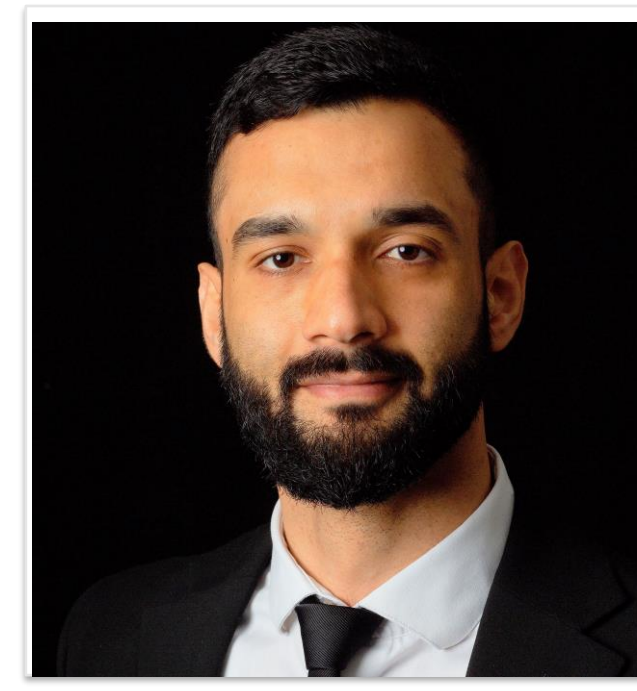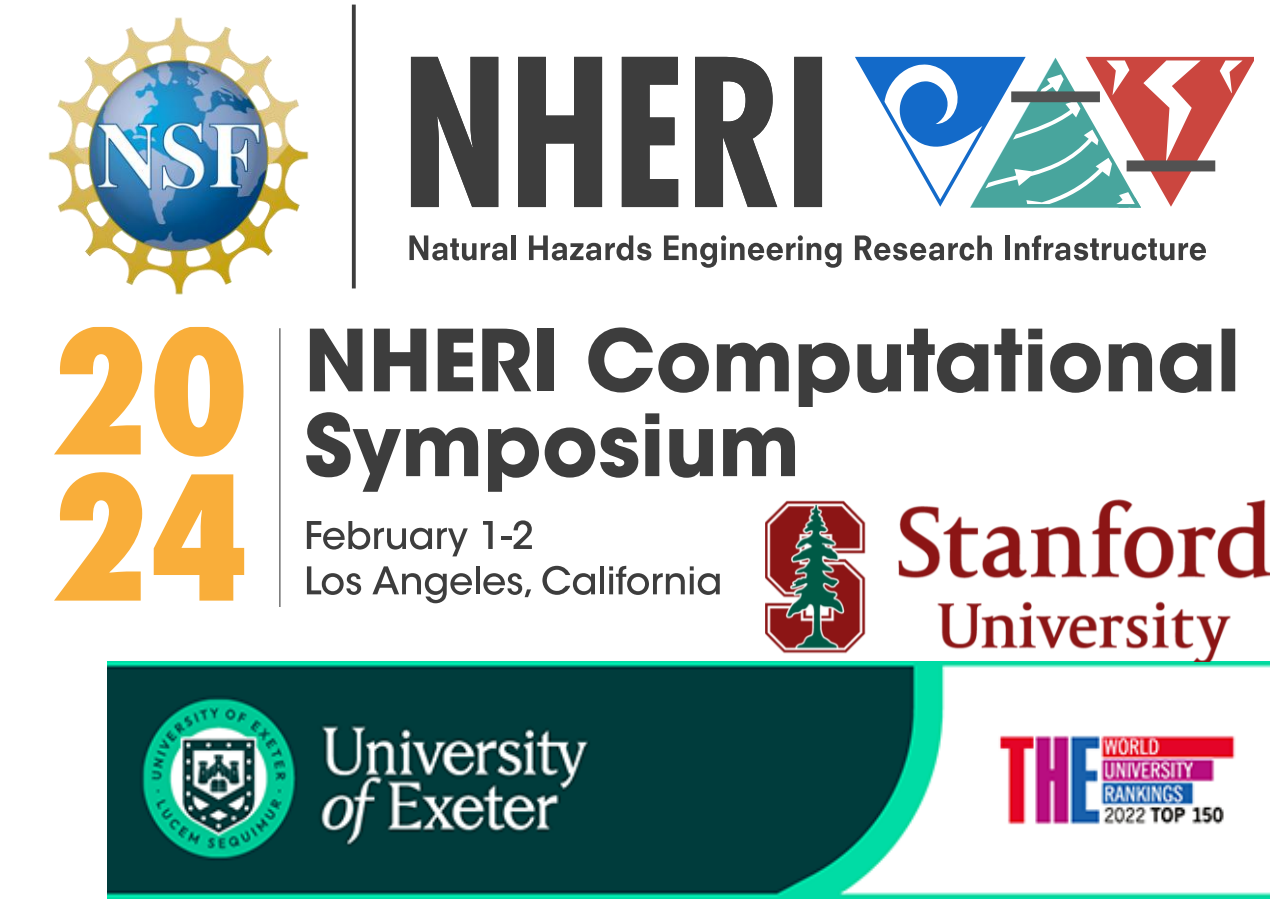# Domain-Informed Bayesian Neural Networks based Structural Surrogate Models for Seismic Demand Estimation of Steel Moment Framed Buildings

Jawad Fayaz[1], Adam Zsarnoczay[2]

[1]*University of Exeter, Exeter, UK,* [2]*Stanford University, CA, USA*

https://jfayaz.github.io/

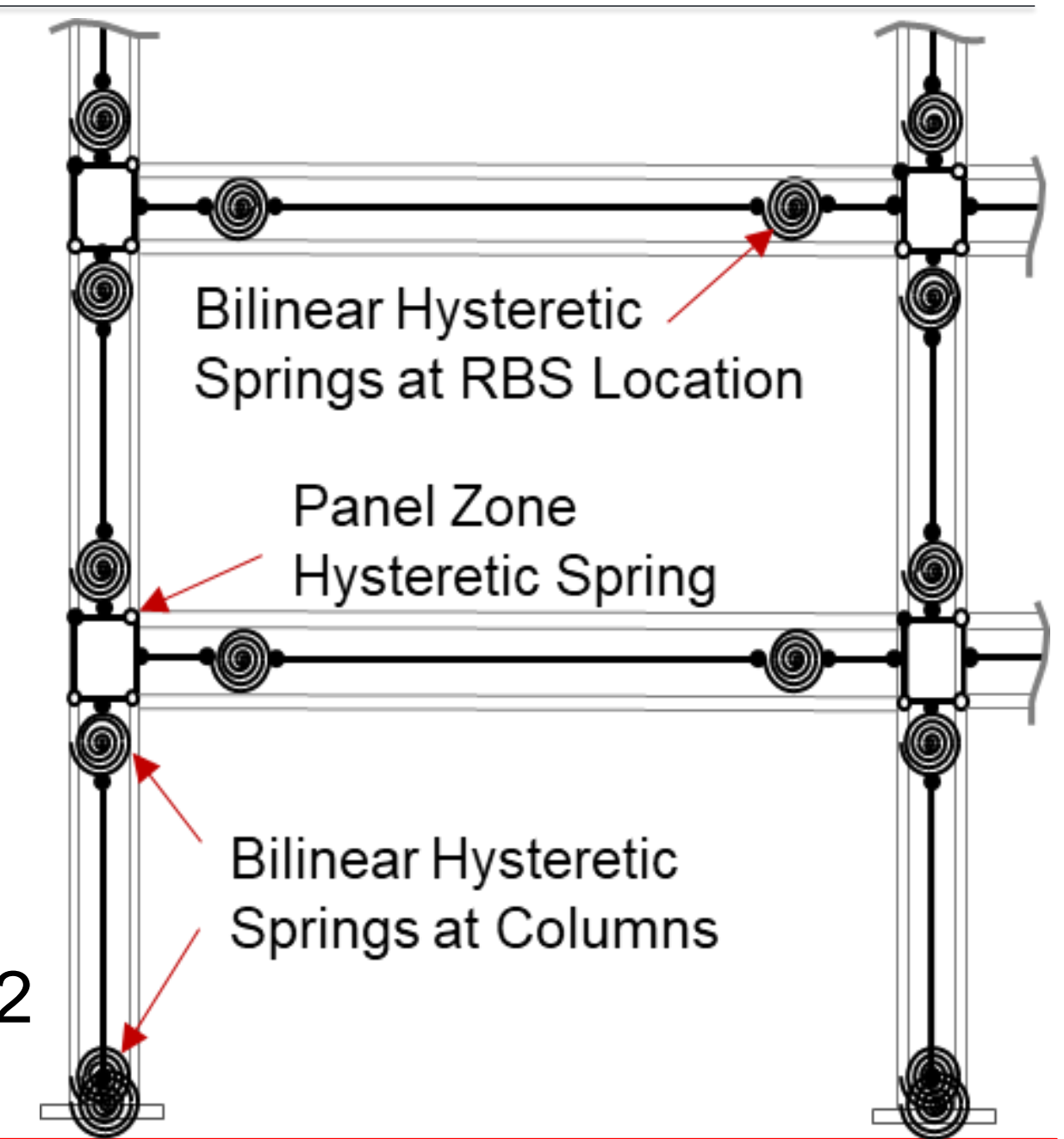**NHERI Computational Symposium**
February 1-2
Los Angeles, California

