IMPERIAL

Application of Machine Learning to Generate Single and Multiphase Pore-Scale Images

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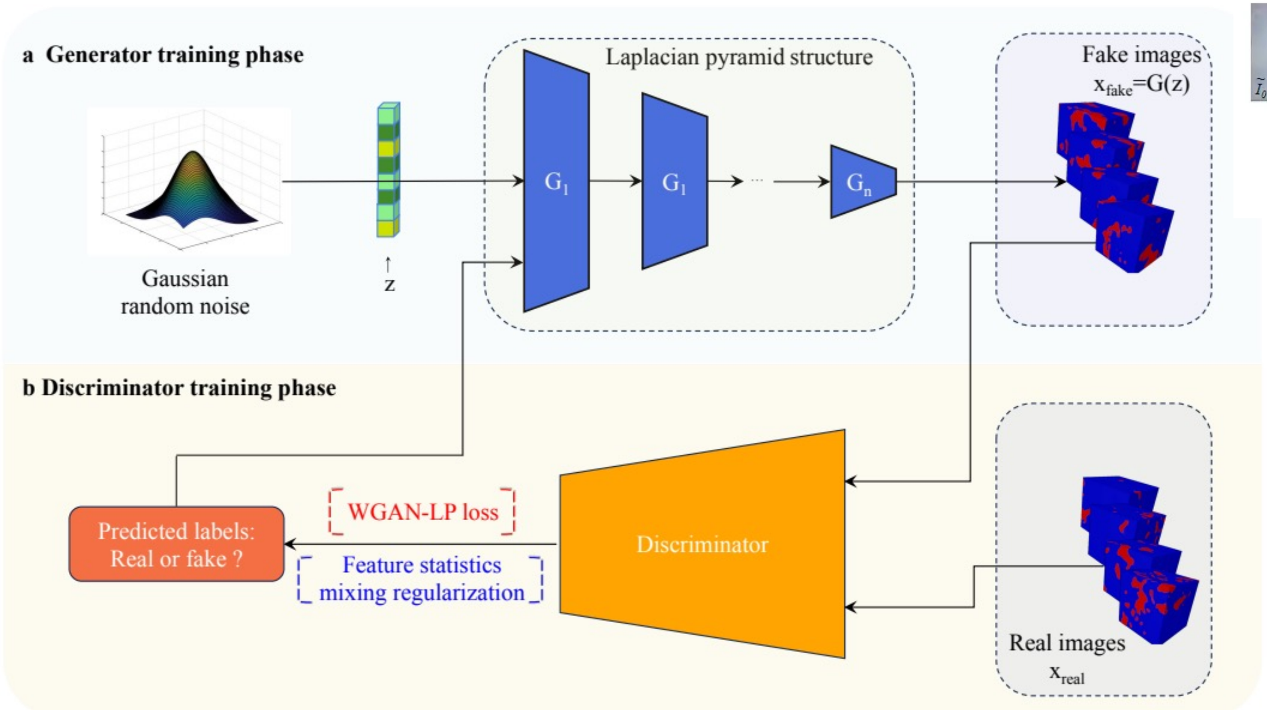
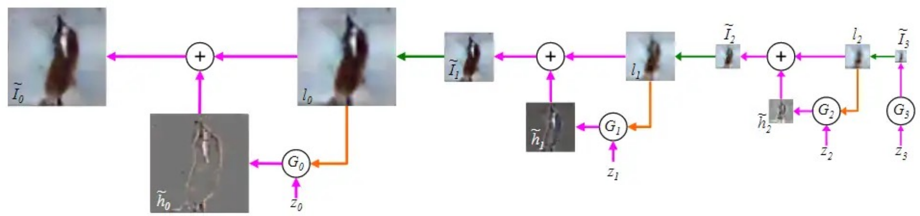
Imperial College London

Previous work: Use Improved Pyramid Wasserstein Generative Adversarial Networks (IPWGAN) to generate pore-space images





Laplacian pyramid generator

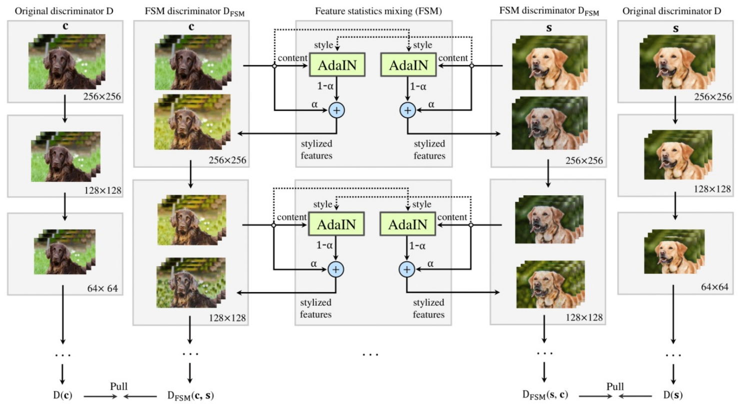


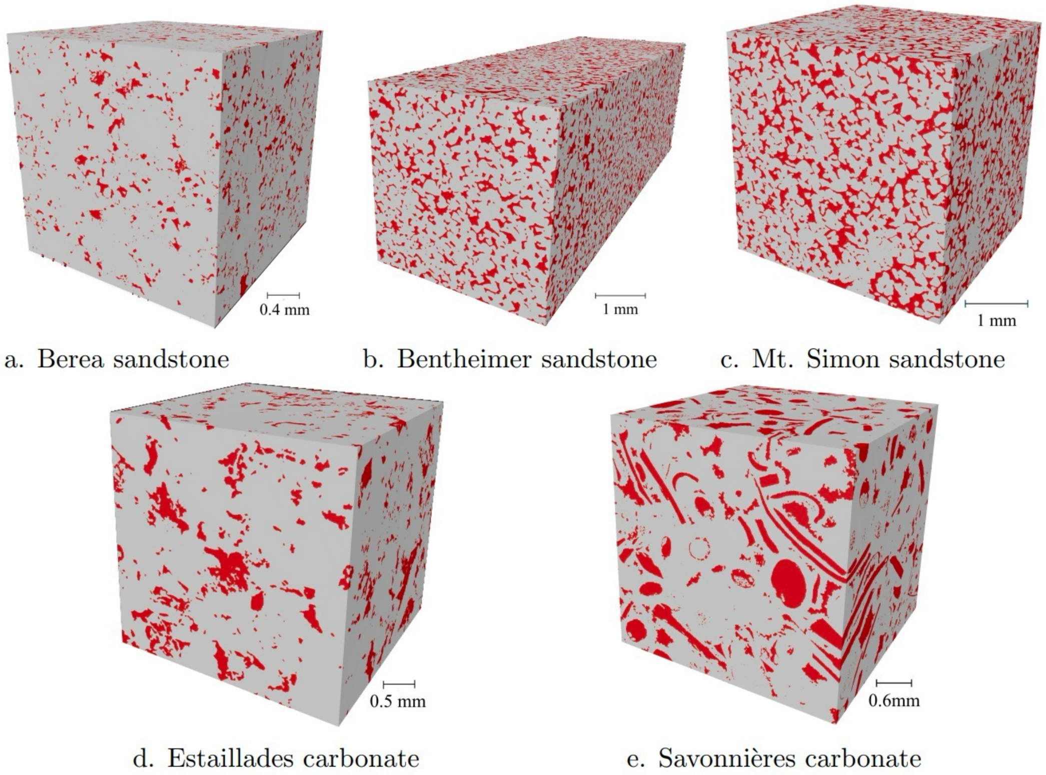
Figure 2. **Overview of feature statistics mixing regularization** (Section 3.2). Within the forward pass in the discriminator, we perturb features by applying AdaIN with a different sample. In deeper layers, the perturbations are applied recursively. A scalar $\alpha \sim$ Uniform(0, 1) moderates their strength. Then we enforce similarity between the original output and the perturbed one.

