Artificial neural network-based ground motion model for next-generation seismic intensity measures

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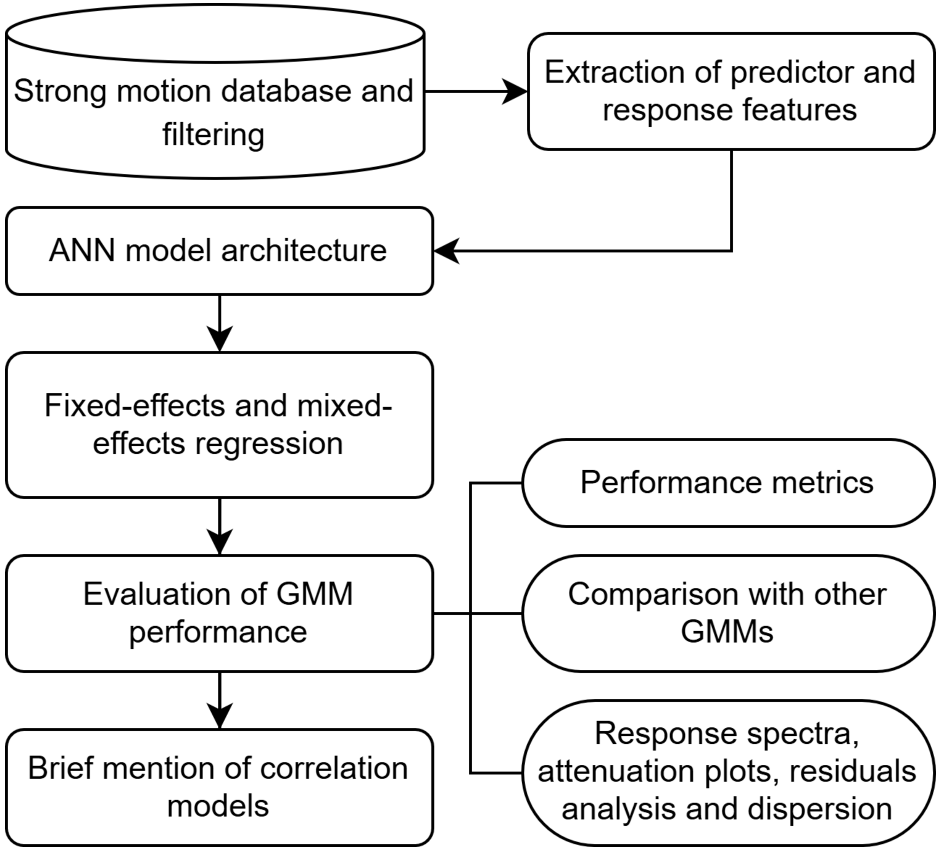
Introduction – Background

- Ground motion models (GMMs) are used to estimate different intensity measures (IMs), given a set of rupture parameters
- For each predictive model the following may vary
  - IM type
  - Ground motion database
  - Regression model
- When different IMs are considered, it can possibly introduce some heterogeneity, which is then propagated into the seismic analysis and risk assessment results
- This heterogeneity can be mitigated with a **generalised ground motion model (GGMM)**
- With a GGMM all the IMs of interest can be included in the same model
  - Interdependencies among multiple IMs can be captured
  - Simultaneous regression of all IMs using a mixed-effects regression
  - Ease of use

Introduction – What is developed in this study

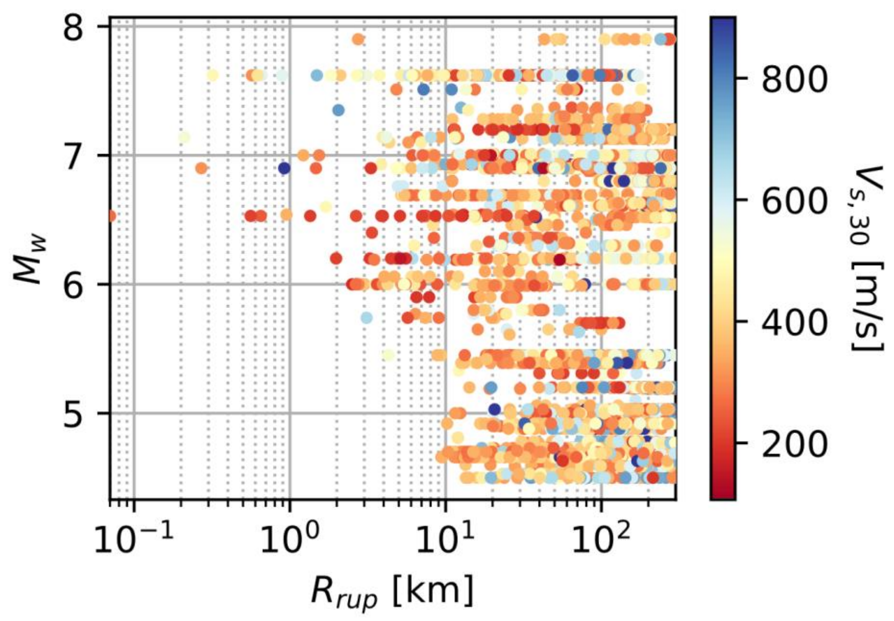
- Artificial neural network (ANN) regression method gives us the flexibility to materialise such model
- Incorporating several traditional and next-generation IMs
- Three different horizontal component definitions were included
- Performance of the GGMM was evaluated using several metrics and compared to various existing GMMs developed with either the classical approach or machine learning methods



