



# Nano-porous Chalk Rock Construction using Deep Convolutional Generative Adversarial Neural Networks



Sung Eun Kim<sup>1</sup>, Jonghyun Harry Lee<sup>1</sup>, Sangwoo Shin<sup>2</sup>, and Hongkyu Yoon<sup>3</sup>

<sup>1</sup>Civil and Environmental Engineering, University of Hawaii at Manoa, Honolulu, HI, USA; <sup>2</sup>Mechanical Engineering, University of Hawaii at Manoa, Honolulu, HI, USA; <sup>3</sup>Geomechanics Department, Sandia National Laboratories, Albuquerque, NM, USA

## Motivations

- **Plenty of pores at sub-micron scale** (nano-pores) in shales and carbonate rocks have become increasingly important for emerging problems such as unconventional gas and oil resources, geologic storage of CO<sub>2</sub> and nuclear waste disposal.
- **Characterizing pore structures of geomaterials** with small, complex pore networks is crucial for controlling and improving unconventional gas and oil recovery, enhanced oil recovery, and geologic sequestration of CO<sub>2</sub>.
- **Realistic reconstruction of pore structure** including topology and connectivity is key to improving the prediction accuracy of coupled geophysical and chemical processes in nano-porous materials.
- **Training image-based geostatistical method using deep learning** have gained attention in the reconstruction of pore networks for scientific geomaterial research.

## Objective

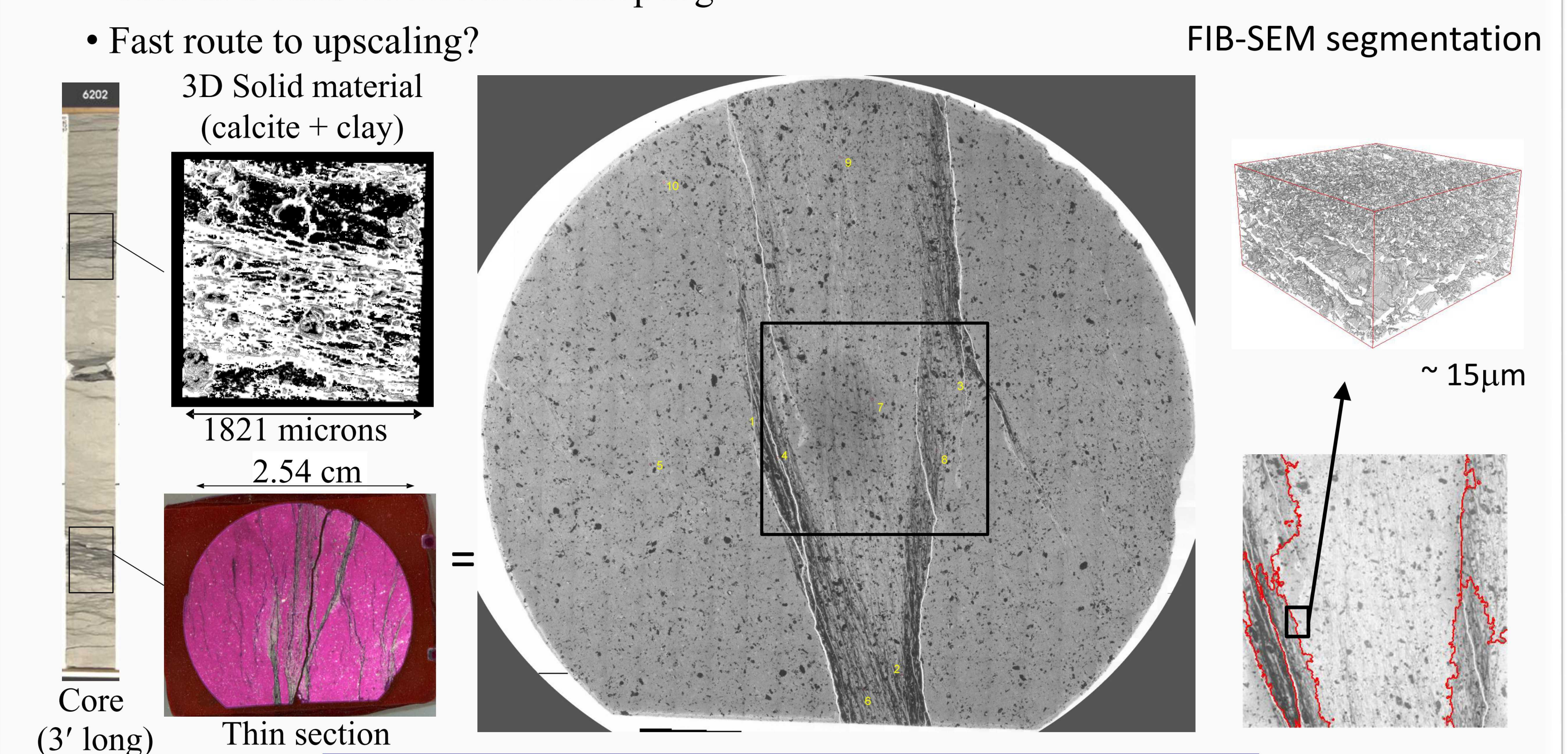
- Generate 3-D stochastic pore structures of micro-scale carbonate chalk based on Deep Convolutional Generative Adversarial Neural Networks (DCGANs) with realistic topology and connectivity of pore networks

