

LOOKING FORWARD AND BACKWARD AT REGIONAL LIQUEFACTION IMPACTS IN M9 CASCADIA SIMULATIONS

(WITH MODELLING OF SUBSURFACE, 1D SITE RESPONSE)

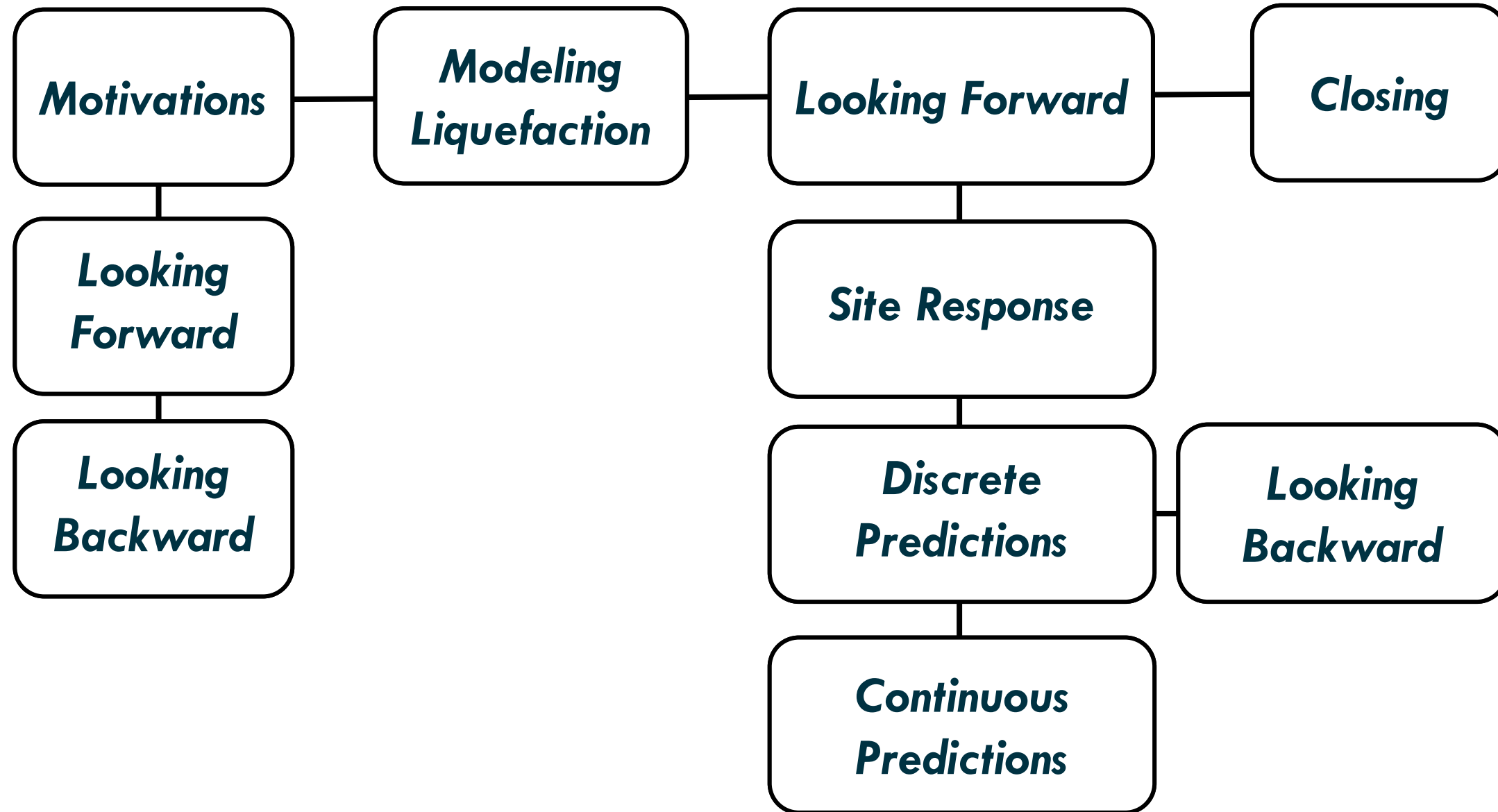
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University of Washington



PEER-LBNL Workshop
18 January 2024

Outline



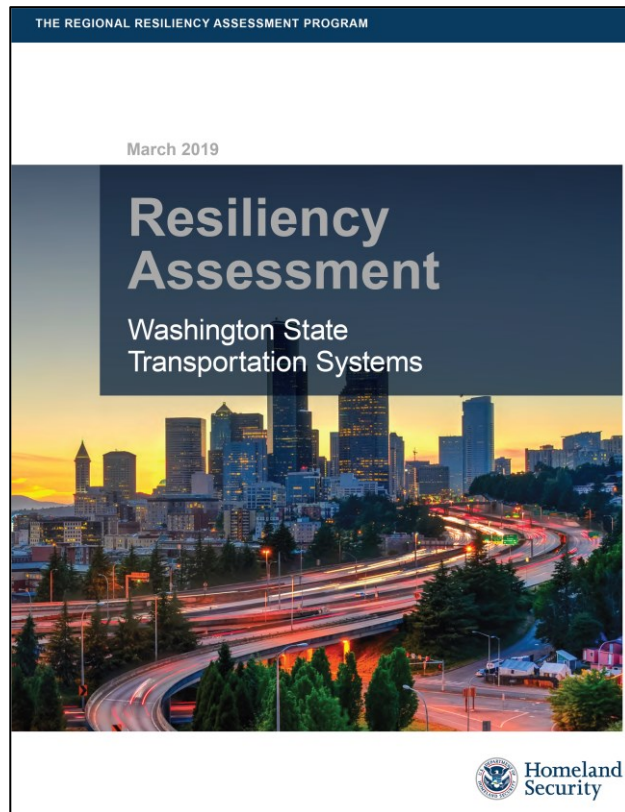
Motivations: Looking Forward

- Liquefaction results in a sudden loss of soil strength, causes permanent ground deformation, and damages a wide array of infrastructure assets:



Motivations: Looking Forward

- *In the Cascadia Subduction Zone (CSZ), regional-scale assessments of liquefaction are limited, have been resigned to many simplifying/conservative assumptions:*

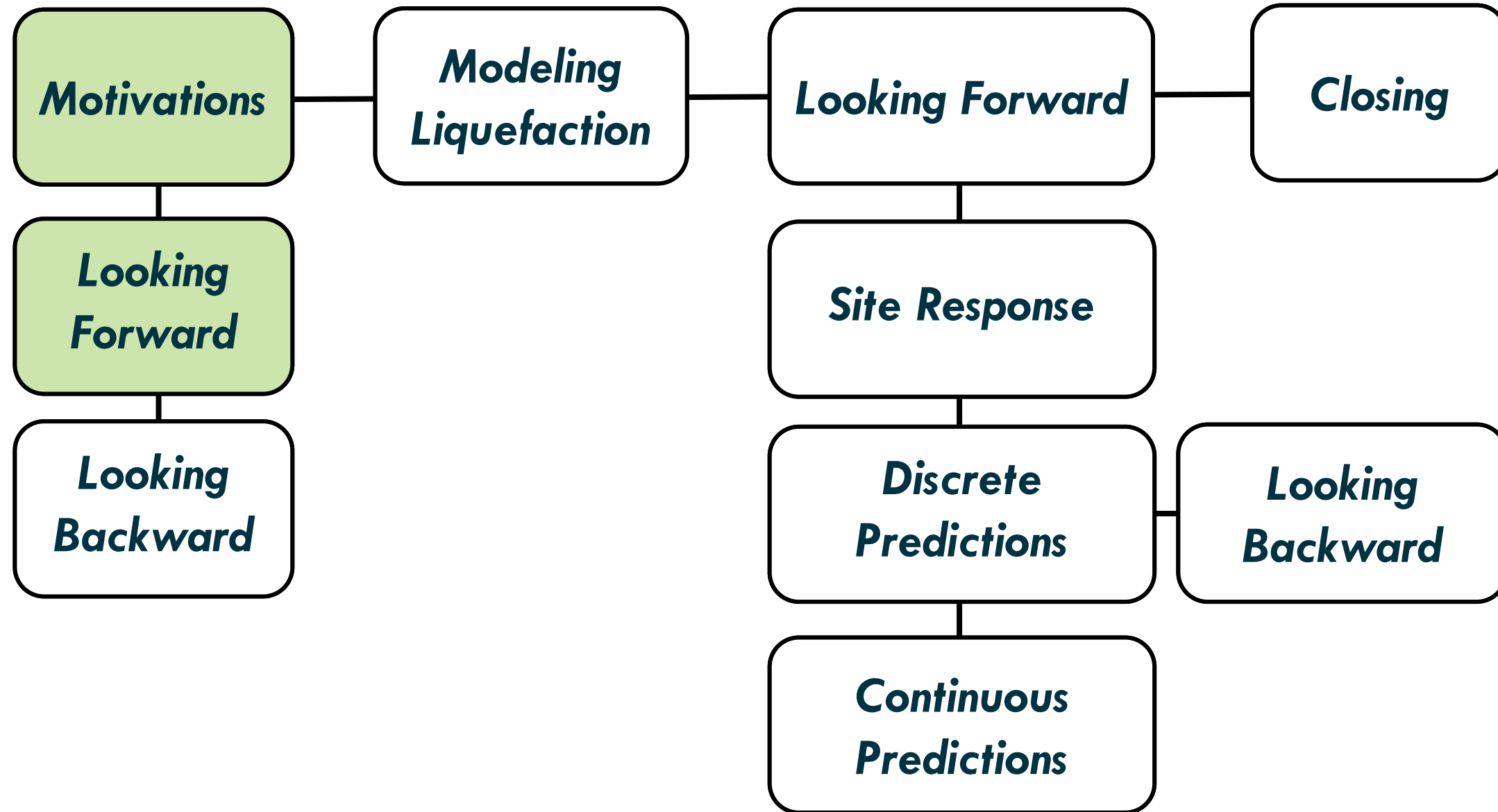


- *Predicted impacts in M9 event using “HAZUS” type approach:*

2,755 km of roads, 1,815 km of rail, 837 bridges, and 8 ports will likely be rendered unavailable due predominantly to liquefaction (considered only WA state infrastructure!).

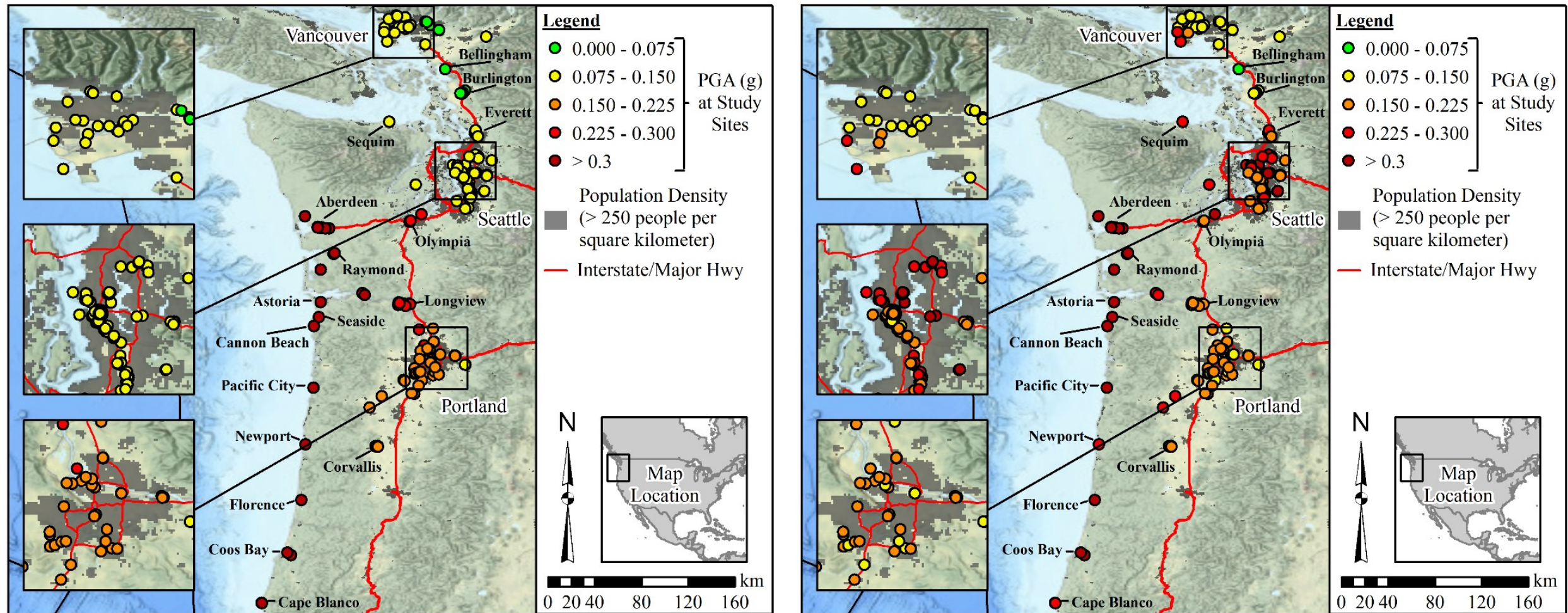
- *Begs further research but highlights liquefaction’s potentially staggering impact.*

Outline



Motivations: Looking Backward

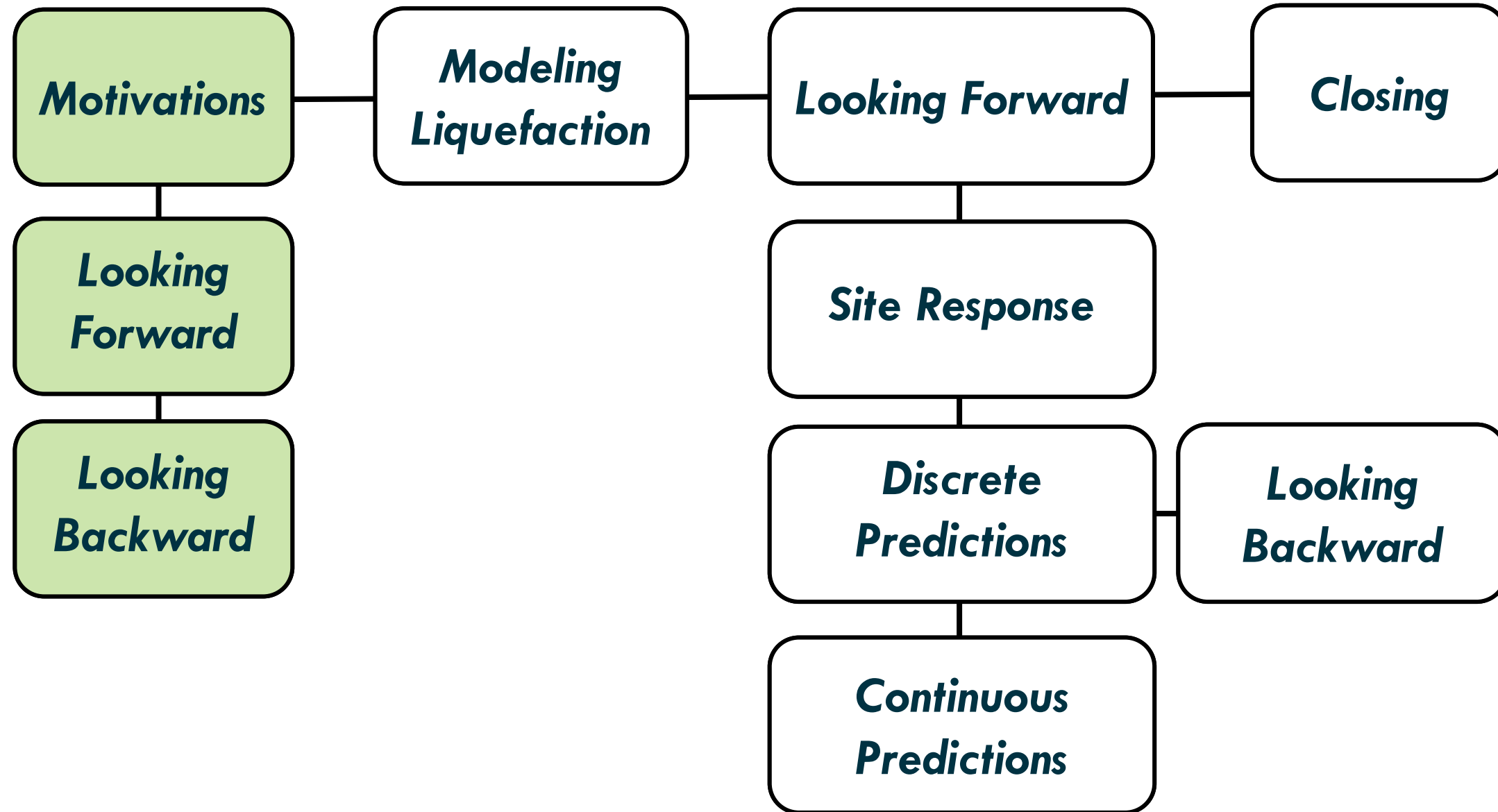
➤ Simulations of CSZ M9 ground motions^[1] are understandably uncertain. For example:



➤ What can paleoliquefaction tell us about motions in the last (1700 CE) CSZ event?

