Synthetic Ground-Motion Wavefields using Generative Adversarial Neural Operators

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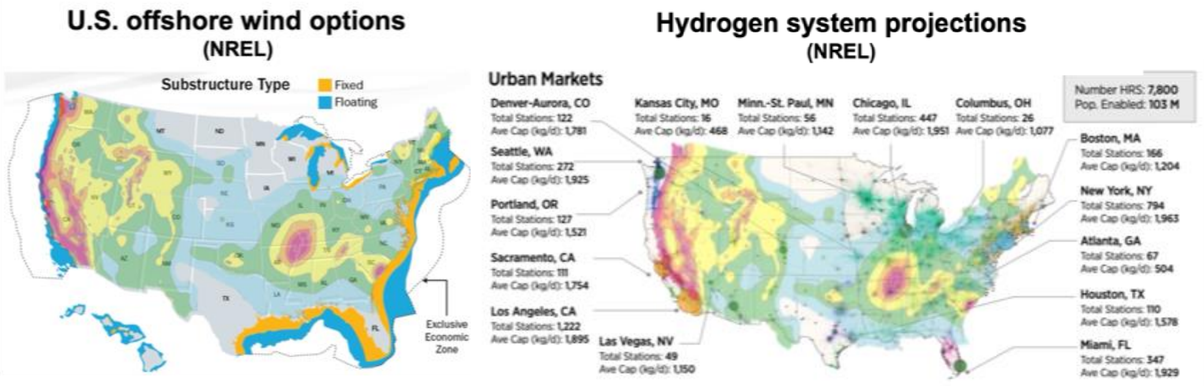
Abstract

We are building a virtual earthquake simulator that will help meet the earthquake-resistant requirements of emerging Earthshot™ systems. We leverage recent DOE Exascale Computing Project (ECP) developments in high-performance computing and cutting-edge advances in deep learning to predict regional ground shaking scenarios on-the-fly for seismic hazard and system-level risk assessment. Through the synergistic integration of models and observed ground-shaking data, our simulator will bridge the gap between historical, statistics-based empirical ground-motion models and physics-based computations by generating ground-shaking scenarios fast, with realistic spatial variability and broadband frequency content– a key to correctly identify the system-level seismic vulnerabilities. Lastly, our machine-learning algorithms will be agnostic to the physics of earthquakes, so our hybridized framework can be seen as a stepping stone to assessing resilience and risk associated with other natural hazards threatening energy systems, such as hurricanes, floods and combinations thereof.

Our mission: *To develop the algorithmic framework that will fuse exascale earthquake simulators with sparsely observed ground shaking data into widely-available, computationally-efficient, and cost-effective earthquake scenario synthetics, for Risk Reduction and Resilience (R3) of Earthshot™ systems.*

Earthshot™ Systems and Seismic Hazard



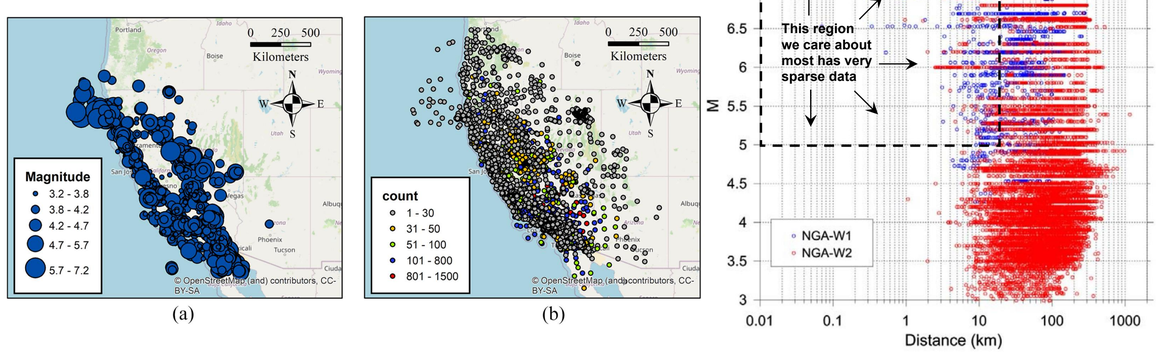
To meet DOE's aggressive clean energy objectives, we cannot afford catastrophic failure or diminished function due to natural hazards: we need **to quantify system level risk for future, rare events**.

