Constraining Earthquake Stress Drop Methods Using Point-Source Simulations for the Community Stress Drop Validation Study

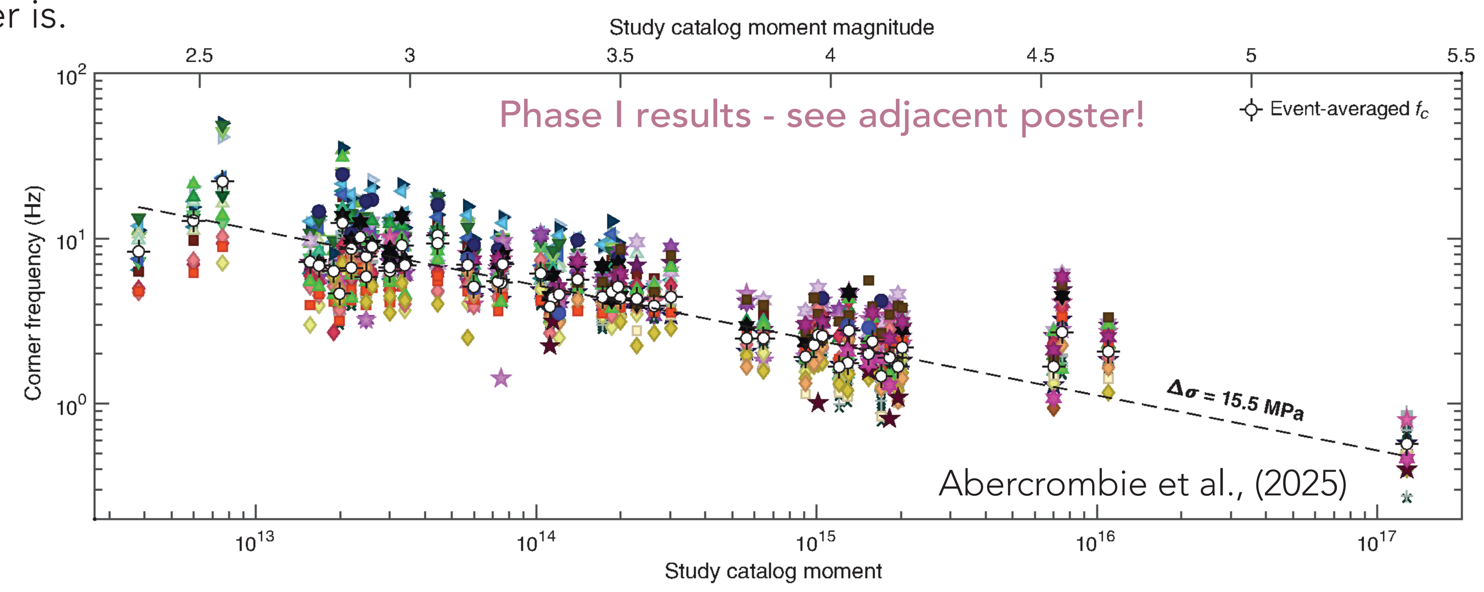
Annemarie Baltay (USGS Moffett Field; abaltay@usgs.gov), Rachel Abercrombie (Boston University), Dino Bindi (GFZ), Peter Shearer (UCSD) & Chen Ji (UCSB)

USGS science for a changing world — BOSTON UNIVERSITY — SCEC

poster B122

Verifying earthquake source parameters using synthetic data

The Problem: Comparisons of fitted corner frequencies (f_c) from the Ridgecrest Study show lots of variability. Difficult to know where differences arise when we don't know what the "CORRECT" answer is.



The Solution? Set up a simple experiment with known source, path, site inputs to test recovery of point-source inputs and method verification.

"Blind" Experiment: Synthetic datasets distributed without giving input parameters -- results were unveiled at a recent workshop. Should future experiments be fully blind? Double blind?

