

Predicting CO₂ Buoyant Flow Saturation in Heterogeneous Geologic Formations with Machine Learning

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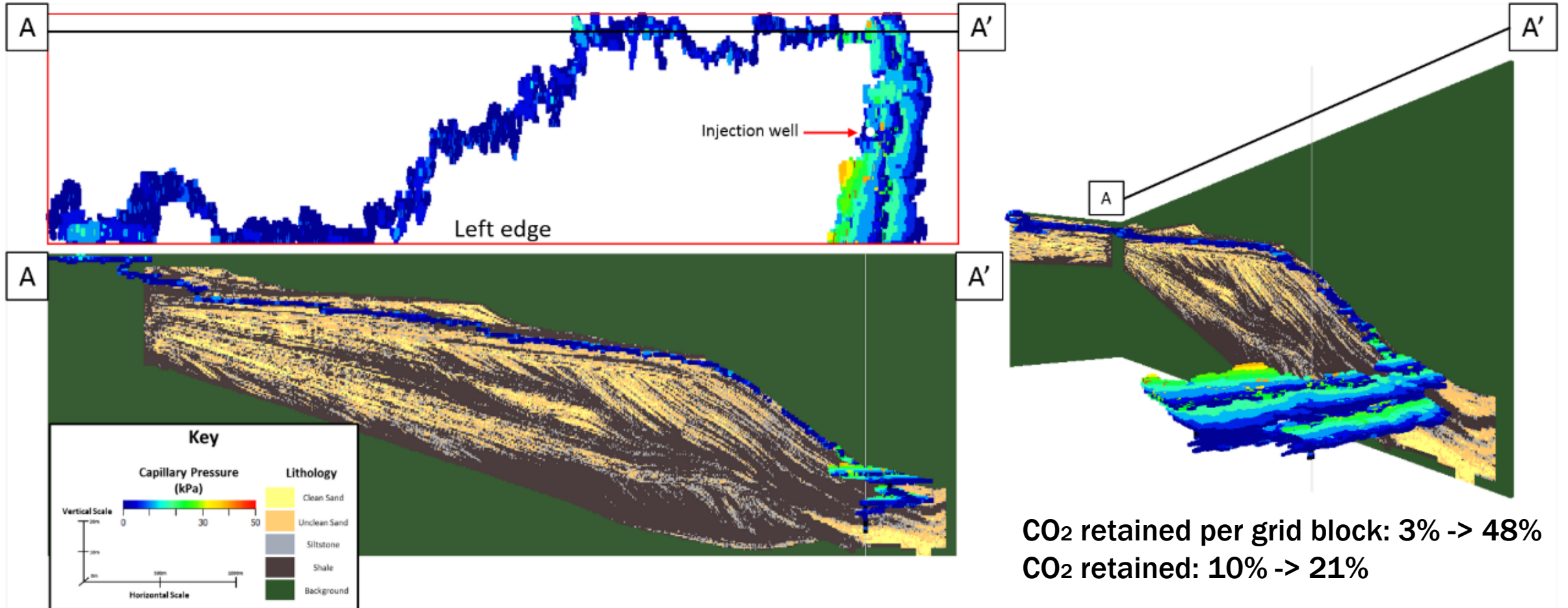
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BUREAU OF
ECONOMIC
GEOLOGY

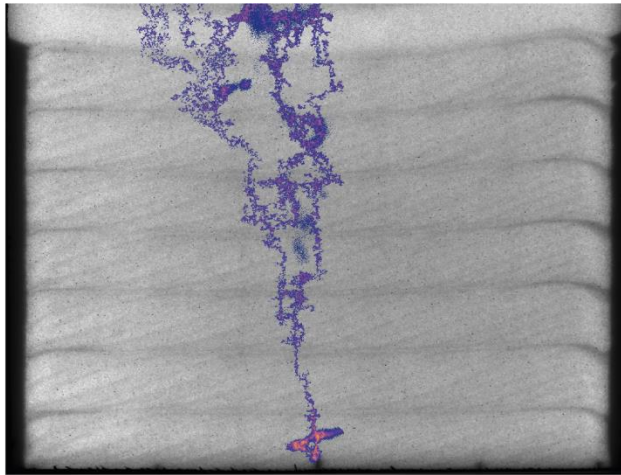
Sub-meter scale barriers can determine migration pathways, speed of plume movement, and CO₂ storage capacity



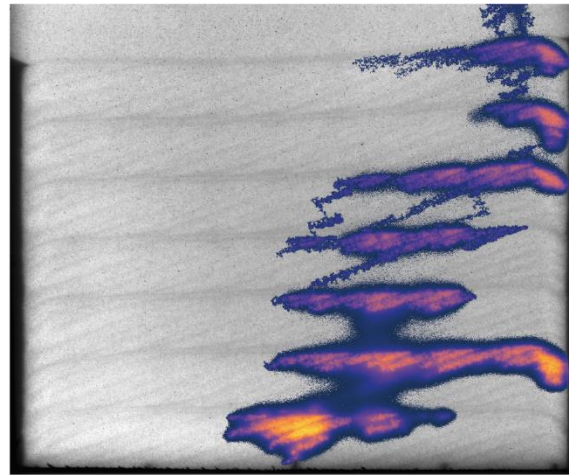
Sub-meter scale barriers can determine migration pathways, speed of plume movement, and CO₂ storage capacity

Increasing grain size contrast between matrix and laminae

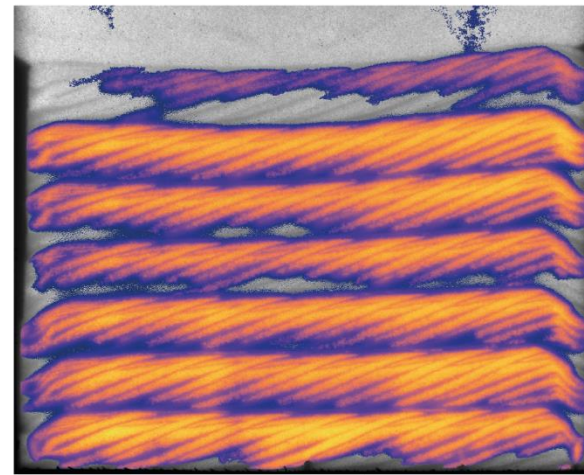
(Increasing degree of heterogeneity)



