

*INFORMING PREDICTIONS FROM ABOVE
WITH COMMUNITY DATA FROM BELOW:
A MECHANICS-INFORMED AI LIQUEFACTION
MODEL FOR RAPID RESPONSE & SIMULATION*

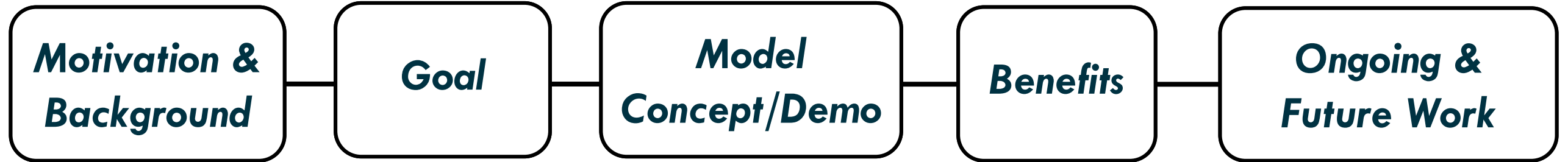
*Morgan Sanger
& Brett Maurer*

University of Washington



*PEER Researcher's Workshop
16 August 2024*

Outline



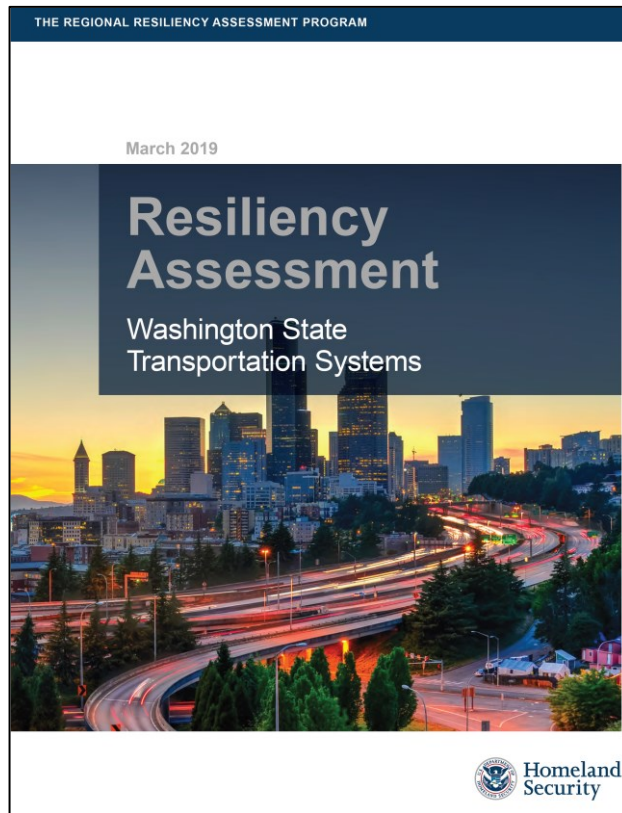
Motivation

- *Liquefaction routinely damages infrastructure, hinders post-event mobility and recovery.*



Motivation

- *Some scenario earthquake studies suggest liquefaction could cause more damage than any other earthquake effect:*



- *The Dept. of Homeland Security (2019) predicted impacts to infrastructure owed by WA state in an M9 earthquake.*

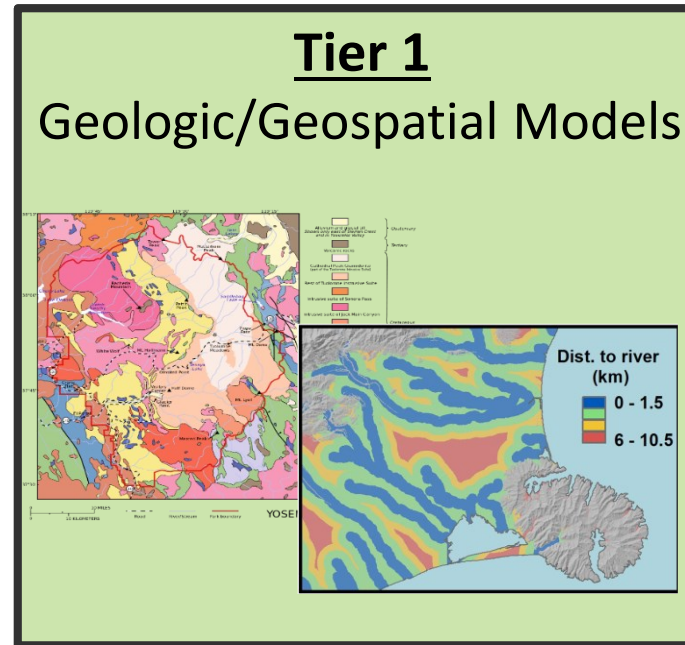
2755 km of road, 1815 km of rail, 837 bridges, and 8 ports are expected to be unavailable due predominantly to soil liquefaction.

- *Draws attention to:*

- 1) Liquefaction's potentially staggering impact (could these predictions be true?!)*
- 2) How liquefaction is predicted at regional scales (DHS used "HAZUS" type model)*

Background

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

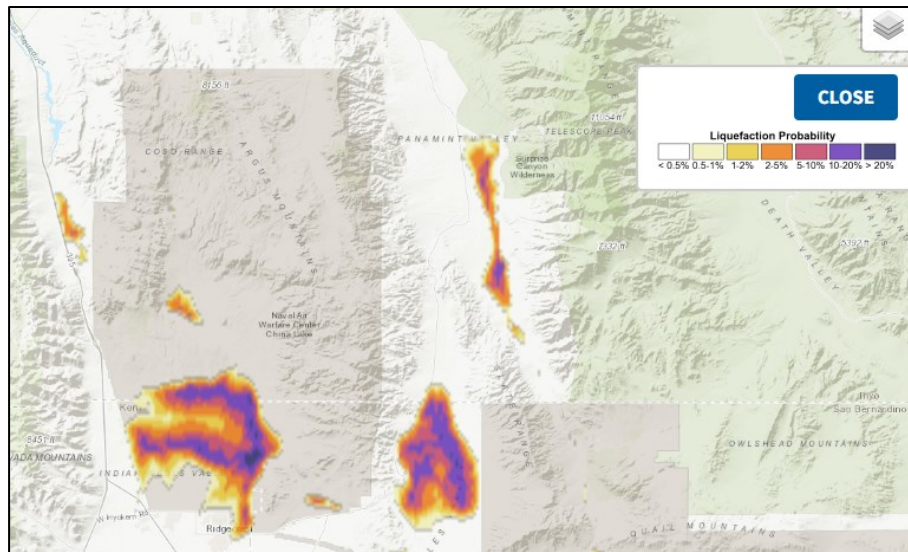


- **Tier 1**: Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface data (e.g., HAZUS).

Background: Tier 1 Models

For example, Rashidian & Baise (2020):

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



M 7.1 - Ridgecrest Earthquake Sequence

2019-07-06 03:19:53 (UTC) | 35.770°N 117.599°W | 8.0 km

[Interactive Map](#) | [Regional Information](#)

Liquefaction Probability

< 0.5% 0.5-1% 1-2% 2-5% 5-10% 10-20% > 20%

[Responses](#)

Contribute to citizen science. Please [tell us](#) about your experience.

