Leveraging Geospatial Technologies and AI for Synthesizing Earthquake-Tsunami Fragility Functions in Infrastructure Digital Twins

Mojtaba Harati (Corresponding Author)1[0000-0002-9722-5219] and John W. van de Lindt1[0000-0001-6386-4509]

[1] Colorado State University, Fort Collins, CO 80523, USA
`m.harati@colostate.edu`

Abstract. This study presents a novel machine learning (ML)-based framework for synthesizing three-dimensional (3D) fragility surfaces for earthquake-tsunami multi-hazard analysis. Traditional fragility functions rely on computationally intensive finite element (FE) simulations or empirical models, limiting scalability for multi-hazard applications. The proposed ML model integrates independent two-dimensional (2D) fragility curves for earthquake and tsunami hazards using Random Forest and Extreme Gradient Boosting algorithms, efficiently generating synthesized fragility surfaces with high predictive accuracy. By incorporating geospatial technologies and artificial intelligence (AI), the framework enables real-time hazard and damage assessment, supporting resilience planning and mitigation strategies. The study further explores applications in structural retrofitting, where ML-generated fragility surfaces inform quantitative evaluations of retrofitting strategies for multi-hazard resilience. The approach is validated using the Pseudo Seaside testbed, demonstrating its capability in community-scale risk assessments. Additionally, digital twin technology is leveraged to integrate ML-assisted fragility surfaces into dynamic resilience planning, enabling real-time monitoring, disaster response, and long-term mitigation optimization. The findings underscore the transformative potential of AI-driven fragility analysis in advancing multi-hazard risk assessment, with future research aimed at expanding applicability across diverse structural systems and hazard scenarios.

Keywords: Earthquake-Tsunami Fragility Functions, Geospatial Technologies, Artificial Intelligence (AI), Infrastructure Digital Twins, Multi-Hazard Risk Assessment, Machine Learning (ML).

1 Introduction

The combined occurrence of offshore earthquakes and subsequent tsunamis poses a severe risk to coastal communities, leading to catastrophic loss of life, widespread structural damage, and prolonged socio-economic disruptions. Events like the 2011 Tohoku earthquake and tsunami in Japan, which resulted in over 19,000 fatalities and $211 billion in damages (Fraser et al., 2013; Iwai & Goto, 2021; Kajitani et al., 2013;

McFall & Fritz, 2016), underscore the devastating impact of these sequential hazards. Effective hazard assessment and mitigation strategies are essential to reducing vulnerability and enhancing community resilience. Fragility functions, which estimate the probability of structural damage under specific hazard intensities, are central to multi-hazard analysis and provide critical input for resilience modeling (Watson et al. 2020). Advancements in geospatial technologies and artificial intelligence (AI) have revolutionized multi-hazard risk analysis, enabling more comprehensive and efficient hazard assessments. Geospatial tools allow for high-resolution mapping of hazard impacts, while AI techniques leverage data-driven approaches to identify complex patterns in structural vulnerabilities. Within this context, infrastructure digital twins—a virtual representation of physical systems—offer a promising framework for integrating geospatial data and AI to simulate the cascading effects of sequential hazards and optimize resilience planning (van de Lindt et al. 2018).

This study introduces a machine learning (ML) model that synthesizes 3D earthquake-tsunami fragility functions from independent 2D fragility curves for each hazard. Utilizing Random Forest and Extreme Gradient Boosting algorithms, the proposed methodology translates hazard-specific exceedance probabilities into unified fragility surfaces. This data-driven approach bypasses the computational intensity of traditional methods reliant on high-performance computing (HPC) and detailed finite element (FE) modeling, offering a scalable solution for multi-hazard resilience analysis (Harati and van de Lindt 2024; 2024b; 2024a). Rigorous validation and sensitivity analyses demonstrate the robustness of the synthesized fragility functions, ensuring reliability across varying structural systems and hazard intensities.

