Partially Non-Ergodic Ground Motion Modelling: Lessons Learned from Japan and Implications for New Zealand

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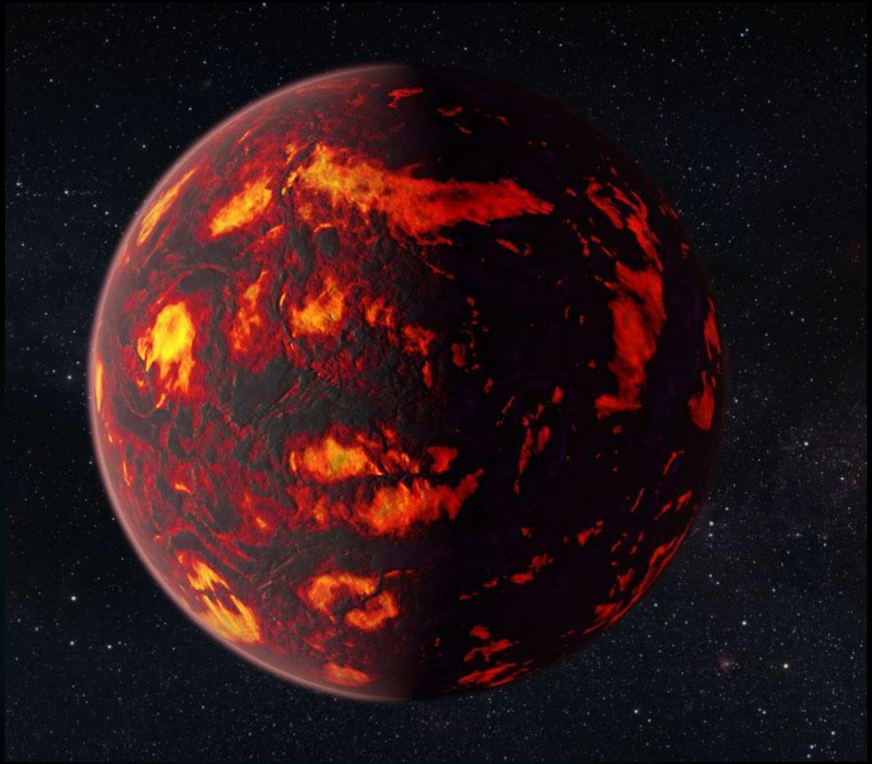
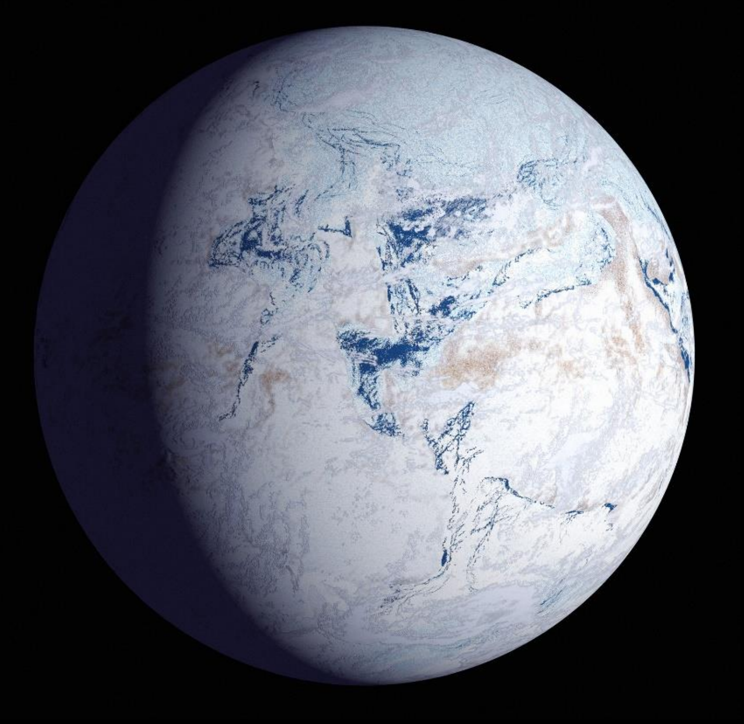
QuakeCoRE: The Centre for Earthquake Resilience
DT1 Meeting
23 November 2022

The Changing Earth & Geohazard



4.5 billion years ago



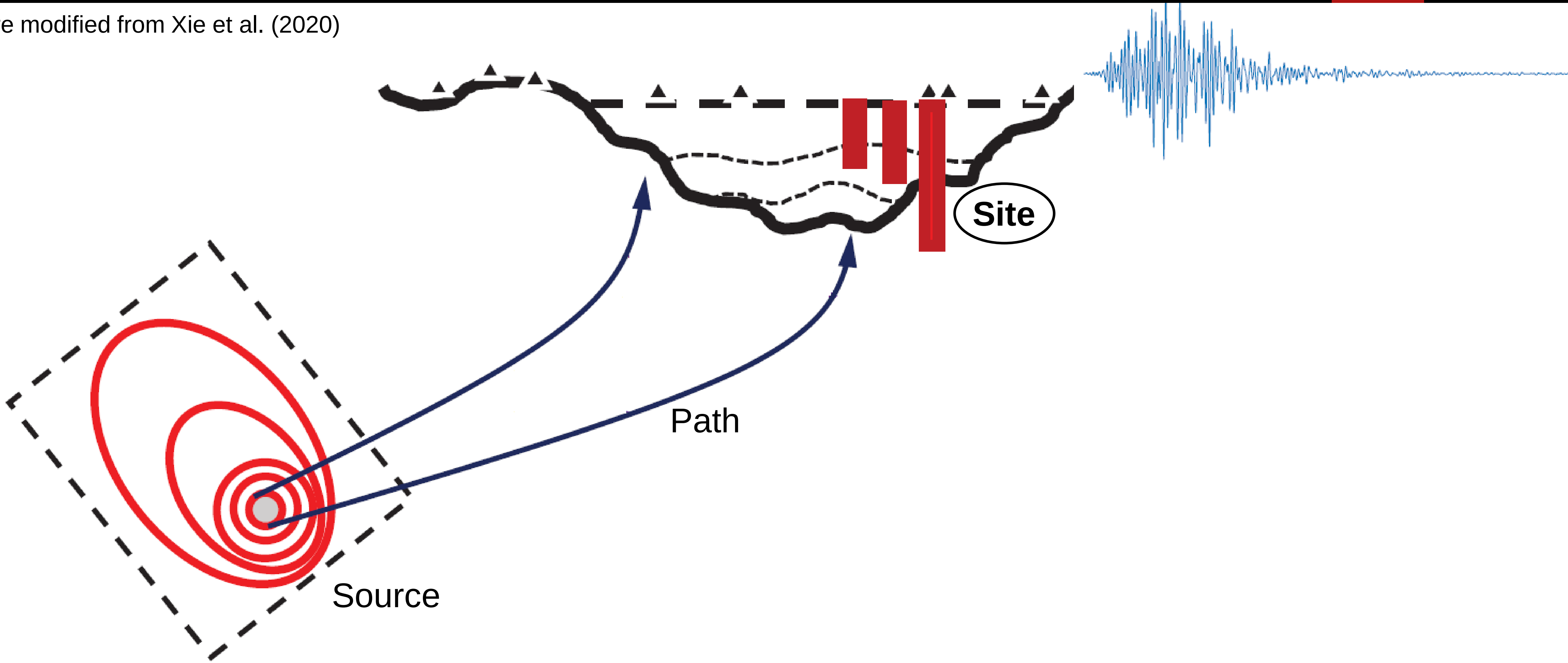
Present day

Source: Google

> *“Humans have always striven to predict and understand the world, and the ability to make better predictions has given competitive advantages in diverse contexts (such as weather, diseases or financial markets).”*
>
> *-- Reichstein et al., 2019, Nature*

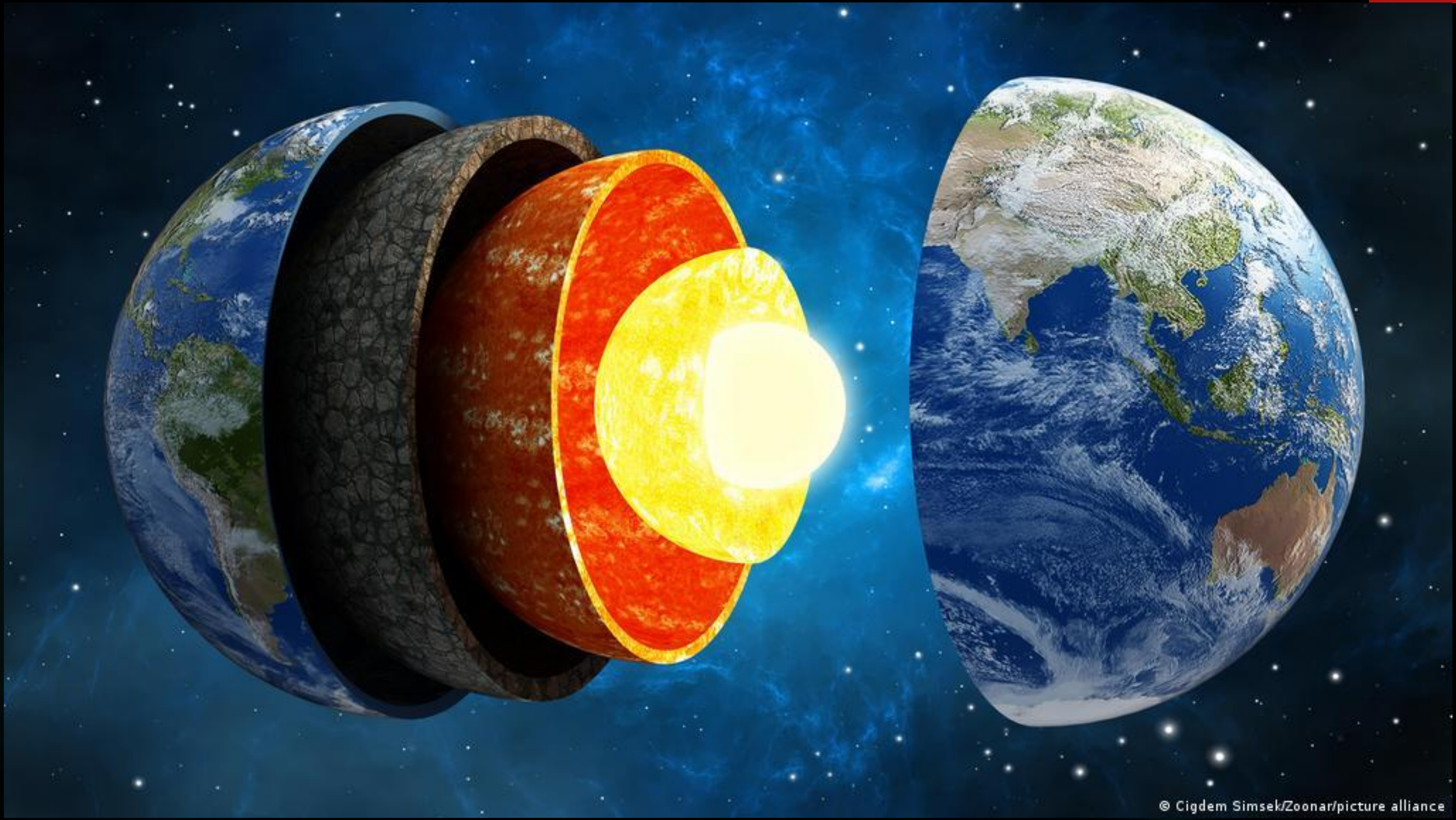
Earthquake Hazard Prediction

figure modified from Xie et al. (2020)



- ❑ The modification effects of the near-surface earth structures to seismic waves passing through them (also called “site response” or simply “amplification”).

Near-Surface Earth Structures



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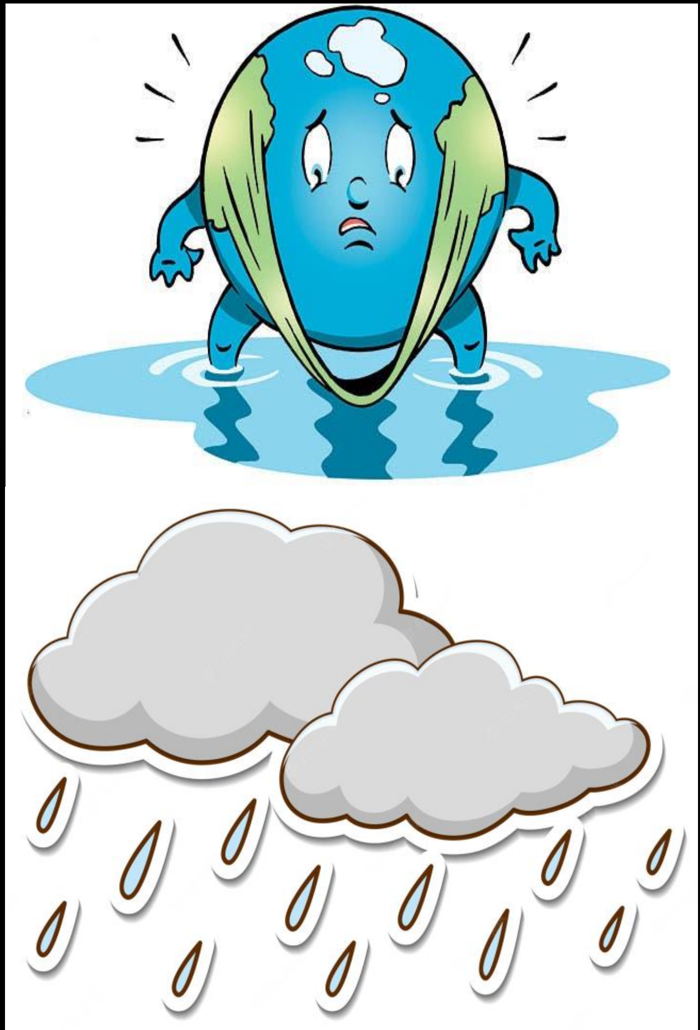
Why Are Site Effects Hard to Predict?

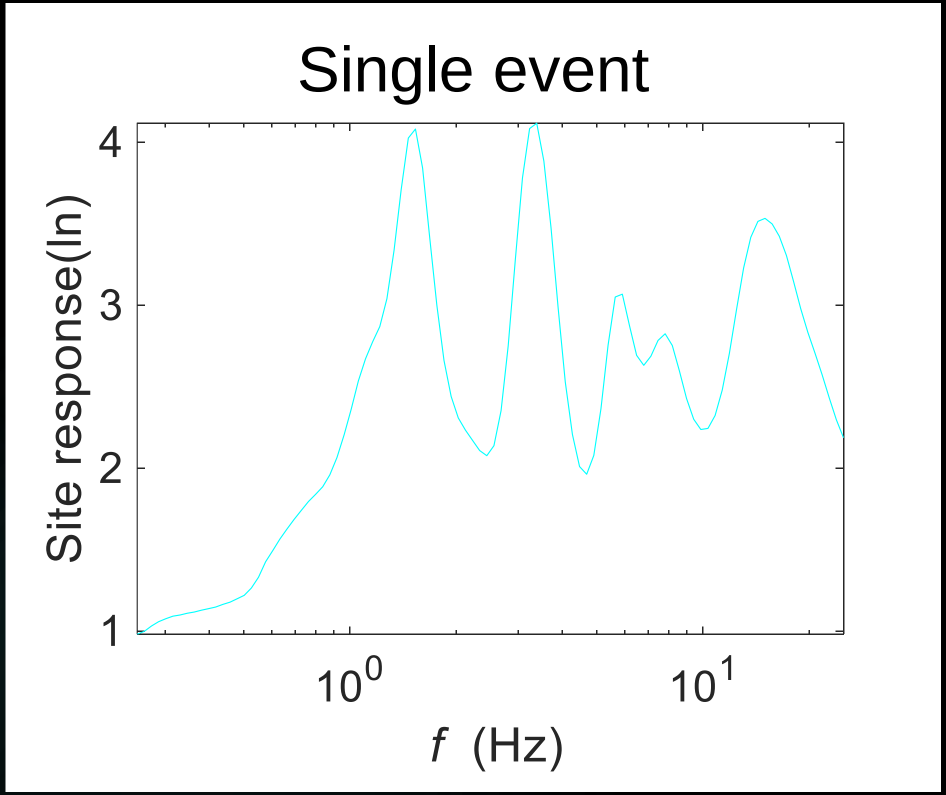


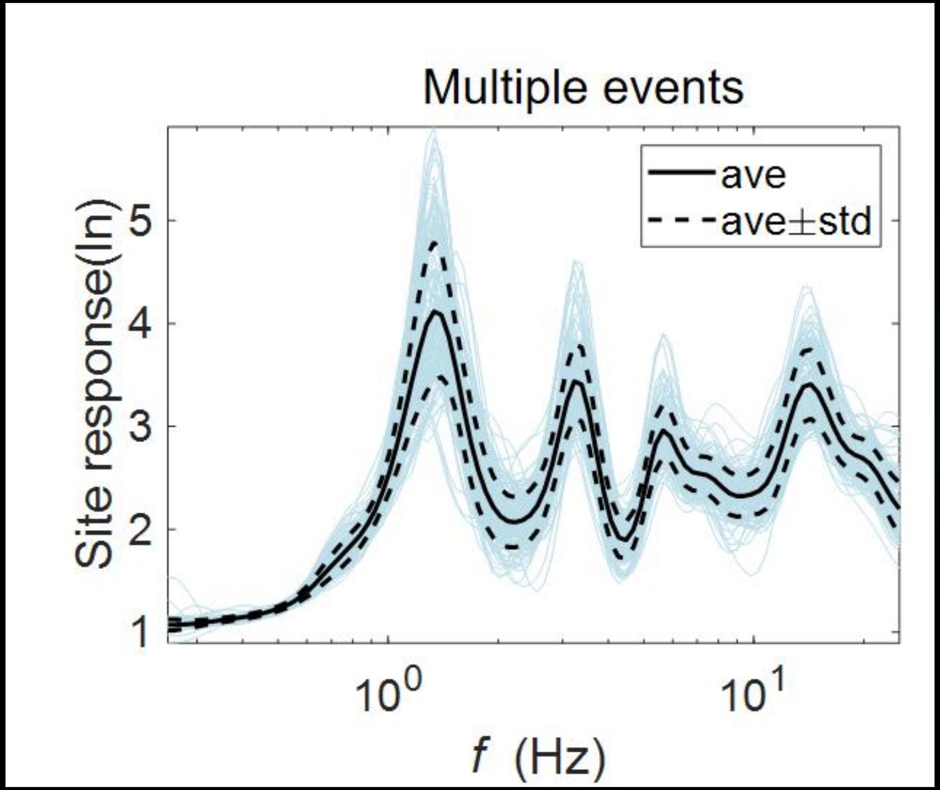
☐ Spatially variable

☐ Temporally variable

✓ Climate change (e.g., permafrost);
✓ Seasonal (e.g., freezing and thawing);
✓ Meterological (e.g., rainfall);
✓ Anthropologic (e..g, evacuation and landfill)
✓ Event-specific site effects (azimuth and complex incident wavefield);