Citizen Scientist Contributions

[Ground Failure](#)

Landslide Estimate

Limited area affected
Little or no population exposed

Liquefaction Estimate

Limited area affected
Little or no population exposed

[Aftershock Forecast](#)

According to our forecast, the chance of at least one aftershock within the next year:

M 7+	< 1%
M 6+	< 1%
M 5+	7%
M 4+	54%
M 3+	> 99%

[Origin](#)

Review Status
REVIEWED

Magnitude
7.1 mw

Depth
8.0 km

Time
2019-07-06 03:19:53 UTC

[CLOSE](#)

Contributed by [CI](#)⁵

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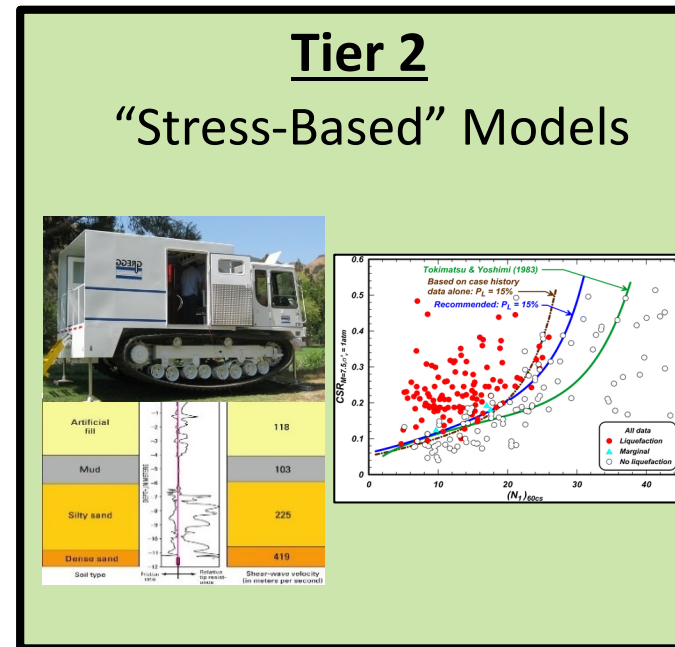
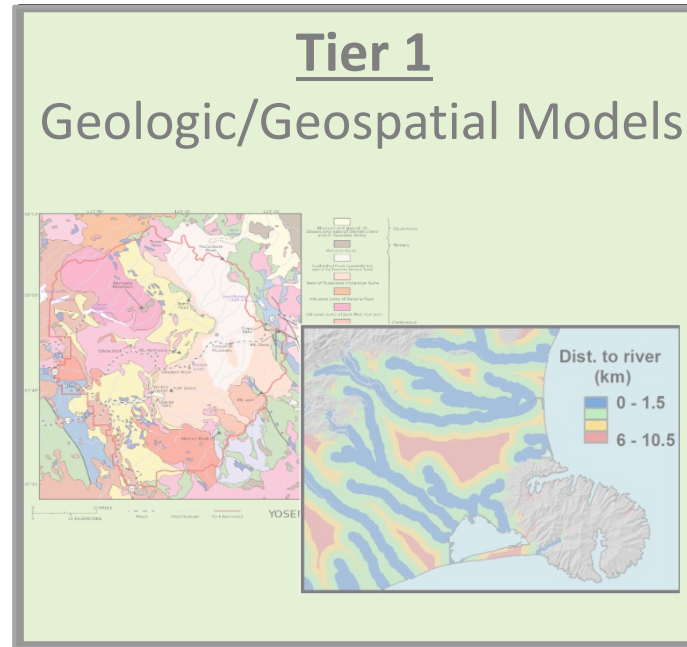
Contributed by [US](#)⁷

Contributed by [CI](#)⁵

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

Background

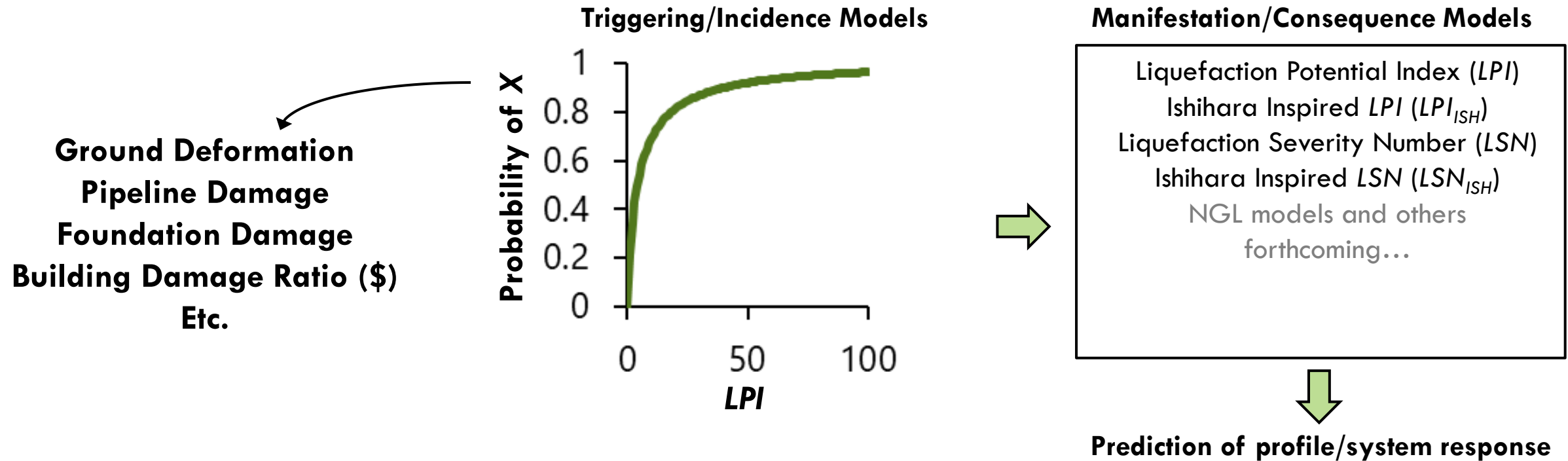
- Liquefaction models can be viewed as having 3 tiers:



- **Tier 1:** Requires only geologic or geospatial data. Used at regional scale. A range of complexities, but all are limited by lack of subsurface 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.

