MECHANICS-INFORMED MACHINE LEARNING FOR GEOSPATIAL MODELING OF LIQUEFACTION: GLOBAL AND NATIONAL SURROGATE MODELS FOR SIMULATION AND NEAR-REAL-TIME RESPONSE

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PEER

PEER Annual Meeting
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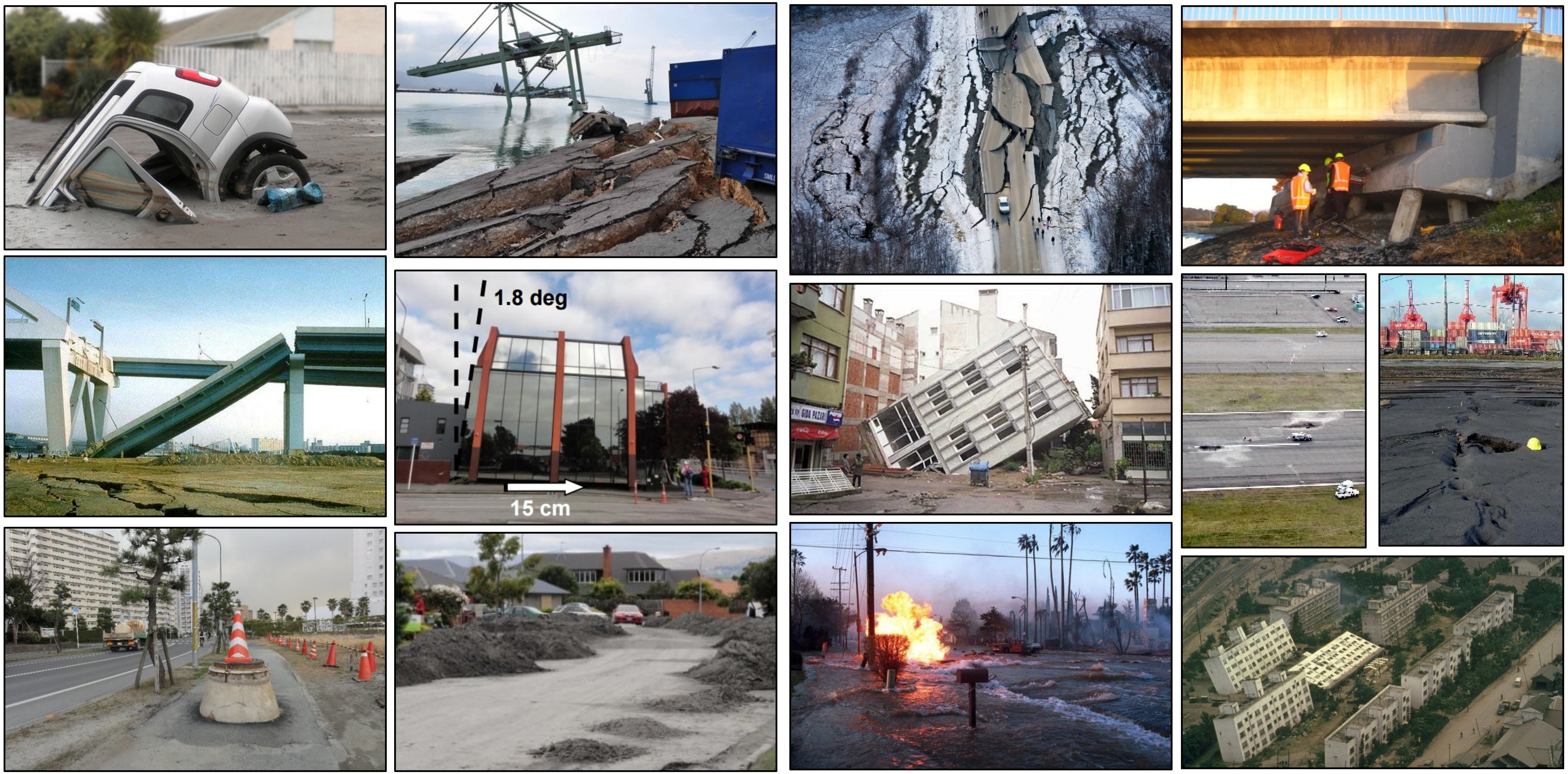
Outline

Motivation & Background — Goal — Model Concept/Demo — Performance — Ongoing Work

Motivation

➢ *Liquefaction routinely damages infrastructure, hinders post-event mobility and recovery, but is very challenging to predict at broad scales.*

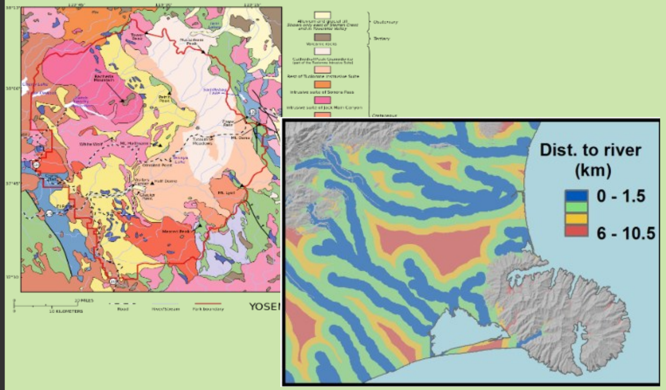


Background

➢ *Liquefaction models can be viewed as having 3 tiers:*

Tier 1

Geologic/Geospatial Models

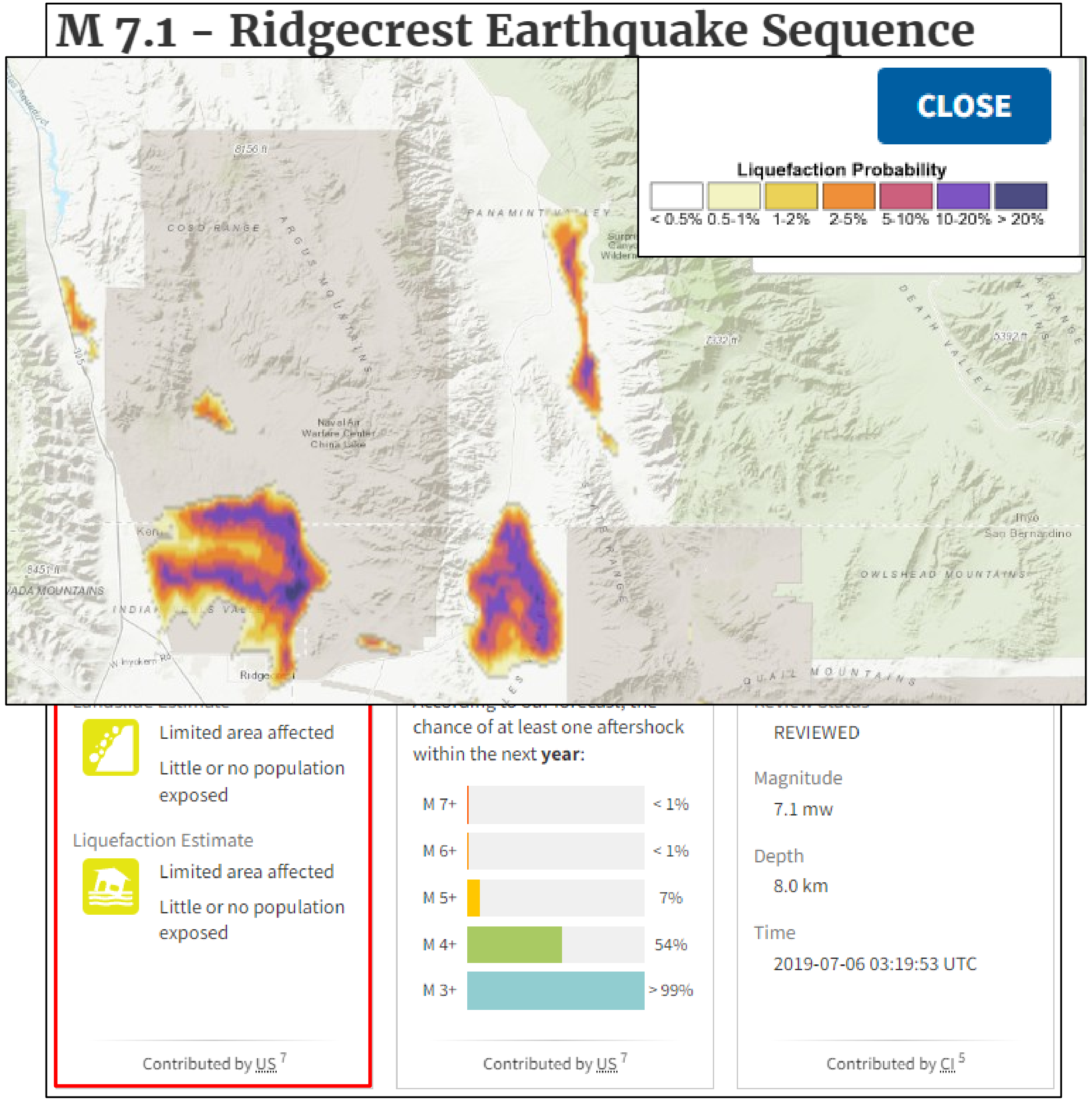


➢ ***Tier 1:*** *Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface data (e.g., HAZUS).*

Background

For example, Rashidian & Baise (2020):

- *Adopted by USGS for regional predictions in near-real-time and for future scenario events.*
- *5 variables: V_{S30}, precipitation, depth to water, distance to water, PGV.*
- *Trained on global liquefaction observations.*
- *Similar models used internationally.*



[1] Rashidian, V., & Baise, L. G. (2020). Regional efficacy of a global geospatial liquefaction model. Engineering geology, 272, 105644.