## Multiscale Analysis of Pore Structure

- Characterization of pore structures, compositional distribution, and surface properties using multiscale imaging techniques (optical and confocal microscopy, x-ray microprobe, QEMSCAN, microCT, FIB-SEM, BIB-SEM, TEM, EDS)

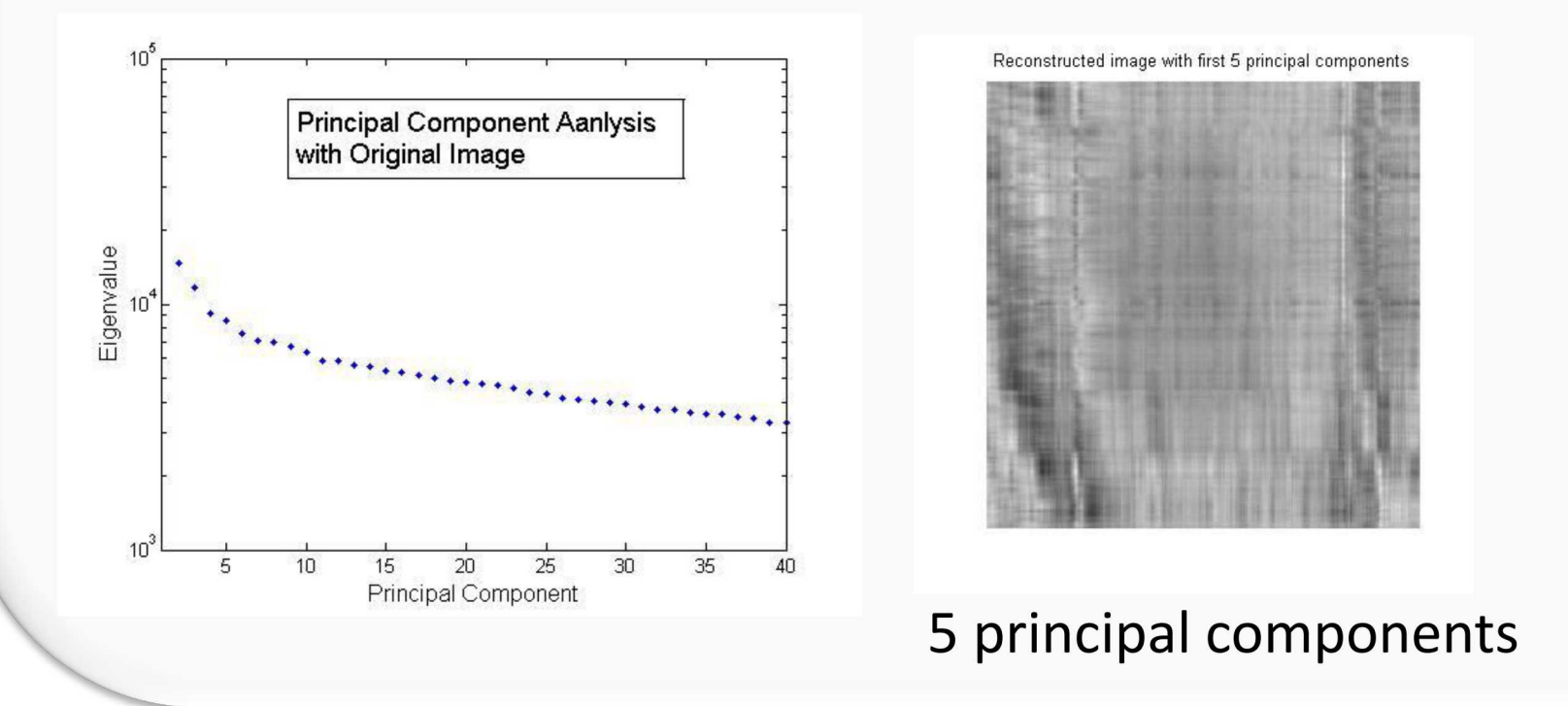
### Fluorescence mapping and feature classification