❖ Surrogate models for SMFs using domain-informed Bayesian ANNs.
❖ Hierarchical variabilities are inherently accounted within the model leading to stochastic predictions rather than point estimates.
❖ Carefully clustered and sampled SMFs based on dynamic properties.
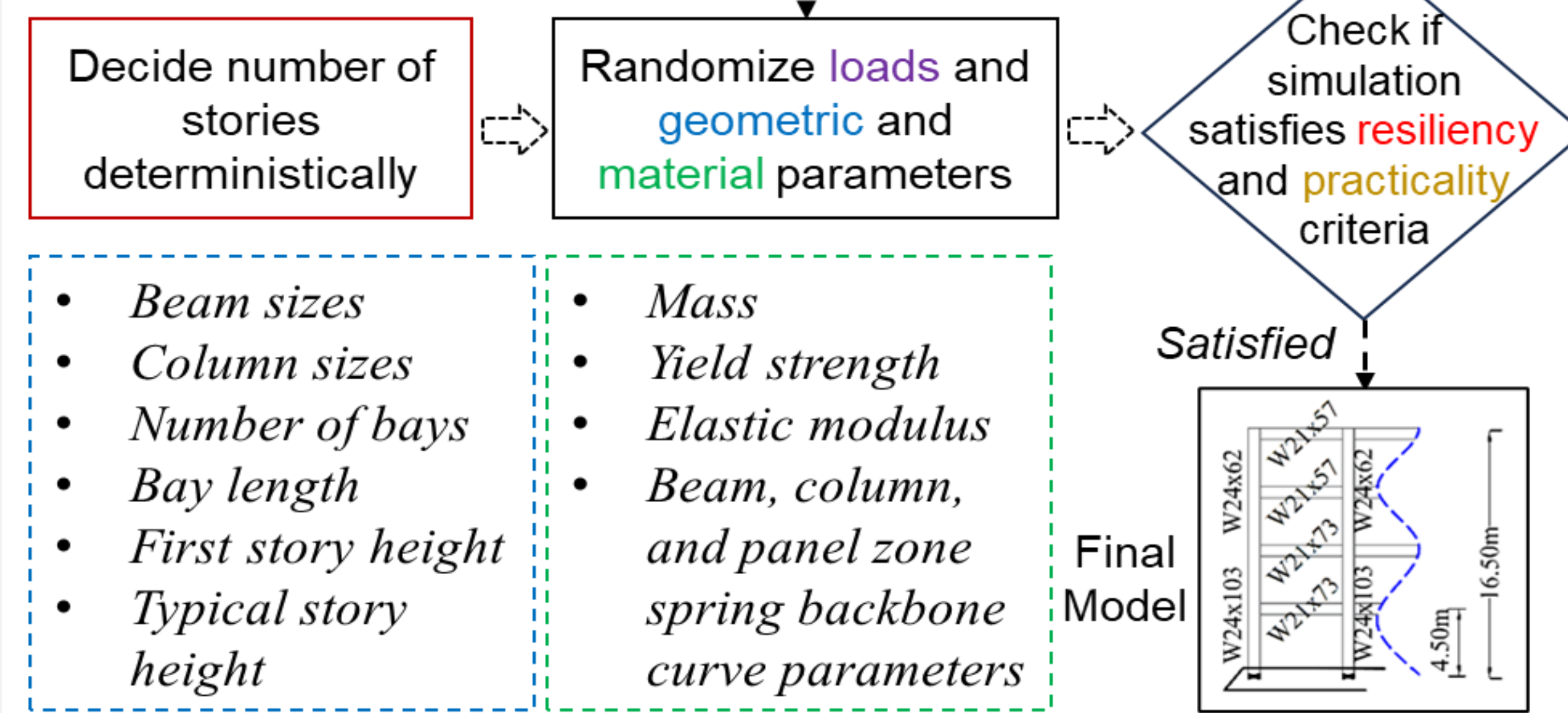❖ Models based on > 1M NLTHA with 2000 ground motions.
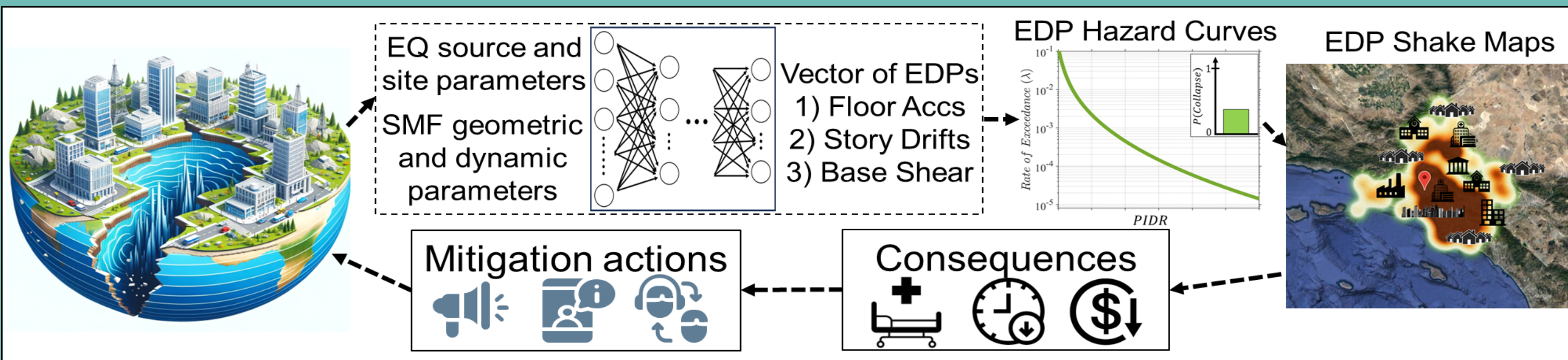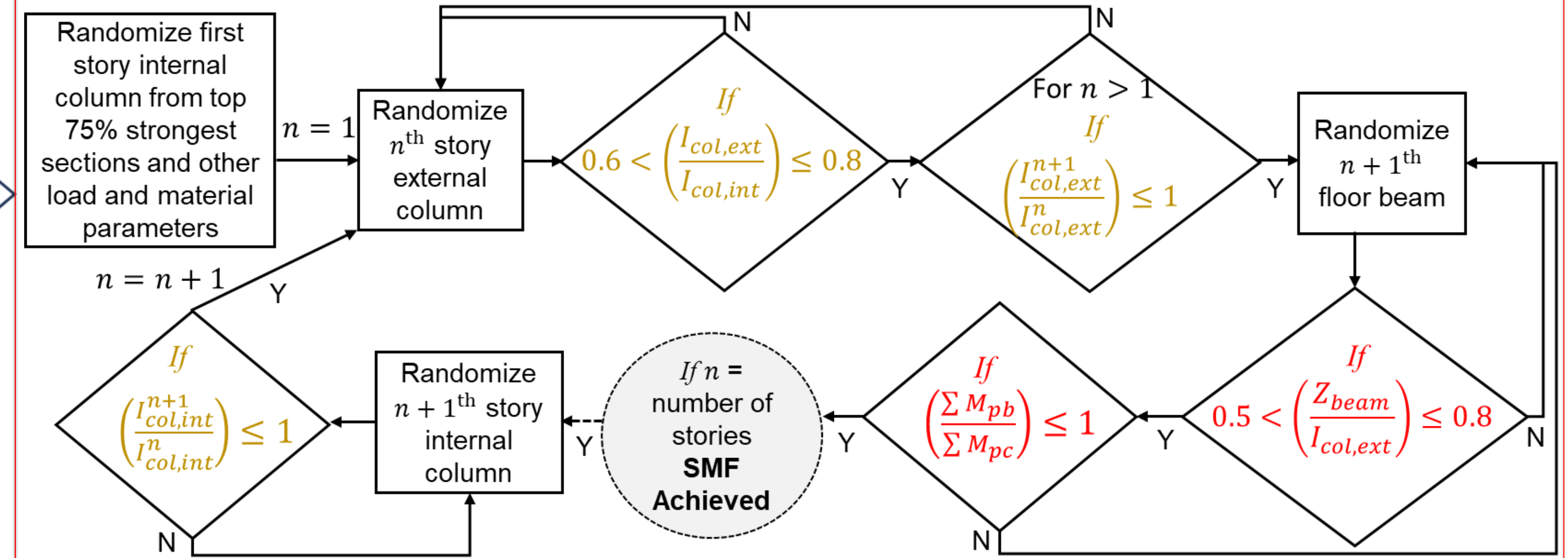