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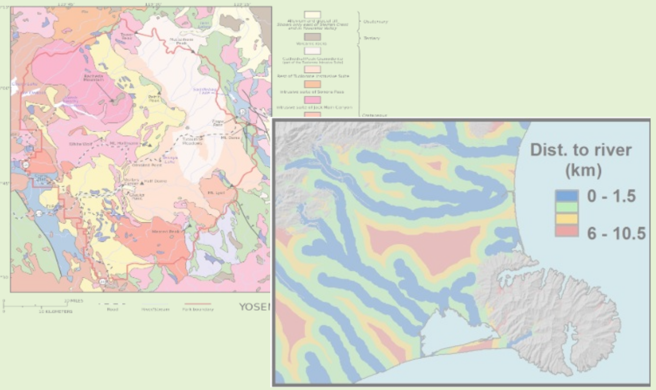
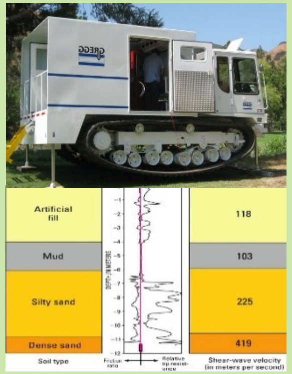
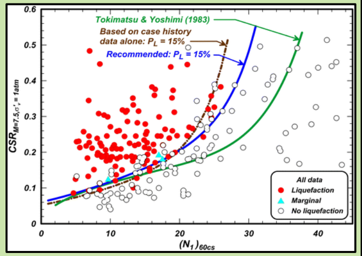


Tier 2

"Stress-Based" Models





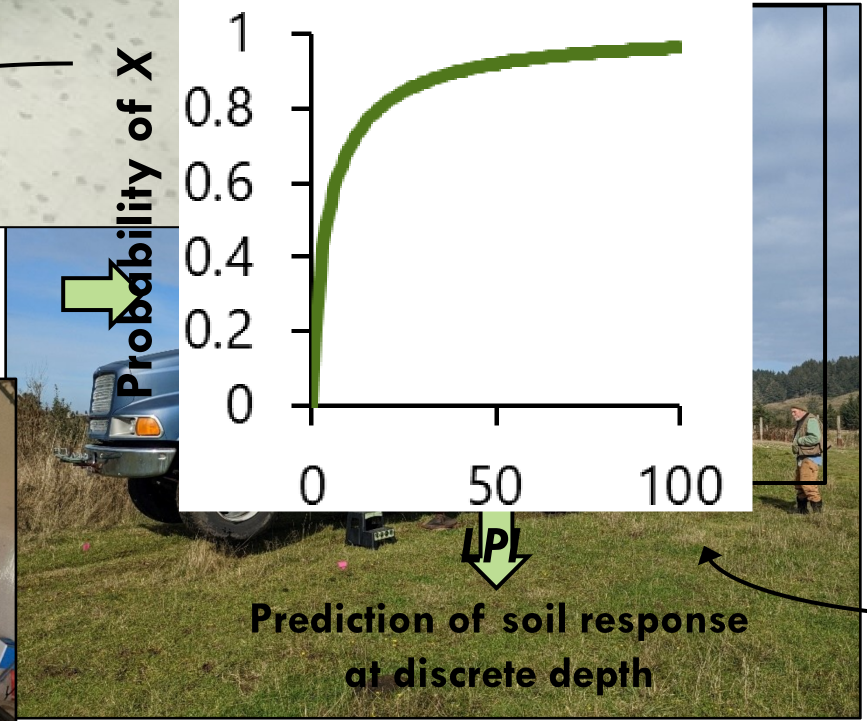
➢ ***Tier 1***: *Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface data (e.g., HAZUS).*

➢ ***Tier 2***: *Requires in-situ geotechnical test data. Used at site scale. Most widely validated and commonly used model in engineering practice.*

Background

➢ *Several types of in-situ data can be used, but Cone Penetration Test (CPT)-based models are generally favored (~$3k-$10k per test):*

Triggering/Incidence Models



LPI

Prediction of soil response at discrete depth

Manifestation/Consequence Models

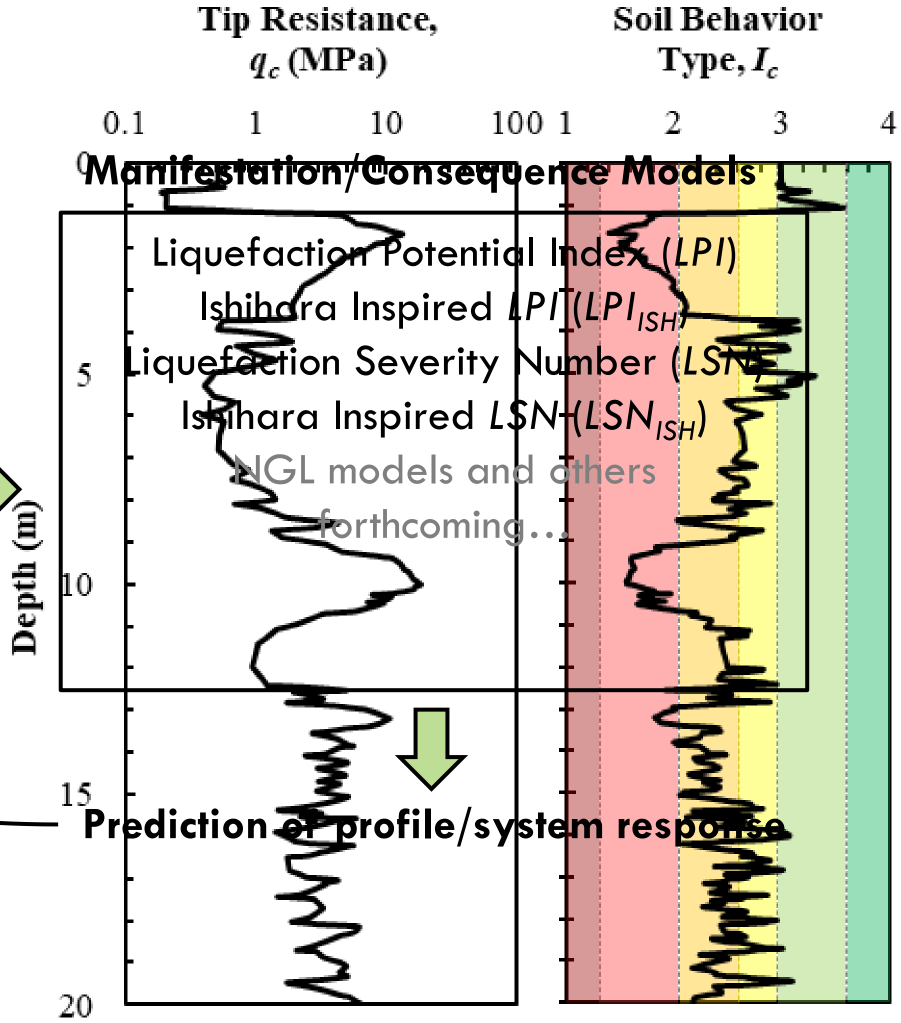
Liquefaction Potential Index (*LPI*)

Ishihara Inspired *LPI* (*LPI*$_{ISH}$)

Liquefaction Severity Number (*LSN*)

Ishihara Inspired *LSN* (*LSN*$_{ISH}$)

NGL models and others forthcoming…



Prediction of profile/system response

Ground Deformation

Pipeline Damage

Foundation Damage

Building Damage Ratio ($)

Etc.

Background

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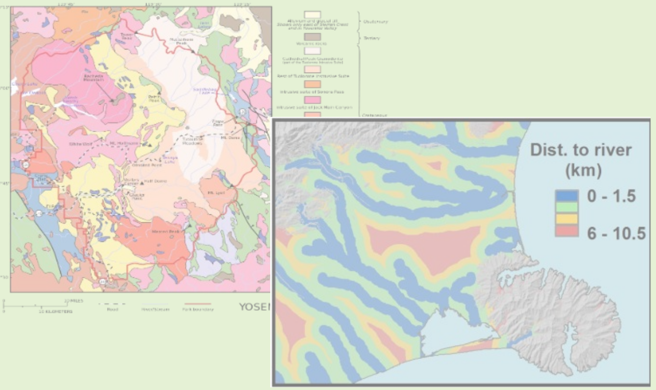
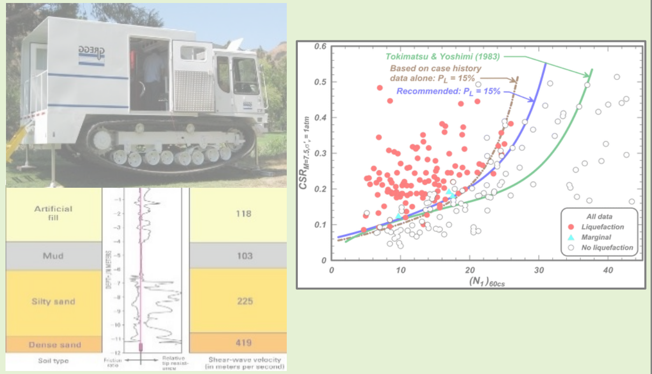
Geologic/Geospatial Models



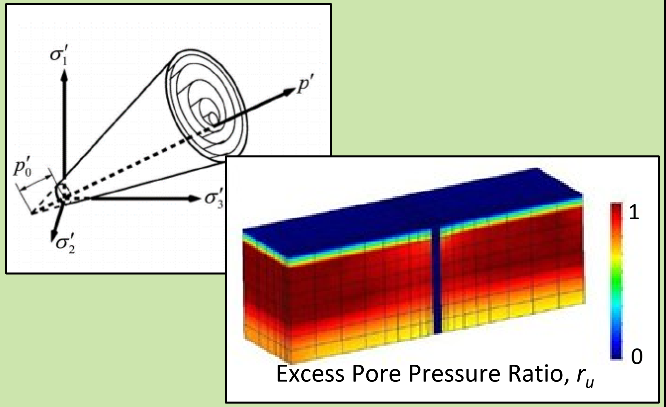
Tier 2

"Stress-Based" Models



Tier 3

Constitutive Models



➢ ***Tier 1**: Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface data (e.g., HAZUS).*

➢ ***Tier 2**: Requires in-situ geotechnical test data. Used at site scale. Most widely validated and commonly used model in engineering practice.*

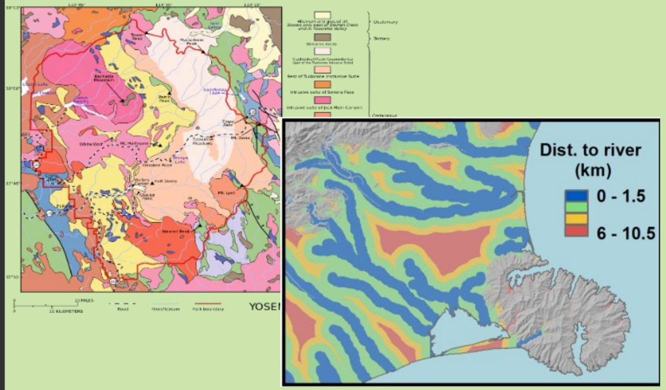
➢ ***Tier 3**: Requires many soil and model parameters. Used at project scale. Can provide additional spatial/temporal insights.*

