Surrogate Modeling of Highway Bridges for Regional Earthquake Simulations of Transportation Networks

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with contributions by Sanjay Govindjee, Sang-ri Yi & Jinyan Zhou

NSF NHERI SimCenter
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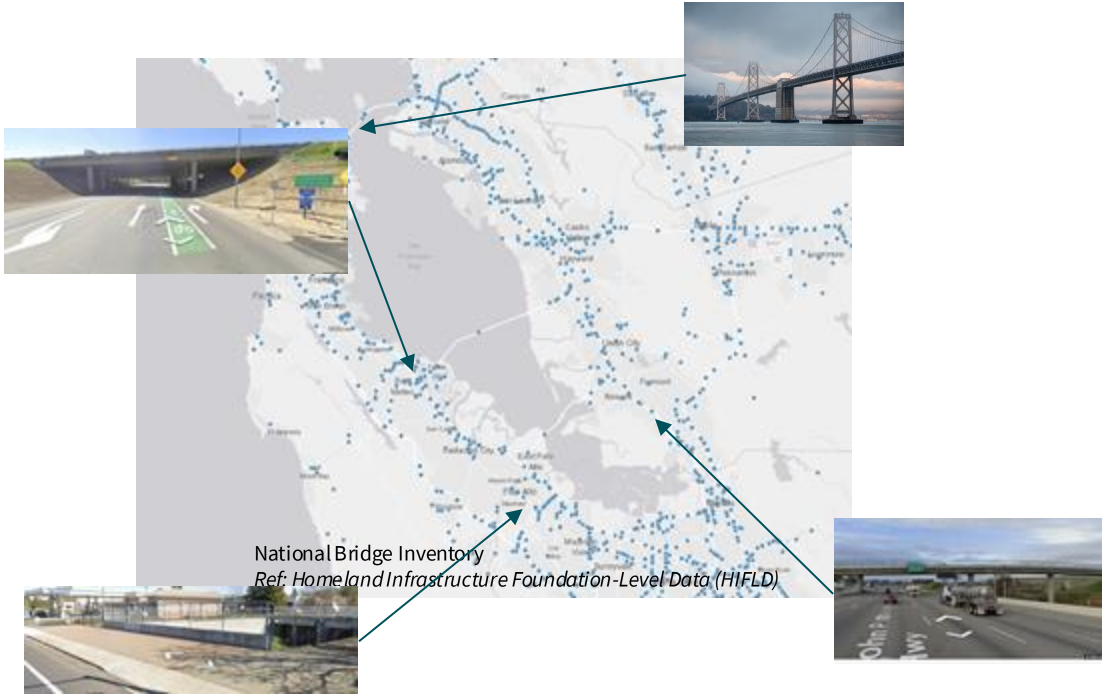
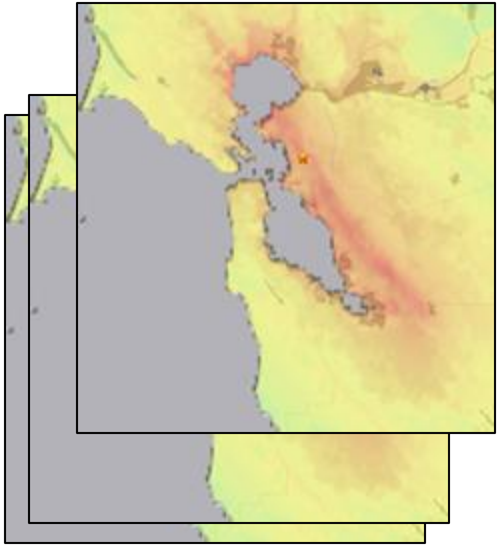
Civil & Environmental Engineering

Motivation

How do we carry out regional seismic risk assessments of bridge networks while capturing the characteristics of individual bridges?



National Bridge Inventory
Ref: Homeland Infrastructure Foundation-Level Data (HIFLD)



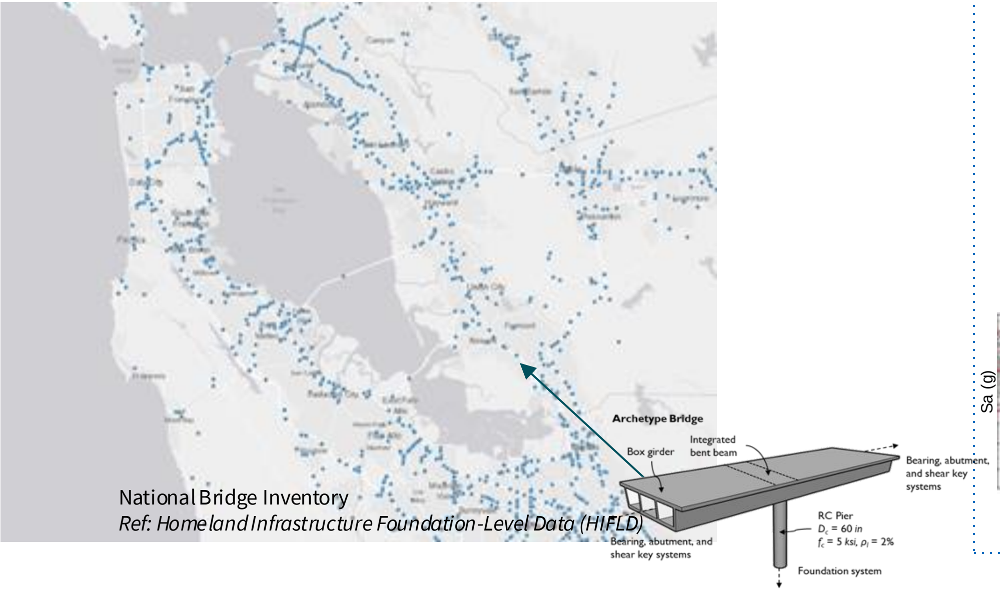
USGS M7.0 Hayward Rodgers Creek Scenario, M6.8 Earthquake HayWired Scenario, …

Motivation

How do we carry out regional seismic risk assessments of bridge networks while capturing the characteristics of individual bridges?

