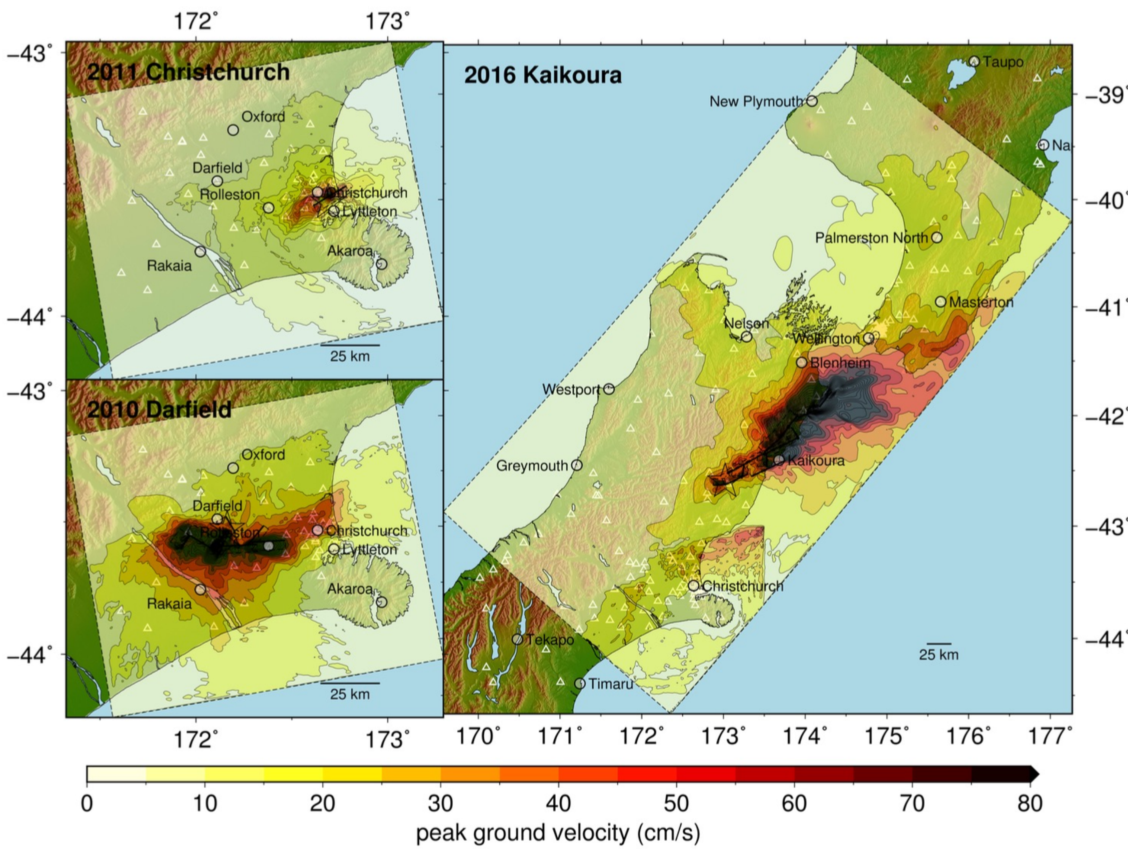
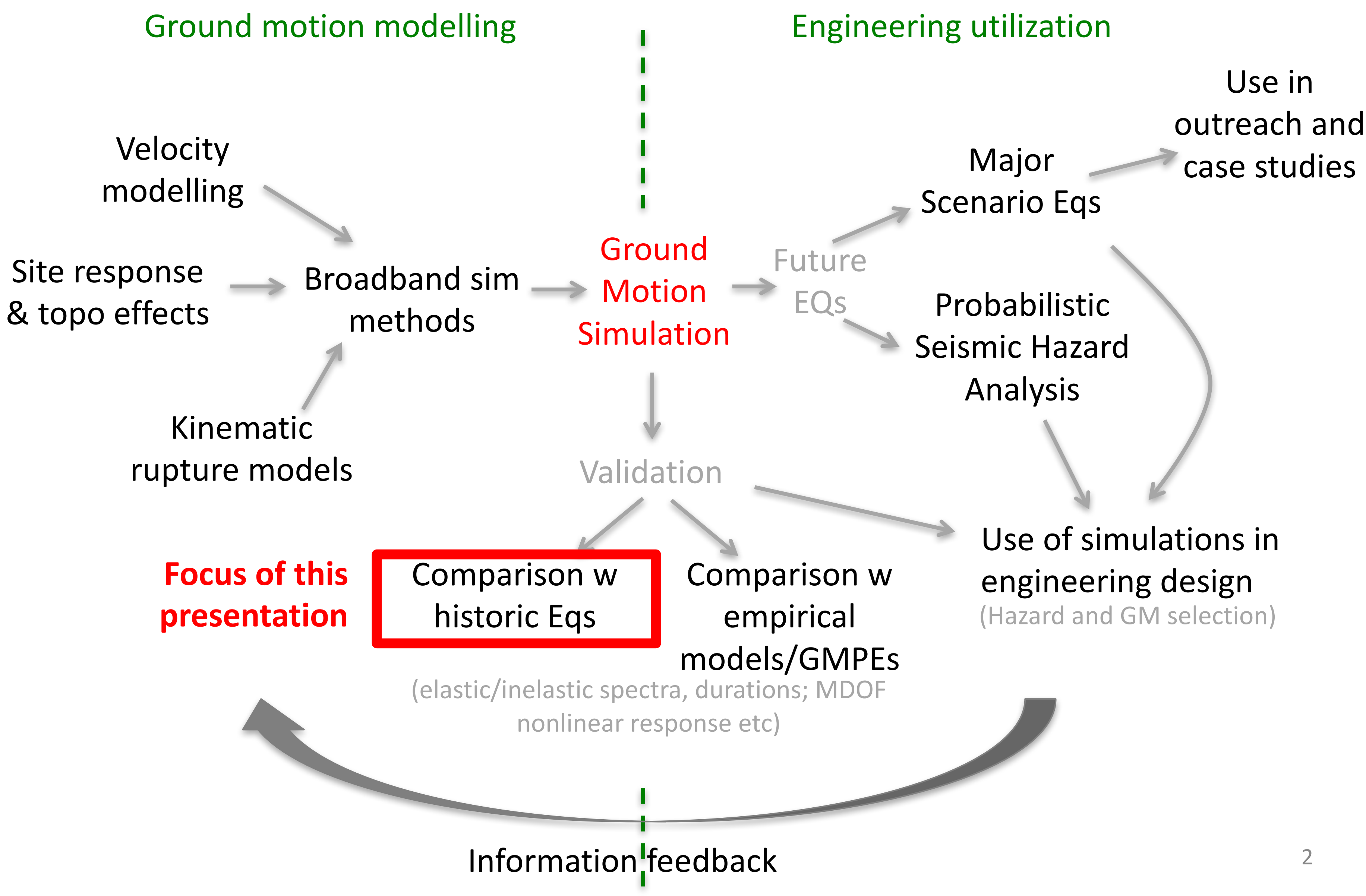
Validation of ground-motion simulations using large datasets in New Zealand

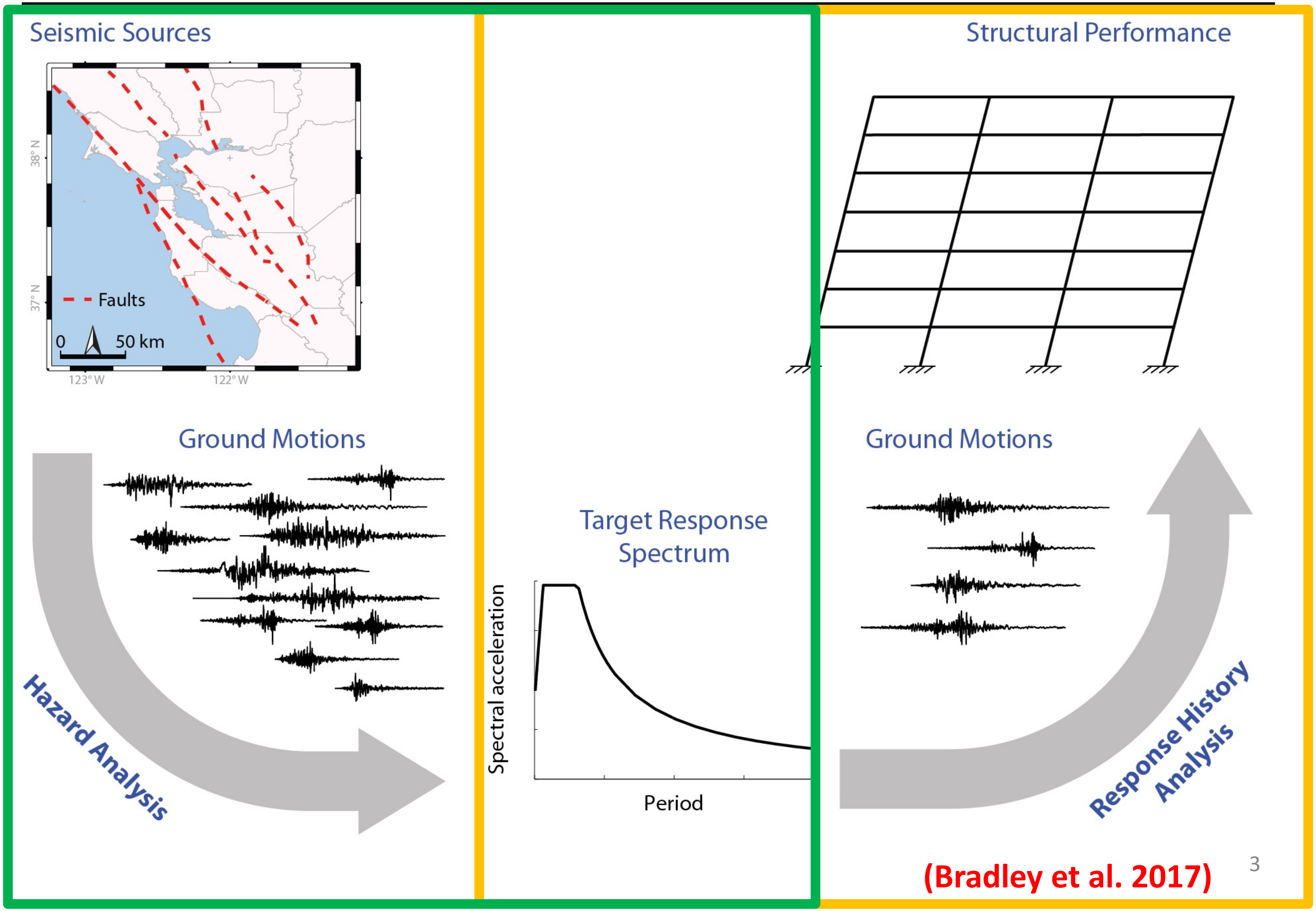


Brendon Bradley, University of Canterbury, New Zealand

Ground motion simulation validation



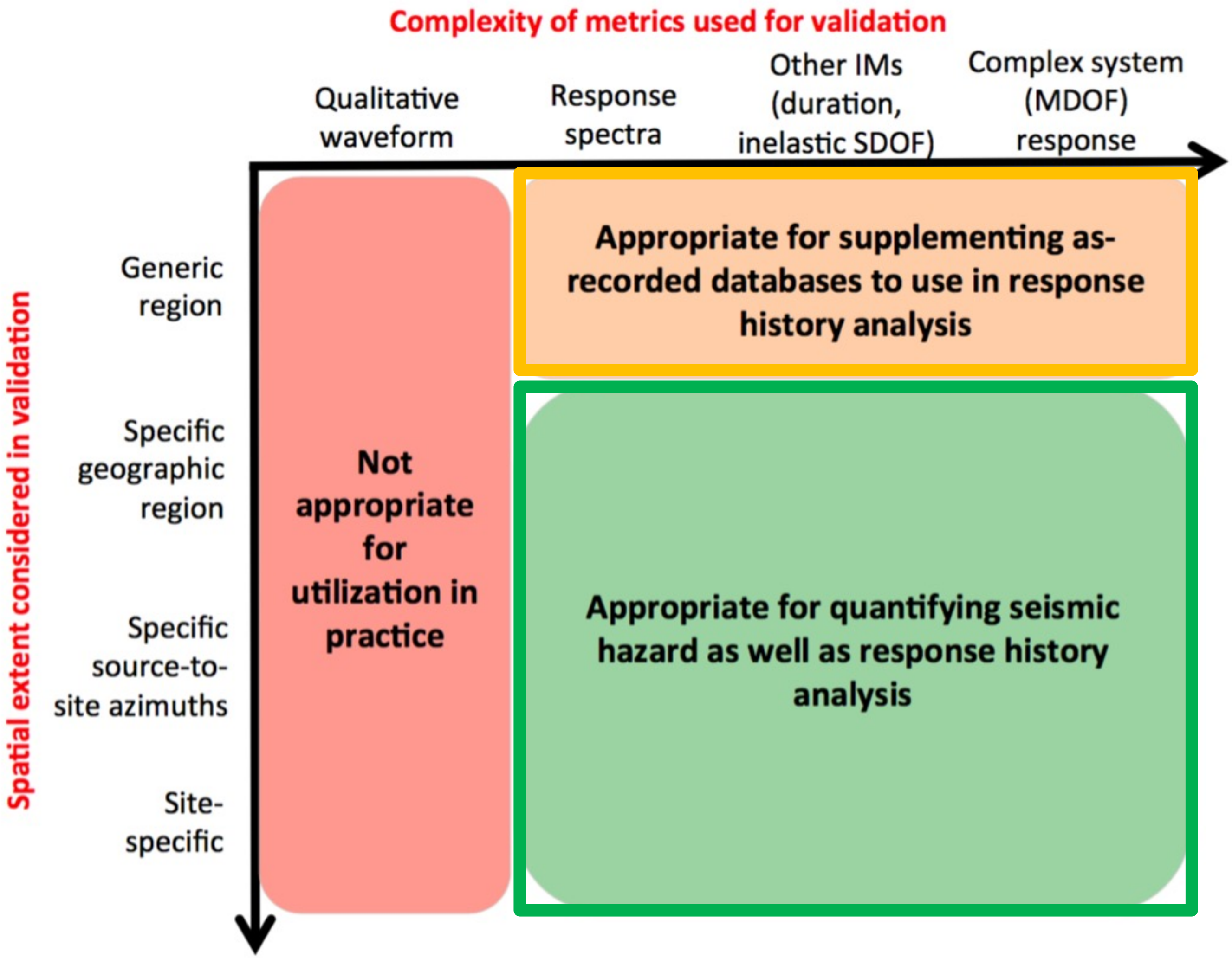
Dependence on use of simulations



(Bradley et al. 2017)