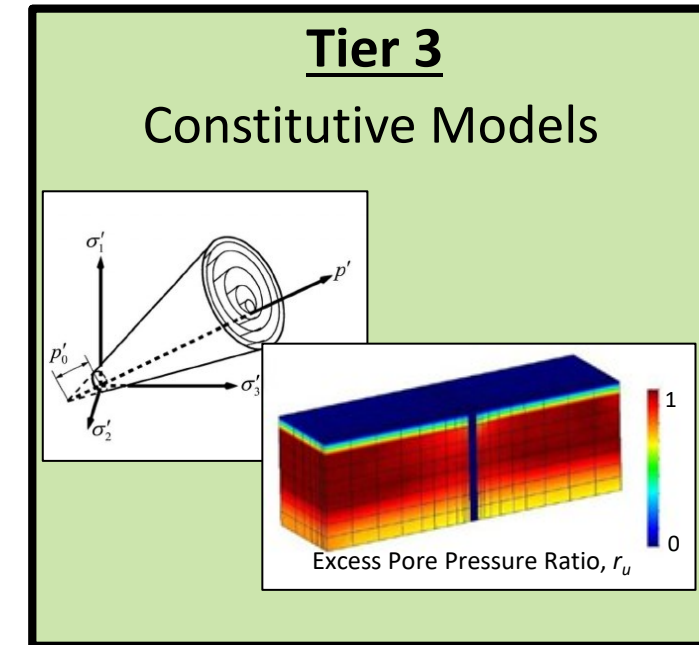
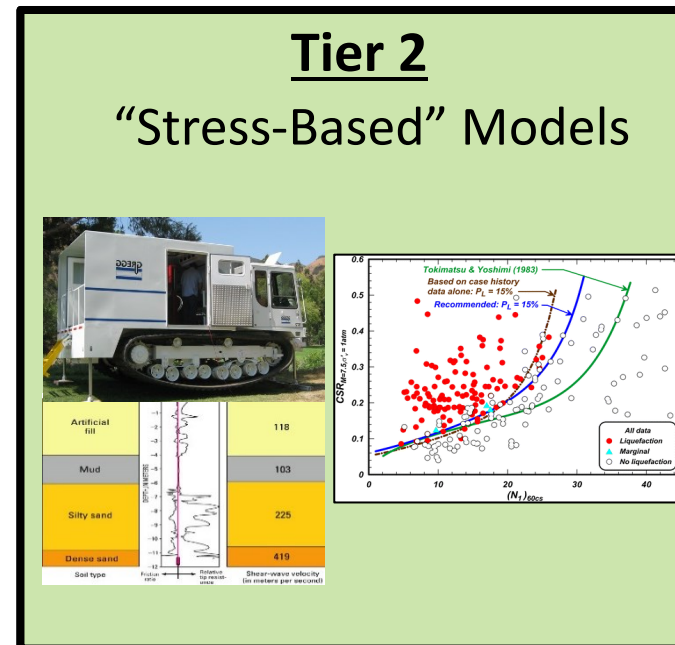
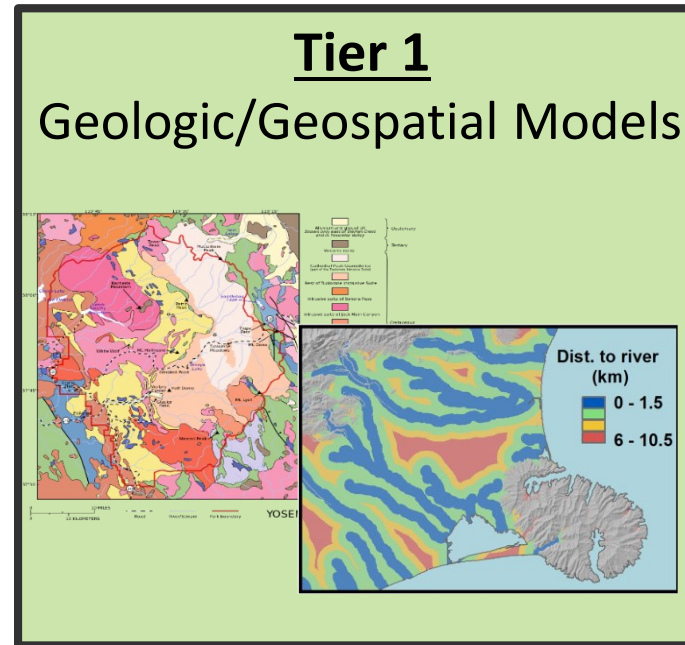
^[1] Frankel, A., Wirth, E., Marafi, N., Vidale, J., & Stephenson, W. (2018). Broadband synthetic seismograms for magnitude 9 earthquakes on the Cascadia megathrust based on 3D simulations and stochastic synthetics. *BSSA* 108(5A), 2347-2369.

Outline



Modeling Liquefaction

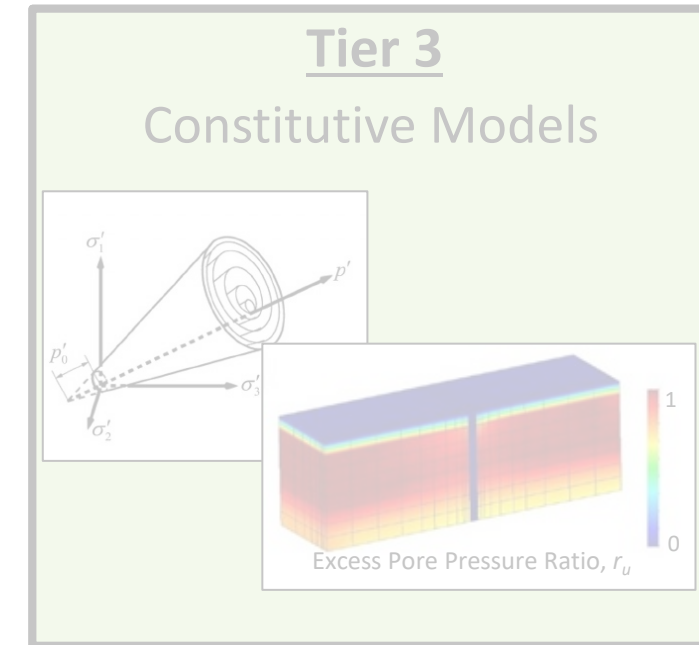
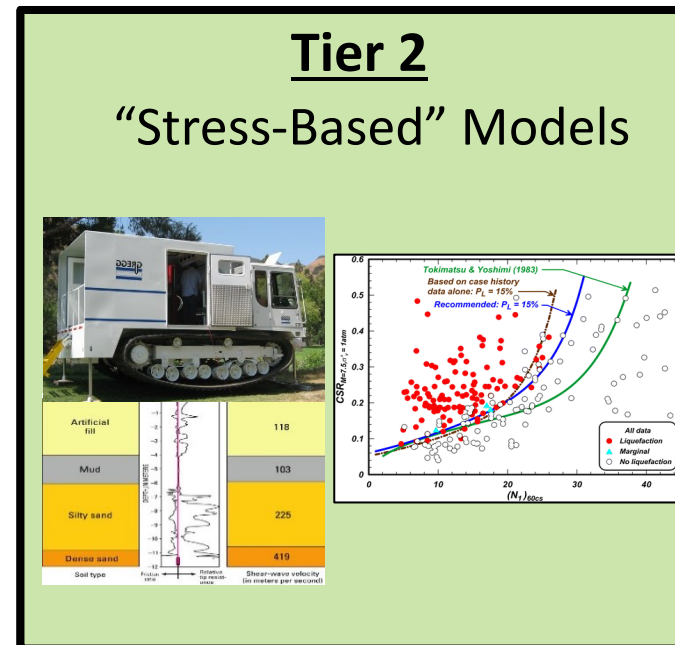
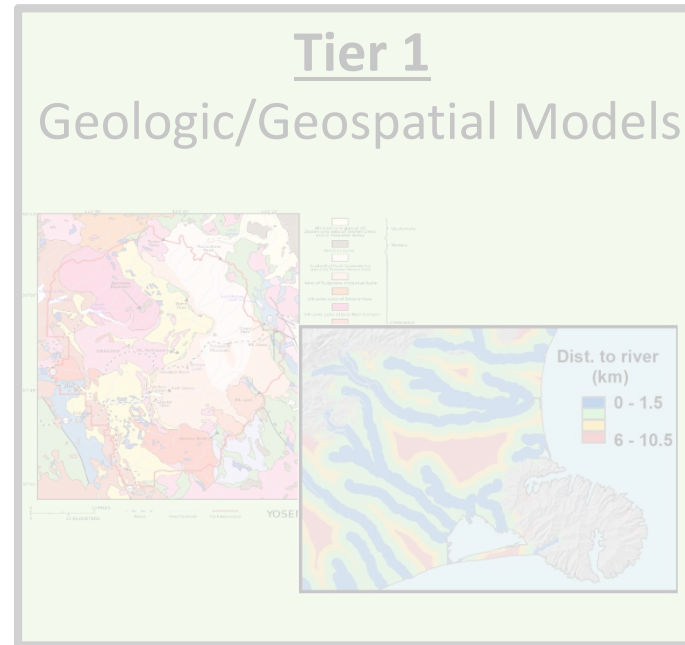
- Liquefaction models generally fall into 3 tiers:



- **Tier 1:** Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface information (e.g., HAZUS).
- **Tier 2:** Requires in-situ geotechnical test measurements. Used at site scale. By far most widely validated and commonly used model in engineering practice.
- **Tier 3:** Requires numerous soil and model parameters (typically calibrated against cyclic lab data). Used at project scale. Can provide additional spatial/temporal insights.

Modeling Liquefaction

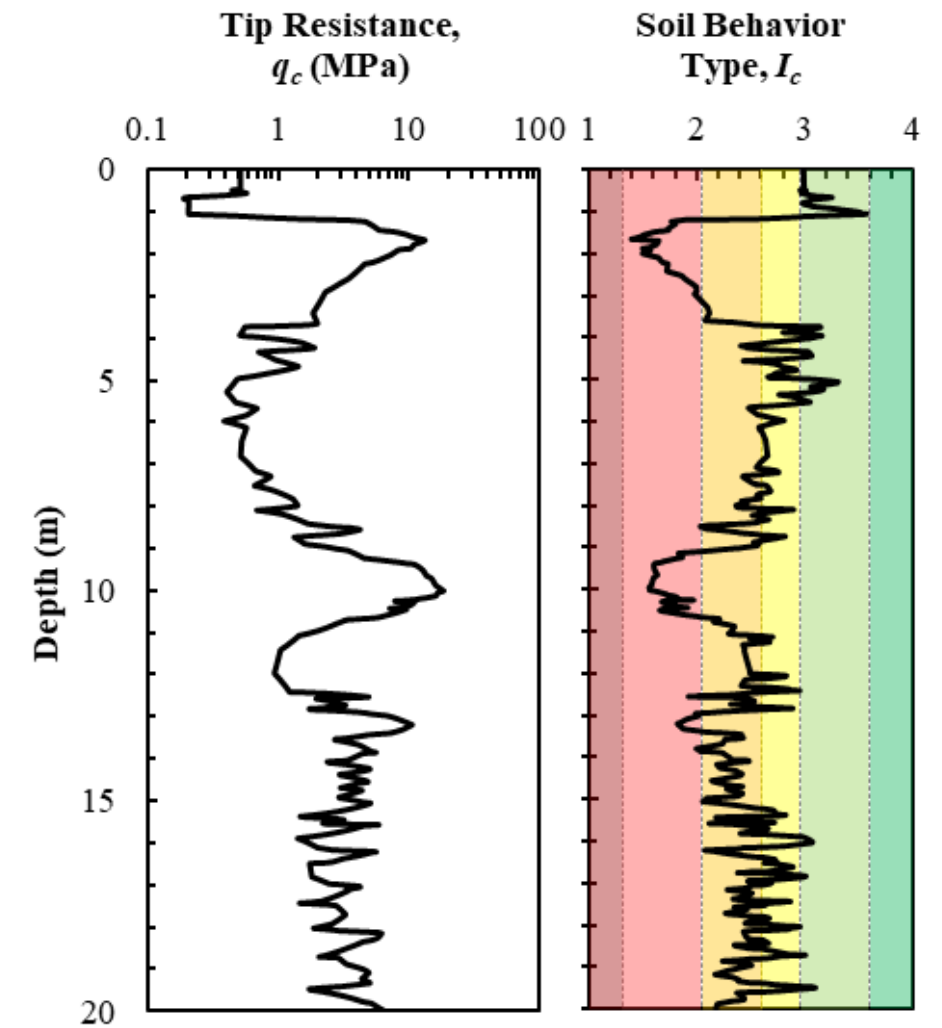
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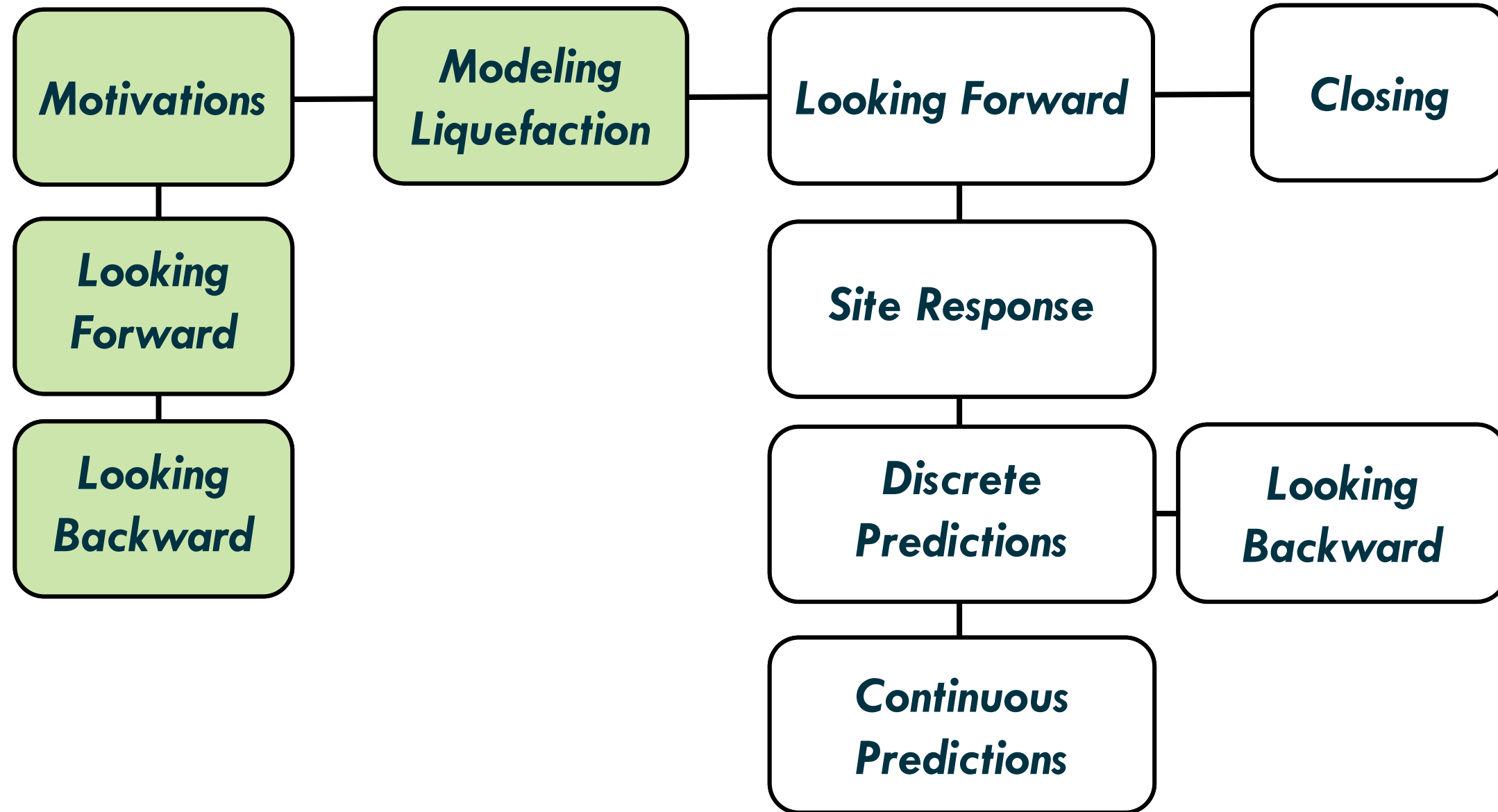
- Tier 1: Requires only geologic or geospatial data. Used at regional scale. A wide range of complexities, but all are limited by lack of subsurface information.
- **Tier 2**: Requires in-situ geotechnical test measurements. Used at site scale. By far most widely used model in engineering practice.
- Tier 3 **Most common/validated approach, but requires site-specific test data...** (against cyclic lab data). Used at project scale. Can provide additional spatial/temporal insights.

Modeling Liquefaction

- Several types of *in-situ* test data can be used to predict liquefaction, but Cone Penetration Test (CPT) data is generally favored (~\$3k-\$10k per test):