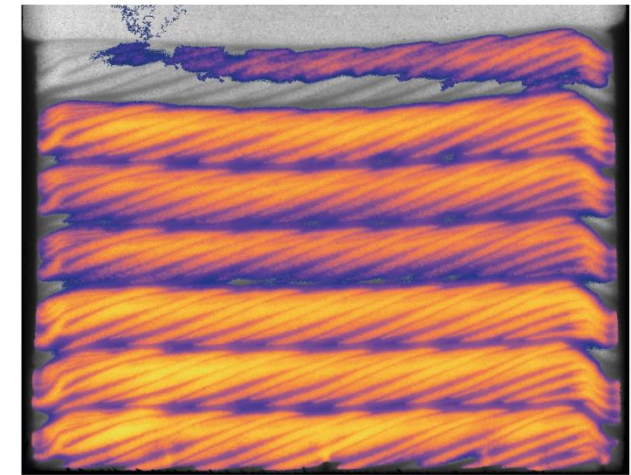
$S_{NWP} = 0.27\%$



$S_{NWP} = 3.24\%$



$S_{NWP} = 31.5\%$



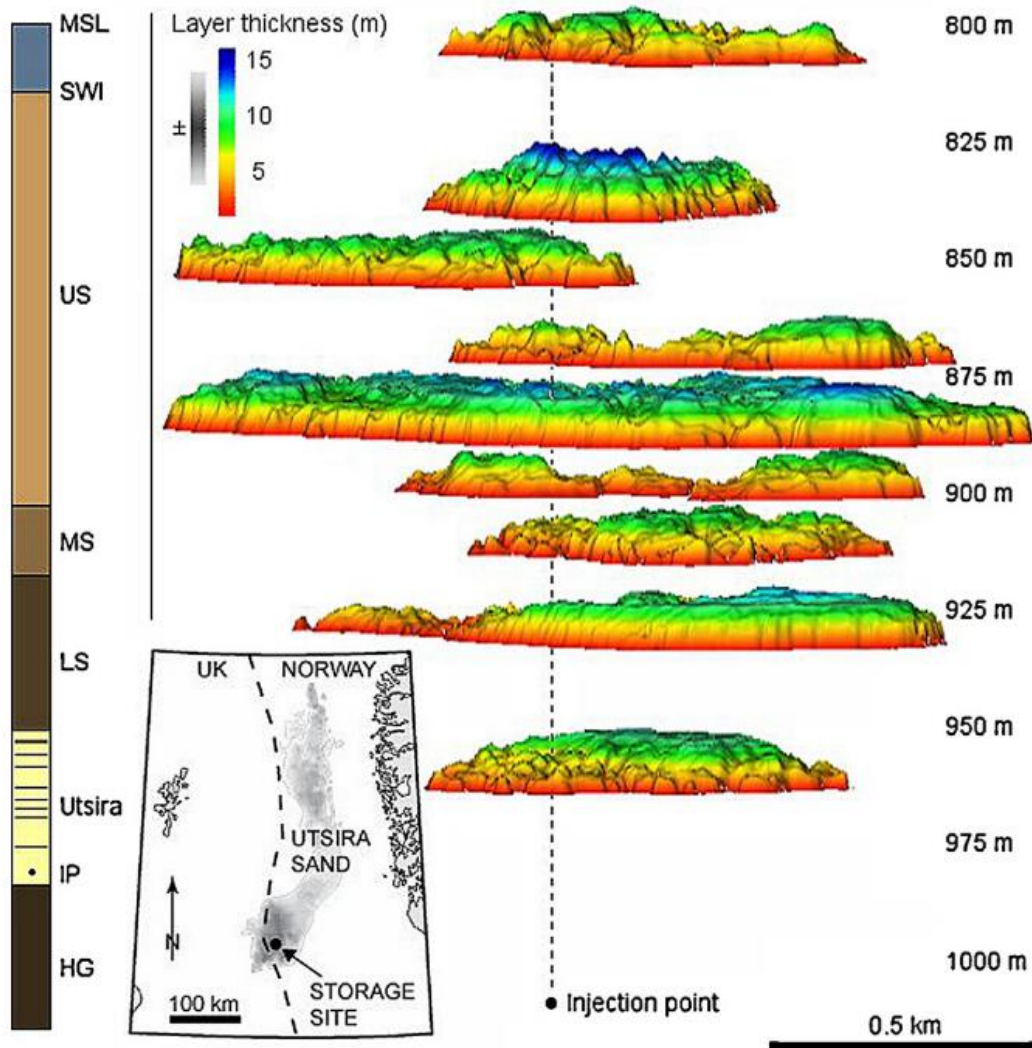
$S_{NWP} = 36.8\%$

CO₂ retained per grid block: 3% -> 48%

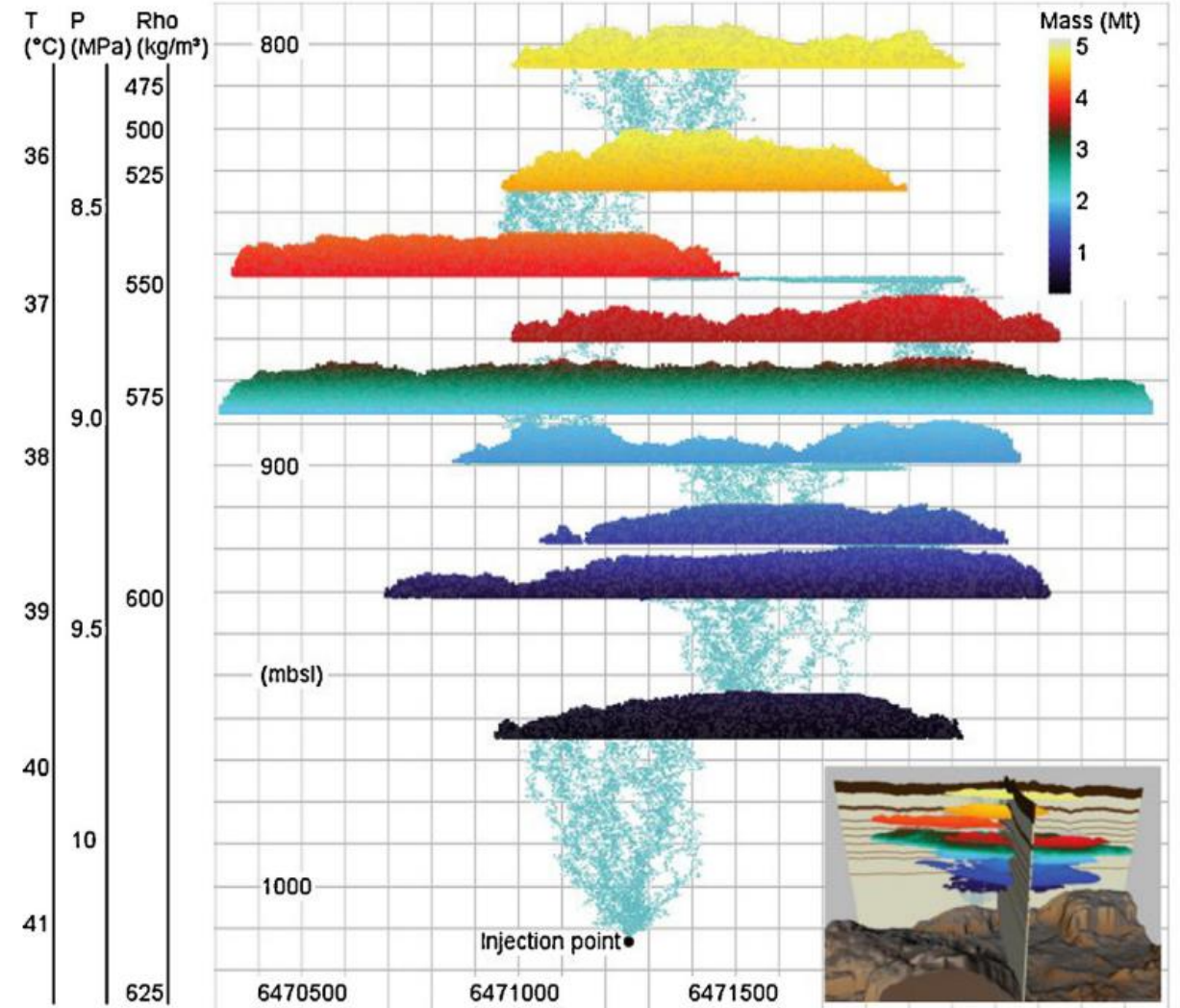
CO₂ retained: 10% -> 21%

Why do modified invasion percolation simulations?

3D representation of the monitored CO₂ plume

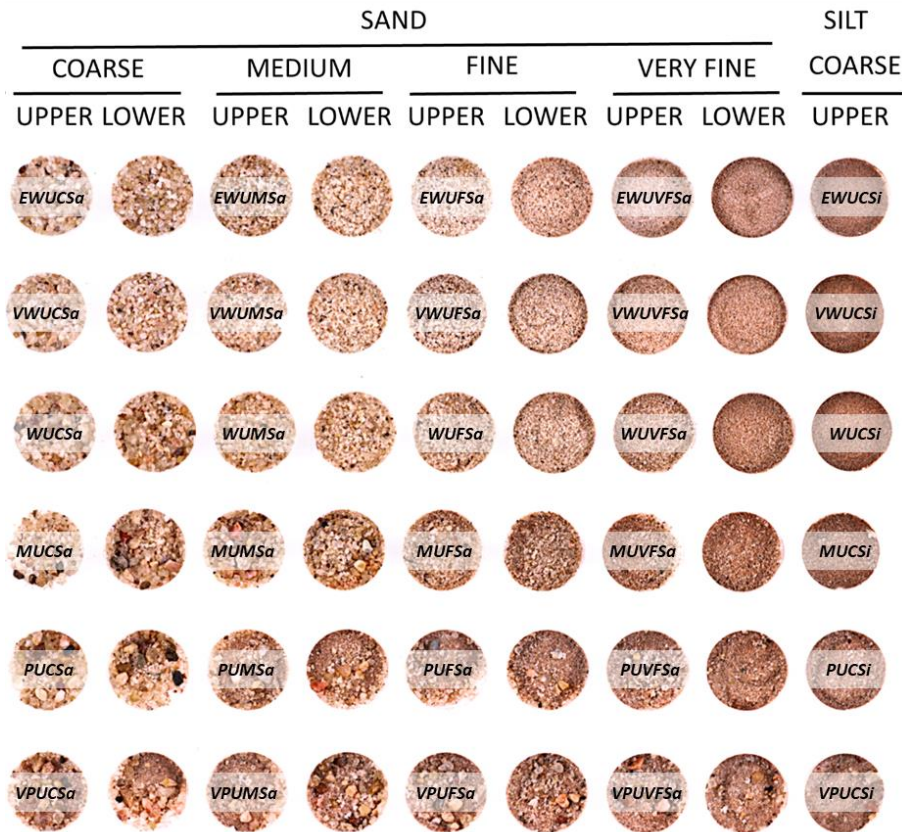


Modified invasion percolation simulation result



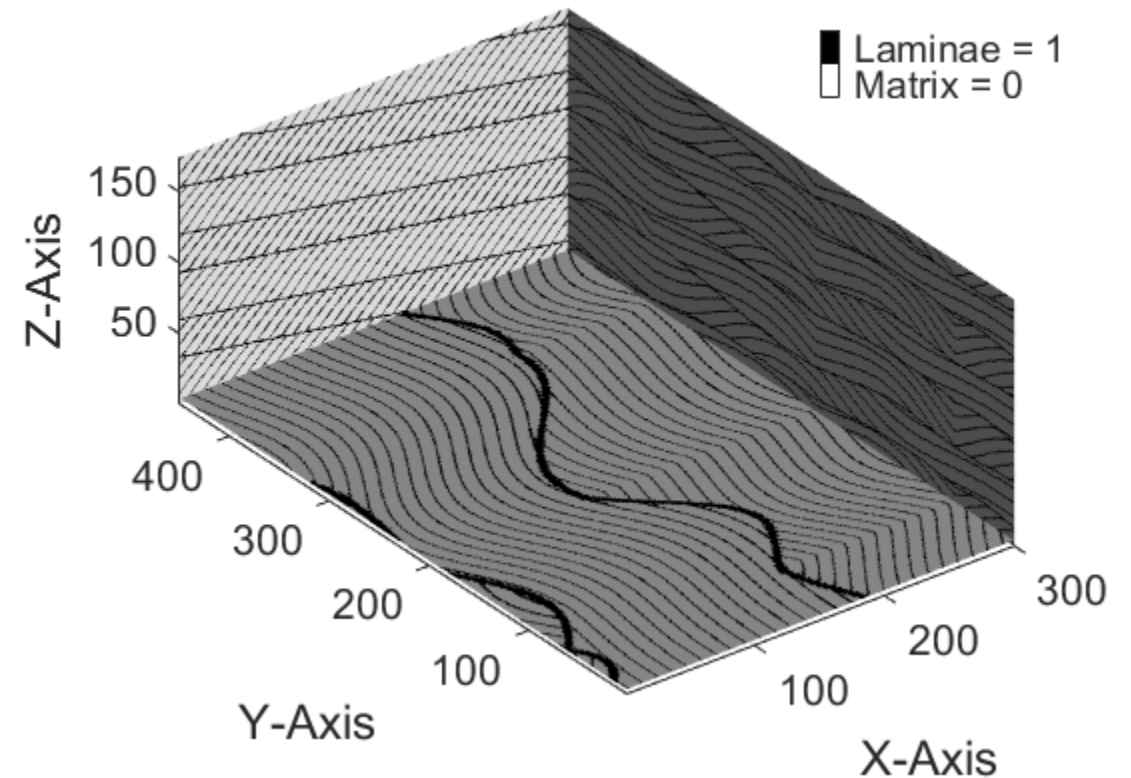
Heterogeneity in natural geologic formations is affected by two major factors

