

DELIVERABLE

D5.10

EOR-PNP Workshop

Globally the overall oil recovery factors for primary and secondary recovery range from 35% to 45% and a tertiary recovery method that can enhance the recovery factor by 10-30% could contribute to energy supply. The use of nanoparticles in enhanced oil recovery (EOR) processes comprise an emerging and well-promising approach. While surfactants injection into geological sites has been a commonly practiced EOR method, the injection of aqueous nanoparticle suspensions is still at its early stages. In the most active period between mid-1970 and mid-1980, there was a significant gap between what was planned in the EOR laboratory and what was achieved in field application, since the reservoir characterization was elementary with no digital geological modeling capabilities, and there were no concepts such as monitoring systems or intelligent completions. Over the years, irrespective of the inclement times in upstream oil industry, fundamental sciences, EOR physics, numerical modeling, monitoring and controlling capabilities, and EOR chemicals all demonstrated advancements. EOR potential for conventional and unconventional reservoirs is still a challenge, and particularly the development of nanotechnology-based new chemicals for the application of more efficient and cost-effective EOR projects. **The methodologies and scientific results of EOR-PNP could contribute not only to the development of cost-effective and high-performance EOR methods, but also on the generation of innovative knowledge that might be helpful in other applications, such as the remediation of soils and aquifers contaminated by hydrocarbons.**

Communication

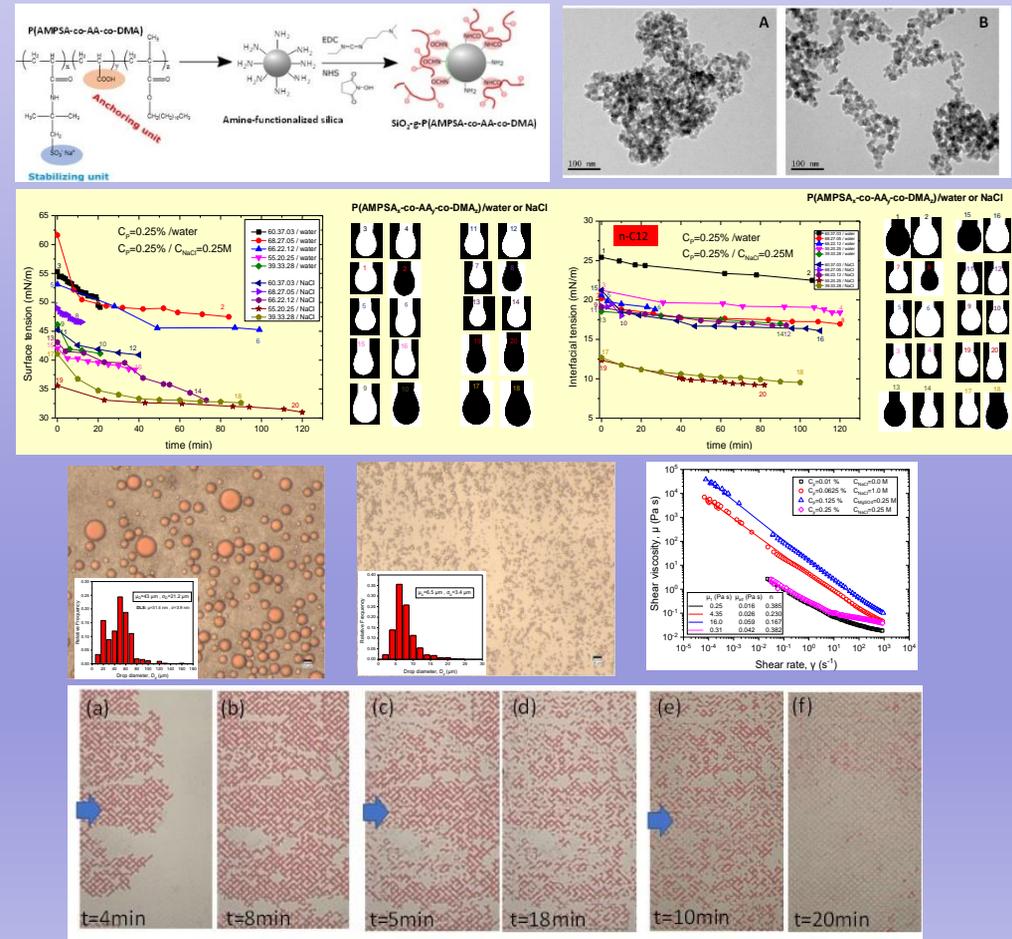
FORTH/ICE-HT, Stadiou str., Platani, 26504 Rio-Patras
 Dr. Christos Tsakiroglou
 Phone.: 2610 965212, E-mail: ctsakir@iceht.forth.gr

Registration
 Ms. Kleanthi Zacharopoulou
 Phone: 2610 965278, E-mail: kleanthi@iceht.forth.gr



Workshop, 12-13 December 2022
 FORTH/ICE-HT, Patras

Advances Toward the Transport of Nanoparticles in Porous Media and Applications to Residual Oil Recovery



**FOUNDATION FOR RESEARCH
AND TECHNOLOGY HELLAS –
INSTITUTE OF CHEMICAL
ENGINEERING SCIENCES
(FORTH / ICE-HT)**

12-13 December 2022

**Auditorium of FORTH/ICE-HT
Conference Center**

The Workshop is organized within the
framework of the Research Project:

**«Enhanced oil recovery by polymer-
coated nanoparticles (EOR-PNP)»**

<http://eorpnp.iceht.forth.gr>

The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment”

Workshop Program

Monday, 12 December 2022

14:30-15:00: Registration

Workshop I.

15:00-15:20. Christos Tsakiroglou, Research Director, FORTH/ICE-HT, «**EOR-PNP – Introduction - Perspectives**»

15:20-15:50. Georgios Bokias, Professor, Department of Chemistry, University of Patras, «**Synthesis and characterization of polymer-coated nanoparticles**»

15:50-16:10. Christina Ntente, Graduate Student, FORTH/ICE-HT & University of Patras, «**Nano-colloid interfacial properties, and emulsion stabilization**»

16:10-16:30. Anastasia Strekla, Graduate Student, FORTH/ICE-HT & University of Patras, «**Visualization EOR studies on glass-etched pore networks**»

16:30-17:00. *Coffee break*

17:00-18:30. **Invited Speaker:** Marios Ioannidis, Professor, Department of Chemical Engineering, University of Waterloo, Canada, «**Nanoparticle interactions with interfaces in porous media: a multiscale perspective**»

Tuesday, 13 December 2022

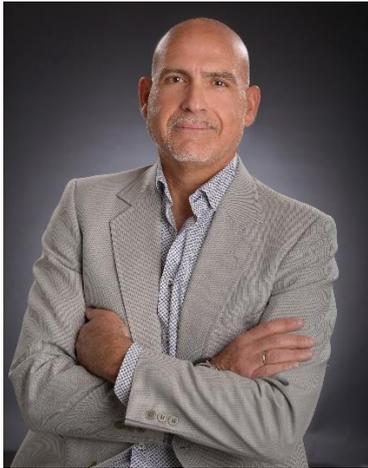
Workshop II.