Background

➢ *Liquefaction models can be viewed as having 3 tiers:*

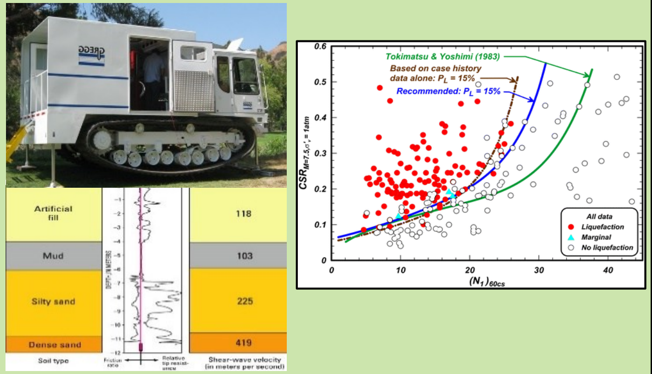
Tier 1

Geologic/Geospatial Models



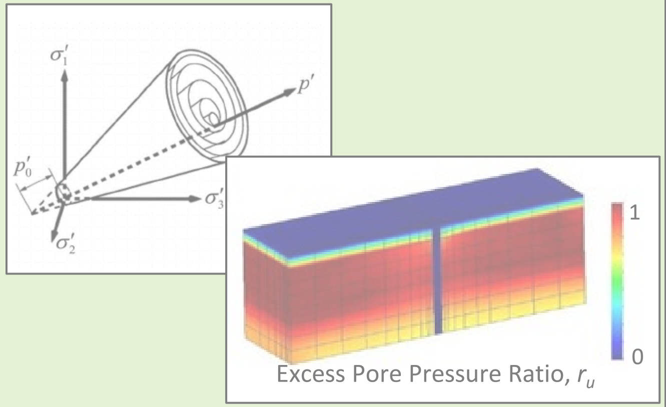
Tier 2

"Stress-Based" Models



Tier 3

Constitutive Models



Our focus.

Tier-1 models have important uses but major limitations.

How can Tier-2 data and models be used to improve them?

Outline

Motivation & Background — Goal — Model Concept/Demo — Performance — Ongoing Work

Project Goal

- ***Current Tier 1 models have some major limitations:***

1. ***They do not exploit the available geospatial information.***
   (accurate inference of subsurface conditions surely requires more than 4 variables)

2. ***They do not benefit from knowledge of liquefaction mechanics developed over 50+ yrs.***
   (models are trained only on observations, have no anchorage to mechanics)

3. ***They are not informed by, or anchored to, measurements of subsurface conditions.***
   (subsurface data is plentiful in many regions but is not used, often contradicts models)

- ***Goal:*** *A Tier-1 model that addresses these limitations by surrogating geotechnical models.*

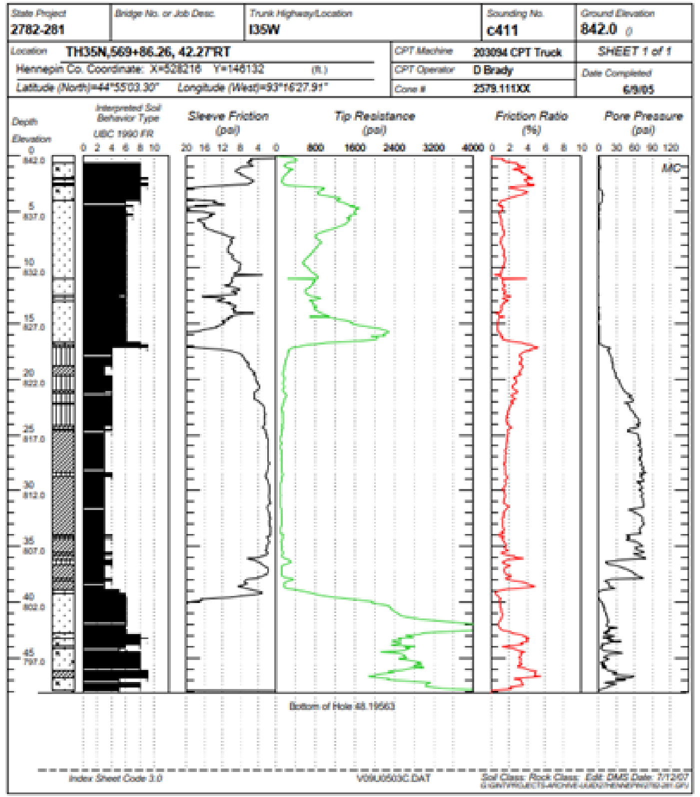
Outline

Motivation & Background — Goal — Model Concept/Demo — Performance — Ongoing Work

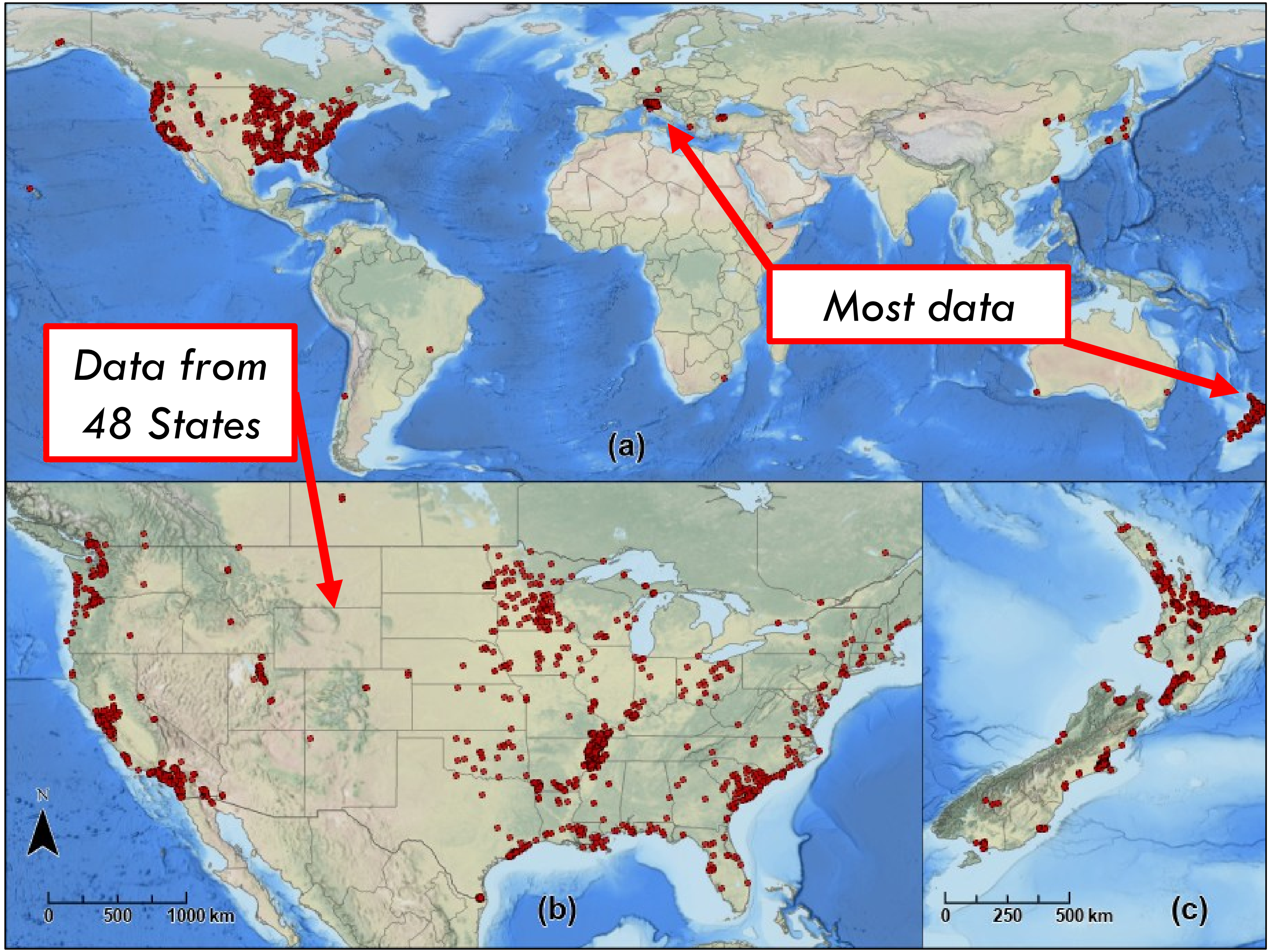
Modeling Concept & Demonstration: Step 1/5

➢ **Step 1/5**: Compile global subsurface geotechnical test data

CPT Data



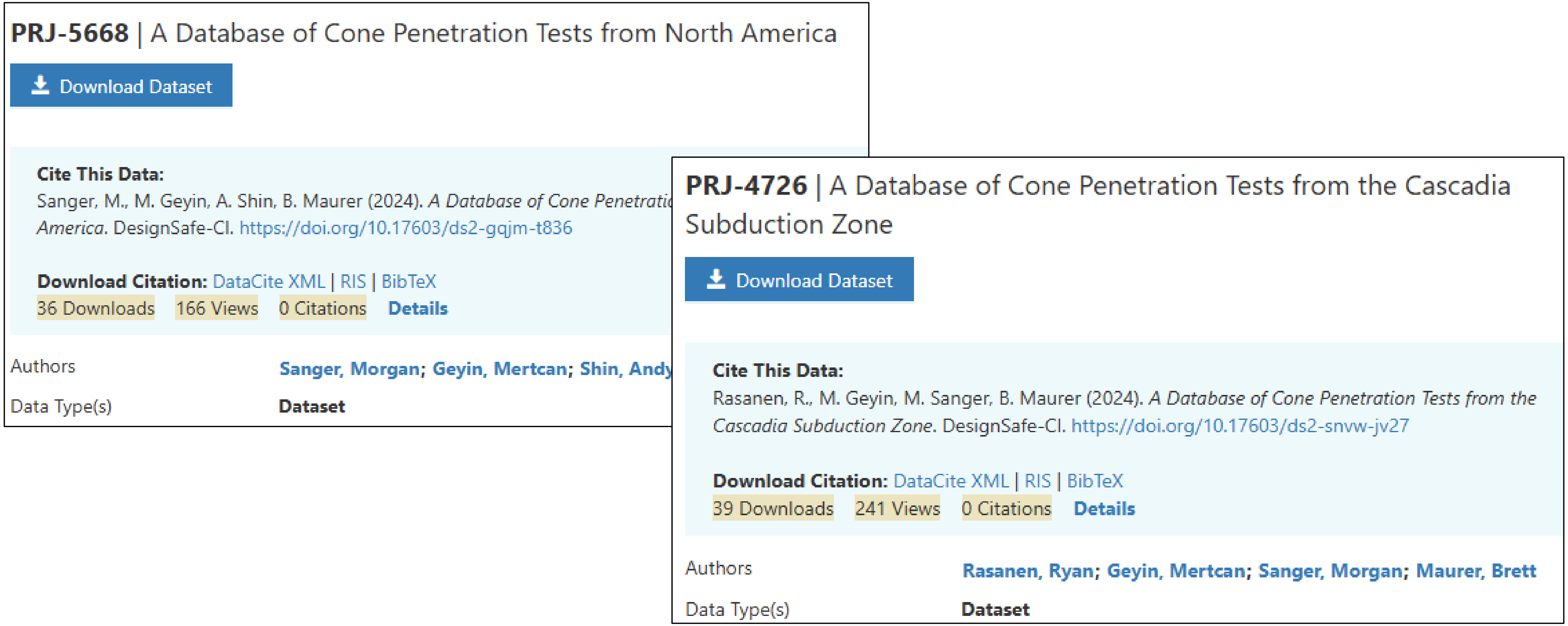
~40,000 CPTs
(weighted by spatial density)



