

Next Generation Liquefaction (NGL) Models for Predicting Triggering and Manifestation of Liquefaction

Scott J. Brandenberg, Kenneth S. Hudson, Kristin J. Ulmer, Paolo Zimmaro,
Jonathan P. Stewart, and Steven L. Kramer

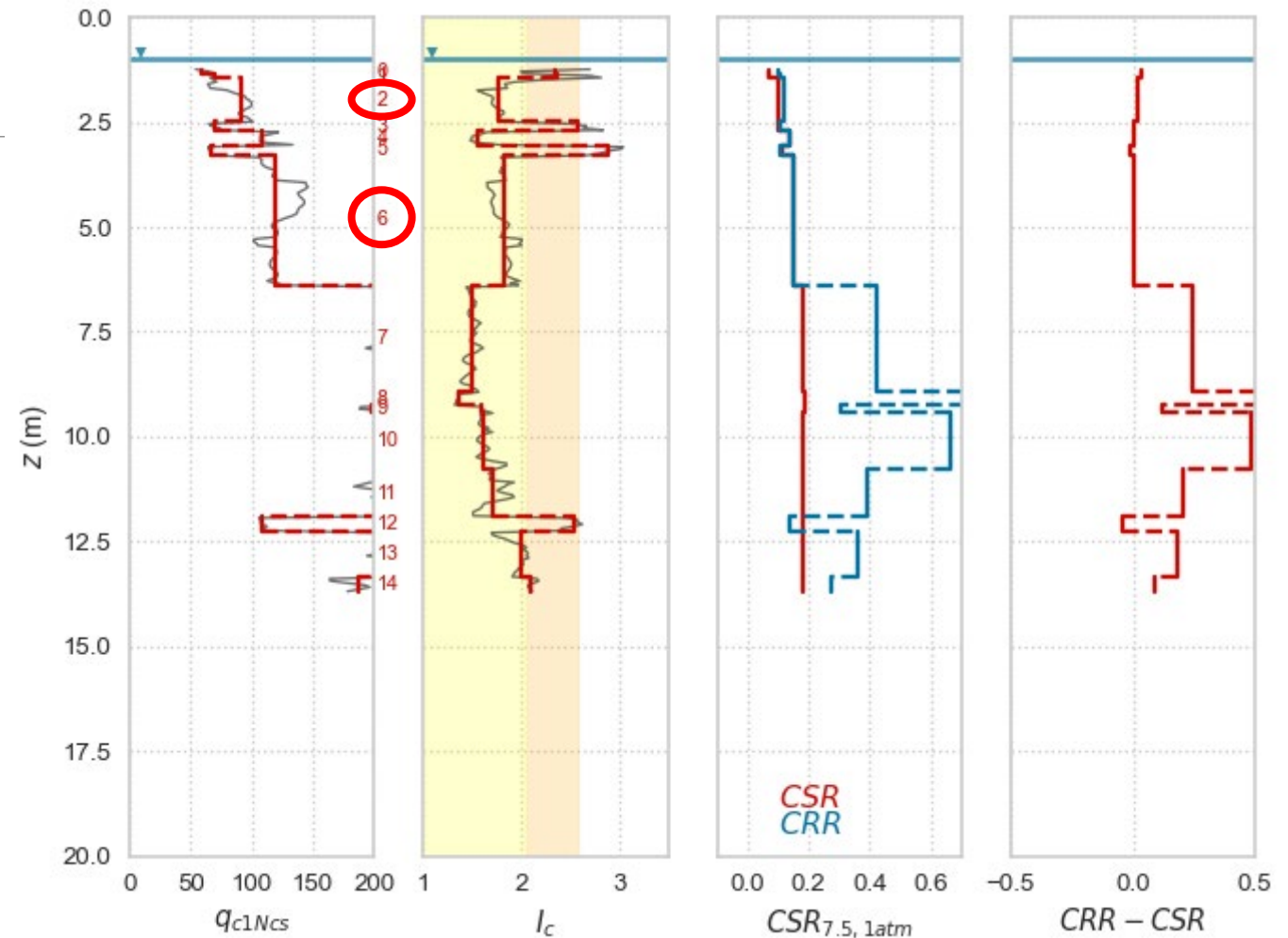
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Topics

- Critical Layers
- Lab-based Bayesian prior triggering model
- Manifestation model
- Posterior triggering model
- Conclusions