Feature statistics mixing regularization (FSMR)

https://github.com/ImperialCollegeLondon/IPWGAN

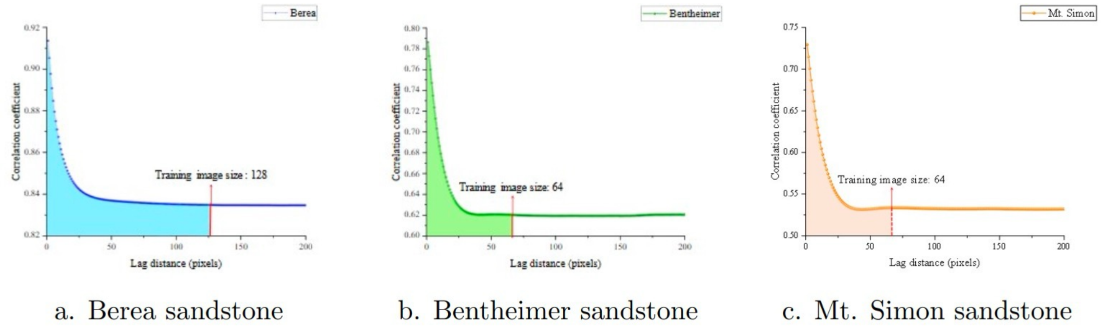
Zhu, L., Bijeljic, B., & Blunt, M. J. (2024). Generation of heterogeneous pore-space images using improved pyramid Wasserstein generative adversarial networks. Advances in Water Resources, 104748.

Use IPWGAN to generate pore-space images



a. Berea sandstone b. Bentheimer sandstone c. Mt. Simon sandstone

d. Estaillades carbonate e. Savonnières carbonate



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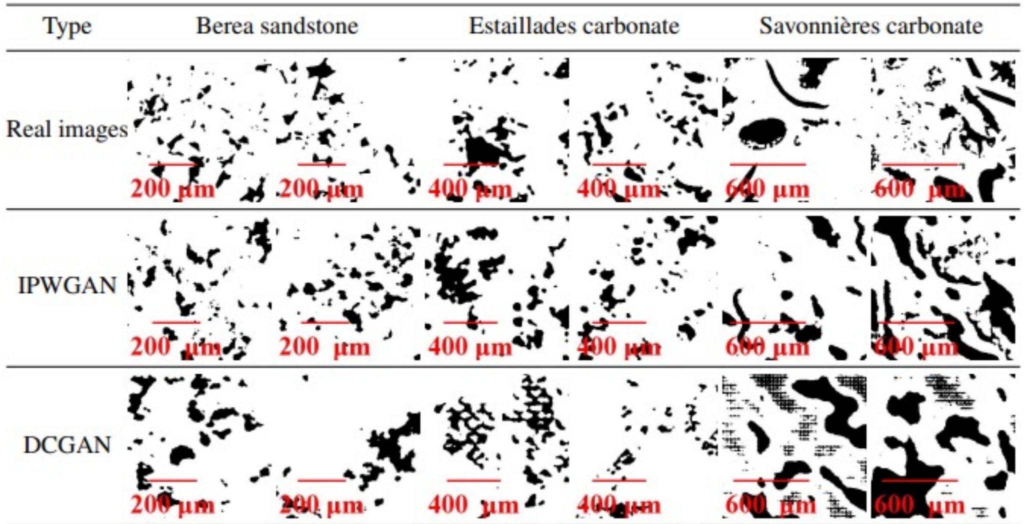
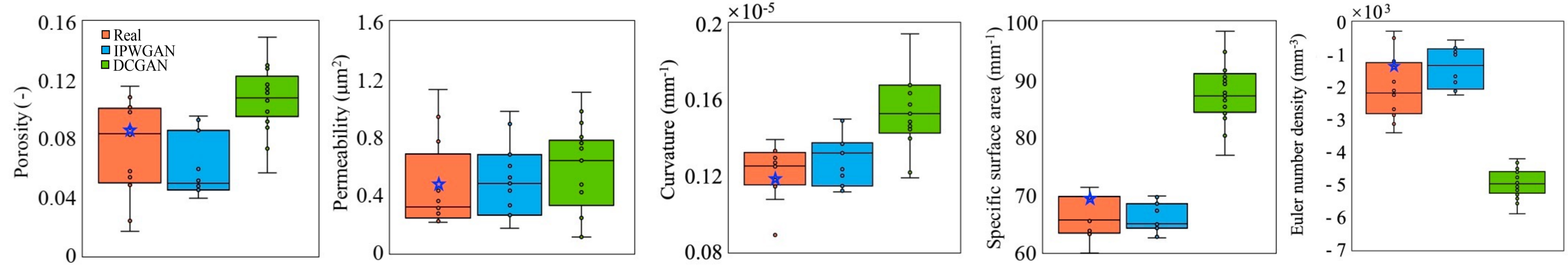
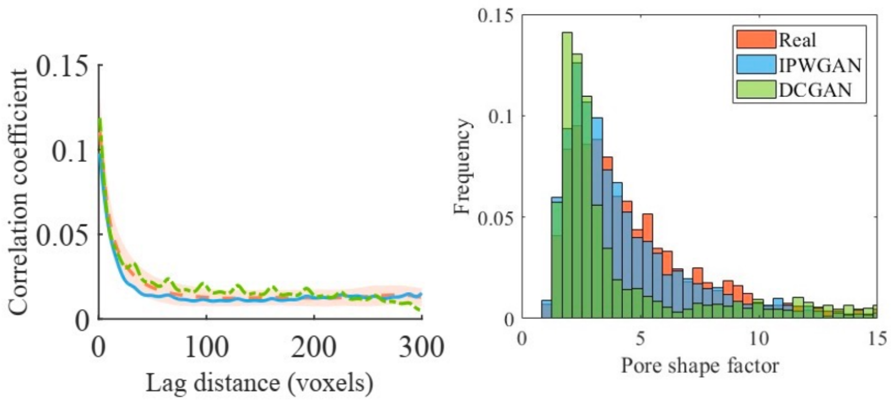