Modeling Concept & Demonstration: Step 1/5

- ***Step 1/5**: Compile global subsurface geotechnical test data (we're using CPTs for now)*

- *Several thousand CPTs newly compiled from analog sources*



PRJ-5668 | A Database of Cone Penetration Tests from North America

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Cite This Data:
Sanger, M., M. Geyin, A. Shin, B. Maurer (2024). *A Database of Cone Penetratio*
America. DesignSafe-CI. https://doi.org/10.17603/ds2-gqjm-t836

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36 Downloads 166 Views 0 Citations **Details**

Authors	**Sanger, Morgan; Geyin, Mertcan; Shin, Andy**
Data Type(s)	**Dataset**

PRJ-4726 | A Database of Cone Penetration Tests from the Cascadia Subduction Zone

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Cite This Data:
Rasanen, R., M. Geyin, M. Sanger, B. Maurer (2024). *A Database of Cone Penetration Tests from the Cascadia Subduction Zone*. DesignSafe-CI. https://doi.org/10.17603/ds2-snvw-jv27

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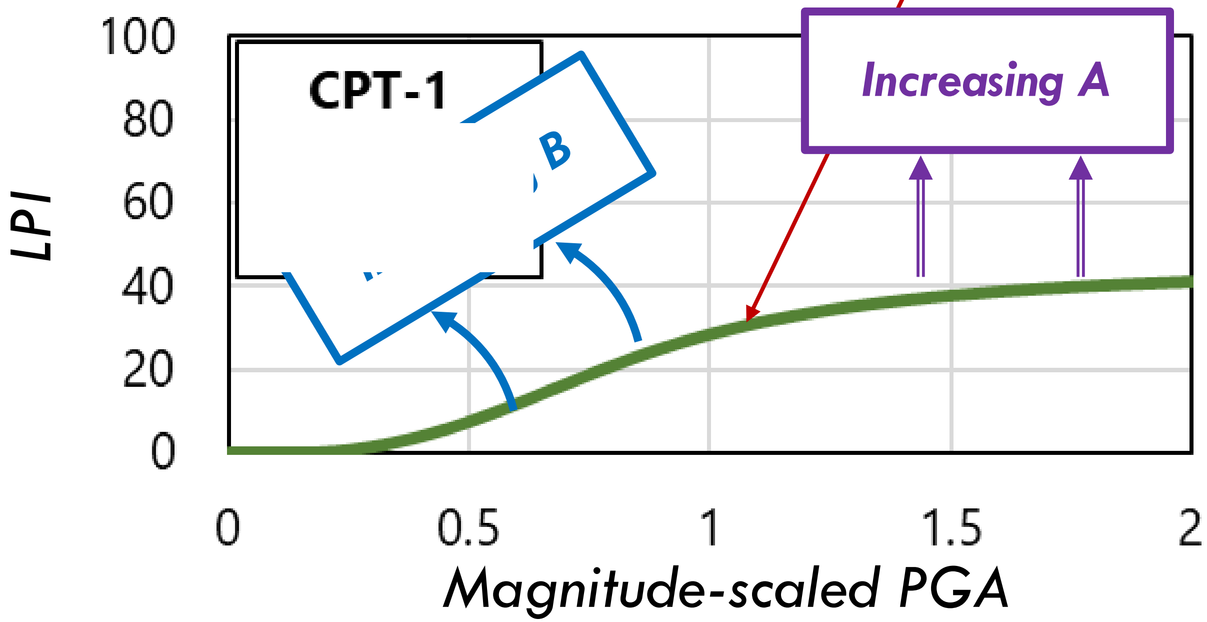
39 Downloads 241 Views 0 Citations **Details**

Authors	**Rasanen, Ryan; Geyin, Mertcan; Sanger, Morgan; Maurer, Brett**
Data Type(s)	**Dataset**

Modeling Concept & Demonstration: Step 2/5

- ***Step 2/5**: Subject each CPT to a spectrum of seismic loading (PGA_M)*
  - *Predict liquefaction response (e.g., LPI) using state-of-practice models*
  - *Fit functional form to this computed response*

$$LPI = A\tan^{-1}\left(B * \left(PGA_M - \left(A/B\right)\right)^2\right) * 100$$



A describes the response at relatively high PGA_M

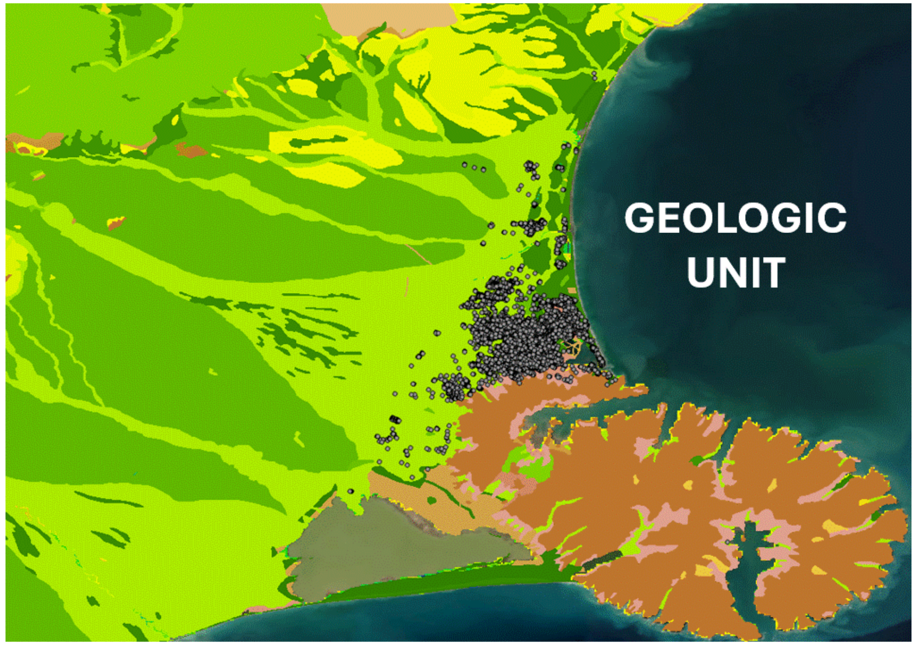
B describes the sensitivity of the response to PGA_M (i.e., how fast the maximum is reached)

- *Performed for 3 manifestation models (LPI, LPI_{ISH}, LSN); models can be ensembled*
- *A & B become our modeling targets…*

Modeling Concept & Demonstration: Step 3/5

➢ ***Step 3/5***: *Compile geospatial features/predictors at CPT locations*

Variable	Description
Convergence	A classifying measure of convergent areas as channels and divergent areas as ridges.
Compound topographic index	A proxy of long-term soil moisture availability, also topographic wetness index.
Depth to bedrock	Interpolated depth to bedrock.
Distance to coast	Minimum distance to coast.
Distance to river	Minimum distance to river computed for different Strahler orders.
Elevation deviation	A measu [illegible]
Geologic unit	Geology [illegible]
Geomorphon	Classifie [illegible] or depression.
Groundwater depth	Interpola [illegible]
Height above nearest drainage	A topogr [illegible] ainage network.
Landform entropy	A texture [illegible] ndow.
Landform uniformity	A texture [illegible]
Major landform	The land [illegible] indow.
Maximum multiscale deviation	The diffe [illegible] n of the window.
Maximum multiscale roughness	The sphe [illegible] ruggedness.
Pfafstetter level	The 'Pfaf [illegible] basins.
Precipitation	Mean an [illegible]
Profile curvature	A measu [illegible] flow.
Roughness	The larg [illegible] ding cells.
Scale of MMD	See Max [illegible]
Scale of MMR	See Max [illegible]
Shannon index	A diversi [illegible] ow.
Soil depth	Qualitati [illegible]
Soil drainage	Qualitati [illegible]
Soil order	Soil classification consistent with the New Zealand Soil Classification (NZSC).
Tangential curvature	The rate of change perpendicular to a slope gradient; relates to sediment accumulation.
Terrain ruggedness index	A measure of the ruggedness and topographic complexity (elevation variability) of landscapes.
Topographic position index	The difference of elevation of a cell and the mean of its 8 surrounding cells.
Topographic slope	The rate of change of elevation in the direction of the water flow line.
Vector ruggedness measure	Quantifies ruggedness via variation in sine and cosine of the slope in three dimensions.
Vs30	Average shear wave velocity of uppermost 30m.