Want to achieve
Scalability

While maintaining
Fidelity



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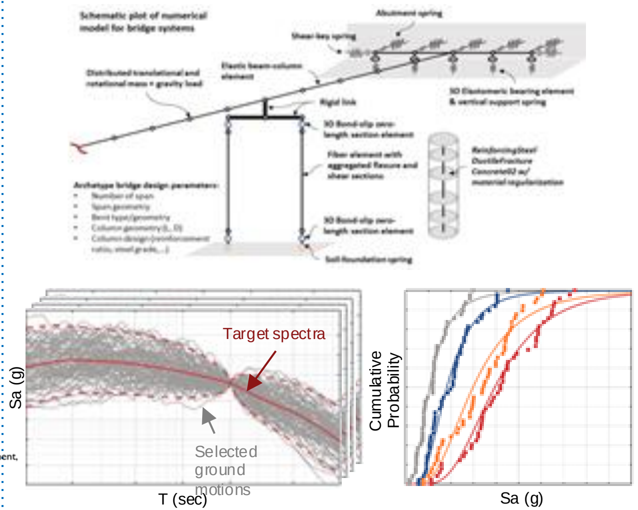
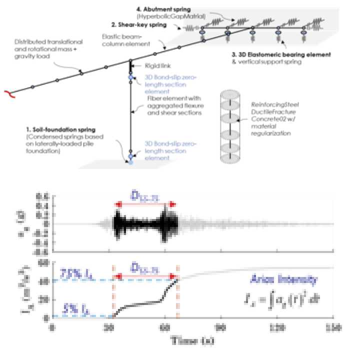
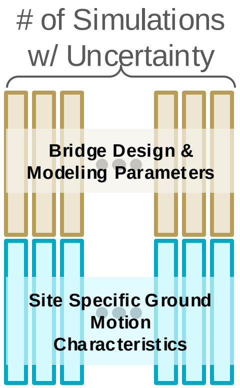


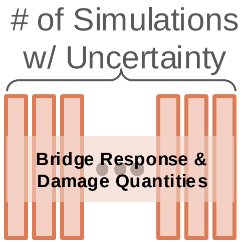
Ground Motions **Fragility Models**

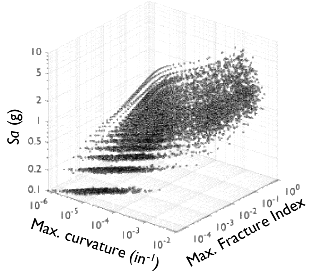
Challenge





?





High-dimensional problem

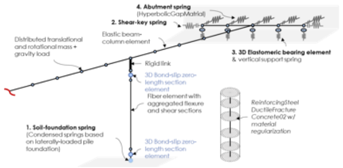
- Various structural design parameters
  (height, size, axial load, concrete strength)
- Site ground motion characteristics
  (intensity, duration, frequency content)

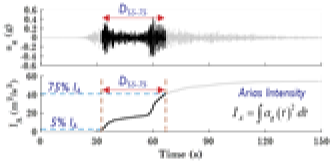
Response predictions

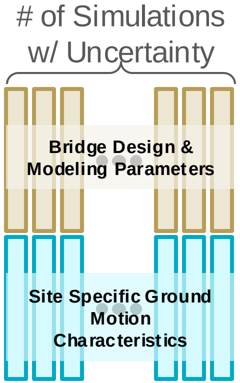
- Bridge structural response
  (drift, curvature, damage)
- Collapse probabilities

Distributions, not single values
Nonlinear

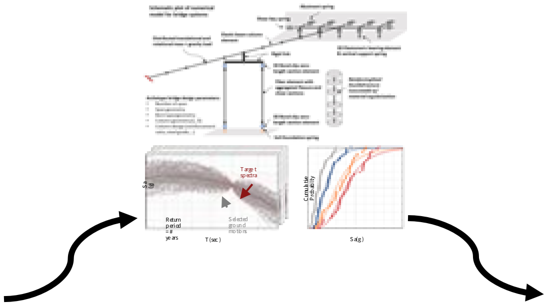
Challenge

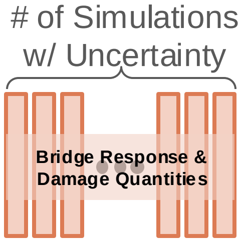


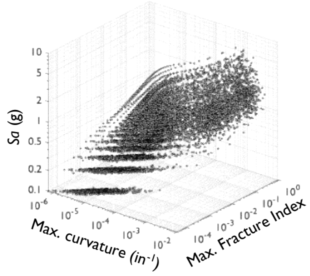




Direct Simulation





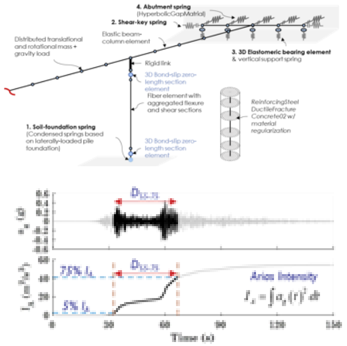


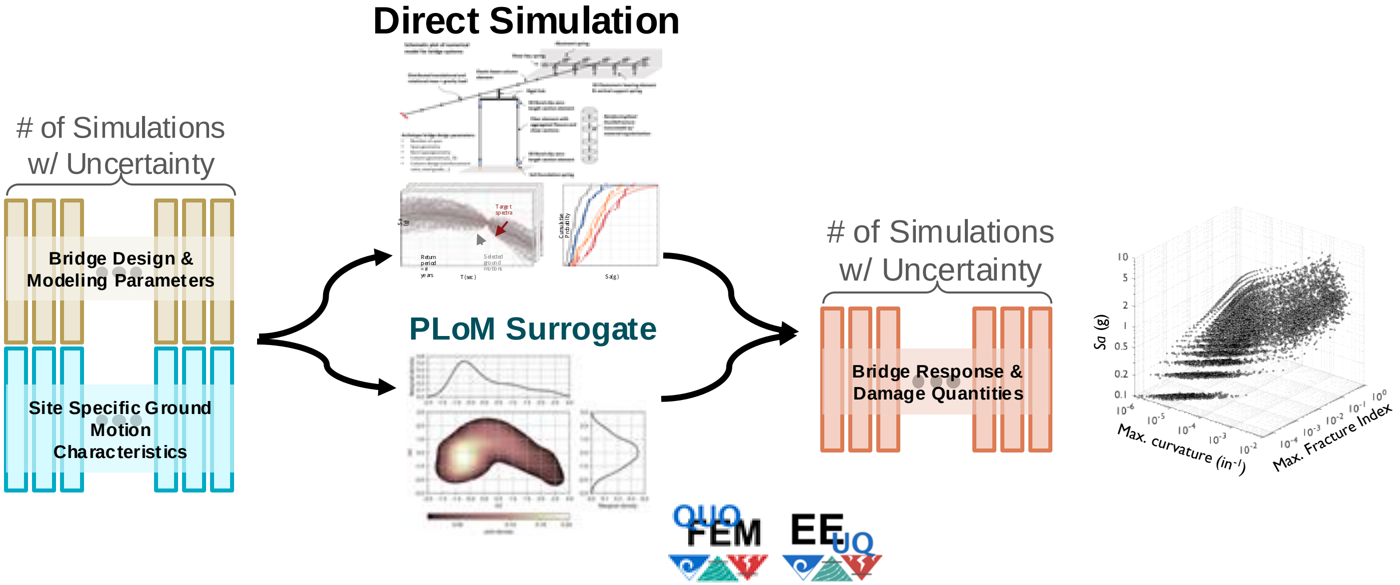
For one regional earthquake scenario…

- up to 26.5 cpu-hr for a single bridge model
- 2100+ bridges in the Bay Area
- 100+ selected ground motion runs

and we need to repeat this for multiple scenarios

Challenge





Use PLoM (Probabilistic Learning on Manifolds) to create surrogate model

- Generates learned dataset that preserves original data structure

Why PLoM?