Outline

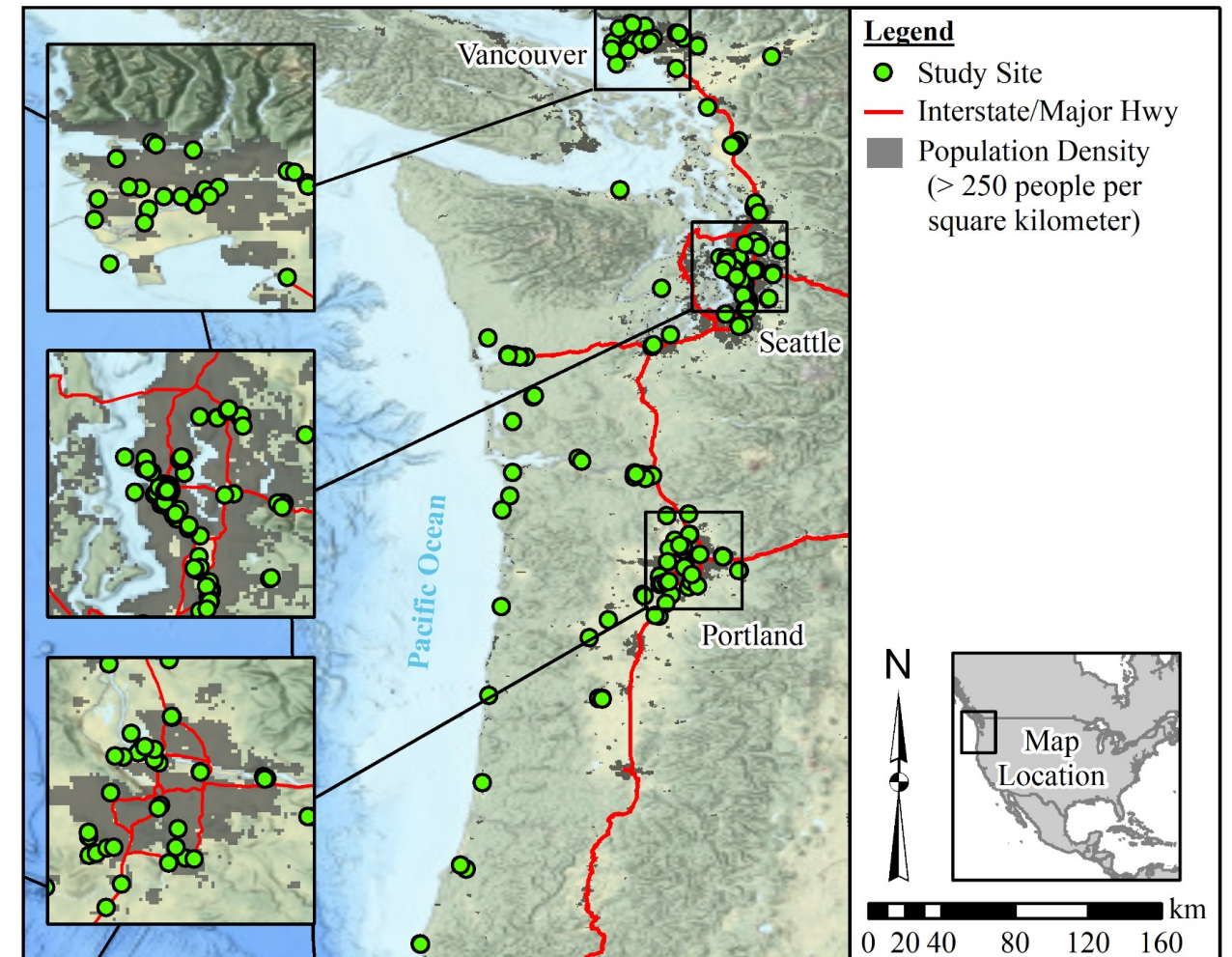


Looking Forward

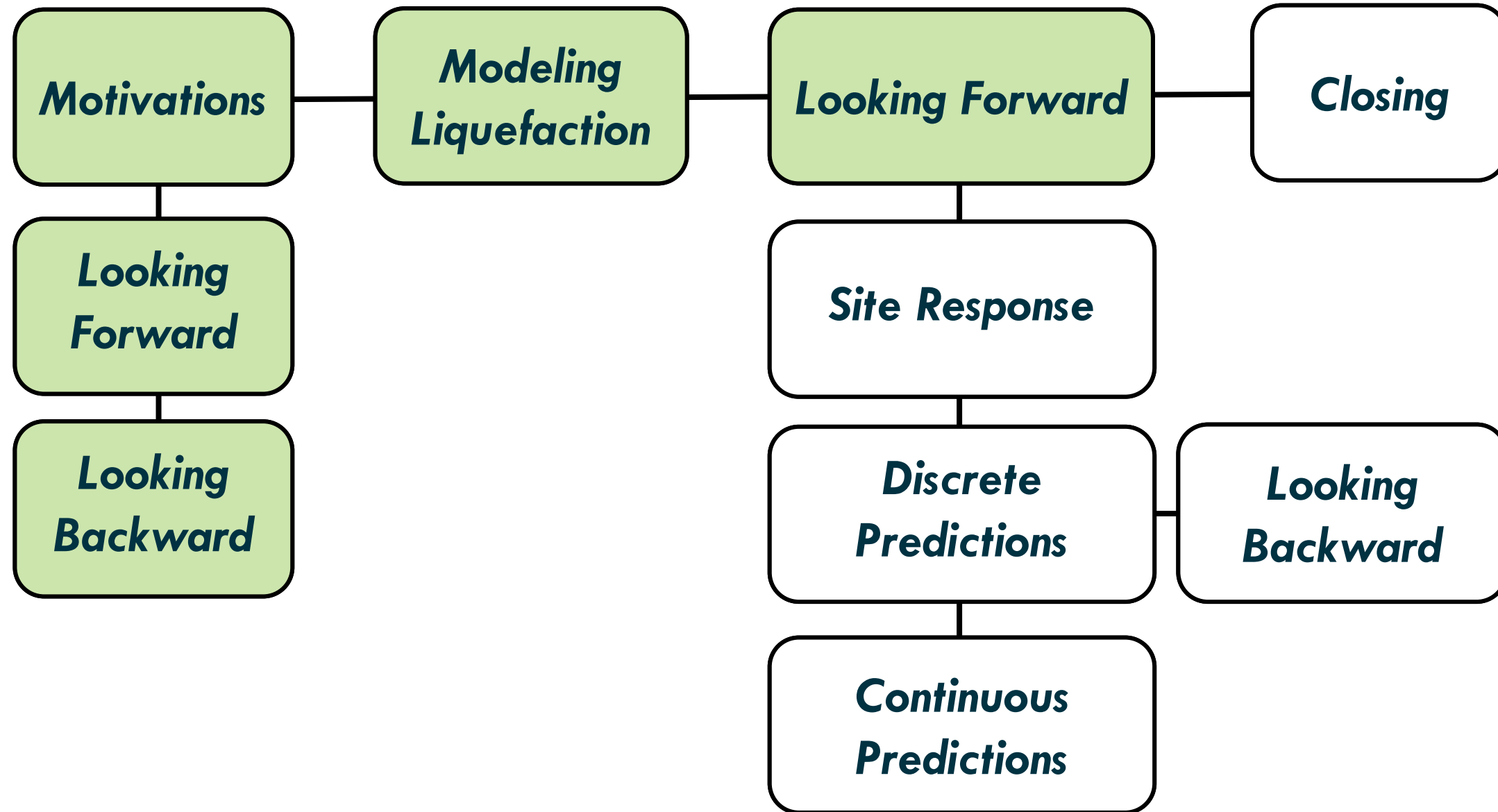
➤ Goal:

➤ **Predict liquefaction-induced ground failure, for each of 30 CSZ M9 simulations, at:**

1. 400 sites where CPT data is available (includes 10 paleoliquefaction sites).
2. Continuously across the region.

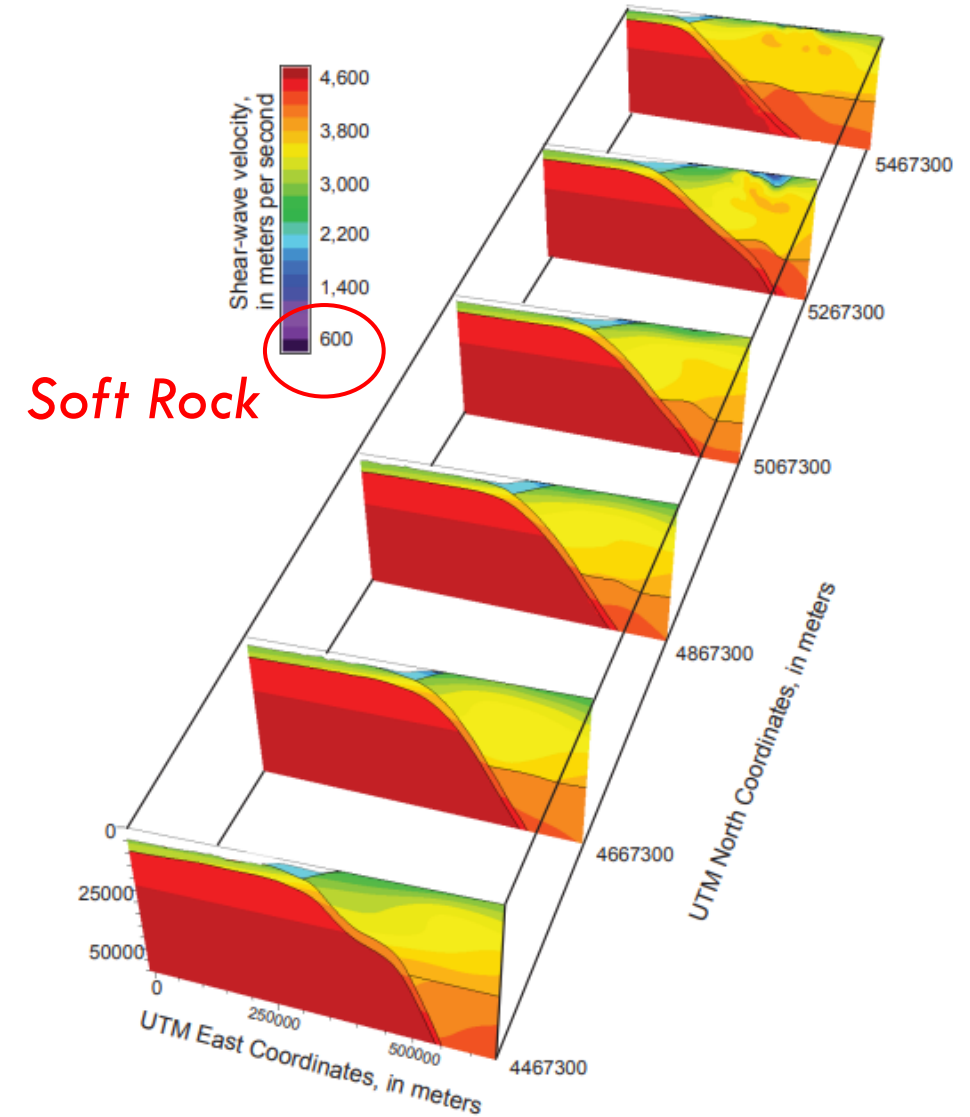
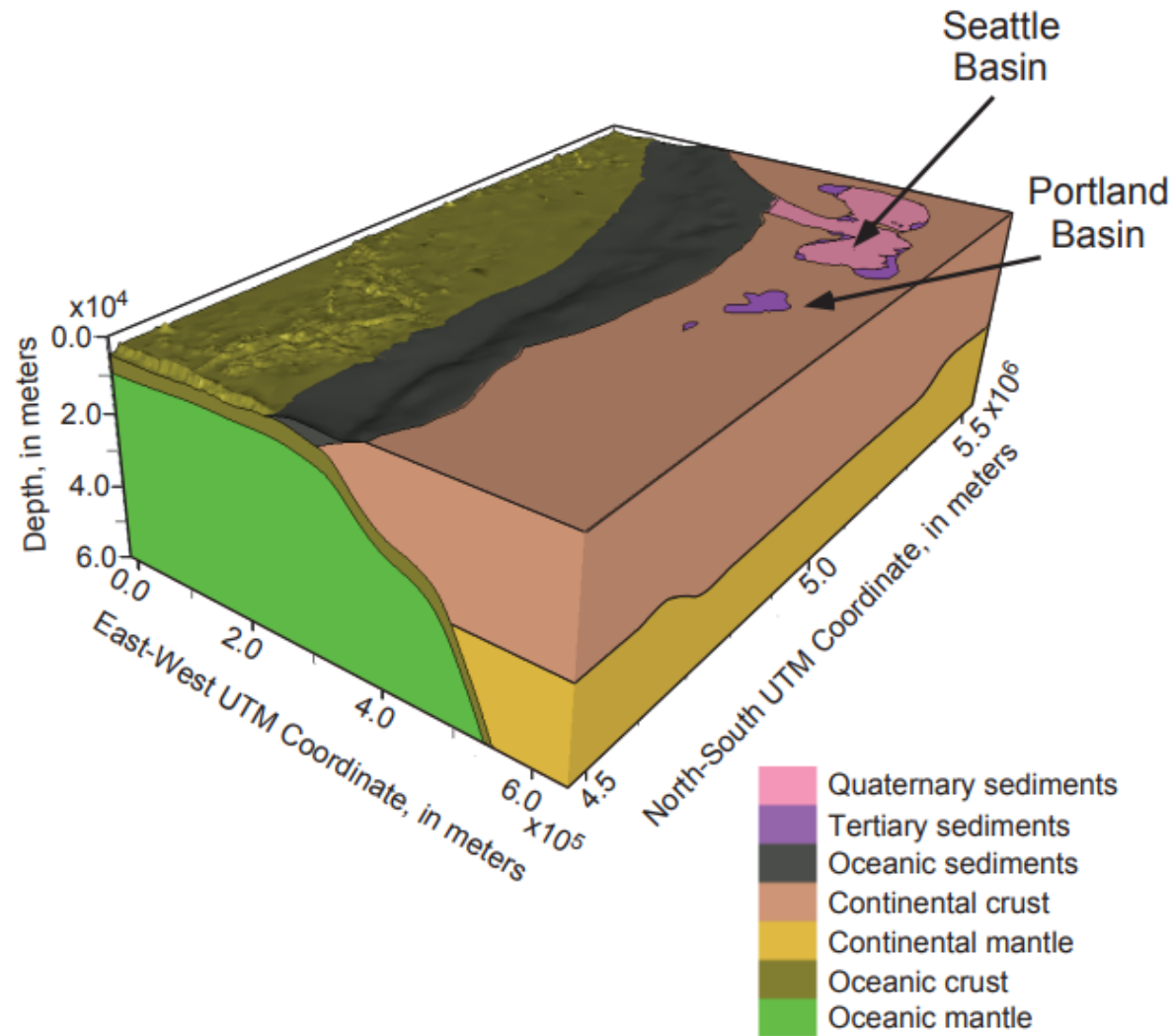


Outline



Looking Forward: Site Response

- M9 CSZ simulations used regional velocity model with minimum V_S of 600 m/s [3].

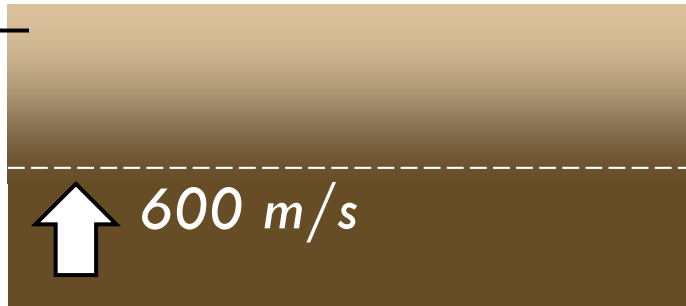


[3] Stephenson, W. J., Reitman, N. G., & Angster, S. J. (2017). P-and S-wave velocity models incorporating the Cascadia subduction zone for 3D earthquake ground motion simulations, Version 1.6—Update for Open-File Report 2007–1348 (No. 2017-1152). USGS.

Looking Forward: Site Response

- *Simulated motions must be modified for local conditions (V_S structure < 600 m/s):*

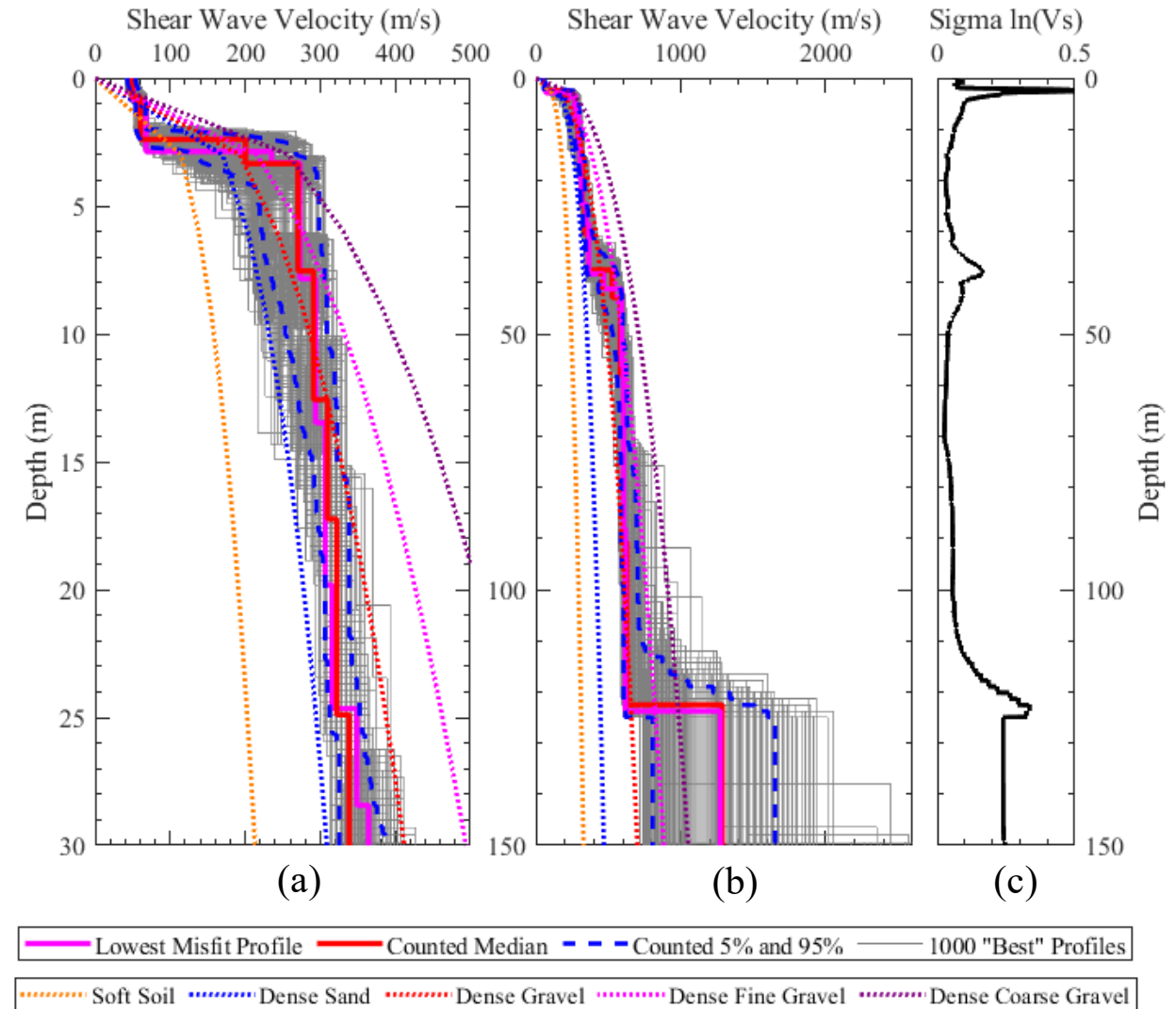
What data is available to
define near-surface
velocity structure?



Looking Forward: Site Response

➤ What data is available to define near-surface velocity structure?

1) Measured V_s profiles (sometimes)



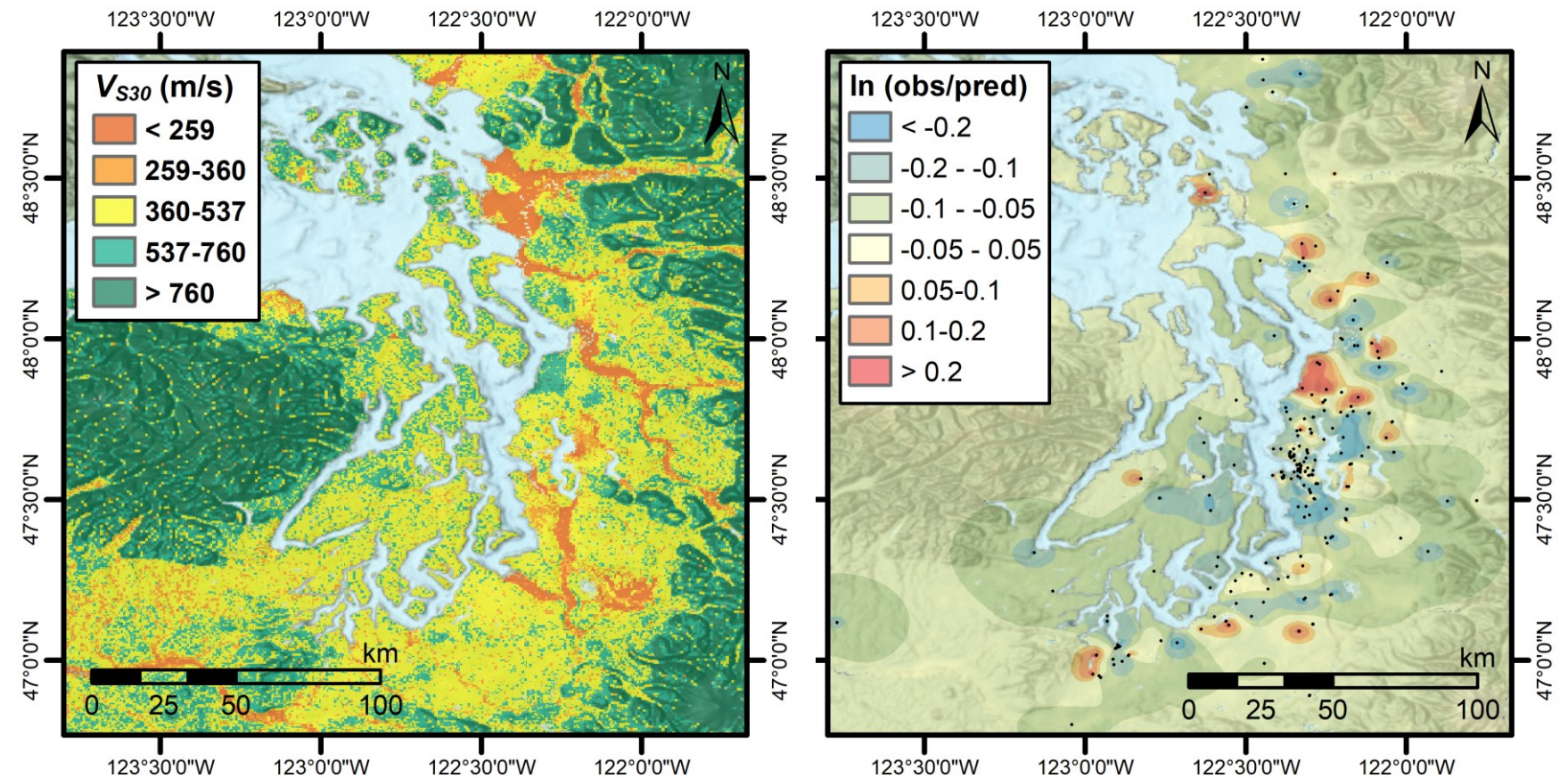
Looking Forward: Site Response

➤ What data is available to define near-surface velocity structure?