Starting Point: ~75 global datasets

Modeling Concept & Demonstration: Step 3/5

- ***Step 3/5**: Compile geospatial features/predictors at CPT locations*

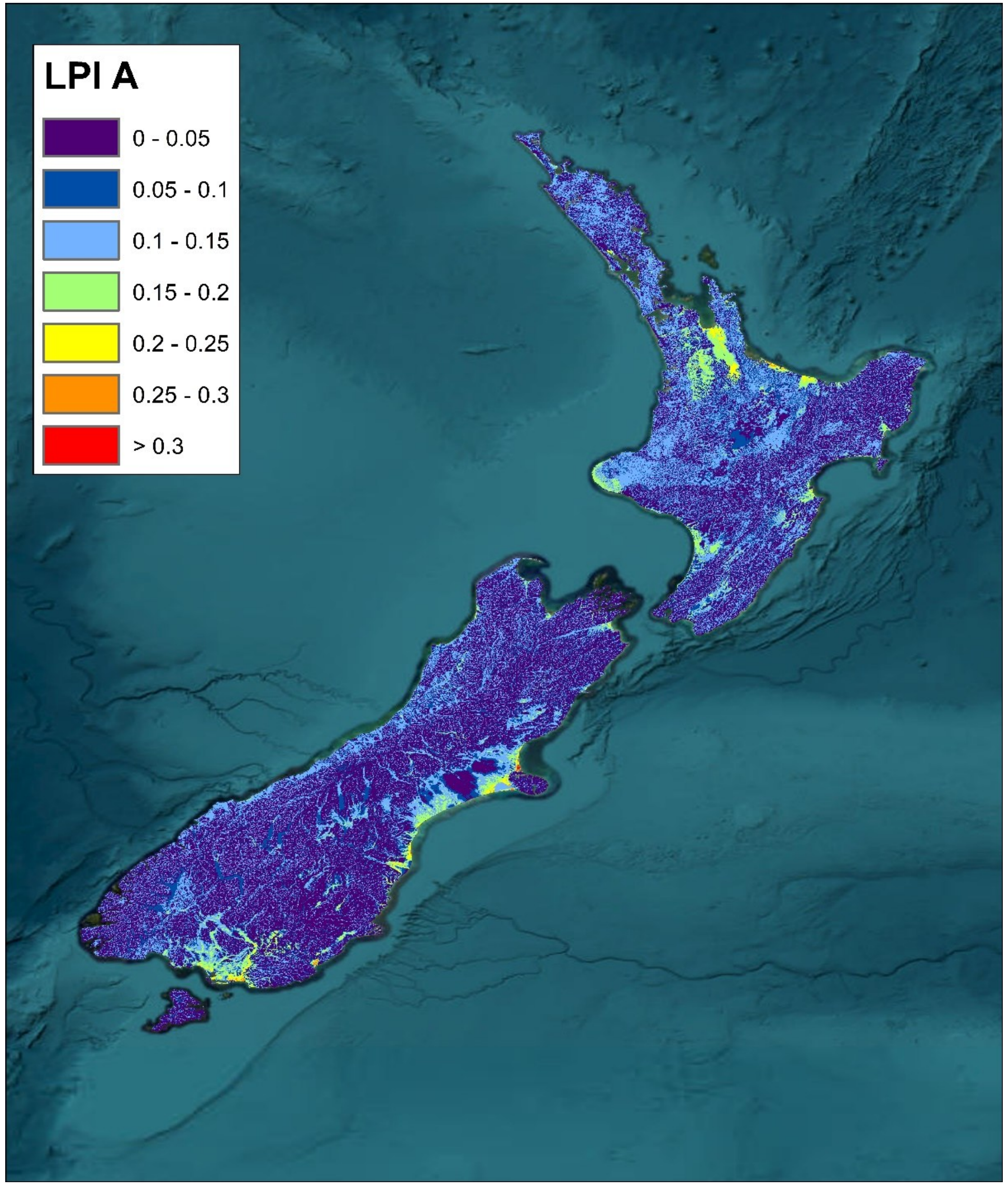
- *Features trimmed to ~40 via domain knowledge, correlation structure, iterative testing, consideration of overfitting behavior.*

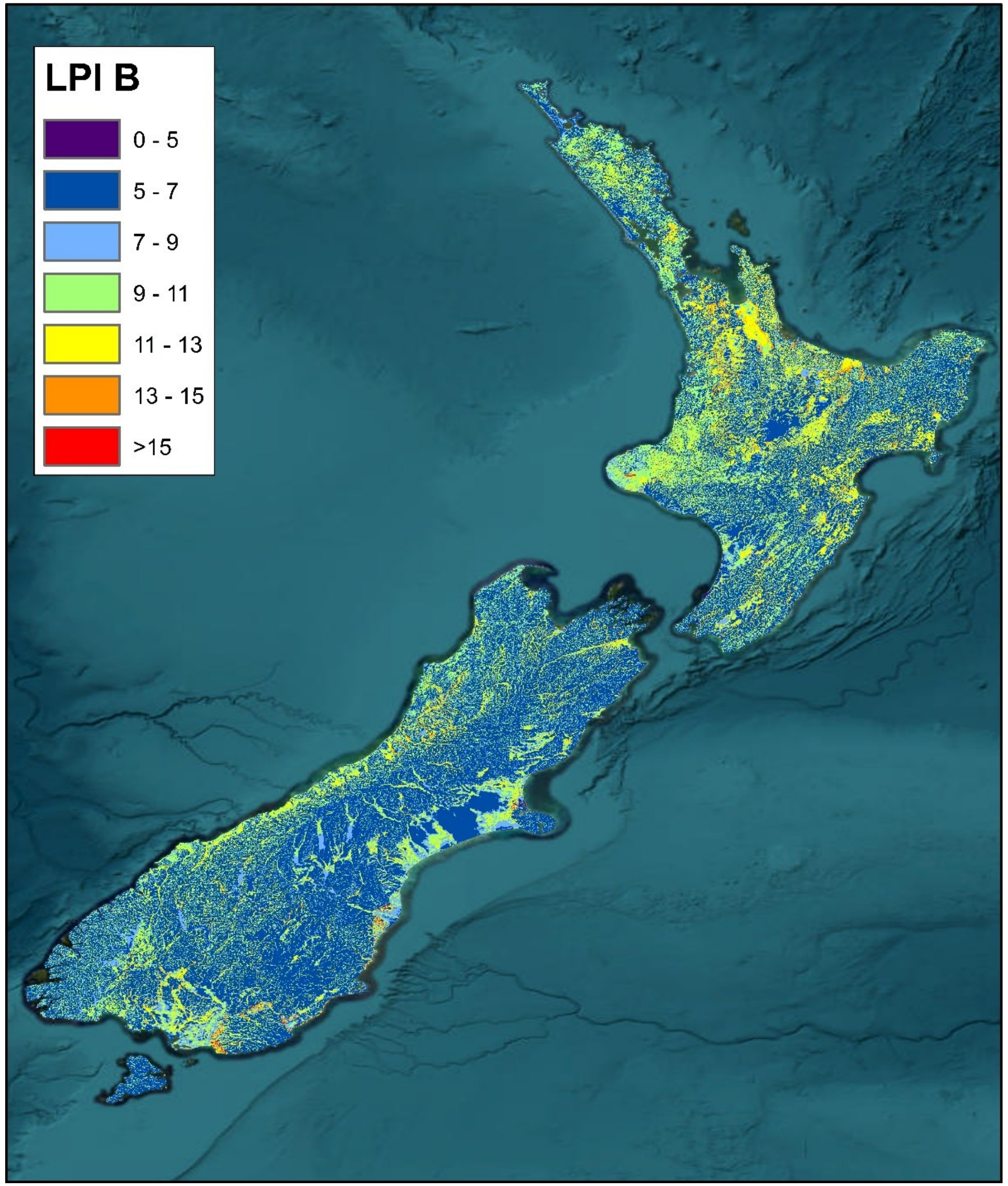
- *2 sets of models trained: (i) global; and (ii) region-specific (New Zealand)*

- *New Zealand has region-specific variables (e.g., geology, soils, V_{S30}), considerable data*
  - *Provides a test of whether regional specificity is advantageous.*

Modeling Concept & Demonstration: Step 4/5

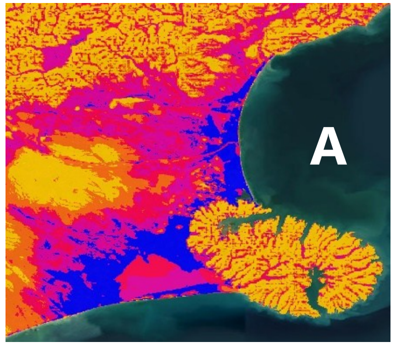
- ***Step 4/5**: Train ML models to predict A & B, then run for 1.3 billion locations with HPC.*





Modeling Concept & Demonstration: Step 4/5

- *Expected liquefaction response is, in effect, precomputed & stored everywhere on earth.*



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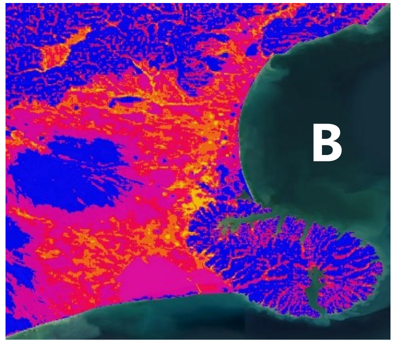