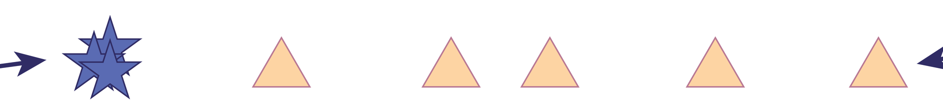
Considerations: How to define noise, randomness, complexity in synthetics? How correlated should sources or sites be? How much complexity in the source, path, or site?

What are we testing? Balance simplicity and knowable inputs with more realistic parameterization. Simplist case: Low/no source, path, site complexity, can we recover input fc? Then add source, path, site complexity to test how these affect the estimates. Create synthetics with different iterations of input sources, velocity structure, etc. to carefully resolve tradeoffs.

The Ultimate Goal: Increase complexity of synthetic experiments to test real-world inputs and tradeoffs using kinematic or dynamic rupture scenarios

Synthetic Experiment One: Starting simple

Experimental Set-Up



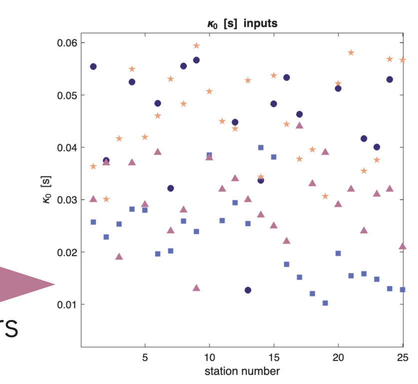
sources: 50 co-located earthquakes, **M** 1.5 - 6; random parameters (f_c, etc) set by developer

sites: 25 stations, 0 - 70km distance. random parameters (V_{s30}, κ_0) set by each developer

path: parameters (Q, etc) set by developer; different kinds of noise, complexity

records: Fourier amplitude spectra provided in simple csv text format

Input site parameters



Four Synthetic Datasets

Four developers/methods each start with point-source, Brune- like source spectra, and then convolve with path and site.

$$u(f) = \frac{M_0}{\left[1+\left(\frac{f}{f_c}\right)^{n\gamma}\right]^{1/\gamma}} \frac{1}{R} \exp(-\pi f \kappa_0)$$

Brune: n=2, γ=1

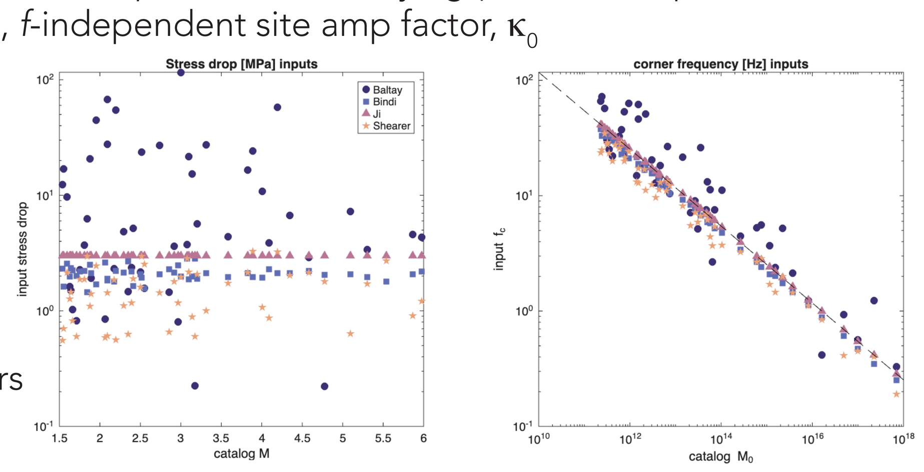
Baltay: Uses SMSIM (Boore, 2003) with random $\Delta\sigma$, constant 1D Q, κ_0, f-dependent site amp, stochastic randomness per record.