10:00-10:30. Nadia Bali, Post-Doctoral Fellow, FORTH/ICE-HT, «**Computational Fluid Dynamic models inside 3D digitally represented rocks and soils**»

10:30-11:30. **Invited Speaker:** Jeff Gostick, Associate Professor, Department of Chemical Engineering, University of Waterloo, Canada, «**Network Modeling and Quantitative Analysis of Volumetric Images: Introduction to OpenPNM and PoreSpy - Part I**»

11:30-12:00. *Coffee break*

12:00-13:00. **Invited Speaker:** Jeff Gostick, Associate Professor, Department of Chemical Engineering, University of Waterloo, Canada, «**Network Modeling and Quantitative Analysis of Volumetric Images: Introduction to OpenPNM and PoreSpy - Part II**»



Marios Ioannidis is a Professor of Chemical Engineering at the University of Waterloo, Canada, where he currently serves as Chair of the Department of Chemical Engineering. Marios first studied chemical engineering at the University of Patras, obtaining the Diploma in Chemical Engineering in 1988, and continued his studies at the University of Waterloo, obtaining a PhD degree in Chemical Engineering in 1993. Marios and his students research fundamental aspects of multiphase flow and transport of solutes and nanoparticles in porous materials of different kinds (fibrous or granular, man-made or natural, etc.). The goal of their research is to enable engineering applications ranging from subsurface remediation and petroleum production to environmental sampling, fuel cell performance optimization and oil spill response. Professor Ioannidis has held numerous administrative positions within the University of Waterloo, including as Director of the Nanotechnology Engineering Program, and is a Fellow of Engineers Canada.

Title: Pore Network Modeling and Quantitative Analysis of Volumetric Images: Introduction to OpenPNM and PoreSpy

Abstract/Description: In this workshop we will cover the use of volumetric or 3D images of porous materials, typically obtained from X-ray tomograph, to study structural and transport properties of computationally. The first half of this workshop will focus on image analysis using tools such as ImageJ and PoreSpy, the latter of which is a Python package we develop and distribute freely. Topics in this segment will span the entire workflow from discussing typical data formats, processing greyscale images, applying simple filters like dilation/erosion, extracting higher level information such as pore size distributions, to finally performing simulations on images to obtain basic transport properties. The second segment will shift to looking at pore network modeling using OpenPNM, a Python package that is also developed by our group and distributed freely. Topics covered here will include the fundamentals of the pore network framework including network representation and determination of conductance values, generating and importing networks, performing multiphase simulations to estimate complex transport properties such as relative permeability curves, and finally ending with a simulation of dispersion in porous media. The program will be interactive, so attendees should bring a laptop and have ImageJ and the Anaconda distribution of Python installed, which includes precompiled and optimized versions of the main numerical packages. Familiarity the Python would be helpful, but attendees with knowledge of other languages such as Matlab or C/C++ should be able to grasp all the concepts with ease.



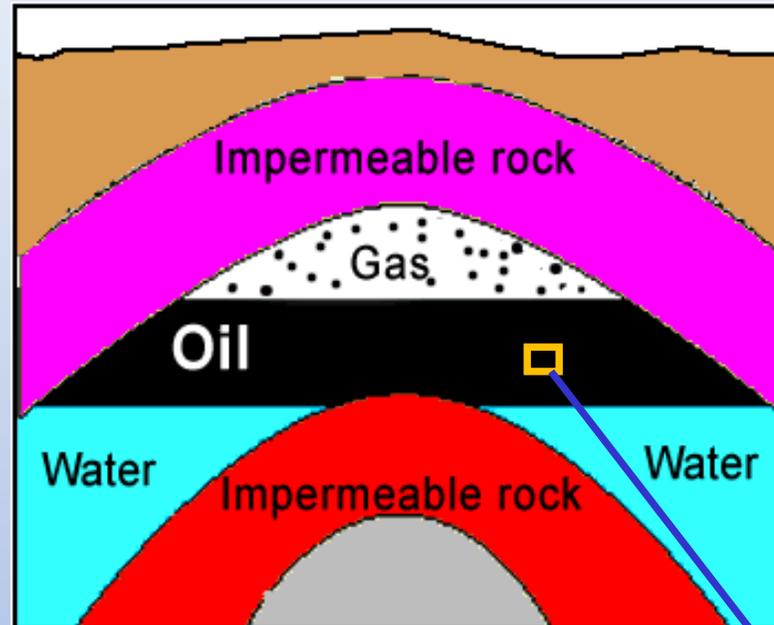
Biography: Jeff Gostick is the Azzam-Dullien Professor in Chemical Engineering at the University of Waterloo where he runs the Porous Materials Engineering & Analysis Lab. His research is centered around understanding the structure-performance relationship in porous electrodes used in hydrogen fuel cell, redox flow systems, zinc-air cells, Li-ion batteries, and super-capacitors. His group uses a combination experimental characterization, novel production methods, and advanced custom computational tools. He is the lead developer of the open-source pore network modeling project OpenPNM (openpnm.org), as well as PoreSpy, a tool for porous media image analysis (porespy.org). Prof Gostick is a licensed professional engineer, has published over 90 journal articles, and was recently named an Emerging Leader by the Canadian Society for Chemical Engineering.