Strong motion dataset and filtering criteria

Starting from the whole NGA-West2 database (Ancheta et al., 2013), we discarded records with:

- $M_w < 4.5$
- $R_{rup} > 300$ km
- Recordings from instruments not on the free field conditions
- $D_{hyp} > 20$ km
- $V_{s,30} > 1300$ m/s
- Minimum usable frequency > 0.25 Hz
- Mw < 5.5 and fewer than five recordings. $5.5 \leq M_w < 6.5$ and fewer than three recordings
- Aftershocks, defined as a 'Class 2' event with centroid Joyner-Boore distance, $CR_{JB} < 10$ km



4,135 records from 102 earthquakes

Predictor and response features

Predictor features		
Description	**Min value**	**Max value**
Moment magnitude, M_w	4.5	7.9
Rupture distance, R_{rup} [km]	0.07	299.59
Hypocentral depth, D_{hyp} [km]	2.3	18.65
Time-averaged shear-wave velocity to 30m depth, $V_{s,30}$ [m/s]	106.83	1269.78
Style of faulting, *SOF**	0	4
Depth to the 2.5 km/s shear-wave velocity horizon (a.k.a., basin or sediment depth), $Z_{2.5}$ [m]	0	7780
Depth to top of fault rupture, Z_{tor} [km]	0	16.23
Joyner-Boore distance, R_{jb} [km]	0	299.44
Distance measured perpendicular to the fault strike from the surface projection of the up-dip edge of the fault plane, R_x [km]	-297.13	292.39

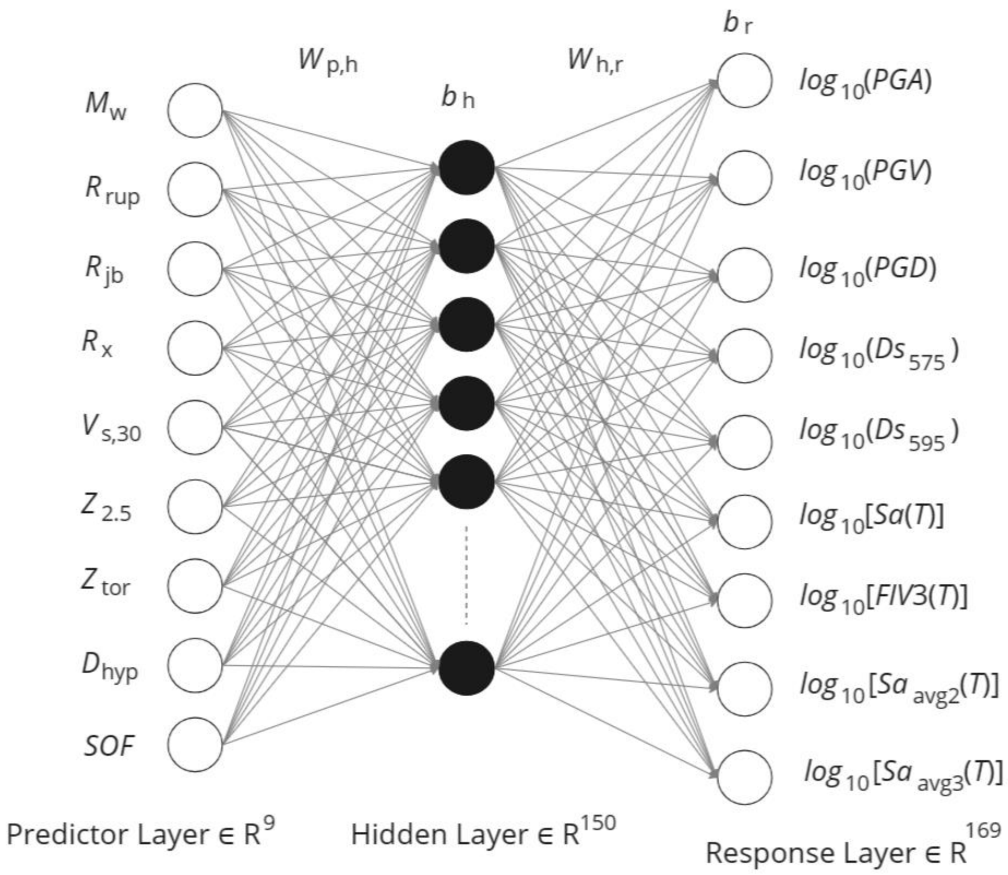
Response features	Horizontal component definition
PGA	*RotD50*
PGV	*RotD50*
PGD	*RotD50*
Ds_{595}	Geometric mean
Ds_{575}	Geometric mean
Sa(T)	*RotD50*, *RotD100*, Geometric mean
FIV3(T)	Geometric mean
$Sa_{avg2}(T)$	*RotD50*, *RotD100*, Geometric mean
$Sa_{avg3}(T)$	*RotD50*, *RotD100*, Geometric mean