Grain size



Trevisan et al., 2017

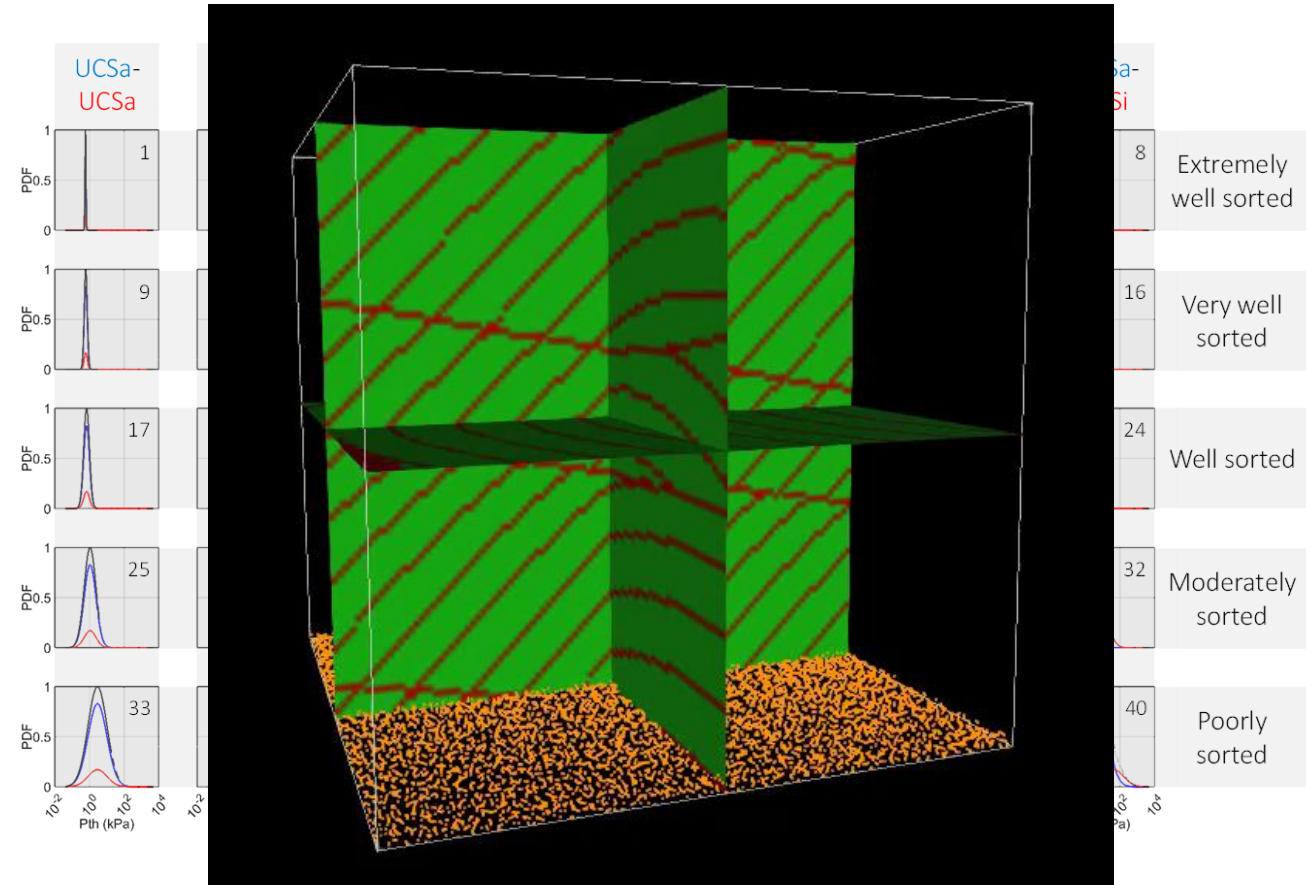
Bedform architecture



Rubin & Carter, 2005; Meckel et al., 2017

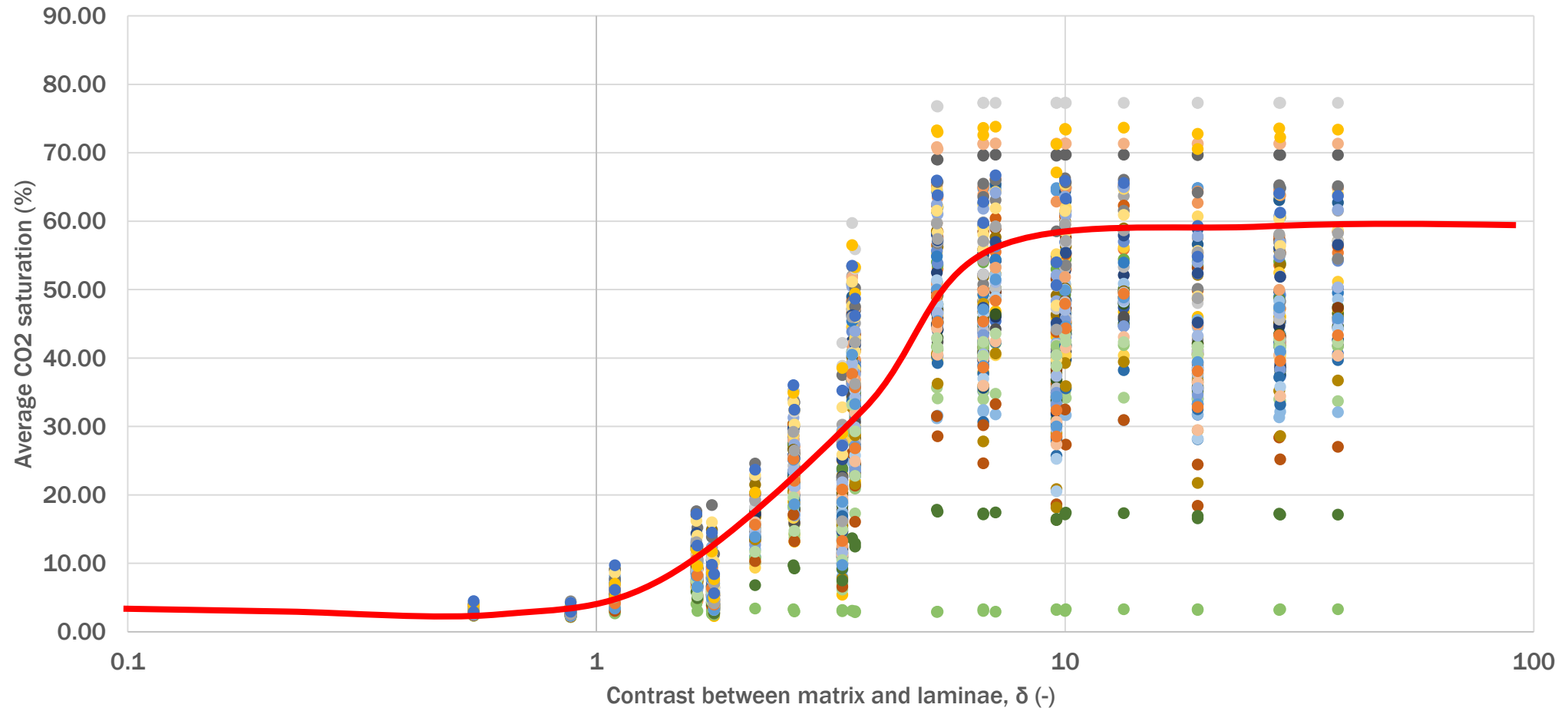
Data generation: modified invasion percolation simulations

- 59 bedform architectures X
- 40 grain size contrast cases X
- 50 stochastic realizations X
- = 118,000 simulations run