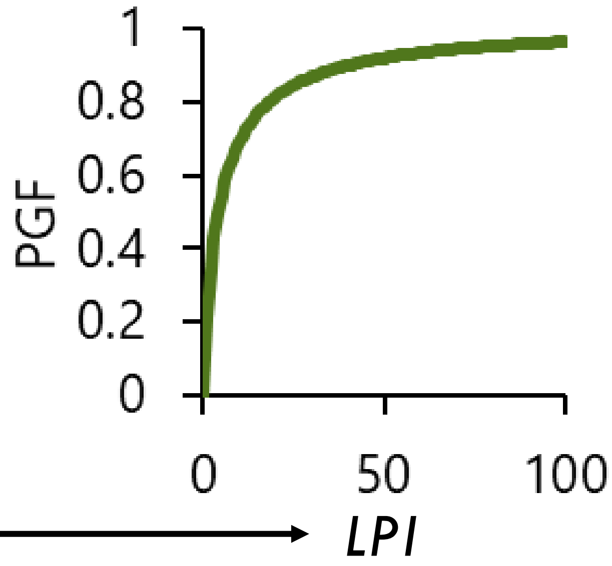

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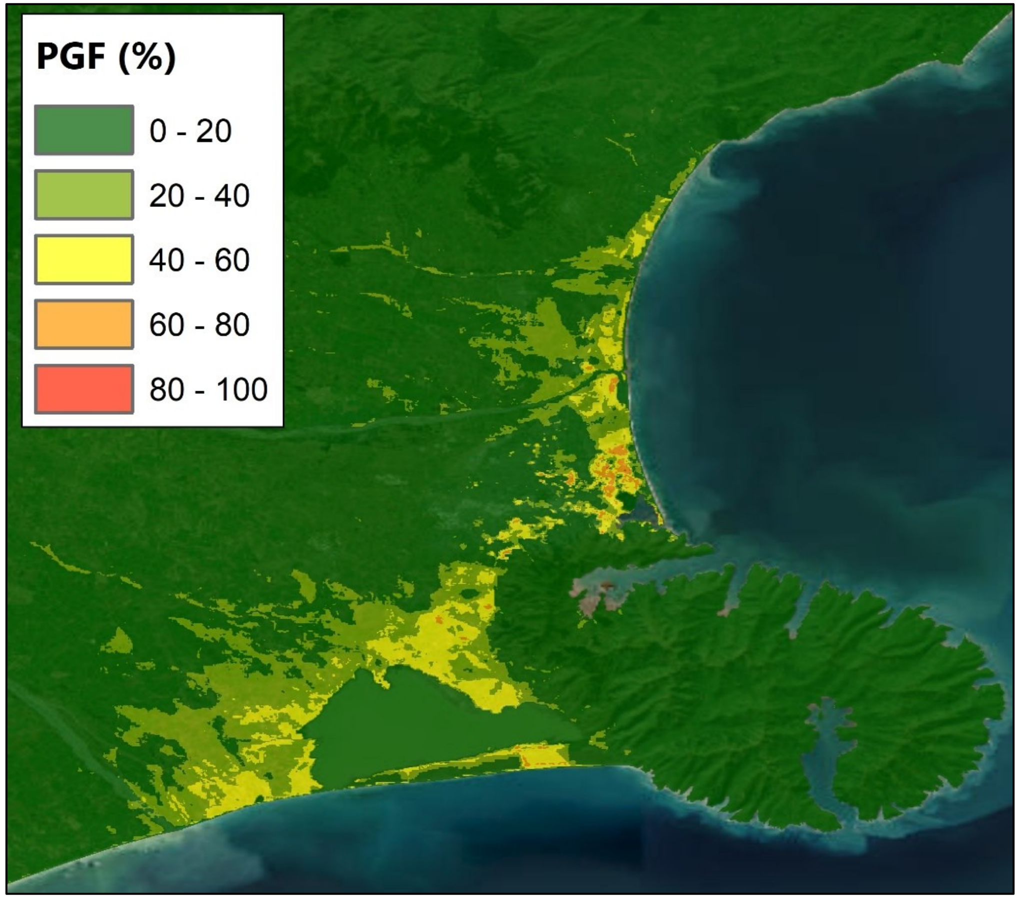

- *Permits rapid prediction of impacts (e.g., probability of ground failure, PGF).*

Modeling Concept & Demonstration: Step 4/5

- *All models bagged decision trees (all common ML/AI architectures tried)*
- *Performance <u>surrogating geotechnical models</u>:*

Model	***A***		***B***		***MI (e.g., LPI)***		***PGF***	
	MAE	**Standard Deviation**	**MAE**	**Standard Deviation**	**MAE**	**MSD**	**MAE**	**MSD**
	Global							
LPI-ML	3.0	7.0	5.0	15.5	4.5	11.3	8%	22%
LPI_{ISH}-ML	3.0	6.8	6.0	17.1	4.6	11.1	6%	25%
LSN-ML	4.0	10.5	18.0	26.8	4.9	16.7	7%	22%

- *Performance abstract until transformation to PGF via fragility function*

Modeling Concept & Demonstration: Step 4/5

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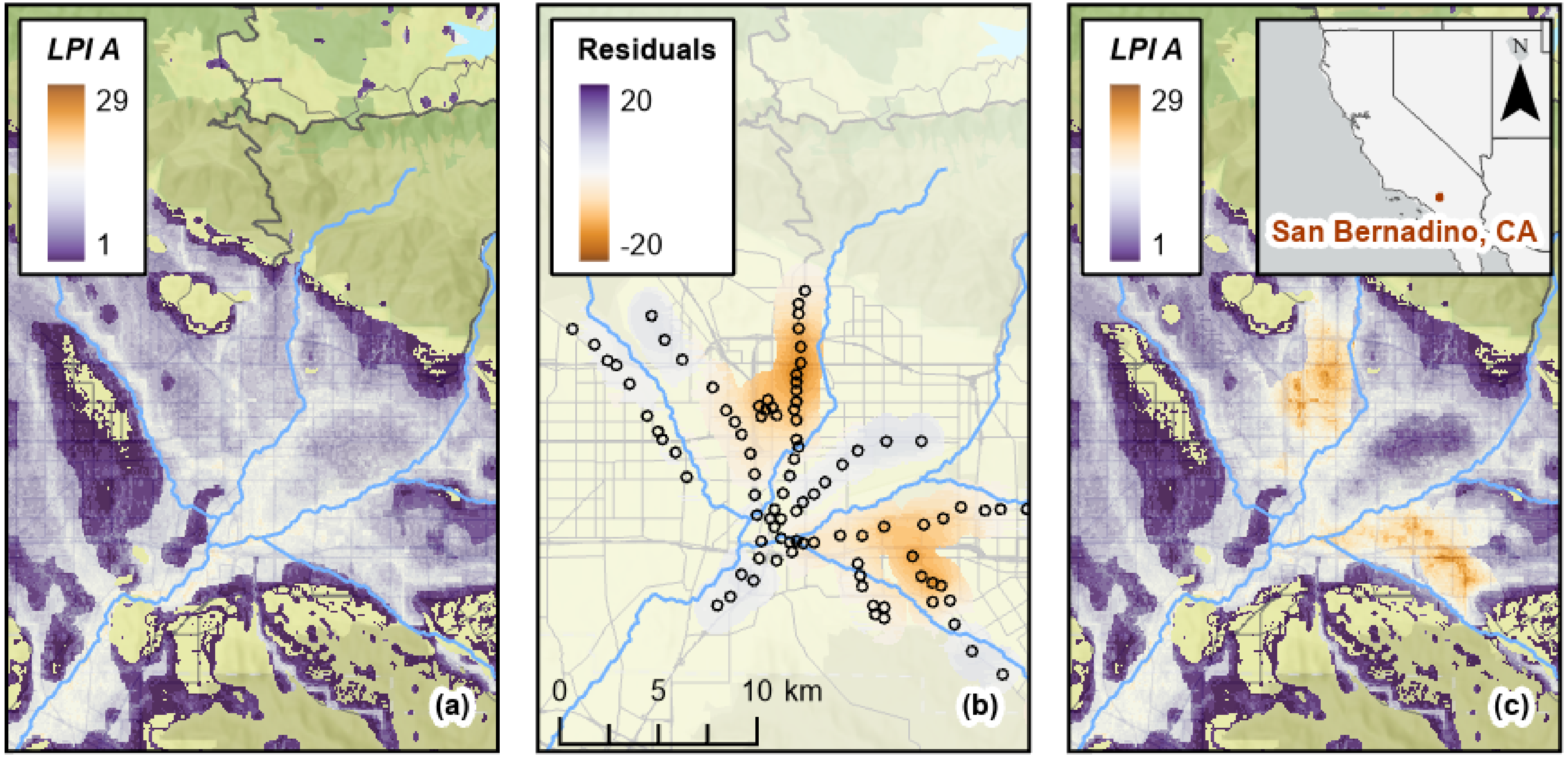
- *Performance abstract until transformation to PGF via fragility function*
- *Surrogating performance good, but doesn't describe ability to predict liquefaction…*

Modeling Concept & Demonstration: Step 5/5

- ***Step 5/5**: ML predictions are geostatistically updated by geotechnical data*

$$A_{Residual} = ln\frac{A_{observed}}{A_{predicted}}$$

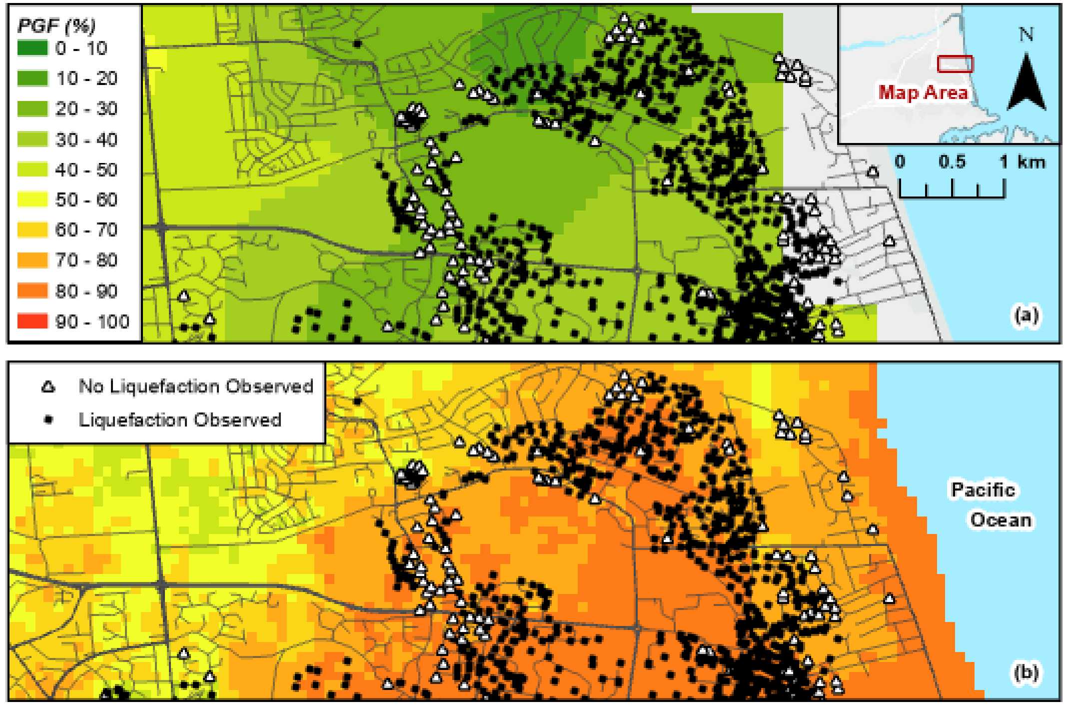


Before local updating

After local updating

Modeling Concept & Demonstration: Application Example

Feb 2011 M6.2 Christchurch Earthquake



Rashidian & Baise (2020)

ML Ensemble (before updating)

