Motivation

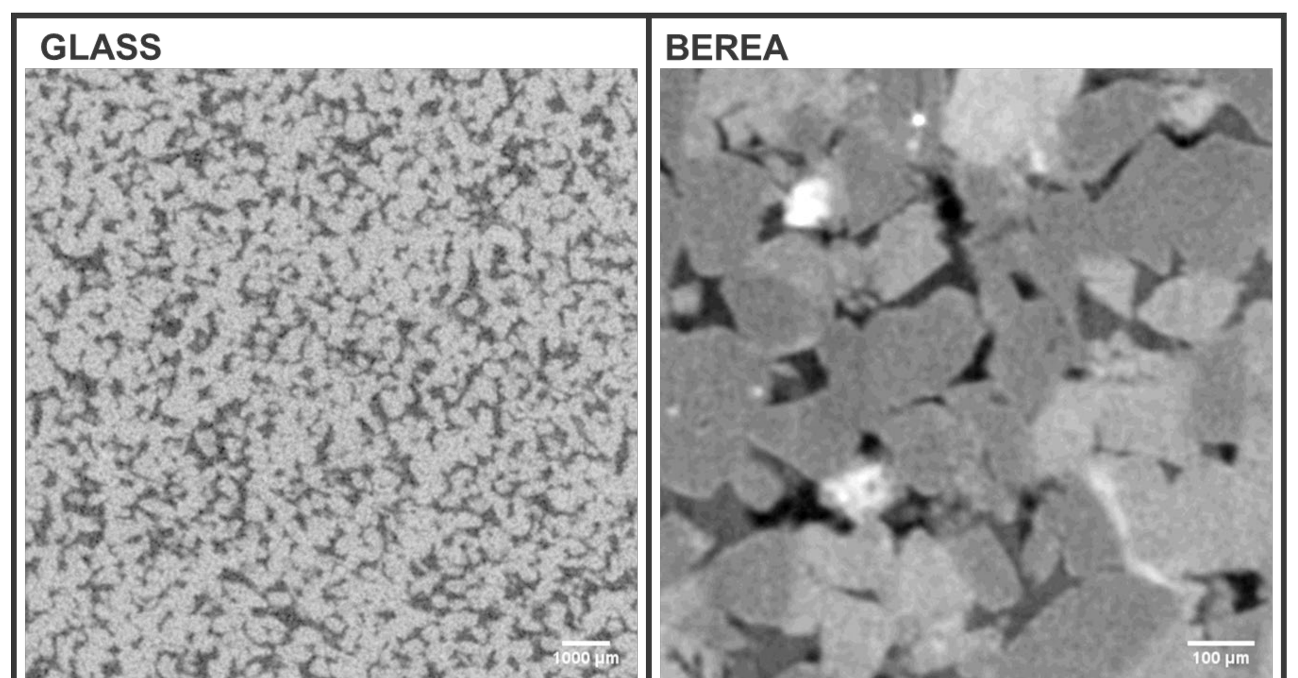
- Computed Tomography (CT) scanning enables µm scale interrogation of rock cores
- Segmentation of CT image features is necessary for quantitative analysis of these samples
- Manual segmentation is time consuming
- Machine learning (ML) methods can overcome this bottleneck
- Rapid CT segmentation is required for inclusion of pore-scale properties in up-scaled flow models

Research Goal

Compare multiple supervised and unsupervised ML techniques to a baseline produced collaboratively using user driven random forest classification techniques with iLastik. Use this base line segmentation to evaluate different techniques for accuracy and processing time.