Validation and utilization guidance

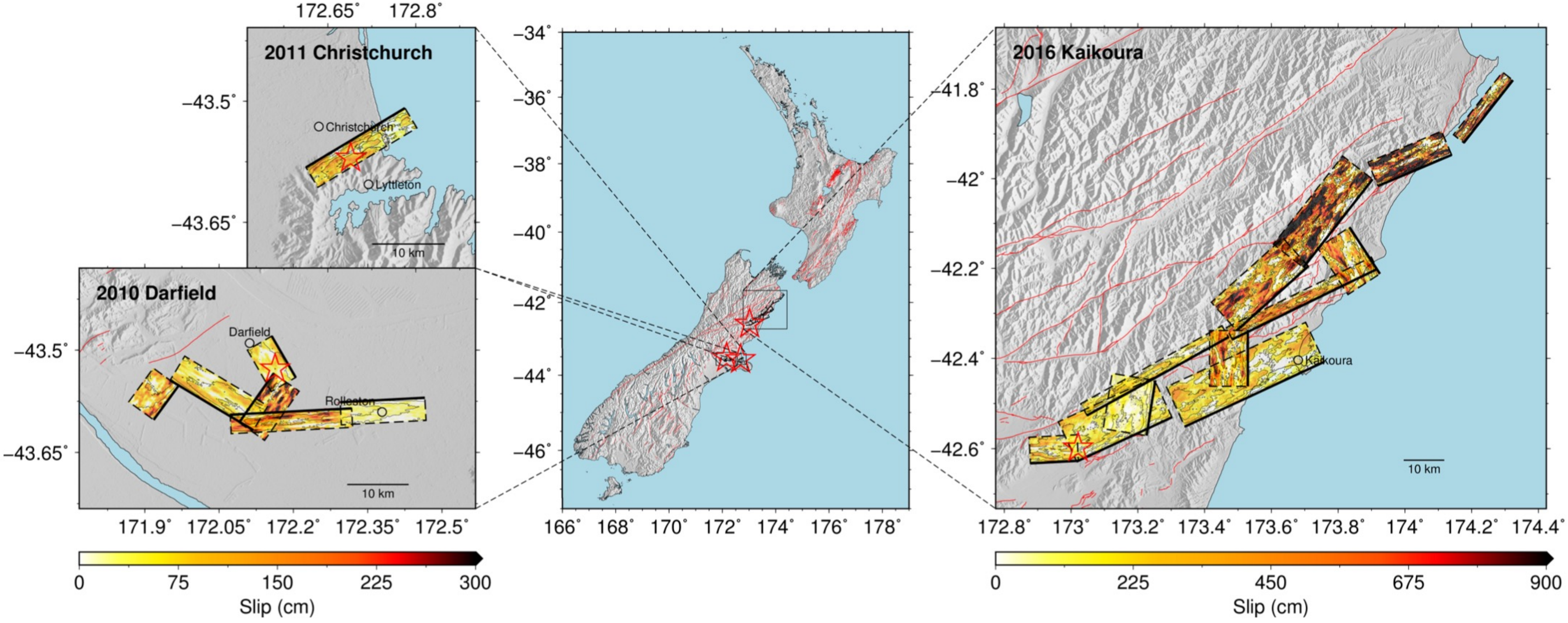
'Validation matrix' for simulation utilization



Bradley et al. (2017)

‘Conventional’ validation for individual earthquake events

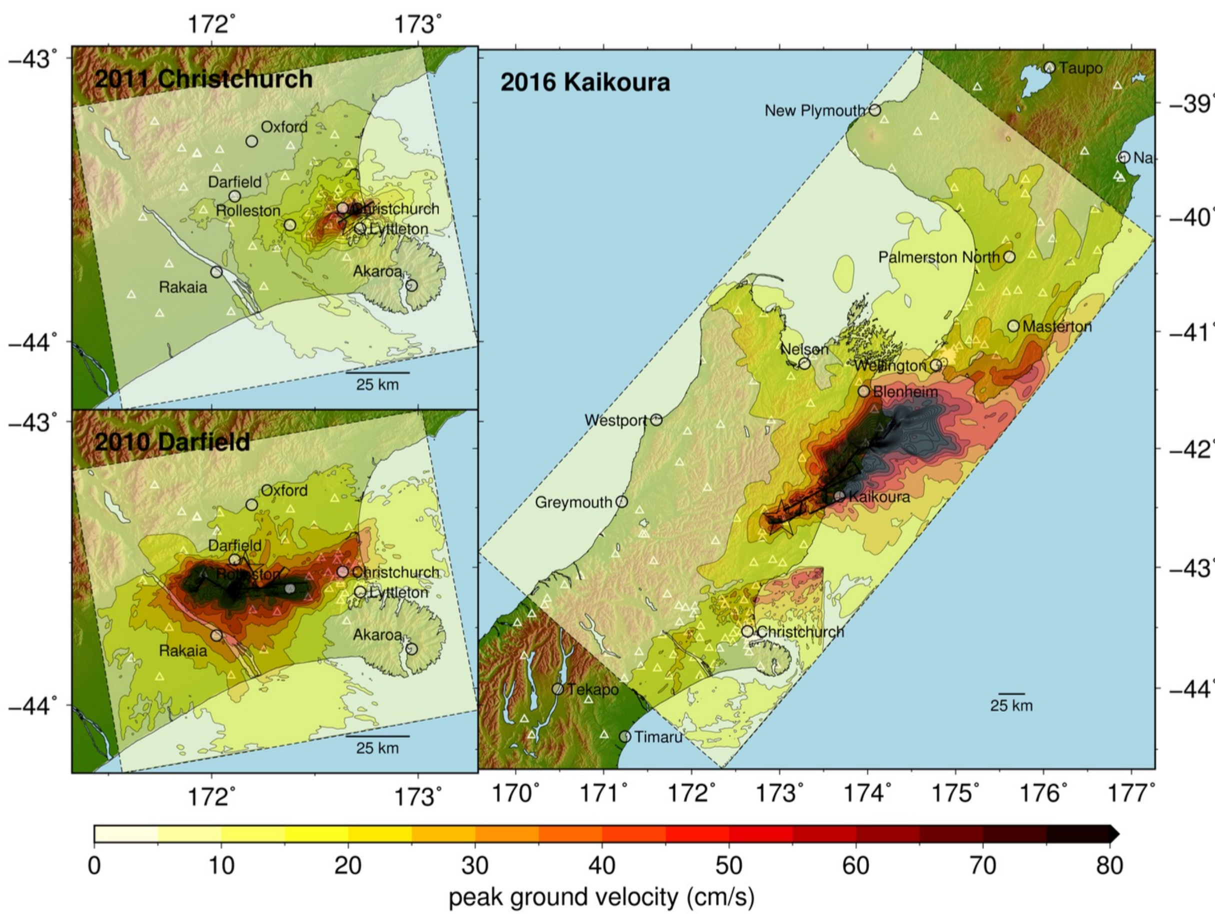
2010-2011 Canterbury and 2016 Kaikōura earthquakes



Bradley (2018)

2010-2011 Canterbury and 2016 Kaikōura earthquakes

All simulations utilize the same methodology and input parameters, with only rupture models and simulation domain varying between events

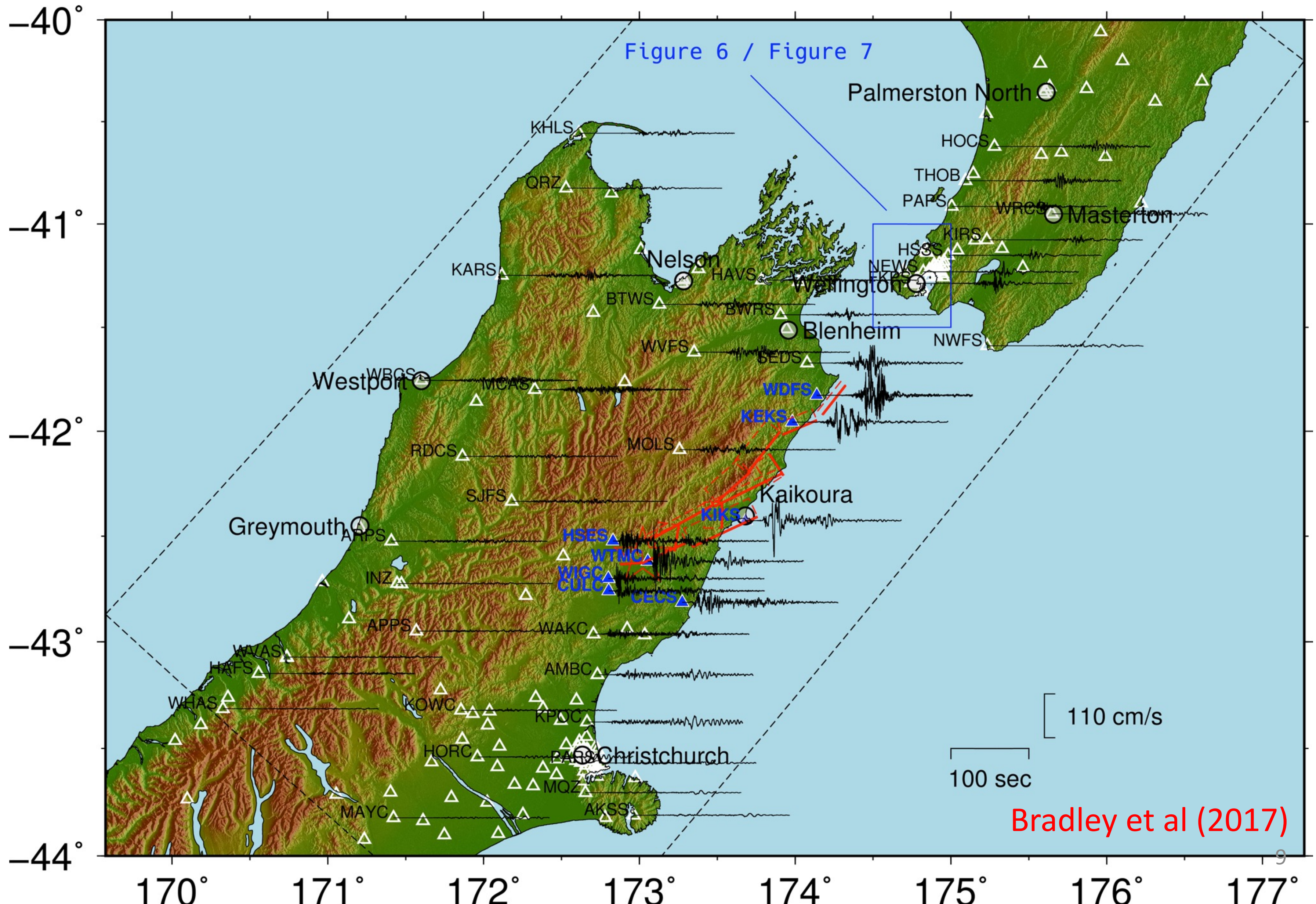


Bradley (2018)

Simulation method summary

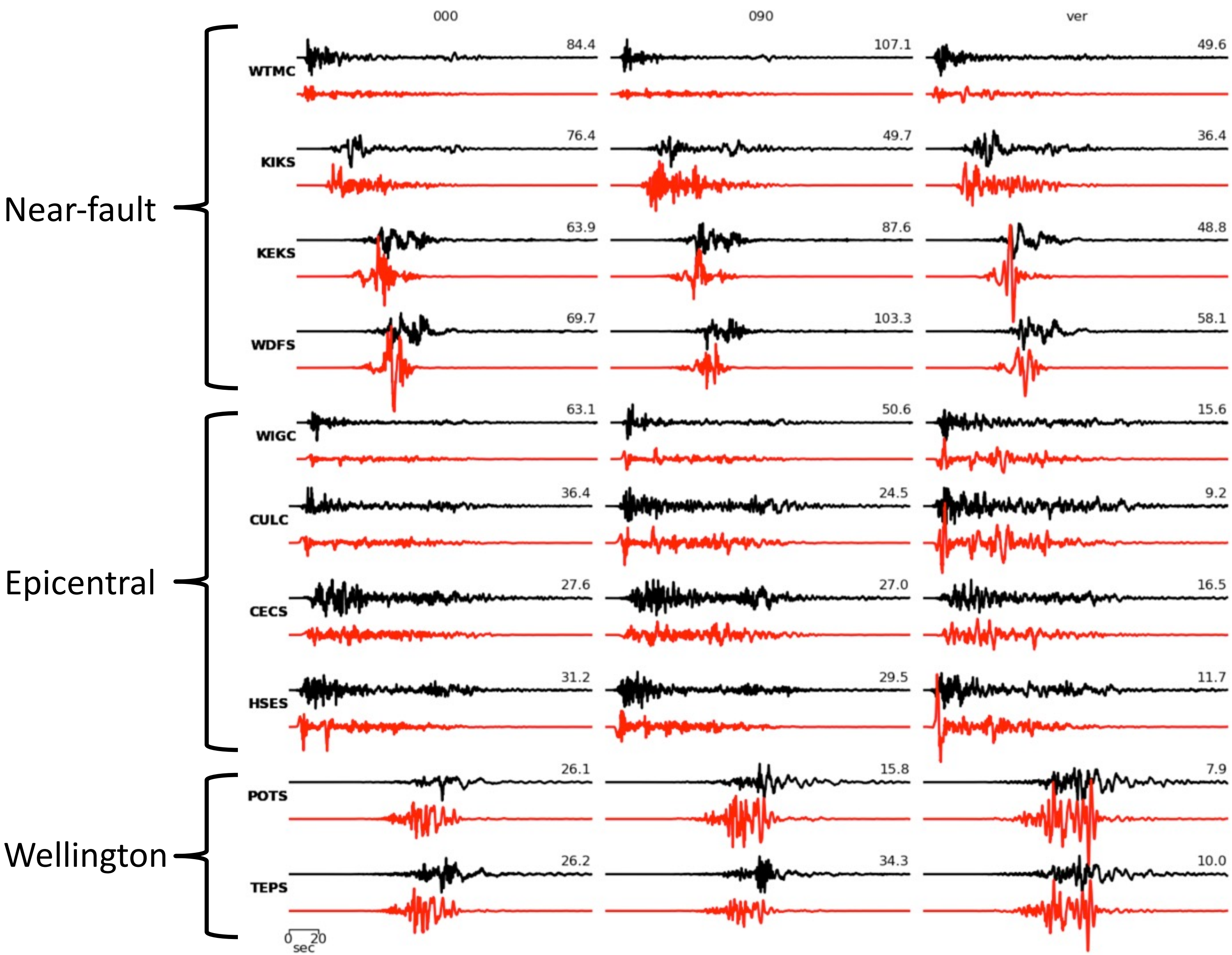
- Graves & Pitarka hybrid broadband approach
  - f=1Hz transition frequency
  - GP10,15,16 rupture generators used
- LF wavefield computed using 3D NZ Velocity model with ~20 sedimentary basins (100m spatial grid). No modification for shallow site effects
- HF wavefield using 1D VM. Vs30-based empirical site response (or 1D site response analysis)