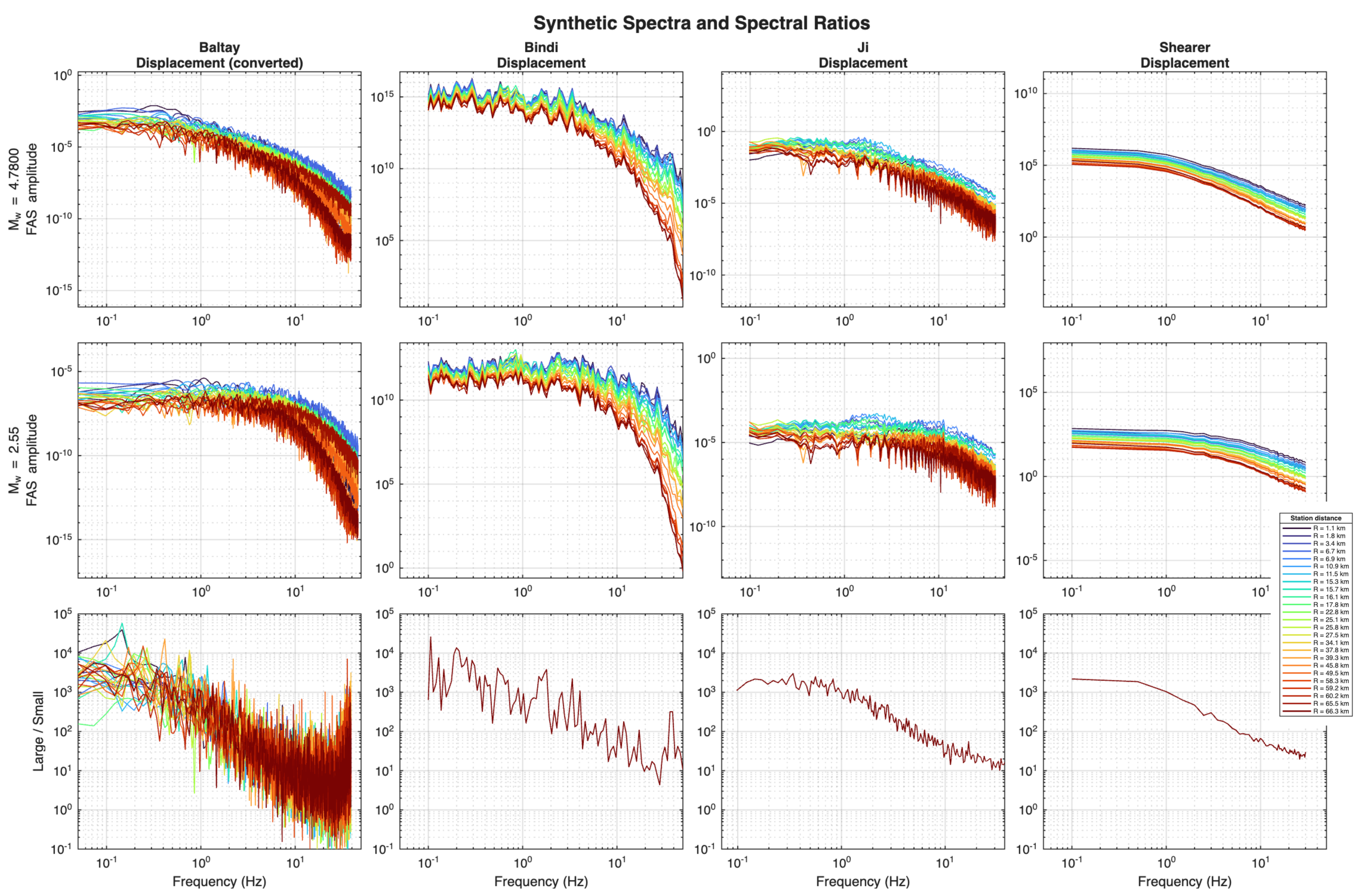
Bindi: Random $\Delta\sigma$ and correlated per- event noise, 1D layered velocity and Q , κ_0,1D site resonance

Ji: Constant stress drop and perturbation, 1D layered SH velocity structure (not strictly 1/R) + isotropic Q(f)=100$f^{0.8}$, Vs30-dependent site amplification (Boore 2016) + κ_0 decay + site perturbations

Shearer: Brune spectrum with varying γ (corner shape) and n (falloff), 1D Q, f-independent site amp factor, κ_0

