Conditional Generative Modeling for Ground Motion

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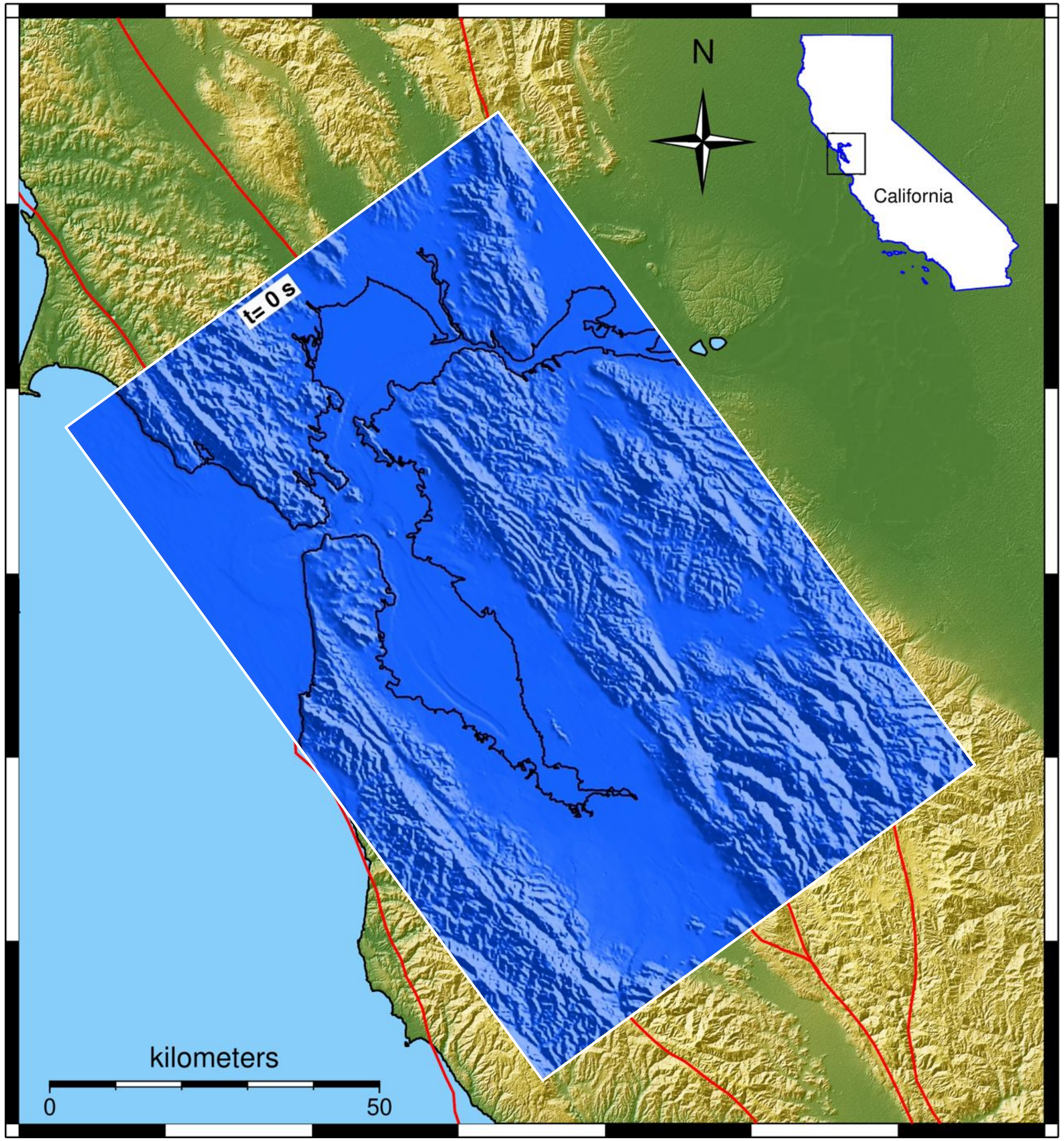
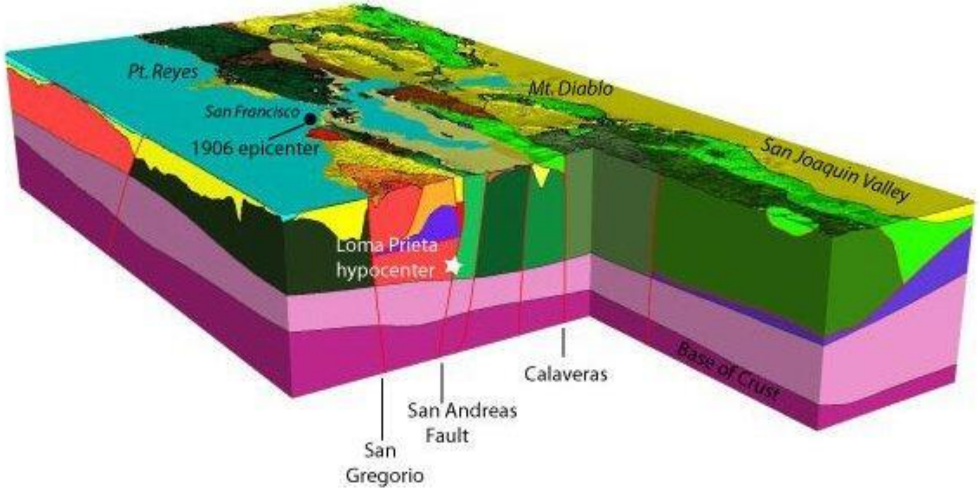
Supported by SCEC 25303, 24123
DOE LDRD/GTO/ASCR

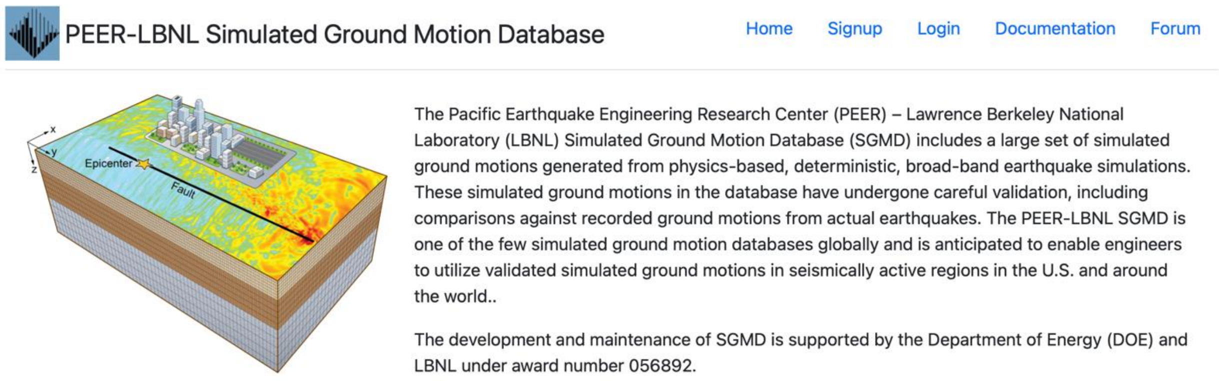
Magnitude 7 EQ at the Hayward fault





USGS, Hirakawa et al., 2022, BSSA

50 realizations are available:



EQSIM: DOE ECP/CESER
McCallen et al., 2025, EQSpectra

Seismic wavefields

wavefields, source, receiver, path

$$d(t, x_s, x_r, m) = S(t, x_s) * R(t, x_r) * G(t, x_s, x_r, m),$$

time, source & receiver locations, model

Numerical simulations suffer from

- Uncertainties/errors in *S, R, m,* x_s
- Physics errors in wave equation
- Computational cost of large-scale 3D simulation
  (e.g., large scale SFBA simulation costs128 A100 GPU nodes x 6 hours)

Deterministic AI (e.g. PINN, Fourier neural operators) learns mapping *f*

$$\hat{d} = f(t).$$

Deterministic AI accelerate the simulation but suffer from

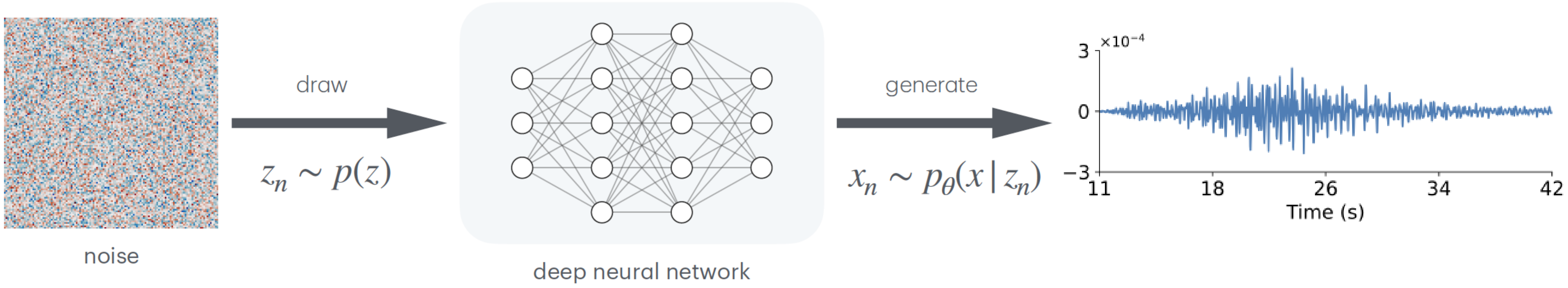
- Uncertainties/errors in *S, R, m,* x_s
- Physics errors in wave equation

$$d(t, x_s, x_r, m) = S(t, x_s) * R(t, x_r) * G(t, x_s, x_r, m),$$

Yang et al., 2021, Seis. Rec., 2023, IEEE TGRS
Majid et al., 2022, JGR, Ren, 2024, CPC , Aquib et al. 2024

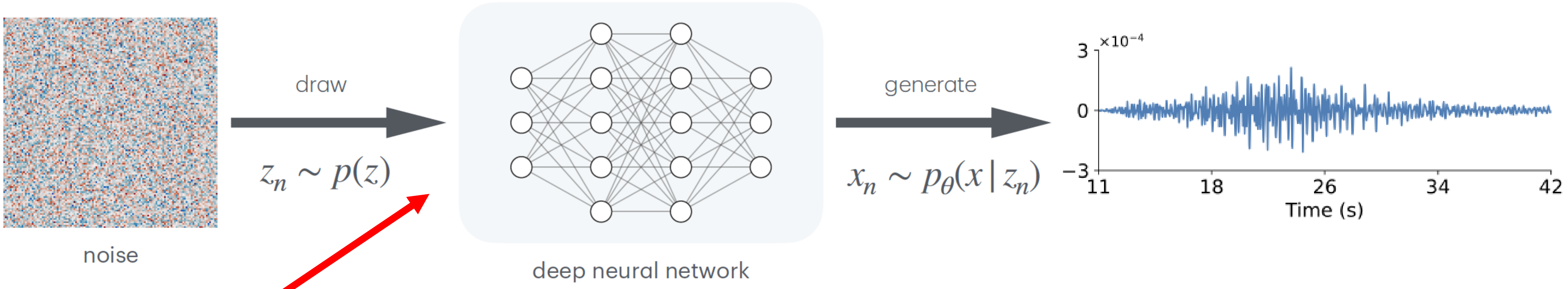
Generative AI learns probability distribution *p* from data distribution p_{data}

$$\hat{d} \sim p(d)$$



“Conditional” generative model (CGM)

$$\hat{d} \sim p(d|v)$$



<u>Conditions</u>

Magnitude, EQ location, Sensor location,……

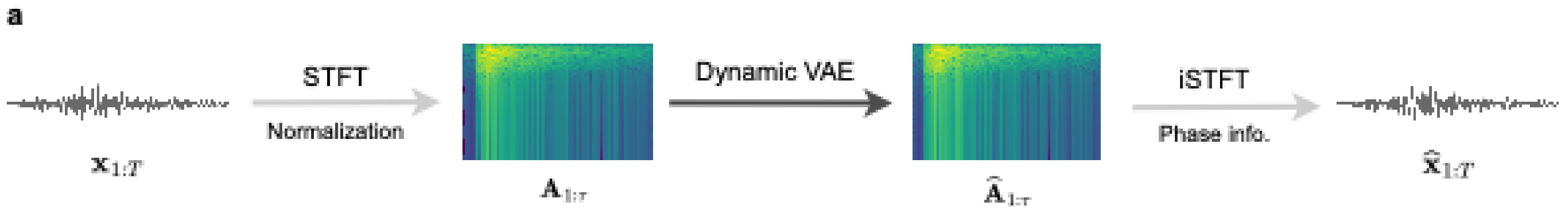
Generative AI can

- Learn “physics”
- Accelerate simulations

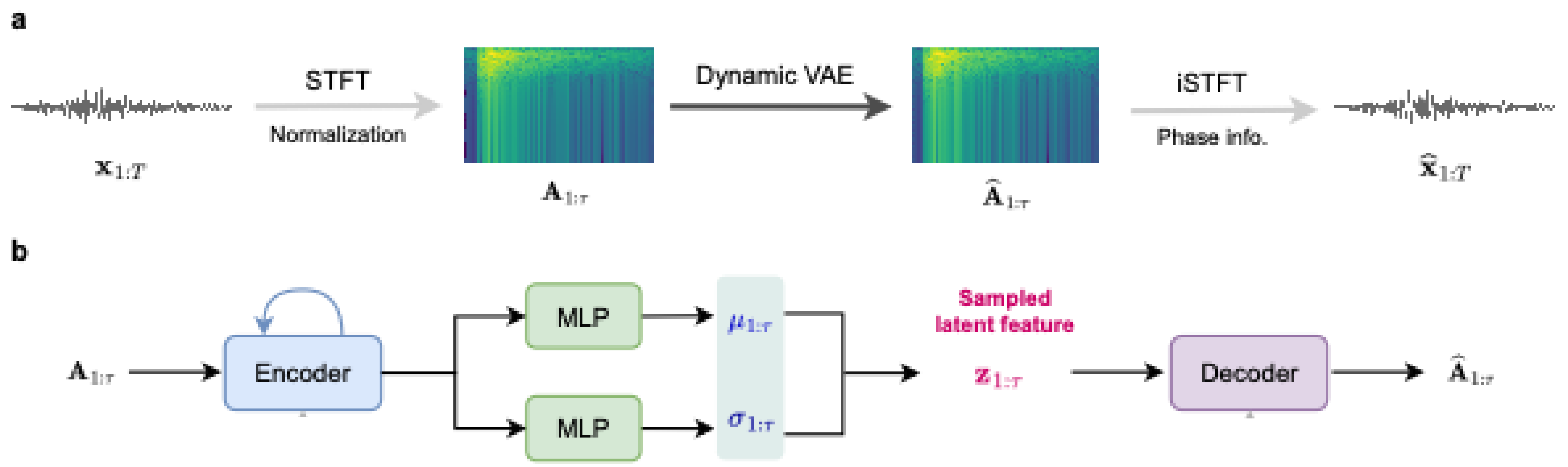
Wang et al., 2021, JGR, Florez et al., 2022, BSSA, Esfahani et al., 2002, BSSA, Shi et al., 2024