- Mapping joint distribution of input parameters to joint distributions of output responses (preserves correlations)
- No prescribed distribution assumption (flexible for nonlinear data structure)
- *Implemented in SimCenter's quoFEM & EE-UQ applications*

Zhong, K., Navarro, J. G., Govindjee, S., & Deierlein, G. G. (2023). Surrogate modeling of structural seismic response using probabilistic learning on manifolds; EESD
Soize, C., & Ghanem, R. (2016). Data-driven probability concentration and sampling on manifold; Jl. Computational Physics
Soize, C., & Ghanem, R. (2020). Physics-constrained non-Gaussian probabilistic learning on manifolds; International Jl. for Numerical Methods in Engineering

Workflow

Training procedure

Bridge Model Database

Grid Ground Motion Set

IDA

Training Data: X_{Train}

- Structure parameters ($\mathbf{X}_S$)
- Intensity measures ($\mathbf{X}_{GM}$)
- Response *EDP* ($\mathbf{X}_R$)
- Collapse *Sa* ($\mathbf{X}_C$)

GM intensity binning

Hyperparameter Functions

- Diffusion maps ε_k and ε_{db}
- As functions of $Sa(1s)$
- Collapse: $f_{H,Col}(Sa)$
- Response: $f_{H,EDP}(Sa)$

PLoM($\mathbf{X}_{Train}$, $\boldsymbol{\varepsilon}$)

Prediction procedure

Site & Bridge Info

Target Predictors: Z_{Tar}

GM Characteristics

- Intensity $Sa^*(1s)$
- Specral shape *SaRatio*
- Duration $D_{S5\text{-}75}$

Structure Param.

- Axial load ratio
- Reinforcement ratio
- Rebar grade

Prediction Setup: $\boldsymbol{\varepsilon}(Z_{Tar})$

Compute hyperparameters

- $f_{H,Col}(Sa^*)$ and $f_{H,EDP}(Sa^*)$

Partition & Amplify Data

- Partition the training data by ±3-σ bounds
- Amplification (optional)

PLoM Constraints

- Mean vector of target GM characteristics & Structure Params $(\boldsymbol{m}_S, \boldsymbol{m}_{GM})^T$

PLoM($\mathbf{X}_{Train}$, $\boldsymbol{\varepsilon}$)

Output

- Structural response
- Collapse fragility

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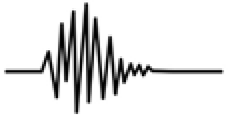
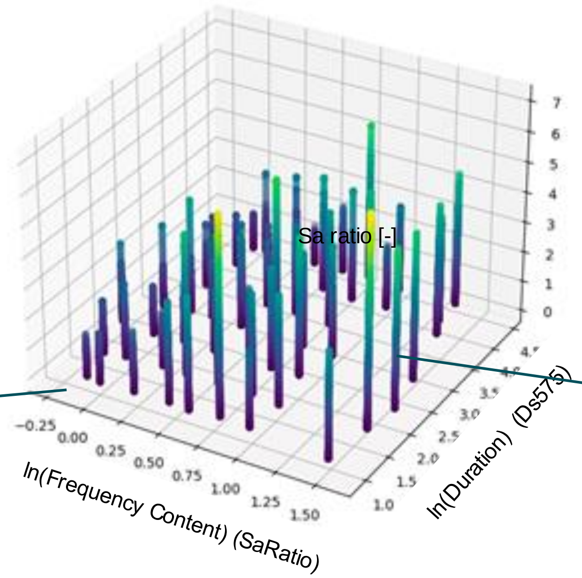
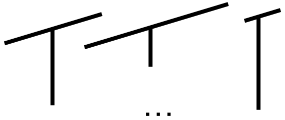
Training design space

Goal: Create a wide design space that can capture both variability in the structural parameters and ground motion characteristics



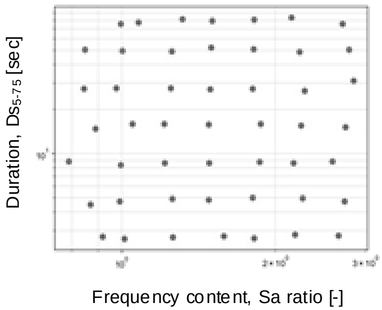


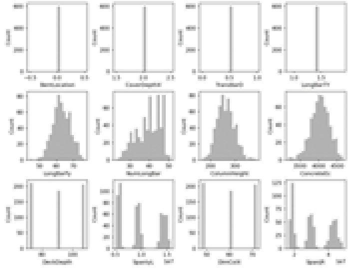
Scale using Incremental Dynamic Analysis



56 ground motions
GM characteristics (X_{GM})

~670 bridge models
Structural parameters (X_S)





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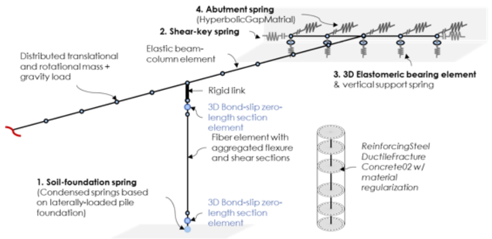
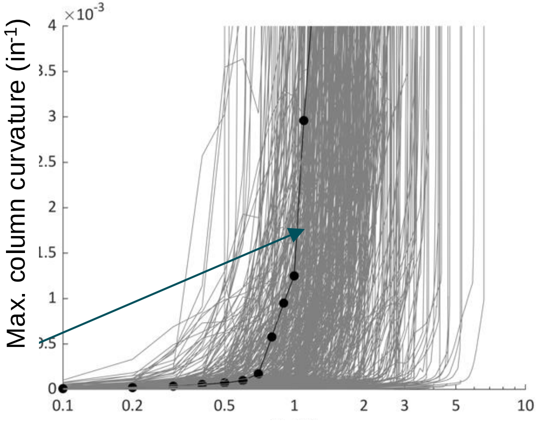
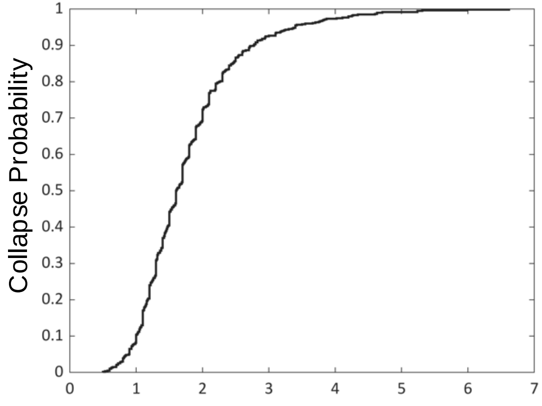


For each of the ~670 bridges, we get

One ground motion out of 56





Increasing earthquake intensity

Bridge response (X_R)