Within-Site Variability

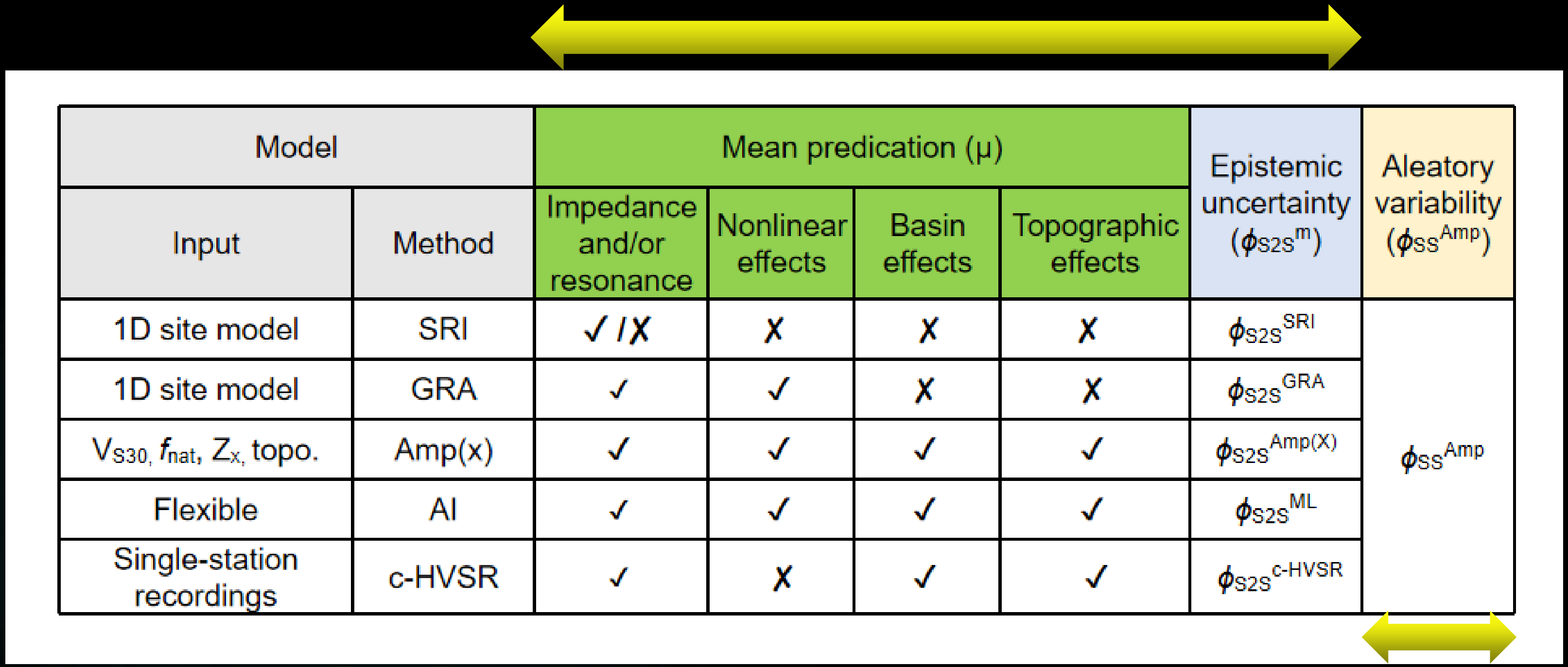




- ❑ Site response is different during different earthquakes, i.e., the within-site variability in site response, which reflects its randomness.
- ❑ We focus on the prediction of the average site response (over different events) at a given location.
- ❑ At a given site, its site response varies but to a limited extent.

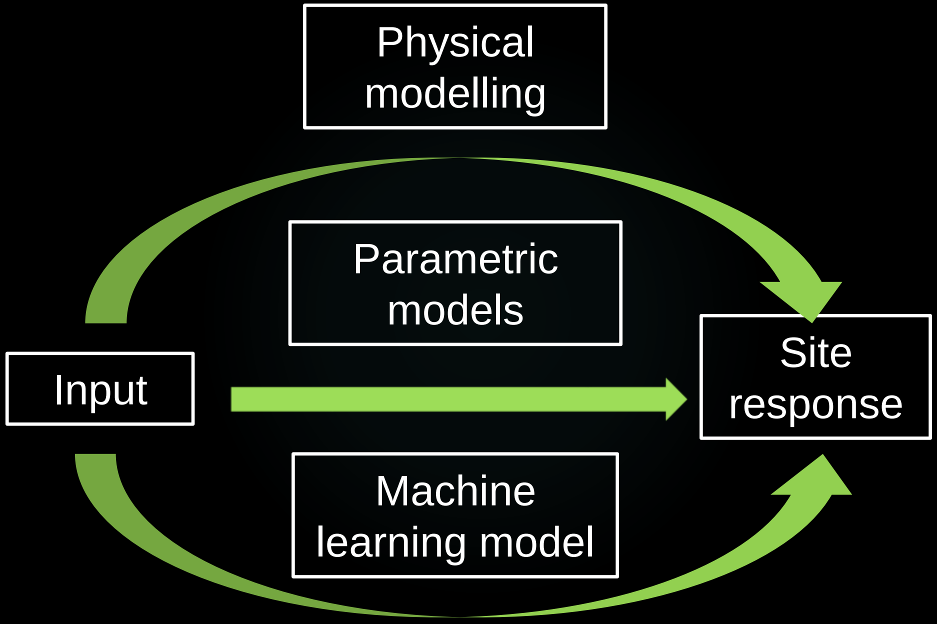
Site Response

Static



Model		Mean predication (μ)				Epistemic uncertainty (ϕ_{S2S}^{m})	Aleatory variability (ϕ_{SS}^{Amp})
Input	Method	Impedance and/or resonance	Nonlinear effects	Basin effects	Topographic effects		
1D site model	SRI	✓ / ✗	✗	✗	✗	ϕ_{S2S}^{SRI}	ϕ_{SS}^{Amp}
1D site model	GRA	✓	✓	✗	✗	ϕ_{S2S}^{GRA}	
V_{S30}, f_{nat}, Z_x, topo.	Amp(x)	✓	✓	✓	✓	$\phi_{S2S}^{Amp(X)}$	
Flexible	AI	✓	✓	✓	✓	ϕ_{S2S}^{ML}	
Single-station recordings	c-HVSR	✓	✗	✓	✓	$\phi_{S2S}^{c\text{-}HVSR}$	

Event/Time-dependent



Physical modelling

Parametric models

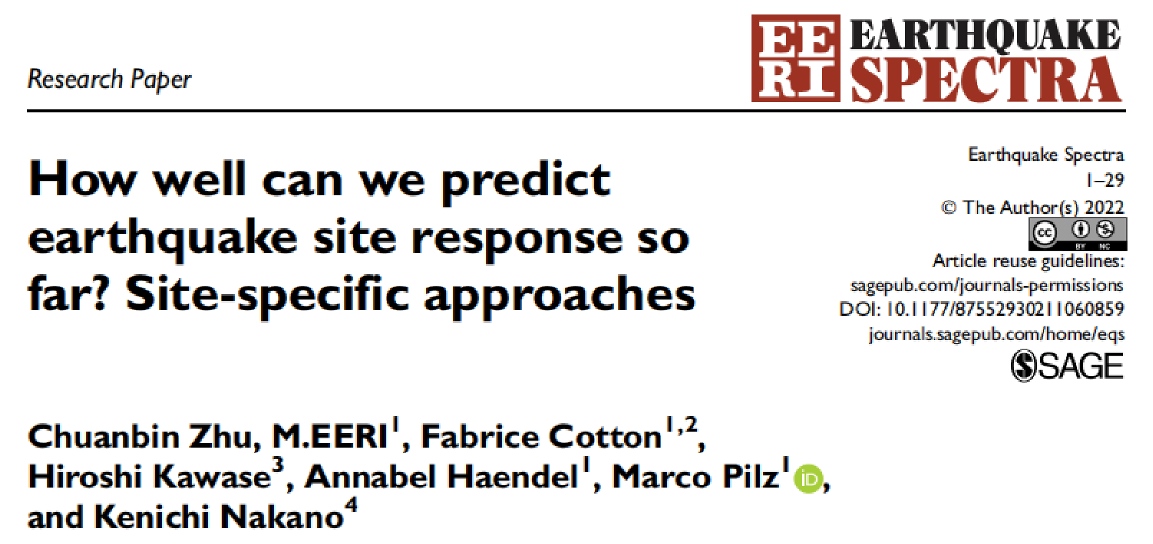
Machine learning model

Input

Site response

Mapping

How Well Can We Predict Site Response?



Research Paper

EE RI EARTHQUAKE SPECTRA

Earthquake Spectra
1–29

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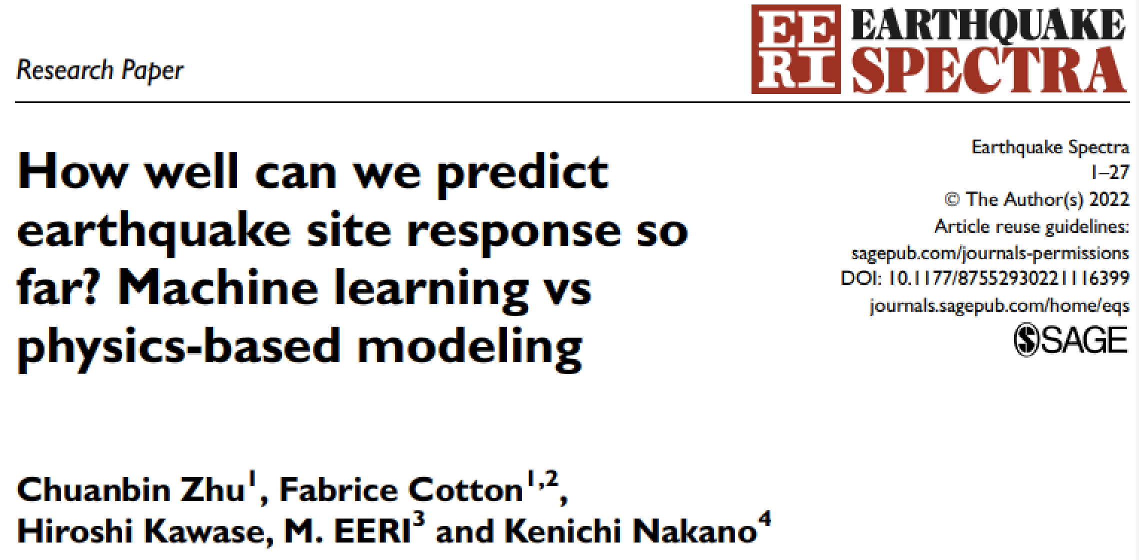
How well can we predict earthquake site response so far? Site-specific approaches

Chuanbin Zhu, M.EERI[1], Fabrice Cotton[1,2], Hiroshi Kawase[3], Annabel Haendel[1], Marco Pilz[1], and Kenichi Nakano[4]



Research Paper

EE RI EARTHQUAKE SPECTRA

Earthquake Spectra
1–27

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How well can we predict earthquake site response so far? Machine learning vs physics-based modeling

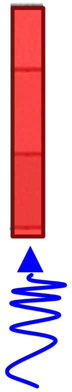
Chuanbin Zhu[1], Fabrice Cotton[1,2], Hiroshi Kawase, M. EERI[3] and Kenichi Nakano[4]

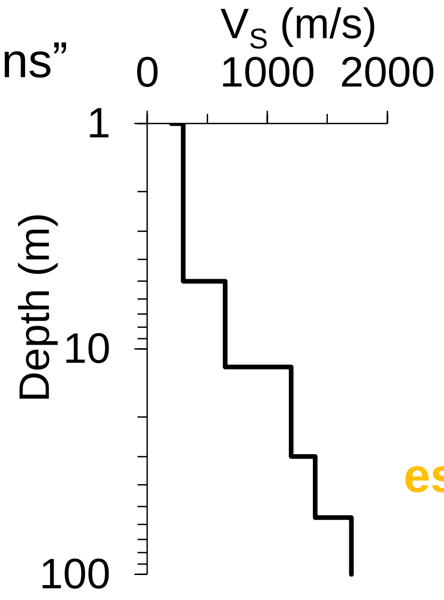
1D GRA & SRI

1D Ground Response Analysis (GRA):

"1DSH assumptions"

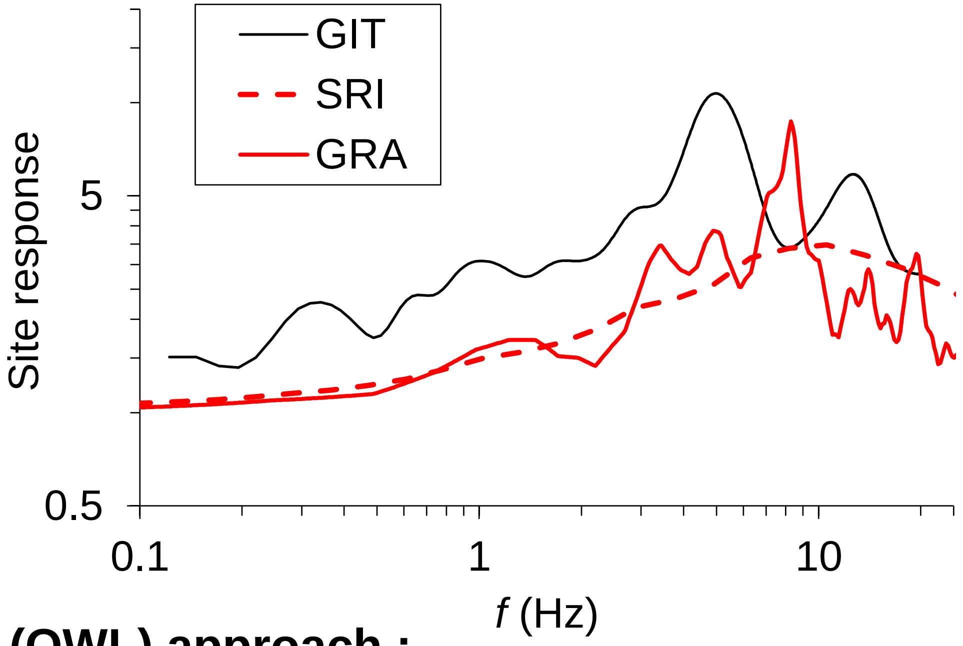
Vertically incident SH waves





1D GRA

a set of established rules



Squre-Root-Impedence (SRI) or Quarter-Wave-Length (QWL) approach :

$$SRI:\ A(f) = \sqrt{\frac{\rho_R V_{S,R}}{\overline{\rho}\overline{V_S}}}\ .\ e^{-\pi\,\kappa_0\, f}\ ,\ \kappa_0 = \kappa_{0,\mathrm{surface}} - \kappa_{0,\mathrm{rock}}\ (\kappa_{0,\mathrm{rock}} = 0.007\ \mathrm{s})$$

- ☐ It represents the state-of-the-practice;
- ☐ Site effects are too complex to be fully described by a set of differential equations;

Corrected HVSR (c-HVSR)

It is first proposed by Kawase et al. (2018) to correct noise HVSR. Zhu et al. (2020) used it to earthquake HVSR.

$$HH_bR(f) = \frac{H(f)}{H_b(f)} \qquad VH_bR(f) = \frac{V(f)}{H_{b(f)}}$$

$$HVSR(f) = \frac{H(f)}{V(f)} = \frac{H(f)}{H_b(f)} \cdot \frac{H_b(f)}{V(f)} = \frac{HH_bR(f)}{VH_bR(f)}$$