Critical Layers

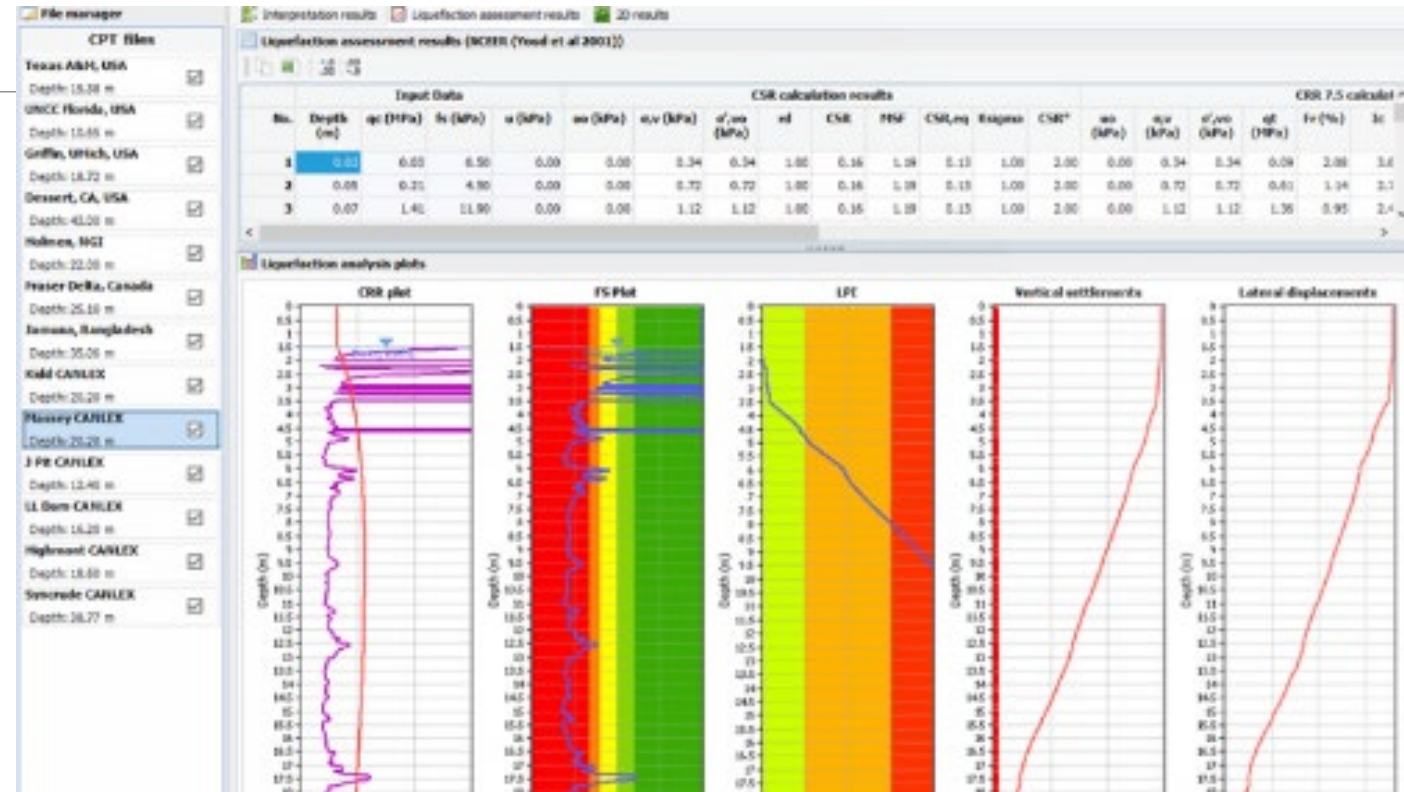
- Layer most likely to liquefy / manifest is selected for plotting cyclic stress ratio vs. penetration resistance
- For case histories, can sometimes be assessed by measured pore pressure (rare) or matching ejecta to layer (error prone)
- Requires judgment. Existing models often used to select critical layer, which creates potential for confirmation bias.