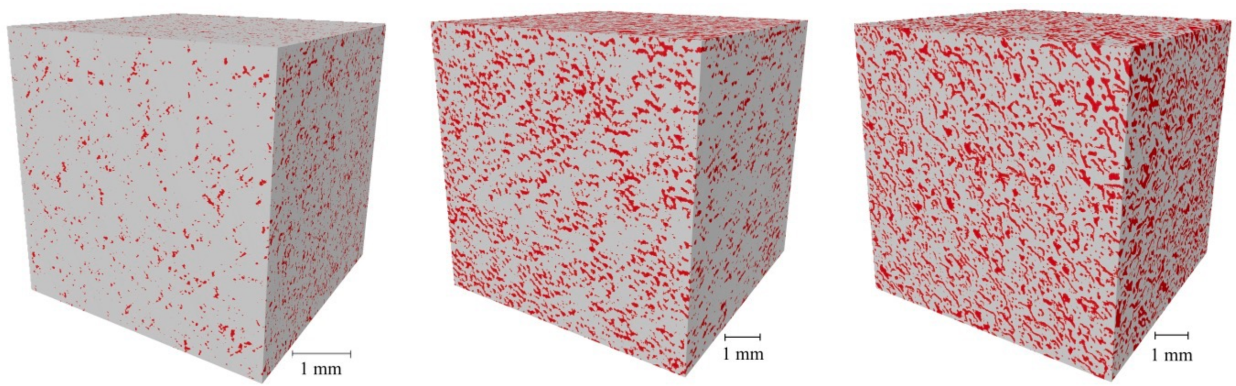
The study of rock sample generation has made it possible to obtain virtual digital rocks with arbitrary scales and feature shapes. (Completed using Imperial high-performance computing)

Zhu, L., Bijeljic, B., & Blunt, M. J. (2024). Generation of heterogeneous pore-space images using improved pyramid Wasserstein generative adversarial networks. Advances in Water Resources, 104748.

Use IPWGAN to generate pore-space images







a. Berea $2{,}200^3$ b. Estaillades $2{,}200^3$ c. Savonnières $2{,}200^3$

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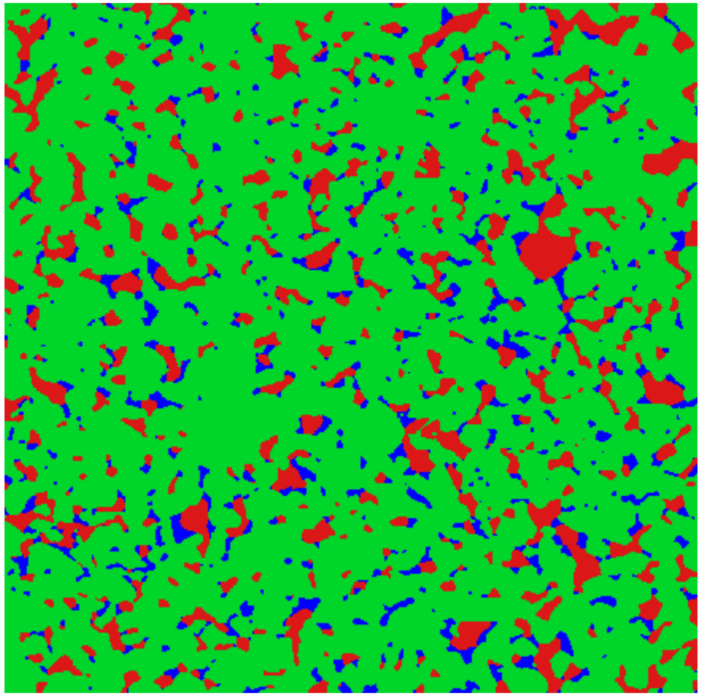
Generate multiphase fluid pore-scale images

Why?

- Generate images of both the pore space and the fluids within.
- Have pore-scale imaging experiments for training.
- Can be used as a basis for simulation to determine relative permeability and capillary pressure.



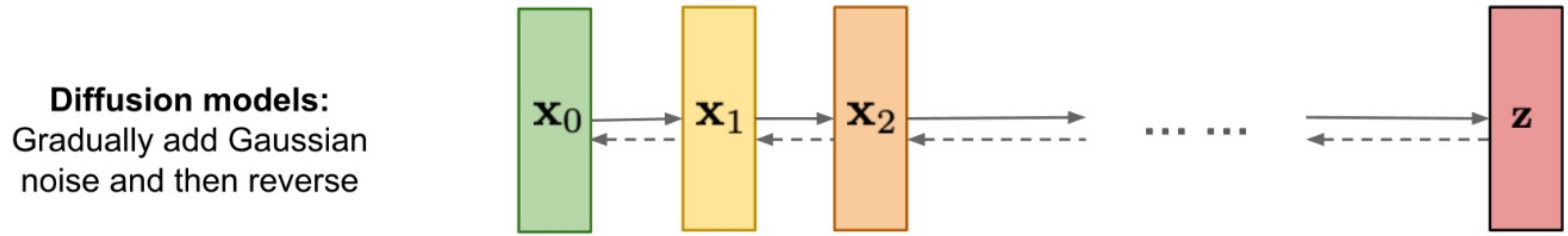
Data: Bentheimer Sandstone (Fw = 0.15)

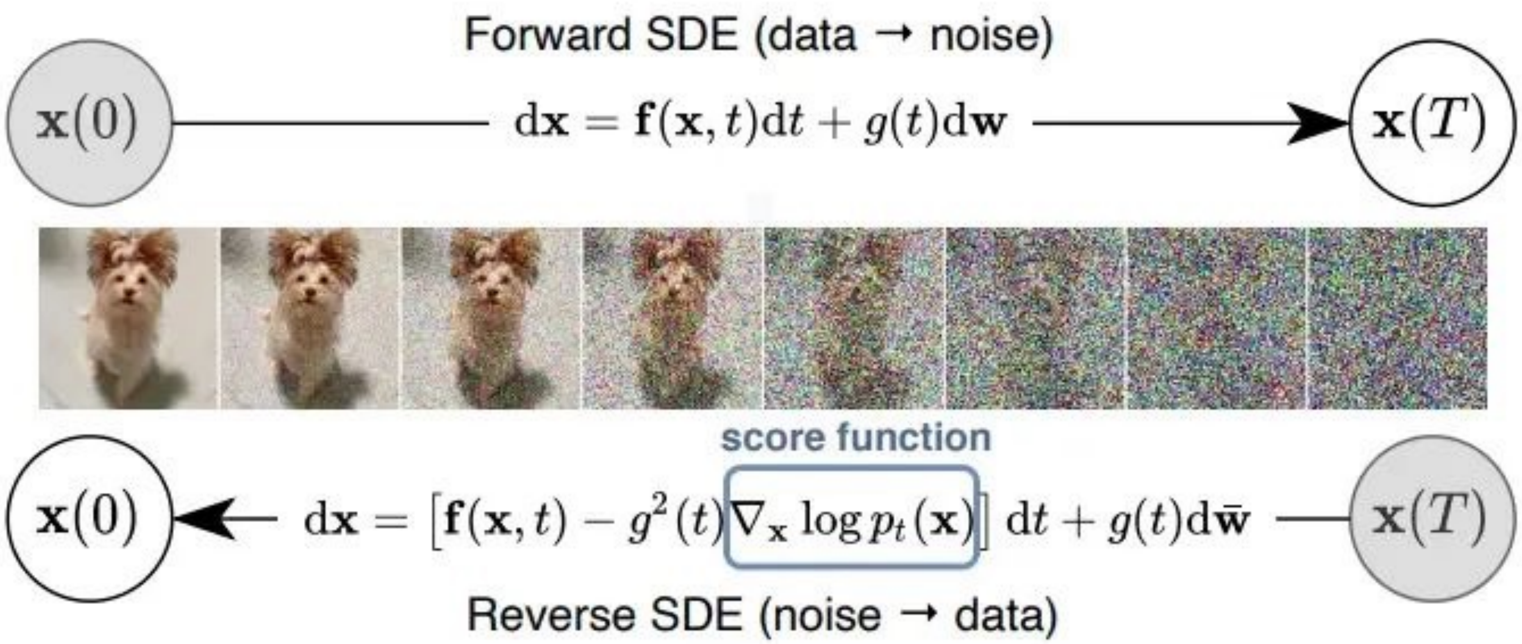
(Voxel size: 3.58 μm, 1000×1000×3600)