Conditional Dynamic Variational Autoencoder

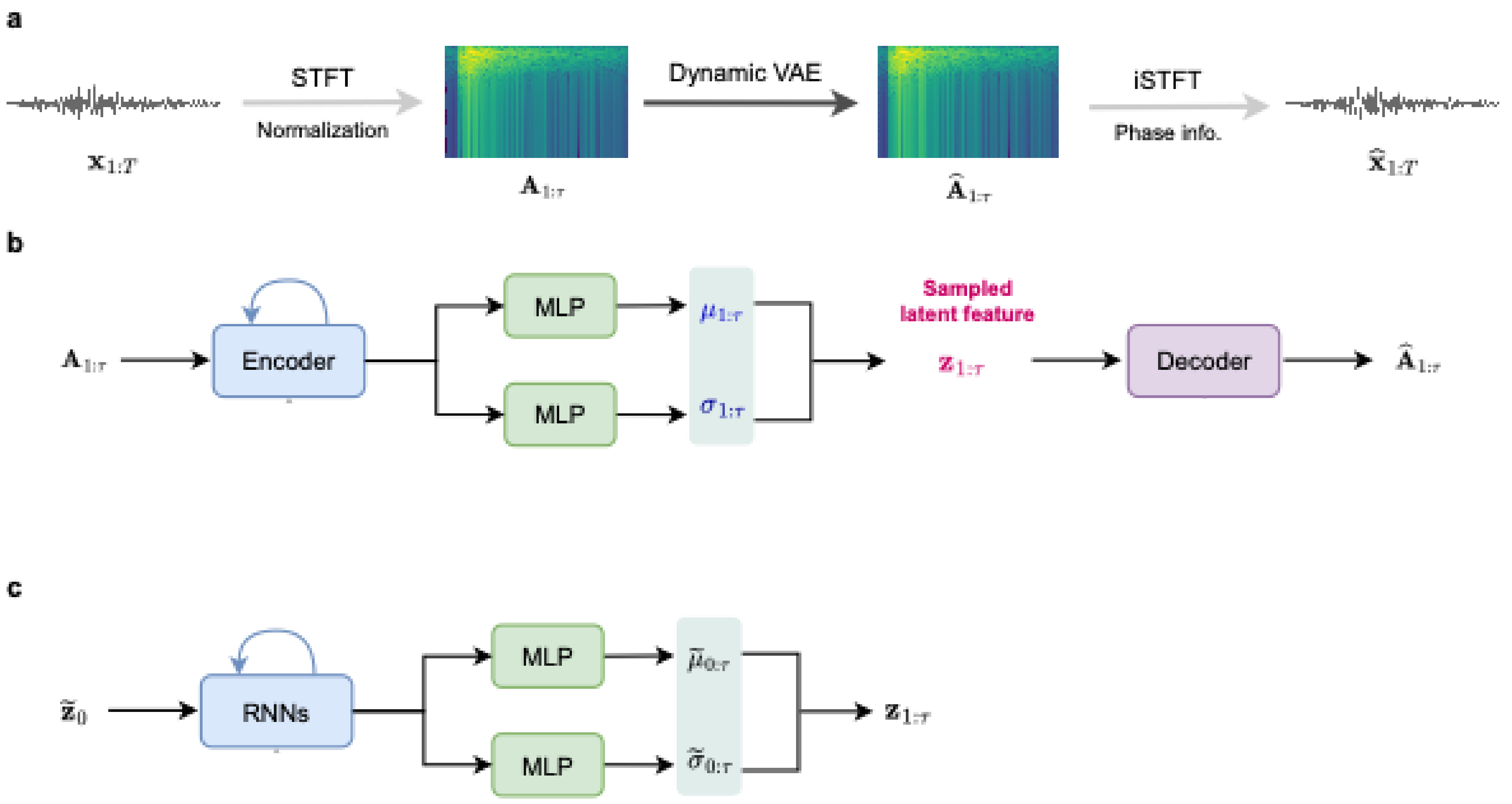
Ren et al., 2024, ArXiv



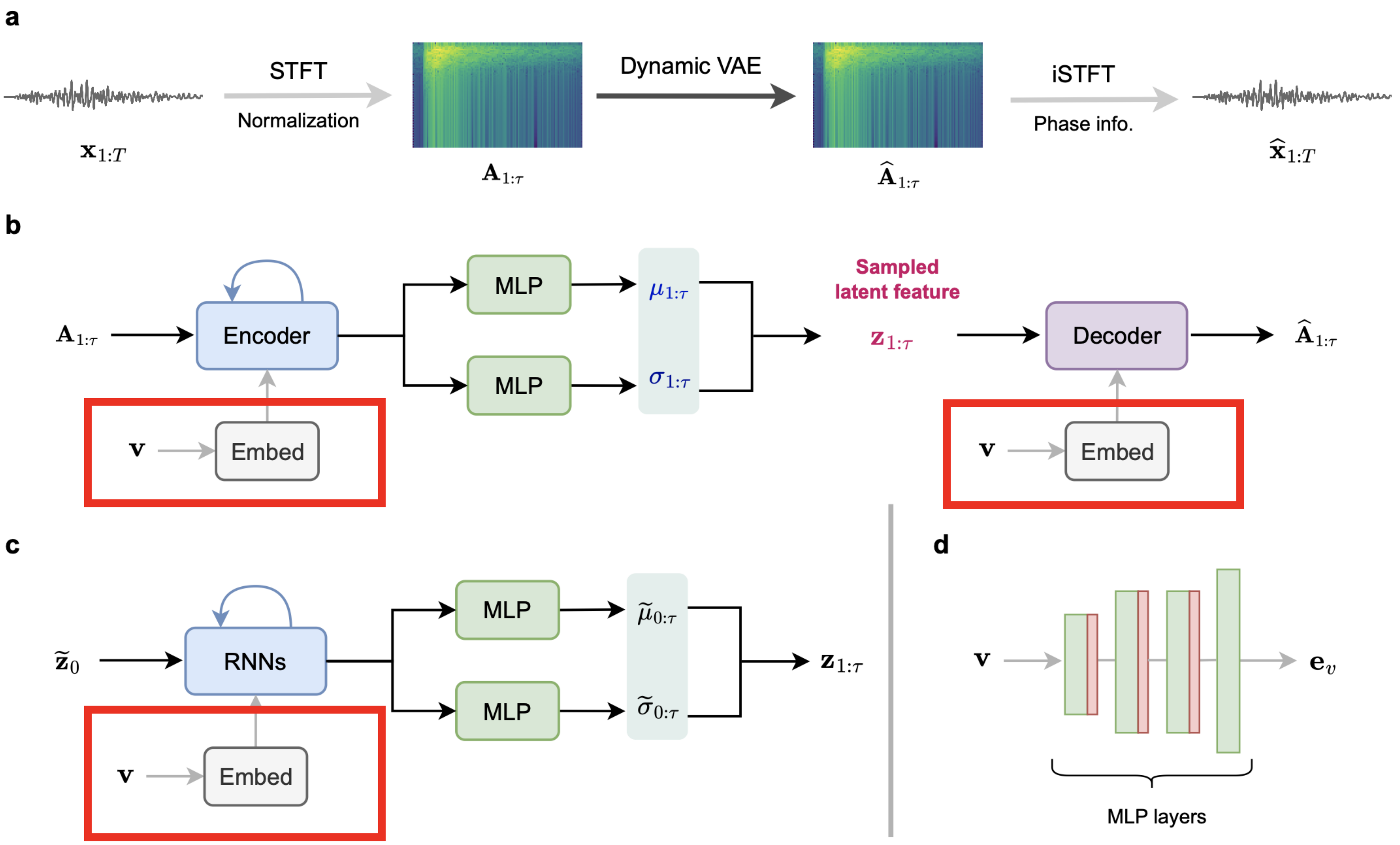
Conditional Dynamic Variational Autoencoder



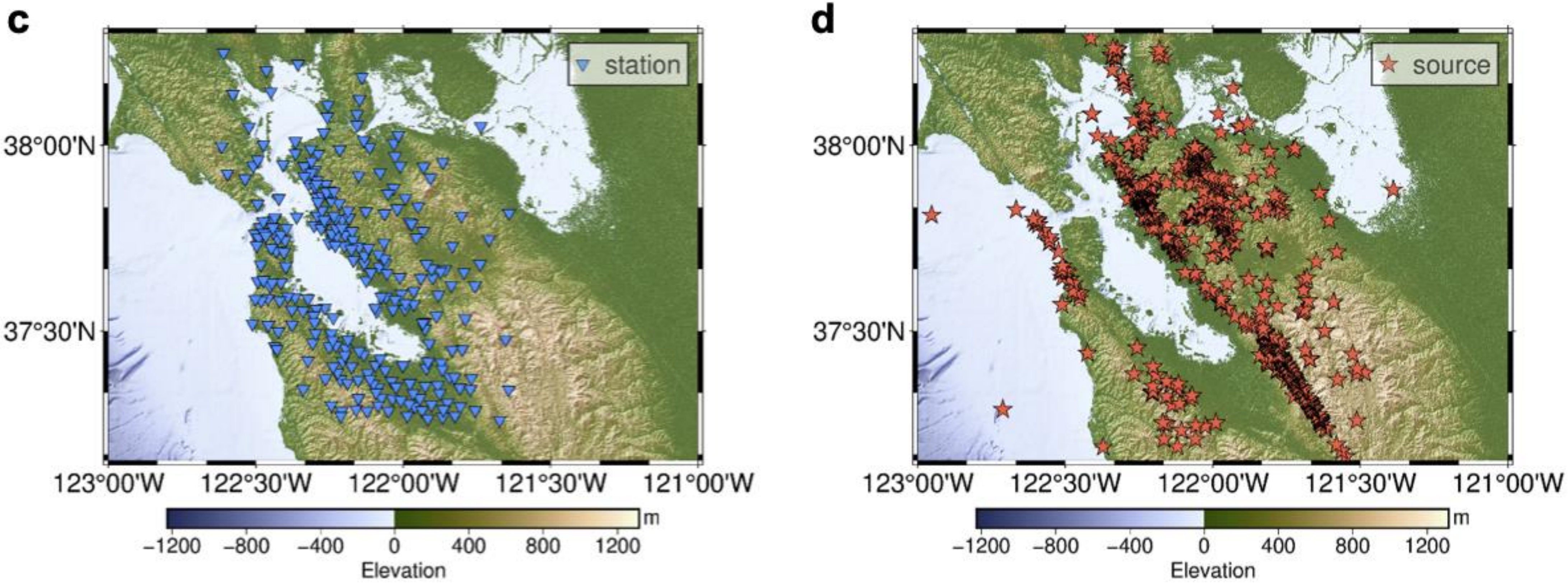
Conditional Dynamic Variational Autoencoder



CGM-GM: Conditional Dynamic Variational Autoencoder

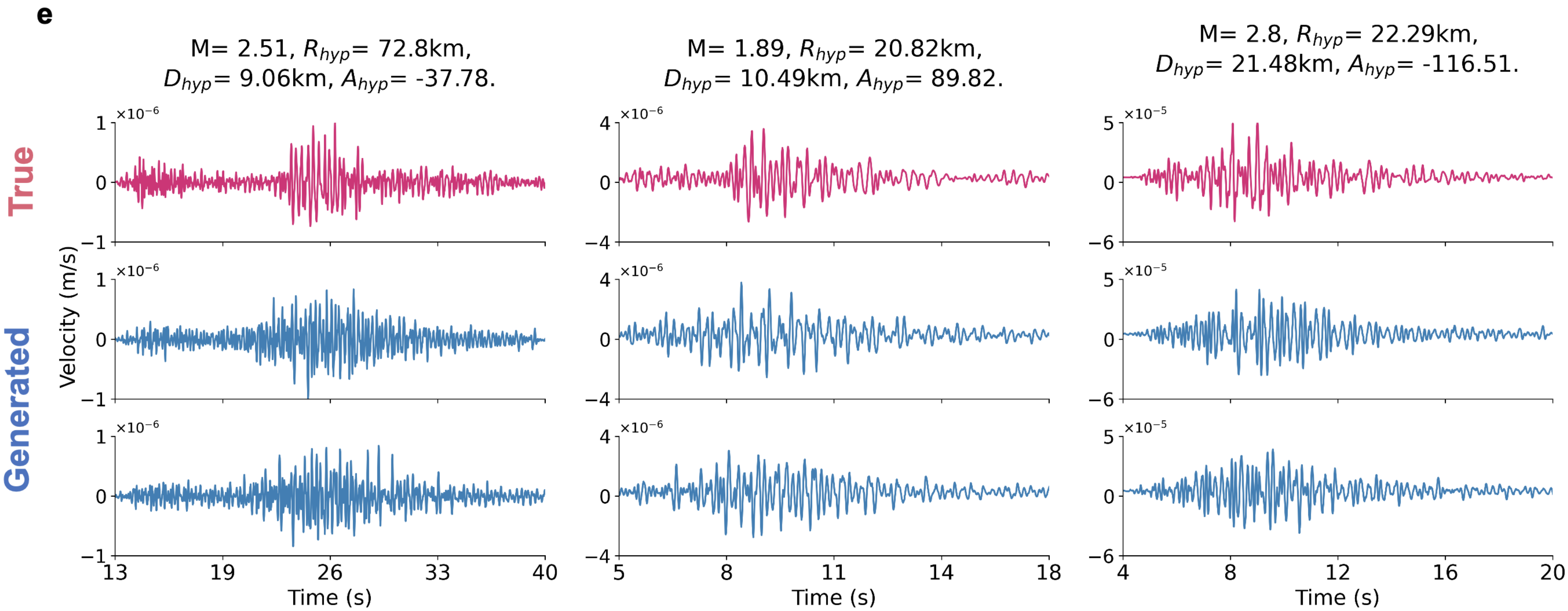


San Francisco Bay Area



- Horizontal component data
- < M4; (3 events > M5 after 2000)
- Downloaded data: 1,375,470
- Training data: 5,194
  (After preprocessing and removal of low SN data)
- Frequency range: 2-15 Hz

