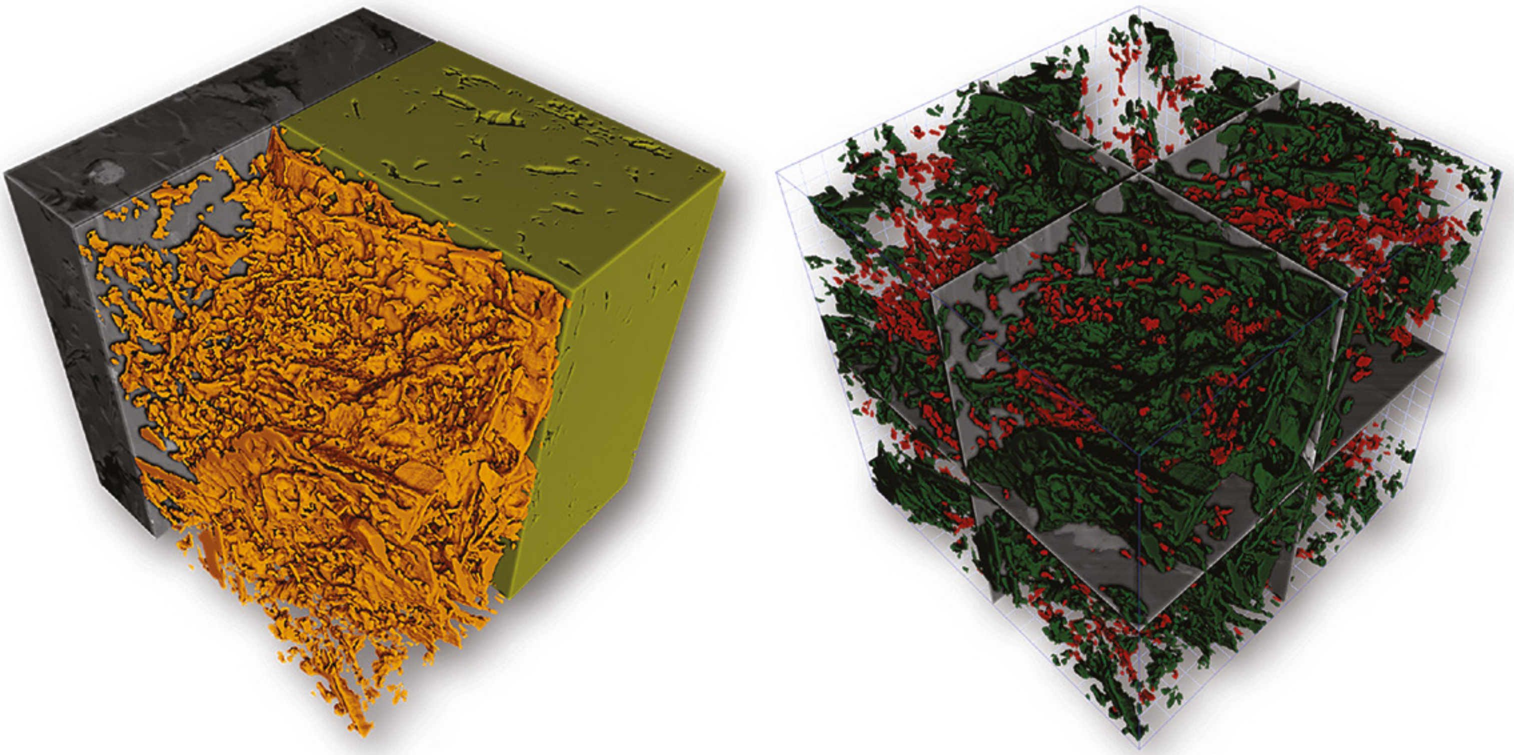
Application Note



Pore Network Modeling of Marcellus Shale using Digital Rock Analysis with Machine Learning Image Segmentation

ZEISS Solutions for Shale Characterization

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Authors: Jan Goral and Milind Deo
Department of Chemical Engineering, University of Utah

Matthew Andrew
ZEISS Microscopy

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Introduction

Oil and gas from unconventional (shale) reservoirs has changed the landscape of North America energy markets. The exploration and production of natural gas from shales in Canada and United States have saturated North American gas markets, boosted Canada's exports, and turned the U.S. into a net exporter of liquefied natural gas (LNG).