$$HH_bR(f) = HVSR(f) \boxed{\cdot VH_bR(f)}$$

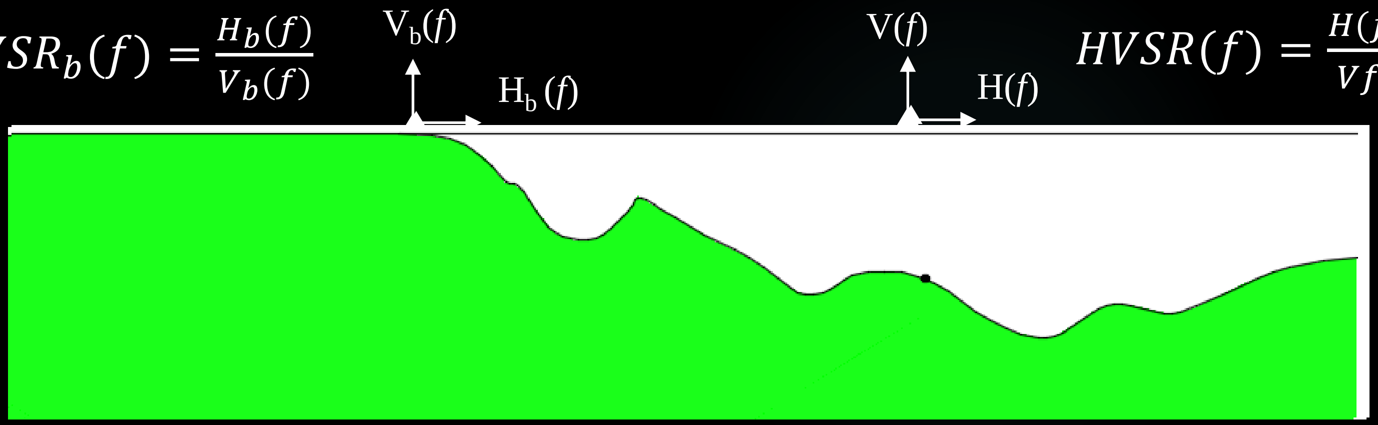
Site-specific

$$\boldsymbol{c - HVSR(f) = HVSR(f)} \boxed{\boldsymbol{\cdot < VH_bR(f) >}}$$

Categorical

$$HVSR_b(f) = \frac{H_b(f)}{V_b(f)}$$

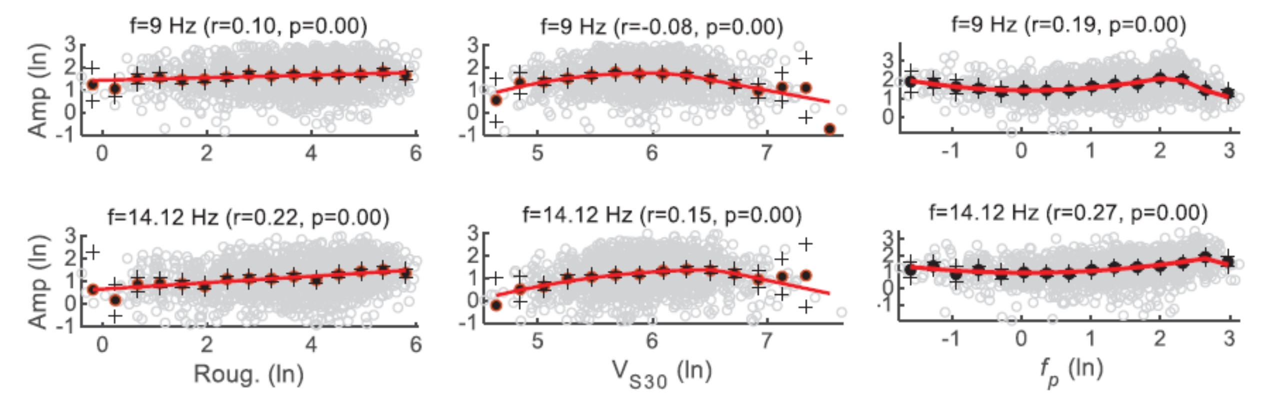
$$HVSR(f) = \frac{H(f)}{Vf)}$$

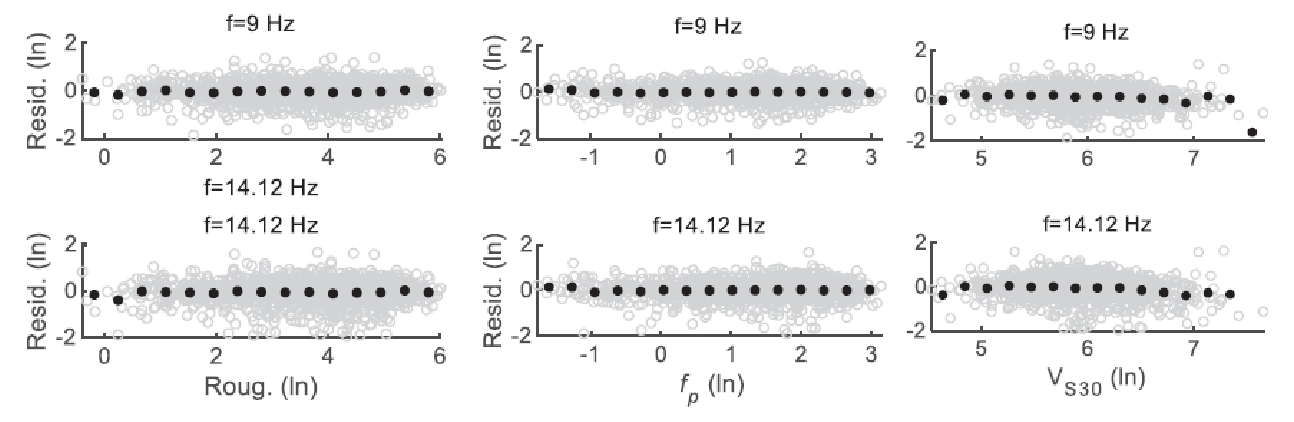


Categorical correction spectra via *k*-means clustering

Zhu C, Pilz M and Cotton F (2020). Evaluation of a novel application of earthquake HVSR in site-specific amplification estimation. Soil Dyn. Earthq. Eng. 139, 106301. https://doi.org/10.1016/j.soildyn.2020.106301.

Parametric Regression Models [Amp(x)]



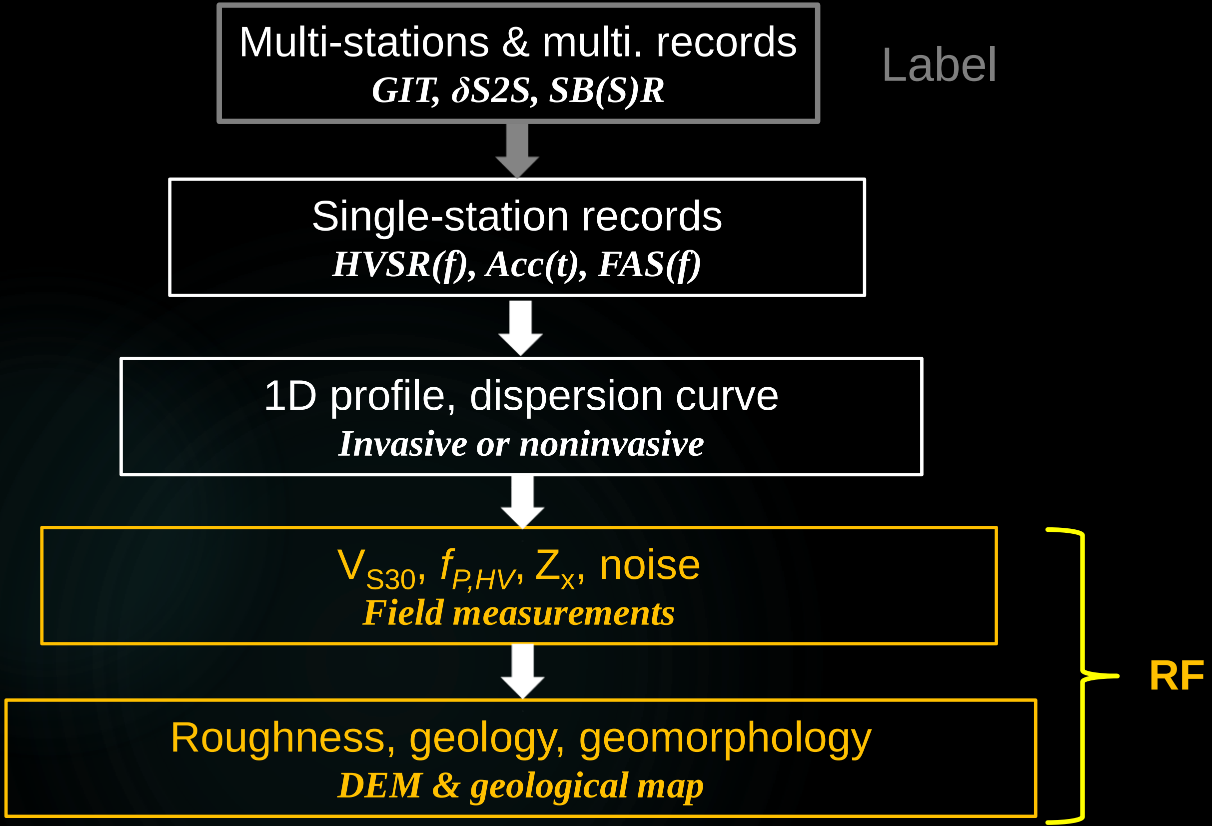


$$\ln \boldsymbol{Amp}(\boldsymbol{V_{S30}}) = \begin{cases} 0 & V_{S30} \geq V_c \\ c_1 \ln\left(\frac{V_{S30}}{V_c}\right) & V_L \leq V_{S30} < V_c \\ c_1 \ln\left(\frac{V_{S30}}{V_c}\right) + c_2 \ln\left(\frac{V_{S30}}{V_L}\right) + c_3 \ln^2\left(\frac{V_{S30}}{V_L}\right) & V_{S30} < V_L \end{cases}$$

$$\ln \boldsymbol{Amp}(\boldsymbol{Roug.}) = c_1 + c_2 \ln(Roug.)$$

$$\ln \boldsymbol{Amp}(\boldsymbol{f_p}) = \begin{cases} c_1 + c_2 \ln\left(\frac{f_p}{f_{osc}}\right) + c_3\, ln^2\left(\frac{f_p}{f_{osc}}\right) & f_p < f_{osc} \\ c_1 + c_4 \ln\left(\frac{f_p}{f_{osc}}\right) + c_5\, ln^2\left(\frac{f_p}{f_{osc}}\right) & f_p \geq f_{osc} \end{cases}$$

Random-Forest Models (RF)



Multi-stations & multi. records
GIT, δS2S, SB(S)R

Label

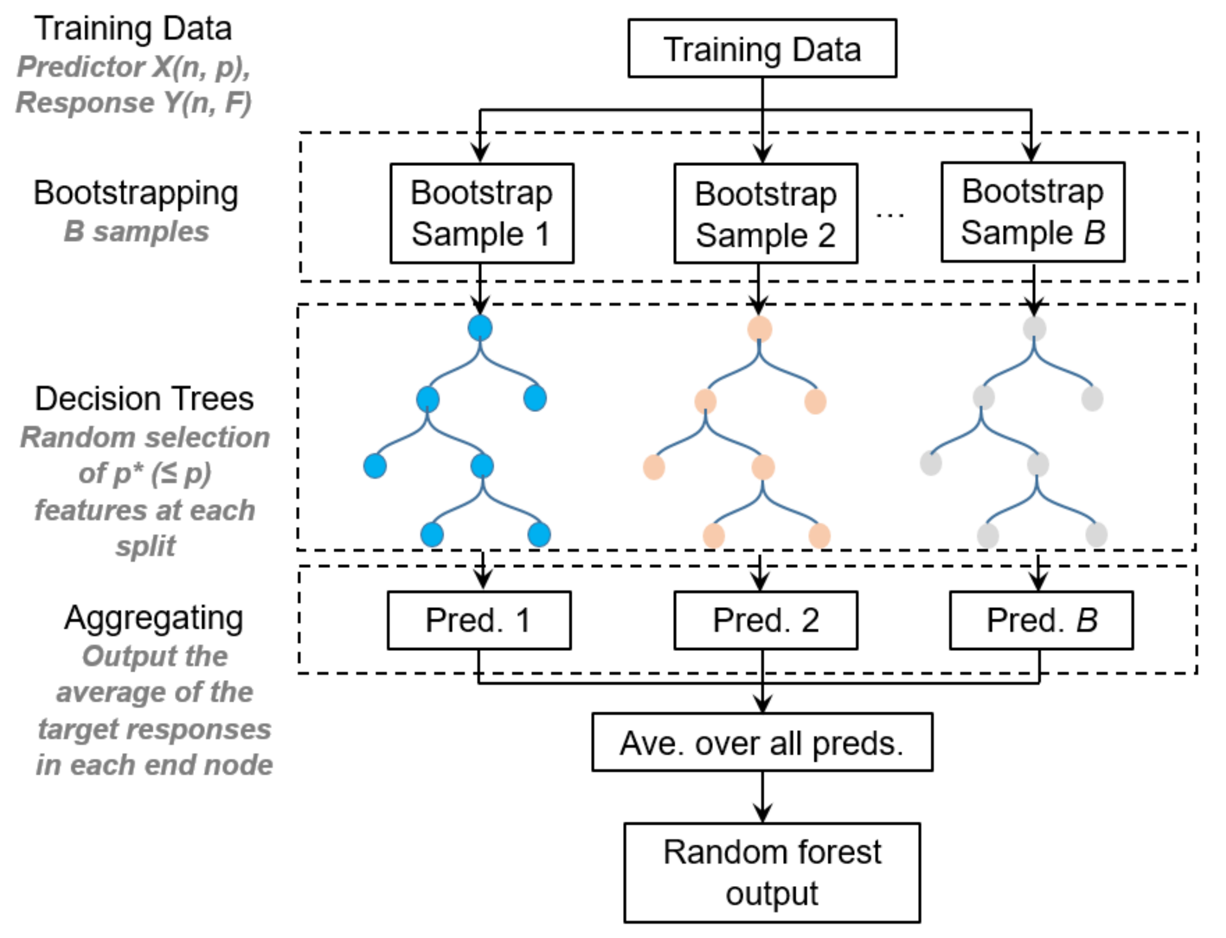
Single-station records
HVSR(f), Acc(t), FAS(f)

1D profile, dispersion curve
Invasive or noninvasive

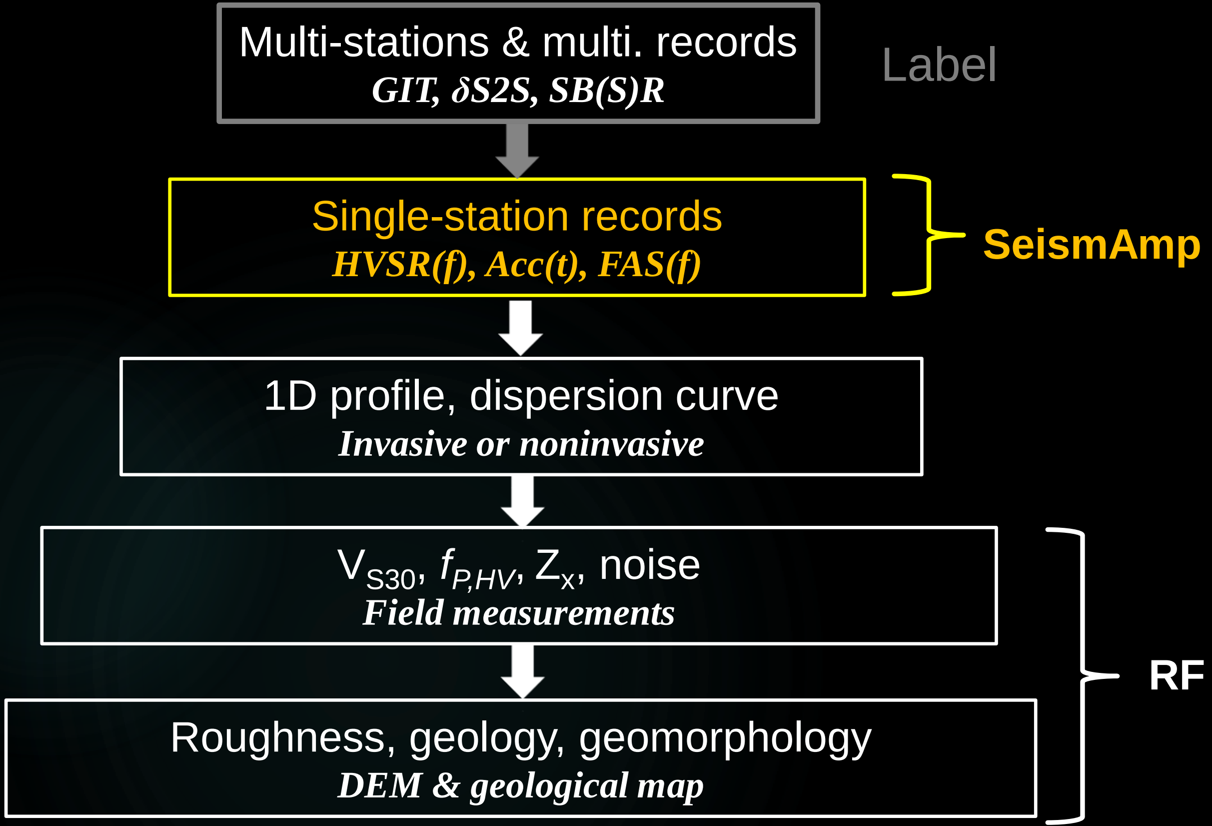
V_{S30}, $f_{P,HV}$, Z_x, noise
Field measurements