Significant duration

Filtered Incremental velocity

From 0.2T to 2.0T
From 0.2 to 3.0T

Model architecture



$$log_{10}(IM_r) = f_{linear}\left[b_r + \sum_{h=1}^{150} W_{h,r} \cdot f_{tanh}\left(b_h + \sum_{p=1}^{9} W_{p,h}X_p\right)\right]$$

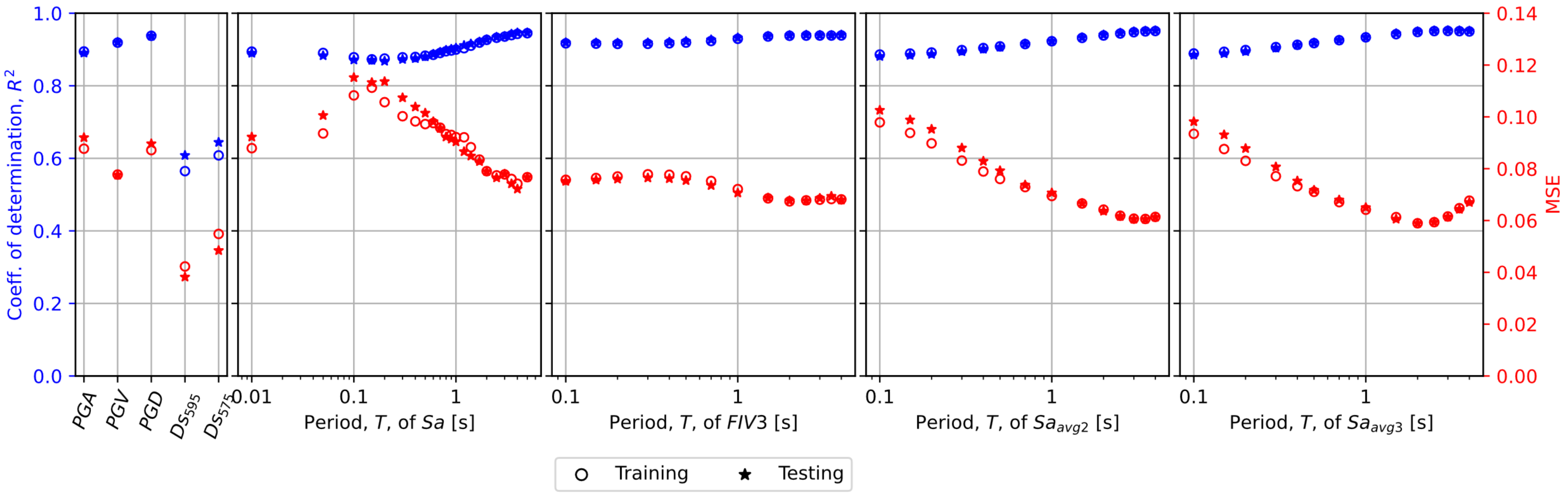
$$\log_{10} IM_i = f_i(\boldsymbol{X}, \boldsymbol{\theta}) + \delta b_i \tau_i + \delta w_i \varphi_i$$