2 Integration of Geospatial Technologies and AI

The integration of geospatial technologies and AI has significantly advanced multi-hazard analysis, particularly for earthquake and tsunami scenarios. Geographic Information Systems (GIS) enable spatial modeling of hazard distributions, infrastructure vulnerabilities, and cascading impacts, leveraging high-resolution datasets like digital elevation models and land use maps. AI, particularly the ML, enhances this capability by processing complex datasets to generate 3D fragility surfaces, as demonstrated by the ML-based fragility synthesis model (Harati and van de Lindt 2024). This integration facilitates the coupling of earthquake and tsunami hazards, improving the accuracy of cascading damage assessments. Additionally, geospatial and AI-driven insights contribute to infrastructure digital twins—virtual replicas of physical systems that simulate real-time hazard impacts—enhancing resilience planning and resource allocation. By combining geospatial analysis with AI, this framework enables scalable, rapid hazard assessments, transforming data into actionable insights that support informed decision-making and real-time risk mitigation.

3 Machine Learning Model for Fragility Function Synthesis

The development of an ML model for fragility function synthesis marks a transformative step in multi-hazard analysis. Traditional methods of generating fragility functions rely on computationally intensive simulations or empirical data, often limited in scope and scalability. The proposed ML-based approach synthesizes 3D fragility surfaces for earthquake and tsunami hazards by leveraging two independent 2D fragility curves—one for each hazard. This novel methodology bypasses the need for HPC infrastructure and complex FE modeling.

Central to this method is the introduction of a "converter function," referred to as the ***g* function**, which translates the exceedance probabilities of individual hazards—$P(EQ)$ and $P(TS)$—into a joint (conditional) exceedance probability, $P(TS \mid EQ)$.

$$P(TS \mid EQ) = g(P(EQ), P(TS)) \qquad (1)$$

The ML model, employing algorithms such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost), is trained to predict this function. Features include hazard intensity measures (e.g., spectral acceleration for earthquakes and momentum flux for tsunamis) and the failure probabilities derived from the input 2D fragility curves. The ML algorithms are tuned and evaluated using metrics like root mean square error (RMSE) and R-squared (R^2) to ensure predictive accuracy and robustness. As can be seen in Fig. 1, it has been found that the ML model (the RF here) shows an accuracy of 99% for the R-squared score.

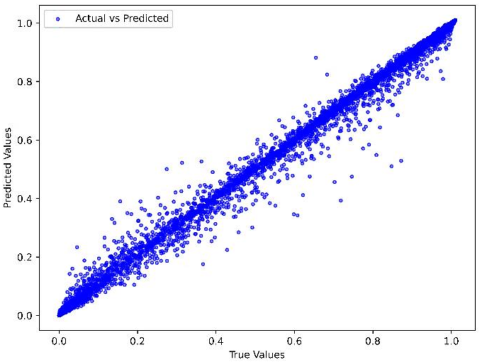
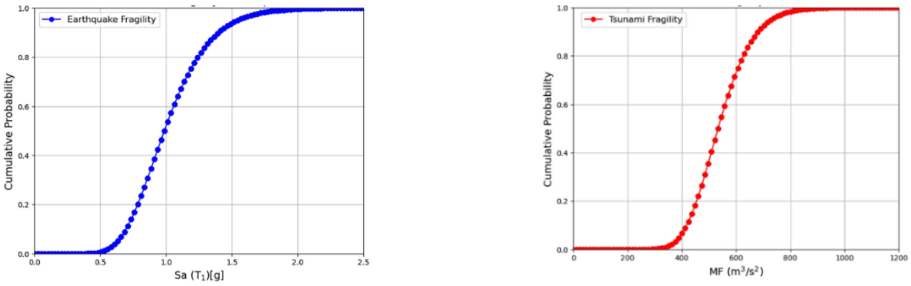


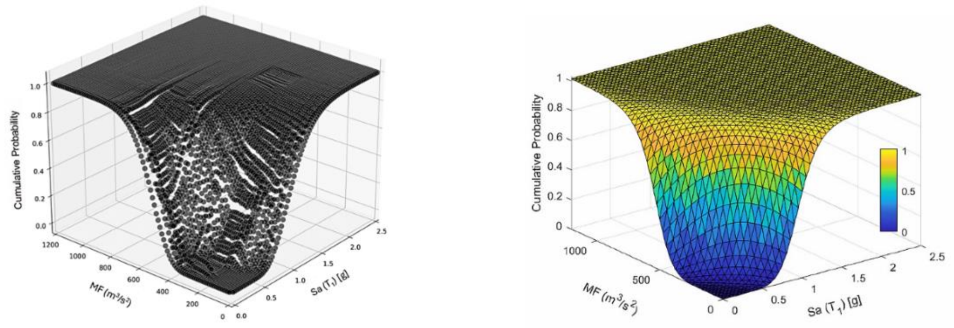
Fig. 1. Correlation between the predicted values versus the true (real simulated) values.