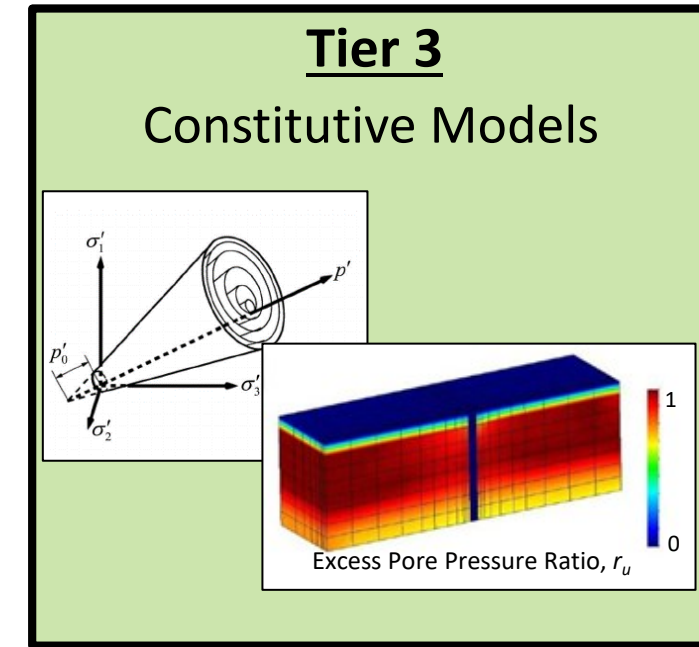
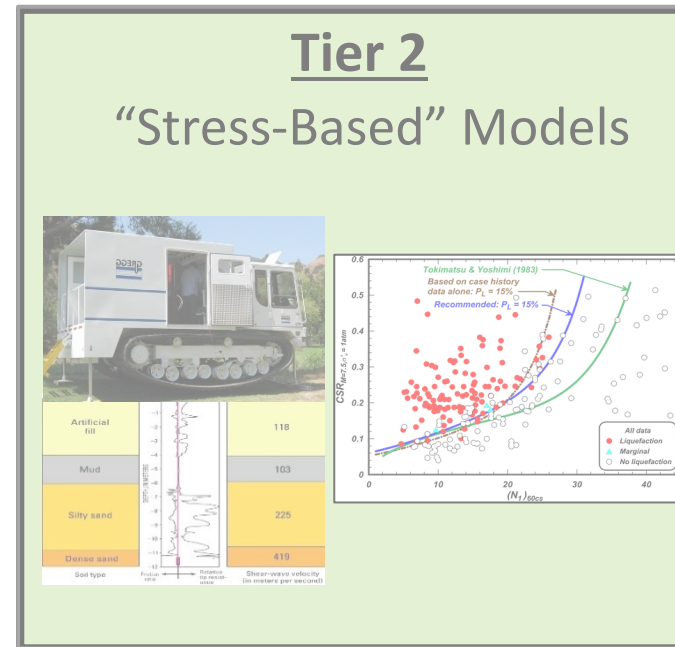
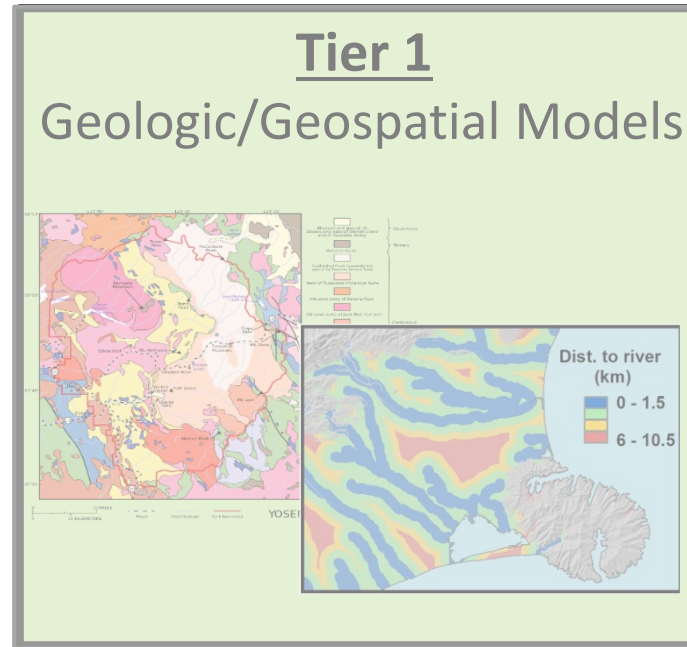
Background: Tier 2 Models

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



Background

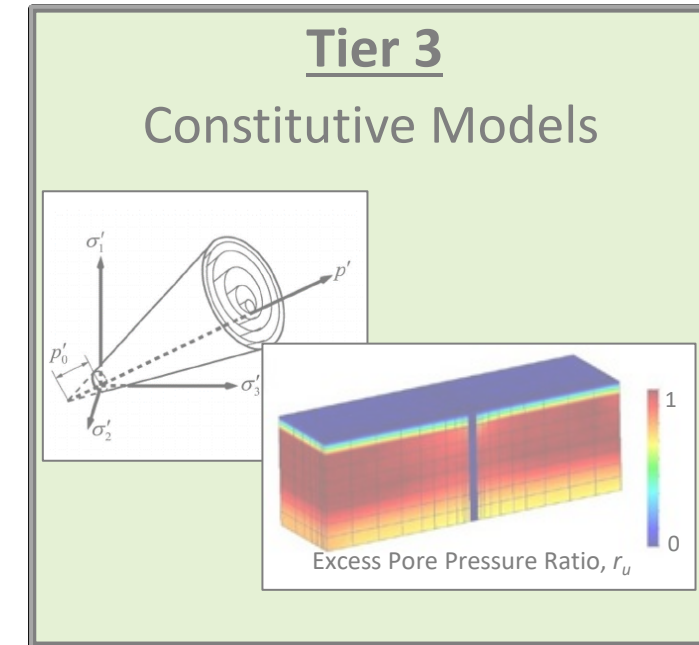
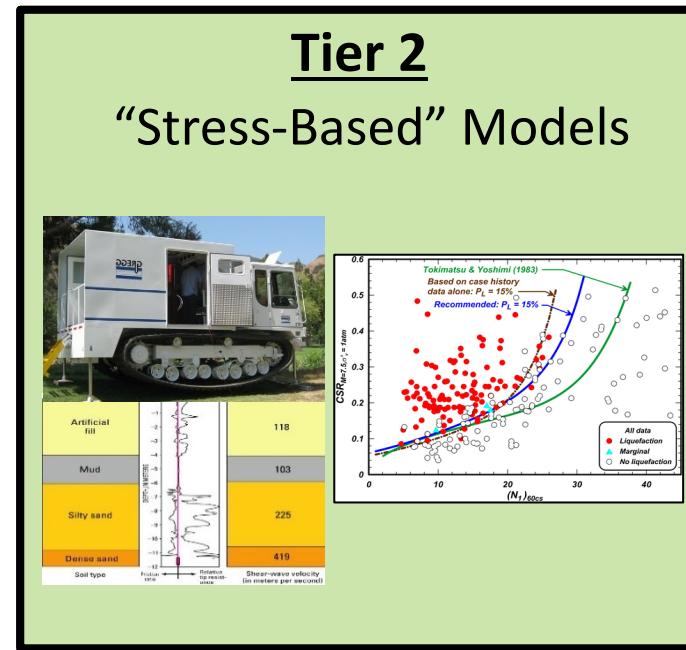
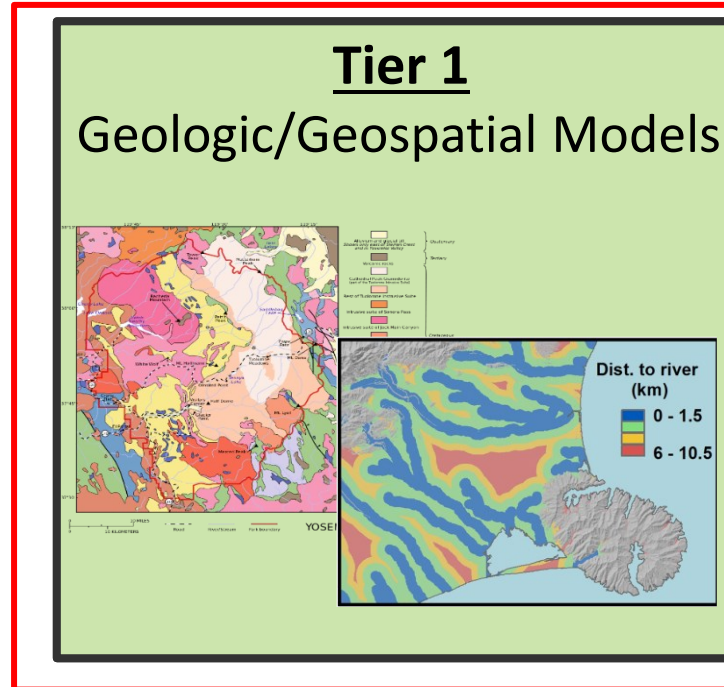
- Liquefaction models can be viewed as having 3 tiers:



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- **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

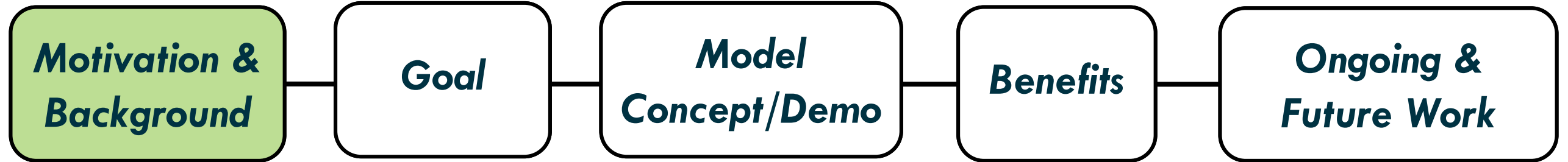
➤ Liquefaction models can be viewed as having 3 tiers:



Our focus.

