1Ncs} , I_c , σ_v , σ'_v , K_{sat} , p_a

Validation figures of the four verifiable liquefaction models are shown in Figures 4.14, 4.15, 4.16, and 4.17.

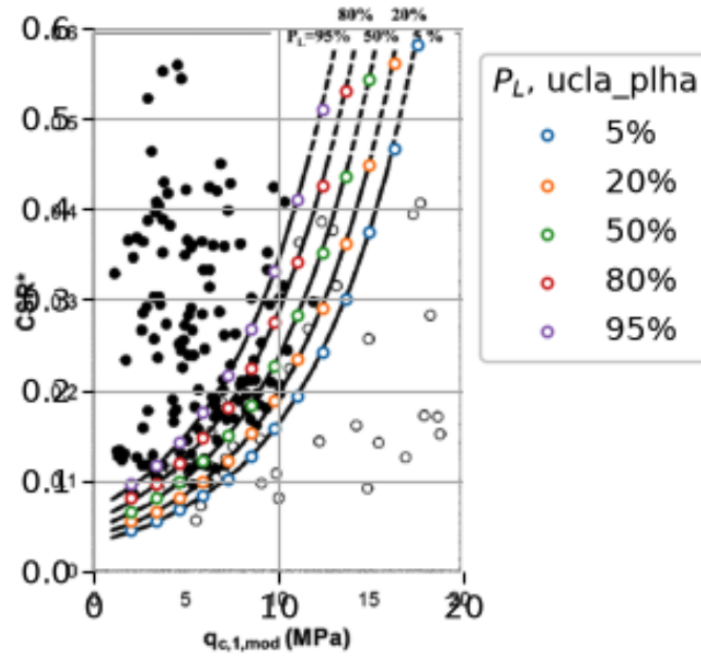


Fig. 6. Contours of 5, 20, 50, 80, and 95% probability of triggering of liquefaction as a function of duration-corrected equivalent uniform cyclic stress ratio (CSR^*) and “fines” adjusted CPT tip resistance ($q_{c,1,mod}$) for $M_w=7.5$, $\sigma'_v=1$ atm. Closed circles are liquefied and open circles are nonliquefied field case histories.

Figure 4.14: Verification of the Moss et al. CPT-based probabilistic liquefaction triggering model (Moss et al., 2006) as implemented in ucla_plha (open circles), overlaid on the published probability contours ($P_L = 5, 20, 50, 80$, and 95%) as a function of duration-corrected cyclic stress ratio (CSR^*) and fines-adjusted CPT tip resistance ($q_{c,1,mod}$) for $M_w = 7.5$ and $\sigma'_v = 1$ atm. Reproduces Figure 6 of Moss et al. (2006); closed and open circles in the background are liquefied and nonliquefied field case histories, respectively.

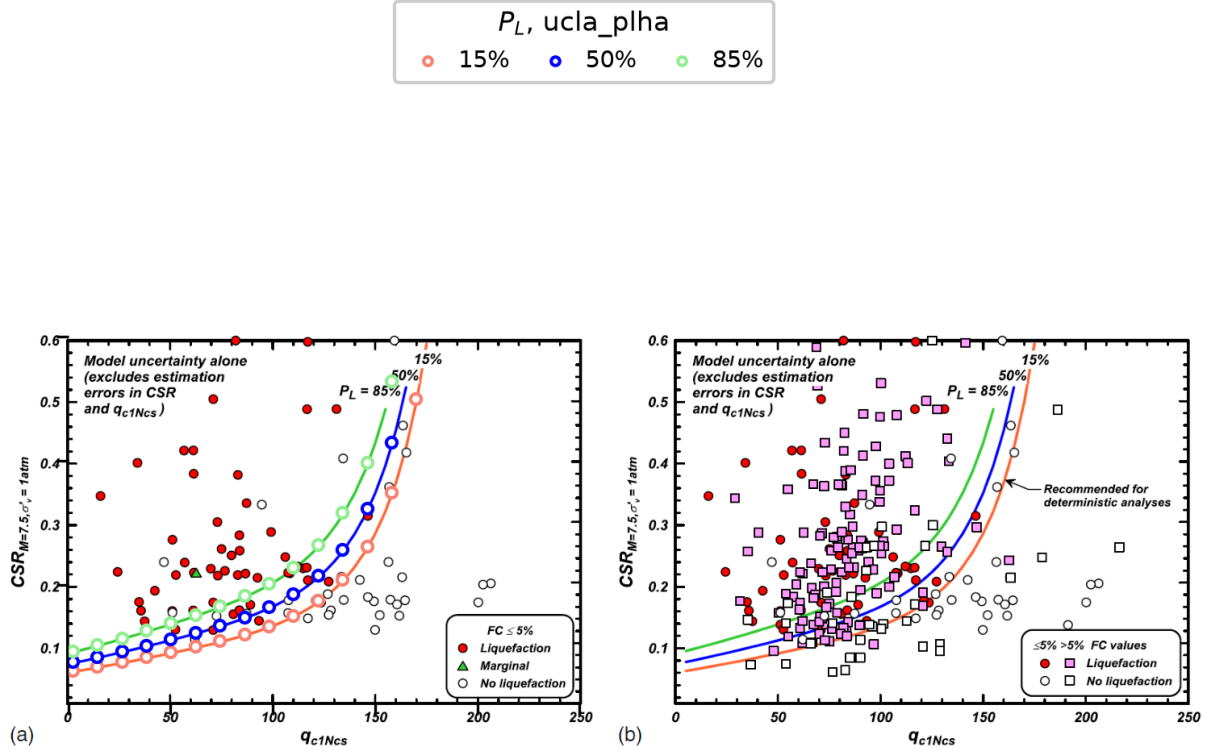


Fig. 11. Curves of $CRR_{M=7.5, \sigma'_v=1 \text{ atm}}$ versus q_{c1Ncs} for probabilities of liquefaction of 15, 50, and 85%: (a) clean sands; (b) all sands

Figure 4.15: Verification of the Boulanger and Idriss (2016) CPT-based probabilistic liquefaction triggering model (Boulanger and Idriss, 2016) as implemented in `ucla_plha` (open markers), overlaid on the published curves of CRR ($M_w = 7.5$, $\sigma'_v = 1 \text{ atm}$) versus q_{c1Ncs} for probabilities of liquefaction of 15, 50, and 85%: (a) clean sands and (b) all sands. Reproduces Figure 11 of Boulanger and Idriss (2016).

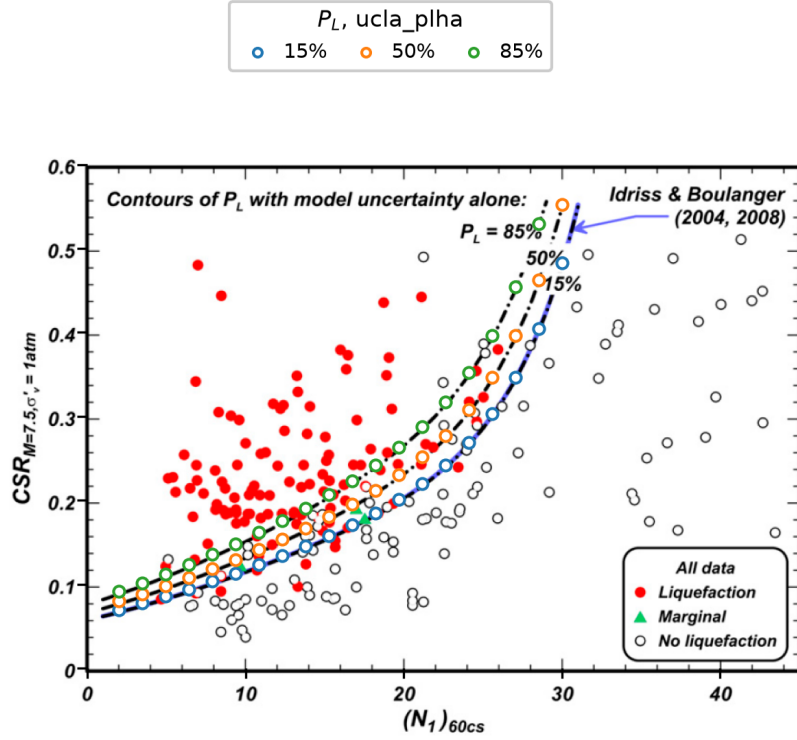


Fig. 6. Curves of $CRR_{M=7.5, \sigma'_v=1 \text{ atm}}$ versus $(N_1)_{60cs}$ for probabilities of liquefaction of 15, 50, and 85%

Figure 4.16: Verification of the Boulanger and Idriss (2012) SPT-based probabilistic liquefaction triggering model (Boulanger and Idriss, 2012) as implemented in ucla_plha (open circles), overlaid on the published curves of CRR ($M_w = 7.5$, $\sigma'_v = 1 \text{ atm}$) versus $(N_1)_{60cs}$ for probabilities of liquefaction of 15, 50, and 85%. Reproduces Figure 6 of Boulanger and Idriss (2012); background markers denote liquefied, marginal, and nonliquefied field case histories.

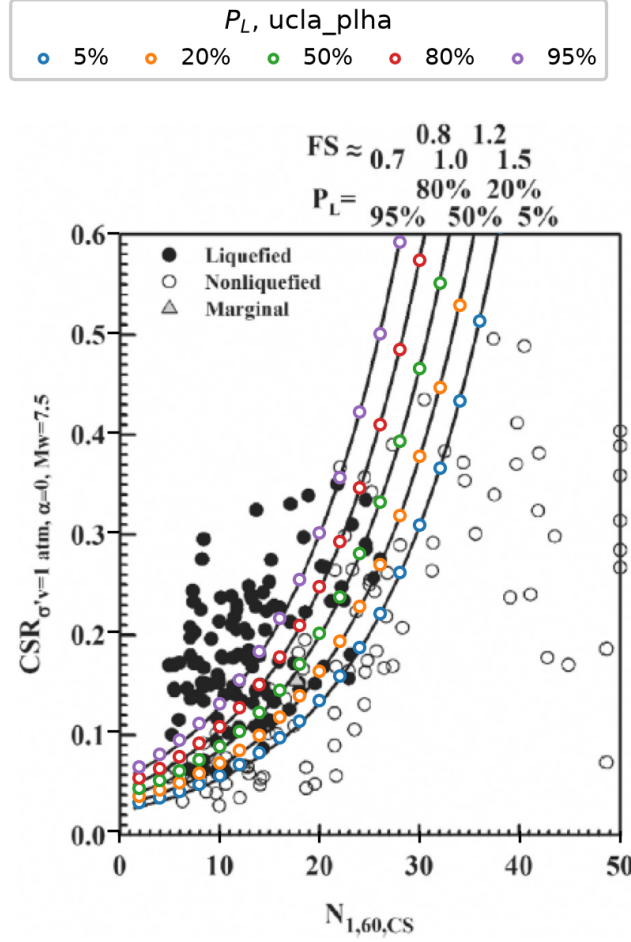


Fig. 1. New probabilistic seismic soil liquefaction triggering curves.

Figure 4.17: Verification of the Cetin et al. SPT-based probabilistic liquefaction triggering model (Cetin et al., 2004, 2018) as implemented in `ucla_plha` (open circles), overlaid on the published probability contours ($P_L = 5, 20, 50, 80,$ and 95%) as a function of CSR ($\sigma'_v = 1$ atm, $M_w = 7.5$) and $N_{1,60,CS}$. Reproduces Figure 1 of Cetin et al. (2004, 2018); background markers denote liquefied, nonliquefied, and marginal field case histories.

4.3.8 Output

Output customization is handled in the config file via an “output” field. Users can specify whether the code should return a PSHA hazard curve, a PLHA hazard curve, or both. When users request a PSHA hazard curve, they must provide an array of PGA values at which to evaluate the curve. Similarly, when users request a PLHA hazard curve, they

must provide an array of FS_L values. Users can also specify whether to return disaggregation results for the PSHA and/or the PLHA. When disaggregation is requested, users must also specify arrays of bin edges for magnitude, distance, and epsilon. Disaggregation bin edges must be specified separately for PSHA and PLHA. Finally, users can provide an optional output file name to which the output data are saved. Output is saved in JSON format, and a copy of the input data is stored in the output file. Regardless of whether the output is written to file, it is returned as a Python dictionary when the `ucla_plha` code is executed.

```
output_dict = ucla_plha.get_hazard('config1.json')
```

Listing 4: Output example

4.3.9 Hazard Curve and Disaggregation Calculations

The seismic hazard curve is computed with the following steps: (1) compute the mean and standard deviation of the natural log of PGA for a ground motion model and an event in the UCERF3 source model, (2) evaluate the complementary cumulative lognormal distribution function at user-specified PGA values, (3) multiply the complementary cumulative distribution by the rate of occurrence for the event, the weight for the source model, and the weight for the ground motion model, and (4) repeat steps (1) through (3) for all events and ground motion models and sum the resulting rate-multiplied complementary cumulative distributions. Disaggregation results are computed based on user-defined bins for magnitude, distance and epsilon. The marginal hazard curve for each bin is defined as the sum of the individual event hazard curves within that bin, and the disaggregation is computed by dividing each marginal hazard curve by the overall hazard curve. The PSHA code has been validated against OpenSHA (Field et al., 2003) and the validation is shown in Figures 4.18, 4.19, 4.20, and 4.21.

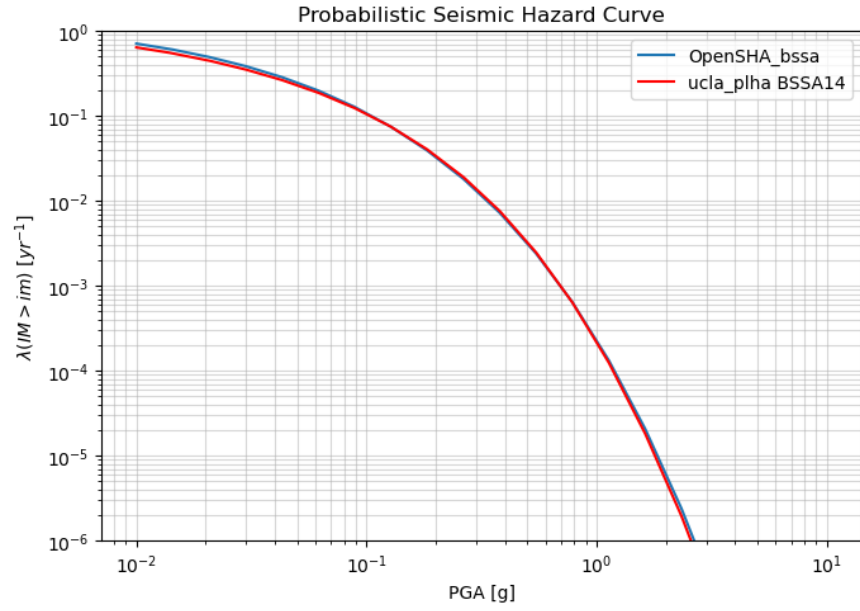


Figure 4.18: [Boore et al.](#) validation against OpenSHA

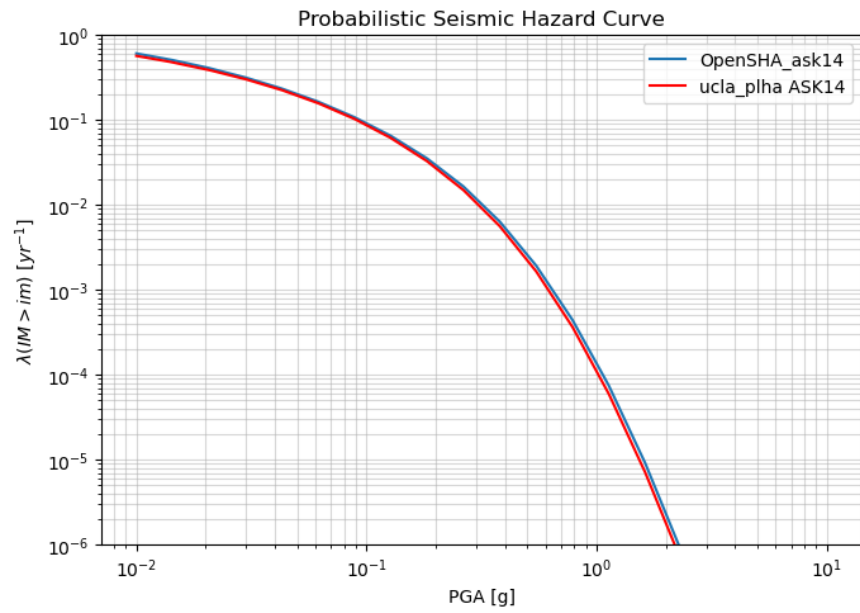


Figure 4.19: [Abrahamson et al.](#) validation against OpenSHA

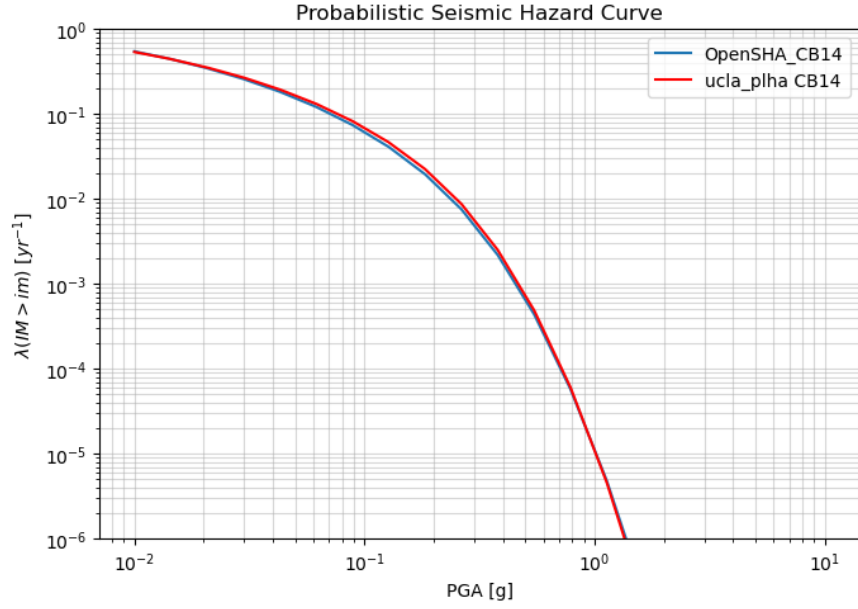


Figure 4.20: [Campbell and Bozorgnia](#) validation against OpenSHA

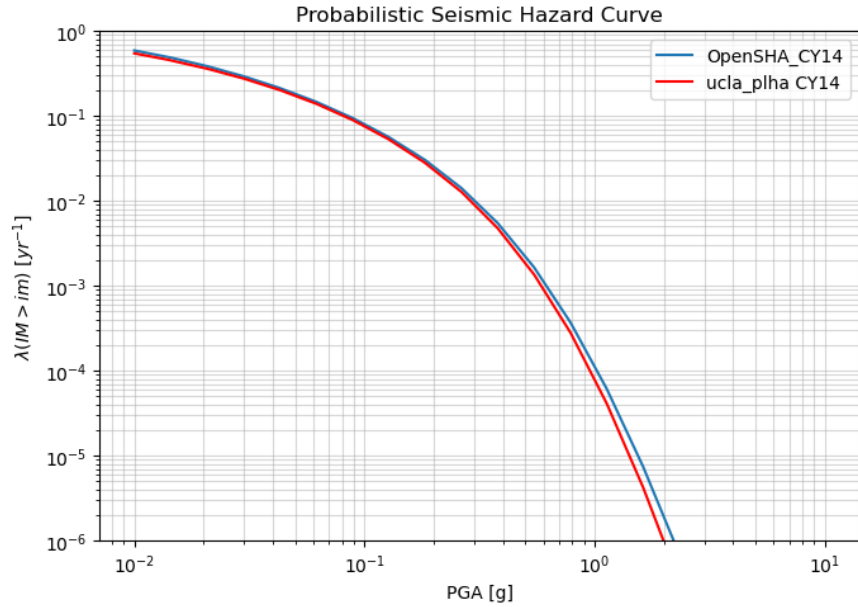


Figure 4.21: [Chiou and Youngs](#) validation against OpenSHA

The seismic hazard disaggregation has also been validated against OpenSHA ([Field et al., 2003](#)) and is shown in Figures 4.22 and 4.23. It should be noted that the disaggregation calculation was vectorized using `np.digitize`; however, due to the nature of the computation, disaggregation can add significant additional compute time.

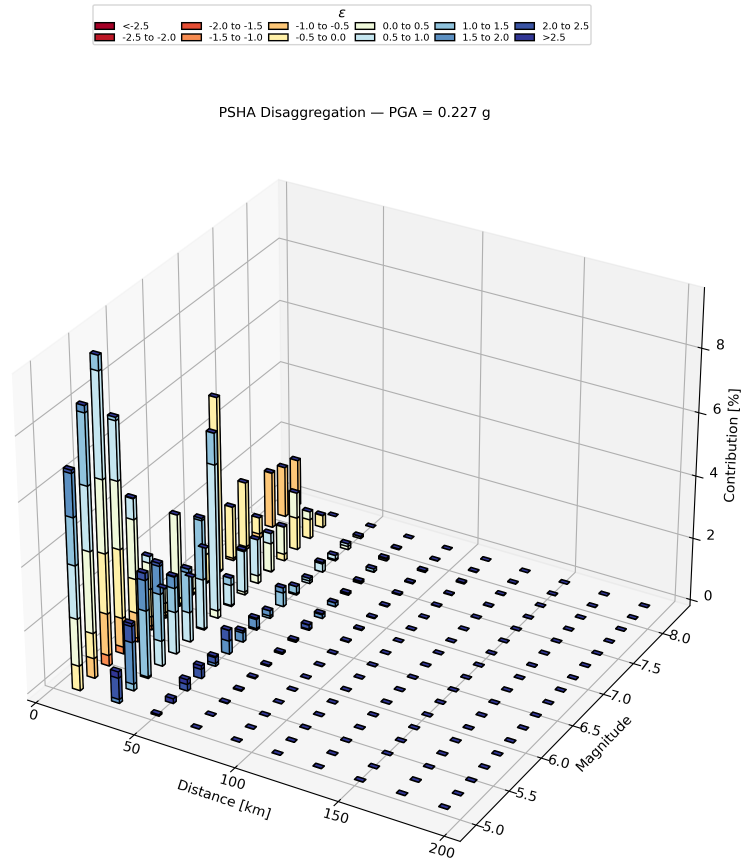


Figure 4.22: ucla_plha disaggregation result compared to OpenSHA result

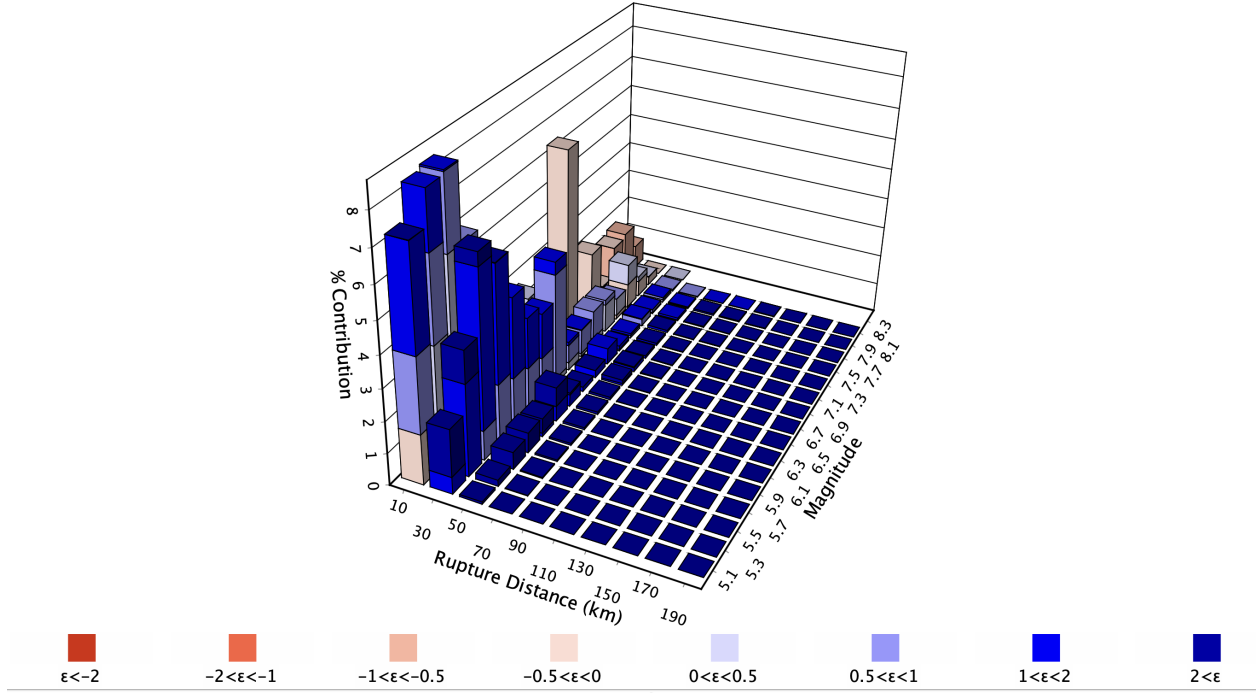


Figure 4.23: OpenSHA comparison for disaggregation

The liquefaction hazard curve is computed following the same steps as the seismic hazard curve, with the only differences being that (1) PGA is replaced by FS_L , (2) the cumulative lognormal distribution of FS_L is used instead of the complementary cumulative lognormal distribution since hazard represents the down-crossing rate (i.e., rate of non-exceedance) rather than the up-crossing rate (i.e., rate of exceedance), as is true for PGA , (3) the logic tree is expanded to include liquefaction models (all combinations of source, ground motion, and liquefaction models are used), and (4) the cumulative distribution function is multiplied by the weight assigned to the liquefaction model in addition to the weights for the source model and ground motion model. Liquefaction disaggregation is computed in the same manner as for seismic hazard.

4.4 NGL SMT 2024 Probabilistic Liquefaction Hazard Framework

The NGL SMT 2024 model (Ulmer et al., 2024) was briefly introduced in Chapter 2; its specific implementation within `ucla_plha` is described here. The implementation will be described in five steps: (1) evaluating the triggering limit state of a single layer for a single event, (2) converting the triggering distribution into a layer manifestation distribution, (3) combining all layers into a profile manifestation distribution, (4) scaling the profile distribution by the annual rate of the event to obtain an event hazard curve, and (5) summing over all events to obtain the liquefaction hazard curve. The conceptual framework is illustrated in Figure 4.24. Throughout the framework explanation, N_E is the number of earthquake events, N_L is the number of soil layers in the profile, and M is magnitude.

Step 1: Triggering of a Layer for a Single Event

For one layer and one event, the triggering limit state function, Z_T , is the natural log of the factor of safety against liquefaction triggering, FS_L ,

$$Z_T = \ln CRR - \ln CSR = \ln\left(\frac{CRR}{CSR}\right) = \ln FS_L \quad (4.32)$$

where CSR is the cyclic stress ratio and CRR is the cyclic resistance ratio. Both are treated as lognormally distributed random variables (Figure 4.24a), so $\ln CSR$ and $\ln CRR$ are normally distributed and Z_T is normally distributed with mean, μ_{Z_T} , and standard deviation, σ_{Z_T} , given by

$$\mu_{Z_T} = \mu_{\ln CRR} - \mu_{\ln CSR} \quad (4.33)$$

$$\sigma_{Z_T} = \sqrt{\sigma_{\ln CRR}^2 + \sigma_{\ln CSR}^2} \quad (4.34)$$

The mean of the natural log of CSR , $\mu_{\ln CSR}$, is

$$\mu_{\ln CSR} = \mu_{\ln PGA} + \ln \left(0.65 \frac{\sigma_v}{\sigma'_v} r_d \right) \quad (4.35)$$

where $\mu_{\ln PGA}$ is the mean of the natural log of peak ground acceleration from the ground motion model, and σ_v and σ'_v are the total and effective vertical stress at the center of the layer. The shear stress reduction factor, r_d , is evaluated at the mid-depth of the layer, $d = (z_{top} + z_{bot})/2$, using the relationship of [Lasley et al. \(2016\)](#),

$$r_d = (1 - \alpha) \exp \left(-\frac{d}{\beta} \right) + \alpha, \quad \alpha = \exp(-4.373 + 0.4491 \mathbf{M}), \quad \beta = -20.11 + 6.247 \mathbf{M} \quad (4.36)$$

The standard deviation of $\ln CSR$ is propagated from the ground motion model, therefore $\sigma_{\ln CSR} = \sigma_{\ln PGA}$.

The mean of the natural log of CRR , $\mu_{\ln CRR}$, is a function of relative density, D_r , the overburden correction factor, K_σ , the static shear stress correction factor, K_α , and the magnitude scaling factor, MSF ,

$$\mu_{\ln CRR} = -2.799 + 0.00092 \hat{D}_r + \ln K_\sigma + \ln K_\alpha + \ln MSF \quad (4.37)$$

where relative density is estimated from the overburden and fines-corrected cone tip resistance, q_{c1Ncs} ,

$$D_r = 47.8 q_{c1Ncs}^{0.264} - 106.3 \quad (4.38)$$

bounded to $0 \leq D_r \leq 160$, and implemented into Eq. 4.37 through the Box-Cox transform

$$\hat{D}_r = \frac{D_r^\lambda - 1}{\lambda}, \quad \lambda = 1.798 \quad (4.39)$$

The overburden correction factor is computed following [Carlton et al. \(2026\)](#),

$$K_\sigma = \left(\frac{\sigma'_v}{p_a} \right)^{-0.0015 D_r} \leq 1.2 \quad (4.40)$$

where p_a is atmospheric pressure in the same units as σ'_v . The static shear stress correction factor, K_α , is included in Eq. 4.37 for completeness; for the level-ground, free-field conditions analyzed in this dissertation, $K_\alpha = 1$. The magnitude scaling factor is computed from the equivalent number of uniform loading cycles, N_{eq} , using the relationship of [Lasley et al. \(2017\)](#),

$$N_{eq} = \exp(0.46305 - 0.4082 e^{\mu_{\ln PGA}} + 0.2332 \mathbf{M}), \quad MSF = \left(\frac{14}{N_{eq}} \right)^{0.2} \quad (4.41)$$

The standard deviation of the natural log of the cyclic resistance ratio is constant, $\sigma_{\ln CRR} = 0.44$.

The probability density function of Z_T (Figure 4.24b) carries uncertainty from both the ground motion model and the triggering model. Integrating it gives the cumulative distribution function (Figure 4.24c), which is the probability factor for triggering conditioned on susceptibility, $PF[T|S]$, defined by Eq. 4.42.

$$PF[T|S] = \Phi \left(\frac{\ln FS_L - \mu_{Z_T}}{\sigma_{Z_T}} \right) \quad (4.42)$$

The term “probability factor” is used rather than “probability” because layer thickness contributes to the probability of manifestation when layers are combined at the profile scale (Step 3), whereas the probability factor for an individual layer is independent of layer thickness. The cumulative distribution is evaluated at a discrete set of factor of safety values. Evaluating it at $Z_T = 0$ gives the probability factor for triggering at $FS_L = 1$, marked in Figure 4.24c, but the NGL SMT implementation retains the entire cumulative distribution rather than this single value, because the hazard calculation is defined over the full range of

FS_L .

The output of a probabilistic liquefaction model is often conceptualized as being a probability of liquefaction. A natural question is therefore whether the liquefaction hazard curve should be developed with probability of liquefaction on the x-axis instead of a limit state function. I argue here that hazard curves should not be developed for probability of liquefaction for three primary reasons, and clearly establish that developing hazard curves in terms of limit state functions is the superior approach. First, a limit state function is more physically meaningful when a point is far above or far below the triggering curve. In many cases, the probability of liquefaction is either 0 or 1 (for practical purposes) and is uninformative about how far away a point is from the triggering curve. On the other hand, a limit state function is a physically meaningful indicator of how far away a point is from a triggering curve, which is valuable when a triggering or manifestation model is convolved with a consequence model. Second, the y-axis of a liquefaction hazard curve is the annual down-crossing rate, and all uncertainty in the analysis should be represented on the y-axis. Representing a probability on the x-axis violates this basic principle of hazard curve development. By analogy, ground motion hazard curves use an intensity measure value on the x-axis. They could conceptually use the probability of exceedance of an intensity measure value instead, but that is not done because uncertainty in the ground motion is directly incorporated into the calculation of rate of exceedance. The limit state functions used in this dissertation are analogous to the value of an intensity measure in a PSHA, and are therefore the appropriate quantity to plot on the x-axis of the liquefaction hazard curve. Third, the distribution function of probability of liquefaction for a particular event is bimodal and does not conform to any well-behaved functional form. When a probabilistic liquefaction triggering analysis is performed using a single deterministic ground motion, as often obtained from a PSHA, the probability of liquefaction is scalar-valued. However, when the ground motion is a random variable, as is the case in the `ucla_plha` code, the probability of liquefaction is also a random variable. Ground motion models generally carry more uncertainty than liquefaction models, and often

contain significant probability density in regions far away from the triggering curve. As a result, the distribution function of probability of liquefaction is bimodal, with large probability density near 0 and 1, and comparatively small probability density in the middle of the distribution. The computational efficiency of the `ucla_plha` code relies upon lognormal distributions. The limit state functions are lognormally distributed, while the probability of liquefaction is not. For these three reasons, I do not compute liquefaction hazard curves in terms of probability of liquefaction.

Step 2: Manifestation of a Layer

The probability factor for surface manifestation of a single layer, $PF[M_L]$, combines the susceptibility term, $PF[S]$, the triggering term, $PF[T|S]$, from Eq. 4.42, the manifestation given triggering term, $PF[M_L|T]$, and the saturation term, K_{sat} ,

$$PF[M_L] = PF[S] PF[T|S] PF[M_L|T] K_{sat} \quad (4.43)$$

The susceptibility factor is a logistic function of the soil behavior type index, I_c ,

$$PF[S] = 1 - \frac{1}{1 + \exp[-14.8 (I_c/2.635 - 1)]} \quad (4.44)$$

which approaches one for sand-like soils (low I_c) and zero for clay-like soils (high I_c). The manifestation given triggering factor is a logistic function of the depth to the top of the layer, z_{top} , and I_c ,

$$PF[M_L|T] = \frac{1}{1 + \exp[-(7.613 - 0.338 z_{top} - 3.042 I_c)]} \quad (4.45)$$

The saturation term, K_{sat} , is a binary indicator equal to 1 for layers below the groundwater table and 0 for layers above it, which removes unsaturated layers from the product.

Multiplying the triggering cumulative distribution by $PF[S]$, $PF[M_L|T]$, and K_{sat} creates the layer manifestation limit state function, Z_{M_L} , whose cumulative distribution function

is the layer manifestation probability factor defined by Eq. 4.46.

$$F(Z_{M_L}) = PF[M_L] \quad (4.46)$$

Equation 4.46 considers uncertainty arising from susceptibility, triggering, layer manifestation, and ground motion. This operation preserves the shape of the triggering cumulative distribution but lowers its horizontal asymptote from 1 to $PF[S] PF[M_L|T] K_{sat}$, shown in Figure 4.24d for a saturated layer. The asymptote lies below 1 because there is some probability that the soil is not susceptible, and some probability that it will not manifest at the surface even if it triggers. As a result, Z_{M_L} is a mixed random variable with some probability mass at $Z_{M_L} = \infty$.

Step 3: Profile Manifestation

Steps 1 and 2 are repeated for every layer in the profile, resulting in a separate manifestation limit state function for each layer. Cumulative distribution functions for the layer manifestation limit state functions are plotted in Figure 4.24e. Each layer approaches its own asymptote at $PF[S] PF[M_L|T] K_{sat}$. The layer limit state functions are then combined into a profile manifestation limit state function, Z_{M_P} , whose cumulative distribution function is defined by Eq. 4.47. Note that the term inside the product is raised to an exponent equal to the layer thickness, $t_j = z_{bot,j} - z_{top,j}$, divided by a characteristic thickness, $t_c = 2.0$ m. This operation is necessary to make the probability of profile manifestation insensitive to layer discretization, and can be conceptualized as accounting for within-layer spatial correlation.

$$PF[M_P] = 1 - \prod_{j=1}^{N_L} (1 - PF[S_j] PF[T_j|S_j] PF[M_{L_j}|T_j] K_{sat,j})^{t_j/t_c} \quad (4.47)$$

Here the subscript j denotes the j th layer and the three factors are Eqs. 4.42, 4.44, and 4.45, together with K_{sat} , evaluated for that layer. Each layer contributes a scaled normal

cumulative distribution in Z_{M_L} , equivalent to a lognormal distribution of the layer factor of safety, but the profile variable Z_{M_P} is neither normal nor lognormal because it is a product over multiple layers. Its cumulative distribution (Figure 4.24f) approaches an asymptote below 1 for the same reason as the individual layers. It is the profile manifestation probability, defined by Eq. 4.48.

$$F(Z_{M_P}) = PF[M_P] \quad (4.48)$$

Equation 4.48 considers uncertainty in susceptibility, triggering, manifestation, and ground motion.

Equation 4.47 has no analytical solution, and does not follow a well-defined distribution function. Rather, it is “lumpy” because each layer contributes to profile manifestation, but the mean of the layer limit state function is different for each layer. As a result, the profile manifestation limit state function is evaluated numerically following the steps below:

1. The user inputs a list of factor of safety values at which to evaluate the profile manifestation limit state function. These factor of safety values are also the values at which Z_T and Z_{M_L} are evaluated because the CDF for Z_{M_L} is a simple scalar multiple of the CDF for Z_T . Stated differently, triggering, layer manifestation, and profile manifestation are all evaluated at the same discrete set of factor of safety values, indicated by the individual symbols in Figure 4.24e, but the probabilities of triggering, layer manifestation, and profile manifestation associated with those factors of safety are different.
2. The CDF of Z_T (i.e., $PF[T|S]$) is computed for each layer at the specified values of FS_L using Eq. 4.42.
3. The CDF of Z_{M_L} (i.e., $PF[M_L]$) is computed using Eq. 4.43 for each discrete value of $PF[T|S]$ computed in step 2.
4. The CDF of Z_{M_P} (i.e., $PF[M_P]$) is computed using Eq. 4.47 for each discrete value of $PF[M_L]$ computed in step 3.

Epsilon values for profile manifestation, ε_M , are reported using Eq. 4.49.

$$\varepsilon_M = \Phi^{-1}(F(Z_{M_P})) \quad (4.49)$$

Epsilon is conventionally the number of standard deviations from the mean of a normally distributed variable. Here the distribution of profile manifestation is not normal and its functional form is not known in closed form: the cumulative distribution is sampled at specified factor of safety values rather than evaluated analytically, so cumulative probability cannot be computed from a mean and a standard deviation. Equation 4.49 is therefore a modeling decision that allows the reported epsilons to be interpreted as corresponding to specific probabilities of exceedance (for example, $\varepsilon_M = +1$ corresponds to a cumulative probability of 0.84), but they should not be interpreted as distances from the mean in standard deviation units. These epsilons also correspond to manifestation rather than triggering, and therefore embed the susceptibility, manifestation given triggering, and saturation terms. Because the manifestation cumulative distribution does not reach 1 (Figure 4.24f), and the probability mass at $Z_{M_P} = \infty$ is never sampled, disaggregation computed from these values is biased toward low epsilon.

Step 4: Event Hazard Curve

The profile manifestation cumulative distribution for event i is multiplied by the annual rate of occurrence of that event, λ_{E_i} , to give the event hazard curve, $\lambda_{M_{P_i}}$, defined by Eq. 4.50 and shown in Figure 4.24g.

$$\lambda_{M_{P_i}} = \lambda_{E_i} F(Z_{M_{P_i}}) \quad (4.50)$$

Scaling by a constant rate preserves the shape of the profile cumulative distribution, so Figure 4.24g reproduces Figure 4.24f with the vertical axis rescaled from a probability to an annual rate, its plateau now at λ_{E_i} times the asymptote of $F(Z_{M_P})$.

Step 5: Liquefaction Hazard Curve

Summing the event hazard curves over all N_E events in the seismic source model gives the liquefaction hazard curve, λ_{MP} (Figure 4.24h), which is the annual rate at which profile manifestation occurs with Z_{MP} less than a given value, defined by Eq. 4.51.

$$\lambda_{MP} = \sum_{i=1}^{N_E} \lambda_{E_i} F(Z_{MP_i}) \quad (4.51)$$

Figure 4.24h shows both the individual event contributions and the overall hazard obtained by their weighted sum.

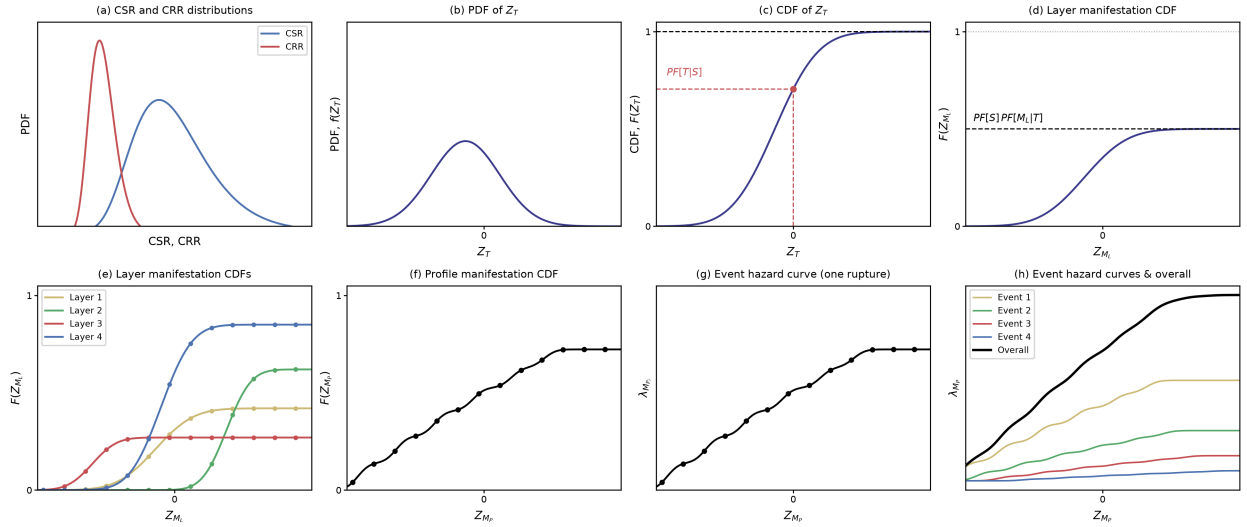


Figure 4.24: Conceptual NGL SMT 2024 PLHA framework as implemented in `ucla_plha` (Ulmer et al., 2024), following the five steps described in the text: (a) lognormal *CSR* and *CRR* distributions for one layer and one event; (b) PDF of the triggering limit state function $Z_T = \ln FS_L$; (c) CDF of Z_T ; (d) layer manifestation CDF, $F(Z_{ML}) = PF[M_L]$; (e) manifestation CDFs for the four layers of an example profile; (f) profile manifestation CDF; (g) event hazard curve λ_{MP_i} for a single event; (h) hazard curves for four individual events and the overall liquefaction hazard curve.

4.5 Example Calculations

The `ucla_plha` code was applied to an example site at Moss Landing in Monterey County, California. Moss Landing is a fishing and harbor town located in the Monterey Bay region, approximately 144 km south of San Francisco (Greene et al., 1991). The Moss Landing sandspit is considered a canonical geotechnical case study due to its many documented liquefaction observations. Moss Landing stratigraphy is heavily influenced by the Salinas River channel that flows through the site. Geotechnical investigations identified that the sandspit consists of thick layers of Holocene aged sand, with clay and sandy gravel lenses. Standard Penetration Test (SPT) blow counts and cone penetration tip resistances are low in many of the sand layers, indicating high liquefaction potential.

During the 1989 $M = 6.9$ Loma Prieta earthquake, several locations at Moss Landing and in the greater Monterey Bay area experienced severe liquefaction damage (Boulanger et al., 1997). Liquefaction-induced deformations were observed along the nearly 300 meter sandspit on the unconsolidated sediment, specifically at the Moss Landing Marine Laboratory. Moss Landing had also previously experienced extensive liquefaction damage during the earlier 1906 San Francisco earthquake (Boulanger et al., 1995). In the following sections, an individual CPT profile is evaluated at Moss Landing to illustrate key features of the PLHA, including the seismic and liquefaction hazard curves, and their associated disaggregations. In Section 4.5.2, the calculation is repeated for all available CPTs at Moss Landing.

4.5.1 Cone Penetration Test

The CPT selected to illustrate the PLHA is test UC-11, which is located within the Moss Landing Woodward Marine Site. This CPT profile was downloaded from the Next Generation Liquefaction (NGL) database (Ulmer et al., 2023). The Boulanger and DeJong (2018) inverse filtering procedure was applied to correct for thin layer effects. The Hudson et al. (2023) agglomerative clustering algorithm was then applied to identify stratigraphic

layers from inverse-filtered cone penetration data. In this case, a $PGA = 0.23g$ and $\sigma_{ln,PGA} = 0.47$ were assigned, which Pretell et al. (2024) interpolated at the site from measured ground motions and analysis of spatial correlation of residuals. Uncertainty in the ground motion is due primarily to kriging interpolation.

Figure 4.25 shows the measured, inverse filtered, and layered cone penetration test data, along with groundwater table depths and critical layers identified by Moss et al. (2006) and by Boulanger and Idriss (2016). Different critical layers were selected at this site, which is due to different interpretations of groundwater. Moss et al. (2006) assigned a groundwater depth of 2.5m, which is not the groundwater depth encountered at the time of the site investigation due to anticipated tidal influence at the time of the earthquake. Boulanger and Idriss (2016) used a groundwater depth of 1.0 m, and identified a shallower critical layer as a result. To demonstrate the NGL SMT model, profiles of computed probabilities and probability factors are presented in Figure 4.26 for the Loma Prieta earthquake. The plots show PF_S , which is the probability factor for susceptibility, $PF_{T|S}$, which is the probability factor for triggering conditioned on susceptibility, $PF_{M|T}$, which is the probability factor for manifestation conditioned on triggering, K_{sat} which is the saturation factor, and PF_M , which is the probability factor for manifestation. Fig. 4.26 shows results for a 1.0m deep groundwater table, though the calculations were also performed for a 2.5 m deep groundwater table. The probability of susceptibility is high at depths less than 5 m, and is near 50% between 5 and 10 m depth. The probability of triggering and manifestation conditioned on triggering are both high between 1 and 3.5 m depth. The probability of manifestation decreases with depth because deeper liquefied layers are less likely to produce surface manifestation. In this case, $P[M_P] = 0.60$ when the groundwater table is at 1.0m depth, and $P[M_P] = 0.26$ when the groundwater table is at 2.5m depth using a $t_c = 2m$. This case highlights the strong influence of tidally induced groundwater fluctuations on liquefaction hazard in coastal areas.