Test Cases

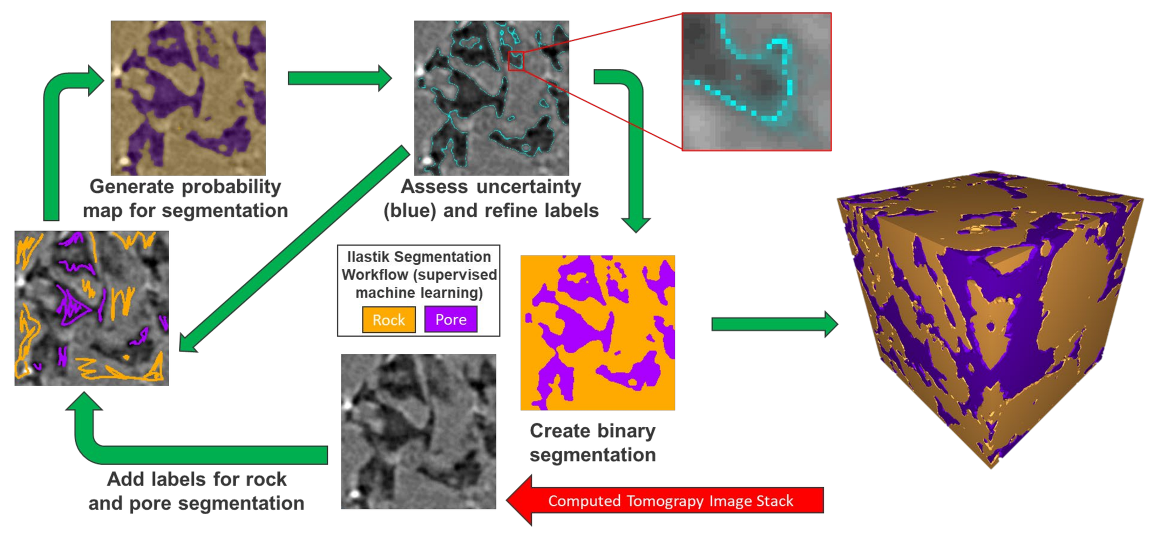
- 512-pixel image cubic volumes
- Two different CT scanners used to image cores with vastly different properties and heterogeneities
- Two samples selected for initial analysis
  - Homogenous – Sintered Glass
  - Heterogenous – Berea Sandstone



GLASS	
Resolution	25µm
Measured Porosity	33%
Measured Permeability	124.7mD

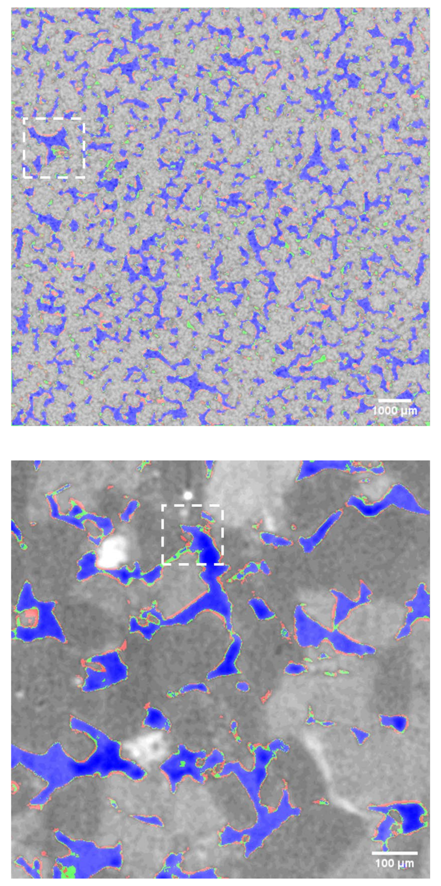
BEREA	
Resolution	1.7679µm
Measured Porosity	18.84%
Measured Permeability	425mD

Segmentation

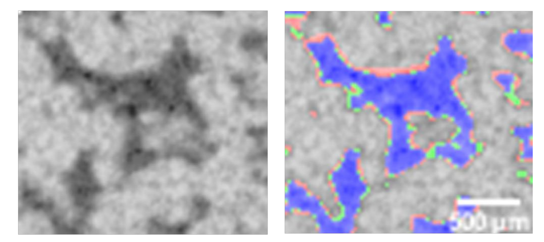


Glass	Porosity
NETL	24.76%
PSU	24.26%
EERC	28.44%
Avg ± SD	25.82 ± 2.28%
Experimental	33%

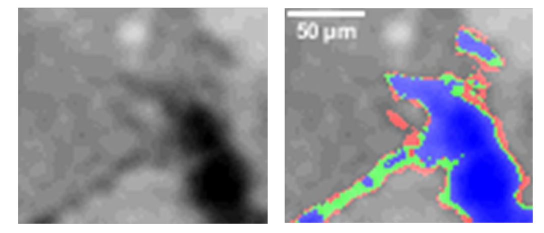
Berea	Porosity
NETL	18.33%
PSU	19.24%
EERC	15.18%
Avg ± SD	17.58 ± 2.14%
Experimental	18.84%