“yes” case: Landing Road Bridge site, 1987 Edgecumbe NZ event

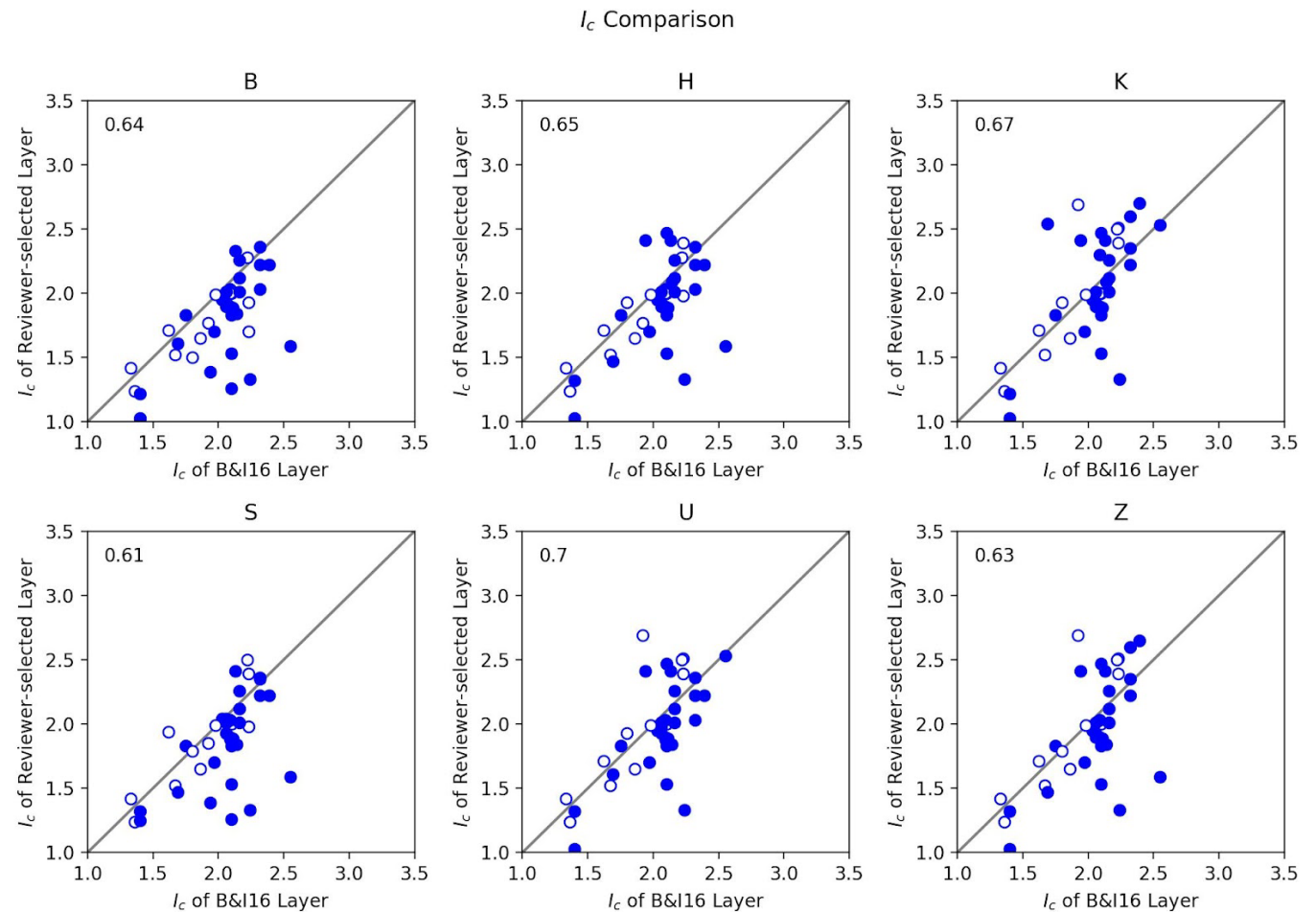
Critical Layers

- Soil profile is represented by the properties of the soil layer deemed most likely to liquefy
- For case histories, can sometimes be assessed by measured pore pressure (rare) or matching ejecta to layer (complicated)
- Requires judgment. Existing models often used to select critical layer, which creates confirmation bias.
- Inconsistent with common usage in forward applications



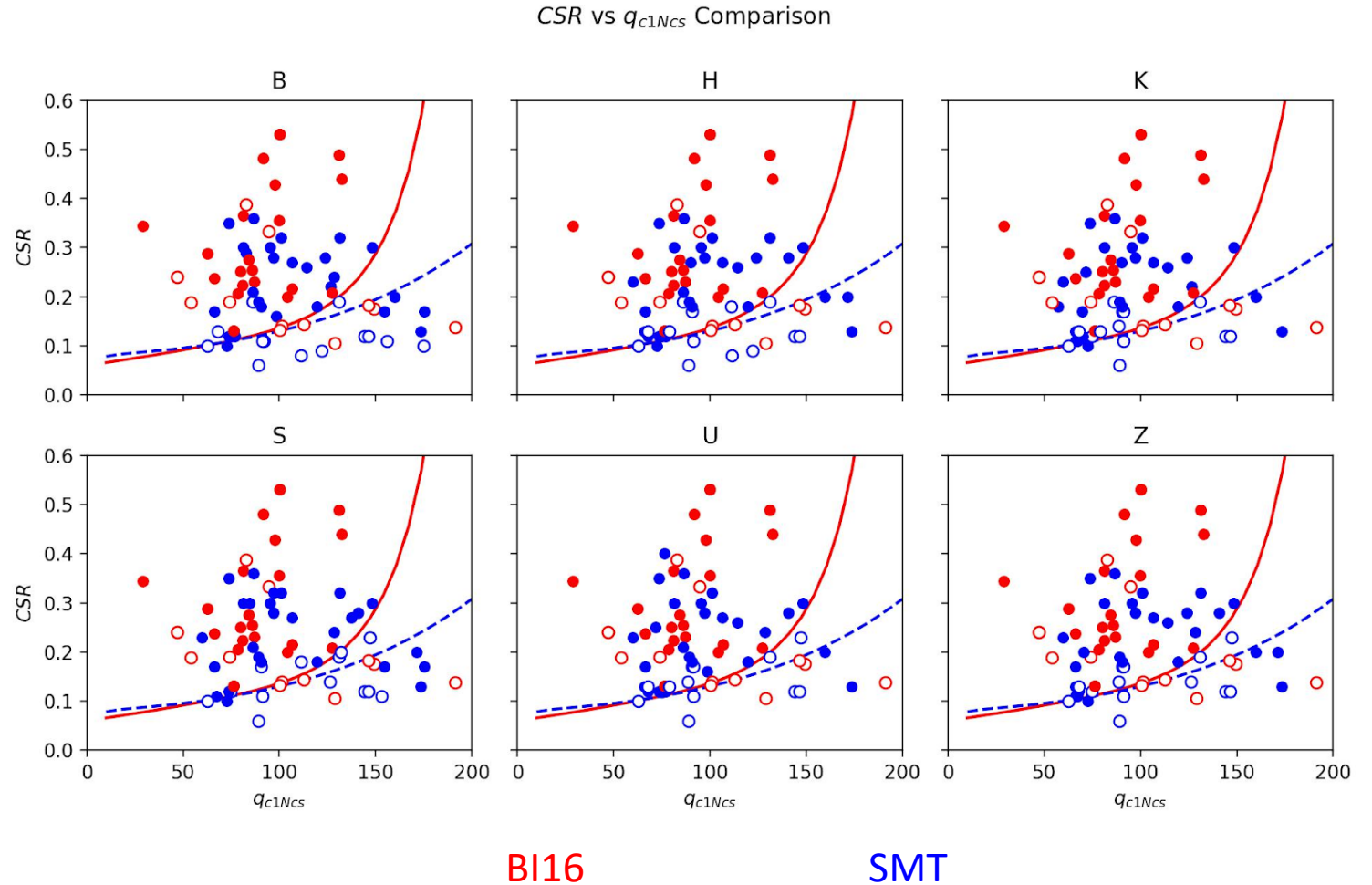
Critical layers

- Study conducted to examine analyst-to-analyst variability in critical layer selection
- Compared in terms of critical layer top depth, I_c , q_{c1Ncs} , CSR*
- Assessments of critical layers by SMT members were inconsistent despite us working closely together for years



