14th International Conference on Structural Safety and Reliability - ICOSSAR'25
1-6 June, 2025 - Los Angeles California, USA
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Machine Learning-Driven Synthesis of Multi-Hazard Fragility Surfaces for Seismic and Tsunami Resilience

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Key words: Machine learning, fragility surfaces, earthquake-tsunami, multi-hazard analysis, community resilience, retrofitting, structural mitigation.

Abstract. Coastal populations are particularly vulnerable to offshore earthquakes and their cascading effects, such as tsunamis. In response to these risks, this study presents a novel machine learning (ML) model for synthesizing 3D fragility surfaces that capture the combined impacts of earthquake and tsunami hazards. The model leverages independently generated 2D fragility curves for each hazard and integrates physics-based simulations to improve accuracy and reliability. By utilizing data-driven approaches, the model offers computational efficiency, reducing the need for high-performance computing resources typically required for such simulations. An important application of the model lies in retrofitting analysis. By using 2D fragility curves for retrofitted structural systems, the model can generate retrofitted earthquake-tsunami fragility surfaces, allowing for more comprehensive mitigation and resilience planning at both building and community levels. This ability to model structural retrofits provides critical insights into the effectiveness of different mitigation strategies for coastal communities facing multi-hazard scenarios. While the model is primarily demonstrated for earthquake-tsunami hazards, the methodology has the potential to be applied to other hazard combinations, making it a versatile tool for broader multi-hazard resilience assessments. The study concludes that machine learning offers a transformative approach to hazard and vulnerability modelings, enhancing decision-making for urban planning and disaster preparedness.

1 INTRODUCTION

Coastal populations face significant risks from offshore earthquakes and their cascading effects, particularly tsunamis. The 2011 Tōhoku earthquake and tsunami in Japan demonstrated the devastating consequences of such events, causing over 19,000 fatalities and extensive economic losses exceeding $211 billion [1]. Modeling and predicting the structural response to these multi-hazard events are critical for enhancing community resilience, urban planning, and disaster mitigation strategies. Traditional fragility modeling approaches rely heavily on physics-based simulations, finite element (FE) modeling, or empirical field studies to generate fragility functions, but these methods are computationally expensive and time-intensive, often requiring weeks or months to complete a single simulation [2]. Additionally, many of these approaches struggle to efficiently account for cascading hazard effects, such as sequential earthquake-tsunami loading, which significantly influences structural damage patterns [4].

This study presents a data-driven machine learning (ML) methodology—three based regressors (see Appendix A)—for synthesizing three-dimensional (3D) earthquake-tsunami fragility surfaces from independently derived two-dimensional (2D) fragility curves. By leveraging ML techniques, the model reduces computational demands while maintaining accuracy in multi-hazard risk estimation. The ability to generate fragility surfaces in seconds rather than days allows for rapid analysis of structural vulnerability across varying hazard intensity levels. Unlike conventional fragility models that require predefined analytical frameworks, this ML-based approach can generalize across different structural types and hazard scenarios, making it adaptable for a broad range of applications in seismic and coastal engineering [5].

A key innovation of this model is its capability to facilitate structural retrofitting analysis by enabling the horizontal shifting of fragility curves to reflect mitigation strategies. This technique provides a scalable framework for evaluating different retrofitting methods and their impact on multi-hazard fragility surfaces, improving decision-making for resilience planning. The model also integrates with IN-CORE, a community resilience modeling platform developed by NIST, allowing researchers to incorporate ML-generated fragility surfaces into broader resilience assessment frameworks [7].

This paper serves as a user guide for researchers and engineers looking to utilize this ML-based fragility modeling approach. It outlines the synthesis process, validation methods, model implementation, and integration with existing hazard assessment tools. The full dataset, ML scripts, and fragility model outputs are available on DesignSafe-CI under Project PRJ-5819 [8] and GitHub [9]. This study contributes to advancing multi-hazard fragility modeling by offering an open-access computational tool that enhances efficiency, scalability, and applicability in resilience-based decision-making.

2 SYNTHESIS PROCESS AND VALIDATION

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. For more information regarding the training procedure of the ML model, readers are referred to a study by Harati and van de Lindt (2024) [5].