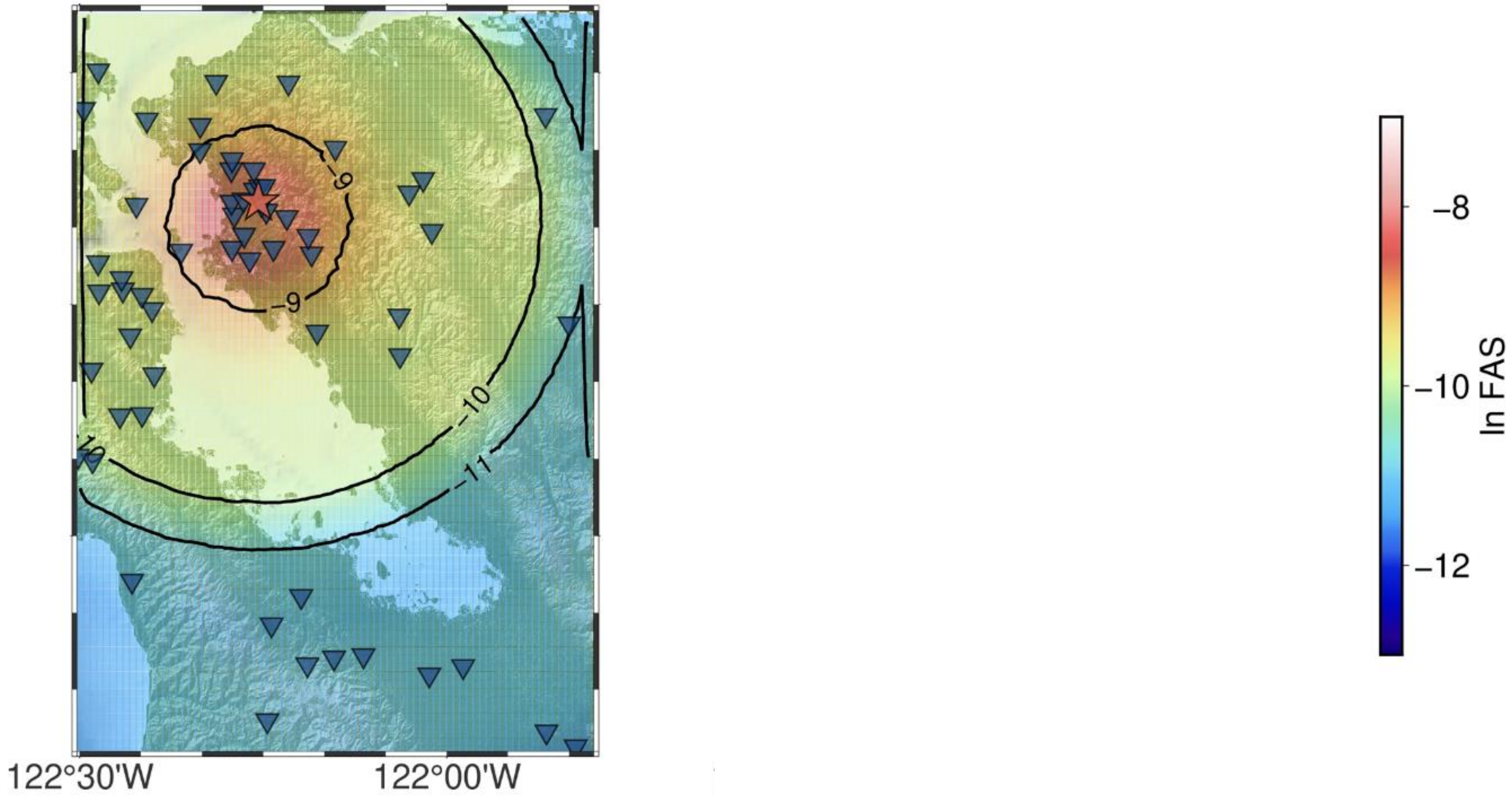
Generated waveforms reproduce P, S, coda, duration



Map view of Ground motion intensity

$$\hat{d} \sim p(d|D, x_s, S)\ .$$

CGM-GM-1D



Fourier Amplitude Spectra at 10 Hz

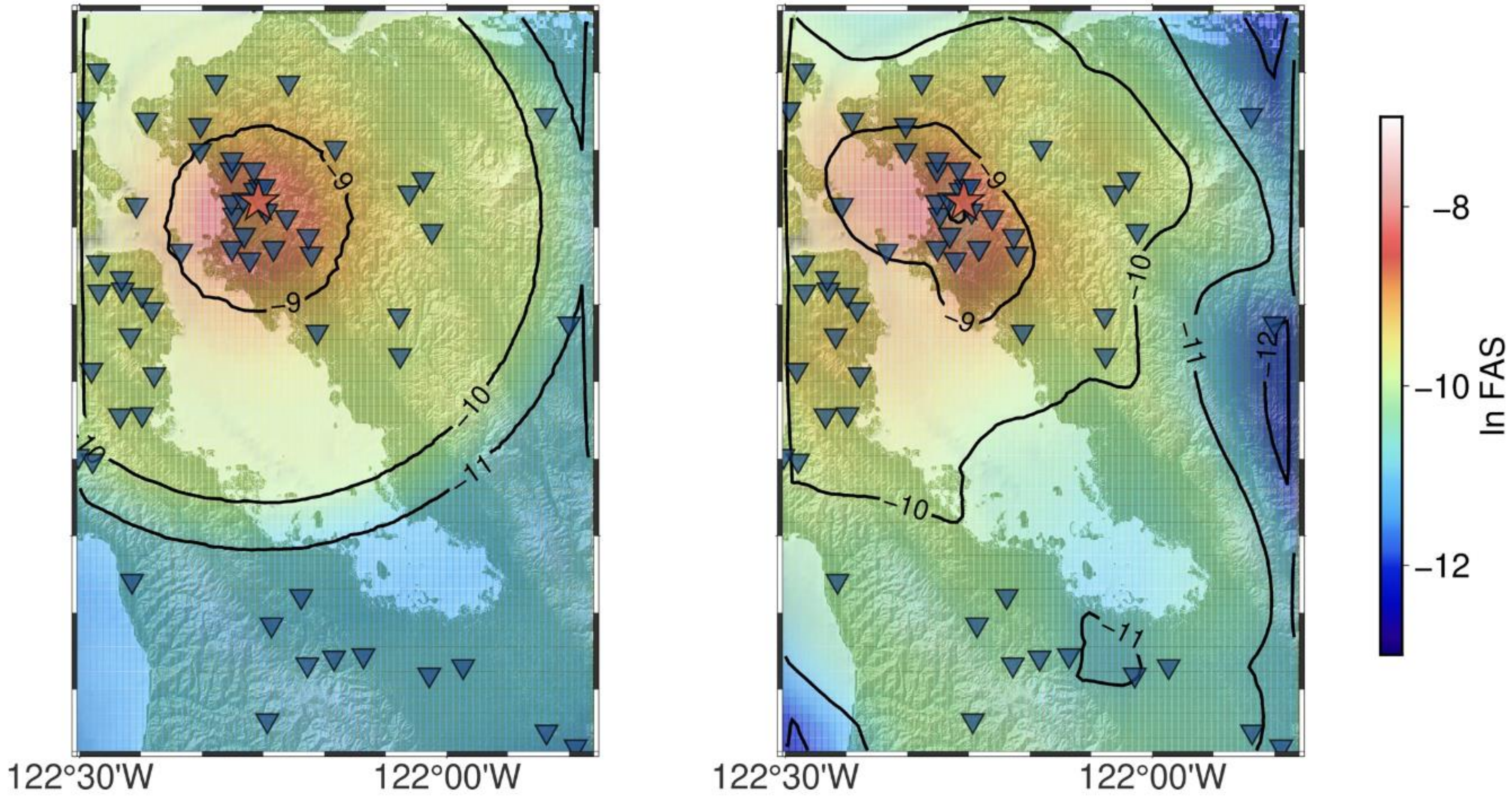
Map view of Ground motion intensity

$\hat{d} \sim p(d|D, x_s, S)$.

CGM-GM-1D

$\hat{d} \sim p(d|x_r, x_s, S)$.

CGM-GM-3D



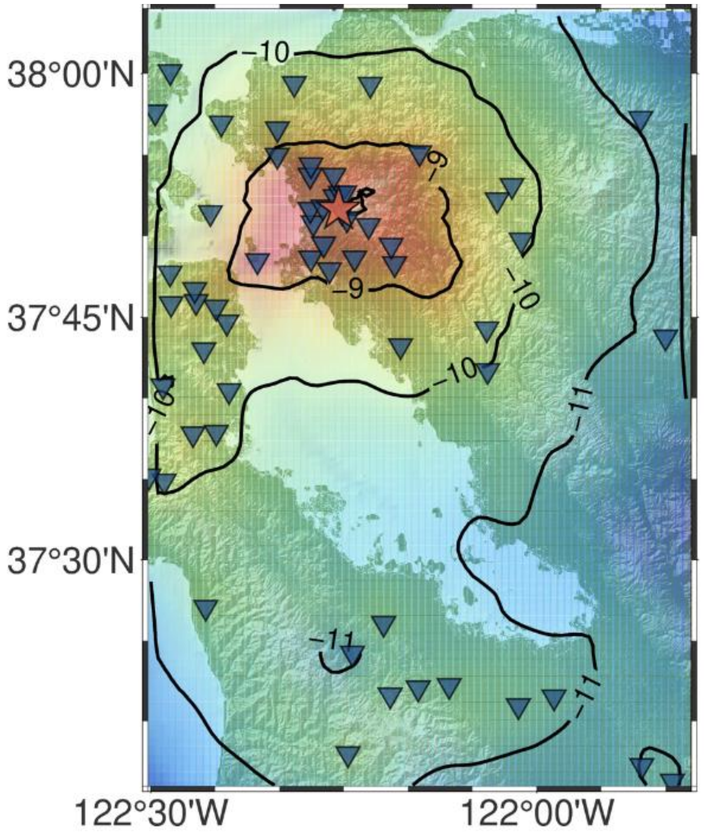
Fourier Amplitude Spectra at 10 Hz

Map view of Ground motion intensity

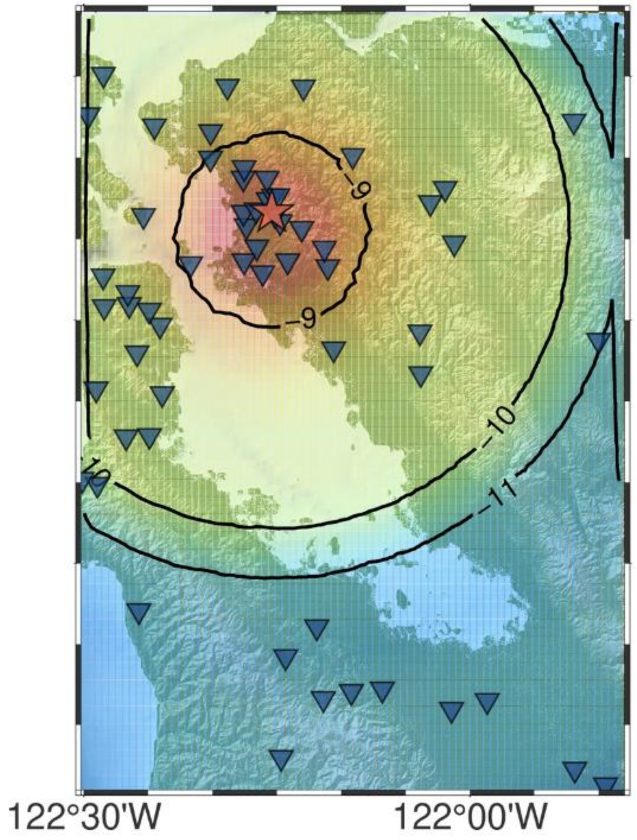
$\hat{d} \sim p(d|D, x_s, S)$.

$\hat{d} \sim p(d|x_r, x_s, S)$.

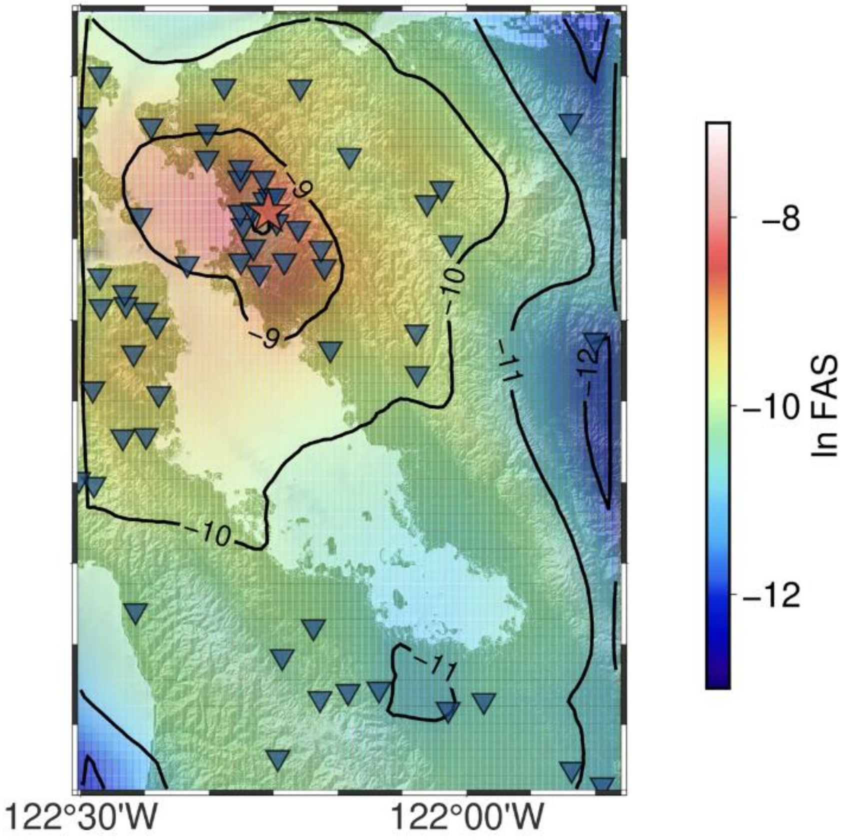
Non Ergodic GMM
Lacour et al., 2025, submitted



