AI and ML on DesignSafe

Krishna Kumar, The University of Texas at Austin

NHERI Computational Symposium, UCLA, 2024.

What is DesignSafe?

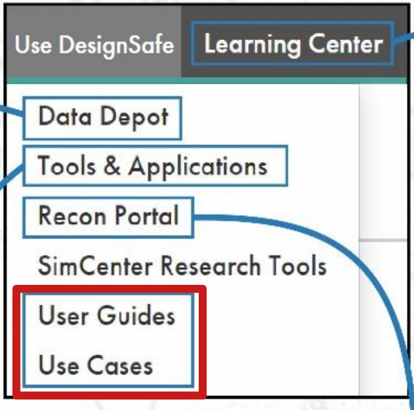
- A web-based research platform that enables transformative research to protect human life and reduce damage during natural hazard events

DesignSafe Vision

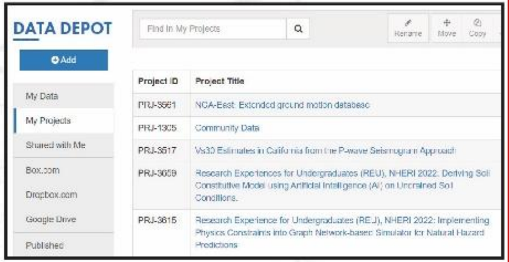
- A cyberinfrastructure (CI) that is an integral part of research discovery
  - Provide a platform for data sharing/publishing
  - Enable research workflows and access to high performance computing (HPC)
  - Deliver cloud-based tools that support the analysis, visualization, and integration of diverse data types
- Amplify and link the capabilities of natural hazards researchers in the US and abroad

DesignSafe Components

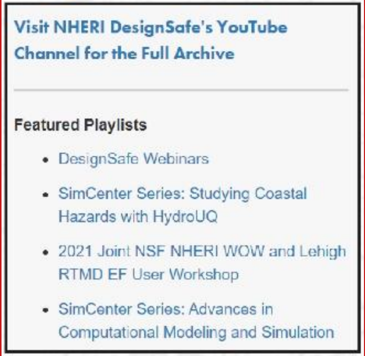
www.designsafe-ci.org



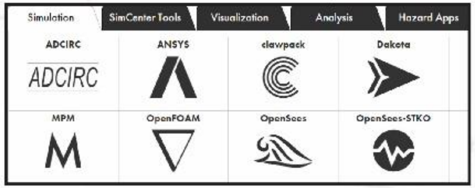
Data



Training/User Support

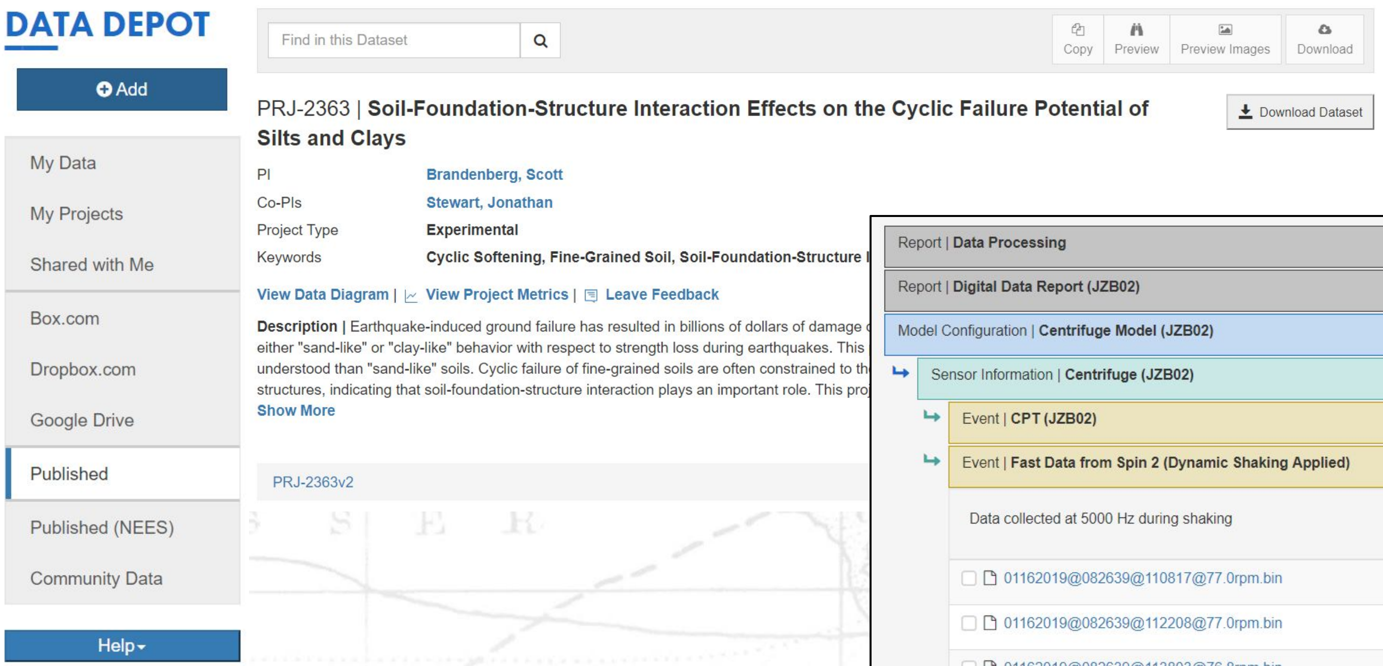


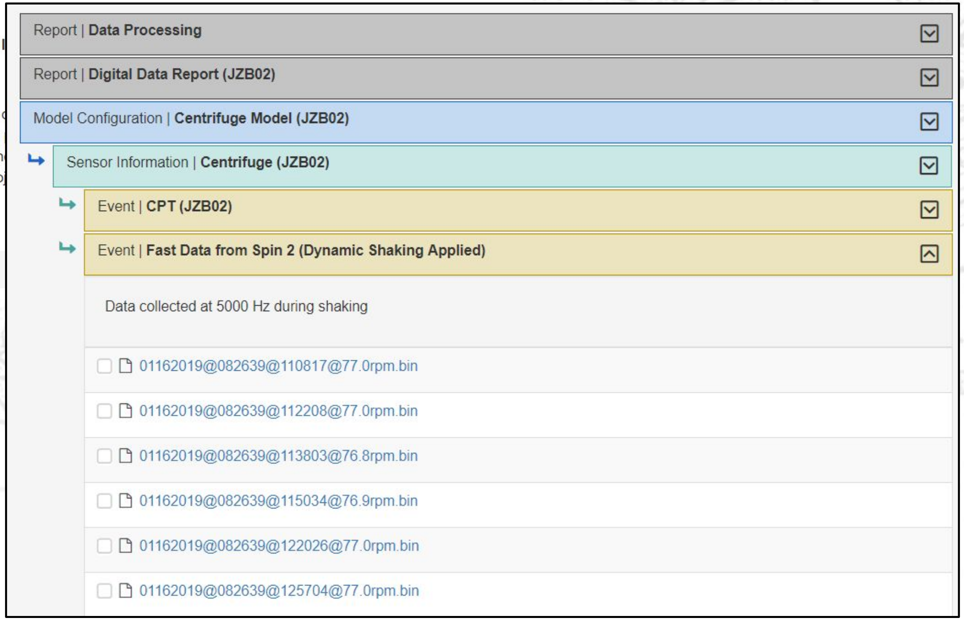
Simulation & Data Analytics



Data

Published Datasets





Published Datasets

DATA DEPOT

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Download Dataset

PRJ-2363 | **Soil-Foundation-Structure Interaction Effects on the Cyclic Failure Potential of Silts and Clays**

PI	Brandenberg, Scott
Co-PIs	Stewart, Jonathan
Project Type	Experimental
Keywords	Cyclic Softening, Fine-Grained Soil, Soil-Foundation-Structure Interaction

View Data Diagram | View Project Metrics | Leave Feedback

Experiment | **Centrifuge Test on Bentonite Clay - Test UCLA JZB01**

Cite this Data:

Buenker, J., S. Brandenberg, M. Eslami, D. Abundis, T. Buckreis, J. Stewart. (2020) "Centrifuge Test on Bentonite Clay - Test UCLA JZB01", in *Soil-Foundation-Structure Interaction Effects on the Cyclic Failure Potential of Silts and Clays*. DesignSafe-CI. https://doi.org/10.17603/ds2-e7s5-b025 v1

Download Citation: DataCite XML | RIS | BibTeX

31 Downloads 141 Views Details

View Data

Experiment | **Centrifuge Testing on Kaolinite Clay - Test UCLA JZB02**

Cite this Data:

Buenker, J., S. Brandenberg, J. Stewart, M. Eslami, T. Buckreis, D. Abundis. (2020) "Centrifuge Testing on Kaolinite Clay - Test UCLA JZB02", in *Soil-Foundation-Structure Interaction Effects on the Cyclic Failure Potential of Silts and Clays*. DesignSafe-CI. https://doi.org/10.17603/ds2-jpwh-nq72 v1

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14 Downloads 42 Views Details

View Data

Data Depot

Searching Published Datasets

Search: japan

Natural Hazard Type: All Types | Year Published: All Years | Clear Filters

Project Title	Project PI	Description	Keywords	Date Published
LEAP-GWU-2022 Experiments: Seismic Performance of Sheet Pile Walls in Liquefiable Soils Experimental	Manzari, Majid	View Description	liquefaction, sheet-pile wall, soils-structure interaction, model tests, round robin tests, centrifuge, experiments, simulations, validation	11/30/2023
LEAP-RPI-2020: Seismic interaction of a liquefiable soil with a cantilever retaining wall Experimental	Zeghal, Mourad	View Description	Soil liquefaction, retaining wall, model tests, round robin tests, centrifuge, experiments, simulations, validation	11/29/2023
GEER - M6.6 Hokkaido, Japan Field Research	grant, alex	View Description	Earthquakes, Landslides, Liquefaction, Housing	10/31/2023

Experimental
Experiment Facility: All Types
Experiment Type: All Types

Simulation
Simulation Type: All Types
Facility: All Facilities

Field Research
Field Research Type: All Types
Facility

Data Depot

DATA DEPOT

Add

Published

Published (NEES)