The synthesis process involves discretizing input fragility curves into datasets that feed the ML model. This data-driven approach allows the model to generalize across a wide range of structural types and hazard scenarios, facilitating the rapid generation of fragility surfaces for varying damage states. Once trained, the ML model can synthesize fragility surfaces within seconds, a notable improvement over conventional simulation methods that often require days or weeks of computation. The proposed ML model is applied to two related 2D fragility curves from past studies at the complete damage state (DS3) for a 3-story steel frame, developed using a consistent structural modeling approach with high-resolution FE modeling and IMK plastic hinges (Lignos and Krawinkler 2013). Ensuring consistency in damage criteria and modeling approaches is crucial for accurately synthesizing 3D fragility surfaces when integrating earthquake and tsunami data. Although generated through separate simulation procedures, the earthquake fragility curve from Attary et al (2021) and the tsunami fragility curve from Attary et al (2017) were discretized and input into the ML model to generate spatially distributed failure probability points representing *P(TS/EQ)*. The surface-fitting optimization technique by Harati and van de Lindt (2024a) was then applied to obtain the synthesized fragility surface.



a) Discretized earthquake fragility

b) Discretized tsunami fragility



c) Discrete points of surface

d) Fitted fragility surface

Fig. 2. Synthesized earthquake-tsunami fragility surface computed based on 2D fragility curves of other studies: a) 2D fragility curve for earthquake from Attary et al. (2021); b) 2D fragility curve for tsunami from Attary et al., (2017); c) failure probability points computed from ML-assisted algorithm, and d) synthesized fragility surface.

This ML-driven framework significantly enhances the practicality and efficiency of fragility analysis, enabling its integration into digital twin platforms and resilience planning tools. By offering a scalable solution that maintains high accuracy, the proposed model expands the scope of multi-hazard fragility analysis, supporting the assessment of cascading damage and informing mitigation strategies at both the structural and community levels.

4 Applications in Risk Assessment and Resilience Planning

The synthesized fragility surfaces generated by the ML model play a pivotal role in advancing risk assessment and resilience planning, particularly in multi-hazard contexts involving earthquakes and tsunamis. By integrating these surfaces into hazard analysis, the ML framework enables the assessment of cascading damage from sequential earthquake-tsunami events, capturing the dynamic interplay between these hazards. Specifically, it models joint exceedance probabilities of structural failure, quantifies the reduced seismic capacity of structures after earthquake-induced damage, and evaluates subsequent vulnerability to tsunami forces. This comprehensive approach enhances risk assessments by accounting for the sequential and compounding effects of multi-hazard scenarios, ultimately improving resilience planning and mitigation strategies.

Traditional retrofitting studies often rely on single-variable fragility curves that inadequately capture multi-hazard interactions. The ML-generated fragility surfaces address this limitation by enabling engineers to model retrofitted systems through the horizontal shifting of 2D fragility curves and synthesizing updated 3D surfaces, thereby providing a quantitative evaluation of retrofitting strategies for earthquake and tsunami hazards. Fig. 3 illustrates the effectiveness of this approach by comparing non-retrofitted and retrofitted fragility surfaces. The earthquake fragility curve (on the right-side boundary) shifts to the right by a factor of 1.33, reflecting increased structural capacity following retrofitting, assuming an upgrade from moderate-code to high-code performance per HAZUS guidelines. Similarly, Fig. 3 shows a rightward shift in the tsunami fragility curve on the left-side boundary, with a shift multiplier of 2 based on FEMA (2022) guidelines. This figure presents the earthquake-tsunami fragility surfaces, demonstrating how the ML model decouples the earthquake and tsunami fragility curves at the boundaries of the non-retrofitted fragility surface, allowing for independent retrofitting of each hazard before reassembling them into a combined retrofitted surface. The ML-derived parameters for the retrofitted and non-retrofitted fragility surfaces were previously reported by Harati and van de Lindt (2024), further validating the applicability of the ML model in fragility-oriented retrofitting applications.