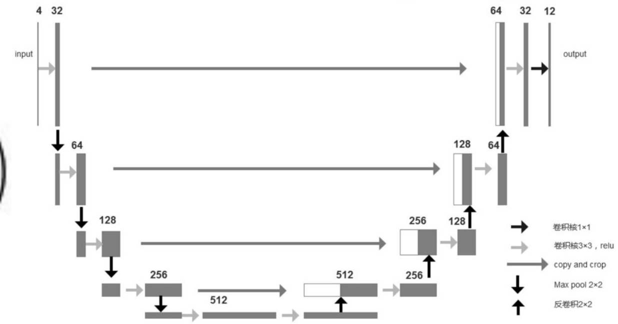
Red: oil; Blue: brine; Green: matrix.

Lin, Q., Bijeljic, B., Pini, R., Blunt, M., Krevor, S. Imaging and measurement of pore-scale interfacial curvature to determine capillary pressure simultaneously with relative permeability. Water Resources Research. 2018.

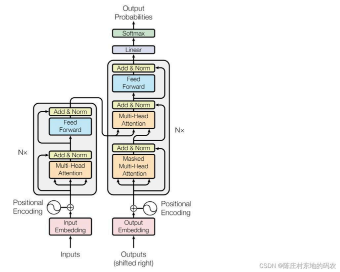
Diffusion models





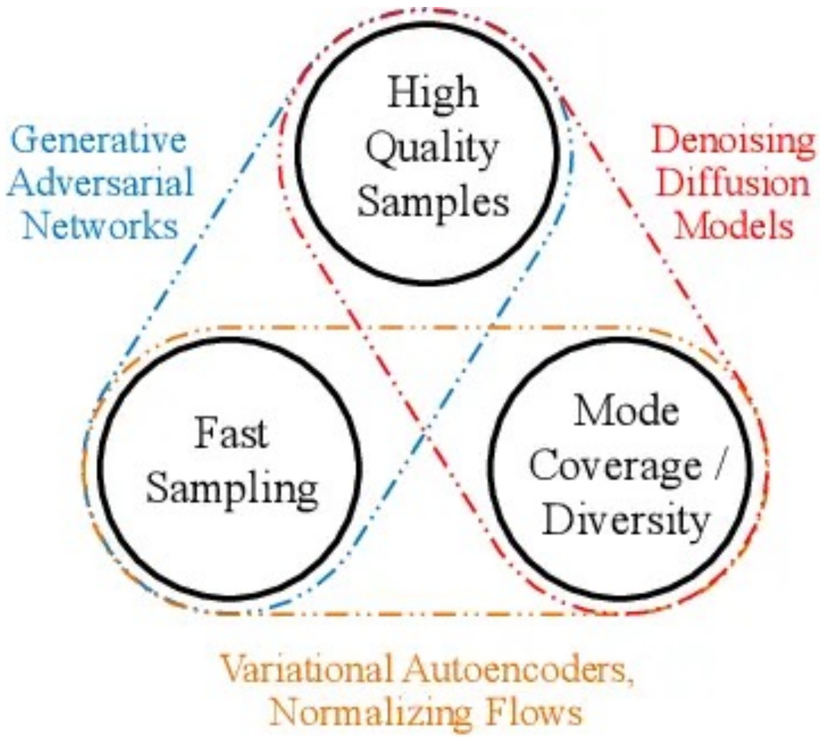


Base model: U-net (✅)



Base model: Transformer

Diffusion models

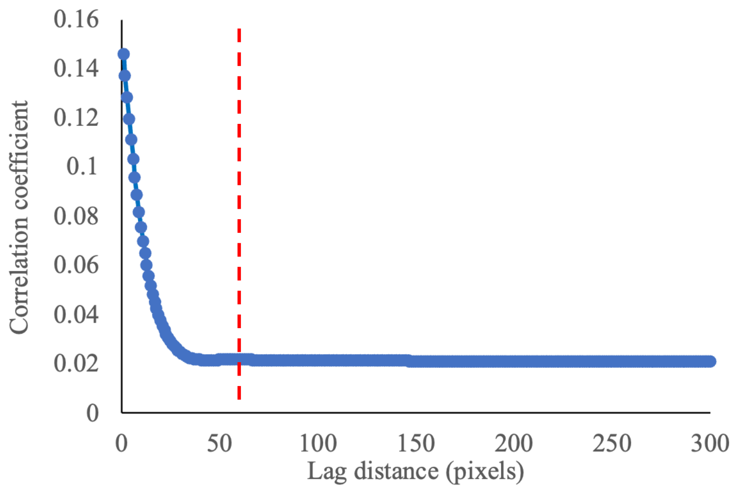


	Diffusion Models	Generative Adversarial Networks
Image quality	Excellent	Fine
Parameter Quantity	Fine	Excellent
Scalability	Fine	Excellent
Advantageous Reasons	Gradually add/remove the properties of noise, only learn large-scale structures, and do not introduce inductive bias	The dynamic confrontation between the generator and the discriminator avoids the Markov chain learning mechanism and eliminates the need for inference during the learning process.
Advantages or Benefits	Better interpretability, high quality generated	Fast sampling speed and flexible design framework
Disadvantages or Drawbacks	Large number of diffusion steps results in slow sampling	Poor interpretability and prone to model collapse

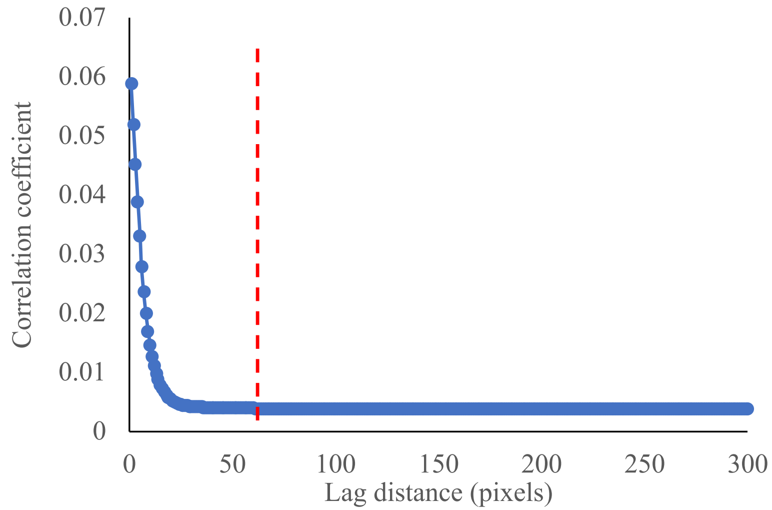
The generation of multiphase fluid pore-scale images involves the pores and the shapes and relationships between the two-phase fluids, which requires higher diversity and authenticity.