Community Data

Help

Find in this Dataset

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PRJ-4139 | **LEAP-GWU-2022 Experiments: Seismic Performance of Sheet Pile Walls in Liquefiable Soils**

Download Dataset

PI	Manzari, Majid
Co-PIs	Zeghal, Mourad
Project Type	**Experimental**
Natural Hazard Type	**Earthquake**
Awards	**Validation Of Constitutive And Numerical Modeling Techniques For Soil Liquefaction Analysis (PI: Manzari) | NSF-CMMI 1635524**

PRJ-4139

Experiment | **Ehime University Centrifuge Experiments of the Seismic Performance of Sheet Pile Walls in Liquefiable Soils**

Cite this Data:

M. Okamura, K. Ono, (2023) "Ehime University Centrifuge Experiments of the Seismic Performance of Sheet Pile Walls in Liquefiable Soils", in *LEAP-GWU-2022 Experiments: Seismic Performance of Sheet Pile Walls in Liquefiable Soils*. DesignSafe-CI. https://doi.org/10.17603/ds2-03km-9v86 v1

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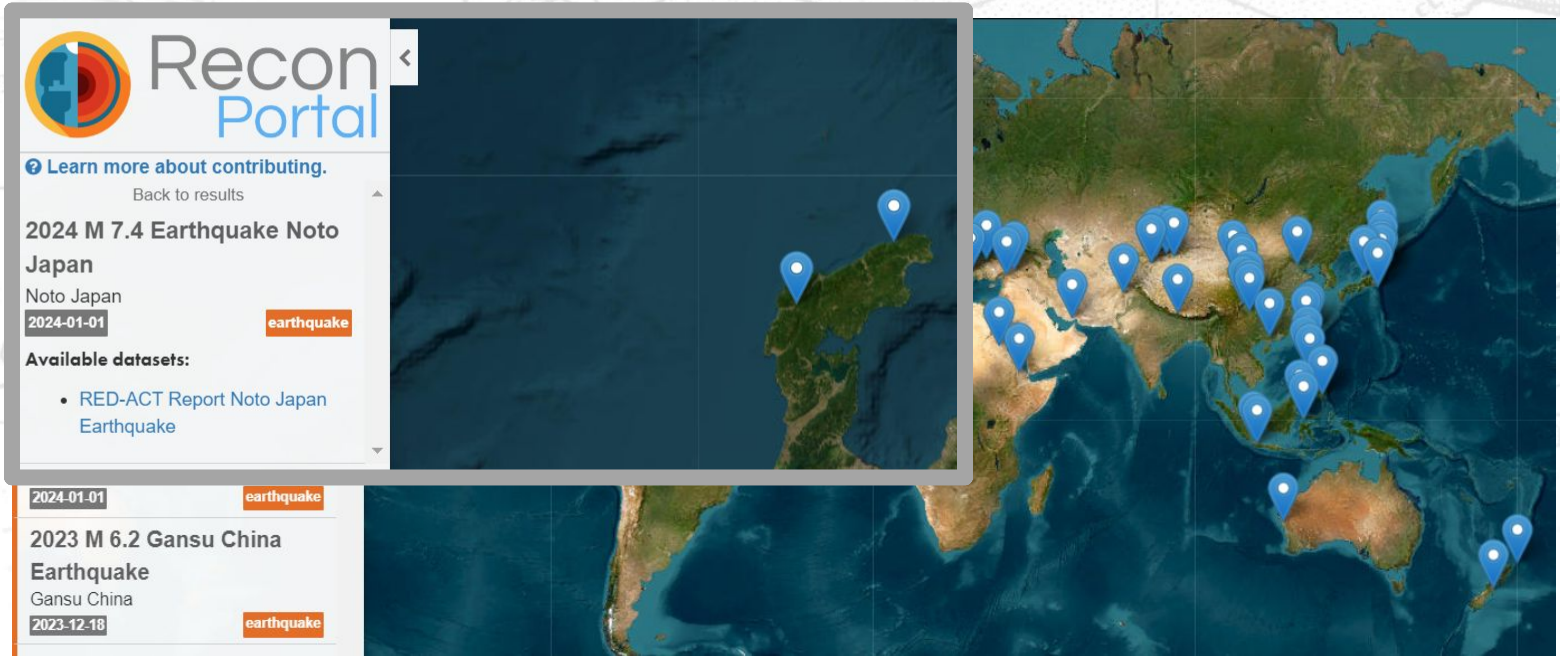
13 Downloads 107 Views 0 Citations Details

View Data

Reconnaissance Portal

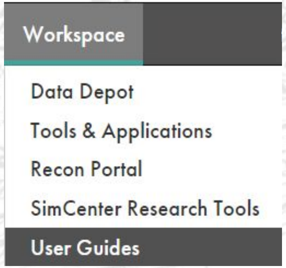
Identifying Datasets from Natural Hazard Events



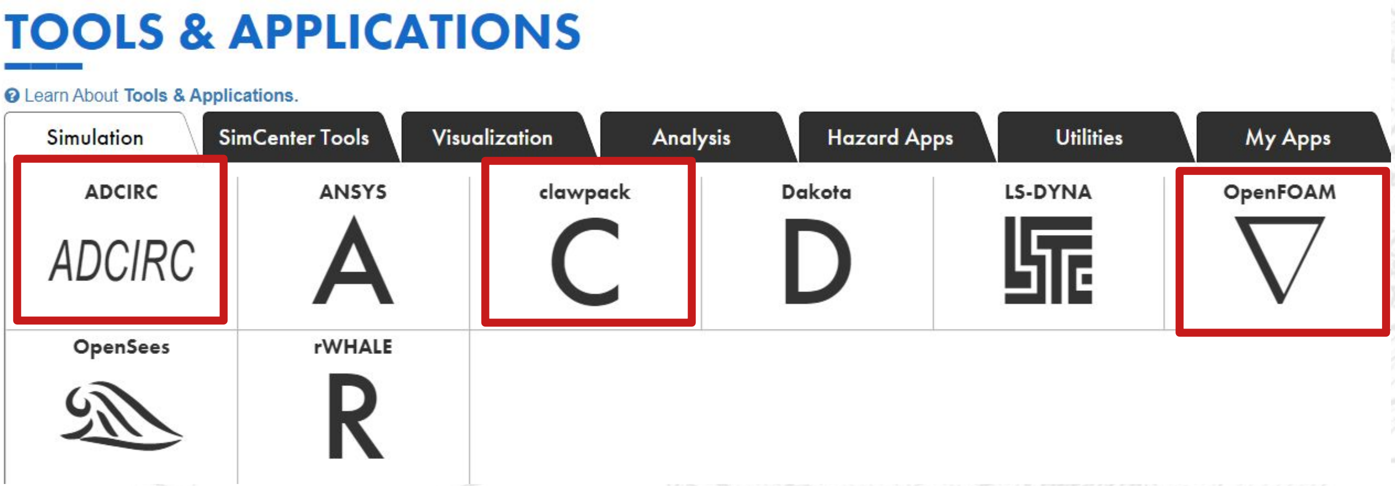
DESIGNSAFE-CI
NHERI: NATURAL HAZARDS ENGINEERING RESEARCH INFRASTRUCTURE
TEXAS The University of Texas at Austin
UCLA
TACC
RICE
Florida Tech

Curation Assistance

- Curation and publication guidelines under ***User Guides***
  - https://www.designsafe-ci.org/rw/user-guides/data-curation-publication/
  - Managing protected/identifiable data – talk to Maria Esteva
- Data transfer methods
  - https://www.designsafe-ci.org/rw/user-guides/data-transfer-guide/
  - Web browser/Dropbox/etc (smaller uploads), Globus, Cyberduck
- Virtual Curation Office Hours
  - DesignSafe Data Curators: Maria Esteva and Craig Jansen
  - Tuesday and Thursday at 1 pm Central (or by appt)
  - https://www.designsafe-ci.org/learning-center/training/

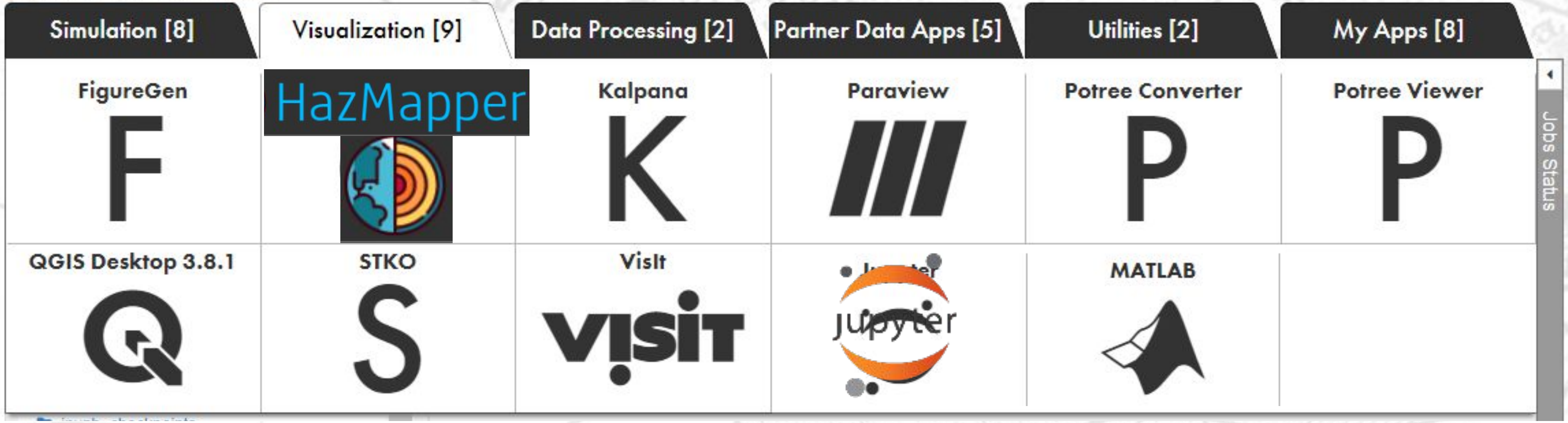


Tools & Apps: Simulation



- HPC-enabled simulation codes (Stampede2, Frontera)
- Available through portal or at the Command Line, easy access to HPC allocation (CPUs, GPUs) through DesignSafe