The evaluation and development of shale reservoirs is guided by reservoir characterization where geological models are populated with petrophysical properties, such as lithology, porosity, permeability, or water/oil saturation. These characteristics can be now determined by a cost- and time-efficient image-based method – digital rock analysis – currently becoming more popular as a complement to traditional laboratory measurements.

Shale (mudrock) is a fine-grained sedimentary rock consisting of indurated interlaminated organic and nonorganic (mineral) matter, and is characterized by its ultra-low porosity and permeability. Organic matter contained within shale formations was compressed and heated deep within the earth over geologic time, forming hydrocarbons including oil and natural gas. These hydrocarbons occur in the pore spaces and micro-fractures in between individual minerals or adsorbed into organic matter. Shale pores, with a diameter that typically ranges between a few nanometers (for organic-matter-hosted pores) to a couple of micrometers (for mineral-matter-hosted pores), create connected and non-connected pore systems. These pore networks, both within organic and mineral matrices, connect to the natural or induced fracture systems that ultimately connect to the wellbore. The structure and the interconnectivity of these highly complex hydrocarbon flow pathways have been of interest to many petroleum industry and academia research and development groups focusing on multi-scale (non)continuum fluid flow and transport phenomena in shales, e.g., through particle-based molecular dynamics (MD), dissipative particle dynamics (DPD), Lattice Boltzmann method (LBM), or mesh-based computational fluid dynamics (CFD) fluid flow and transport simulations.[1]

Although there is significant interest in modeling and simulation of fluid flow and transport phenomena in shale pore network models, there is very little study focused on investigating representative – connected (effective) – 3D "real-world" shale reservoir pore systems responsible for hydrocarbon production and storage. In this study, we image and analyze pore volume and connectivity for connected and disconnected pore networks within an organic-rich mudrock sample from Marcellus Shale in 3D with ultra-high-resolution (5 nm/voxel) focused ion beam scanning electron microscopy (FIB-SEM) tomography (serial-sectioning).

Digital Rock Analysis with Machine Learning Image Segmentation

In shales, understanding intricate pore networks, their geometry, connectivity, and distribution (both within organic and mineral matrix) are key factors affecting hydrocarbon production and storage mechanisms. They are often difficult, if not impossible, to measure by conventional slow and expensive lab techniques.

Digital rock analysis provides qualitative and quantitative understanding of these petrophysical properties using multi-scale 2D and/or 3D imaging data without completely destroying valuable rock samples.

Figure 1 depicts the overall digital rock physics workflow presenting step-by-step procedure of going from imaging, through image processing and segmentation, to digital (porous) rock model reconstruction used for pore network modeling study.

Although mudrock heterogeneity can be observed and imaged over multiple scales by a variety of scientific digital imaging techniques (i.e., light, X-ray, or electron microscopy), dual-beam/cross-beam focused ion beam (FIB) scanning electron microscopy (SEM) serial sectioning provides the best 3D resolution for nano- and micro-pore imaging.[2] FIB-SEM serial sectioning is a high-precision tomographic imaging technique in which cross-section gallium ion milling is used to controllably remove 5- to 20-nm-thin layers of material (“slices”) of the sample, and electron imaging is used to characterize the freshly prepared sample surface.

Automated sequential FIB milling and SEM imaging allows for the acquisition of a series of 2D images, which in turn allows for the reconstruction of a 3D model. ZEISS Crossbeam 550 FIB-SEM, used in this study, allows for simultaneously imaging the sample with both secondary and backscattered electrons. These two signals can be then blended into a single image to optimize contrast across pores, organics, and multiple mineral phases.

As the accuracy of petrophysical properties (measured with digital rock analysis) heavily relies on the quality of reconstructed digital rock models, any performance gap in image processing or segmentation will lead to misleading reservoir quality assessment. For example, incorrect segmentation can result in over- or underestimation of porosity by few percent, which will consequently create significant error in reserves estimation calculations. An inaccurate segmentation can also result in even more significant errors in permeability simulations, as permeability is highly sensitive to small changes in critical pore throat diameter.

The last decade has seen a transformation in our ability to analyze and quantify complex data through the use of machine learning algorithms. These algorithms identify patterns in complex multidimensional data and use these patterns to perform classification or segmentation.

As a result, machine learning segmentation is a powerful tool for the transformation of challenging image datasets, which may carry a variety of modality-specific artifacts and noise, into segments (labels), representing different groups of features of the rock microstructure, e.g., pores or minerals, previously too difficult to segment by threshold-based approaches.[3] This advanced image analysis technique utilizes a learning classifier system that is trained using a “Forest of Random Trees” approach,[4] segmentation labels (identified and marked by a user with a paint tool), mask(s), and/or (filtered) dataset(s).[5] Once the classifier is trained, it can be used for segmenting the same or similar image data.