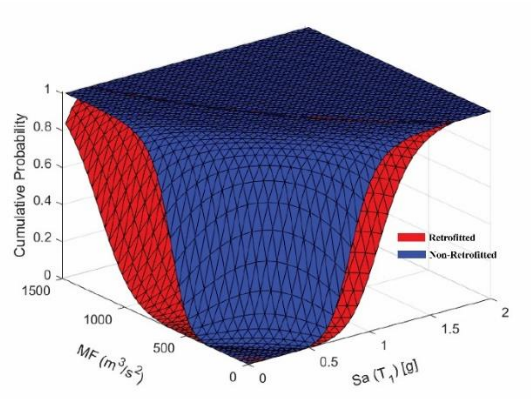


Fig. 3. Retrofitted and non-retrofitted synthesized fragility surfaces.

The ability to rapidly generate fragility surfaces across multiple structural archetypes and hazard scenarios enhances the scalability of resilience planning. For example, infrastructure portfolios, such as transportation networks or water distribution systems, can be evaluated for their vulnerability to multi-hazard events. The ML model's efficiency supports large-scale analyses, allowing for the prioritization of critical assets and the development of targeted mitigation measures. See more details in Harati and van de Lindt (2024)

This study presents an ML-assisted mitigation analysis for fragility-oriented structural retrofitting (Fig. 4), enabling the creation and evaluation of retrofitted fragility surfaces under different scenarios (Harati 2024). The framework integrates hazard intensity data from joint earthquake-tsunami events with GIS-based building exposure data, including location, land price, replacement cost, and construction year, accessible through resilience analysis platforms like IN-CORE (van de Lindt et al. 2023). Vulnerability functions for different archetypes are essential for community resilience assessments within this testbed (Harati and van de Lindt 2024a).

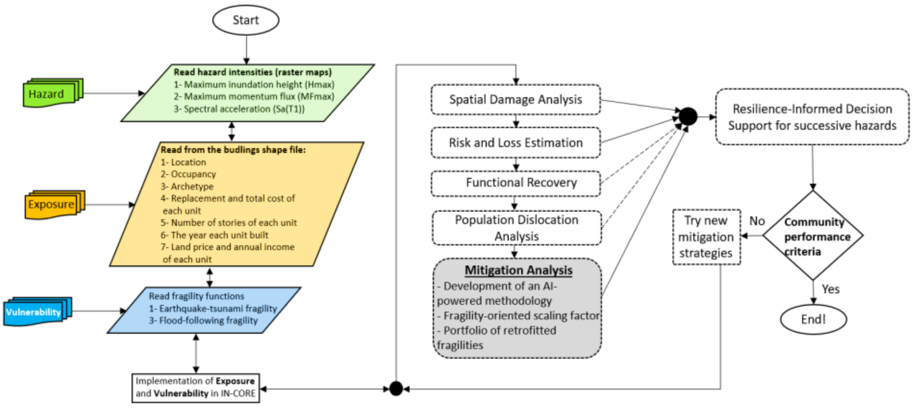
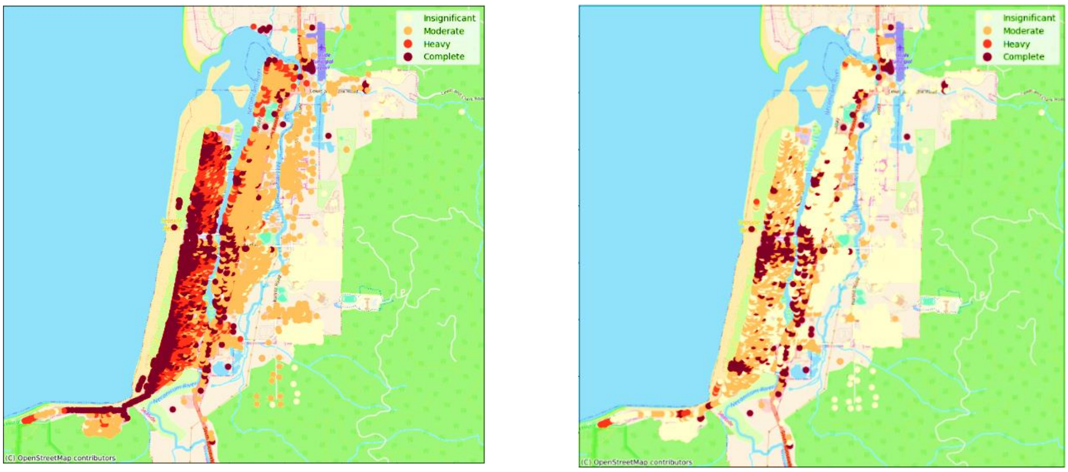