Tools & Apps: Data Analysis



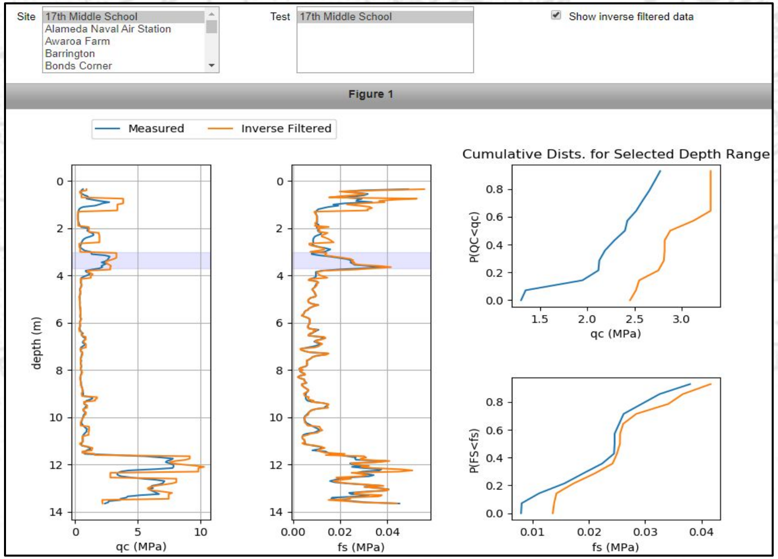
- Cloud-based tools for data analysis and visualization
- Access to files in Data Depot

Jupyter Notebooks

- Electronic notebooks in Python or R
- JupyterHub in DesignSafe
  - Access to Data Depot files
- Interactive data viewer
- Can write scripts for data processing, AI or machine learning
- Publish for use by others

jupyterhub

Next Generation Liquefaction



From Scott Brandenberg (UCLA)

Learning Center

DESIGNSAFE

Workspace | Learning Center

Education & Training

Archived DesignSafe Webinars

https://tinyurl.com/DesignSafe-Webinars

DesignSafe Tutorials

NEW **Development and utilization of a relational database to support post-earthquake building damage and recovery assessment**

March 12, 2021

- Watch Tutorial

Experimental Data Workflow for Real Time Decision Making Using Python and Jupyter Notebooks

February 3, 2021

- Watch Tutorial

Leveraging DesignSafe with TAPIS

December 17, 2020

- Watch Tutorial

Best Practices to Enhance the Quality, Discoverability and Re-Use Potential for Post-Event Reconnaissance Data

November 11, 2020

- Watch Tutorial
- Presentation Slides

SimCenter Webinars

NEW **Physical Modeling of Wave Attenuation & Wave Force Reduction by a Mangrove Forest**

December 4, 2020

- Watch Webinar

Computational Frameworks for the Implementation of Performance-Based Wind Engineering

November 23, 2020

- Watch Webinar

Partial Turbulence Simulation for Predicting Peak Wind Loads on Buildings

October 16, 2020

- Watch Webinar

Hurricane Loss Analysis for Single-Family Houses Considering Current and Changing Climate Conditions

October 6, 2020

- Watch Webinar

DesignSafe: We are here for you!

Available to the Global Natural Hazards Research Community

Analyze, Simulate & Share	Start Your Experiments	Expand Your Skills	Join the Community

slack

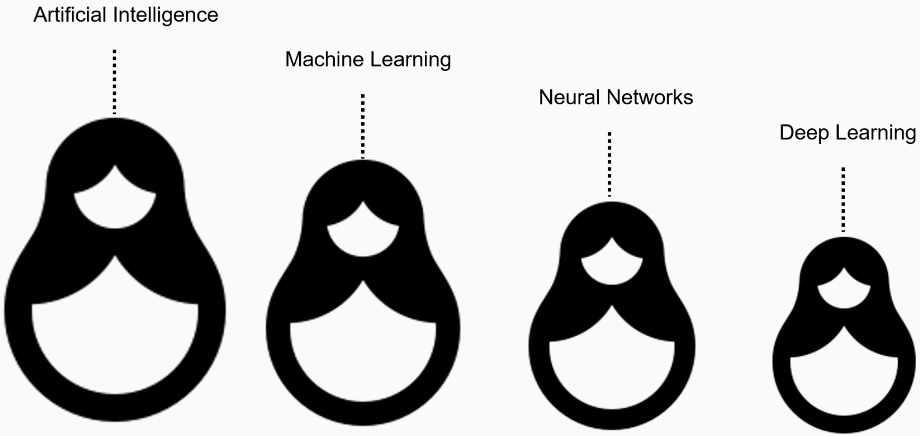
- Interact with us and the community using the DesignSafe Slack team
- Cite data using DOIs in your reference list!

MAKE DATA COUNT

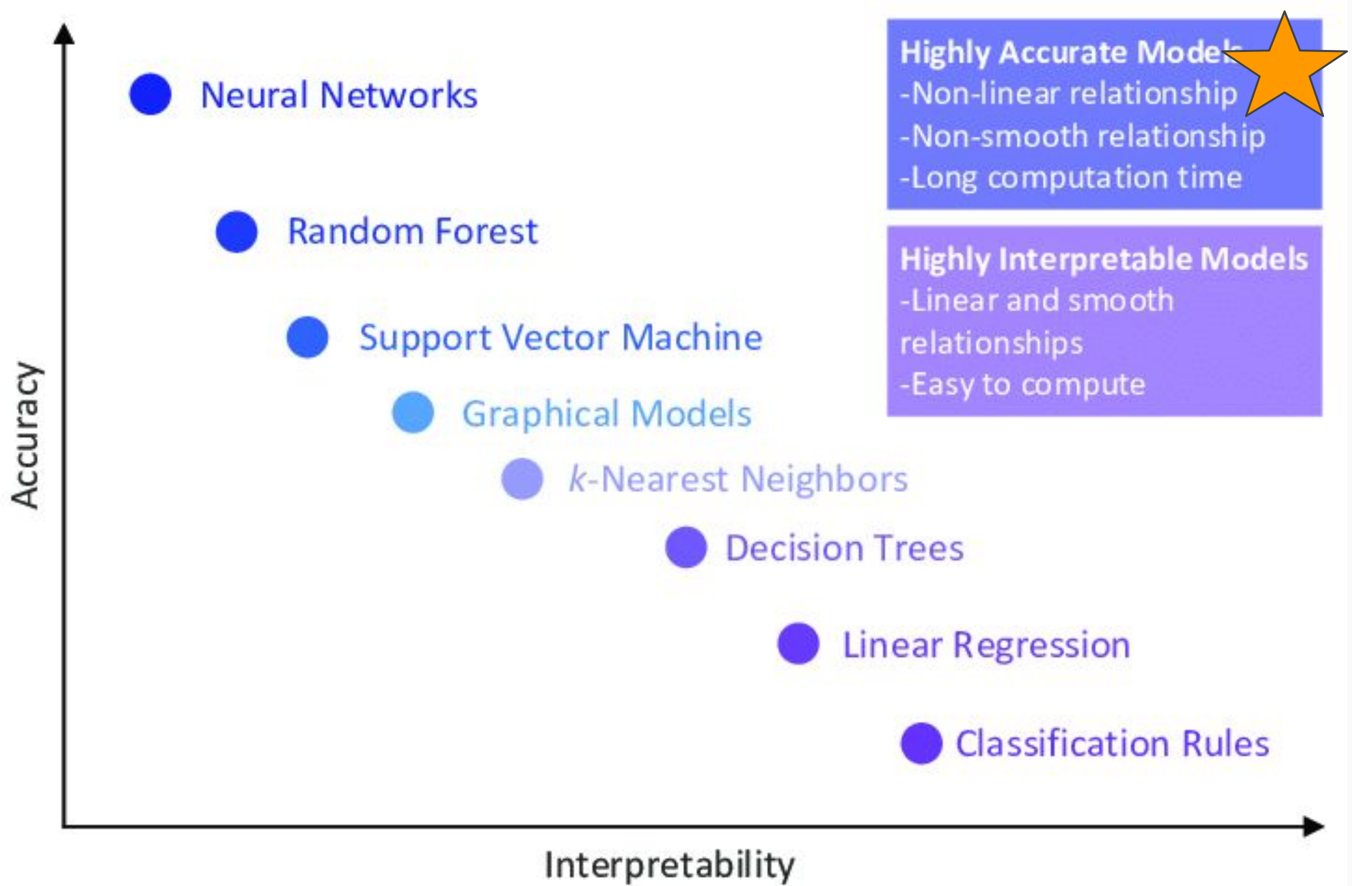
Please share your feedback, ideas, experiences!

AI vs Machine Learning vs Deep Learning

- **Artificial intelligence**: build intelligent programs and machines that can creatively solve problems, which has always been considered a human prerogative.
- **Machine learning** is a subset of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. In ML, there are different algorithms (e.g. neural networks) that help to solve problems.
- **Deep learning** is a subset of machine learning, which uses the neural networks to analyze different factors with a structure that is similar to the human neural system.