Modeling Concept & Demonstration: Products

PRJ-5732 | Mechanics-informed machine learning for geospatial modeling of soil liquefaction: global model map products for LPI, LPIish, and LSN

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Cite This Data:
Sanger, M., M. Geyin, B. Maurer (2024). *Mechanics-informed machine learning for geospatial modeling of soil liquefaction: global model map products for LPI, LPIish, and LSN* [Version 2]. DesignSafe-CI. https://doi.org/10.17603/ds2-c0z7-hc12

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Authors **Sanger, Morgan**; **Geyin, Mertcan**; **Maure**

Data Type(s) **Model**

A & B Maps
(models masked to limit extrapolation beyond parameter space)

Scripts to run on DesignSafe VM
(calls USGS ShakeMap URL)

PRJ-5745 | Mechanics-informed machine learning for geospatial modeling of soil liquefaction: example model implementation in Jupyter Notebook and Matlab

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Cite This Data:
Sanger, M., M. Geyin, B. Maurer (2024). *Mechanics-informed machine learning for geospatial modeling of soil liquefaction: example model implementation in Jupyter Notebook and Matlab* [Version 2]. DesignSafe-CI. https://doi.org/10.17603/ds2-sp3e-dp21

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Authors **Sanger, Morgan**; **Geyin, Mertcan**; **Maurer, Brett**

Data Type(s) **Jupyter Notebook**

Modeling Concept & Demonstration: Benefits

- *Trains on subsurface measurements (vast training set), not on liquefaction case histories (small and slow to grow training set).*

- *Mechanics-informed (geotechnical backbone guides response and scaling).*

- *Geostatistical updating anchors ML to reality.*

- *Is <u>very</u> easy for end-users to implement, test, critique, etc.*

- *Will continuously improve with more data and better geotechnical models (inevitable)*

Outline

Motivation & Background — Goal — Model Concept/Demo — Performance — Ongoing Work

Performance Tests vs. Rashidian & Baise (2020) [RB20]

- *One simple performance metric (among others) is* ***Brier Score:***

Predicted probability of observation

Observation (0 or 1)

$$\boldsymbol{Brier\ Score(BS) = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2}$$

- *0 = perfect model, 0.5 = random guessing, 1 = perfectly useless model.*
- *To assess statistical significance, we compute confidence intervals, Kolmogorov-Smirnov (KS) stats, and Cohen's d effect on BS samples.*
- *BS data resampled via agglomerative clustering to reduce autocorrelation effects (small).*

Model Performance Tests vs. Rashidian & Baise (2020) [RB20]

- ***Test 1: Does the model perform better in unbiased regions with zero geotechnical data?***
- *Test set = Events that postdate RB20 training set and where **no geotech data** is available.*
  - *Inventories from 2019 Ridgecrest, 2019 Puerto Rico, and 2023 Turkey Earthquakes*

Model	Mean *BS*	99% Confidence Interval of Mean *BS*	Comparison Against RB20	
			KS Test Statistic	Cohen's *d* Effect
RB20	0.393	0.380 - 0.407	-	-
LPI-ML	0.153	0.143 - 0.162	0.56	-1.51
LPI_{ISH}-ML	0.128	0.120 - 0.137	0.62	-1.62
LSN-ML	0.180	0.170 - 0.191	0.49	-1.46
Ensemble	0.146	0.138 - 0.155	0.57	-1.59

- *ML outperforms RB20 to significant degree (large improvements per KS, d)*

Model Performance Tests vs. Rashidian & Baise (2020) [RB20]

- ***Test 2: Does geostatistical updating improve the model's performance?***
- *Test set = Inventories from* ***24 global events in areas with geotech data***

Model	Mean *BS*	99% Confidence Interval of Mean *BS*	Comparison Against RB20	
			KS Test Statistic	Cohen's *d* Effect
RB20	0.299	0.292-0.305	-	-
Before Updating				
LPI-ML	0.231	0.226-0.237	0.24	-1.05
LPI_{ISH}-ML	0.228	0.223-0.233	0.22	-1.11
LSN-ML	0.234	0.228-0.241	0.19	-0.99
Ensemble	0.228	0.222-0.233	0.24	-1.09

- *ML outperforms RB20 to significant degree (moderate-to-large improvements per KS, d)*
- *Local updating further improves performance*

Model Performance Tests vs. Rashidian & Baise (2020) [RB20]

- ***Test 3: Does model regionalization improve performance before updating?***
- *Test set = Applied **global** vs **region-specific model** to **3 events in Canterbury NZ***

Model	Mean *BS*	99% Confidence Interval of Mean *BS*	Comparison Against RB20	
			KS Test Statistic	Cohen's *d* Effect
RB20	0.204	0.200-0.207	-	-
Global				
LPI-ML	0.143	0.139-0.147	0.40	-1.20
LPI_{ISH}-ML	0.127	0.123-0.132	0.52	-1.08
LSN-ML	0.187	0.183-0.191	0.21	-1.30
Ensemble	0.146	0.142-0.149	0.40	-1.24

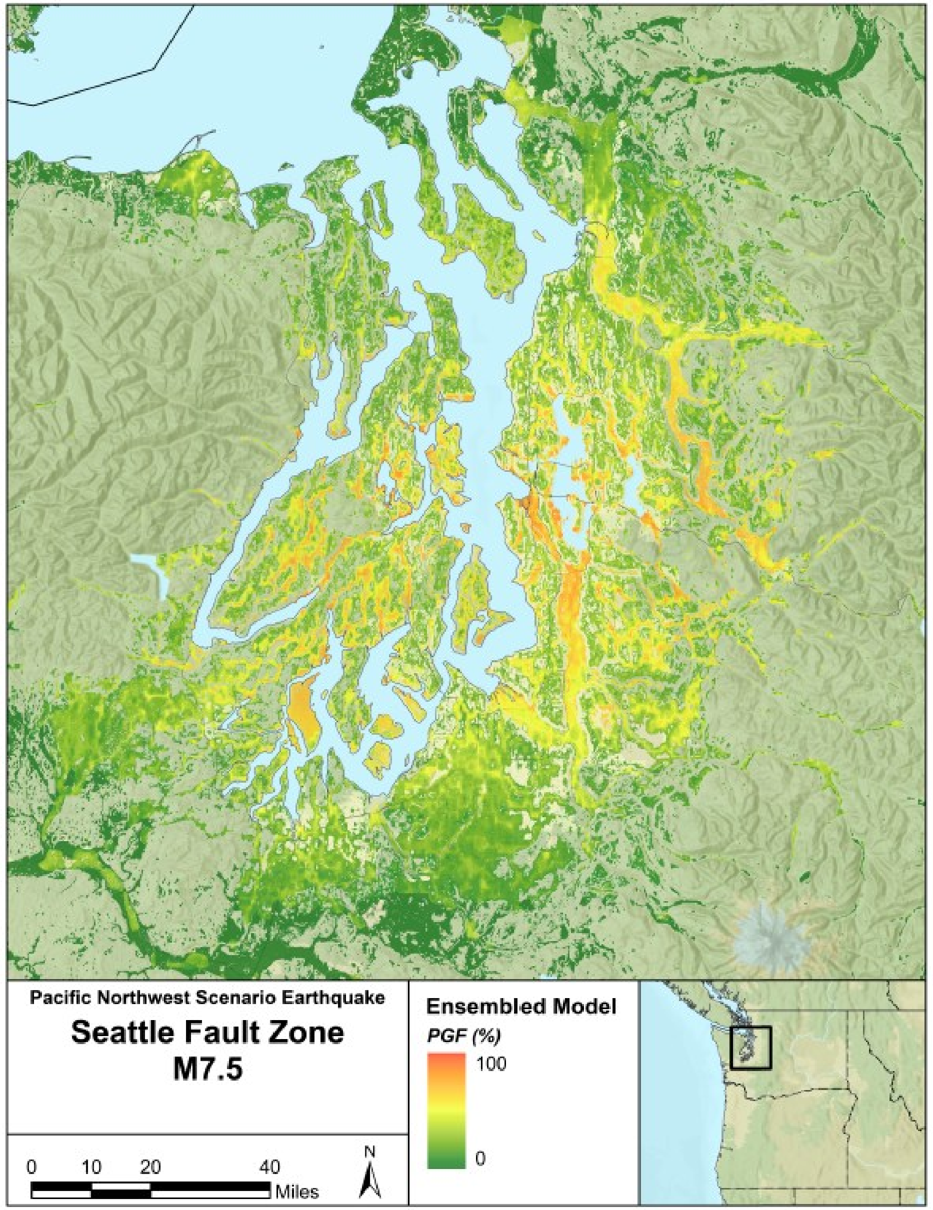
- *ML outperforms RB20 to significant degree (moderate-to-large improvements per KS, d)*
- *Regional model performs only marginally better*