- 1) Measured V_s profiles (sometimes)
- 2) V_{S30} predictions (always)

Geyin & Maurer^[4] V_{S30} Model:

- Data from 7000 sites
- 17 geospatial predictors
- ML ensemble model
- Predictions updated in field
- US national coverage



[4] Geyin, M., & Maurer, B. W. (2023). US National V_{S30} Models and Maps Informed by Remote Sensing and Machine Learning. *Seismological Research Letters* 94 (3): 1467–1477

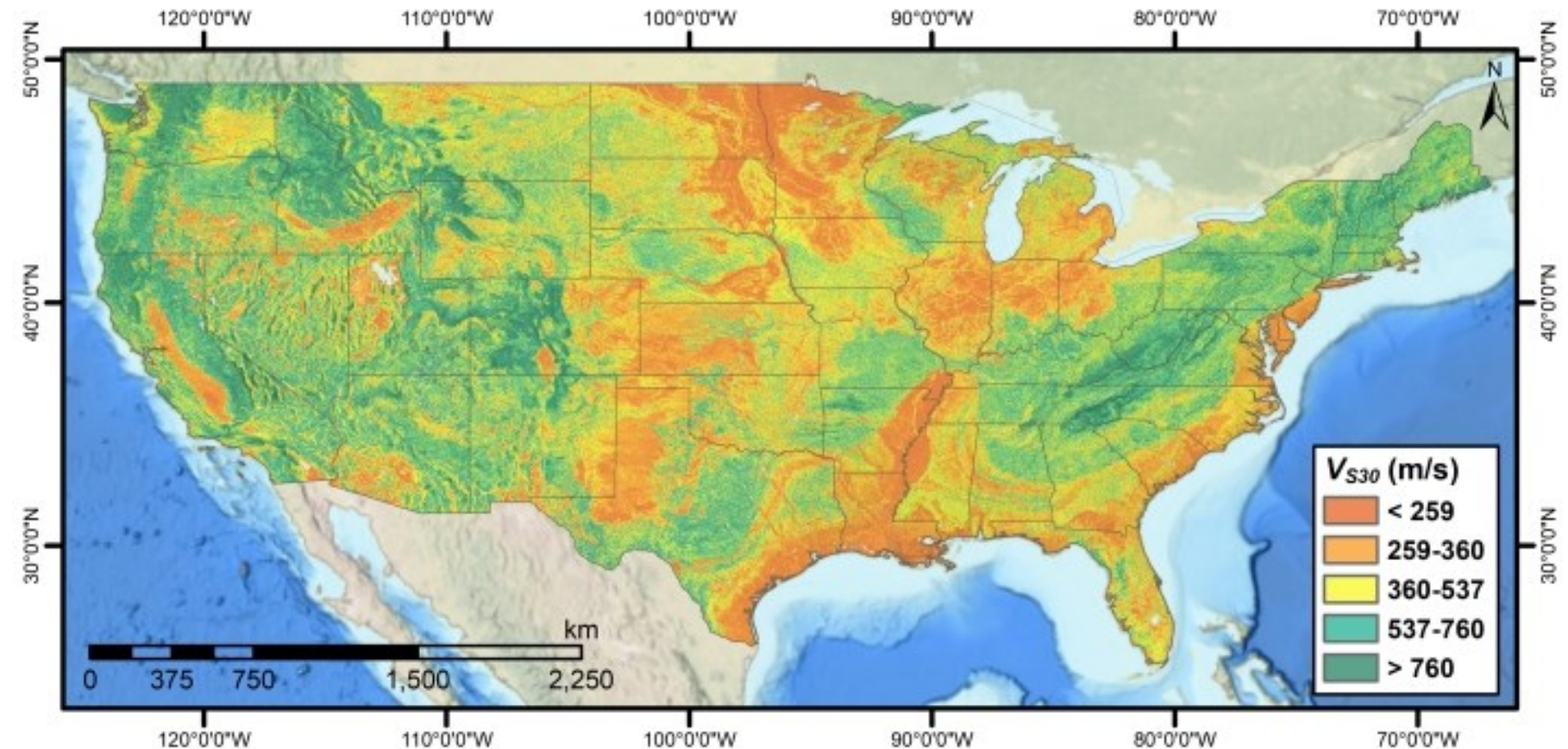
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➤ What data is available to define near-surface velocity structure?

- 1) Measured V_s profiles (sometimes)
- 2) V_{s30} predictions (always)
- 3) V_s profile predictions (always)**

Several general and region-specific soil velocity models are available (e.g., Shi and Asimaki^[5])

$$V_s(z) = \begin{cases} A & , \quad z < 2.5 \text{ m} \\ A(1 + B(z - 2.5))^{\frac{1}{C}} & , \quad z \geq 2.5 \text{ m} \end{cases}$$

- A, B, C are fitting parameters conditioned on V_{s30} .
- Trained on California profiles.
- Others (e.g., Wirth et al. 2021) have since trained similar models on Pacific Northwest profiles.
- Limitation: all sites with same V_{s30} have same V_s profile.

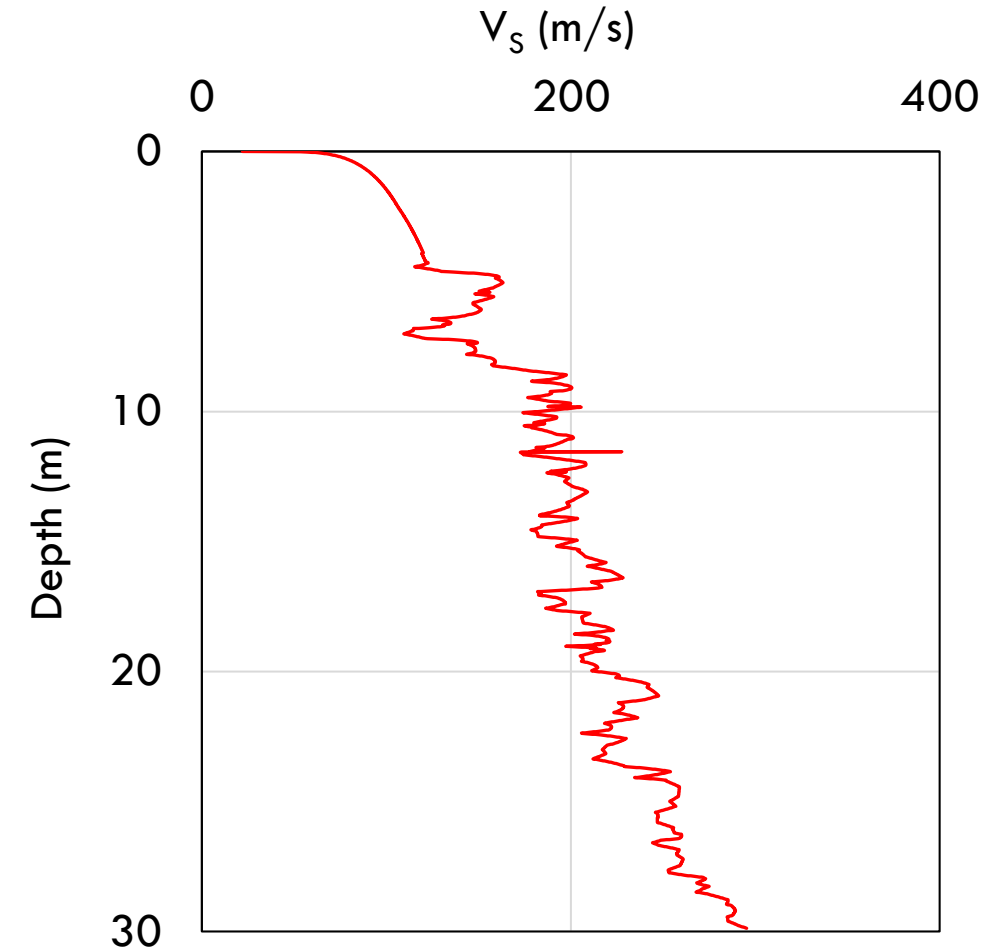
^[5] Shi, J., & Asimaki, D. (2018). A generic velocity profile for basin sediments in California conditioned on VS30. *Seismological Research Letters*, 89(4), 1397-1409.

Looking Forward: Site Response

➤ What data is available to define near-surface velocity structure?

- 1) Measured V_s profiles (sometimes)
- 2) V_{s30} predictions (always)
- 3) V_s profile predictions (always)
- 4) **CPT data (sometimes)**

Many CPT- V_s models are available, including some that are region specific [7]

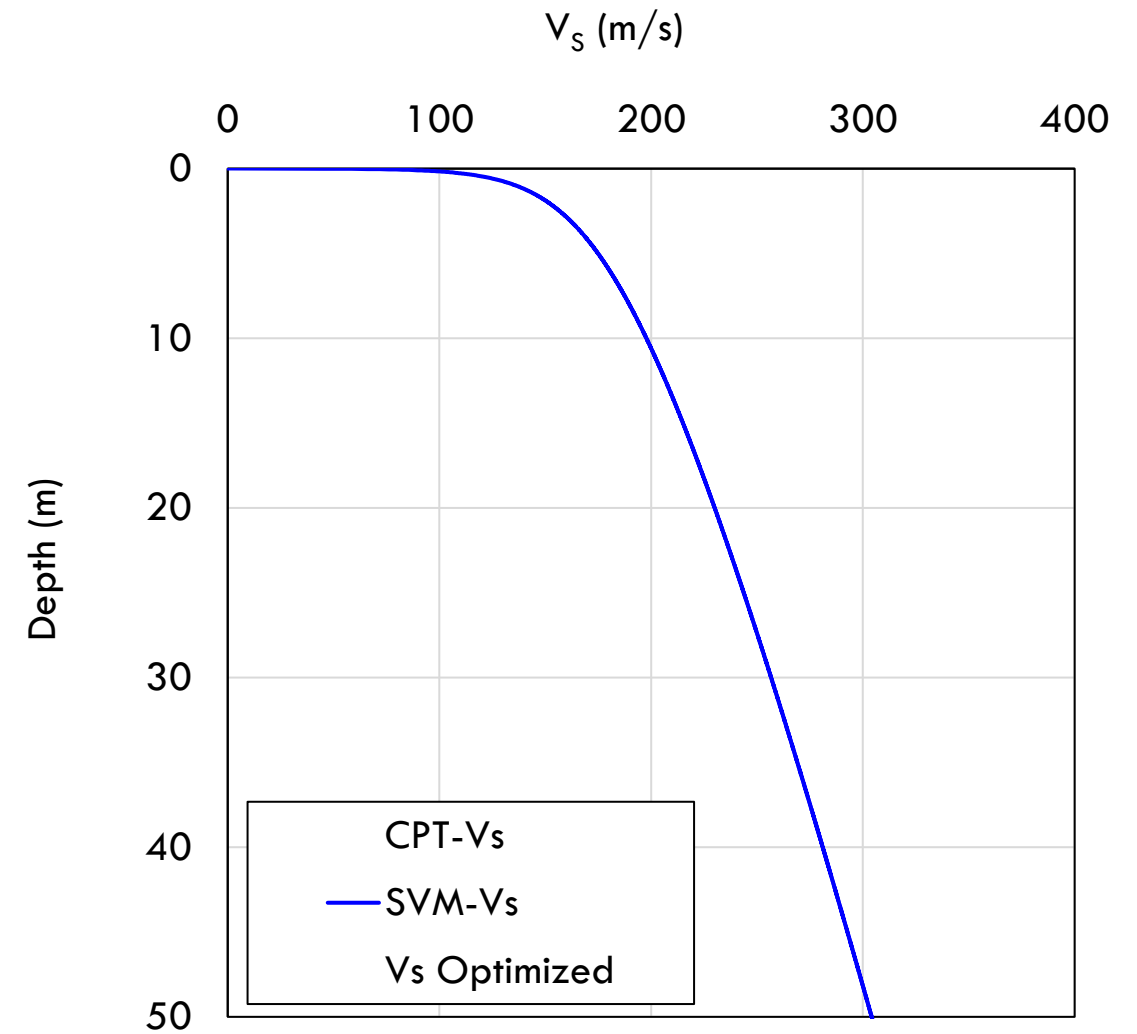


[7] Assaf, J., Molnar, S., & El Naggaf, M. H. (2023). CPT- V_s correlations for post-glacial sediments in Metropolitan Vancouver. *Soil Dynamics and Earthquake Engineering*, 165, 107693.

Looking Forward: Site Response

➤ Approach in absence of site-specific V_S profile:

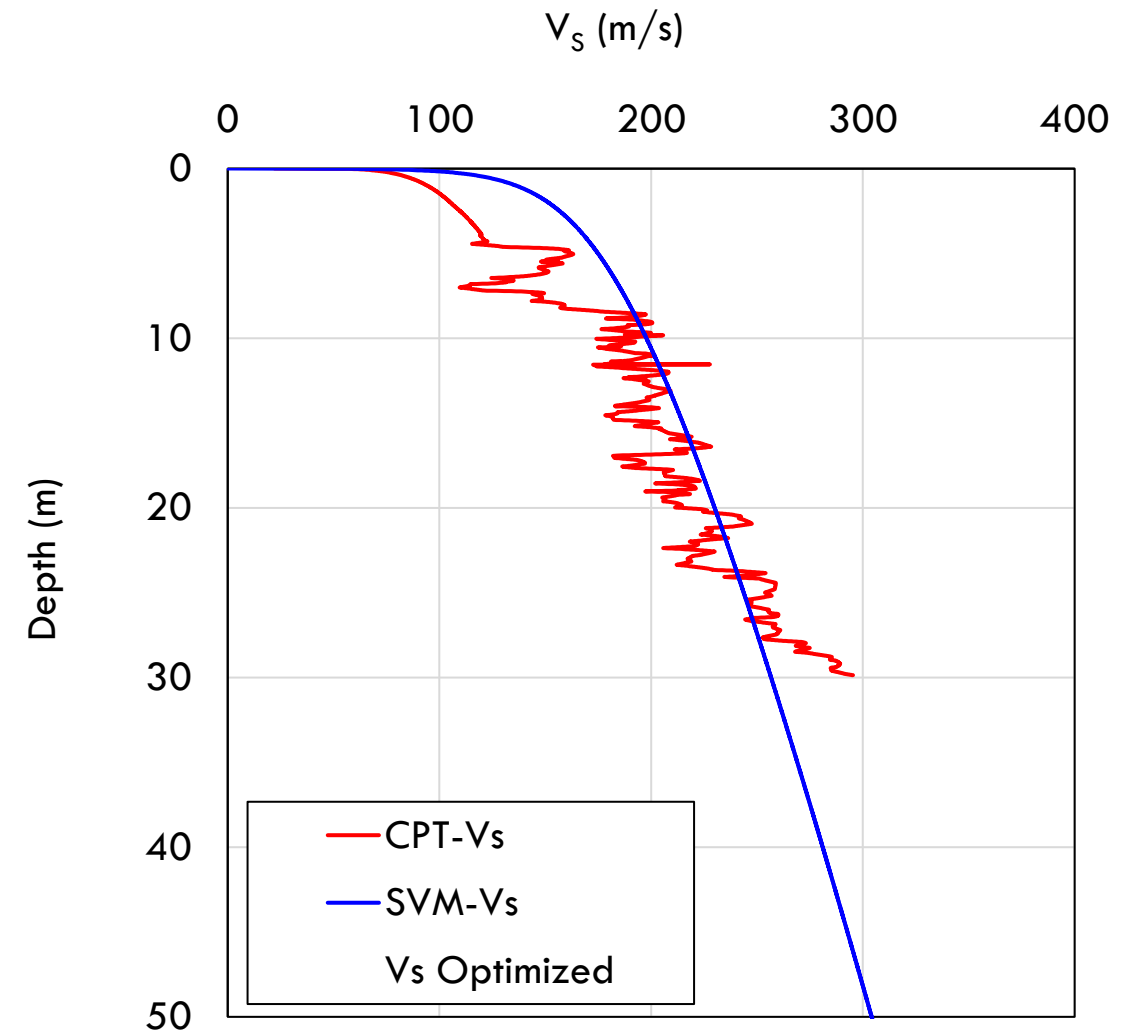
- 1) Predict V_{S30} by Geyin and Maurer (2023)
- 2) Predict V_S -depth by Wirth et al. (2021)



Looking Forward: Site Response

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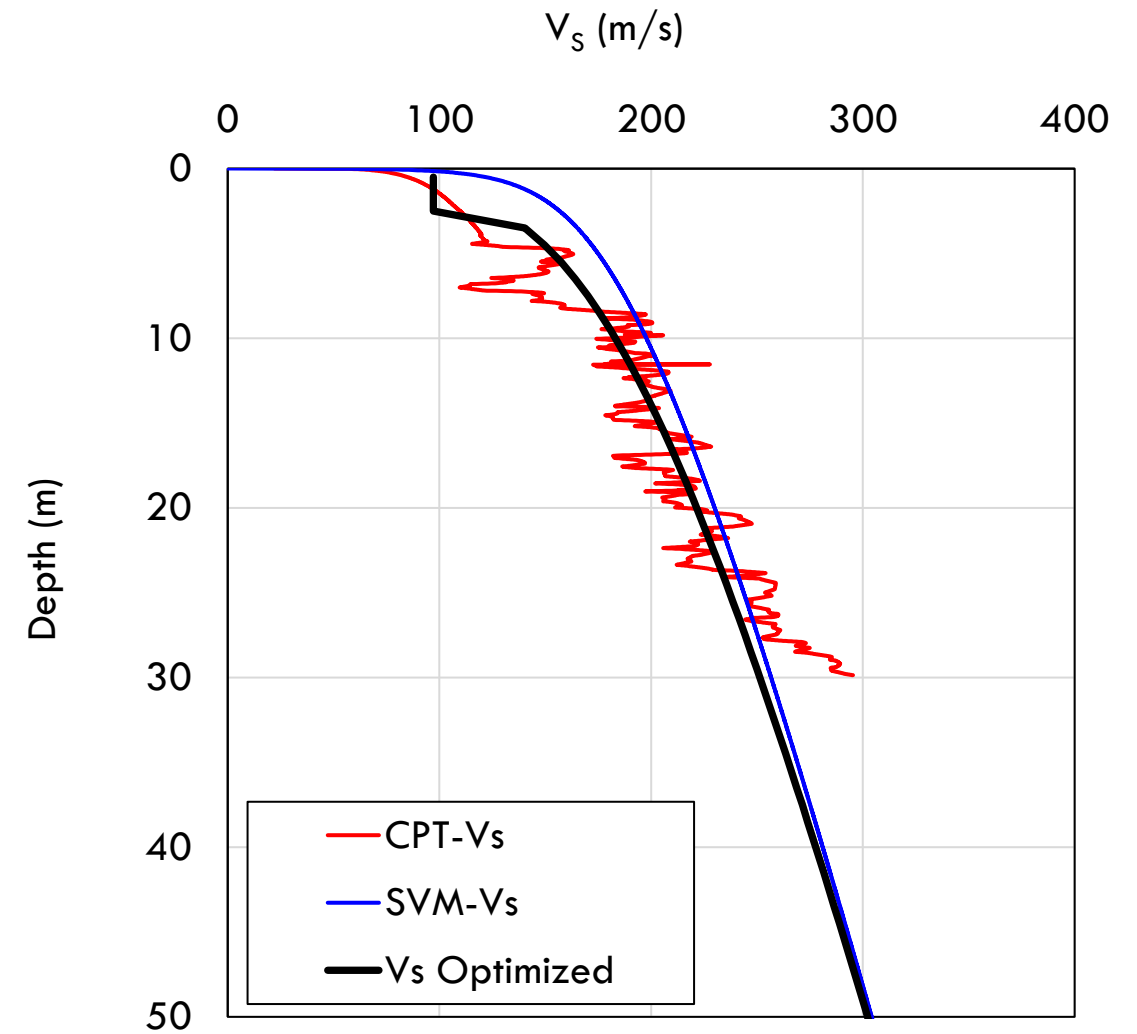
- 1) Predict V_{S30} by Geyin and Maurer (2023)
- 2) Predict V_S -depth by Wirth et al. (2021)
- 3) When available, predict V_S -depth via ensemble of 6 CPT- V_S models