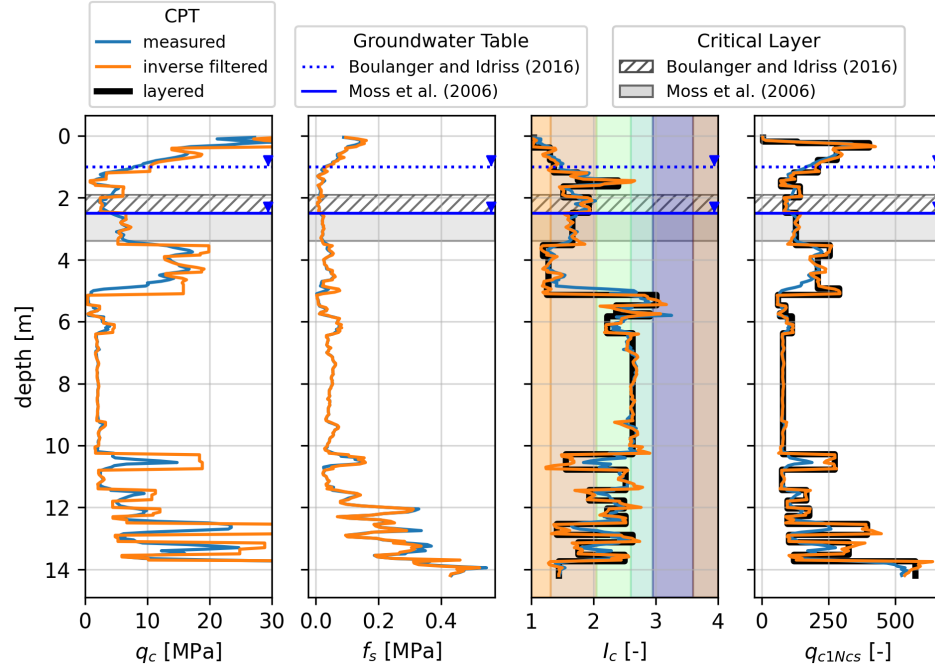


Figure 4.25: CPT UC-11 properties and inverse layering using NGL SMT

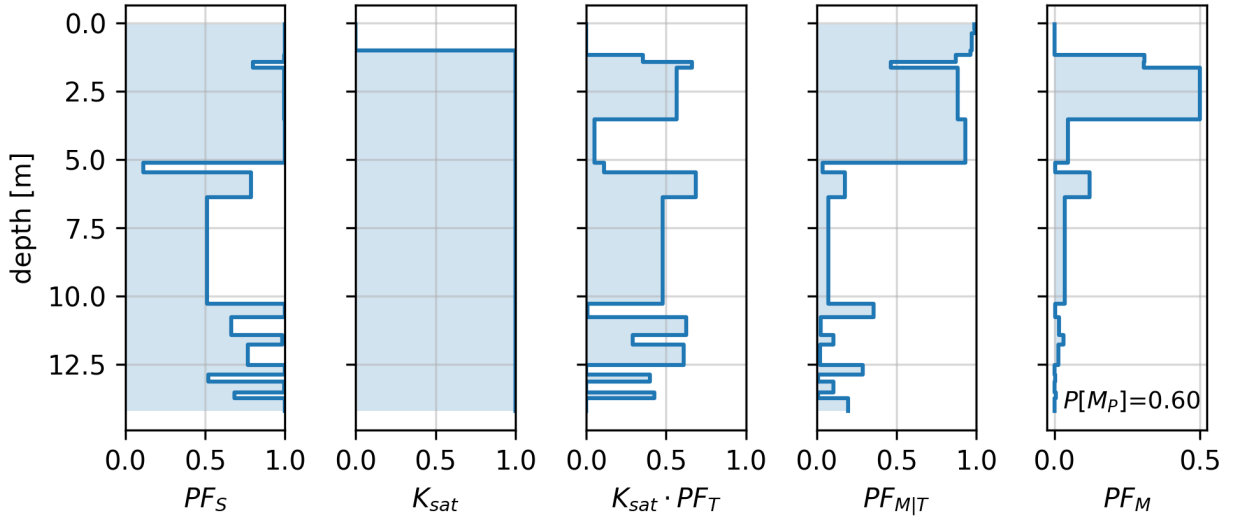


Figure 4.26: NGL SMT model (Ulmer et al., 2024) predictions for UC-11 with $a_{max} = 0.23g$ and $M=6.9$.

Having demonstrated the liquefaction evaluation procedure for a single earthquake, the PSHA and PLHA results are calculated using the `ucla_plha` code. Figure 4.27 shows seismic hazard curves for the four GMMs along with the average hazard curve using a logic tree with a weight of 0.25 assigned to each GMM. The seismic hazard used a maximum distance of 200 km, and a minimum magnitude of 5.0. Values of PGA for the four GMMs ranged from about 0.23 to 0.32g for a return period of 100 years, and from 0.5 to nearly 0.9g for a return period of 2475 years. The four seismic hazard curves are reasonably similar, with differences increasing as PGA increases. These differences represent epistemic uncertainty, which is larger where measurements are scarce.

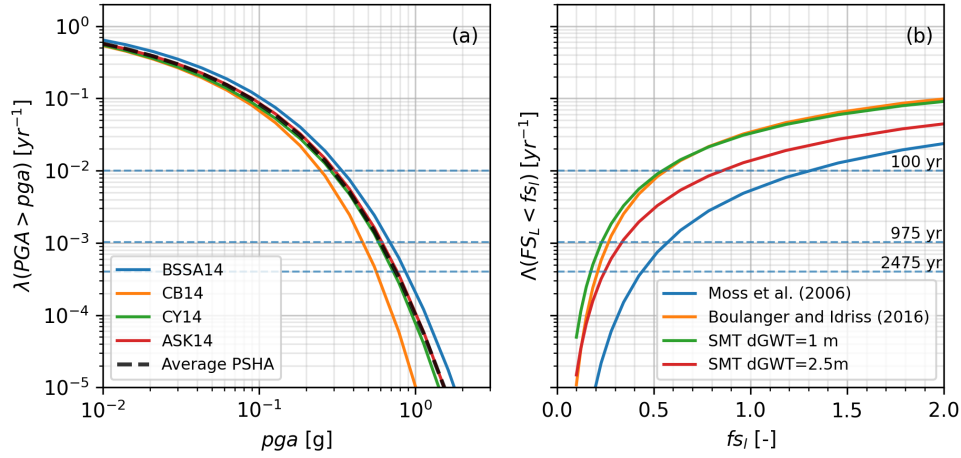


Figure 4.27: a) Seismic hazard curves for four ground motion models and average hazard curve b) Liquefaction hazard curves for three liquefaction models.

Also shown in Fig. 4.27 are the liquefaction hazard curves, each computed using a weighted average of the four GMMs, with a weight of 0.25 assigned to each GMM. The value of FS_L ranges from about 0.55 to 1.3 for a return period of 100 years, and from about 0.18 to 0.43 for a return period of 2475 years. Return periods for $fs_l = 1.0$ are 188, 29, 30, and 72 years for Moss et al. (2006), Boulanger and Idriss (2016), and the Ulmer et al. (2024) model with 1.0m and 2.5m groundwater table depths, respectively. The liquefaction hazard curves exhibit more epistemic uncertainty (i.e., they are further apart) than the seismic hazard curves, due primarily to differences in groundwater table depth. Although not shown in

Figure 4.27, the Moss et al. (2006) and Boulanger and Idriss (2016) hazard curves agree well when the same groundwater table and critical layer are selected. Groundwater elevation and critical layer selection are therefore important sources of epistemic uncertainty.

Figure 4.28 presents disaggregation of the PSHA and PLHA at a 2475 year return period for the three models, where $d_{GWT} = 1.0\text{ m}$ was used for the NGL SMT model; the $d_{GWT} = 2.5\text{ m}$ disaggregation was similar. Disaggregations at a return period of 2475 years were interpolated from the PGA or FS_L values at which the hazard was computed.

Beginning with the seismic hazard disaggregation, background seismicity is a significant contributor to the hazard, as evidenced by the large contribution from magnitudes less than about 6.5 at distances shorter than 20 km, and the modal magnitude is 5.5. The PSHA disaggregation agrees well with OpenSHA, as shown in the validation folder of the GitHub `ucla_plha` repository. Seismic hazard from sources further than 50 km is negligible. Seismic hazard is dominated by higher epsilons in the range from 1.0 to > 2.5 , which is a common attribute of 2475 year disaggregations.

Two key points emerge from the liquefaction hazard disaggregation plots. First, the PLHA disaggregation is dominated by negative epsilons rather than positive epsilons, which is the opposite trend compared to the PSHA disaggregation. This is because higher than median ground motions (i.e., positive epsilon) are associated with lower than median factors of safety (i.e., negative epsilon), with all other factors equal. Second, the modal magnitude is 7.1 for all three PLHA disaggregations, which is much higher than the PSHA modal magnitude of 5.5. This disaggregation shift is caused by the magnitude scaling factor applied in the liquefaction hazard analysis (called a duration weighting factor by Moss et al. (2006)). For a given shaking intensity, liquefaction resistance decreases as magnitude increases due to increasing duration, which increases the contribution of large magnitude events to the liquefaction hazard.

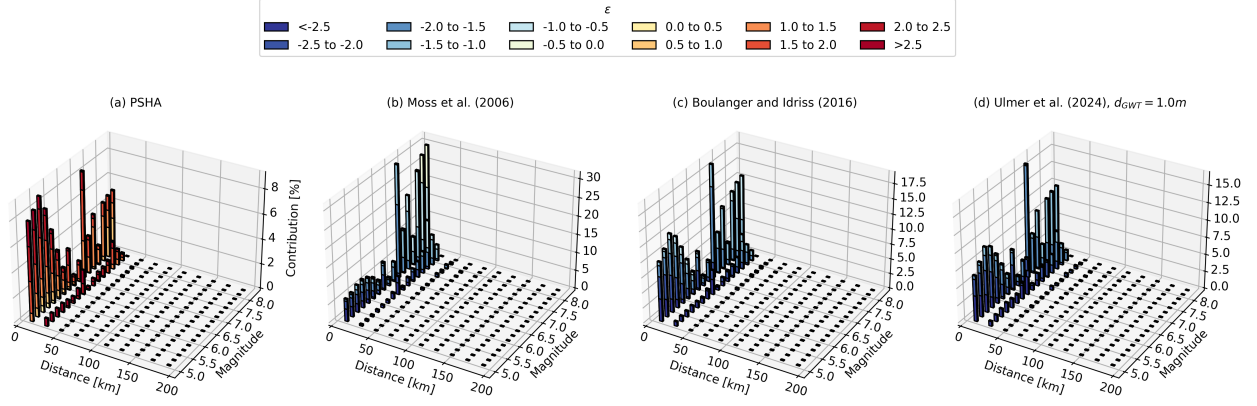


Figure 4.28: Seismic and liquefaction hazard disaggregation for 2475 year return period.

The traditional approach used in liquefaction evaluation is to select a design-level ground motion and representative magnitude corresponding to a predefined return period (often 2475 years), and subsequently perform a deterministic liquefaction evaluation. The PSHA modal magnitude is often selected for this purpose. This approach neglects the fact that many magnitudes contribute to liquefaction hazard, and that the PLHA disaggregation is different from the PSHA disaggregation.

Deterministic liquefaction models are often associated with a 15th percentile CRR value to approximately account for uncertainty in the liquefaction evaluation. However, the return period of the resulting FS_L value is generally not quantified; therefore, its level of conservatism is unknown. To evaluate potential biases in the traditional approach, FS_L is computed using the traditional method, and the corresponding return period is then interpolated. The calculation is repeated for a range of different magnitudes. Table 4.5 presents the FS_L and return period values. Three observations are made here, and subsequently discussed in more detail. First, the return periods are not equal to 2475 years, but rather range from 1255 to 72288 years and increase as M increases. Second, the Moss et al. (2006) model has a significant range of return periods, from 2674 to 72288 years, while the other models have a smaller range. Third, the NGL SMT model has return periods smaller than 2475 years for $M \leq 5.5$, while the other models have return periods larger than 2475 years.

The return periods for the computed FS_L values are not equal to 2475 years because un-

Table 4.5: Factors of safety for traditional liquefaction evaluation method and associated return periods, T . $PGA = 0.75g$, corresponding to PSHA 2475 year return period. 15th percentile CRR values used in liquefaction assessment.

M	MEA06		BI16		UEA24			
	$d_{GWT} = 2.5m$		$d_{GWT} = 1.0m$		$d_{GWT} = 1.0m$		$d_{GWT} = 2.5m$	
	FS_L	T [yr]	FS_L	T [yr]	FS_L	T [yr]	FS_L	T [yr]
5.0	0.431	2674	0.209	2558	0.198	1614	0.309	1255
5.5	0.424	2822	0.200	3070	0.183	2088	0.279	1665
6.0	0.369	5073	0.192	3608	0.172	2627	0.259	2126
6.5	0.324	8781	0.185	4168	0.161	3310	0.244	2562
7.0	0.288	14871	0.179	4953	0.152	3983	0.230	3071
7.5	0.258	25743	0.173	5777	0.145	4820	0.218	3705
8.0	0.232	42249	0.168	6627	0.139	5710	0.208	4384
8.5	0.211	72288	0.164	7494	0.133	6648	0.198	5097

certainty in the liquefaction evaluation contributes to liquefaction hazard, and is imperfectly captured by the use of a 15th percentile value in the deterministic liquefaction evaluation. The reason why this matters is related to why a particular return period was selected in the first place. The 2475 year return period is often used for design-level ground motions because such motions are associated with an acceptable probability of exceedance over the design life of the structure (approximately 2% in 50 years). Using the same return period for liquefaction evaluation therefore makes sense. The return periods in Table 4.5 indicate that, in general, a deterministic liquefaction evaluation tends to be overly conservative with respect to the target return period.

The shift in disaggregation results in Fig. 4.28 can be explained by the magnitude sensitivity of the liquefaction model. Models with stronger magnitude dependence will have a larger shift, while a model with no magnitude dependence will have no shift at all. This concept can be clarified by evaluating fragility functions representing the probability of triggering $P[T]$ for Moss et al. (2006) and Boulanger and Idriss (2016) or probability of profile manifestation $P[M_P]$ for Ulmer et al. (2024) conditional on peak surface acceleration, as illustrated in Figure 4.29. The Moss et al. (2006) fragility functions exhibit the most

magnitude dependence, as evidenced by the fragility functions being more separated for the different magnitudes. As a result, the disaggregation shift is largest for the Moss et al. (2006) model.

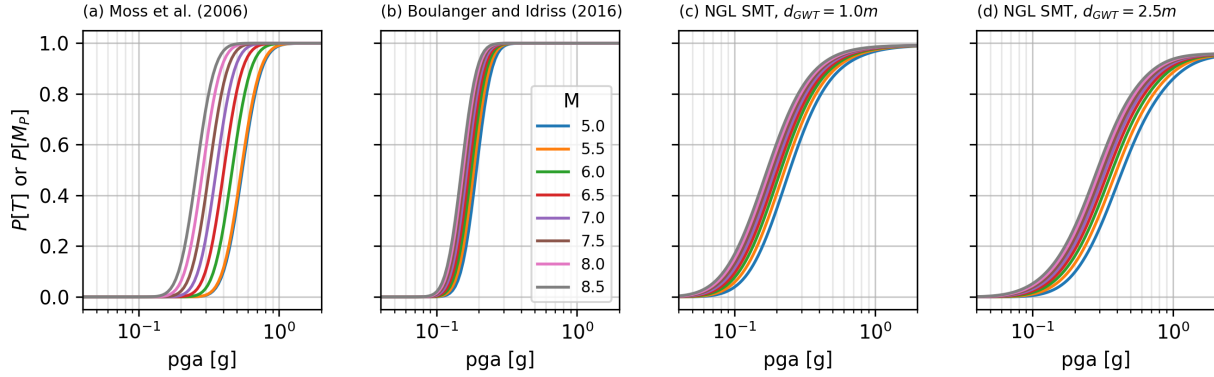


Figure 4.29: Liquefaction fragility functions for (a) Moss et al. (2006), (b) Boulanger and Idriss (2016), and Ulmer et al. (2024) with (c) $d_{GWT} = 1.0m$ and (d) $d_{GWT} = 2.5m$

Finally, the NGL SMT model is the only one for which any of the return periods are less than 2475 years, indicating it is the only model for which a deterministic liquefaction evaluation would not be conservative for this particular site and soil profile, provided a small enough magnitude is used. Liquefaction hazard has contributions from ground motion uncertainty, and from liquefaction evaluation uncertainty. The NGL SMT fragility functions are flatter than those of the other two, indicating more uncertainty. As a result, the 15th percentile liquefaction resistance may not be conservative when small magnitudes are used.

4.5.2 Example for Multiple Sites at Moss Landing

The hazard example in Section 4.5.1 is for a single location. Because of the abundance of cone penetration tests (CPTs) in the region, liquefaction hazard analysis was performed at more than 20 CPT locations around Moss Landing. This multi-site analysis used a weighted average of the four ground motion models, with the NGL SMT model as the liquefaction triggering model. The CPT data were obtained from the Next Generation Liquefaction (NGL) database (Ulmer et al., 2023).

The probabilistic liquefaction hazard code was run for these CPTs using the NGL SMT model, accessing the location and CPT data through the database’s application programming interface (API) from its copy on DesignSafe (Rathje et al., 2017). For each location, the annual rate of non-exceedance was calculated for a liquefaction factor of safety (FS_L) of 1. These rates, together with their corresponding return periods, were plotted spatially as a heat map created with the *Folium* package (Story et al., 2022). This map is the first of the two panels in Figure 4.30.

The second panel indicates whether surface manifestation was observed during the Loma Prieta earthquake, drawing on the field-reconnaissance records for each liquefaction case history in the NGL database (Zimmaro et al., 2019). Each location is labeled *Liquefaction Observed* or *No Liquefaction Observed* and plotted accordingly. Spatially, the two panels correspond reasonably well: sites with no surface evidence coincide with the longer return periods, whereas the short-return-period sites fall among locations where liquefaction was observed. The agreement is not exact, however, and some sites depart from this pattern, as Figure 4.30 shows. The most severe case has a return period of 29 years for $FS_L = 1$.

This setting also makes Moss Landing a natural case study for sea level rise: as a low-lying, tidally influenced coastal site with a shallow, hydraulically connected water table, it is precisely where rising groundwater would submerge more of the soil profile and intensify the hazard. In Chapter 6, the sensitivity of these return periods to water table depths is examined.

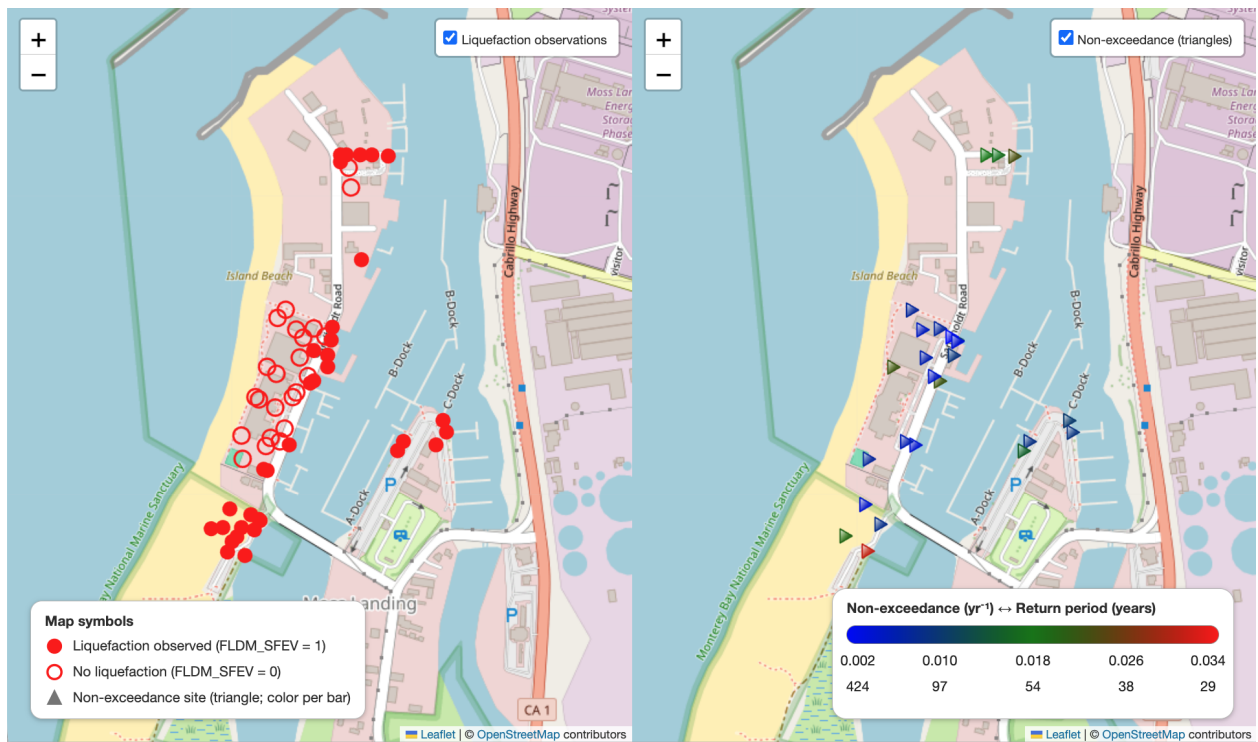


Figure 4.30: Moss Landing CPT hazard analysis and surface evidence

CHAPTER 5

Incorporating Groundwater Simulations in Liquefaction Analysis

Groundwater elevation is an influential parameter in liquefaction hazard analysis; it contributes to vertical effective stress, and therefore the overall strength of the soil (NASEM, 2021). As shown through the example in Chapter 4, even a small change in the water table can alter the liquefaction hazard and shift the selection of the *critical layer*. It is also one of the most poorly constrained parameters. In practice, groundwater levels are often measured at the time of a site investigation and then treated as a static value. This assumption often does not hold in coastal areas, where the water table fluctuates in response to tides, waves, and estuarine and back-bay influences.

This chapter describes how two-dimensional groundwater simulations of sea level rise and tidal forcing were propagated into inputs for the broader PLHA modeling (Chapter 6). The groundwater simulations were completed by Margit Maple, a PhD candidate, and Dr. Timu Gallien of the Coastal Flood Lab at the University of California, Los Angeles, using PFLOTRAN (Hammond et al., 2014) and are described in Section 5.1. The figures and model details were all provided by Margit Maple and will also be available in her thesis. Section 5.2 details how the groundwater outputs are distilled and used in the PLHA workflow.

It should also be noted that the groundwater model is in the preliminary stages, and currently still in development. Specifically, for locations with especially low permeability, the model is currently experiencing instabilities. The model will serve as a proof of concept of the workflow, but the results will be refined.

5.1 Groundwater Model

I include only a brief description of the model here, sufficient to interpret the outputs used in the hazard analysis; readers are referred to Margit Maple’s thesis for its full extent and intricacies. The model is intended to serve as a screening tool that identifies locations where the combination of groundwater variability, topography, and sea level rise poses an elevated liquefaction hazard. The site specific model inputs are the elevations and tidal-gauge forcing, whereas the hydraulic conductivity and stratigraphy are held constant across sites. The pore pressure outputs used in this dissertation are extracted from two-dimensional PFLOTRAN models. The remainder of this section summarizes the groundwater modeling approach, model setup, forcings and boundary conditions, and the outputs carried into the PLHA.

5.1.1 Previous Groundwater Modeling Work and Motivation for Current Groundwater Model

Measurements used for groundwater analysis and subsequently liquefaction analysis typically consist of discrete observations from borings or monitoring wells. Resolving groundwater levels spatially and temporally across a broad region has therefore been deemed difficult and uncertain ([Chung and Rogers, 2013](#); [Bosslerelle et al., 2022](#)). Groundwater is also commonly treated as a static value, which is a particularly poor assumption in dynamic coastal aquifers ([Hoover et al., 2017](#); [Habel et al., 2017](#)).

Numerical modeling can help resolve some of these physical processes, moving beyond interpolation of isolated point measurements ([Habel et al., 2019](#); [Maple, 2024](#)). Several studies have applied numerical models to study the effects of SLR on groundwater ([Befus et al., 2020](#); [Habel et al., 2017](#)). The present model is based on the approach of [Befus et al. \(2020\)](#) and will be summarized here. [Befus et al. \(2020\)](#) simulated how groundwater changes with SLR along the California coast, under an assumption of uniform hydraulic

conductivity and aquifer thickness. Models that incorporate SLR ([Befus et al., 2020](#); [Rotzoll and Fletcher, 2013](#)) usually assume the water table to be steady state, referenced either to mean sea level (MSL) or mean higher high water (MHHW). MSL and MHHW are tidal datums defined by averaging water levels across a 19-year tidal epoch, which smooths out shorter term variability ([NOAA, 2001](#)).

Those previous studies share a simplifying assumption: the water table is taken as steady state, referenced to a tidal datum such as MSL or MHHW. Steady-state, datum-referenced approaches are valuable for long-term adaptation planning, but assessing flooding and liquefaction risk requires characterizing present and future groundwater extremes and their variability ([Chung and Rogers, 2013](#); [Maple, 2024](#)). Current California SLR guidance, for instance, recommends evaluating coastal hazards under 100-year storm conditions but does not address how groundwater responds to such events ([OPC, 2024](#); [Maple, 2024](#)). The groundwater modeling summarized here is therefore aimed at capturing typical groundwater conditions, their variability and the transient increases driven by ocean and estuary oscillations, simulated in two-dimensional coastal cross-sections across a range of SLR scenarios, so that liquefaction hazard can be evaluated against groundwater extremes rather than a single reference level.

5.1.2 Regional Modeling Approach

The groundwater model is built from a collection of two-dimensional transects oriented perpendicular to the shoreline, at intervals of 100 m alongshore. These transects are positioned at the Coastal Data Information Program (CDIP) Monitoring and Prediction (MOP) locations ([O'Reilly et al., 2016](#)). Tying the transects to the MOP locations standardizes their placement and ensures sufficient wave information at every profile. Each of the MOP transects runs inland through the low elevation coastal zone (LECZ), beginning at the shoreline and extending to the 10 m MSL elevation contour, or to 2 km inland, whichever is reached first. Transects that fail to reach at least 200 m inland before crossing the 10 m contour

are excluded. The two-dimensional model domains are built from high-resolution digital elevation models that capture the beach face, beach slope, backshore topography, and bay or estuary channel depths. Two transects are carried throughout this chapter as contrasting examples: L0711 at Santa Monica, an open-coast, cliff-backed site, and MO899 at Moss Landing, a low lying site backed by estuaries. Their setups are shown in Figures 5.1 and 5.2.

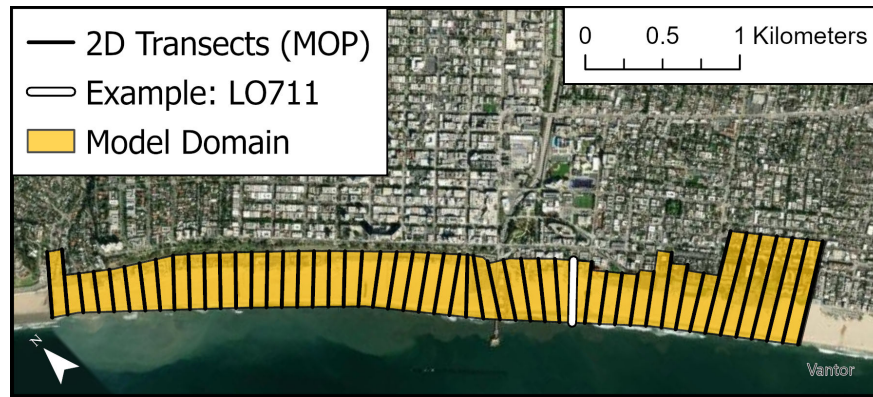


Figure 5.1: Regional Model Setup at Santa Monica (L0711), an open coast, cliff backed site, with the example transect L0711 highlighted. Figure courtesy of M. Maple

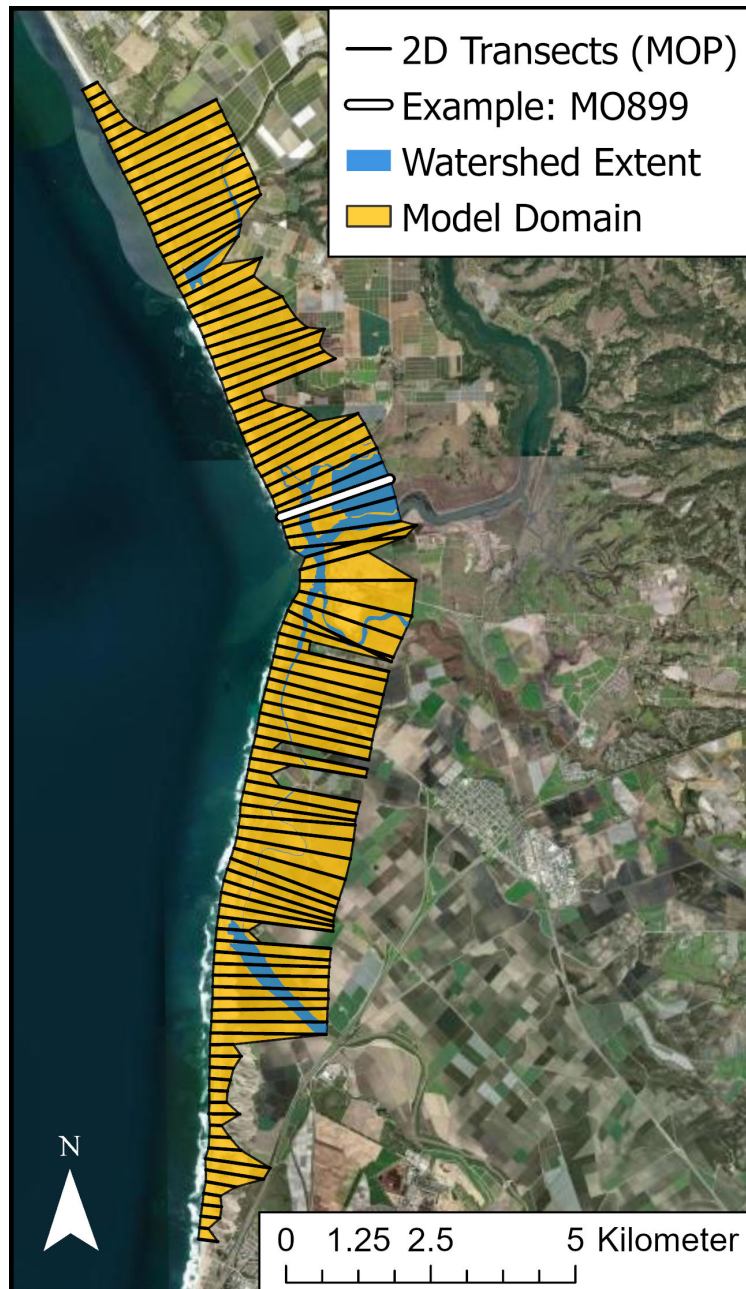


Figure 5.2: Regional Model Setup at Moss Landing (MO899), a low lying site with the example transect MO899 highlighted. Figure courtesy of M. Maple

5.1.3 PFLOTRAN Model Setup and Relevant Boundary Conditions

The groundwater simulations were performed with PFLOTRAN, an open source code for multiphase flow and reactive transport that handles variably saturated conditions under a

range of boundary conditions (Hammond et al., 2014). It solves a system of nonlinear partial differential equations with an implicit Newton-Raphson solver using the mixed form of the Richards equation (Celia et al., 1990; Hammond et al., 2014; Maple, 2024). This specific model domain is discretized on a refined rectangular grid. Salt transport is additionally included to capture saline and freshwater interactions, following the methods of Befus et al. (2020).

Two materials are defined. A beach sand fills the domain with anisotropic hydraulic conductivity $K_h = 1$ m/d and $K_v = 0.1K_h$. A confining layer with $K_h = 0.01$ m/d (two orders of magnitude lower) is placed wherever an inland watershed is hydraulically connected to the ocean and represents a silty/clayey sand. Unsaturated soils also have a lower hydraulic conductivity and modeling this confining layer as such was a motivating factor.

Boundary Conditions

The boundary conditions broadly follow the configuration shown in Figure 5.3 for a specific MOP line at Moss Landing (MO899). The base and the inland vertical boundary of the domain are set as no flow boundaries. The seaward boundary and the lower beach face are assigned a hydrostatic seepage condition. Since the beach slope and infiltration cause the water table to fall more gradually than the ocean water level does, this condition reproduces the seepage face that forms on the beach. The upper beach and the inland land surface are assigned a Dirichlet seepage condition at atmospheric pressure, which allows groundwater to discharge. A low permeability zone beneath the inland surface represents the confining sediments. Resolving these lower permeability sediment deposits is crucial since confining layers carry ocean fluctuations farther inland, causing higher peak groundwater levels and artesian pressures. This behavior is central to interpreting the alongshore variability in the outputs, as it controls how far ocean forcing penetrates into the backshore. By contrast, the Santa Monica profile shown in Figure 5.4 is short and steep with no confining layer.

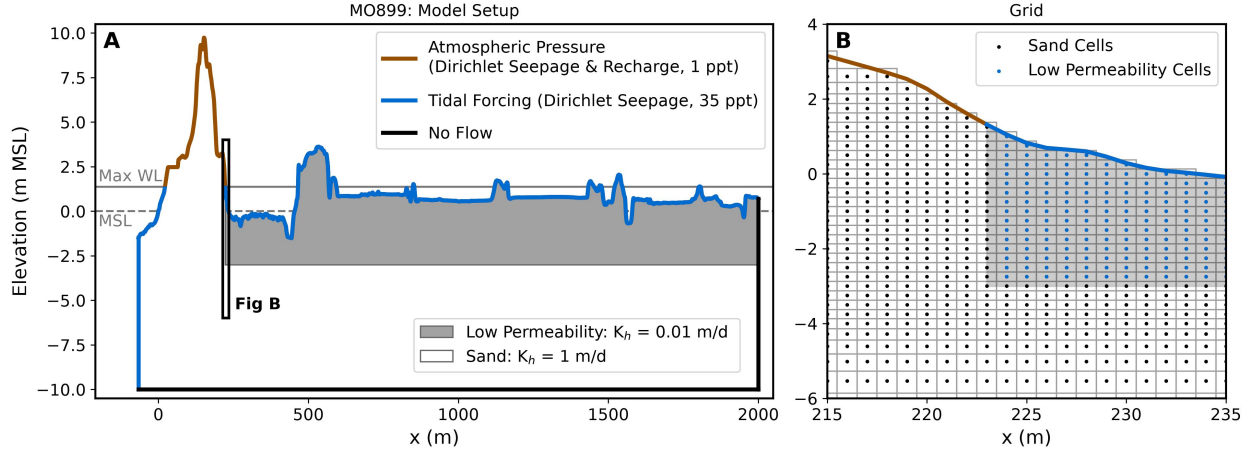


Figure 5.3: Model Setup for MOP line MO899 at Moss Landing. (A) Cross-shore domain and boundary conditions (B) Detail of the computational grid, distinguishing sand and low permeability cells. Figure courtesy of M. Maple

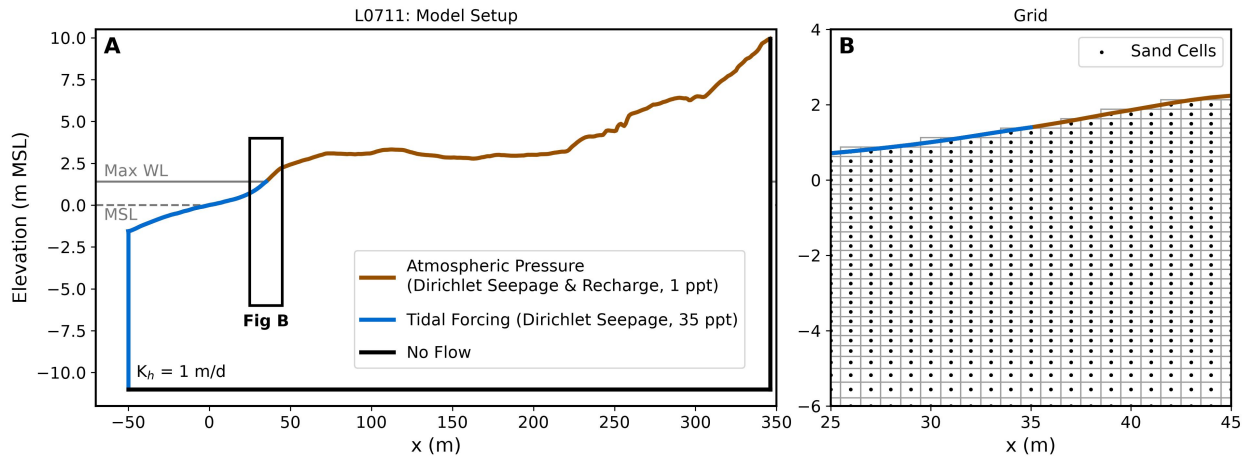


Figure 5.4: Model Setup for MOP line L0711 at Santa Monica (A) The short, steep, cliff backed profile consists entirely of sand with no low permeability layer. (B) Detail of the computational grid. Figure courtesy of M. Maple

5.1.4 Input Data Sources

Elevation data are taken from the USGS seamless topographic bathymetric model of the California coast (Danielson et al., 2016). Ocean water levels are imposed as a five year synthetic tidal time series constructed from the nearest NOAA tide gauge with a matching coastal setting or geometry (NOAA, 2024). For example, an open-coast gauge is selected for

sites with direct ocean exposure, whereas a tide gauge within an embayment or tidal inlet is used where the local tidal range and mean water level differ from open-coast conditions. Four years are used for spin-up and one year for computing statistics and the wave-driven contribution to the water levels.

Information on back bay and estuary extents is drawn from the 2025 TIGER (Topologically Integrated Geographic Encoding and Referencing) shapefiles ([U.S. Census Bureau, 2025](#)). TIGER/Line is a US Census format that describes physical features from highways to rivers and lakes ([U.S. Census Bureau, 2025](#)). Specifically, the area hydrography shapefiles contain the geometry and attributes of features hydraulically connected to the ocean.

Initial conditions

Because the groundwater response equilibrates slowly, a reliable initial condition is essential; therefore, the initial conditions are taken from [Befus et al.](#)’s model. Following [Befus et al. \(2020\)](#), a surface recharge flux is imposed using the 2000–2013 mean effective recharge of [Reitz et al. \(2017\)](#). Flux-controlled steady-state groundwater heads provide the starting condition for each SLR scenario (0, 50, 100, and 200 cm). Ocean salinity is set from the NOAA World Ocean Atlas at a 10 m depth.

Wave runup, the wave-driven flow that carries water up and down the beach, is included following [Stockdon et al. \(2006\)](#). Precipitation and beach erosion are beyond the present scope.

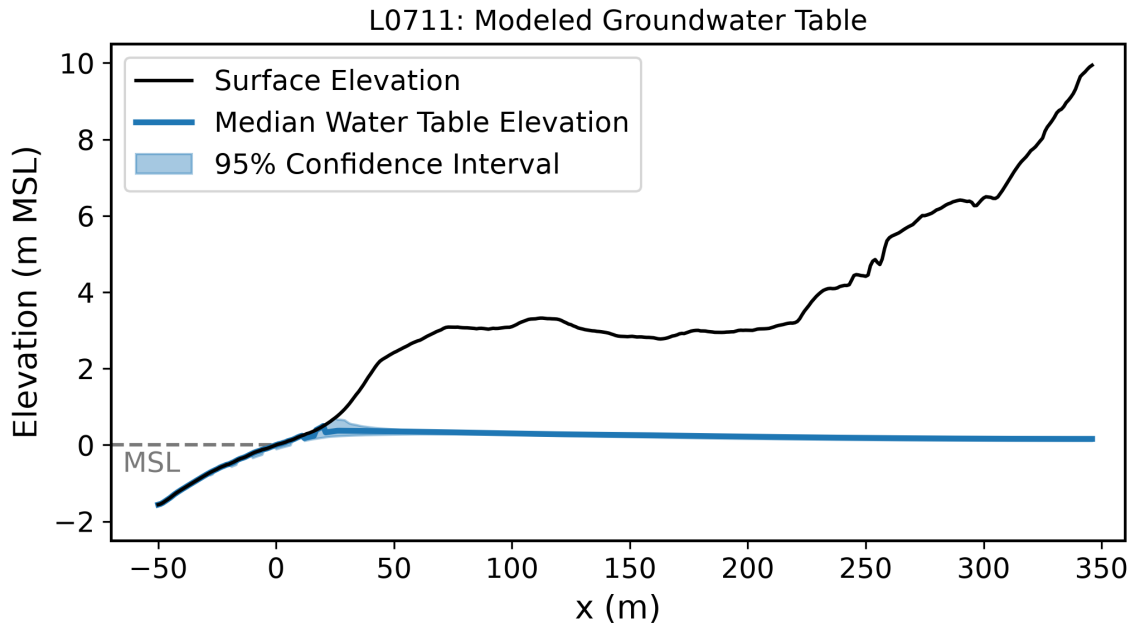
5.1.5 Groundwater Model Outputs

For each transect and SLR scenario, the model writes its output to an HDF5 file containing the absolute pore pressure at every grid cell, reported at 0.25 h timestep over the one year analysis period. This pore pressure field is the model output used in this work. The model additionally derives the water table elevation (the level at which absolute pressure equals atmospheric pressure) and the groundwater depth below the ground surface. The use

of these outputs is detailed in Section 5.2.

Additionally, the contrast between the two example sites is evident in the modeled water table (Figure 5.5). At L0711, the median water table tracks mean sea level with a narrow confidence interval, indicating little temporal variability. At MO899, the interval widens beneath the low permeability layer, reflecting the larger tidally driven fluctuations transmitted inland. This is specifically evident in Figure 5.6, which shows the modeled groundwater table at $Z = -3.5m$ *MSL* under the confining layer.

(a) Santa Monica (L0711)



(b) Moss Landing (MO899)

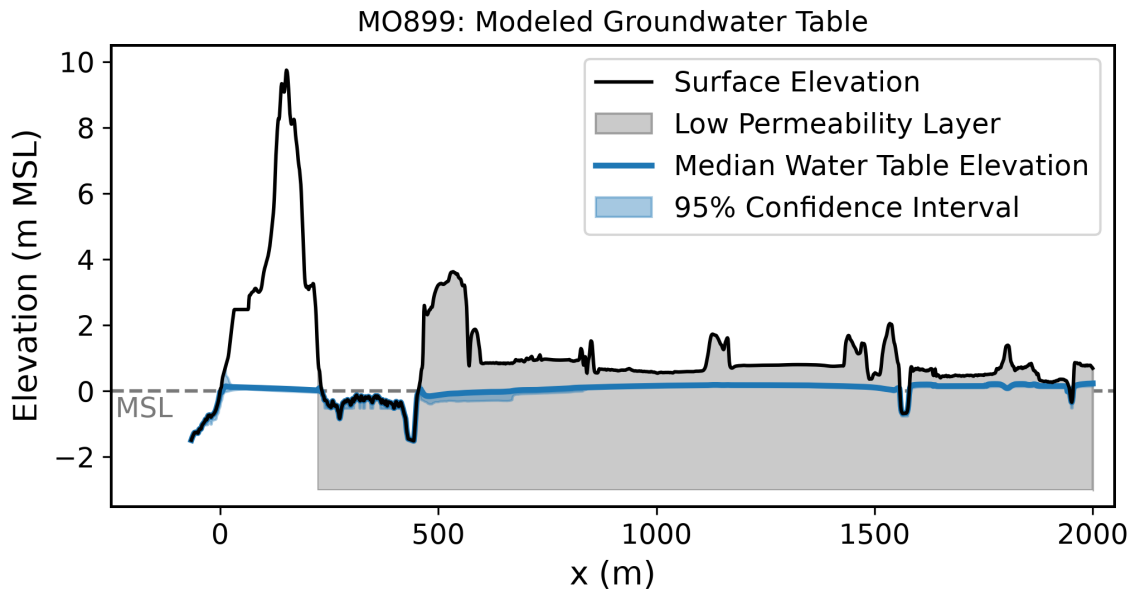


Figure 5.5: Modeled Water Table at the two Example Transects (surface elevation in black, median water table in blue, 95% confidence interval shaded). (a) L0711 (Santa Monica). (b) MO899 (Moss Landing). Figure courtesy of M. Maple.