Input source parameters

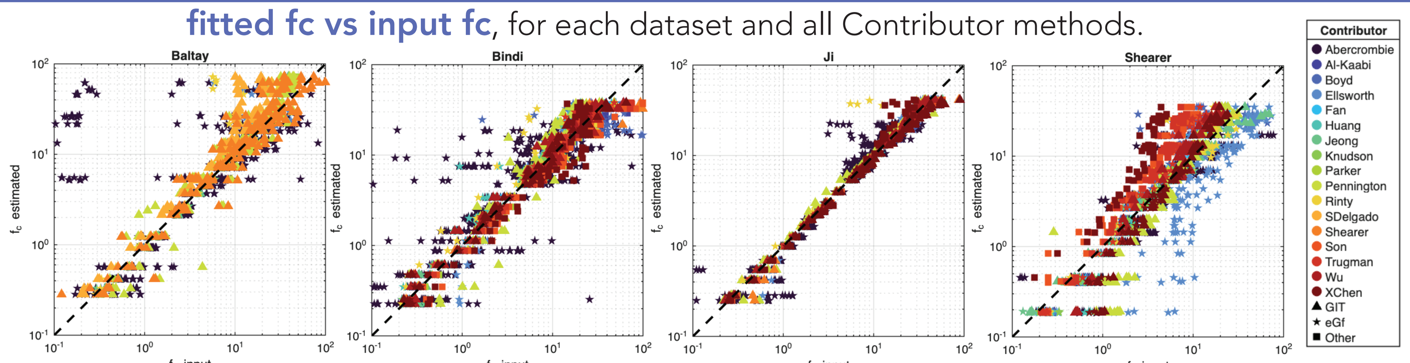




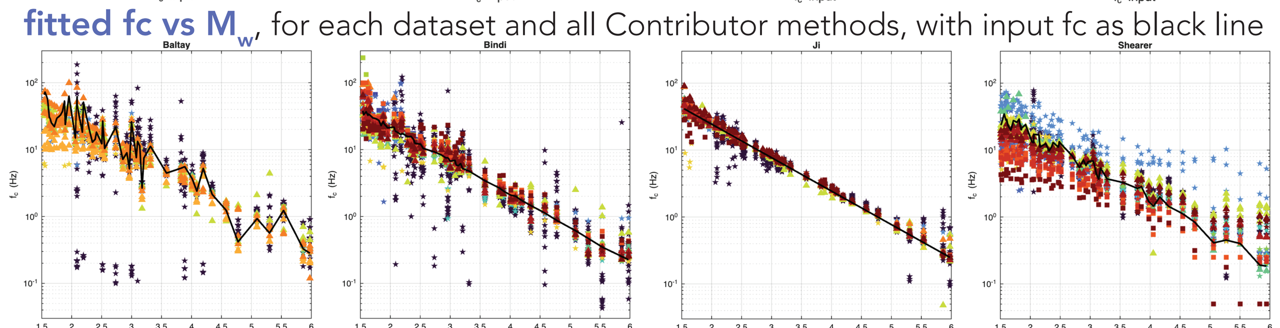
Comparison of submitted f_c and κ_0 results: Effect of different methods and different datasets

Thank you to our 18 Contributors for analyzing synthetics and sharing results!

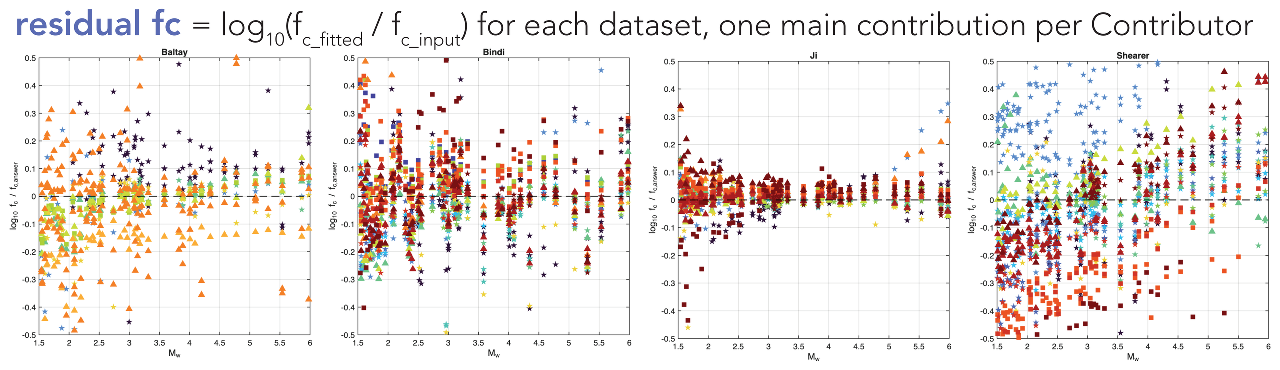
fitted fc vs input fc, for each dataset and all Contributor methods.



