2023 GEM CONFERENCE

TEXAS
The University of Texas at Austin

REGIONAL RISK ASSESSMENT: LIQUEFACTION

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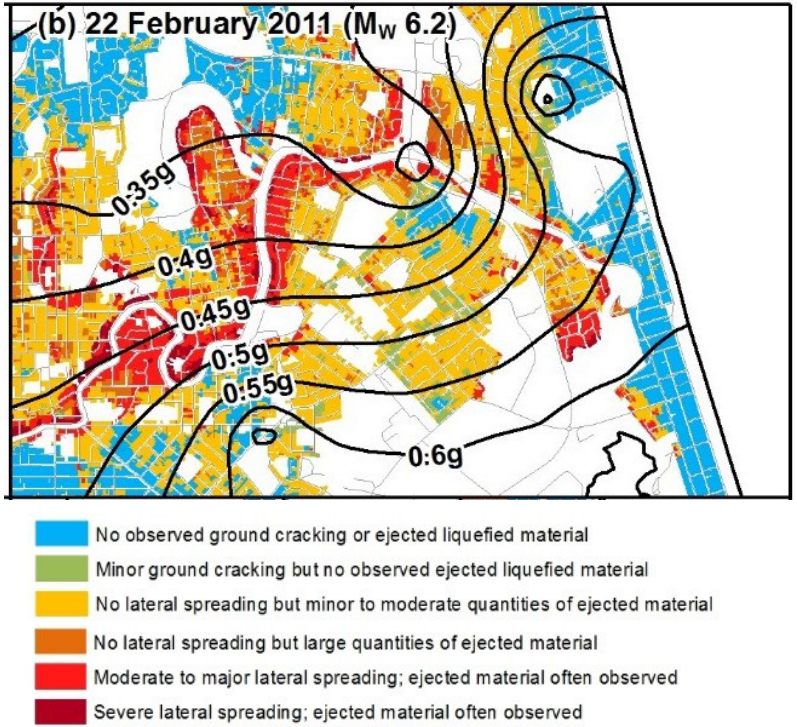
USGS
science for a changing world

NSF

2011 Christchurch Earthquake



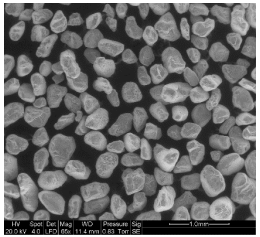
Van Ballegooy and Russell (2015) *Tonkin + Taylor Report*

Liquefaction Effects

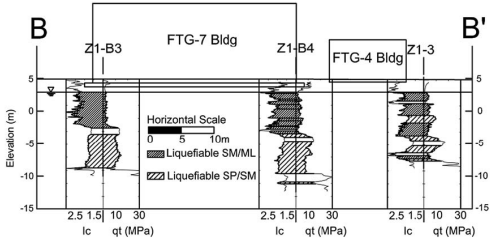
- 60,000 of 150,000 single family homes affected; 8,000 homes demolished
- No rebuilding in red-zone along river
- Half of $30 billion NZD losses associated with liquefaction

Liquefaction at what scale?

Micro Scale

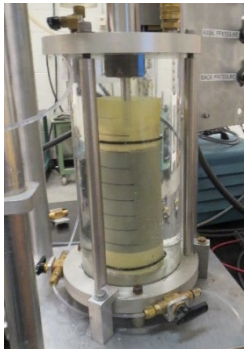


Site Scale

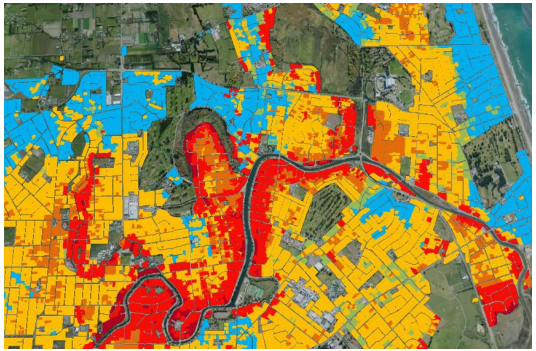


Bray et al. (2014)