Looking Forward: Site Response

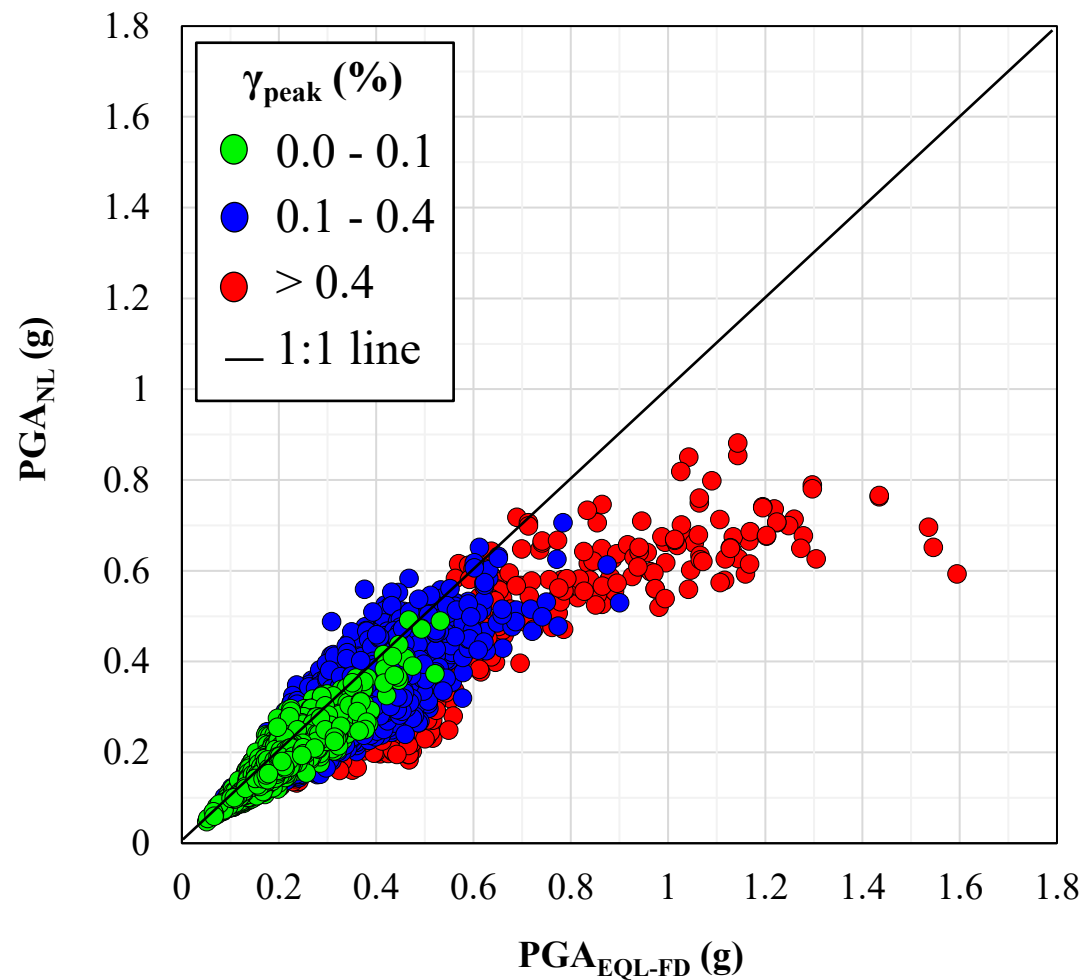
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- 4) Update regional model

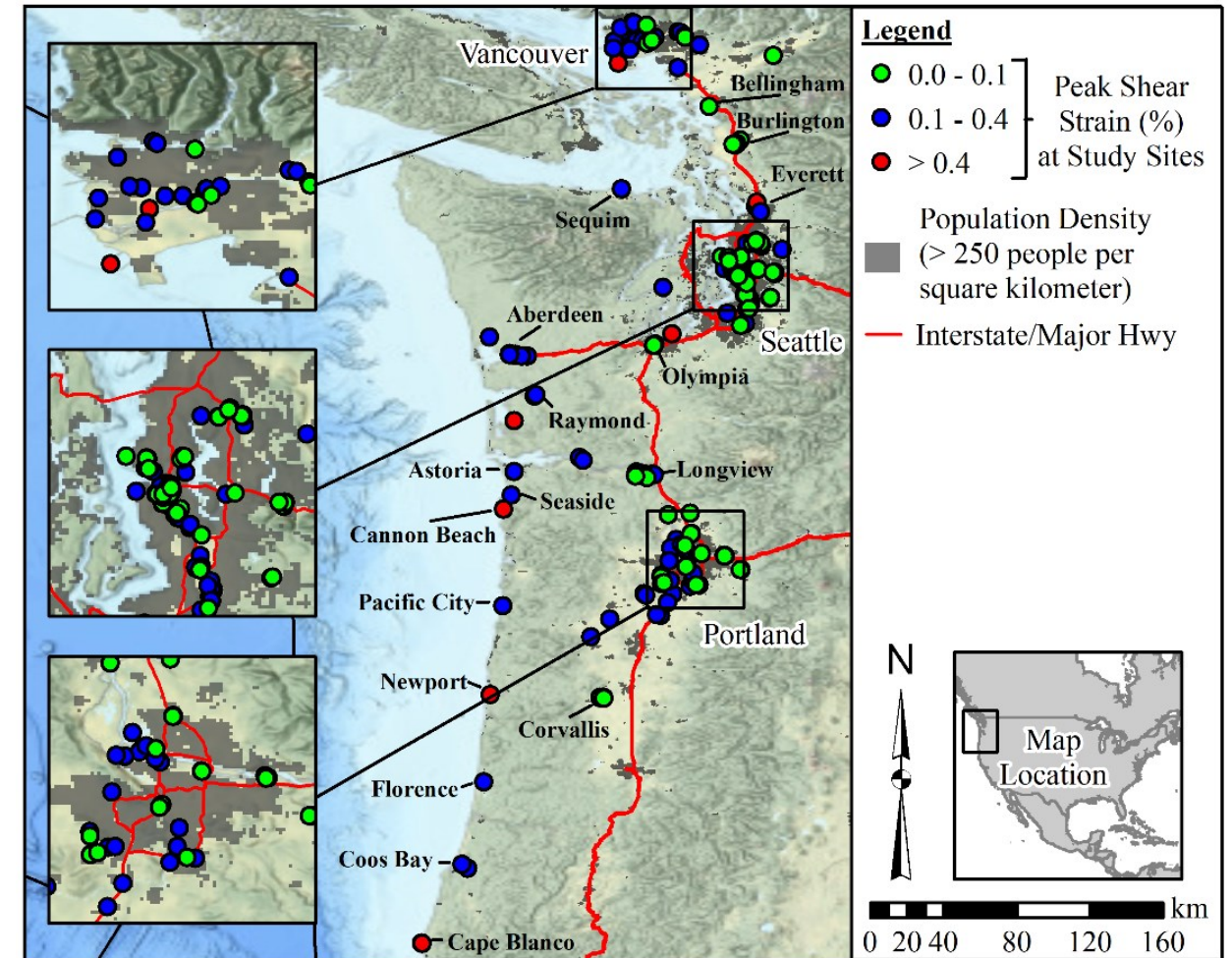


Looking Forward: Site Response

- Total-stress site-response analyses performed via *PySeismoSoil* (Asimaki and Shi, 2017)
- Hybrid Hyperbolic soil model; properties estimated from V_S in each layer
- Both EQL-FD and NL analyses performed (NL adopted)

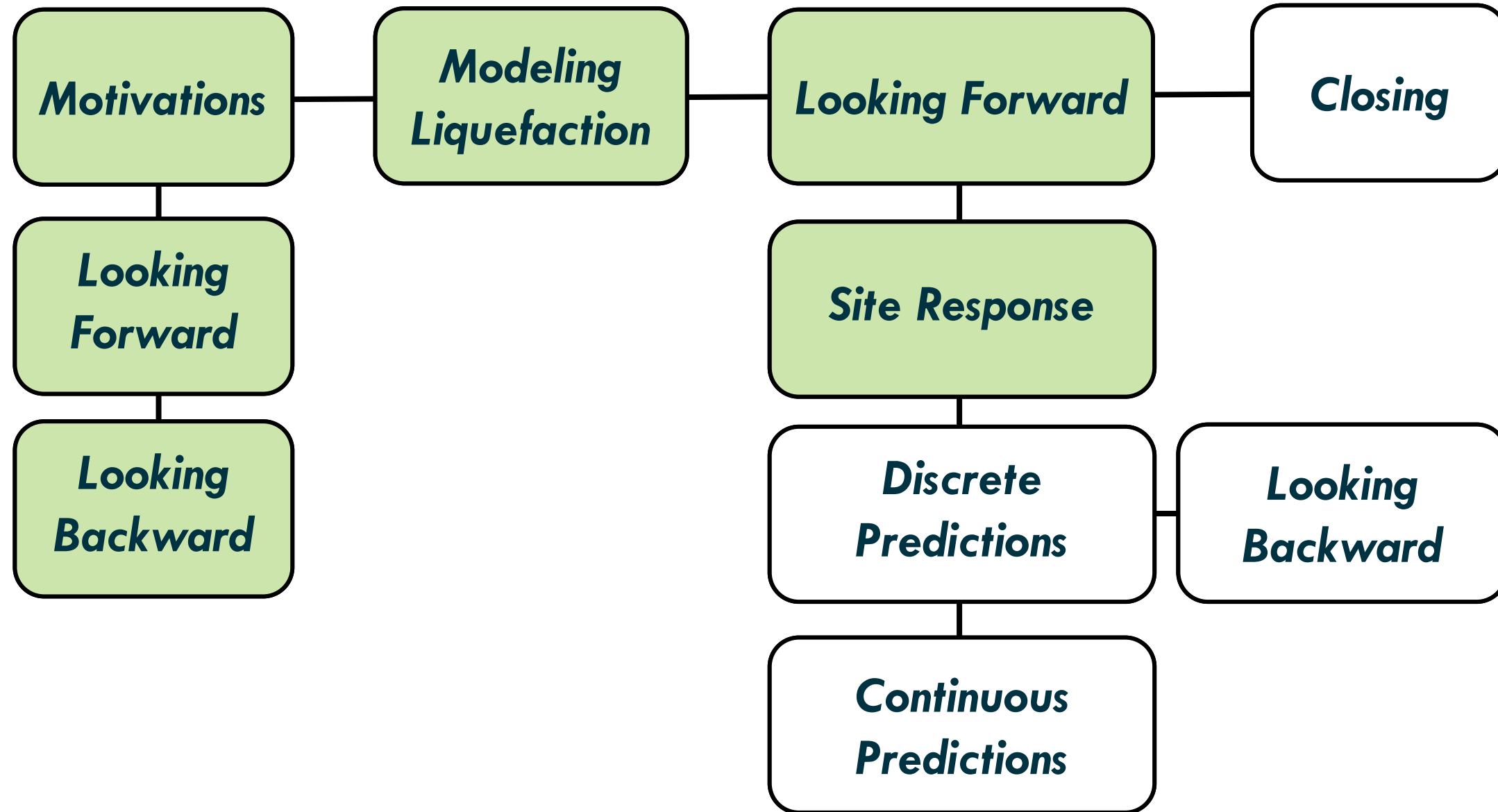


NL vs EQL-FD PGAs for 400 sites, 30 sims



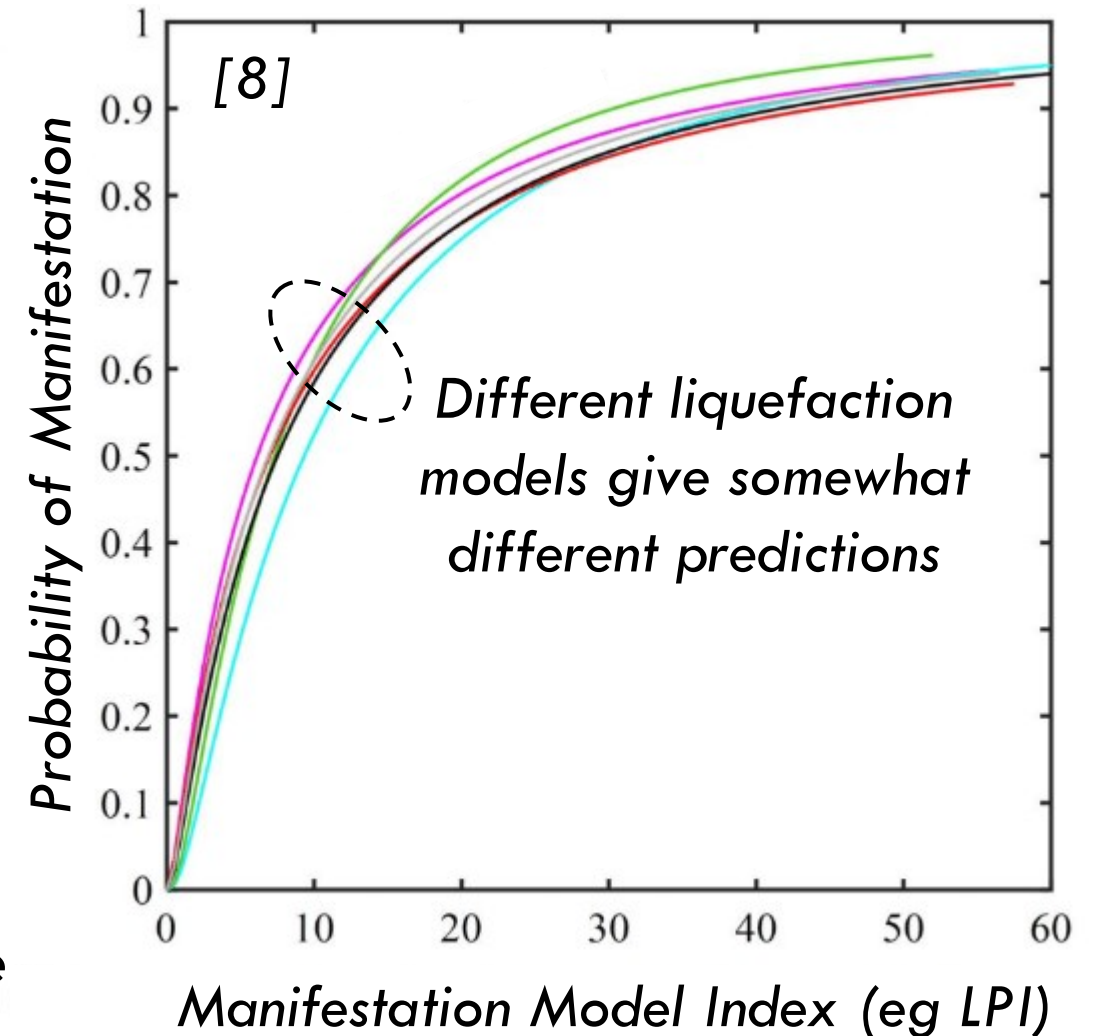
Median peak shear strain (%) across 30 sims

Outline



Looking Forward: Discrete Predictions

- 18 CPT-based liquefaction models ensembled
- 6 Triggering Models x 3 Manifestation Models
 - Robertson and Wride 1998
 - Architectural Inst. of Japan 2001
 - Moss et al. 2006
 - Idriss & Boulanger 2008
 - Boulanger & Idriss 2014
 - Green et al. 2019
 - LPI (Liquefaction Potential Index)
 - LPI_{ISH} (Modified LPI)
 - LSN (Liquefaction Severity Number)
- Fragility functions conditioned on these models have been trained from global data to predict the probability of liquefaction surface manifestation.



[8] Geyin, M., & Maurer, B. W. (2020). Fragility functions for liquefaction-induced ground failure. *Journal of Geotechnical and Geoenvironmental Engineering*, 146(12), 04020142.

Looking Forward: Discrete Predictions

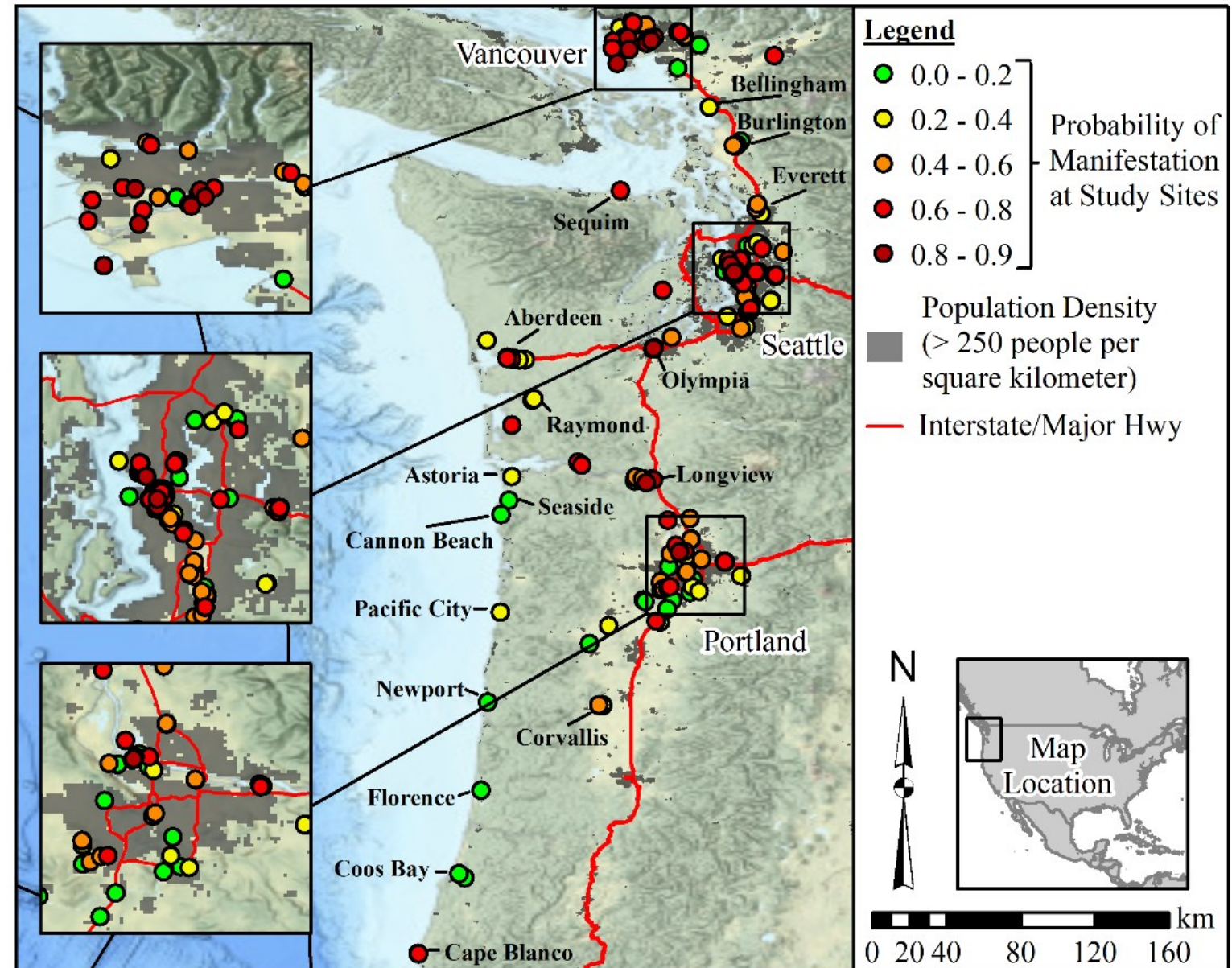
- What is liquefaction surface manifestation?
 - Liquefaction ejecta or ground deformation
 - Indicates instability, reduced bearing capacity
 - A practical proxy of damage potential for various near-surface infrastructure assets