Observed ground motions



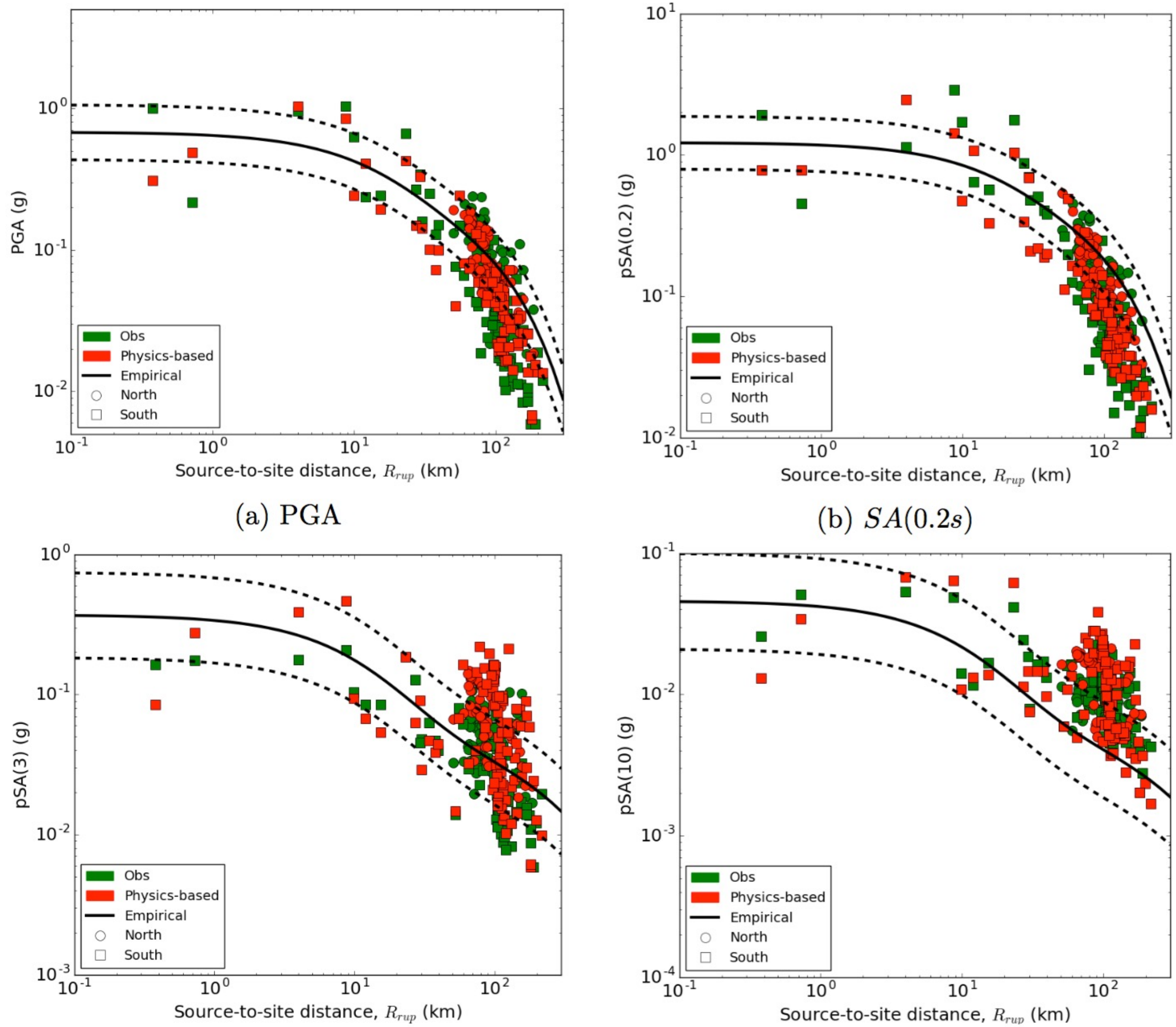
Bradley et al (2017)

Observed and simulated motions



Bradley et al (2017)

Observed and simulated response spectra



(a) PGA

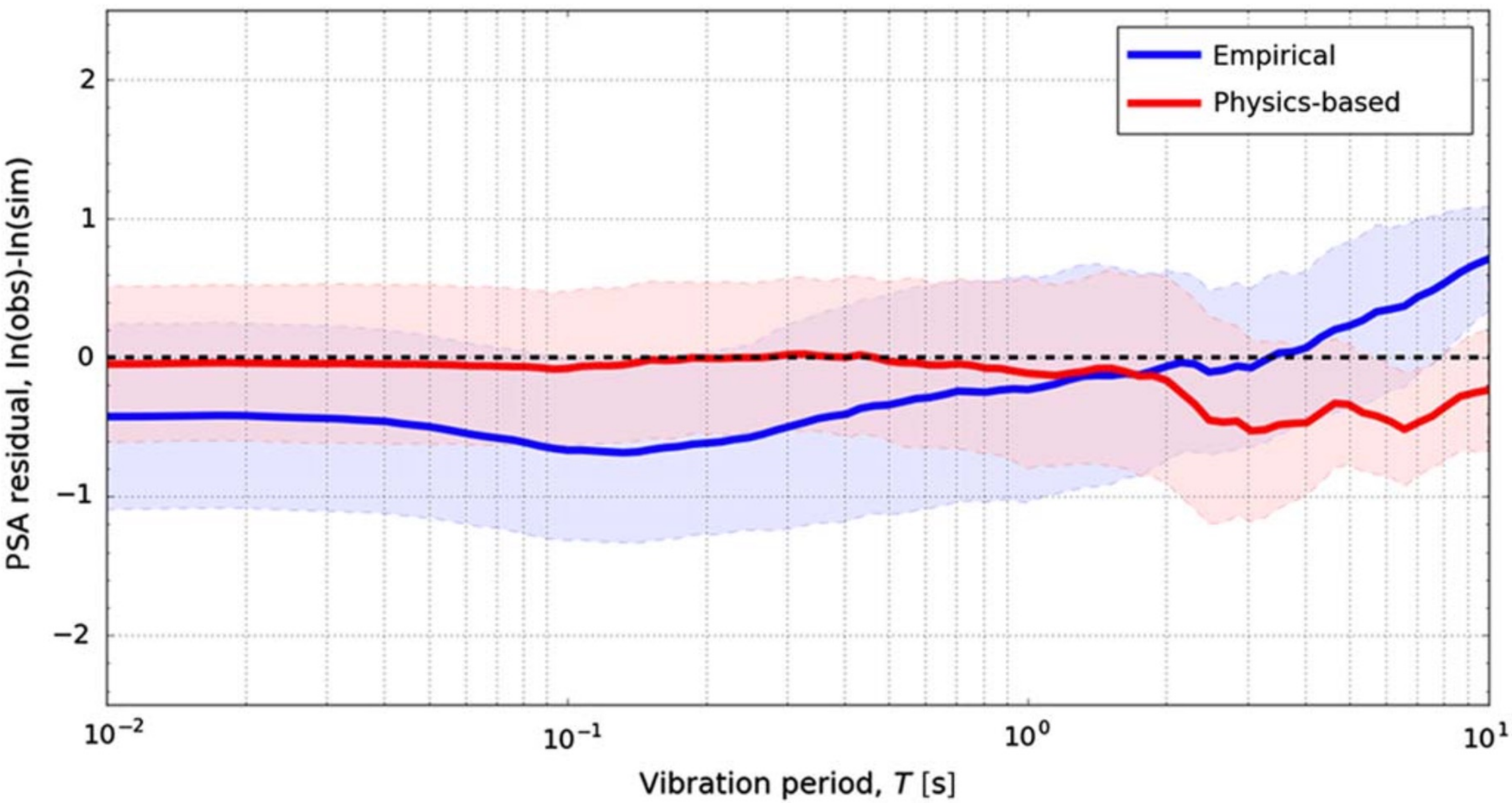
(b) $SA(0.2s)$

(c) $SA(3.0s)$

(d) $SA(10.0s)$

Bradley et al (2017)

Response spectra residual distribution



Bradley et al (2017)

Inferences?

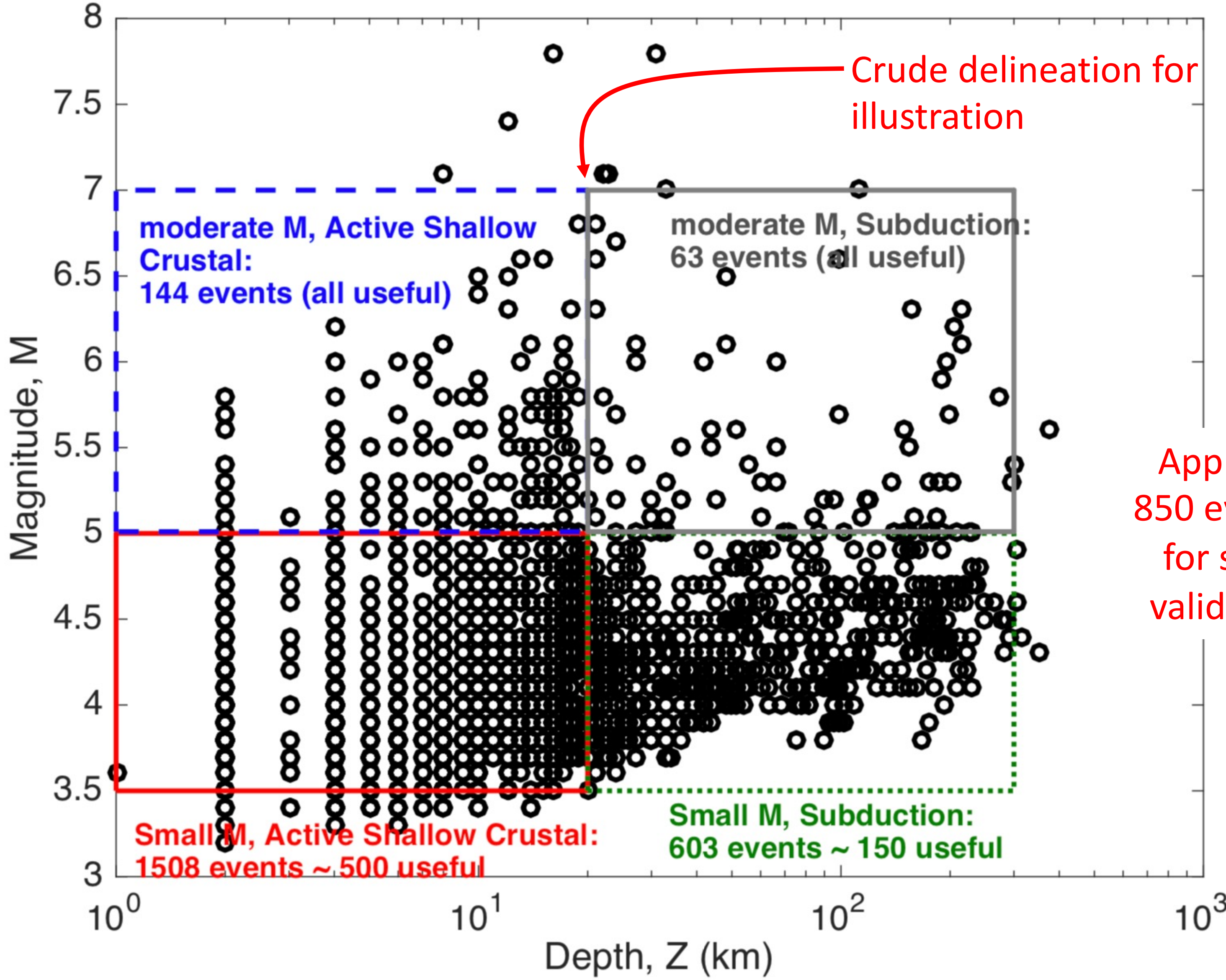
How much of the misfit between observations and prediction is due to an imperfect simulation methodology, or crustal & rupture models, or incorrect parameter values?

-> Without multiple events, and multiple recordings at specific sites, it is not possible to differentiate