Fig. 4. The algorithm proposed in this study to perform mitigation analysis for a community under a multi-hazard scenario of earthquake and near-field tsunami hazards.

The Pseudo Seaside testbed (Harati and van de Lindt 2024a) is used to illustrate the proposed mitigation analysis, featuring a mix of RC buildings and woodframe structures, with the latter being more prevalent. Woodframe buildings are categorized by occupancy type (W1 for residential, W2 for industrial) and ductility level (1–3), while RC structures are classified into ductile (RC1–RC6) and non-ductile (RC7–RC10) designs. The testbed integrates simulated earthquake-tsunami fragility surfaces and 2D fragility curves for non-retrofitted models based on long-duration earthquake and near-field tsunami scenarios. Retrofitted vulnerability models were developed by extracting and horizontally shifting 2D fragility curves to elevate design levels, using scale factors derived from HAZUS (2020) and FEMA (2022). The ML model then synthesized updated retrofitted fragility surfaces, with scale factors reported in Harati (2024). For mitigation analysis, only woodframe buildings were structurally retrofitted as part of a community-wide plan. As shown in Fig. 5, the retrofitting reduced damage levels from complete (DS3) and heavy (DS2) to moderate (DS1) and insignificant (DS0) across many structures, demonstrating the effectiveness of the presented mitigation strategy. For further details on the machine learning framework and community-level analyses, readers are referred to Harati and van de Lindt (2025a, 2025b, 2025c), which provide data, methods, and results related to earthquake-tsunami fragility surfaces, multi-hazard resilience analysis, and mainshock-aftershock fragility modeling in the Pseudo Seaside Testbed.



a) Non-retrofitted archetypes b) Retrofitted archetypes

Fig. 5. Damage state patterns of Pseudo Seaside under a multi-hazard scenario of earthquake and near-field tsunami hazards at an intensity level of a 1000-year MRI using two different fragility suites: a) based on non-retrofitted archetypes; and b) from retrofitted archetypes.

5 Advancing Infrastructure Resilience through Digital Twins

Digital twin frameworks have become transformative tools in infrastructure resilience planning, offering dynamic, real-time, and predictive insights into system performance under various hazards. By integrating ML-generated synthesized fragility surfaces, digital twins enhance multi-hazard resilience analysis, particularly for earthquake-tsunami events. These fragility surfaces provide a data-driven foundation for assessing structural vulnerabilities and improving disaster preparedness.

The integration of fragility surfaces into digital twins enables real-time monitoring of infrastructure by incorporating data from sensors, satellite imagery, and geospatial analyses. This continuous updating of structural vulnerability assessments allows digital twins to predict failure probabilities during unfolding hazard scenarios, enhancing situational awareness and supporting faster, data-driven decision-making. Additionally, simulations of multiple hazard scenarios help planners understand cascading effects, such as how an earthquake-induced reduction in structural stiffness increases vulnerability to subsequent tsunami impacts, guiding proactive interventions.

Beyond disaster response, digital twins support long-term resilience planning by optimizing resource allocation and evaluating mitigation strategies. Synthesized fragility surfaces help identify the most vulnerable structures, prioritize retrofitting efforts, and minimize recovery time. Furthermore, digital twins enable planners to test the effectiveness of interventions like urban planning adjustments and hazard mitigation strategies. By simulating future hazard scenarios, including climate change-induced intensifications, digital twins ensure that resilience measures remain adaptive, cost-effective, and robust.