**Tier-1 models have important uses but major limitations.
How can Tier-2 data and models be used to improve them?**

Outline



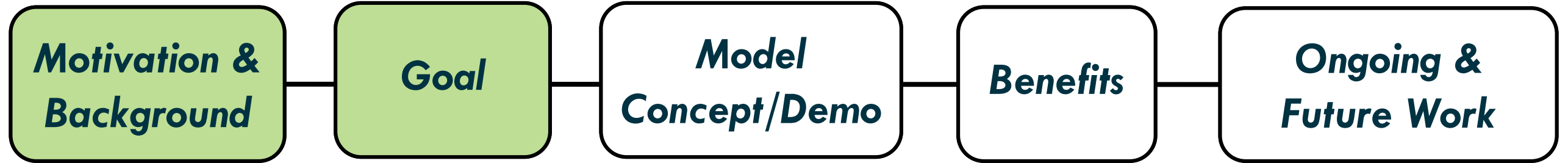
Project Goal

➤ **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 mechanistic backbone)
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:** *Development of a Tier-1 model that addresses each of these limitations.*

Outline

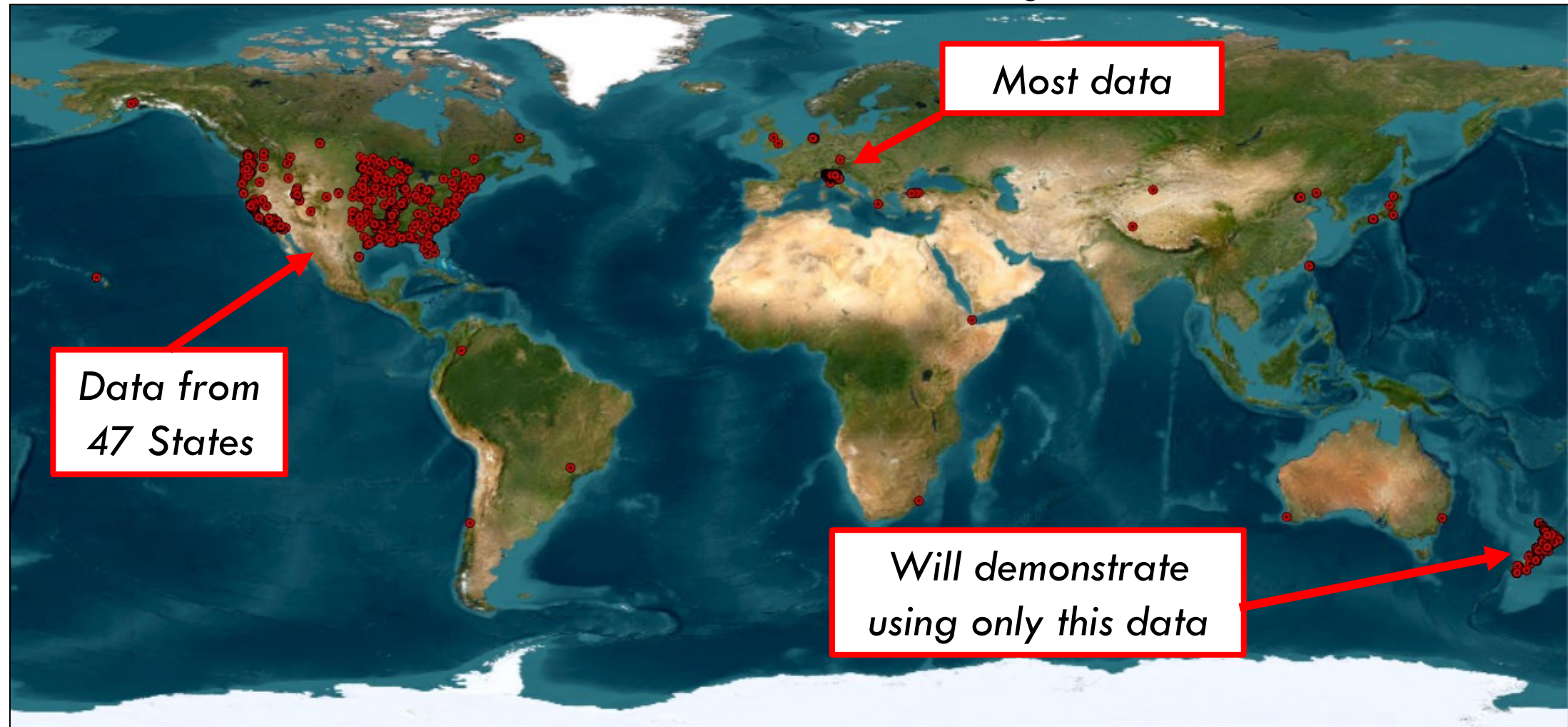
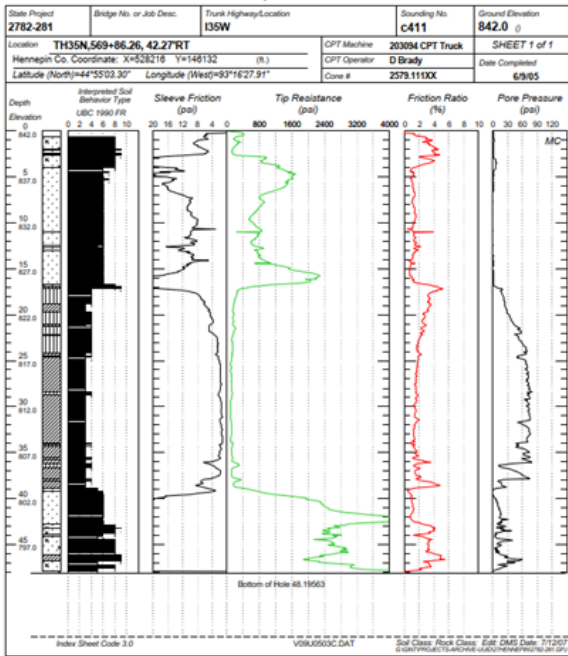


Modeling Concept & Demonstration in New Zealand

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

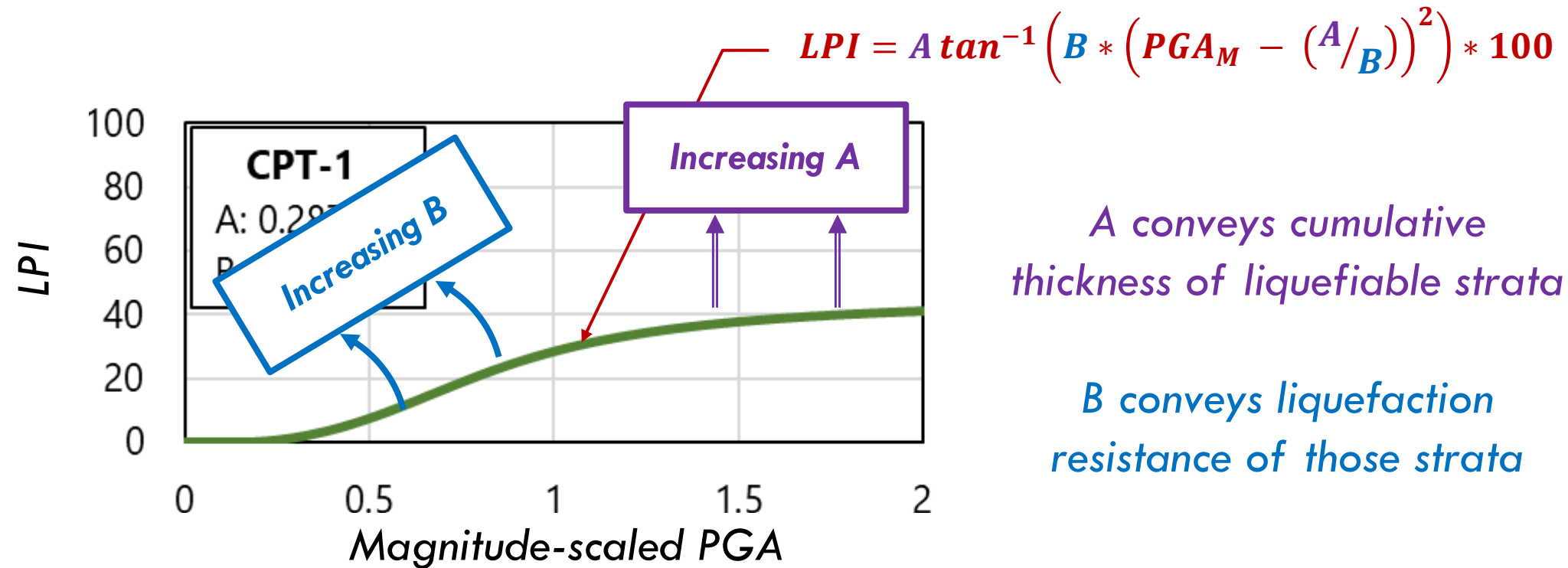
~ 45,000 CPTs and counting...