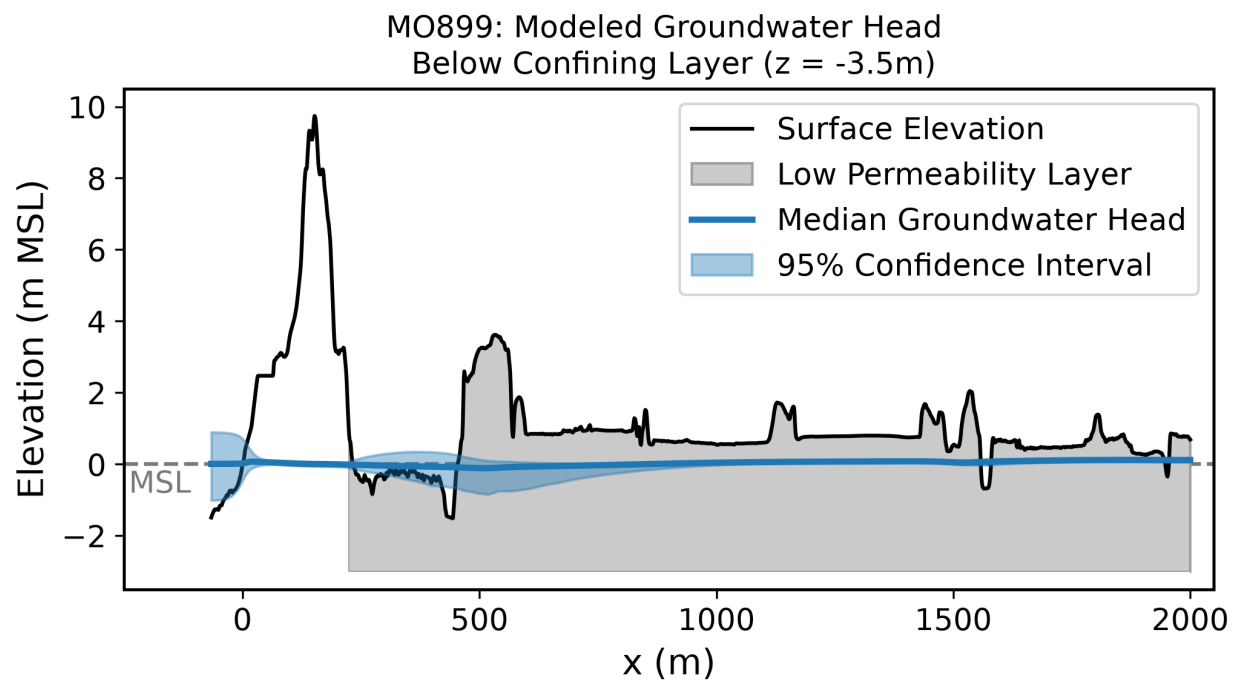


Figure 5.6: Modeled Groundwater Table at MO899 (Moss Landing) at -3.5m MSL. Figure courtesy of M. Maple

Figures 5.7 and 5.8 show pore pressure profiles (u versus depth) at fixed transect locations, sampled at six timesteps across one modeled year for two different locations at 0 *cm* and 200 *cm* SLR.

The sharp near surface step in the MO899 profile (Figure 5.7) is due to the confining layer present at this location and not at Santa Monica. The permeability in that region is so low that the water table barely moves within it, even under large changes in tide or underlying groundwater. At timesteps when the shallow groundwater can respond to the tides, its head is drawn lower, and the profile stays close to hydrostatic. Below that confining layer the pore water has no path to drain, so the pore pressure remains elevated, producing the sharp offset.

MO899 — pore pressure vs depth

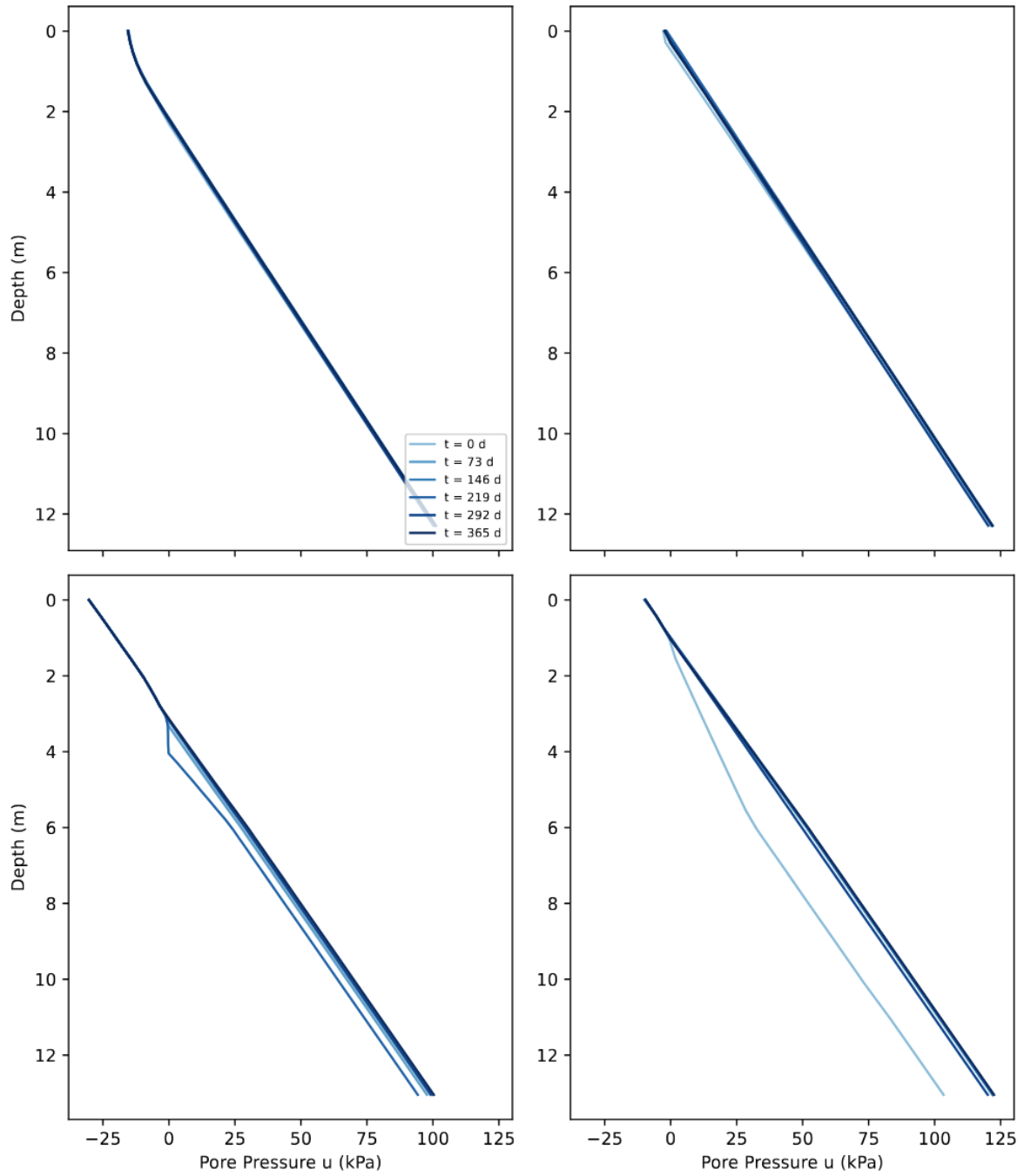


Figure 5.7: Simulated pore pressure versus depth at the Moss Landing transect (MO899) for two shore normal locations ($x = 50$ and 500 m) under 0 cm (left) and 200 cm (right) of sea level rise.

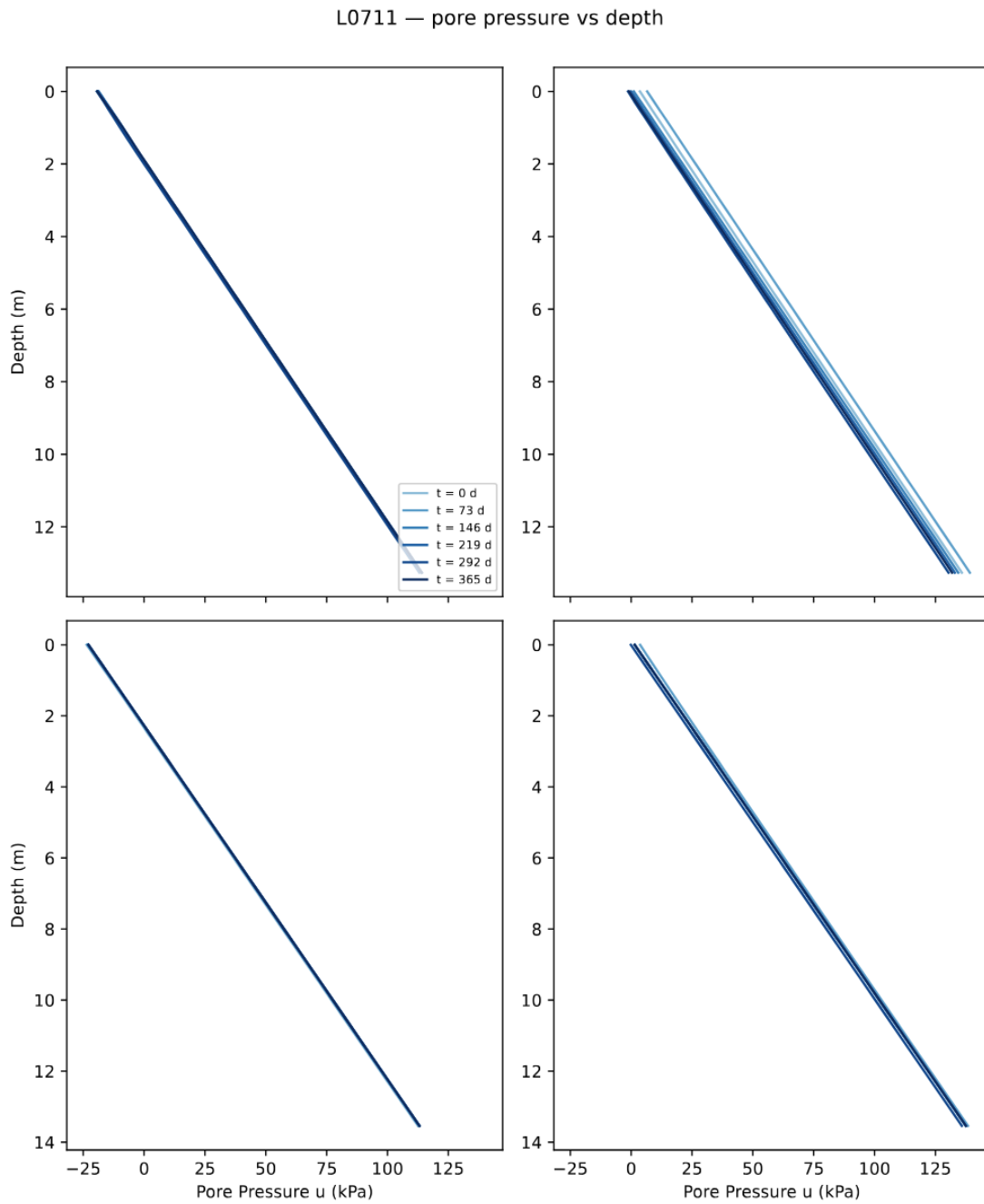


Figure 5.8: Simulated pore pressure versus depth at the Santa Monica transect (L0711) for two shore normal locations ($x = 50$ and 150 m) under 0 (left) and 200 (right) of sea level rise.

5.2 Use of PFLOTTRAN Outputs for Liquefaction Hazard Analysis

For each transect and SLR scenario, the groundwater model (Section 5.1) produces a one-year time history of pore pressure at every cell of a refined two-dimensional mesh. This section details a workflow that turns the pore pressure fields into PLHA inputs, by creating the config files required for evaluating the hazard for every combination of location and SLR scenario. Eventually the data and results are stored in a SQLite (Gaffney et al., 2022) database.

As illustrated in Figure 5.9, the pipeline comprises four stages, shown here for a single transect. The steps will be detailed throughout Section 5.2.

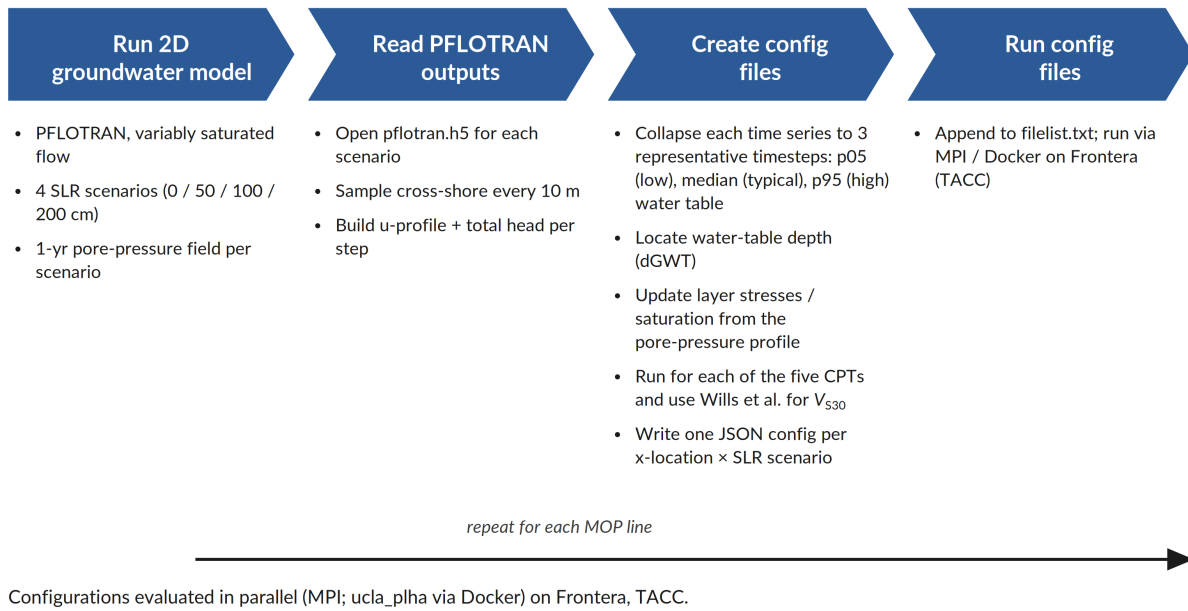


Figure 5.9: Configuration file generation workflow for one MOP transect.

5.2.1 Soil Profiles from the CPTs

The soil (CPT) profiles used to create the config files are the representative tests selected in Chapter 3 on the basis of their manifestation fragility (probability of surface manifesta-

tion). Because measured tests are unavailable at most coastal locations, this representative set stands in for site specific data. The five chosen profiles deliberately span the observed range of manifestation fragility. After applying the inverse layering algorithm (Hudson, 2023) to the profiles, using the groundwater depth at the time of the test for analyzing the cone data (e.g., I_c and q_{c1Ncs}), the profiles are saved in a column-oriented binary file format (Parquet). The file is read once during config file creation and loaded once into the database. This is efficient when many MPI (Message Passing Interface) ranks read the same dataset.

5.2.2 Time-Averaged Shear Wave Velocity in the upper 30m, V_{S30}

The ground motion models require a shear wave velocity at every location. Due to a lack of site specific data (*Measured V_{S30}*) at most coastal locations, the geology and terrain based California V_{S30} map of Thompson (2018), distributed as a statewide raster, is used. The raster estimates the time-averaged shear wave velocity in the upper 30 m from mapped surface geology and is calibrated against measured velocities.

At each unique cross-shore location on a transect, the raster is sampled at the point's latitude and longitude. If the map has no value at a point, the gap is filled with the first valid velocity encountered moving landward along the transect. The result is a per-transect table of cross-shore position and paired V_{S30} .

5.2.3 Water Table and Effective Stress Calculation

Once the CPT soil parameters are set, the next stage reads the `pflotran.h5` files that are the outputs of the analysis described in Section 5.1. For each transect and SLR scenario, the `h5` file is read together with a cell location table (`Cell_Loc.csv`). `Cell_Loc.csv` contains columns *lon*, *lat*, *x_MSL*, *z_MSL*, *surface_el_MSL*, *depth*. This file maps mesh nodes to cross-shore position, surface elevation, and depth.

The config files and subsequent hazard are computed at 10 m intervals along the transect (the spacing labeled as `X_STEP`), with the final position of the transect always included in

the analysis. This is fine enough to resolve the cross-shore changes in groundwater (for transects that could span up to 2 km inland), but coarse enough to keep the number of configurations reasonable. At each output timestep, the pore pressure is calculated and referenced to atmospheric pressure, and then at each cross-shore position, the total head is taken as the depth averaged value over the column. The one year record at every position (i.e., `X_STEP`) is then reduced to three timesteps, when the averaged total head equals the 5th, 50th, and 95th percentiles of the annual distribution. Collapsing the time series into these states keeps the data manageable, while still capturing the temporal variability.

To support the assignment of stratigraphic layers, the water table is located as the shallowest depth at which the pore pressure profile crosses zero. The NGL SMT liquefaction triggering model (Ulmer et al., 2024) is used for the analysis. The model requires the CPT profile to be discretized into layers, with a layer boundary at the groundwater table. Therefore, if the depth falls within the profile and does not already coincide with a layer boundary, a layer boundary is inserted there so that no layer straddles the water table. The pore pressure computed by numerical groundwater analysis is then interpolated to each layer midpoint and used for effective stress calculations.

The saturation flag, K_{sat} , is set to unity for every layer whose midpoint lies at or below d_{GWT} and to zero otherwise.

For every calculation point, the code returns a layered profile where q_{c1Ncs} and I_c are inherited from the CPT preprocessing while the other parameters such as σ_v , σ'_v , and K_{sat} are derived from the groundwater simulation. Across the SLR scenarios, these values change and modify the liquefaction hazard. The code is shown in Appendix A in Listing 12.

5.2.4 Creation of Configuration Files

From all these calculations, each unique combination (transect, SLR scenario, `X_STEP`, and percentile) is translated into a self-contained JSON config file. A baseline template config file provides some basic analysis settings such as the logic trees for the four ground

motion models and seismic (source and background) faults. The config file contains all the inputs required for the hazard calculation, as described in Chapter 4. This includes the seismic source model (UCERF3 FM3.1 and FM3.2 at equal weight, together with the gridded and point sources), the ground motion models (the four NGA-West2 models), the source distance and minimum magnitude constraints, the site coordinates, elevation, and the V_{S30} assigned for that point. The NGL Model inputs are also included within the liquefaction model with the required inputs which include: **ztop**: top of layer boundary, **zbot**: bottom of layer boundary, **qc1Ncs**: equivalent clean sand normalized cone tip, **Ic**: soil behavior type index, **sigmav**: total vertical stress, **sigmavp**: vertical effective stress, **Ksat**: saturation flag, **weight**: model weight. It also includes the PGA and FS_L levels for the hazard curve tabulation, and the groundwater derived layered profile for the NGL SMT triggering model.

An example config file is shown in Listing 5.


```

{
  "site": {
    "latitude": 34.025599, "longitude": -118.518976,
    "elevation": 0.269, "vs30": 352.01
  },
  "constraints": {"dist_cutoff": 200, "m_min": 5.0},
  "source_models": {
    "fault_source_models": {
      "ucerf3_fm31": {"weight": 0.5},
      "ucerf3_fm32": {"weight": 0.5}
    },
    "point_source_models": {
      "ucerf3_fm31_grid_sub_seis": {"weight": 0.25},
      "ucerf3_fm31_grid_unassociated": {"weight": 0.25},
      "ucerf3_fm32_grid_sub_seis": {"weight": 0.25},
      "ucerf3_fm32_grid_unassociated": {"weight": 0.25}
    }
  },
  "ground_motion_models": {
    "bssa14": {"weight": 0.25}, "ask14": {"weight": 0.25},
    "cb14": {"weight": 0.25}, "cy14": {"weight": 0.25}
  },
  "output": {
    "psha": {"pga": [0.01, 0.014, 0.021, ..., 10.0]},
    "plha": {"fsl": [0.1, 0.123, 0.151, ..., 5.0]},
    "outputfile": ".../output/pflotran_0cm_cpt0_x-5.0_median.json"
  },
  "additional_info": {
    "x_location": -5.0, "scenario": "median",
    "timestep": "6078 Time 1.26625E+02 d",
    "time_days": 126.625, "cpt_site_id": 336, "cpt_id": 32
  },
  "liquefaction_models": {
    "ngl_smt_2024": {
      "ztop": [0.1006, 0.1250, 0.2256, ..., 15.1257],
      "zbot": [0.1250, 0.2256, 0.5243, ..., 15.2522],
      "qc1Ncs": [55.90, 56.23, 223.51, ..., 258.66],
      "Ic": [3.743, 4.463, 1.685, ..., 1.954],
      "sigmav": [7.15, 8.50, 12.79, ..., 318.88],
      "sigmavp": [1.74, 3.09, 5.93, ..., 217.91],
      "Ksat": [1.0, 1.0, 1.0, ..., 1.0],
      "weight": 1.0, "pa": 101.325
    }
  }
}

```

Listing 5: Example configuration file for a single case.

The input file name includes the SLR scenario, CPT index, cross-shore location, and percentile (e.g., `pflotran_0cm_cpt0_x-6.0_p05.json`). The CPT index in the file name (e.g., `cpt0`) is a local, per-transect counter over the five representative soundings, whereas the `cpt_site_id` and `cpt_id` fields in the config record the corresponding Coastal Geotechnical Database identifiers. The former keeps file names short and readable, while the latter preserve traceability back to the source CPT. Files are organized per transect: each MOP line has an `input` directory that holds all of its configuration files and an `output` directory that receives the results. An output file carries the same name as its input configuration but resides under the `output` folder, and each configuration records this path in its `outputfile` field. Every result is traceable to the configuration that produced it (due to the one-to-one naming), which also allows the two directories to be compared to find cases that did not complete.

As the configurations are written, their absolute paths are appended to a per-transect list (`filelist.txt`) and, on completion, to a master list (`filelist_all.txt`). The lists also make runs resumable: any case already present is skipped, so an interrupted or partial run continues from where it stopped rather than recomputing completed cases. The total configuration count is the product of the number of transects, four SLR scenarios, five soundings, evaluation points per transect, and three water table states. At a broader, eventual regional scale this reaches many tens of thousands to millions of files.

5.2.5 High Performance Computing: Parallel Execution on Frontiera

The two processing stages run as separate Slurm jobs. The relevant files are shown in Appendix A. This is because generation of the files is short compared to the evaluation, so coupling them would tie up a larger allocation. The two stages are therefore parallelized independently, as described below; the container image in which the hazard stage runs and the batch scripts that launch both stages are presented in the subsections that follow.

5.2.6 Parallel Generation of Configuration Files

The generation of the configuration files is parallelized with `mpi4py`. The process of opening all the HDF5 files is computationally intensive, and greatly benefits from parallelization. Rank 0 enumerates the jobs (transects and scenarios) and then distributes them using a scatter/gather approach across ranks. Each rank then reads the HDF5 output for its assigned jobs and writes the corresponding configuration files independently, after which Rank 0 gathers the results into a master list. This stage is built on Frontera’s native Intel MPI and parallel-HDF5 modules, which read the simulation files concurrently. The stage completes in a few minutes of wall-clock time on a few nodes. An example file to generate the config files is included in Appendix A in Listing 6.

5.2.7 Parallel Evaluation of the Liquefaction Hazard

The hazard evaluation is the secondary, much larger job. Rank 0 reads the master list, removes any cases whose output file already exists so that interrupted runs resume rather than recompute completed work, and splits the remaining cases into contiguous blocks that are scattered across the MPI ranks spanning multiple nodes. Each rank then works through its block, and every calculation writes both the seismic and liquefaction hazard curves at that location to the output path. An example file for parallel evaluation is shown in Appendix A in Listing 7.

5.2.8 Containerization with Docker and Apptainer

For portability and reproducibility, the `ucla_plha` package and its MPI driver are distributed as a container image rather than installed directly into a user environment on the cluster.

The image builds on a TACC base, adds Python and a source build of `mpi4py`, installs `ucla_plha` and its dependencies, and bundles the driver. An example Dockerfile is shown

in Listing 8. The base image, `tacc/tacc-ubuntu18-mvapich2.3-ib`, is a TACC-provided Ubuntu image. Using the TACC image ensures that MPI inside the container targets Frontera’s high-speed network.

The remaining dependencies (`ucla_plha` and `numpy`) are standard packages requiring no special treatment, and the final `ADD` instruction copies the MPI driver into the image at the path used by the hazard job.

The image is published on Docker Hub (`meerakota/ucla_plha`). Because Docker is not permitted on shared HPC systems, the image is converted on Frontera to an Apptainer image (`ucla_plha.sif`) and used with `apptainer exec` for the hazard calculations. Containerization fixes the versions of `ucla_plha`, `mpi4py`, and the underlying numerical libraries within the image, so that an analysis can be reproduced exactly from that same image on another machine or at a later date. The Dockerfile is available at the `ucla_plha` GitHub at this URL https://github.com/meerakota/ucla_plha/blob/main/utilities/Dockerfile.

5.2.9 Running the Analysis on Frontera

Both stages are launched with `ibrun`, TACC’s MPI launcher, which can be invoked directly on a compute node, for example within an interactive `idev` session while testing. Alternatively, for production runs, it can be run from a Slurm batch script. The config file generation is submitted with the script in Listing 9 in Appendix A: it loads Frontera’s native Intel MPI, parallel-HDF5, and Python modules and runs `process_h5_MPI.py` directly, since this stage does not require the container.

The hazard evaluation is submitted with the script in Listing 10 in Appendix A. It requests many more nodes and loads the Apptainer module and runs the containerized driver with `apptainer exec`. The master list of calculations is distributed across the requested MPI ranks, and each calculation writes its result to the output path recorded in the corresponding configuration file.

5.2.10 Results Storage and Database Schema

The outputs are loaded into a SQLite database whose schema is defined from Table 5.1 to Table 5.9. A loader iterates over the result files, extracting the layered profile and metadata from each configuration and the hazard curves from each output. Each liquefaction hazard evaluation is keyed through a metadata table to its transect, SLR scenario, CPT, percentile, and cross-shore location. Its associated liquefaction hazard curve is stored as (FS_L, rate) pairs. The seismic hazard curve is not dependent on groundwater and is therefore stored once per coordinate as (PGA, rate) pairs.

The results database is organized into the tables described below. Column types are SQLite storage classes, and foreign-key (FK) columns hold the `id` of the referenced table. The database stores both the liquefaction hazard (FS_L) and the underlying seismic hazard (PGA) .

Table 5.1: MOP_LINES: one row per MOP transect.

Column	Type	Description
<code>id</code>	INTEGER	Primary key
<code>name</code>	TEXT	Transect name (unique)
<code>county</code>	TEXT	County
<code>start_lat, start_lon</code>	REAL	Shoreward endpoint
<code>end_lat, end_lon</code>	REAL	Inland endpoint

Table 5.2: COORDINATES: evaluation points along each transect.

Column	Type	Description
<code>id</code>	INTEGER	Primary key
<code>mop_line_id</code>	INTEGER	FK, references MOP_LINES
<code>latitude, longitude</code>	REAL	Point location
<code>x_location</code>	REAL	Cross-shore position
<code>vs30</code>	REAL	Site shear-wave velocity

Table 5.3: SLR_SCENARIOS: the four SLR levels.

Column	Type	Description
id	INTEGER	Primary key
rise	TEXT	SLR level, e.g. 0cm–200cm (unique)

Table 5.4: CPT_METADATA: one row per CPT sounding.

Column	Type	Description
id	INTEGER	Primary key
site_id	INTEGER	Source-database site ID
name	TEXT	Sounding name

Table 5.5: CPT_DATA: processed CPT profile (per depth).

Column	Type	Description
id	INTEGER	Primary key
cpt_metadata_id	INTEGER	FK, references CPT_METADATA
depth	REAL	Depth
qt, fs	REAL	Tip resistance, sleeve friction
Ic	REAL	Soil behavior type index
qc1N, qc1Ncs	REAL	Normalized / clean-sand-equivalent tip resistance
sigmav, sigmavp	REAL	Total, effective vertical stress

Table 5.6: CPT_LAY_DATA: layered CPT profile used by the triggering model.

Column	Type	Description
id	INTEGER	Primary key
cpt_metadata_id	INTEGER	FK, references CPT_METADATA
depth_top, depth_bot	REAL	Layer top, bottom
qc1Ncs	REAL	Clean-sand-equivalent tip resistance
Ic	REAL	Soil behavior type index
sigmav, sigmavp	REAL	Total and effective vertical stress
Ksat	REAL	Saturation flag (1 below water table)

Table 5.7: FSL_HAZARD_METADATA: one row per liquefaction-hazard evaluation.

Column	Type	Description
id	INTEGER	Primary key
mop_line_id	INTEGER	FK, references MOP_LINES
slr_id	INTEGER	FK, references SLR_SCENARIOS
cpt_id	INTEGER	FK, references CPT_METADATA
percentile	TEXT	Water-table state (p05/median/p95)
datetime	TEXT	Representative timestep
time_days	REAL	Representative time (days)
x_location	REAL	Cross-shore position

Table 5.8: FSL_HAZARD_DATA: liquefaction hazard curve.

Column	Type	Description
id	INTEGER	Primary key
hazard_metadata_id	INTEGER	FK, references FSL_HAZARD_METADATA
fsl	REAL	Factor of safety against liquefaction
rate	REAL	Annual rate of non-exceedance

Table 5.9: SEISMIC_HAZARD_DATA: seismic (PSHA) hazard curve.

Column	Type	Description
id	INTEGER	Primary key
coordinate_id	INTEGER	FK, references COORDINATES
pga	REAL	Peak ground acceleration
rate	REAL	Annual rate of exceedance

This schema makes the broader scale products of Chapter 6 directly queryable. In addition, already computed cases are skipped on restart, and new transects and/or scenarios can be appended immediately. The loader separates the two hazard curves from each output before insertion. Querying the database is much more efficient than reading thousands of JSON files.

An example query to access the database is shown in Listing 11. This query shows an example of extracting a single FS_L hazard curve (factor of safety of liquefaction vs. annual rate of non-exceedance) for one transect, one SLR scenario for one CPT, for one X location along the transect.

This chapter has described how the outputs of the groundwater model are processed into inputs for the PLHA workflow. Results from this workflow are presented in Chapter 6.

CHAPTER 6

Coupling Probabilistic Liquefaction Hazard Analysis with Numerical Groundwater Simulations: Two Example Sites

This chapter uses the outputs of the PFLOTRAN groundwater simulations as inputs to probabilistic liquefaction hazard analyses, working up in scale from a single transect to city scale maps. Two contrasting sites are carried through from Chapter 5 to the discussion in this chapter: transect L0711 in Santa Monica, which is a cliff backed site where water table fluctuations follow sea level rise (SLR) closely, and transect MO899 at Moss Landing, which is a low lying estuary site with a shallow confining layer and is tidally driven. The transects are also expanded to the surrounding regions, with 50 Monitoring and Prediction (MOP) transects at Santa Monica and 99 at Moss Landing.

It should be noted that the groundwater model used in this dissertation is preliminary and still in development, specifically for the lower permeability sites at Moss Landing. The results shown here are an example of the capabilities of the coupled workflow, but at the time of this dissertation all results should be considered preliminary.

The chapter begins with a discussion of the CPTs chosen and their behavior. The five CPTs introduced in Chapter 3 serve as representative CPTs selected to stand in for site specific data. Each CPT was paired with the numerical groundwater simulation and the appropriate V_{S30} at every evaluation point. PLHA calculations were performed at 149 transects (with the number of x locations ranging from 30 to 200 per transect), under four sea level rise scenarios for five CPTs.

Then liquefaction hazard will be shown for individual CPTs at one location. The chapter then pairs seismic and liquefaction hazard curves at individual points along each transect, examines the sensitivity of the hazard to the tidal envelope alone at the transect level, and shows how the return period changes with distance inland for five CPTs across two transects. Finally, the 0 *cm*, 50 *cm*, 100 *cm*, and 200 *cm* SLR scenarios are presented as interpolated heat maps across both regions.

6.1 Liquefaction Hazard for Individual CPTs at One Location

This section briefly describes the five representative CPTs, and specifically their behavior under a rising water table. Understanding the CPT profiles is important for interpreting and understanding the mechanisms behind the figures in this chapter. This will then be followed by showing the five CPTs at a single point at each transect $x \approx 300$ *m* for Santa Monica’s L0711 transect, and $x \approx 500$ *m* for Moss Landing MO899 transect.

6.1.1 CPT Behavior Explored Per Transect

The five CPT curves, and the change in return period each one has under sea level rise, are set by the depth and the resistance of the susceptible layers in that profile, and specifically by whether 0.5–2 m of SLR is enough to raise the water table across one of those layers.

- **CPT 336** is the most sand-dominated profile, with I_c in the clean to silty sand range, but with high cone tip resistance, so triggering demands large ground motions. Its recorded water table is 3.05 m, and a loose lens sits at 1.4–2.2 m (Figure 6.1).
- **CPT 365** is interbedded clean and silty sand of moderate resistance, with a recorded water table at 2.44 m. It has a dense crust from 0.3 to 1.5 m over a loose interval at

1.7–3.7 m, then interbedded material to 12 m (Figure 6.2).

- **CPT 274** is not a strongly susceptible profile: a predominantly fine-grained column of lower cone resistance, with thin, deeper sandier interbeds where I_c drops into the liquefiable range. Its recorded water table is 3.05 m (Figure 6.3).
- **CPT 324** has low q_c with thin susceptible layers among fine grained material and a recorded water table at 2.44 m. It is the weakest profile in the set, with susceptible bands throughout (Figure 6.4).
- **CPT 888** has predominantly granular soil in the upper 8 m and fines below, with a recorded water table at 2.70 m. Shallow sandy material overlies a clay layer at 2.0–2.9 m, with susceptible sands below (Figure 6.5).

The five soundings are shown at both transects in Figures 6.1–6.5. Because the same representative CPTs are reused at each location, the four soil panels (q_c , f_s , I_c , q_{c1Ncs}) are identical between the two transects; only the water table lines move. The four water table lines rise monotonically with SLR, so the deepest line is the 0 cm baseline and the shallowest is 200 cm; the layered profile used in the analysis is the stepped black line. Each pair therefore isolates the effect of the site specific groundwater regime, since the horizontal lines are the simulated PFLOTRAN water table at 0/50/100/200 cm SLR at the evaluation point.

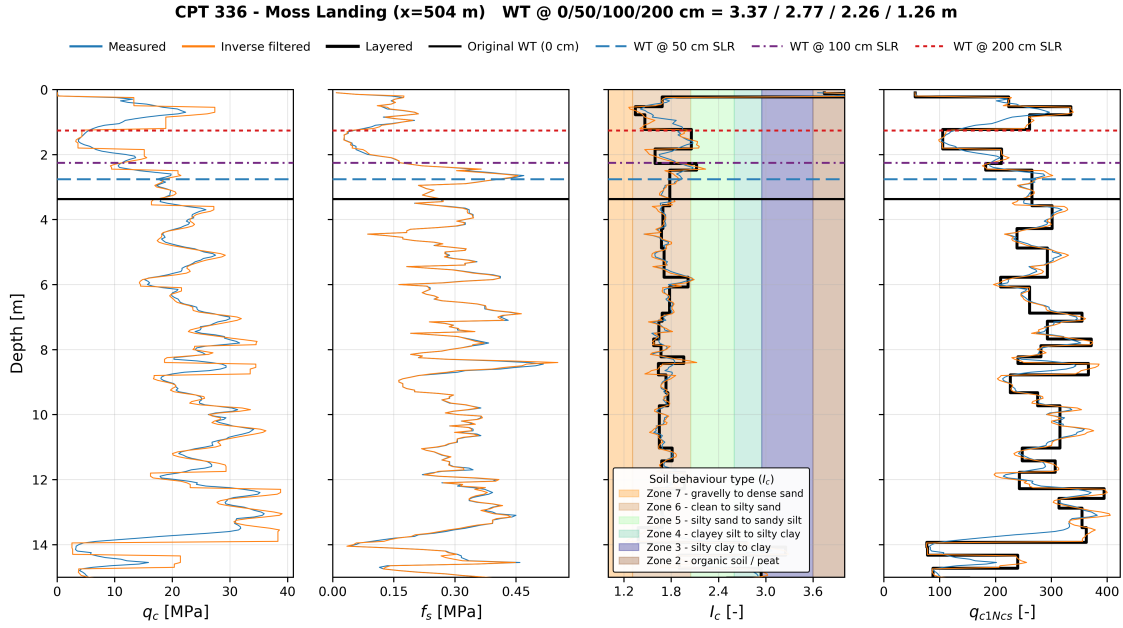
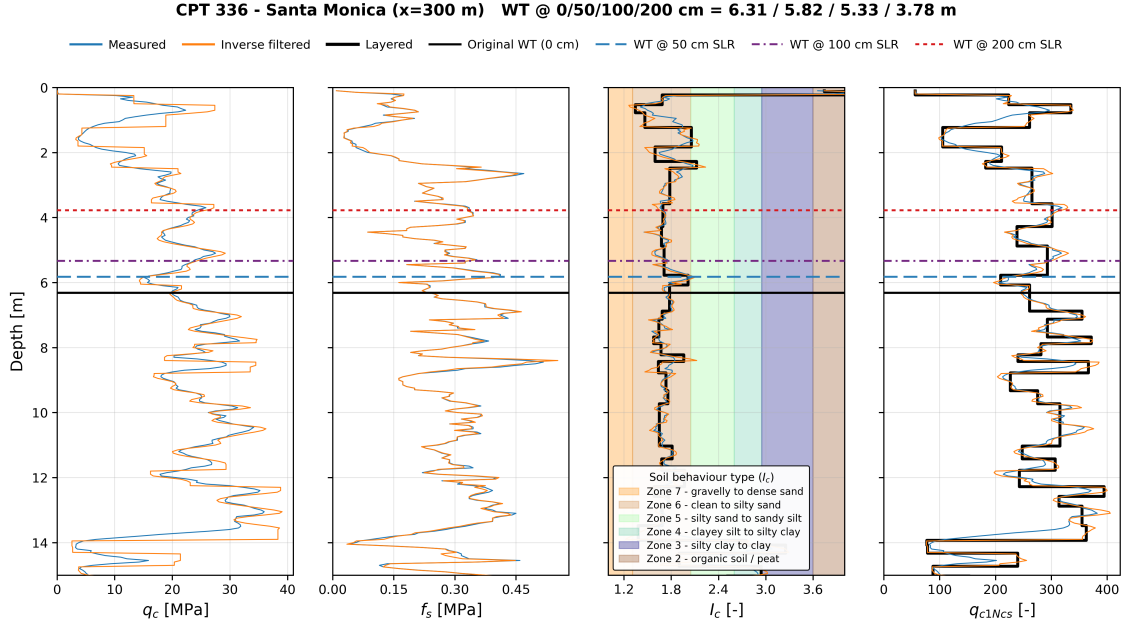


Figure 6.1: CPT 336 shown at (a) Santa Monica L0711 and (b) Moss Landing MO899. Panels, left to right: cone tip resistance q_c , sleeve friction f_s , soil behavior type index I_c (shaded by SBT zone), and normalized clean sand cone resistance q_{c1Ncs} . Measured (blue), inverse filtered (orange), and layered (black) profiles are shown, with horizontal lines marking the simulated water table at 0/50/100/200 cm SLR.

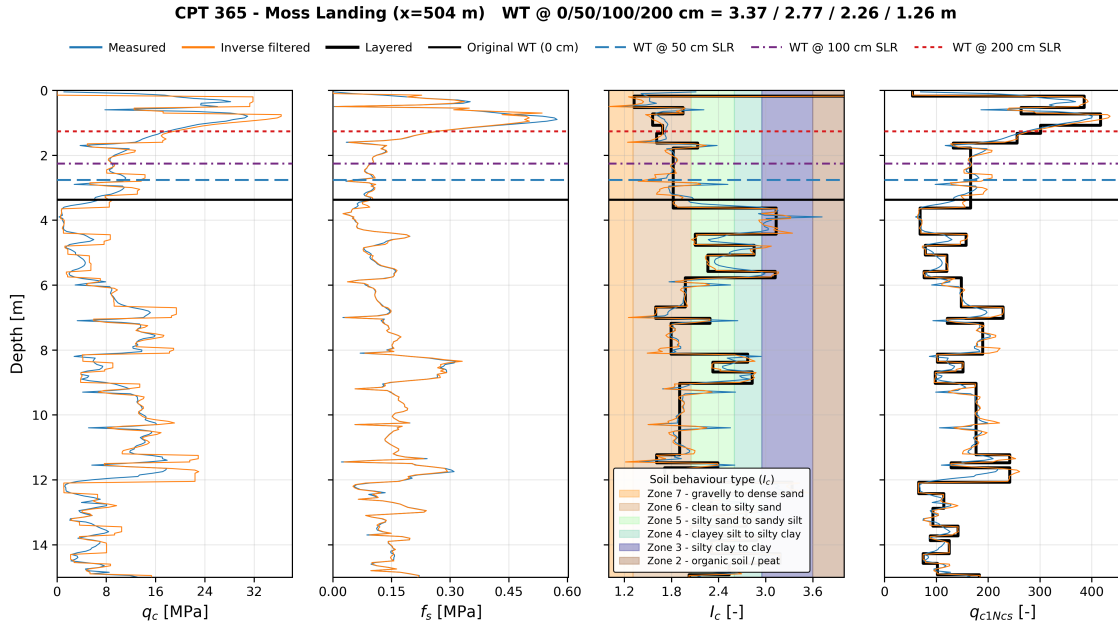
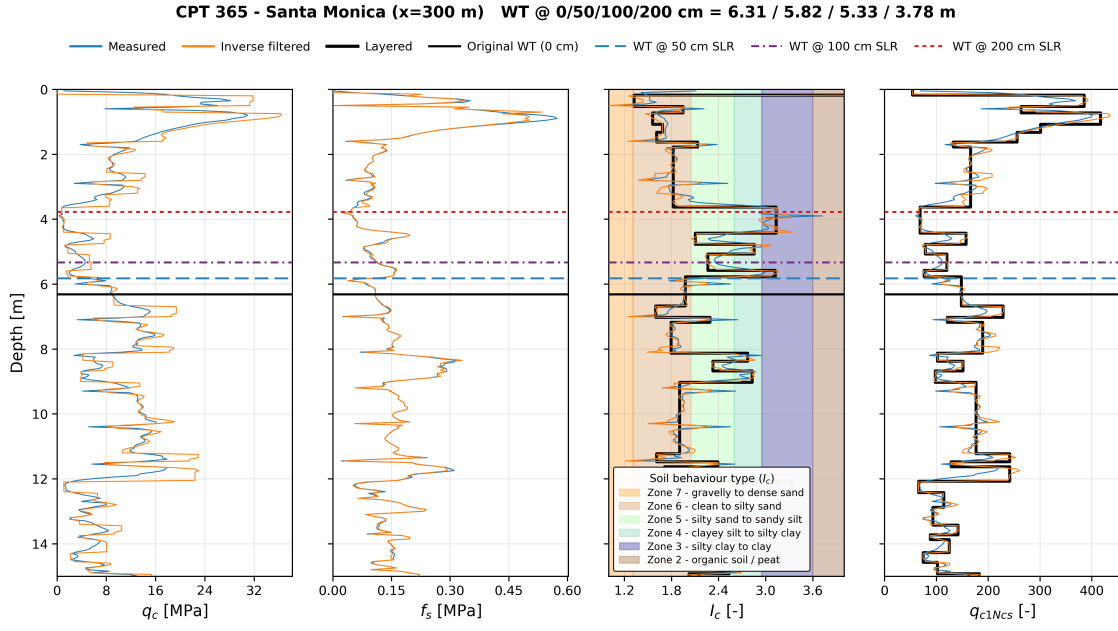


Figure 6.2: CPT 365 shown at (a) Santa Monica L0711 and (b) Moss Landing MO899. Panels and line styles as in Figure 6.1; horizontal lines give the simulated water table at 0/50/100/200 cm SLR.