- *Drift & curvature demands*
- *Rebar fracture indices*
- *Damage states*

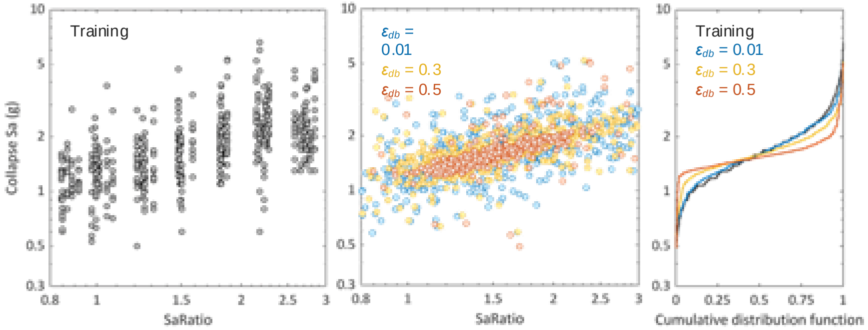
Collapse probabilities (X_C)

Likelihood of bridge collapse

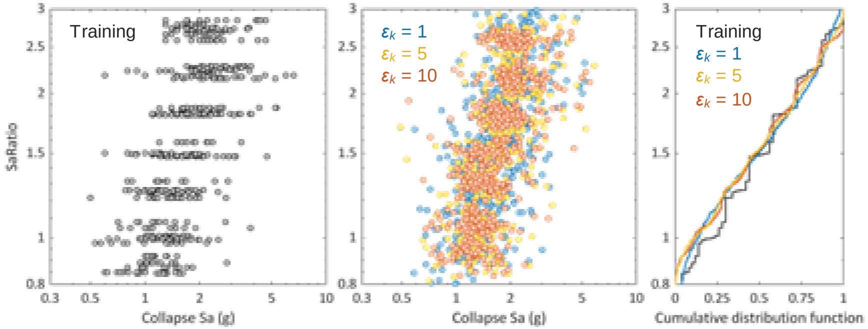
Preliminary observations

- **The predictions are heavily affected by the two key PLoM hyperparameters ϵ_{db} and ϵ_k**

  - ϵ_{db} : threshold for selecting diffusion-based components *(how centralized)*

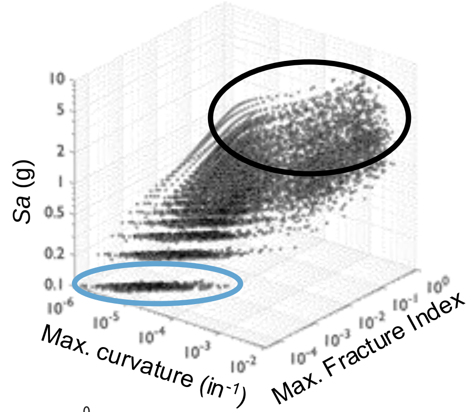


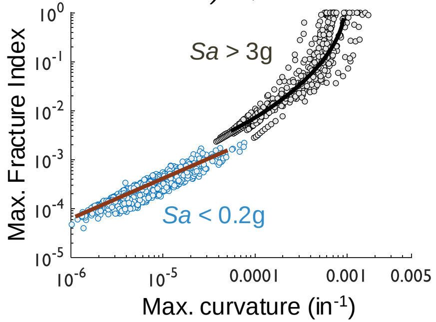
  - ϵ_k : kernel parameter for localization *(how clustered)*



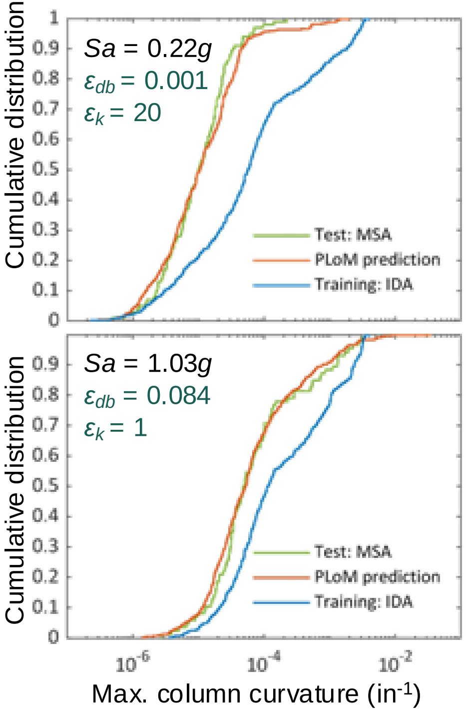
Hyperparameter calibration approach

Data exhibit localized nonlinear correlation at different Sa intensity levels



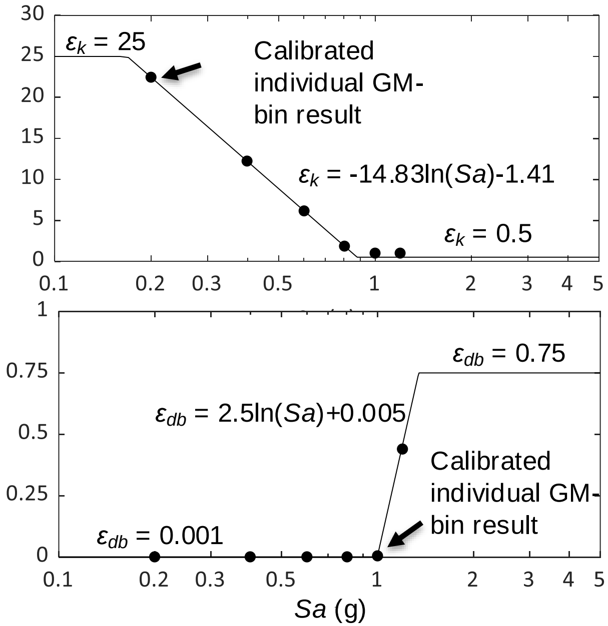


Optimal values (ϵ_{db}, ϵ_k) are found for varying Sa intensities (Lee et al., 2023)



Hyperparameter functions are developed (via GM binning method)

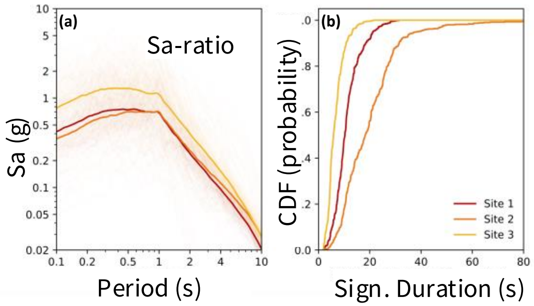
- Collapse: $\boldsymbol{f}_{\mathbf{H,Col}}(Sa)$
- Structural response: $\boldsymbol{f}_{\mathbf{H,EDP}}(Sa)$