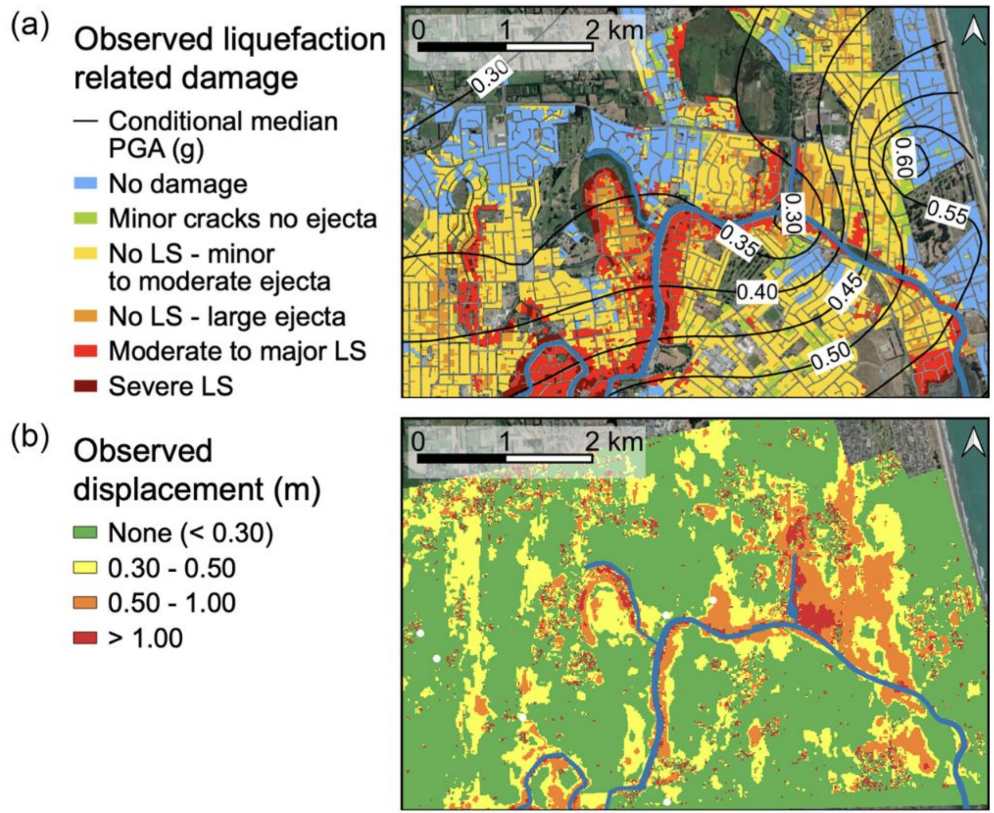
Interpretability vs accuracy



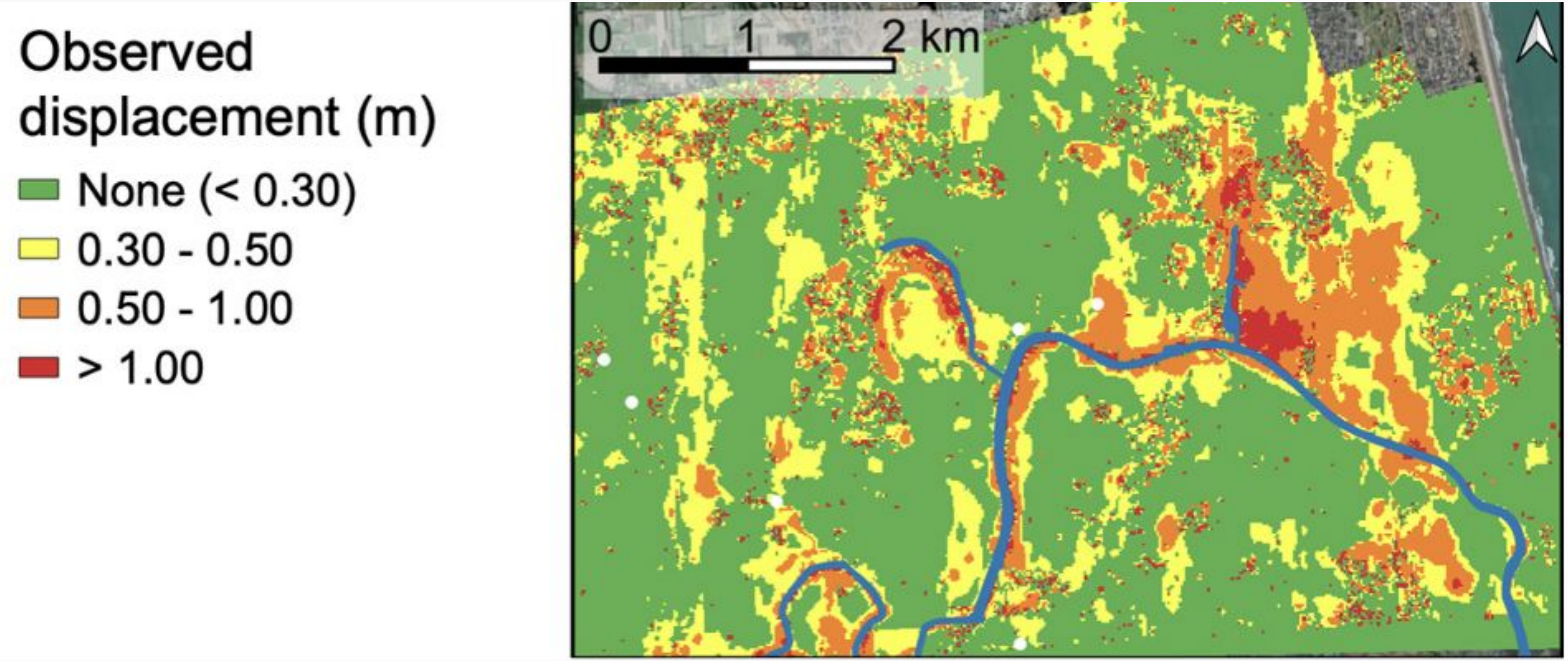
Lateral Spreading

Decision Trees & Random Forest

Liquefaction in NZ



Predicting lateral spreading in NZ



Durante and Rathje, 2021

Predicting lateral spreading in NZ

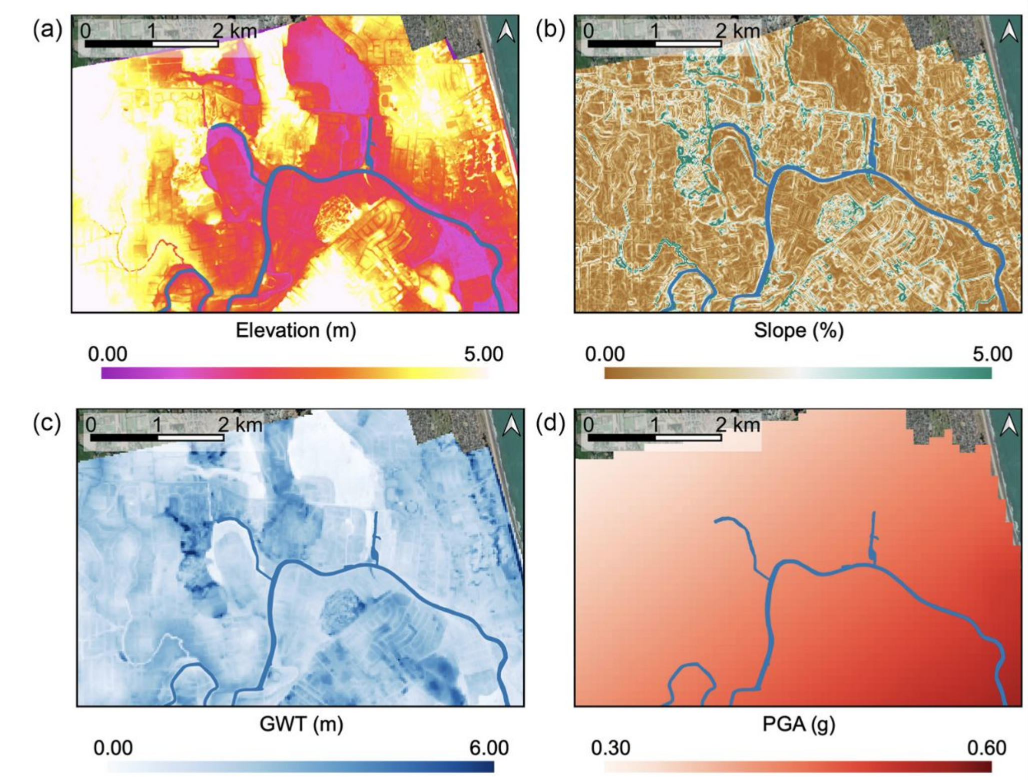
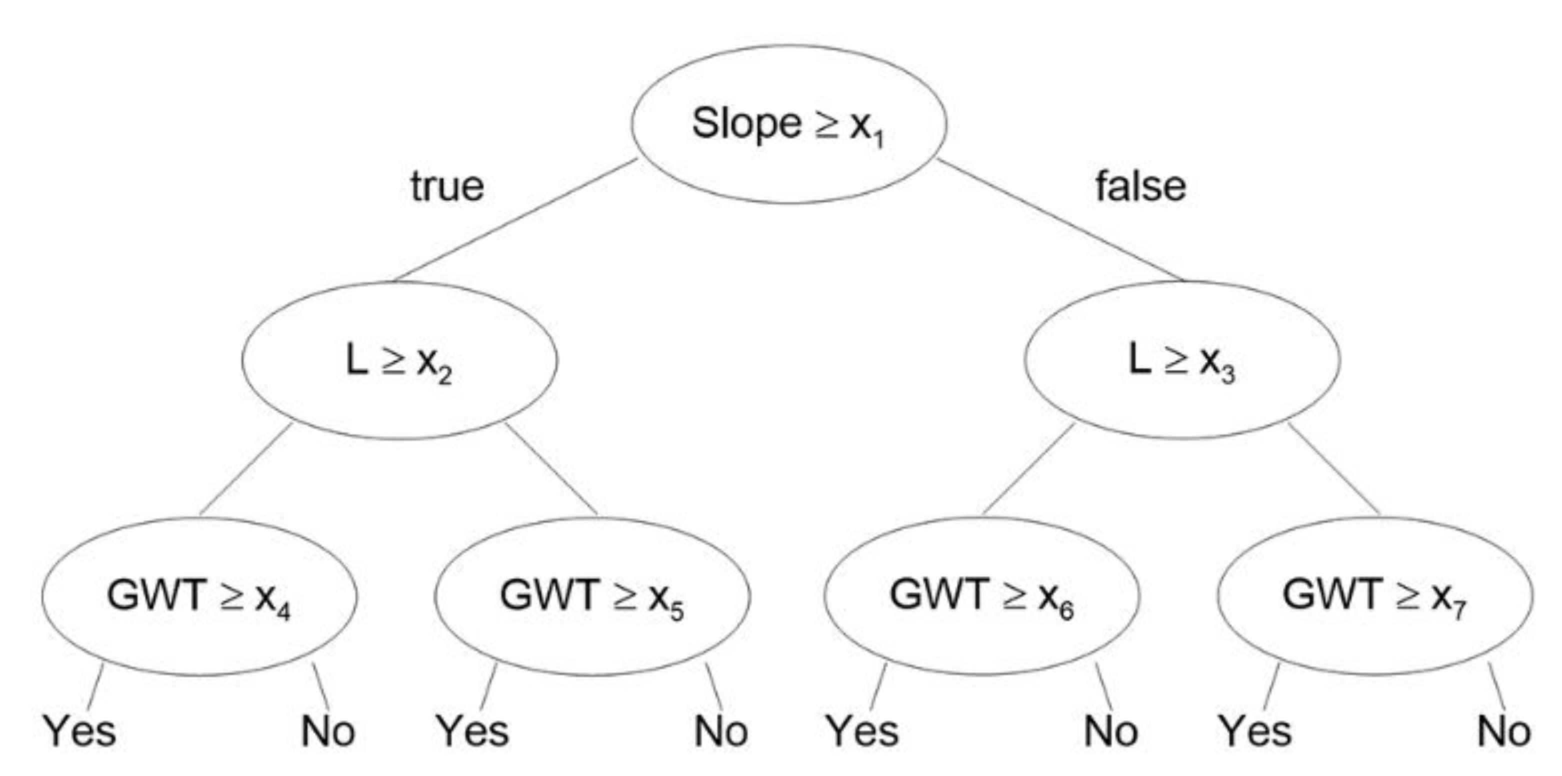