Advances Toward the Transport of Nanoparticles in Porous Media and Applications to Residual Oil Recovery

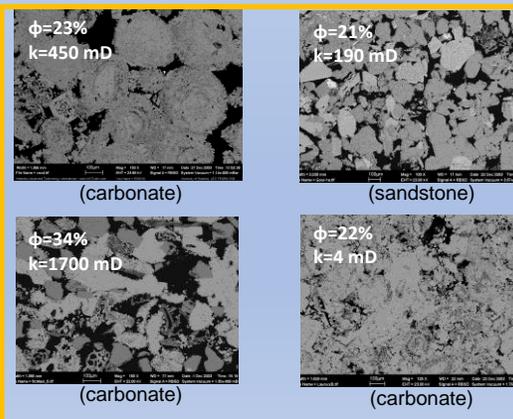
The Workshop is organized within the framework of the Research Project:
«**Enhanced oil recovery by polymer-coated nanoparticles (EOR-PNP)**»
(Duration: 1/1/2020-31/12/2023)
<http://eorpnp.iceht.forth.gr>

The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment

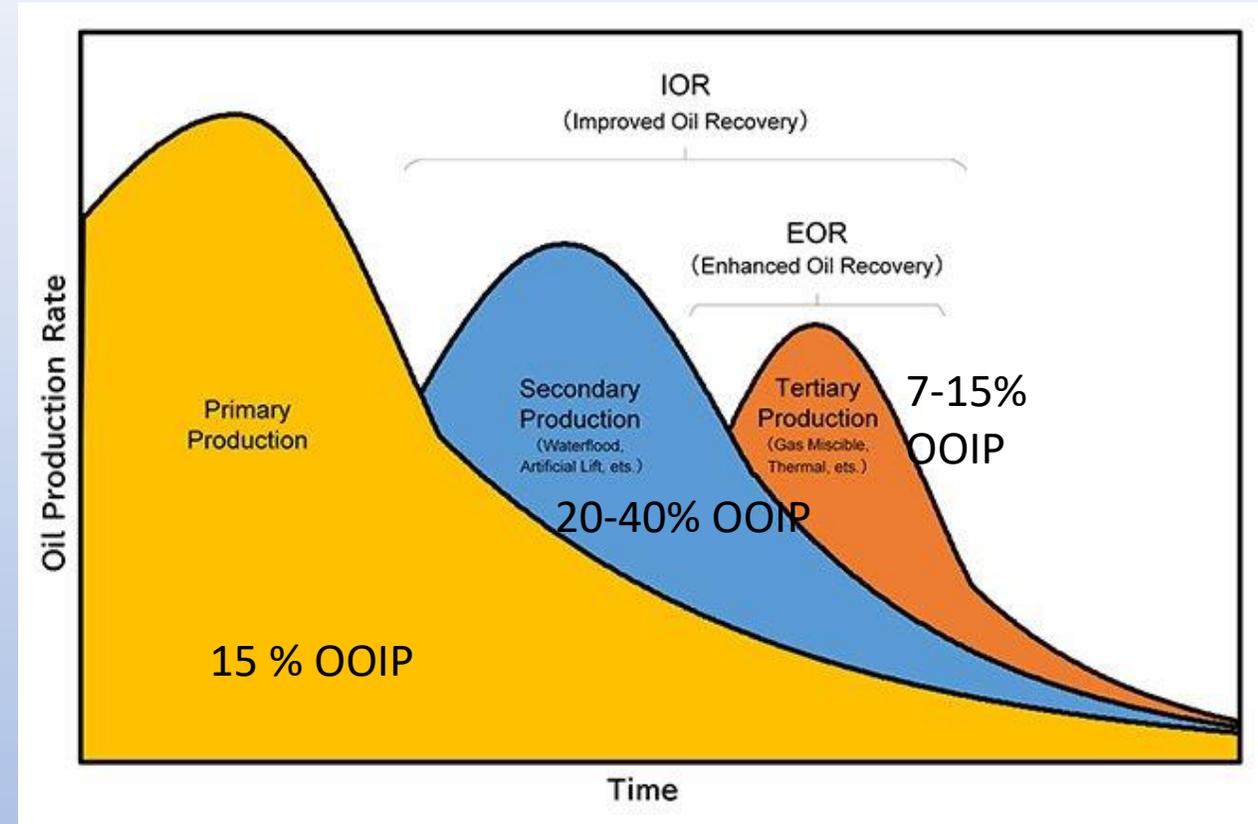
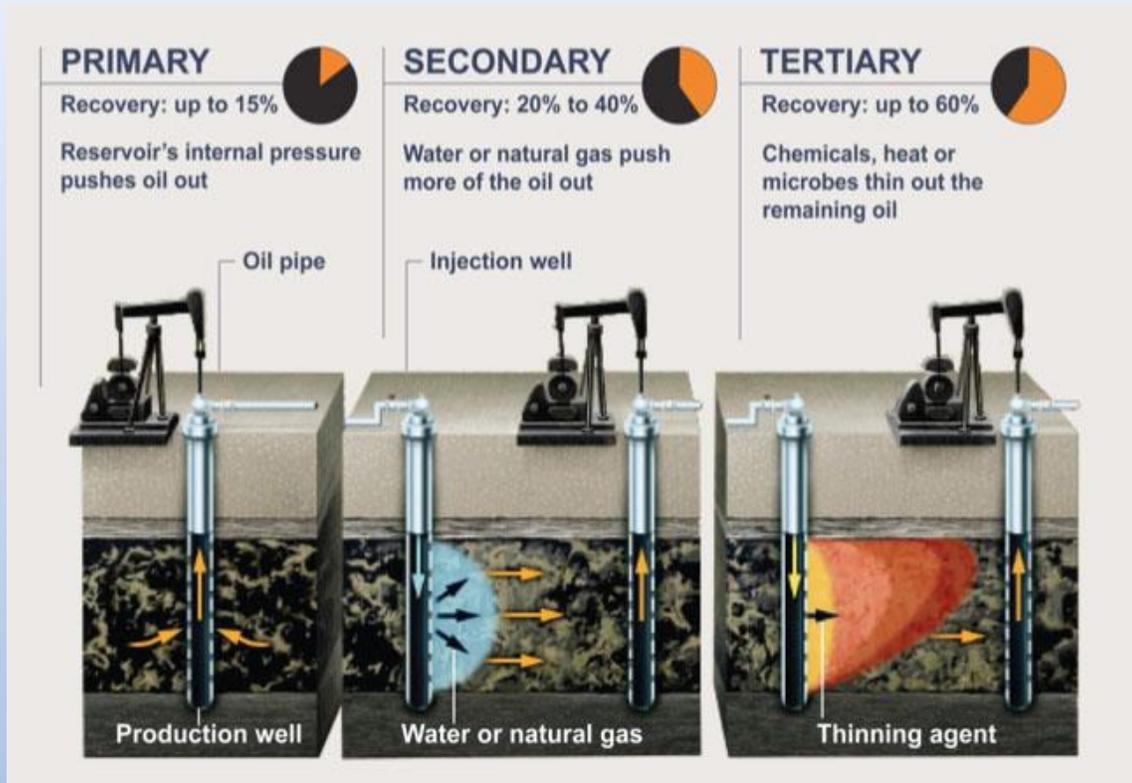
OIL AND GAS RESERVOIRS