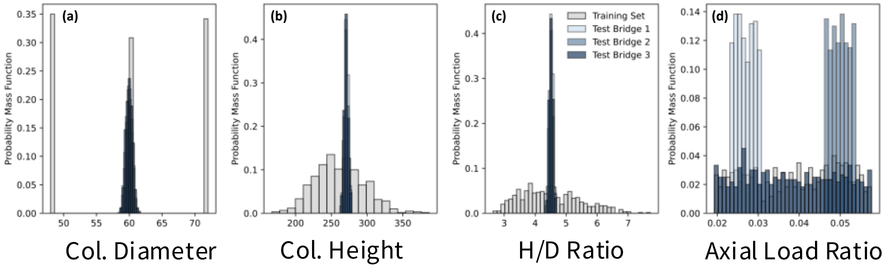


Validation study (ground truth -- multi-stripe analyses)

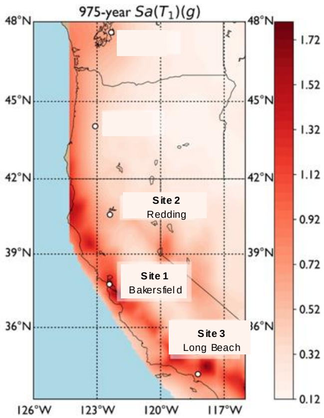
Test the model using 3 sample bridges, each placed at 3 sites with distinct GM characteristics

	Site 1 Baseline	**Site 2** High duration	**Site 3** High Sa/ Sa ratio
Bridge 1 Low axial load ratio	●	●	●
Bridge 2 No control	●	●	●
Bridge 3 High axial load ratio	●	●	●





Generate **600 points** of test data
(100 GM x 6 return periods)
for each bridge/site combination

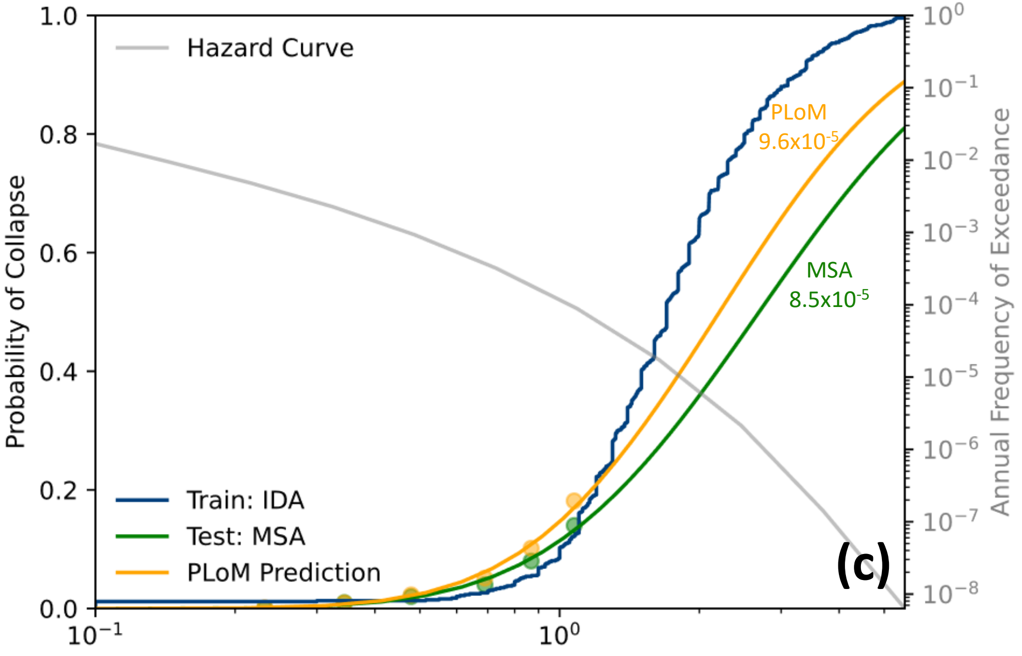


Validation results

Collapse probabilities

	Site 1 Baseline	**Site 2** High duration	**Site 3** High Sa/ Sa ratio
Bridge 1 Low axial load ratio	●	●	●
Bridge 2 No control	●	●	●
Bridge 3 High axial load ratio	●	●	●

Structure 3, Site 1



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Bridge 1 Low axial load ratio	●	●	●
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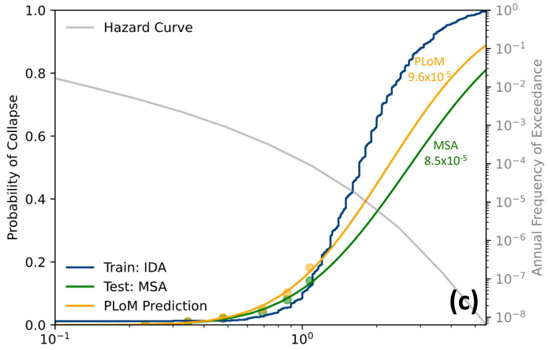
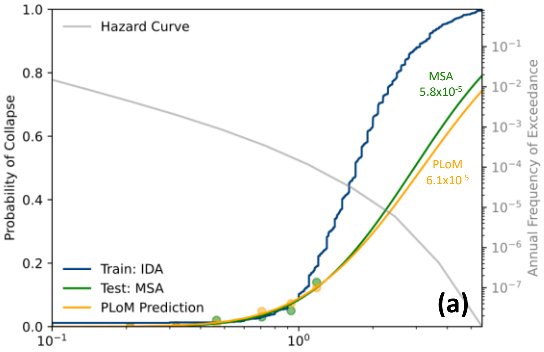
Annual collapse rate per structure and site ($\times 10^{-5}$)

	Structure 1		Structure 2		Structure3	
	MSA	PLoM	MSA	PLoM	MSA	PLoM
Site 1	5	8	13	11	9	10
Site 2	6	6	15	14	9	11
Site 3	17	24	37	42	26	40

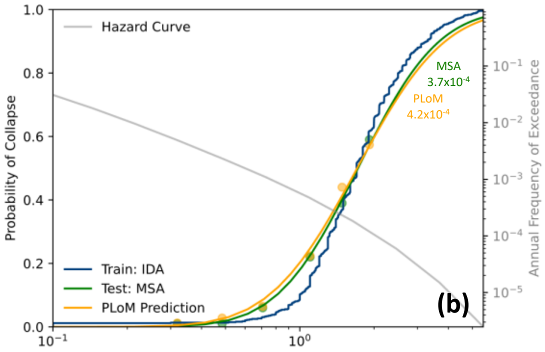
Structure 3, Site 1



Structure 1, Site 2



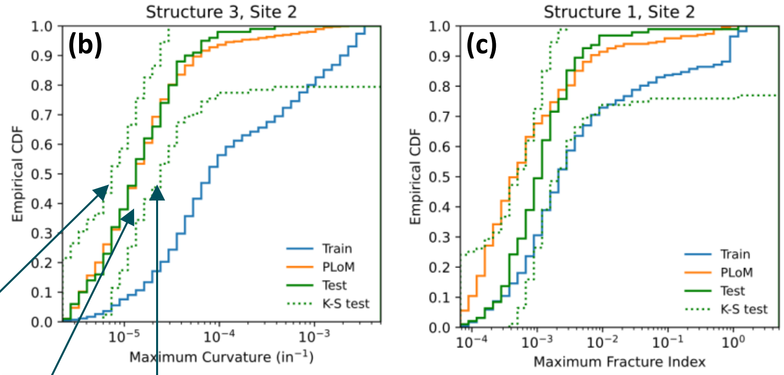
Structure 2, Site 3



Validation results

Structural response

- Kolmogorov–Smirnov (KS) test to evaluate the PLoM prediction as a “pass” or “fail”