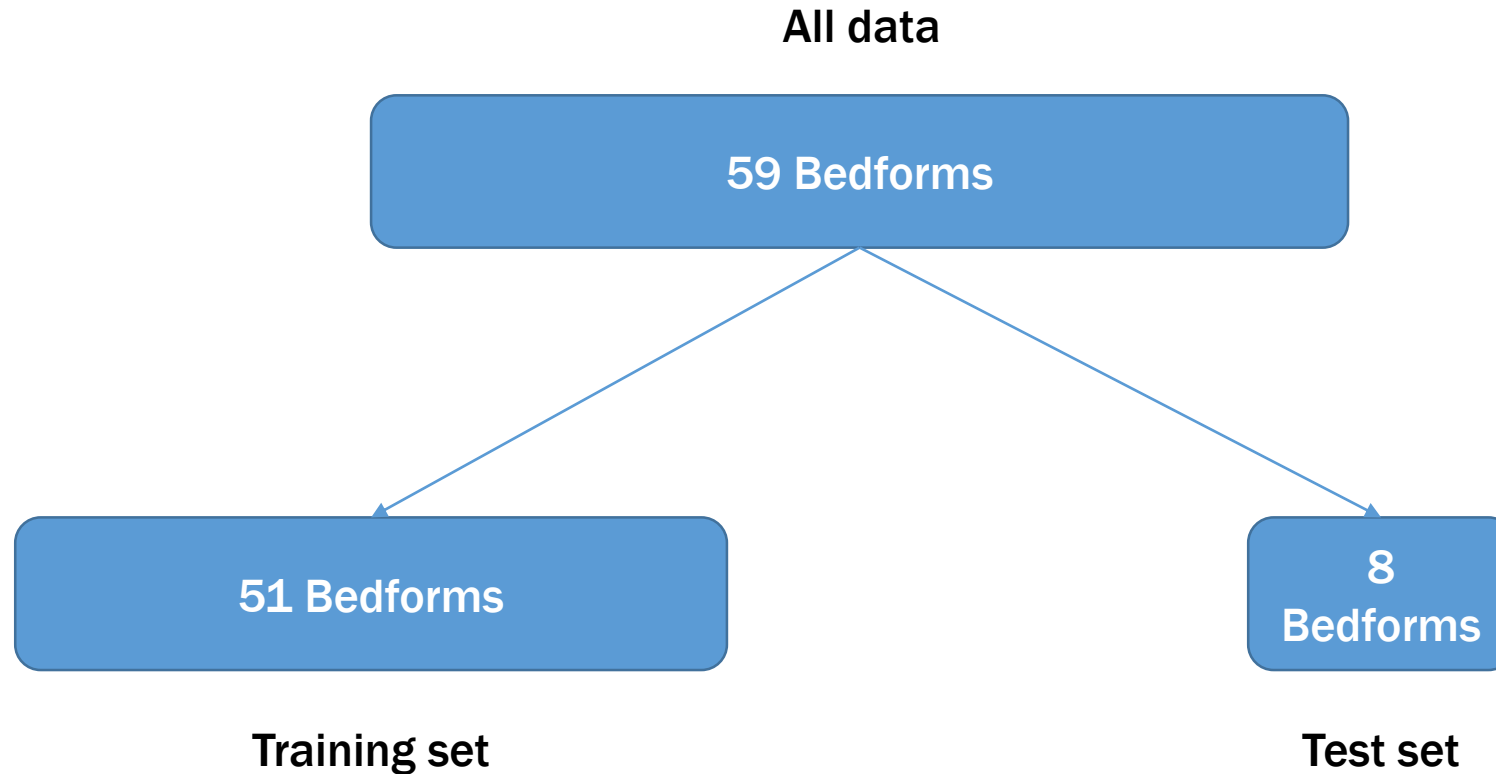
Rubin & Carter, 2005; Meckel et al., 2017;
Trevisan et al., 2017

Data: first look



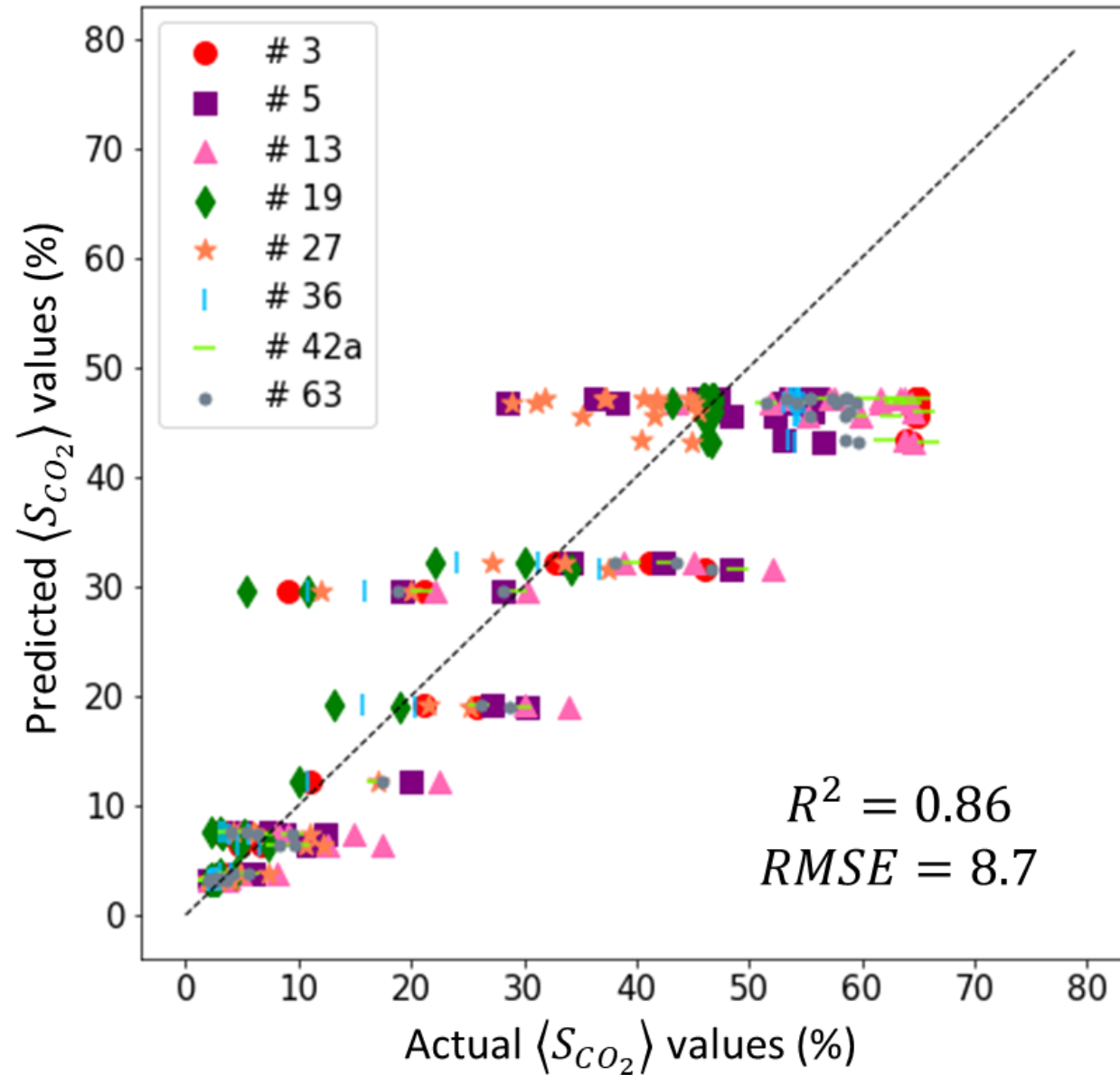
- Bedform**
- # 3
 - # 5
 - # 13
 - # 19
 - # 27
 - # 36
 - # 42a
 - # 63
 - # 4
 - # 15
 - # 16
 - # 17
 - # 18
 - # 21
 - # 22a
 - # 22b
 - # 25
 - # 29
 - # 32a
 - # 32b
 - # 32c
 - # 34a
 - # 34b
 - # 34c
 - # 38
 - # 40
 - # 42b
 - # 43a
 - # 43b
 - # 45
 - # 46a
 - # 46b
 - # 46c
 - # 46d
 - # 46e
 - # 46f
 - # 46g
 - # 46h
 - # 46i
 - # 46j
 - # 46k
 - # 46l
 - # 46m
 - # 46n
 - # 55
 - # 56
 - # 58
 - # 59
 - # 65
 - # 66
 - # 67
 - # 69
 - # 71
 - # 72
 - # 73
 - # 74
 - # 77
 - # 78
 - # 79

Model training: training and test set



Each bedform architecture model has all of its 40 grain size contrast cases included.