SMF Buildings Details

- 2 to 20 storied SMF buildings
- 3 to 8 bays
- FE models based on FEMA-P695 and Torres-Rodas *et al* (2018)
- Randomly simulated 10,000 variations for each SMF building
- Internal columns and externals columns at each story are same
- Beams at each floor are same
- Structural members change every 2 stories

Bilinear Hysteretic Springs at RBS Location
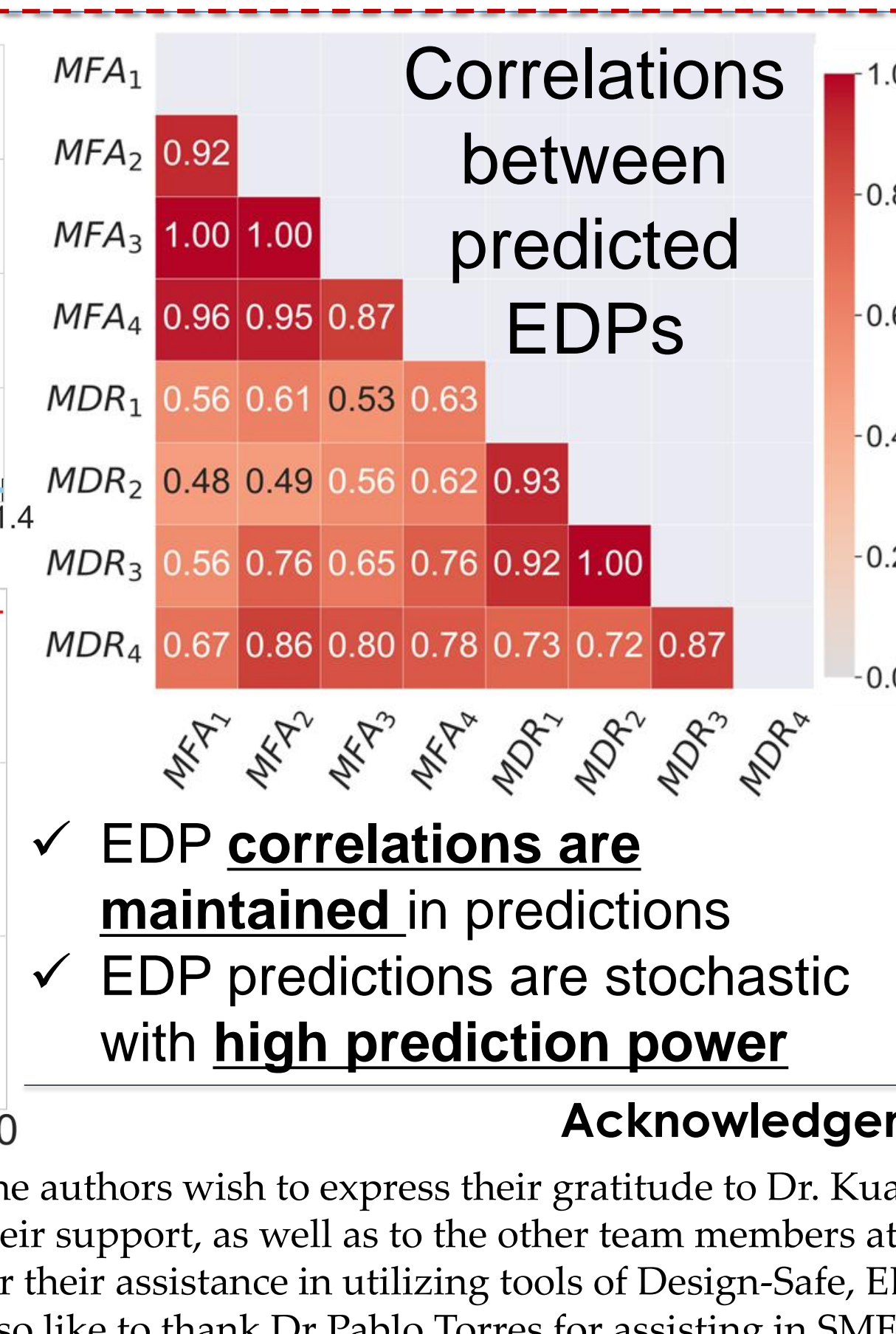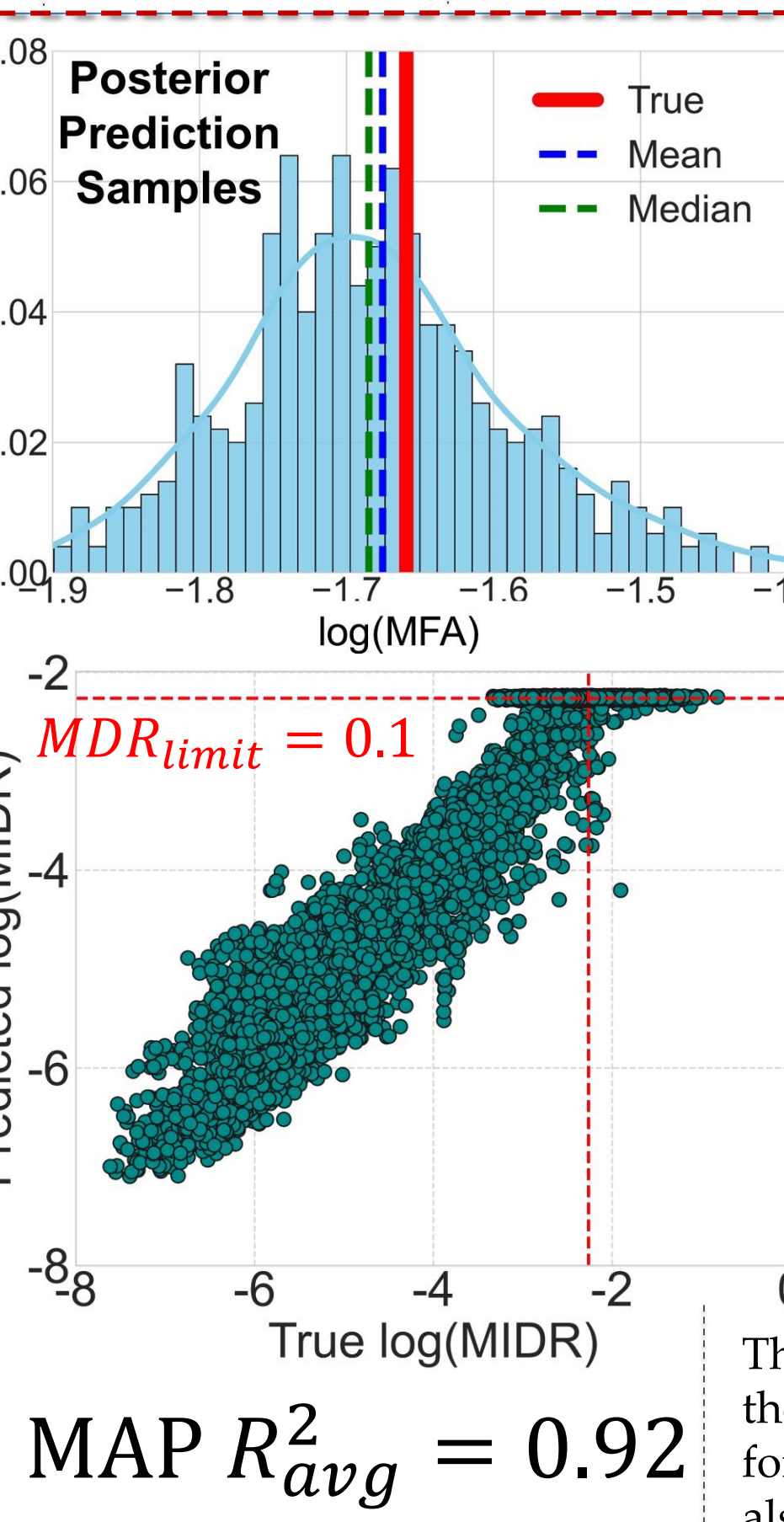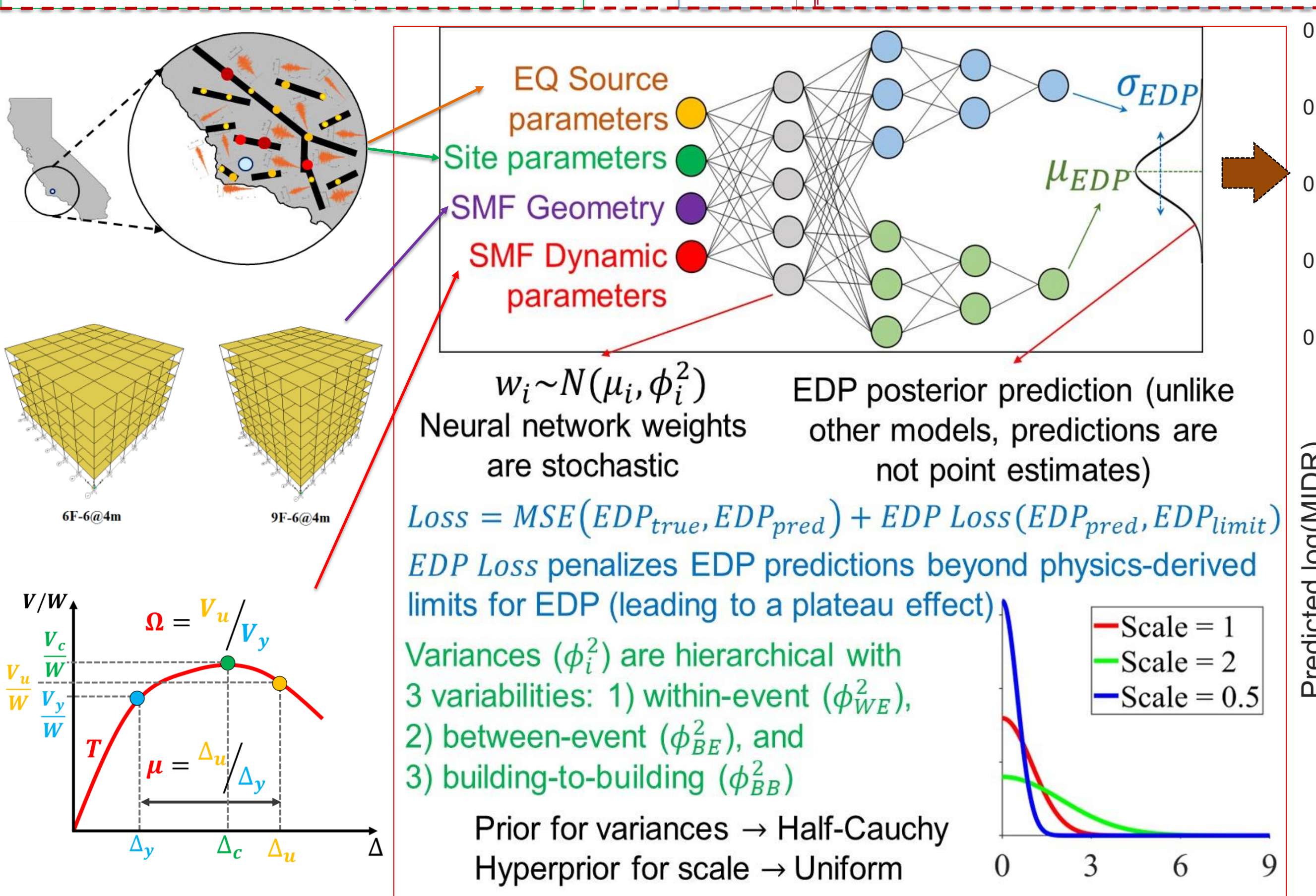Panel Zone Hysteretic Spring
Bilinear Hysteretic Springs at Columns

SMF Building Randomization algorithm

Not Satisfied

Decide number of stories deterministically → Randomize loads and geometric and material parameters → *Revise parameters* → Check if simulation satisfies resiliency and practicality criteria