$$\sigma = \sqrt{\tau^2 + \varphi^2}$$

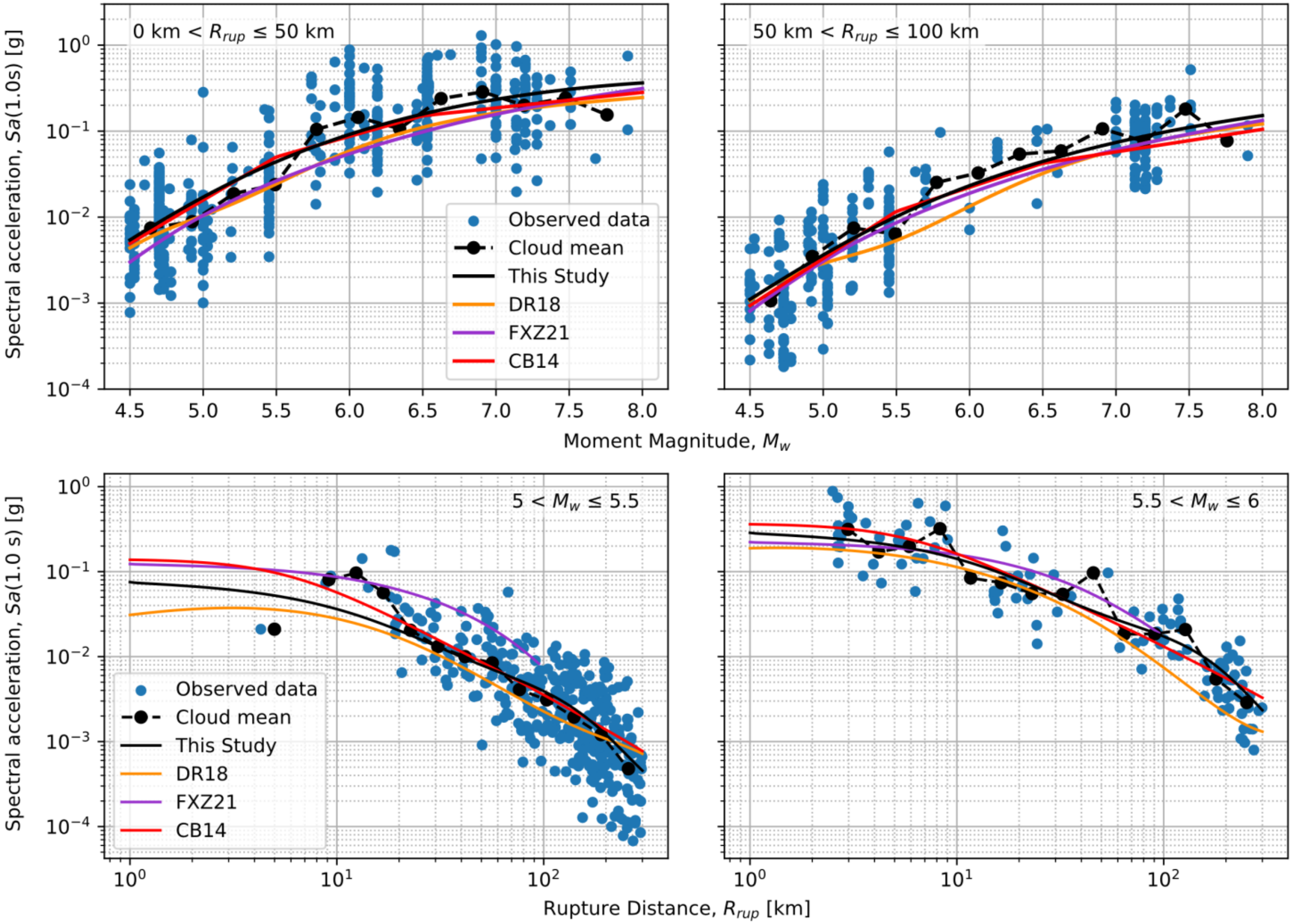
- *MinMax* normalisation
- log_{10} transformation in the vector of IMs
- Activation functions: *softmax*, *tanh*, and *linear* in the input, hidden and output layers, respectively
- Loss function: MSE
- Training and test set split: 80:20 ratio