Validation against small-, moderate-, and large-magnitude NZ events

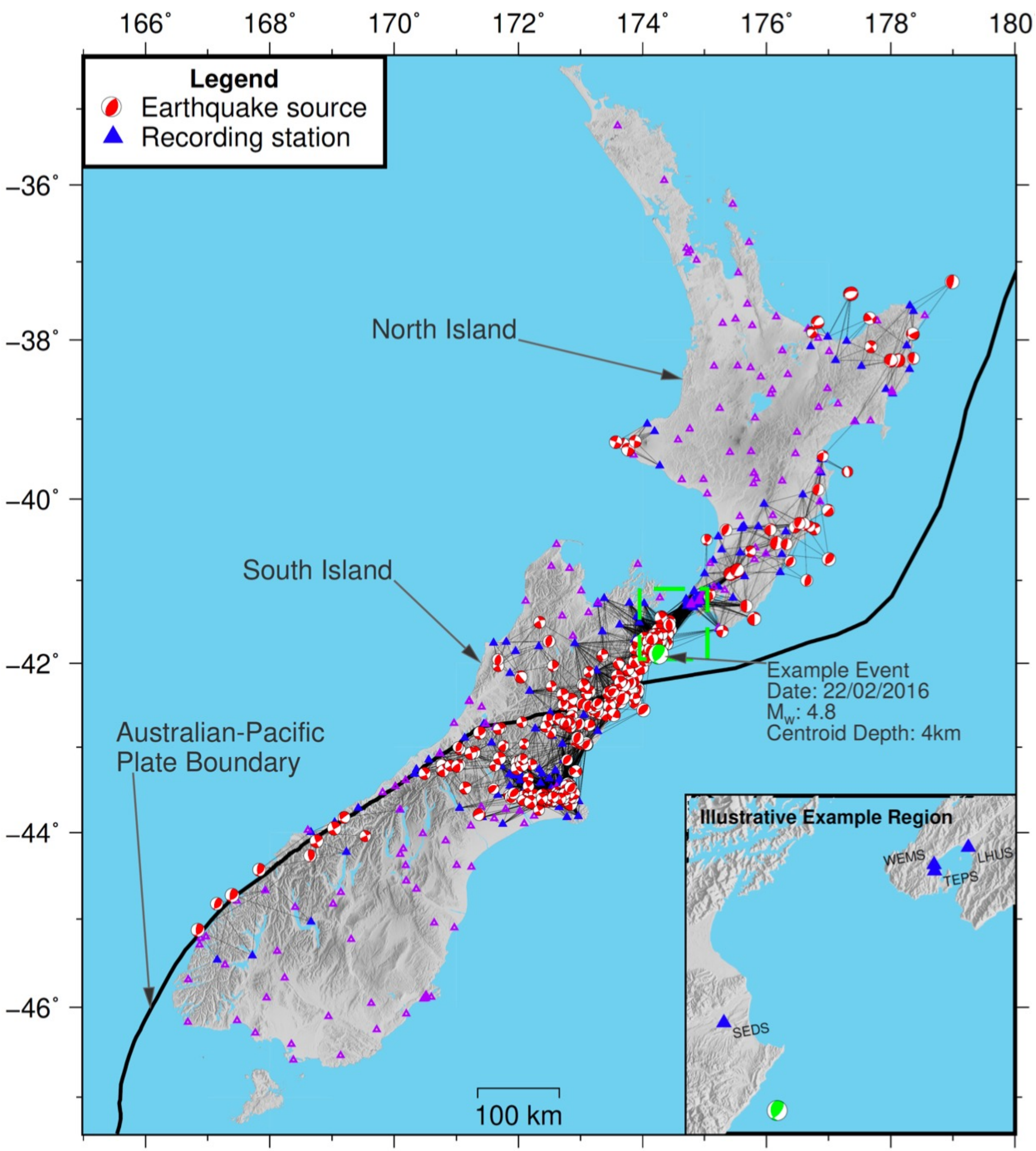
Potential validation events

M-Depth distribution NZ CMT catalogue



Approximately 850 events useful for simulation validation in NZ

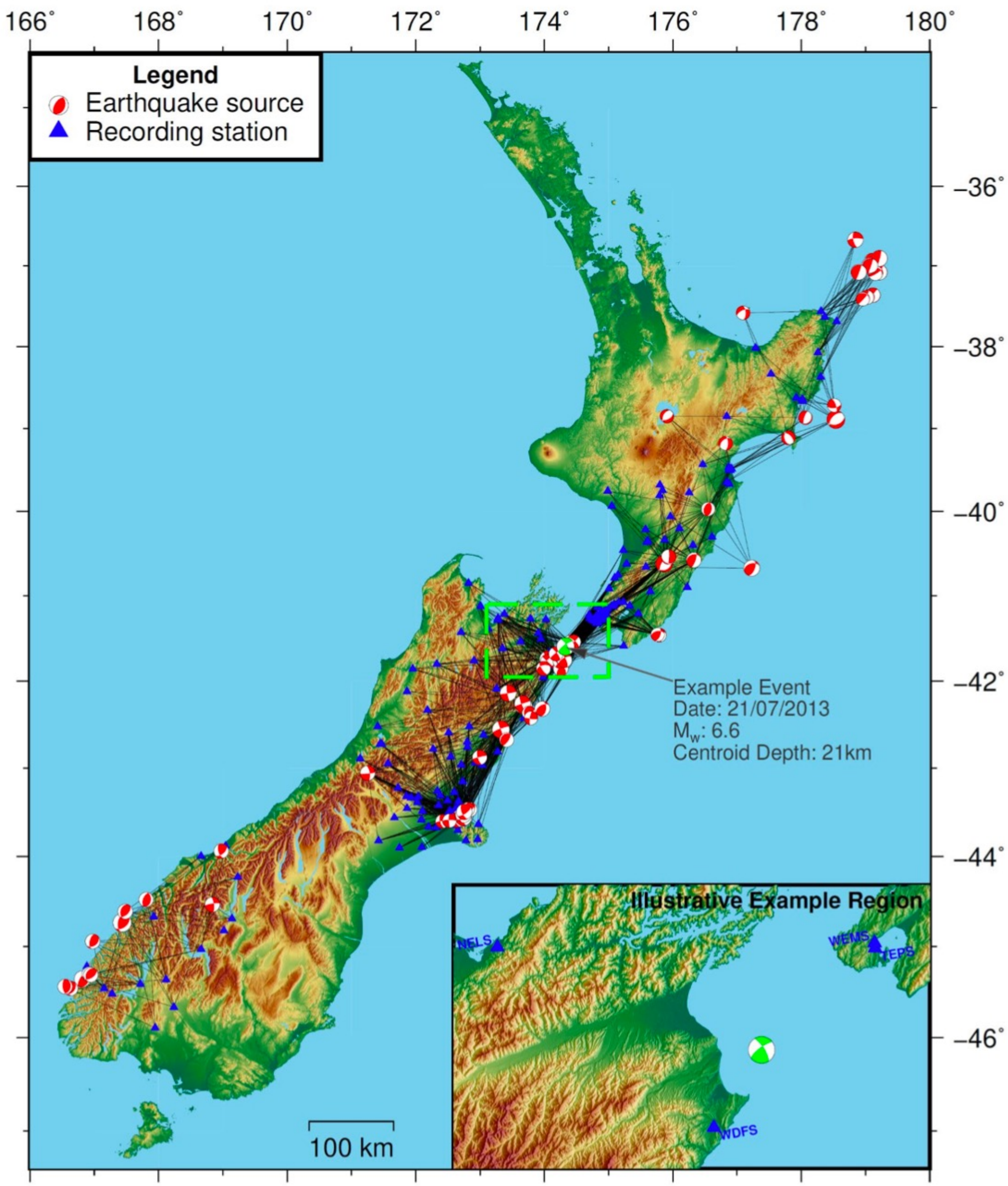
Validation: M3.5-5 events



- 479 EQs
- 5218 GMs
- 212 stations

Lee et al. (2020; EQS)
Lee et al. (2021; in review)

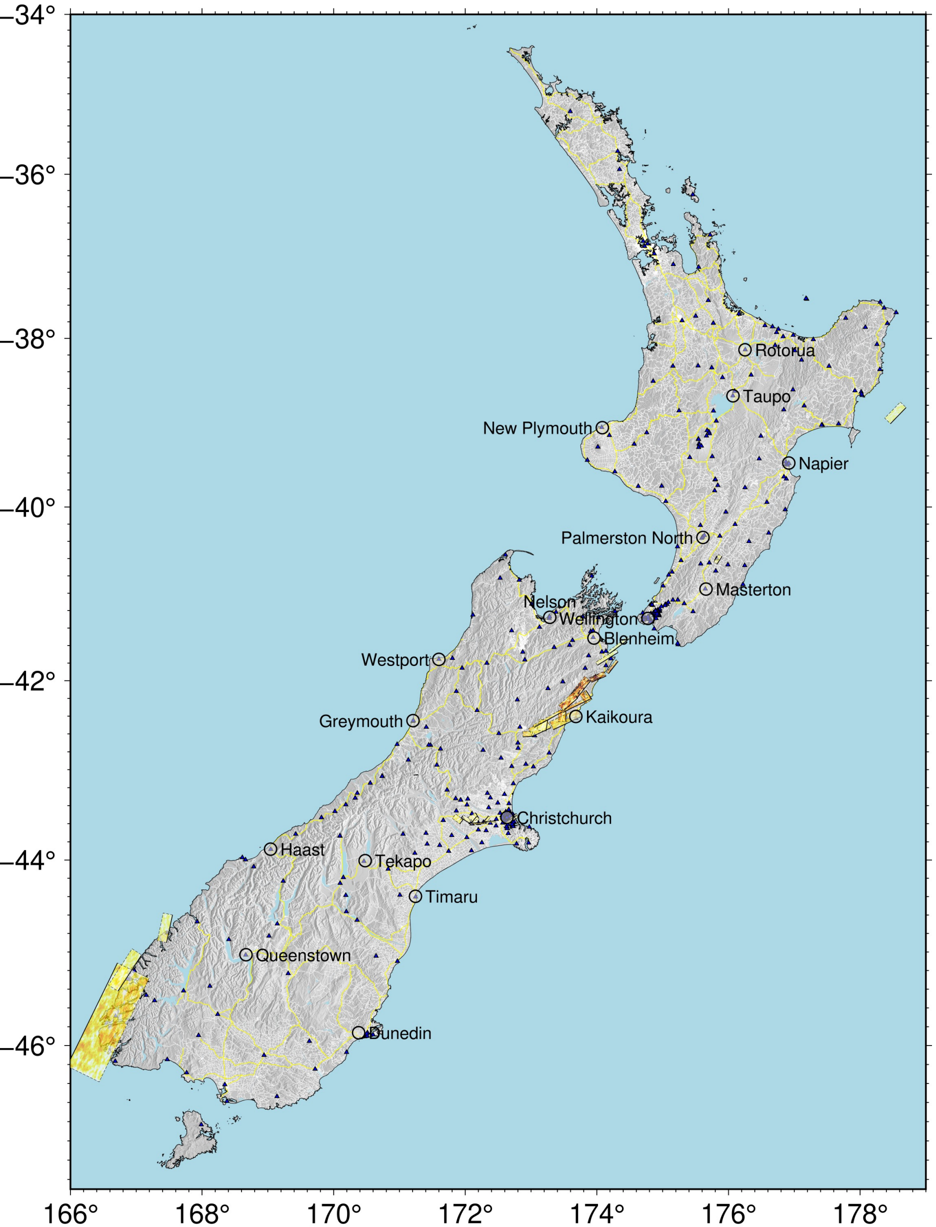
Validation: M5-7 events



- 75 EQs
- 2042 GMs
- 220 stations

Lee et al. (2021; NZSEE conference)

Validation: M6-8 with event-specific finite faults



14 EQs

- 2003, ‘07, ‘09 Fiordland (3)
- 2010-11 Canterbury (3)
- 2013 Cook Strait (2)
- 2016 Kaikōura

- For largest/complex events, rupture uncertainty tends to dominate simulation uncertainty – limiting validation inferences

(unpublished)

Residual partitioning via ME regression

Observed

Simulated

Between-event residual

'remaining' residual

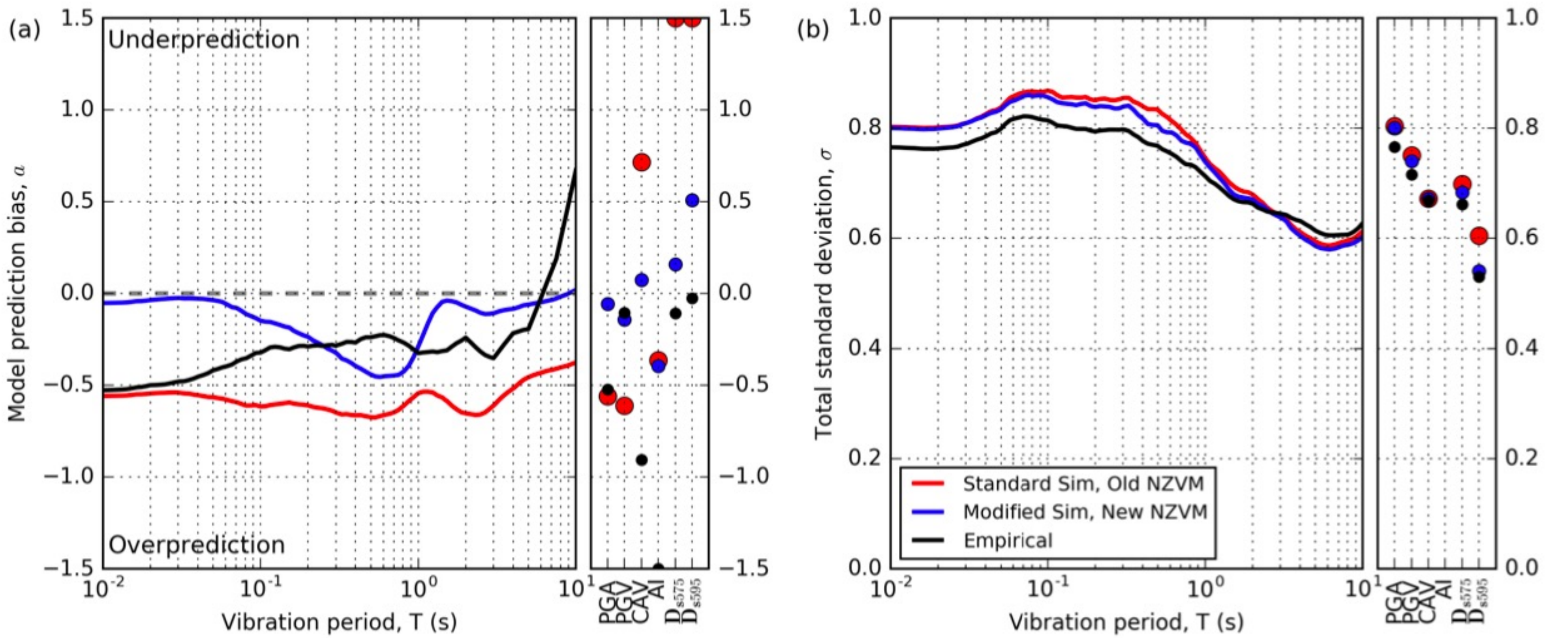
$$\ln \mathrm{IM}_{es} = f_{es} + a + \delta B_e + \delta S2S_s + \delta W^0_{es}$$

Bias over all events and sites

Between-site residual

Overall performance (M3.5-5 events)

- NZ-wide dataset

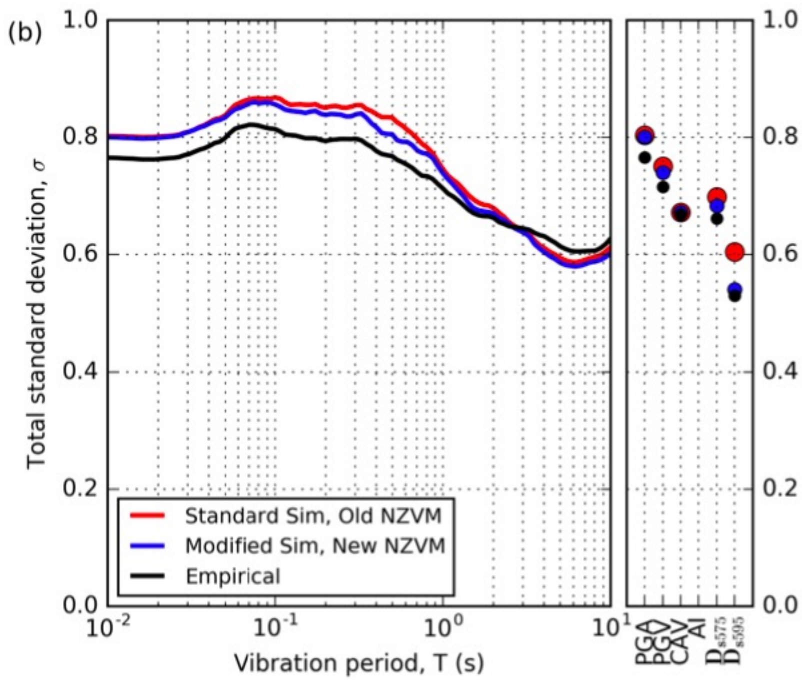


Lee et al. (2021; in review)

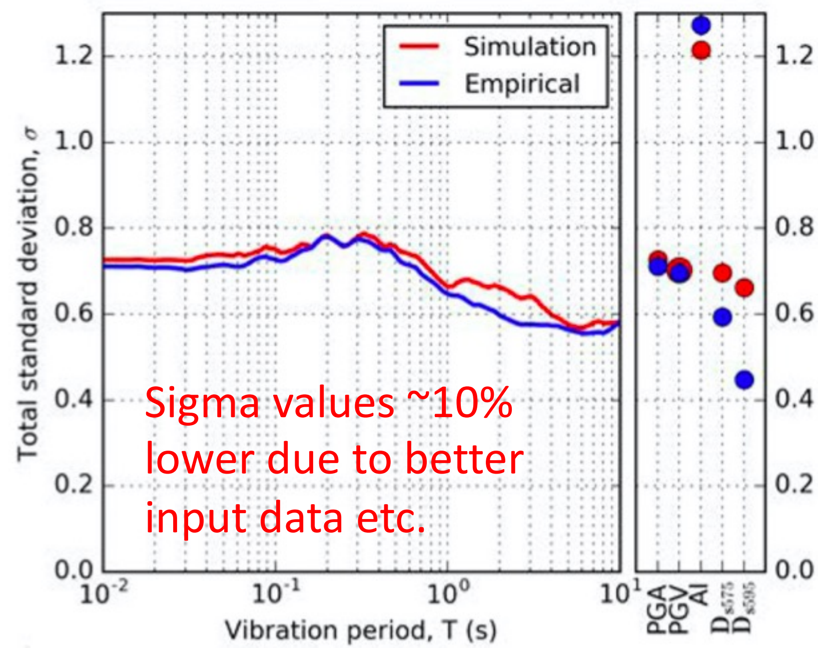
Overall performance (M3.5-5 events)