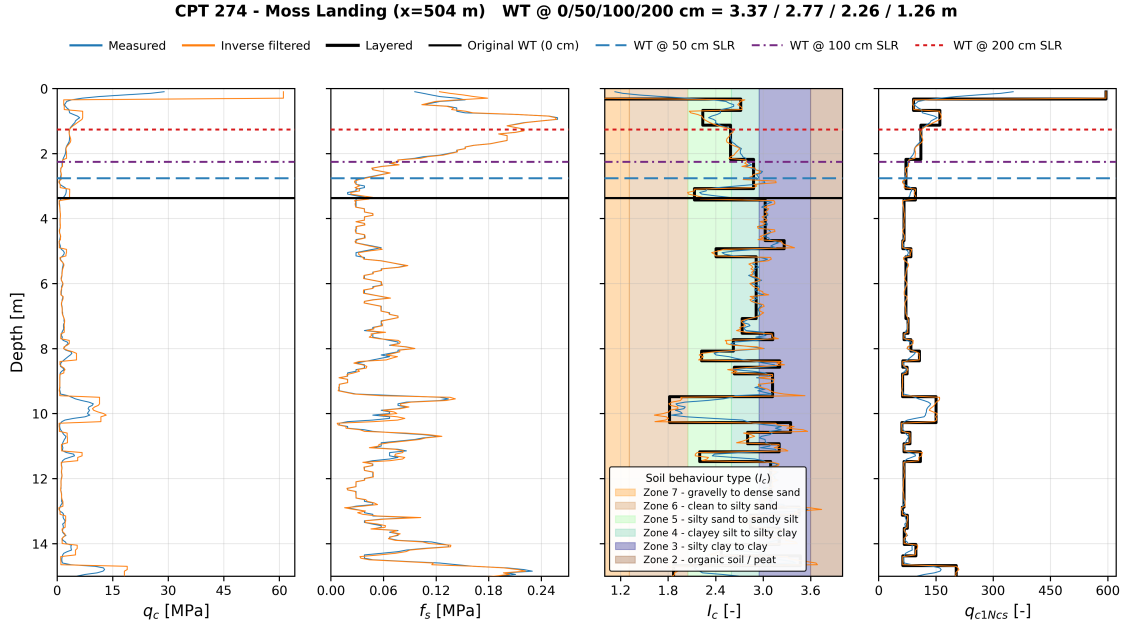
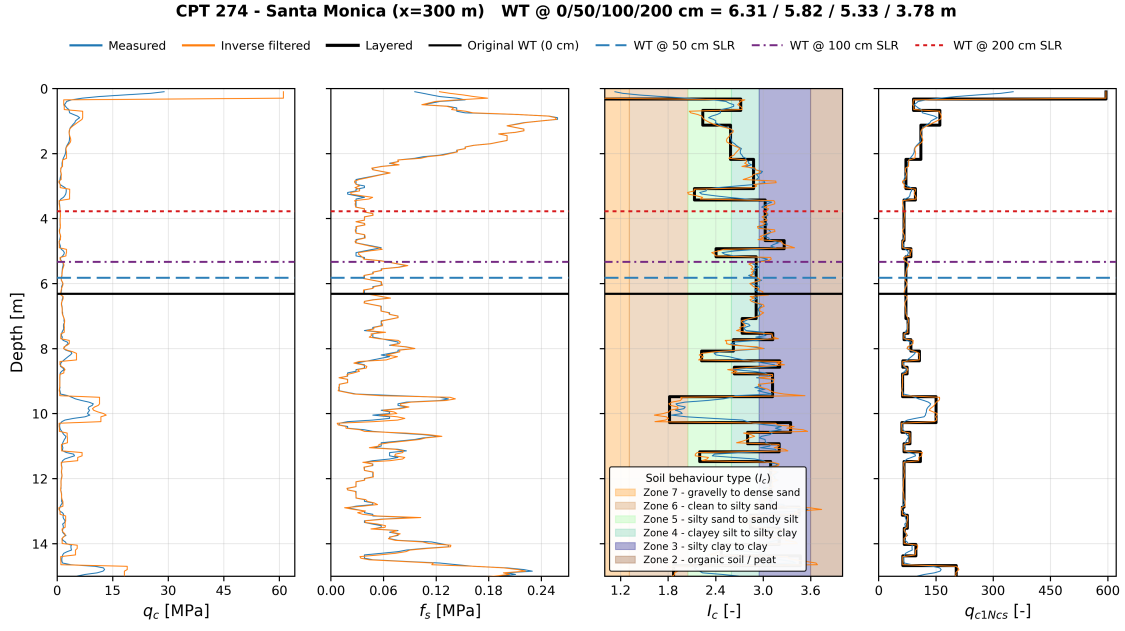
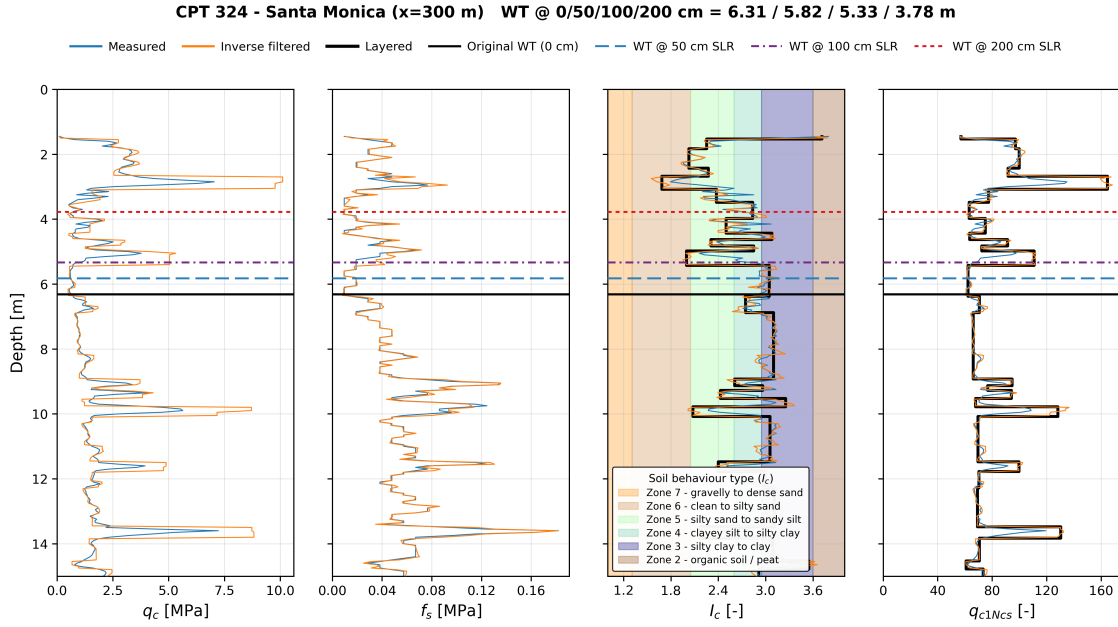
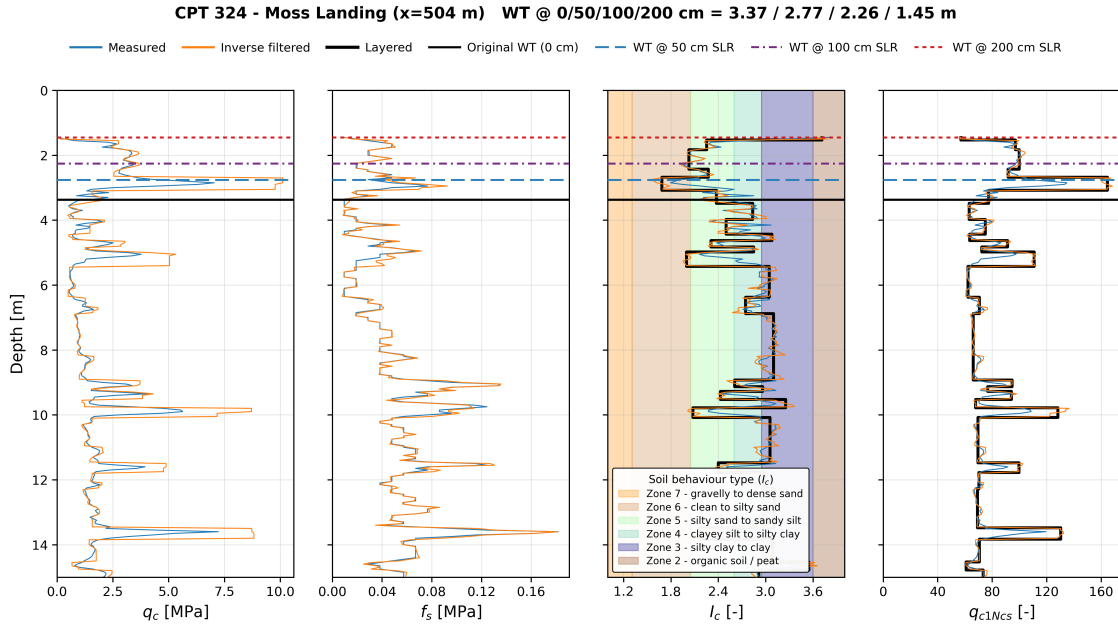


Figure 6.3: CPT 274 shown at (a) Santa Monica L0711 and (b) Moss Landing MO899. Panels and line styles as in Figure 6.1; horizontal lines give the simulated water table at 0/50/100/200 cm SLR.

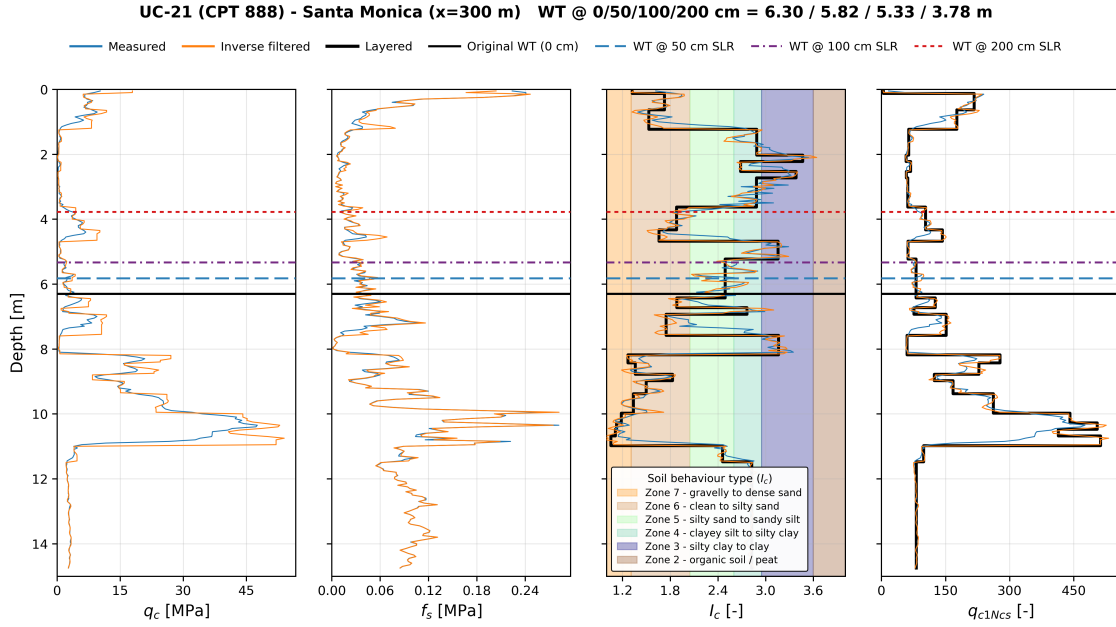


(a) Santa Monica L0711 ($x \approx 300$ m).

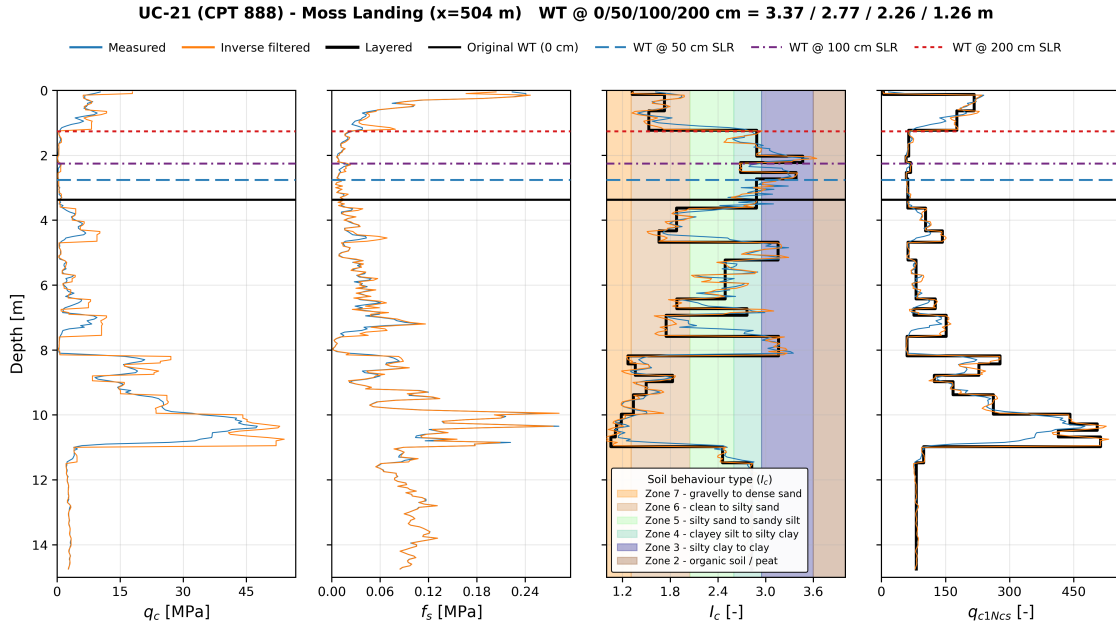


(b) Moss Landing MO899 ($x \approx 504$ m).

Figure 6.4: CPT 324 shown at (a) Santa Monica L0711 and (b) Moss Landing MO899. Panels and line styles as in Figure 6.1; horizontal lines give the simulated water table at 0/50/100/200 cm SLR.



(a) Santa Monica L0711 ($x \approx 300$ m).



(b) Moss Landing MO899 ($x \approx 504$ m).

Figure 6.5: CPT 888 shown at (a) Santa Monica L0711 and (b) Moss Landing MO899. Panels and line styles as in Figure 6.1; horizontal lines give the simulated water table at 0/50/100/200 cm SLR.

The water table depths noted above are those recorded with each CPT sounding, and they were used for initial profile calculations. However, the recorded water table is replaced by the simulated water table from the PFLOTRAN model at the evaluation point in question. Raising the water table switches the binary K_{sat} saturation flag in the NGL SMT Model (Ulmer et al., 2024), which was explained in Chapter 4. Once previously dry layers become saturated, they begin to contribute to liquefaction triggering and ultimately to surface manifestation. A higher water table also lowers the vertical effective stress, σ'_v , through the increase in pore pressure. The soil characterization is therefore an essential input alongside the pore pressures from the numerical groundwater modeling, and the two should be interpreted together.

To understand how the fragility changes for both sites, the manifestation fragility curves for a Magnitude $M_w = 7$ are plotted for both locations in Figures 6.6 and 6.7. Using the NGL SMT Model (Ulmer et al., 2024), the baseline and 200 cm SLR condition are plotted. At both sites, sea level rise increases the probability of manifestation. At Santa Monica the shift is largest for CPT 888, whose plateau climbs toward unity, and for CPT 324, whose plateau rises from below 0.1 to about 0.3, while CPT 274 changes only slightly. At Moss Landing the baseline curves start higher and the gap to 200 cm is narrower; the CPT 274 plateau roughly doubles, and CPT 336 shifts mainly toward lower accelerations.

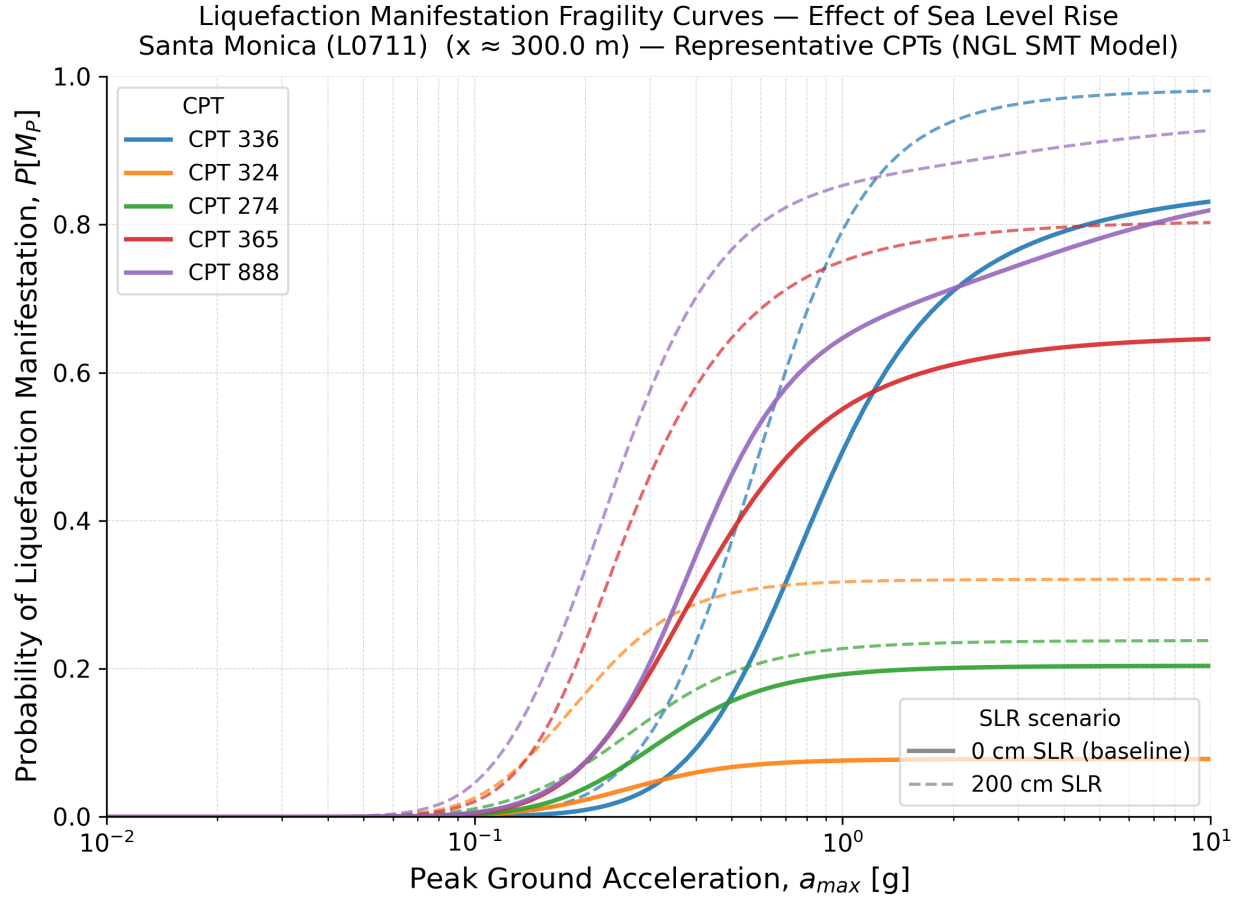


Figure 6.6: Manifestation Fragility Curves ($P[M_P]$ vs. a_{max}) for the five representative CPTs at Santa Monica L0711 ($x \approx 300$ m) under the NGL SMT model (Ulmer et al., 2024). Solid: 0 cm baseline; dashed: 200 cm SLR.

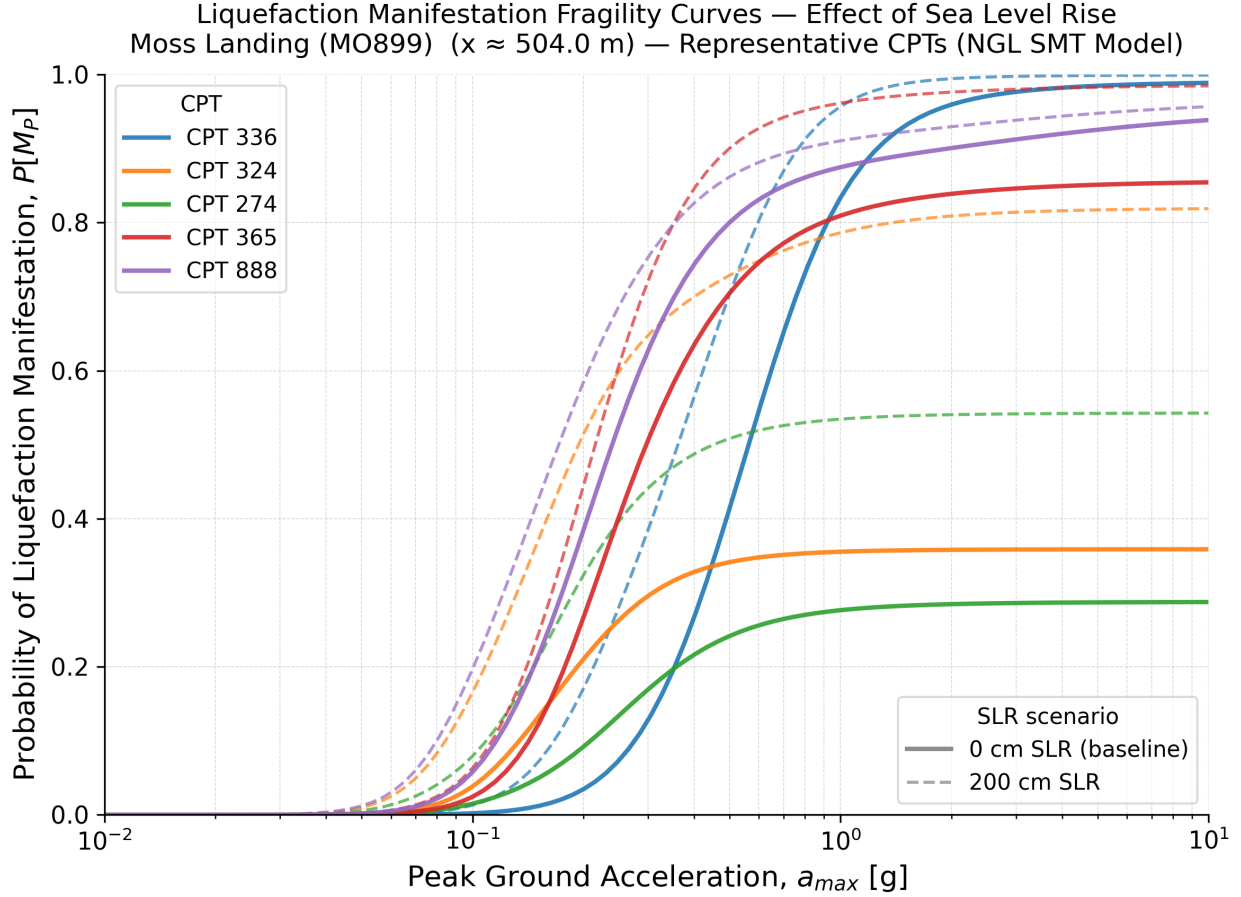


Figure 6.7: Manifestation Fragility Curves ($P[M_P]$ vs. a_{max}) for the five representative CPTs at Moss Landing MO899 ($x \approx 504$ m) under the NGL SMT model (Ulmer et al., 2024). Solid: 0 cm baseline; dashed: 200 cm SLR.

The underlying hazard curves at the representative point on each transect are shown in Figures 6.8 and 6.9: the mean annual rate of non-exceedance against Factor of Safety of Liquefaction, FS_L , for all five representative CPTs, with the 0 cm baseline solid and the 200 cm SLR condition dashed. The contrast between sites is clear: Santa Monica has low baseline curves but a wide separation at 200 cm, whereas Moss Landing has higher baseline curves and a narrower gap, since several susceptible layers there are already saturated at baseline. At Santa Monica the CPT 888 and CPT 365 curves sit highest across the plotted range and CPT 324 lowest; at Moss Landing CPT 888 and CPT 324 is highest and CPT 336 lowest, with the remaining profiles between them.

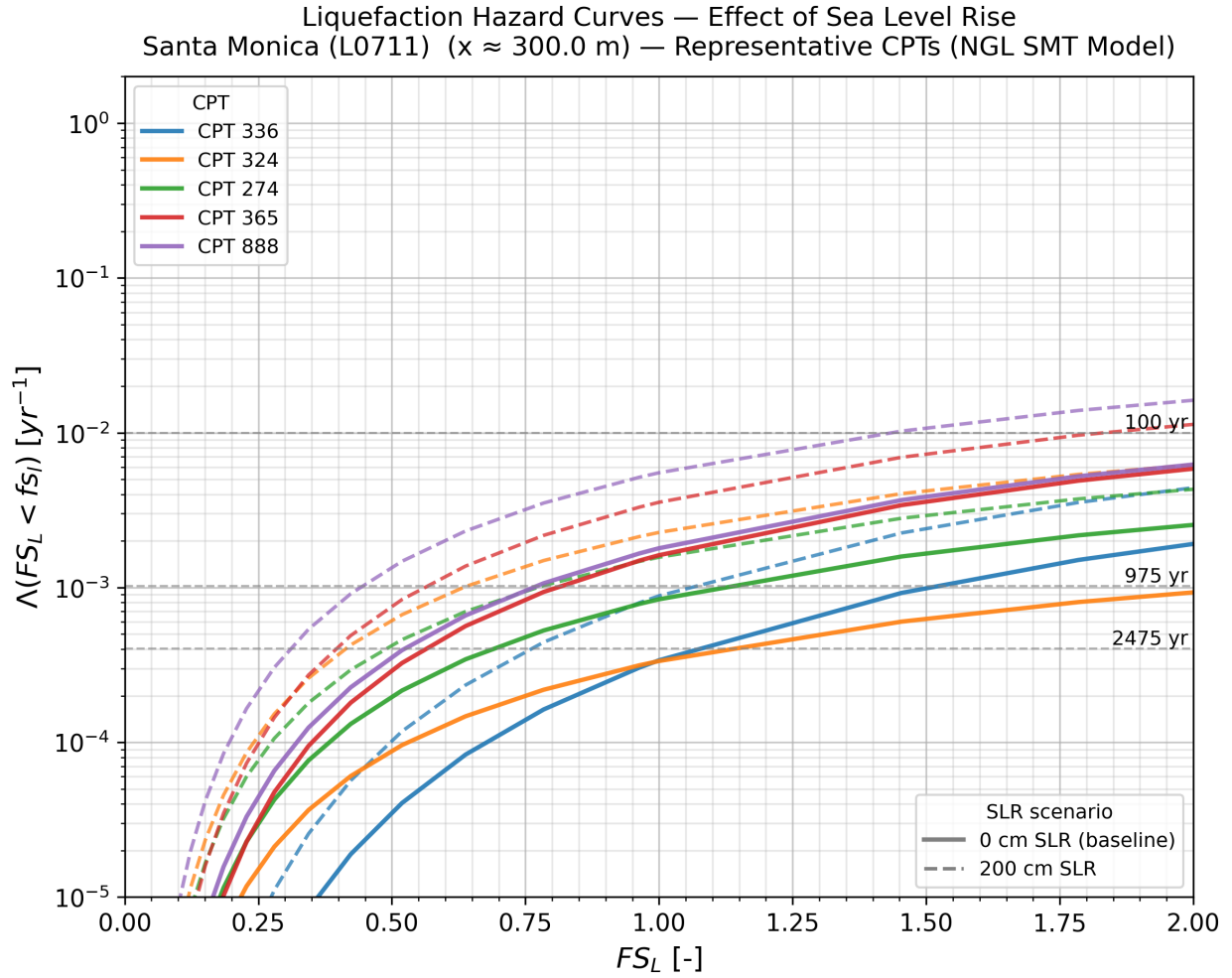


Figure 6.8: Liquefaction Hazard Curves for the five representative CPTs at Santa Monica L0711 ($x \approx 300$ m), NGL SMT model (Ulmer et al., 2024). Solid: 0 cm baseline; dashed: 200 cm SLR. Reference lines mark the 100-, 975-, and 2475-yr return periods.

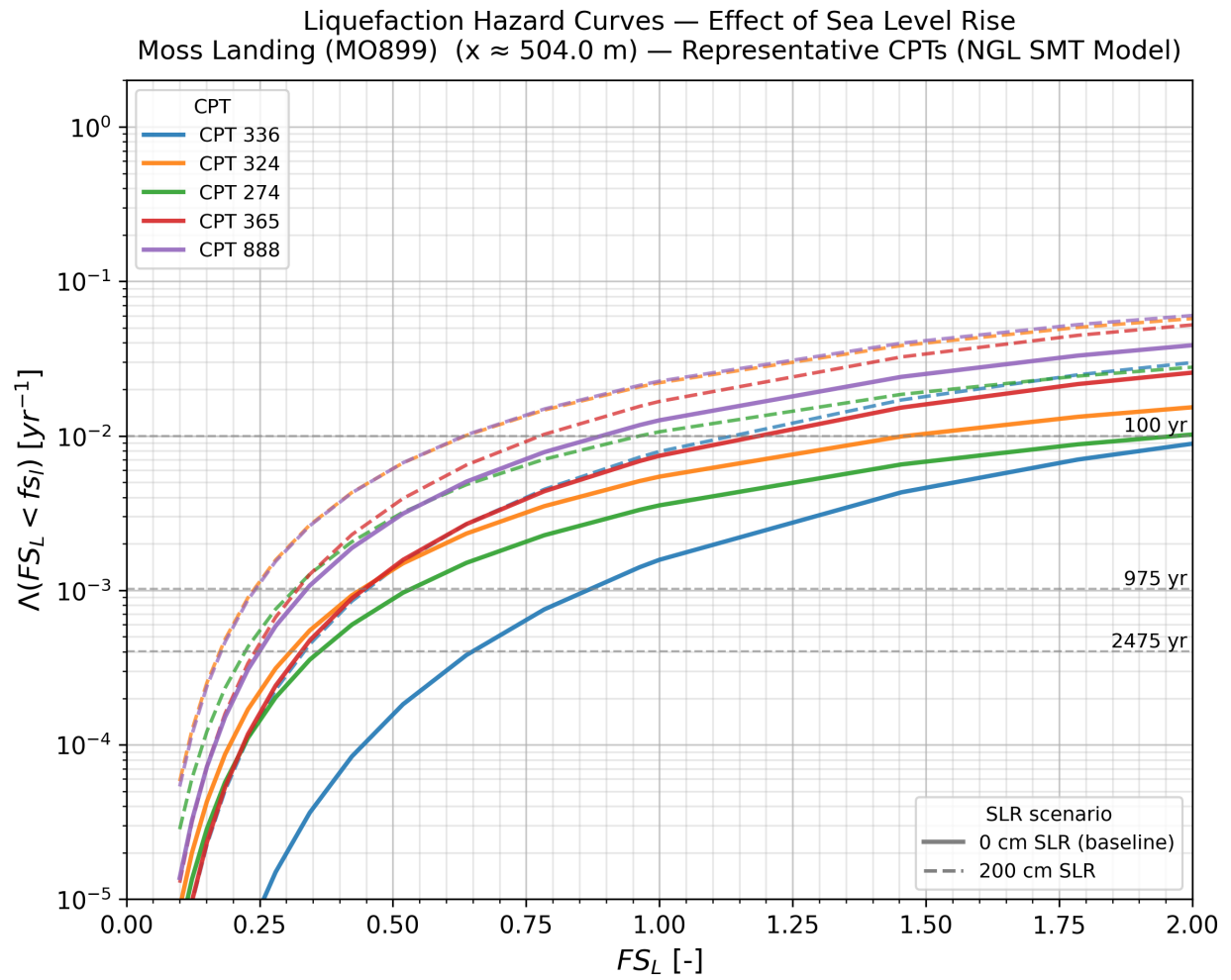


Figure 6.9: As in Figure 6.8, for Moss Landing MO899 ($x \approx 504$ m).

It should also be noted that for CPT 324, the cone profile did not have data in the upper 1.45 m. Additionally, as part of the code, the water table was constrained and could not be placed above the shallowest layer. Therefore, in the simulations the water table is floored at 1.45 m, although the simulated value could have been shallower. The return periods and return period ratios that these profiles produce under SLR are examined in Sections 6.3.1 and 6.3.2.

Within this chapter, the main quantity mapped is the annual rate of non-exceedance and its reciprocal, the return period for a $FS_L = 1$. Unless otherwise stated, the plots show the median or 50th percentile values. There are four sea level increments used throughout, 0 *cm*, 50 *cm*, 100 *cm*, and 200 *cm*, which align with current conditions and plausible mid and end of century conditions (California Sea Level Rise Science Task Force, 2024). Lastly, reporting the hazard as a return period allows anchoring the result to real life design brackets - this is shown with the 475 and 2475 year return periods appearing on the figures' colorbars. All elevations reported in this chapter, including ground surface elevations, water table elevations, and the sea level increments themselves, are referenced to Mean Sea Level (MSL).

Throughout the chapter the effect of sea level rise is reported as the return period ratio

$$\frac{RP_{0\text{cm}}}{RP_{\text{scenario}}} \quad (6.1)$$

so that a ratio > 1 denotes a shortening of the return period, i.e. an increase in hazard, and a ratio < 1 denotes the reverse.

6.2 Hazard Along a MOP Line Transect

6.2.1 Hazard Curves at Various Locations Along a Transect

Figures 6.10 and 6.11 present the paired PSHA and PLHA hazard curves at Santa Monica (L0711) and at Moss Landing (MO899) for the median water table values for a

single CPT (365), as an example. Each curve color indicates the distance inland from the MOP shoreline origin ($x=0$), as shown with the color bar.

Given how the PFLOTRAN data was distilled, the liquefaction hazard database is calculated at a single median timestep per spatial location and that day differs from location to location. To isolate the spatial signal, only locations whose sampled days fall within a narrow window are plotted together, so that time is approximately held constant across the transect. The number of curves in each fan therefore reflects how many locations happened to be sampled within that shared time window.

The left panels for both sites show the seismic hazard curves from a conventional PSHA, with annual rate of exceedance against PGA using the four NGA-West2 V_{S30} dependent ground motion models. The right panels show the corresponding PLHA results, plotting annual rate of non-exceedance of FS_L . The seismic hazard is essentially uniform across the transect, which is to be expected. The source to site distances calculated for the PSHA, such as R_{JB} and R_{RUP} to the nearby faults, differ only slightly over these distances, and the seismic hazard is also partially controlled by the distance to background seismicity. The V_{S30} assigned at each location along the transect varies as it is taken from the [Thompson \(2018\)](#) raster, and this also contributes to the very moderate fanning seen in the PSHA curves.

By comparison, the PLHA curves differ by several orders of magnitude. Variation in the water table changes both the effective stress and which layers are saturated, and both effects shift the liquefaction triggering and hazard. At Santa Monica, the return period increases with distance inland, whereas at Moss Landing the trend is reversed. This difference reflects the CPT profile, the transect location, and the topography of each site. Specifically, Moss Landing has low elevation and shallow groundwater farther inland, and also has a higher elevation berm near the coast that causes these differences.

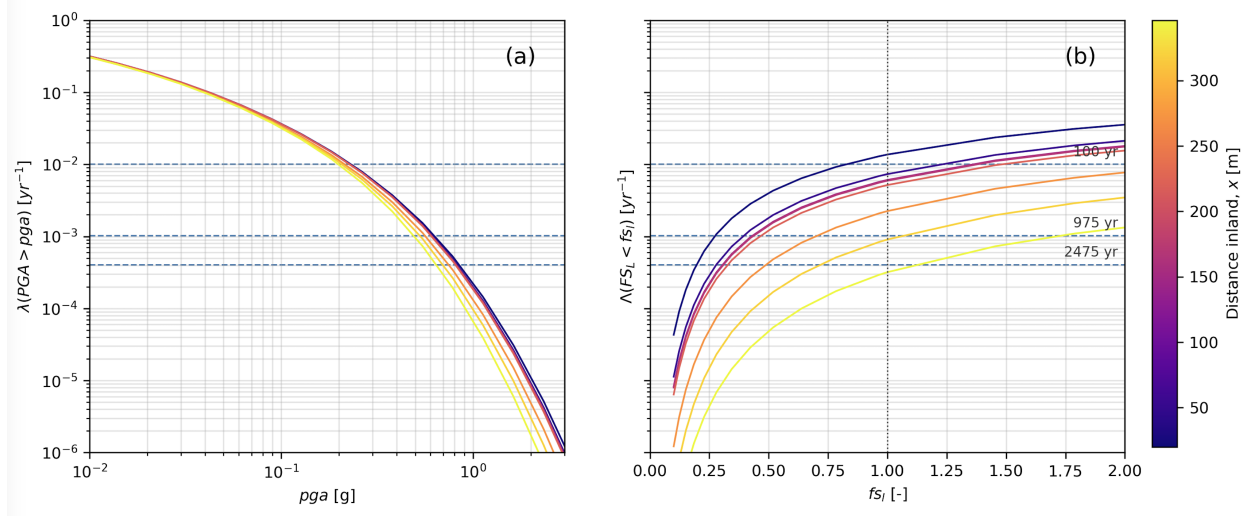


Figure 6.10: PSHA and PLHA Curves along L0711 (Santa Monica), CPT 365, median water table. Color denotes distance inland from the MOP shoreline origin.

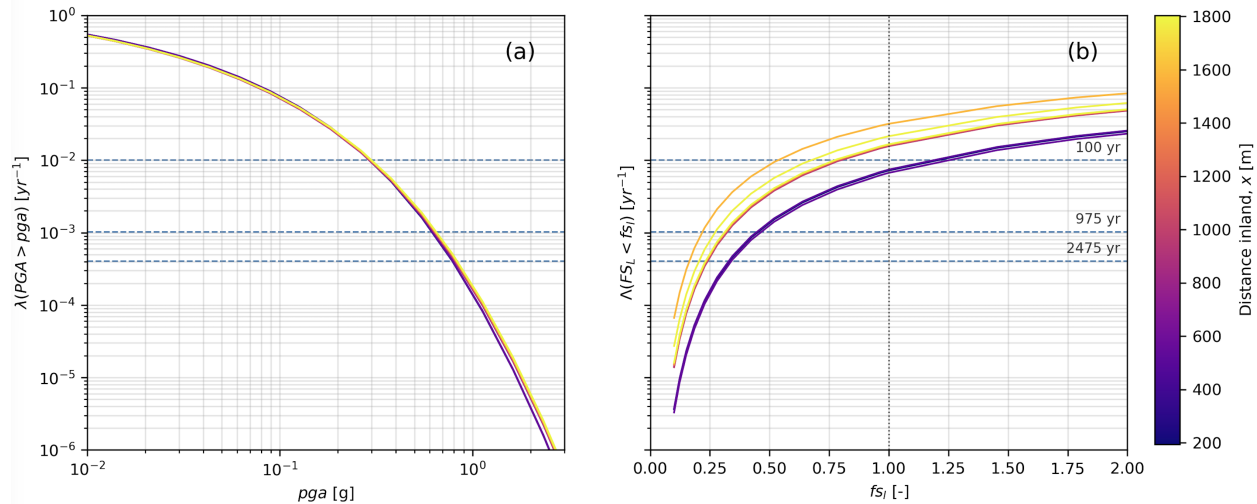


Figure 6.11: PSHA and PLHA Curves along MO899 (Moss Landing), CPT 365, median water table. Color denotes distance inland from the MOP shoreline origin.

6.2.2 Tidal Fluctuations Along the Five CPTs

It is first worth establishing how much the hazard fluctuates under the baseline tidal forcing envelope. Figures 6.12–6.16 plot the return period for $FS_L = 1$ along the Santa Monica transect for each of the five representative CPTs; within every panel the median is

drawn as a solid line and the 5th–95th percentile spread of the numerically simulated tidal range is shown as a shaded band, for both 0 and 200 cm of SLR. Figures 6.17–6.21 show the equivalent comparison for Moss Landing. In every panel the 200 cm curve lies below the 0 cm curve, since SLR shortens the return period at every location, and the shaded band is drawn around its own median line.

At both sites, the return period closely follows the ground surface elevation of the transect (shown in the inset of each figure). This is because the water table near coastal locations tracks mean sea level, so the depth to groundwater, an important parameter in liquefaction triggering, is controlled by the surface elevation.

At Santa Monica, in both the 0 cm and 200 cm cases, the tidal bands show some fluctuation within roughly the first one to two hundred meters of the shoreline but then converge farther inland (Figures 6.12–6.16). This is consistent with the site’s cliff backed topography: the tidal fluctuation attenuates rapidly with distance. A practical implication is that at a site like L0711 a single representative (median) water table is an adequate description of the tidal state for hazard purposes more inland. There is some deviation from the median, especially in the 200 cm case, which can extend over 100 m inland.

Moss Landing behaves differently, which can be attributed to the transect being located within a low lying estuary with a long, shallow confining layer. Tidal fluctuations again begin at the shoreline, but they propagate much further inland than at Santa Monica (Figures 6.17–6.21). In the 0 cm case, fluctuations continue until roughly 750 m inland. In the 200 cm case the tidal signal is not damped and fluctuations propagate to the inland boundary at 2000 m. In that scenario, the tidal range is enough to saturate some previously dry soil layers even in the median case, shortening the return period significantly. This can be attributed mainly to the shallow confining layer that extends more than 1500 m inland and transmits the tidal forcing signal, raising and confining the artesian pressures, which increases the annual rates of non-exceedance and decreases the return periods.

Although there are fluctuations driven by the tidal signal alone, it will be shown that

SLR plays a much more significant role in the overall change in return period. The median is therefore used in the remainder of the analysis, with the understanding that the 5th and 95th percentiles bound a wider range of return periods.

Santa Monica Tidal Fluctuations

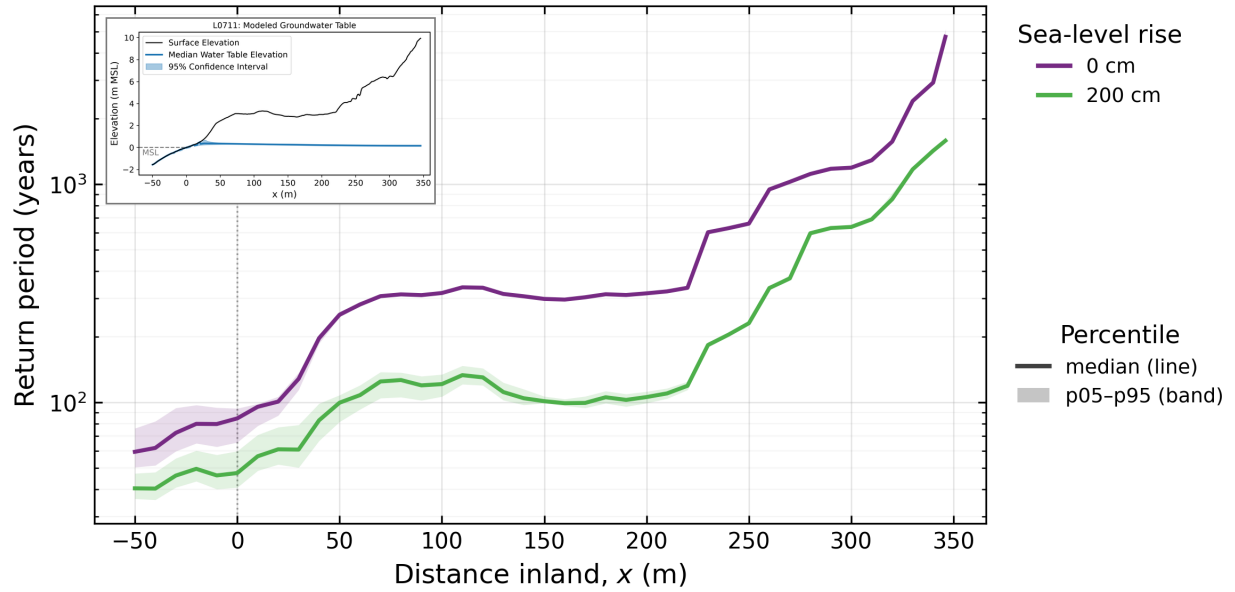


Figure 6.12: Return period for liquefaction triggering at $FS_L = 1$ at CPT 274 along the Santa Monica transect L0711 for tidal fluctuations (5th, 50th, and 95th percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

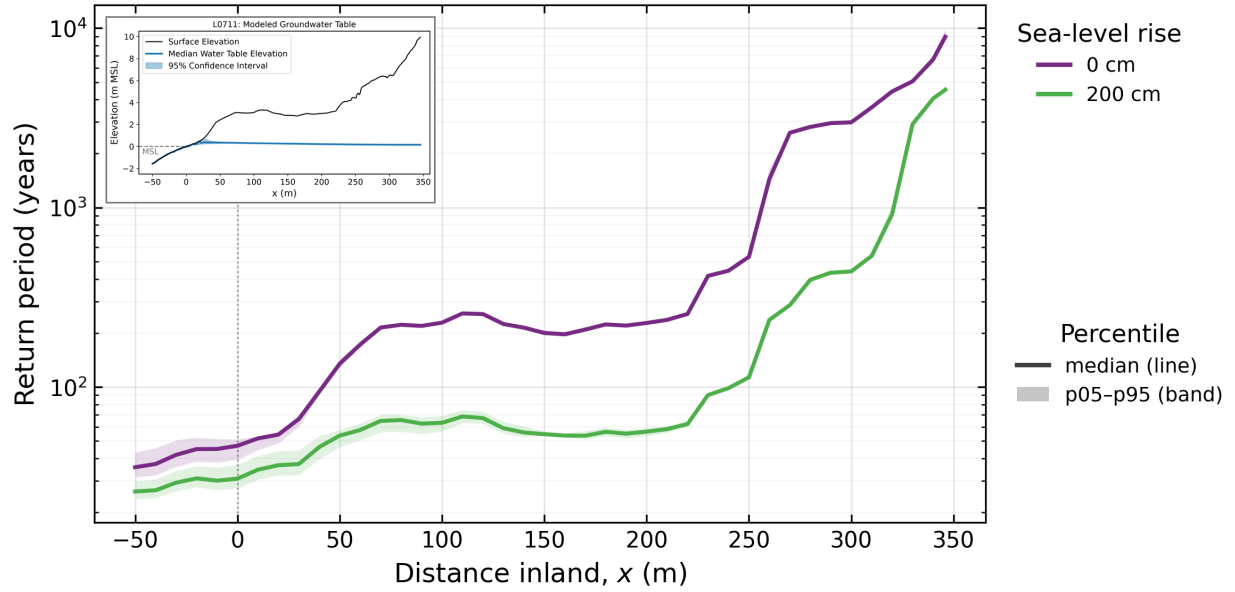


Figure 6.13: Return period for liquefaction triggering at $FS_L = 1$ at CPT 324 along the Santa Monica transect L0711 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

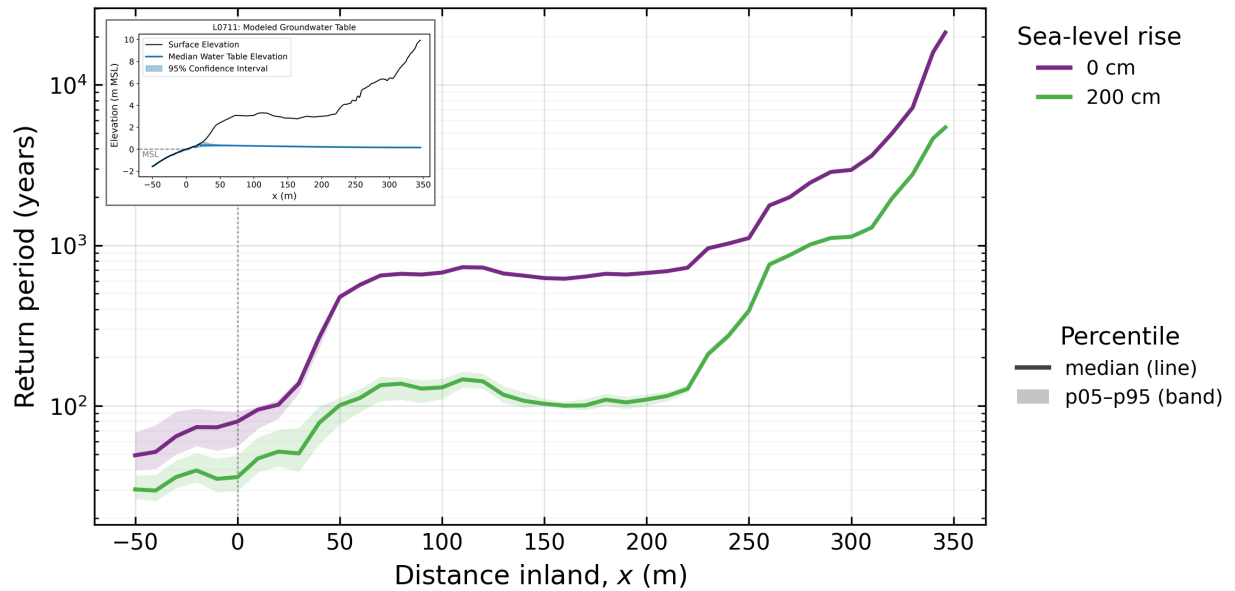


Figure 6.14: Return period for liquefaction triggering at $FS_L = 1$ at CPT 336 along the Santa Monica transect L0711 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