CPT Data



Modeling Concept & Demonstration in New Zealand

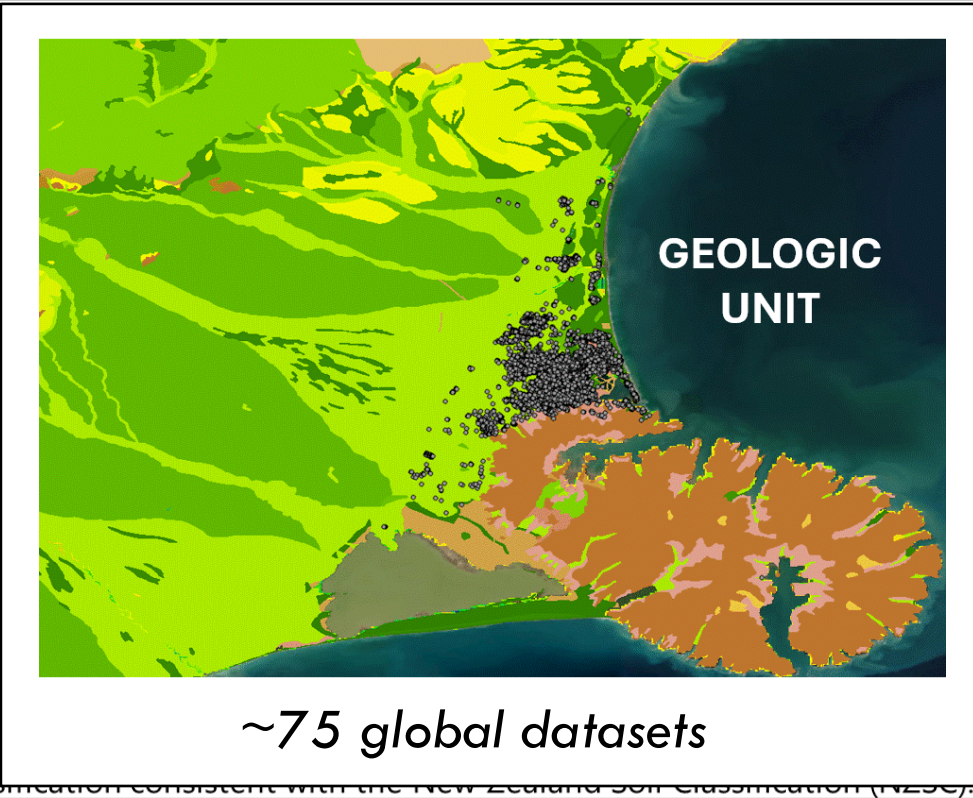
- **Step 2/5:** Subject each CPT to a spectrum of seismic loading (PGA_M)
Predict liquefaction response (e.g., LPI) using Tier-2 models
Fit functional form to this computed response



Modeling Concept & Demonstration in New Zealand

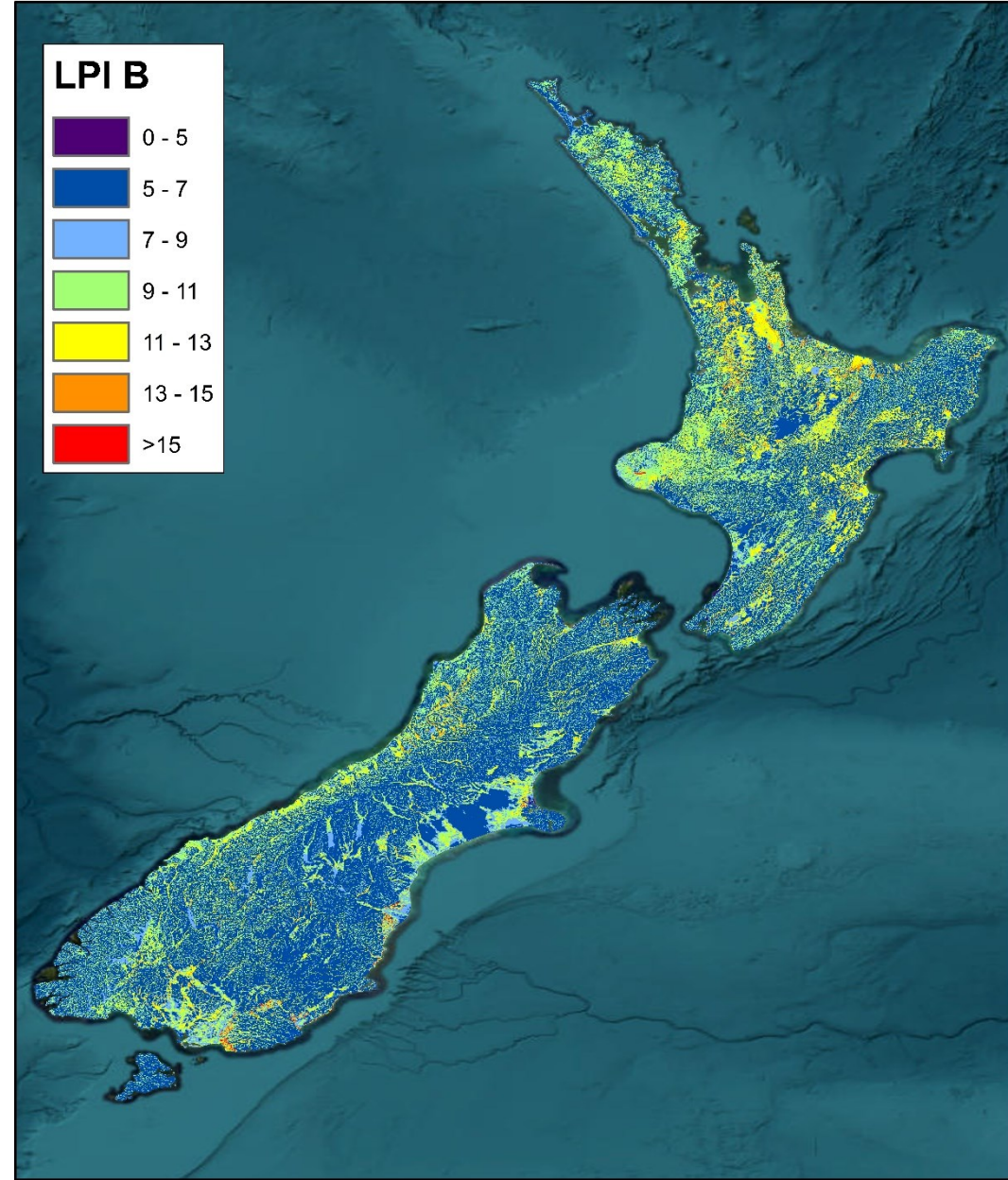
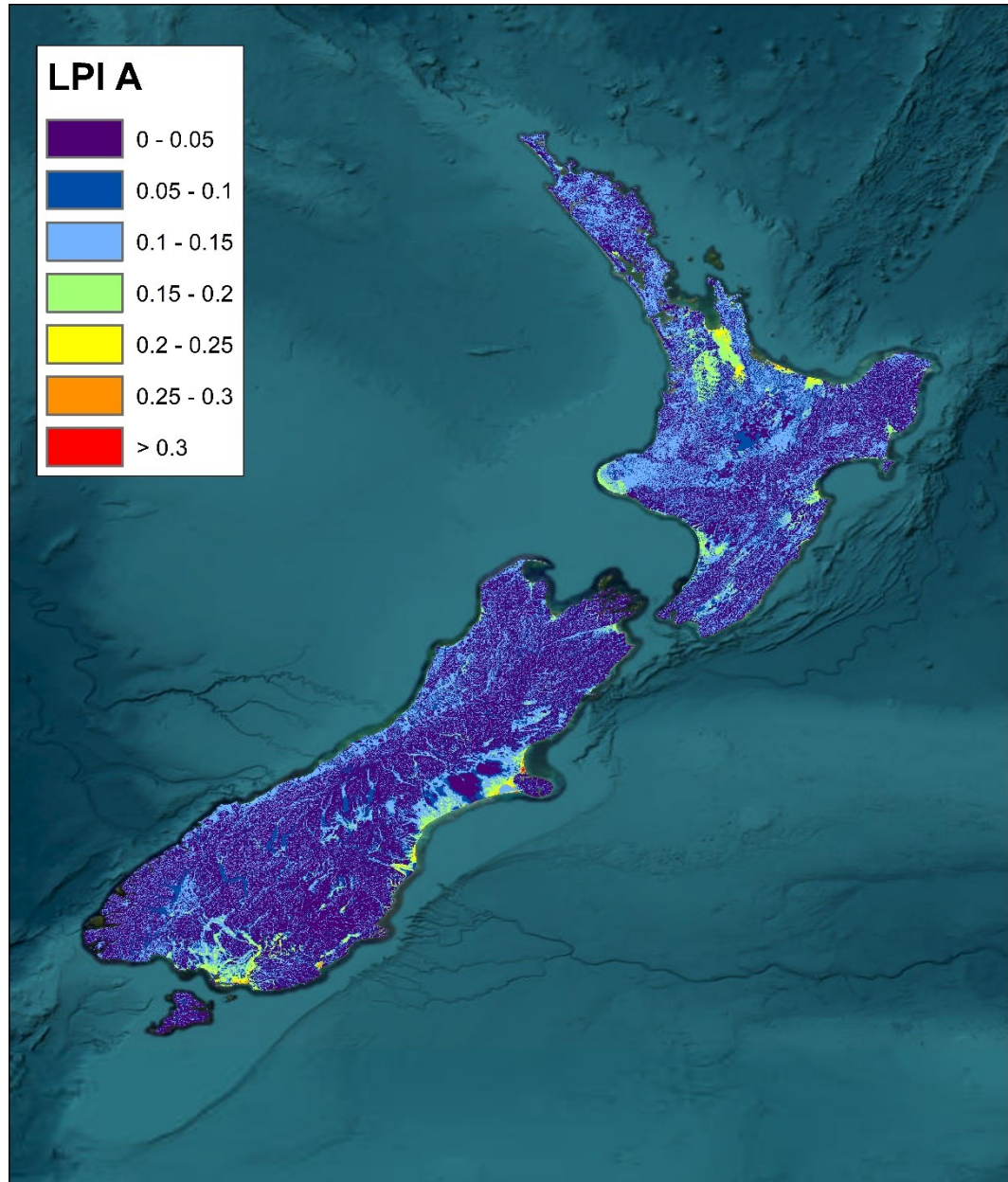
➤ Step 3/5: Compile geospatial features/predictors at CPT locations