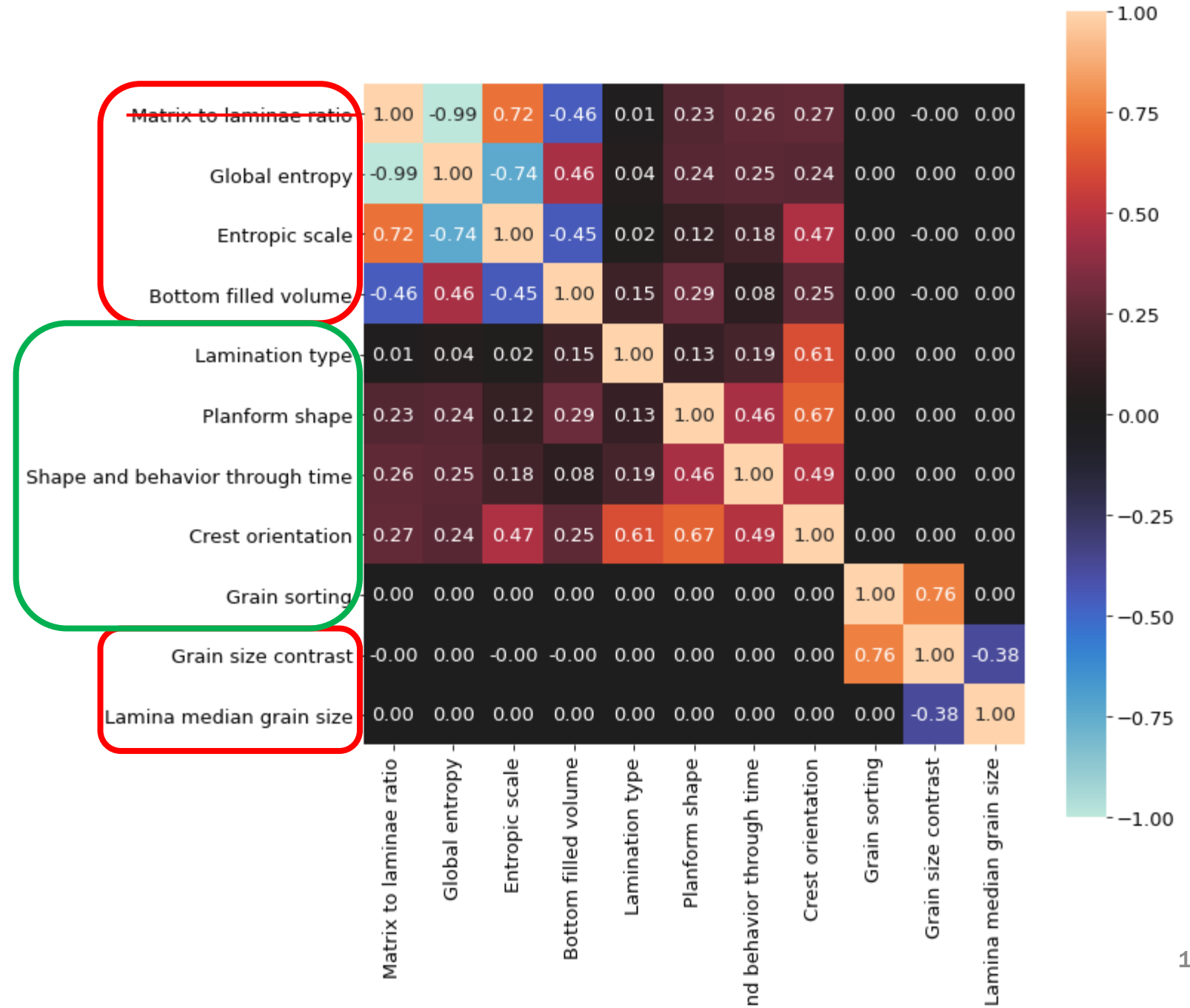
Model results: first model



Model building: with machine learning

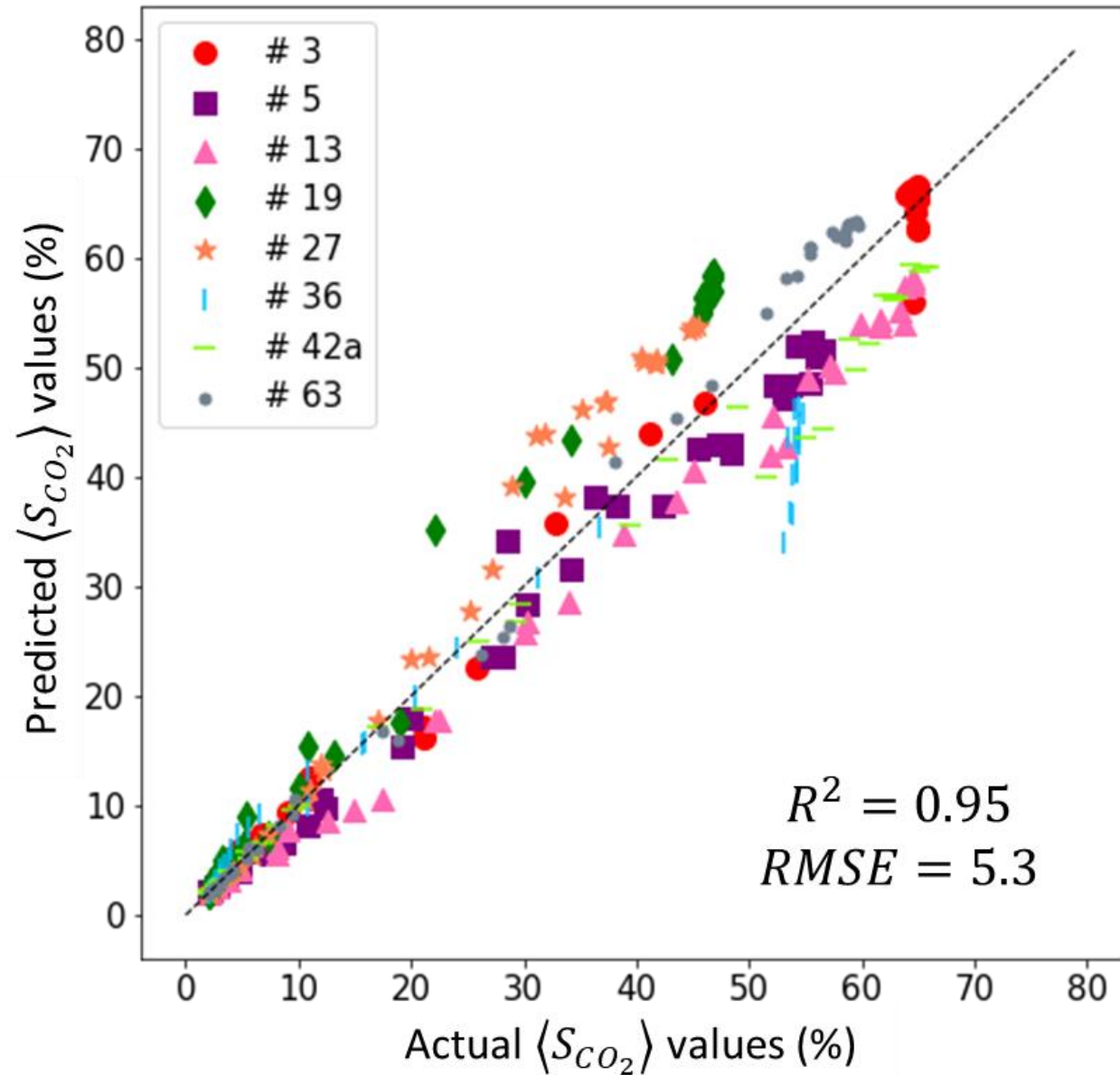
- **Add more features**
 - Grain sorting
 - Geological entropy
 - **Bedform descriptors**
 - Planform shape
 - Shape and behavior through time
 - Crest orientation
 - Lamination type and shape
- **Try different machine learning regression models**
 - K nearest neighbors
 - Linear regression
 - **Tree-based ensemble models**
 - Random forest
 - Gradient-boosted trees
 - **Artificial neural networks**