Roughness, geology, geomorphology
DEM & geological map

RF



SeismAmp



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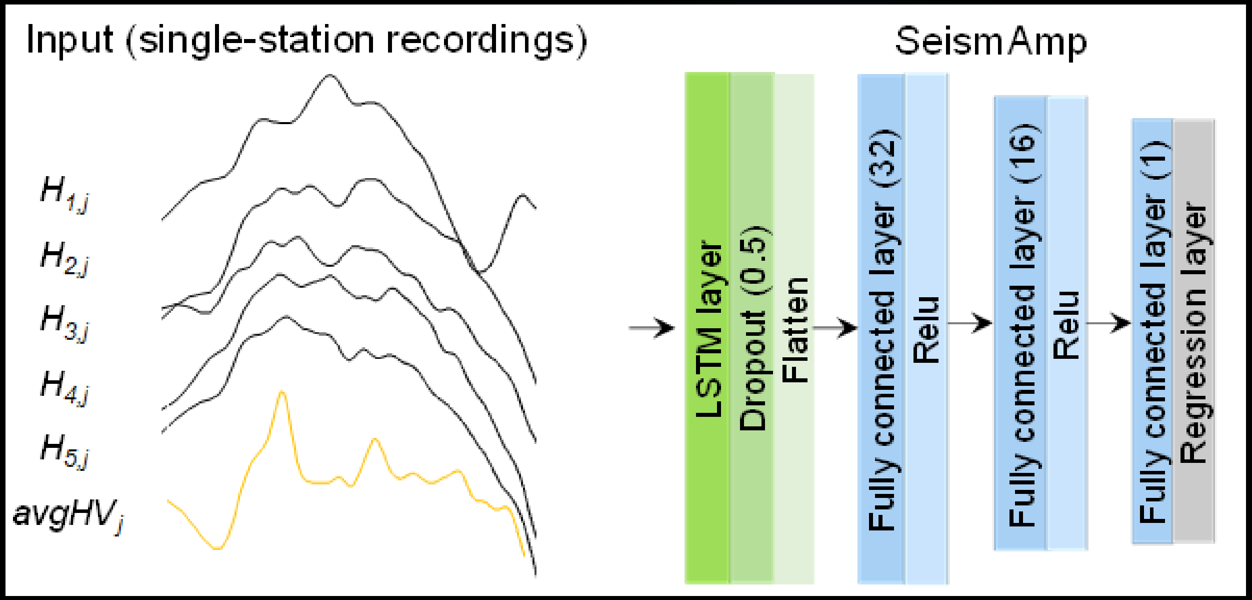
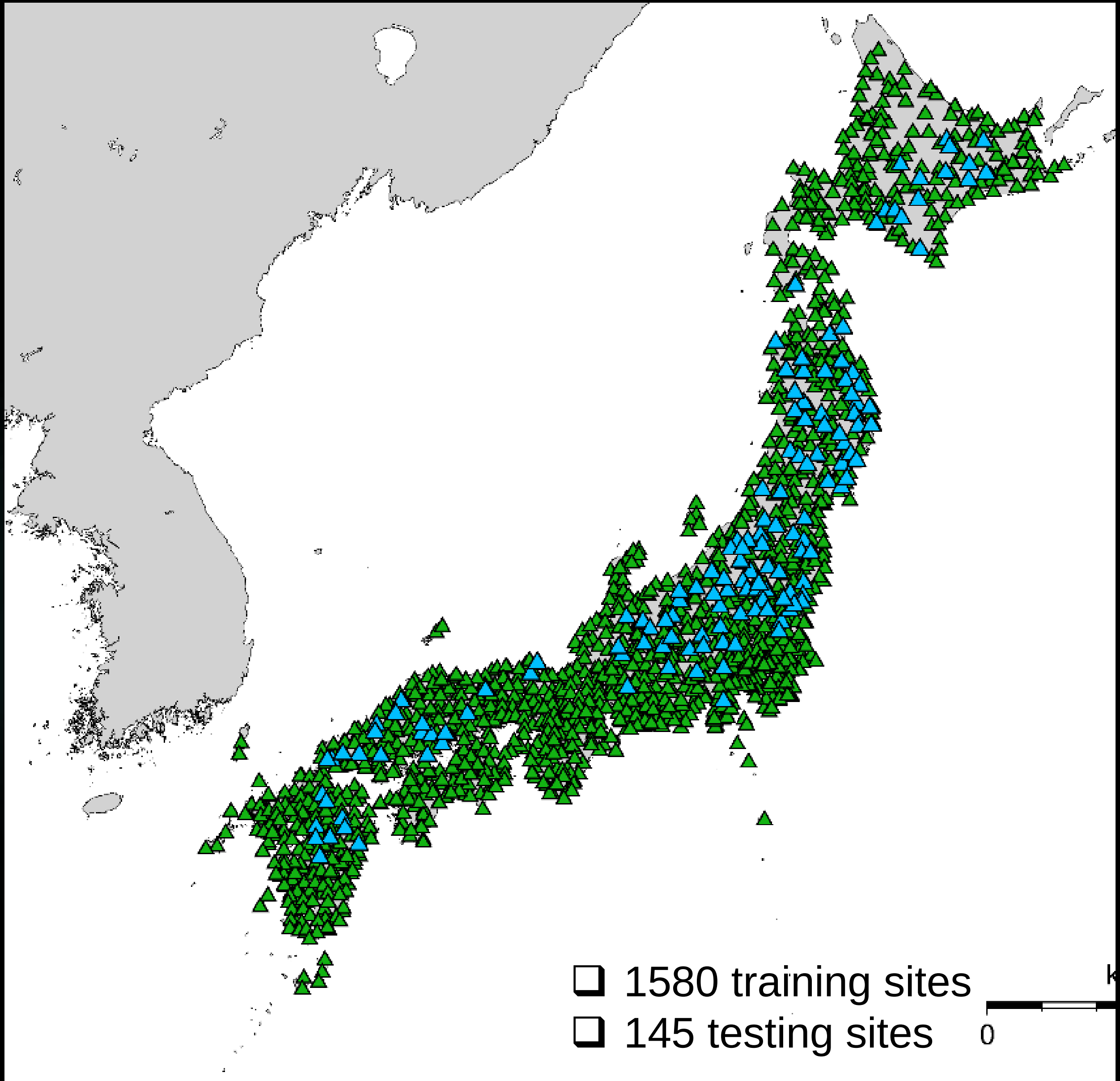
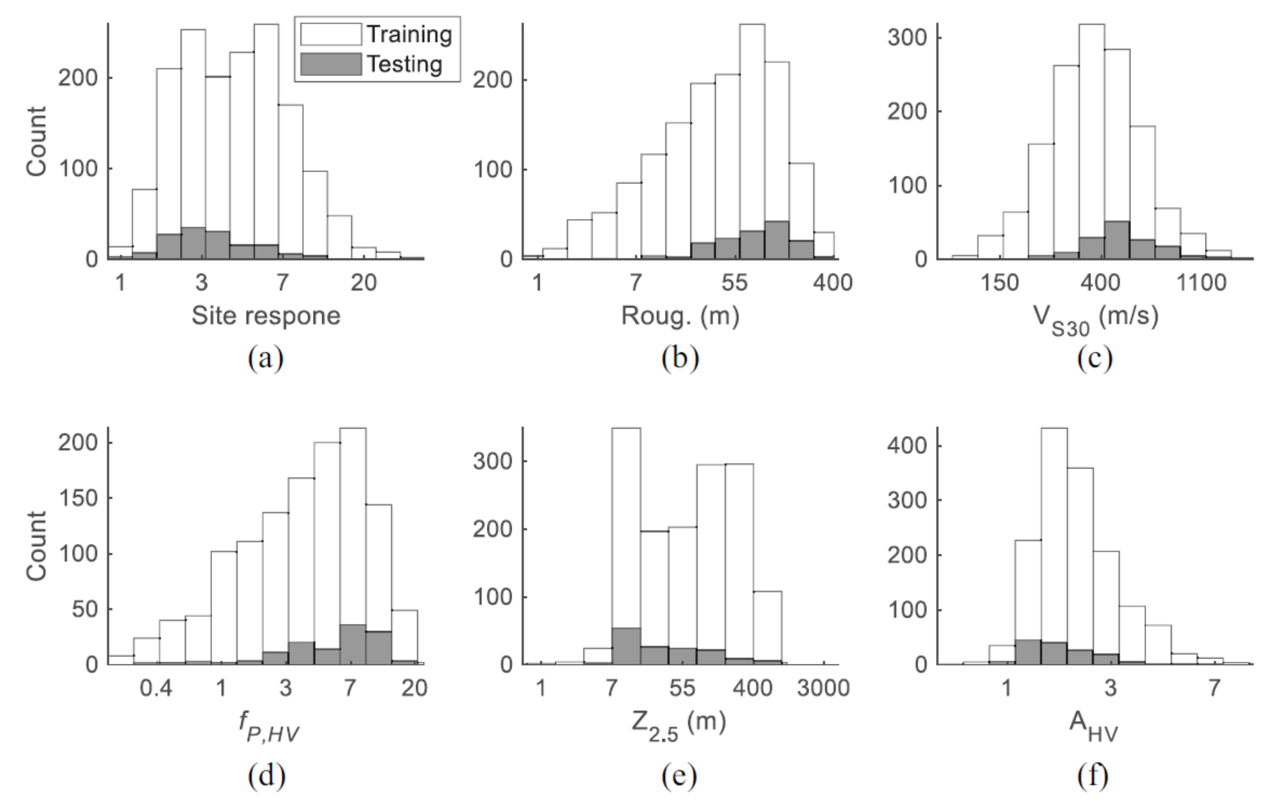


Zhu et al. (2022). Separating Broad-Band Site Response from Single-Station Seismograms (under review).

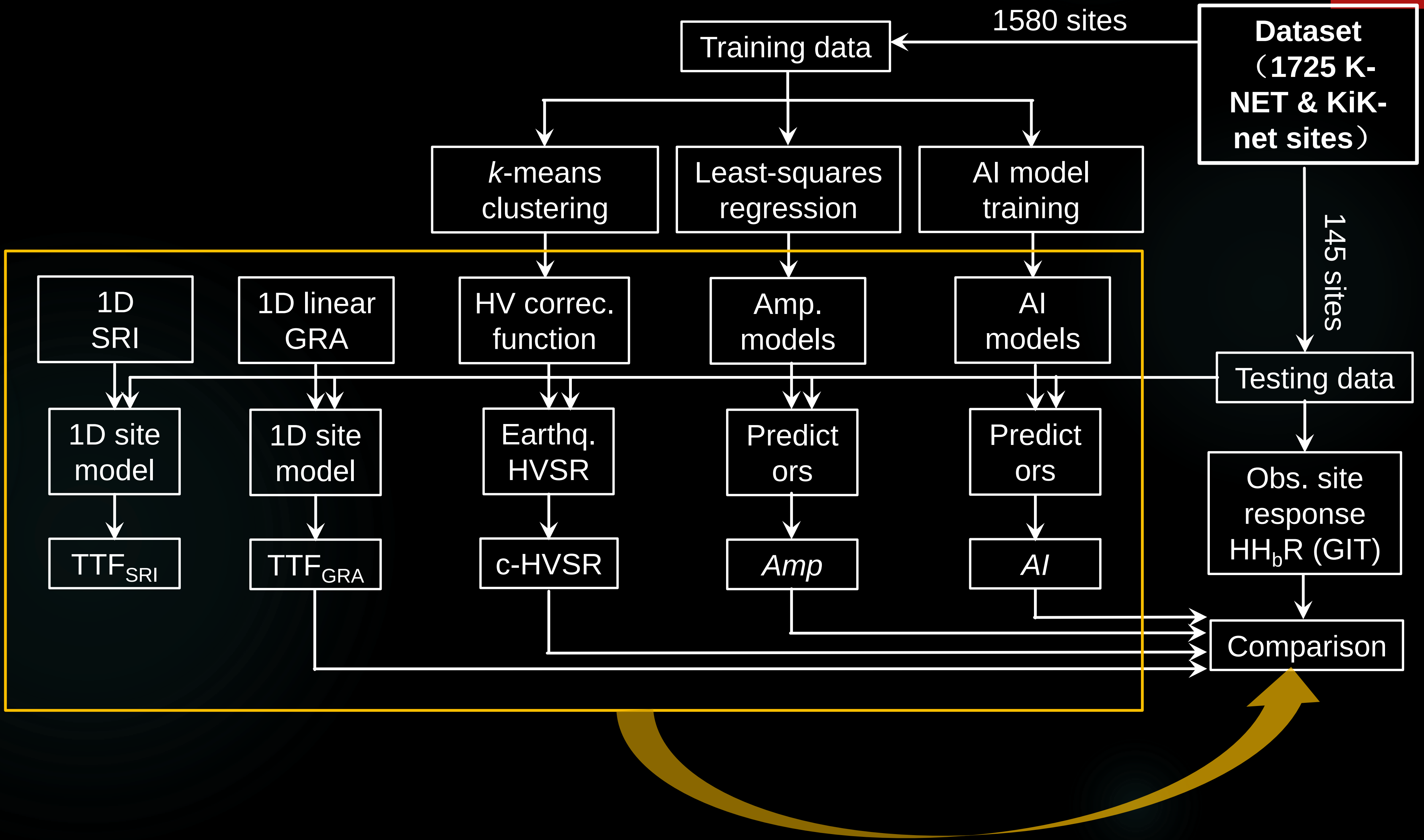
Dataset



- ☐ 1580 training sites
- ☐ 145 testing sites

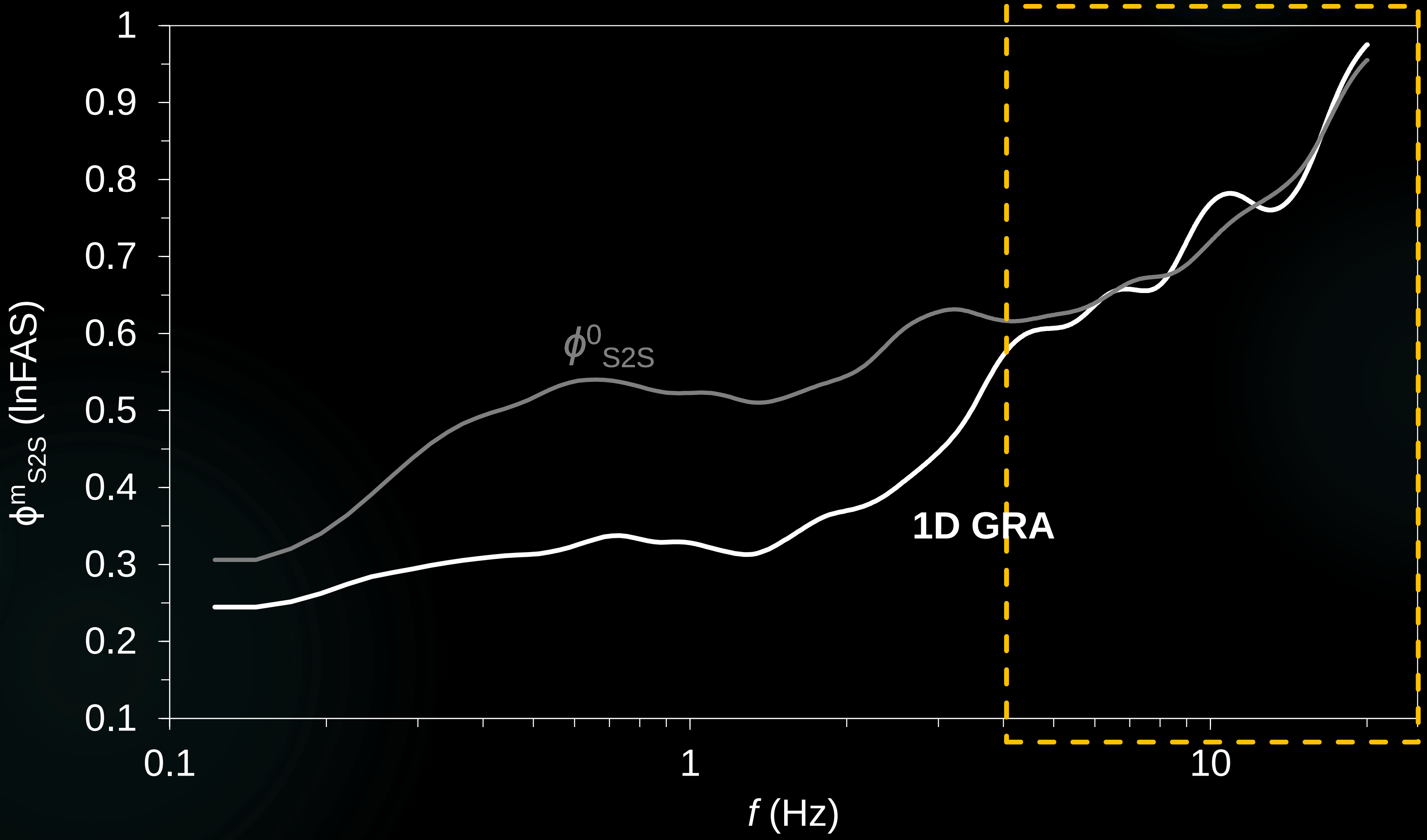


Workflow



1580 sites
Training data
Dataset （1725 K-NET & KiK-net sites）
k-means clustering
Least-squares regression
AI model training
145 sites
1D SRI
1D linear GRA
HV correc. function
Amp. models
AI models
Testing data
1D site model
1D site model
Earthq. HVSR
Predictors
Predictors
TTF$_{SRI}$
TTF$_{GRA}$
c-HVSR
Amp
AI
Obs. site response HH$_b$R (GIT)
Comparison

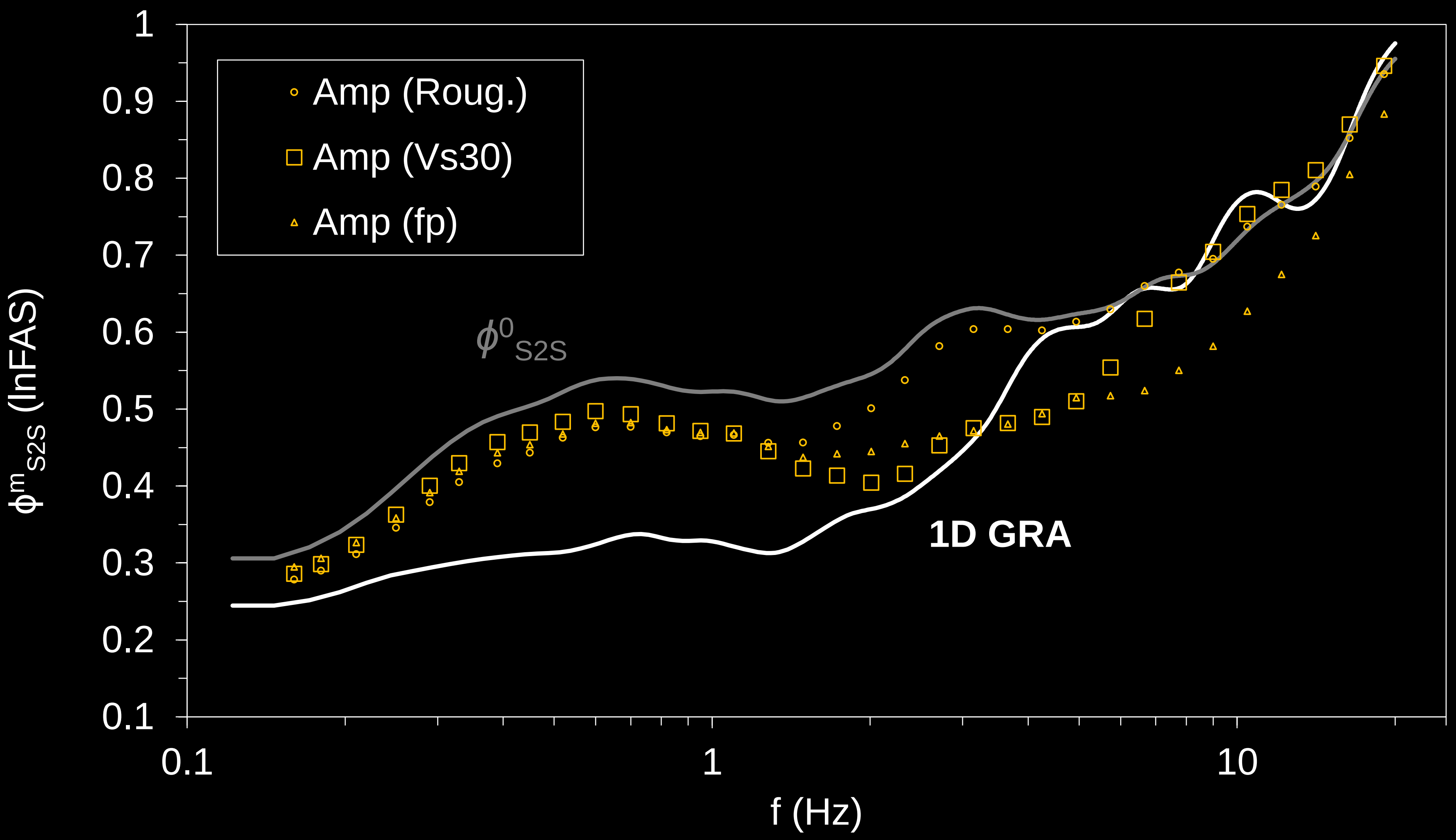
Results: 1D GRA



High uncertainty

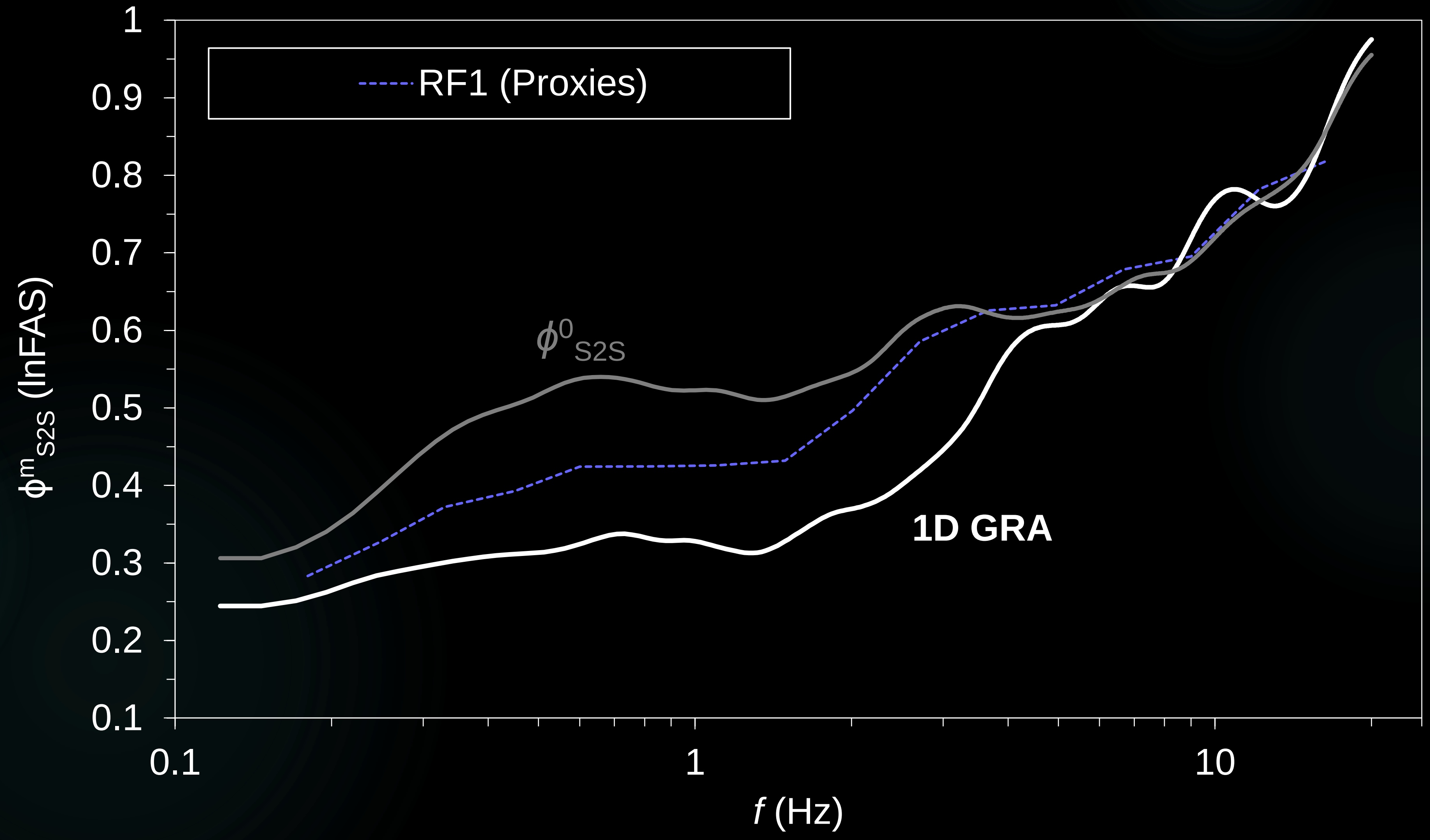
- ☐ φ^{m}_{S2S} : standard deviation of residual between observation and prediction of a model (m) at the testing sites;
- ☐ φ^{0}_{S2S} : standard deviation in full site response with the use of any model;
- ☐ Standard deviation of 1D GRA remains hight at high frequencies (> 2-4 Hz);