Total residual standard deviations

NZ-wide dataset

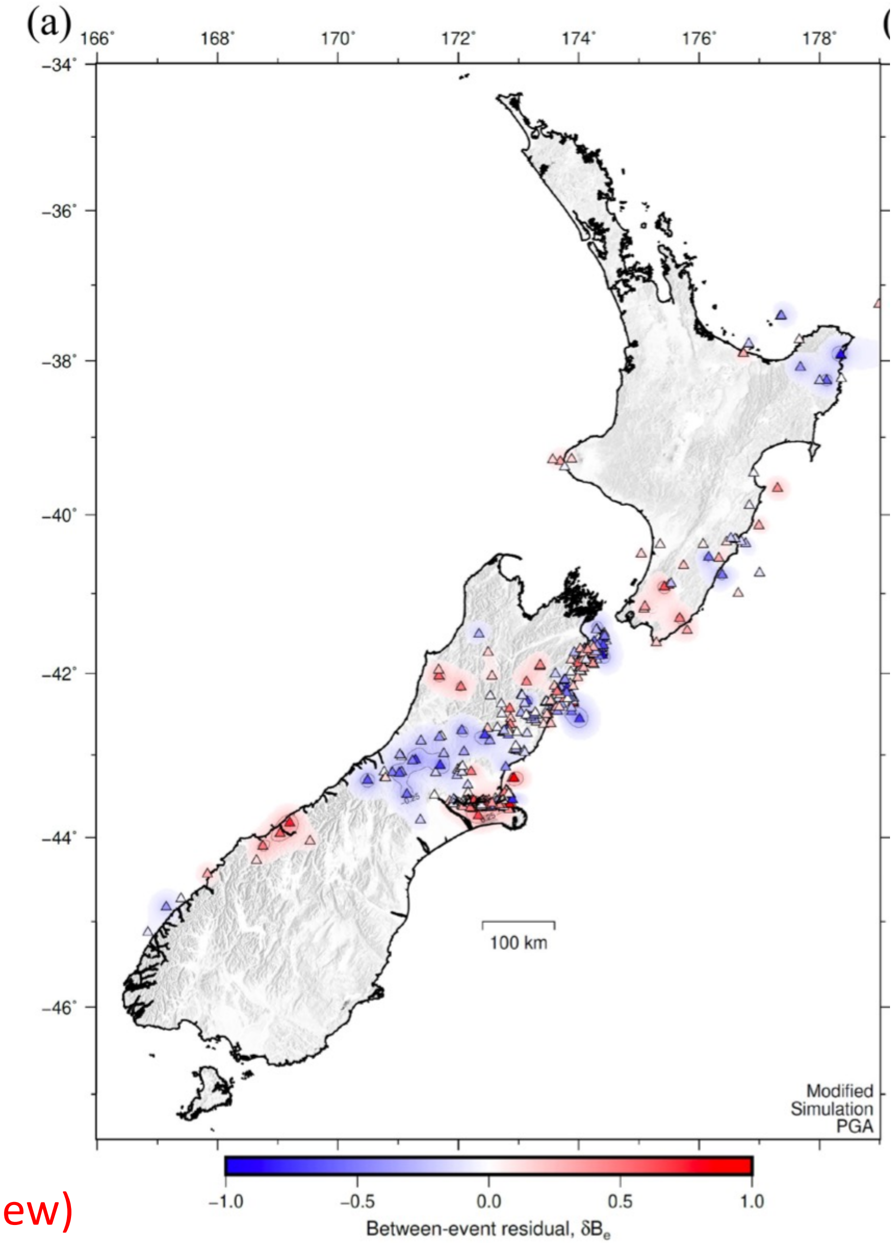


Canterbury only



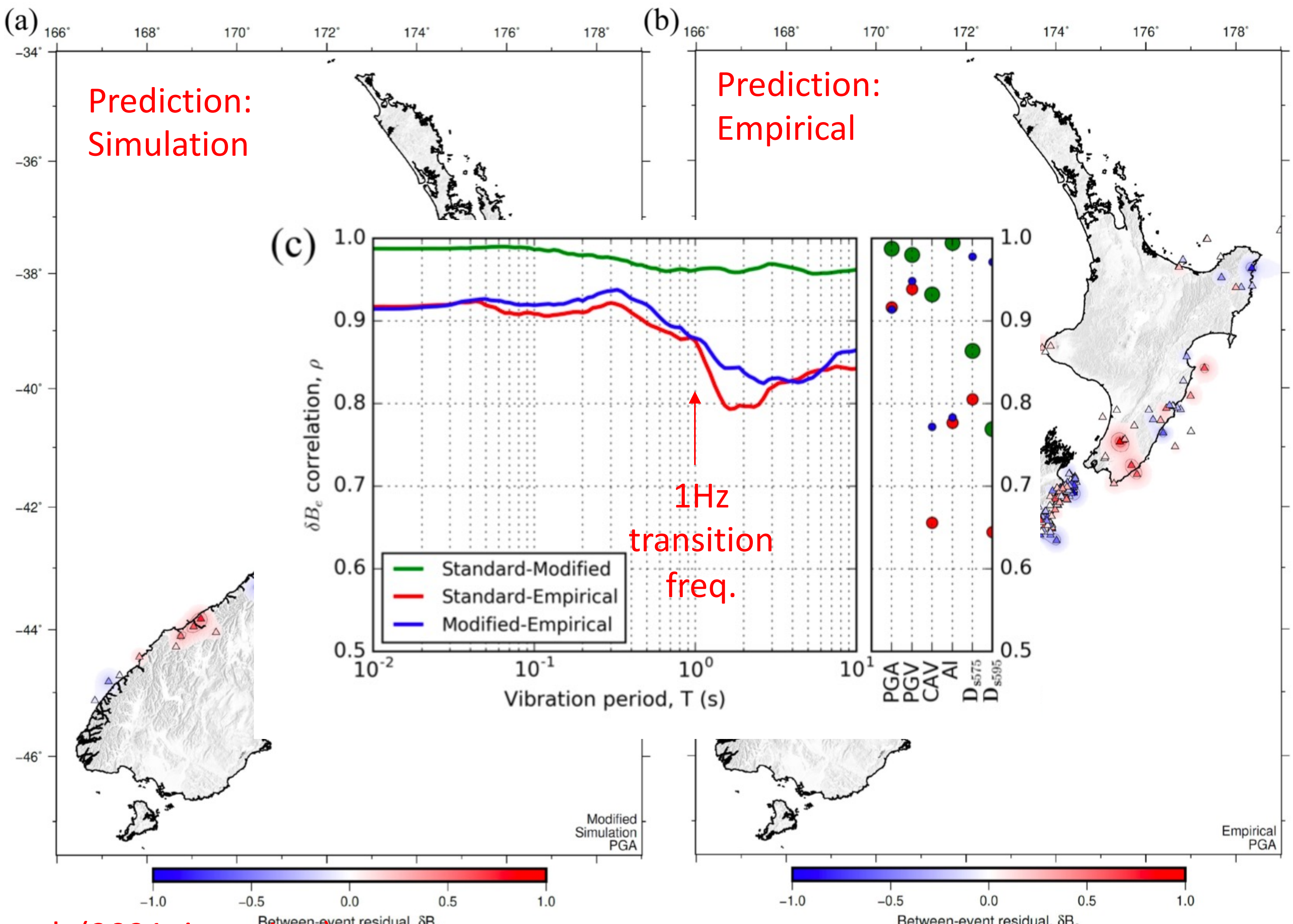
Lee et al. (2020; EQS)
Lee et al. (2021; in review)

Spatial variation in model performance



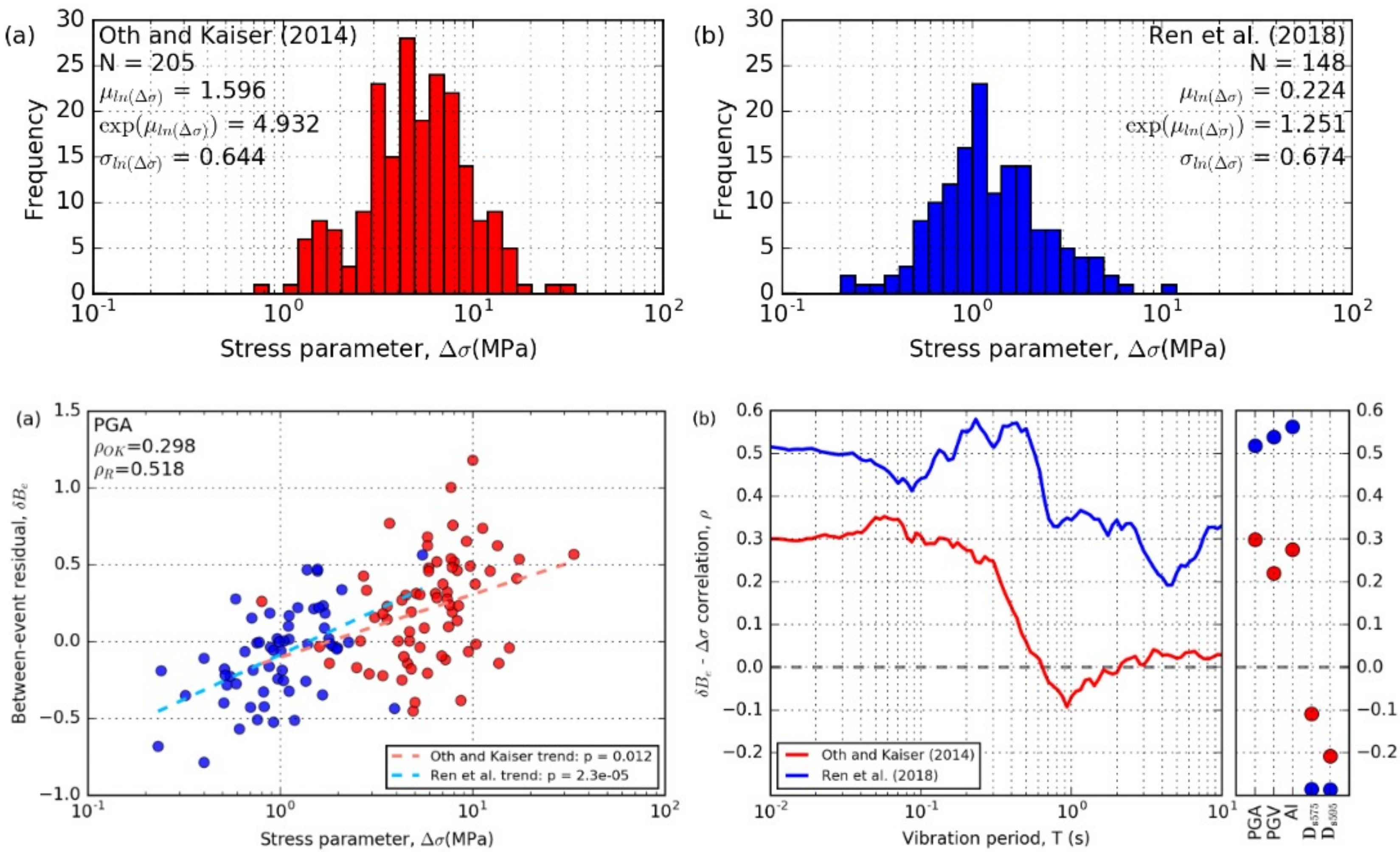
Lee et al. (2021; in review)

Spatial variation in model performance: Between—event residuals



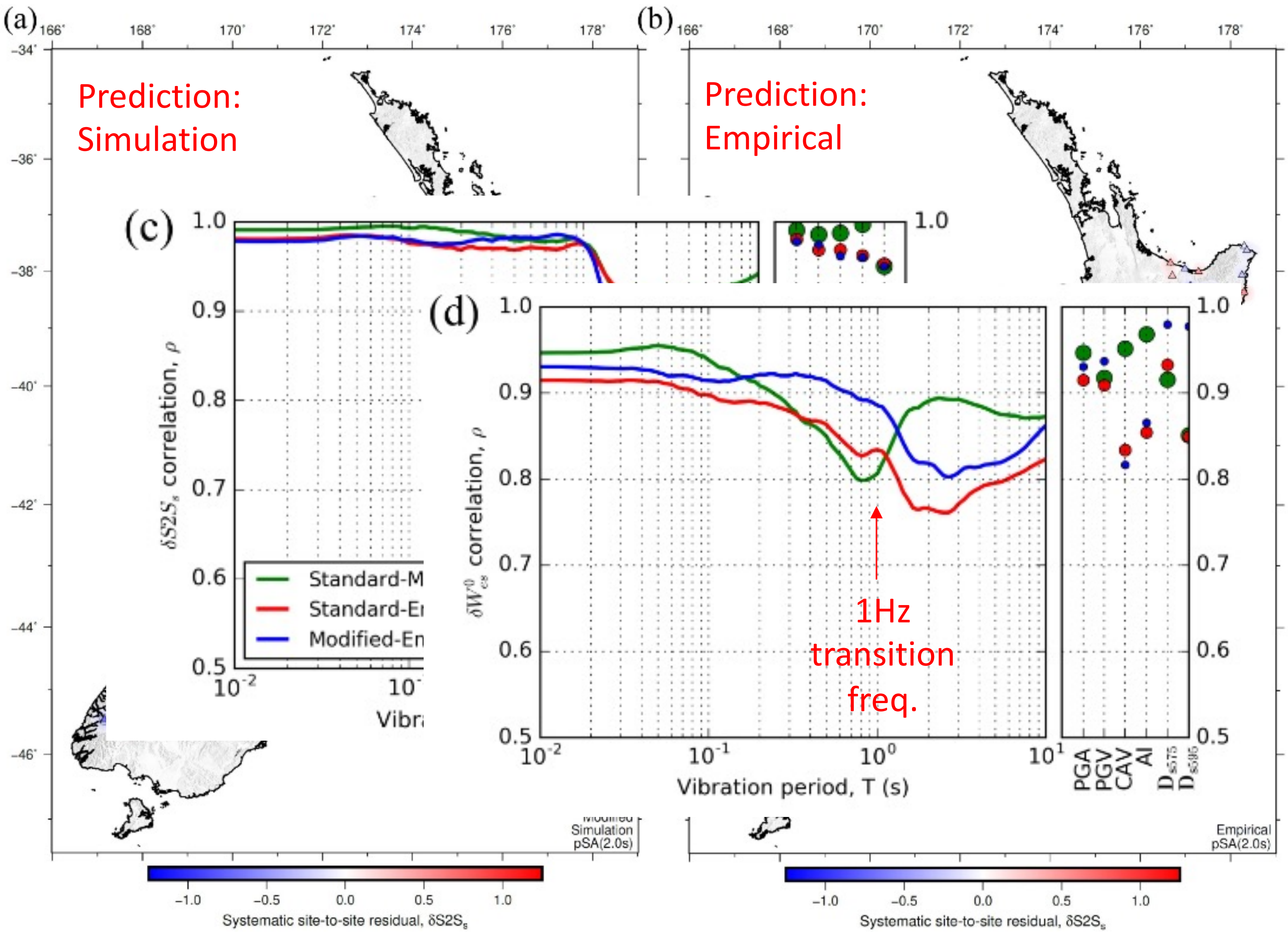
Lee et al. (2021; in review)