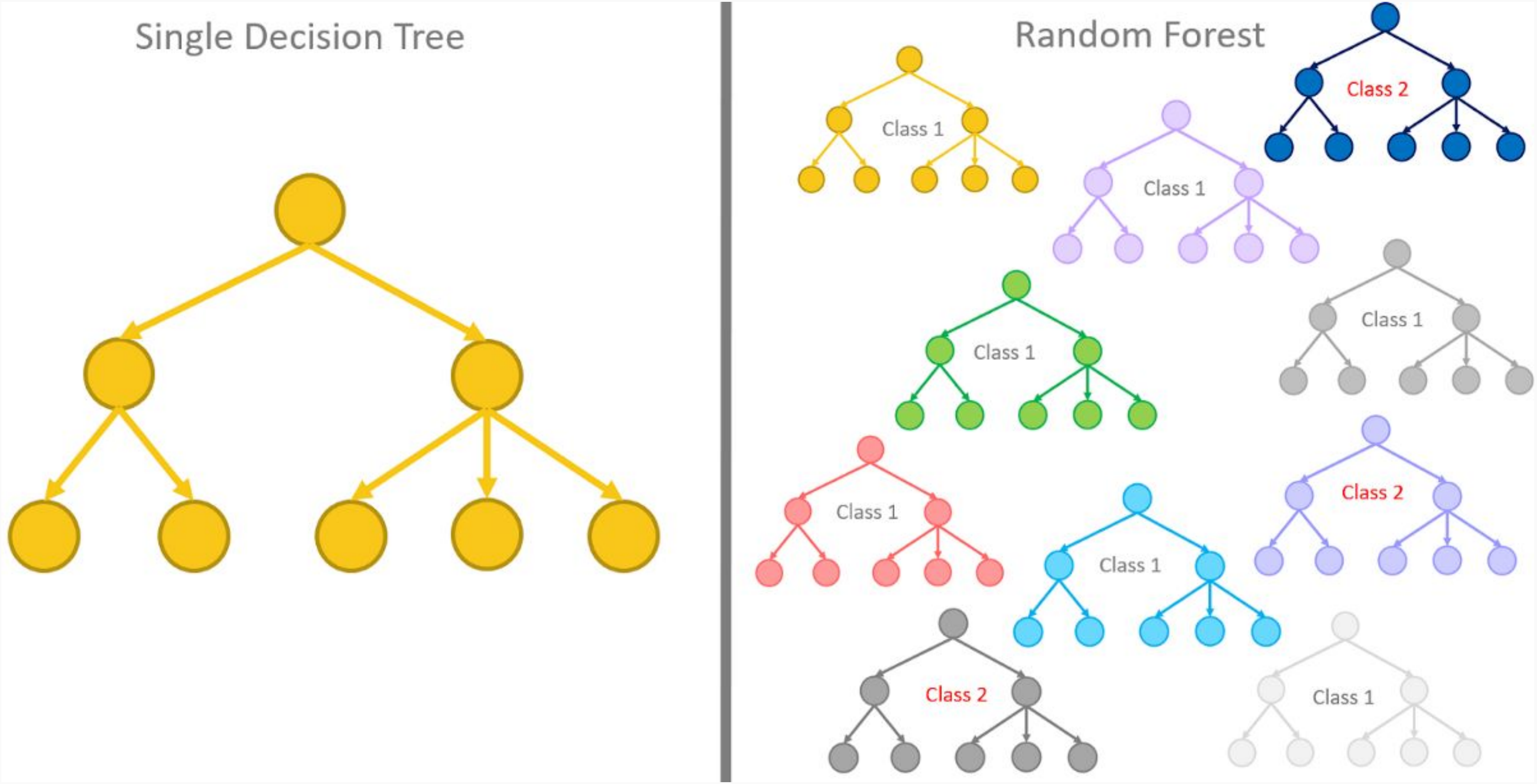
Figure 4. Spatial distribution of geometric and event-specific input features considered in ML models: (a) ground elevation, (b) ground slope, (c) GWT depth, and (d) PGA.

Durante and Rathje, 2021

Classification - Decision Tree



Random Forest



Random Forest model

Table 3. Summary of features used in each RF model analyzed

		Feature					
		L (m)	GWT (m)	Slope (%)	PGA (g)	Elevation (m)	CPT data
No CPT data	Model 0	✓	✓	✓	O	O	O
	Model 1	✓	✓	✓	✓	O	O
	Model 2	✓	✓	✓	O	✓	O
	Model 3	✓	✓	✓	✓	✓	O
CPT data	Model 4	✓	✓	✓	✓	O	✓
	Model 5	✓	✓	✓	✓	✓	✓

GWT: ground water table; PGA: peak ground acceleration; CPT: cone penetration tests.

Durante and Rathje, 2021

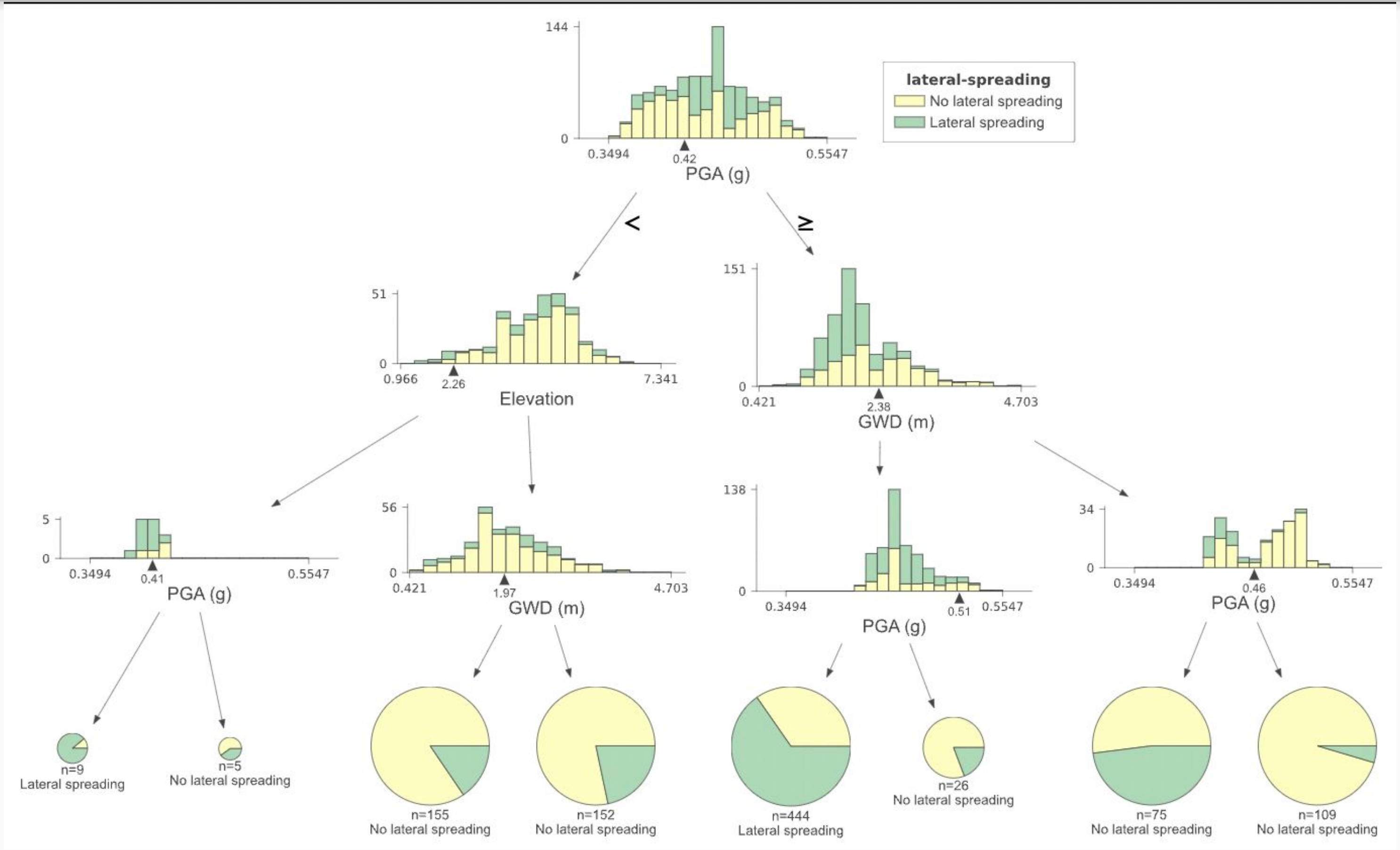
Random Forest - Performance

Table 4. Evaluation metrics for RF models for Yes/No and displacement classification problems