- A good reservoir is:
 - **Porous:** holes of size < 1 mm
 - **Permeable:** the holes are interconnected
 - ...so that the fluids are able to be **produced** (removed from the reservoirs)



ENHANCED OIL RECOVERY (EOR)

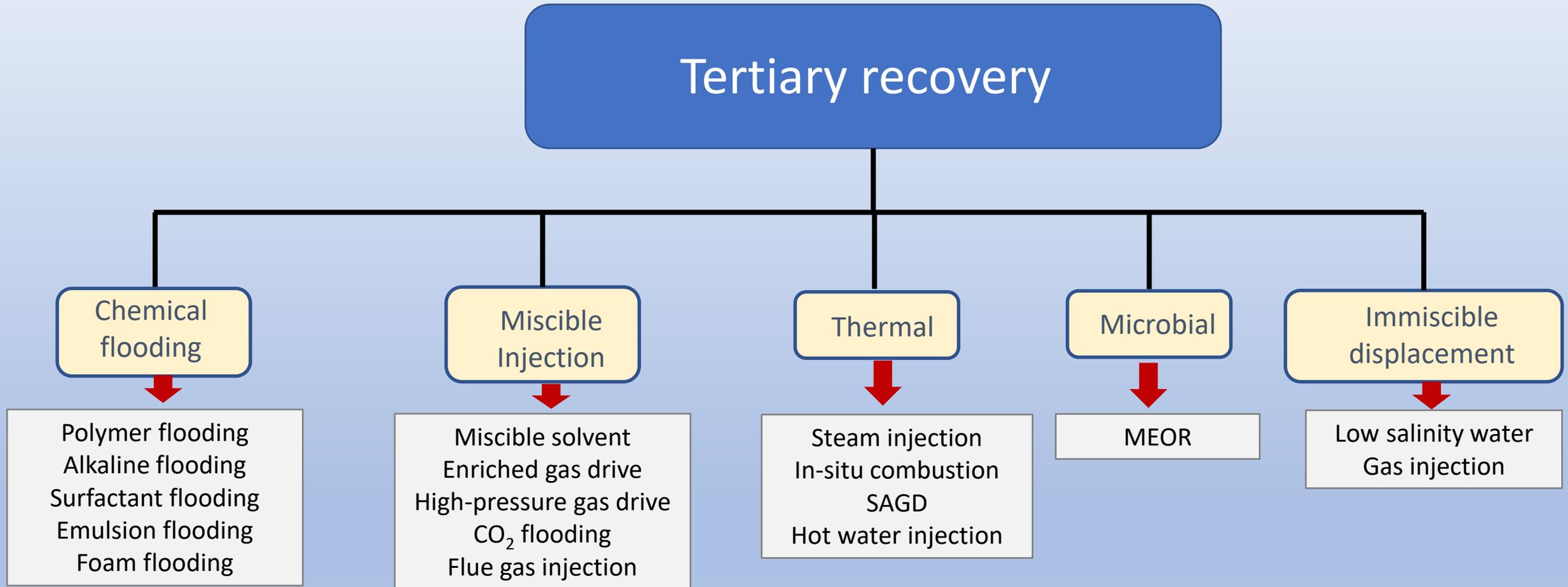


- Depletion of oil resources
- Increasing global energy demand
- Current high oil prices
- Increasing maturity of major oil fields



EOR can significantly impact oil production, as increase in the recovery rate of oil by even a small margin could bring significant revenues without developing unconventional resources