Correlation with stress parameter studies



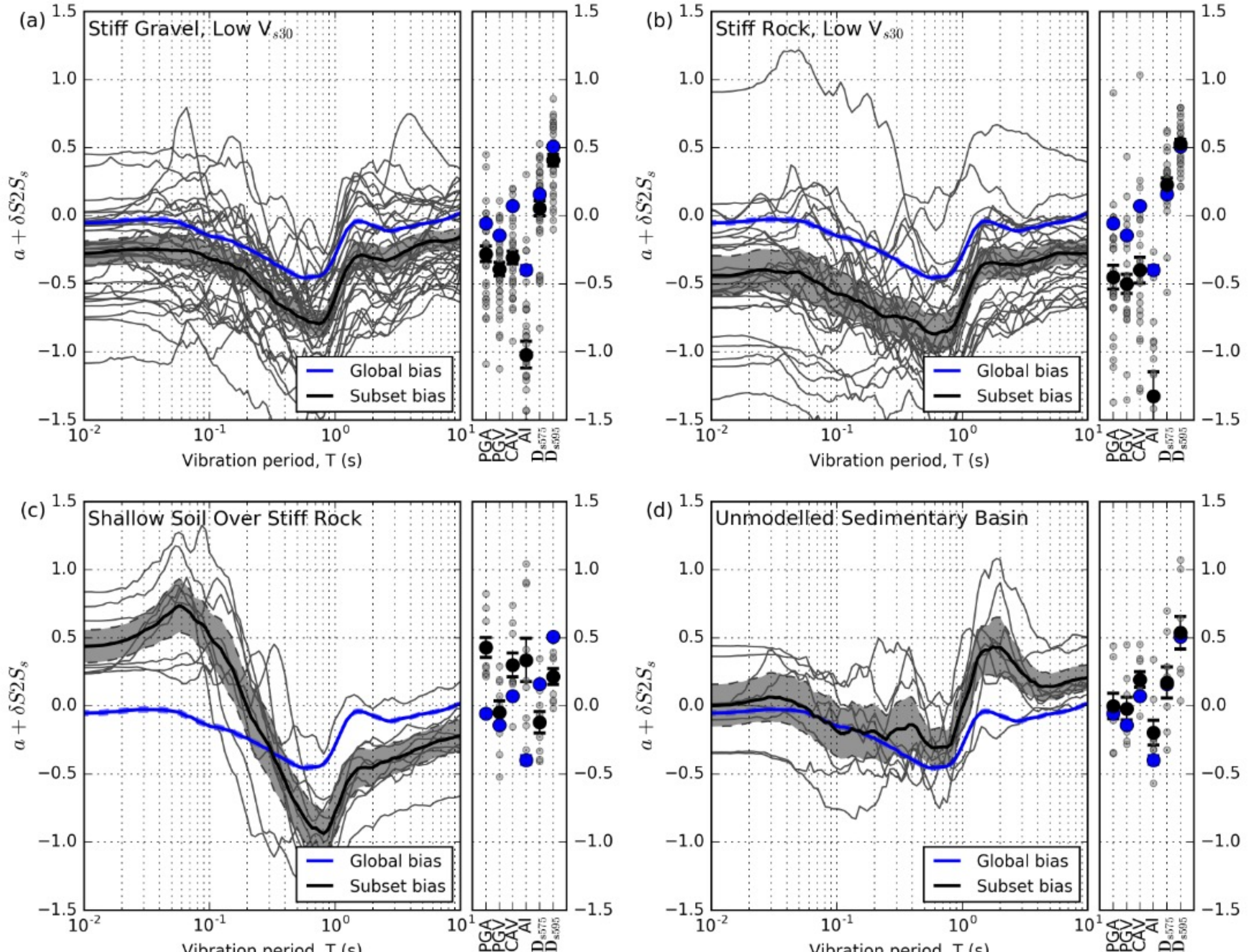
Lee et al. (2021; in review)

Spatial variation in model performance: Site-specific residuals



Lee et al. (2021; in review)

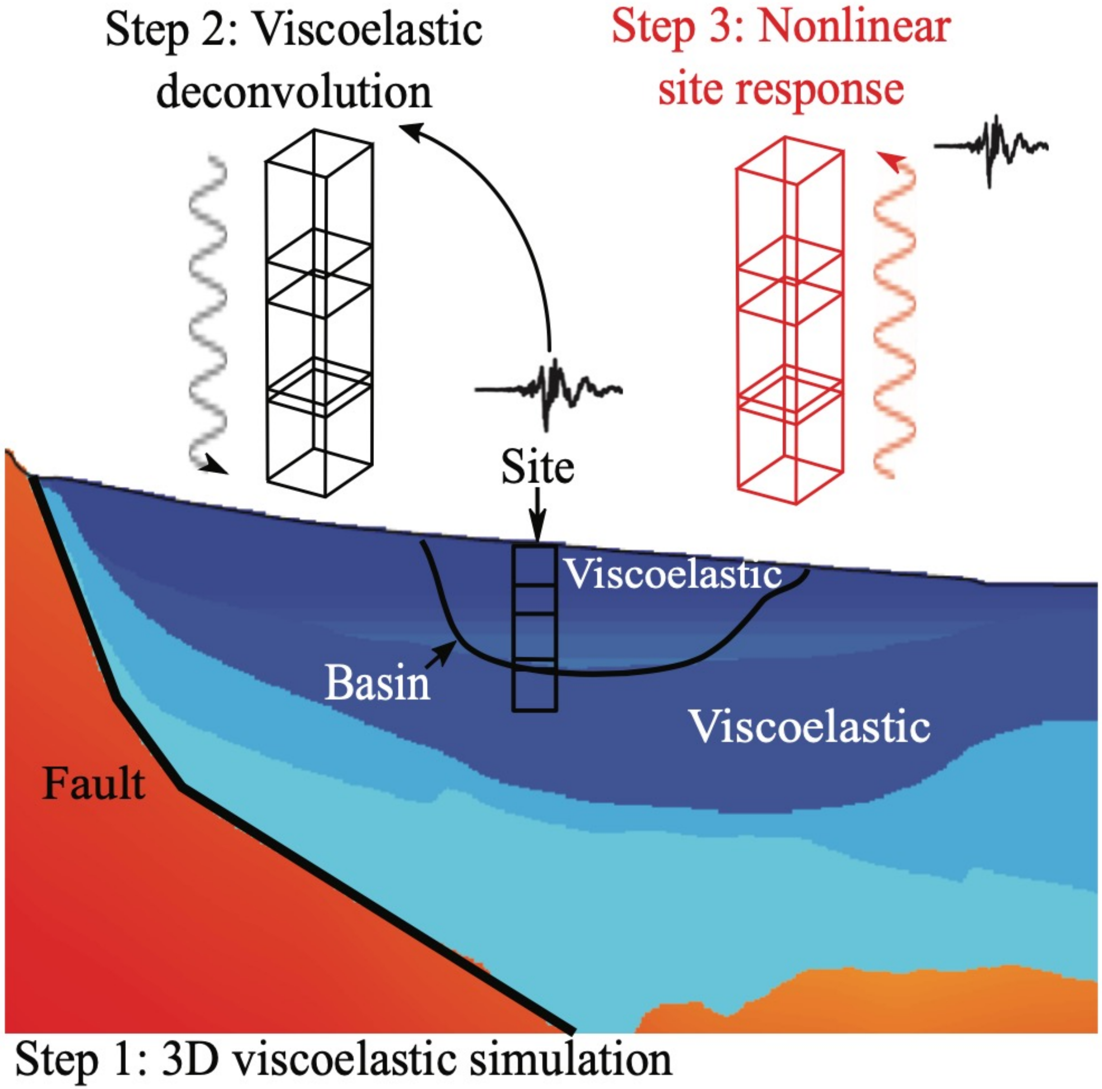
Site-specific residuals: site grouping



Lee et al. (2021; in review)

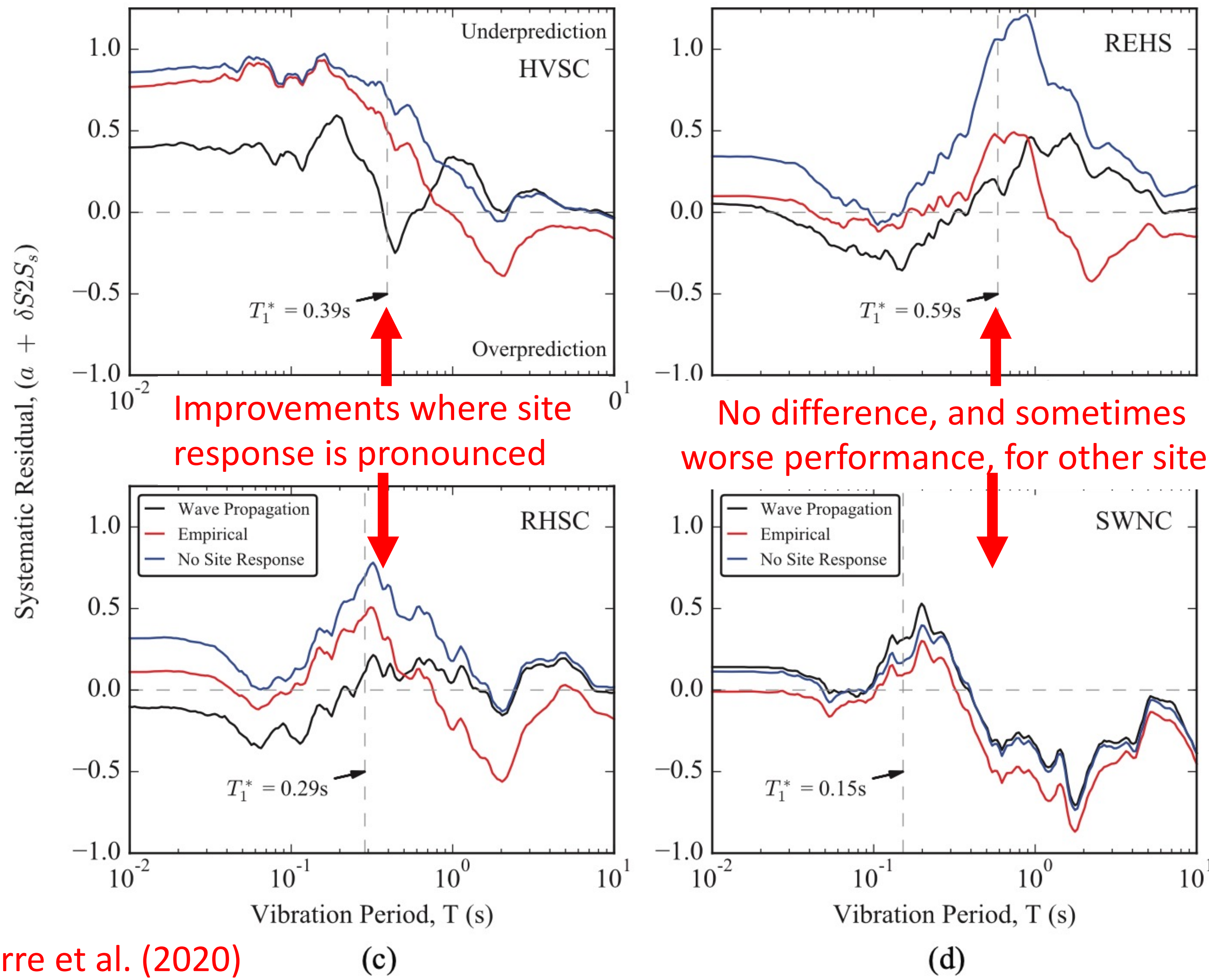
Simulation validation with site-specific 1D response analysis

Uncoupled approach to site-specific response analysis



de la Torre et al. (2020)

Bias-adjusted site-specific residuals



Improvements where site response is pronounced

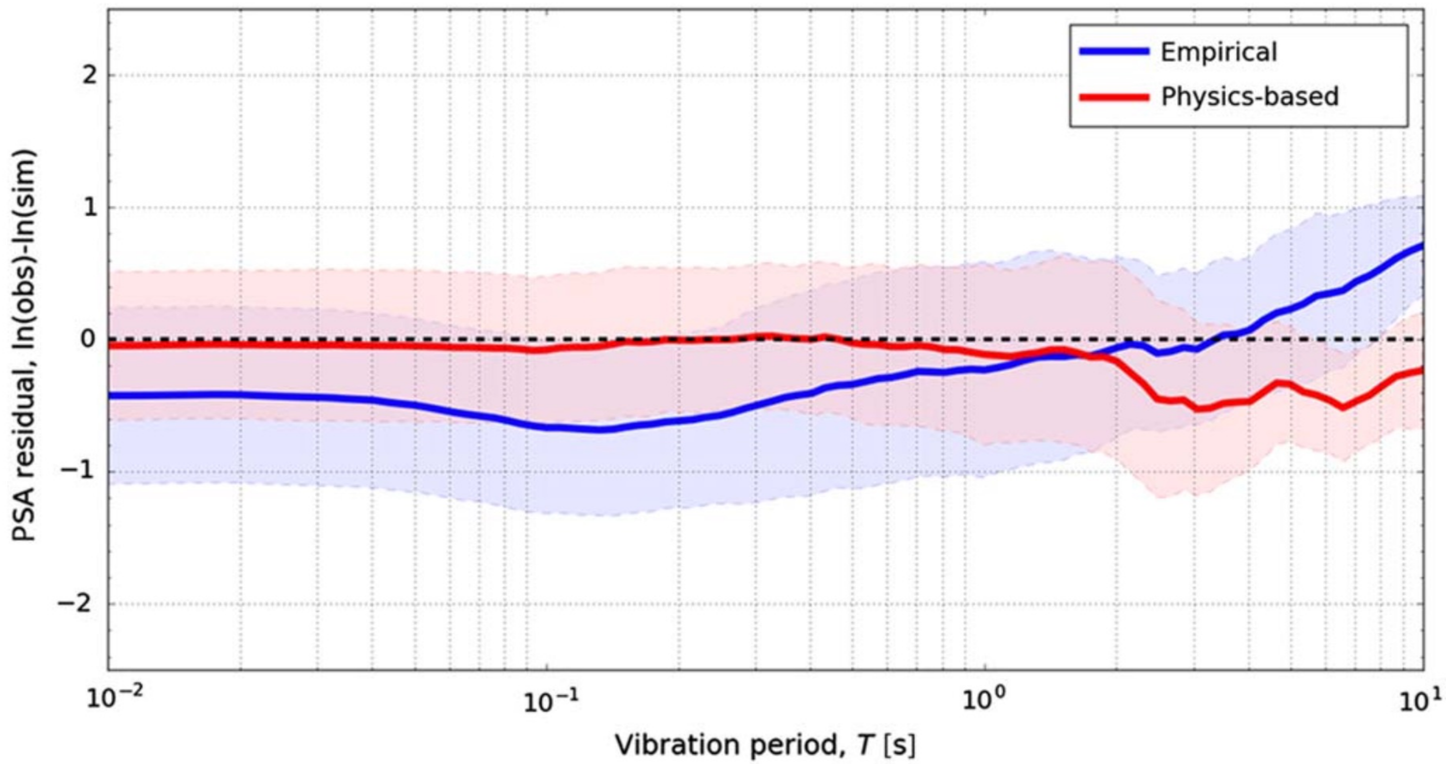
No difference, and sometimes worse performance, for other sites

de la Torre et al. (2020)