CGM-GM-1D

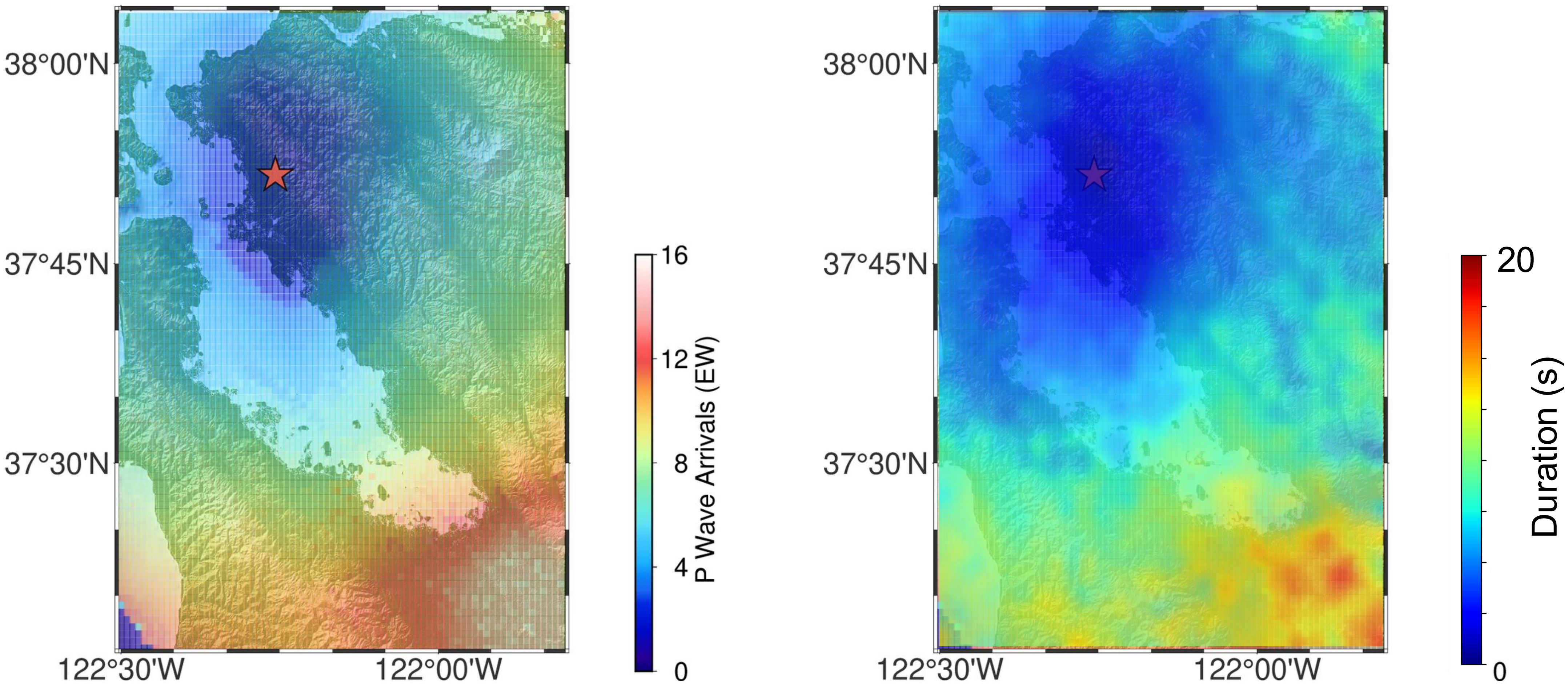


CGM-GM-3D

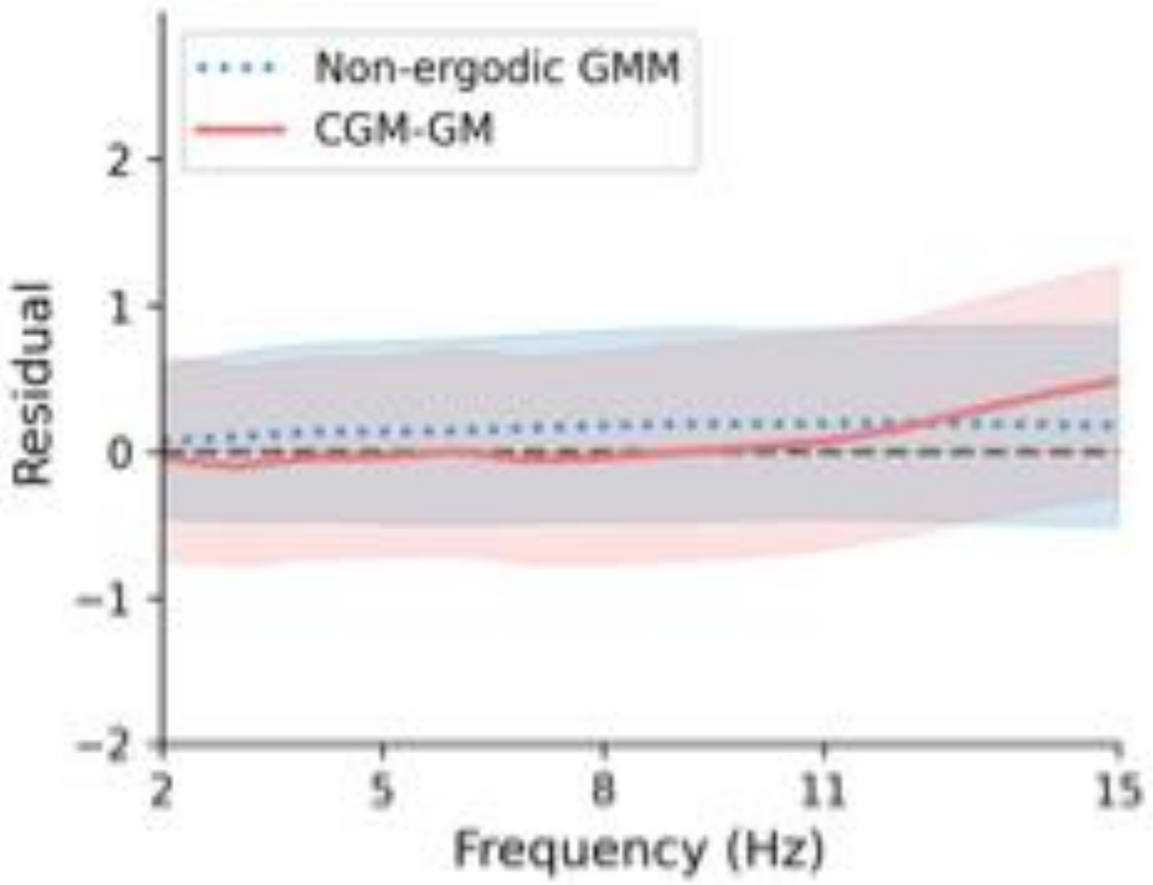


Fourier Amplitude Spectra at 10 Hz

Map view of P-wave arrival time

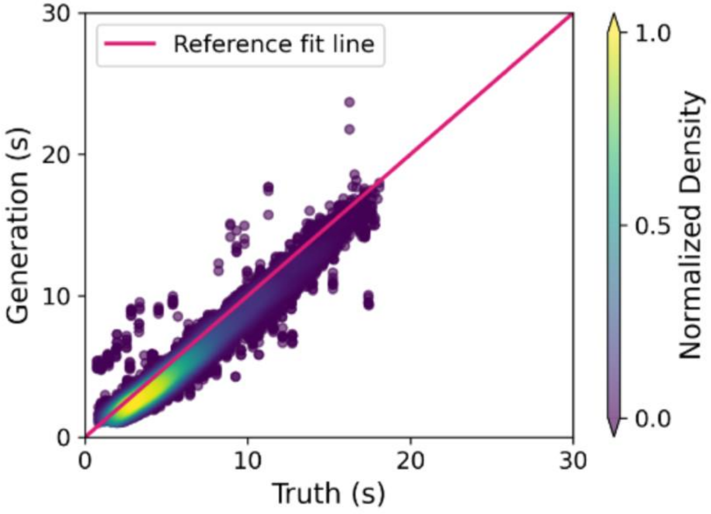


Residual comparisons

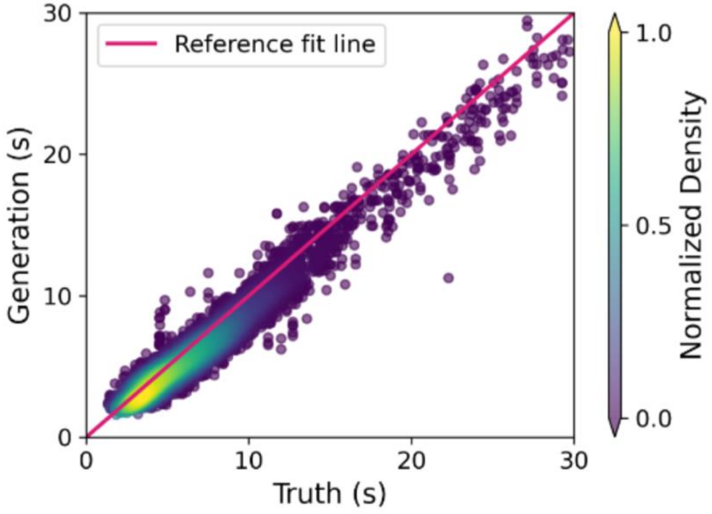


P and S arrivals and Duration match observations

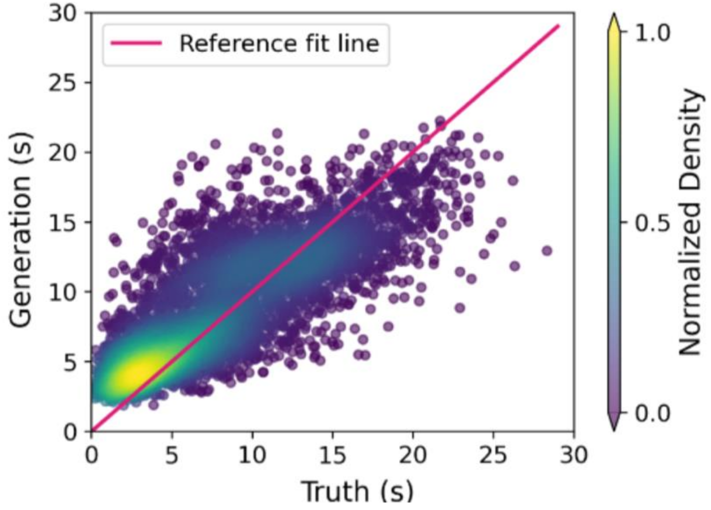
P arrival



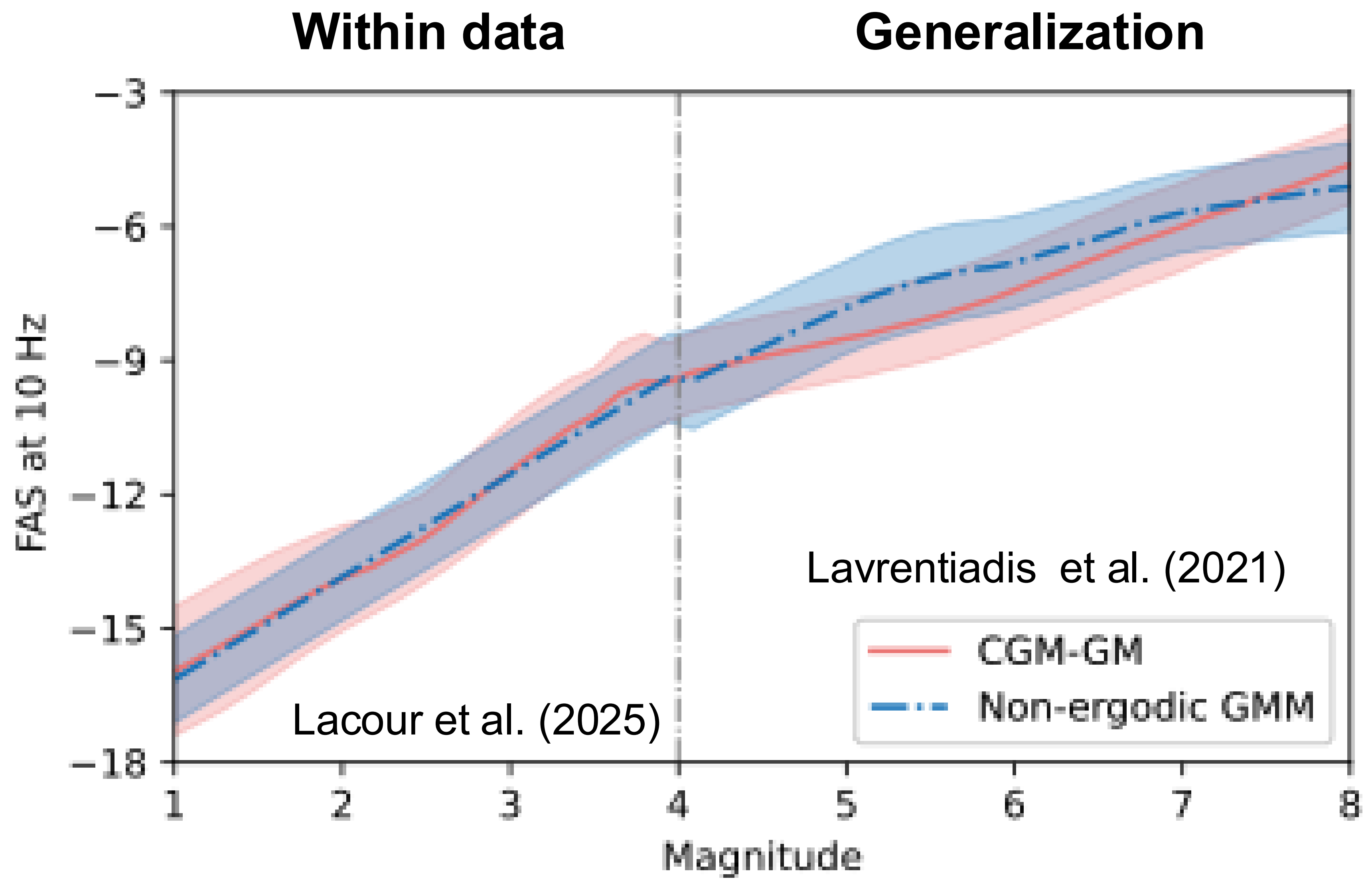
S arrival



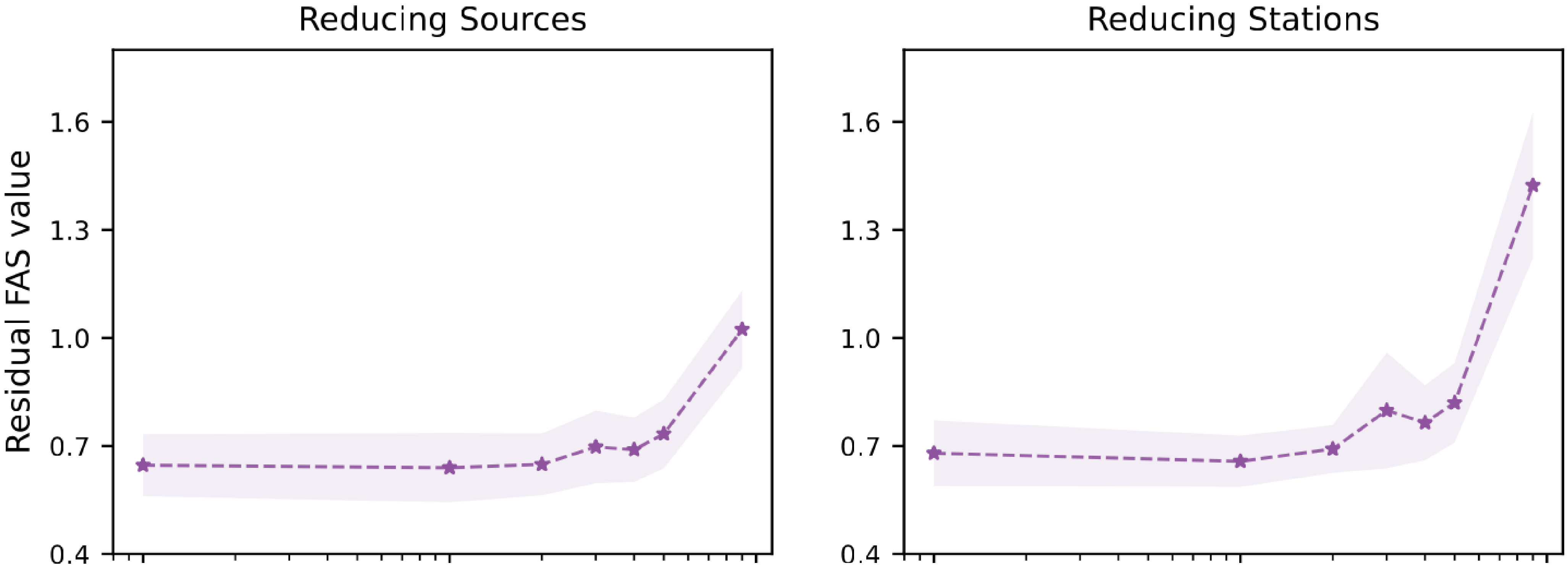
Duration (D_{95})