Looking Forward: Discrete Predictions

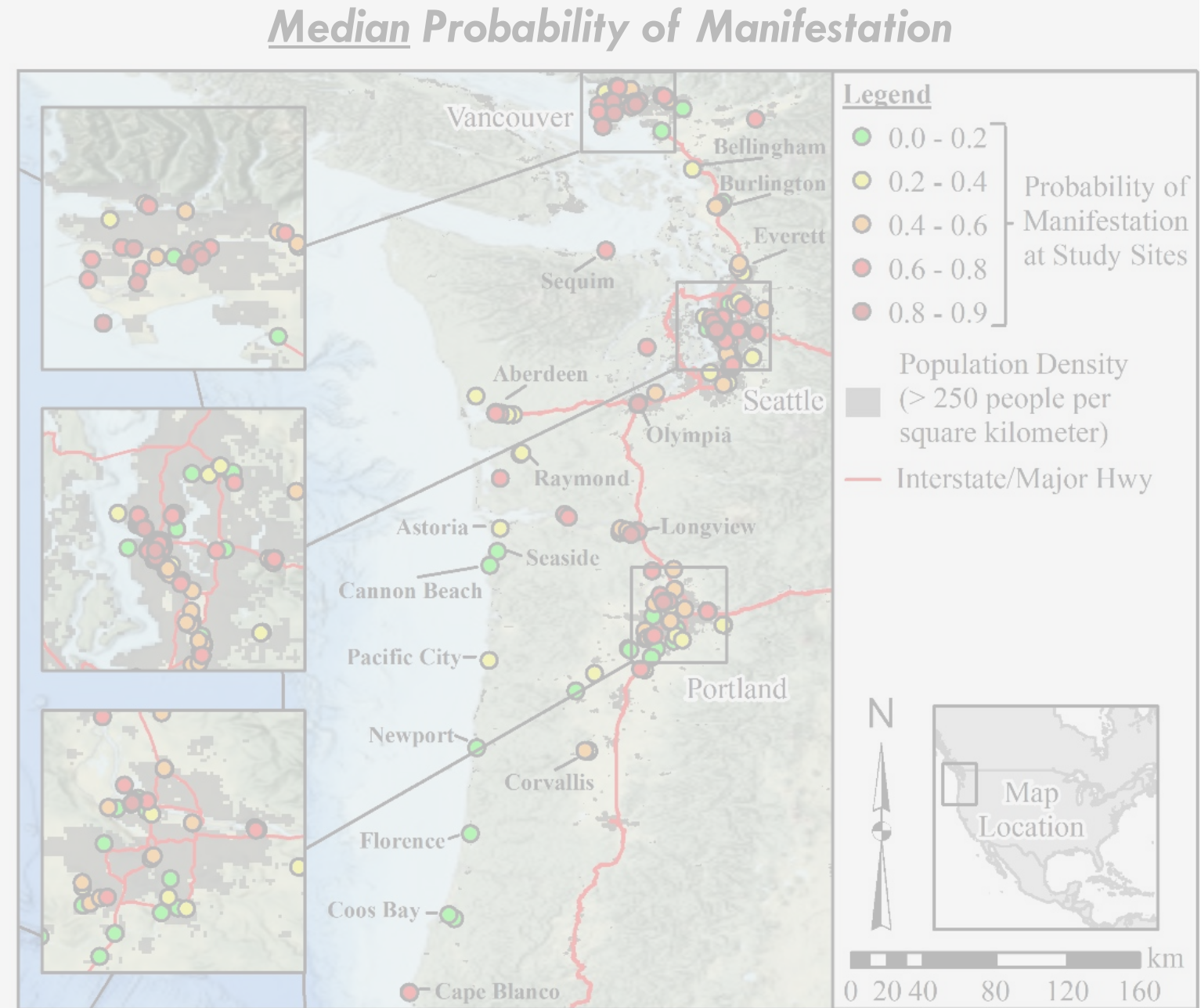
- Regional observations:
- Probability of manifestation $>60\%$ at most Vancouver sites; $>40\%$ at most Seattle & Portland sites.
- Many coastal test sites do not contain liquefaction-susceptible soils (could exist at unsampled locales).
- Scale of impact is immense.
- Liquefaction could be pervasive, affect major hubs of population, transportation, and commerce.

Median Probability of Manifestation



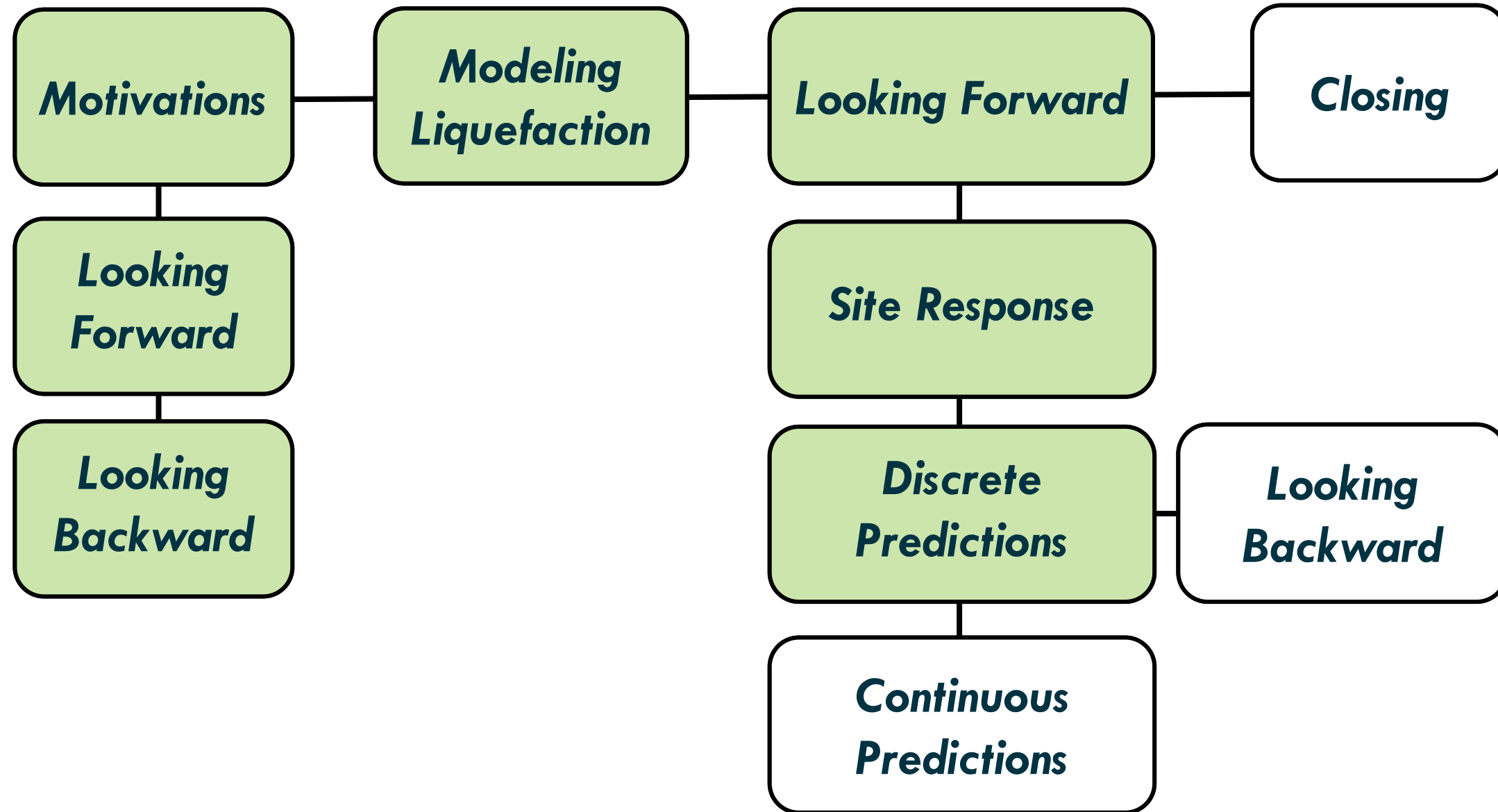
Looking Forward: Discrete Predictions

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- **Discrete predictions are useful but must be continuous for complete assessment of impacts.**

Outline



Looking Backward

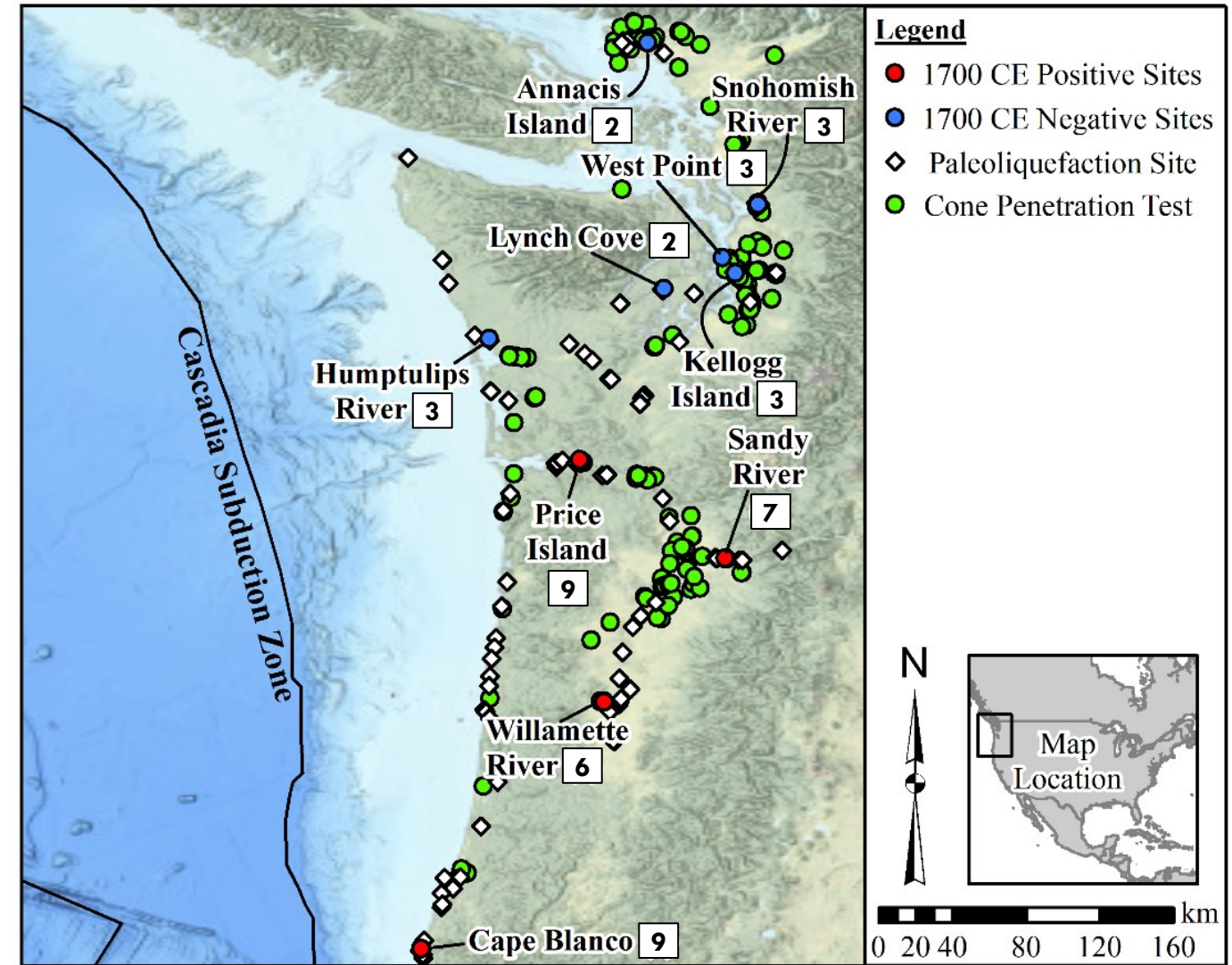
➤ **Goal:**

- *Having predicted liquefaction for various M9 CSZ simulations, do any match the interpreted 1700 CE paleoliquefaction evidence better or worse?*
- *In other words, can the ground motions experienced in 1700 CE be constrained?*

Looking Backward

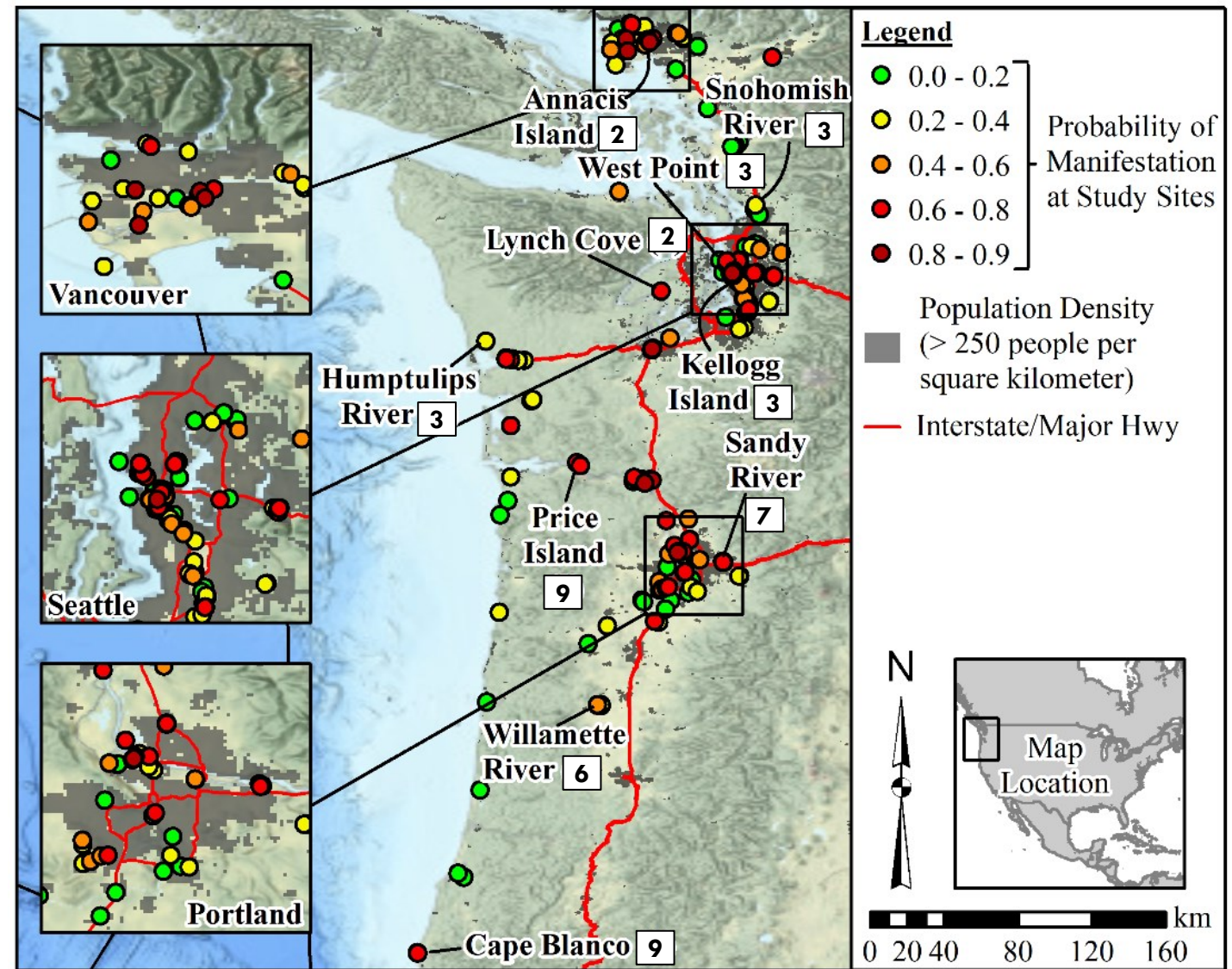
- Performed analysis using 10 distributed paleoliquefaction study sites:
- Whether liquefaction did, or did not, occur in 1700 CE has uncertainty.
- Uncertainties assigned to each study site considering all evidence.

Site Score	Probability that 1700 Observation is Positive (%)	Probability that 1700 Observation is Negative (%)
0	0	100
1	10	90
2	20	80
3	30	70
4	40	60
5	50	50
6	60	40
7	70	30
8	80	20
9	90	10
10	100	0



Looking Backward

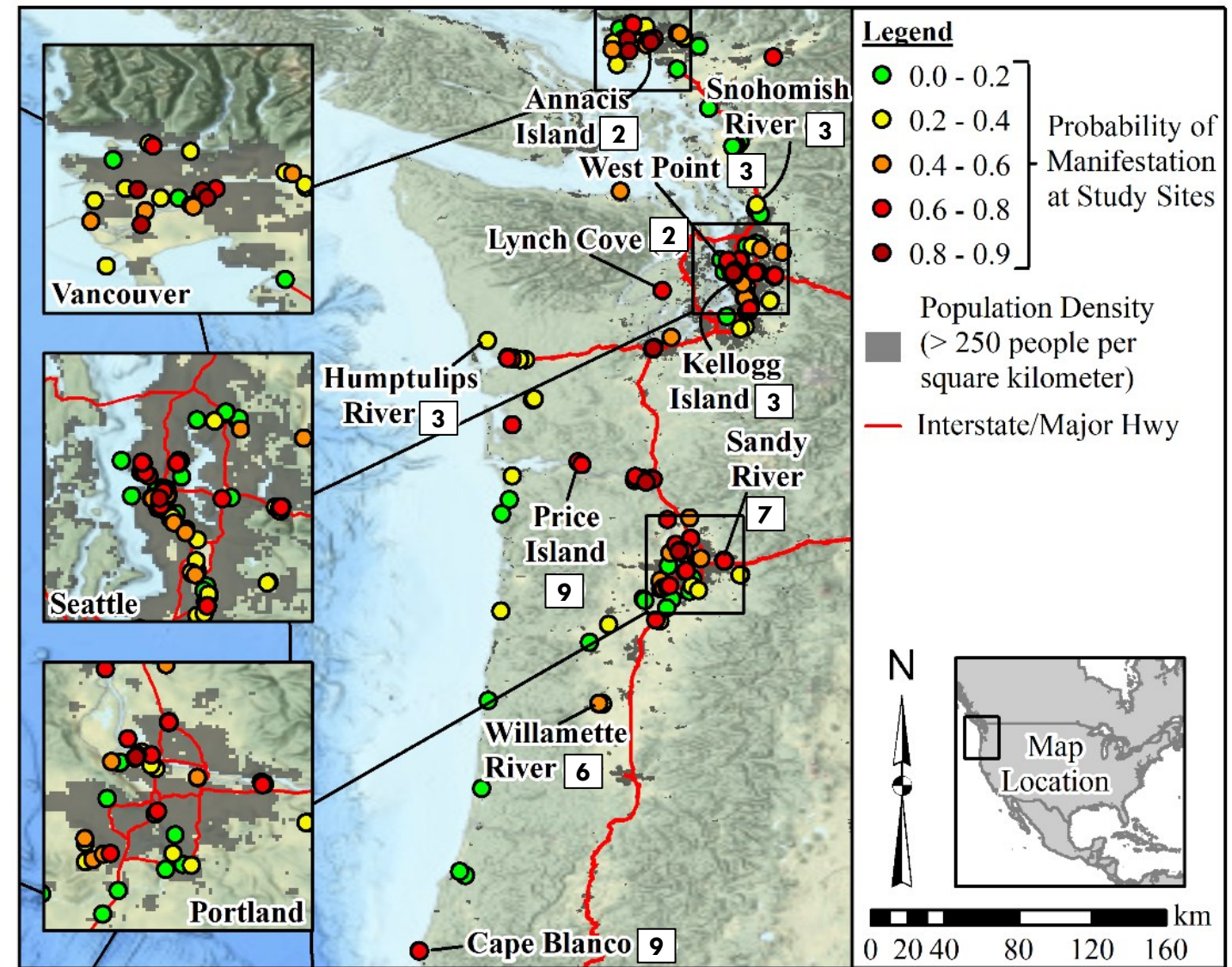
- Most notably, even the “best fitting” simulation does not fit the evidence especially well...
- Predictions suggest liquefaction should be relatively common throughout Puget Lowlands, but there is not yet obvious/proposed/apparent/favored evidence of 1700 CE liquefaction.



