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同濟大學
TONGJI UNIVERSITY



Research Division on
Bridge Earthquake Resistance
Towards Next-Generation Resilient Bridges

Time Varying Seismic Analysis of Costal Bridges Considering Durability Damages in Service Life

Yan Xu (PhD, Professor)

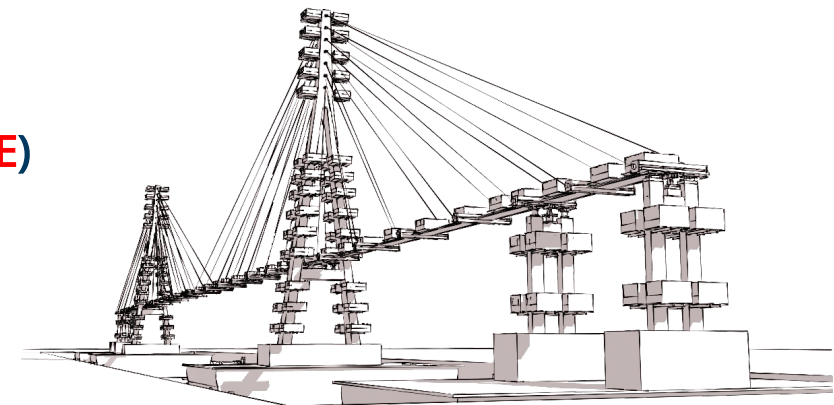
yanxu@tongji.edu.cn

Vice Director of the International Joint Research Lab of Earthquake Engineering(ILEE)

Tongji Multi-functional Shaking Tables Lab (Jiading Campus)

Department of Bridge Engineering, College of Civil Engineering

Tongji University



2026/06/0

Outlines

1. Background

2. Time Varying Seismic Fragility and Risk Analysis Method

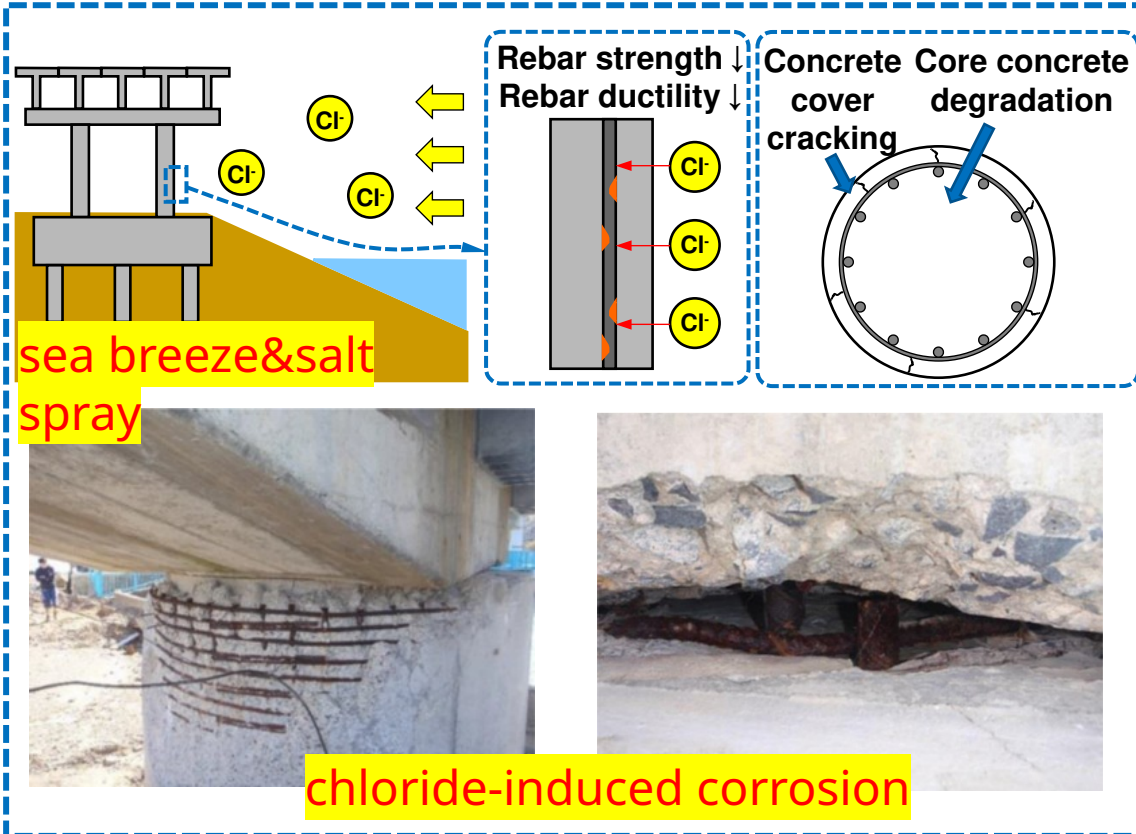
3. Uncertainty-Included Time Varying Bridge Modeling

4. Results and Conclusions

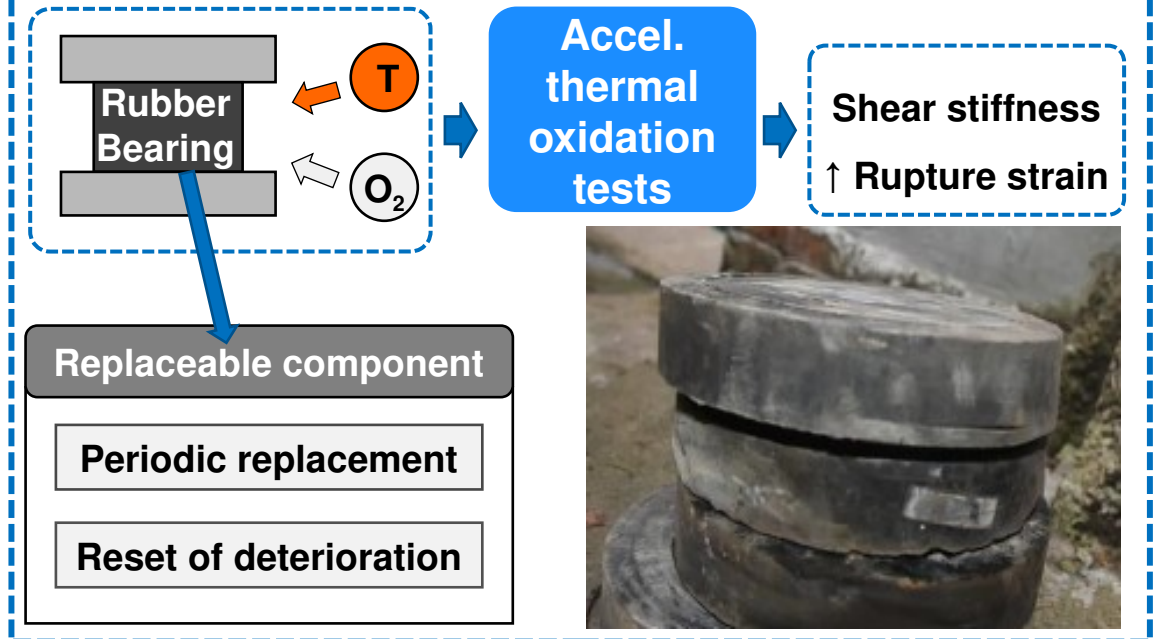
1. Background

➤ Time Varying Service Condition of Costal Bridges

Corrosion-induced deterioration in RC columns



Thermal oxidative aging and replacement of rubber bearings



A Scenario yet not fully studied: RC Column corrosion + rubber bearing aging + bearing periodic replacement

[1] Akiyama M, Frangopol DM, Ishibashi H. Toward life-cycle reliability-, risk- and resilience-based design and assessment of bridges and bridge networks under independent and interacting hazards: emphasis on earthquake, tsunami and corrosion. Structure and Infrastructure Engineering. 2019;16:26–50.

[2] Itoh Y, Gu HS. Prediction of Aging Characteristics in Natural Rubber Bearings Used in Bridges. Journal of Bridge Engineering. 2009;14:122–8.