Figure 1 illustrates the overall framework of the ML-based approach for synthesizing earthquake-tsunami fragility functions. The model development begins by pre-processing independently derived 2D fragility curves for earthquake and tsunami hazards, ensuring that they are formatted consistently in terms of damage state definitions and intensity measures. These fragility curves, which represent the probability of structural failure at different intensity measures, are then discretized into probabilistic datasets that serve as inputs to the ML framework. The model is trained on an extensive set of simulation data, allowing it to capture and learn the interaction effects between the two hazards. Once trained, the ML algorithm processes new fragility curves and generates a corresponding three-dimensional fragility surface, estimating the probability of exceedance for different earthquake and tsunami intensity levels.

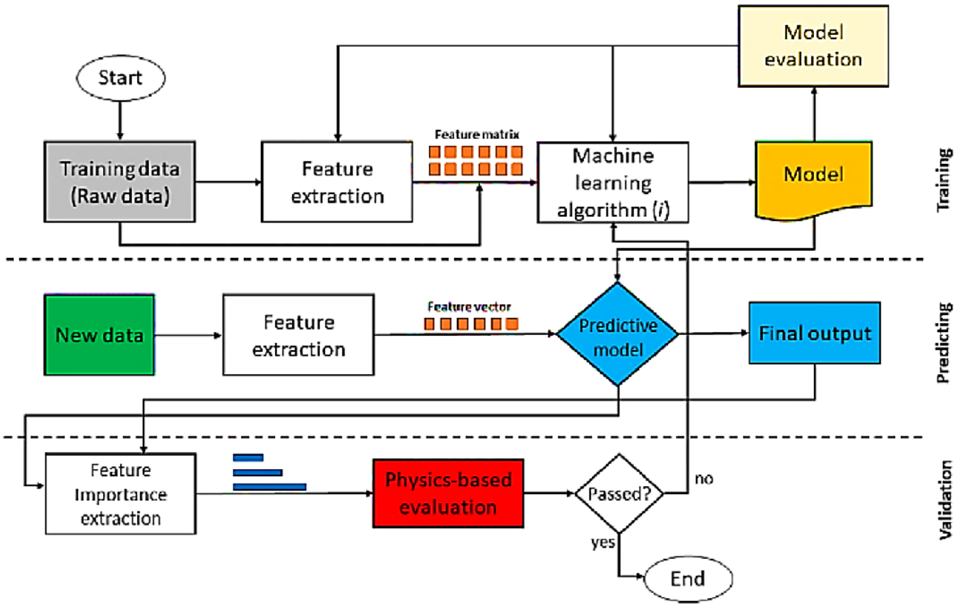
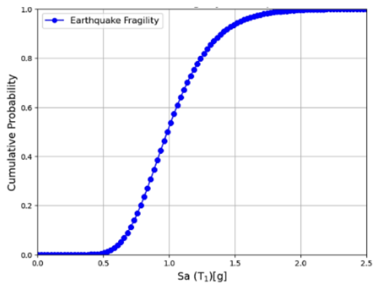


Figure 1: The proposed framework for the data-driven machine learning (ML) modeling for generating the synthesized earthquake–tsunami fragility functions [5].

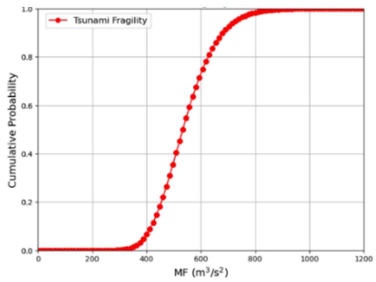
To validate the effectiveness of the ML-generated fragility surfaces, the model was applied to two related 2D fragility curves from past studies at the complete damage state (DS3) for a 3-story steel frame. These curves were developed using a consistent structural modeling approach that incorporated high-resolution finite element (FE) modeling and IMK plastic hinges, ensuring the robustness of the underlying structural response predictions [5]. The selection of DS3 as the validation criterion was based on its relevance in representing complete structural failure, making it a critical benchmark for assessing the accuracy of fragility modeling in extreme multi-hazard scenarios.

Ensuring consistency in damage criteria and modeling approaches is crucial for accurately synthesizing 3D fragility surfaces when integrating earthquake and tsunami data. Even though the earthquake and tsunami fragility curves were developed through separate simulation procedures, maintaining uniformity in structural assumptions, material properties, and failure thresholds was essential to ensure a meaningful synthesis. In this study, the earthquake fragility curve from [6] and the tsunami fragility curve from [4] were both discretized into a probabilistic dataset before being fed into the ML model. This preprocessing step allowed the ML framework to analyze and generate spatially distributed failure probability points, effectively capturing the dependency of tsunami-induced damage on prior earthquake loading conditions, represented as $P(TS|EQ)$.