Model performance – Performance metrics

- After mixed effects
- Optimal model selected



Model performance – Attenuation plots and comparison with other GMMs



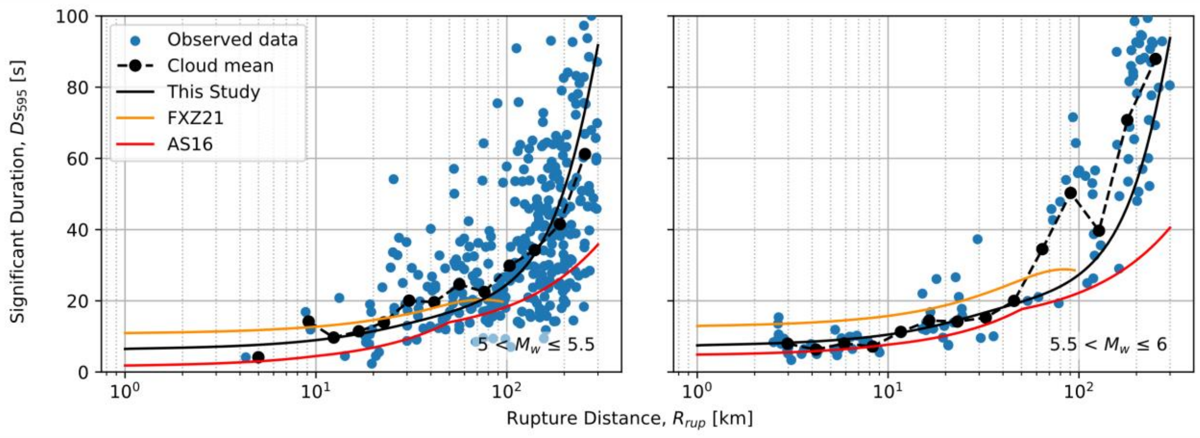
Machine learning models

GMM	Abbreviation	IMs
Campbell and Bozorgnia (2014)	CB14	*PGA*, *PGV*, *Sa*, Sa_{avg}
Dhanya and Raghukanth (2018)	DR18	*Sa*
Fayaz et al. (2021)	FXZ21	*Sa*, Ds_{595}
Campbell and Bozorgnia (2014)	CB08	*PGD*
Afshari and Stewart (2016)	AS16	Ds_{575}, Ds_{595}
Dávalos et al. (2020)	DHM20	*FIV3*
Dávalos and Miranda (2021)	DM21	Sa_{avg3}