1. Background

➤ Limitations of Current Time Varying Fragility Analysis

Probabilistic demand and capacity modeling

Traditional

$$P_f = \Phi \left[\frac{\ln(EDP) - \ln(LS)}{\sqrt{\beta_D^2 + \beta_C^2}} \right]$$

Time-invariant

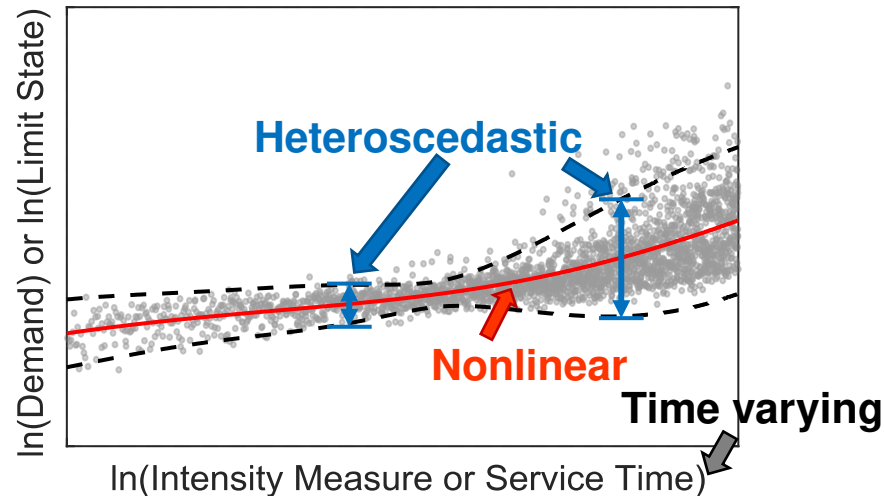
$$\ln(EDP) = a + b \ln(IM) \quad \text{Engineering Demand Parameter}$$

Linear

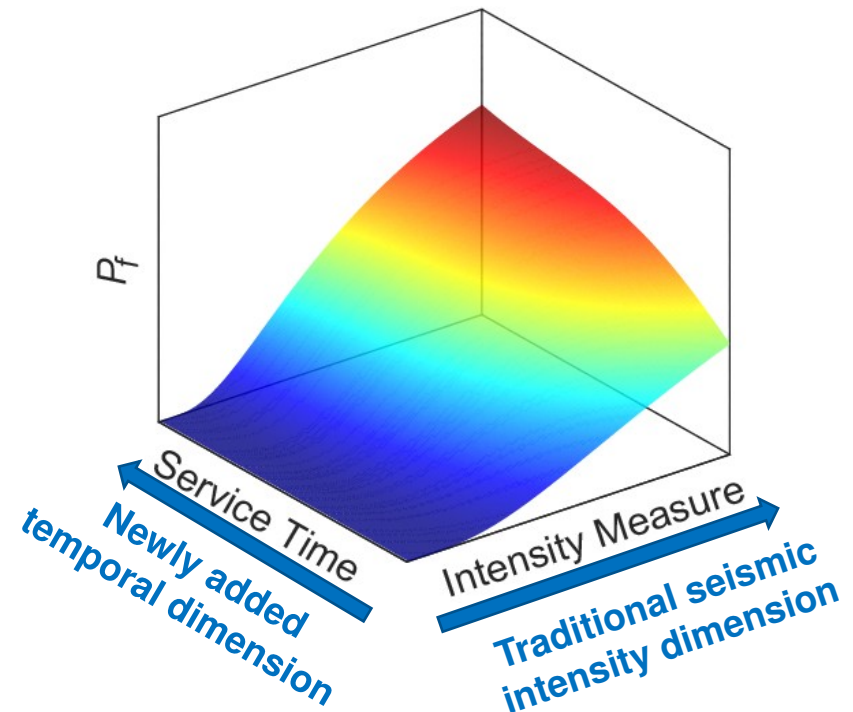
$$\beta_D = \sqrt{\frac{\sum_{i=1}^N [\ln(EDP_i) - [a + b \ln(IM)]]^2}{N - 2}}$$