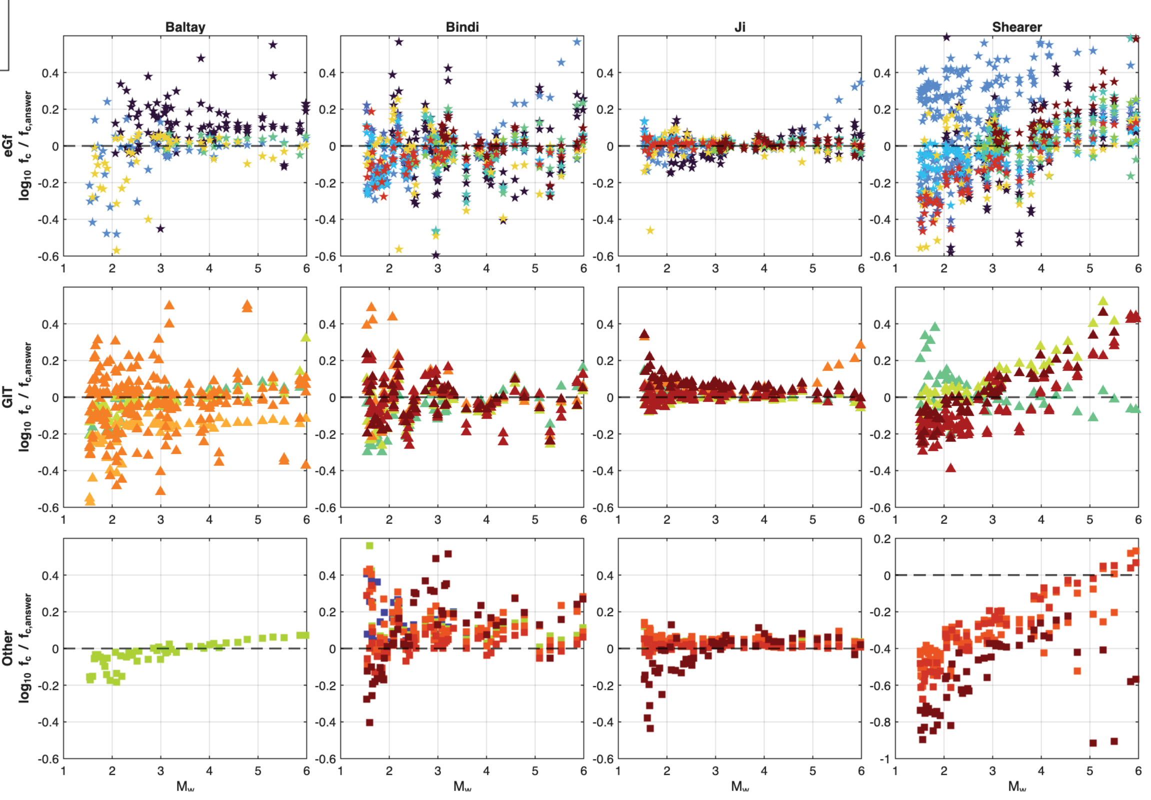
fitted fc vs M_w, for each dataset and all Contributor methods, with input fc as black line