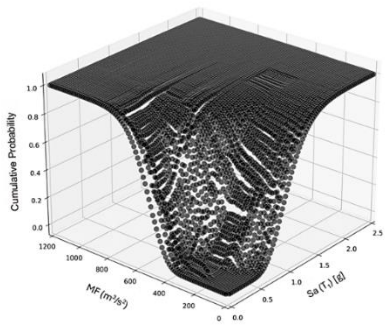
The synthesized fragility surface was constructed by applying a surface-fitting optimization technique adapted from [2], which refines the probabilistic failure data into a continuous, multidimensional fragility function. This technique ensures that the ML-generated fragility surface remains smooth and physically interpretable while accurately reflecting the observed hazard interactions. The resulting fragility surface effectively captures the compounding effects of earthquake and tsunami loading, providing insights into structural vulnerabilities that would be challenging to obtain using traditional empirical or simulation-based methods.



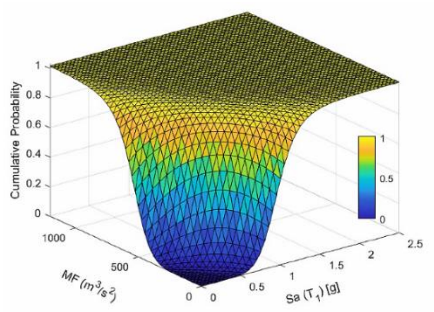
a) Discretized earthquake fragility



b) Discretized tsunami fragility



c) Discrete points of surface



d) Fitted fragility surface

Figure 2: Synthesized earthquake-tsunami fragility surface computed based on 2D fragility curves of other studies: a) 2D fragility curve for earthquake from [6]; b) 2D fragility curve for tsunami from [4]; c) failure probability points computed from ML-assisted algorithm; and d) synthesized fragility surface [5].

To assess the reliability of the ML-assisted methodology, the synthesized fragility surface was rigorously compared against physics-based fragility models derived from high-fidelity numerical simulations. The comparison demonstrated that the ML-generated fragility surfaces closely approximate the results of computationally intensive physics-based models, with minor deviations primarily attributable to the discretization process and the inherent statistical nature of machine learning approximations [5]. These findings confirm that ML-generated fragility surfaces provide a computationally efficient alternative to traditional physics-based simulations while maintaining a high degree of accuracy in structural vulnerability assessment. Furthermore, the ability to generate fragility surfaces rapidly allows for a more extensive exploration of different hazard intensity combinations, facilitating a more robust and scalable approach to multi-hazard risk analysis.

3 MODEL IMPLEMENTATION AND INTEGRATION WITH IN-CORE

To effectively utilize this model, users will need access to machine learning model files provided in the dataset [8], a training dataset from DesignSafe containing validated fragility data for earthquakes and tsunamis, and computational tools and platforms, including IN-CORE for further resilience analysis [7].

The model follows a structured workflow to generate fragility surfaces. Users provide two separate two-dimensional fragility curves representing the vulnerability of structures to earthquakes and tsunamis. The ML algorithm processes these curves and generates a combined fragility surface, capturing interaction effects [4]. The results can be utilized in hazard mitigation strategies and urban planning. The generated fragility surfaces help in estimating the likelihood of structural damage under different earthquake-tsunami intensity scenarios, allowing for improved decision-making in risk assessment. The full dataset and implementation scripts are available at GitHub [9].

The integration with IN-CORE enables researchers and engineers to further utilize the ML-generated fragility surfaces for comprehensive community resilience modeling. IN-CORE provides a platform to analyze multi-hazard scenarios by incorporating hazard data and infrastructure vulnerability functions, enhancing disaster preparedness and mitigation planning [7]. The fragility surfaces generated by this ML model can be directly applied to define earthquake-tsunami vulnerability functions within IN-CORE, allowing users to simulate cascading hazard impacts on urban environments. The ability to extract parameters from the ML model and input them into IN-CORE streamlines the process of multi-hazard risk assessment, making it a valuable tool for policymakers, engineers, and researchers involved in disaster risk reduction. By integrating fragility surfaces with IN-CORE, users can evaluate the spatial distribution of risk across different infrastructure systems, test various retrofitting strategies, and optimize resilience-based decision-making at both structural and community levels.