K-S test bound

Test data

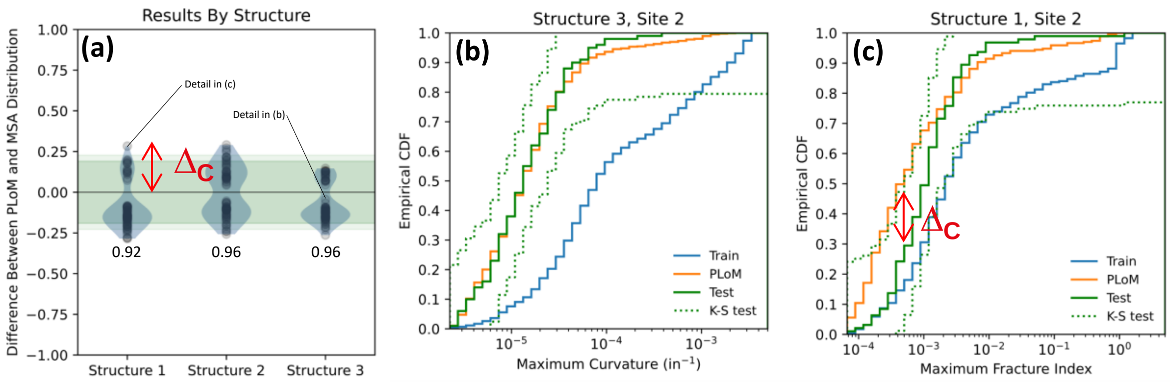
K-S test bound

Validation results

Structural response

- Kolmogorov–Smirnov (KS) test to evaluate the PLoM prediction as a “pass” or “fail”

- Plot distance between PLoM prediction and test data **(blue dots)**



Validation results

Structural response

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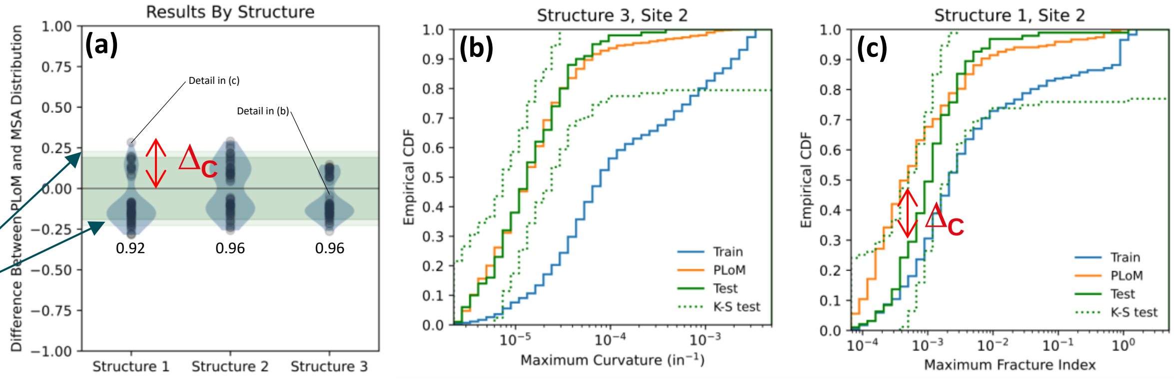
- Plot distance between PLoM prediction and test data **(blue dots)**
- Most predictions fall within the K-S test "pass" boundary **(green band)**



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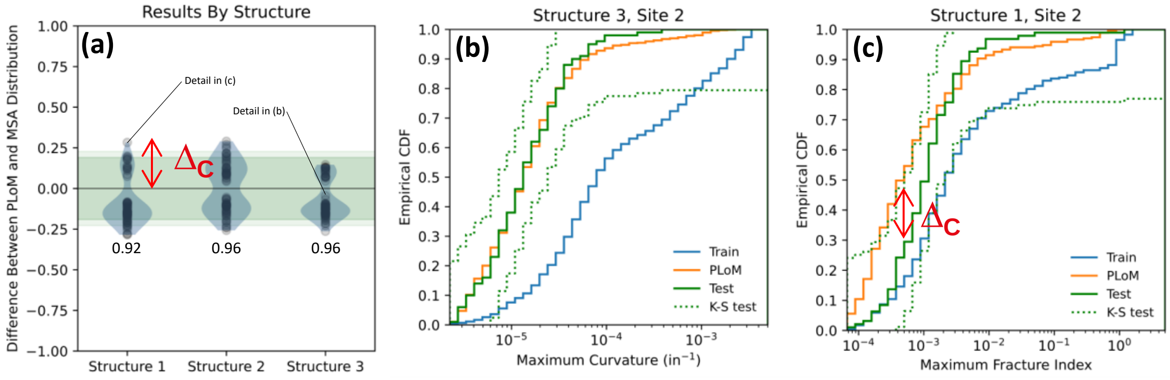
- Checks are carried out for
  - ✓ **(a)** 3 bridges



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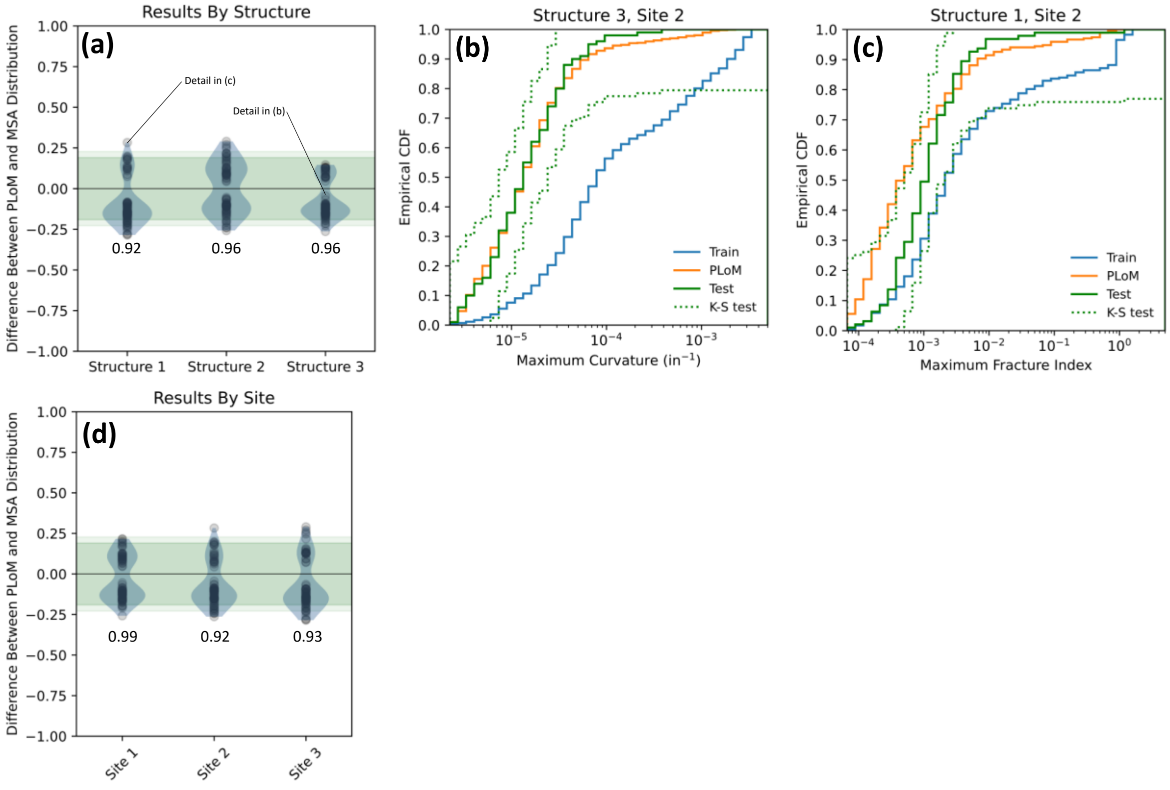