Results: Amp(x)



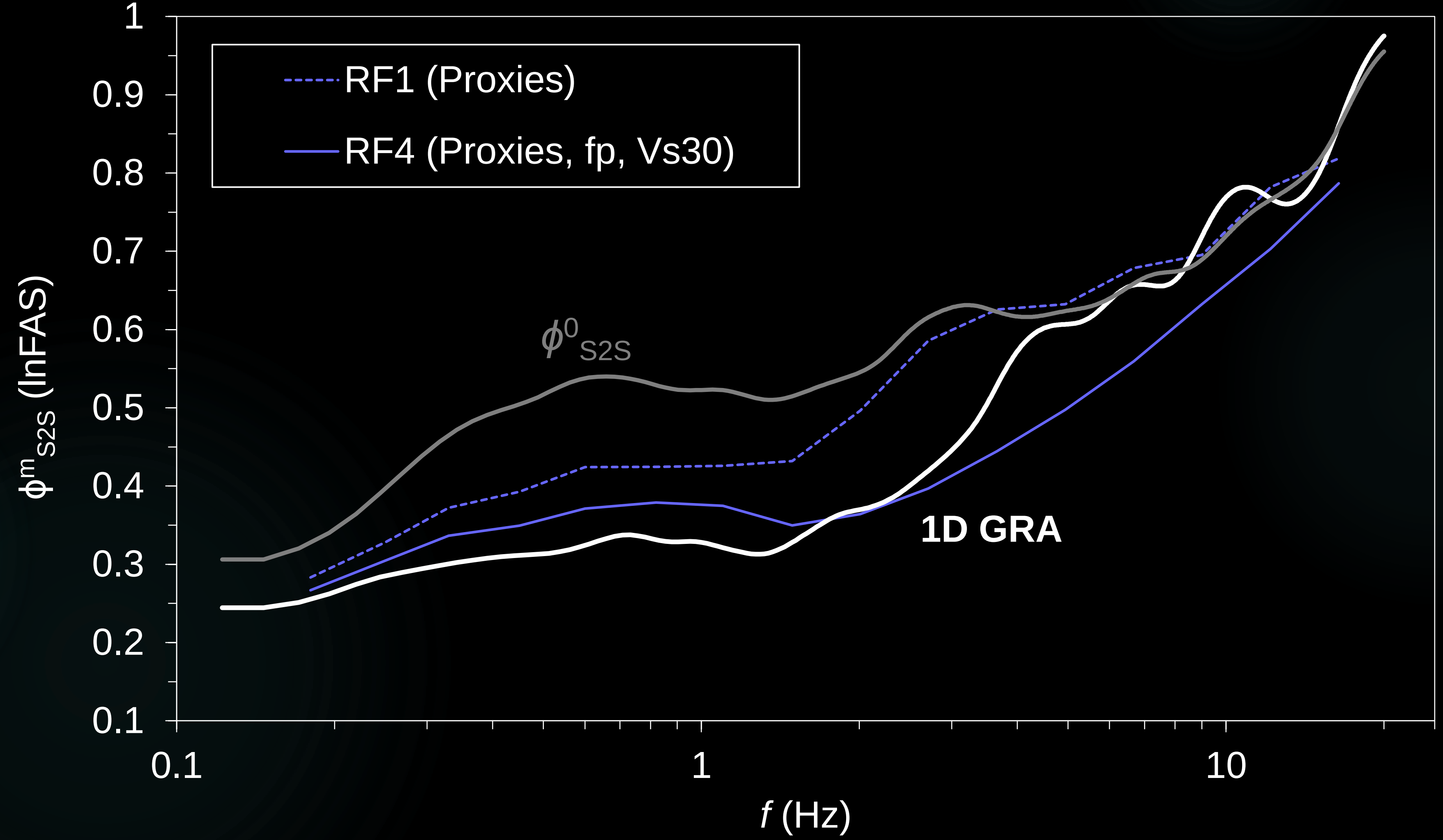
- ❑ 1D GRA vs Amp(V_{S30})
- ❑ What if we use a few more site parameters in empirical models (RF)?

Results: RF



- ❑ Proxies: roughness, geology and geomorphology;
- ❑ Roughness is a continuous variable whereas the later two are categorical;

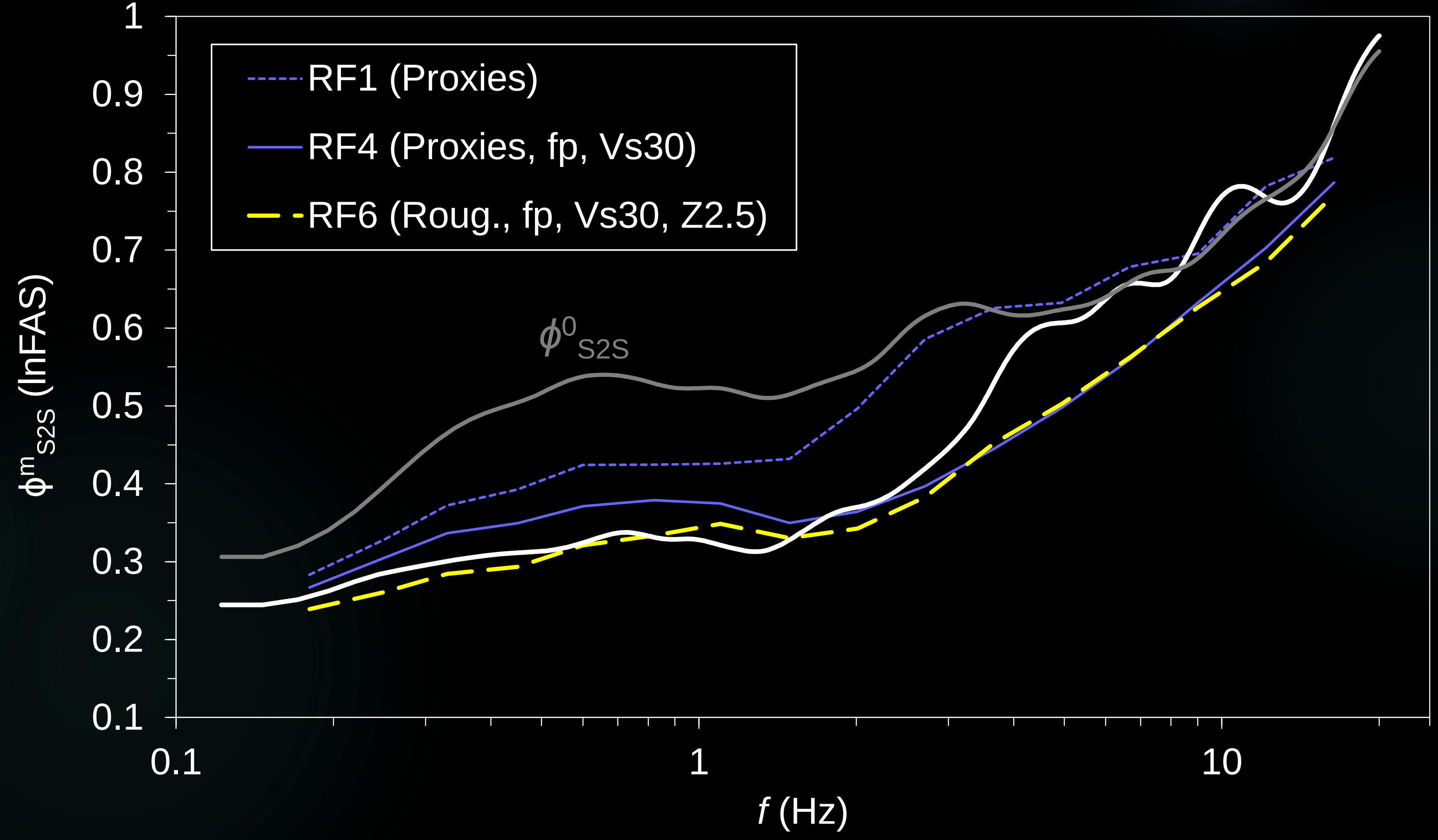
Results: RF



Relative reduction in standard deviation (average over 0.1-10 Hz):

f (Hz)	GRA	RF4
0.1-10.0	25%	26%

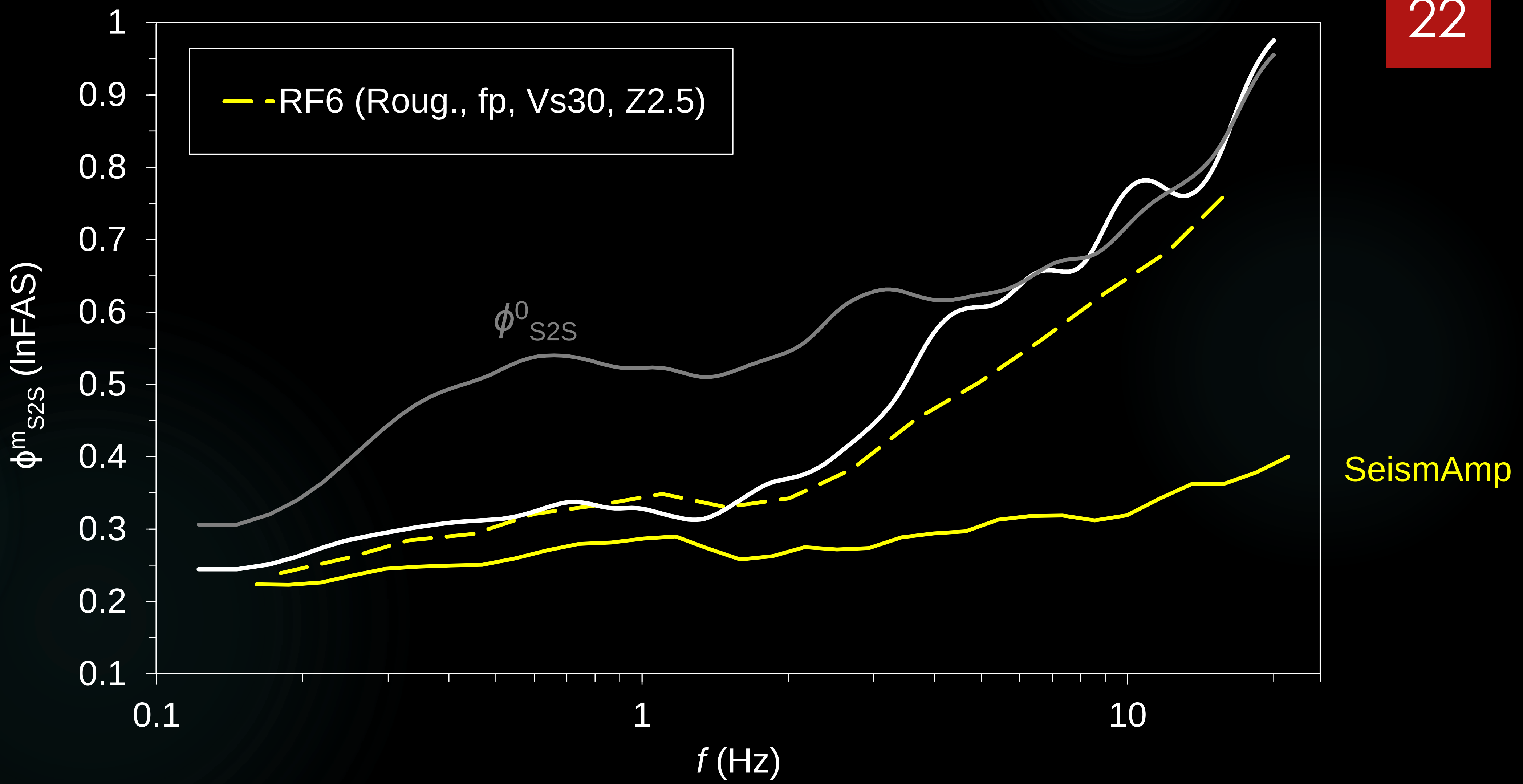
Results: RF



Relative reduction in standard deviation (average over 0.1-10 Hz):