Homoscedastic

Our Study



Time varying seismic fragility surface



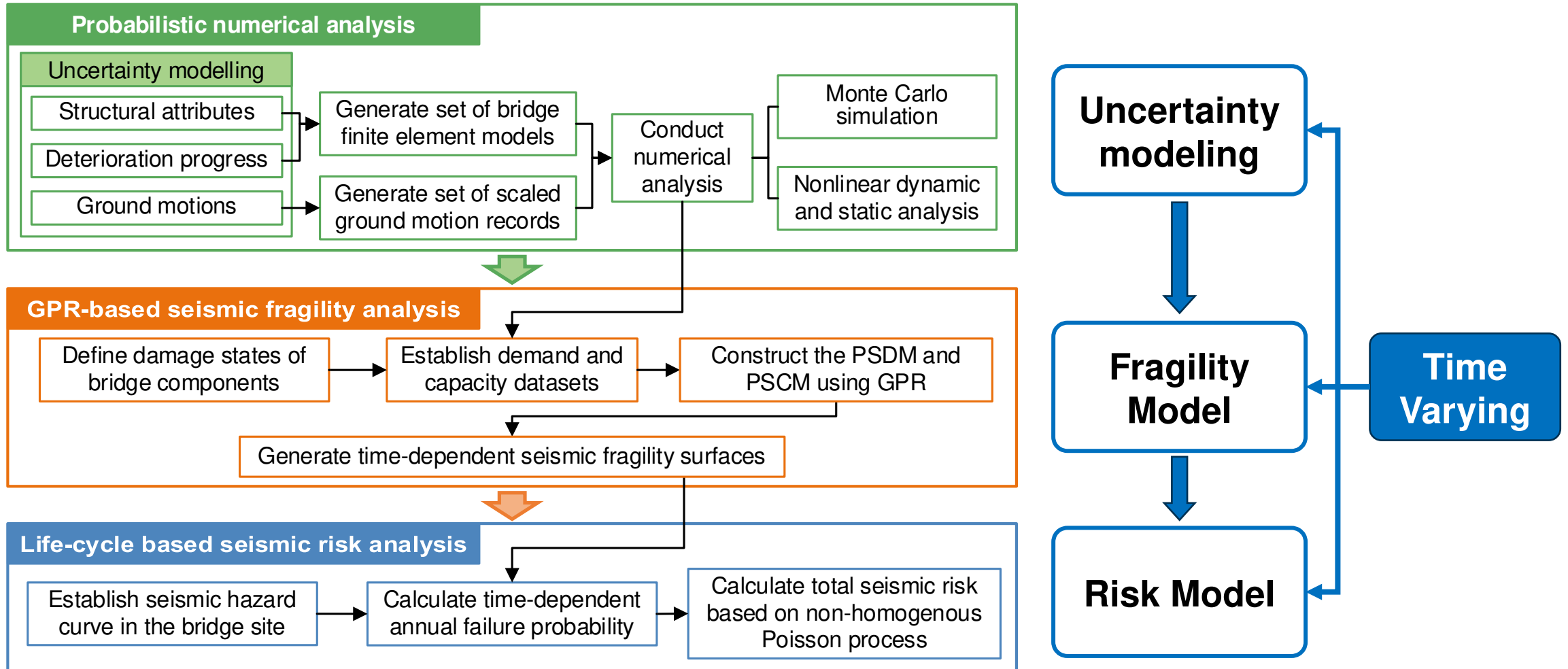
Challenge: massive nonlinear analyses



Solution: machine learning-based surrogate model

2. Time Varying Seismic Fragility and Risk Analysis Method

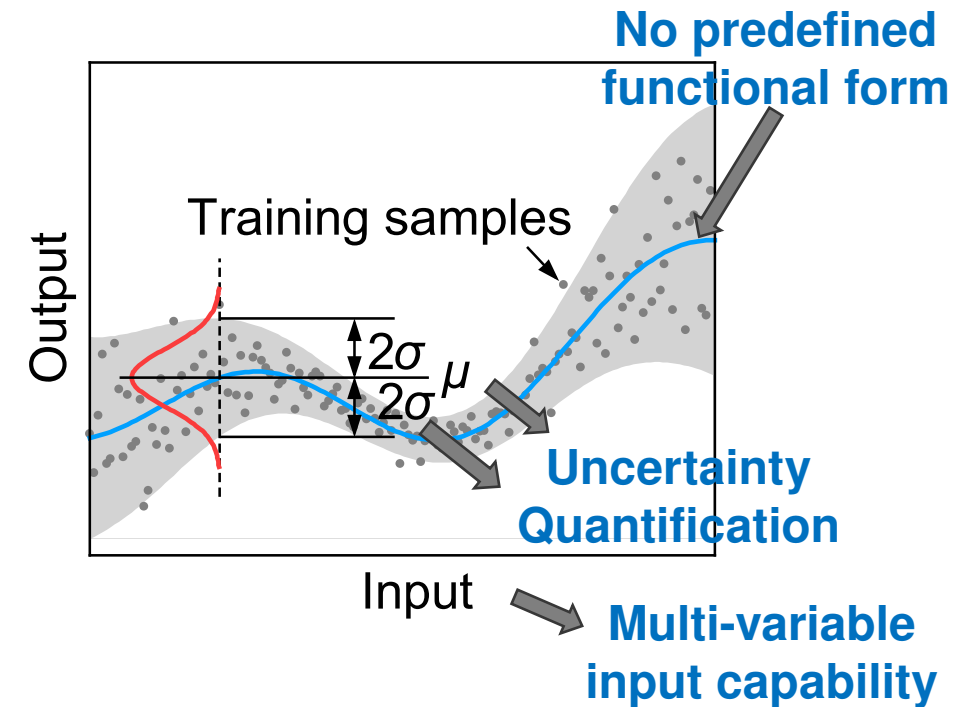
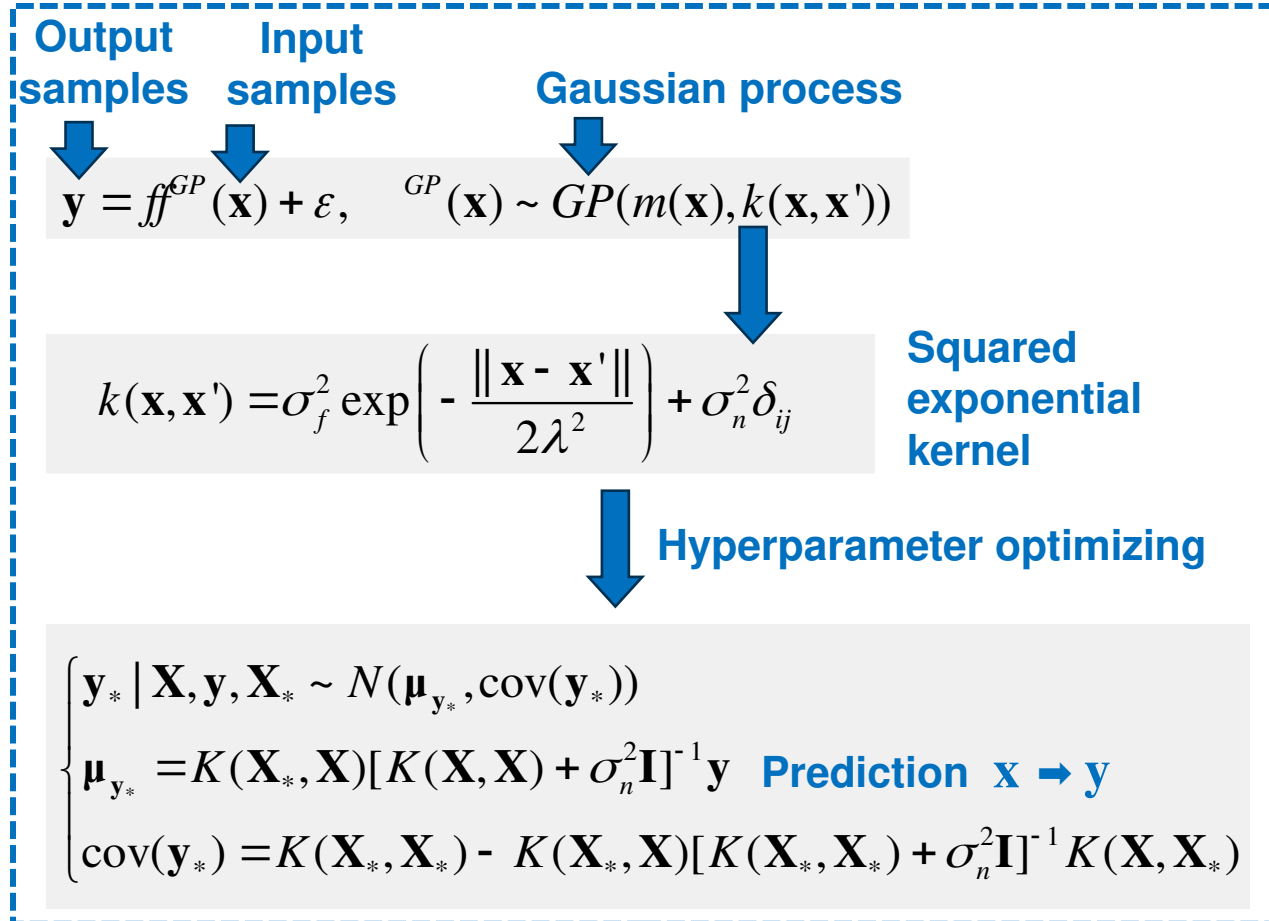
➤ Time Varying Seismic Fragility and Risk Analysis Framework



2. Time Varying Seismic Fragility and Risk Analysis Method

➤ Surrogate Modeling Approach: Gaussian Process Regression (GPR)

Gaussian process regression (GPR)



2. Time Varying Seismic Fragility and Risk Analysis Method

➤ GPR-Driven Seismic Demand and Capacity Modeling

GPR-driven time varying seismic demand and capacity model

$$\begin{cases} \ln(\mathbf{EDP})_* | \mathbf{X}_D, \ln(\mathbf{EDP}), \mathbf{X}_{D*} \sim N(\mu_{\ln(\mathbf{EDP})_*}, \text{cov}(\ln(\mathbf{EDP})_*)) \\ \beta_{D*} | \mathbf{X}_D, \sqrt{(\ln(\mathbf{EDP}) - \mu_{\ln(\mathbf{EDP})_*})^2}, \mathbf{X}_{D*} \sim N(\mu_{\beta_{D*}}, \text{cov}(\beta_{D*})) \\ \mathbf{X}_D = \{\ln(\mathbf{IM}), \mathbf{t}\} \end{cases}$$

Log-mean estimate of seismic demand
Log-dispersion estimate of seismic demand

$$\begin{cases} \ln(\mathbf{LS})_* | \mathbf{X}_C, \ln(\mathbf{LS}), \mathbf{X}_{C*} \sim N(\mu_{\ln(\mathbf{LS})_*}, \text{cov}(\ln(\mathbf{LS})_*)) \\ \beta_{C*} | \mathbf{X}_C, \sqrt{(\ln(\mathbf{LS}) - \mu_{\ln(\mathbf{LS})_*})^2}, \mathbf{X}_{C*} \sim N(\mu_{\beta_{C*}}, \text{cov}(\beta_{C*})) \\ \mathbf{X}_C = \{\mathbf{t}\} \end{cases}$$

Log-mean estimate of capacity
Log-dispersion estimate of capacity

Input
sample

Intensity measure

Service time

Output
sample

Nonlinear time
history and
pushover analyses

EDP and LS

Root of squared
deviation from the
log-mean estimates

Estimate

Log-mean
estimates

Log-dispersion
estimates

Two-stage

2. Time Varying Seismic Fragility and Risk Analysis Method

➤ Time Varying Seismic Fragility and Risk Modeling

GPR-driven time varying seismic demand and capacity model

$$\begin{cases} \ln(\mathbf{EDP})_* | \mathbf{X}_D, \ln(\mathbf{EDP}), \mathbf{X}_{D*} \sim N(\mu_{\ln(\mathbf{EDP})_*}, \text{cov}(\ln(\mathbf{EDP})_*)) \\ \beta_{D*} | \mathbf{X}_D, \sqrt{(\ln(\mathbf{EDP}) - \mu_{\ln(\mathbf{EDP})_*})^2}, \mathbf{X}_{D*} \sim N(\mu_{\beta_{D*}}, \text{cov}(\beta_{D*})) \\ \mathbf{X}_D = \{\ln(\mathbf{IM}), \mathbf{t}\} \end{cases}$$

Log-mean estimate of seismic demand
Log-dispersion estimate of seismic demand

$$\begin{cases} \ln(\mathbf{LS})_* | \mathbf{X}_C, \ln(\mathbf{LS}), \mathbf{X}_{C*} \sim N(\mu_{\ln(\mathbf{LS})_*}, \text{cov}(\ln(\mathbf{LS})_*)) \\ \beta_{C*} | \mathbf{X}_C, \sqrt{(\ln(\mathbf{LS}) - \mu_{\ln(\mathbf{LS})_*})^2}, \mathbf{X}_{C*} \sim N(\mu_{\beta_{C*}}, \text{cov}(\beta_{C*})) \\ \mathbf{X}_C = \{\mathbf{t}\} \end{cases}$$

Log-mean estimate of capacity
Log-dispersion estimate of capacity

Total seismic risk over remaining service life modeled as a non-homogeneous Poisson process

GPR-based time varying seismic fragility model

$$P_f(\text{DS} | \mathbf{X}_D, \mathbf{X}_C) = \Phi \left[\frac{\mu_{\ln(\mathbf{EDP})_*} - \mu_{\ln(\mathbf{LS})_*}}{\sqrt{\mu_{\beta_{D*}}^2 + \mu_{\beta_{C*}}^2}} \right]$$