In order to speed up the generation, we chose Denoising Diffusion Implicit Models (DDIM)

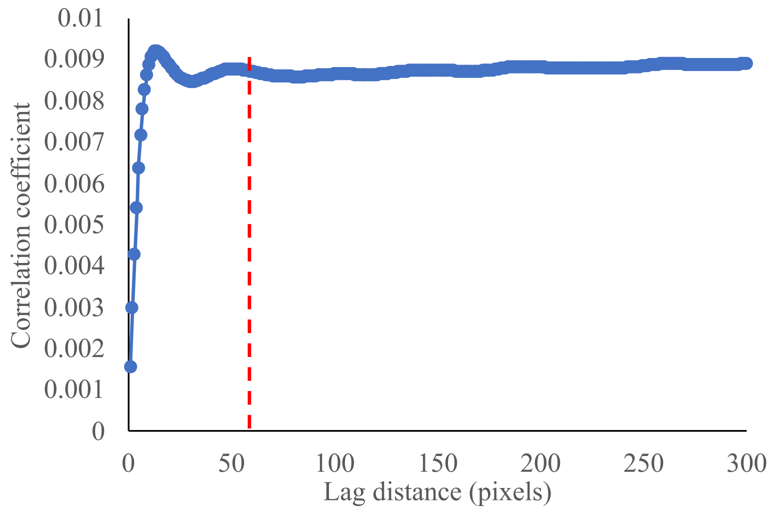
Data



Two-point correlation function (pore)



Two-point correlation function (brine)



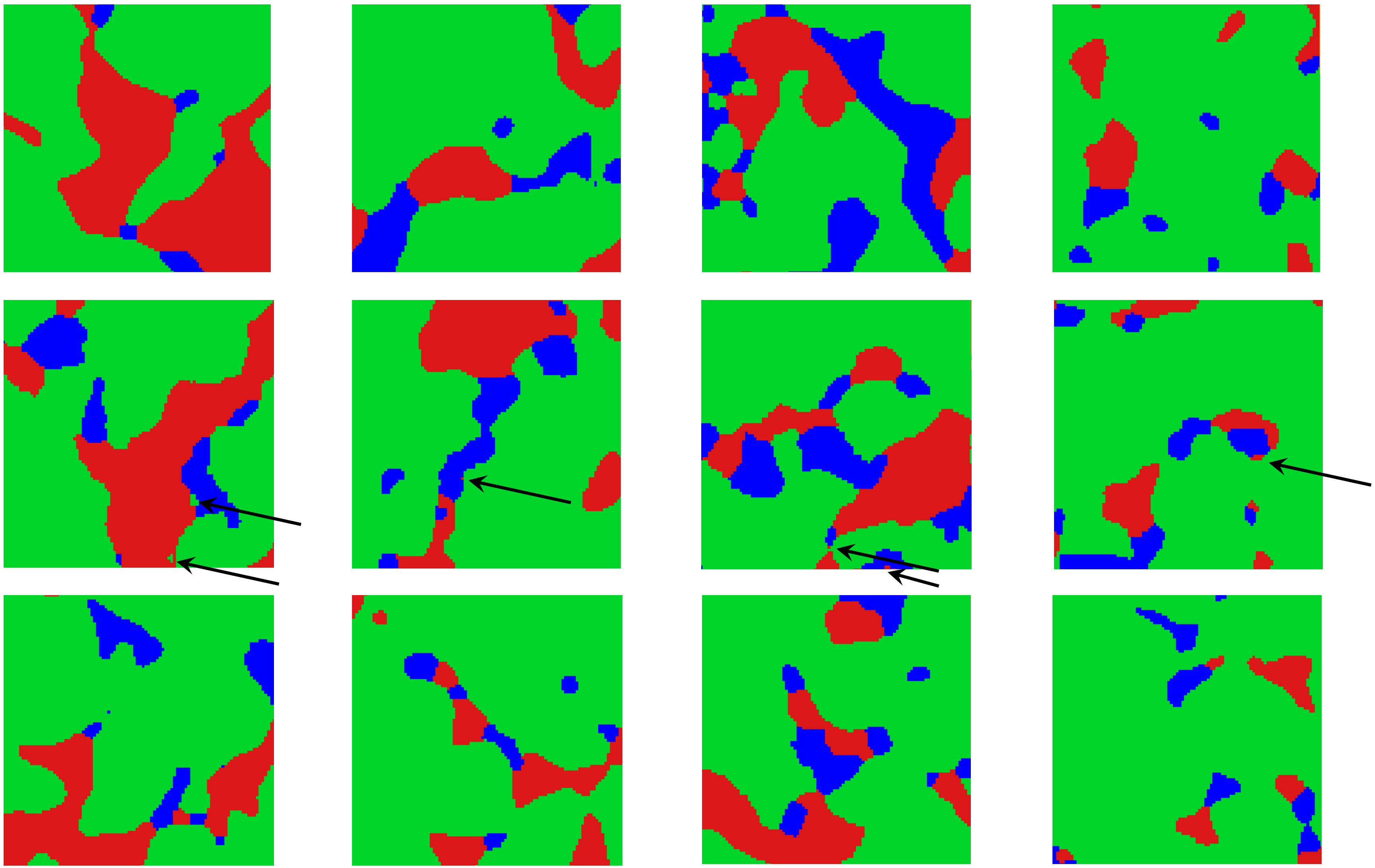
Two-point cross-correlation function (oil-water)

The probability of the two points being "oil" and "water" respectively at any distance

① The entire image can be divided into several sub images for model training

② we can choose 64 voxel as training image. Train dataset include 13,000 data.