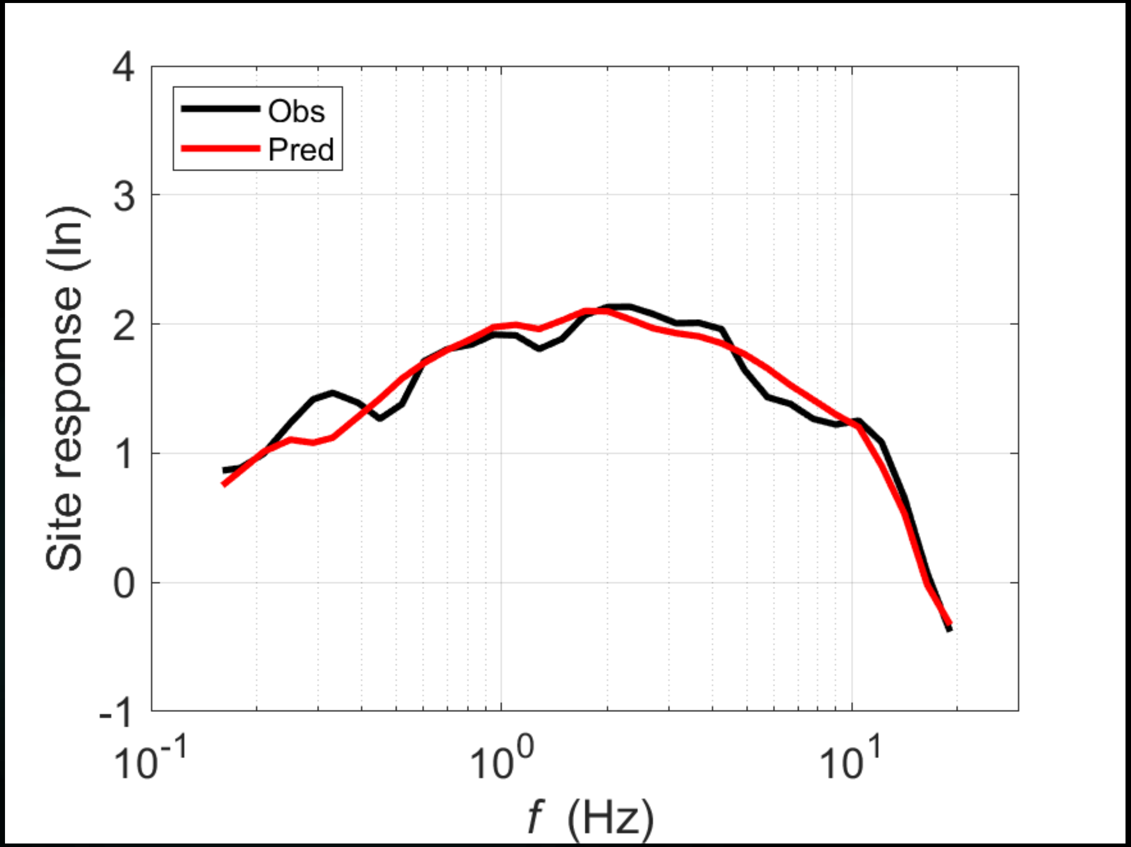
f (Hz)	GRA	RF4	RF6
0.1-10.0	25%	26%	31%

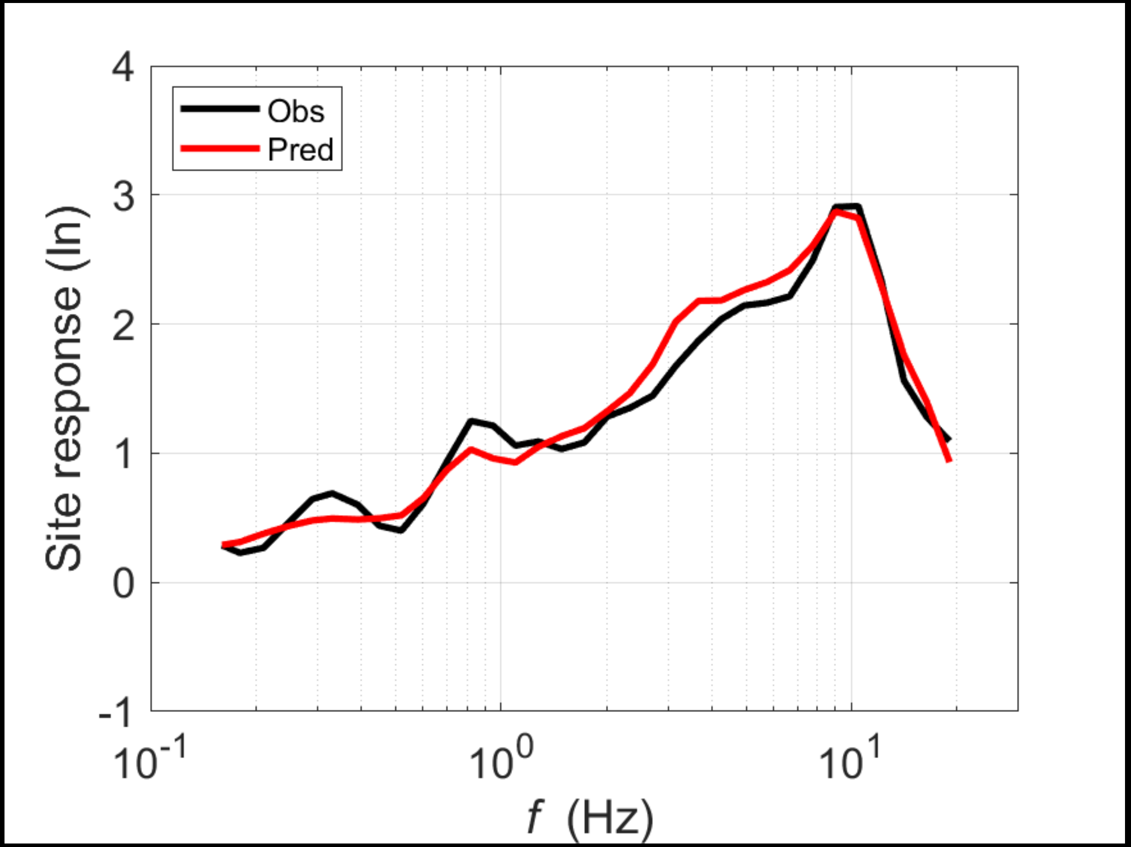
Results: SeismAmp



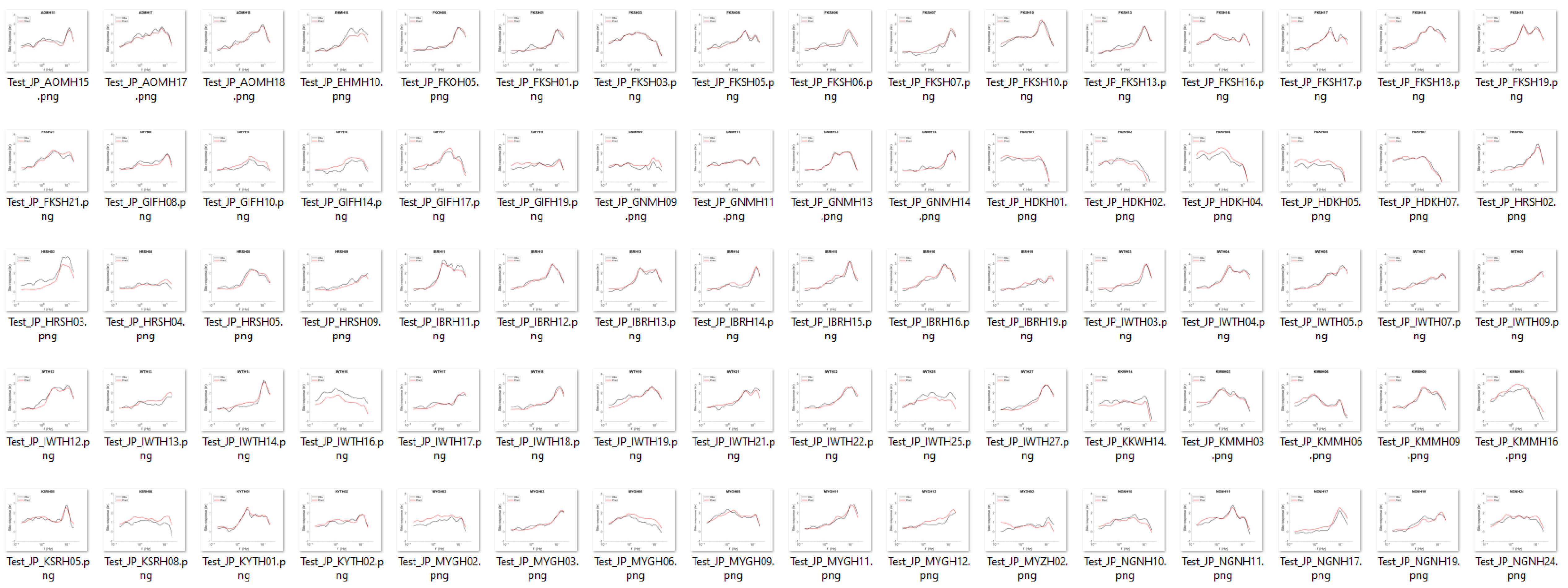
- ❑ SeismAmp is a single-station end-to-end approach (seismograms → amplificaiton).
- ❑ Rethink the use of the best use of single-station recordings if our end goal is to predict amplification.
- ❑ The individual components of ground motions carry salient information on site response, part of which is lost in HVSR.

SeismAmp Predictions at Testing Sites

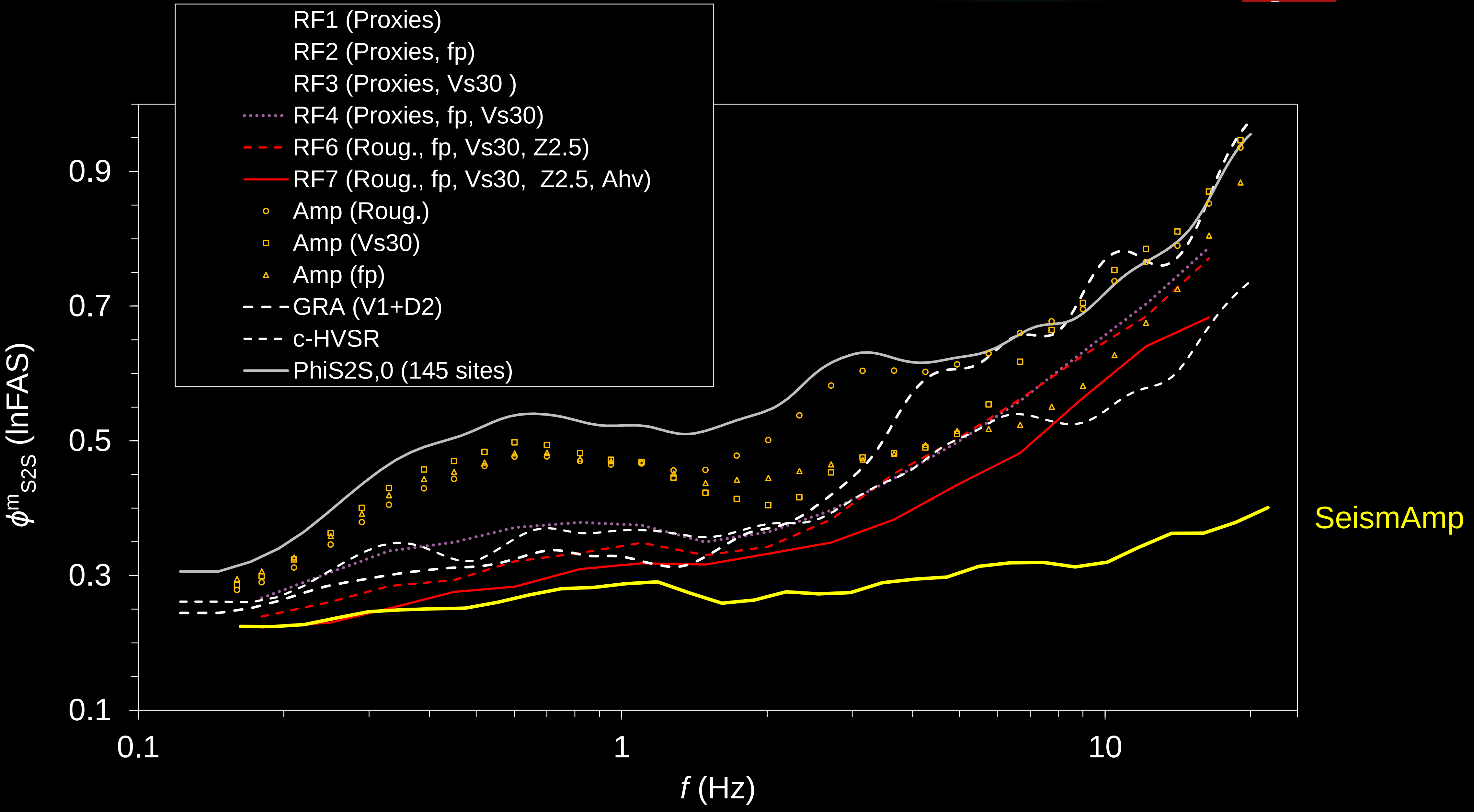




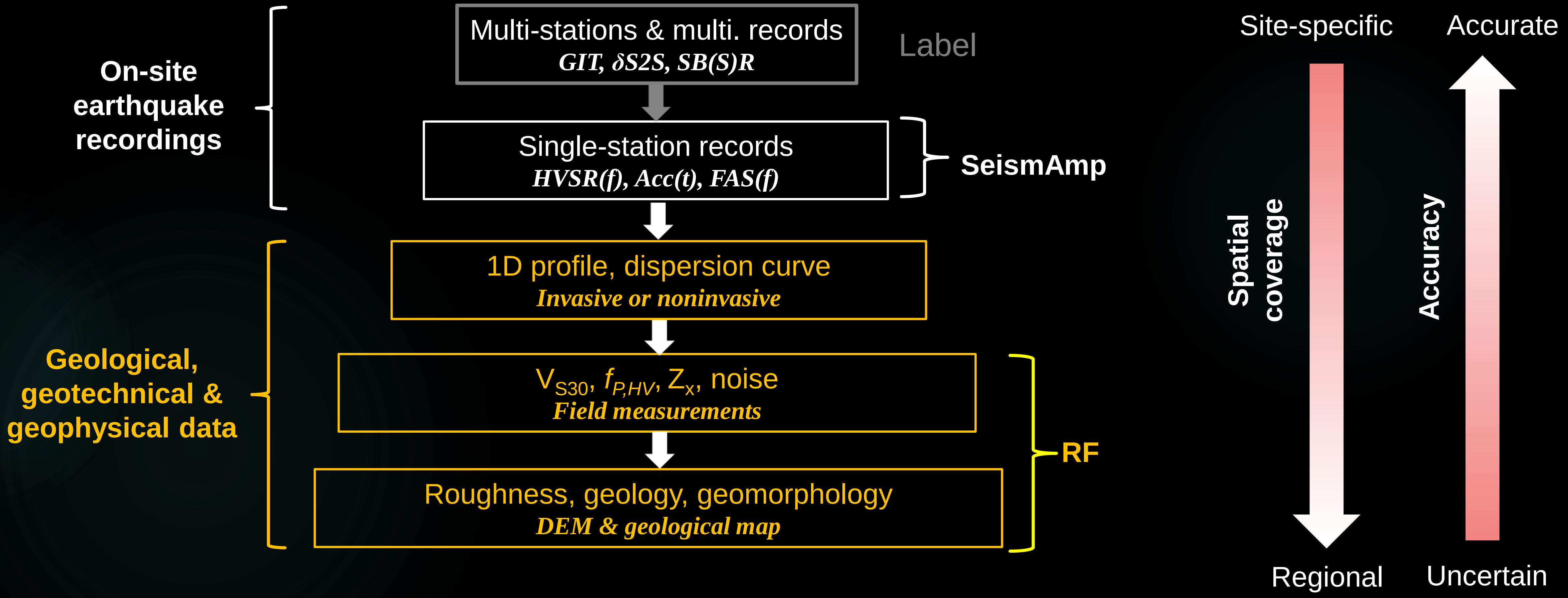
SeismAmp Predictions at Testing Sites



Results: All


RF1 (Proxies)
RF2 (Proxies, fp)
RF3 (Proxies, Vs30)
RF4 (Proxies, fp, Vs30)
RF6 (Roug., fp, Vs30, Z2.5)
RF7 (Roug., fp, Vs30, Z2.5, Ahv)
Amp (Roug.)
Amp (Vs30)
Amp (fp)
GRA (V1+D2)
c-HVSR
PhiS2S,0 (145 sites)
SeismAmp
ϕ^{m}_{S2S} (lnFAS)
0.9
0.7
0.5
0.3
0.1
0.1
1
10
f (Hz)

Site Information Pyrimid



On-site earthquake recordings

Multi-stations & multi. records
GIT, δS2S, SB(S)R

Label

Single-station records
HVSR(f), Acc(t), FAS(f)

SeismAmp

Geological, geotechnical & geophysical data

1D profile, dispersion curve
Invasive or noninvasive

V_{S30}, $f_{P,HV}$, Z_x, noise
Field measurements

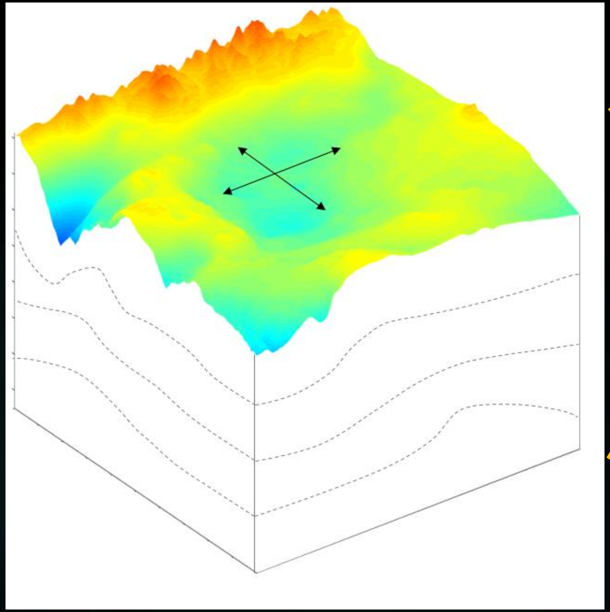
Roughness, geology, geomorphology
DEM & geological map

RF

- ❑ In site-specific applications, we often have 1D velocity profiles;
- ❑ **What is the the best way to use Vs profile whenever available?**

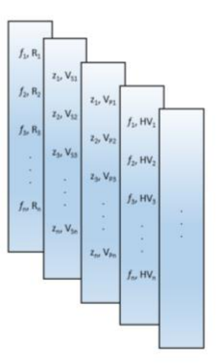
Optimal Way to Use Vs Porfile?

Input (given)



1D GRA

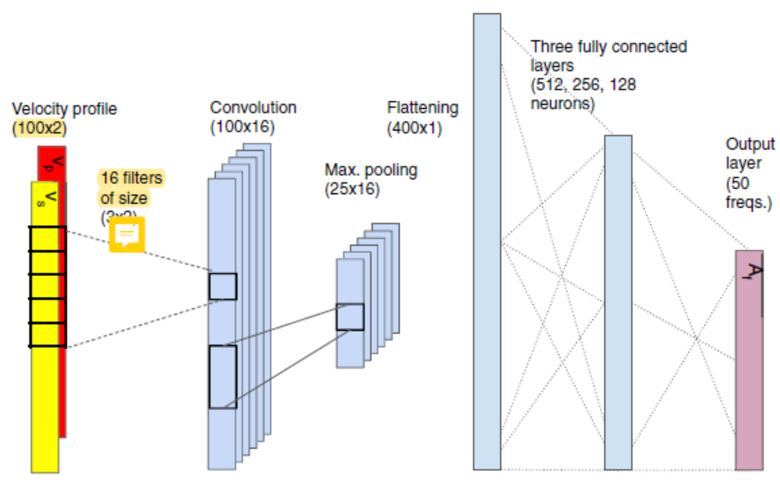
Feature engineering

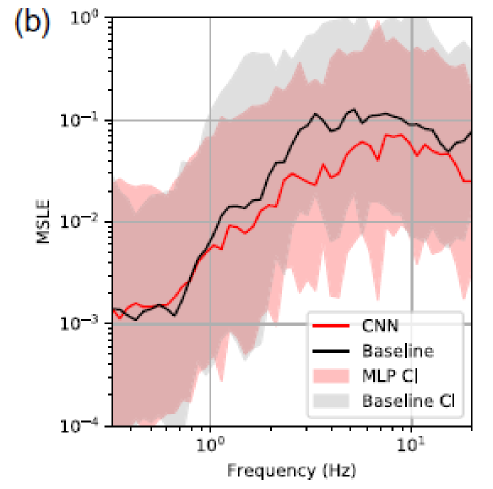


Machine Learning (ML)

Deep Learning

Roten and Olsen (2021)





Lessons Learnt from Data in Japan

- ❑ 1D GRA has a high level of (parametric and modelling) uncertainty (success rate < 50%);

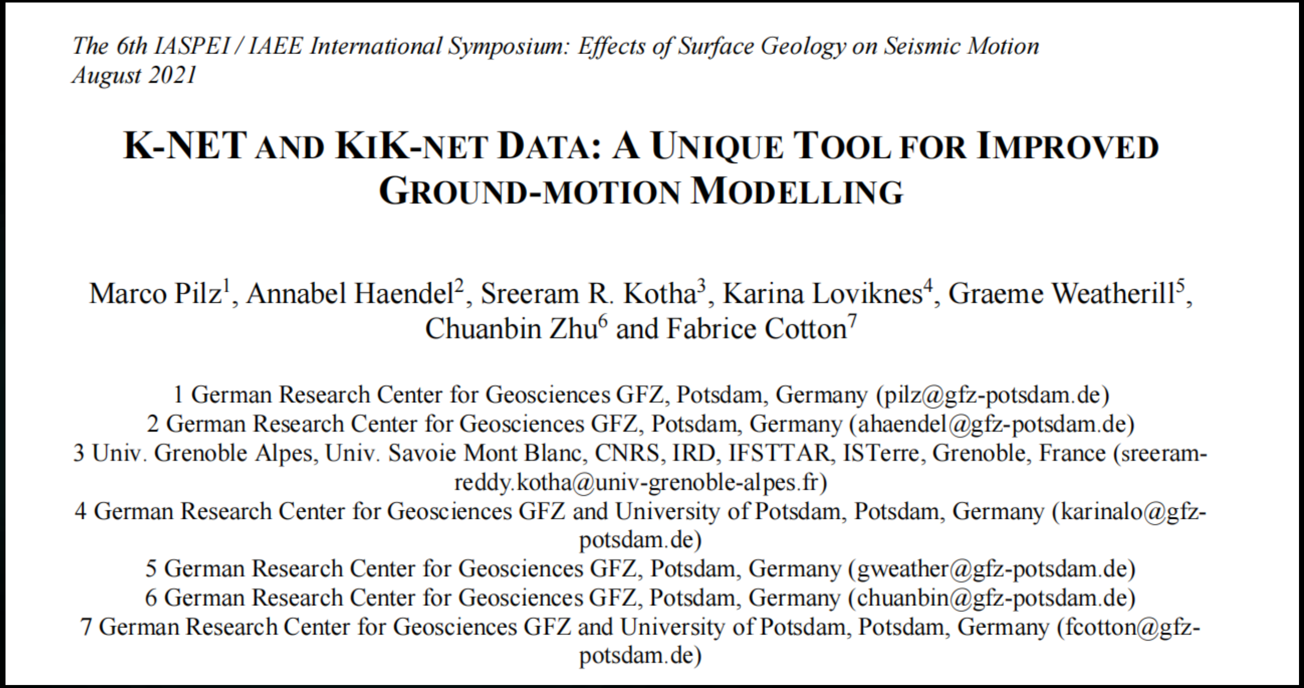
- ❑ AI is more efficient in utilizing given information than 1D GRA;