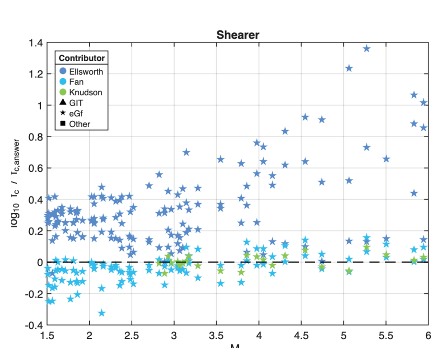
residual fc = $\log_{10}(f_{c\_fitted} / f_{c\_input})$ for each dataset, one main contribution per Contributor



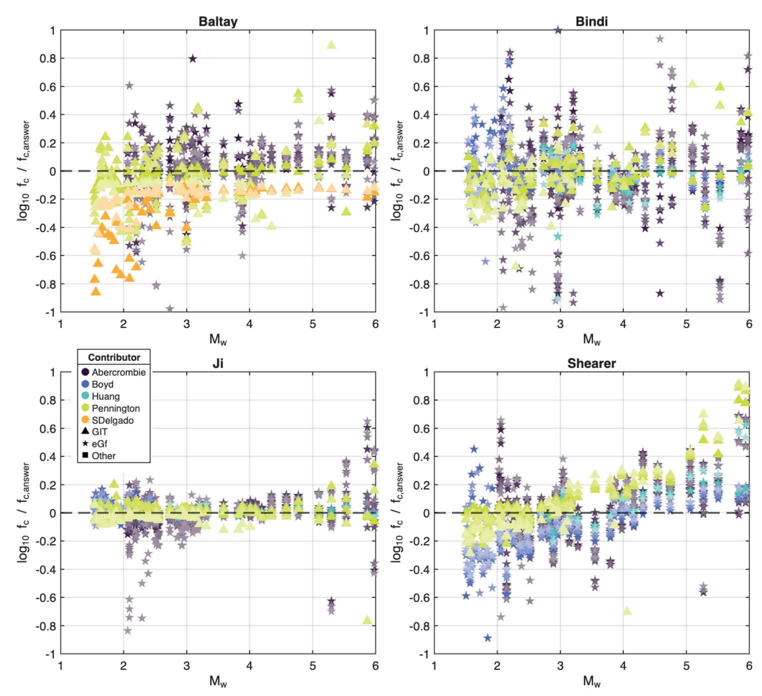
Comparison of different datasets highlights methodological tradeoffs and different assumptions in dataset development. Datasets that deviated from simple Brune models were harder to accurately fit. Shearer dataset has varied input n falloff rate, but most methods fixed n=2, greatly increasing scatter in fitted f_c. Most Contributors have best fit for Ji data, due to constant $\Delta\sigma$?



* all plots use same colors and symbology!



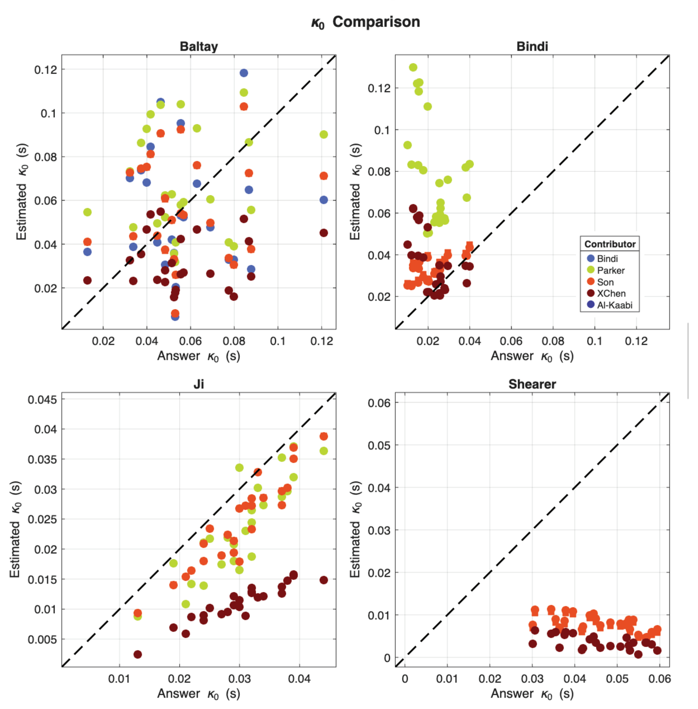
effect of varying n: Shearer dataset varied n per earthquake with average input of n=1.7. Knudson method fixed n=1.7 while Fan and Ellsworth methods allowed n as a free parameter. Some of these recover the true fc better than those that fixed n=2.