Simulation validation with explicit uncertainty incorporation and propagation

Incorrect 'target' for comparison

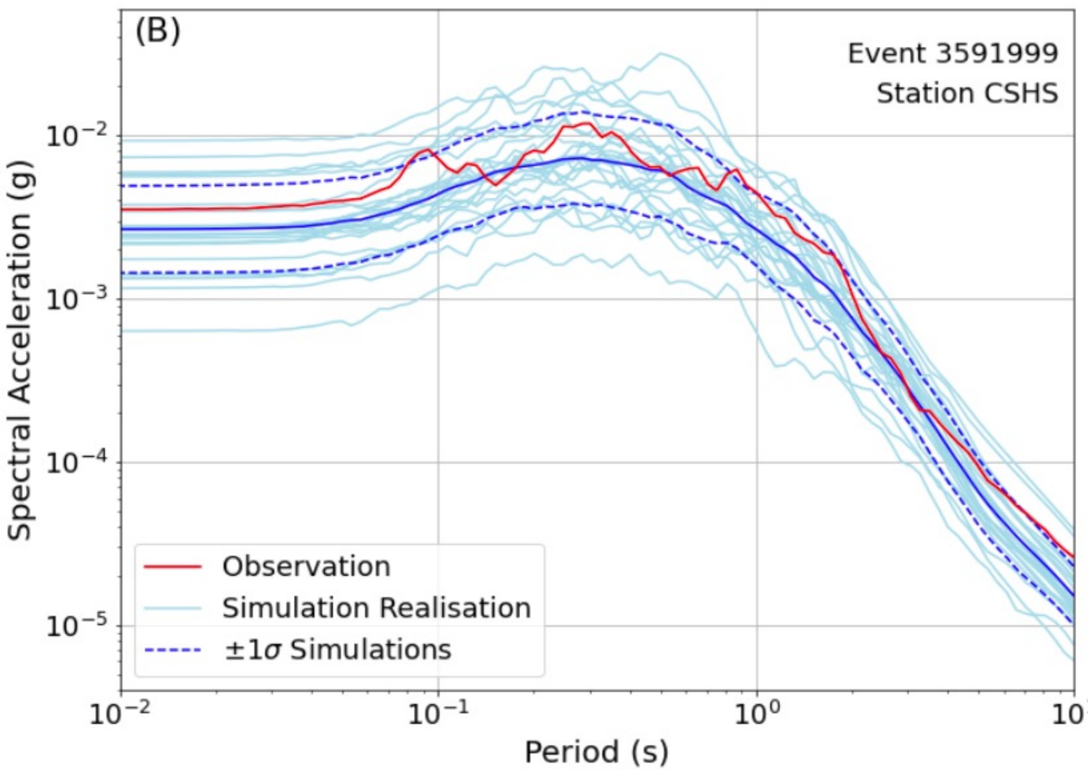
- Aiming for simulations to have a similar residual variance to empirical predictions is not the correct 'target'



Bradley et al (2017)

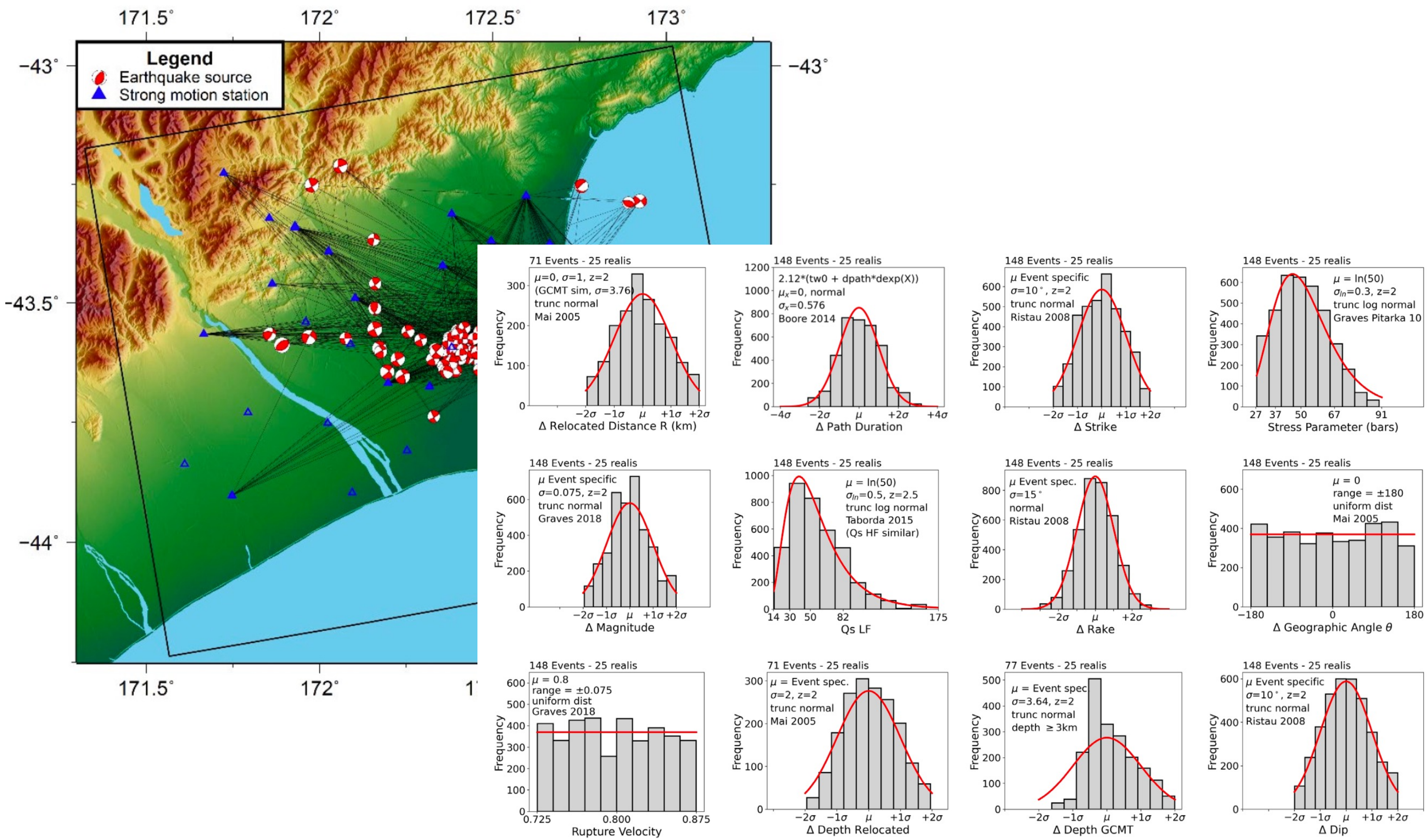
Simulations with explicit uncertainties

- The residual variance in multiple simulation realizations should be such that normalized residuals confirm to a standard normal distribution



Neill et al. (2021)

Uncertainty study in Canterbury

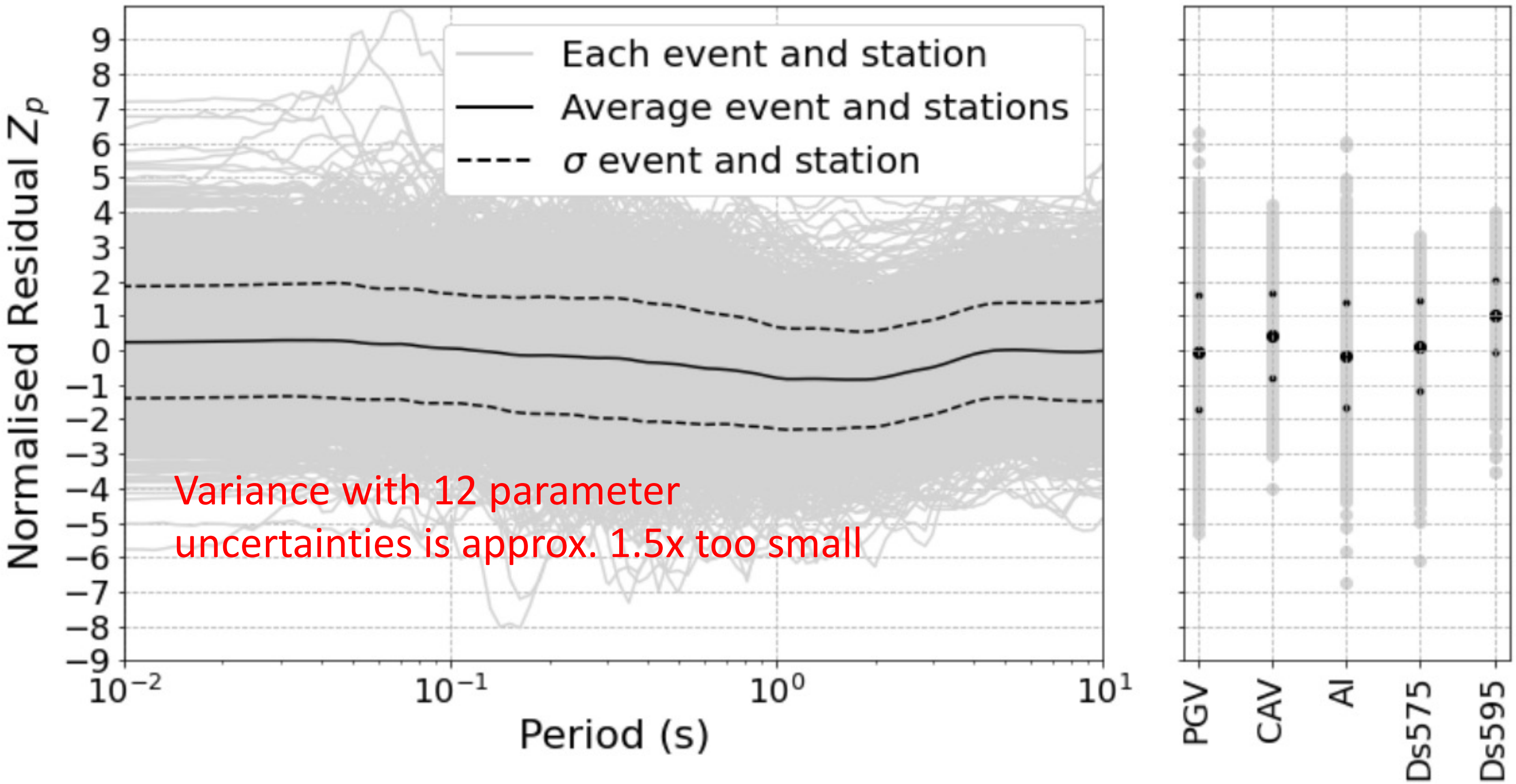


Neill et al. (2021)

Normalized residual variance

$$Z_p = \frac{\ln IM_{obs} - \mu_{\ln IM_{sim}}}{\sigma_{\ln IM_{sim}}}$$

Residual normalized by simulation sigma



Neill et al. (2021)

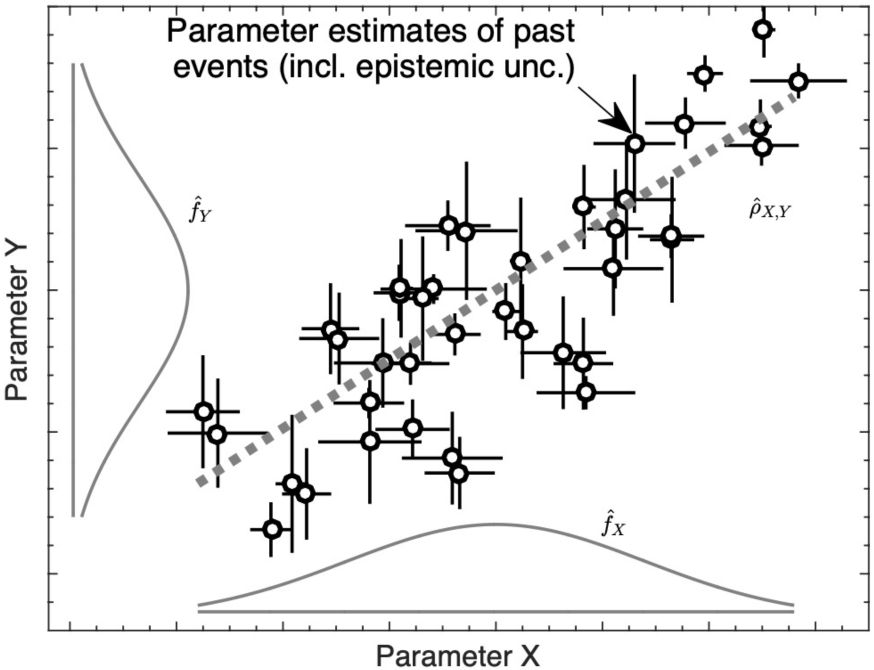
Parametric and modeling uncertainties

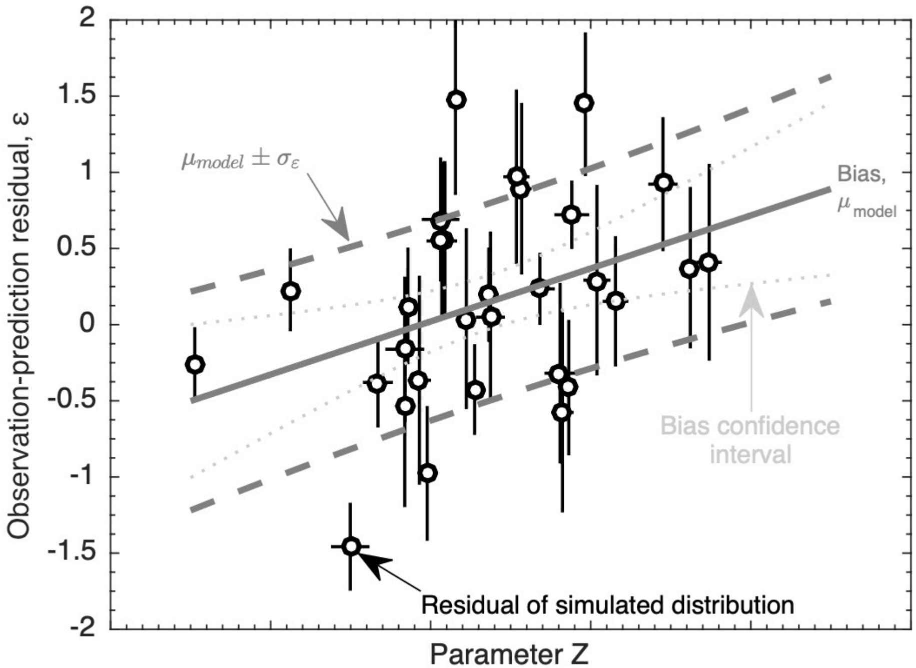
Table 5.1 Partitioning of uncertainty in ground-motion prediction using physics-based GMMs, and variable definitions related to the resulting ground-motion prediction.