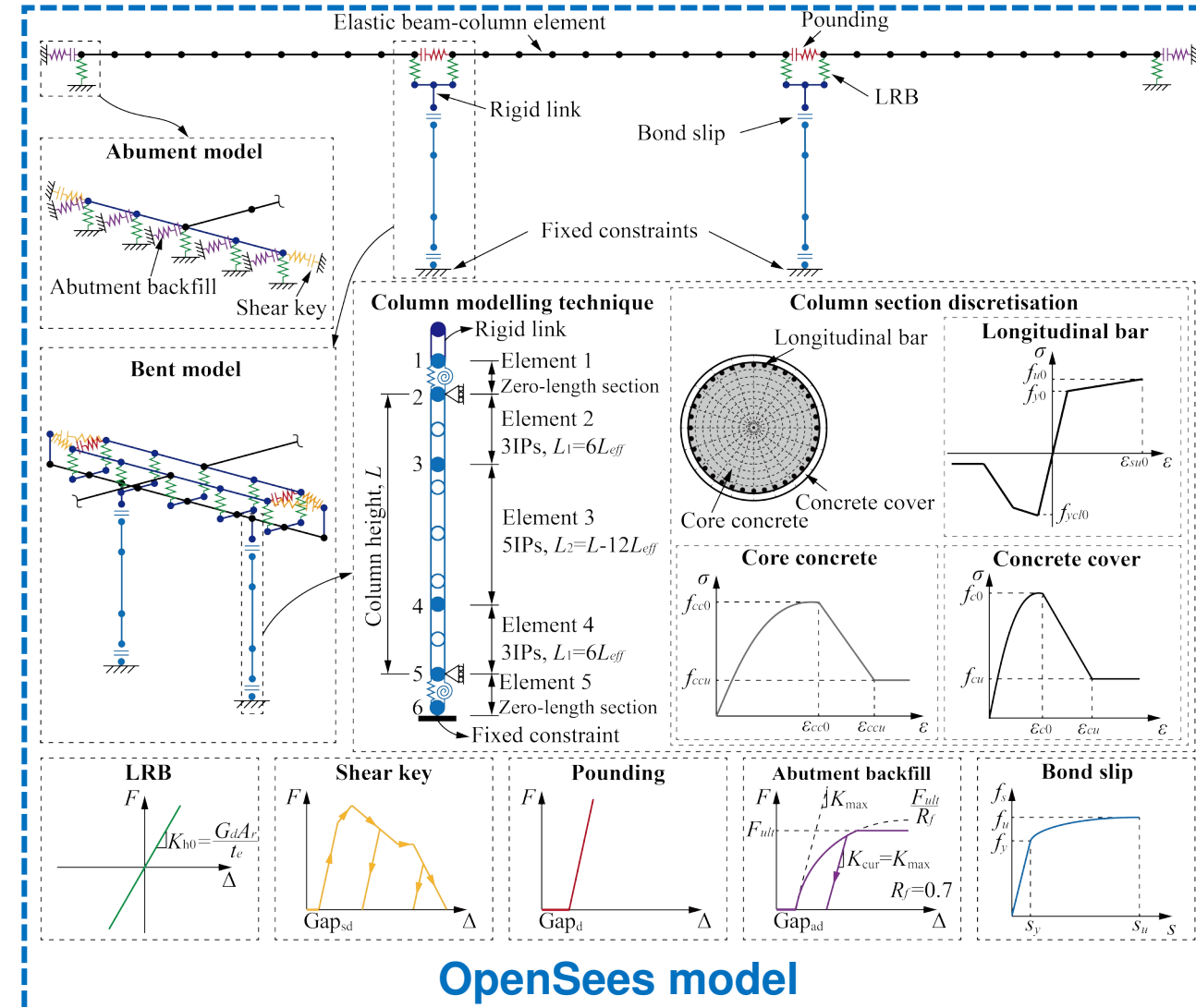
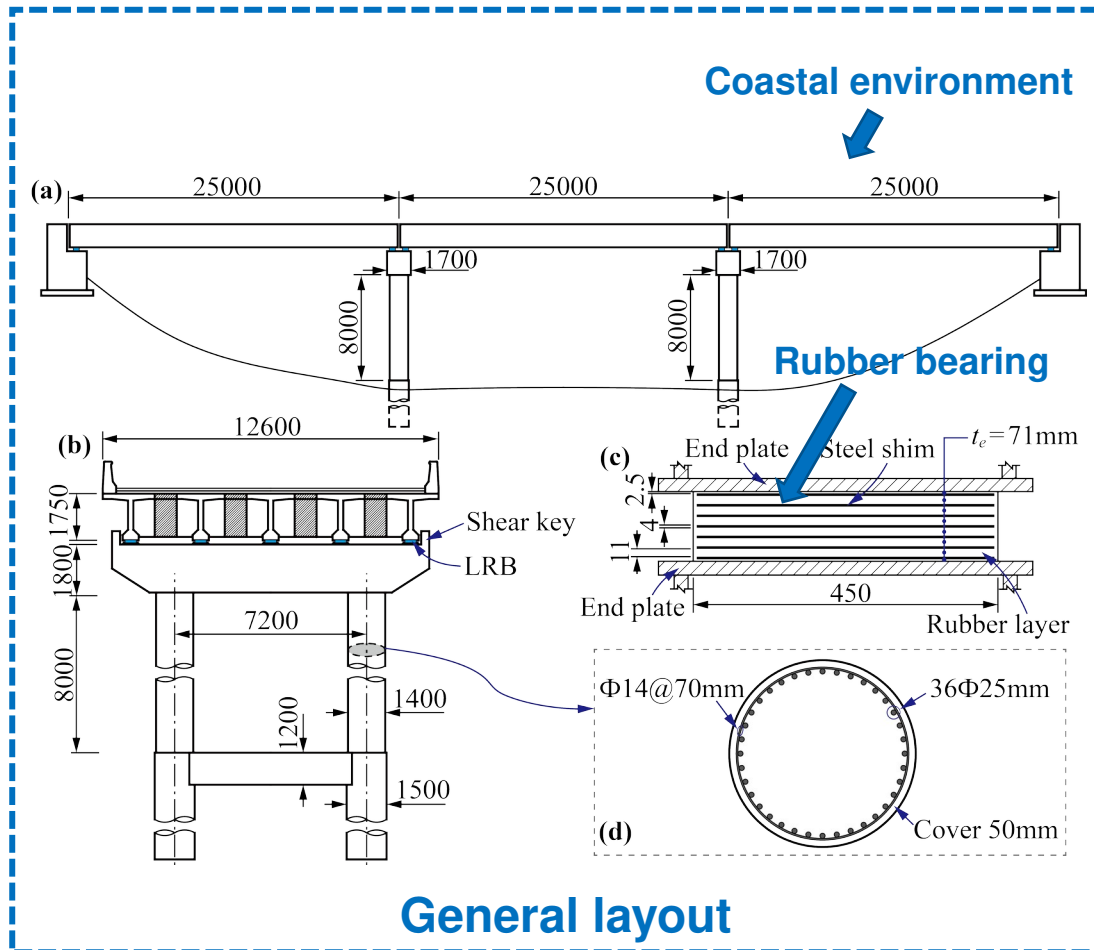
Life-cycle based total seismic risk model

$$\begin{aligned} H(\mathbf{IM}) &= k_0 \mathbf{IM}^{-k_1} \\ v(\text{DS} | t) &= \int_0^\infty P_f(\text{DS} | \mathbf{IM} = im, t) |dH(im) / \dim | \dim \\ P(\text{DS} | t_r) &= 1 - \exp \left[- \int_{t_r}^T v(\text{DS} | \tau) d\tau \right] \\ &= 1 - \exp \left[- \sum_{\tau=T-t_r}^{t_r/\Delta t} v(\text{DS} | \tau) \Delta t \right] \end{aligned}$$