Satisfied

- Beam sizes
- Column sizes
- Number of bays
- Bay length
- First story height
- Typical story height

- Mass
- Yield strength
- Elastic modulus
- Beam, column, and panel zone spring backbone curve parameters

Final Model

SMF Building Generation Algorithm

Randomize first story internal column from top 75% strongest sections and other load and material parameters

Randomize nth story external column

$0.6 < \left(\frac{I_{col,ext}}{I_{col,int}}\right) \leq 0.8$

For $n > 1$: $\left(\frac{I^{n+1}_{col,ext}}{I^n_{col,ext}}\right) \leq 1$

Randomize $n+1$th floor beam

$0.5 < \left(\frac{Z_{beam}}{I_{col,ext}}\right) \leq 0.8$

$\left(\frac{\sum M_{pb}}{\sum M_{pc}}\right) \leq 1$

If $n =$ number of stories **SMF Achieved**

Randomize $n+1$th story internal column

$\left(\frac{I^{n+1}_{col,int}}{I^n_{col,int}}\right) \leq 1$

Pushovers are *clustered* as per their *period*, *ductility capacity*, *overstrength factor*, and *yield strength*

For each SMF, **10000 models** are simulated

2000 GMs are undersampled from the NGAWest2 database

From each cluster, **20 models** are randomly sampled for NLTHA

$\mu = \frac{\Delta_u}{\Delta_y}$, $\Omega = \frac{V_u}{V_y}$

No. of NLTHA for each SMF