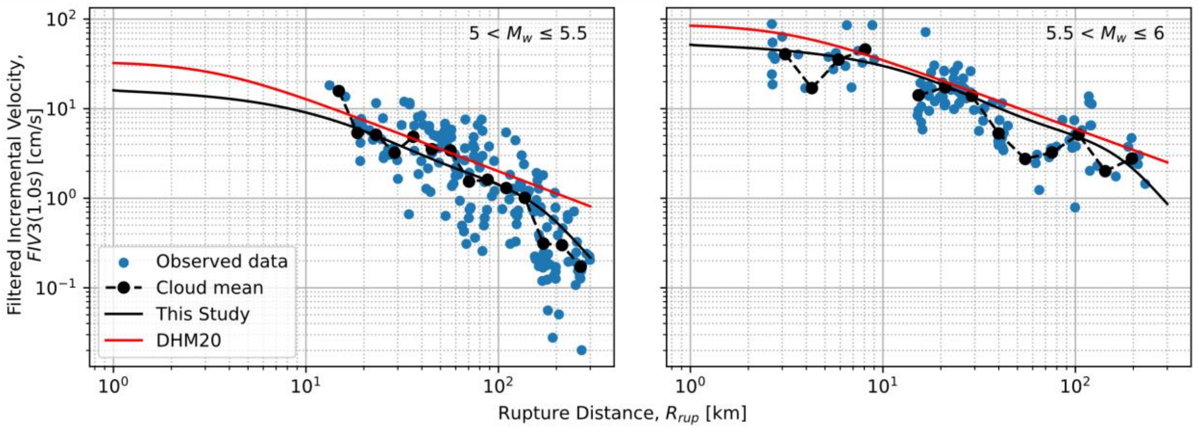
Based on NGA-West2 Database

Model performance – Attenuation plots and comparison with other GMMs

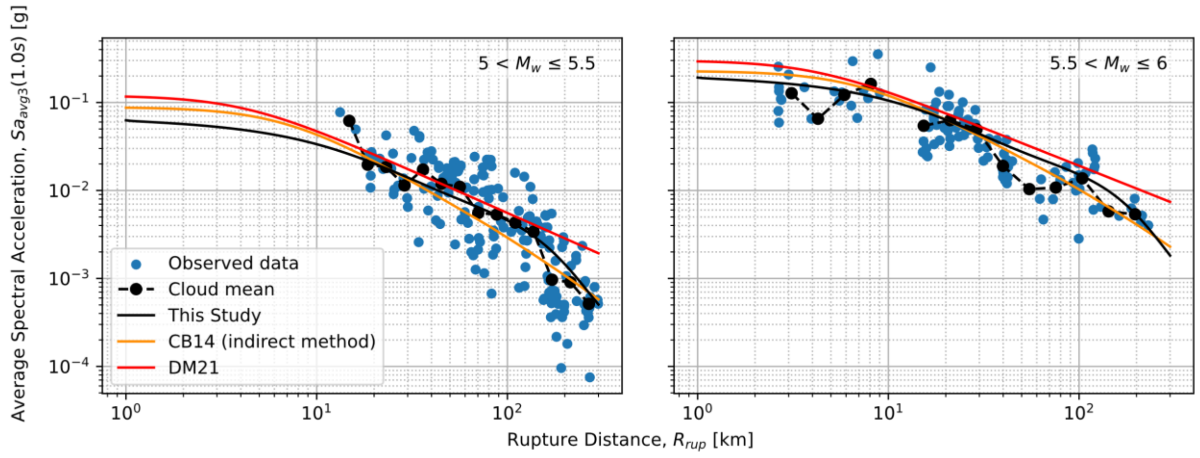
Significant duration, *Ds*



Filtered incremental velocity, FIV3



Average spectral acceleration



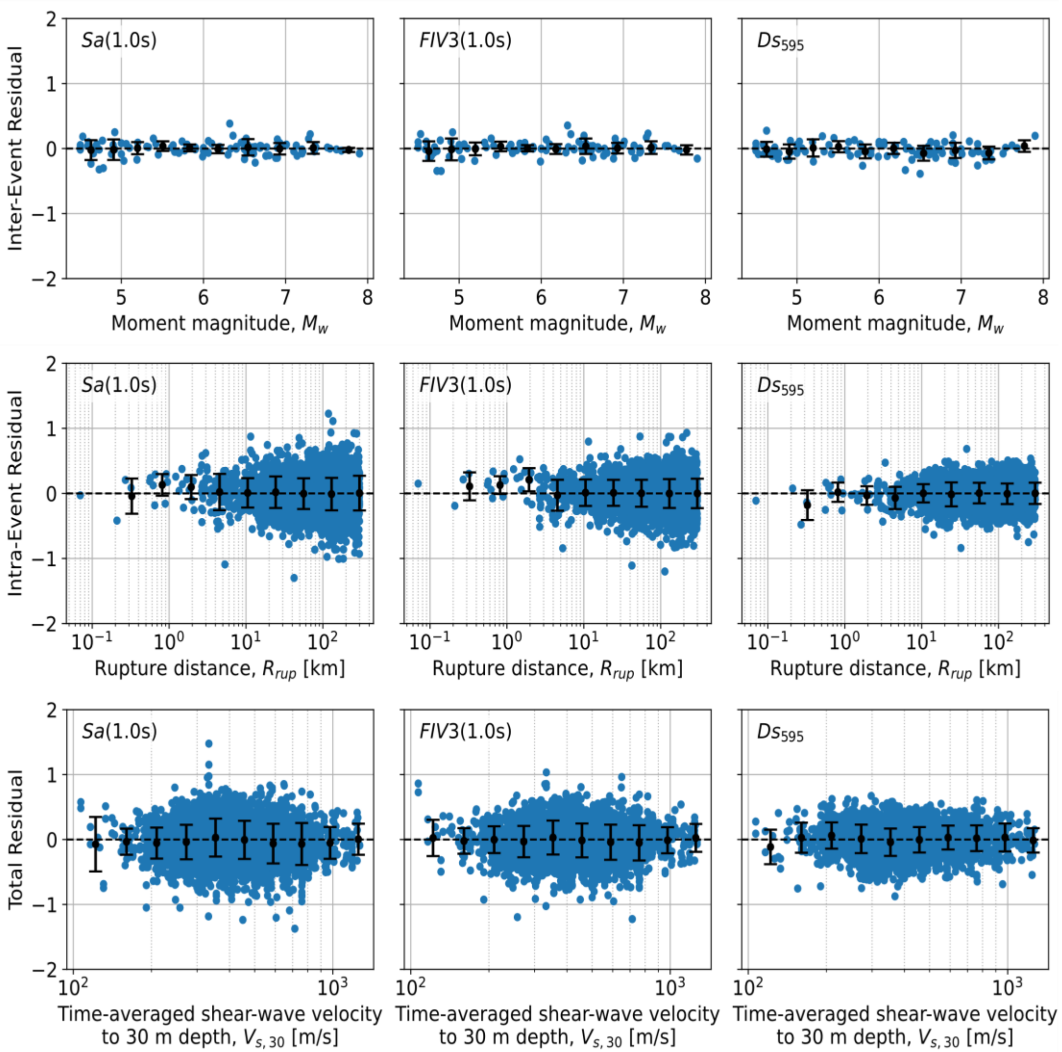
vs Rupture distance

Model performance – Residuals