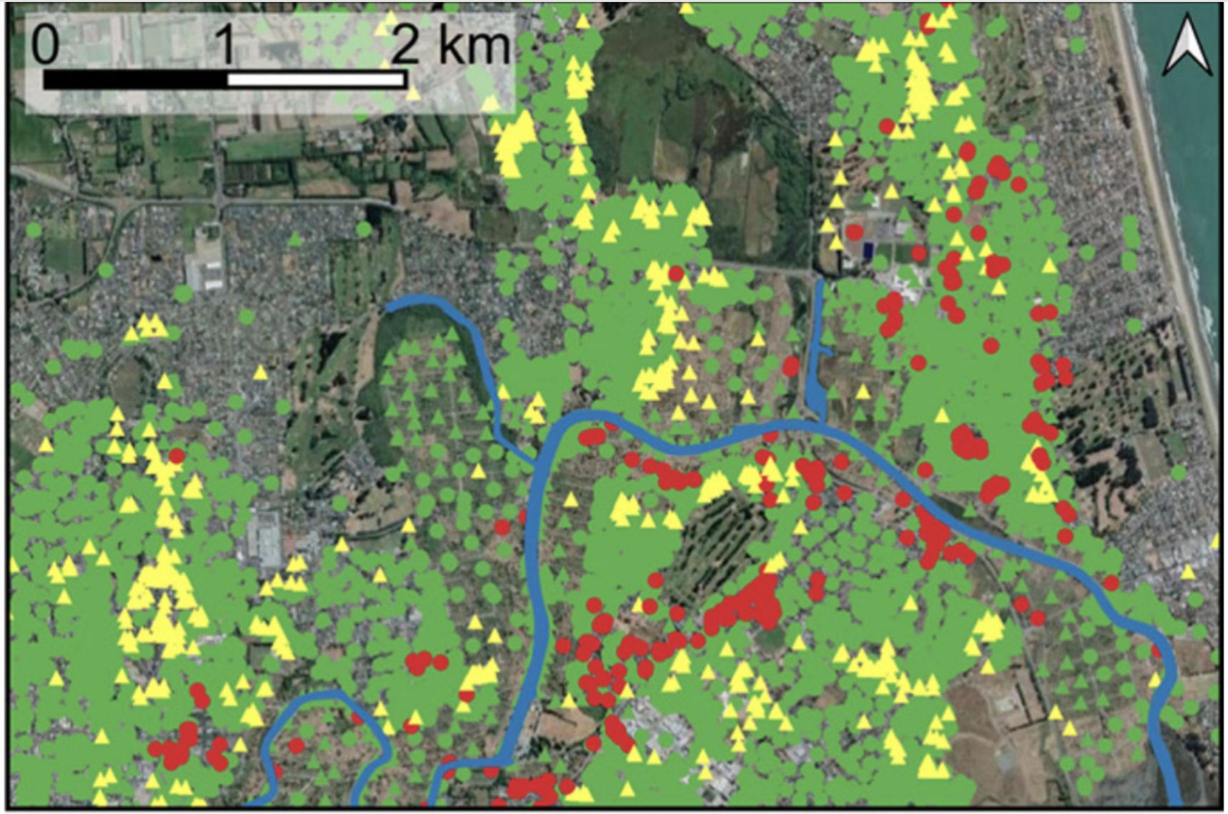
		No CPT data				CPT data	
		Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Y/N	Accuracy (Overall)	0.76	0.85	0.82	0.88	0.85	0.87
	Recall—Yes	0.58	0.75	0.74	0.82	0.76	0.78
	Recall—No	0.90	0.92	0.88	0.93	0.92	0.93
	Precision—Yes	0.80	0.88	0.82	0.89	0.87	0.89
	Precision—No	0.75	0.84	0.83	0.87	0.84	0.85
	ROC AUC	0.76	0.88	0.84	0.90	0.86	0.88
DISPL	Accuracy (Overall)	0.78	0.88	0.86	0.89	0.88	0.89
	Recall—Class 0	0.88	0.91	0.93	0.92	0.91	0.91
	Recall—Class 1	0.67	0.87	0.79	0.89	0.88	0.90
	Recall—Class 2	0.27	0.42	0.33	0.42	0.53	0.49
	Precision—Class 0	0.79	0.90	0.86	0.92	0.90	0.92
	Precision—Class 1	0.74	0.84	0.84	0.85	0.85	0.84
	Precision—Class 2	0.97	0.98	0.97	0.94	0.95	0.93
	ROC AUC	0.82	0.89	0.87	0.90	0.86	0.88

CPT: cone penetration tests; ROC: receiver operating characteristic; AUC: area under the ROC curve; Y/N: Yes/No Classification problem; DISP: Class Displacement Classification problem.

Visualizing the first tree in RF



Random forest prediction of lateral spreading



Durante and Rathje, 2021

▲ True Positive (TP) ● True Negative (TN) ● False Positive (FP) ▲ False Negative (FN)

SHAP Value: Contribution of each variable

A: $v(\{A\}) - v(\{\}) = 10 - 0 = 10$

B: $v(\{A, B\}) - v(\{A\}) = 60 - 10 = 50$

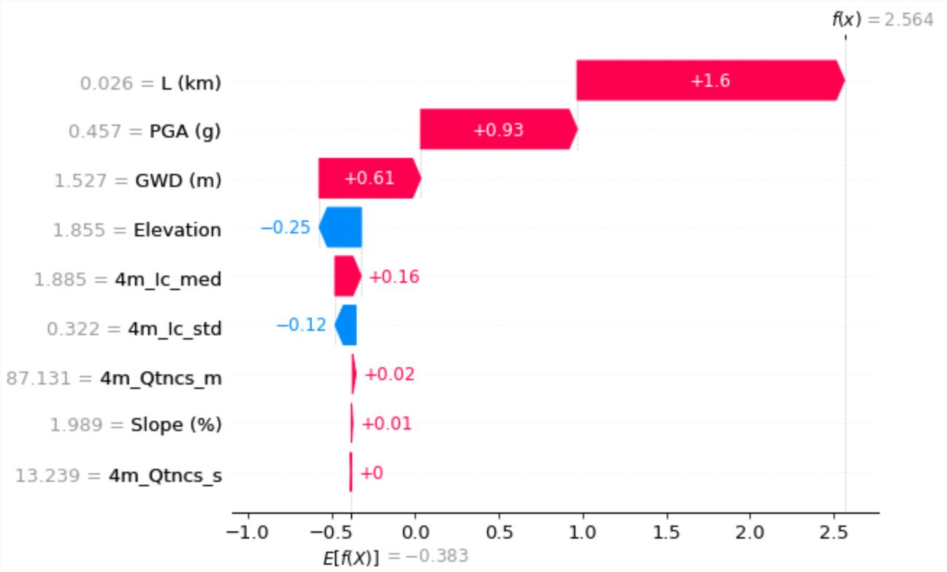
C: $v(\{A, B, C\}) - v(\{A, B\}) = 100 - 60 = 40$

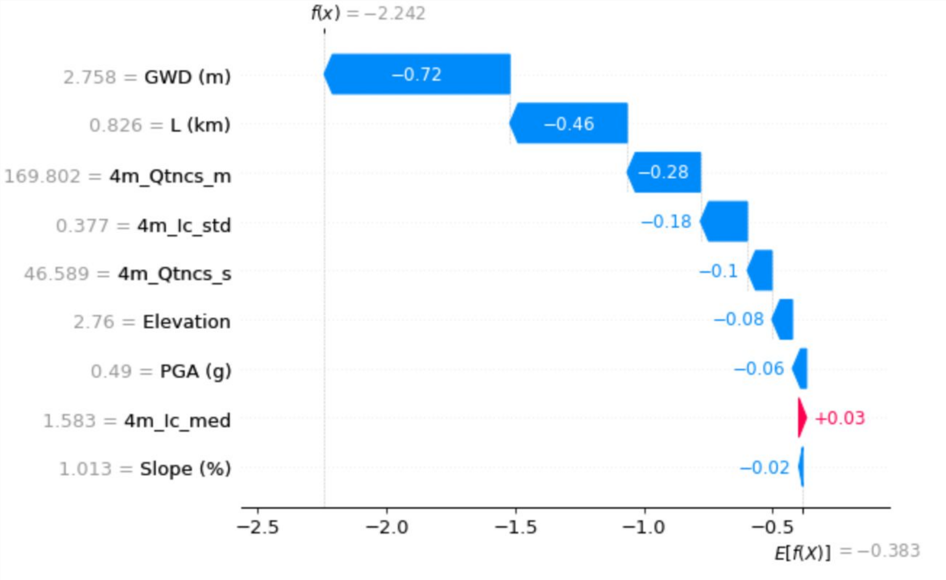
$$
\begin{aligned}
v(\{\}) &= 0 \\
v(\{A\}) &= 10 \\
v(\{B\}) &= 20 \\
v(\{C\}) &= 30 \\
v(\{A,B\}) &= 60 \\
v(\{B,C\}) &= 70 \\
v(\{A,C\}) &= 90 \\
v(\{A,B,C\}) &= 100
\end{aligned}
$$

$$
\begin{aligned}
&\{\} \rightarrow \{A\} \rightarrow \{A,\ B\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 10,\ B = 50,\ C = 40 \\
&\{\} \rightarrow \{A\} \rightarrow \{A,\ C\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 10,\ B = 10,\ C = 80 \\
&\{\} \rightarrow \{B\} \rightarrow \{A,\ B\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 40,\ B = 20,\ C = 40 \\
&\{\} \rightarrow \{B\} \rightarrow \{B,\ C\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 30,\ B = 20,\ C = 50 \\
&\{\} \rightarrow \{C\} \rightarrow \{B,\ C\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 30,\ B = 40,\ C = 30 \\
&\{\} \rightarrow \{C\} \rightarrow \{A,\ C\} \rightarrow \{A,\ B,\ C\} \,\|\, A = 60,\ B = 10,\ C = 30
\end{aligned}
$$