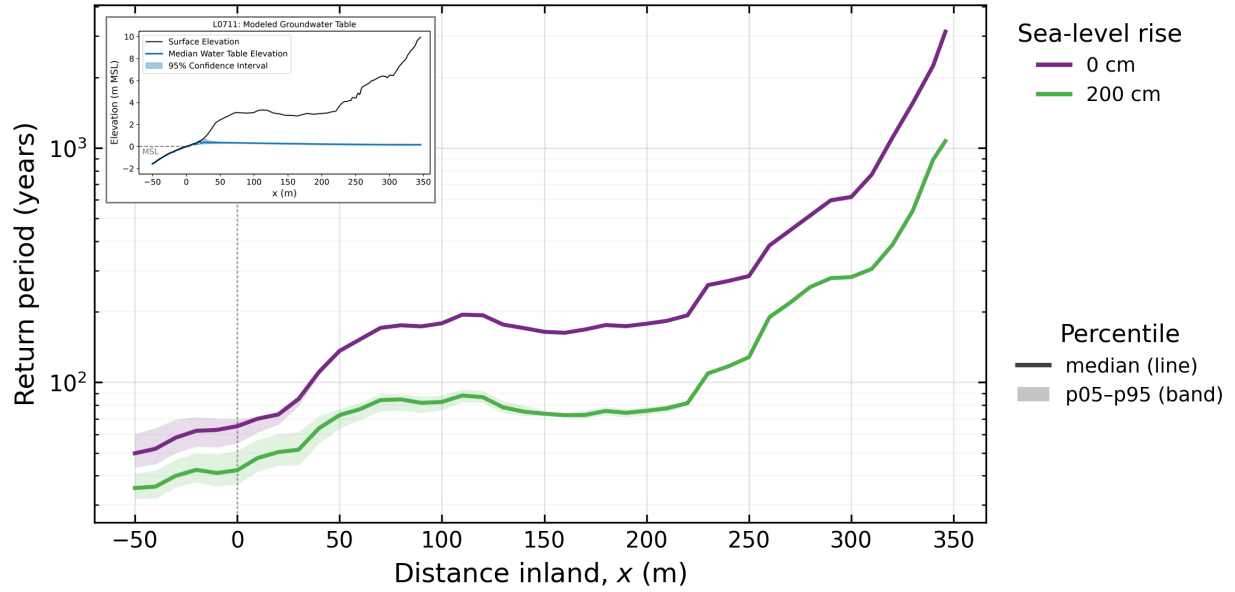


Figure 6.15: Return period for liquefaction triggering at $FS_L = 1$ at CPT 365 along the Santa Monica transect L0711 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

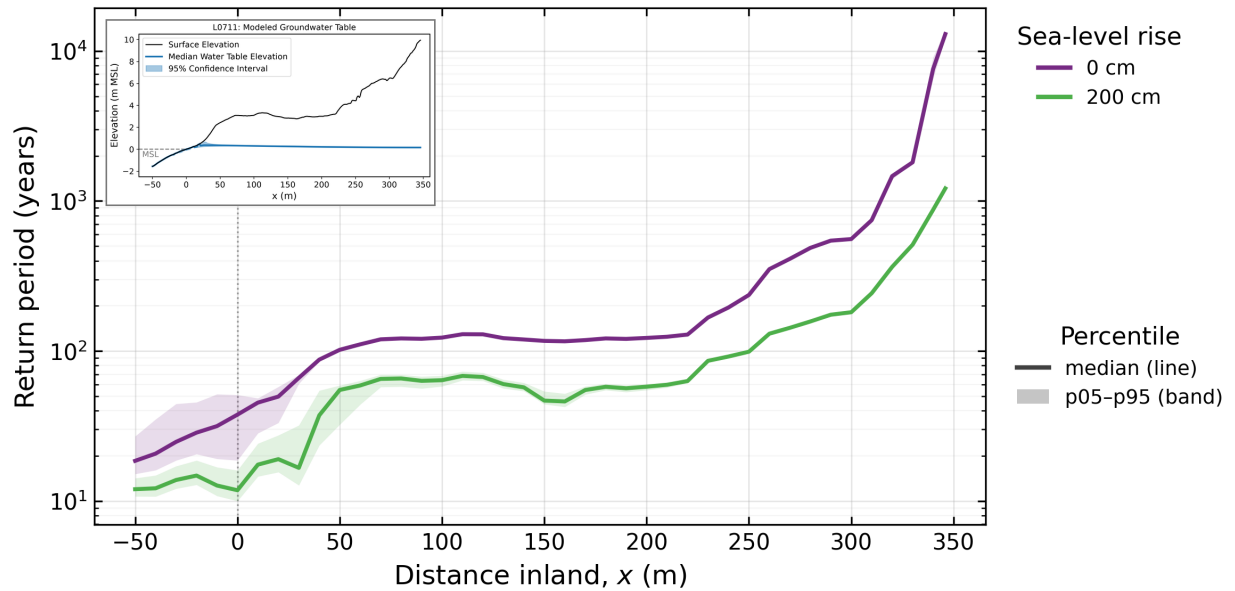


Figure 6.16: Return period for liquefaction triggering at $FS_L = 1$ at CPT 888 along the Santa Monica transect L0711 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

Moss Landing Tidal Fluctuations

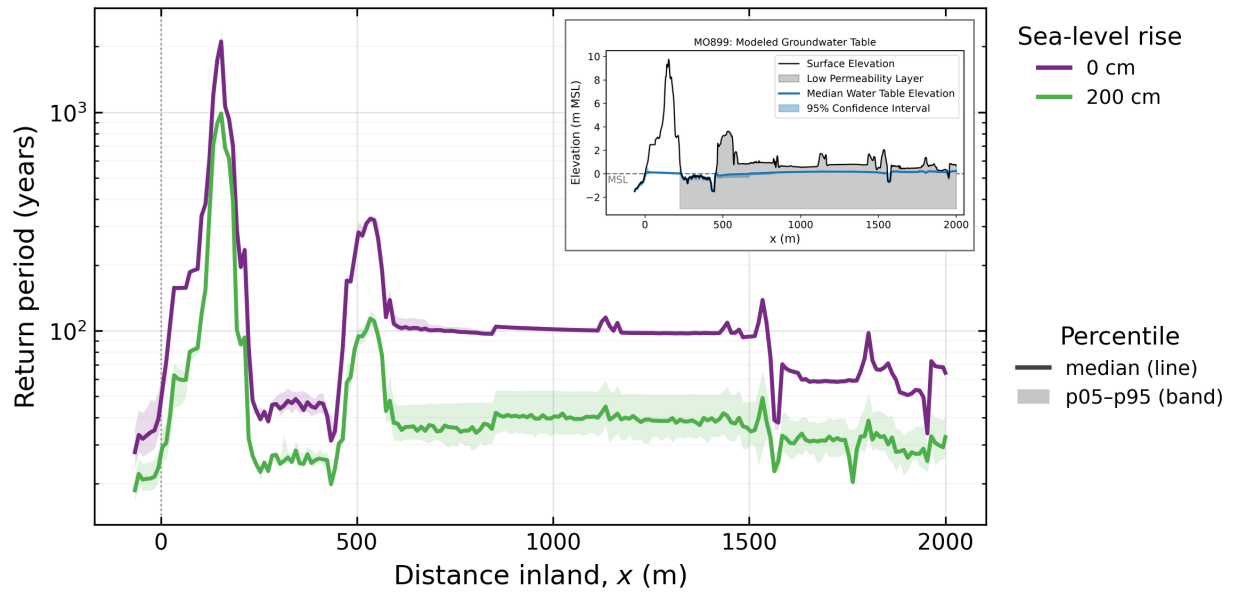


Figure 6.17: Return period for liquefaction triggering at $FS_L = 1$ at CPT 274 along the Moss Landing transect MO899 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

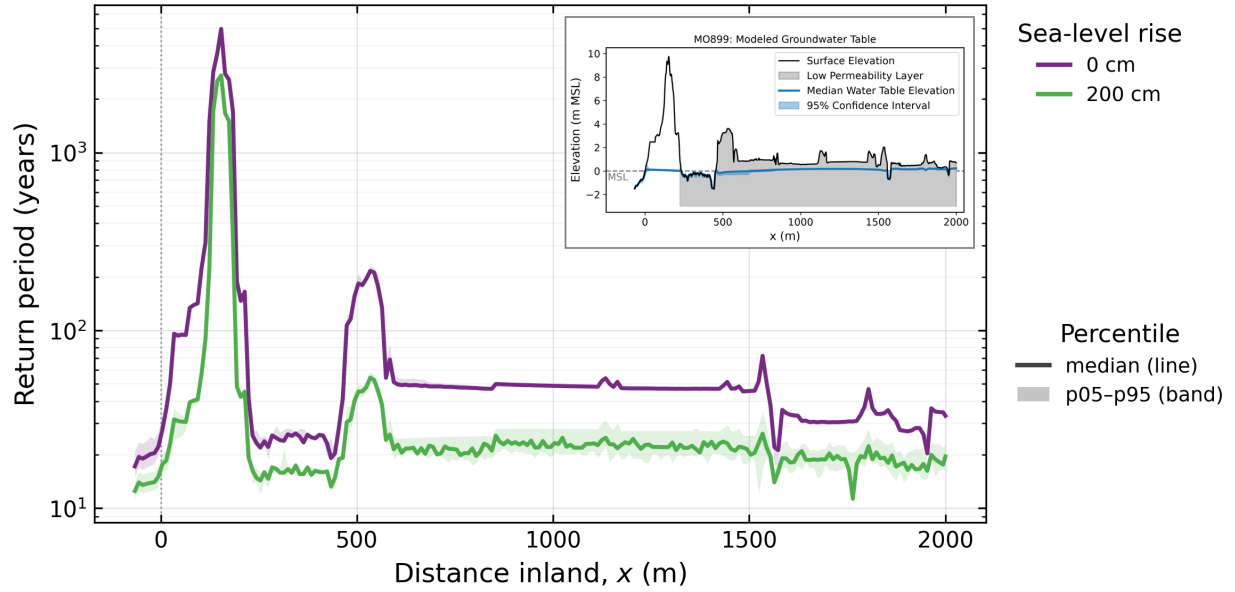


Figure 6.18: Return period for liquefaction triggering at $FS_L = 1$ at CPT 324 along the Moss Landing transect MO899 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

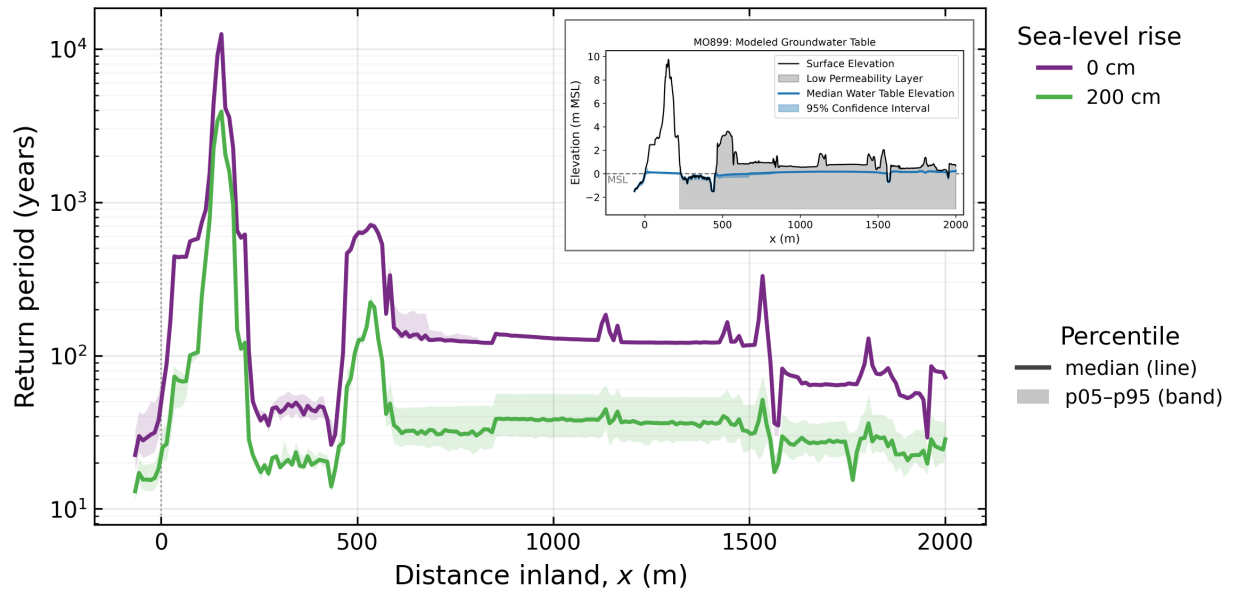


Figure 6.19: Return period for liquefaction triggering at $FS_L = 1$ at CPT 336 along the Moss Landing transect MO899 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

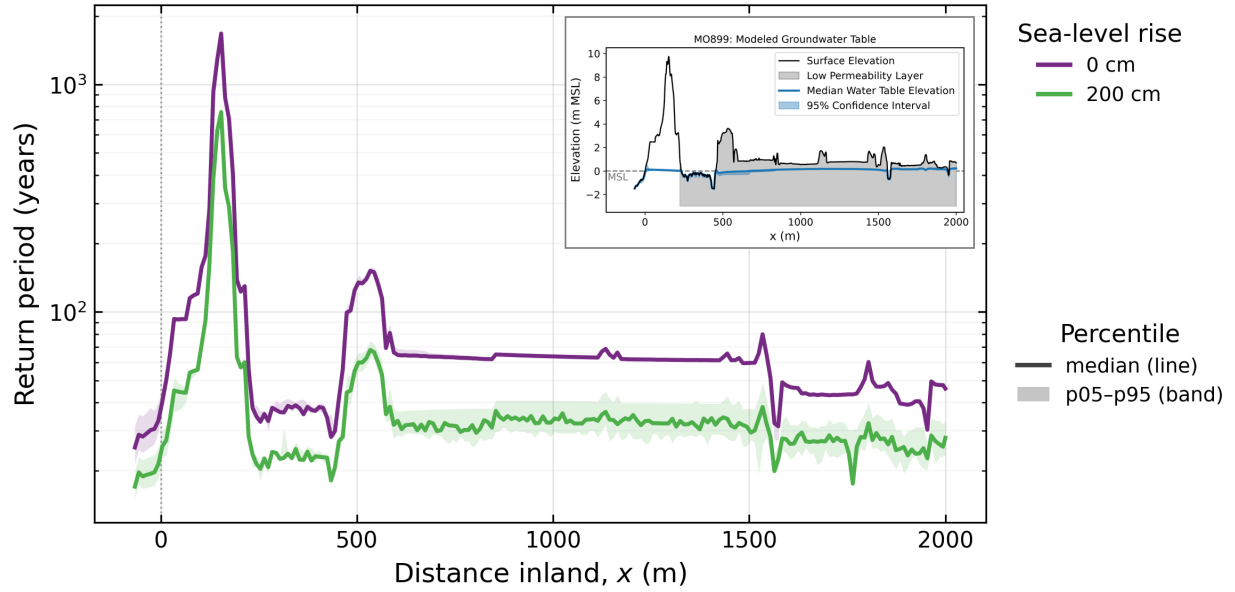


Figure 6.20: Return period for liquefaction triggering at $FS_L = 1$ at CPT 365 along the Moss Landing transect MO899 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

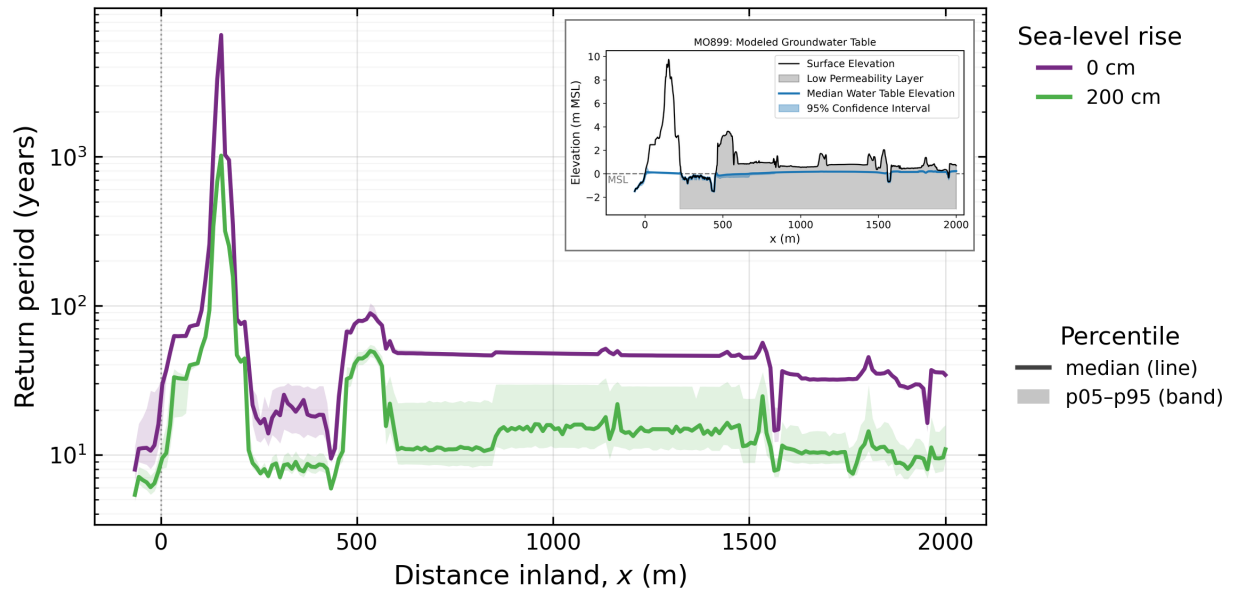


Figure 6.21: Return period for liquefaction triggering at $FS_L = 1$ at CPT 888 along the Moss Landing transect MO899 for tidal fluctuations (5^{th} , 50^{th} , and 95^{th} percentiles) at 0 cm and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

6.2.3 SLR Scenarios

Return Period Behavior in Transects with SLR

The transects were also analyzed for SLR, in terms of the return period for a Factor of Safety of Liquefaction $FS_L = 1$ for 0, 50 cm, 100 cm, and 200 cm of SLR. Figures 6.22–6.26 show the median return period along the Santa Monica transect, and Figures 6.28–6.32 show the same for Moss Landing. Each site is represented by five figures, one per representative CPT, so that the groundwater and the soil profile response can be interpreted together. In every figure the four curves are strictly ordered: each increment of SLR lowers the curve, so the uppermost curve is the 0 cm baseline and the lowest is 200 cm. The insets reproduce the modeled ground surface elevation and median water table elevation, as they are the key to interpreting the along transect hazard: the same pore pressure field produces very different hazard changes depending on whether the newly saturated layers coincide with susceptible layers in that particular CPT. Because the simulated water table is nearly flat and effectively pinned to mean sea level across both transects, depth to groundwater at any evaluation point is controlled almost entirely by ground surface elevation. The return period therefore mirrors the topographic profile.

At Santa Monica, the return period increases close to monotonically with distance inland, because the ground surface rises steadily from the beach to the cliff, as shown in the inset of Figures 6.22–6.26. Median return periods across the five CPTs rise from roughly 50 yr on the beach and berm ($x < 20$ m) to more than 1000 yr on the cliff face ($x > 290$ m). Because each representative CPT is applied at every evaluation point along the transect, the soil profile within any one curve is held fixed, so variation along that curve is produced by the change in depth to groundwater rather than by changes in stratigraphy. For a single profile, the return period at a given location can change significantly between the baseline and 200 cm cases, whereas the seismic hazard at that same location is essentially unchanged. It should be understood that even though Figure 6.27 may show very extreme ratios between the

SLR scenario and baseline, the actual return periods being compared are often quite long. Therefore, SLR may not have much practical impact for many of the CPTs at Santa Monica.

The Moss Landing ground surface is not as monotonic, and this is what produces the strong along transect fluctuations shown in Figures 6.28–6.32. The dune ridge at $x \approx 120$ –200 m, where the surface rises to nearly 10 m MSL, carries the longest return periods anywhere on the transect. Immediately behind the ridge, between $x \approx 200$ and 320 m, the ground drops back to near MSL and the return periods reduce by two orders of magnitude. From $x \approx 620$ to 1450 m, where the low permeability layer shown in the inset extends continuously inland, the curves are nearly flat but visibly ragged. Beyond $x \approx 1700$ m the medians fall again. The character of the Moss Landing curves can be attributed to the tidally driven, confined system described above. Where the confining layer transmits the tidal signal inland, the water table sits within roughly a meter of the ground surface along most of the transect, so even small changes in surface elevation are enough to move the water table across a layer boundary in the CPT and switch that layer between the saturated and unsaturated states. Santa Monica, which drains freely into the beach aquifer and has no comparable confining unit, produces level curves by comparison.

Santa Monica SLR transects

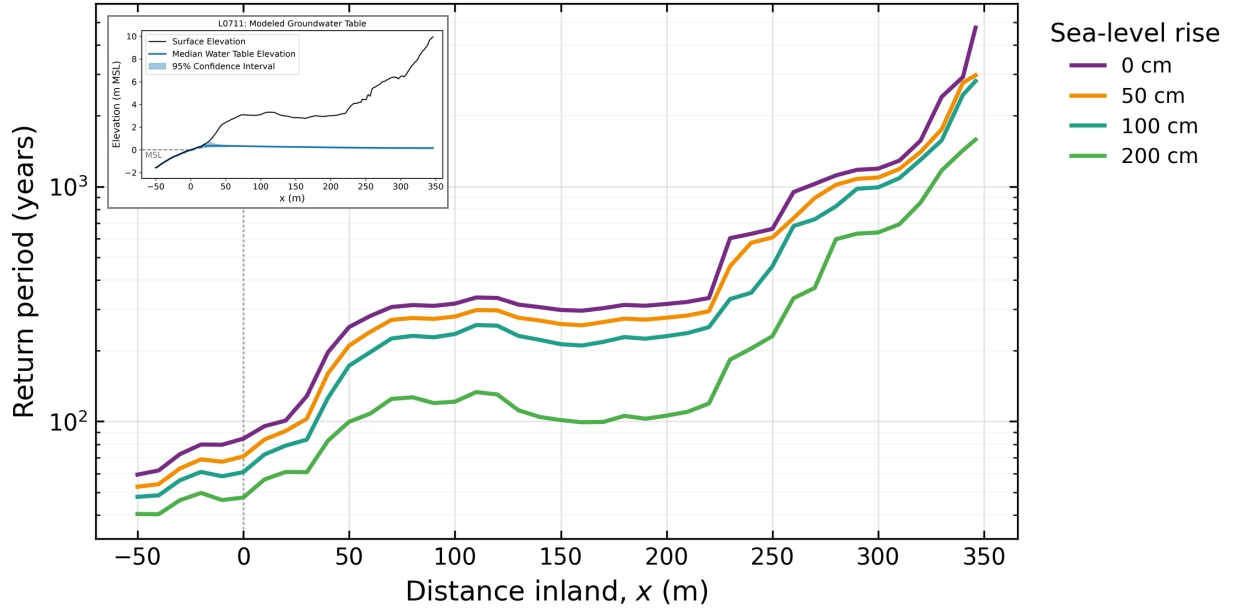


Figure 6.22: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 274 along the Santa Monica transect L0711 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

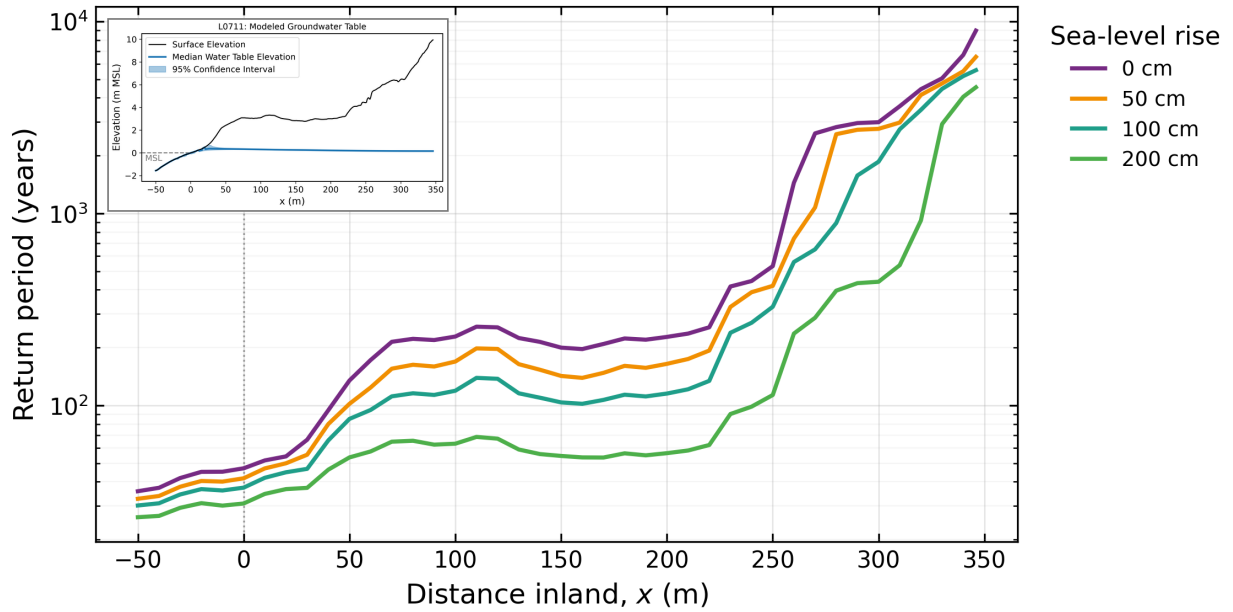


Figure 6.23: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 324 along the Santa Monica transect L0711 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

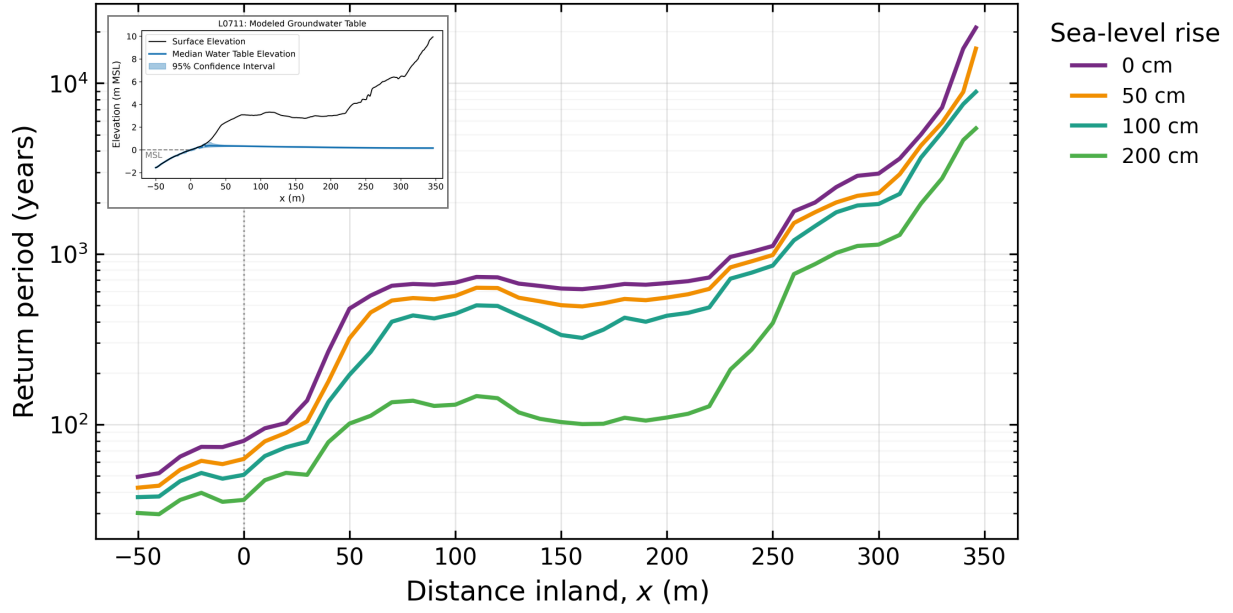


Figure 6.24: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 336 along the Santa Monica transect L0711 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

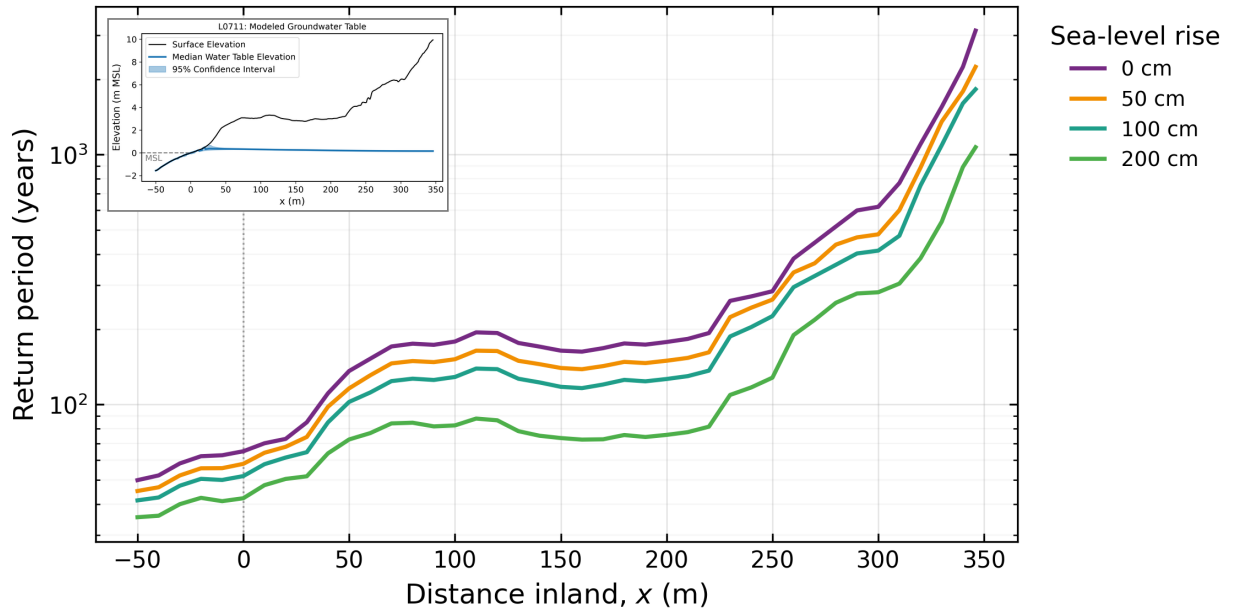


Figure 6.25: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 365 along the Santa Monica transect L0711 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

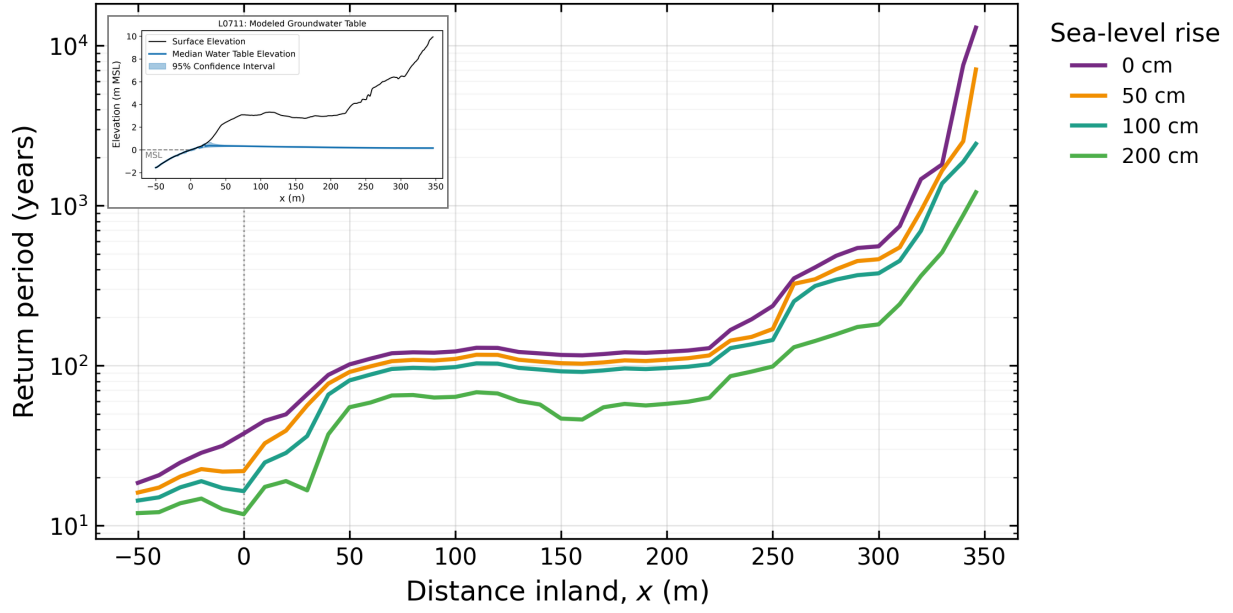


Figure 6.26: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 888 along the Santa Monica transect L0711 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

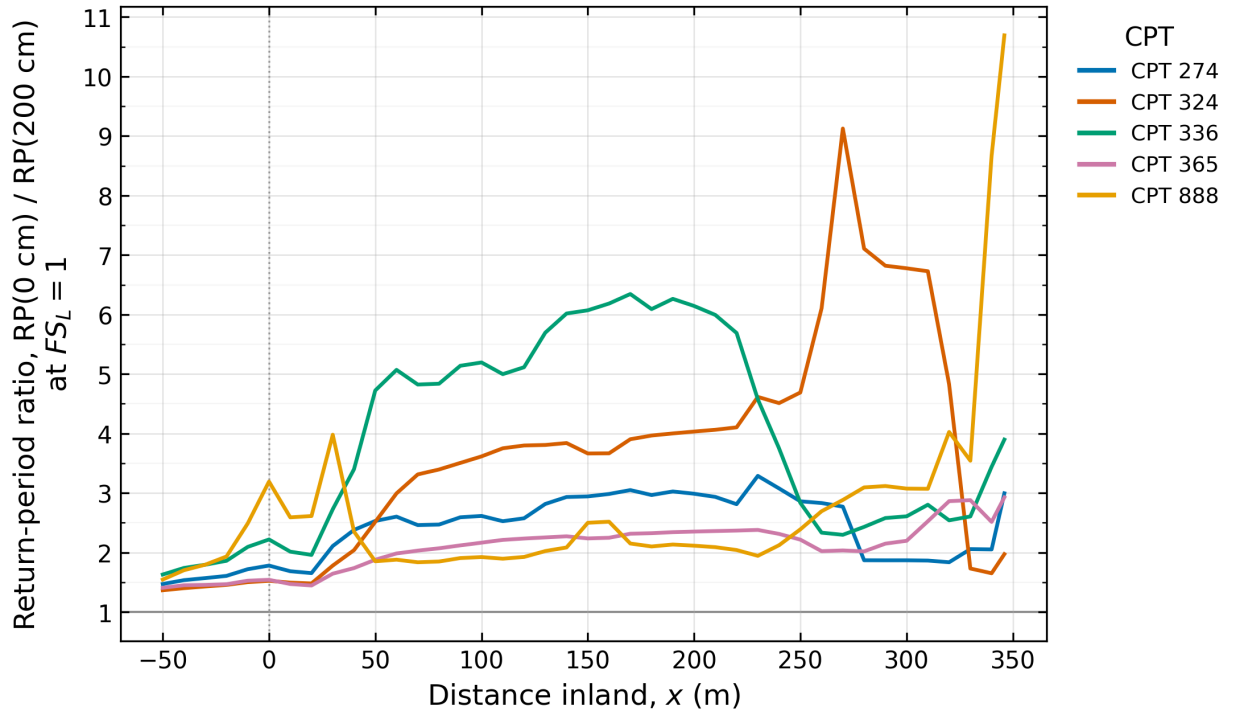


Figure 6.27: Return period ratio for a $FS_L = 1$ for liquefaction triggering along the Santa Monica transect L0711 (median water table).

Along the Santa Monica transect, CPT 336 sustains the highest ratios through the middle of the transect, near 5 to 6, while CPT 324 spikes above 9 near $x = 270$ m and CPT 888 exceeds 10 at the far inland end; CPT 274 holds near 3 and CPT 365 remains lowest, near 2, throughout.

Moss Landing SLR transects

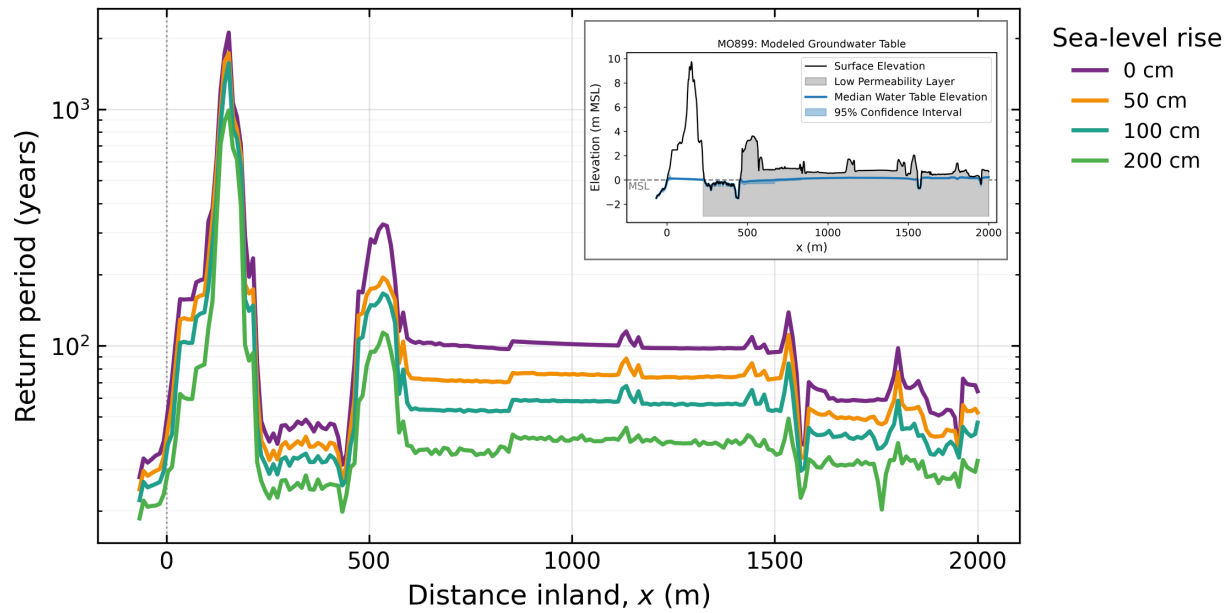


Figure 6.28: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 274 along the Moss Landing transect MO899 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

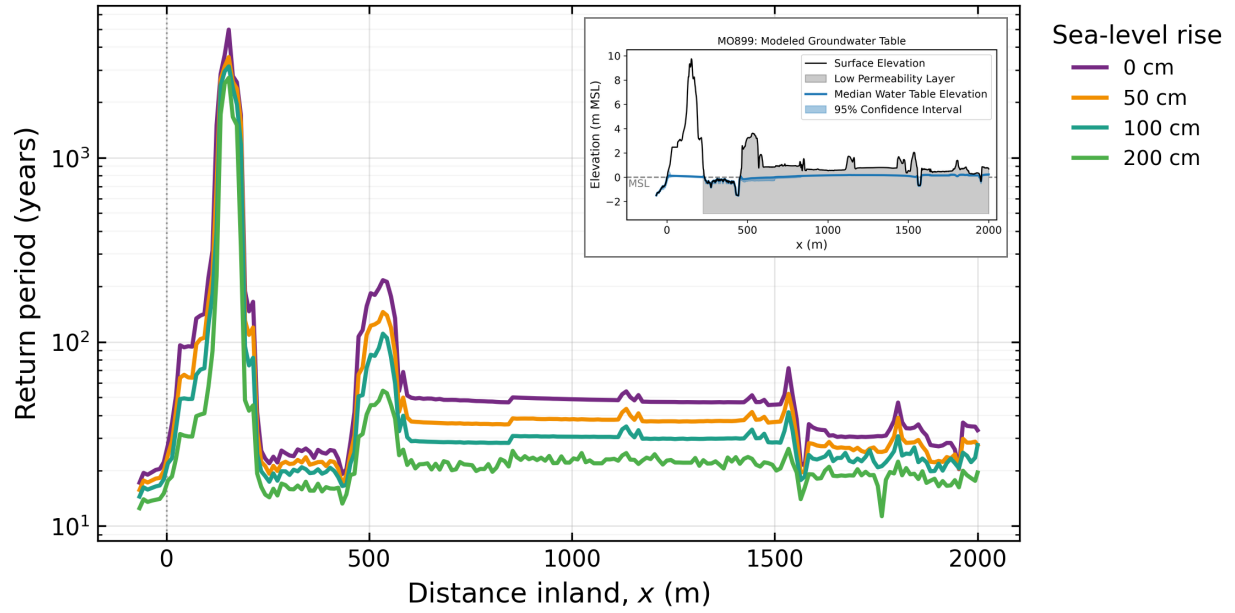


Figure 6.29: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 324 along the Moss Landing transect MO899 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

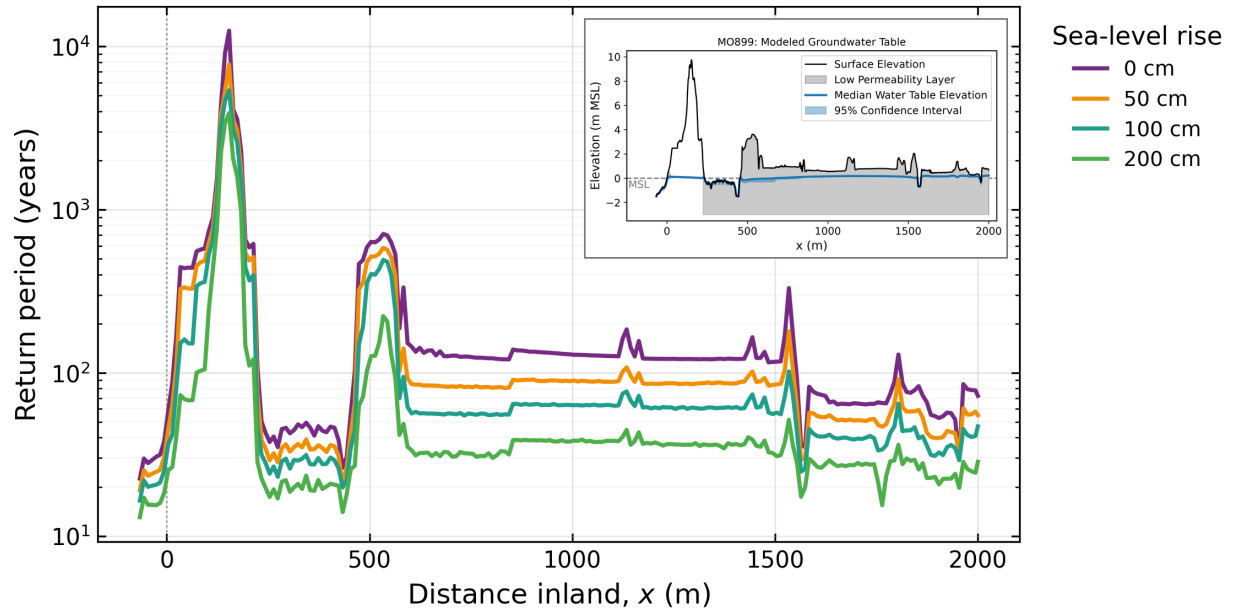


Figure 6.30: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 336 along the Moss Landing transect MO899 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

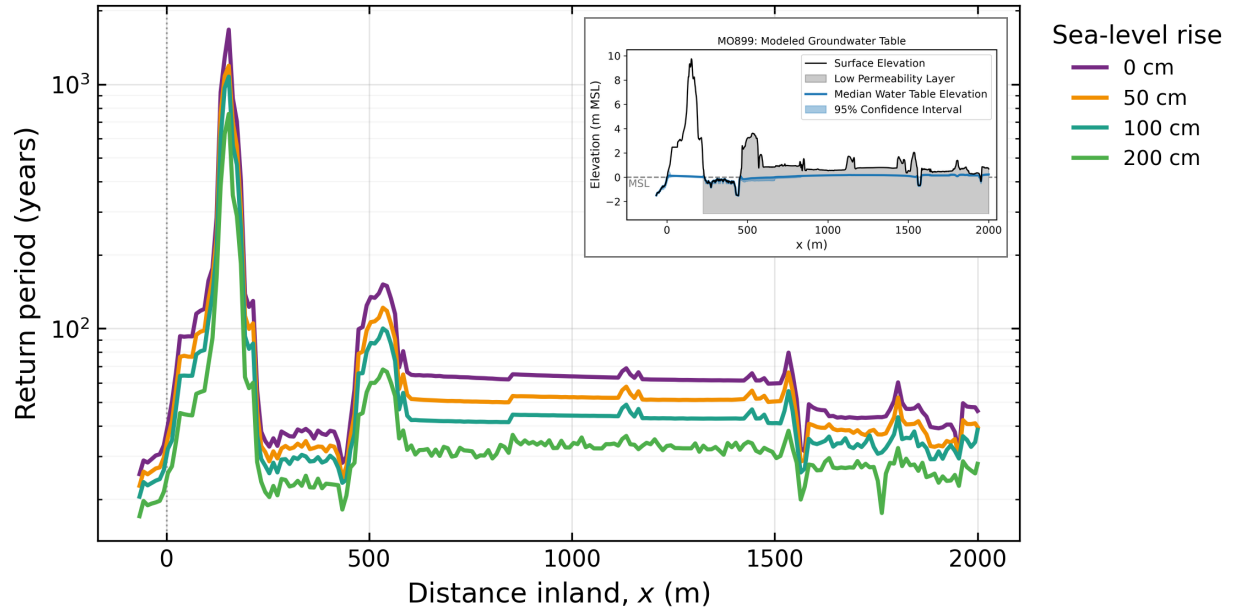


Figure 6.31: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 365 along the Moss Landing transect MO899 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

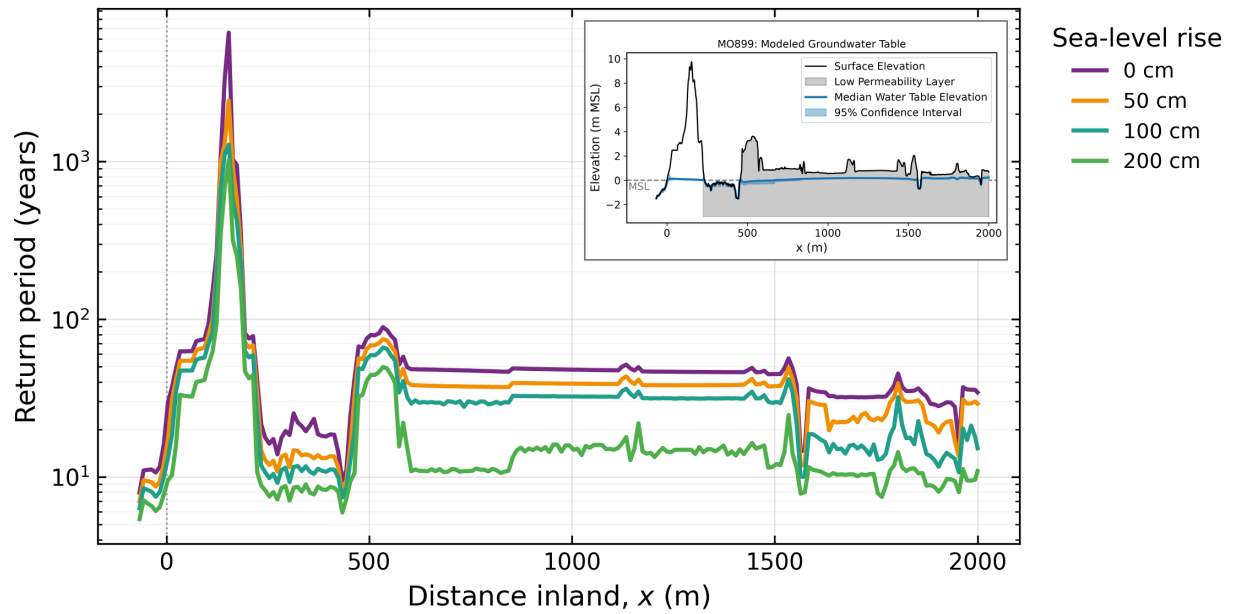


Figure 6.32: Median return period for liquefaction triggering at $FS_L = 1$ at CPT 888 along the Moss Landing transect MO899 under 0, 50, 100, and 200 cm of sea level rise. The inset shows the modeled groundwater system for the transect relative to mean sea level.