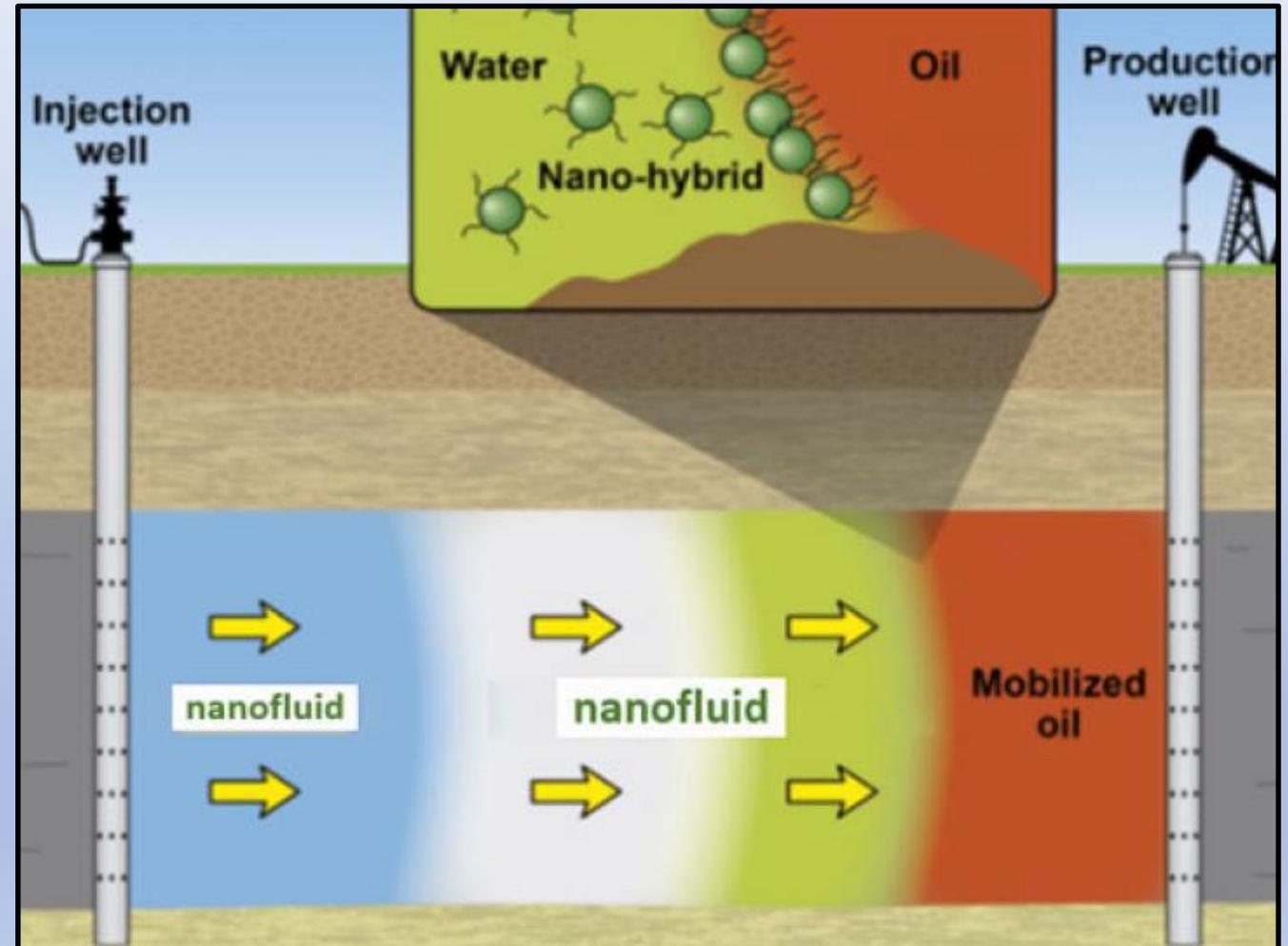
EOR METHODS



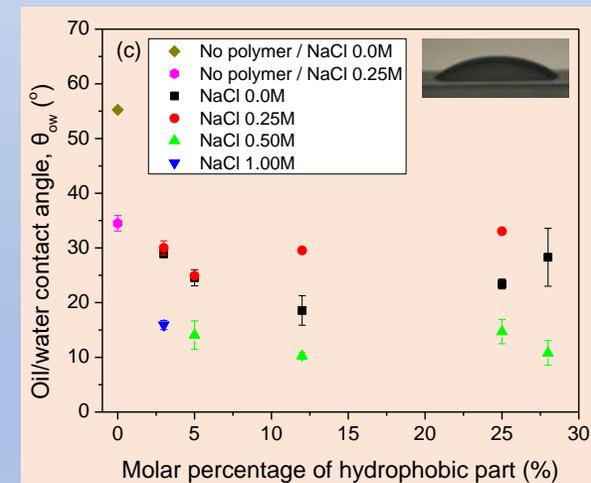
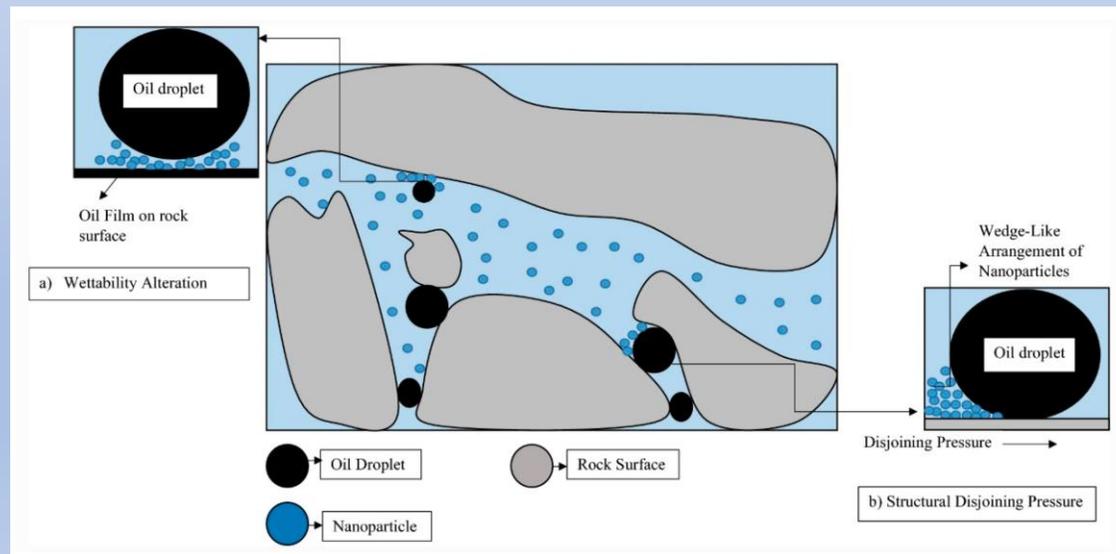
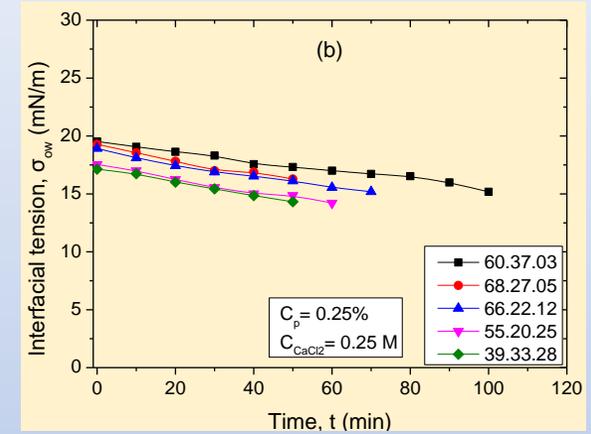
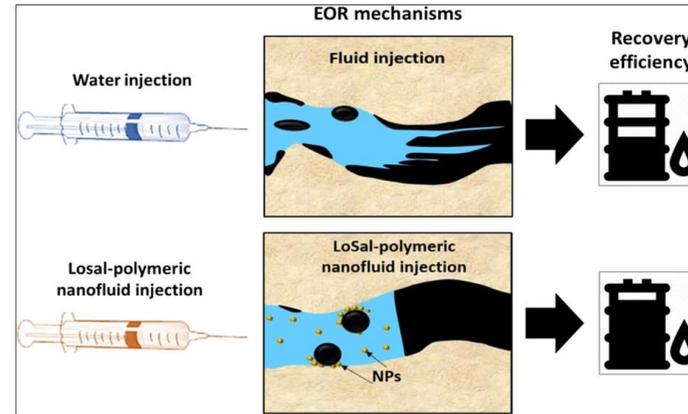
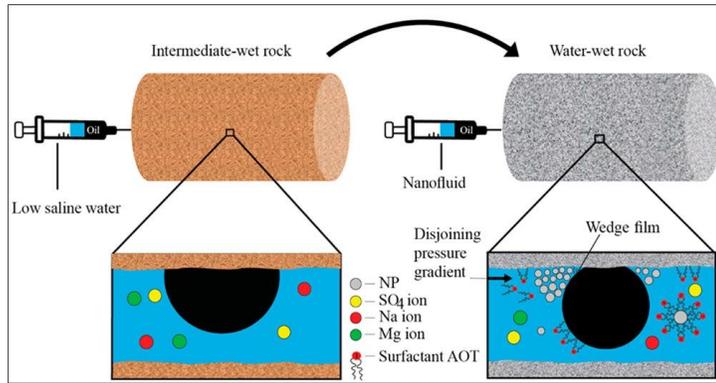
EOR-PNP - INTRODUCTION - PERSPECTIVES