- ❑ Site response can be accurately seperated from single-station seismograms in a data-driven manner. We need to re-think the way we use EQ recordinngs whenever available;

- ❑ We need, at least, single-station earthquake recordings to accurately characerize site-specific amplification in a broad frequency range. If we have something short of earthquake reocordings, we shall live with a higher level of uncertainty in our prediction, then uncertainty quantification is the key;

Japan: A Natural Laboratory

- ☐ A large quantiy and high quality data (~2000 SM stations with inter-station distance < 20 km)



The 6th IASPEI / IAEE International Symposium: Effects of Surface Geology on Seismic Motion
August 2021

K-NET AND KIK-NET DATA: A UNIQUE TOOL FOR IMPROVED GROUND-MOTION MODELLING

Marco Pilz[1], Annabel Haendel[2], Sreeram R. Kotha[3], Karina Loviknes[4], Graeme Weatherill[5], Chuanbin Zhu[6] and Fabrice Cotton[7]

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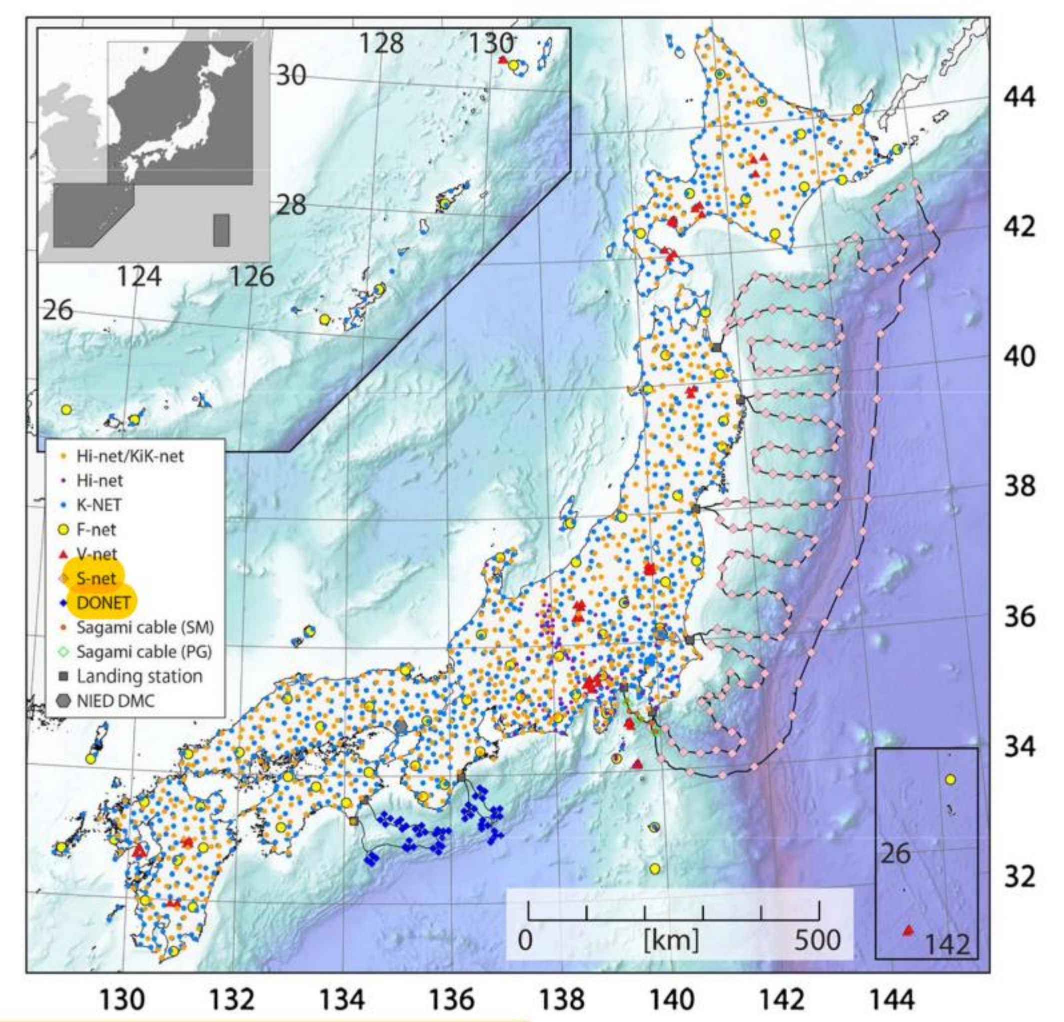
6 German Research Center for Geosciences GFZ, Potsdam, Germany (chuanbin@gfz-potsdam.de)
7 German Research Center for Geosciences GFZ and University of Potsdam, Potsdam, Germany (fcotton@gfz-potsdam.de)

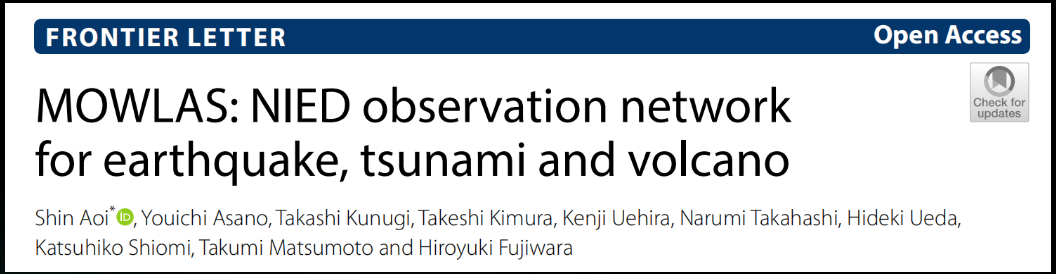


Aoi et al. (2020)

Japan: A Natural Laboratory

☐ Easy to use (NIED website and three papers)

Network



FRONTIER LETTER Open Access

Check for updates

MOWLAS: NIED observation network for earthquake, tsunami and volcano

Shin Aoi*, Youichi Asano, Takashi Kunugi, Takeshi Kimura, Kenji Uehira, Narumi Takahashi, Hideki Ueda, Katsuhiko Shiomi, Takumi Matsumoto and Hiroyuki Fujiwara

Ground motion database

Research Paper

EERI EARTHQUAKE SPECTRA

An updated database for ground motion parameters for KiK-net records

Earthquake Spectra
2021, Vol. 37(1) 505–522
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DOI: 10.1177/8755293020952447
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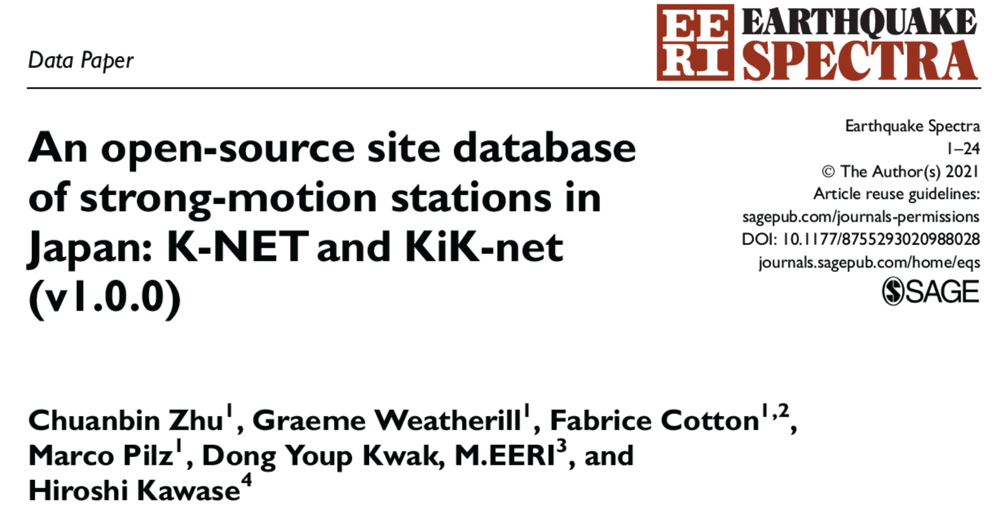
Mahdi Bahrampouri, M.EERI[1], Adrian Rodriguez-Marek, M.EERI[1], Shrey Shahi[2], and Haitham Dawood[3]

Site database



Data Paper

EERI EARTHQUAKE SPECTRA

An open-source site database of strong-motion stations in Japan: K-NET and KiK-net (v1.0.0)

Earthquake Spectra
1–24
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DOI: 10.1177/8755293020988028
journals.sagepub.com/home/eqs
SAGE

Chuanbin Zhu[1], Graeme Weatherill[1], Fabrice Cotton[1,2], Marco Pilz[1], Dong Youp Kwak, M.EERI[3], and Hiroshi Kawase[4]

NZ: A Natural Laboratory

- ❑ NZ NSHM project

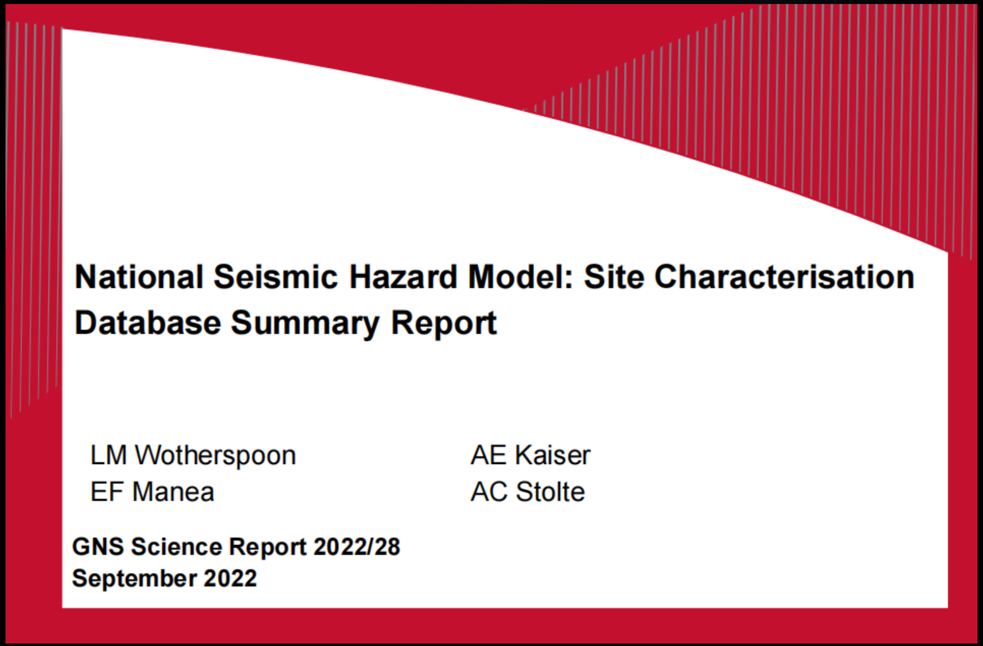
Ground motion database

2021 New Zealand Ground-Motion Database

J Hutchinson
LM Wotherspoon
J Motha
BA Bradley
M Dupuis
AE Kaiser
RL Lee
C Schill
EF Manea

GNS Science Report 2021/56
September 2022

Site database



National Seismic Hazard Model: Site Characterisation Database Summary Report

LM Wotherspoon
EF Manea
AE Kaiser
AC Stolte

GNS Science Report 2022/28
September 2022

1D GRA in NZ

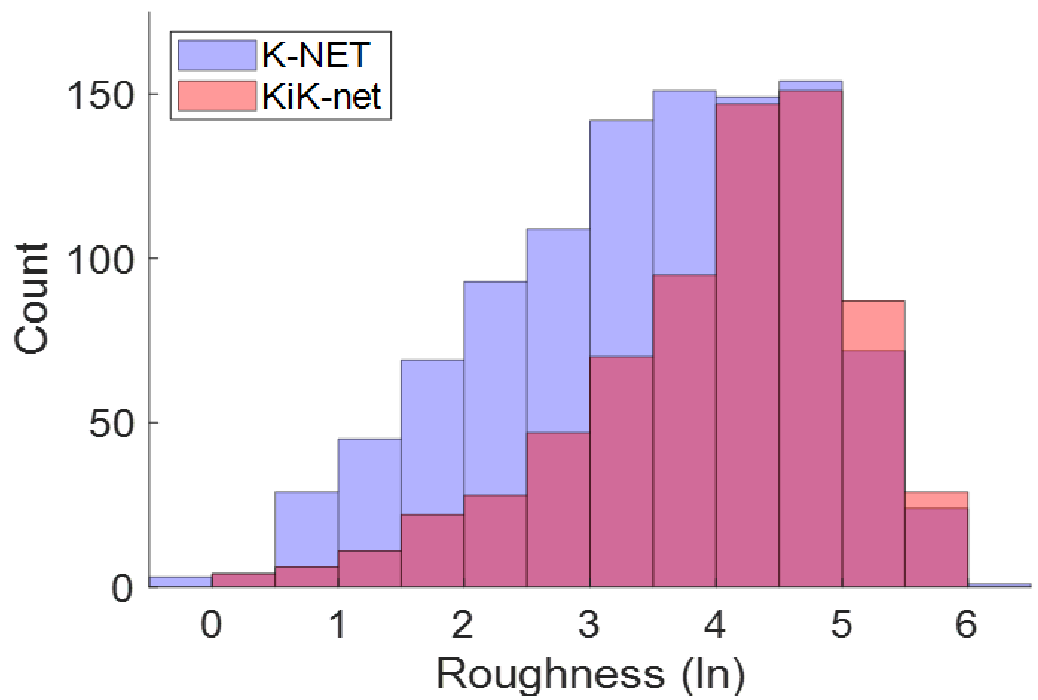
Effectiveness of 1D GRA at KiK-net sites, Japan.

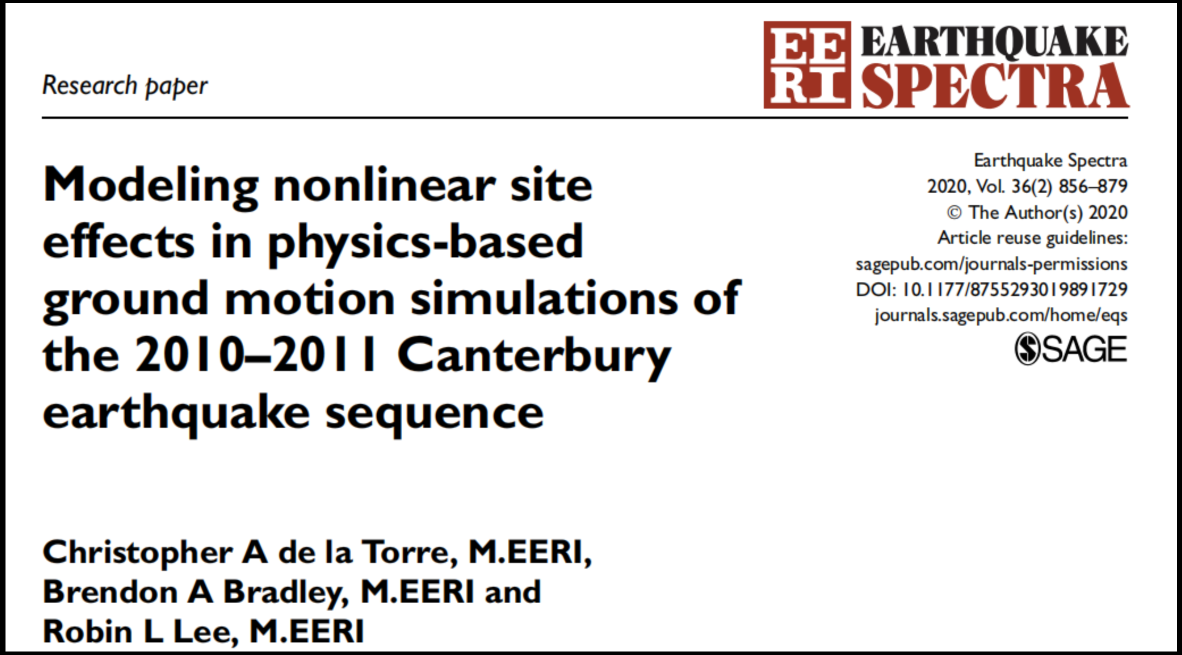
GRA	Reference	Observation	No. of sites	Good match	Success rate
TTF_{base}	Zhu et al. (2021)	GIT	145	r > 0.6	**41%**
TTF_{rnd}	**Zhu et al. (2020)**	**SBSR**	**90**	**r > 0.6**	**27%**
TTF_{base}	Zhu et al. (2020)	SBSR	90	r > 0.6	16%
TTF	Kaklamanos & Bradley (2018)	SBSR	114	r > 0.6	18%
TTF	Thompson et al. (2012)	SBSR	100	r > 0.6	18%