4 CONCLUSIONS AND FUTURE APPLICATIONS

This ML-based fragility modeling framework provides a computationally efficient and scalable alternative to traditional physics-based fragility assessments. Key contributions of the model include improved computational efficiency for generating fragility surfaces, enhanced accuracy in multi-hazard risk estimation, seamless integration with IN-CORE for resilience-based decision-making, and support for structural retrofitting analysis to optimize mitigation strategies.

Future work will focus on expanding the model to other multi-hazard scenarios beyond earthquake-tsunami interactions, developing real-time fragility surface generation using live hazard data inputs, and validating the model against empirical disaster data to enhance reliability. This research provides an open-access ML framework for hazard mitigation and resilience planning, with datasets and tools available on DesignSafe [8] and GitHub [9] for broader research applications.

ACKNOWLEDGEMENTS

The Center for Risk-Based Community Resilience Planning is a NIST-funded Center of

Excellence; the Center is funded through a cooperative agreement between the U.S. National Institute of Standards and Technology and Colorado State University (NIST Financial Assistance Award Numbers: 70NANB15H044 and 70NANB20H008). The views expressed are those of the presenter and may not represent the official position of the National Institute of Standards and Technology or the U.S. Department of Commerce.

DATA AVAILABILITY

The dataset, ML scripts, and fragility model outputs are available on DesignSafe-CI [10] and GitHub [11] for broader research applications.

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component databases for performance-based earthquake engineering." *Journal of Structural Engineering*, 139, 1382–1394.

APPENDIX A: TREE-BASED MACHINE LEARNING REGRESSORS

A.1 INTRODUCTION

Machine learning regression models play a critical role in predicting structural responses and synthesizing fragility functions in multi-hazard resilience analysis. Among these models, tree-based regressors have demonstrated high accuracy and robustness, particularly in non-linear and high-dimensional datasets. This appendix discusses two widely used tree-based regressors: Extreme Gradient Boosting (XGBoost) and Random Forest (RF), which have been employed for synthesizing multi-hazard fragility functions.

A.2 EXTREME GRADIENT BOOSTING (XGBOOST)

XGBoost is an advanced implementation of gradient boosting, designed for computational efficiency and predictive accuracy. As illustrated in Figure 1, XGBoost builds decision trees iteratively, where each new tree corrects the residual errors of the previous trees. The process starts with a dataset that is sequentially split into subsets, and residuals (errors) from previous trees are used to train subsequent trees. Each tree improves upon its predecessor, and the final prediction is obtained by summing the weighted outputs of all trees. This boosting approach enhances predictive performance by reducing bias and variance, making XGBoost highly effective for structured datasets. However, due to its sequential nature, XGBoost can be computationally expensive and requires careful tuning of hyperparameters.