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 measure of elevation deviation from the mean.
Geologic unit	Geology
Geomorphon	Classified geomorphons
Groundwater depth	Interpolated groundwater depth
Height above nearest drainage	A topographic measure of height above the nearest drainage network.
Landform entropy	A texture measure of landform diversity.
Landform uniformity	A texture measure of landform uniformity.
Major landform	The landform class of a cell.
Maximum multiscale deviation	The difference between the maximum and minimum elevation in the window.
Maximum multiscale roughness	The sphere of influence of a cell.
Pfafstetter level	The 'Pfafstetter level' of a cell.
Precipitation	Mean annual precipitation.
Profile curvature	A measure of profile curvature.
Roughness	The large-scale roughness of a cell.
Scale of MMD	See Maximum multiscale deviation.
Scale of MMR	See Maximum multiscale roughness.
Shannon index	A diversity measure of landform classes.
Soil depth	Qualitative soil depth.
Soil drainage	Qualitative soil drainage.
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.



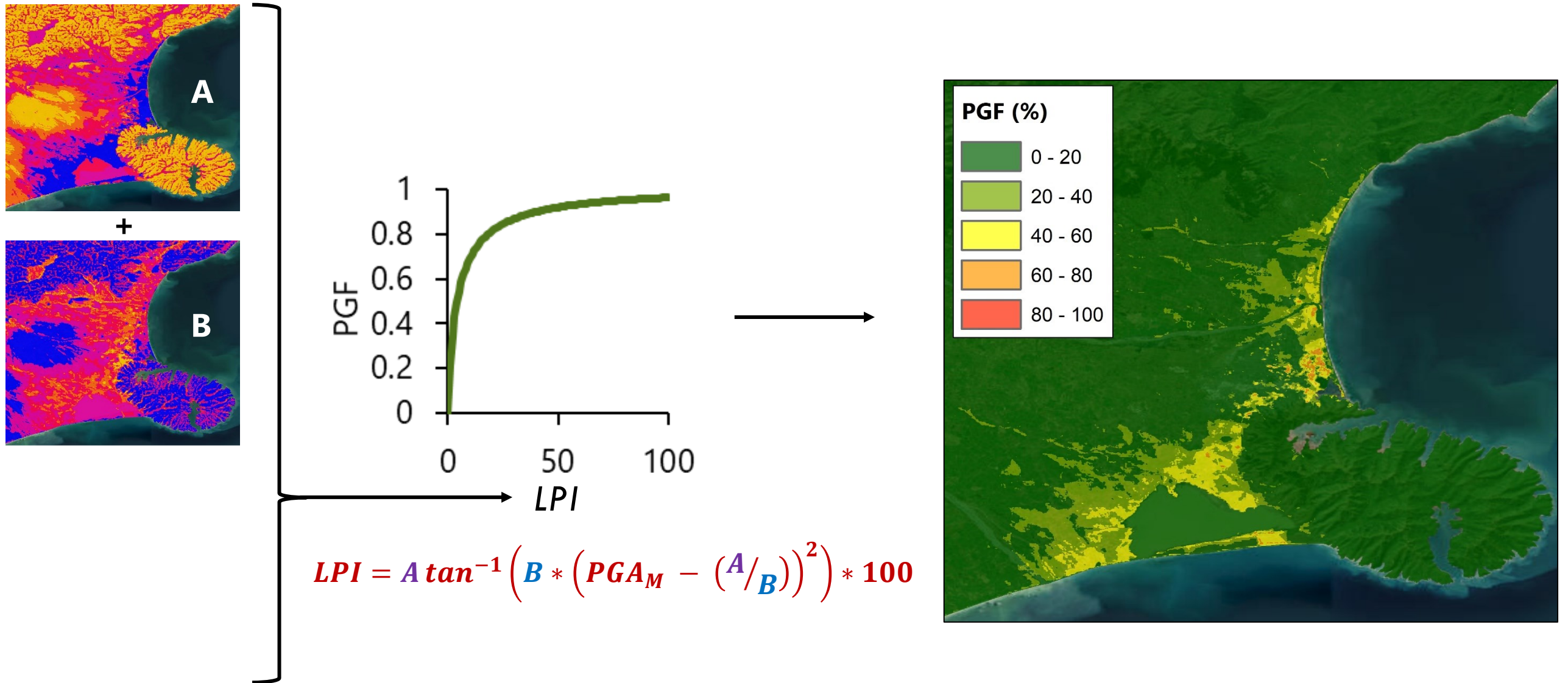
Modeling Concept & Demonstration in New Zealand

- **Step 4/5:** Train ML model to predict A & B, then run models everywhere.