System-level seismic risk assessment paradigms

a. The empirical (data-driven) approach

PROS: Proliferation of high-quality strong motion inst

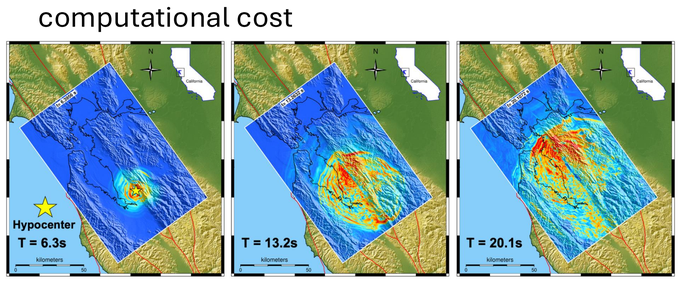
CONS: Historical data rarely 'sample' the rare events



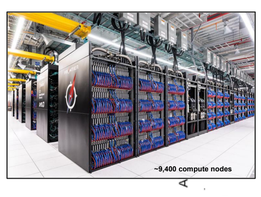
b. The physics-based simulation approach
(e.g. ECP EQSIM cutting edge hi-fi regional-scale simulations)

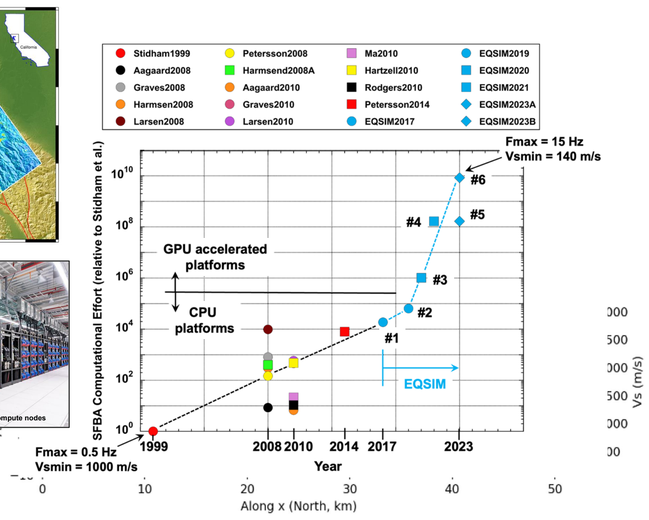
PROS: Enables simulations of rare events yet to occur → sample the tail of the distribution

CONS: Not possible (yet) to sample the full ground motion distribution due to computational cost



Simulation of large unobserved event: Snapshot of M7 on the Hayward fault (McCallen et al, 2024).