$= K$ clusters $\times$ 20 models $\times$ 2000 GMs

EE$_{UQ}$

Mean / Median / Probability of Collapse 0.04

Correlations between EDPs
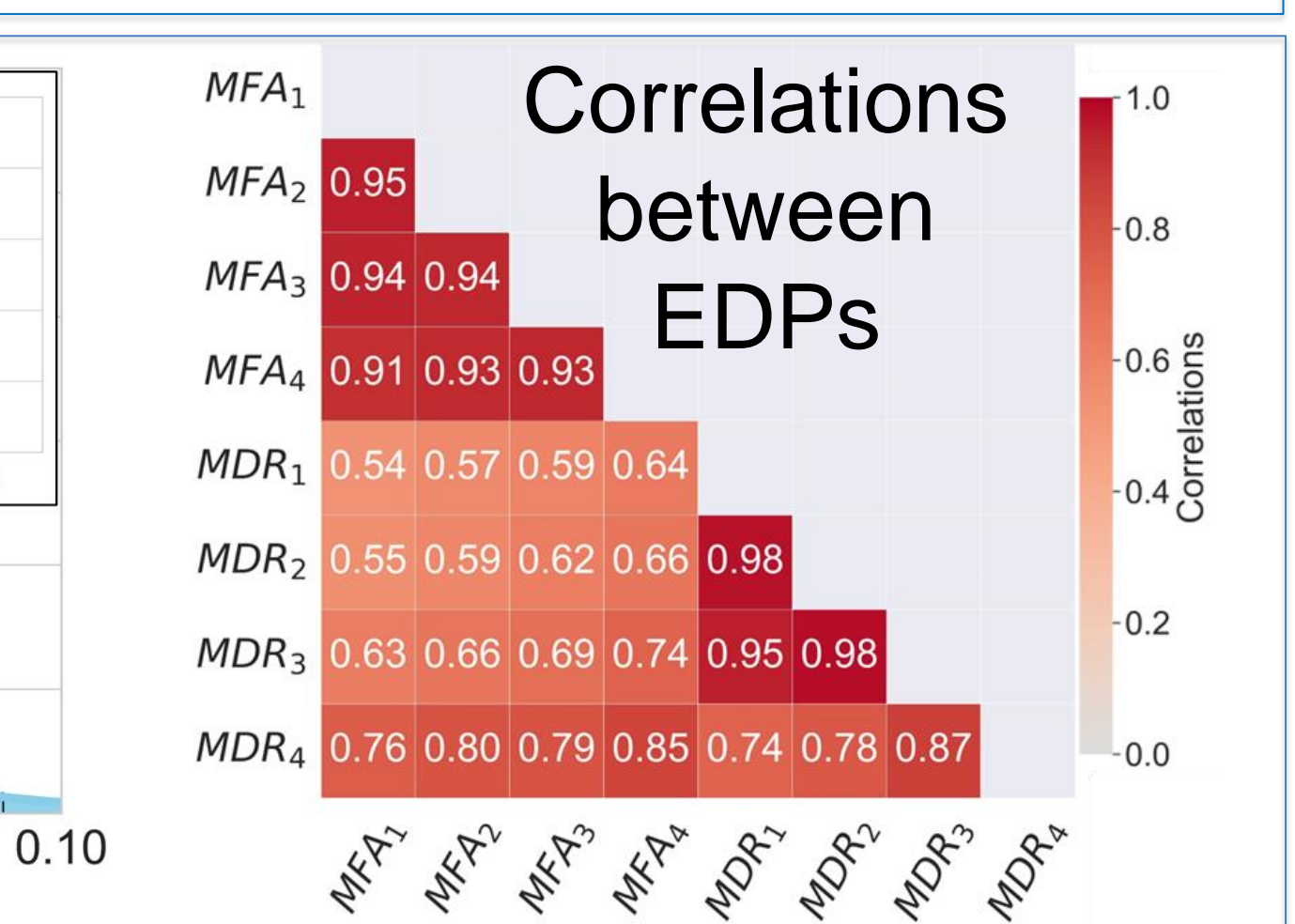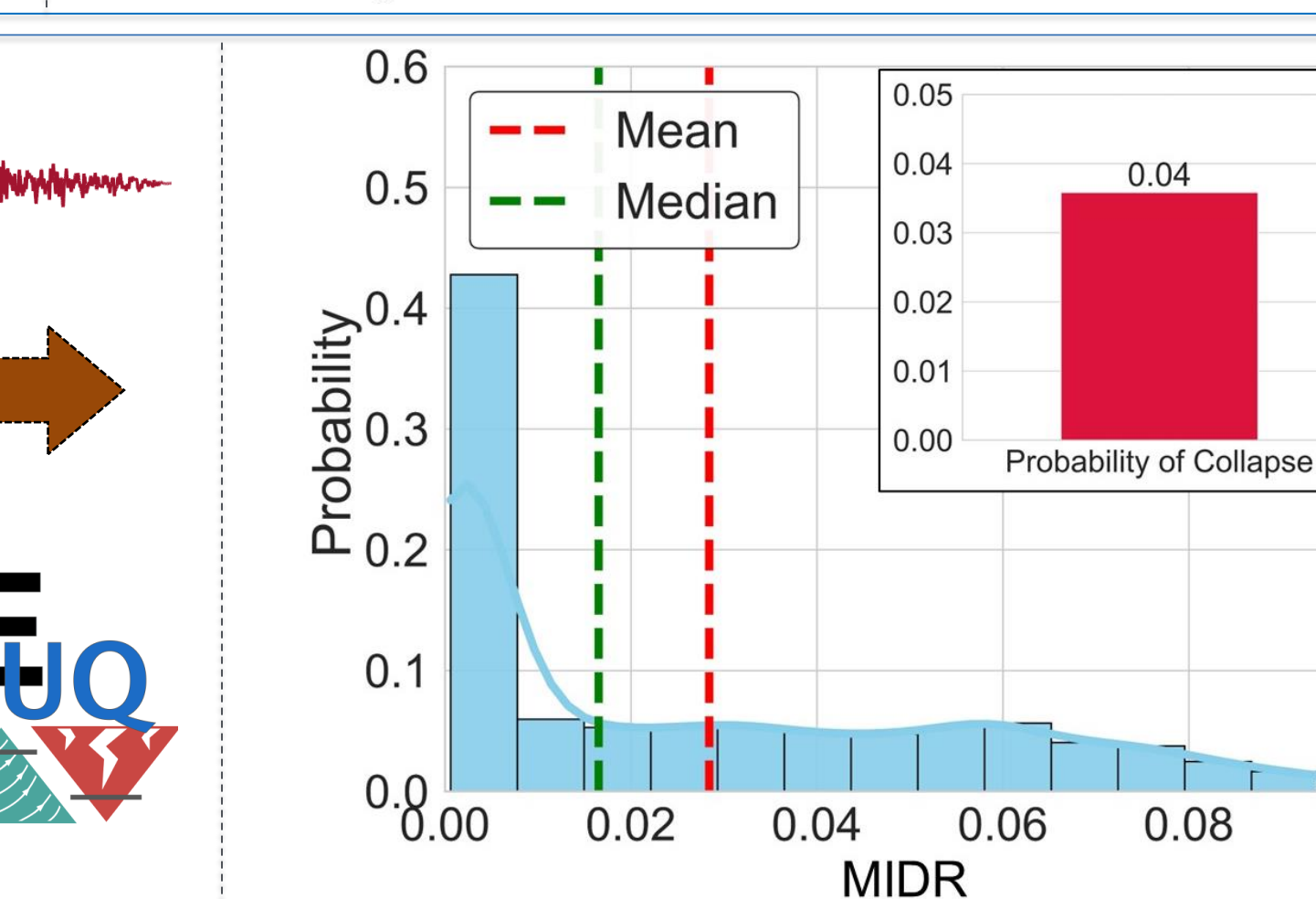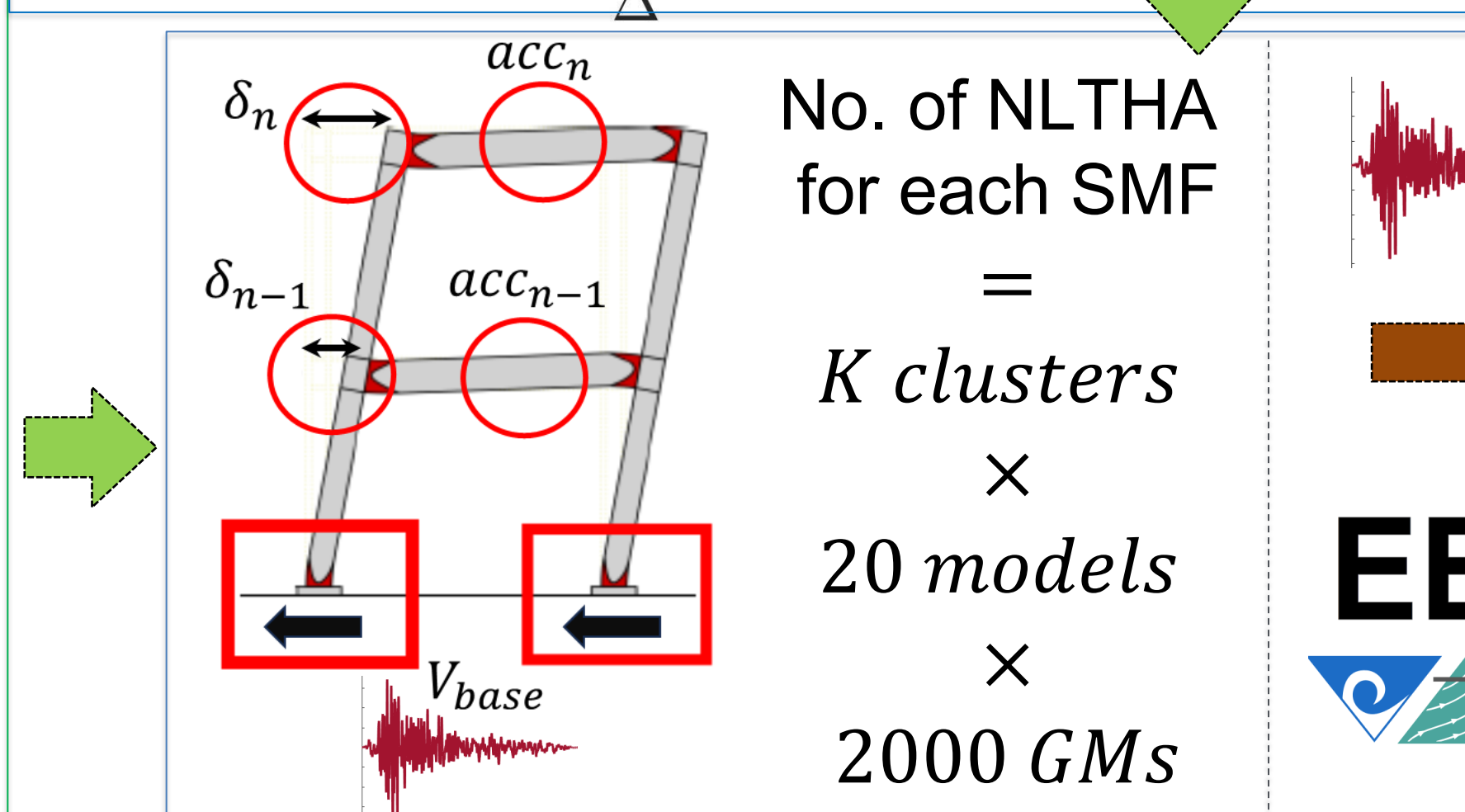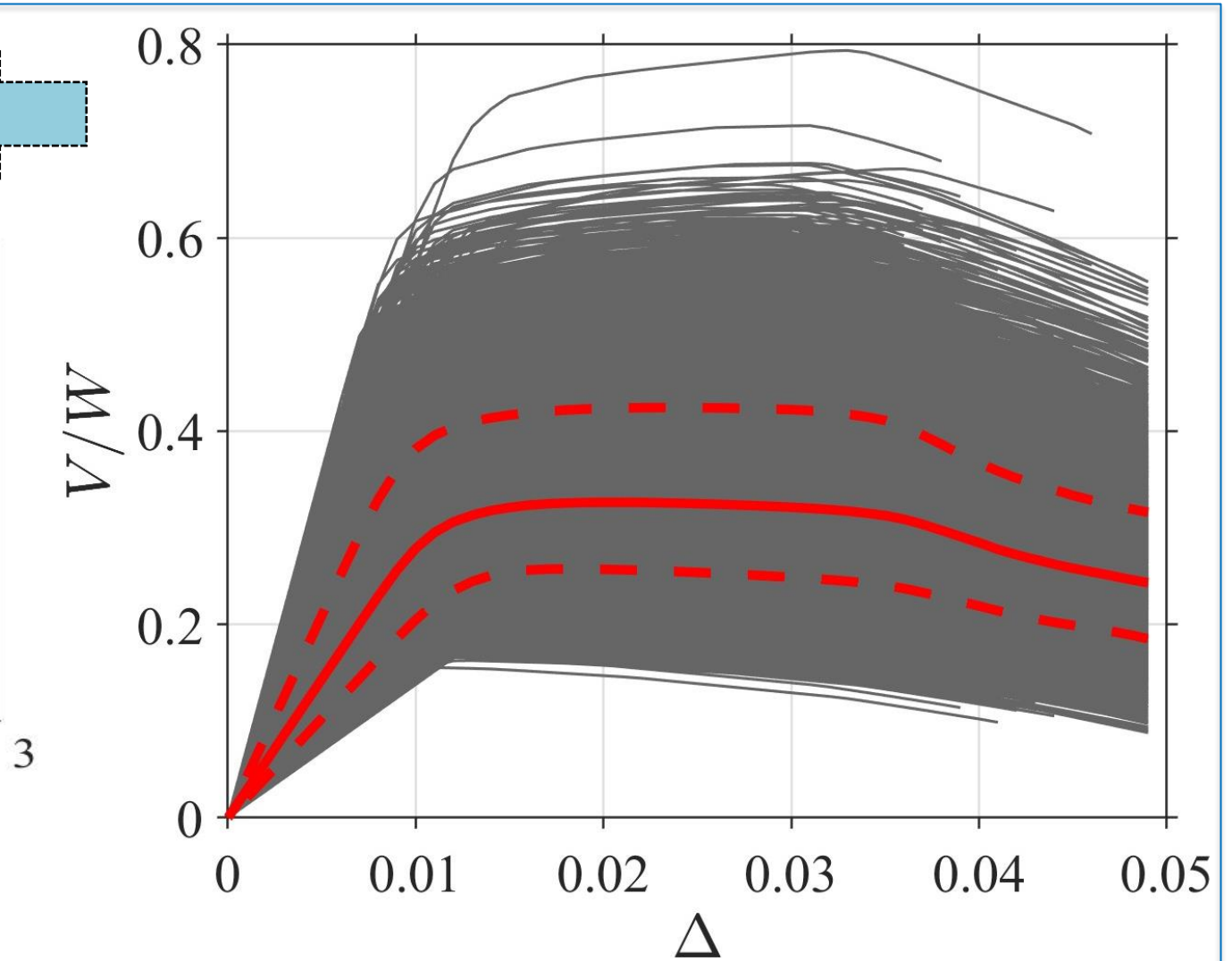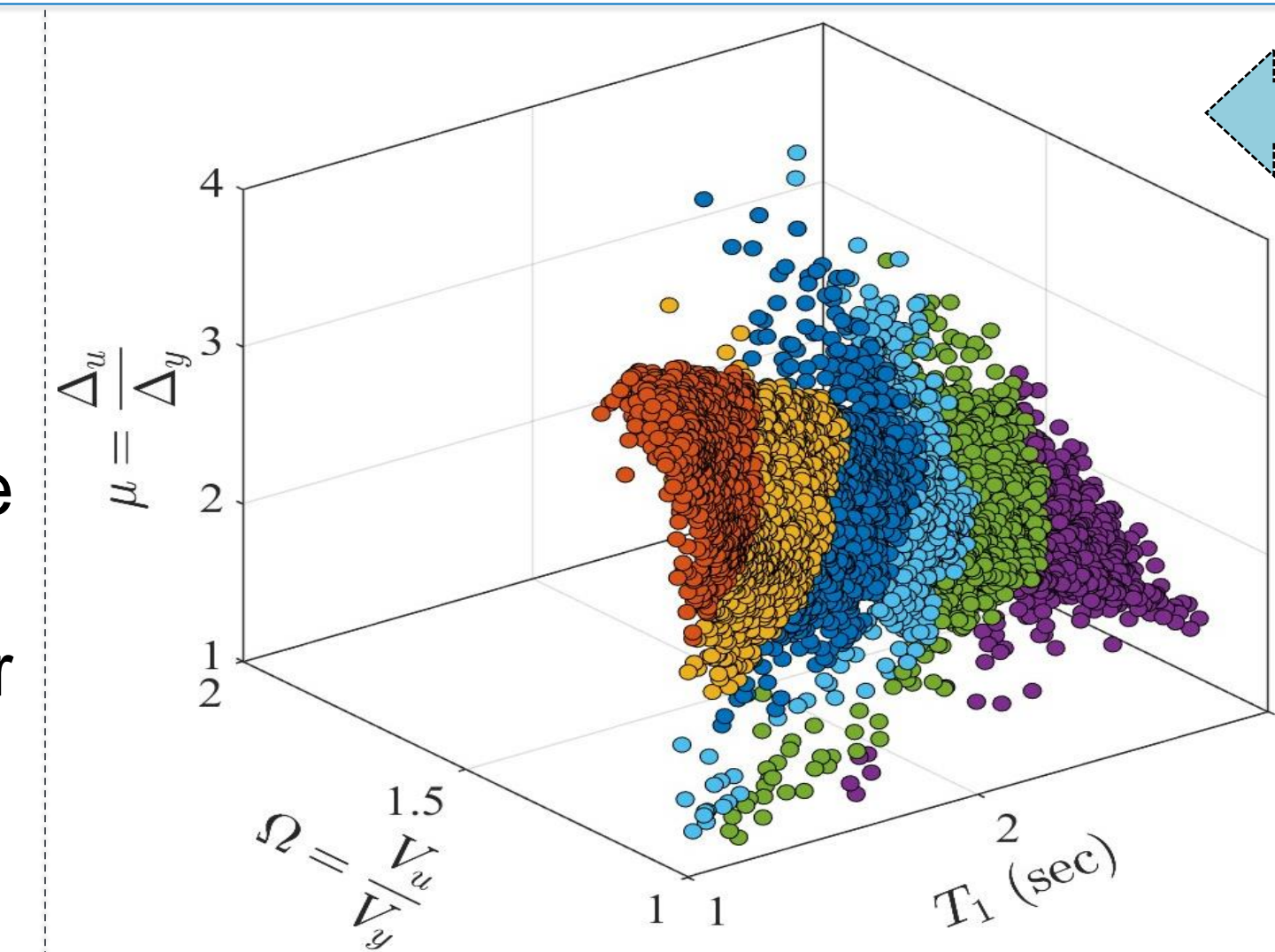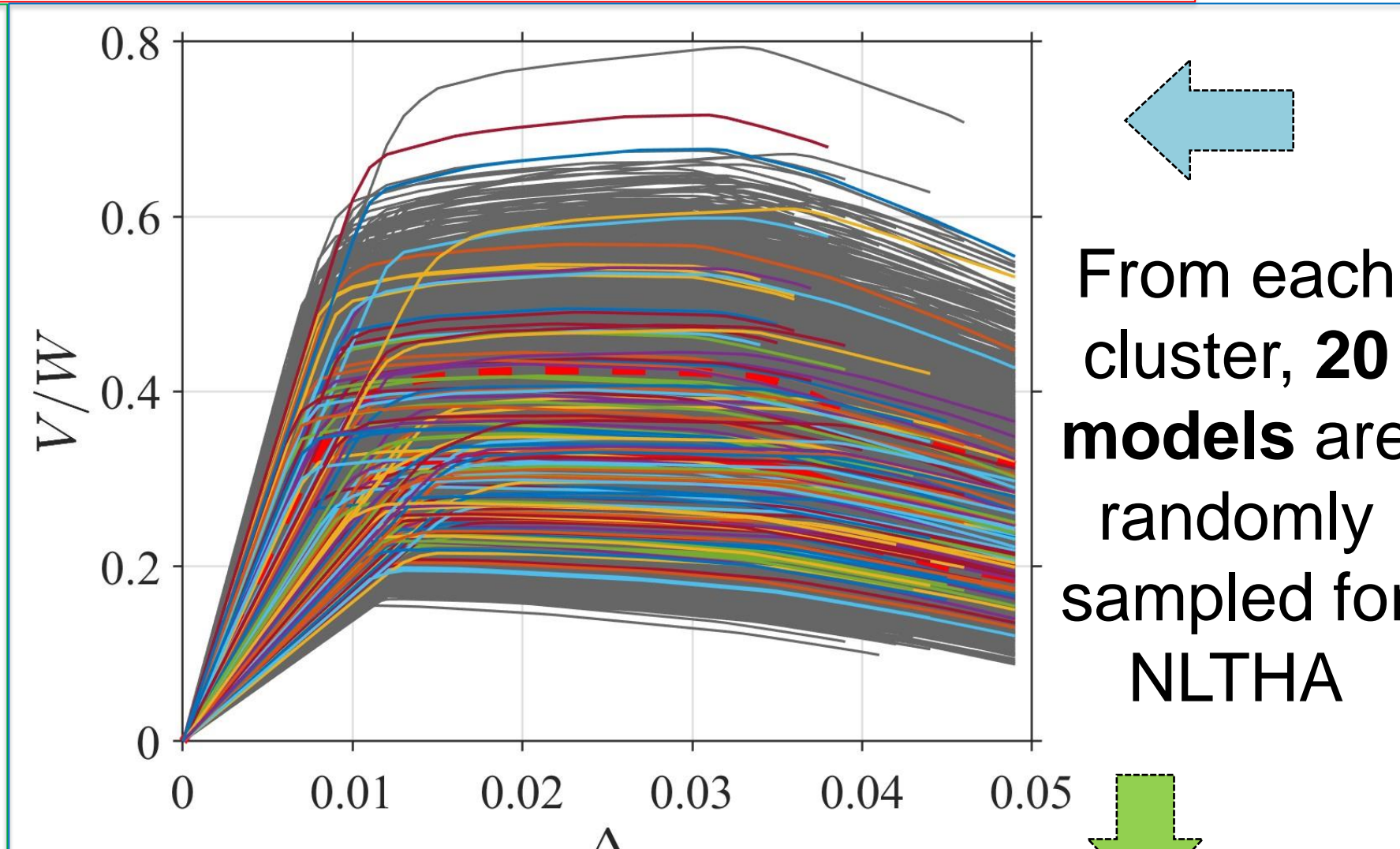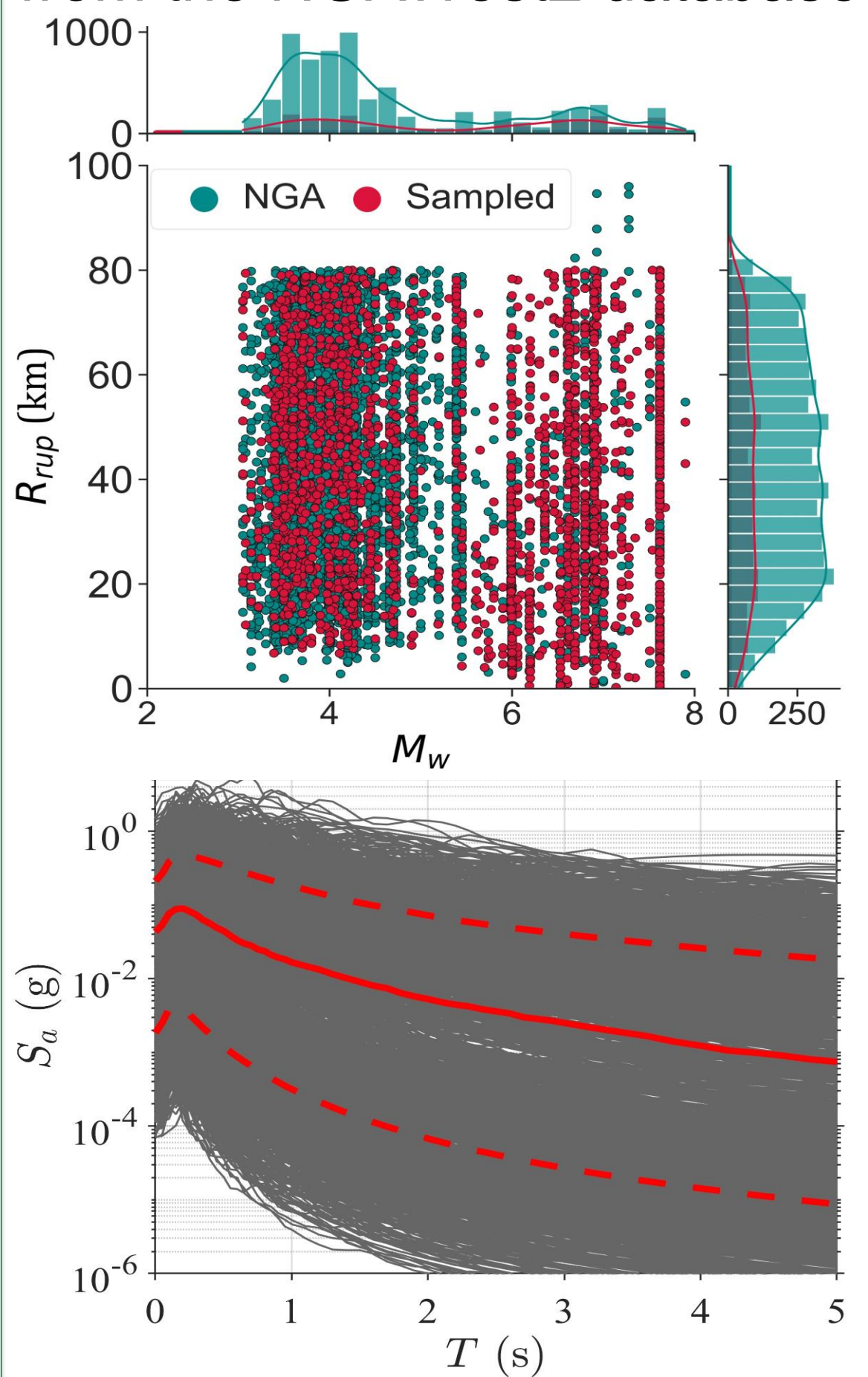
Current Directions