Results: visualization of 2D cross-sections of 3D images (size: 96^3)

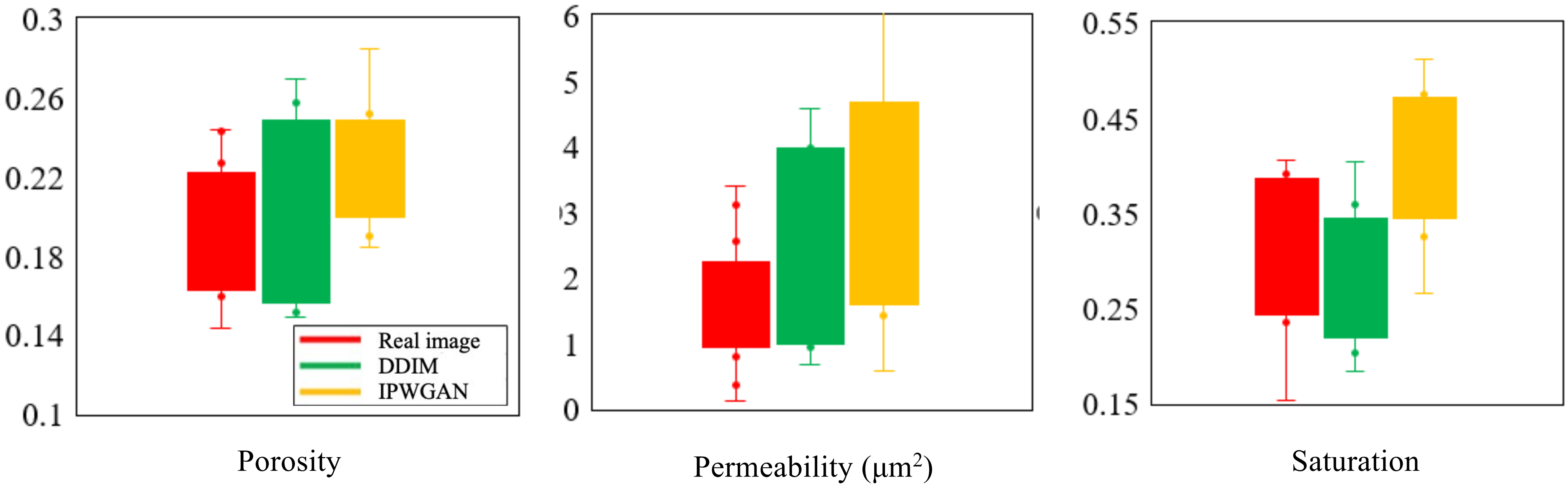


Real wet image

IPWGAN wet image

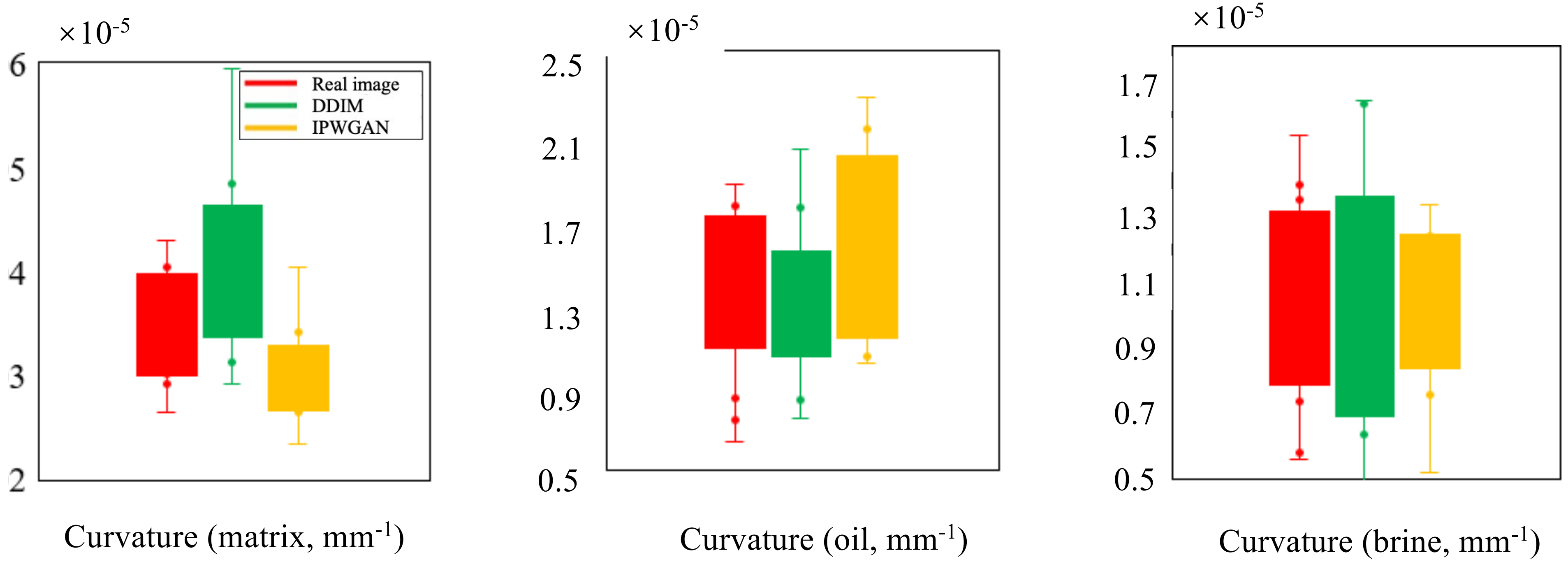
DDIM wet image

Results: Porosity, permeability and saturation parameters



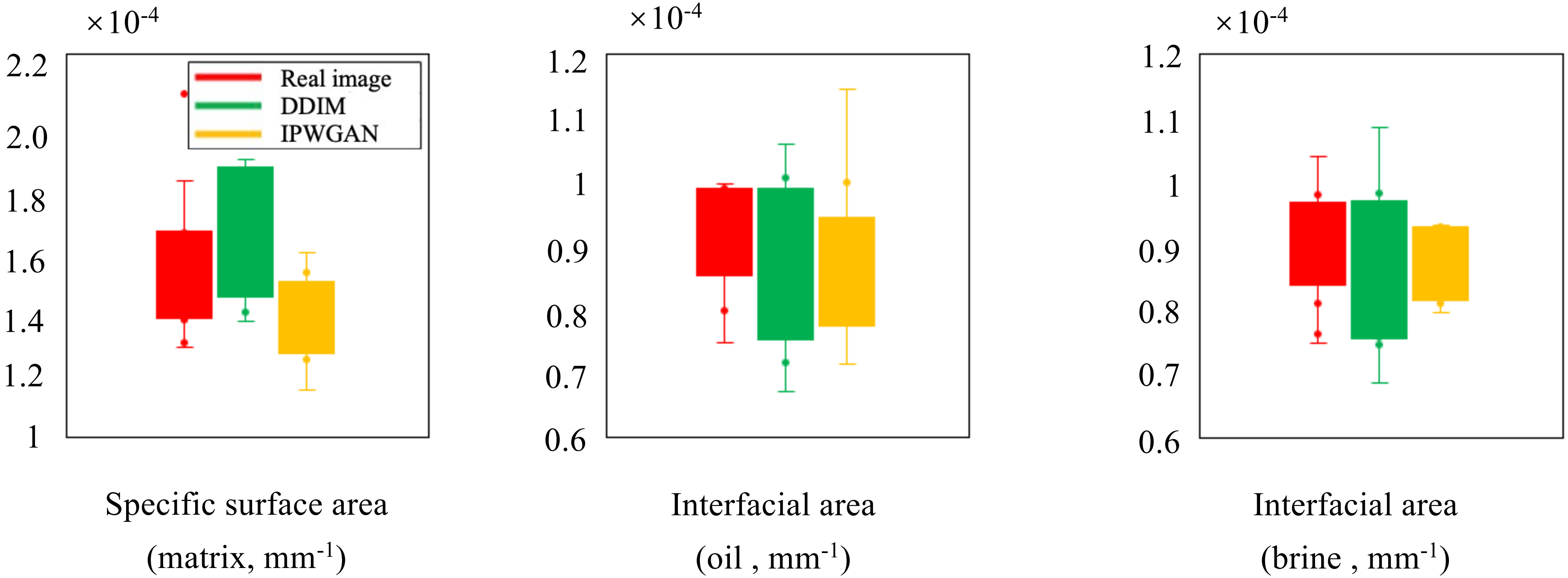
Red: Real image, Green: DDIM, Yellow: IPWGAN. Image size: 96 cubes