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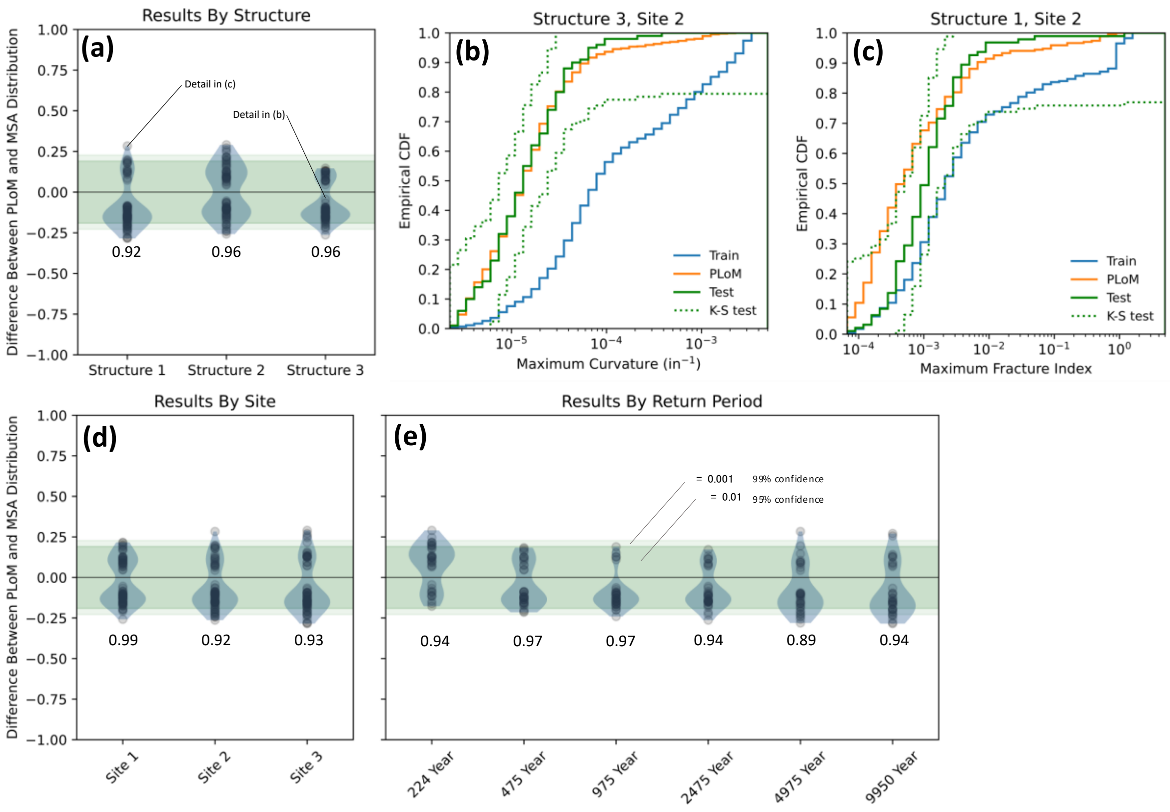
  - ✓ **(d)** 3 sites
  - ✓ **(e)** 6 intensity levels



Frequent

Rare

Validation results

Structural response

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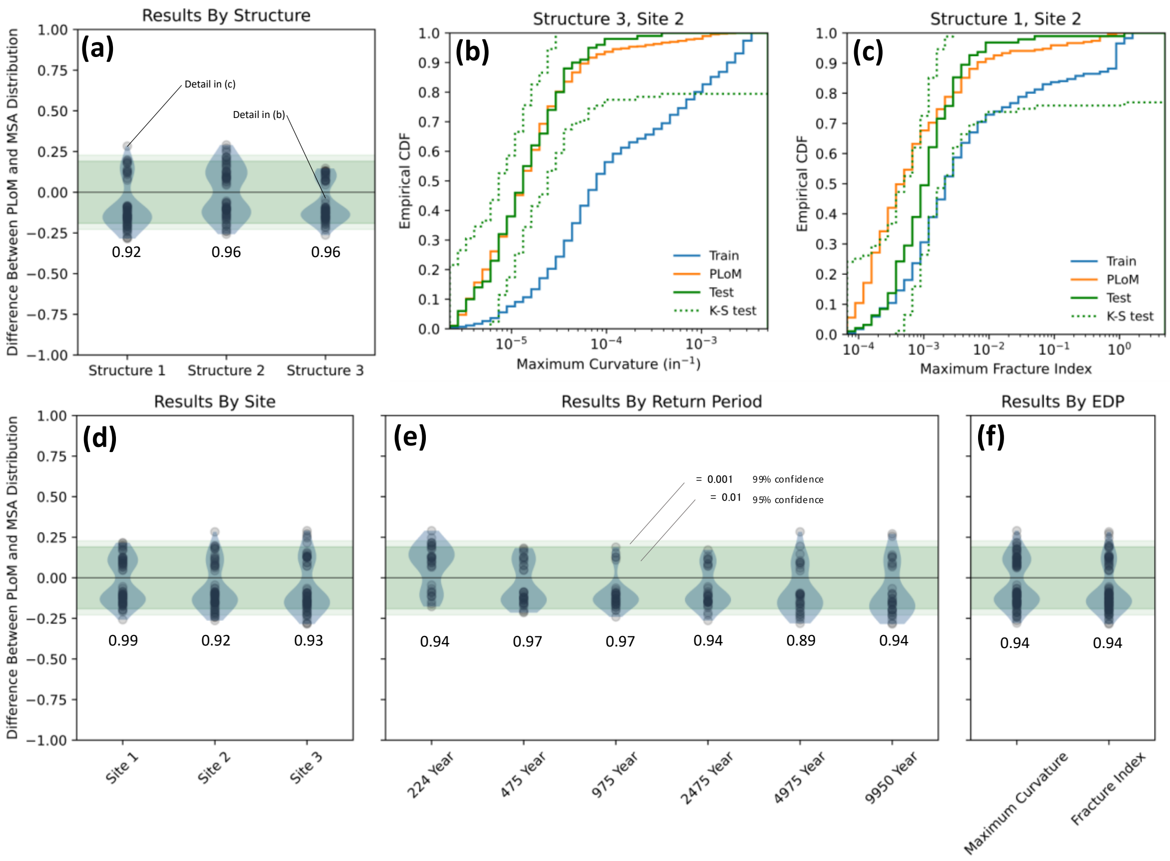
- Most predictions fall within the K-S test “pass” boundary **(green band)**
- Checks are carried out for
  - ✓ **(a)** 3 bridges
  - ✓ **(d)** 3 sites
  - ✓ **(e)** 6 intensity levels
  - ✓ **(f)** 2 responses/stripe