residual fc = $\log_{10}(f_{c\_fitted} / f_{c\_input})$ for each dataset, for Contributor methods that varied the fitted bandwidth, shown in different shades of each color

residual fc = $\log_{10}(f_{c\_fitted} / f_{c\_input})$ for each dataset, one main contribution per Contributor, grouped by method type: spectral ratio/eGf, spectral decomposition/GIT, or other (combination or ground-motion based). Different method types performed similarly, more dependent on dataset.

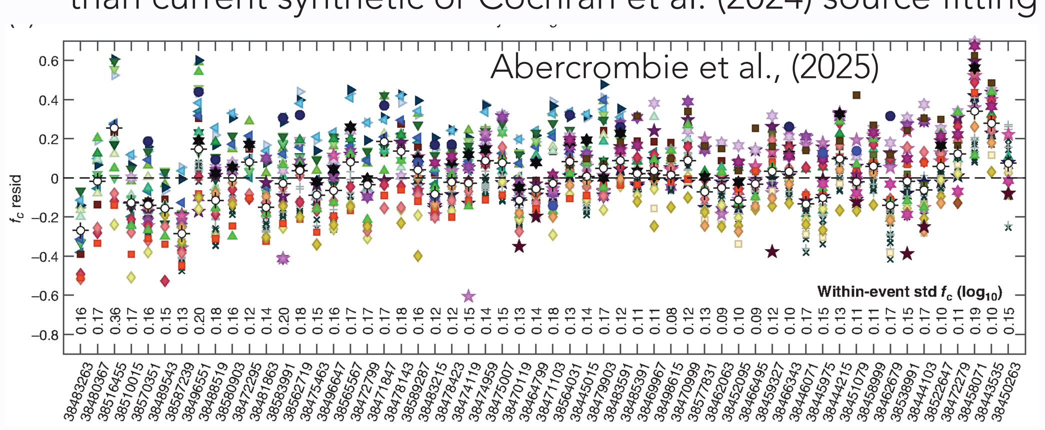
κ_0 comparison f-dependent amplification in Baltay dataset was difficult for Contributors to identify. Shearer smaller n falloff rate was misfit as weaker attenuation (smaller κ_0). Contributors were able to model Ji's κ_0 well perhaps due to relatively simpler FAS.

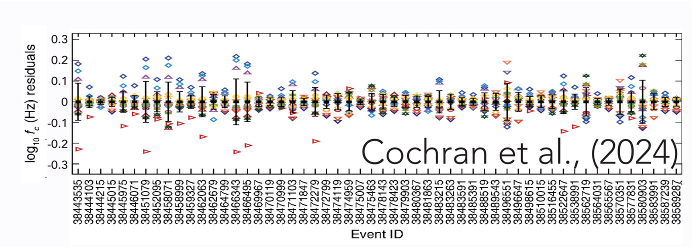


Method-to-method f_c variability compared to Ridgecrest study

Comparing inter-method variability as std(log10 fc).

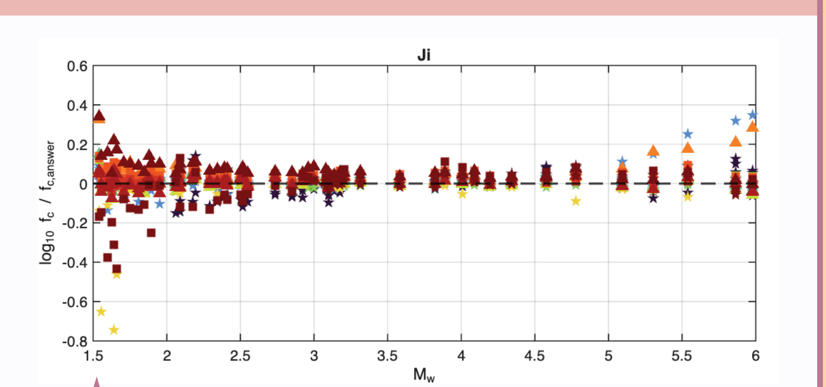
Full empirical Ridgecrest study shows much more variability than current synthetic or Cochran et al. (2024) source fitting