Generalization: beyond training dataset

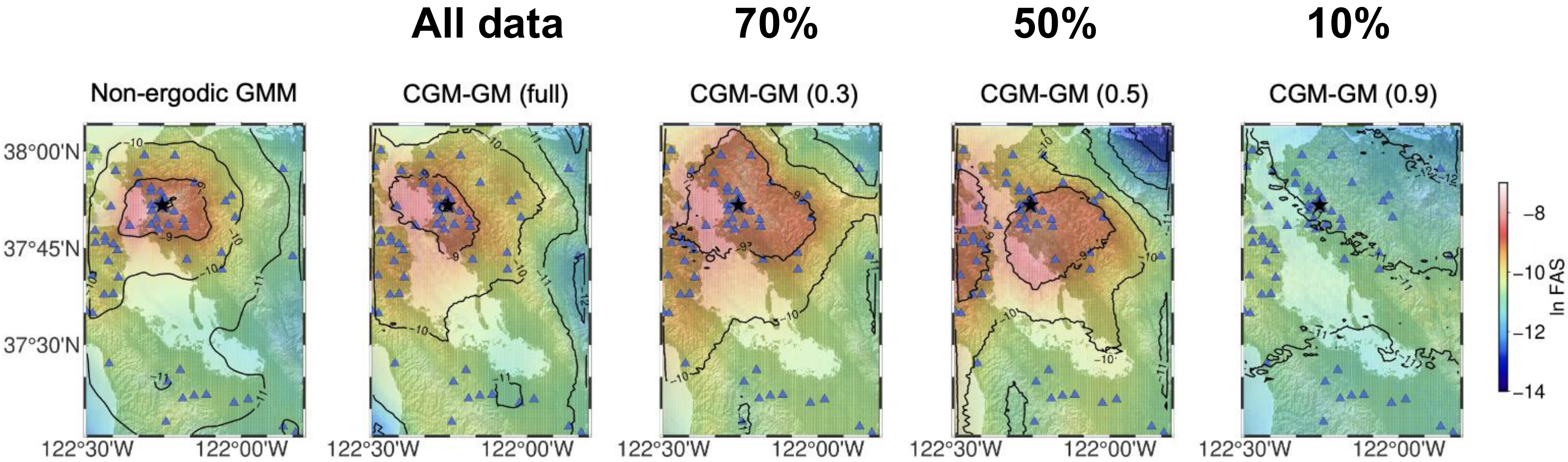


of data points vs performance



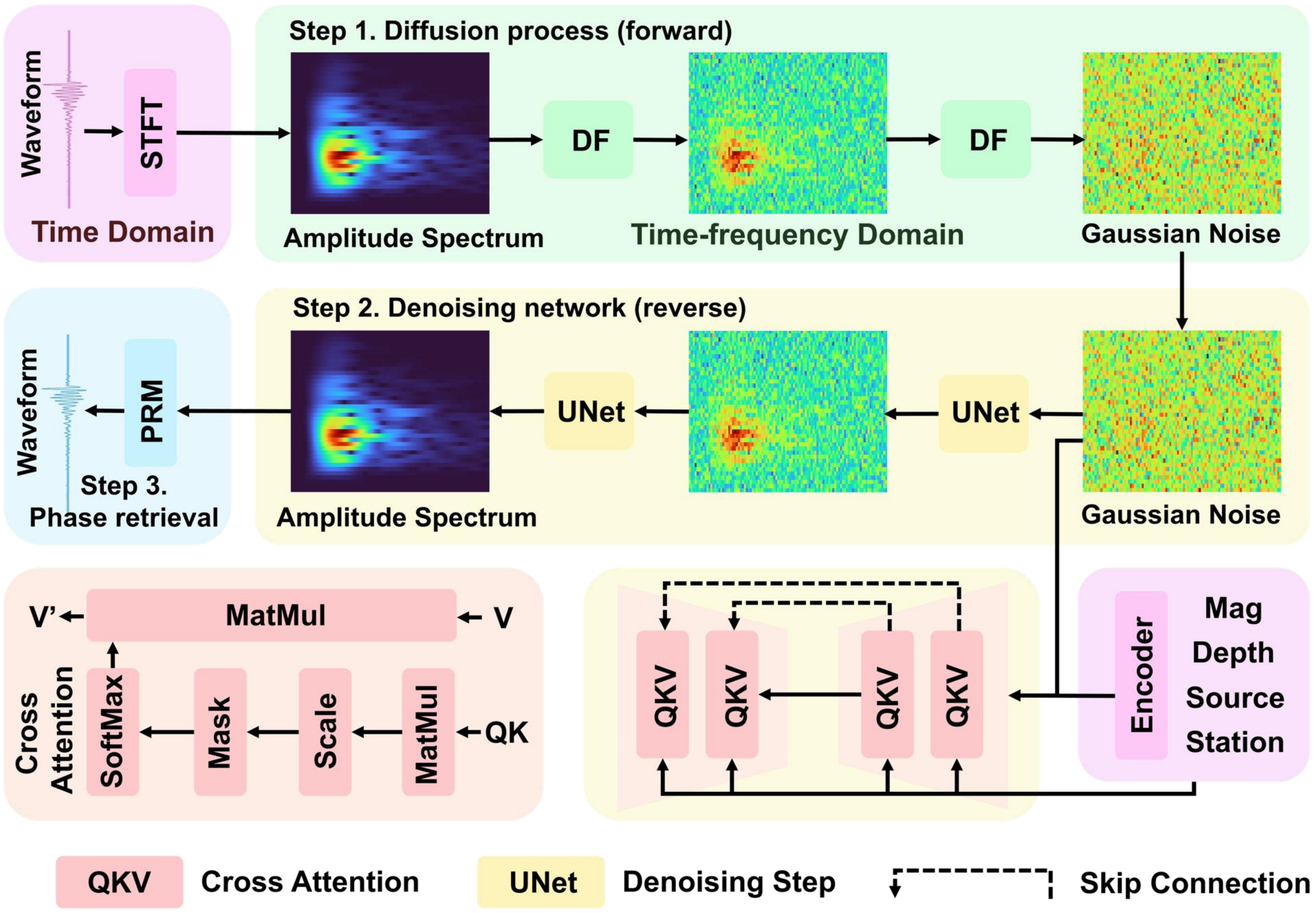
Using 99% **10%** **99%** **10%**

of data points vs performance

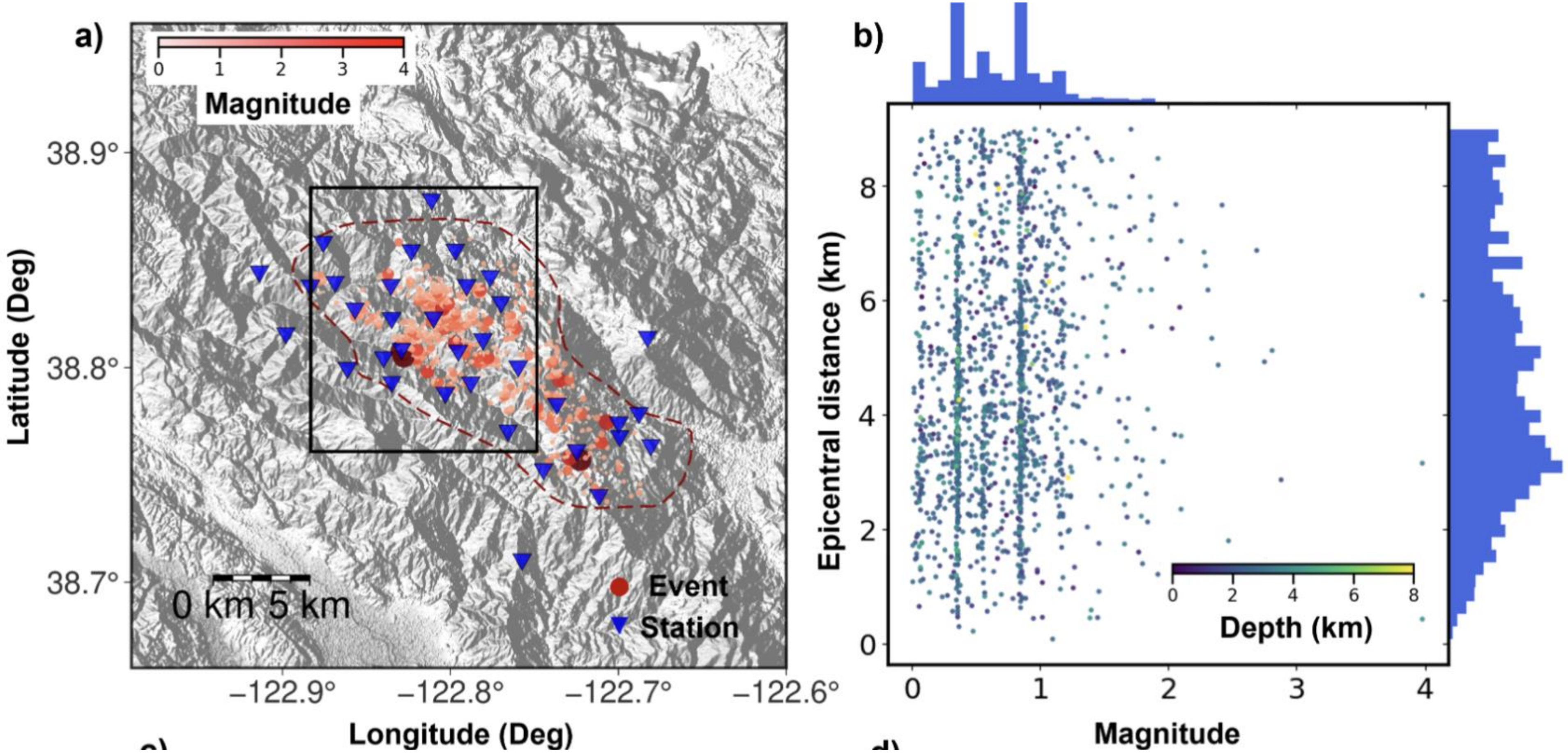


CGM-wave: diffusion model for higher resolution

Bi et al., 2025, IEEE TGRS



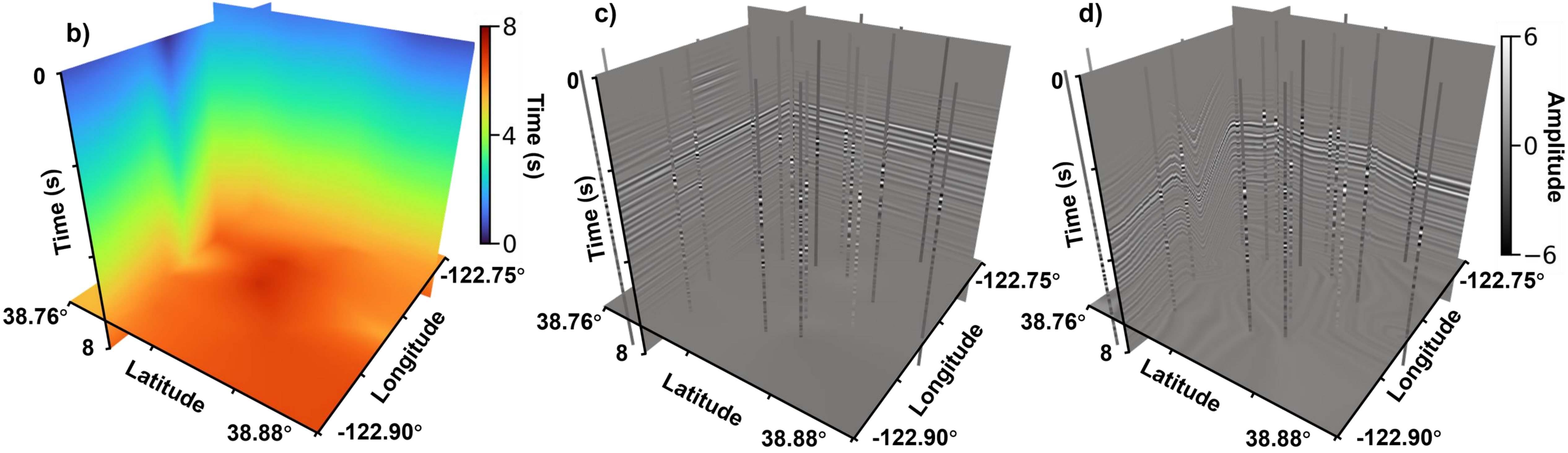
Geysers Geothermal Field



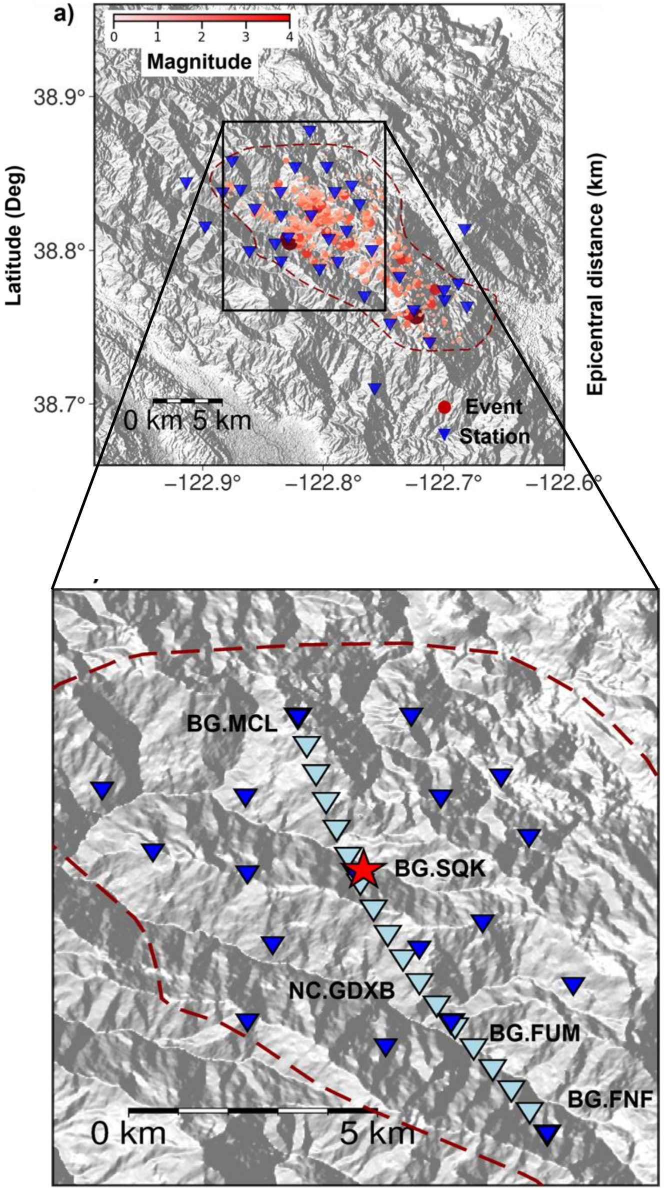
35 stations, 500 events in 2020-2021, 17,500 traces

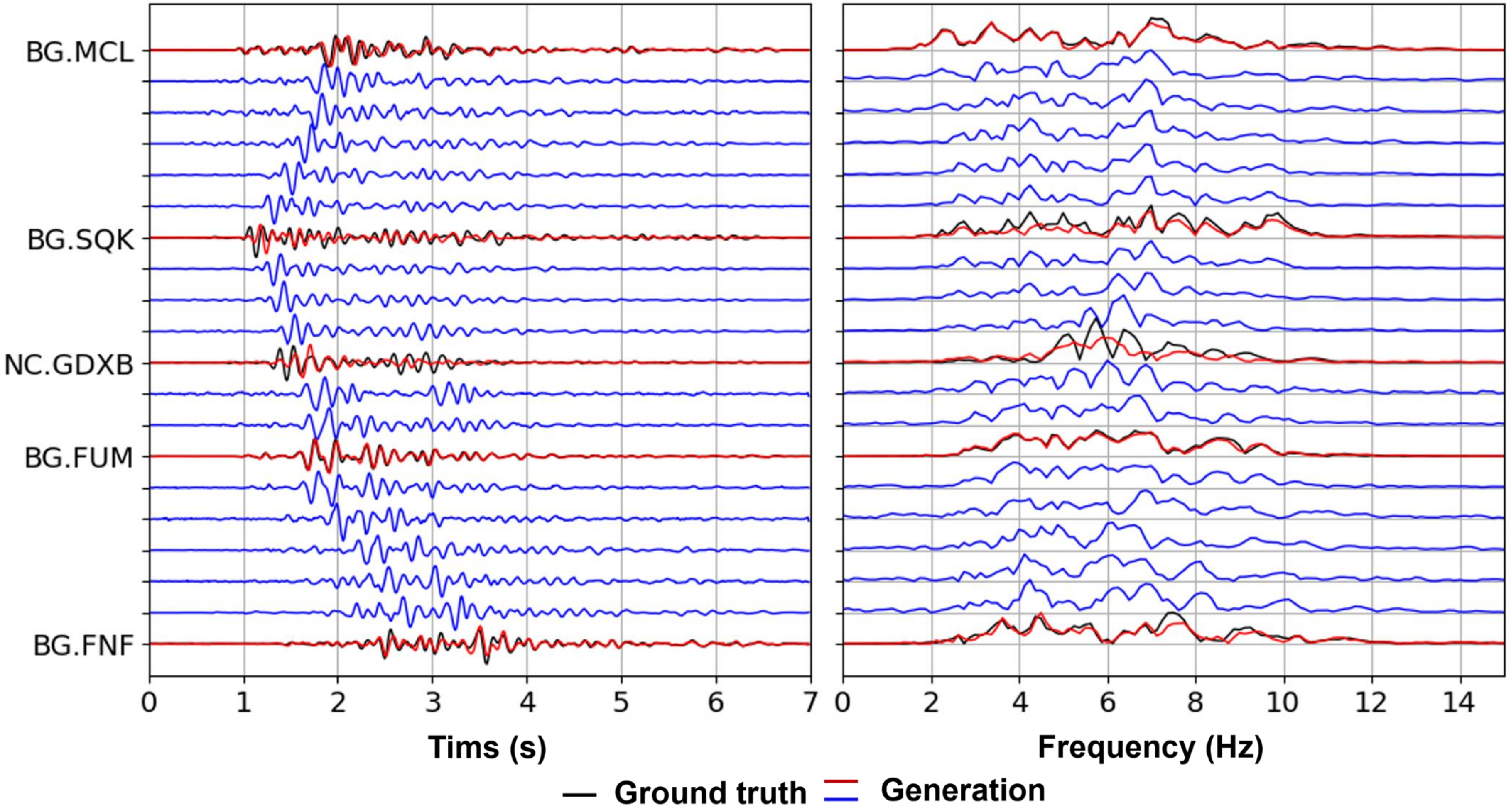