Element Scale



Regional Scale

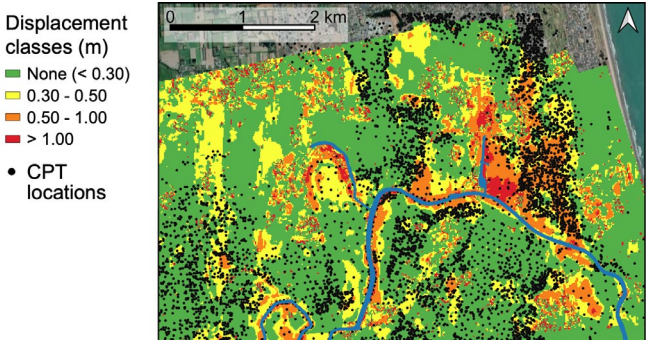


Regional Liquefaction Assessment

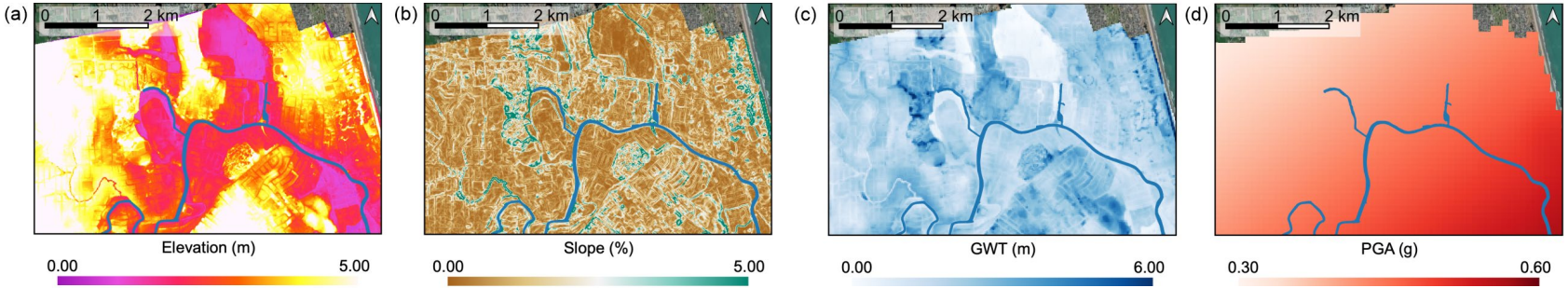
- Predict the occurrence of liquefaction and its consequences using globally (or regionally) available features
  - Shaking intensity, PGA or PGV (ShakeMap)
  - Digital elevation model (resolution?), slope S (resolution?)
  - Groundwater depth (GWD)
  - Distance to river/coast/water (L)
- Previous models
  - Zhu, Baise, et al. (2015, 2017) – Occurrence
  - Bozzoni et al. (2020) – Occurrence
  - Todorovic and Silva (2022) – Occurrence
  - Durante and Rathje (2021) – Lateral spreading (DR21)

DR21 Predictive Model: Goals and Data

- **Goal:** Predict occurrence of lateral spreading and associated displacement
- **Given:** PGA, Elevation, Slope, GWD, Distance to river (L)



Durante and Rathje (2021) *EQ Spectra, https://doi.org/10.1177/87552930211004613*