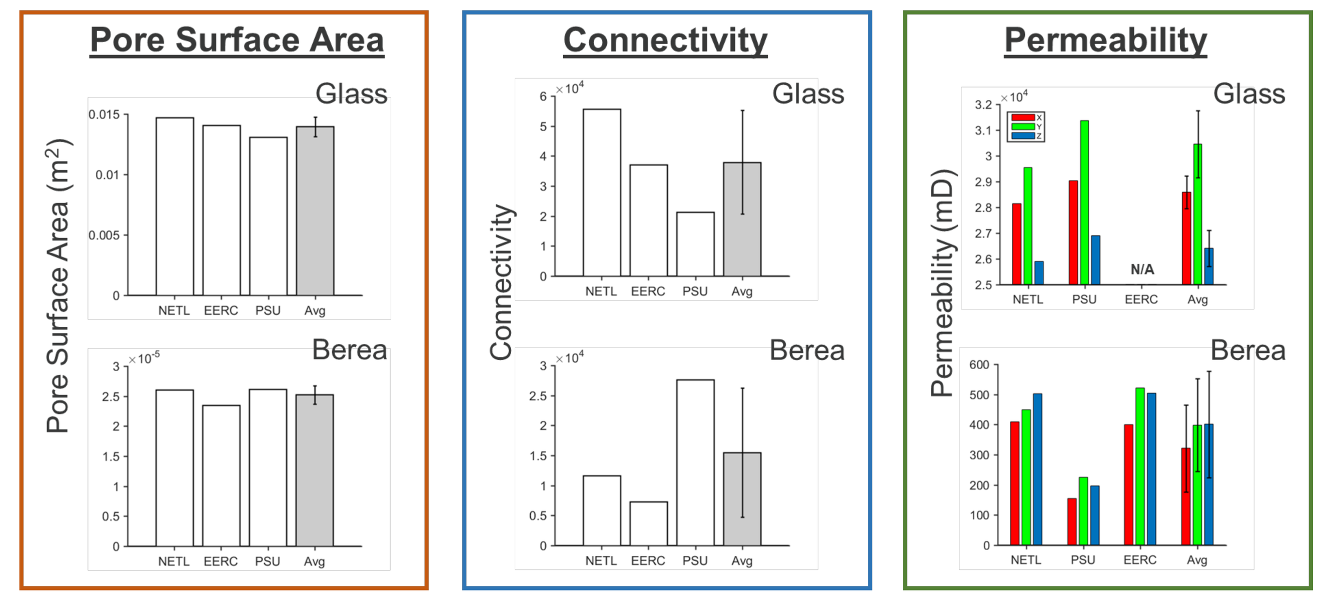


Pore Segmentation Agreement	% of all Pore Labels
Three Segmentations	68.64
Two Segmentations	11.47
Unique Pore Labels	19.89