Critical layers

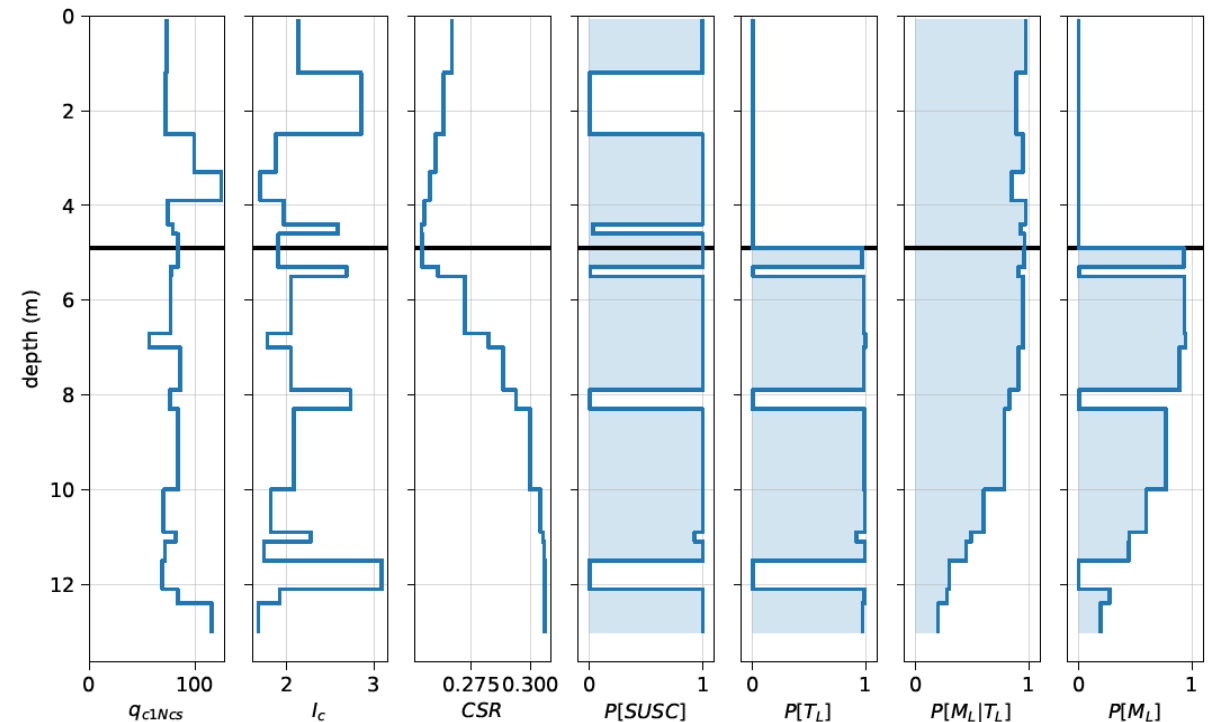
- Study conducted to examine analyst-to-analyst variability in critical layer selection
- Compared in terms of critical layer top depth, l_c , q_{c1Ncs} , CSR*
- Assessments of critical layers by SMT members were inconsistent despite us working closely together for years
- Compared data points in legacy triggering model space



Profile-Based Manifestation Model

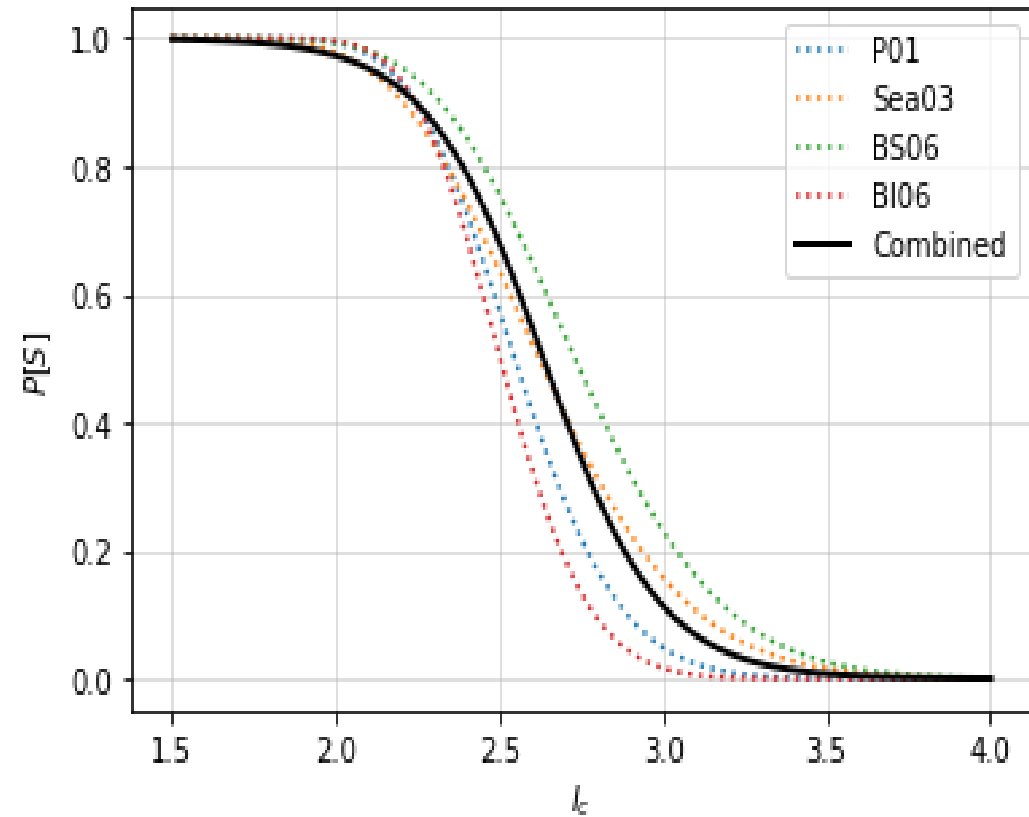
- Rather than selecting a single critical layer to represent a profile, the SMT has developed a procedure that accounts for contributions of all layers to manifestation.
- Each layer is assigned a probability of susceptibility, and a probability of triggering
- Each layer is assigned a probability of creating surface manifestation based on variables like I_c , z_{top} , etc.
- Layer manifestation probabilities are then combined to compute a profile manifestation probability.