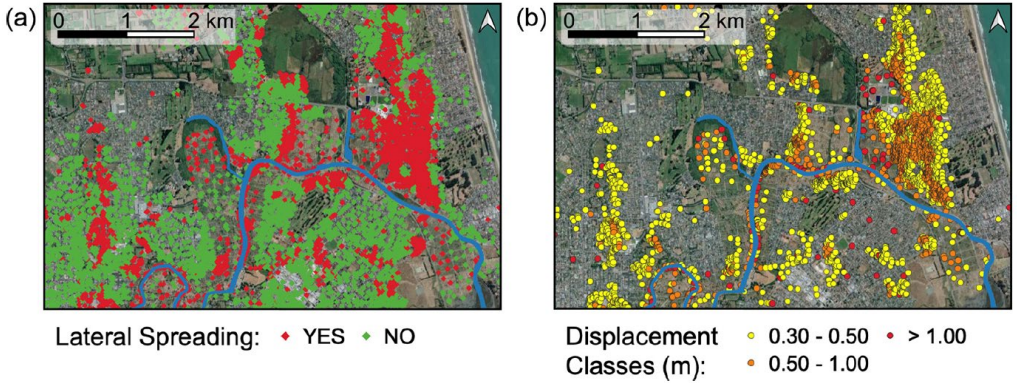


Training Data

- ~7300 pts where displacement and CPT data are both available
  - Inputs (PGA, L, S, Elev, GWD) from regional data
  - Displacements from optical image correlation (Rathje et al. 2017)
  - CPT data from NZ Geotechnical Database (NZGD)
- Random forest ML classification with K-fold cross validation

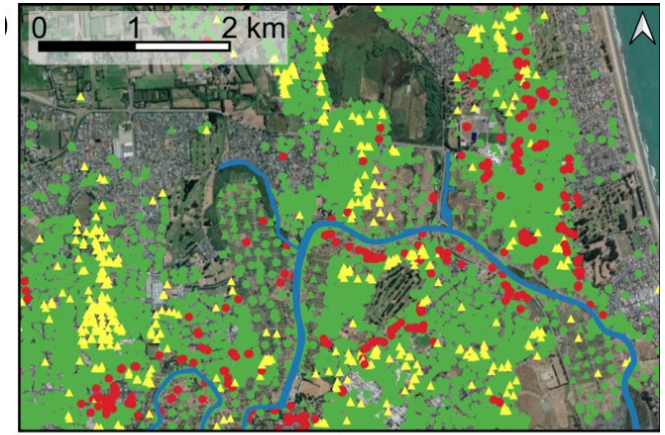
Occurrence		
Class 0	No Lateral Spread	4236 pts
Class 1	Yes Lateral Spread	3055 pts
Displacement		
Class 0	0.3–0.5 m	1799 pts
Class 1	0.5–1.0 m	1138 pts
Class 2	>1.0 m	118 pts

7291 pts ***3055 pts***



DR21 Results: Lateral Spread Occurrence

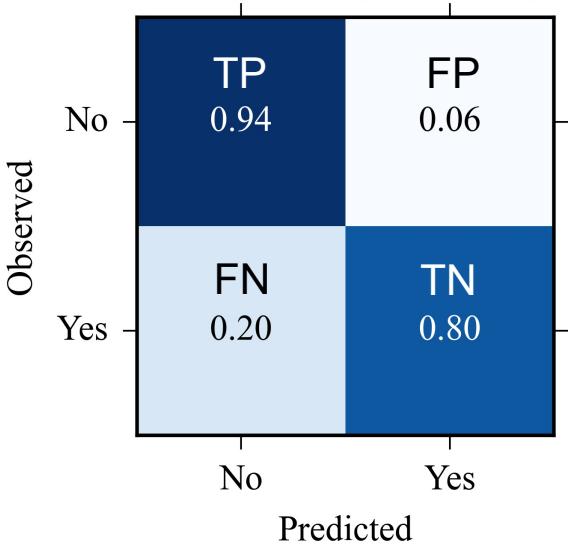
Accuracy: 88%



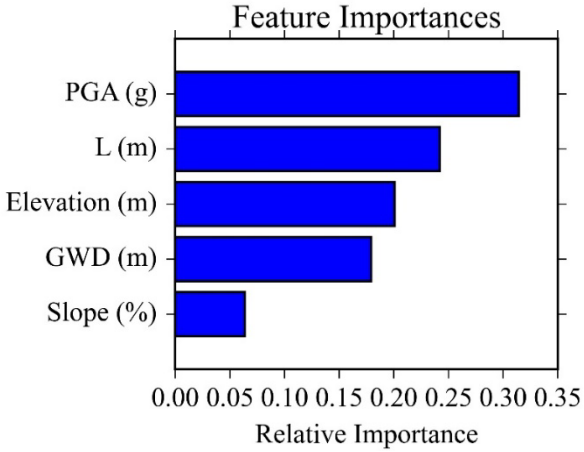
Model 3

- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

Confusion Matrix



Feature Importance



DR21 Data Publication

www.designsafe-ci.org

PRJ-2998 | **Machine Learning Models for the Evaluation of the Lateral Spreading Hazard in the Avon River Area Following the 2011 Christchurch Earthquake**