- Fluorescence detection of fluorochromes impregnated in pores
- Spectral segmentation algorithm [e.g., Kim et al. 2013]
- Used as a basis for FIB/SEM sampling
- Fast route to upscaling?

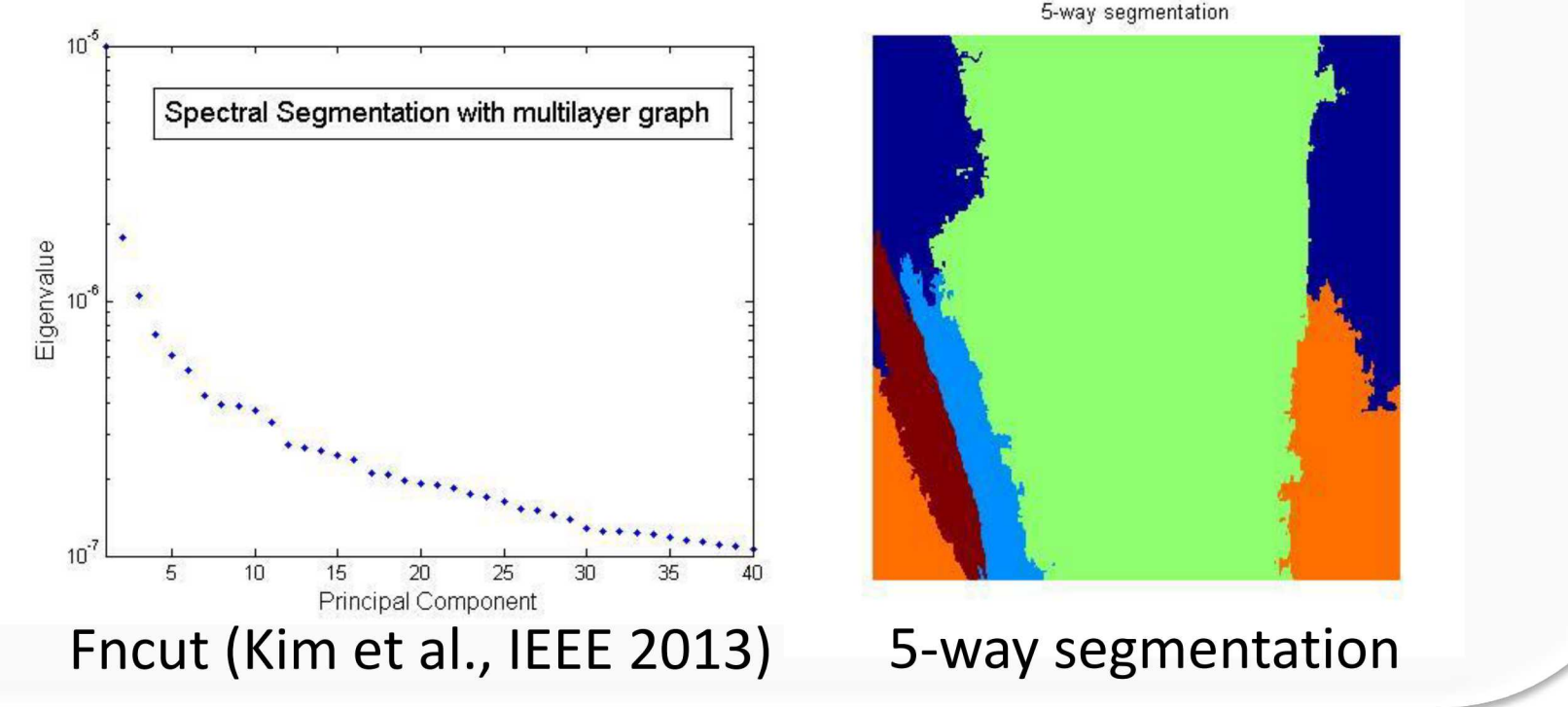


Rhodamine-B scan of thin section & FIB-SEM Locations

### Principal Component Analysis

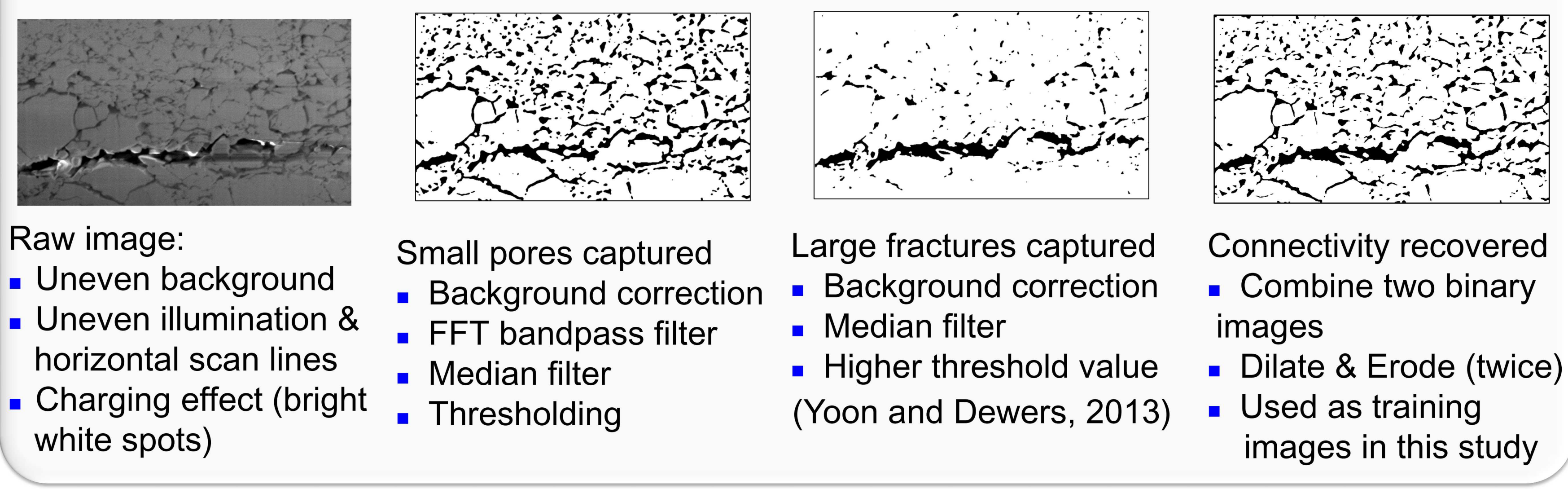


### Graph-based Spectral Segmentation



## Image Analysis for Training Images (TI)

- Image processing (segmentation) for the construction of training images



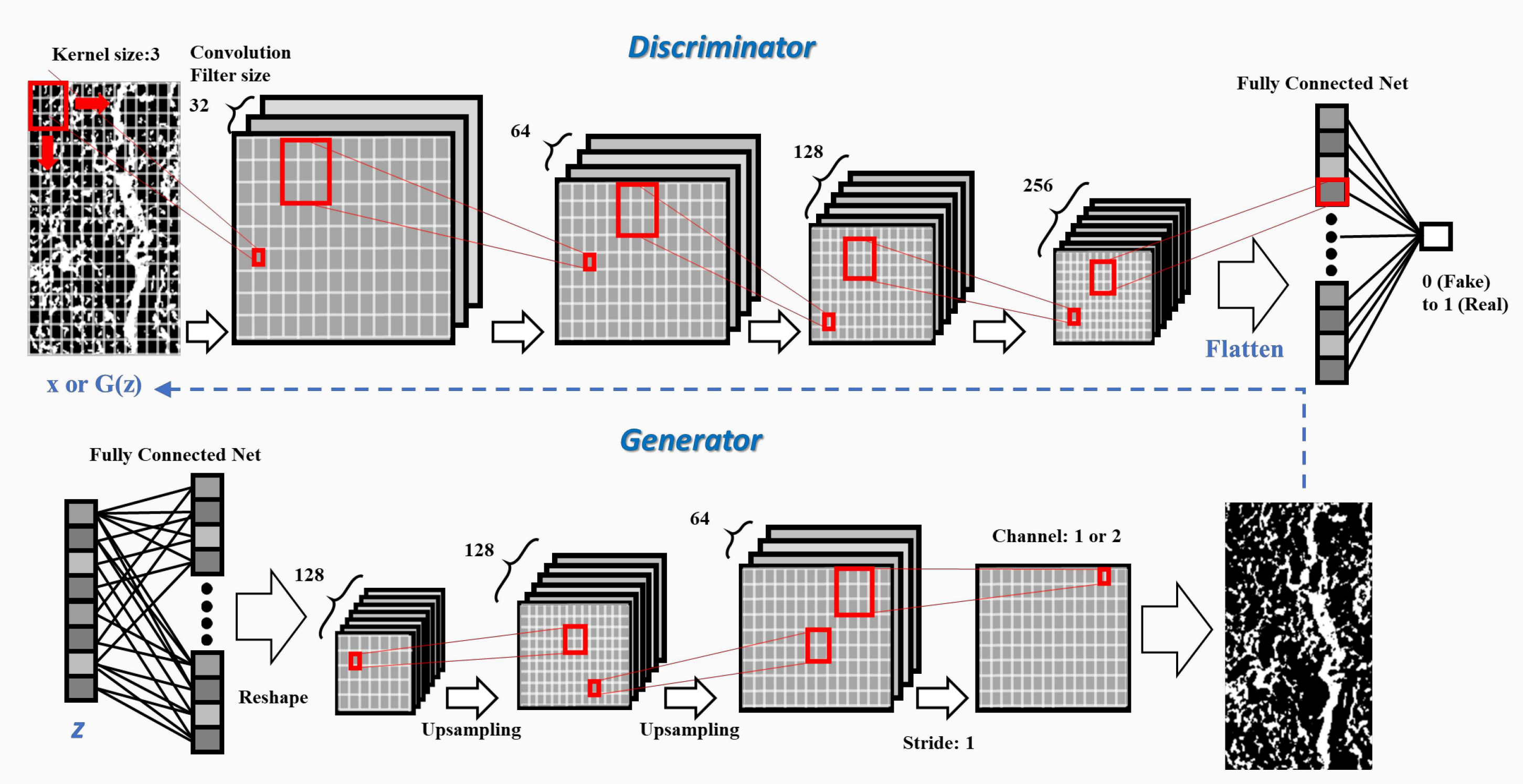
## Deep Convolutional Generative Adversarial Neural Network (DCGANs)

- Generative Adversarial Neural Networks (GANs)

- GANs are one of deep neural networks, which have a new framework for estimating generative models via adversarial two neural network models.
- G model (generator) – a generative model generates samples through learning to map from a latent space to a particular data distribution of real samples
- D model (discriminator) – a discriminative model determines whether given samples were a generated (fake) sample by G model or real samples.

- Architecture of D and G models in GANs

- Deep convolution neural network was adopted to develop the GANs in this study.
- Fully convolutional nature of GANs allows the stable training and the generation of large samples that contain the similar properties with computational efficiency (Radford et al., 2016).



- Training DCGANs

- DCGANs was trained by the Adam (adaptive momentum estimation) optimization algorithm with mini-batches of 32.
- The loss of DCGANs was estimated by binary cross-entropy function.