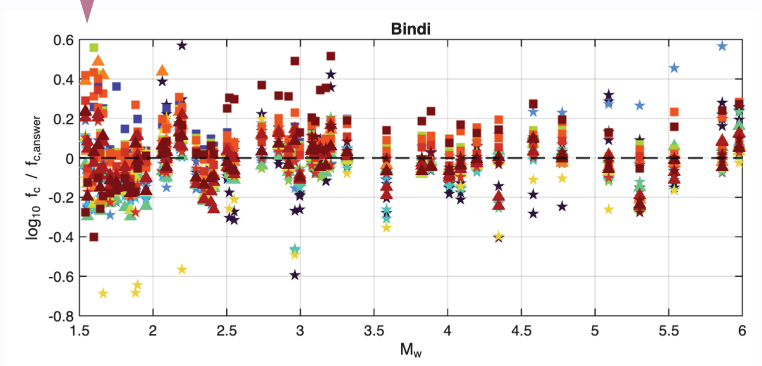


Cochran et al. (2024) tested variability due to source spectral fitting only. Less variable than current synthetic study.

*all on the same y-axis scale



Ji dataset yields lowest per-event variability. Bindi highest with similar assumptions.



Next steps

More with this Experiment One: Set up a simple experiment with known source, path, site inputs to test recovery of point-source inputs and rigourously compare source and site spectra. Consider tradeoffs in these parameters. What are the effects of limited bandwidth? How do we define noise, un-modelled complexity, etc? Now that inputs are known to Contributor analysts, what do you need to change in your method to get the "right" answer?

Iterate and add more real world complexity: How much source, site, path complexity of noise is necessary to create records or results that look like the real world? What should we test next - complex/compound sources? realistic velocity models? noisier sites?

Simulation method affects results: Continue to use a variety of synthetic datasets and consider goals for each experiment when designing synthetics

Join the mailing list!

Download synthetic data!

Many thanks to all who have participated in and encouraged the SCEC/USGS Community Stress Drop Validation TAG. Many thanks especially those who recently submitted results to the synthetic experiment: Daniel Trugman, Rachel Abercrombie, Susana Delgado Andino, Muntadher Al-Kaabi, Xiaowei Chen, Wenyuan Fan, Bill Ellsworth, Trey Knudson, Oliver Boyd, Yihe Huang, Peter Shearer, Dino Bindi, Qimin Wu, SeongJu Jeong, Colin Pennington, Minkyung Son, Grace Parker, Sadia Rinty

SCEC Awards 26018, 26069, 25134, 24067, 23107, 23108, 22034, 22042, 22101, 22027, 21032, 21045, 21083, 21114, 21169

Abercrombie, R. E., A. Baltay, S. Chu, T. Taira, D. Bindi, O. S. Boyd, X. Chen, E. S. Cochran, E. Devin, D. Dreger, et al. (2025). Overview of the SCEC/ USGS community stress drop validation study using the 2019 Ridgecrest earthquake sequence, Bull. Seismol. Soc. Am. doi:10.1785/0120240158.

Boore, D. M. (2003), Simulation of ground motion using the stochastic method, Pure Appl. Geophys. 160, no. 3, 635–676.

Cochran, E. S., A. Baltay, S. Chu, R. E. Abercrombie, D. Bindi, X. Chen, G. A. Parker, C. Pennington, P. M. Shearer, and D. T. Trugman (2024). SCEC/USGS community stress drop validation study: How Spectral fitting approaches influence measured source parameter, Bull. Seismol. Soc. doi: 10.1785/0120240140.