Download Dataset

Cite this Data:

Durante, M., E. Rathje. (2021) "Machine Learning Models for the Evaluation of the Lateral Spreading Hazard in the Avon River Area Following the 2011 Christchurch Earthquake." DesignSafe-CI. https://doi.org/10.17603/ds2-3zdj-4937 v2

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https://doi.org/10.17603/ds2-3zdj-4937

Author(s)	Durante, Maria Giovanna; Rathje, Ellen
Data Type	**Jupyter Notebook**
Natural Hazard Type	**Earthquake**

Description | This project contains a Jupyter Notebook and python codes to run a suite of machine learning Random Forest Classifier a
induced lateral spreading displacement. This study is trained using data from the 2011 Christchurch earthquake in the Avon River area.
the range of applicability reported in the ReadMe file. The Jupyter Notebook example files can be adapted to train any dataset. All the in
ReadMe file.

PRJ-2998v2

Name
Model Development
Model Usage
ReadMe.pdf

DESIGNSAFE-CI
A NATURAL HAZARDS ENGINEERING COMMUNITY

jupyter nbviewer

JUPYTER FAQ

In [12]:
```
#define function to find best parameter combination based on Cohen's kappa co
def rfr_model(X, y):
# Perform Grid-Search
    kappa_scorer = make_scorer(cohen_kappa_score)
    gsc = GridSearchCV(
        estimator=RandomForestClassifier(),
        param_grid={
            'max_depth': range(2,10),
            'n_estimators': (5,10, 50, 100, 1000),
            'max_features': ('auto','sqrt','log2'),
            'criterion': ('gini','entropy'),
        },
        cv=10, verbose=0, n_jobs=-1,scoring=kappa_scorer)

    grid_result = gsc.fit(X, y)
    best_params = grid_result.best_params_

    rfr = RandomForestClassifier(max_depth=best_params["max_depth"],
                                 n_estimators=best_params["n_estimators"],
                                 max_features=best_params["max_features"], cr
    # Perform K-Fold CV
    scores = cross_val_score(rfr, X, y, cv=10)
    predictions = cross_val_predict(rfr, X, y, cv=10)
    optimised_random_forest = gsc.best_estimator_
```

Can we use DR21 model globally?

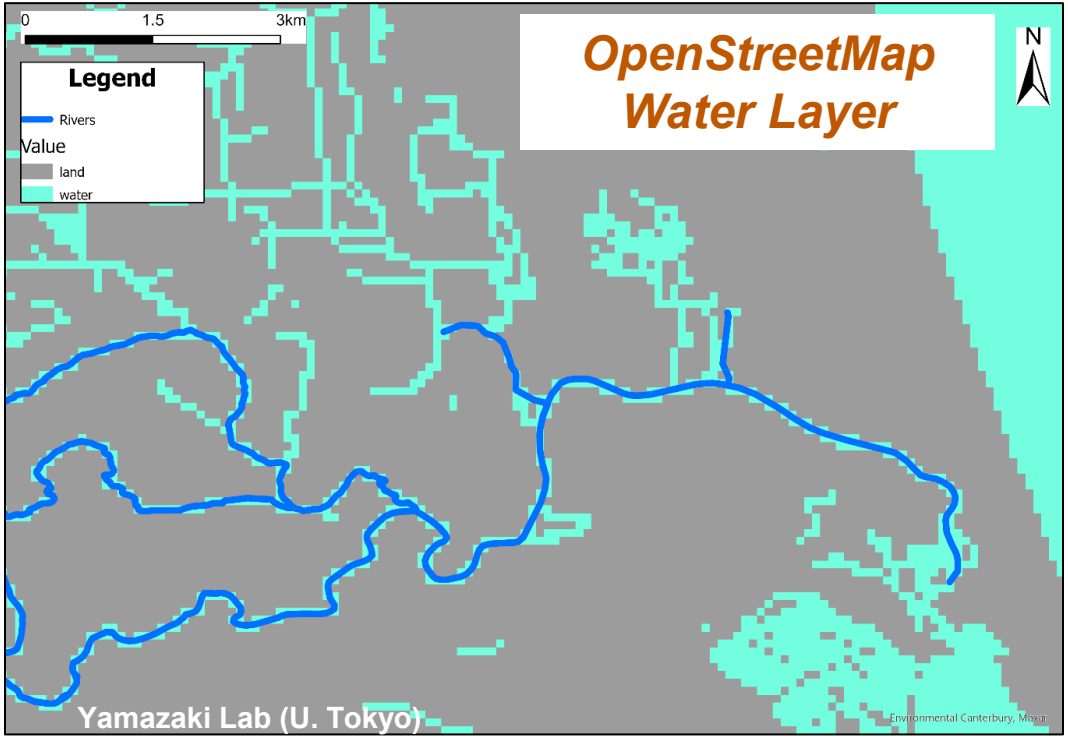
- Next Generation Liquefaction (NGL) lateral spread dataset
  - 3374 samples from 18 earthquakes