Physics-inspired data augmentation with spatial continuity

Dynamic time warping for interpolating wavefields between receivers.



Generate array observations





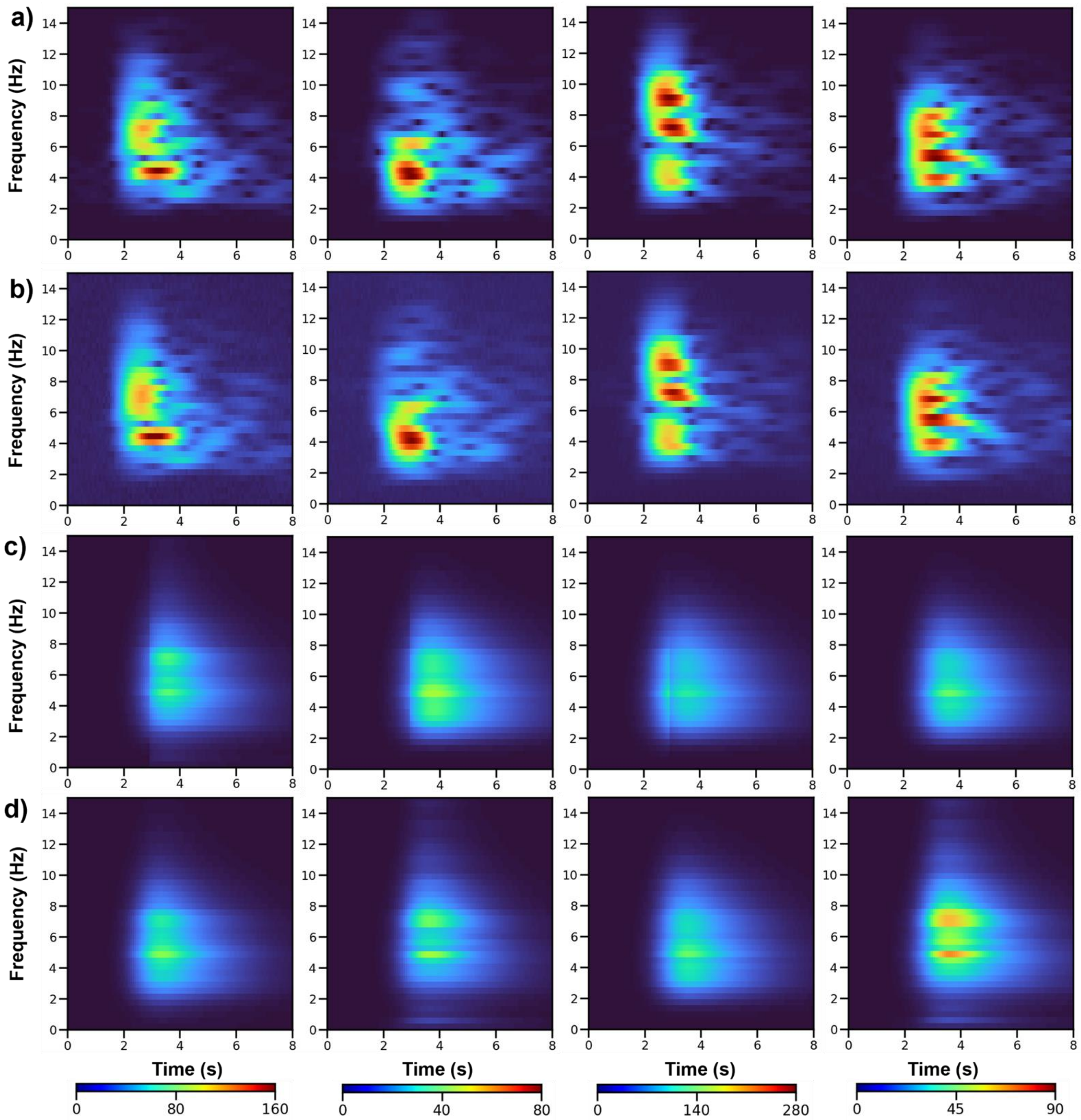
Spectrogram comparison

True

Diffusion model

VAE

VAE-GAN



Instead of time series, directly predict FAS (Path effects)

Lacour et al., 2025, in prep

Non-ergodic GMM (based on Gaussian Process)

$$\hat{d} \sim p_{\underline{\theta_{\mathrm{GP}}}}(d|x_s, x_r) \sim N(\mu_{\theta_{\mathrm{GP}}}, \sigma_{\theta_{\mathrm{GP}}})$$