Modeling Concept & Demonstration in New Zealand

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



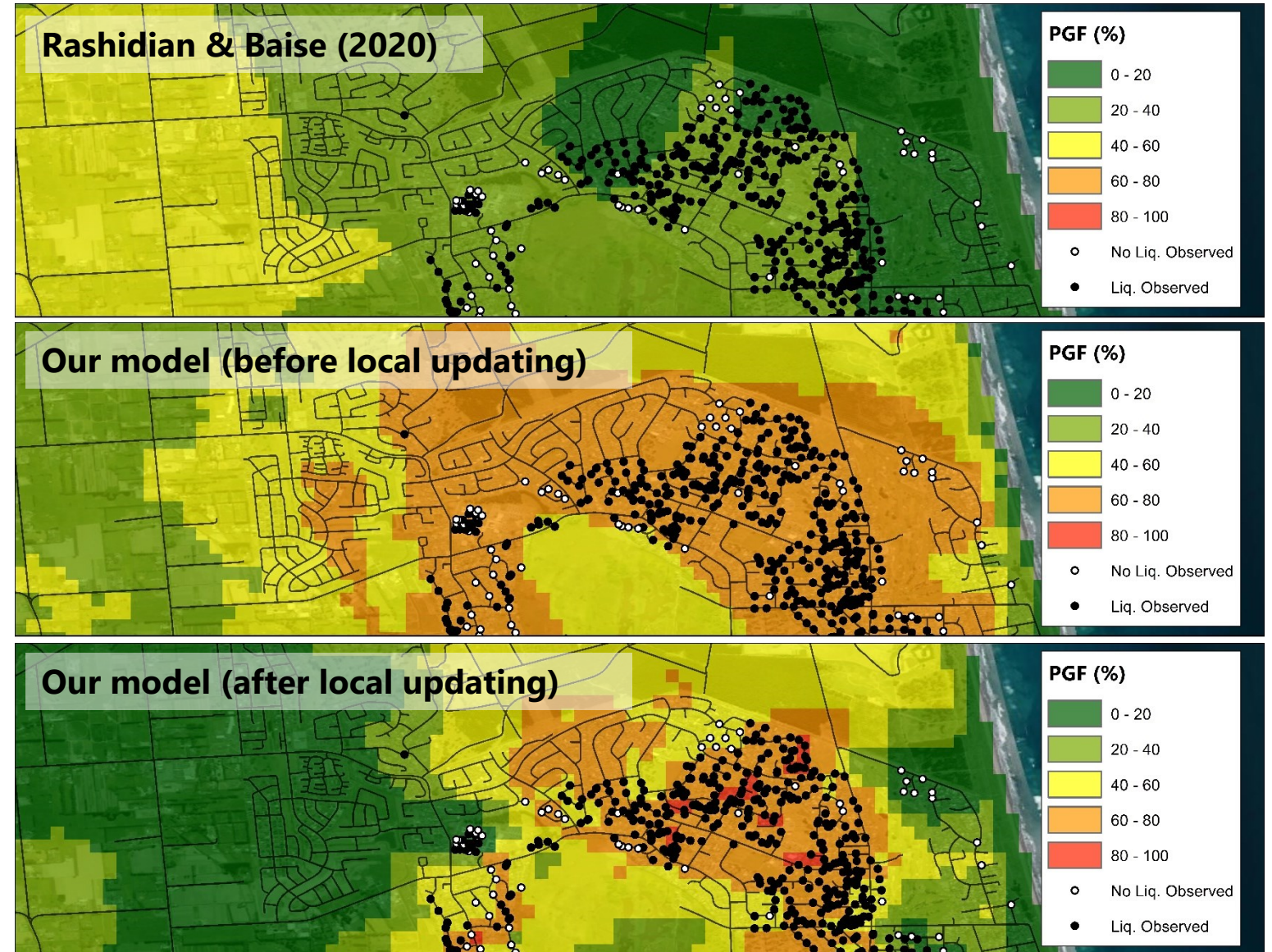
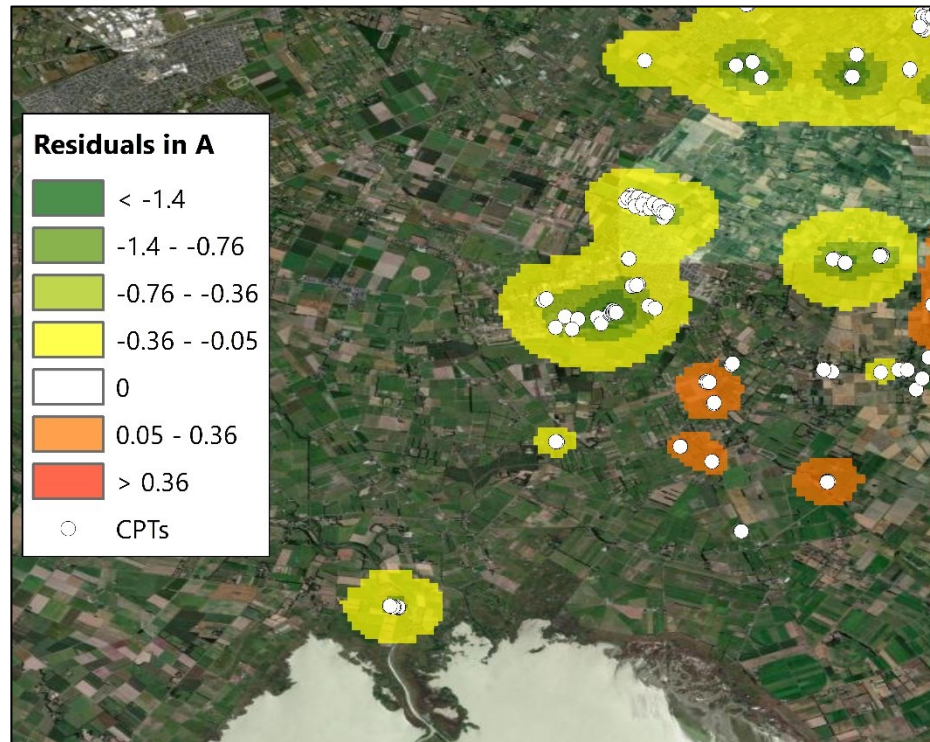
- Permits rapid prediction of impacts (e.g., probability of ground failure, PGF).