Global Geospatial Features

	Local Source	Global Source
L	Manual, local imagery	OpenStreetMap
Elev	5-m LIDAR DEM	30-m ASTER DEM
Slope	5-m LIDAR DEM	30-m ASTER DEM
GWD	NZGD	Fan et al. (2013)
PGA	NZGD	ShakeMap

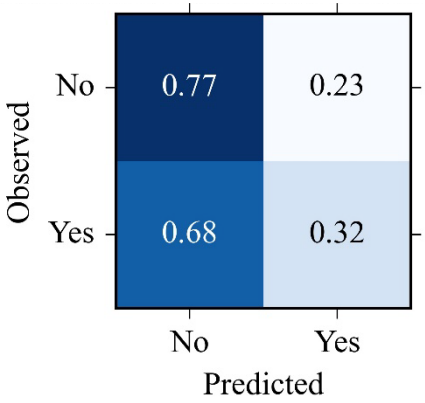
No	Country/Region	Earthquake name	UTC date	Mw	No. LS
1	New Zealand	Edgecumbe	1987-03-02	6.6	74
2	New Zealand	Darfield	2010-09-03	7.0	803
3	New Zealand	Christchurch	2011-02-21	6.2	1548
4	Japan	Niigata	1995-01-16	6.9	575
5	Japan	Nihonkai-Chubu	2011-03-11	9.1	37
6	Japan	Kushiro	1983-05-26	7.7	3
7	Japan	Kobe, Japan	1964-06-16	7.6	2
8	Japan	Tokachi	1993-01-15	7.6	1
9	Japan	Tohoku-oki	2003-09-25	8.3	1
10	USA	San Fernando	1971-02-09	6.6	0
11	USA	Imperial Valley-06	1979-10-15	6.5	33
12	USA	Superstition Hills-02	1987-11-24	6.5	6
13	USA	Loma Prieta	1989-10-18	6.9	11
14	Mexico	El Mayor-Cucapah	2010-04-04	7.2	3
15	Chile	Maule, Chile	2010-02-27	8.8	78
16	Philippines	Luzon, Philippines	1990-07-16	7.7	13
17	Taiwan	Chi-Chi, Taiwan	1999-09-20	7.6	28
18	Turkey	Kocaeli, Turkey	1999-08-17	7.5	158