6 Conclusion and Future Directions

This study presents an ML-based framework for synthesizing 3D fragility surfaces that integrate earthquake and tsunami hazards, addressing the limitations of traditional fragility modeling. By leveraging geospatial technologies and AI, the proposed approach significantly enhances multi-hazard risk assessment and resilience planning. The developed ML model enables rapid generation of fragility surfaces, overcoming computational constraints associated with HPC and FE modeling. The integration of synthesized fragility functions into infrastructure digital twins facilitates real-time hazard simulations and supports data-driven decision-making for both structural and community-level resilience assessments. Furthermore, the application of ML-generated fragility surfaces in retrofitting analysis demonstrates their utility in evaluating and optimizing mitigation strategies, ensuring targeted interventions for enhancing structural resilience.

The findings underscore the potential of ML in revolutionizing fragility modeling by offering a scalable and computationally efficient alternative for multi-hazard analysis. The synthesized fragility surfaces capture the complex interactions between earthquake and tsunami hazards, improving the accuracy of cascading damage assessments. Additionally, the framework’s adaptability across various structural archetypes enables broader applicability in resilience planning. The case study application within the Pseudo Seaside testbed validates the effectiveness of the proposed methodology in identifying vulnerability patterns and optimizing retrofitting strategies, further reinforcing the practical value of the developed ML model.

Future research should explore the integration of additional hazard types, such as windstorms and flooding, into the fragility synthesis model to enhance multi-hazard resilience analysis. Expanding the database of fragility curves and incorporating real-world post-disaster data could improve the predictive accuracy of the ML model, ensuring robust performance across diverse structural typologies and hazard scenarios. Additionally, coupling ML-driven fragility functions with real-time sensor data in digital twin frameworks could enable dynamic updates to vulnerability assessments, enhancing disaster preparedness and response. Advancing ML interpretability techniques will also be crucial for increasing trust in AI-driven risk assessment models, ensuring transparency and reliability in resilience decision-making. By continuing to refine and expand the proposed framework, future research can further contribute to the development of resilient, adaptive, and data-informed disaster mitigation strategies.

References

Attary, Navid, Vipin U. Unnikrishnan, John W. van de Lindt, Daniel T. Cox, and Andre R. Barbosa. 2017. “Performance-Based Tsunami Engineering Methodology for Risk Assessment of Structures.” *Engineering Structures* 141 (June):676–86. https://doi.org/10.1016/j.engstruct.2017.03.071.

Attary, Navid, John W. Van De Lindt, Andre R. Barbosa, Daniel T. Cox, and Vipin U. Unnikrishnan. 2021. “Performance-Based Tsunami Engineering for Risk Assessment of Structures Subjected to Multi-Hazards: Tsunami Following Earthquake.” *Journal of Earthquake Engineering* 25 (10): 2065–84. https://doi.org/10.1080/13632469.2019.1616335.

Fraser, Stuart, Alison Raby, Antonios Pomonis, Katsuichiro Goda, Siau Chen Chian, Joshua Macabuag, Mark Offord, Keiko Saito, and Peter Sammonds. 2013. “Tsunami Damage to Coastal Defences and Buildings in the March 11th 2011 M w 9.0 Great East Japan Earthquake and Tsunami.” *Bulletin of Earthquake Engineering* 11 (1): 205–39. https://doi.org/10.1007/s10518-012-9348-9.

Harati, Mojtaba. 2024. “Simulation of Successive Events for Multi-Hazard Community Resilience Analysis.” Doctoral Dissertation, Colorado State University.

Harati, Mojtaba, and John W. van de Lindt. 2024. “Methodology to Generate Earthquake-Tsunami Fragility Surfaces for Community Resilience Modeling.” *Engineering Structures* 305 (April):117700. https://doi.org/10.1016/j.engstruct.2024.117700.

Harati, Mojtaba and van de Lindt, John W. 2024a. “Community-Level Resilience Analysis Using Earthquake-Tsunami Fragility Surfaces.” *Resilient Cities and Structures*.

Harati, Mojtaba, and John W. Van De Lindt. 2024. “Data-driven Machine Learning for Multi-hazard Fragility Surfaces in Seismic Resilience Analysis.” *Computer-Aided Civil and Infrastructure Engineering*, October, mice.13356. https://doi.org/10.1111/mice.13356.