Simulation most likely to produce 1700 CE liquefaction evidence

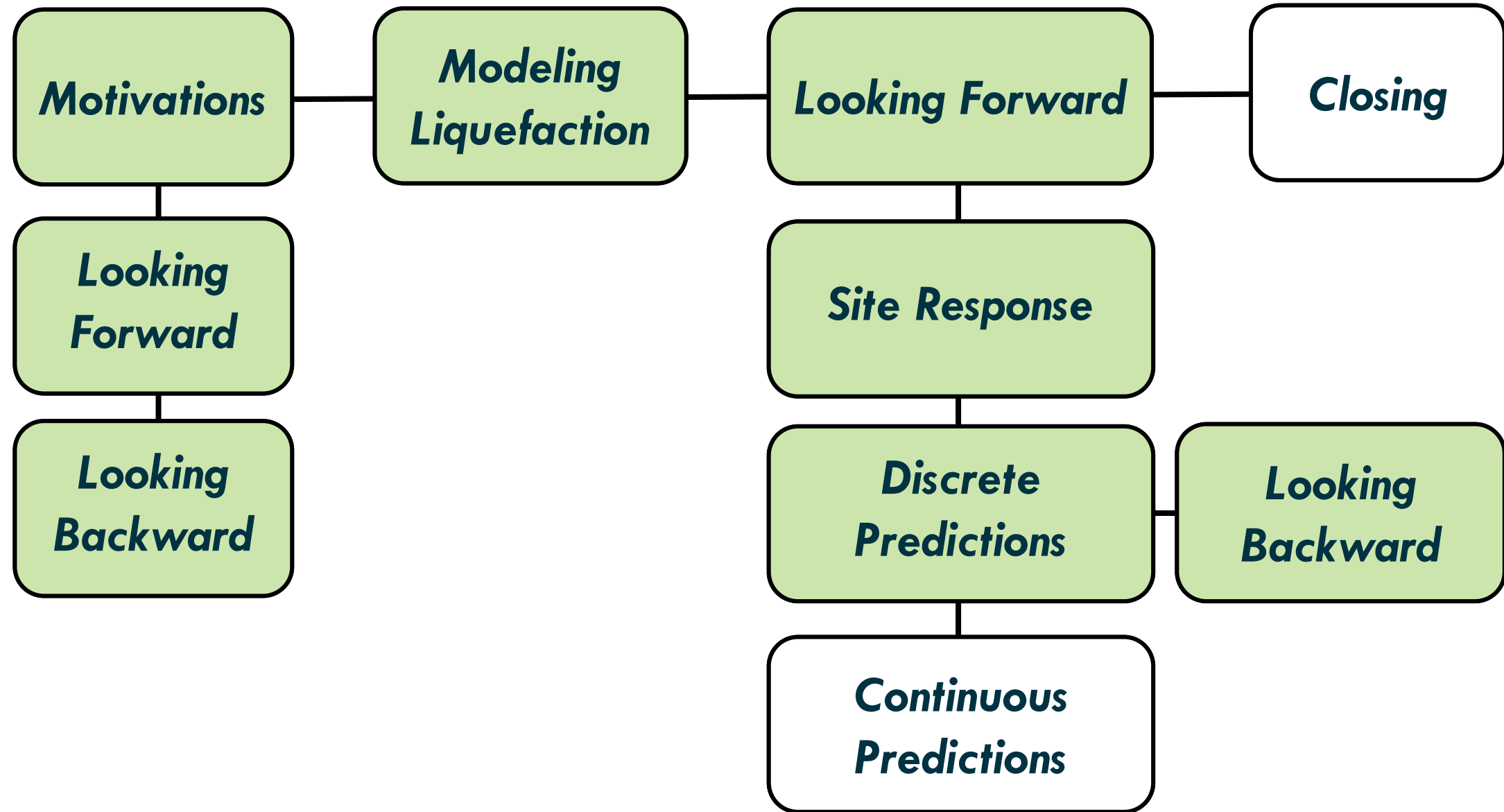
Looking Backward

- How to interpret this difference?
- 1) Significant 1700 liquefaction evidence awaits discovery?
 - 2) Component models used to predict site response, liquefaction are erroneous?
 - 3) 1700 motions were less than expected from M9 sims in portions of CSZ?
 - 4) If so, was 1700 slightly smaller than M9? Not a full-margin rupture? Why were the motions less?



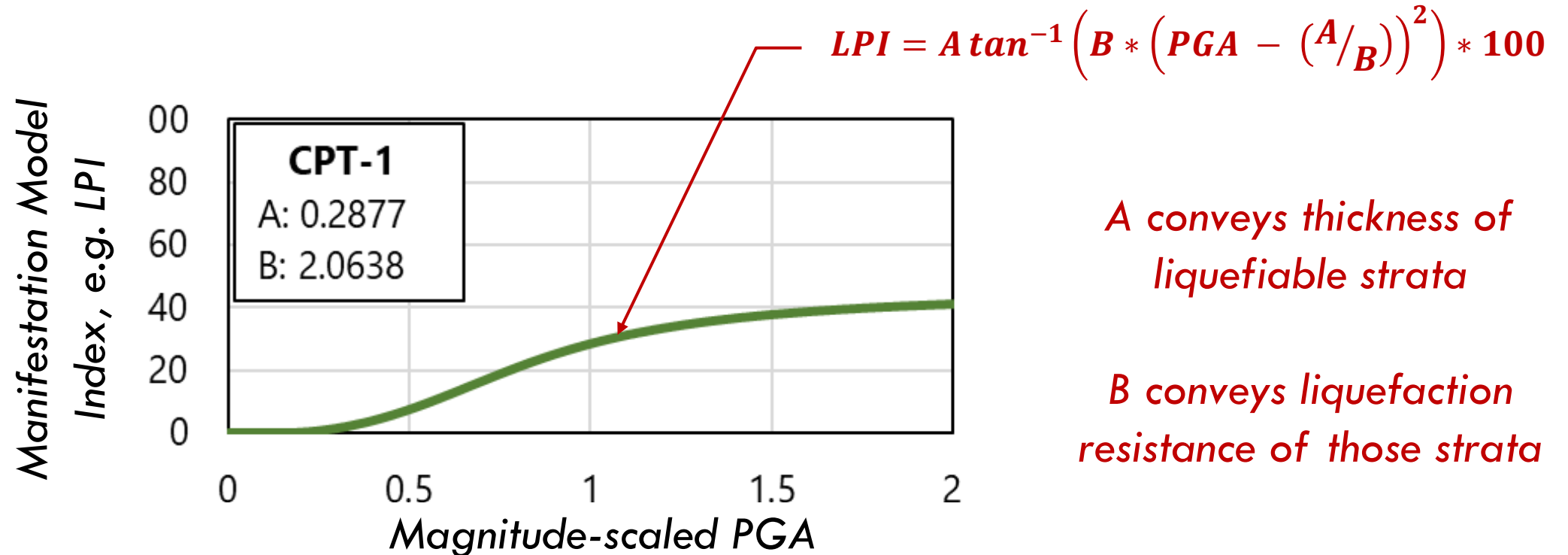
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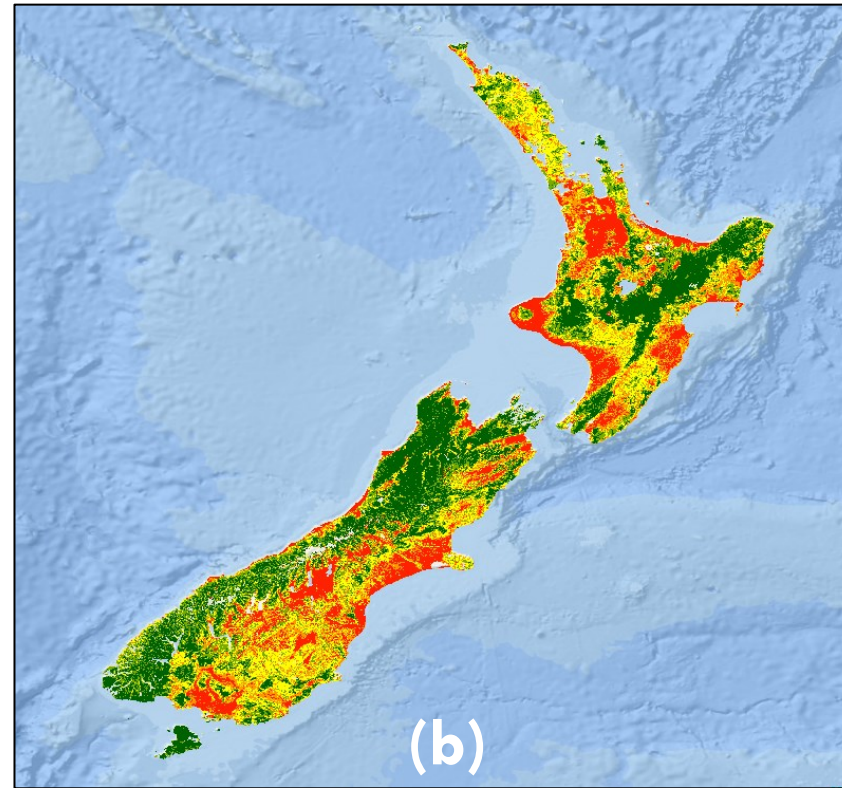
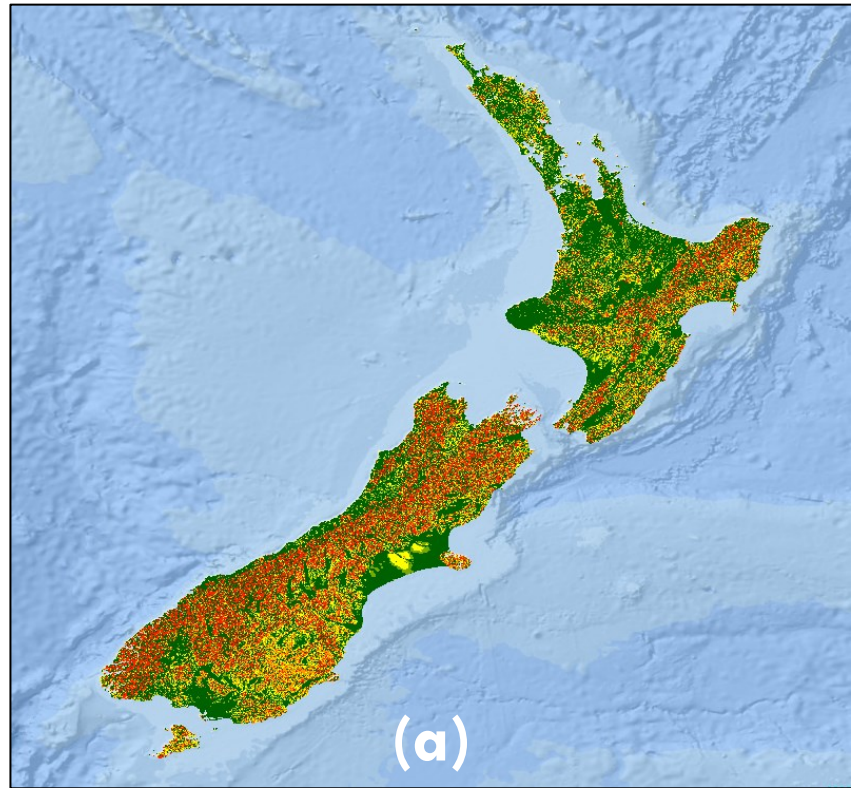
Looking Forward: Continuous Predictions [ongoing in US; trialed in NZ]

- Solution: a mechanics-informed machine learning model anchored to in-situ test data.
- **Step 1/3:** Subject CPTs (400 CSZ + 50,000 global) to wide range of ground motions
Predict liquefaction response using CPT-based models
Fit functional form to manifestation model index vs PGA response



Looking Forward: Continuous Predictions [ongoing in US; trialed in NZ]

- **Step 2/3:** Train ML models to predict “A” and “B” via 30 geospatial predictor variables.
- These variables aim to predict below-ground conditions using above-ground observations (e.g., satellite sensed) and mapped information (all freely available):



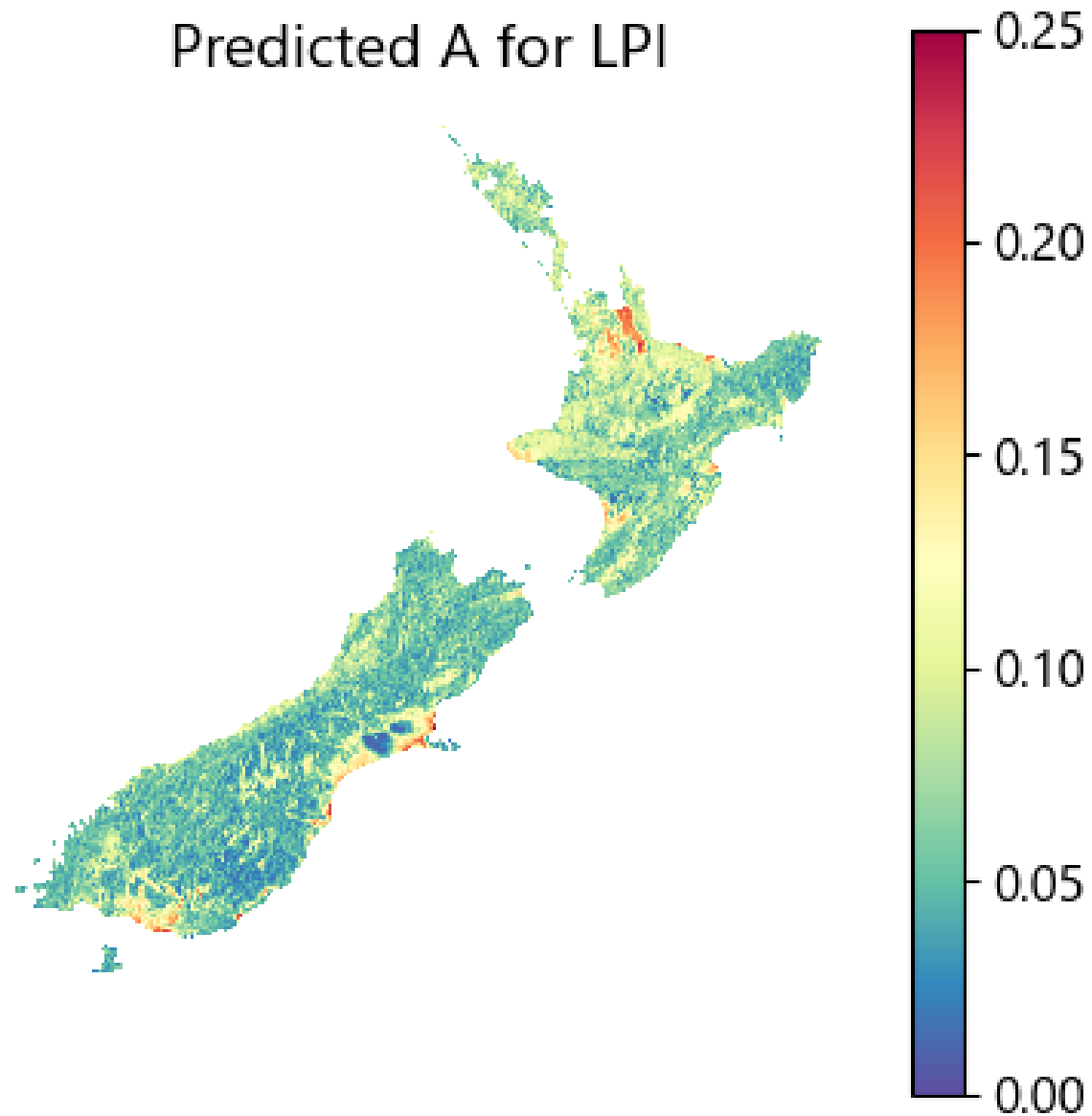
Example predictors: (a) depth to groundwater; (b) depth to bedrock

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 measure of the amount of elevation variation within a dataset.
Geologic unit	Geology units categorized into "Simple names."
Geomorphon	Classified as flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, or depression.
Groundwater depth	Interpolated depth to groundwater.
Height above nearest drainage	A topographic normalization to the local relative heights found along the drainage network.
Landform entropy	A texture metric of the spatial disorderliness of landform types within the window.
Landform uniformity	A texture metric of the uniformity of landform types within a window.
Major landform	The landform (classification) that covers most grid cells of the aggregation window.
Maximum multiscale deviation	The difference in elevation across a window divided by the standard deviation of the window.
Maximum multiscale roughness	The spherical standard deviation of 3-dimensional vectors to calculate vector ruggedness.
Pfafstetter level	The 'Pfafstetter' coding system implemented as 12 hierarchically nested sub-basins.
Precipitation	Mean annual precipitation.
Profile curvature	A measure of the rate of change of a slope; affects the acceleration of water flow.
Roughness	The largest inter-cell absolute elevation difference of a cell and its 8 surrounding cells.
Scale of MMD	See Maximum multiscale deviation.
Scale of MMR	See Maximum multiscale roughness.
Shannon index	A diversity index based on the proportion of landform types within the window.
Soil depth	Qualitative soil depth classifier.
Soil drainage	Qualitative soil drainage classifier.
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.