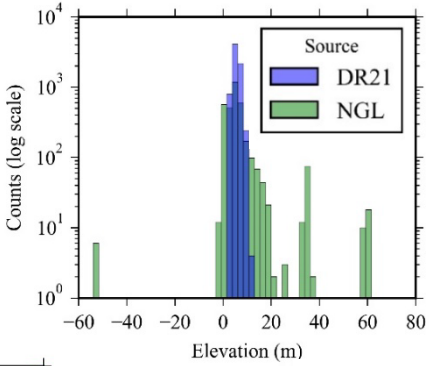
Distance to River/Coast/Water

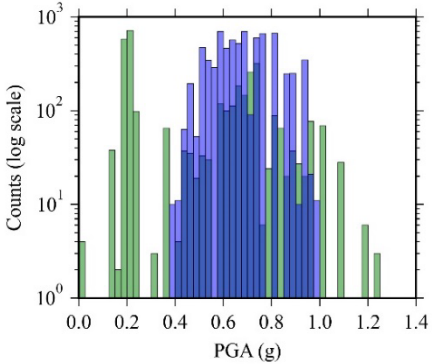


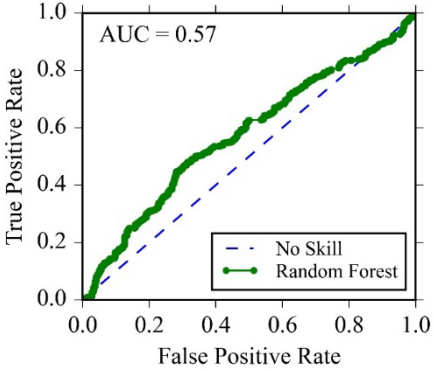
Evaluate DR21 ChCh Model (pt 1)

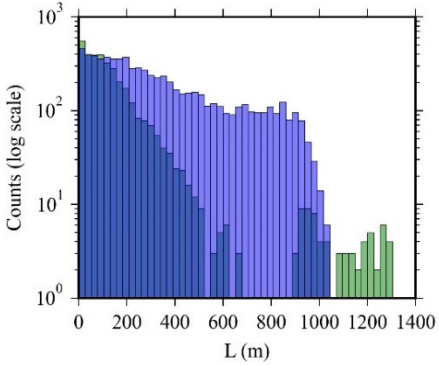
- For **NGL dataset**, use global inputs in DR21 lateral spread model trained using local inputs