P[MP]: 0.907
FLDM_SFEV: Yes
FLDM_SNBL: Unknown
Site Name: Miller Farm (CMF)
Event Name: Loma Prieta
Test Name: CMF009
FLDM_DESC: CMF-9: Liquefaction manifestation (Bennett and Tinsley 1995, Toprak and Holzer 2003)



Susceptibility prior

We treat susceptibility as a probabilistic function of soil behavior type index, following Maurer et al. (2017)



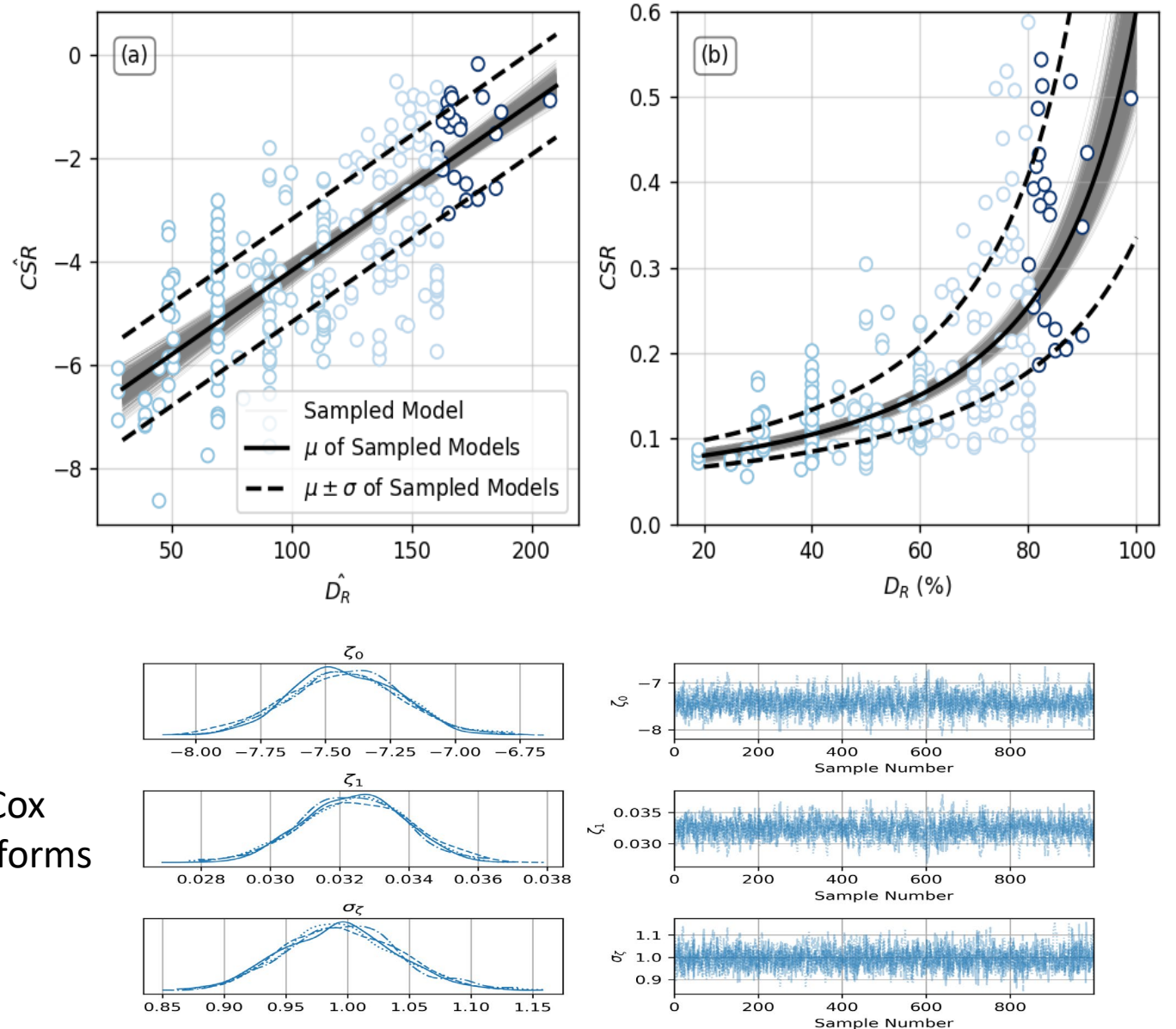
Triggering Prior

- Laboratory test data compiled by Ulmer and Carlton were utilized to develop a Bayesian “prior” triggering model.
- Lab data do not capture fabric and age of soils in the field, so prior is updated using Bayesian inference based on manifestation observations.

$$\widehat{CSR} = \frac{CSR^{\lambda_{CSR}} - 1}{\lambda_{CSR}} \quad \widehat{D}_R = \frac{D_R^{\lambda_{DR}} - 1}{\lambda_{DR}}$$

Box-Cox transforms

$$\widehat{CRR} = \zeta_0 + \zeta_1 * \widehat{D}_R + \varepsilon * \sigma_\zeta$$



Profile-Based Manifestation Model

$$PF_{M|T} = \frac{1}{1 + \exp(-\beta^T X)}$$

$PF_{M|T}$ = probability factor for manifestation of a layer conditional on triggering of that layer.