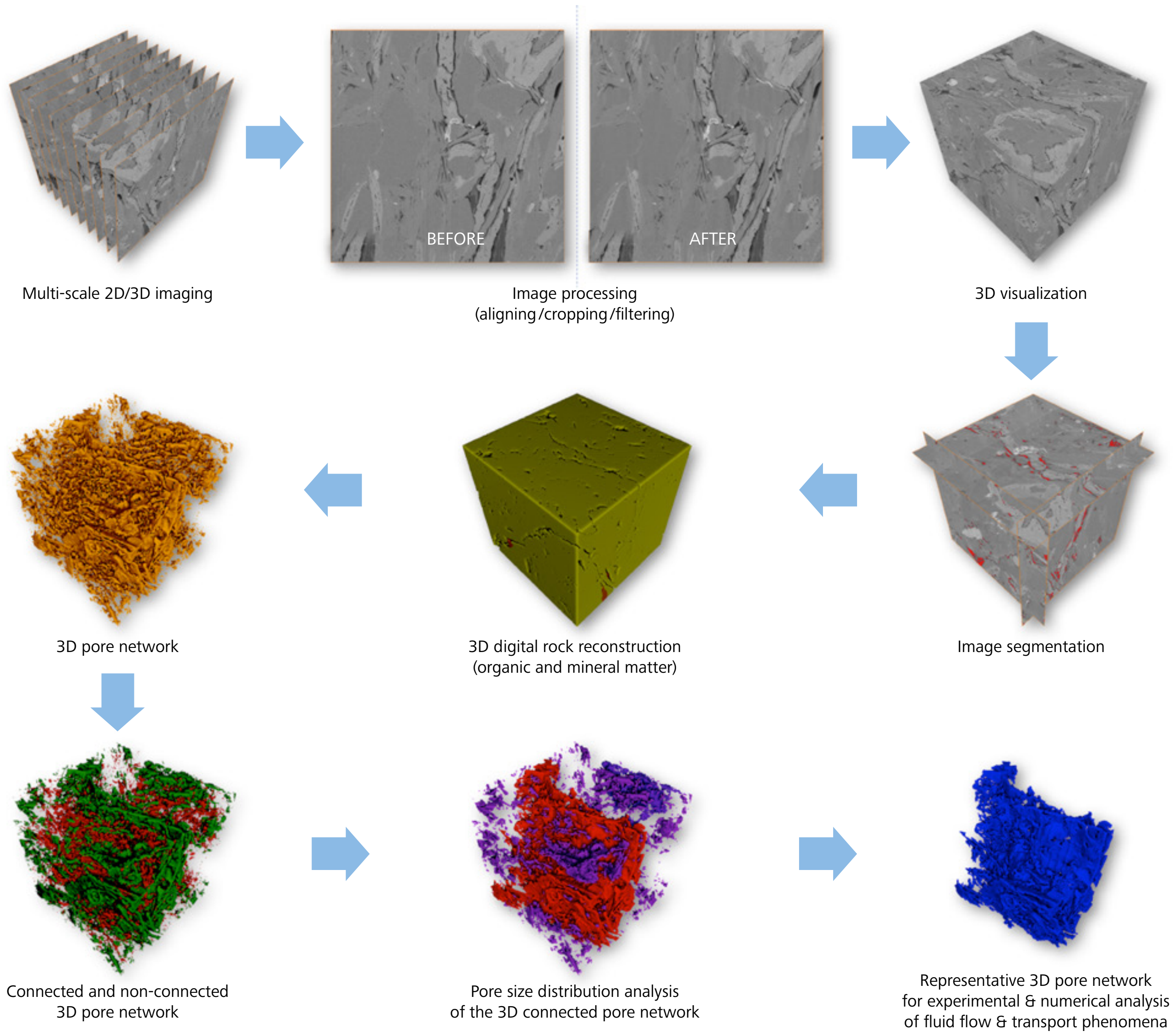


Figure 1 *Schematic of the digital rock analysis/physics workflow. First, a series of 2D images is acquired by e.g., FIB-SEM tomography; second, the images are aligned with each other, cropped, and filtered; third, the image dataset is segmented into different phases, such us pores, organics, or minerals; fourth, pores are divided into connected (effective) and non-connected (isolated) porosity; and fifth, representative 3D pore networks are determined, through pore size distribution analysis, and separated out for any further fluid flow and transport phenomena studies.*