spatial correlation length and standard deviation

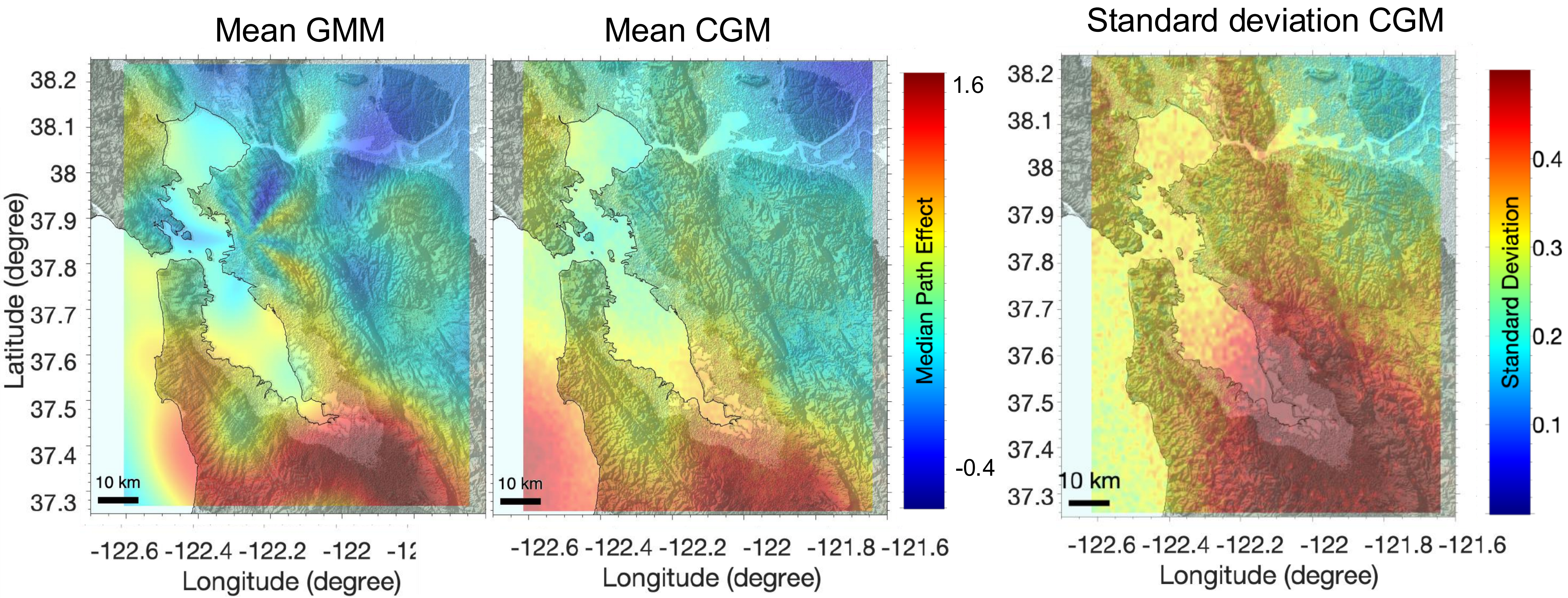
CGM-FAS

$$\hat{d} \sim p_{\underline{\theta_{\mathrm{CGM}}}}(d|x_s, x_r)$$

Neural network

Replacement of STFT to Fourier transform

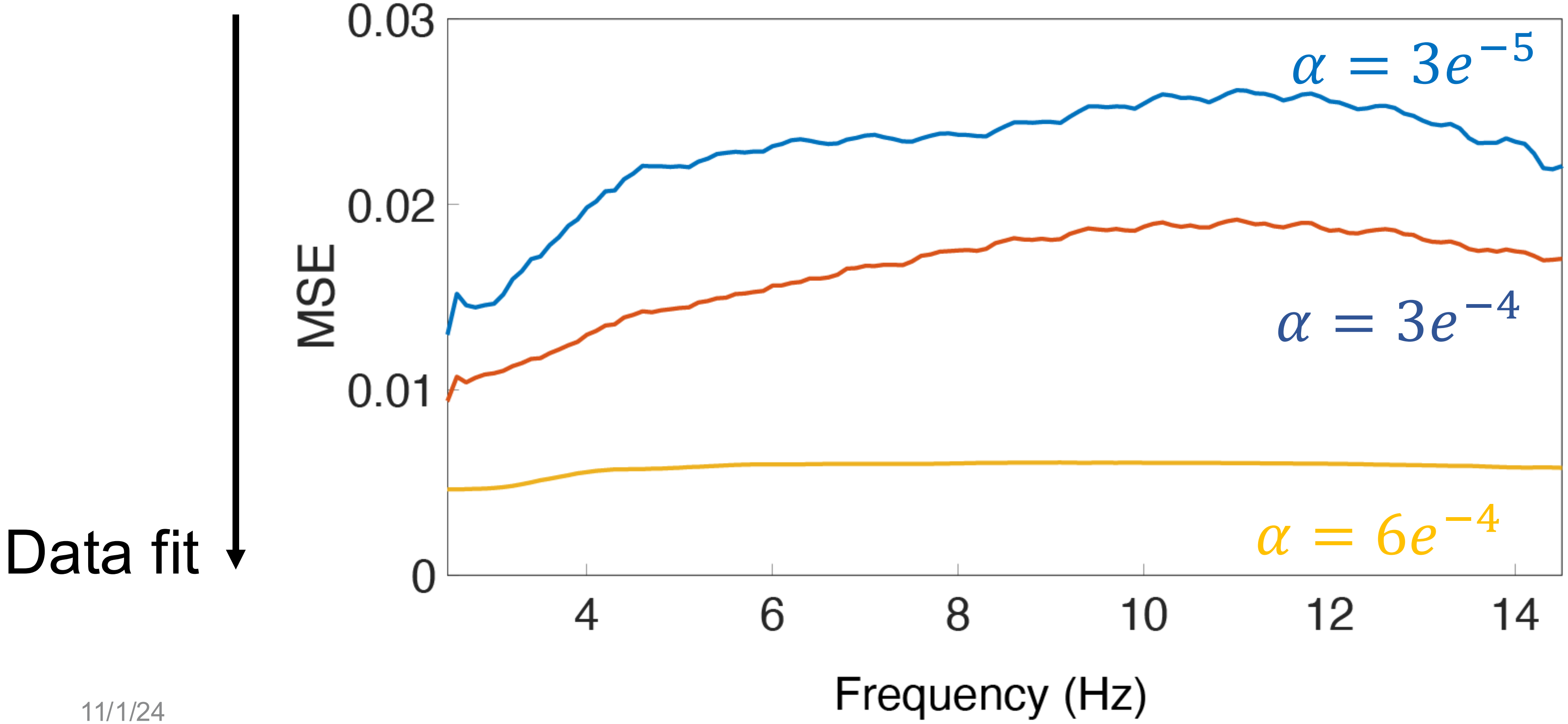
CGM-FAS: Fourier amplitude spectra



- Faster inference, Smoother and more robust mean and standard deviation predictions by CGM
- Do not differentiate aleatory and epstemic uncertainties

Fitting data and keeping variability

Loss function: $L = \mathrm{MSE} + \alpha \cdot D_{KL}$

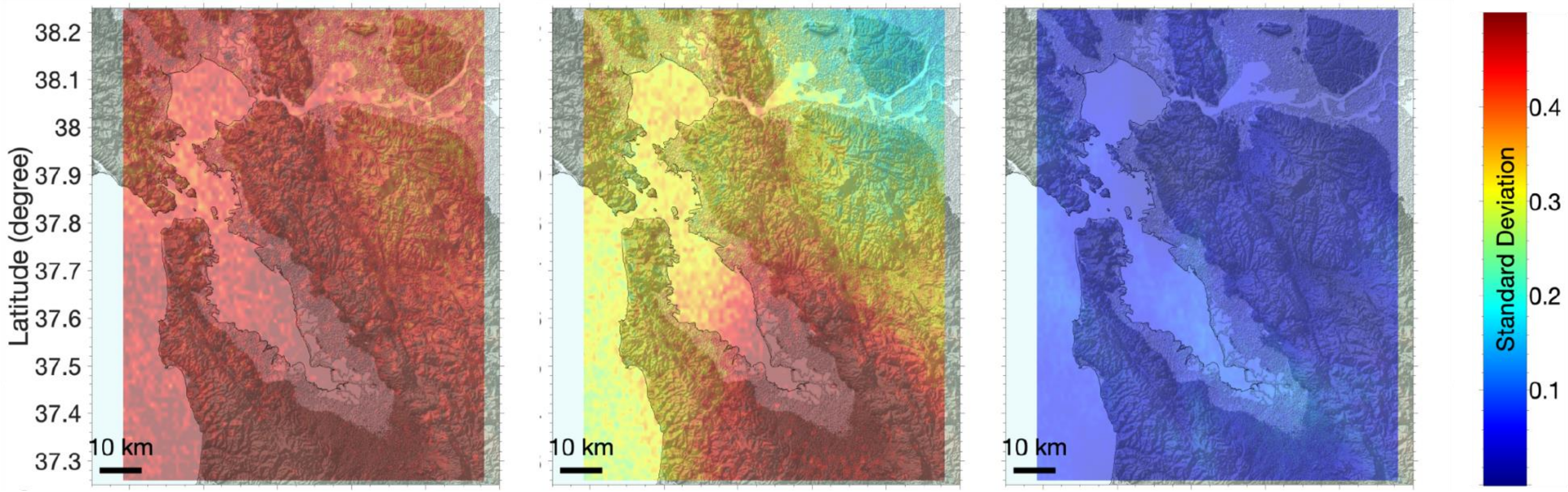


Fitting data reduce spatial variability of data generation

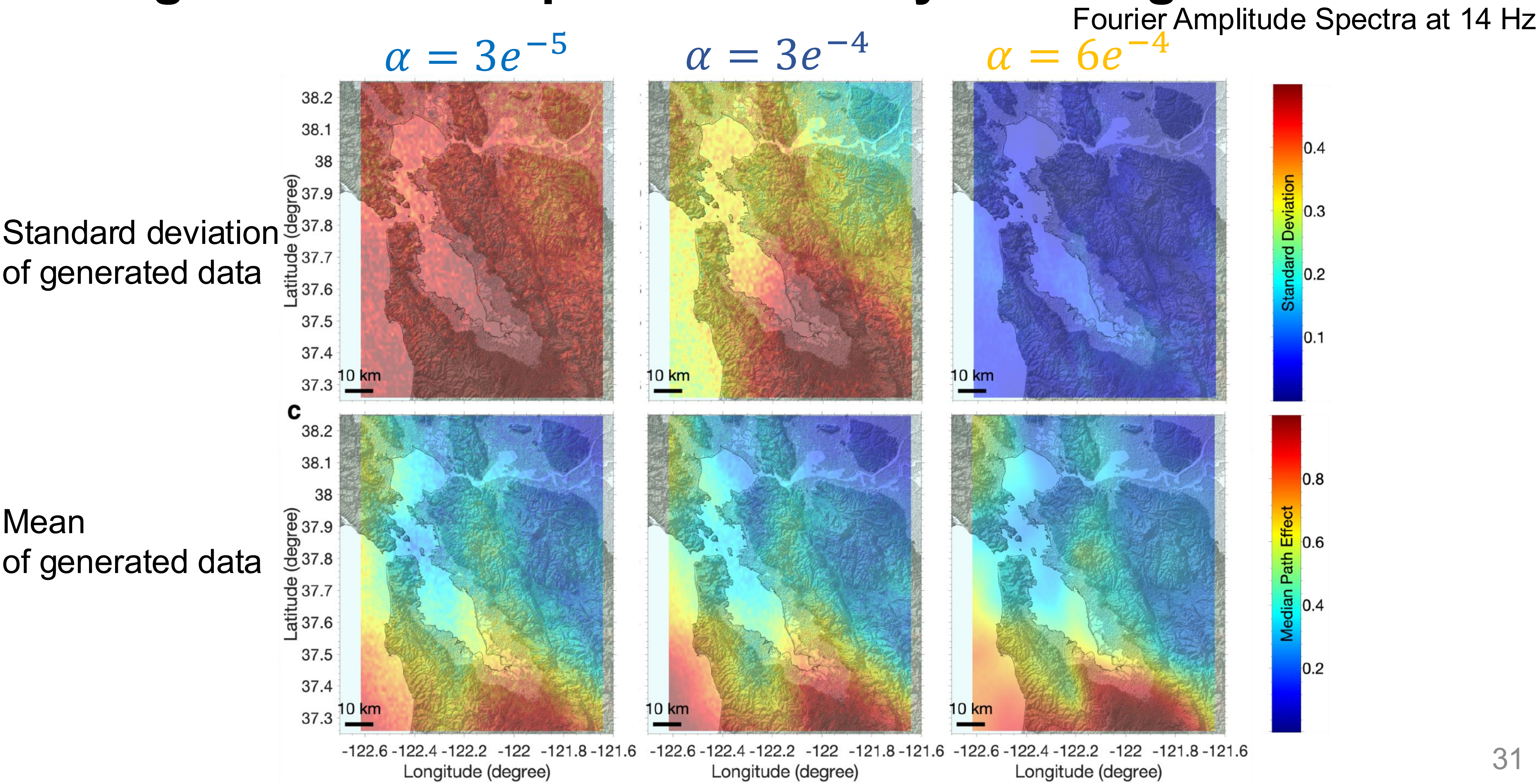
Fourier Amplitude Spectra at 14 Hz

$\alpha = 3e^{-5}$ $\alpha = 3e^{-4}$ $\alpha = 6e^{-4}$

Standard deviation of generated data

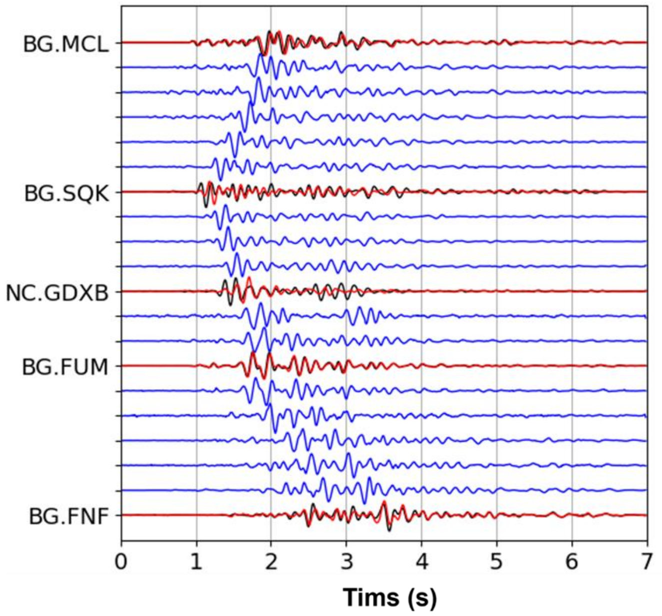


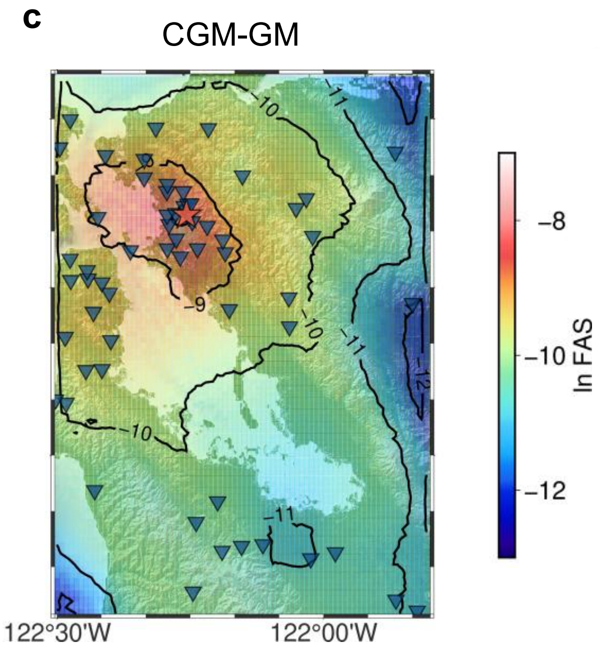
Fitting data reduce spatial variability of data generation

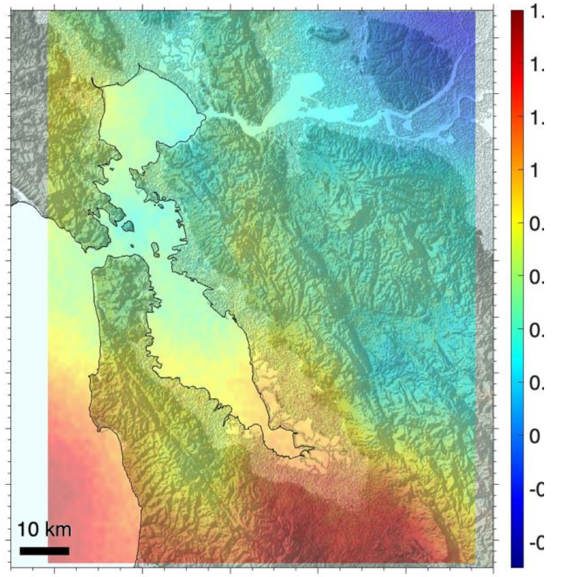


Conclusions

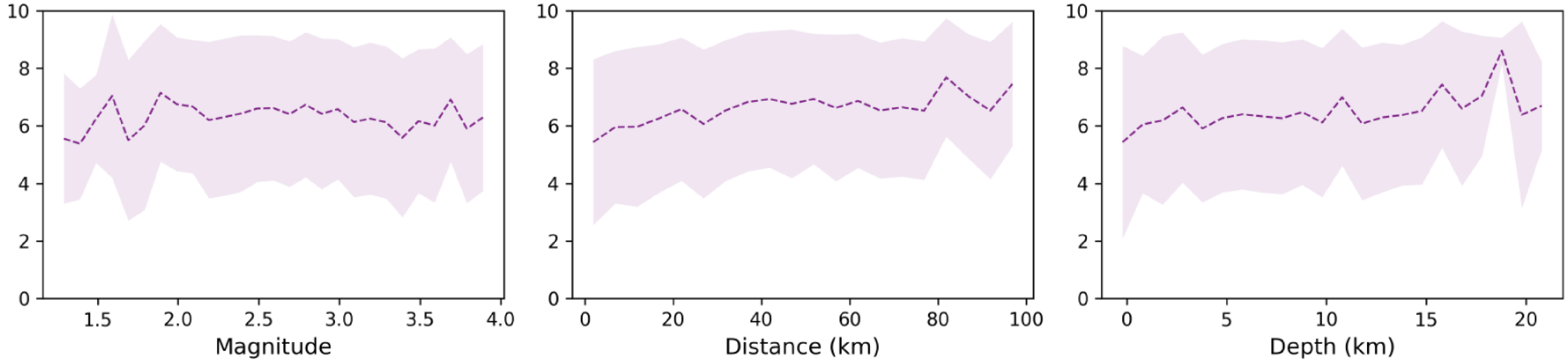
- GenAI can provide the approximation of synthetic wavefields.
  - No physics constraints, Interpolation, Uncertainty quantification
  - Strong motion simulation/Ground motion prediction
  - Seismic imaging, inversion….
- Currently working on evaluating credibility, resolution, generalization
  - Develop ergodic GMM using NGA-West2 data (Supported by SCEC)
  - Synthetic tests to evaluate “physics”
  - Inversion