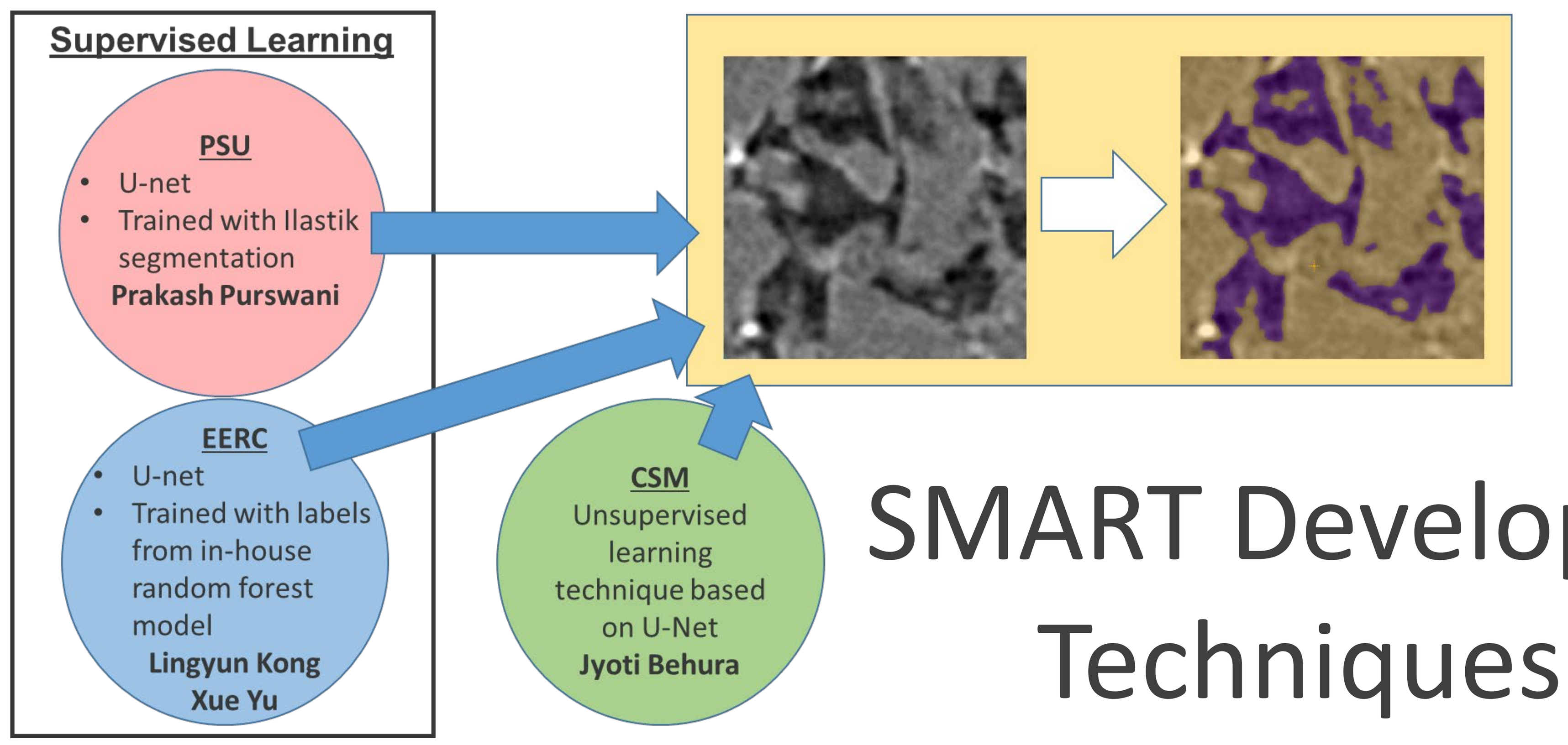


Pore Segmentation Agreement	% of all Pore Labels
Three Segmentations	67.24
Two Segmentations	13.08
Unique Pore Labels	19.68