X = model features

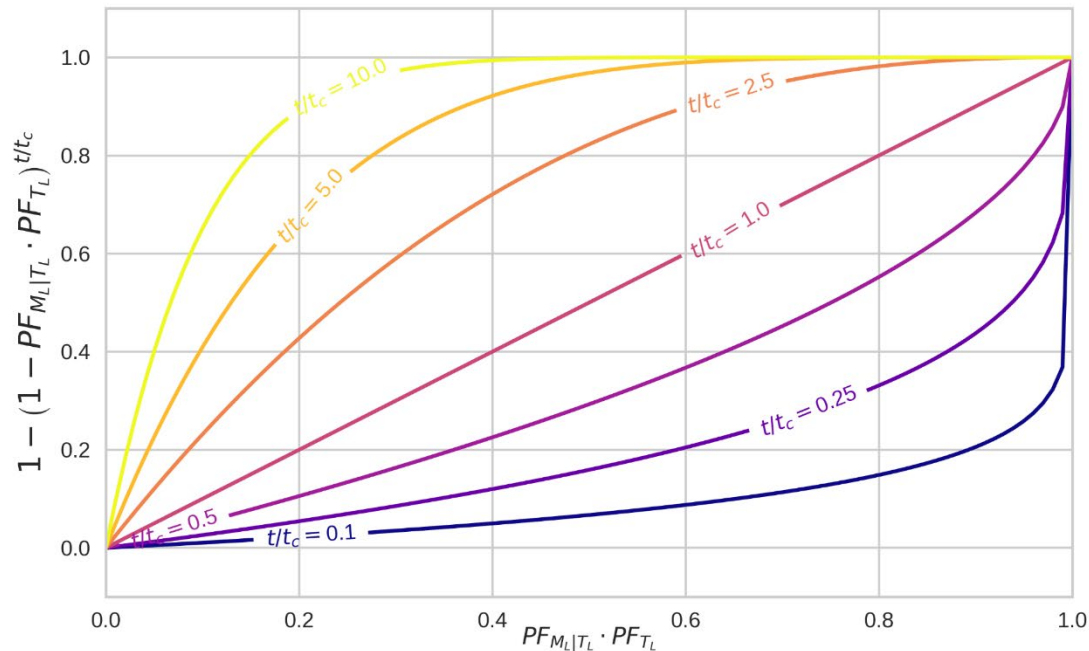
β = model coefficients, regressed from observations

Example logistic function using I_c and z_{top}

$$PF_{M|T} = \frac{1}{1 + \exp\left[-\left(\beta_0 + \beta_1 I_c + \beta_2 z_{top}\right)\right]}$$

Profile-Based Manifestation Model

$$P[M_P] = 1 - \prod_{i=1}^{N_L} (1 - PF_{M_i|T_i} PF_{T_i|S_i} PF_{S_i})^{t_i/t_c}$$



$P[M_P]$ = probability that a profile will manifest
 $PF_{M_i|T_i}$ = probability factor for manifestation conditioned on triggering

$PF_{T_i|S_i}$ = probability factor for triggering conditioned on susceptibility

PF_{S_i} = probability factor for susceptibility

N_L = number of layers

t_i = thickness of layer i

t_c = characteristic thickness (constant)

The purpose of the t/t_c exponent is to reduce dependence of the solution on layer discretization decisions.

Profile-Based Manifestation Model

$$L = \frac{1}{N_P} \sum_{k=1}^{N_P} \left[y_k \ln(P[M_P]_k) + (1 - y_k) \ln(1 - P[M_P]_k) \right]$$

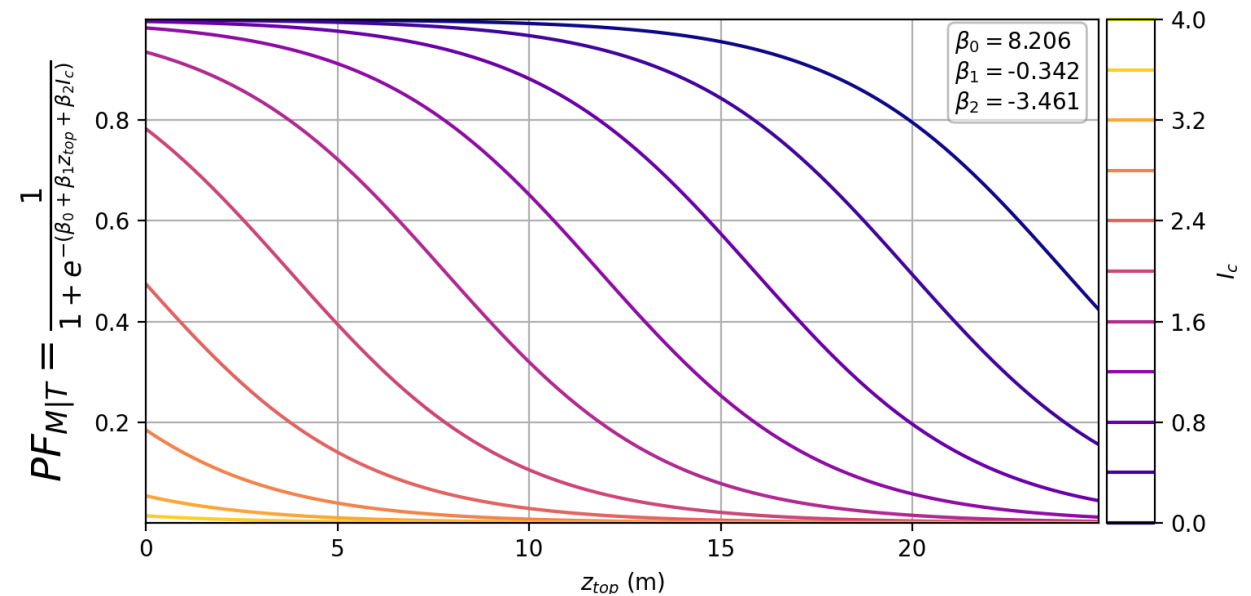
L = Likelihood function

N_P = number of profiles

y_k = 1 if manifestation was observed, 0 if it was not

Manifestation Model

- Many features were considered in manifestation model.
- Balancing model simplicity and accuracy, we recommend a model conditioned on z_{top} and I_c .