Harati, Mojtaba and van de Lindt, John W. 2024b. “Fragility Function Development of RC Building Portfolio for Use in Earthquake-Tsunami Community Resilience Studies.” *Journal of Performance of Constructed Facilities*, no. Uner Riview.

Harati, Mojtaba and van de Lindt, John W. 2024c. “Impact of Long-Duration Earthquakes on Successive Earthquake-Tsunami Fragilities for Reinforced Concrete Frame Archetypes.” *Journal of Structural Engineering* 150 (10): 1–19.

Harati, M., J. van de Lindt (2025a). "Multi-Hazard Community Resilience Analysis Using Earthquake-Tsunami Fragility Surfaces: Damage and Economic Loss Assessment in the Pseudo Seaside Testbed", in Community-Level Multi-Hazard Resilience Analysis Using Earthquake-Tsunami Fragility Surfaces and Monte Carlo Simulation in the Pseudo Seaside Testbed. DesignSafe-CI. https://doi.org/10.17603/ds2-cnn2-jm75

Harati, M., J. van de Lindt (2025b). "Machine Learning-Assisted Multi-Hazard Fragility Surface Dataset for Earthquake-Tsunami Resilience Analysis", in Development and Application of Machine Learning-Based Multi-Hazard Fragility Surfaces for Earthquake-Tsunami Resilience Analysis. DesignSafe-CI. https://doi.org/10.17603/ds2-d155-yt55

Harati, M., J. van de Lindt (2025c). "Fragility Analysis of Buildings Under Mainshock-Aftershock Sequences: Simulation Data and Results", in Single-Variable Fragility Analysis of Mainshock-Aftershock Sequences for Community Resilience Studies: Data and Code. DesignSafe-CI. https://doi.org/10.17603/ds2-3z11-d239

Iwai, Shohei, and Kazuhisa Goto. 2021. “Threshold Flow Depths to Move Large Boulders by the 2011 Tohoku-Oki Tsunami.” *Scientific Reports* 11 (1): 13434. https://doi.org/10.1038/s41598-021-92917-2.

Kajitani, Yoshio, Stephanie E. Chang, and Hirokazu Tatano. 2013. “Economic Impacts of the 2011 Tohoku-Oki Earthquake and Tsunami.” *Earthquake Spectra* 29 (1_suppl): 457–78. https://doi.org/10.1193/1.4000108.

Lignos, Dimitrios G., and Helmut Krawinkler. 2013. “Development and Utilization of Structural Component Databases for Performance-Based Earthquake Engineering.” *Journal of Structural Engineering* 139 (8): 1382–94. https://doi.org/10.1061/(ASCE)ST.1943-541X.0000646.

Lindt, John W. van de, Bruce Ellingwood, Therese P. McAllister, Paolo Gardoni, Daniel Cox, Walter G. Peacock, Harvey Cutler, et al. 2018. “Modeling Community Resilience: Update on the Center for Risk-Based Community Resilience Planning and the Computational Environment IN-CORE.” *NIST*, November. https://www.nist.gov/publications/modeling-community-resilience-update-center-risk-based-community-resilience-planning.

Lindt, John W. van de, Jamie Kruse, Daniel T. Cox, Paolo Gardoni, Jong Sung Lee, Jamie Padgett, Therese P. McAllister, et al. 2023. “The Interdependent Networked Community Resilience Modeling Environment (IN-CORE).” *Resilient Cities and Structures*, Integrated Modeling of Cities to Improve Natural Hazards Resilience, 2 (2): 57–66. https://doi.org/10.1016/j.rcns.2023.07.004.

McFall, Brian C., and Hermann M. Fritz. 2016. “Physical Modelling of Tsunamis Generated by Three-Dimensional Deformable Granular Landslides on Planar and Conical Island Slopes.” *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 472 (2188): 20160052. https://doi.org/10.1098/rspa.2016.0052.

Watson, Maria, Yu Xiao, Jennifer Helgeson, and Maria Dillard. 2020. “Importance of Households in Business Disaster Recovery.” *Natural Hazards Review* 21 (4): 05020008. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000393.