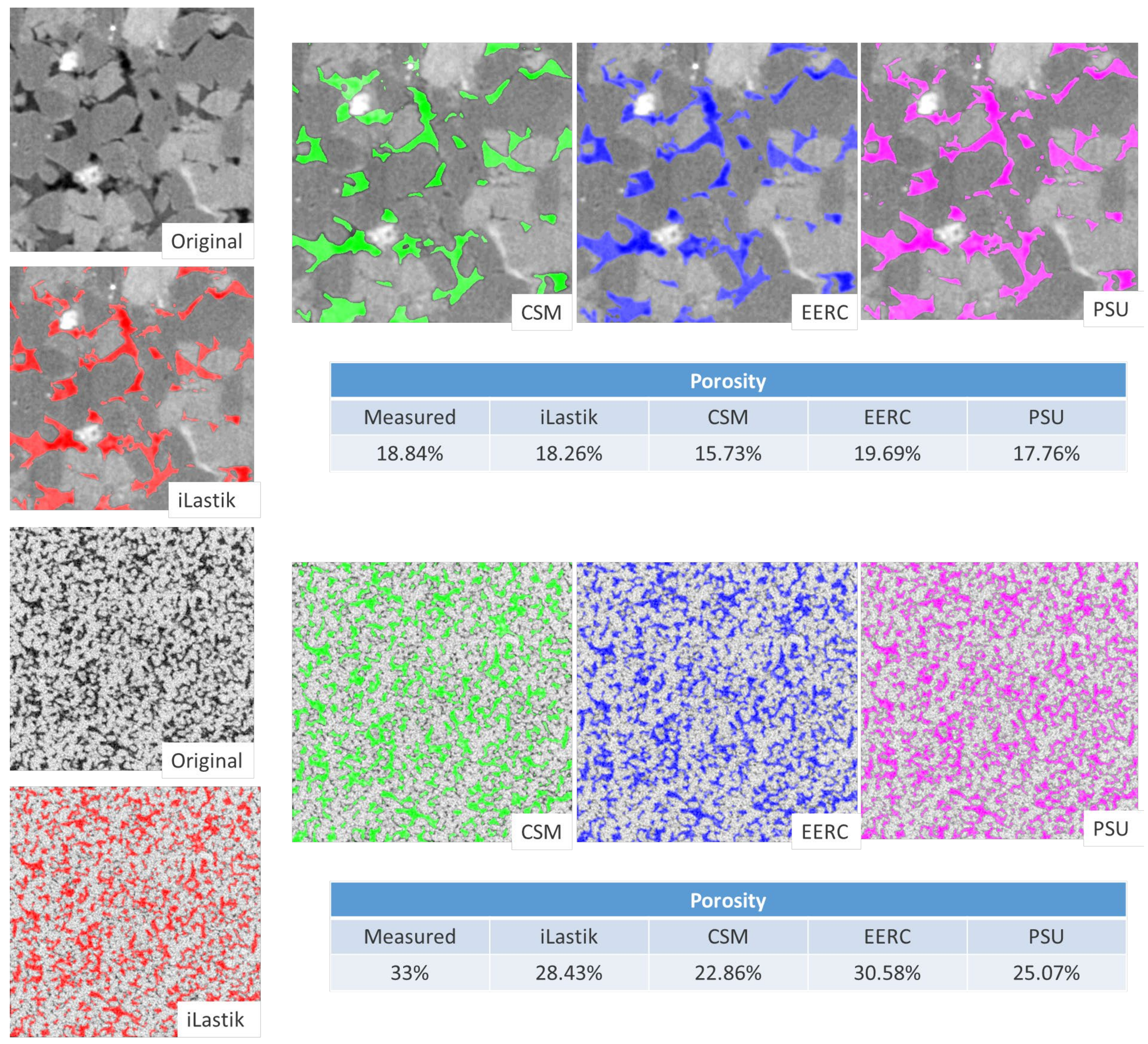


- Pore labeling varied between iLastik segmentations performed across labs, with porosity agreement ~70% between all three segmentations
- Connectivity varied more significantly in segmented volumes, and the resultant permeability estimates using an open-source Finite-difference method Stokes solver (FDMSS) highlights this variability



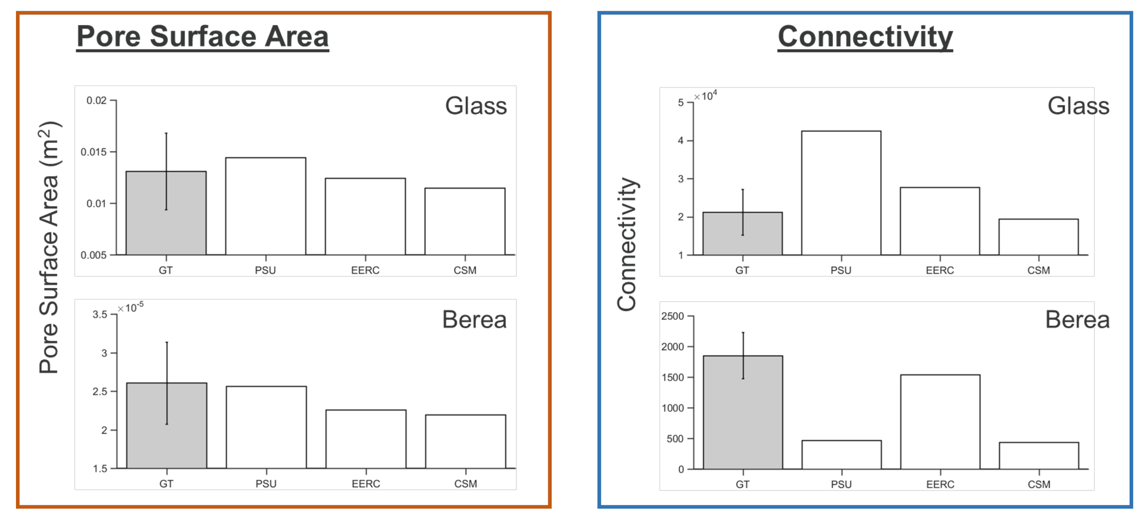
SMART Developed Techniques

Lab Comparisons



Porosity				
Measured	iLastik	CSM	EERC	PSU
18.84%	18.26%	15.73%	19.69%	17.76%

Porosity				
Measured	iLastik	CSM	EERC	PSU
33%	28.43%	22.86%	30.58%	25.07%



Summary

- The use of advanced ML techniques developed by the SMART labs have a similar porosities to the random forest classification technique but tend to run faster and with less direct expert input.
- Incorporation of these methods in the workflow to upscale properties to grid blocks and field scale models is being explored in parallel with efforts to improve the speed, repeatability, and accuracy of the segmentation techniques.

References

Gerke, K.M., Vasilyev, R.V., Khirevich, S., et al. **Finite-difference method Stokes solver (FDMSS) for 3D pore geometries: Software development, validation and case studies**. Comp & Geosciences, 114: 41-58 (2018).

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