Results: Curvature



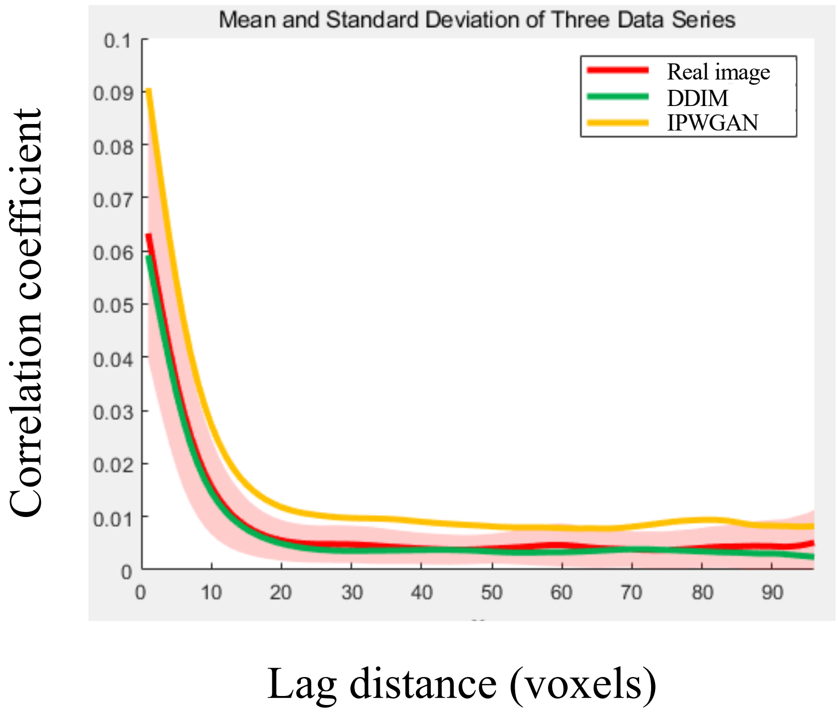
Red: Real image, Green: DDIM, Yellow: IPWGAN. Image size: 96 cubes