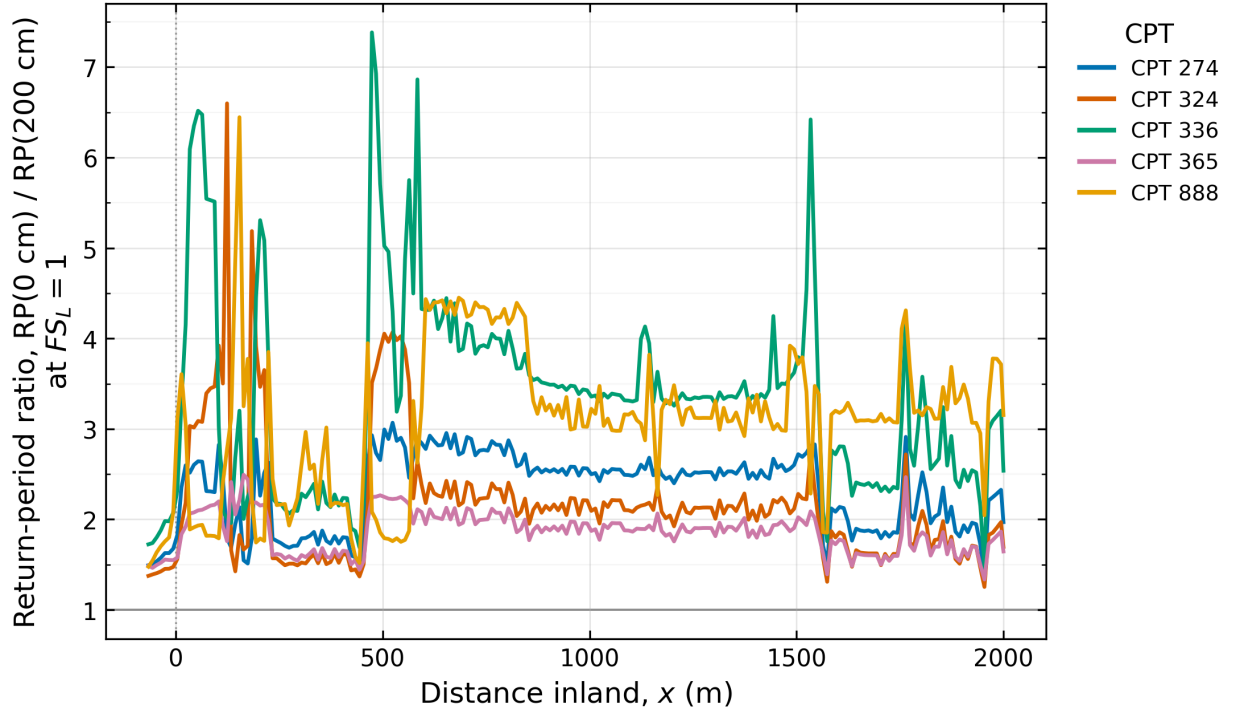


Figure 6.33: Return period ratio for a $FS_L = 1$ for liquefaction triggering along the Moss Landing transect MO899 (median water table).

6.2.4 Preliminary Conclusions from Transect Level Analysis

There are some general observations from the transect scale results that can be carried forward. First, the spatial variability of liquefaction hazard along a shore normal transect is controlled by the groundwater response, and is much more significant than the spatial variability of the seismic hazard. PSHA curves are effectively uniform over these distances while PLHA return periods can vary by orders of magnitude. Second, tidal fluctuations can be meaningful and are directly related to the geology and ocean dynamics of the site. Also, SLR increases tidal influence, and its influence can extend reasonable distances inland. Third, the inland influence of SLR on PLHA varies by location and is larger at estuary sites like Moss Landing. Lastly, the influence of SLR is more significant for profiles with shallow susceptible layers that are currently unsaturated but become submerged as sea level rises. Both of these transects illustrate the site specific nature of this problem and are further explored in Section 6.3.

Sea level rise therefore does not fundamentally alter the hazard at already marginal sites such as Moss Landing, where the susceptible layers are saturated at baseline and the return periods are short before any rise is applied. The largest changes occur instead where susceptible material still sits above the present water table and then becomes saturated with SLR.

As noted at the start of this chapter, the groundwater model underlying these results is preliminary, particularly at the lower permeability Moss Landing site. The PLHA results may change when the groundwater simulations are refined.

6.3 Mapping Influence of SLR on PLHA

For the final evaluation of these two sites, a full scale analysis was completed. The regional analysis comprised over 1,000,000 individual probabilistic liquefaction hazard calculations across the Santa Monica and Moss Landing study regions. The variation and large number of config files came from the multiple CPTs, the three water table percentiles, four sea level rise scenarios, and every `X_STEP` of 10m along the transect. Moss Landing, due to the increased number and length of transects (99 MOP lines versus 50 at Santa Monica), was about eight times larger in terms of the number of input files. Each config file produced a full hazard curve, totaling more than 20 million factor of safety of liquefaction values. Run serially and locally at approximately one minute per calculation, this workflow would require on the order of 1 million CPU minutes, or roughly 714 days (almost two years) of continuous single core computation. Parallelized across the Texas Advanced Computing Center's Frontera system ([Stanzione et al., 2020](#)) using an MPI driven, containerized pipeline discussed in Chapter 5, the two full production runs completed in approximately 47 hours of wall-clock time with an effective speedup of roughly 365.

This section interpolates the transect results onto continuous maps, for each of the five representative CPTs, under each sea level rise increment. Figures 6.34 to 6.63 each contain

three panels drawn over a basemap of Esri World Imagery: (a) the median return period for $FS_L = 1$ under baseline (0 cm) groundwater conditions, (b) the same quantity under the respective SLR scenario (50, 100, or 200 cm), and (c) the ratio of the two. The white lines overlaid on every panel are the MOP transects that supply the underlying data.

The hazard maps are created using a two-step linear interpolation: first, linearly along each transect in the cross-shore direction, then linearly between neighboring transects along-shore. Each transect’s evaluation points are first resampled onto a common cross-shore axis at 10m spacing. The transect geometry (longitude and latitude as functions of cross-shore distance x) is interpolated along this axis and extended linearly where a transect is shorter than its neighbors, so that every cell has complete corner coordinates. Hazard values themselves are never extrapolated. Alongshore, each cell takes a linear blend of the two transects bracketing it, weighted by its position between their shoreline origins. A single mesh therefore serves all four scenarios of a given CPT, so the baseline, scenario, and ratio panels share identical cells and each ratio is an exact cell-by-cell ratio. Return periods use a logarithmic color scale, fixed per CPT from the range across all four scenarios so that a given CPT’s three scenario maps are directly comparable; the ratio scale is symmetric about unity and clipped at the 95th percentile.

6.3.1 Santa Monica

The Santa Monica hazard maps (Figures 6.34 to 6.48) show a shore parallel strip roughly 350 m wide, terminating inland where the MOP transects end. Under baseline conditions (panel a), the strip is dominated by return periods of a few hundred to a few thousand years, depending on the CPT, with the shortest values along its seaward edge. Under 200cm of SLR (panel b) the same strip shifts to shorter return periods throughout. This decrease can be attributed to the baseline water table lying deep beneath the ground surface: up to 2m of SLR newly saturates susceptible layers that were previously dry, bringing them into triggering.

The ratio panels (panel c) are elevated across the entire map footprint and generally increase inland, confirming that SLR raises the hazard everywhere along the strip. The five CPTs behave differently, however, and the hazard is strongly dependent on the profile itself: CPT 365 has the minimum ratio between the 0cm and 200cm return periods, and CPT 888 the largest. The two also differ in spatial character. Additionally, the CPT 336 panel is strongly colored almost everywhere, because its shallow loose interbed lies above the baseline water table along most of the transect, so the response is widespread. CPT 888, by contrast, shows low ratios across most of its area with high values confined to small patches: its water table must rise past a threshold before it reaches the susceptible layers, so a hazard change appears only where SLR is large enough to cross it, and only over the narrow zone where that condition is met.

Santa Monica Hazard Maps

CPT 274 - Santa Monica

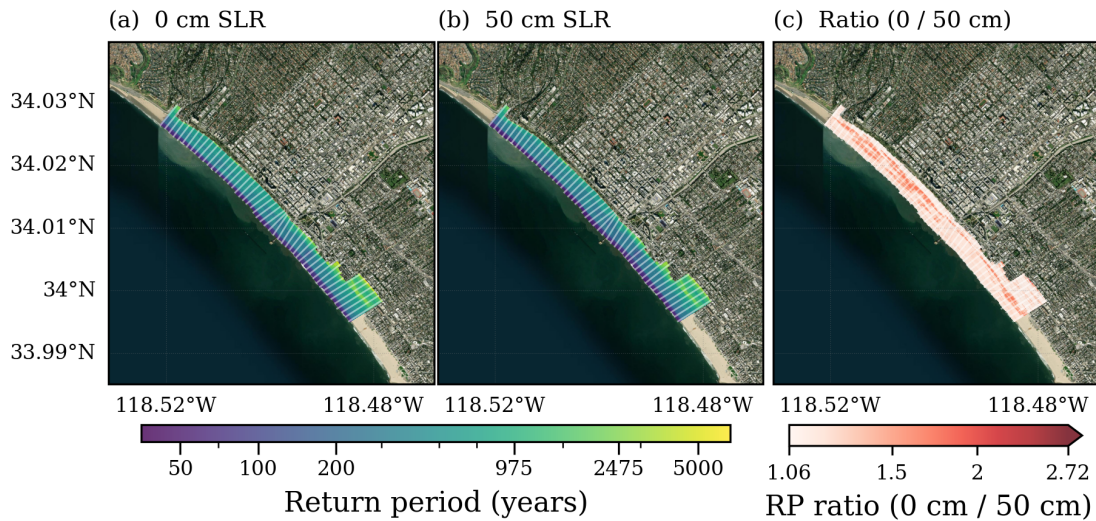


Figure 6.34: Median liquefaction hazard at Santa Monica for CPT 274: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

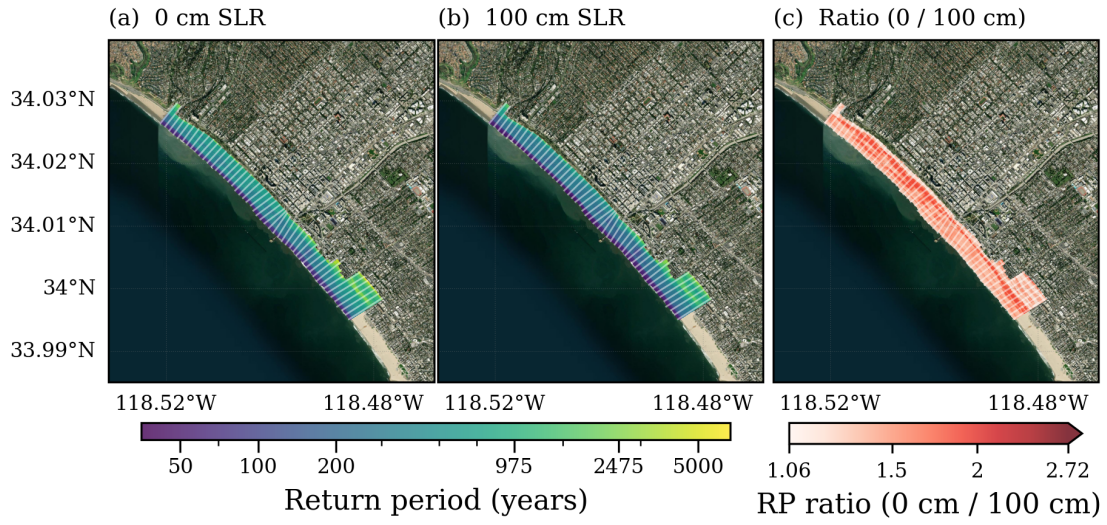


Figure 6.35: Median liquefaction hazard at Santa Monica for CPT 274: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

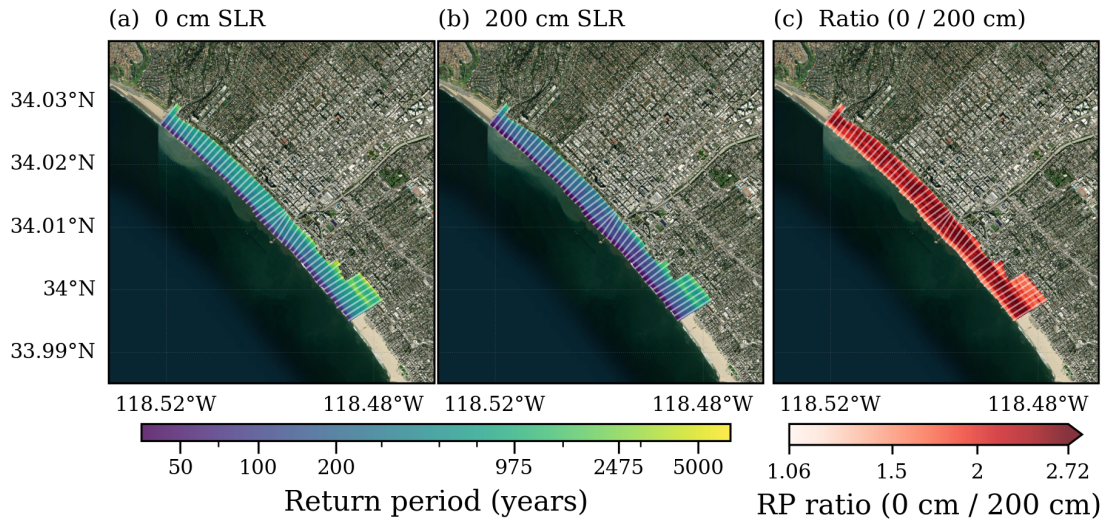


Figure 6.36: Median liquefaction hazard at Santa Monica for CPT 274: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 324 - Santa Monica

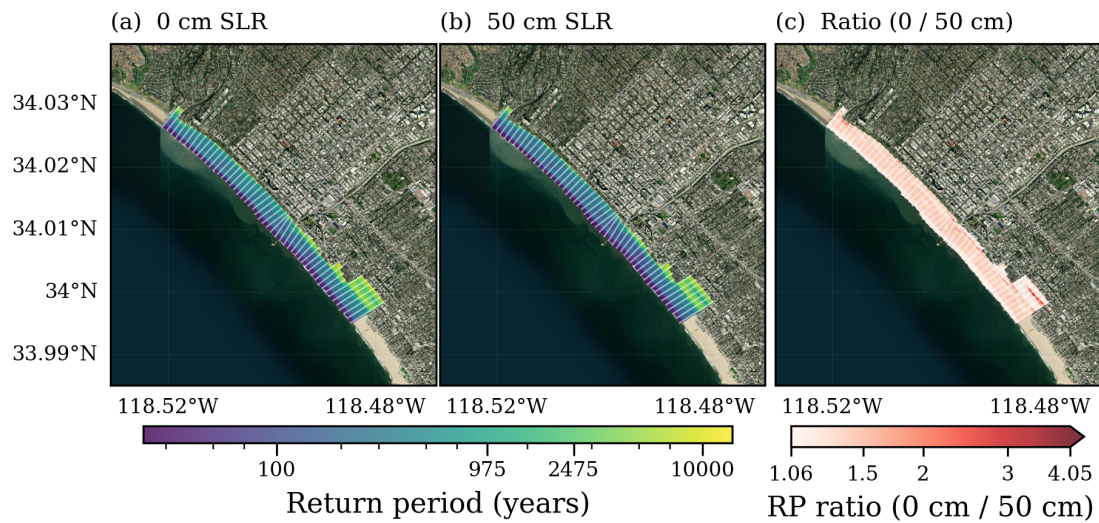


Figure 6.37: Median liquefaction hazard at Santa Monica for CPT 324: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

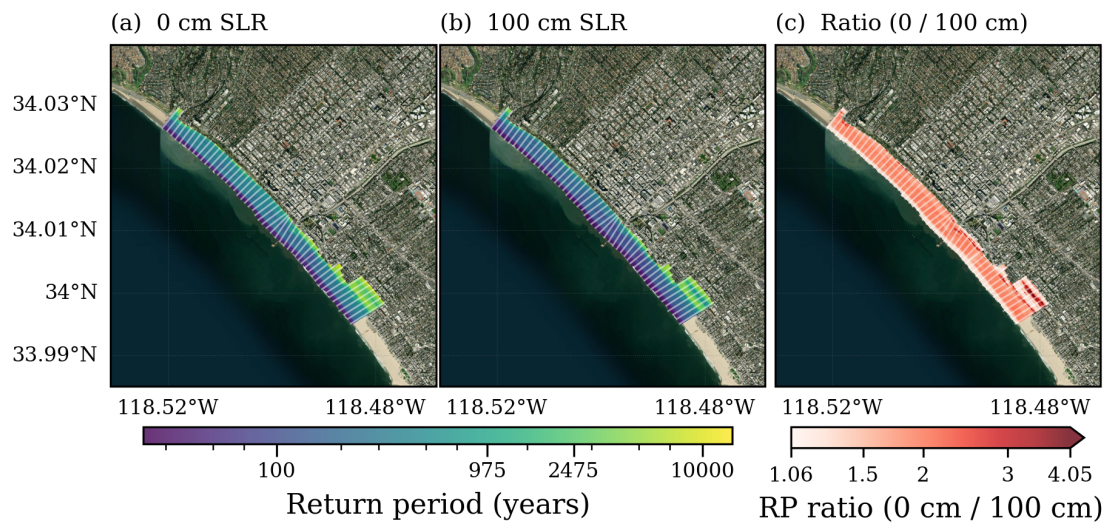


Figure 6.38: Median liquefaction hazard at Santa Monica for CPT 324: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

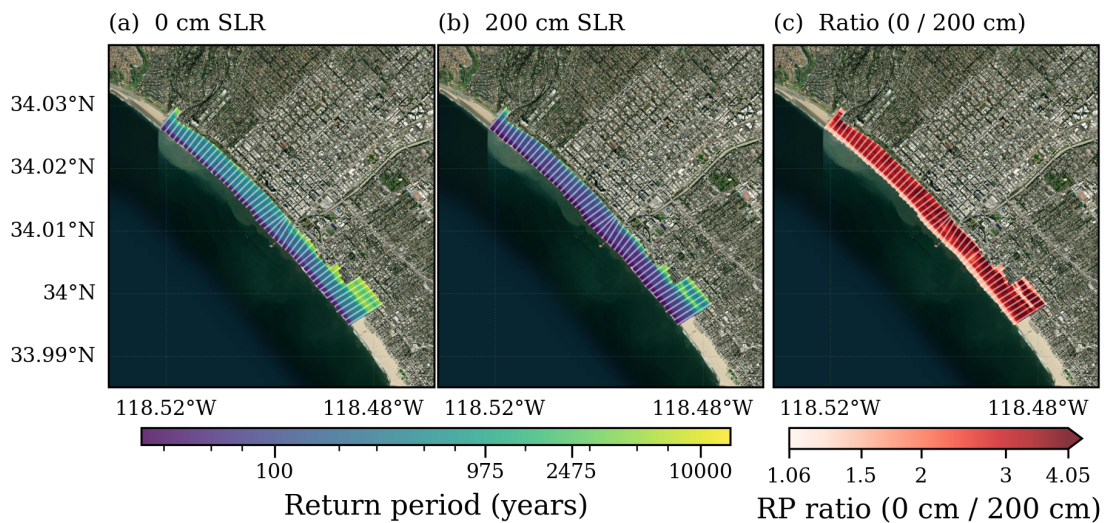


Figure 6.39: Median liquefaction hazard at Santa Monica for CPT 324: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 336 - Santa Monica

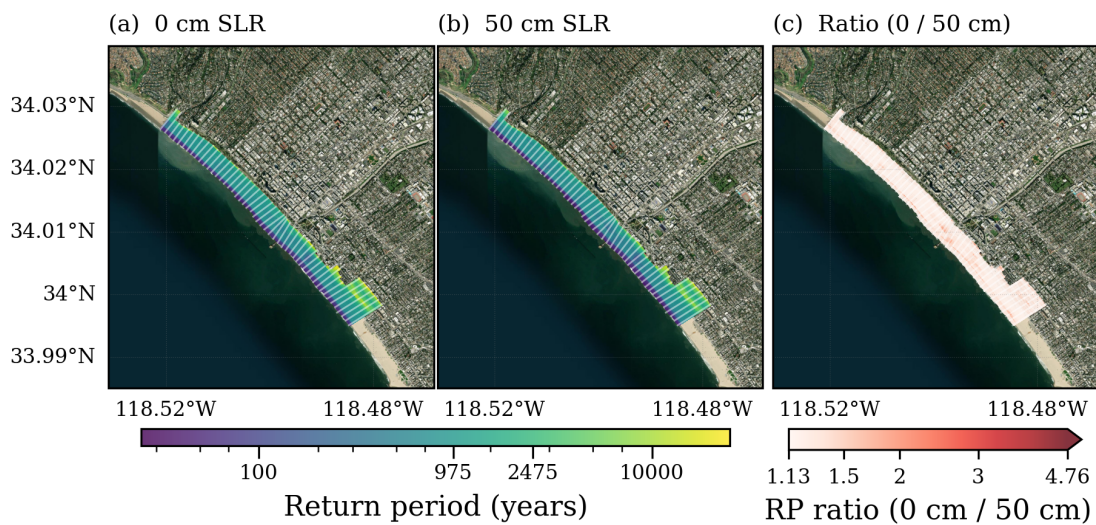


Figure 6.40: Median liquefaction hazard at Santa Monica for CPT 336: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

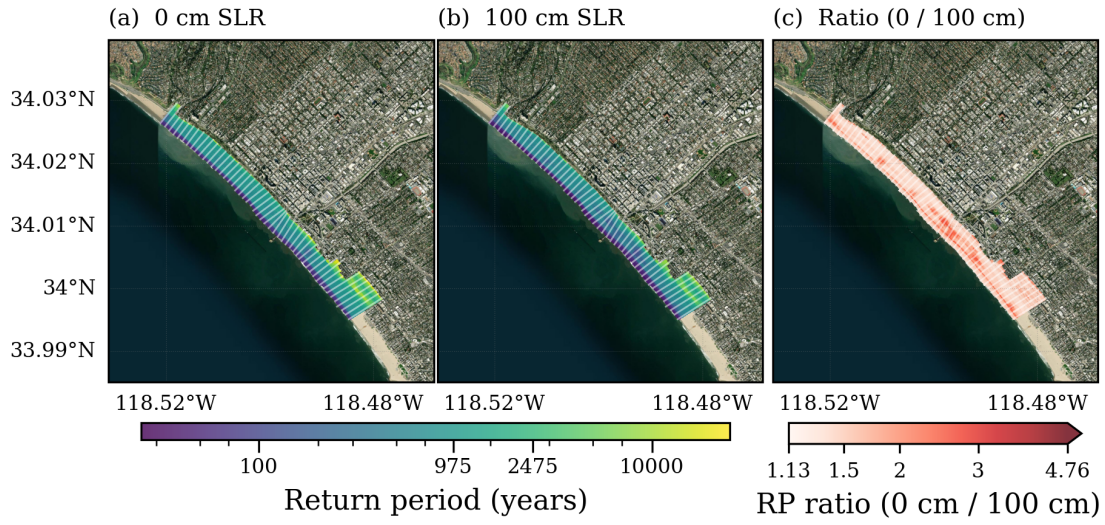


Figure 6.41: Median liquefaction hazard at Santa Monica for CPT 336: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

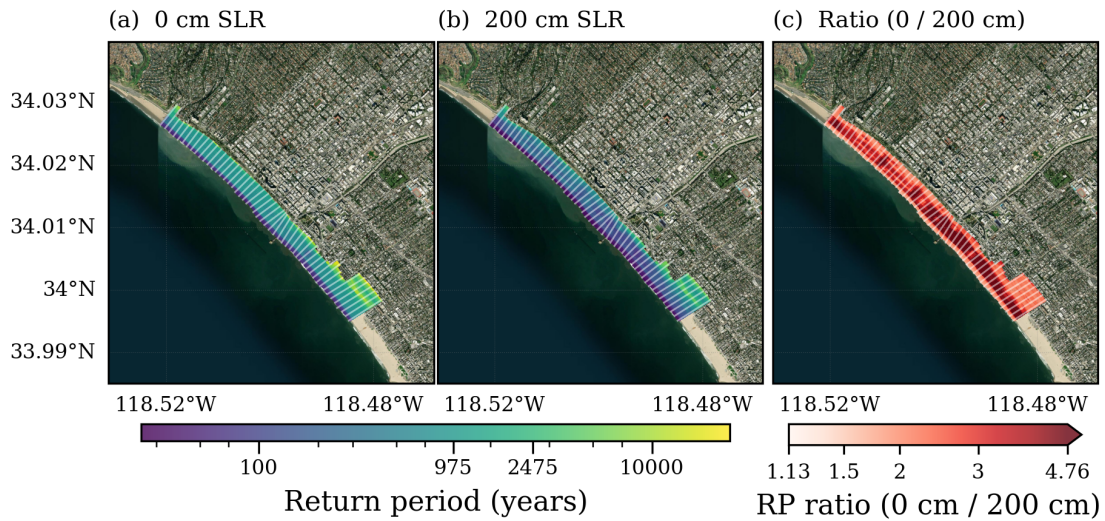


Figure 6.42: Median liquefaction hazard at Santa Monica for CPT 336: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 365 - Santa Monica

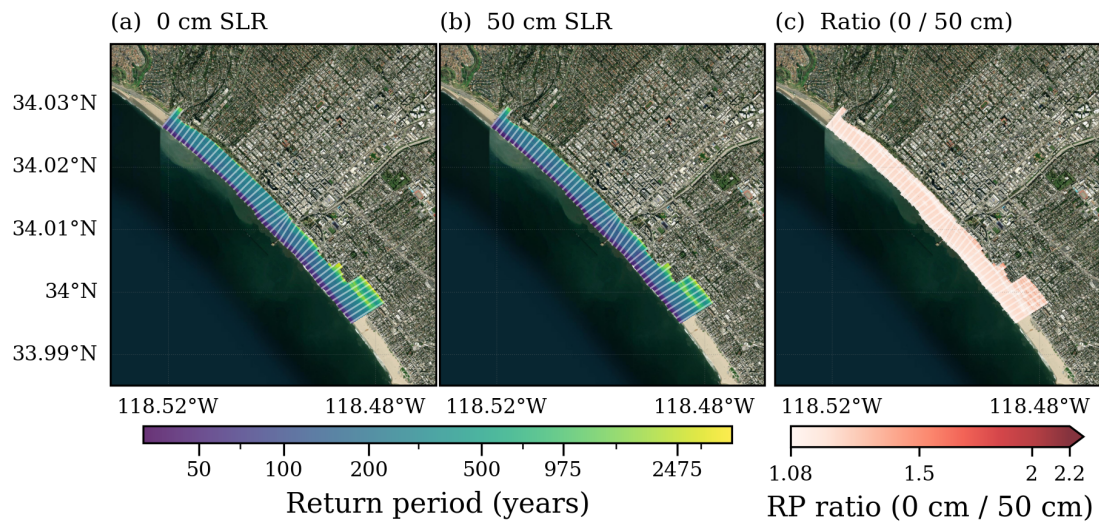


Figure 6.43: Median liquefaction hazard at Santa Monica for CPT 365: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

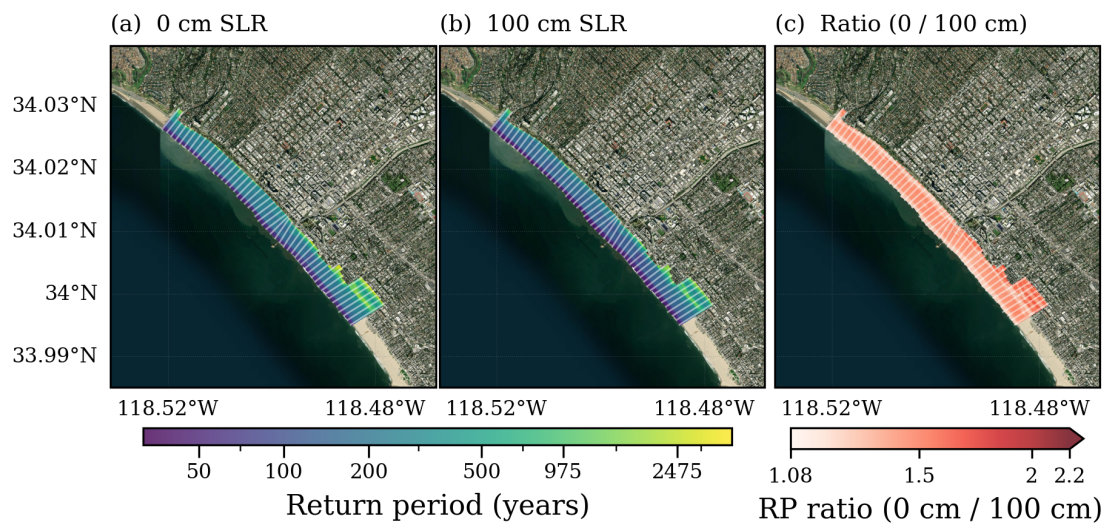


Figure 6.44: Median liquefaction hazard at Santa Monica for CPT 365: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

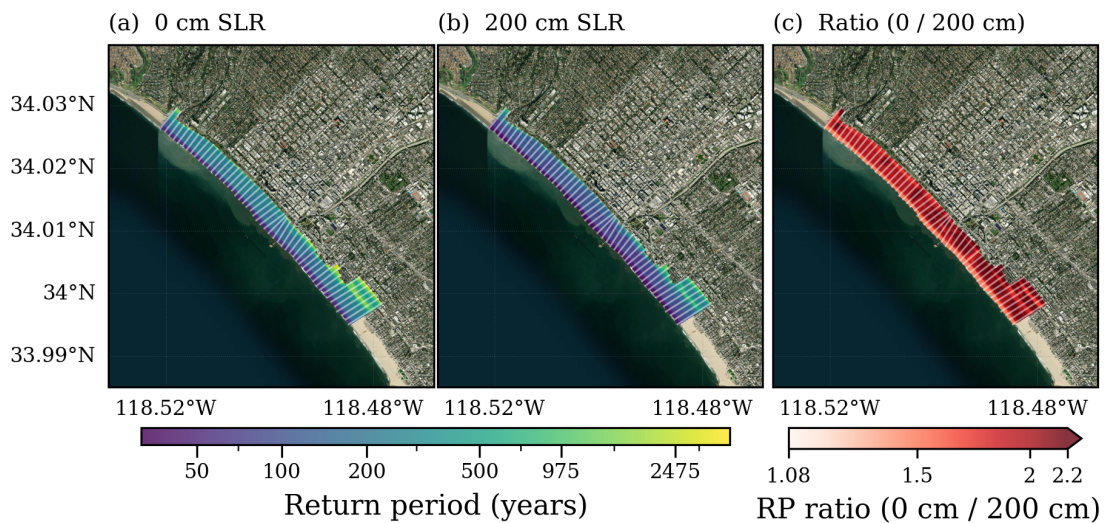


Figure 6.45: Median liquefaction hazard at Santa Monica for CPT 365: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 888 - Santa Monica

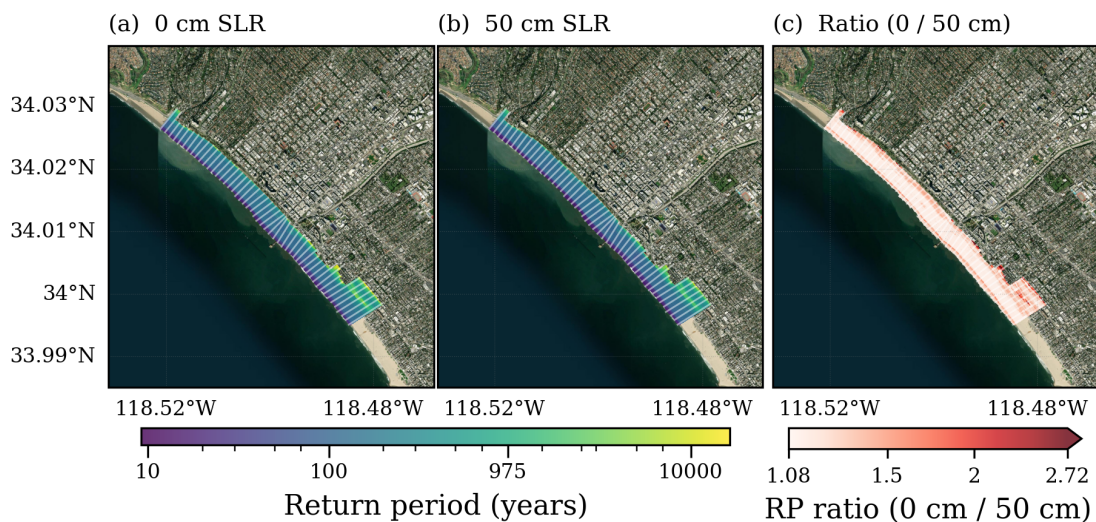


Figure 6.46: Median liquefaction hazard at Santa Monica for CPT 888: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

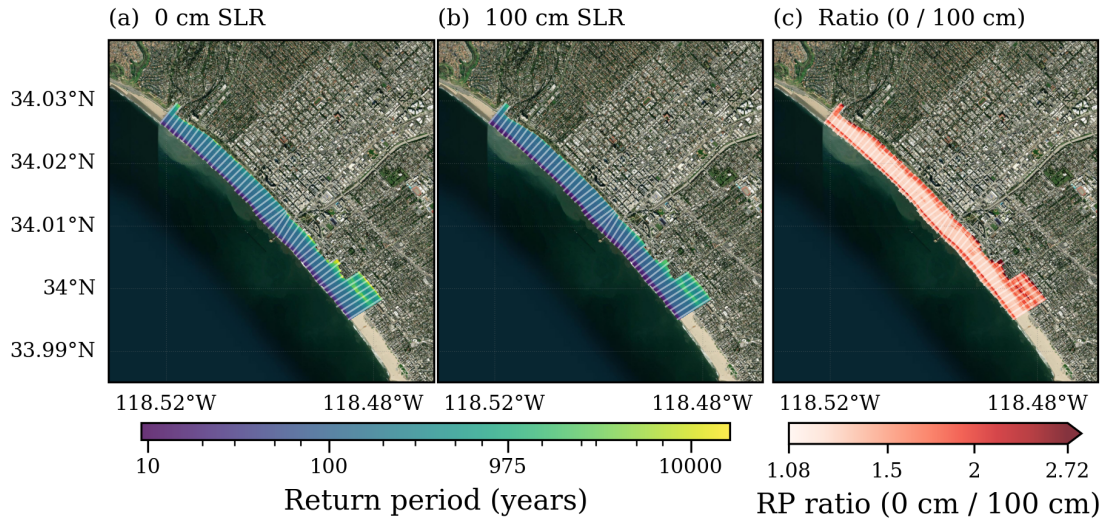


Figure 6.47: Median liquefaction hazard at Santa Monica for CPT 888: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

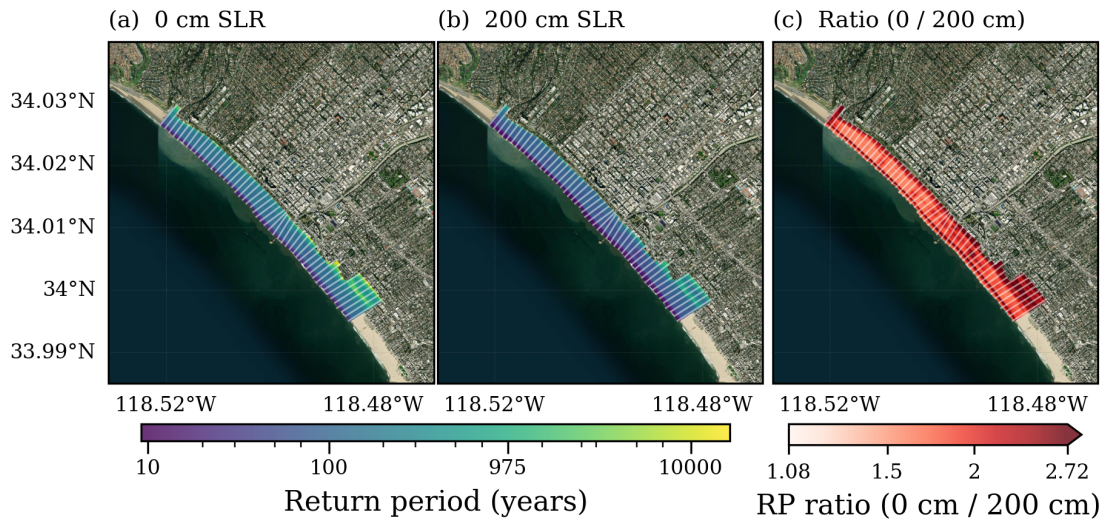


Figure 6.48: Median liquefaction hazard at Santa Monica for CPT 888: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

6.3.2 Moss Landing

The Moss Landing maps differ significantly from those at Santa Monica. The mapped field extends almost two kilometers inland, because the ground surface elevation remains below 10 m over that distance, and the tidally influenced area is considerably larger, because the local Salinas River and Elkhorn Slough carry the tidal signal along the transects. In both the baseline maps (panel a) and the sea level rise maps (panel b), a narrow shore parallel band of longer return periods traces the seaward edge of the dune, where the ground surface elevation is highest. Behind this band the low lying estuary surface sits within about a meter of mean sea level, and median return periods there are short, marking the zone of highest hazard, with the exact values varying from profile to profile. Overall, Moss Landing carries higher baseline liquefaction hazard than Santa Monica, but it is less sensitive to sea level rise, because several of the critical soil layers are already saturated under the baseline condition. Across the five representative profiles the hazard maps share this common spatial pattern but differ in how strongly the return periods shorten from panel a to panel b: CPTs 336, 365, and 888 drive the return periods down, whereas the return periods for CPTs 274 and 324 remain higher, reflecting a less susceptible critical layer.

The ratio panels (panel c), which express the baseline return period relative to the sea level rise return period, show that the relative effect of sea level rise is concentrated precisely where the baseline hazard is lowest: the largest ratios fall on the higher standing ground that had the longest baseline return periods, while the already hazardous estuary surface changes comparatively little. The amplitude of this response is profile dependent; pooled across the three scenarios, the smallest ratios occur for CPT 365 and the largest for CPT 336. Unlike at Santa Monica, the Moss Landing ratio panels also contain discrete patches where the ratio falls below one, indicating a lengthening of the return period, and therefore a reduction in hazard under sea level rise. These patches are attributed to numerical instability in the preliminary groundwater model, arising from the assigned low permeability layer, rather than to any physical reduction in liquefaction hazard, and they should not be interpreted

as such. These ratios are likely to rise above 1.0 when the groundwater model is refined. However, it is possible that SLR may actually reduce groundwater levels in some scenarios.