Inter-event

Intra-event

Total

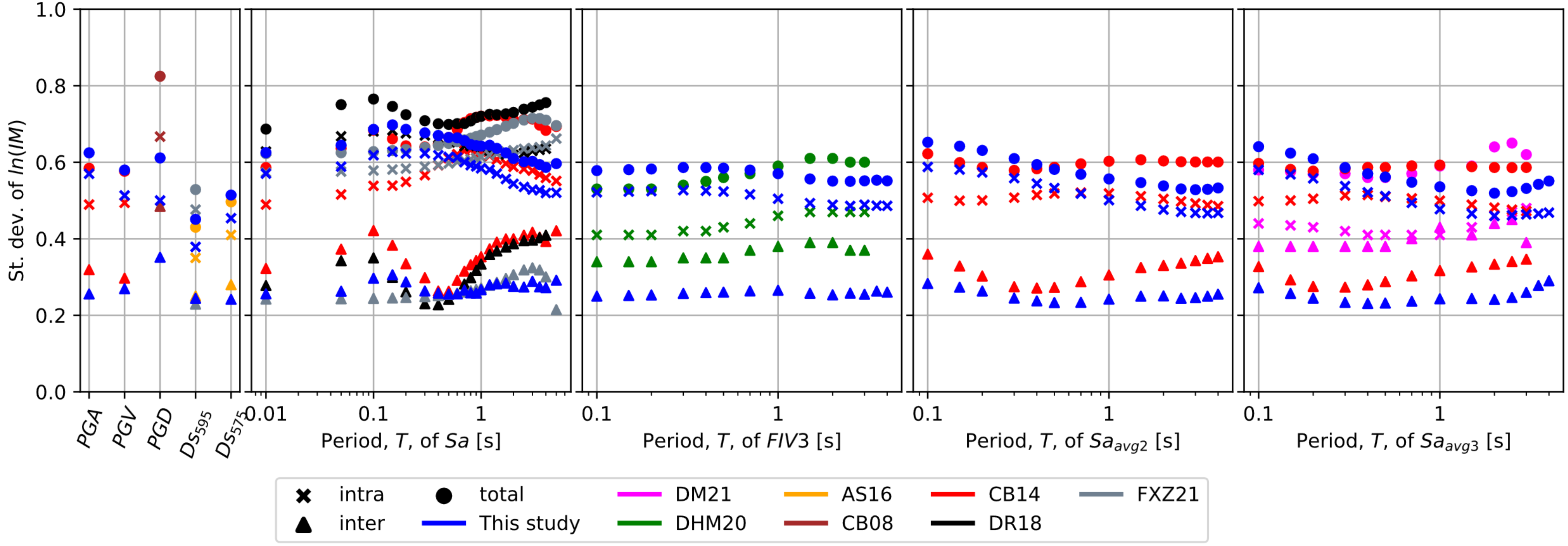


$$\log_{10} IM_i = f_i(\boldsymbol{X}, \boldsymbol{\theta}) + \delta b_i \tau_i + \delta w_i \varphi_i$$

$$\sigma = \sqrt{\tau^2 + \varphi^2}$$

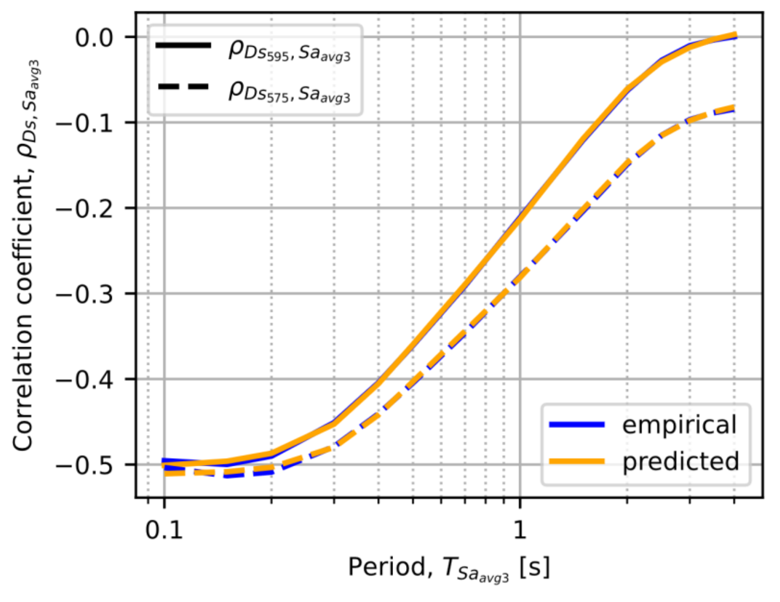
- No strong dependency on rupture parameters
- No bias
- Homoscedasticity assumption seems reasonable