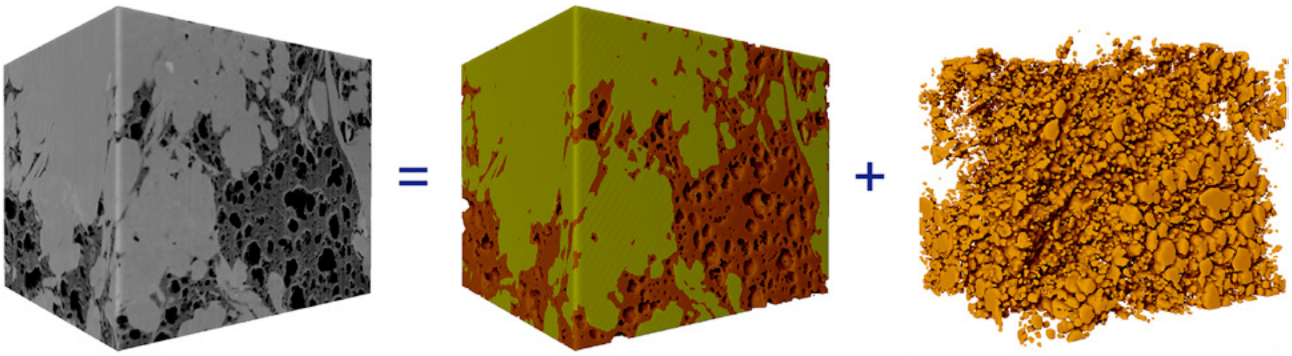


Figure 2 *Digital rock model of the Marcellus Shale Sample-1 – pores (yellow), organic matter (brown), mineral matter (green).*

Pore Network Modeling

In this paper, using ultra-high-resolution (voxel size: 5 nm x 5 nm x 5 nm) FIB-SEM serial sectioning image data, we investigate pore networks in two organic-rich regions of interest (ROIs) of Marcellus Shale.

First, image processing is used to improve image quality. In this process, we apply a combination of different filters and operations to remove noise, blur, and other background intensity variations from the images. Second, the image data is segmented, using machine learning, into three phases: pores, organic matter, and mineral matter. Third, the processed and segmented images are reconstructed into two digital rock models with dimensions of 3430 nm x 2785 nm x 2930 nm for Sample-1 (Figure 2) and 3845 nm x 2515 nm x 2100 nm for Sample-2 (Figure 3). The volume fractions of the mineral and organic phases are 49.74% and 33.99% (for Model-1), and 64.23% and 19.82% (for Model-2) respectively.

Figure 3 *Digital rock model of Marcellus Shale Sample-2 – pores (yellow), organic matter (brown), mineral matter (green).*

Next, as seen in Figure 4 and Figure 5, the total porosity – 16.27% for Sample-1 and 15.95% for Sample-2 – is separated out into connected (effective) and non-connected (isolated) pores. The effective porosity – 12.48% (Model-1) and 11.37% (Model-2) – is determined based on its connectivity to the digital rock model boundaries, while isolated porosity is simply the remaining pores. Note, that connected pores can be attached to some other pore networks outside of the boundary box of the digital rock models. Similar total and connected porosity values, for both digital rock models, show that porosity is uniformly distributed throughout the investigated organic-rich Marcellus Shale rock sample. In reservoir characterization, total porosity is used for the overall hydrocarbon storage assessment, while effective porosity is used for permeability (hydrocarbon production) calculations. It is, therefore important to gain insights into both types of porosity with a simultaneous study of the possibility of connecting isolated pores, through e.g., hydraulic fracturing design.

Finally, we provide two charts on the next page, with pore size distribution (PSD), comparing total and connected pore networks within both Marcellus Shale rock samples. As shown in Graph 1 (for Sample-1) and Graph 2 (for Sample-2), both FIB-SEM digital rock models contain pores with diameters that range between 15 nm to 200 nm. Pores with diameters from 15 nm to 30 nm are the most abundant within both Sample-1 and Sample-2 – almost 80% of the total number of pores. Although the average volume fraction of the connected porosity (12%) within both investigated Marcellus Shale rock samples is quite large (almost 75% of the average total pore volume of 16%), the number (frequency) of the connected pores is rather small. The high percentage of the average connected pore volume together with their relatively low frequency (as compared to the total porosity) is due to the fact that pores with diameters of around 150-200 nm – hence, with bigger pore volumes – are the primary contributors to the connected porosity. Contrarily, smaller pores (with diameter of around 15-50 nm) have very little to no contribution to the connected pore network, hence fluid flow and transport within shale oil and gas reservoirs.