Anderson’s Criteria



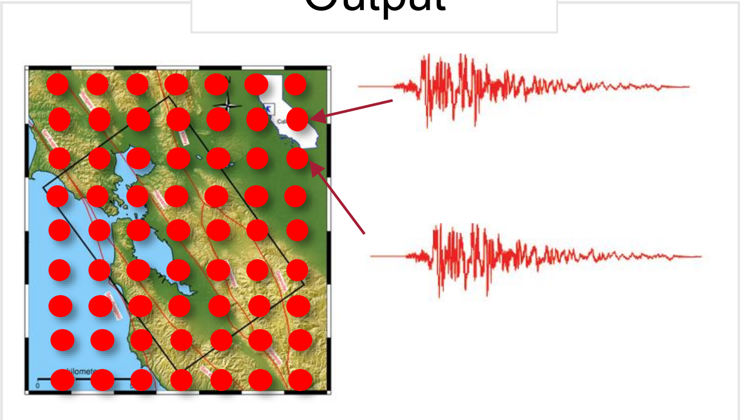
Physics-based EQSIM: DOE Exascale computing project (ECP)

Input

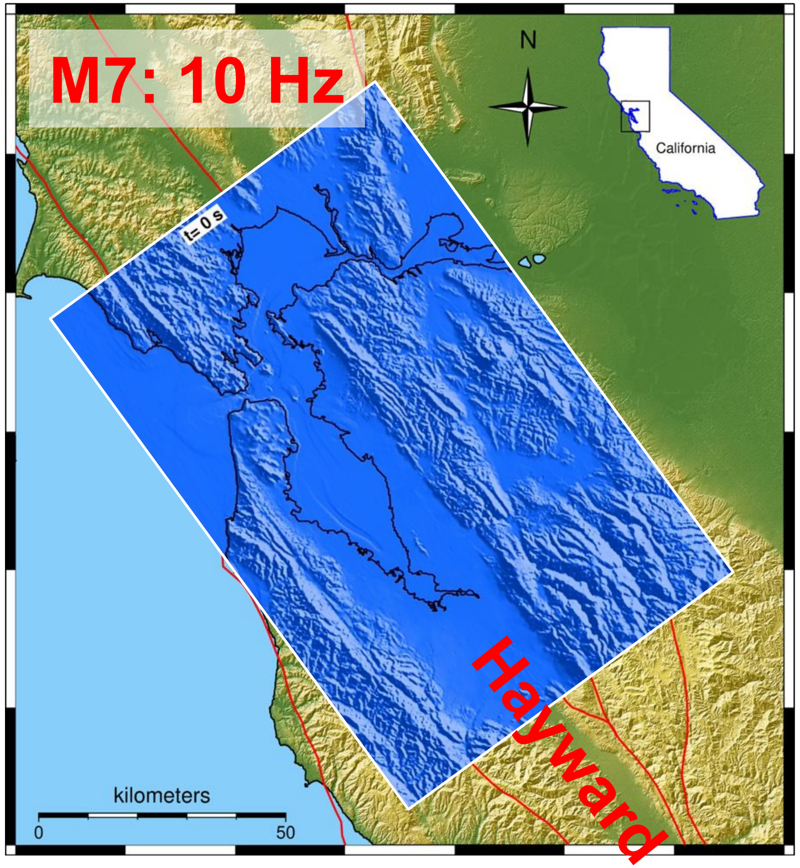
3D Earth model
Earthquake scenarios
Sensor locations

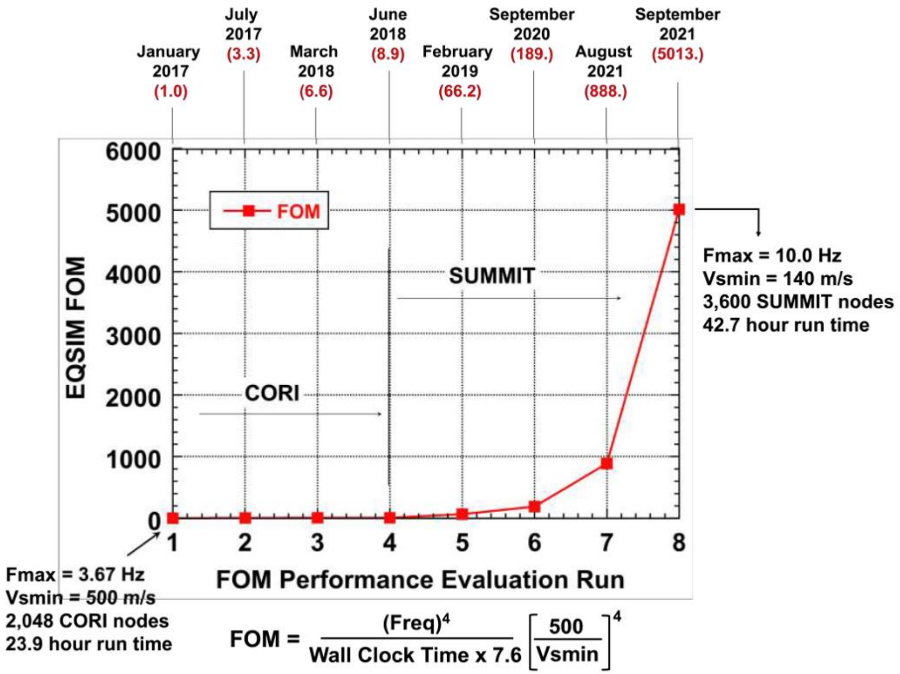
Phys. EQSIM

Output

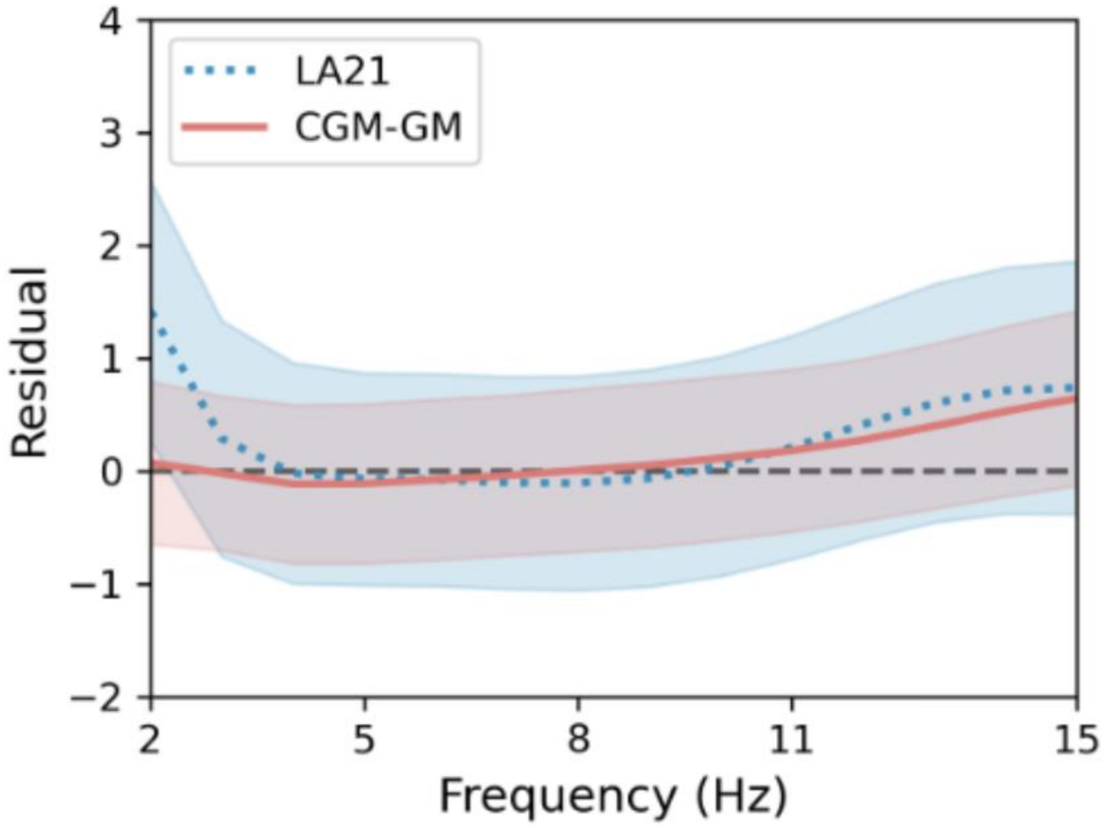


M7 Hayward
Fmax = 10 Hz
Computational domain
120 x 80 x 30 km
Grid points
391 billion
Grid size at ground surface
1.75 m
3,600 Summit GPU nodes
42.7 hour run time
Ground motion data
267 TB (2.6 TB comp)





$$FOM = \frac{(Freq)^4}{\text{Wall Clock Time} \times 7.6}\left[\frac{500}{Vsmin}\right]^4$$


LA21
CGM-GM
Residual
Frequency (Hz)
4
3
2
1
0
−1
−2
2
5
8
11
15

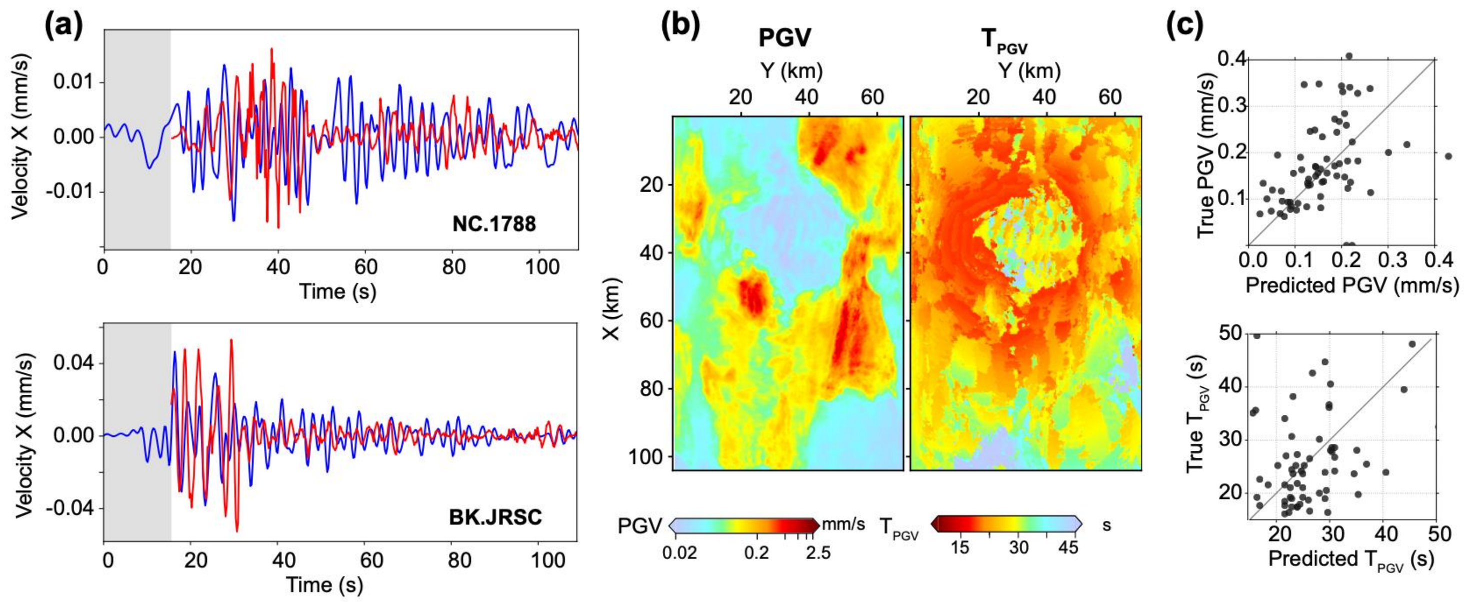
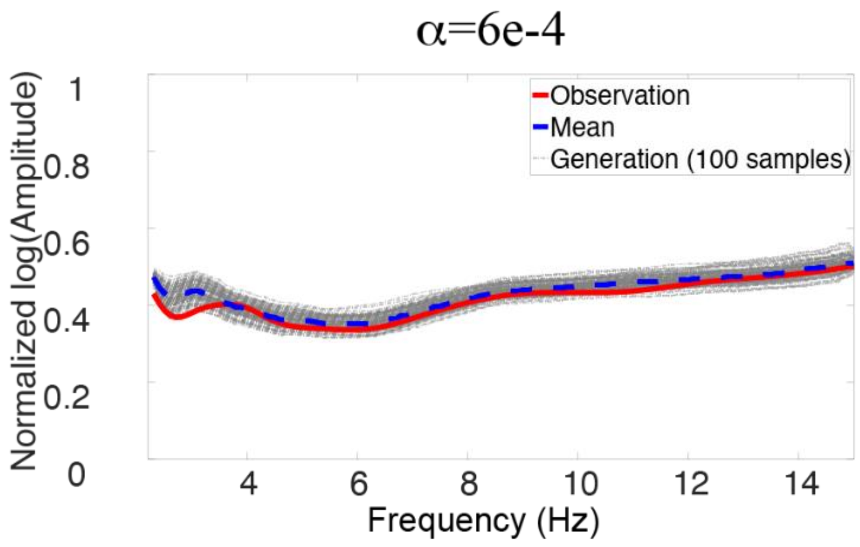


Figure 8: Results for a real-data example in which WaveCastNet is applied to the 2018 Berkeley earthquake (magnitude 4.4, depth 12.3 km). (a) X-component velocity waveforms at stations NC.1788 (San Jose) and BK.JRSC (Palo Alto), with WaveCastNet predictions shown in red and observed waveforms in blue. The gray shaded regions indicate the 15.6-second input window used for inference. (b) Spatial maps of predicted peak ground velocity (PGV, left) and its arrival time T_{PGV} (right). (c) Scatter plots comparing predicted and observed values for PGV (top) and T_{PGV} (bottom).

Model	High fidelity	Fast sampling	Training stability	Compression
VAE	✗	✓	✓	✓
GAN	✓	✓	✗	✗
DM	✓	✗	✓	✗

100 realizations for the best data fit



Fitting data can reduce data variability