Modeling Concept & Demonstration in New Zealand

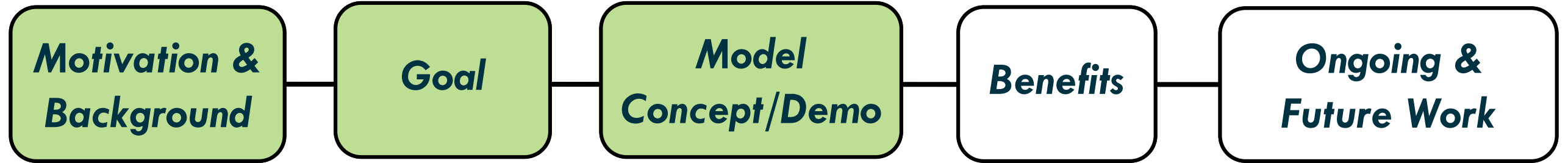
➤ **Step 5/5:** ML predictions are geostatistically updated by geotechnical data

e.g., Feb 2011 M6.2 Christchurch Earthquake

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



Outline



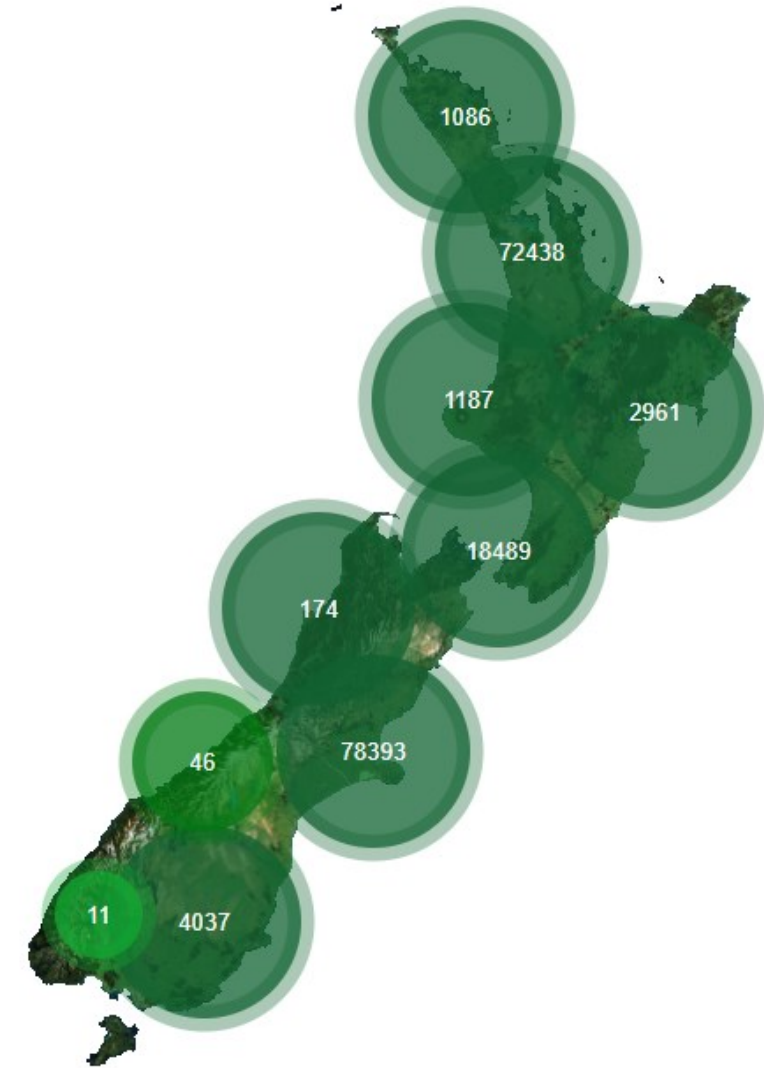
Benefits

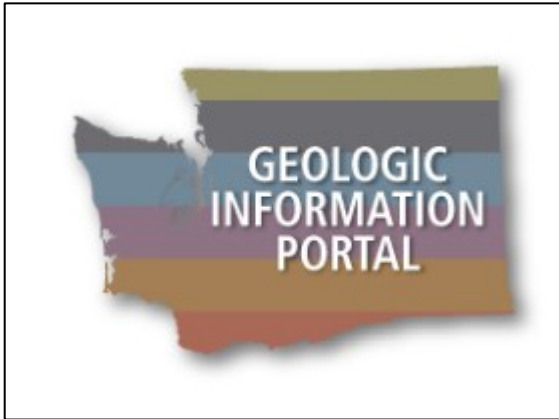
- *Trains on subsurface measurements (vast training set), not on liquefaction case histories (small and slow to grow training set).*
- *ML can manage, exploit many potentially-useful predictors.*
- *Mechanics-informed (geotechnical backbone guides sensible response and scaling).*
- *Geostatistical updating anchors ML predictions to reality.*
- *Is very easy for end-users to implement, test, critique, etc.*
- *Will continuously improve with more data (global trend toward shared data)...*

New Zealand Geotechnical Database



100,000+ geotechnical explorations...





Washington DNR Data Portal

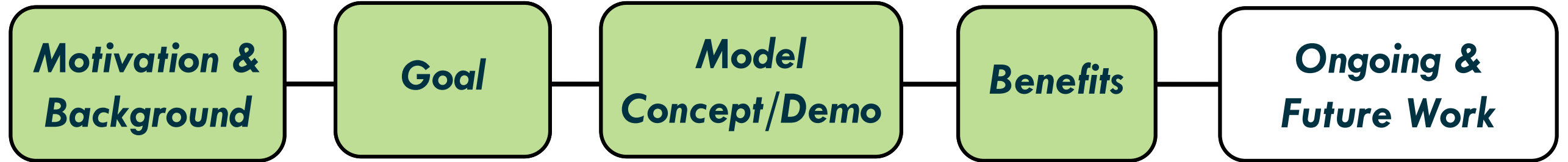


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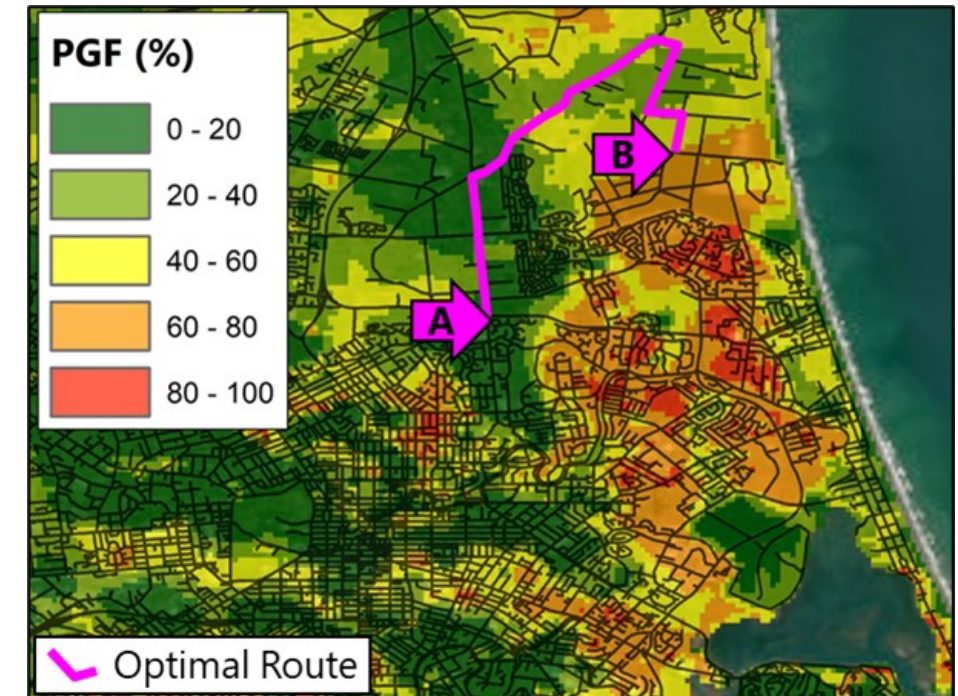
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- *Is very easy for end-users to implement, test, critique, etc.*
- *Will continuously improve with more data (global trend toward shared data).*
- *All code on GitHub; designed for frequent version updates with new community data.*

Outline



Ongoing and Future Work

- *Data Intake, especially in PEER Territory (currently ~3,500 CPTs)*
- *Regional vs. National vs. Global Models*
- *Integration with SimCenter Tools (R2D)*
- *Network Modelling in Scenario Events*
 - *Merging with Bridge Damage (UW Structures)*
 - *Traffic Impacts*
 - *Access to HealthCare*
 - *Demographic Analyses*
- *Maps also permit PBEE analyses at regional scale (e.g., return period of damage)*



Acknowledgements

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Morgan Sanger, PhD Candidate, University of Washington

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Pedro Arduino, University of Washington

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