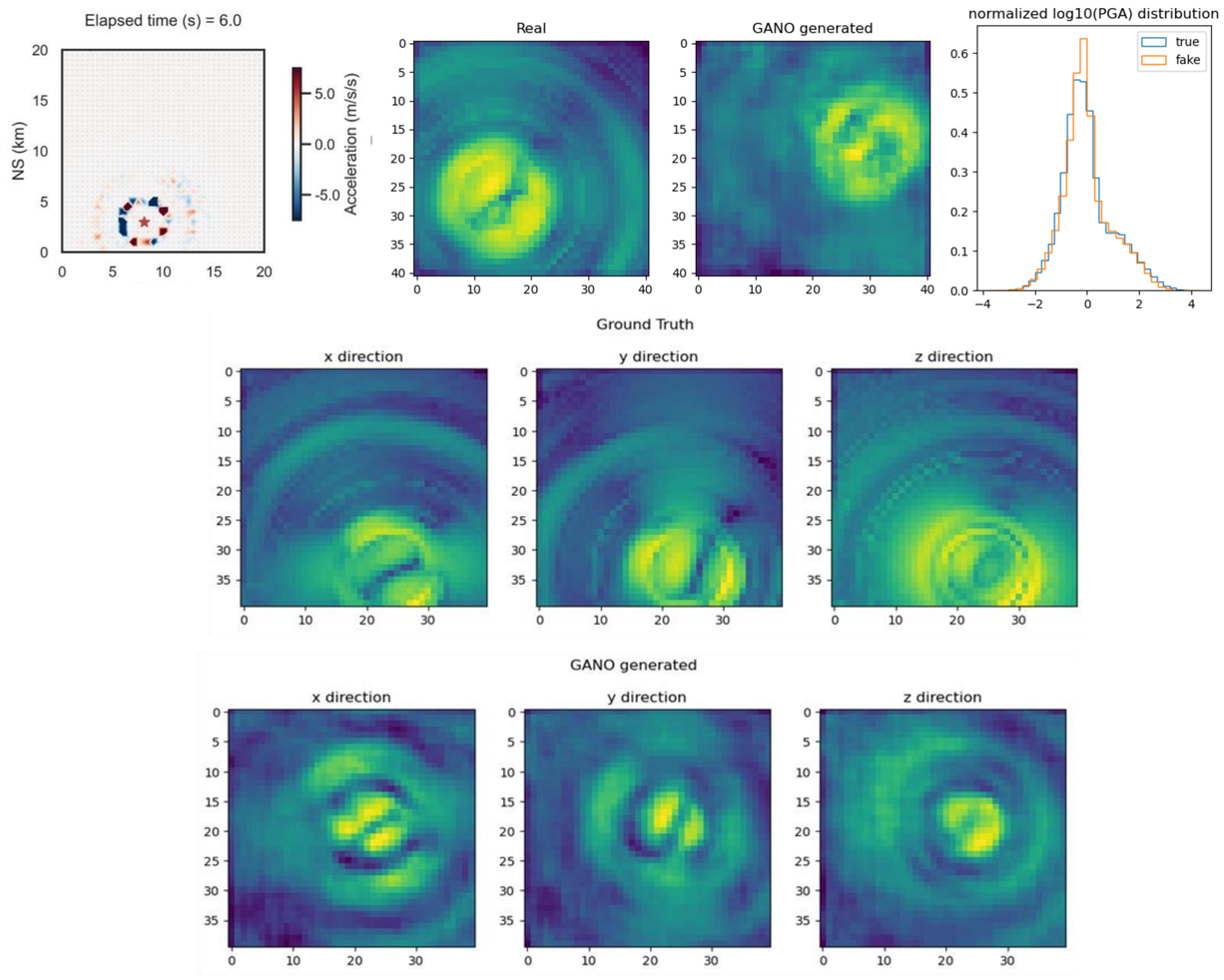




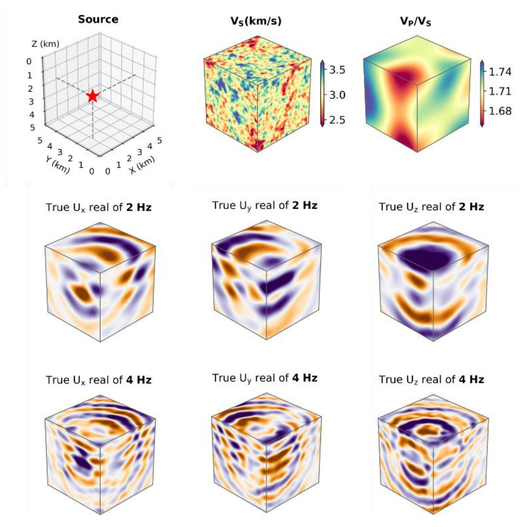
Learning from Simulations

Our ongoing research indicates that adversarially trained generative models are able to learn the spatial and temporal variability of ground motions from 3D simulations, offering an efficient approach for sampling realistic 3D ground-shaking scenarios.