3. Uncertainty-Included Time Varying Bridge Modeling

➤ Uncertainties Included Rubber Bearing Supported Bridge Analysis Modeling

Finite element modeling of bridge structure

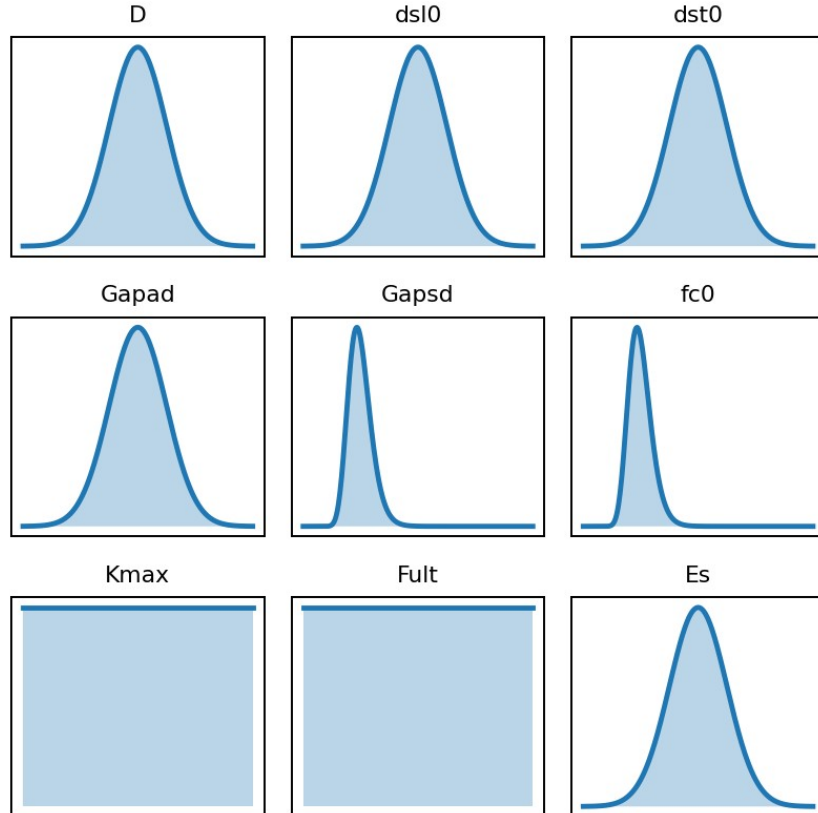


3. Uncertainty-Included Time Varying Bridge Modeling

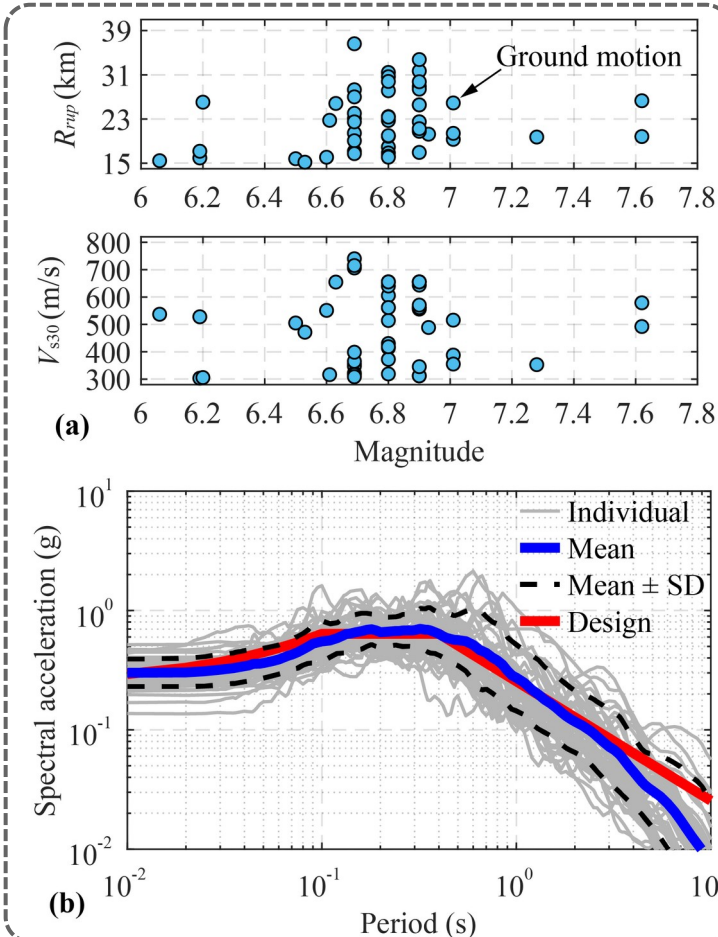
➤ Uncertainties Included Rubber Bearing Supported Bridge Analysis Modeling

Uncertainty modelling

□ Uncertainty of structural attributes



□ Uncertainty of ground motions



PEER strong motion database

↓ Spectrum matching

50 far-field ground motion records

↓ Amplitude Scaling

3,000 ground motions

3. Uncertainty-Included Time Varying Bridge Modelling

➤ Uncertainties Included Rubber Bearing Supported Bridge Analysis Modeling

Uncertainty modeling

□ Uncertainty of deterioration progress of RC bridge columns

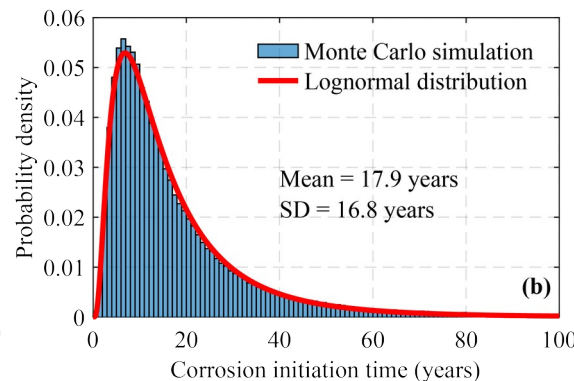
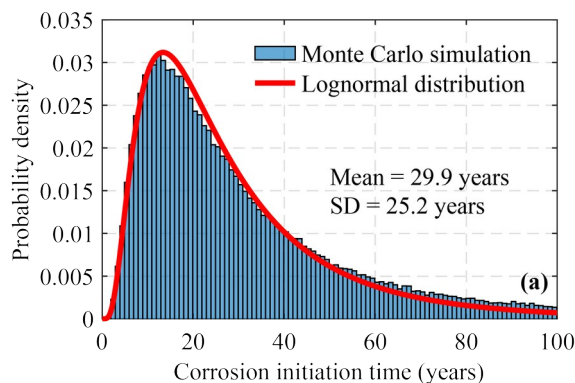
• Corrosion initiation time

Duracrete model

$$T_{\text{init}} = X_I \left[\frac{d_c^2}{4k_e k_t k_c D_0 (t_0)^n} \left[\text{erf}^{-1} \left(1 - \frac{C_{cr}}{A_{cs}(w/b) + \epsilon_{cs}} \right) \right]^{-2} \right]^{1/(1-n)}$$



Model Parameter Uncertainty



Probability distribution of corrosion initiation time

• Deterioration modelling of RC columns

Material	Mechanical properties
Steel rebar	Cross section area included pitting corrosion effect
	Tensile yield strength
	Tensile ultimate strength
	Ultimate tensile strain
	Compressive yield strength
Concrete cover	Compressive strength
Core concrete	Peak compressive stress
	Strain at peak compressive stress
	Ultimate compressive strain
Bond slip	Yield slip
	Ultimate slip

3. Uncertainty-Included Time Varying Bridge Modeling

- Uncertainties included rubber bearing supported bridge analysis modeling

Uncertainty modeling

- Uncertainty of deterioration progress of rubber bearing

Thermal oxidative aging modelling of rubber bearings

$$\underline{K}_h = (1 + k_s \Delta f_s) K_{h0} = (1 + k_s \Delta f_s) G_d A_r / t_e$$

Shear stiffness

$$k_s = 2\alpha_t [\underline{l} + \underline{m} - \alpha_t \exp(\beta_t / T_{ave})] \times \exp(\beta_t / T_{ave}) / (3lm)$$

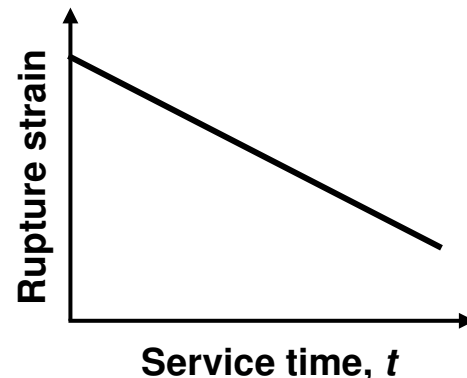
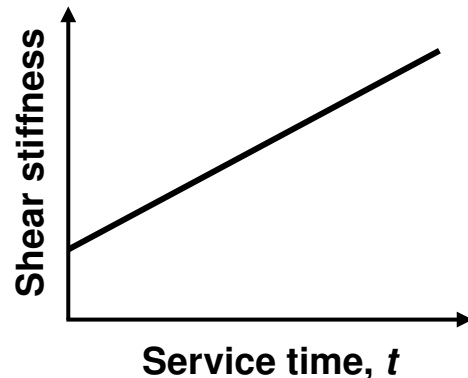
Bearing dimensions Average temperature

$$f_s = 0.066 \times \left[\frac{365t}{\text{Service time}} \times \exp(E_a (1/T_{ref} - 1/T_{ave}) / R) \right]^{0.515}$$

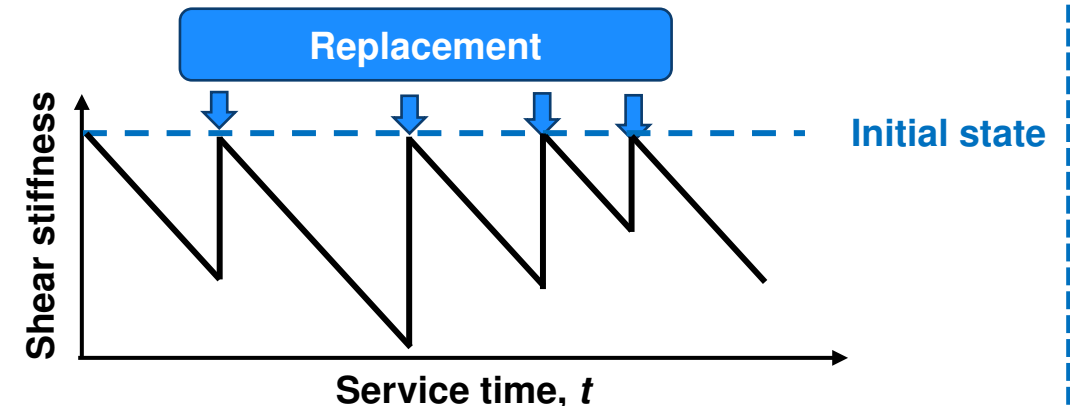
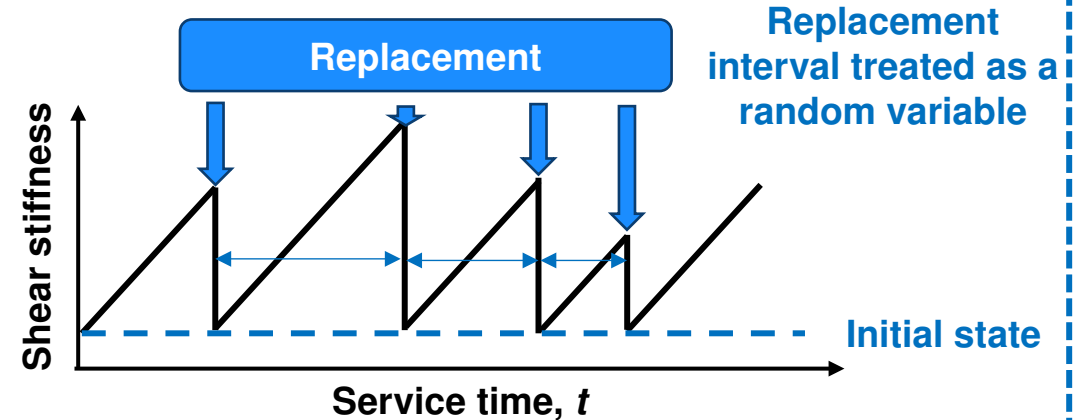
Service time