Outcrop

Borehole

1D GRA in NZ




Research paper

EARTHQUAKE SPECTRA

Earthquake Spectra
2020, Vol. 36(2) 856–879

DOI: 10.1177/8755293019891729
journals.sagepub.com/home/eqs
SAGE

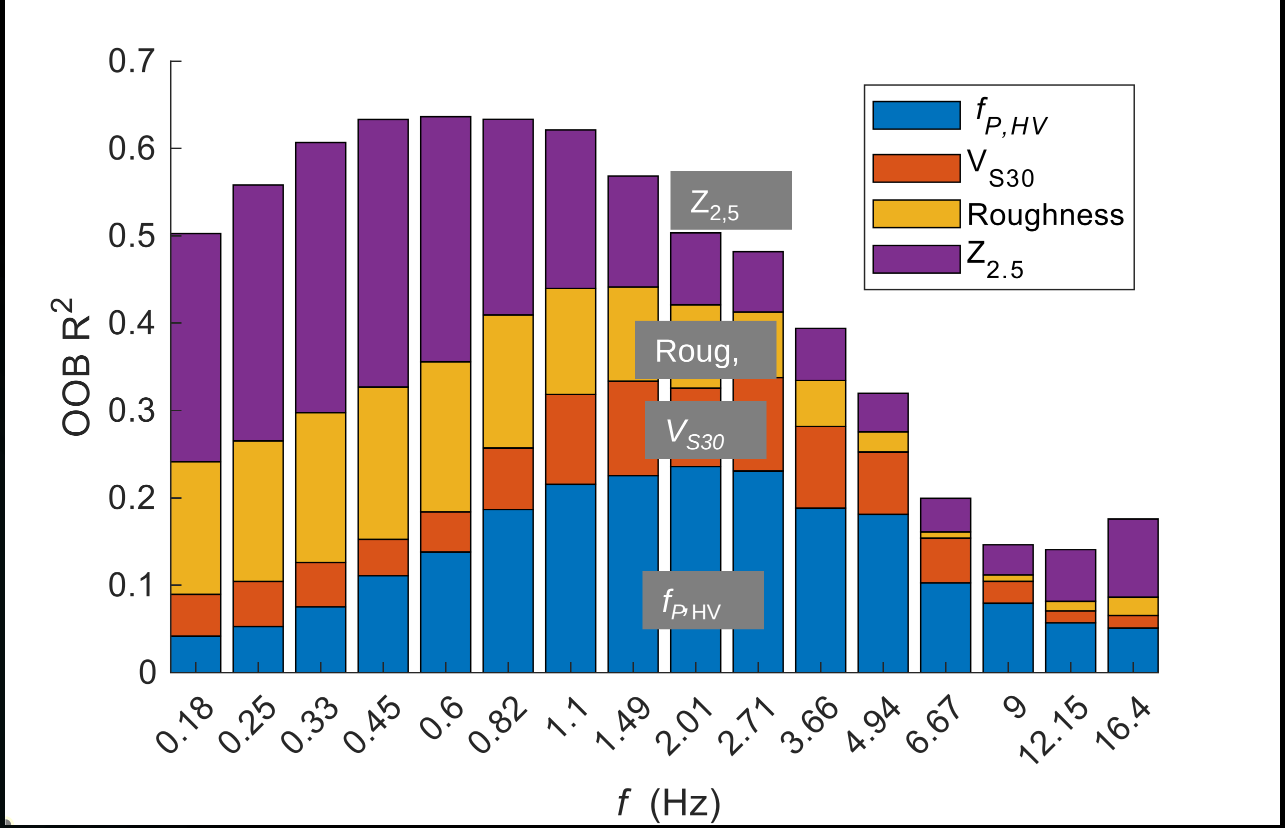
Modeling nonlinear site effects in physics-based ground motion simulations of the 2010–2011 Canterbury earthquake sequence

**Christopher A de la Torre, M.EERI,
Brendon A Bradley, M.EERI and
Robin L Lee, M.EERI**

- KiK-net sites tend to be stiffer and rougher than K-NET sites;
- 1D GRA performs less well at stiffer and rougher sites;
- KiK-net site conditions are less favorable for 1D GRA than K-NET;
- More studies are needed using sites other than KiK-net sites.

Empirical Modelling in NZ

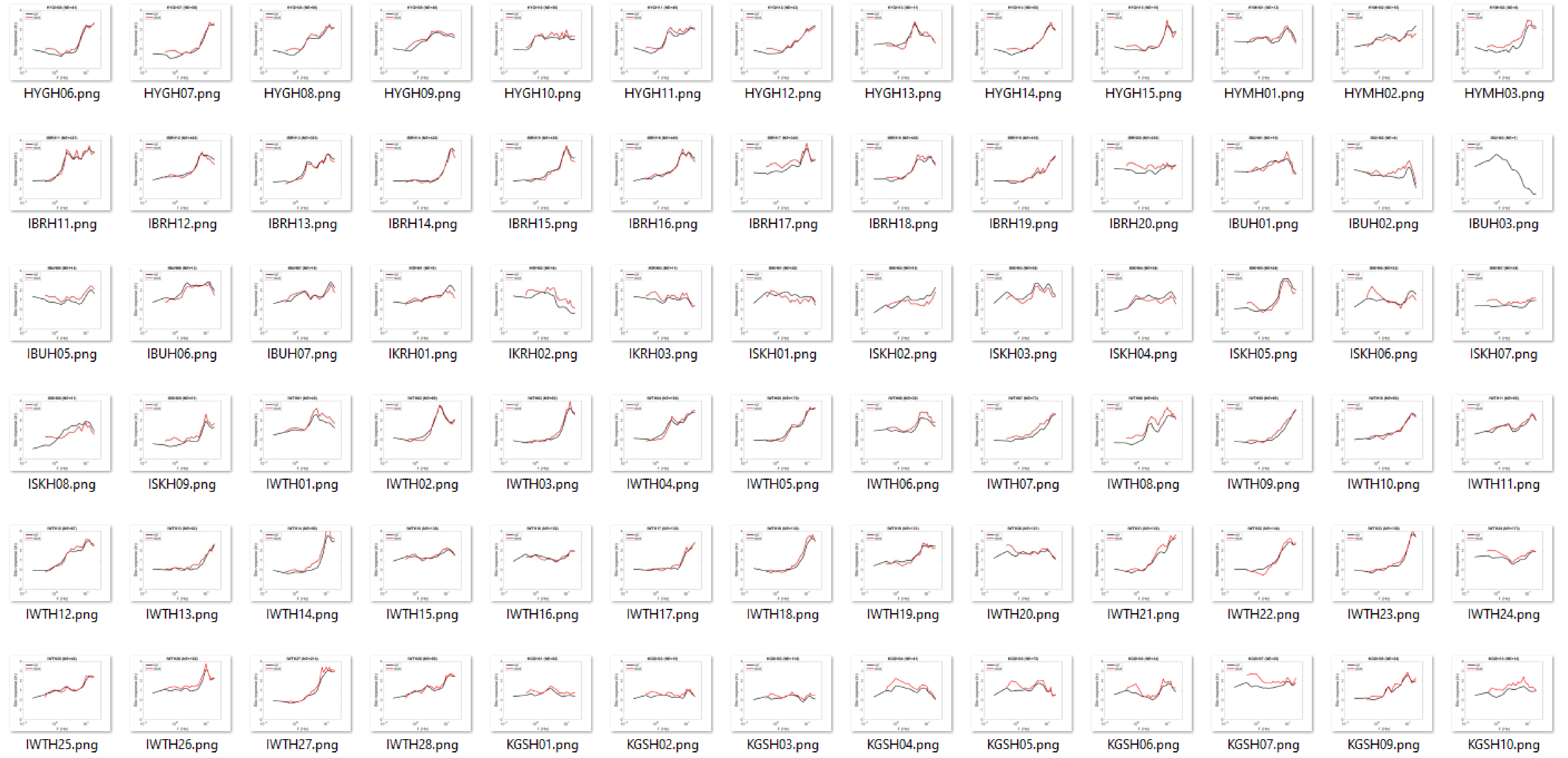
Relative predictor importance of RF6 (roug., f_p, V_{S30}, $Z_{2.5}$)



- ☐ What is/are the best predictor(s) for NZ?

Site Response in JP

Nakano et al. (2105, BSSA)



HYGH06.png HYGH07.png HYGH08.png HYGH09.png HYGH10.png HYGH11.png HYGH12.png HYGH13.png HYGH14.png HYGH15.png HYMH01.png HYMH02.png HYMH03.png

IBRH11.png IBRH12.png IBRH13.png IBRH14.png IBRH15.png IBRH16.png IBRH17.png IBRH18.png IBRH19.png IBRH20.png IBUH01.png IBUH02.png IBUH03.png

IBUH05.png IBUH06.png IBUH07.png IKRH01.png IKRH02.png IKRH03.png ISKH01.png ISKH02.png ISKH03.png ISKH04.png ISKH05.png ISKH06.png ISKH07.png

ISKH08.png ISKH09.png IWTH01.png IWTH02.png IWTH03.png IWTH04.png IWTH05.png IWTH06.png IWTH07.png IWTH08.png IWTH09.png IWTH10.png IWTH11.png

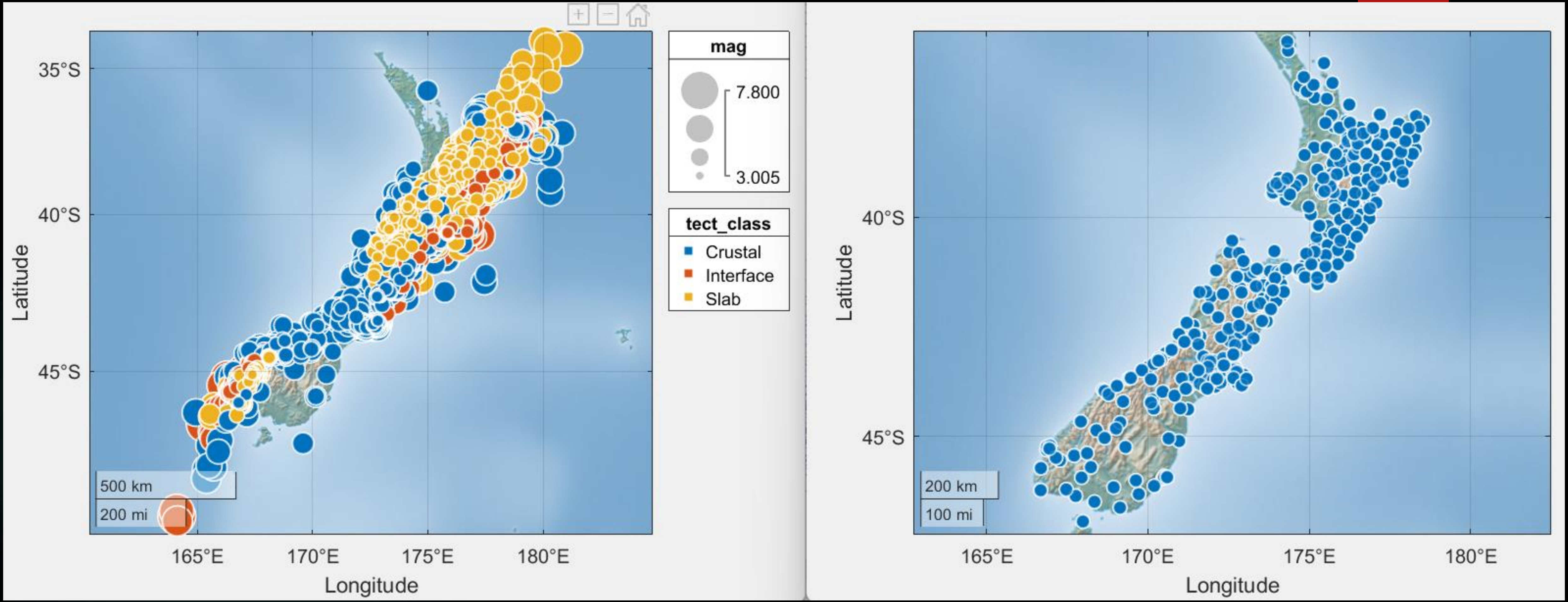
IWTH12.png IWTH13.png IWTH14.png IWTH15.png IWTH16.png IWTH17.png IWTH18.png IWTH19.png IWTH20.png IWTH21.png IWTH22.png IWTH23.png IWTH24.png

IWTH25.png IWTH26.png IWTH27.png IWTH28.png KGSH01.png KGSH02.png KGSH03.png KGSH04.png KGSH05.png KGSH06.png KGSH07.png KGSH09.png KGSH10.png

Site Response in NZ

Lee et al. (2022, ES)

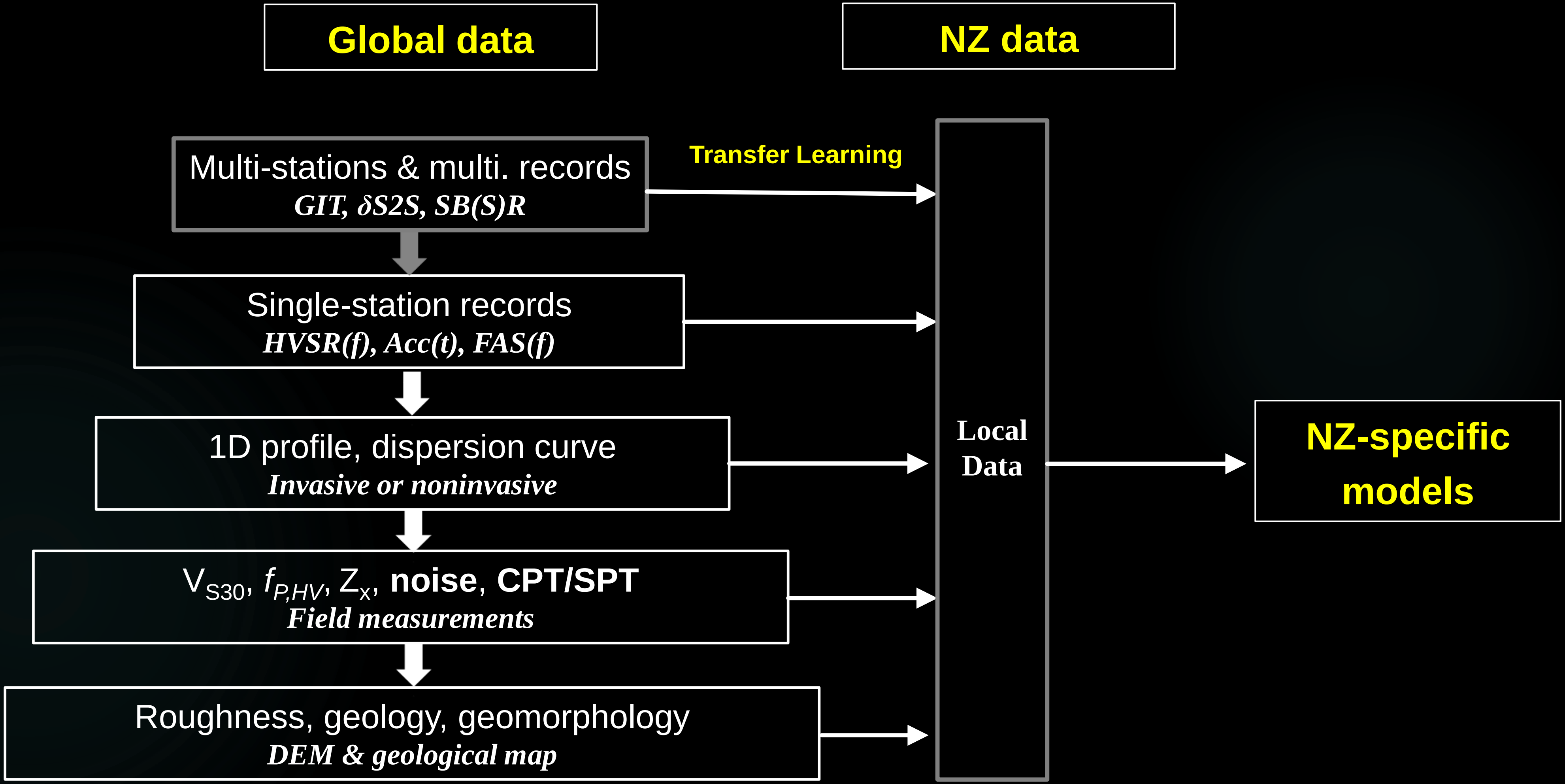
AI in NZ



After data selection:

- ☐ No. of total, crustal, slab and interface events: 2826, 1403, 938, 485
- ☐ No. of sites: 521

AI in NZ



Global data

NZ data

Multi-stations & multi. records
GIT, δS2S, SB(S)R

Transfer Learning

Single-station records
HVSR(f), Acc(t), FAS(f)

1D profile, dispersion curve
Invasive or noninvasive

V_{S30}, $f_{P,HV}$, Z_x, **noise**, **CPT/SPT**
Field measurements

Roughness, geology, geomorphology
DEM & geological map

Local Data

NZ-specific models

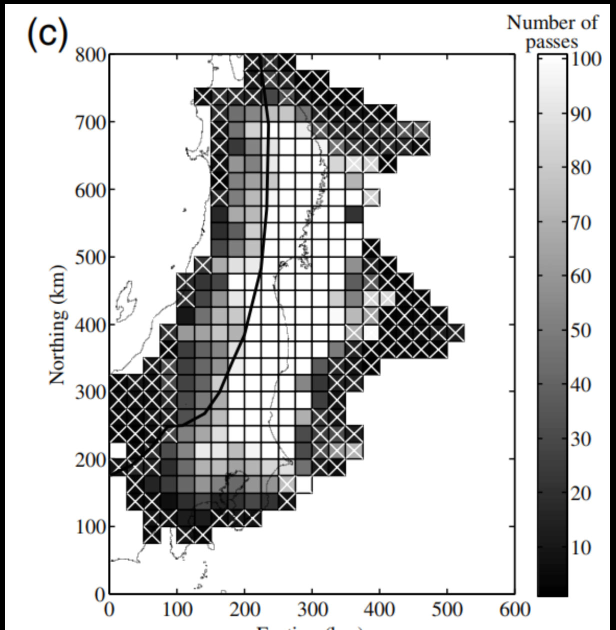
From Single-Site to Single-Path in NZ?

$$\ln H_{i,j}(f) = \ln E_i(f) + \boxed{\ln P_{i,j}(f,R)} + \ln S_j(f)$$

Tectonic class
Region-independent

Cell-based single-path analysis (2D attenuation):

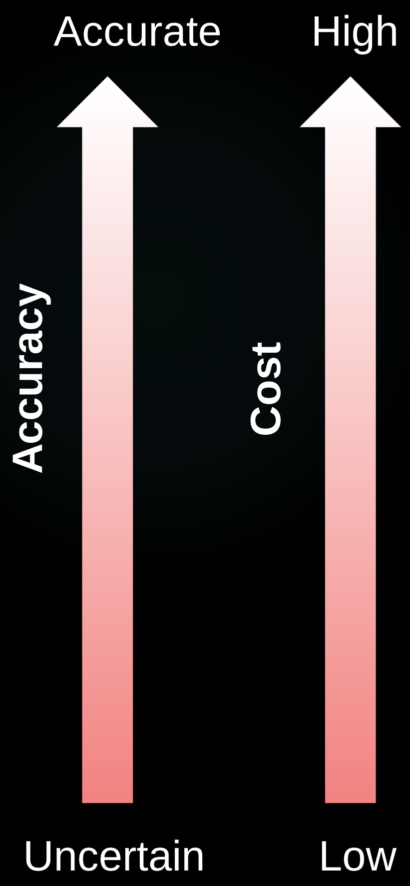
$$\boldsymbol{residual = FAS_{obs} - FAS_{GIT}}$$



Dawood and Rodriguez-Marek (2013, BSSA)

Final Remark

Site-specific amplification characterization is an engineering question, and its prediction accuracy depends on how much we would like to invest (cheap topo proxy - highly uncertain, single-station records – highly accurate). The question might be how to achieve the required level of accuracy with lower costs.



Accurate

High

Accuracy

Cost

Uncertain

Low

Thank you !