2D-space Fourier Neural Operator (GANO-FNO-unconditional)

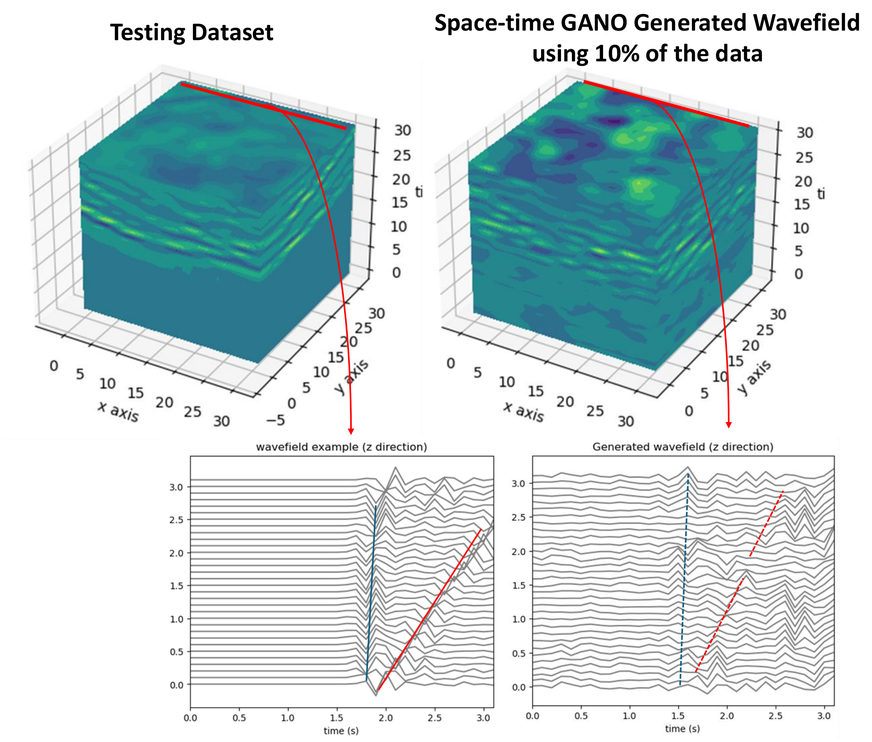


3D-space Fourier Neural Operator (space-time model)



Training dataset

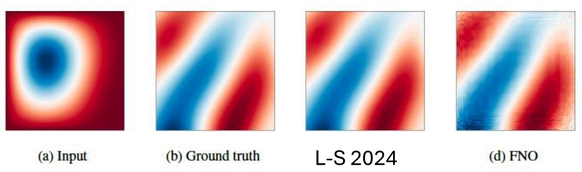
Background medium Vs= 3km/s
Von Karman variability
10% fluctuation magnitude
Hurst exponent 5%
8 cells correlation length
V_p/V_s = 1.732
Perturbation : Gaussian field with std 2% and correlation length 32 cells.
Ricker input motion f_c = 3Hz
(from Zou et al, 2023)



Next Steps

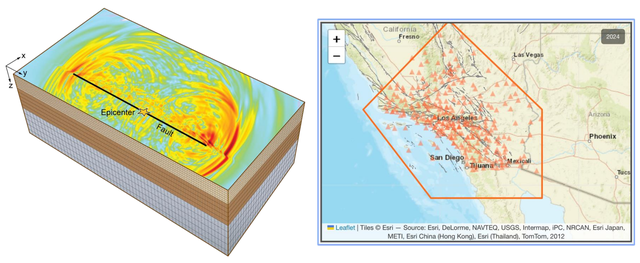
Neural Operators with localized kernels (for mesoscale)

Current results indicate that global convolutional layers, such as FNO, tend to produce overly smoothed synthetic ground motions. To address this limitation, we plan to implement localized kernels (Liu-Schiaffini et al., 2024) within the generative model.



Integrate a Graph Neural Operator

Integrating numerical simulations with instrumented data requires learning ground motion across both standard and irregular grids. Our ultimate goal is to capture the fine spatial correlation structure from simulations while extracting high-frequency content from recordings.



Acknowledgments

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