$$\underline{\gamma}_h = (1 - k_s \Delta f_s) \gamma_{h0}$$

Rupture strain



- Replacement of rubber bearings



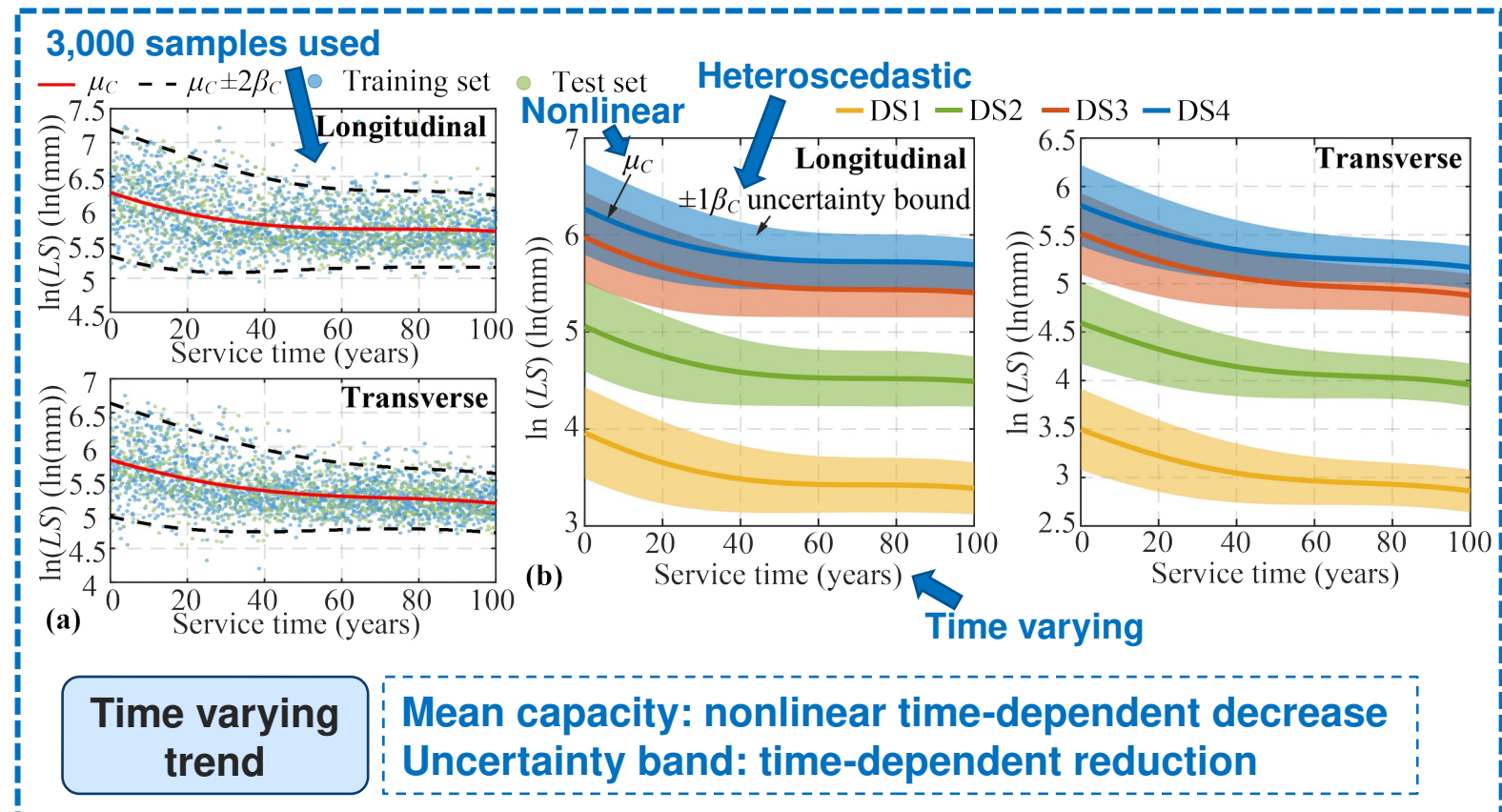
4. Results and Conclusions

➤ Seismic Fragility Analysis

GPR-driven probabilistic capacity model of RC columns

Limit state definition

Damage State	Description	Drift Limit
DS1	Slight	$0.10 \times \text{DS4}$
DS2	Moderate	$0.30 \times \text{DS4}$
DS3	Extensive	$0.75 \times \text{DS4}$
DS4	Complete	First occurrence of: longi. bar fracture / core concrete crushing / longi. bar buckling



4. Results and Conclusions

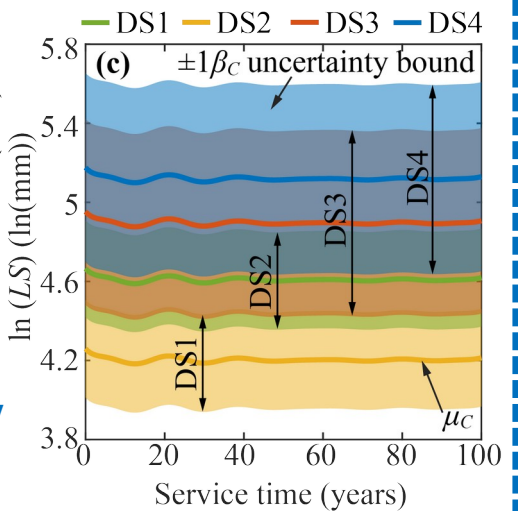
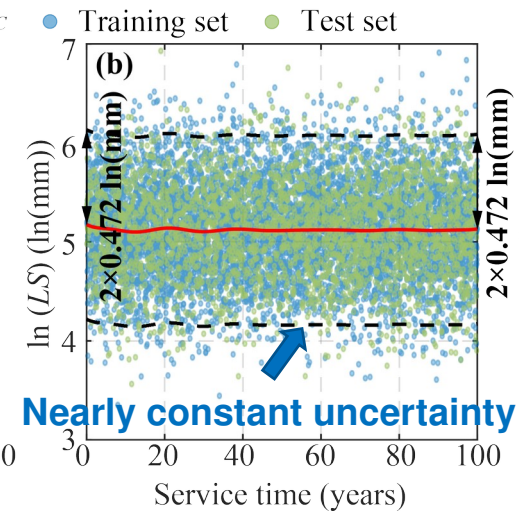
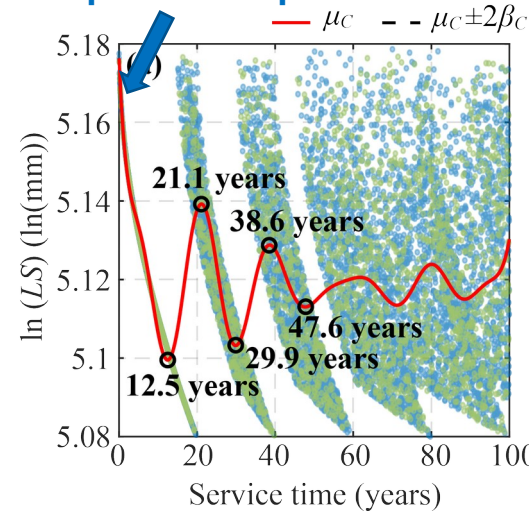
➤ Seismic Fragility Analysis

GPR-driven probabilistic capacity model of rubber bearings

Limit state definition

Damage State	Median LS (mm)	Log-dispersion (ln(mm))
DS1 – Slight	71.0	0.246
DS2 – Moderate	106.5	0.246
DS3 – Extensive	142.0	0.472
DS4 – Complete	177.5	0.472