Model building: feature selection

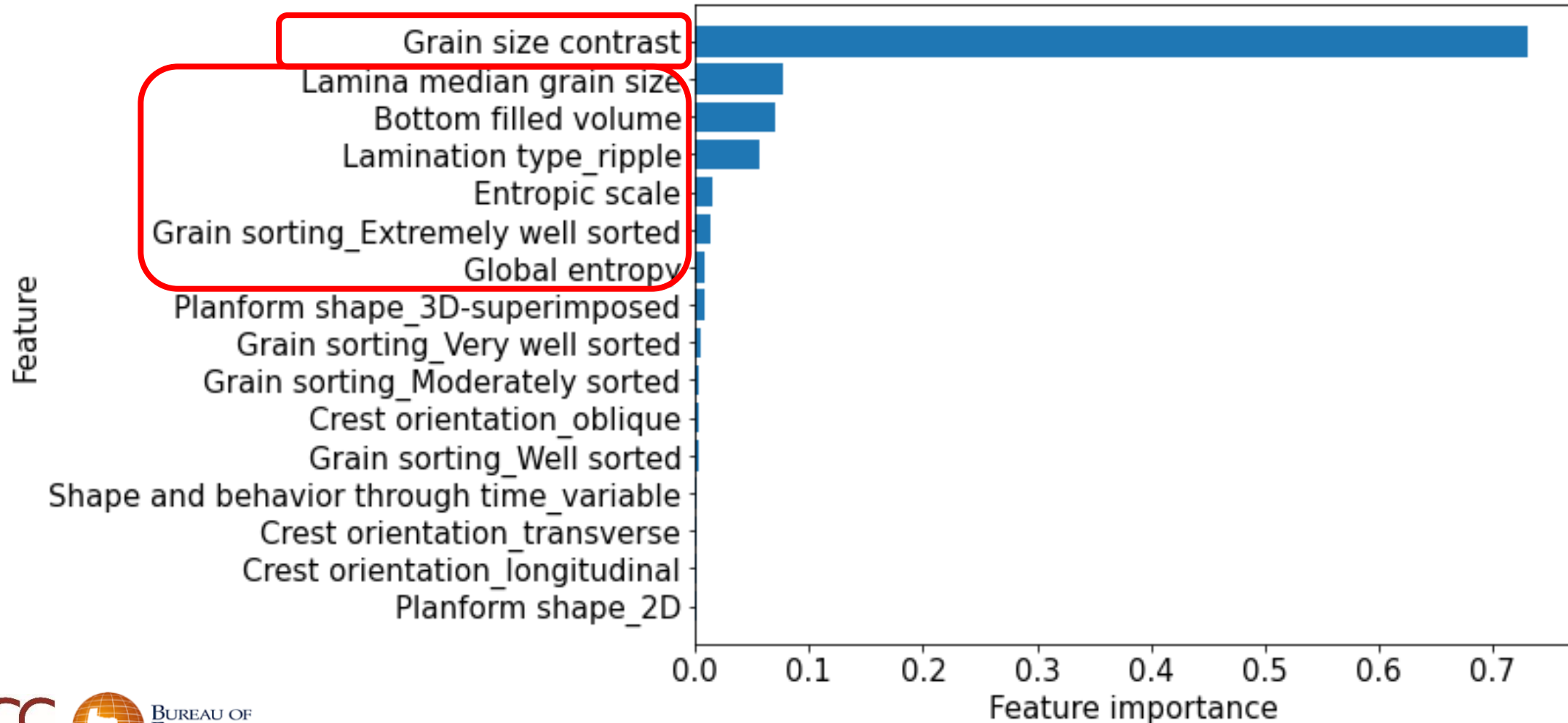


Model results: second model

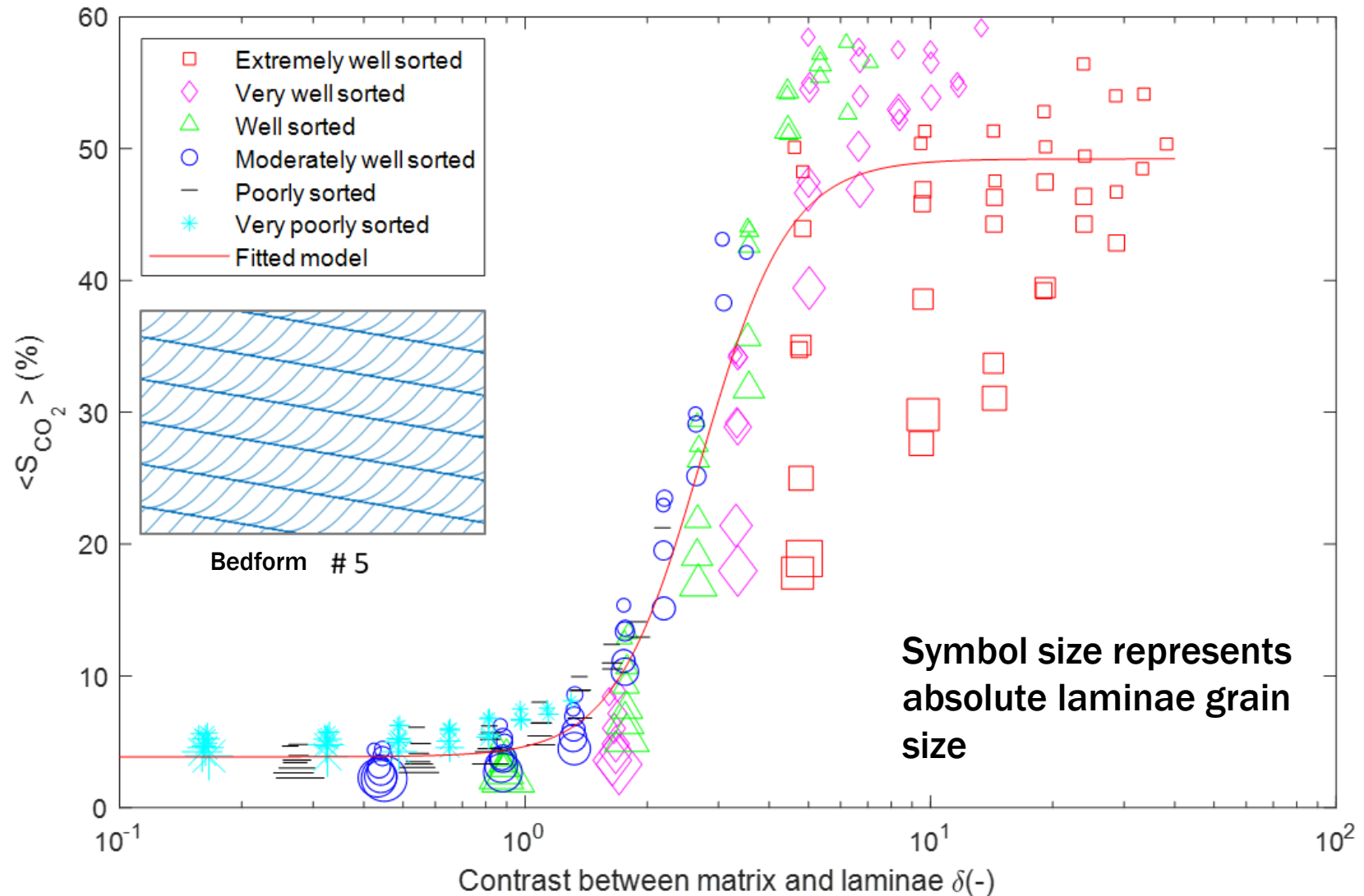
- Random forest model



Model results: feature importance



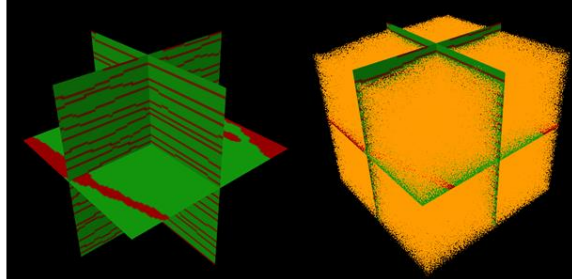
Important features: grain sorting and laminae grain size



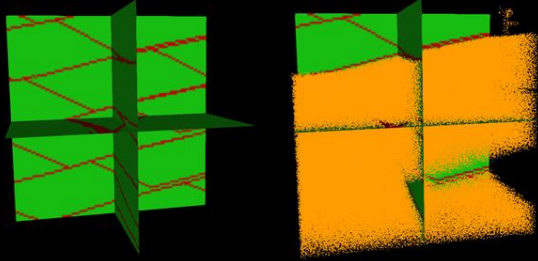
Important features: lamination type and shape

- High CO₂ saturation:
 - Continuous ripple lamination
- Low CO₂ saturation:
 - Discontinuous cross-lamination

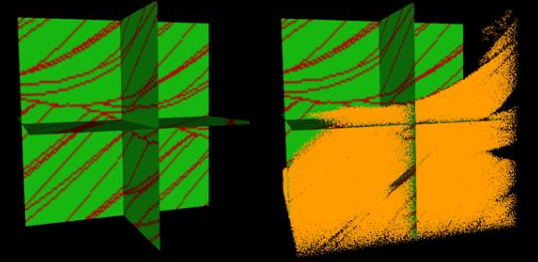
67



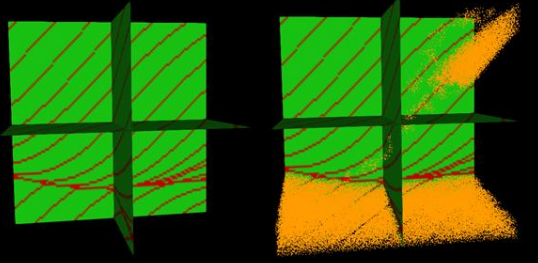
43a



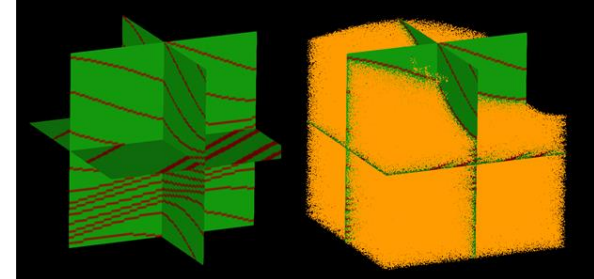
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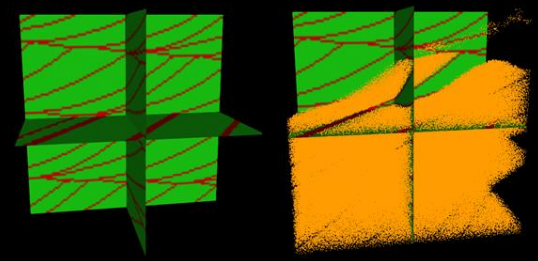
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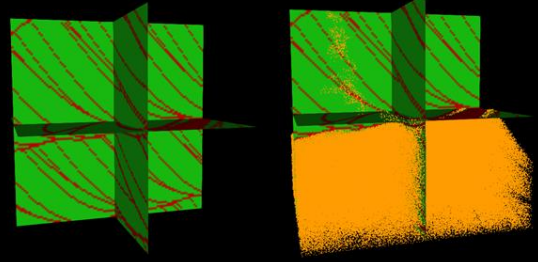
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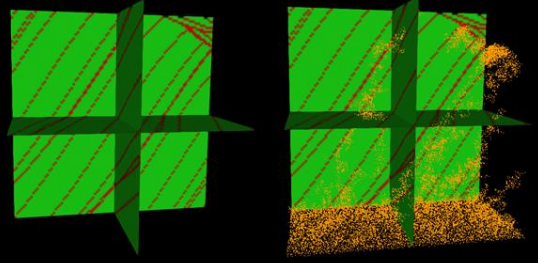
22b