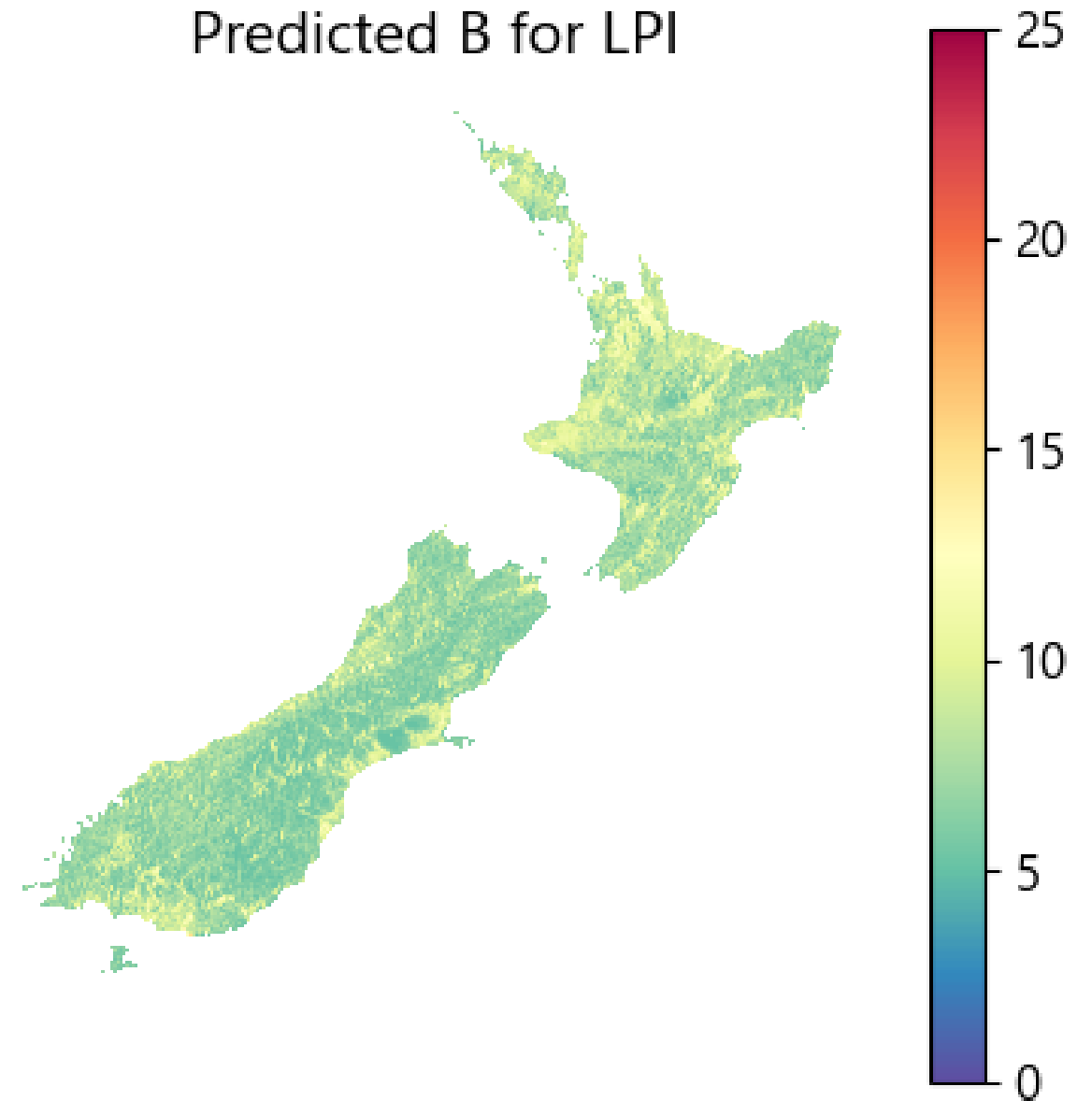
Looking Forward: Continuous Predictions [ongoing in US; trialed in NZ]

- **Step 2/3:** Train ML models to predict “A” and “B” via 30 geospatial predictor variables.

Predicted A for LPI

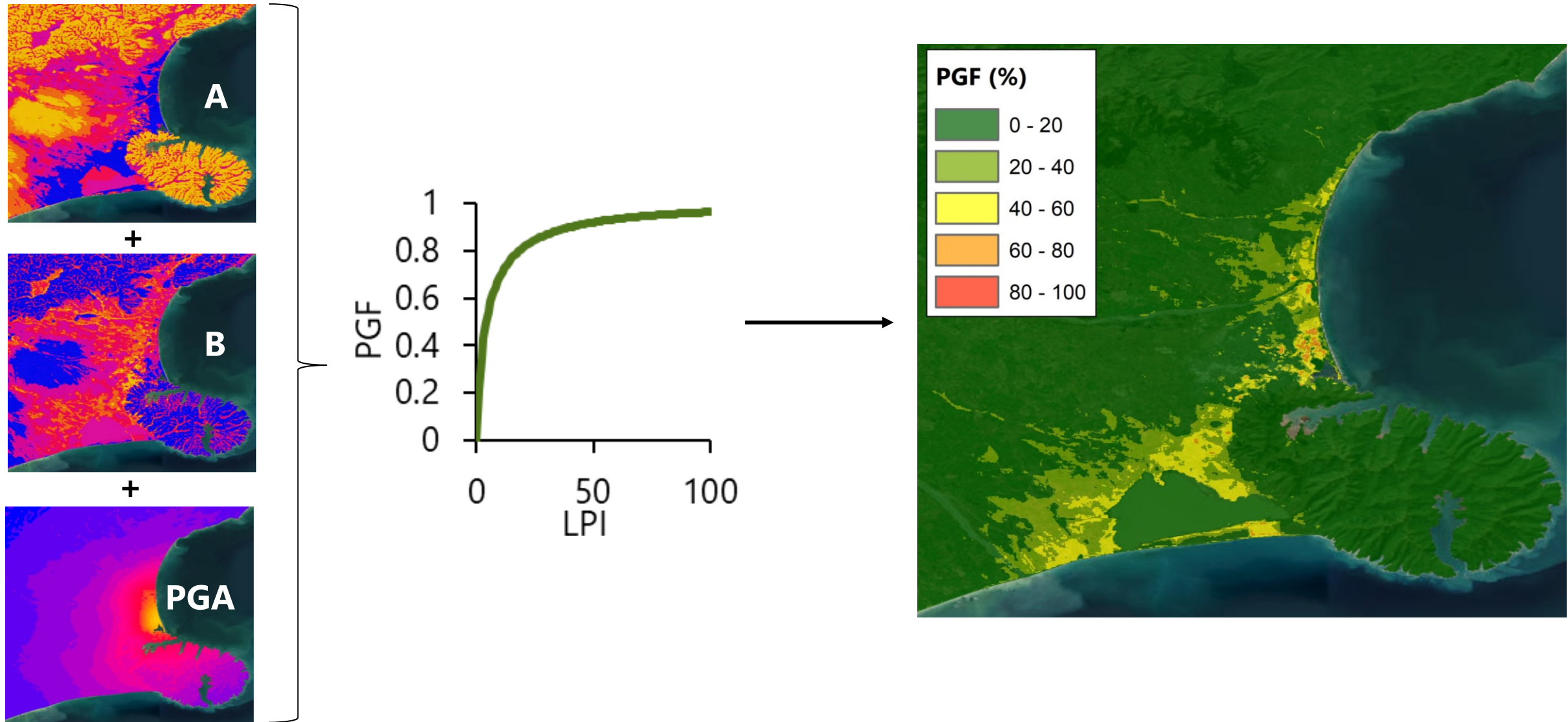


Predicted B for LPI



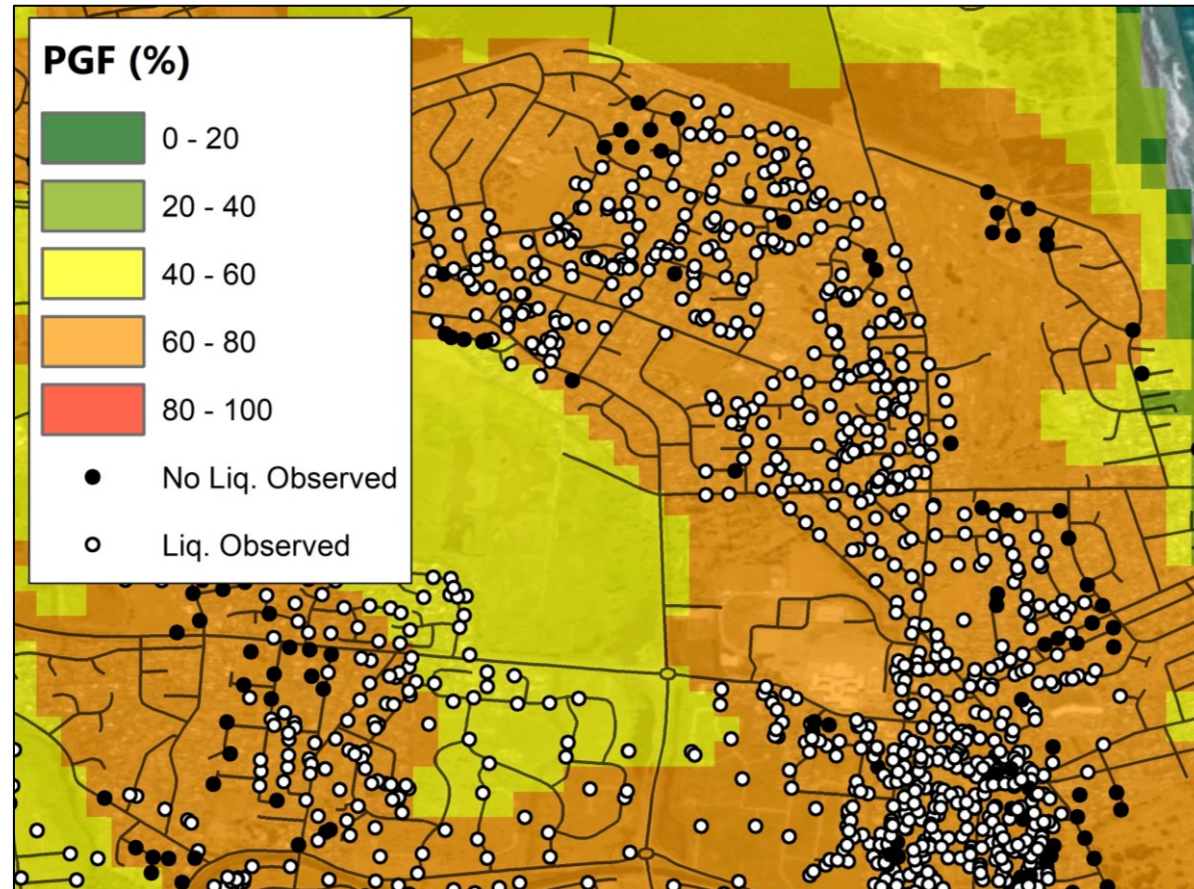
Looking Forward: Continuous Predictions [ongoing in US; trialed in NZ]

- *With this approach, rapid prediction of probability of ground failure (PGF) is trivial:*

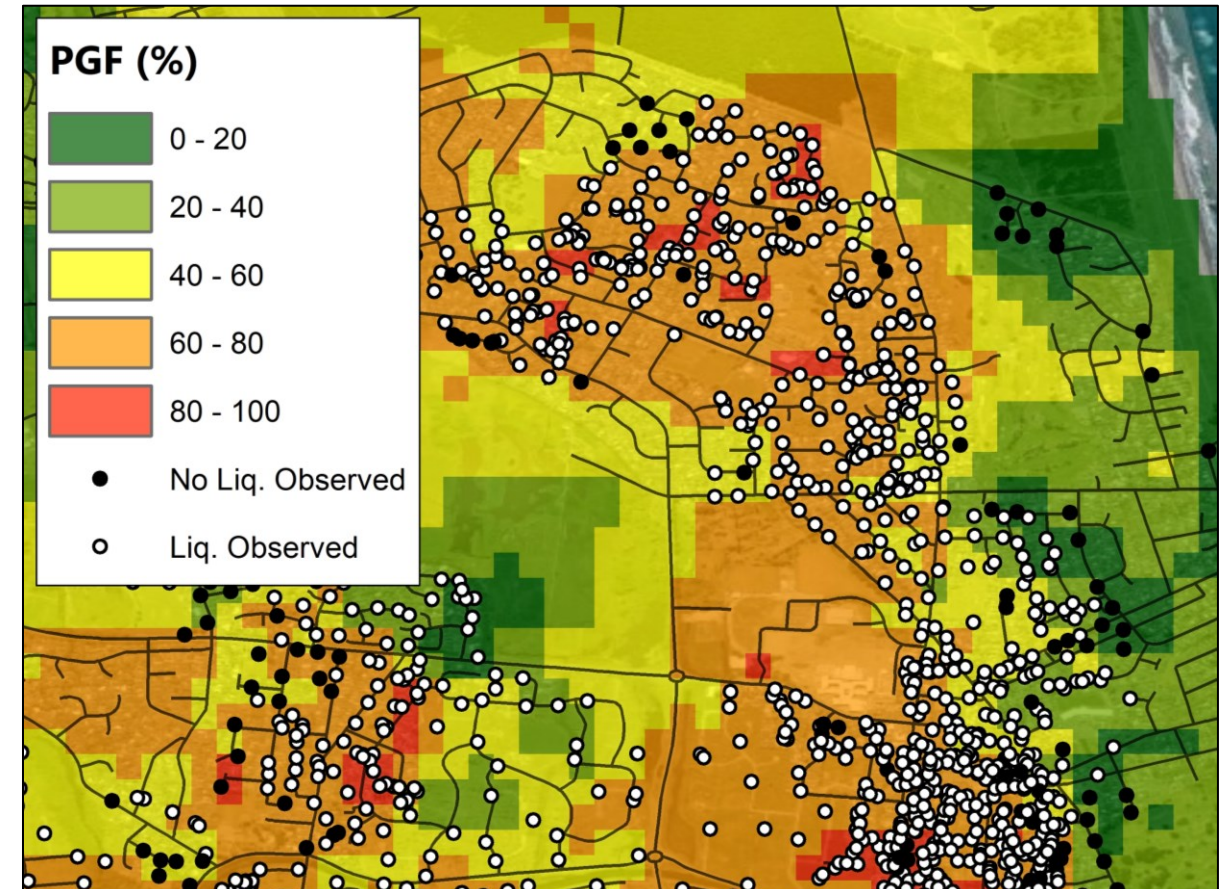


Looking Forward: Continuous Predictions [ongoing in US; trialed in NZ]

- **Step 3/3:** Use geostatistics to update ML predictions of A, B using CPT measurements.

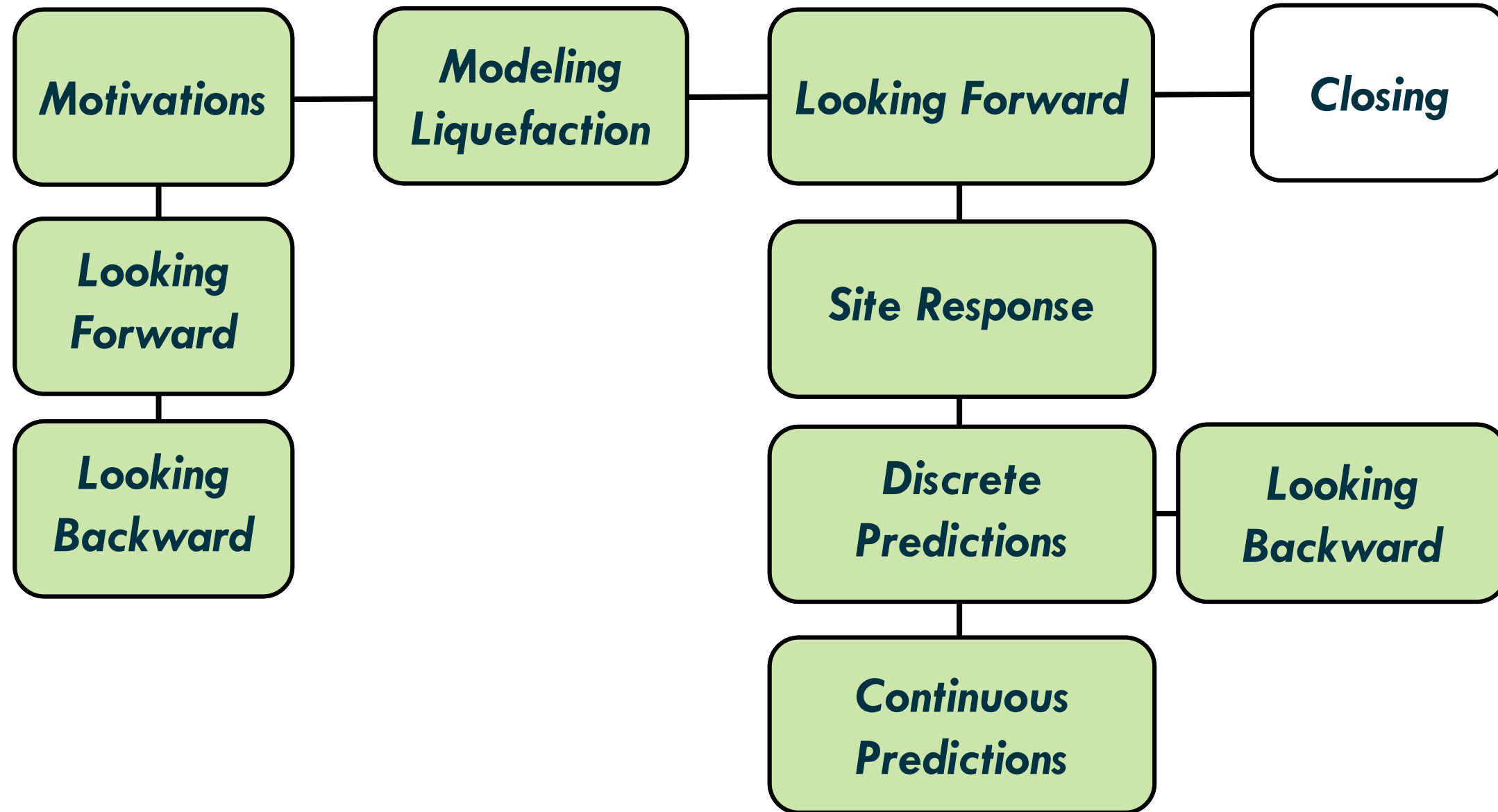


Machine Learning predictions
before geostatistical updating



Machine Learning predictions
after geostatistical updating

Outline



Closing

➤ **Looking forward**

- Discrete predictions suggest liquefaction could be pervasive in M9 CSZ events, affect major hubs, but (like ground motions) expected response varies widely.
- Continuous predictions (ongoing) are needed to fully assess impacts, network reliability.

➤ **Looking backward**

- The lack of clear/proposed 1700 liquefaction evidence in the Puget Lowland is interesting (forward predictions of M9 ruptures suggest it should be somewhat common).
- 1700 ground motions may have been less than expected from M9 simulations in some areas (e.g., Seattle), but this is only one of several reasonable interpretations.

➤ **General**

- ML can effectively exploit large quantities of above-ground geospatial information to predict below-ground conditions/traits/responses

Acknowledgements

Ryan Rasanen, Washington Dept. of Transportation
Morgan Sanger, PhD candidate, University of Washington
Alex Grant, United States Geological Survey
Mertcan Geyin, Norwegian Geotechnical Institute
Marc Eberhard, University of Washington
Erin Wirth, United States Geological Survey
Andrew Makdisi, United States Geological Survey
Brian Atwater, United States Geological Survey
Jeff Berman, University of Washington