Fluctuations induced by aging and periodic replacements



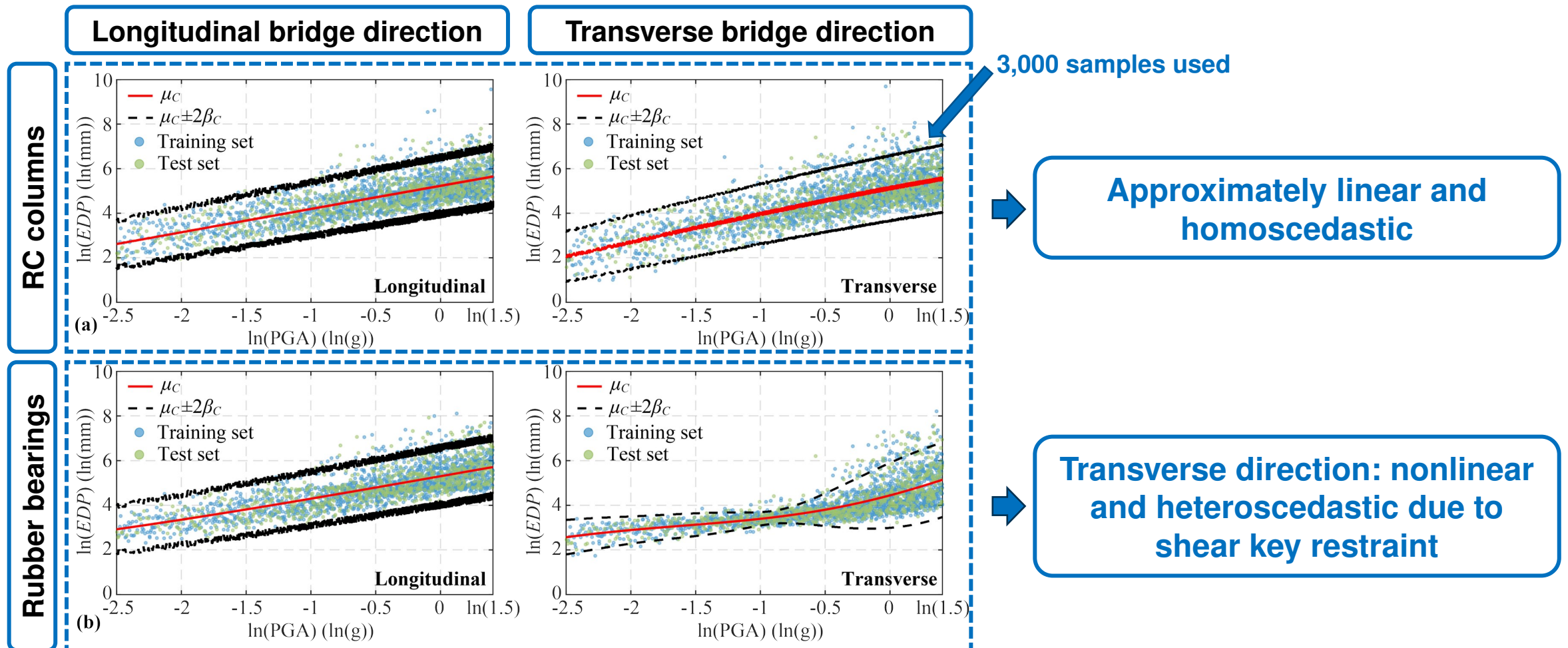
Time varying trend

Mean capacity: oscillatory time-varying trend
Uncertainty band: nearly constant over time

4. Results and Conclusions

➤ Seismic Fragility Analysis

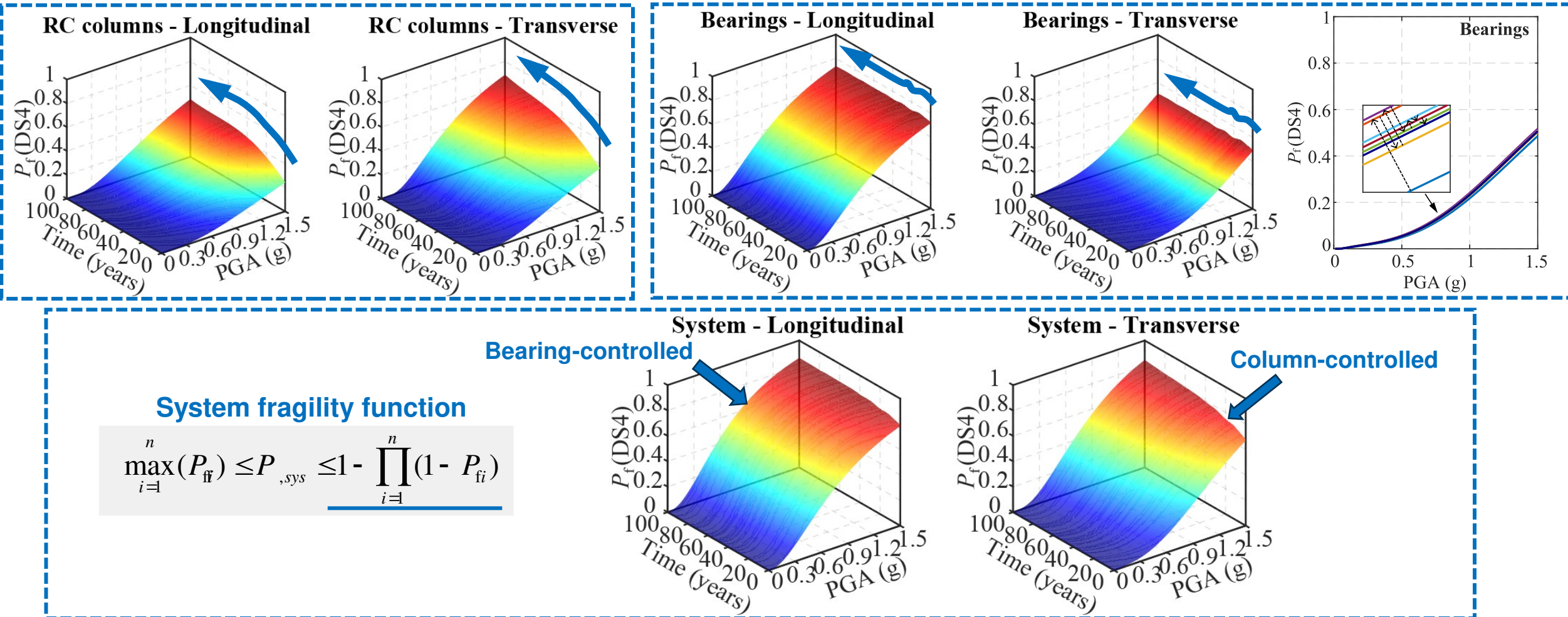
GPR-driven probabilistic seismic demand model



4. Results and Conclusions

➤ Seismic Fragility Analysis

Time varying seismic fragility surface

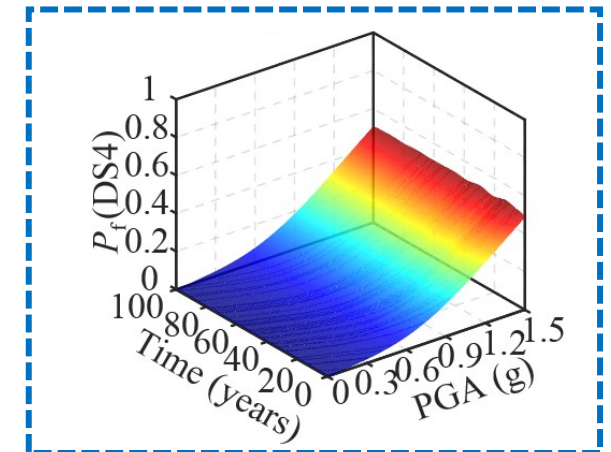
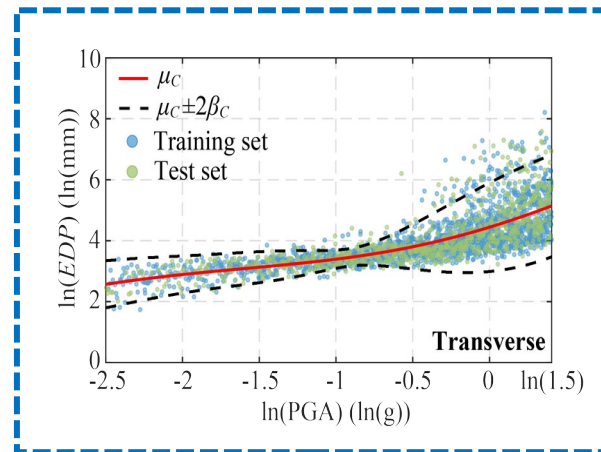
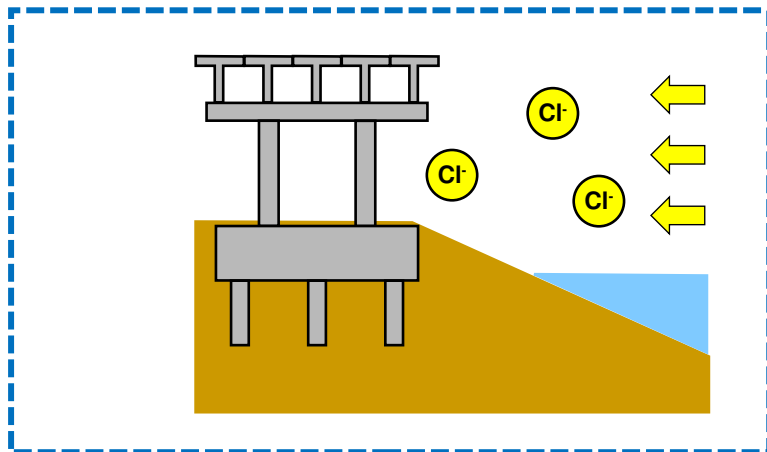


4. Results and Conclusions

➤ Seismic Fragility Analysis

Efficiency analysis

- **Analysis conducted:** 3,000 NLTHA + 3,000 pushover + 20 GPR → time-dependent seismic fragility surface.
- **Traditional approach:** 50 ground motions × 6 scaling factors × 100 years → 30,000 NLTHA + 30,000 pushover + 200 regression analyses.
- **Efficiency gain:** GPR requires only ~10% of the computations of traditional time-discrete methods, significantly reducing computational cost.