$$A_{avg} = 30\,,\ B_{avg} = 25\,,\ C_{avg} = 45$$

Random Forest post-hoc explanation

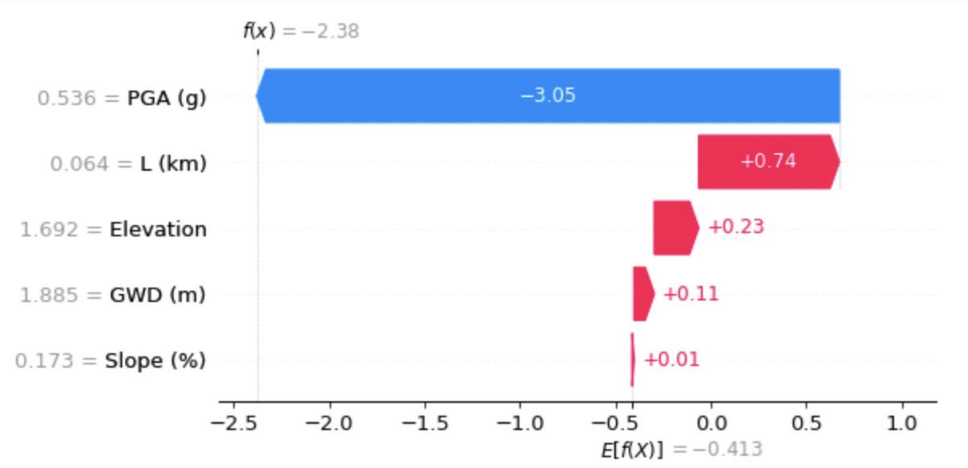


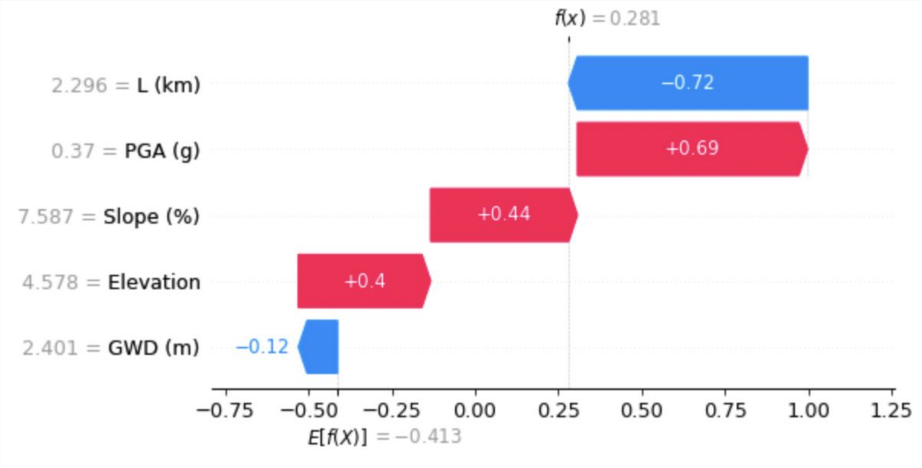


Lateral spreading - Prob (Lat spread) = 90%

No lateral spreading - Prob (Lat spread) = 7%

Incorrect learning

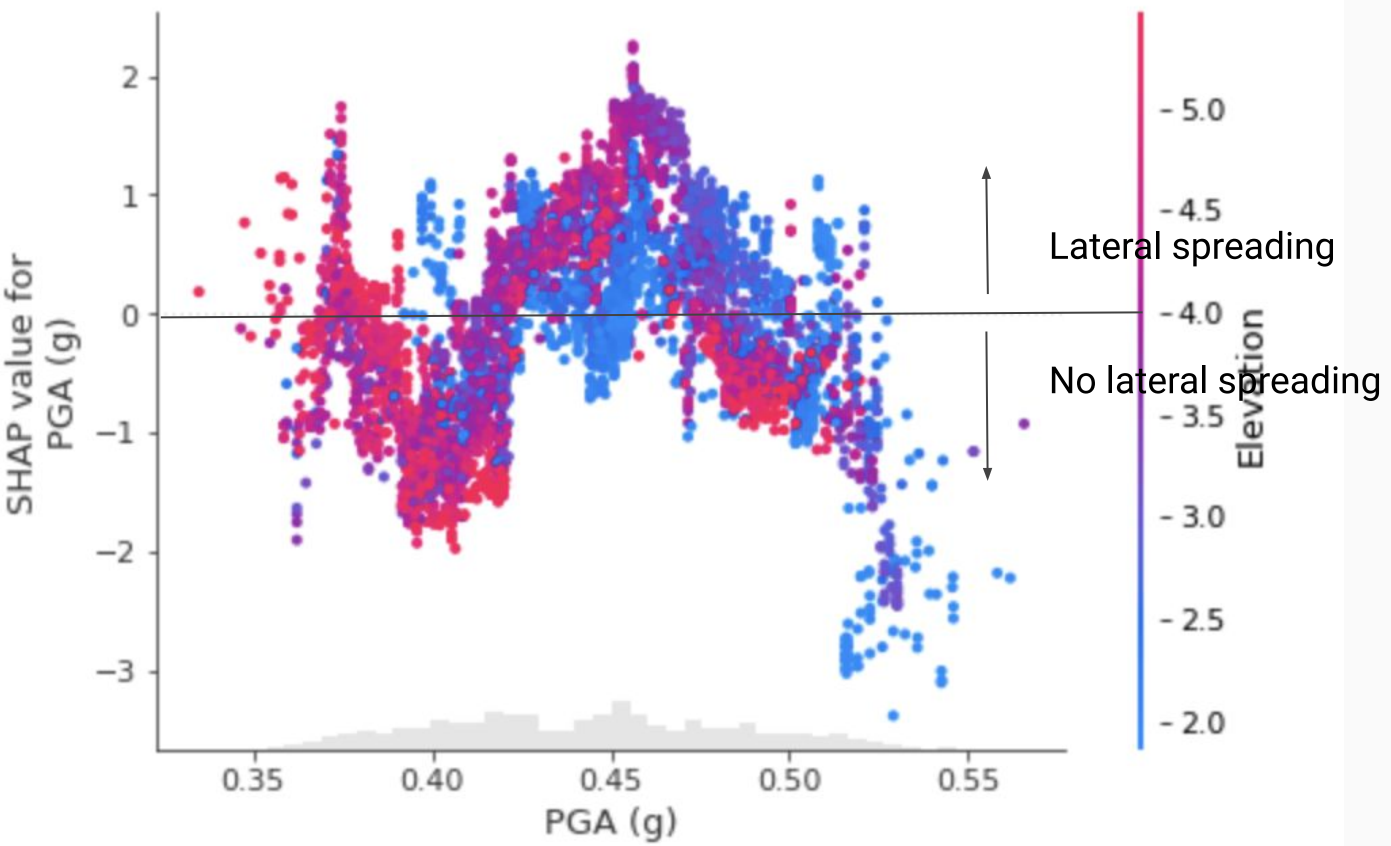




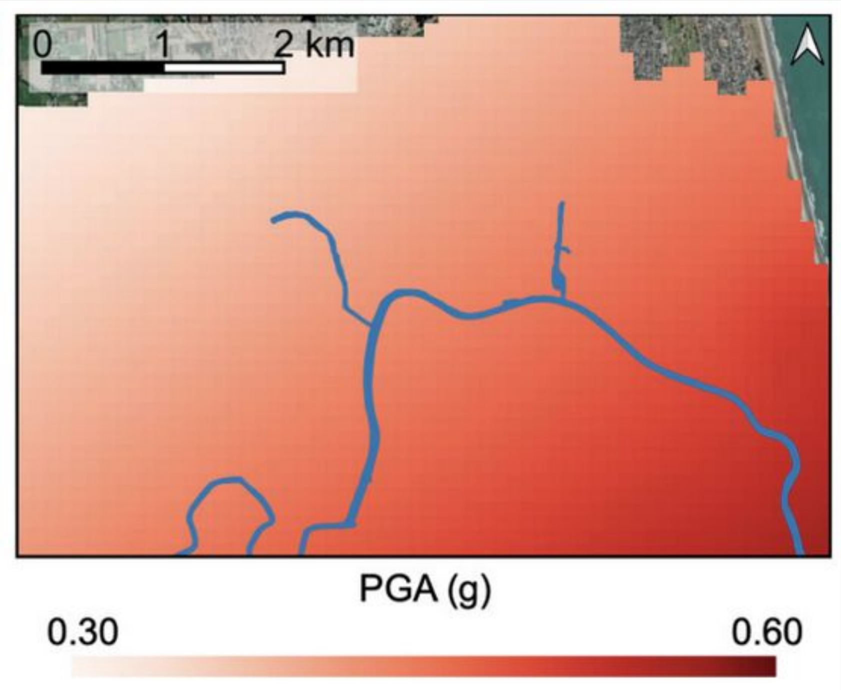
Incorrectly predicting no lateral spreading
Prob (Lat spread) = 8%

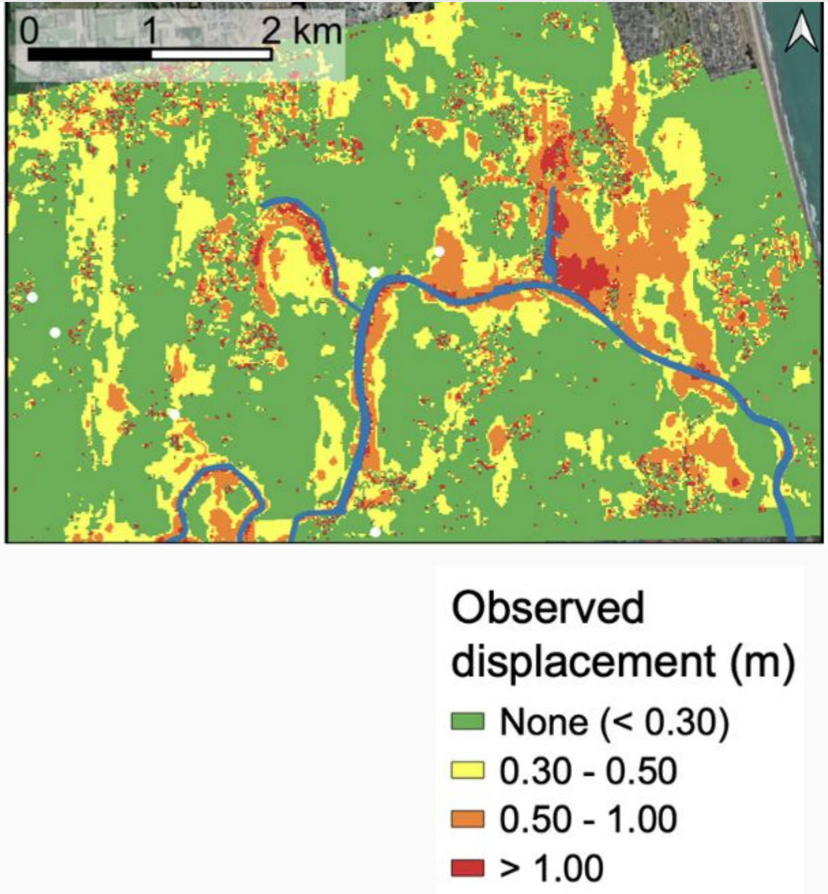
Incorrectly predicting lateral spreading
Prob (Lat spread) = 53%

Why PGA has a bad influence?