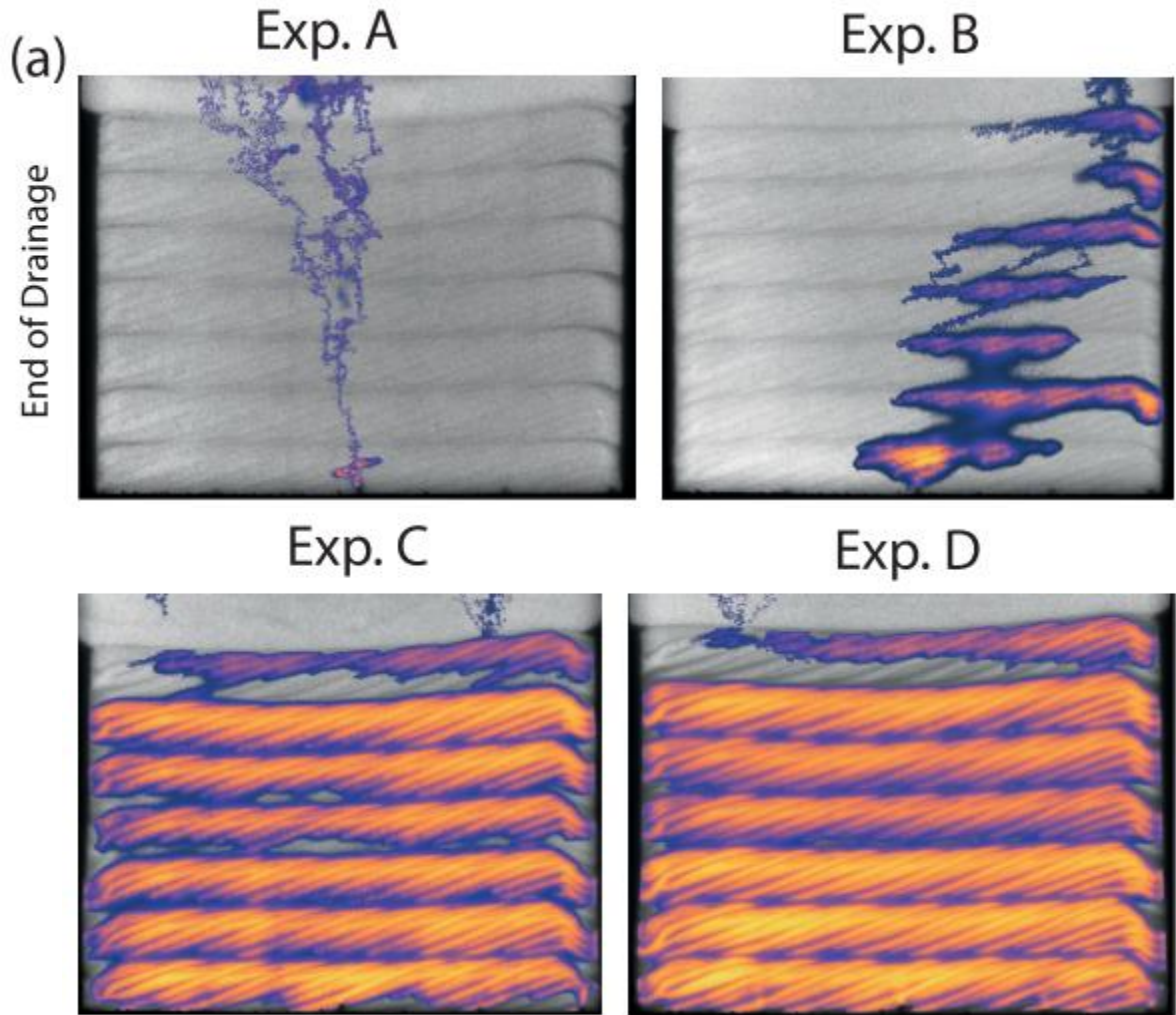
46n



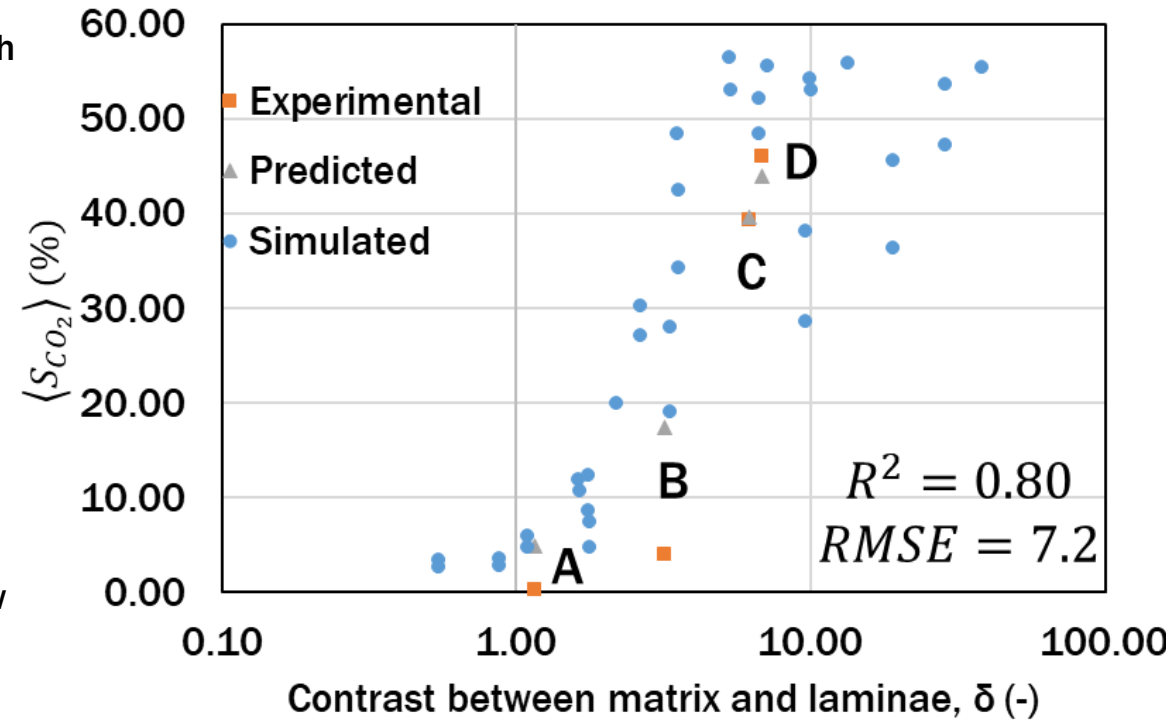
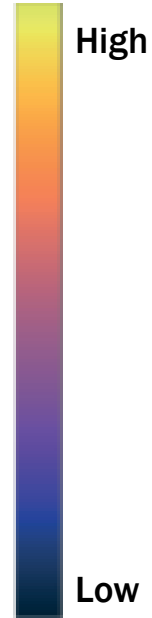
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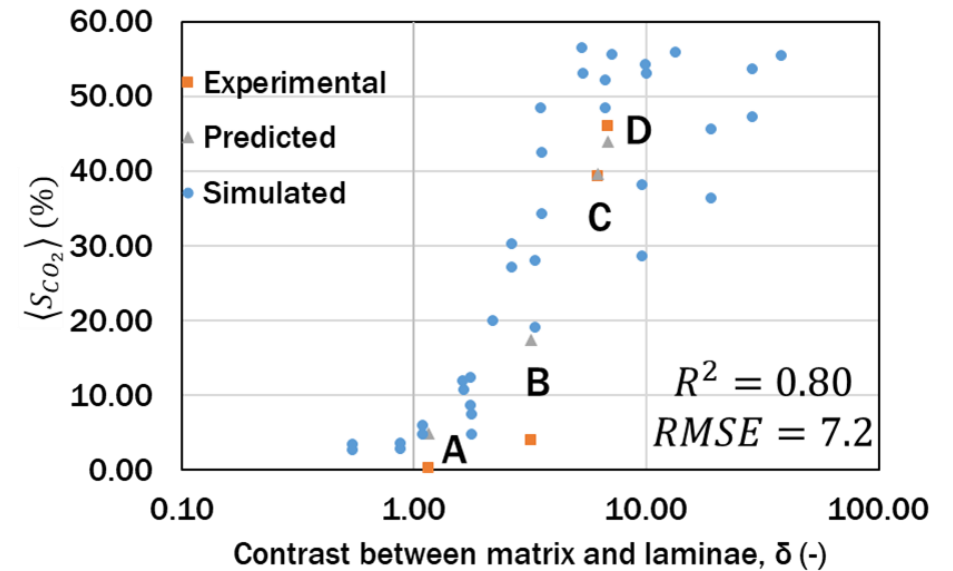
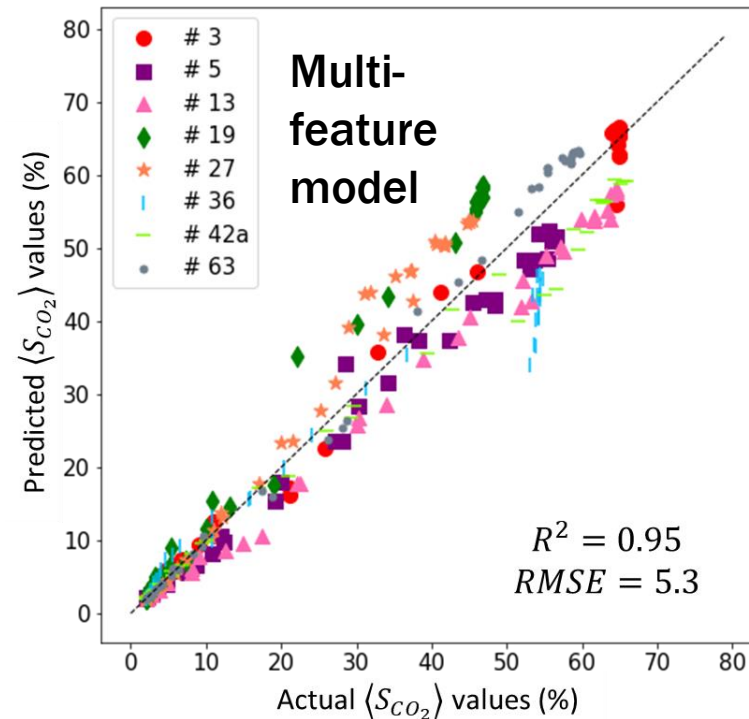
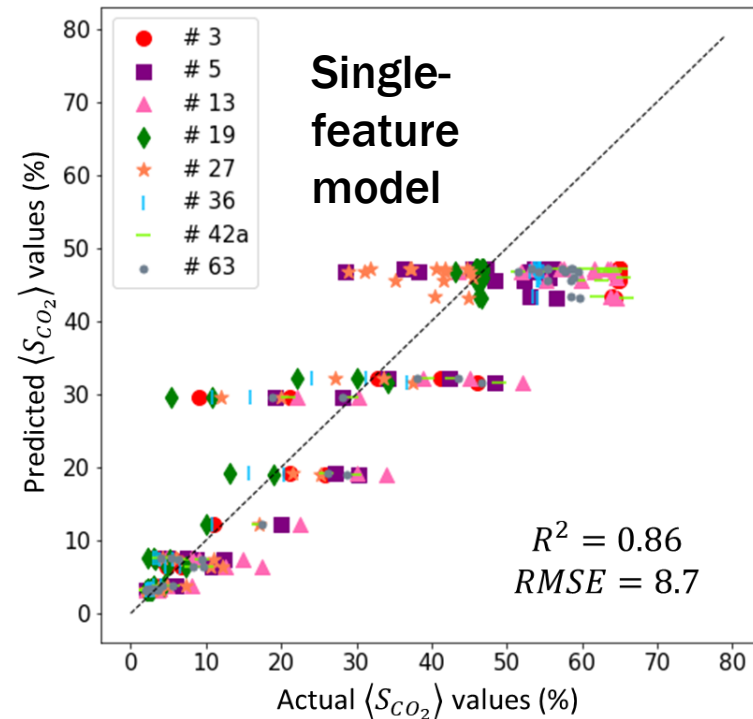
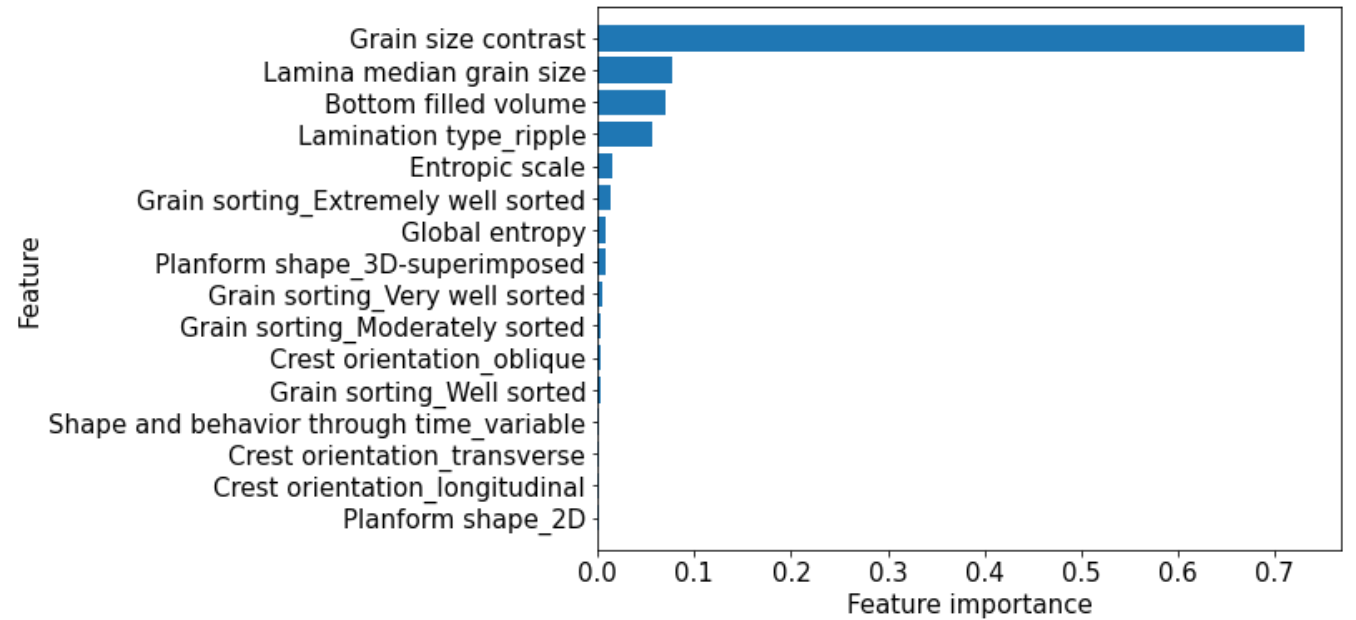
Validation: experiments