GOAL OF THE PROJECT

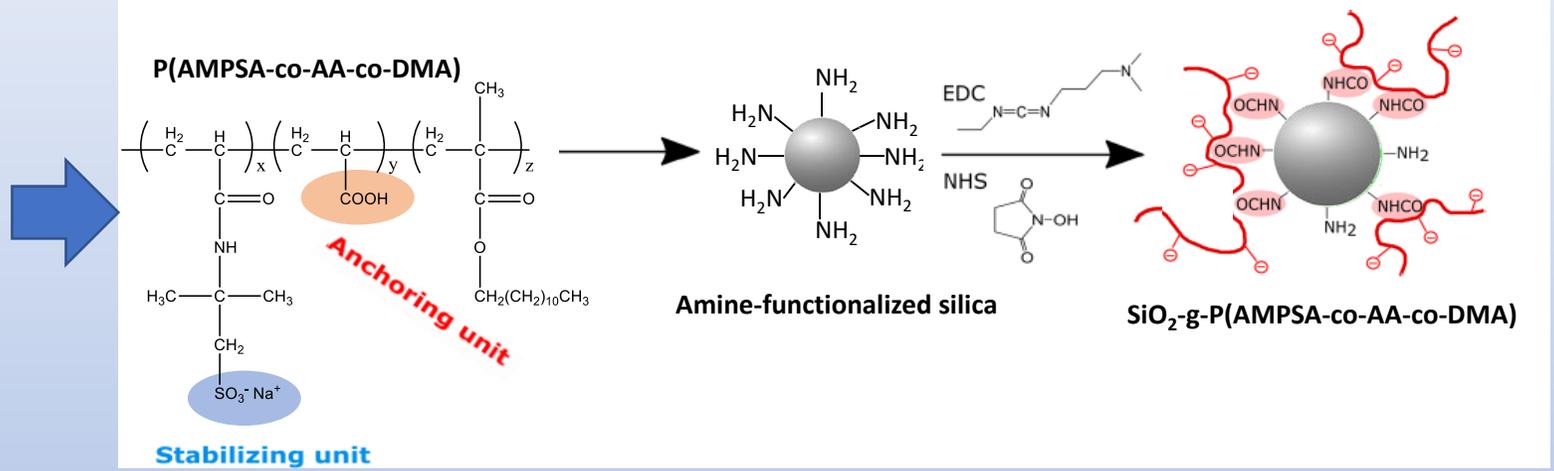
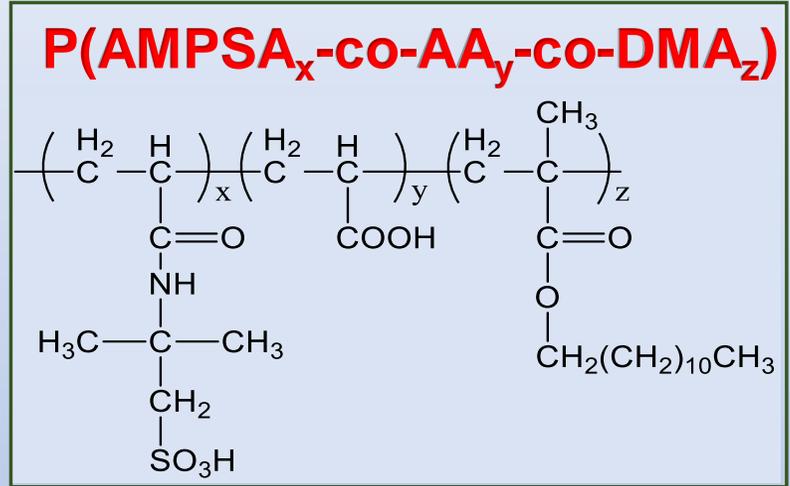
- Nanoparticle stabilization in aqueous solutions with polymer coatings (Synthesis /characterization)
- Stabilization of emulsions and foams
- Enhancement of the oil recovery by injecting nano-colloid solutions (nanofluid) in porous media models and cores
- Simulation of the displacement process in 3-D reconstructed pore networks
- Selection of the most efficient fluid systems



NANOFLUIDS AS EOR AGENTS

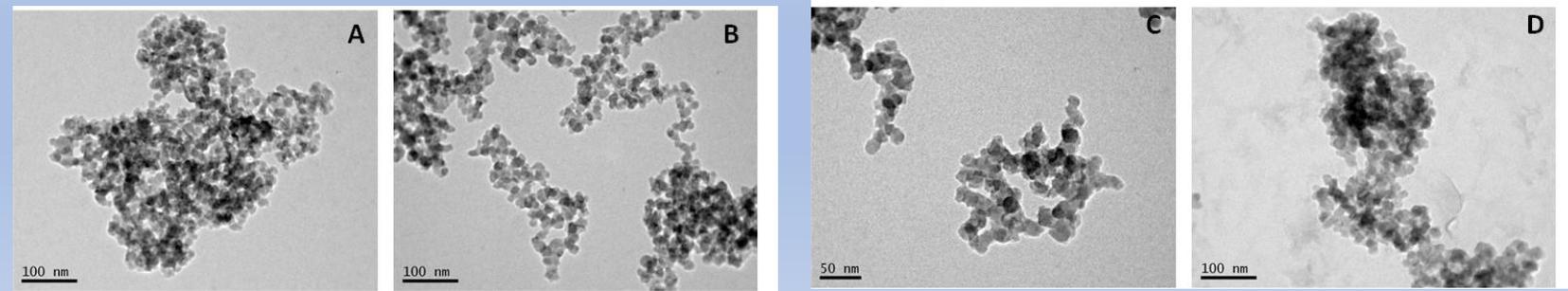


SYNTHESIS OF POLYMER-COATED NANOPARTICLES (PNP)