Moss Landing Hazard Maps

CPT 274 - Moss Landing

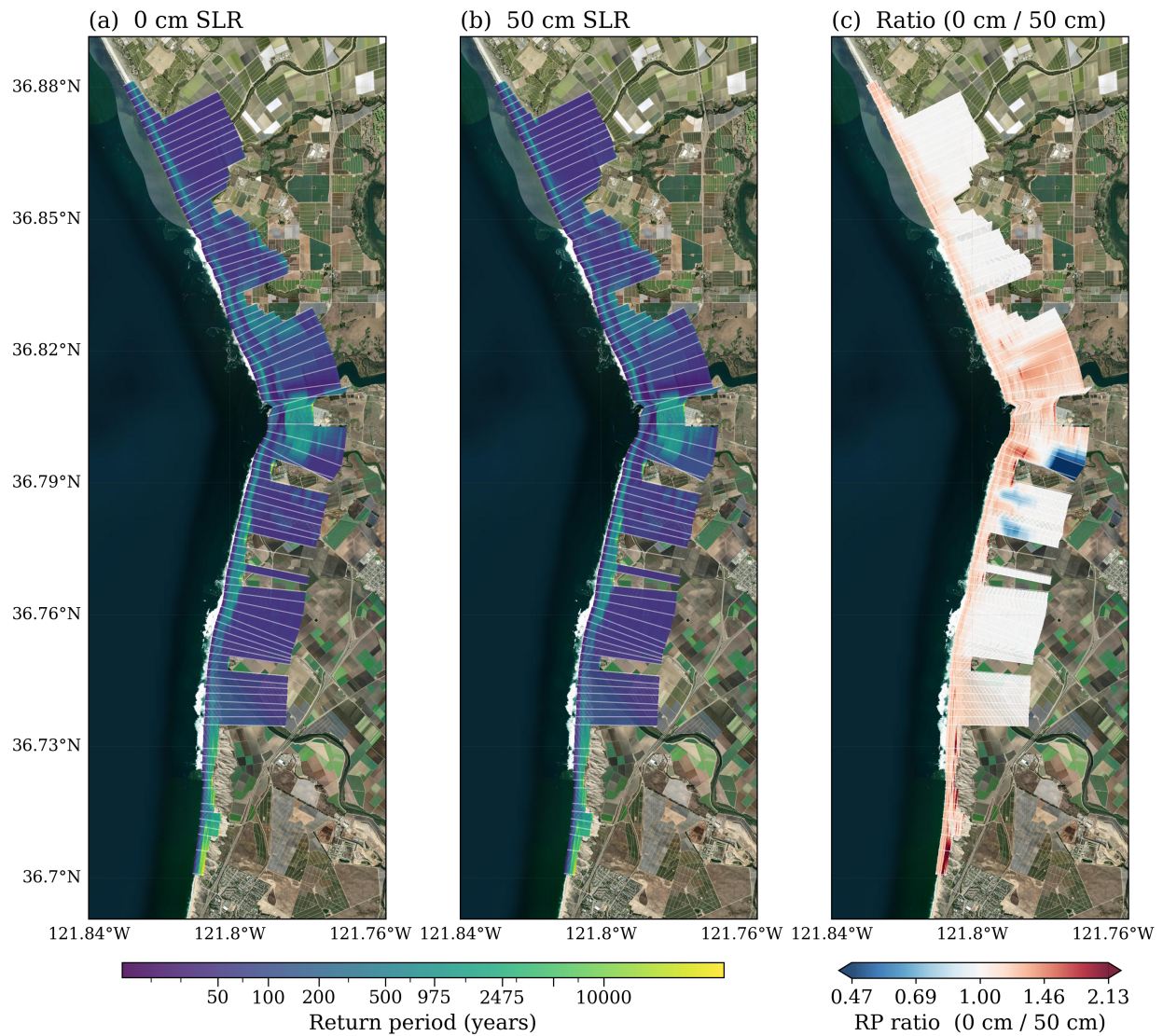


Figure 6.49: Median liquefaction hazard at Moss Landing for CPT 274: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

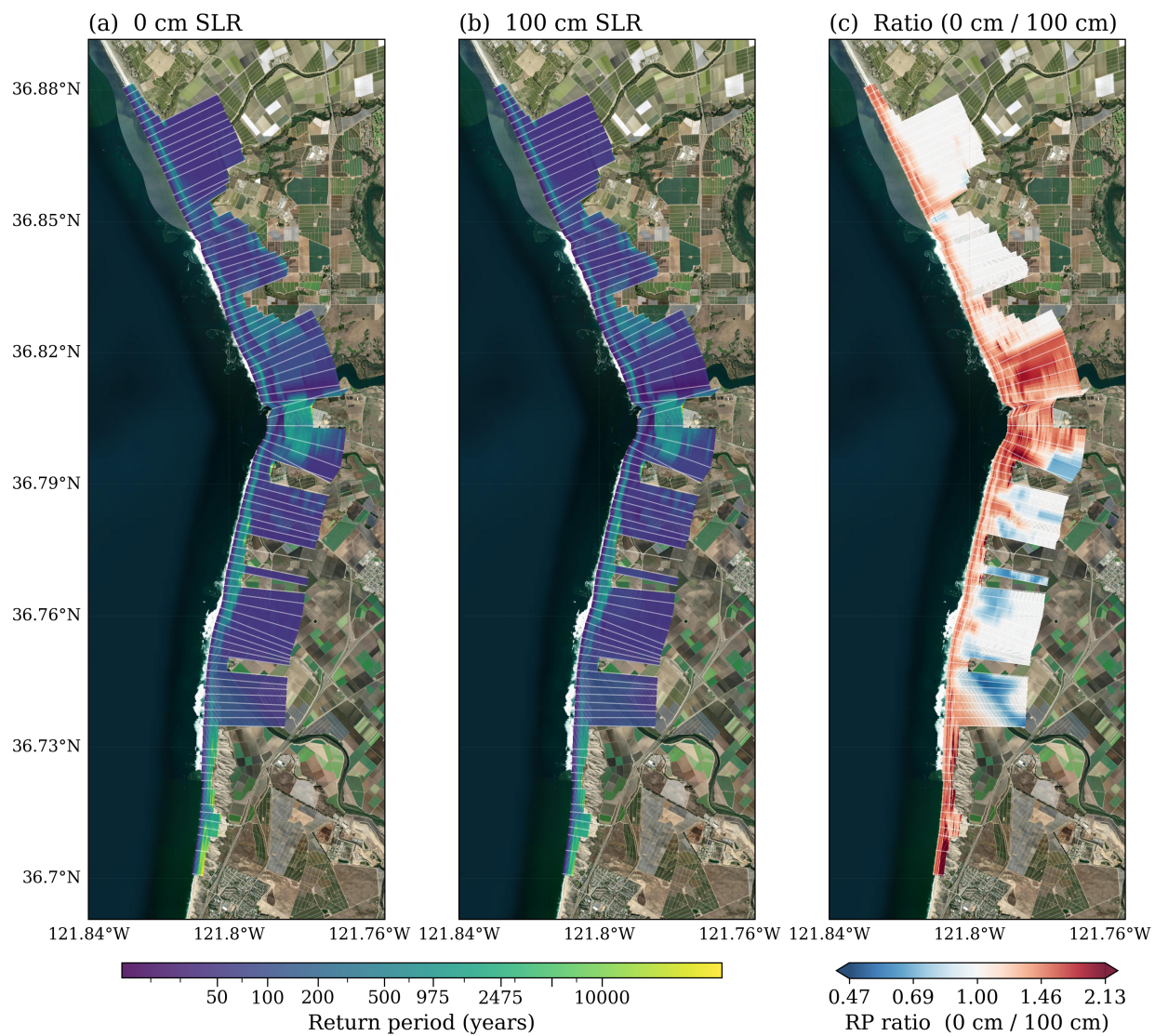


Figure 6.50: Median liquefaction hazard at Moss Landing for CPT 274: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

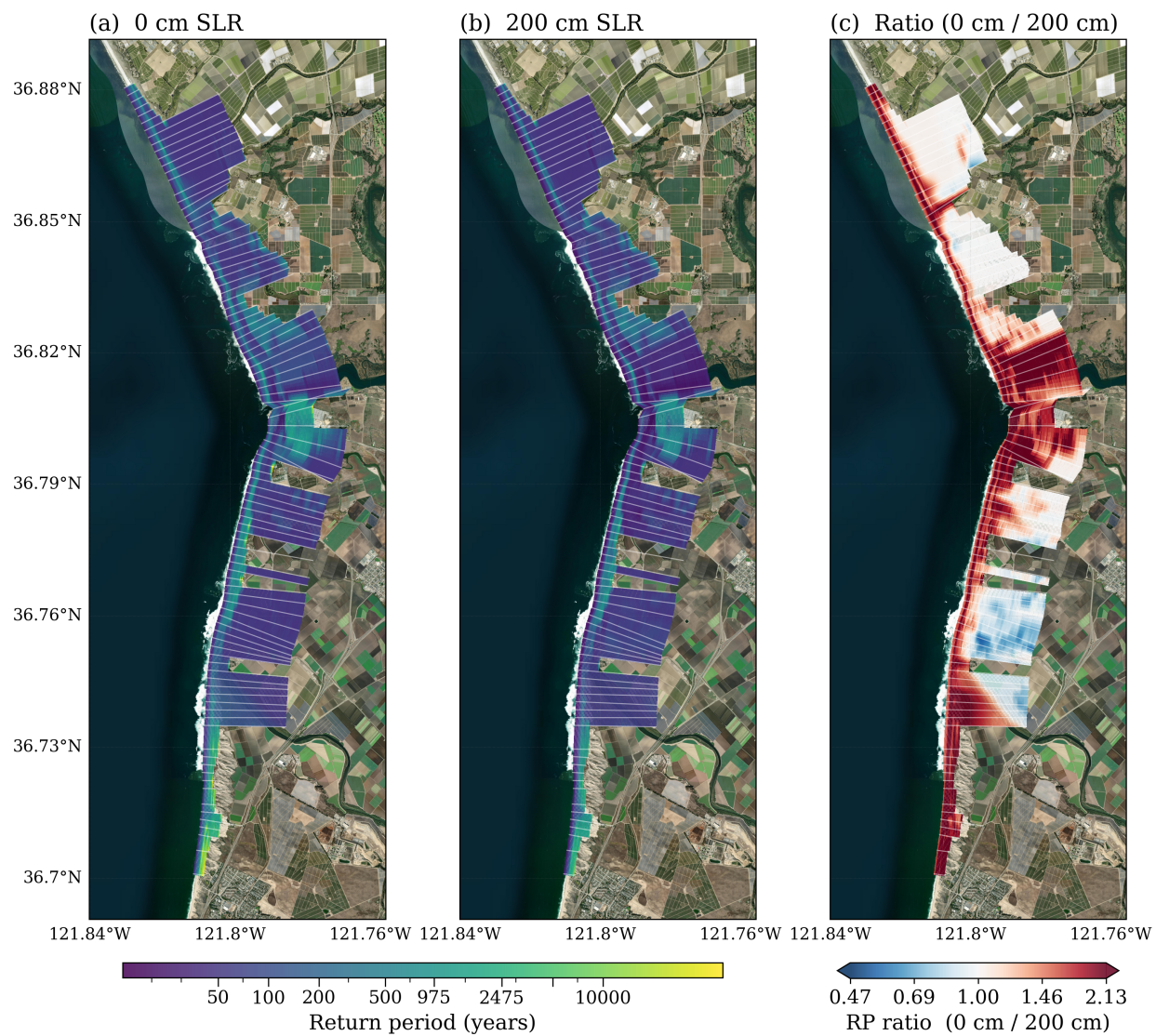


Figure 6.51: Median liquefaction hazard at Moss Landing for CPT 274: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 324 - Moss Landing

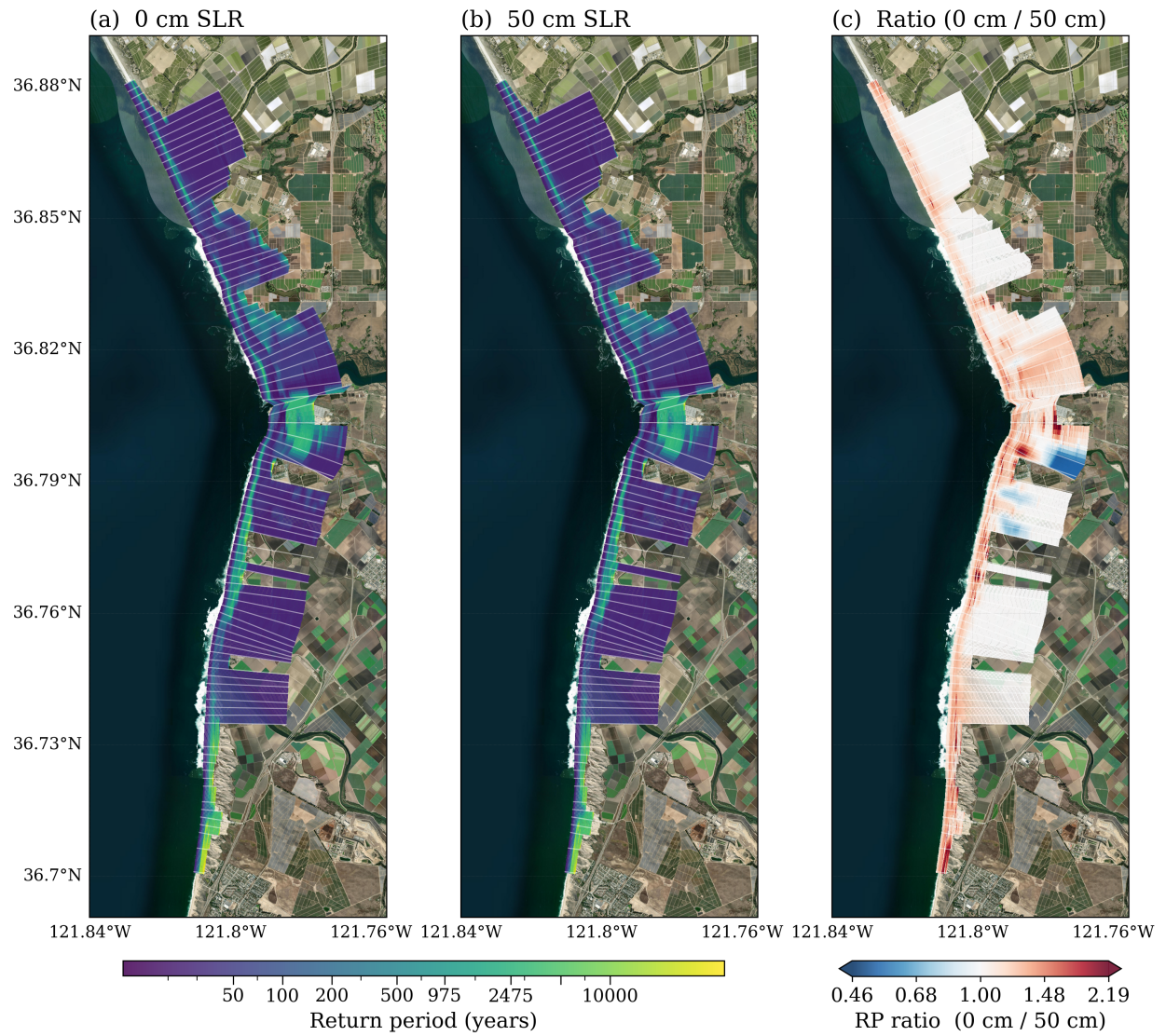


Figure 6.52: Median liquefaction hazard at Moss Landing for CPT 324: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

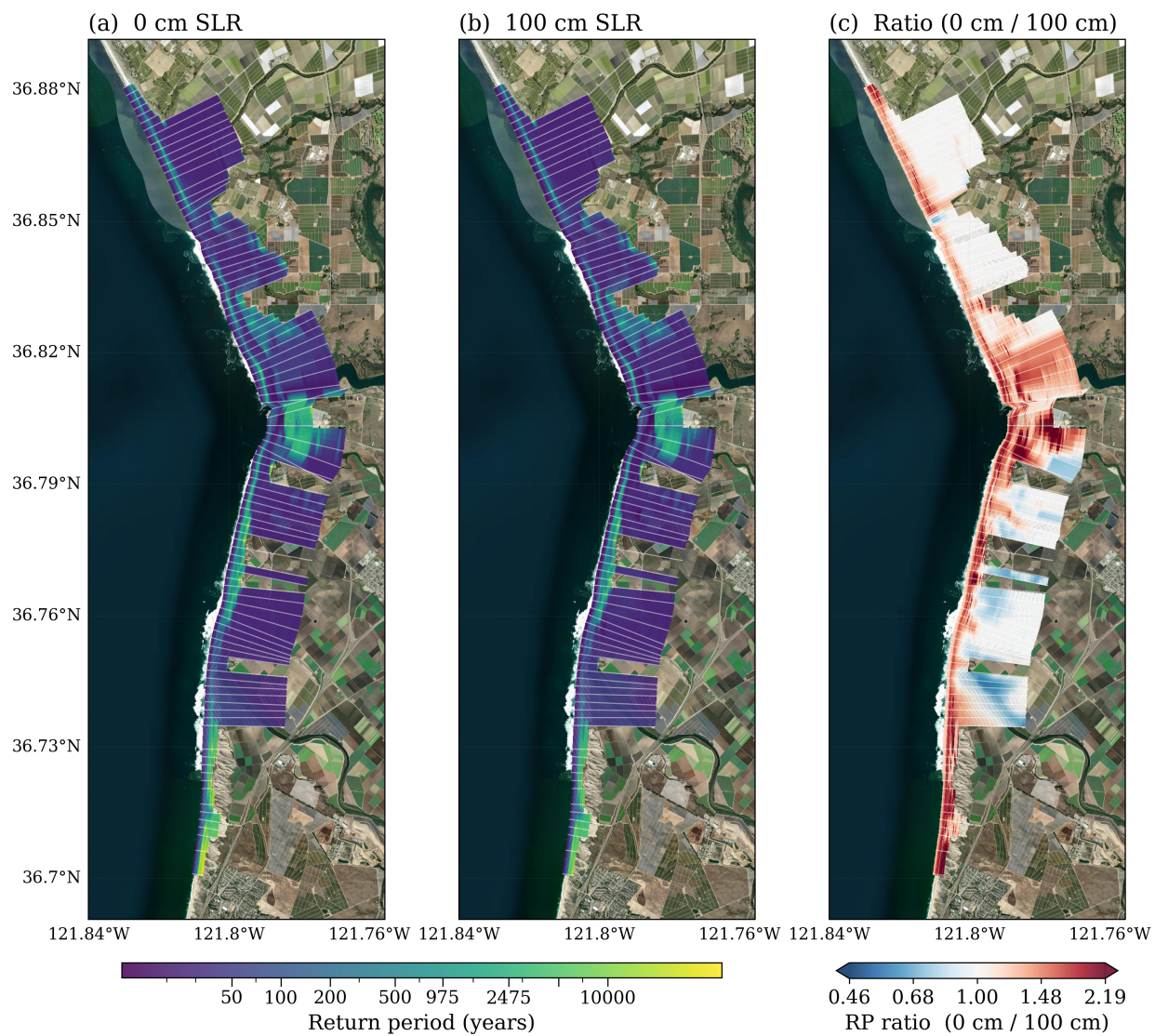


Figure 6.53: Median liquefaction hazard at Moss Landing for CPT 324: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

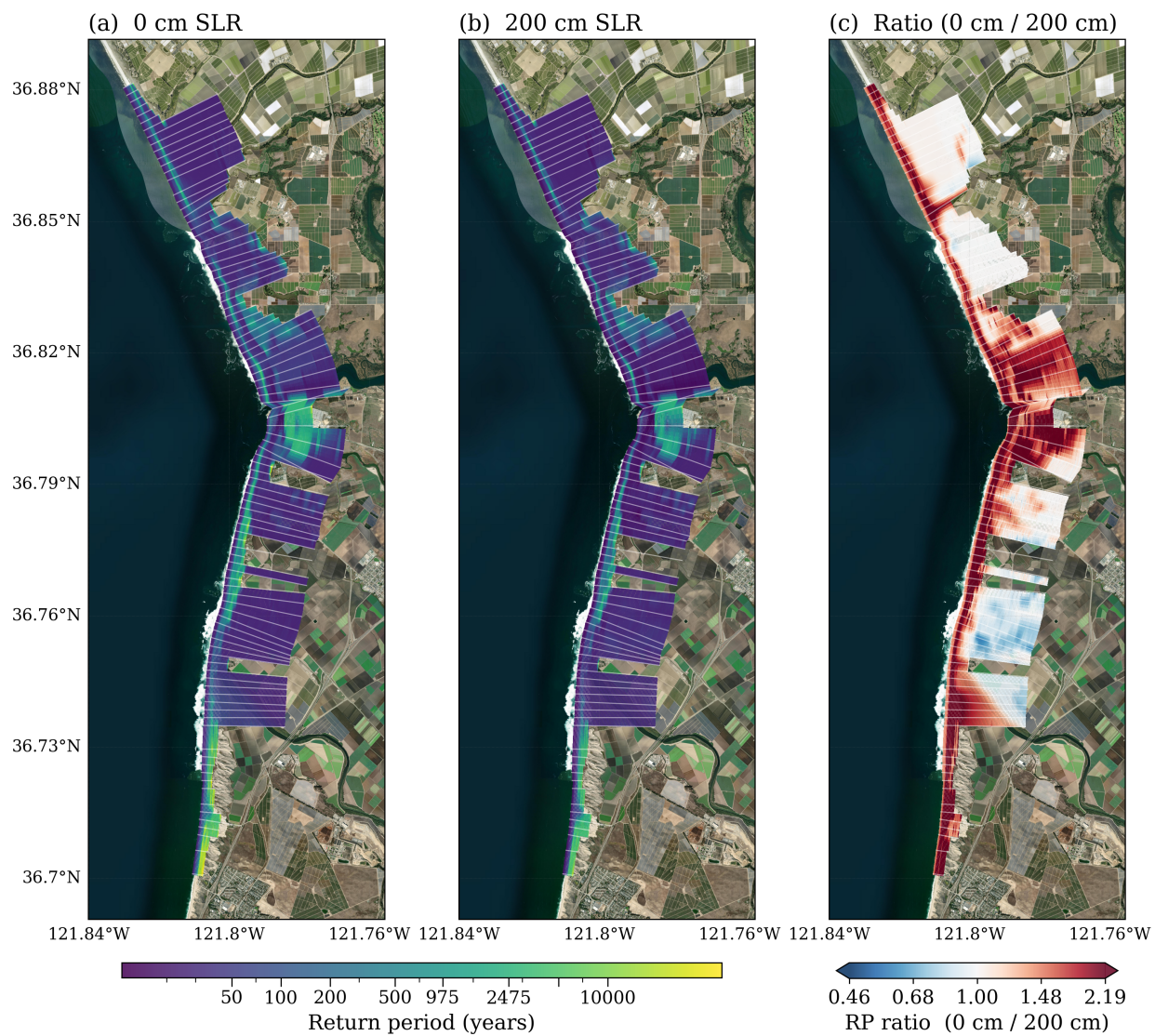


Figure 6.54: Median liquefaction hazard at Moss Landing for CPT 324: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 336 - Moss Landing

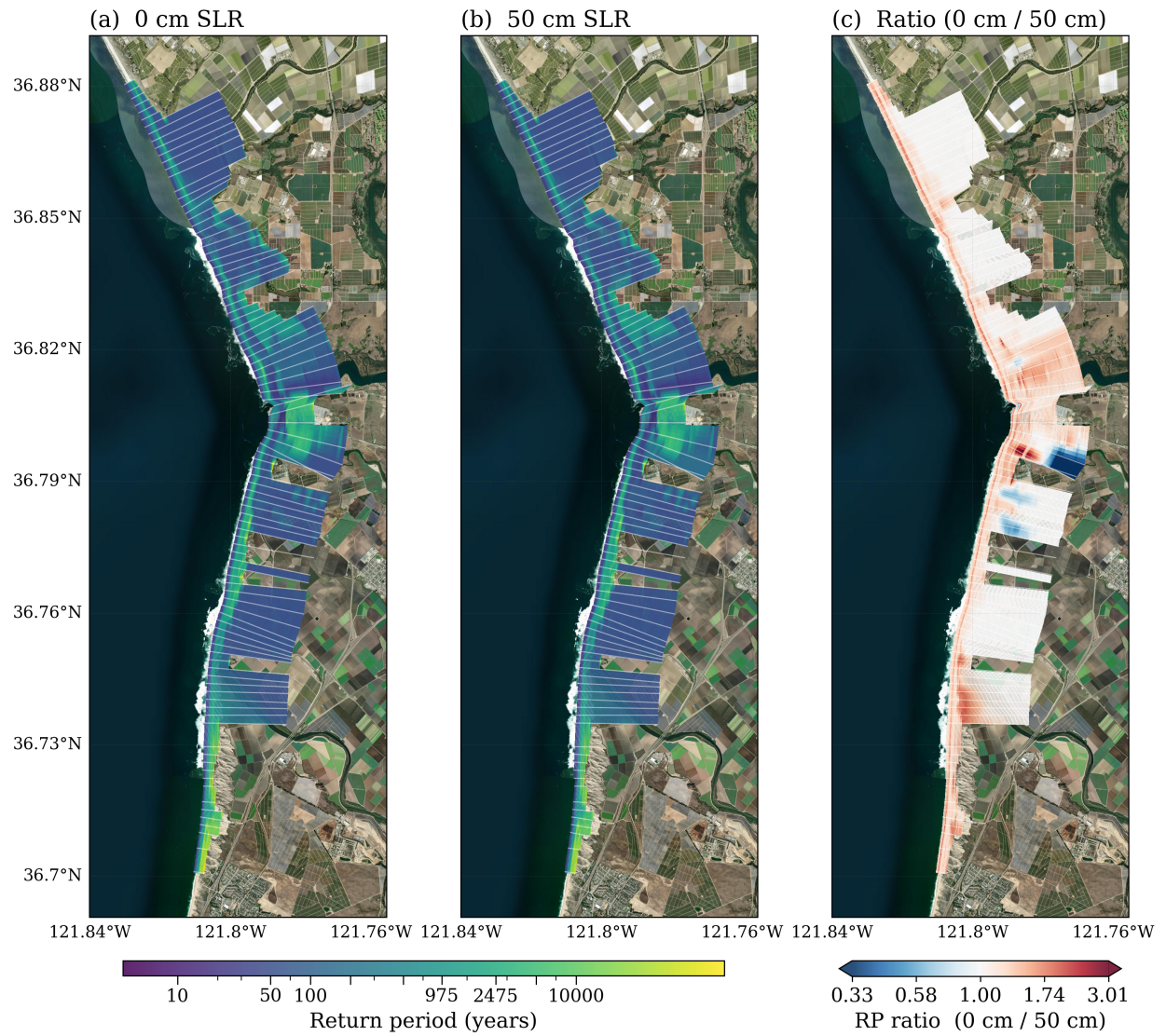


Figure 6.55: Median liquefaction hazard at Moss Landing for CPT 336: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

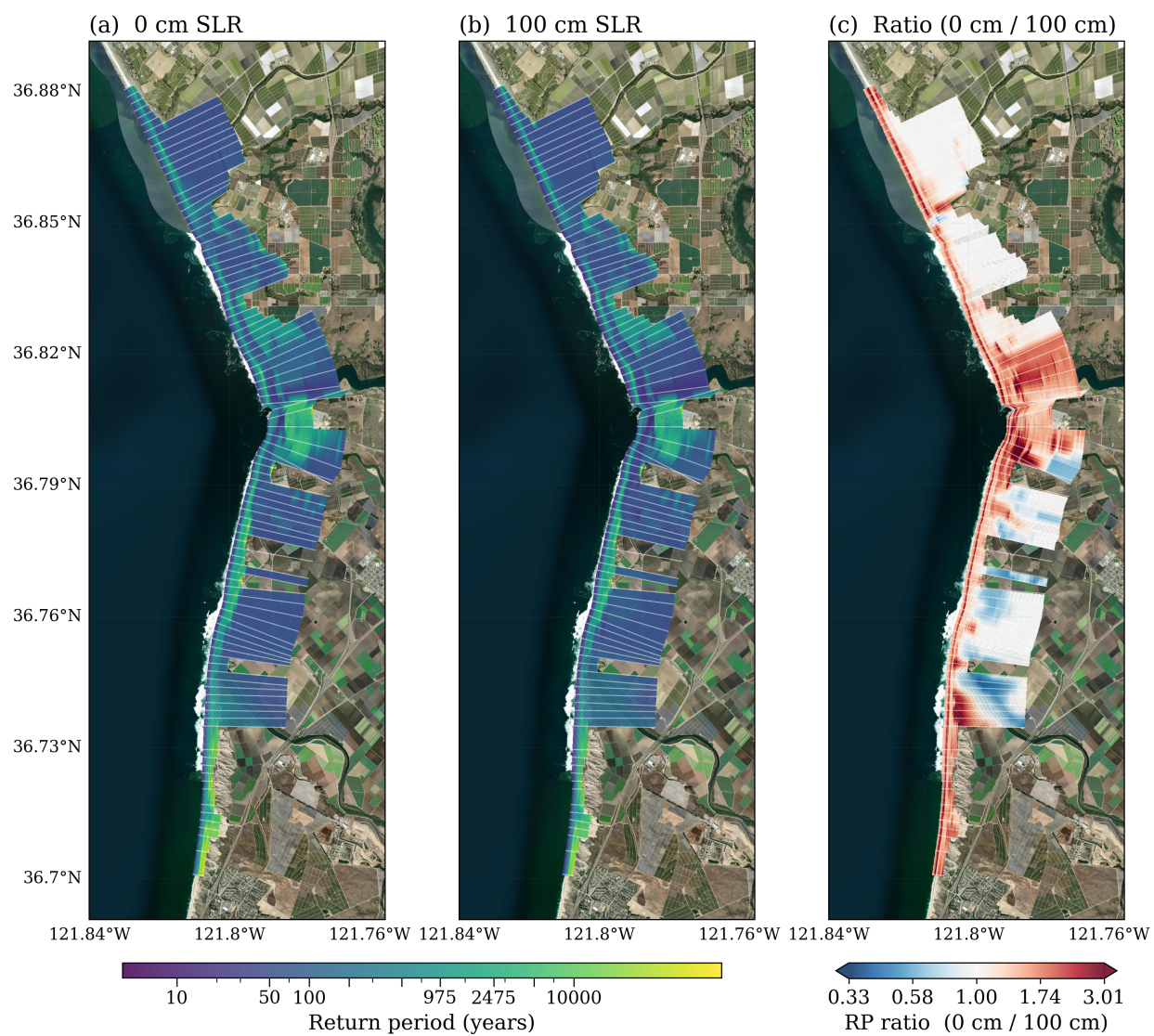


Figure 6.56: Median liquefaction hazard at Moss Landing for CPT 336: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

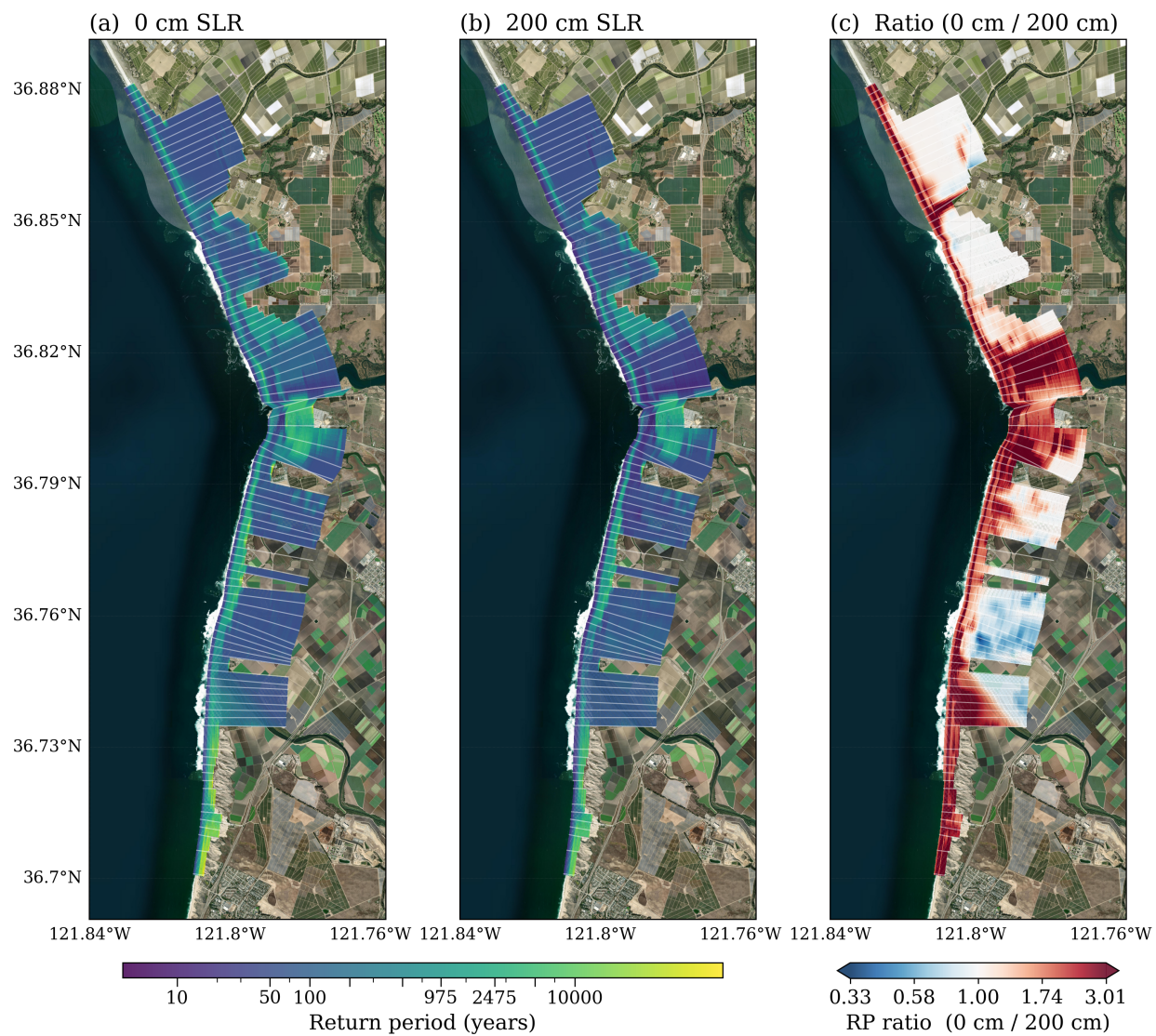


Figure 6.57: Median liquefaction hazard at Moss Landing for CPT 336: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 365 - Moss Landing

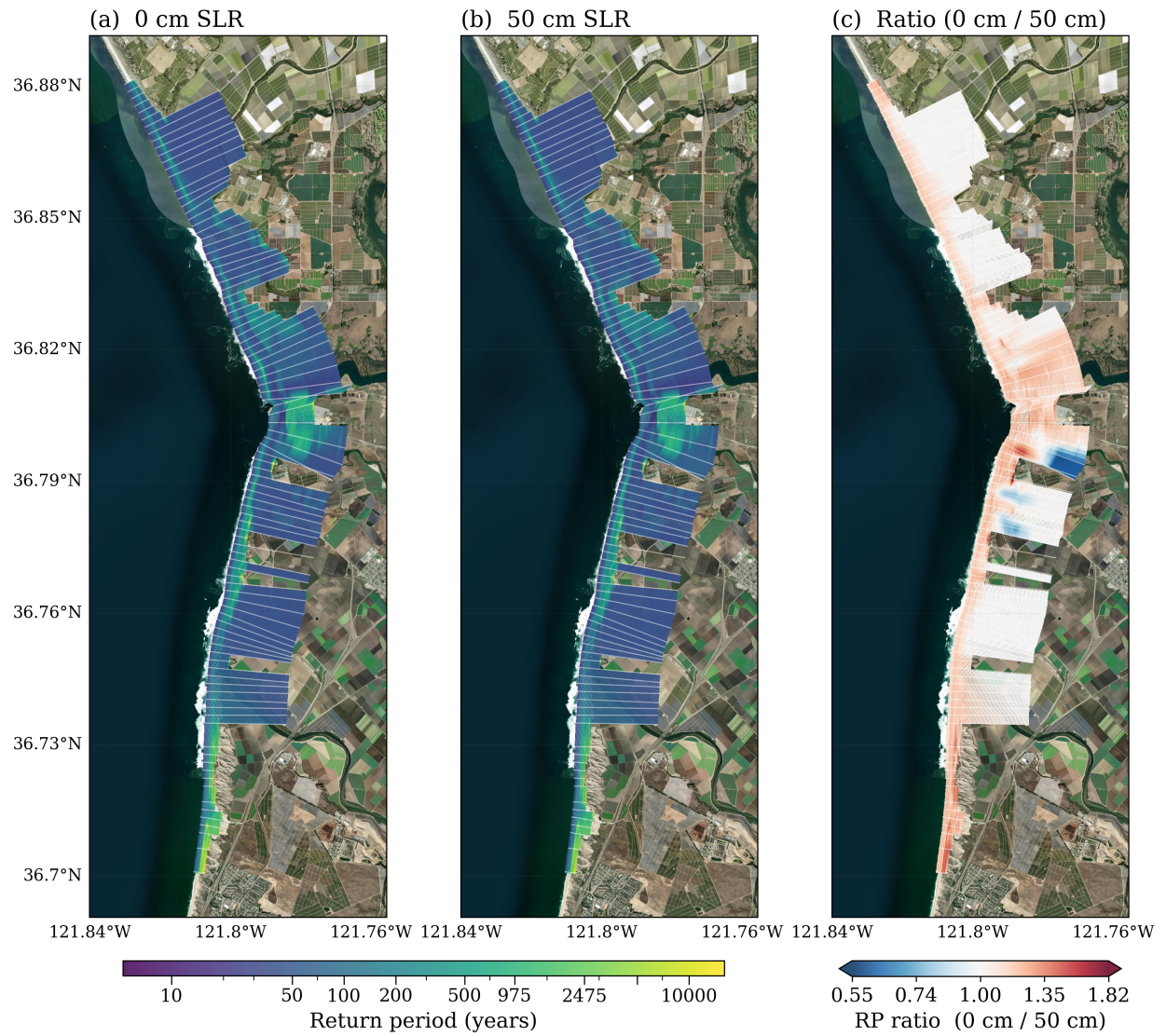


Figure 6.58: Median liquefaction hazard at Moss Landing for CPT 365: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

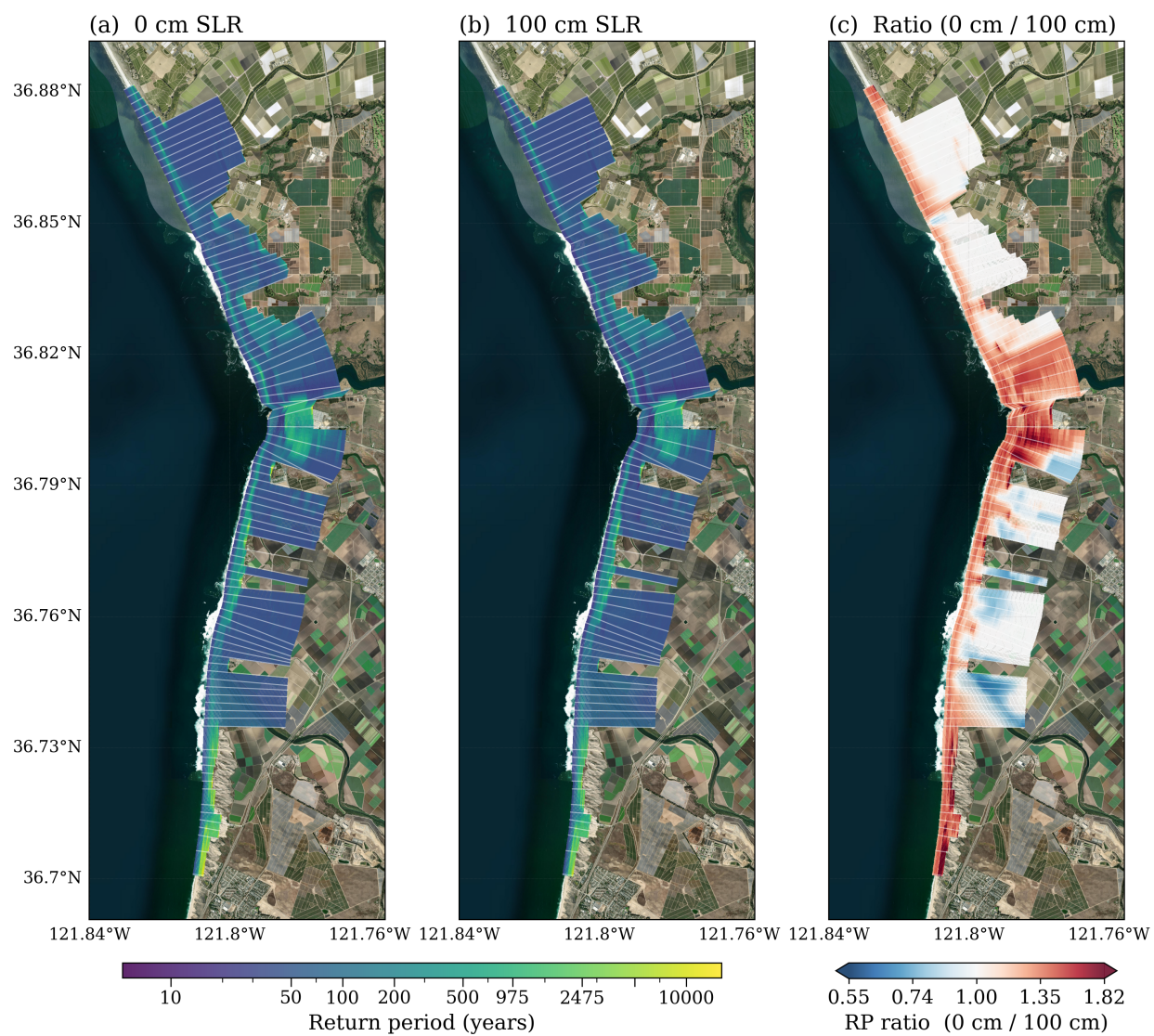


Figure 6.59: Median liquefaction hazard at Moss Landing for CPT 365: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

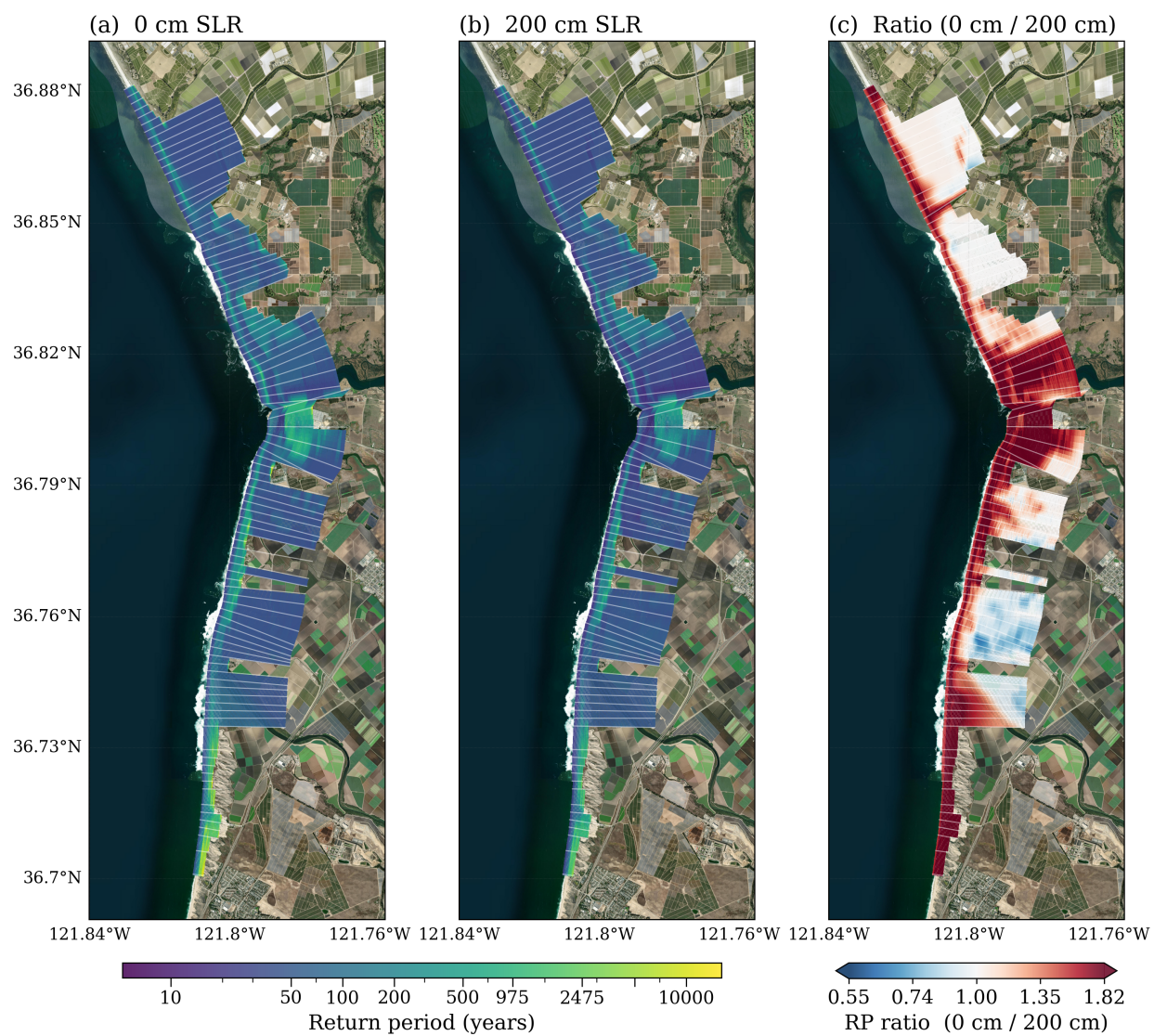


Figure 6.60: Median liquefaction hazard at Moss Landing for CPT 365: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

CPT 888 - Moss Landing

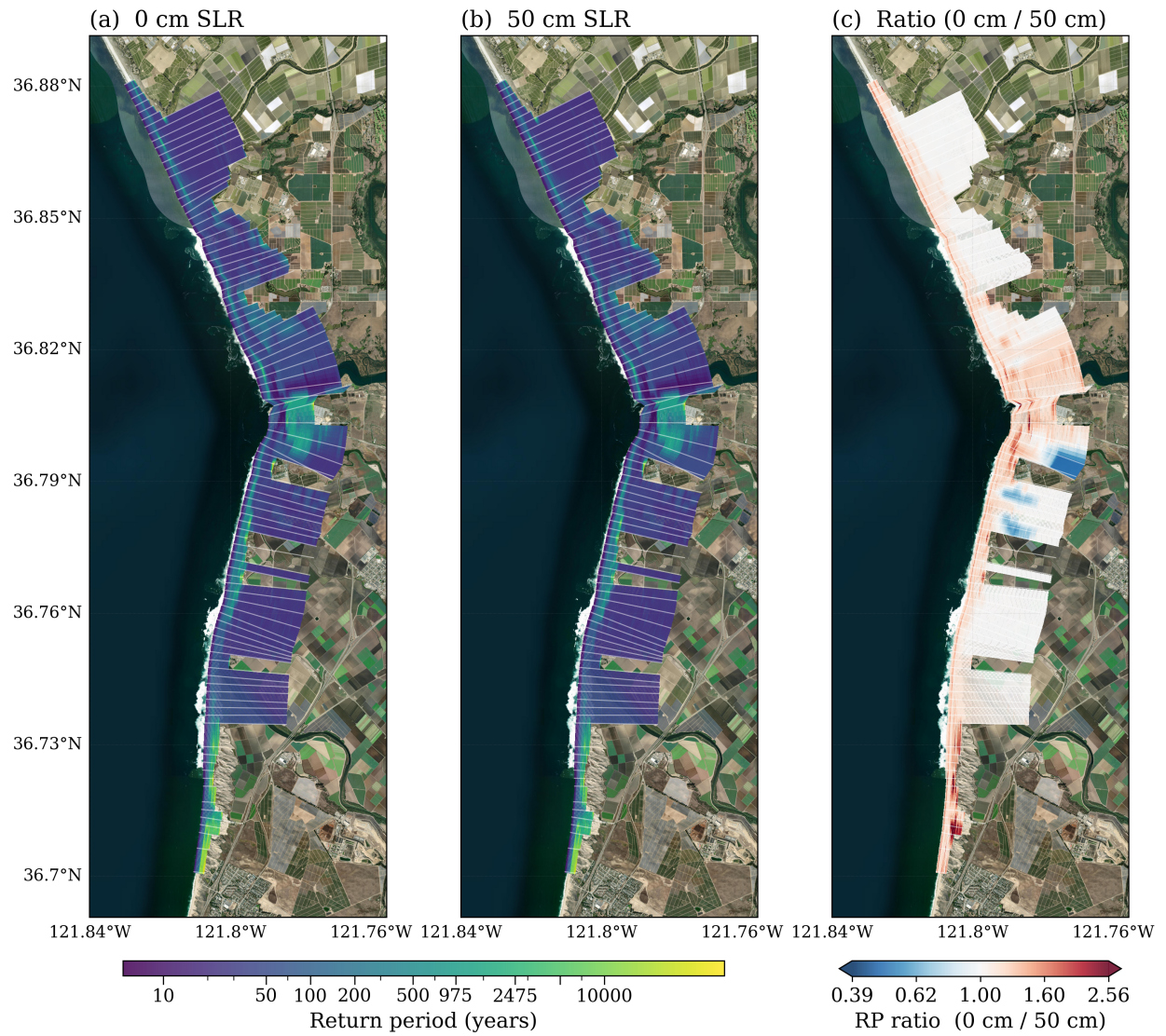


Figure 6.61: Median liquefaction hazard at Moss Landing for CPT 888: baseline groundwater conditions, 50 cm of sea level rise, and the ratio of the two.

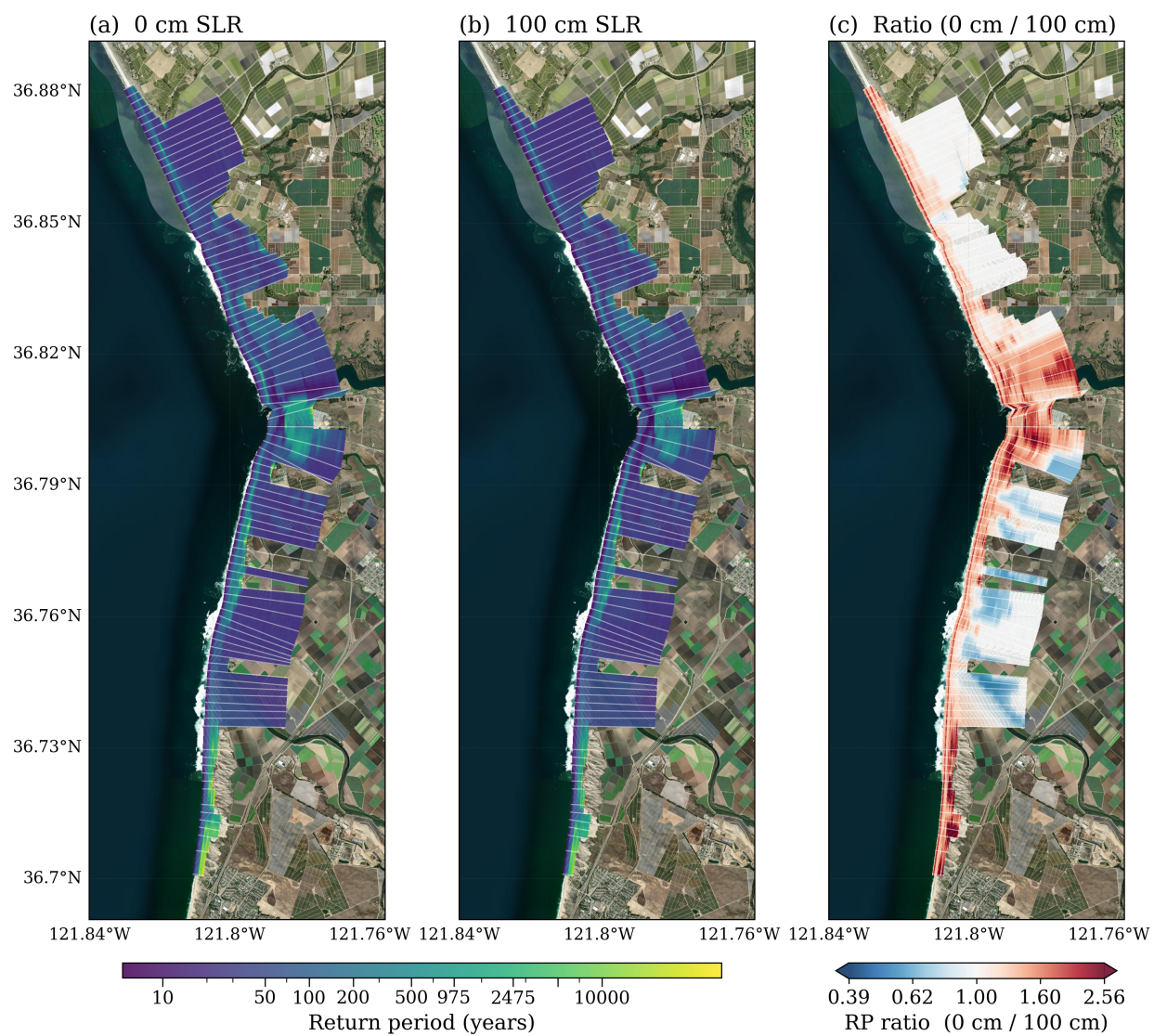


Figure 6.62: Median liquefaction hazard at Moss Landing for CPT 888: baseline groundwater conditions, 100 cm of sea level rise, and the ratio of the two.