Results: Interfacial area

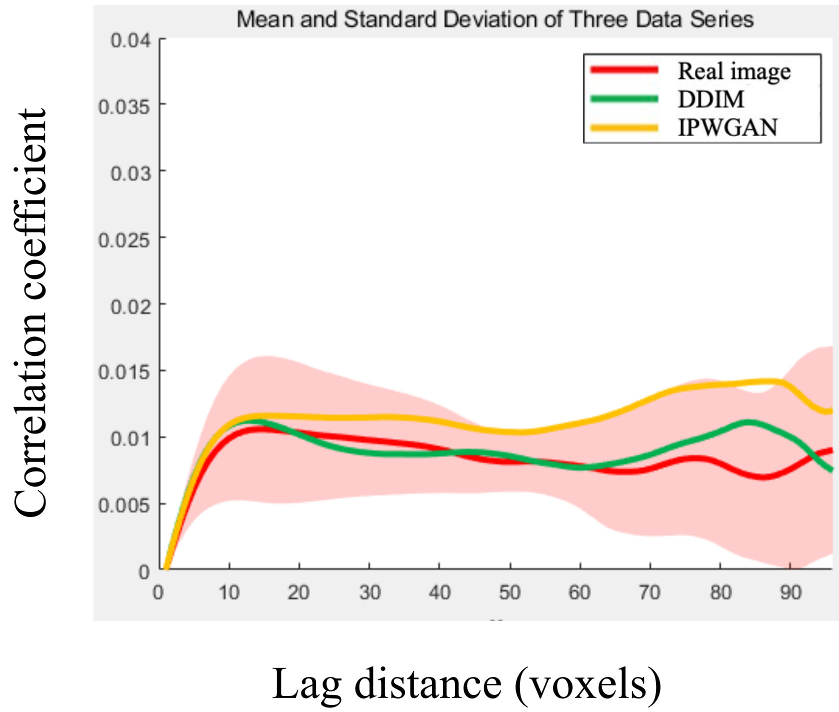


Red: Real image, Green: DDIM, Yellow: IPWGAN. Image size: 96 cubes

Results: correlation functions



Two-point correlation functions, brine



Two-point cross-correlation function, oil-brine

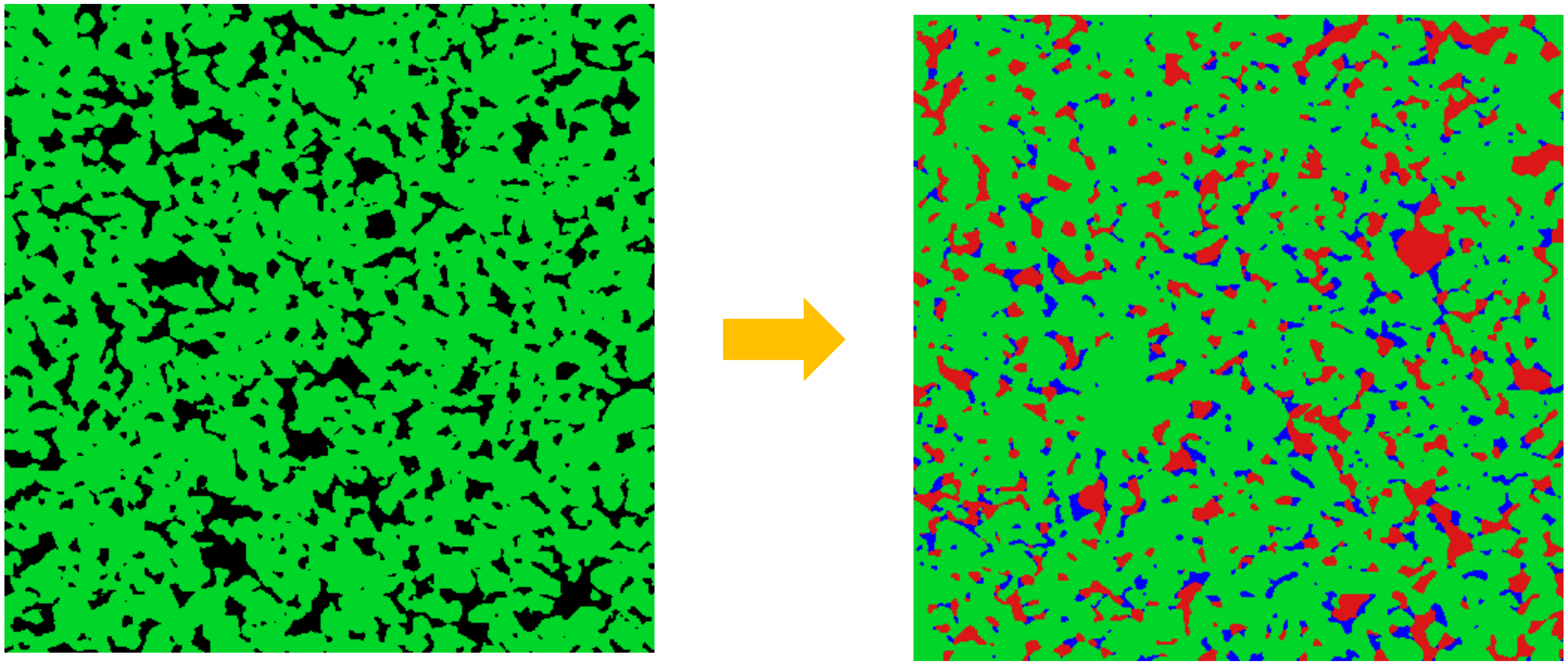
https://github.com/ImperialCollegeLondon/DDIM

Zhu, L., Bijeljic, B., & Blunt, M. J. (2025). Diffusion Model-Based Generation of Three- Dimensional Multiphase Pore-Scale Images. Transport in Porous Media, Under review.

Next steps and conclusions

Diffusion models provide good images of both the pore space and fluids within them with a superior performance compared to GANs.

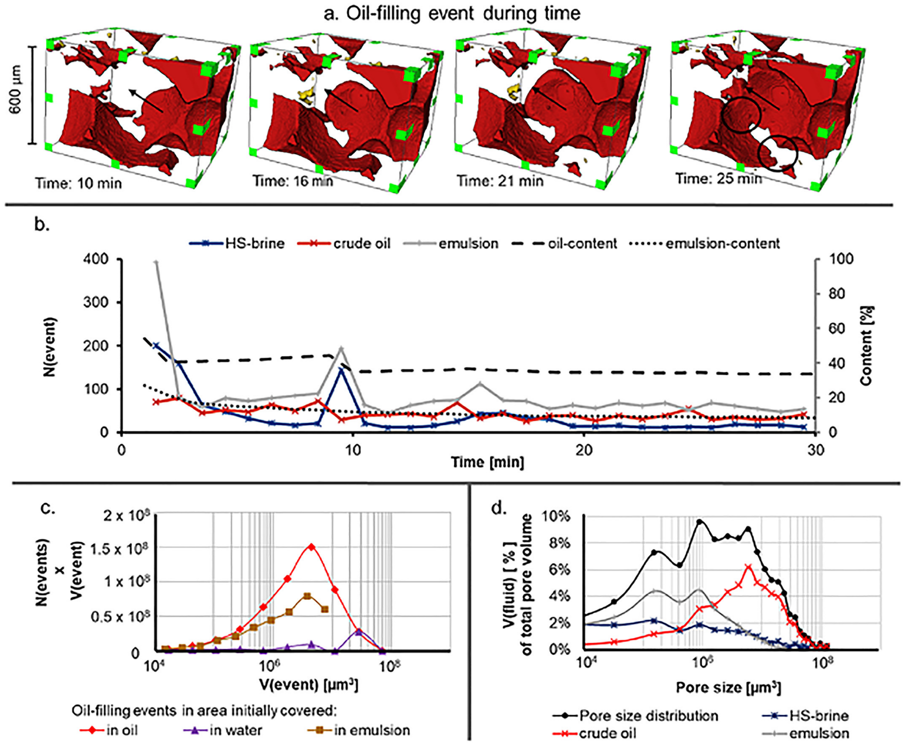
Work on further testing and training.



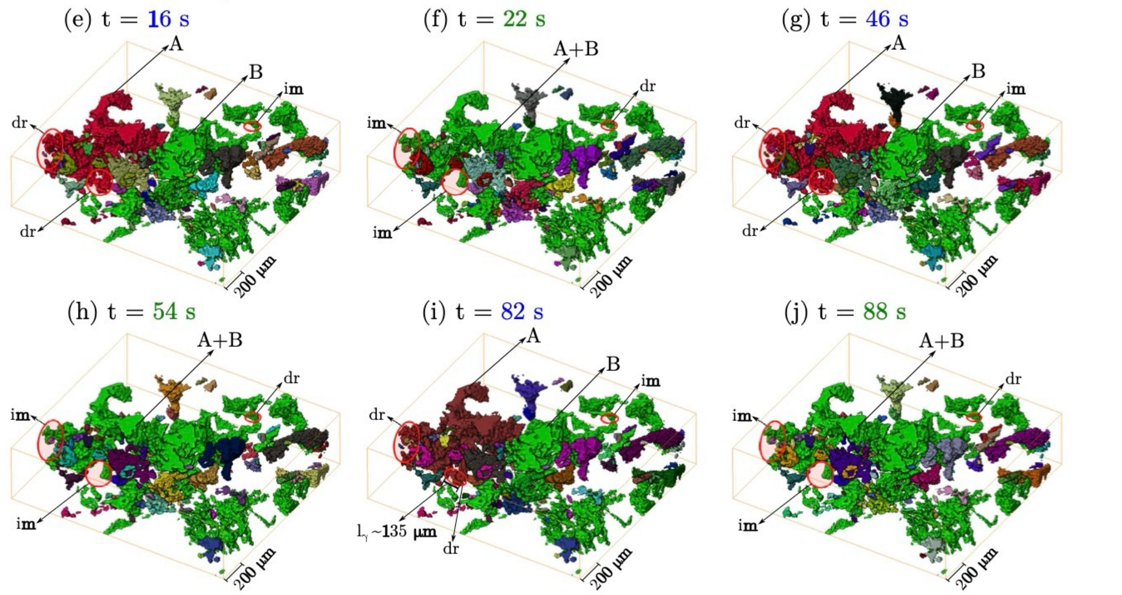
Each fluid distribution, under any conditions we want

Two-phase flow, capillary trapping, ripening, reactive transport…

Next steps and conclusions



Kamal's data



Catherine's data

Thanks for your attention!

Continuing progress in AI for dynamic flow in porous media to

advance pore-scale modelling and imaging research!

We gratefully acknowledge the assistance provided by the other group members

(e.g., Sajjad Foroughi, Zhuangzhuang Ma, Asli Gundogar, Min Li…) throughout this research.