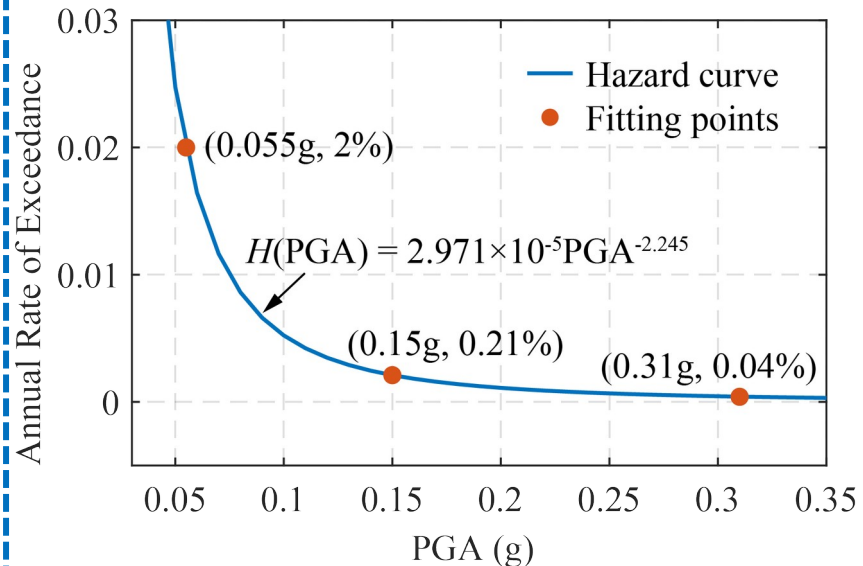
4. Results and Conclusions

➤ Life-Cycle Based Seismic Risk Analysis

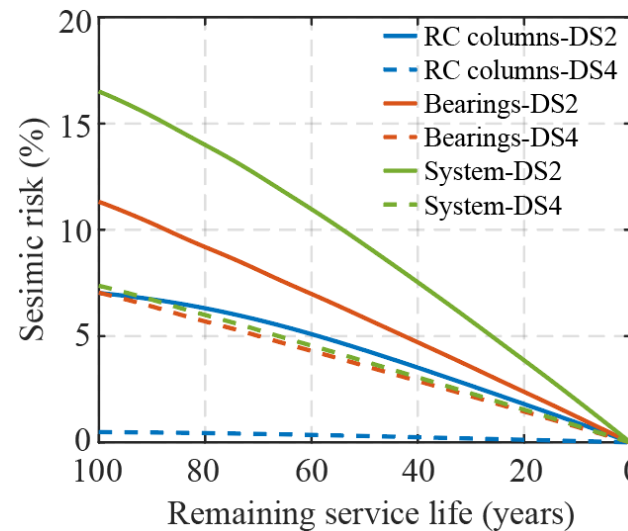
Seismic hazard analysis

Log-linear
fitted seismic
hazard curve

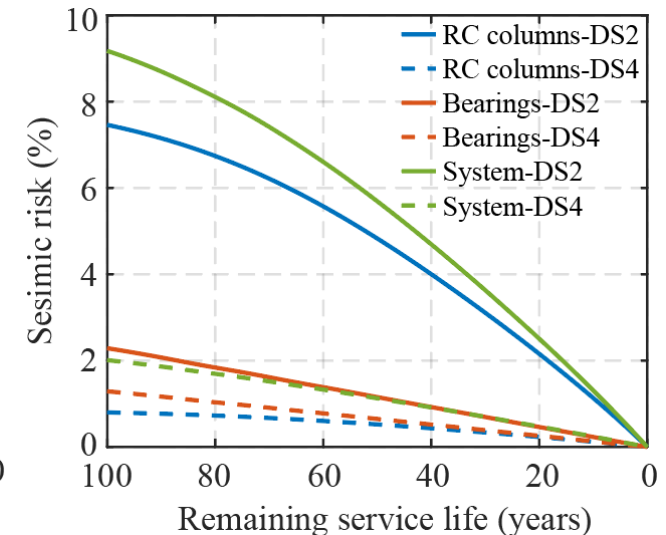
$$H(IM) = k_0 IM^{-k_1}$$



Life-cycle based total seismic risk curve



Longitudinal bridge direction



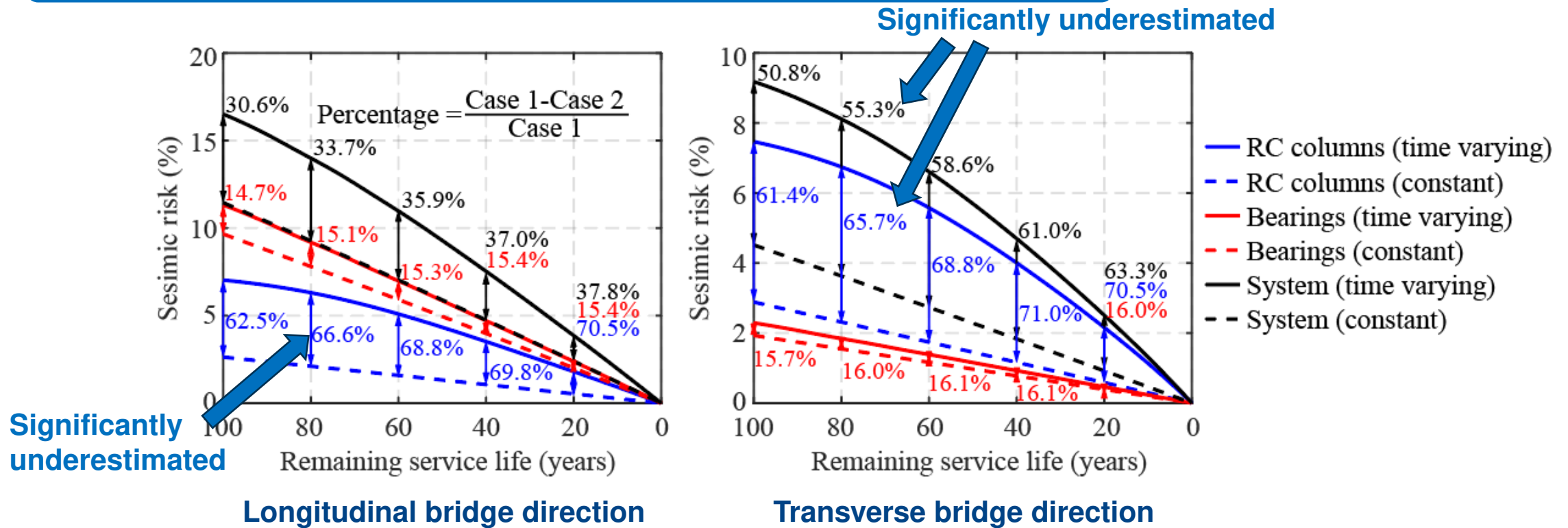
Transverse bridge direction

Life-cycle based total seismic risk decreases with decreasing remaining service life because hazard reduction outweighs fragility increase

4. Results and Conclusions

➤ Life-Cycle Based Seismic Risk Analysis

Life-cycle based total seismic risk: time-varying vs constant



Ignoring deterioration leads to significant underestimation of total seismic risk, particularly for RC columns and system.

4. Results and Conclusions

➤ Conclusions

1

GPR enables efficient time-dependent seismic fragility analysis, capturing nonlinear and heteroscedastic behavior of probabilistic demand and capacity models, and is estimated to reduce computational cost by ~90% compared to traditional methods.

2

Component-level fragility evolves differently: RC columns steadily deteriorate due to corrosion; rubber bearings fluctuate due to aging and replacement; system-level control may shift between components, highlighting the need to consider multi-component deterioration.

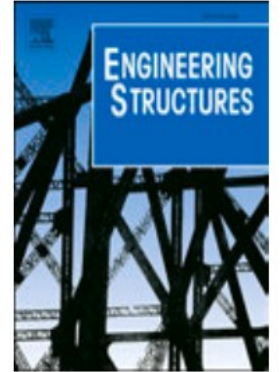
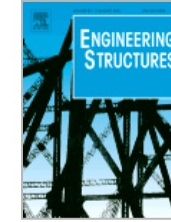
3

Total seismic risk decreases with remaining service life, but neglecting deterioration—especially RC column corrosion—can significantly underestimate risk (up to >60%), emphasizing the importance of including deterioration, replacement, and time-dependent hazard in life-cycle analysis.



Engineering Structures

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Gaussian process r
and risk assessmen
bridges subjected t

Life-cycle based time-dependent seismic design of reinforced concrete bridge piers empowered by data-driven fragility analysis

ility



Kangshuai Yin, Yan Xu

Kangshuai Yin^a, Xinzhi Duan^b, Xun Zhou^a, Yan Xu^a  , Yin Gu^c

State Key Laboratory for Disaster Reducti

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