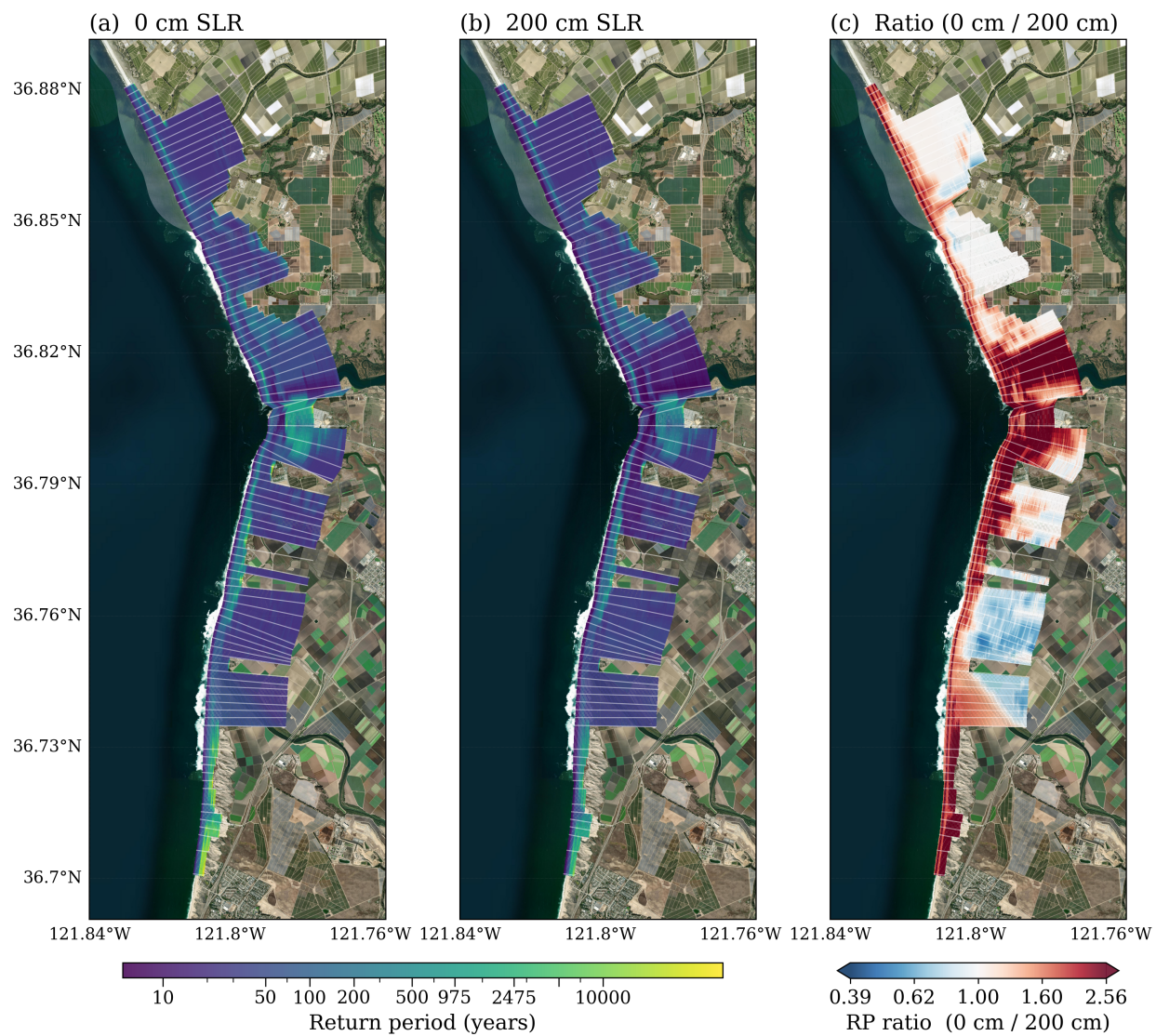


Figure 6.63: Median liquefaction hazard at Moss Landing for CPT 888: baseline groundwater conditions, 200 cm of sea level rise, and the ratio of the two.

6.3.3 Preliminary Conclusions: Regional Scale

The maps confirm and extend the initial transect results shown earlier in the chapter. Sea level rise increases liquefaction hazard, and the two sites bracket the range of that behavior and indicate how much of the California coast may respond to SLR. At cliff backed Santa Monica, the affected zone is a shore parallel strip in which the hazard change tends to increase with distance from the shoreline. Across the low lying Moss Landing estuary plain, the affected zone is the entire two kilometer analysis domain, but the change is concentrated on the near shore dune, because the back bay plain behind it consists of soil that is already nearly fully saturated. In both cases, the controlling variable is the depth to groundwater, which under a water table pinned to mean sea level is set by ground surface elevation. The contrast between the sites is one of topography and the presence of a confining layer.

The representative CPTs show that the same groundwater change maps onto very different hazard changes depending on the soil profile, and that the difference is not predictable from the baseline hazard alone. Profiles that still hold unsaturated susceptible material within reach of a rising water table respond strongly; profiles whose susceptible layers are already saturated respond weakly. Finally, the below unity ratio patches at Moss Landing mark the current limit of the groundwater model, and further refinement of the low permeability layers must be addressed.

6.4 Moving Toward Regional Analysis

The workflow demonstrated in this chapter is complete end-to-end: PFLOTRAN pore pressures on a shore normal mesh, per evaluation point PSHA and PLHA, a queryable hazard database, and interpolation from transects onto continuous hazard maps. It was executed here for two contrasting sites, but some limitations remain on extending it to the rest of the California coast.

The groundwater model is the first constraint. Its instability in low permeability domains

must be resolved before the results in those settings can be interpreted quantitatively. Once the model is stabilized, by decreasing the timestep for example, it can be applied to the more than 2000 transects remaining along the coastline. For locations that show a more pronounced response to sea level rise, replacing the representative CPTs with more site specific data would yield a refined hazard map suitable for design.

Overall, the contrast between Santa Monica and Moss Landing developed in this chapter provides the template for that regional effort. The two sites differ in three properties: the presence or absence of a confining layer, the coastal geomorphology, and the inland extent of low lying ground. Together these begin to classify the California coast and set expectations for how a given shoreline is likely to respond.

Once the regional groundwater analysis has been completed, it will be used to complete a full suite of PLHA calculations, and associated maps for specific regions will be created. Additional CPTs will be necessary to run such simulations. Currently, the analysis is limited to representative CPTs due to the lack of available site specific data.

CHAPTER 7

Conclusions, Recommendations, and Future Work

The main objective of this dissertation was to quantify the change in hazard for earthquake-induced soil liquefaction during tidal fluctuations and sea level rise (SLR) along the California coastline. SLR and tidal fluctuations elevate coastal groundwater levels, a key driver of liquefaction hazard. Yet standard practice along California’s densely developed coast commonly assumes static groundwater and evaluates liquefaction deterministically. Understanding the coupled effect of coastal processes on liquefaction hazard is therefore essential. Coastal beach sands are especially susceptible to liquefaction owing to their loose, coarse grained nature. A rising ocean compounds this by elevating the groundwater table, saturating previously dry soils and increasing the liquefaction hazard. The central aim of this dissertation was to couple probabilistic liquefaction hazard analysis (PLHA) with a two-dimensional numerical groundwater model. This chapter summarizes the scope of work and the primary contributions of this dissertation, highlights the major findings, and presents recommendations for geotechnical practice and future research.

7.1 Scope of Research and Summary of Major Findings

The first contribution of this dissertation was the development of the open source Python package, `ucla_plha` (Kota and Brandenburg, 2025), which performs PLHA directly inside the seismic hazard integral and whose methodology is presented in Chapter 4. Unlike a

decoupled approach, in which the magnitude-dependent liquefaction hazard is calculated separately after a probabilistic seismic hazard analysis (PSHA), the `ucla_plha` formulation calculates liquefaction hazard directly and efficiently alongside the PSHA. Furthermore, the use of vectorized operations makes the computational demand of a PLHA for a single soil layer comparable to that of a PSHA. The package includes the UCERF3 fault and gridded source model (Field et al., 2013), four NGA-West2 ground motion models (Abrahamson et al., 2014; Boore et al., 2014; Campbell and Bozorgnia, 2014; Chiou and Youngs, 2014), and five liquefaction models (Moss et al., 2006; Boulanger and Idriss, 2012, 2016; Cetin et al., 2018; Ulmer et al., 2024). The code was validated against other open source PSHA software, and the ground motion and liquefaction models were checked against figures from the original publications as well as against other open source validation tools (e.g., `pygmm` (Kottke et al., 2025)).

The second contribution was the creation of the UCLA Coastal Geotechnical Database (https://uclageo.com/coastal_database/), which is presented in Chapter 3. This effort involved student support for digitizing existing geotechnical data along coastal California. The California Geological Survey (CGS), a partner on the UC Climate Action Seed Grant, provided the research team with numerous soil boring logs and cone penetration test (CPT) reports. The requested data included boring logs and CPTs for school and hospital developments within ten kilometers inland of the California coast. At the time of this dissertation, more than 750 boring logs have been digitized and 162 CPTs have been entered into the database. The subsurface soil data in the subsequent SLR analysis were drawn primarily from the UCLA Coastal Geotechnical Database. Representative CPTs were selected from this database for the analysis based on probability of liquefaction manifestation.

The third contribution was the development of a coupled workflow linking the 2D groundwater model and its outputs with PLHA. Groundwater conditions were simulated using the variably saturated flow solver PFLOTRAN (Hammond et al., 2014) under present day tidal forcing and a range of SLR scenarios. CPT profiles were paired with pore pressure pro-

files extracted from the PFLOTRAN simulations to calculate liquefaction hazard values. The workflow coupling the numerical groundwater model with the PLHA code was demonstrated at two sites with different geologic conditions, Santa Monica and Moss Landing. In total, more than one million calculations were processed using high performance computing on the TACC Frontera system (Stanzione et al., 2020), and the results were collated into a SQLite database. The results were then synthesized into interpolated maps of the return period at which Factor of Safety of Liquefaction, FS_L , equals 1.

7.1.1 Major Findings

Several general trends emerged consistently across both study sites. First, liquefaction hazard varies over tidal cycles and generally increases (possibly up to a factor of ten) with sea level rise, although the magnitude of the increase depends on the soil profile. The controlling mechanism is saturation: specifically whether susceptible layers become saturated as the groundwater table moves. Liquefaction hazard is therefore governed primarily by the depth to the water table. Where groundwater is shallow, loose and contractive soils may be saturated near the ground surface, where effective stresses are low and liquefaction hazard is correspondingly high. Where groundwater is deeper, potentially liquefiable layers may remain unsaturated or be overlain by denser material, making liquefaction triggering less likely except during rare, intense shaking associated with long return periods. SLR can therefore increase the volume of liquefiable material at a site without any change to the seismic environment. The magnitude of this effect depends on the depth and gradient of the present day water table and on the amount of projected rise.

Second, the computed liquefaction return period tracks surface topography closely, and the elevation contrast between the two study sites is itself a meaningful result. In a coastal setting the water table is pinned near mean sea level (MSL), so the depth to water is essentially the height of the ground surface above MSL, and hazard remains elevated until the surface rises far enough inland to lift the liquefiable layers out of the saturated zone. The

NGL SMT model also penalizes depth, so deeper layers are less likely to produce surface manifestation. At the two extremes represented here, the steep, cliff backed profile at Santa Monica climbs above the hazardous elevation range within a few hundred meters, confining the vulnerable zone; the low lying estuary plain at Moss Landing barely rises above sea level over many kilometers, so the entire back bay lies within the hazardous band. Transect length is, in effect, a direct measure of the width of the coastal zone over which the ocean influences groundwater and, by extension, liquefaction hazard. This has an important practical implication: the impact of SLR at a site is not captured by the pointwise increase in hazard alone, because the aggregate consequence for buildings, lifelines, and other infrastructure scales with the area over which hazard is elevated.

Finally, beyond the coastal groundwater trends, this dissertation confirms the value of evaluating liquefaction hazard probabilistically and within the hazard integral rather than through the traditional deterministic route. Pairing a single design level ground motion with a deterministic assessment produces a factor of safety against liquefaction, FS_L , whose effective return period varies widely from site to site and is not known in advance. Evaluating the value of FS_L tied to a target return period provides a far more rational and internally consistent basis for hazard evaluation. The historical absence of practical computational tools has impeded the routine use of PLHA in engineering practice; `ucla_plha` directly addresses that gap for both researchers and practitioners.

This work also has limitations. Assumptions regarding boundary conditions and hydraulic conductivity were required to apply the groundwater model to a regional scale. Additionally, the groundwater model remains under development because of numerical instabilities at low permeability sites such as Moss Landing; these instabilities must be addressed in future work. Likewise, using five representative CPTs rather than site specific data was a simplifying assumption necessary to scale the PLHA calculations. The results should therefore be interpreted in the context of these assumptions and the associated uncertainty.

7.2 Recommendations

Several practical recommendations have emerged from this dissertation. In geotechnical earthquake engineering practice, ground motion hazard is characterized probabilistically through a PSHA formulation that has become standard and is embedded in national seismic hazard models and in design codes. When the workflow moves to liquefaction, however, it becomes deterministic: a single ground motion intensity is extracted from the hazard curve, a single depth to groundwater is assumed, and a single triggering curve is applied. The uncertainty from the seismic hazard is not propagated through the liquefaction analysis. [Kramer and Mayfield \(2007\)](#) identified this problem nearly two decades ago, concluding that conventional procedures based on a single ground motion level produced widely inconsistent estimates of liquefaction hazard, and the return period comparisons in Chapter 4 show that the inconsistency remains substantial.

The first recommendation of this dissertation follows directly: probabilistic liquefaction hazard analysis should become more integrated into the standard of practice. For practitioners, this shift is less drastic than it may appear, because the structural profession has already made it. The risk targeted maximum considered earthquake (MCE_R) ground motions in ASCE 7 ([American Society of Civil Engineers, 2017](#)) are obtained by convolving the site seismic hazard curve with a lognormal collapse fragility function, which is the same methodology as the PLHA integral formulated in Chapter 4. Modern liquefaction models can be represented as fragility functions, so the framework transfers to liquefaction without modification. What the profession currently lacks is a consensus on performance based return periods grounded in risk rather than hazard. This would help tie liquefaction return periods to performance based engineering objectives such as lifeline functionality, repair costs, and downtime during emergencies. The computational barrier has also begun to fall: this dissertation demonstrated a site specific PLHA at a single CPT sounding running in seconds on a laptop, and the regional pipeline developed here shows that the full coupled analysis, comprising more than one million calculations across the two study areas, is tractable on

high performance computing resources. Accordingly, liquefaction hazard should be evaluated at its own target return period, which need not match the return period adopted for ground motion.

The second recommendation concerns the uncertainty in the inputs. Whether the analysis is deterministic or probabilistic, the calculated hazard is governed by the depth to the groundwater table, as this dissertation has shown repeatedly, and site investigation programs should treat that depth as a distribution rather than as a single value. Cone penetration testing, particularly seismic CPT with pore pressure measurement, should be routine at coastal sites, where soil type and thin lenses in the stratigraphy can shift the computed return period appreciably. The common practice of recording a single depth to groundwater at the time of drilling is inadequate on a coast where the water table responds to tides on a daily cycle and to sea level rise on a longer time scale. Site investigation programs should therefore include monitoring wells or vibrating wire piezometers left in place so that groundwater levels and pore pressure fluctuations can be observed over time. From there, practitioners should evaluate a range of plausible groundwater conditions based on historical highs as well as real time variability captured by in situ monitoring.

7.3 Future Research Needs

Several directions extend naturally from the work presented here. First, the regional analysis should be extended along the full California coast. The computational pipeline is in place and has been demonstrated over the current study areas, but comprehensive statewide maps of coastal liquefaction return periods await completion of the corresponding groundwater simulations. Once the groundwater simulations are extended to the remaining coastline, the coupled PLHA–groundwater workflow can be applied across the full set of coastal sites to produce a statewide assessment of how SLR reshapes liquefaction hazard. Such a product would provide planners, regulators, and infrastructure owners with a probabilistically

grounded basis for anticipating the consequences of SLR.

Second, future work should expand the intensity measures and hazards supported by `ucla_plha`. The code currently uses peak ground acceleration (*PGA*) as its sole intensity measure, which is appropriate for liquefaction analysis but insufficient for representing a broader range of seismic ground failures. Incorporating peak ground velocity (*PGV*) and other intensity measures would allow the same framework to be applied to additional hazards. Because the methodology directly integrates fragility functions, it can be applied to any hazard response that can be represented by a lognormal fragility function. For example, liquefaction induced settlement and lateral spreading could be incorporated, and the approach could be extended beyond liquefaction to hazards such as seismic slope displacement and structural damage. Implementing these responses alongside the existing triggering models would broaden `ucla_plha` into a more general code for seismic damage hazard analysis. Additionally, because the code is open source, additional source models, ground motion models, and fragility functions can be contributed by the broader community as well. The framework could also be extended beyond California; this would require a fault source model formatted consistently with the UCERF3 inputs and the addition of regionally appropriate ground motion models (e.g., subduction zone models for the Pacific Northwest).

A third extension concerns the treatment of partial saturation. Both `ucla_plha` and standard procedures treat the water table as a binary boundary: soil below it is taken as fully saturated and liquefiable, and soil above it as incapable of triggering. The physical transition, however, is gradual because the degree of saturation varies through the capillary transition zone above the water table. One approach for incorporating this behavior is to apply a saturation correction factor, K_{sat} , to the cyclic resistance ratio. Because K_{sat} influences the liquefaction resistance of a partially saturated layer, it should be treated as a dynamic quantity rather than as a fixed value. This treatment is particularly important under tidal forcing and SLR, which shift the location and thickness of the partially saturated zone over time. It is also possible that K_{sat} is not the appropriate formulation, and that an

adjustment applied directly to CRR would better represent the transition from unsaturated to saturated conditions.

APPENDIX A

Supplementary Source Code

A.1 Python Code for HPC

```
1 from mpi4py import MPI
2
3 comm = MPI.COMM_WORLD
4 rank, size = comm.Get_rank(), comm.Get_size()
5
6 # rank 0 enumerates every job (transect x SLR scenario) ...
7 if rank == 0:
8     job_list = discover_jobs()
9     if not job_list:
10         comm.Abort(1)
11     # ... and distributes them round-robin across the ranks
12     chunks = [[] for _ in range(size)]
13     for i, job in enumerate(job_list):
14         chunks[i % size].append(job)
15 else:
16     chunks = None
17
18 local_jobs = comm.scatter(chunks, root=0)
19
20 # each rank reads its HDF5 files and writes config files independently,
21 # appending completed paths to its per-transect filelist.txt
22 local_written = []
23 for job in local_jobs:
24     local_written.extend(process_h5(**job))
25
26 # rank 0 gathers the per-rank lists into the master list (filelist_all.txt)
27 all_written = comm.gather(local_written, root=0)
28 if rank == 0:
29     master = [f for sub in all_written for f in sub]
30     write_master_filelist(sorted(master))
```

Listing 6: Scatter/gather distribution of configuration file generation with `mpi4py`.

```

1  from mpi4py import MPI
2  import numpy as np
3  from ucla_plha import plha
4  import sys
5  import os
6
7
8  def run_plha(comm, rank, size, filenames):
9      if rank == 0:
10         # skip files that already have an output
11         remaining = []
12         for f in filenames:
13             fname = os.path.basename(f)
14             mop_dir = os.path.dirname(os.path.dirname(f))
15             output = os.path.join(mop_dir, "output", fname)
16             if not os.path.exists(output):
17                 remaining.append(f)
18         print(f"Total: {len(filenames)}, "
19               f"Already done: {len(filenames) - len(remaining)}, "
20               f"Remaining: {len(remaining)}", flush=True)
21         chunks = np.array_split(remaining, size)
22     else:
23         chunks = None
24
25     my_files = comm.scatter(chunks, root=0)
26
27     for f in my_files:
28         try:
29             plha.get_hazard(f)
30         except Exception as e:
31             print(f"[rank {rank}] FAILED {f}: {e}", flush=True)
32
33
34 if __name__ == '__main__':
35     comm = MPI.COMM_WORLD
36     rank = comm.Get_rank()
37     size = comm.Get_size()
38
39     if len(sys.argv) != 2:
40         if rank == 0:
41             print("Usage: <launcher> ucla_plha_mpi.py <filelist.txt>",
42                   flush=True)
43             sys.exit(1)
44
45     try:
46         with open(sys.argv[1]) as fh:
47             filenames = [line.strip() for line in fh if line.strip()]
48     except OSError as e:
49         if rank == 0:
50             print(f"Unable to read {sys.argv[1]}: {e}", flush=True)
51             sys.exit(1)
52

```

```
53 run_plha(comm, rank, size, filenames)
```

Listing 7: Distribution of the hazard calculations across MPI ranks, with a resumability filter that skips already completed cases.

A.2 Container and Batch Scripts

```
1 FROM tacc/tacc-ubuntu18-mvapich2.3-ib
2 # build an MPI-aware Python stack, then install ucla_plha
3 RUN pip3 install --no-binary=mpi4py mpi4py \
4     && pip3 install ucla_plha numpy
5 ADD ./ucla_plha_mpi.py /usr/local/bin/ucla_plha_mpi.py
```

Listing 8: Dockerfile for the ucla_plha MPI container image.

```
1 #SBATCH -N 4
2 #SBATCH --ntasks-per-node=7
3 #SBATCH -t 00:30:00 -A BCS22014 -p normal
4 module load intel/19.0.5 impi/19.0.5 \
5     phdf5/1.10.4 python3/3.9.2
6 cd $WORK/RegionalGW
7 ibrun python3 process_h5_MPI.py
```

Listing 9: Slurm batch script for the parallel HDF5 processing run on Frontera.

```
1 #SBATCH -N 64
2 #SBATCH --ntasks-per-node=14
3 #SBATCH -t 06:00:00 -A BCS22014 -p normal
4 module load tacc-apptainer
5 cd $WORK/RegionalGW
6 ibrun -n 896 apptainer exec \
7     ucla_plha.sif \
8     python3 /usr/local/bin/ucla_plha_mpi.py \
9     MossLanding/filelist_all.txt
```

Listing 10: Slurm batch script for the containerized PLHA sweep across all transects and SLR scenarios on Frontera.

A.3 Database Query

```
1 SELECT d.fsl AS factor_of_safety,
2        d.rate AS annual_rate_of_nonexceedance
3 FROM    FSL_HAZARD_DATA      AS d
4 INNER JOIN FSL_HAZARD_METADATA AS m ON d.hazard_metadata_id = m.id
5 INNER JOIN MOP_LINES          AS ml ON m.mop_line_id        = ml.id
6 INNER JOIN SLR_SCENARIOS      AS s  ON m.slr_id             = s.id
7 INNER JOIN CPT_METADATA       AS cm ON m.cpt_id              = cm.id
8 WHERE   ml.name                = 'M0899'    -- Moss Landing transect
9        AND s.rise               = '100cm'   -- sea level rise scenario
10        AND cm.site_id          = 3         -- CPT profile
11        AND m.x_location        = 250.0     -- distance along transect (m)
12        AND m.percentile        = 'median'  -- hazard percentile branch
13 ORDER BY d.fsl;
```

Listing 11: Example query retrieving a single factor of safety against liquefaction (FS_L) hazard curve from the regional database. Values in FSL_HAZARD_DATA are joined back through FSL_HAZARD_METADATA to isolate one transect, sea level rise scenario, CPT profile, and along-transect location.

A.4 Groundwater Output Processing

```
1 import copy
2 import json
3 import os
4 import re
5 import sys
6 from pathlib import Path
7
8 import numpy as np
9 import pandas as pd
10 import h5py
11 from mpi4py import MPI
12
13
14 # -----
15 # Run configuration
16 # -----
17 # To apply the workflow to a different region or run, edit only this block;
18 # the logic below is general.
19
20 COUNTY = "MossLanding"      # label used for output subfolders
21
22 # Groundwater transects to process (mesh/line identifiers).
23 TARGET_LINES = {"M0919", "M0920", "M0921",
24                "SC001", "SC002", "SC003", "SC004"}
```



```

25
26 # Input and working/output trees. Host-specific; replace for the current
27 # machine. GW_ROOT holds the PFLOTRAN outputs (read-only inputs); MY_ROOT is
28 # the working/output root.
29 GW_ROOT = Path("/path/to/groundwater_outputs/MossLanding")
30 MY_ROOT = Path(os.environ["WORK"]) / "RegionalGW"
31
32 # Sea level rise scenarios, given as subfolder names under each transect.
33 SLR_FOLDERS = ["0cm", "50cm", "100cm", "200cm"]
34
35 # x position -> Vs30, per transect
36 VS30_CSV = MY_ROOT / "vs30_lookup_MossLanding.csv"
37
38 # Shared inputs: processed CPT profiles and the ucla_plha config template.
39 CPT_PKL = "cpt_5_sites_processed.parquet"
40 BASELINE_JSON = "config_baseline.json"
41
42 PA = 101.325 # atmospheric pressure [kPa]
43 GAMMAW = 9.81 # unit weight of water [kN/m^3]
44
45 X_STEP = 10 # sample every X_STEP-th unique horizontal position
46
47
48 # -----
49 # Geometry and input loading
50 # -----
51
52 def load_cell_loc(cell_loc_csv):
53     """Load mesh geometry and index helpers from a Cell_Loc.csv.
54
55     Returns the full table (with an added row index that aligns CSV rows
56     with HDF5 node order), one representative row per unique horizontal
57     position, and a mapping from each x position to the row indices of its
58     vertical column.
59     """
60     cell_loc = pd.read_csv(
61         cell_loc_csv,
62         usecols=["lon", "lat", "x_MSL", "z_MSL", "surface_el_MSL", "depth"],
63     )
64     # align CSV rows with HDF5 nodes
65     cell_loc["idx"] = np.arange(len(cell_loc))
66     # one row per column
67     cell_loc_unique = cell_loc.drop_duplicates(subset=["x_MSL"])
68     # x -> row indices of its column
69     x_column_indices = cell_loc.groupby("x_MSL").indices
70     return cell_loc, cell_loc_unique, x_column_indices
71
72
73 def load_cpt(cpt_df, cpt_index):
74     """Return one processed CPT profile (a single row of cpt_df) as arrays."""
75     cpt_row = cpt_df.iloc[cpt_index]
76     return {
77         "site_id": cpt_row["site_id"],
78         "id": cpt_row["id"],

```

```

79         "dGWT":      cpt_row["dGWT"],
80         "ztop":      np.array(cpt_row["ztop"]),
81         "zbot":      np.array(cpt_row["zbot"]),
82         "qc1Ncs_lay": np.array(cpt_row["qc1Ncs_lay"]),
83         "Ic_lay":     np.array(cpt_row["Ic_lay"]),
84         "sigmav_lay": np.array(cpt_row["sigmav_lay"]),
85         "depth":      np.array(cpt_row["depth"]),
86         "sigmav":     np.array(cpt_row["sigmav"]),
87     }
88
89
90 def load_vs30_lookup(csv_path, mop_line):
91     """Return a {x_position: Vs30} map for one transect."""
92     df = pd.read_csv(csv_path)
93     df = df[df["mop_line"] == mop_line]
94     return dict(zip(df["x_MSL"], df["vs30"]))
95
96
97 def get_x_targets(cell_loc):
98     """Sampled horizontal positions: every X_STEP-th unique x, always
99     keeping the last one."""
100     x_all = np.sort(np.unique(cell_loc["x_MSL"].to_numpy()))
101     x_targets = list(x_all[:X_STEP])
102     if x_targets[-1] != x_all[-1]:
103         x_targets.append(x_all[-1])
104     return x_targets
105
106
107 # -----
108 # Pore-pressure profiles and groundwater state
109 # -----
110
111 def get_pore_pressure_profile(x_target, u_all, x_column_indices,
112                             depth_arr, idx_arr):
113     """Extract the depth-sorted pore-pressure profile for the column at
114     x_target."""
115     row_ids = x_column_indices[x_target]
116     node_ids = idx_arr[row_ids] # corresponding HDF5 node indices
117     depth_u = depth_arr[row_ids]
118     u_profile = u_all[node_ids]
119     order = np.argsort(depth_u) # sort shallow -> deep
120     return depth_u[order], u_profile[order]
121
122
123 def find_water_table(depth_u, u_profile):
124     """Depth of the water table for a column.
125
126     Located at the shallowest depth where pore pressure crosses zero, found
127     by linear interpolation between the two points that bracket the sign
128     change. If pressure never changes sign, the column is treated as fully
129     saturated (water table at the surface, 0.0) or fully unsaturated (NaN).
130     """
131     sign_changes = np.where(np.diff(np.sign(u_profile)) != 0)[0]
132     if len(sign_changes) == 0:

```

```

133         return 0.0 if u_profile.min() > 0 else np.nan
134
135     i          = sign_changes[0]          # first (shallowest) crossing
136     u_local    = u_profile[i:i + 2]
137     depth_local = depth_u[i:i + 2]
138     if u_local[0] > u_local[1]:          # np.interp needs ascending x
139         u_local    = u_local[::-1]
140         depth_local = depth_local[::-1]
141     return np.interp(0.0, u_local, depth_local)
142
143
144 def compute_total_head(depth_u, u_profile, surface_el):
145     """Mean total head over the column: elevation head plus pressure head."""
146     return np.mean((surface_el - depth_u) + u_profile / GAMMAW)
147
148
149 def get_site_info(cell_loc_unique, x_target):
150     """Return lat/lon/surface elevation for the column nearest to x_target."""
151     x_values = cell_loc_unique["x_MSL"].to_numpy()
152     idx      = np.argmin(np.abs(x_values - x_target))
153     row      = cell_loc_unique.iloc[idx]
154     return {
155         "lat":      float(row["lat"]),
156         "lon":      float(row["lon"]),
157         "surface_el": float(row["surface_el_MSL"]),
158     }
159
160
161 # -----
162 # Layer construction and stress state
163 # -----
164
165 def insert_gwt_break(ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer, dGWT):
166     """Split the soil layer containing the water table so dGWT becomes a
167     boundary.
168
169     The upper and lower sublayers inherit the original layer's properties.
170     The layers are returned unchanged if the water table is undefined,
171     already a layer boundary, or outside the profile.
172     """
173     if not np.isfinite(dGWT):          # no water table
174         return ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer
175     if (dGWT in ztop) or (dGWT in zbot):          # already a boundary
176         return ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer
177     if (dGWT <= np.min(ztop)) or (dGWT >= np.max(zbot)):          # outside profile
178         return ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer
179
180     ztop, zbot = list(ztop), list(zbot)
181     qc1Ncs_layer = list(qc1Ncs_layer)
182     Ic_layer     = list(Ic_layer)
183     sigmav_layer = list(sigmav_layer)
184
185     for i in range(len(ztop)):          # find and split the host layer
186         if ztop[i] < dGWT < zbot[i]:

```

```

187         zbot_orig = zbot[i]
188         zbot[i] = dGWT
189         ztop.insert(i + 1, dGWT)
190         zbot.insert(i + 1, zbot_orig)
191         qc1Ncs_layer.insert(i + 1, qc1Ncs_layer[i])
192         Ic_layer.insert(i + 1, Ic_layer[i])
193         sigmav_layer.insert(i + 1, sigmav_layer[i])
194         break
195
196     return (np.array(ztop), np.array(zbot),
197            np.array(qc1Ncs_layer), np.array(Ic_layer), np.array(sigmav_layer))
198
199
200 def update_layers_for_u(cpt_data, u_profile, depth_u, dGWT):
201     """Recompute layer stresses and saturation for a given pore-pressure
202     profile.
203
204     Inserts a layer break at the water table, interpolates pore pressure to
205     each layer midpoint, and returns total stress, effective stress, and a
206     saturation flag per layer.
207     """
208     ztop = cpt_data["ztop"].copy()
209     zbot = cpt_data["zbot"].copy()
210     qc1Ncs_layer = cpt_data["qc1Ncs_layer"].copy()
211     Ic_layer = cpt_data["Ic_layer"].copy()
212     sigmav_layer = cpt_data["sigmav_layer"].copy()
213
214     ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer = insert_gwt_break(
215         ztop, zbot, qc1Ncs_layer, Ic_layer, sigmav_layer, dGWT
216     )
217
218     zmid = 0.5 * (ztop + zbot) # layer midpoints
219     u_layer = np.interp(zmid, depth_u, u_profile) # u at each midpoint
220     u0 = max(np.interp(0.0, depth_u, u_profile), 0.0) # u at the surface
221
222     sigmav_layer_adjusted = u0 + sigmav_layer # total vertical stress
223     sigmavp_layer = sigmav_layer_adjusted - u_layer # effective stress
224
225     # 1 at/below the water table, else 0
226     Ksat_layer = (
227         np.where(zmid >= dGWT, 1.0, 0.0) if np.isfinite(dGWT)
228         else np.zeros_like(zmid)
229     )
230
231     return {
232         "ztop": ztop,
233         "zbot": zbot,
234         "qc1Ncs_layer": qc1Ncs_layer,
235         "Ic_layer": Ic_layer,
236         "sigmav_layer": sigmav_layer_adjusted,
237         "sigmavp_layer": sigmavp_layer,
238         "Ksat_layer": Ksat_layer,
239     }
240

```

```

241
242 # -----
243 # Config assembly
244 # -----
245
246 def build_config(baseline, site_info, cpt_data, results,
247                 x_target, scenario_name, time_key, time_days, dGWT):
248     """Assemble a ucla_plha config dict from the baseline template and one
249     profile."""
250     cfg = copy.deepcopy(baseline)
251
252     cfg["additional_info"] = {                                # provenance metadata
253         "x_location": float(x_target),
254         "scenario": scenario_name,
255         "timestep": time_key,
256         "time_days": time_days,
257         "cpt_site_id": int(cpt_data["site_id"]),
258         "cpt_id": int(cpt_data["id"]),
259     }
260
261     cfg.setdefault("site", {})
262     cfg["site"]["latitude"] = site_info["lat"]
263     cfg["site"]["longitude"] = site_info["lon"]
264     cfg["site"]["elevation"] = site_info["surface_el"]
265     cfg["site"]["vs30"] = site_info["vs30"]
266     # replaced with a real path by the caller
267     cfg["output"]["outputfile"] = "default"
268
269     cfg["liquefaction_models"] = {
270         "ngl_smt_2024": {
271             "ztop": results["ztop"].tolist(),
272             "zbot": results["zbot"].tolist(),
273             "qc1Ncs": results["qc1Ncs_lay"].tolist(),
274             "Ic": results["Ic_lay"].tolist(),
275             "sigmav": results["sigmav_lay"].tolist(),
276             "sigmavp": results["sigmavp_lay"].tolist(),
277             "Ksat": results["Ksat_lay"].tolist(),
278             "weight": 1.0,
279             "pa": PA,
280         }
281     }
282     return cfg
283
284
285 def load_done_set(filelist_path):
286     """Load the set of already-written config paths, so an interrupted run
287     can resume."""
288     done = set()
289     if os.path.isfile(filelist_path):
290         with open(filelist_path) as f:
291             for line in f:
292                 parts = line.strip().split("\t")
293                 abs_path = parts[-1]
294                 if abs_path:

```

```

295         done.add(abs_path)
296     return done
297
298
299 # -----
300 # Per-file processing
301 # -----
302
303 def process_h5(h5_path, cell_loc_csv, cpt_df, baseline,
304               cpt_indices, in_path, out_path, done_set, vs30_lookup):
305     """Generate every config file for one HDF5 file (one transect + SLR
306     scenario).
307
308     Reads the HDF5 pore-pressure fields and Cell_Loc geometry once, then
309     loops over CPT profiles, sampled x positions, and the three
310     representative groundwater states, writing one JSON config per
311     combination. Returns the list of absolute config paths written.
312     """
313     h5_stem = Path(h5_path).stem
314     slr_name = Path(h5_path).parent.name
315
316     in_path = Path(in_path)
317     out_path = Path(out_path)
318     in_path.mkdir(parents=True, exist_ok=True)
319     out_path.mkdir(parents=True, exist_ok=True)
320
321     # Spatial data (read once per file).
322     cell_loc, cell_loc_unique, x_column_indices = load_cell_loc(cell_loc_csv)
323     x_targets = get_x_targets(cell_loc)
324     depth_arr = cell_loc["depth"].to_numpy()
325     idx_arr = cell_loc["idx"].to_numpy()
326     site_infos = {x: get_site_info(cell_loc_unique, x) for x in x_targets}
327     for x, info in site_infos.items():
328         info["vs30"] = vs30_lookup.get(x, float("nan"))
329
330     # Read the HDF5 once and collect one pore-pressure profile per x per
331     # output time.
332     timestep_data = {x: [] for x in x_targets}
333     with h5py.File(h5_path, "r") as f:
334         time_keys = [k for k in f.keys() if "Time" in k]
335         for time_key in time_keys:
336             # time in days
337             m = re.search(r"([\d.eE+-])\s*d", time_key, re.IGNORECASE)
338             time_days = float(m.group(1)) if m else None
339             # Convert PFLOTRAN liquid pressure [Pa] to gauge pore pressure
340             # [kPa].
341             u_all = np.asarray(f[time_key]["Liquid Pressure [Pa]"], float)
342             u_all = u_all / 1000.0 - PA
343
344             for x_target in x_targets:
345                 depth_u, u_profile = get_pore_pressure_profile(
346                     x_target, u_all, x_column_indices, depth_arr, idx_arr
347                 )
348                 surface_el = site_infos[x_target]["surface_el"]

```

```

349         timestep_data[x_target].append({
350             "time_key":    time_key,
351             "time_days":   time_days,
352             "total_head":  compute_total_head(depth_u, u_profile,
353                                             surface_el),
354             "depth_u":     depth_u,
355             "u_profile":   u_profile,
356         })
357
358     # Select three representative groundwater states per x from the
359     # total-head distribution over all times
360     # (dry / typical / wet ~ 5th / 50th / 95th percentile).
361     scenario_indices = {}
362     for x_target in x_targets:
363         total_heads = np.array([d["total_head"]
364                                for d in timestep_data[x_target]])
365         p05 = np.percentile(total_heads, 5)
366         p50 = np.median(total_heads)
367         p95 = np.percentile(total_heads, 95)
368         scenario_indices[x_target] = {
369             "p05":    np.argmin(np.abs(total_heads - p05)),
370             "median": np.argmin(np.abs(total_heads - p50)),
371             "p95":    np.argmin(np.abs(total_heads - p95)),
372         }
373
374     written_files = []
375
376     # Iterate over CPT profiles x sampled positions x the three groundwater
377     # states.
378     for cpt_index in cpt_indices:
379         cpt_data = load_cpt(cpt_df, cpt_index)
380
381         for x_target in x_targets:
382             site_info = site_infos[x_target]
383             data_list = timestep_data[x_target]
384
385             for scenario_name, idx in scenario_indices[x_target].items():
386                 filename = in_path / (
387                     f"{h5_stem}_{slr_name}_cpt{cpt_index}"
388                     f"_x{x_target:.1f}_{scenario_name}.json"
389                 )
390                 abs_filename = str(filename.resolve())
391                 # resume: skip configs already written
392                 if abs_filename in done_set:
393                     continue
394
395                 data      = data_list[idx]
396                 dGWT      = find_water_table(data["depth_u"], data["u_profile"])
397                 results    = update_layers_for_u(cpt_data, data["u_profile"],
398                                                 data["depth_u"], dGWT)
399                 cfg        = build_config(
400                     baseline, site_info, cpt_data, results,
401                     x_target, scenario_name, data["time_key"],
402                     data["time_days"], dGWT,

```

```

403         )
404         cfg["output"]["outputfile"] = str(
405             (out_path / filename.name).resolve()
406         )
407
408         with open(filename, "w") as fp:
409             json.dump(cfg, fp, indent=2)
410
411         written_files.append(abs_filename)
412
413     return written_files
414
415
416 # -----
417 # Job discovery (rank 0)
418 # -----
419
420 def discover_jobs():
421     """Build the list of per-HDF5 jobs to distribute across ranks.
422
423     Loads the shared CPT and baseline inputs once, then walks the target
424     transects and their SLR-scenario subfolders, emitting one job per HDF5
425     file that has both a pflotran.h5 and a Cell_Loc.csv.
426     """
427     cpt_pkl_path = MY_ROOT / CPT_PKL
428     baseline_path = MY_ROOT / BASELINE_JSON
429
430     # Use Abort (not sys.exit) on missing inputs: this runs on rank 0 only,
431     # and a bare exit would leave the other ranks blocked forever in
432     # comm.scatter.
433     if not cpt_pkl_path.is_file() or not baseline_path.is_file():
434         print(f"Missing {cpt_pkl_path} or {baseline_path}", flush=True)
435         MPI.COMM_WORLD.Abort(1)
436
437     cpt_df = pd.read_parquet(cpt_pkl_path)      # shared inputs, loaded once
438     with open(baseline_path) as bf:
439         baseline = json.load(bf)
440     num_cpts = len(cpt_df)
441
442     job_list = []
443     try:
444         mop_lines = sorted(os.listdir(GW_ROOT))
445     except FileNotFoundError:
446         print(f"GW_ROOT not found: {GW_ROOT}", flush=True)
447         MPI.COMM_WORLD.Abort(1)
448
449     for mop_line in mop_lines:
450         mop_src = GW_ROOT / mop_line
451         # only the requested transects
452         if mop_line not in TARGET_LINES:
453             continue
454         if not os.path.isdir(mop_src):
455             continue
456         if not (mop_line.startswith("MO") or mop_line.startswith("SC")):

```



```

457         continue
458     # must have at least one SLR case
459     if not any((mop_src / s).is_dir() for s in SLR_FOLDERS):
460         continue
461
462     mop_dst      = MY_ROOT / COUNTY / mop_line
463     input_folder = str(mop_dst / "input")
464     output_folder = str(mop_dst / "output")
465     done_set     = load_done_set(str(mop_dst / "filelist.txt"))
466     vs30_lookup  = (load_vs30_lookup(VS30_CSV, mop_line)
467                     if VS30_CSV.is_file() else {})
468
469     for slr_folder in SLR_FOLDERS:
470         slr_src = mop_src / slr_folder
471         if not os.path.isdir(slr_src):
472             continue
473
474         h5_path      = slr_src / "pflotran.h5"
475         cell_loc_csv = slr_src / "Cell_Loc.csv"
476         try:
477             if not h5_path.is_file() or not cell_loc_csv.is_file():
478                 continue
479         except PermissionError:
480             print(f"Permission denied: {h5_path}, skipping", flush=True)
481             continue
482
483         job_list.append(dict(
484             h5_path      = str(h5_path),
485             cell_loc_csv = str(cell_loc_csv),
486             cpt_df       = cpt_df,
487             baseline     = baseline,
488             cpt_indices  = list(range(num_cpts)), # every CPT profile
489             in_path      = input_folder,
490             out_path     = output_folder,
491             done_set     = done_set,
492             vs30_lookup  = vs30_lookup,
493         ))
494
495     return job_list
496
497
498 # -----
499 # Entry point
500 # -----
501
502 if __name__ == "__main__":
503     comm = MPI.COMM_WORLD
504     rank = comm.Get_rank()
505     size = comm.Get_size()
506
507     # Rank 0 discovers all jobs and distributes them round-robin across
508     # ranks.
509     if rank == 0:
510         print("Rank 0: discovering jobs", flush=True)

```

```

511     job_list = discover_jobs()
512     print(f"Rank 0: found {len(job_list)} jobs, scattering", flush=True)
513     if not job_list:
514         comm.Abort(1)
515
516     chunks = [[] for _ in range(size)]
517     for i, job in enumerate(job_list):
518         chunks[i % size].append(job)                # round-robin
519 else:
520     chunks = None
521
522 local_jobs = comm.scatter(chunks, root=0)
523
524 # Each rank processes its jobs and appends what it wrote to a
525 # per-transect filelist.
526 local_written = []
527 for job in local_jobs:
528     try:
529         written = process_h5(**job)
530         local_written.extend(written)
531         if written:
532             filelist_path = Path(job["in_path"]).parent / "filelist.txt"
533             with open(filelist_path, "a") as fl:
534                 for fpath in written:
535                     fl.write(f"{Path(fpath).name}\t{fpath}\n")
536     except Exception as e:
537         print(f"Rank {rank} error on {job['h5_path']}: {e}", flush=True)
538
539 # Rank 0 collects every rank's outputs into one master filelist for
540 # ucla_plha_mpi.py.
541 all_written_lists = comm.gather(local_written, root=0)
542 if rank == 0:
543     all_config_files = [f for sublist in all_written_lists for f in sublist]
544     if not all_config_files:
545         sys.exit(0)
546
547     master_filelist = MY_ROOT / COUNTY / "filelist_all.txt"
548     master_filelist.parent.mkdir(parents=True, exist_ok=True)
549     with open(master_filelist, "w") as fl:
550         for fpath in sorted(all_config_files):
551             fl.write(f"{fpath}\n")

```

Listing 12: Code to process groundwater PFLOTRAN HDF5 files into ucla_plha configuration files.

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