Key Contributions

Developed a **PLoM surrogate model** to predict structural responses given

- Structural design parameters (bridge-specific)
- Ground motion characteristics (site-specific)

$\epsilon_{db}, \epsilon_k$

Proposed a **systematic procedure for training and prediction** using PLoM

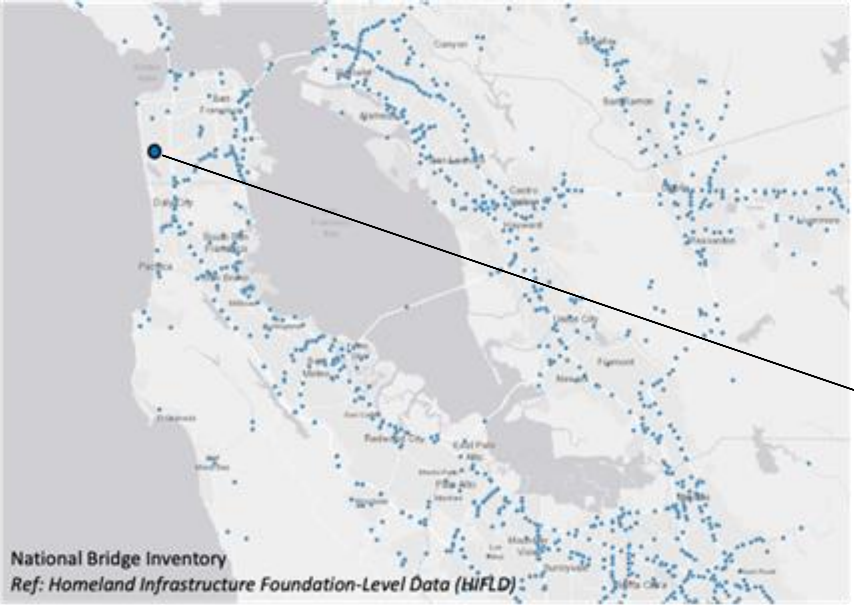
- Hyperparameter calibration embedded within the model

Validated the model using a grid of various bridge designs across three California sites

Reduced computational demand compared to conventional nonlinear modeling

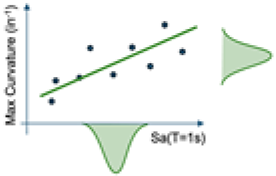
- 0.04% of OpenSees computational cost after training

Comparison with alternative surrogate models



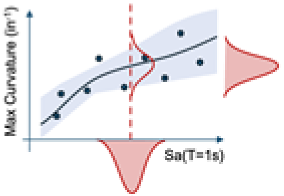
SURROGATE MODELS

Multivariate Log Linear Regression



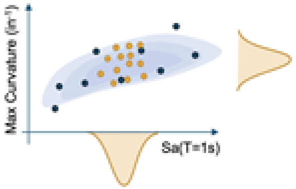
Best linear fit through the data found by minimizing mean squared error

Gaussian Process Model (GP)



Defines response distributions over functions of input variables

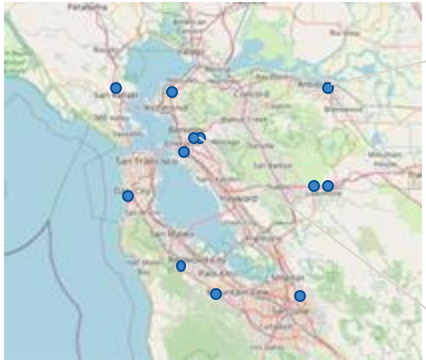
Probabilistic Learning on Manifolds (PLoM)



Generates a learned dataset that preserves the original data structure

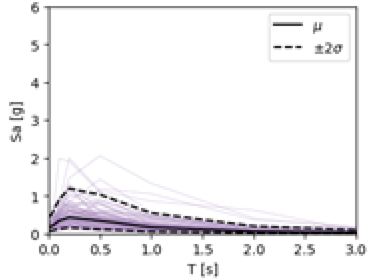
Implementation in R2D for Regional Simulations

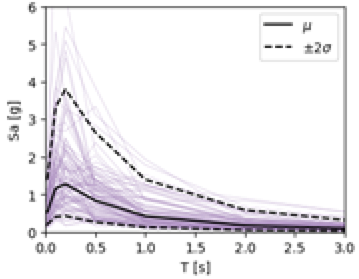
Bridge Information (National Bridge Inventory)



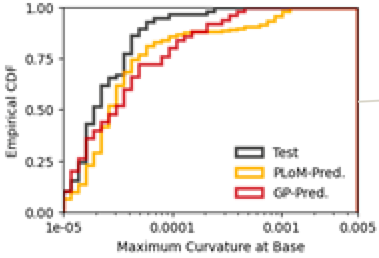
Generate Correlated Ground Motion Realizations

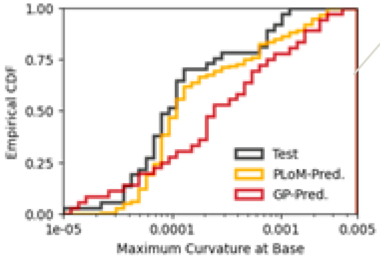
R2D



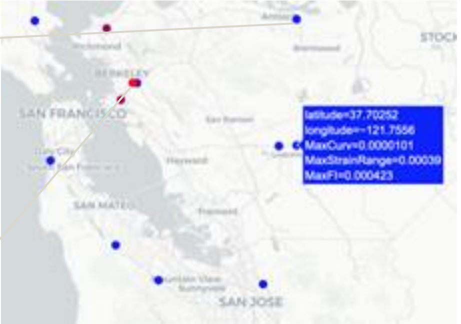


Interrogate Surrogate Model to Extract Performance





Assess Bridge Response & Damage



Ongoing work:

- publish & document surrogate models in R2D library
- testing, validation & comparison to other models
- extension/training to other bridge configurations

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