➤ More physics-informed (satisfying dynamic equation).
➤ 100 sample models per cluster to represent building to building variability
➤ Incorporate XAI for interpretability

EQ Source parameters
Site parameters
SMF Geometry
SMF Dynamic parameters
σ_{EDP}
μ_{EDP}

$w_i \sim N(\mu_i, \phi_i^2)$
Neural network weights are stochastic

EDP posterior prediction (unlike other models, predictions are not point estimates)

Posterior Prediction Samples
True / Mean / Median

Correlations between predicted EDPs

$MDR_{limit} = 0.1$

$Loss = MSE(EDP_{true}, EDP_{pred}) + EDP\ Loss(EDP_{pred}, EDP_{limit})$

EDP Loss penalizes EDP predictions beyond physics-derived limits for EDP (leading to a plateau effect)

Variances (ϕ_i^2) are hierarchical with 3 variabilities: 1) within-event (ϕ_{WE}^2), 2) between-event (ϕ_{BE}^2), and 3) building-to-building (ϕ_{BB}^2)

Prior for variances → Half-Cauchy
Hyperprior for scale → Uniform

Scale = 1
Scale = 2
Scale = 0.5

$\Omega = \frac{V_u}{V_y}$, $\mu = \frac{\Delta_u}{\Delta_y}$

$MAP\ R^2_{avg} = 0.92$

✓ EDP **correlations are maintained** in predictions
✓ EDP predictions are stochastic with **high prediction power**