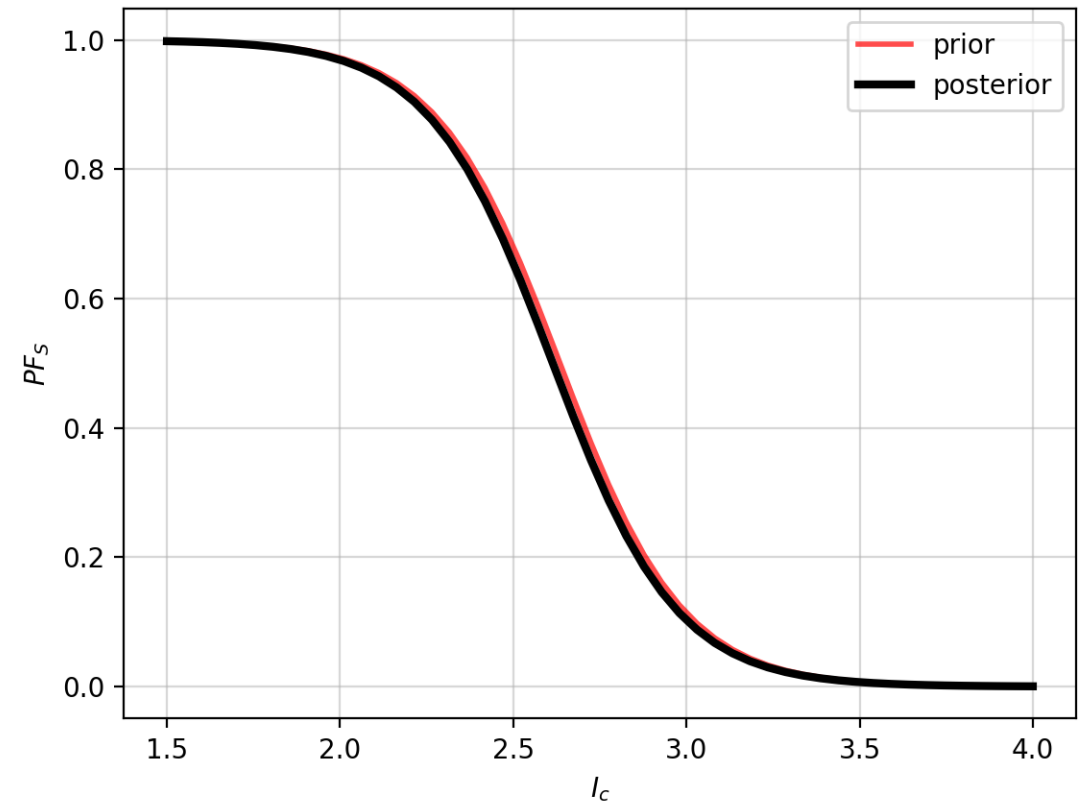


$$PF_{M|T} = \frac{1}{1 + \exp\left(-\left(8.206 - 0.342 \cdot z_{top} - 3.461 \cdot I_c\right)\right)}$$

Susceptibility Posterior

The posterior susceptibility relationship remained essentially the same as the prior, indicating that the data was not able to resolve susceptibility.

There is some tradeoff between the susceptibility model and the manifestation model, which also uses I_c .



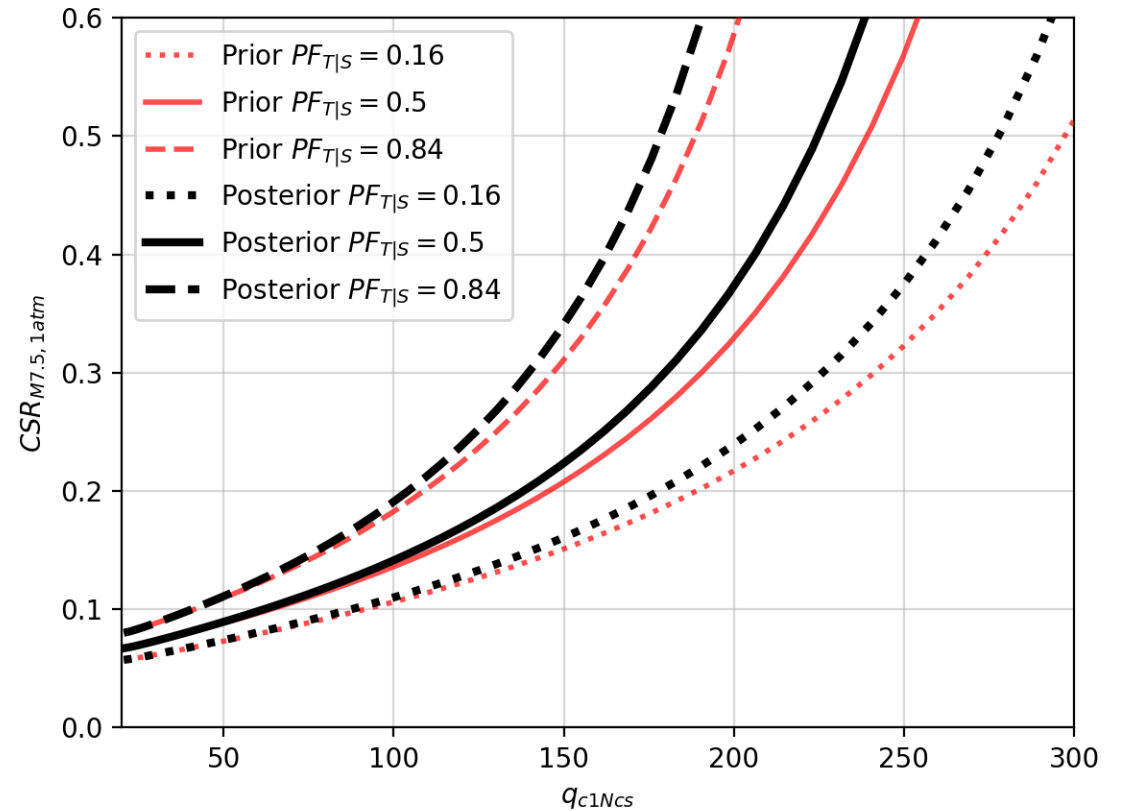
Triggering Posterior

- Posterior model is higher than prior.
- Relatively independent of assumption about prior, so largely data-driven.