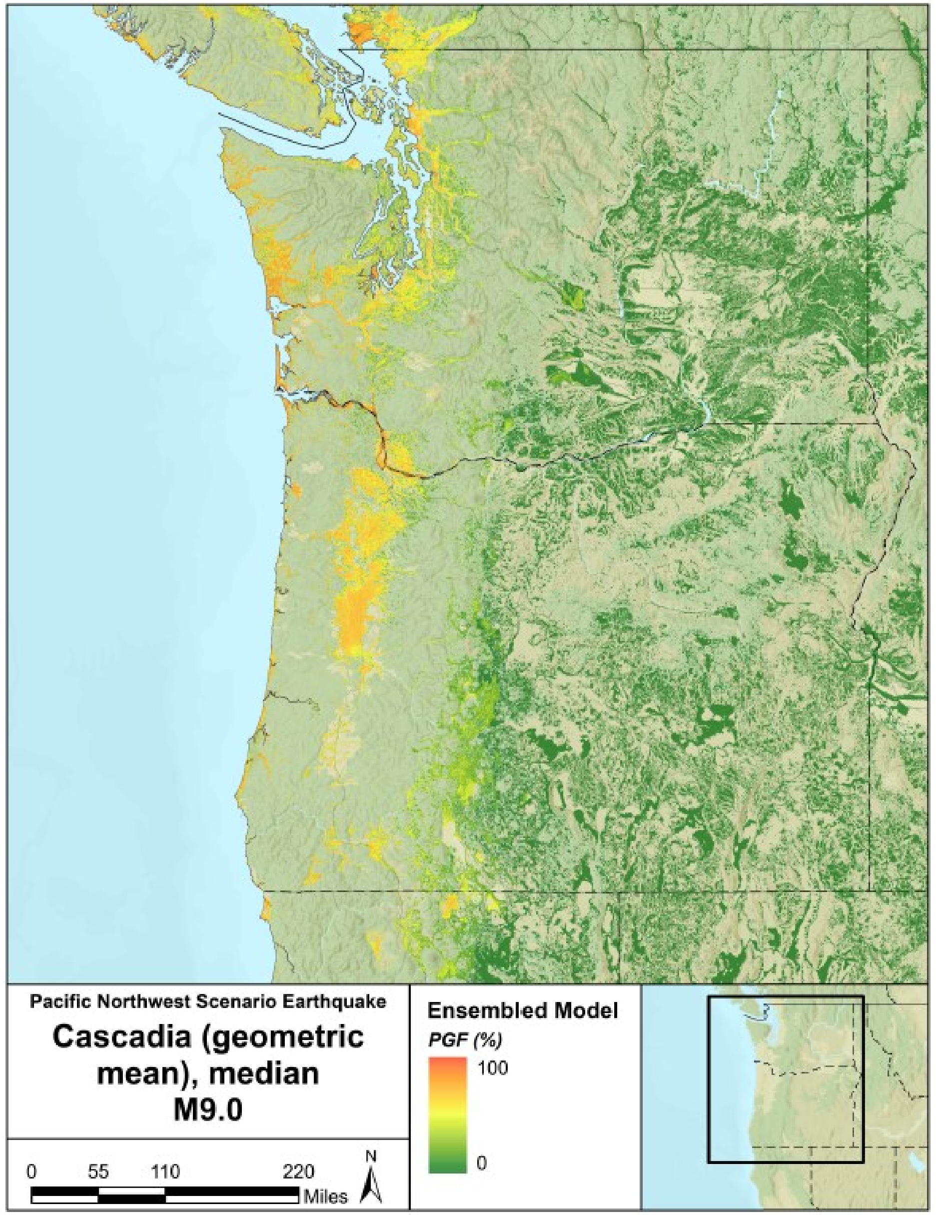
Outline

Motivation & Background — Goal — Model Concept/Demo — Global Performance — Ongoing Work

Ongoing Work

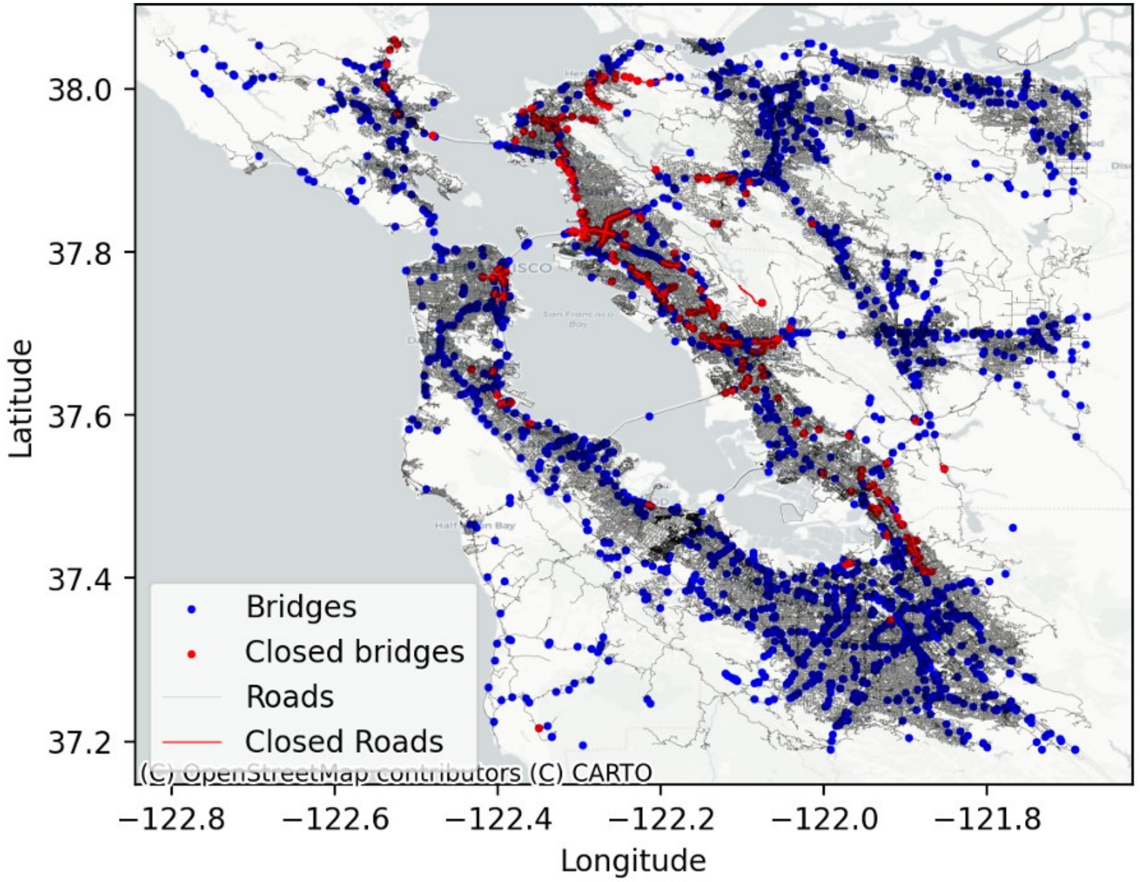
- *Integration with SimCenter tools (R2D) and USGS information products*
- *PEER scenario events*

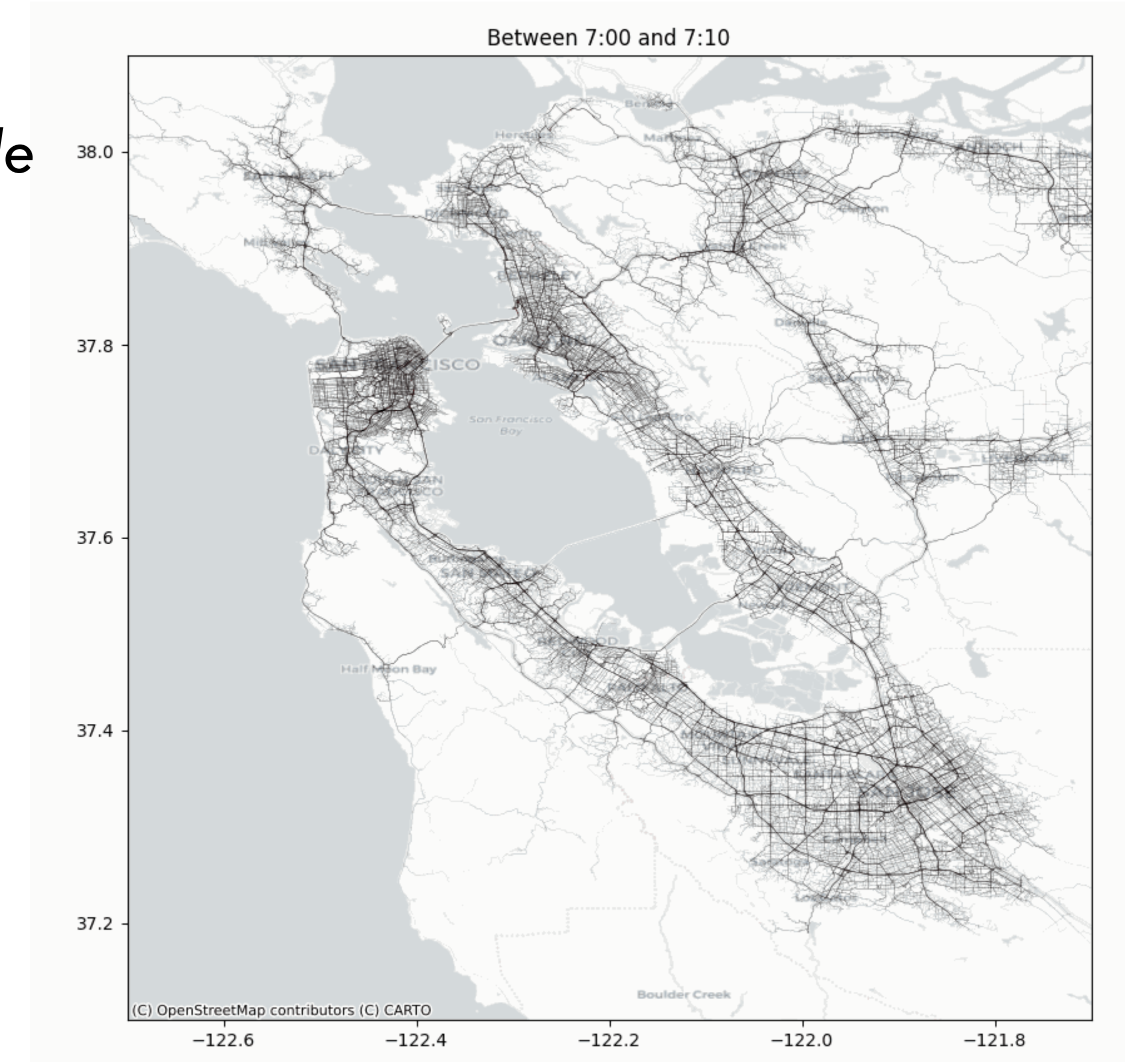




Ongoing Work

- *Integration with SimCenter tools (R2D) and USGS information products*
- *PEER scenario events*
- *Network modelling in scenario events*
- *Maps also permit PBEE analyses at national scale*





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References

- *Sanger, M.D., Geyin, M., and Maurer (2025). "Mechanics-Informed Machine Learning for Geospatial Modeling of Soil Liquefaction: Global and National Surrogate Models for Simulation and Near-Real-Time Response." Journal of Geotechnical and Geoenvironmental Engineering, ASCE, In Review.*
- *Maurer, B.W. and Sanger, M.D. (2023). "Why 'AI' Models for Predicting Liquefaction have been Ignored, Plus some that Shouldn't Be." Earthquake Spectra, 39(3): 1883-1910.*
- *Geyin, M. and Maurer, B.W. (2020). "Fragility functions for liquefaction-induced ground failure." Journal of Geotechnical and Geoenvironmental Engineering, 146(12): 04020142, ASCE.*
- *Sanger, M.D., Geyin, M., and Maurer, B.M. (2024). "Rapid Map: A mechanics-informed machine learning model for regional liquefaction hazard planning and response." Earthquake Engineering Research Institute Annual Meeting, 9-12 April, Seattle, USA.*