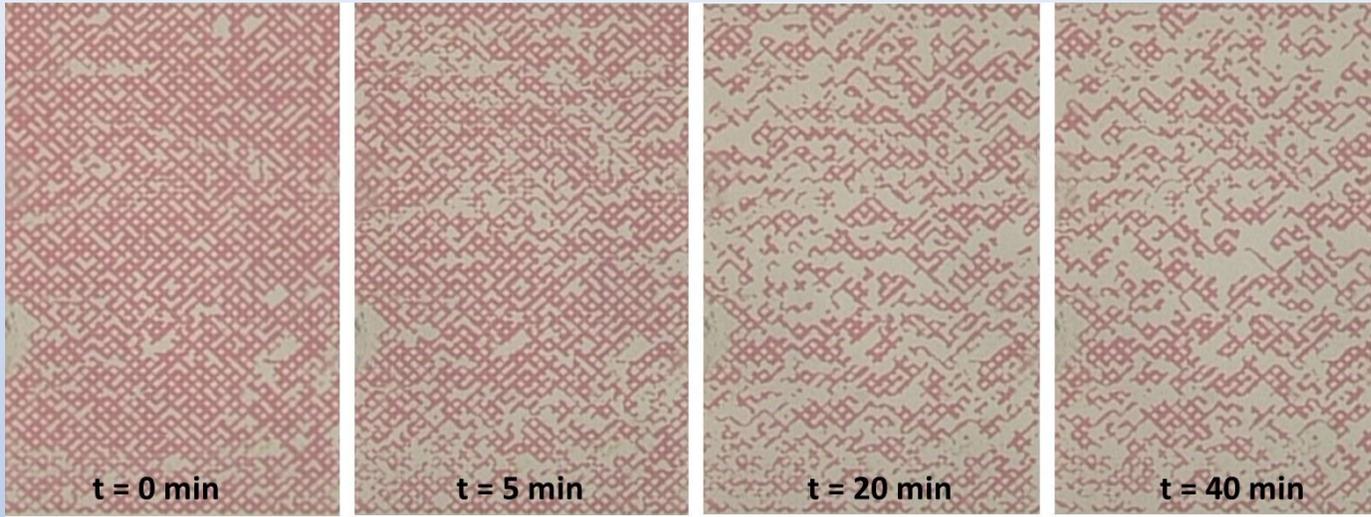
2-acrylamido-2-methyl-1-propanesulfonic acid (AMPSA) & acrylic acid (AA) & dodecyl methacrylate (DMA)

TEM images of (A) 2_SiO₂-PAMPSA; (B) 3_SiO₂-PAMPSA; (C) 2_SiO₂-g-P(AMPSA60-co-AA20-co-DMA20); (D) 3_SiO₂-g-P(AMPSA67-co-AA22-co-DMA11) NPs.

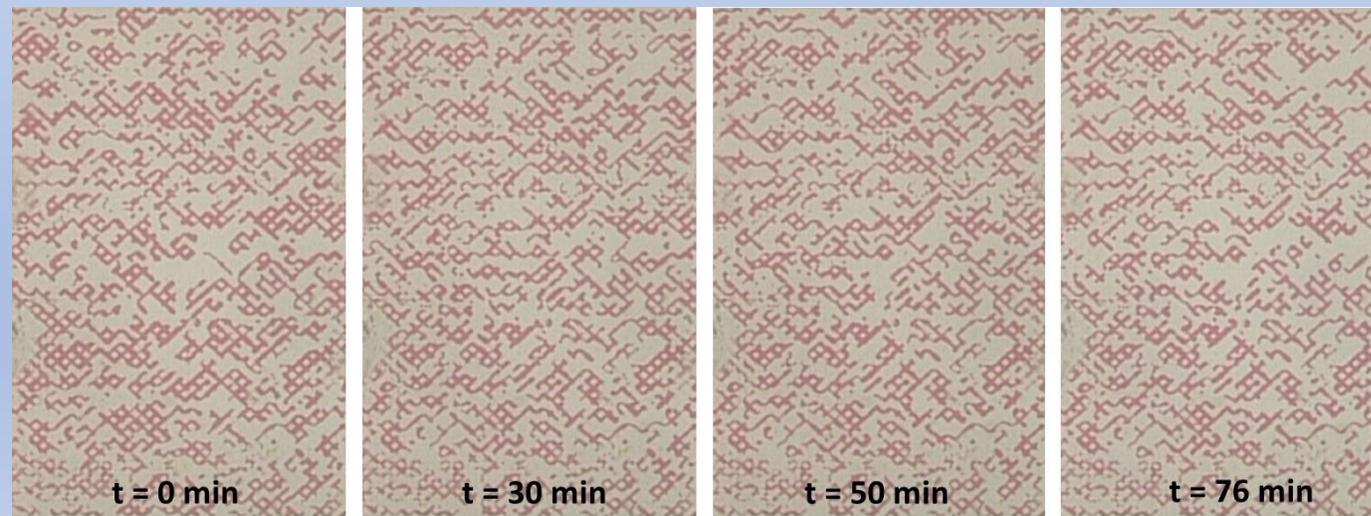


Main barrier:
The small quantities synthesized are insufficient to extend the studies to sand columns and rock plugs