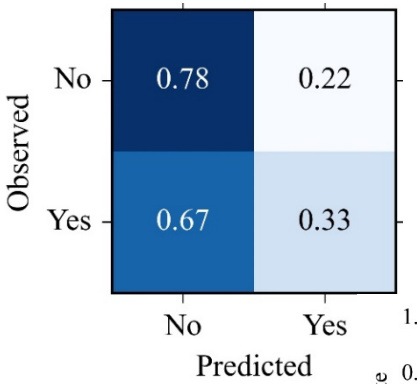


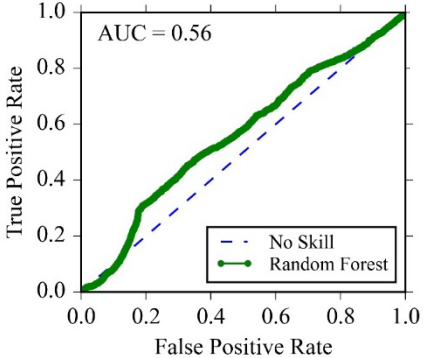


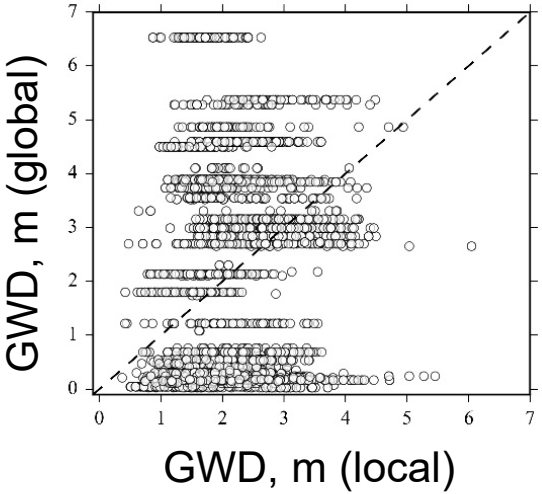


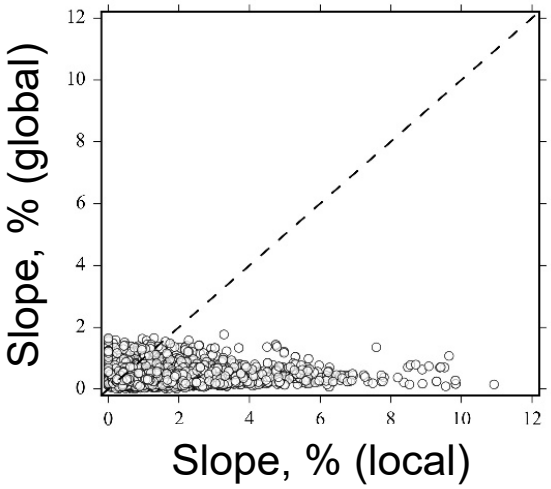
Evaluate DR21 ChCh Model (pt 2)

- For **Christchurch event**, use global inputs in DR21 lateral spread model trained using local inputs





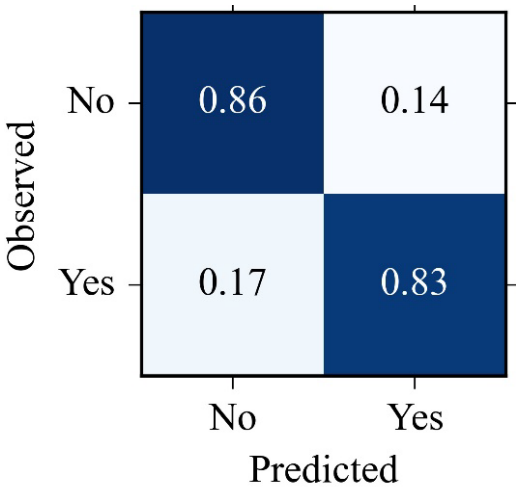




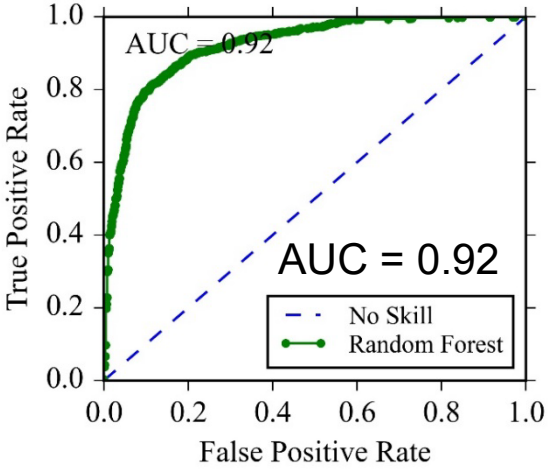
Train Global Model

- For **NGL + DR21 data**, train lateral spread model using global inputs

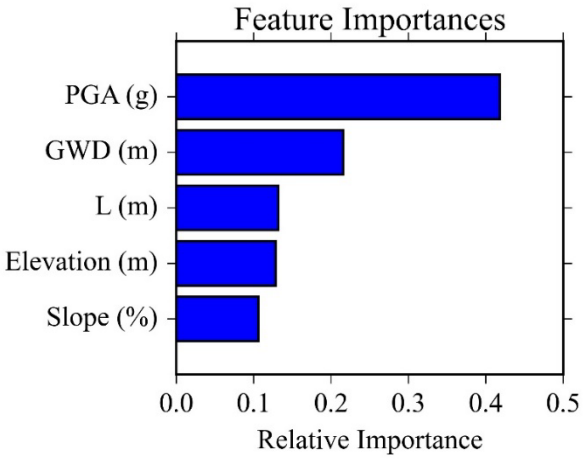
Confusion Matrix



ROC Curve



Feature Importance



Conclusions

- Regional liquefaction models are needed to incorporate liquefaction into seismic risk assessments
  - Liquefaction occurrence
  - Liquefaction consequences (lateral spreading, settlement, displacement)
  - Model inputs must be globally available and models must be trained on global parameters
- Data, data, data
  - Reconnaissance needs to collect the data needed to build/evaluate regional liquefaction models
  - Formally publish (and cite) data, scripts, etc. to accelerate research