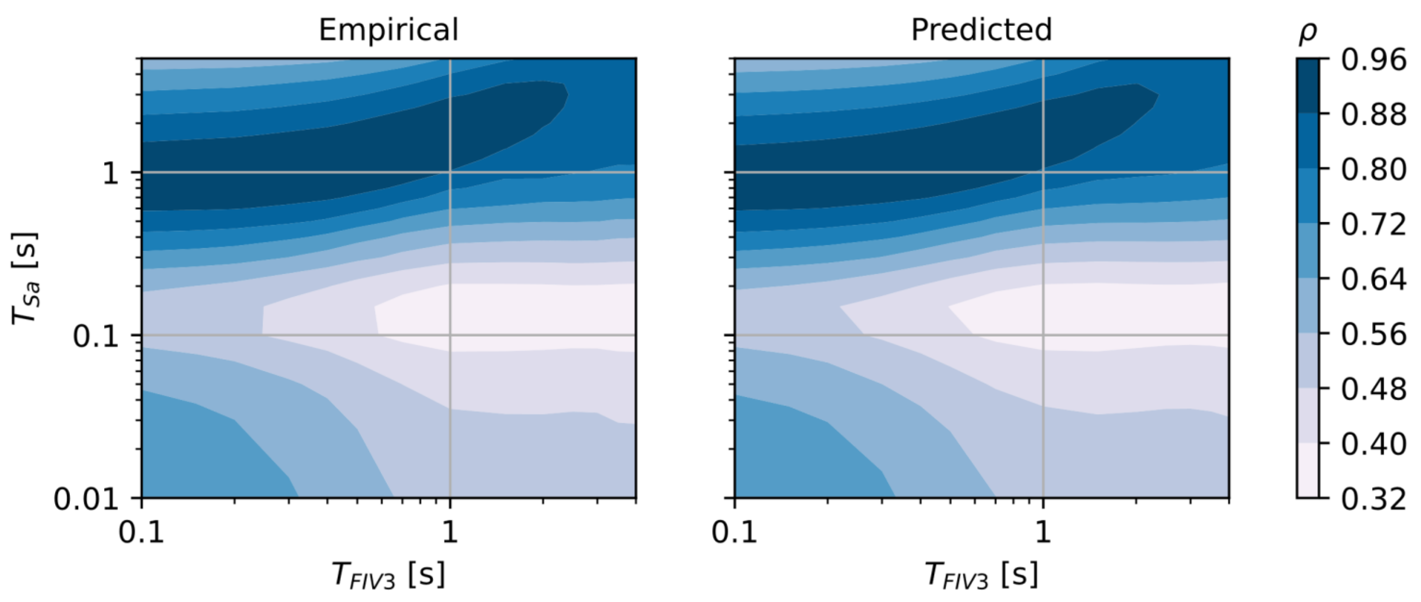
Model performance – Dispersion



Total standard deviation lowest for most IMs when using the GGMM

Correlation models (sneak peek)





Summary and conclusions

- This study proposed a generalised ground motion model (GGMM) for active shallow crustal earthquakes
- Stringently filtered subset of NGA-West2 database
- Miscellaneous amplitude and cumulative-based intensity measures (IMs)
- More IMs can be seamlessly added to the model's outputs with only minor modifications
- Different horizontal component definitions included
- The proposed GMM was validated through performance metrics and comparisons with other GMMs
- Dispersion of residuals (aleatory uncertainty) is low and performance metrics (i.e., R^2 and *MSE*) are good

Why is there a need for yet another model?

- Explored the potential of ANN to include various IMs and horizontal component definitions in a single model
  - User can use a single model to output several IMs → Which accommodates ease of use
  - Effectively captured the complex relationships and interactions between different IMs
  - Consistent and unified treatment of IM correlations since they come from the same database and GMM
- Recent research highlighted the potential of those next-generation intensity measures for a better characterisation of structural response (i.e., sufficiency, efficiency etc.)
- This model adds to the very limited pool of GMMs that estimate filtered incremental velocity, or average spectral acceleration
- More refined predictions of next-generation IMs using the ANN

Aristeidou, S., Shahnazaryan, D. and O'Reilly, G.J. (2024) 'Artificial neural network-based ground motion model for next-generation seismic intensity measures', Under Review

Thank you!

Model is available to use at:
https://github.com/Savvinos-Aristeidou/ANN-GGMM.git

Soon to be implemented in OpenQuake

Questions?

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