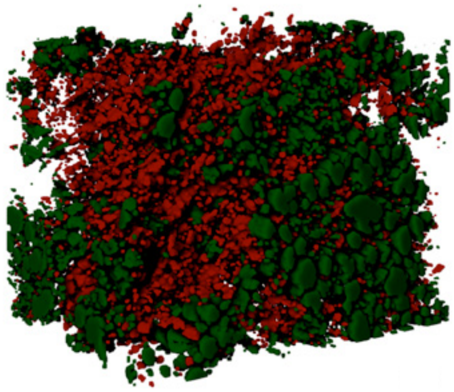


Figure 4 *Sample-1: Connected (effective) and non-connected (isolated) pore networks of the Marcellus Shale – connected pores (green), non-connected pores (red).*

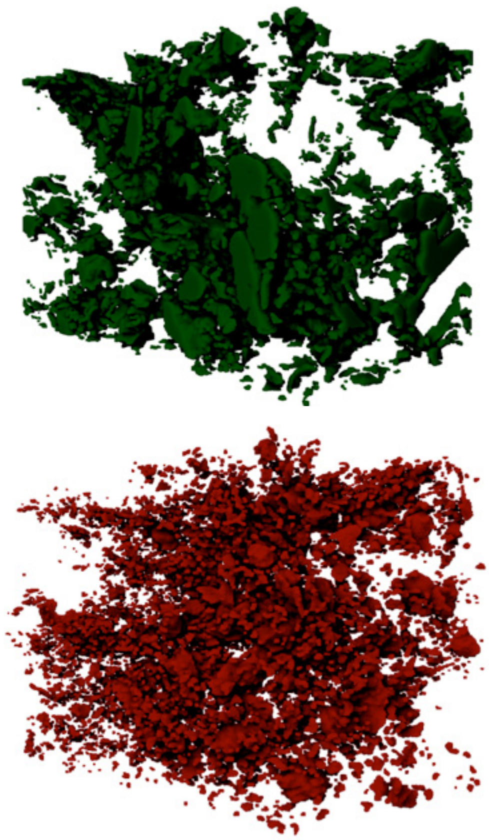
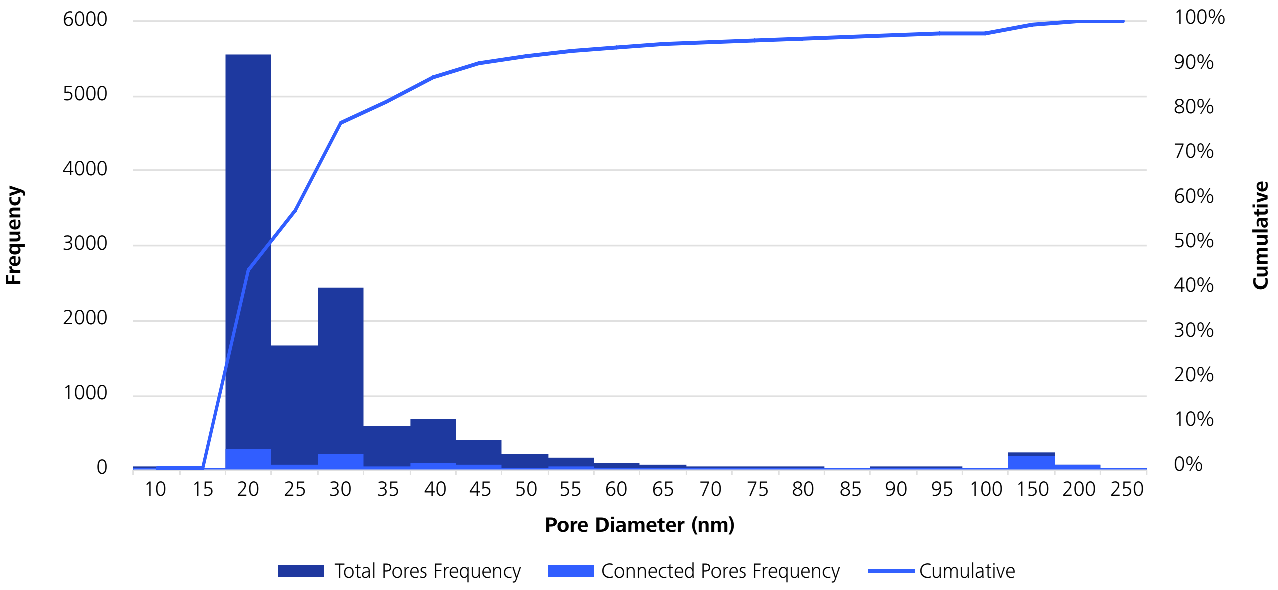
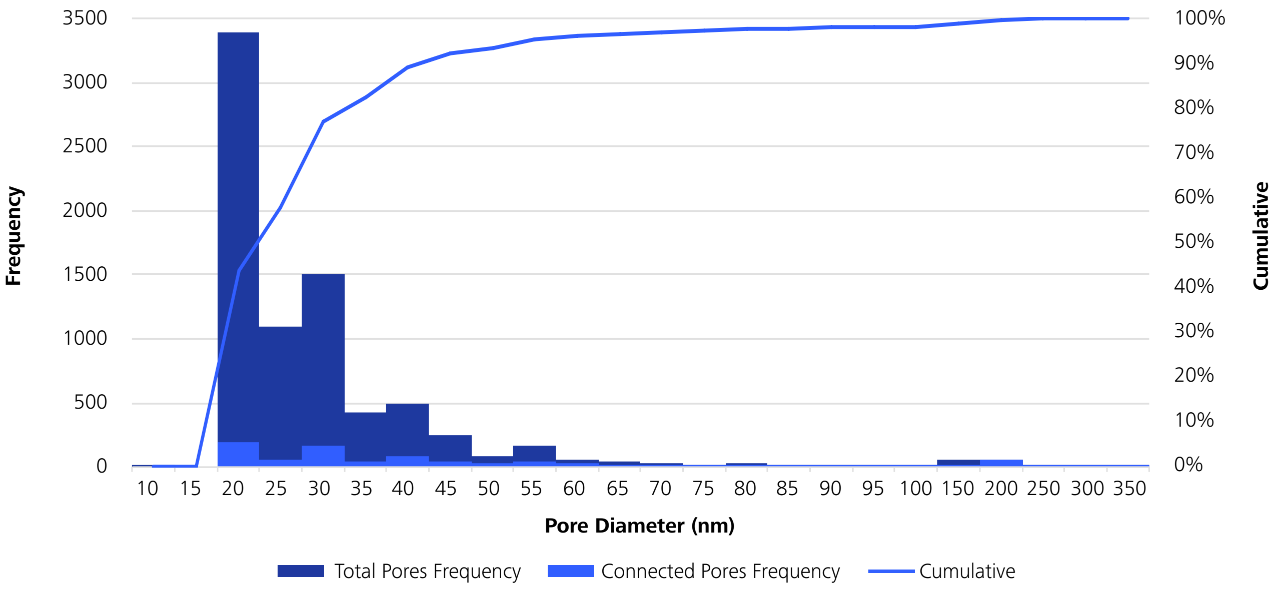


Figure 5 *Sample-2: Connected (effective) and non-connected (isolated) pore networks of Marcellus Shale – connected pores (green), non-connected pores (red)*



Graph 1 *Pore size distribution (PSD) of the total and connected (effective) porosity within the Marcellus Shale Sample-1.*



Graph 2 *Pore size distribution (PSD) of the total and connected (effective) porosity within the Marcellus Shale Sample-2.*

Conclusions

Machine learning image segmentation is a powerful tool that complements digital rock analysis and allows for characterizing challenging image data representing rock features, such as pores, micro-fractures, organic, or mineral matter naturally existing at multiple length scales in shales – unconventional oil and gas reservoirs.

In this study, pore network modeling of two organic-rich FIB-SEM digital rock models of the Marcellus Shale has been performed. It has been shown that pores with diameters smaller than 50 nm and high frequency (predominantly found within organic matter) have little to no contribution to connected porosity, whereas pores with diameter greater than 150 nm and low frequency contribute the most to the connected pore network. These bigger connected pores will be responsible for hydrocarbon production and storage, whereas the remaining non-connected pores will have some storage capacity.

References:

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Carl Zeiss Microscopy GmbH
07745 Jena, Germany
microscopy@zeiss.com
www.zeiss.com/microscopy