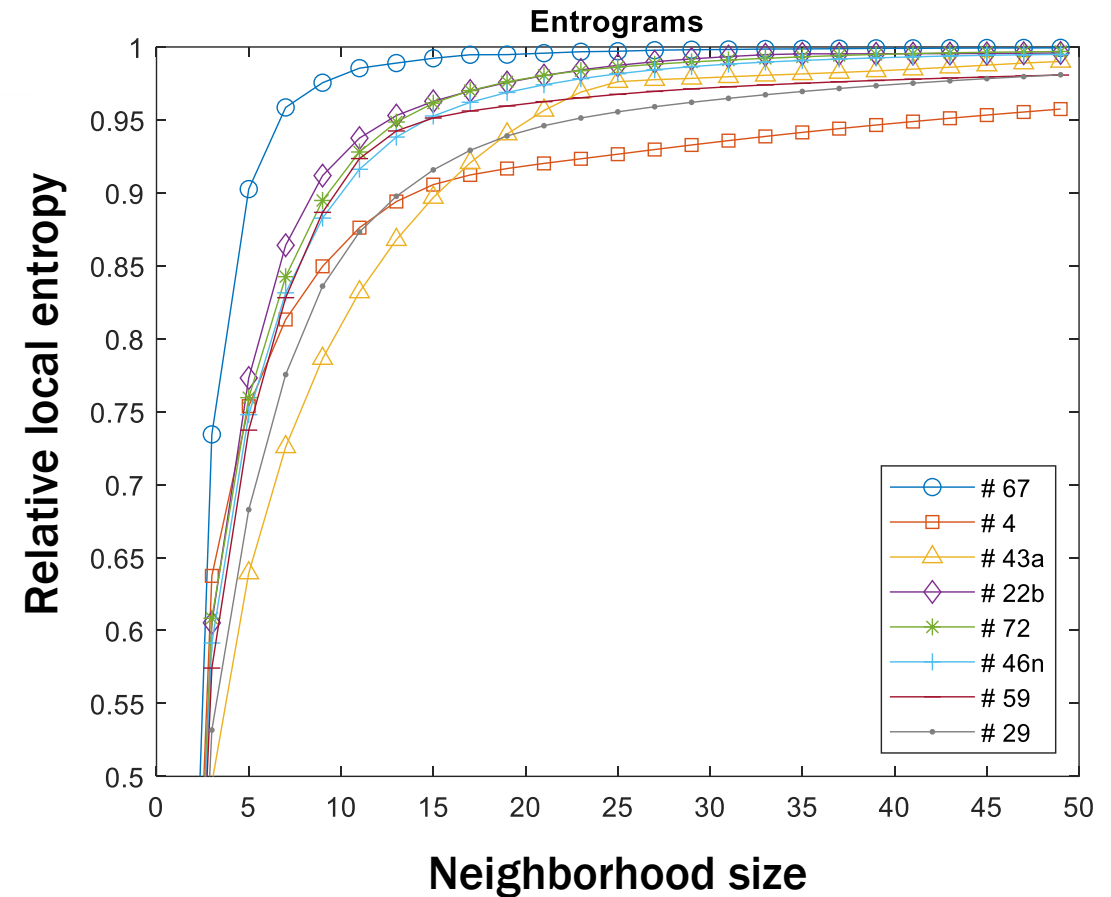
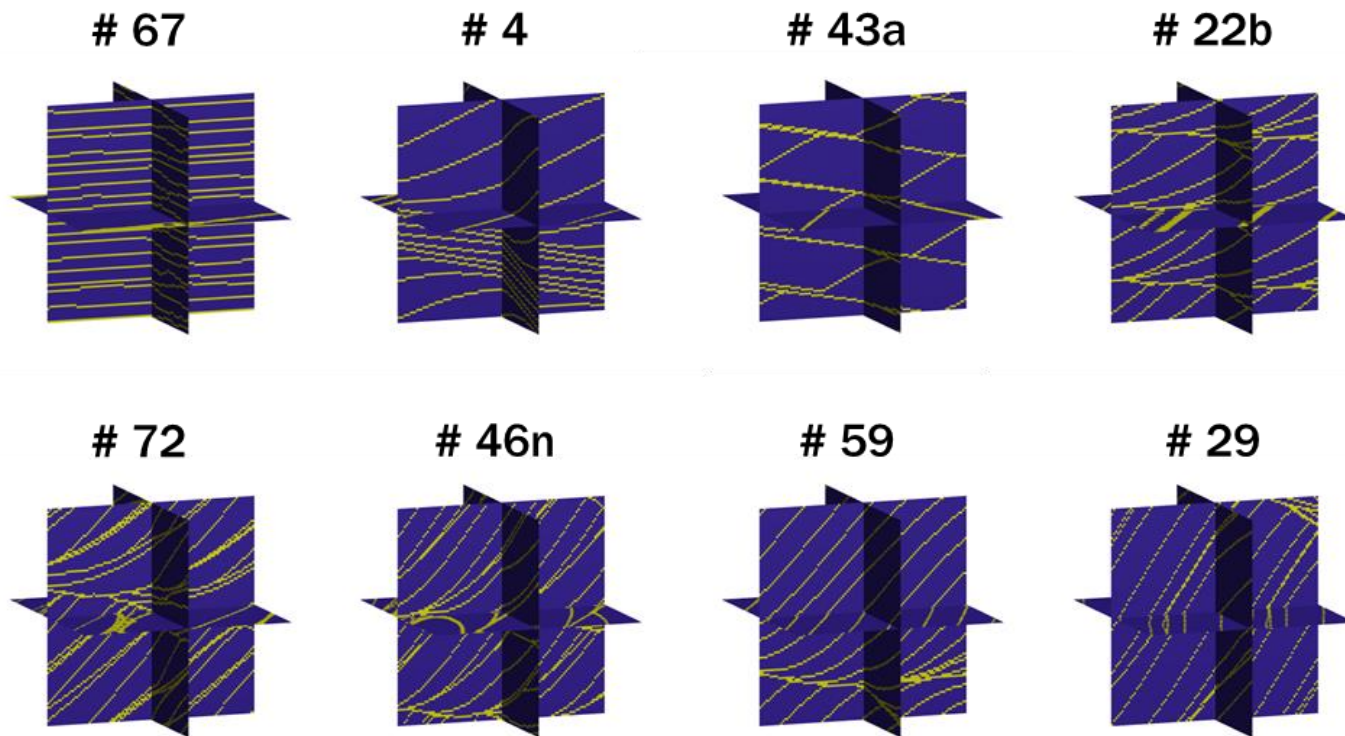
CO₂ saturation



Conclusions



Important features: geological entropy and entrograms



Potential model use case: upscaling critical CO₂ saturation for heterogeneous domains