Bad learning of PGA relation





Other Examples

AI/ML

- Building Classification
- Graph Network Simulators

Building damage classifier - an explanation

Undamaged

Partially-damaged

Completely-destroyed

Explaining a building image classifier

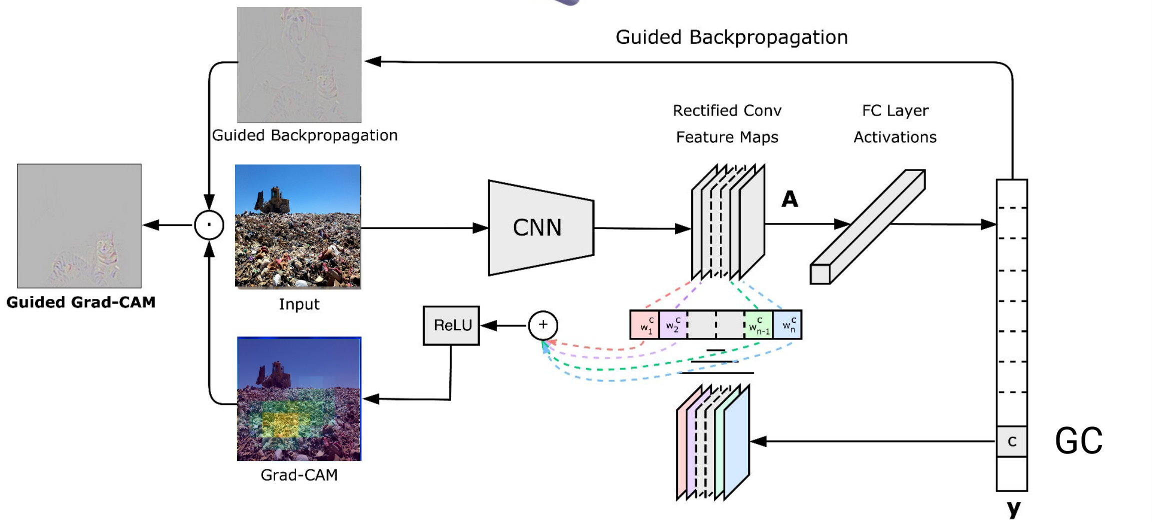
Sky

rubble

Predicted class: General Collapse

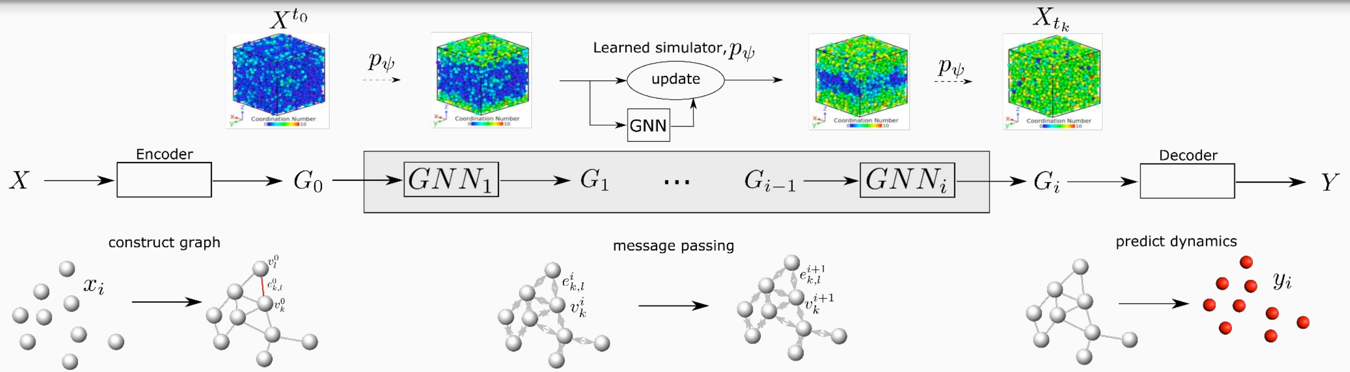
Transfer learning prediction: Ants

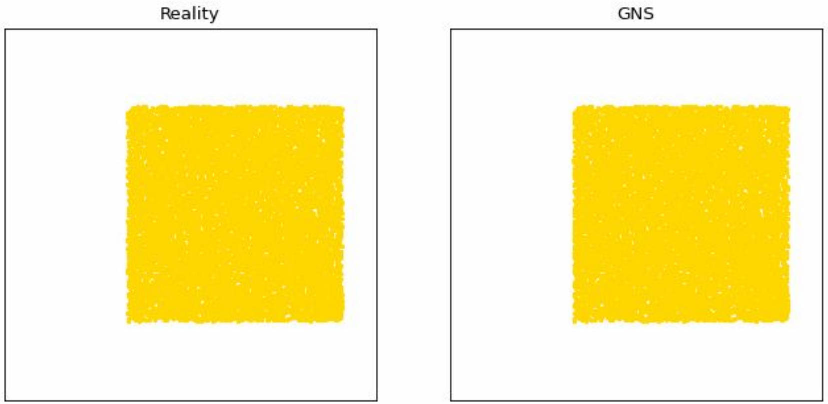
GradCAM Explanation

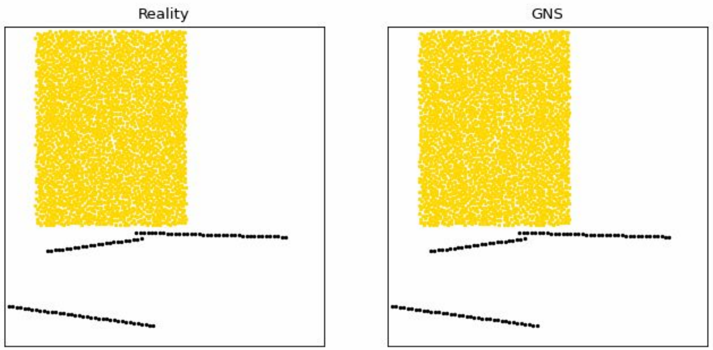


http://gradcam.cloudcv.org/

ML prediction of granular flows



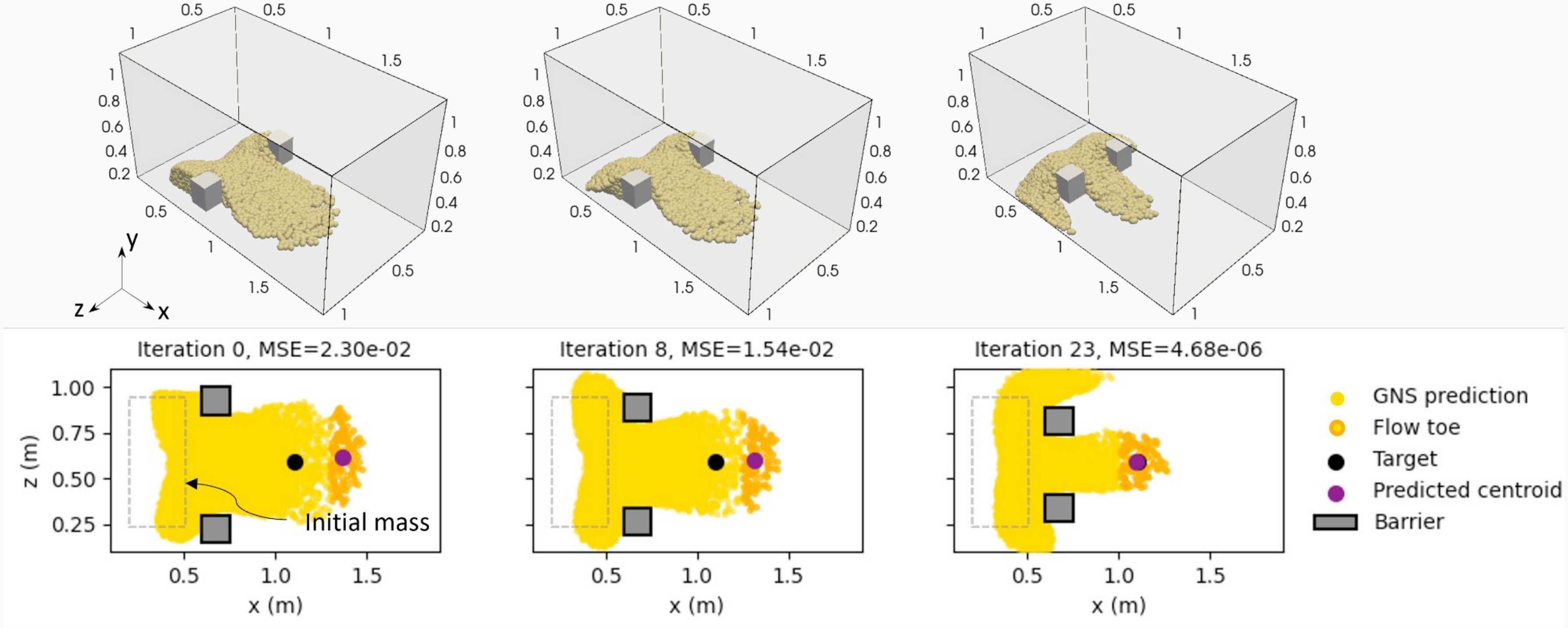




2.5 hours

20 s

GNS based optimization



NSF Chishiki AI Fellowships

- Fully funded fellowships for working in AI in Civil Engineering
- 5 Graduate and 5 Undergraduate fellows every year
- Deadline February 6th!
- Visit **https://www.chishiki-ai.org/**


Hook 'em Horns!