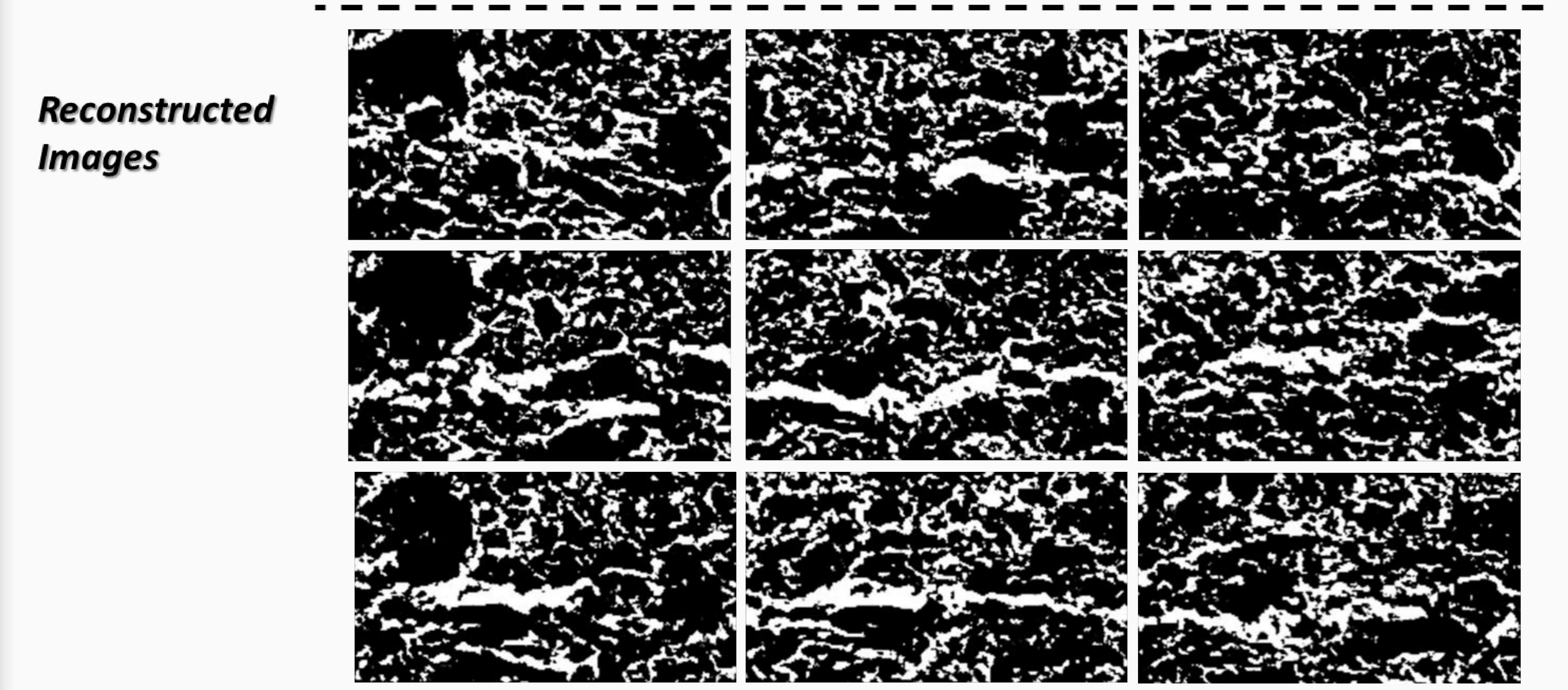
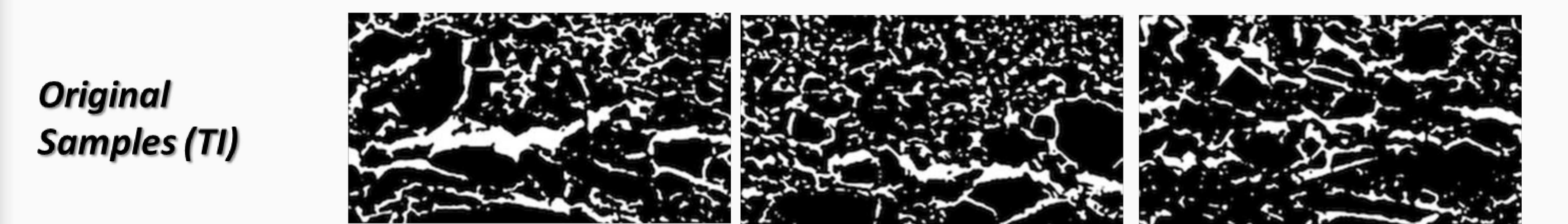
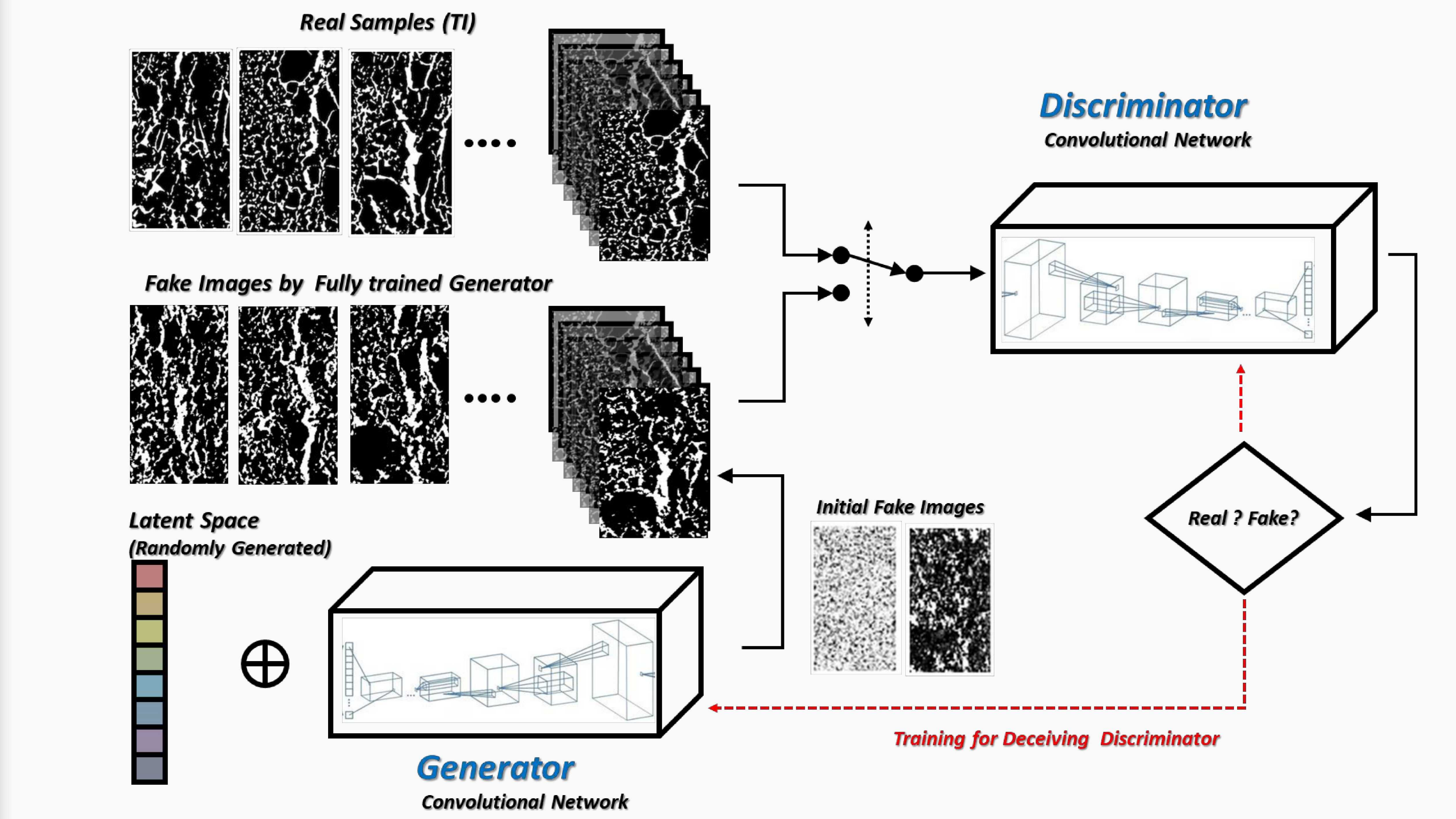
$$\text{Loss of D model: } \min J^{(D)} = -\frac{1}{2} \{ E_{x \sim P_{\text{Data}}(x)} [\log D(x)] + E_{z \sim P_z(z)} [\log(1 - D(G(z)))] \}$$

$$\text{Loss of G model: } \min J^{(G)} = -\frac{1}{2} E_{z \sim P_z(z)} [\log(D(G(z)))]$$

## Reconstruction of 3D Stochastic Pore Structure

- Pore structure generation using DCGANs

- DCGANs were trained and evaluated on Amazon AWS equipped with NVIDIA K80 GPUs, Intel Xeon E5-2686 v4 and 6256G RAM.



- The DCGANs successfully generated the pore structure with realistic connectivity of pore network.
- DCGANs is effective to avoid the artifact and can account for realistic features of complex pore networks.

## Research Directions

- Nonlinear dimension reduction will be applied to reduce the size of training images to represent the stochastic properties of chalk.
- Pore scale single- and multi-phase flow modeling and reactive transport modeling will be performed to assess the accuracy and efficiency of the proposed method.
- The proposed method will support microfluidics design for flow and transport experiments.

## References

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