$$PF_{T|S} = \frac{1}{1 + \exp\left(\frac{-1.702 \cdot (\widehat{CSR} - \widehat{CRR})}{0.985}\right)}$$

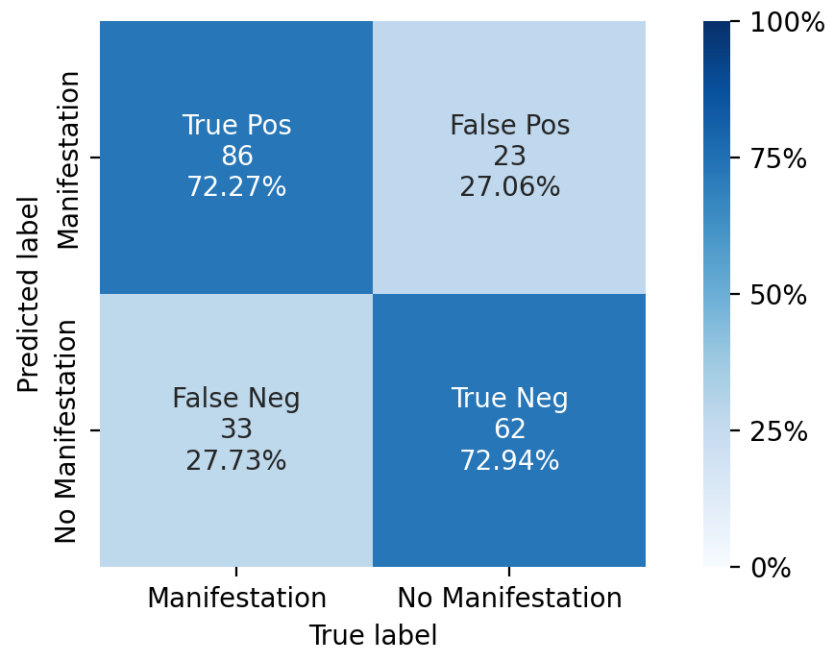
$$\widehat{CSR} = \frac{(CSR_{M7.5,1atm}^{-0.6566} - 1)}{-0.6566}$$

$$\widehat{CRR} = -7.427 + 0.0338 \cdot \widehat{D}_R$$



Model Accuracy

Training Dataset (NGL database)



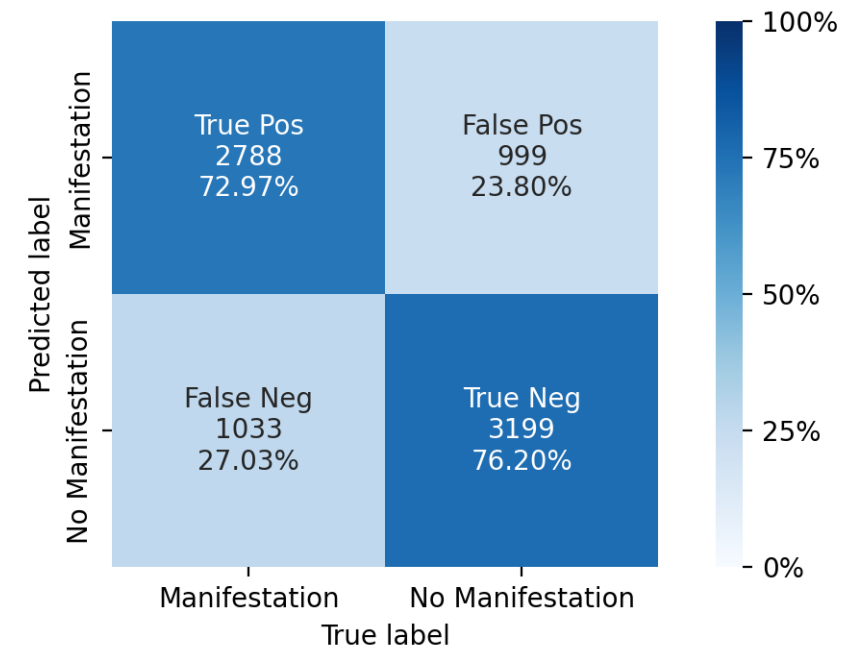
$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} = 0.725$$

$$\text{Precision} = \frac{TP}{TP + FP} = 0.789$$

$$\text{Recall} = \frac{TP}{TP + FN} = 0.723$$

$$\text{F1 Score} = \frac{2 * \text{precision} * \text{recall}}{(\text{precision} + \text{recall})} = 0.754$$

Test Dataset (Geyin et al. 2020, Canterbury data)



$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} = 0.747$$

$$\text{Precision} = \frac{TP}{TP + FP} = 0.736$$

$$\text{Recall} = \frac{TP}{TP + FN} = 0.730$$

$$\text{F1 Score} = \frac{2 * \text{precision} * \text{recall}}{(\text{precision} + \text{recall})} = 0.733$$

Conclusions

- The SMT model separates triggering from manifestation, recognizing that a layer can trigger without manifesting at the surface.
- The triggering model uses a Bayesian prior from lab tests that is updated based on case history data. Updating moves it up slightly. Susceptibility prior is essentially unchanged.
- The manifestation model depends on layer thickness, soil behavior type index, and depth to the top of the layer.
- The model was similarly accurate for the test dataset (actually better) than the training set