	Aleatory variability	Epistemic uncertainty
Parametric	Event-to-event variation in source, path, and site-specific parameters of the model for future events (σ^2_{param})	Uncertainty in the probabilistic description of model parameters (*e.g.*, mean, variance, and distribution shape for each parameter; and correlation among parameters) ($Var[\mu_{param}]$, $Var[\sigma^2_{param}]$)
Modeling	Unexplained variability between observations and simulations due to physical processes imperfectly represented (or omitted entirely) from the model; and chaotic processes that are inherently random (σ^2_{model})	Uncertainty in the probabilistic description (*e.g.*, mean, variance, distribution shape) of the model due to the finite number of observations ($Var[\mu_{model}]$, $Var[\sigma^2_{model}]$)
Total	Inherent variability in the prediction of future events associated with variability in model parameters and limitations in the modeling approach itself ($\sigma^2_{\ln IM}$)	Uncertainty in the probabilistic description of both model parameters and model distribution due to finite observation and calibration data ($Var[\mu_{\ln IM}]$, $Var[\sigma^2_{\ln IM}]$)

Baker, Bradley, Stafford (2021)

Interaction of uncertainties in validation





Parametric uncertainty:

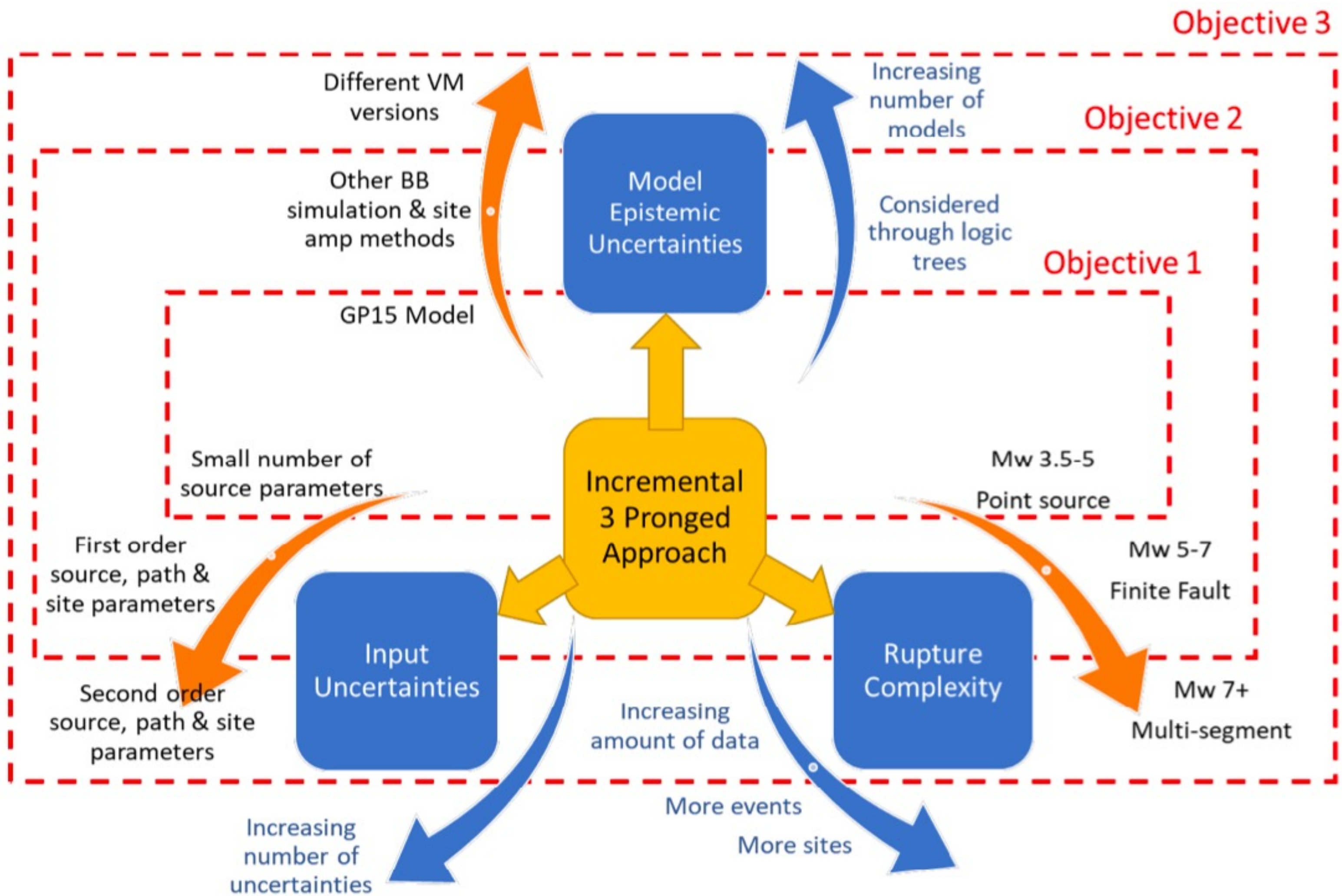
- Correlation between parameters
- Epistemic uncertainty in values inferred from observations

Modelling uncertainty:

- Misfit to observations
- Avoid double counting contribution from propagated parameter uncertainty

Baker, Bradley, Stafford (2021)

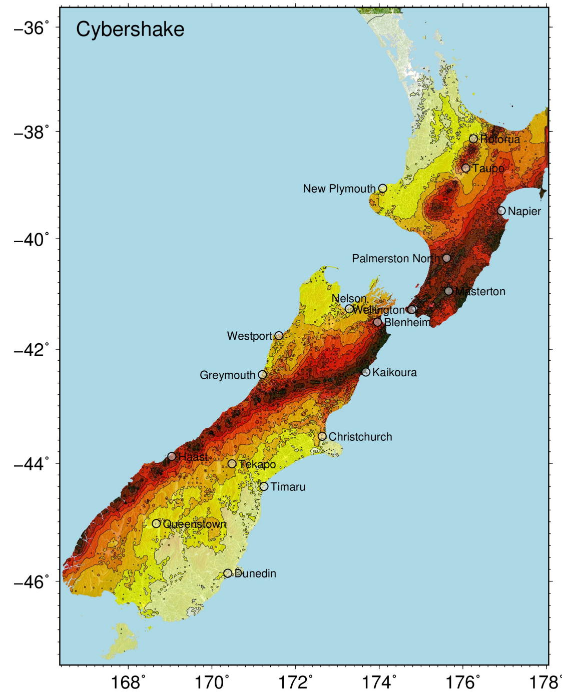
Staged approach toward validation with explicit uncertainty incorporation



Neill et al. (2019)

Summary

- Validation is essential for demonstrating the predictive capability of simulations
- Requires a systematic and comprehensive approach considering many events and stations
  - Validation should be on the same datasets used for development/calibration of empirical GMMs
  - Need to untangle simulation vs. source, crustal/velocity, site modelling methodologies
  - Expect pronounced regional variations in predictive capability (particularly due to crustal/site modelling quality)
- Explicit treatment of simulation uncertainties, and their validation, is a critical element toward the direct use of simulations in PSHA

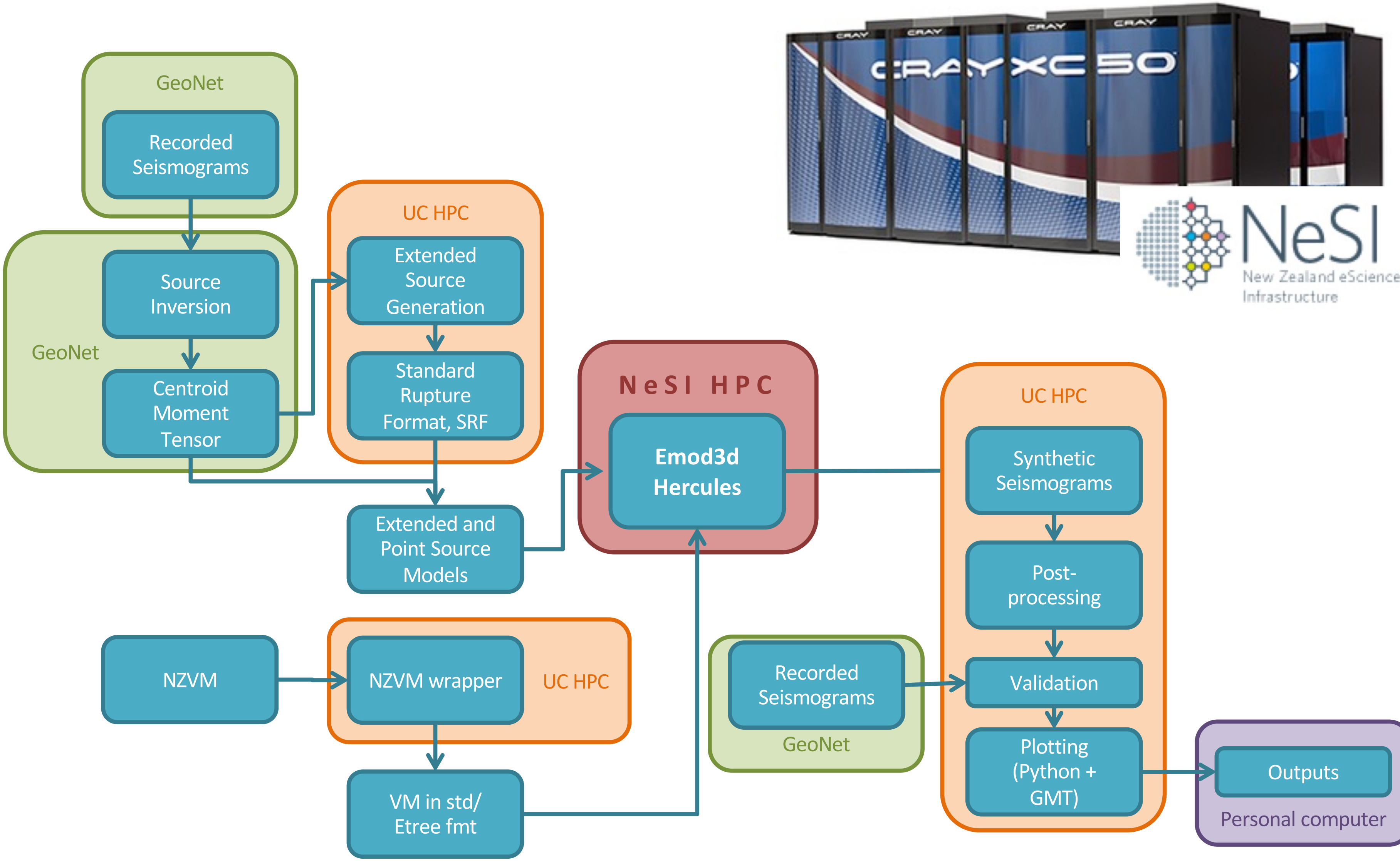


Thank you for your attention

https://sites.google.com/site/brendonabradley/

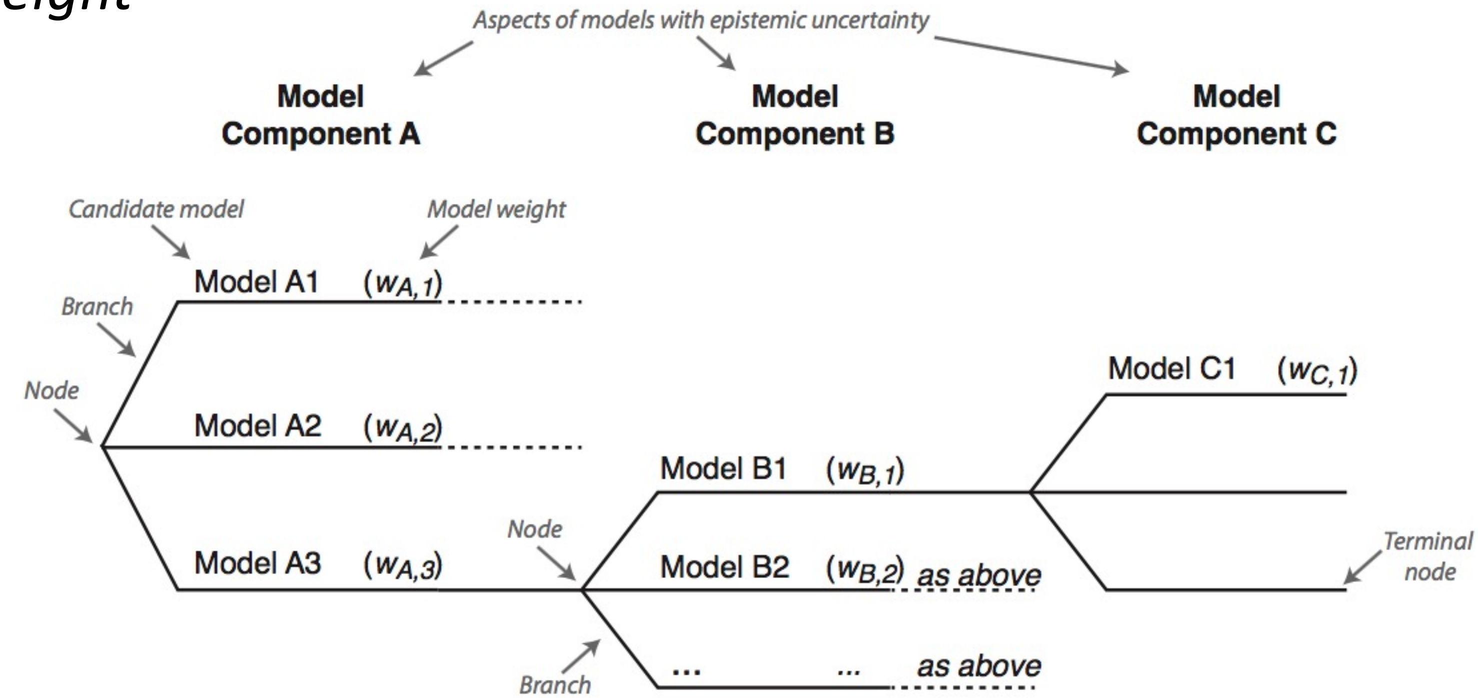
Supported by:

Software workflow and Integration



Logic trees for model uncertainty

- Simulation-based ground motion prediction incorporated in logic tree along with empirically-based predictions
- *Predictive capability* of modelling alternatives drives *model weight*



Baker, Bradley, Stafford (2021, Cambridge University Press)