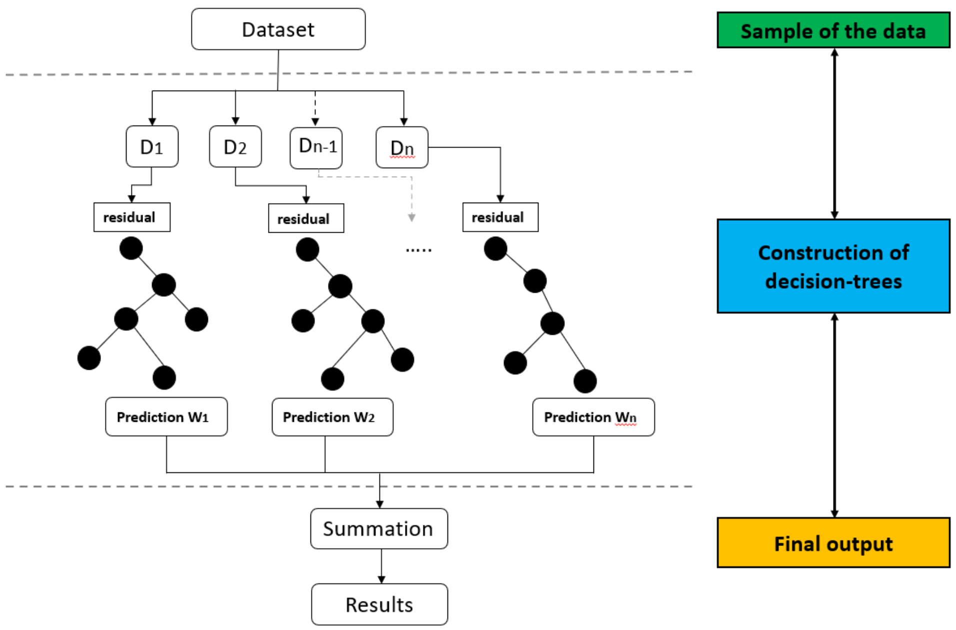

Figure 1: Gradient Boosting Decision Tree (GBDT) process, where sequential decision trees correct residuals to improve prediction accuracy.

A.3 Random Forest (RF)

Random Forest, on the other hand, is an ensemble learning method that constructs multiple independent decision trees and aggregates their predictions. Figure 2 illustrates this process, where an input query (Q) is used to generate multiple decision trees trained on random subsets of the data. Each tree provides an independent prediction, and the final output is determined by averaging these predictions. Unlike XGBoost, Random Forest does not rely on residual-based learning but instead leverages bootstrap aggregation (bagging) to improve model stability and generalization. This approach makes RF less sensitive to noise and more efficient for large datasets, particularly when the relationships between input features and target variables are complex and non-linear.

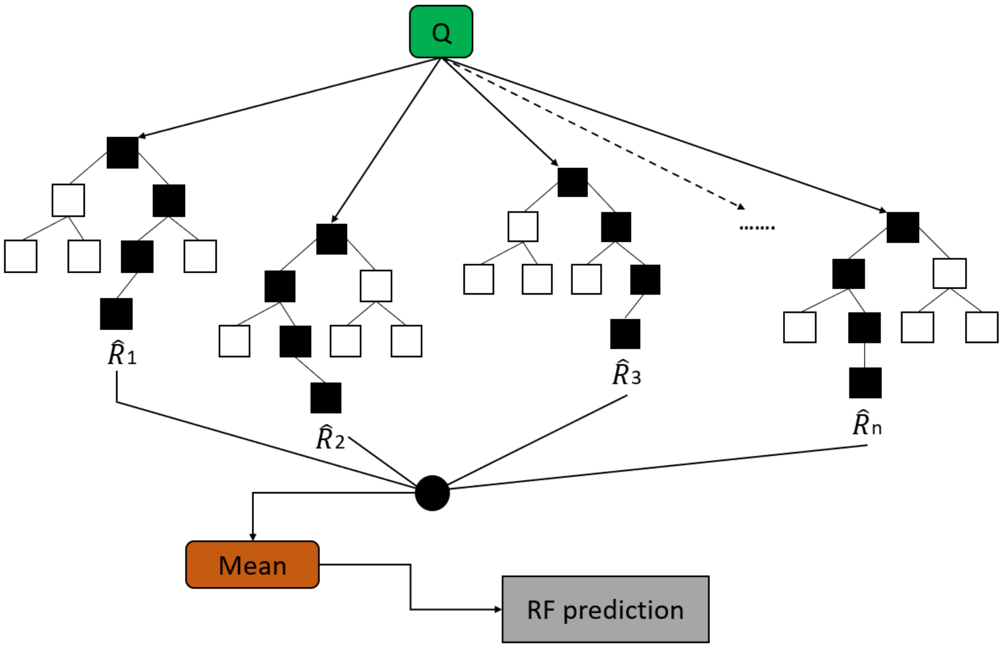

Figure 2: Random Forest regression process, where multiple decision trees are trained on random subsets of data, and their predictions are averaged to generate the final output.

A.4 Sensitivity Analysis and Model Selection

In Harati and van de Lindt (2024) [5], a comprehensive sensitivity analysis was conducted to evaluate the predictive performance of XGBoost and Random Forest in synthesizing multi-hazard fragility functions. The analysis considered key performance metrics such as mean squared error (MSE), R-squared (R^2), Feature Importance Analysis (FIA) and computational efficiency. The results demonstrated that while XGBoost provides strong predictive capabilities, Random Forest achieved the best overall performance, balancing accuracy, interpretability, and computational cost. Therefore, in this study, RF is selected as the primary predictive model for synthesizing earthquake-tsunami fragility functions and assessing structural resilience under sequential hazard events.