OIL DISPLACEMENT BY PNP SUSPENSIONS

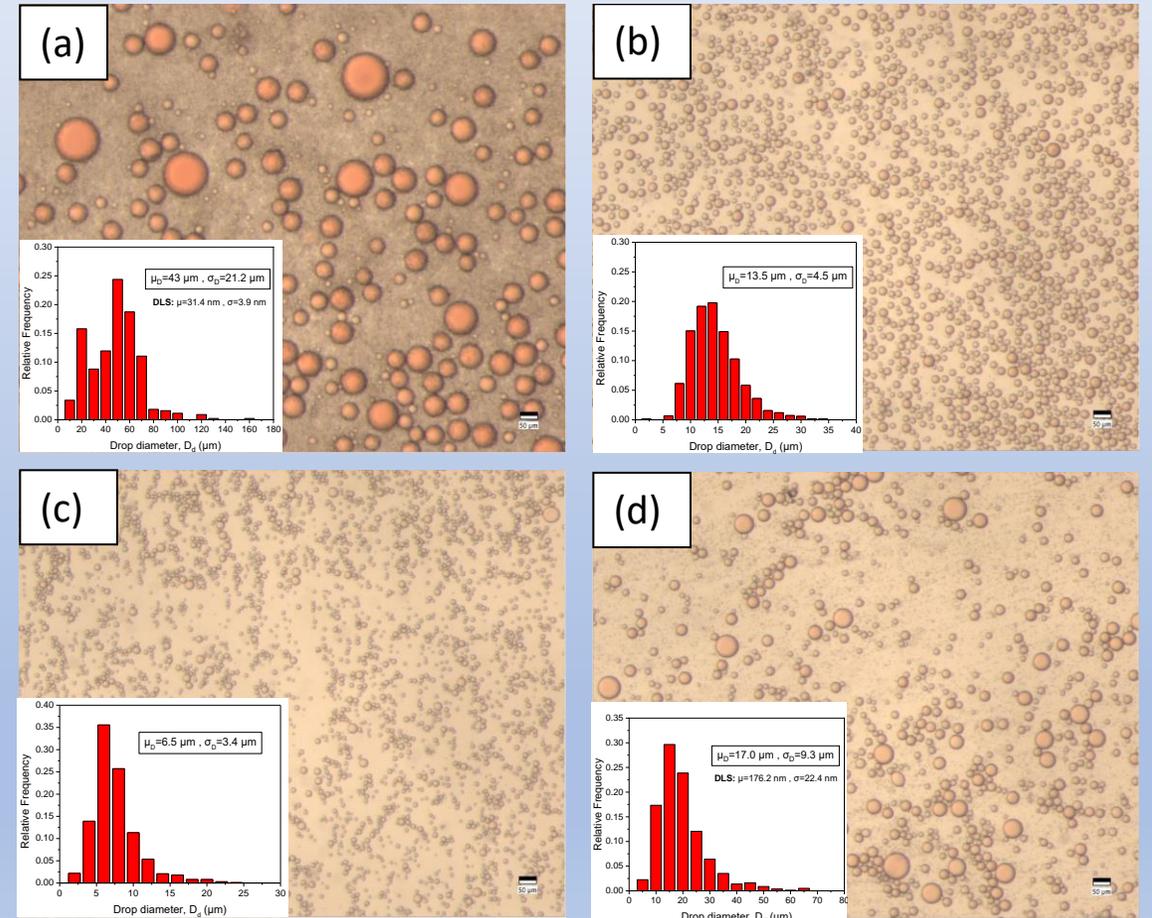
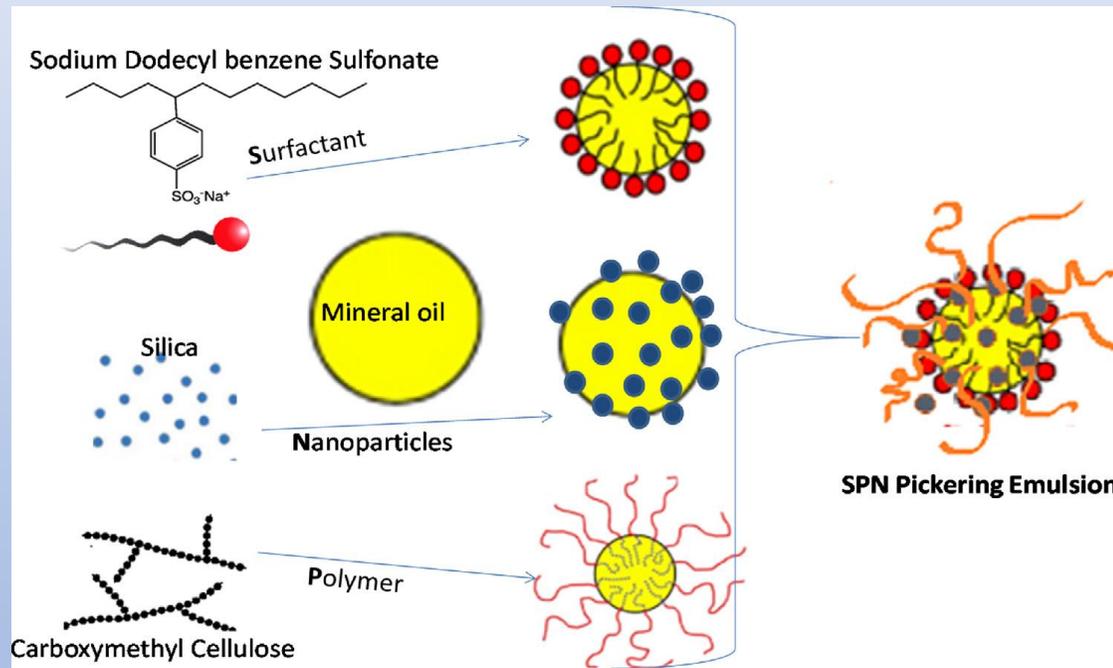


Displacement
of paraffin oil
by brine
(NaCl 1M)
 $S_{or}=0.457$

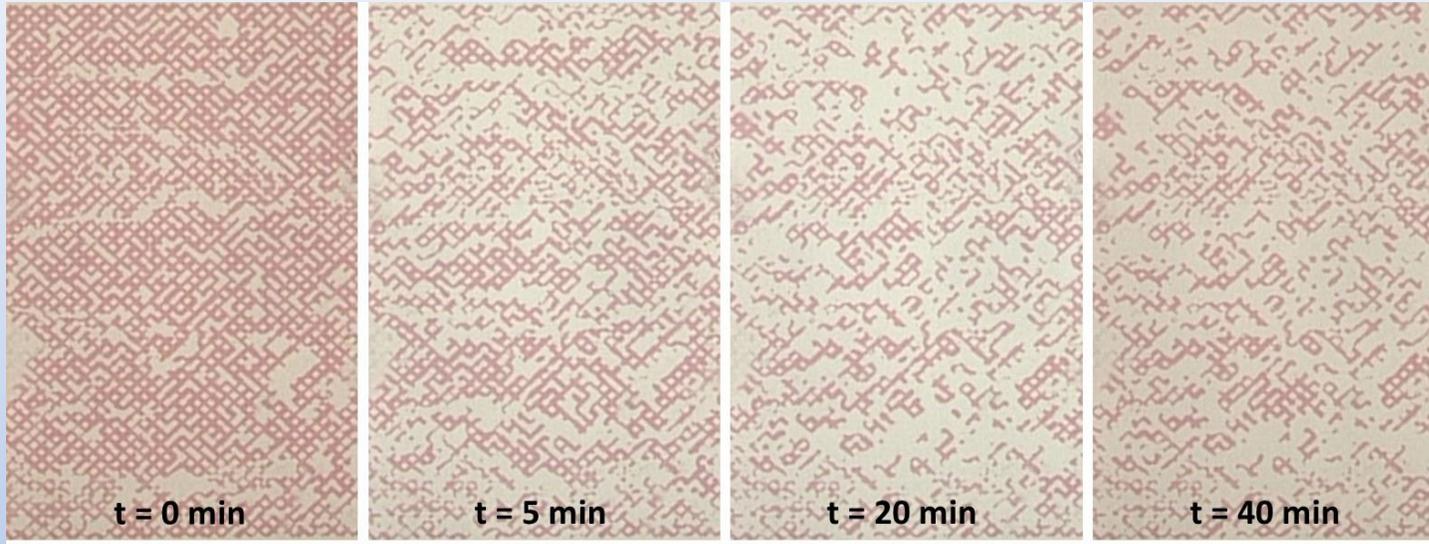


Displacement of
residual paraffin oil by
AMPSA 75-25 0.25% -
NaCl 1M
 $S_{or}=0.403$

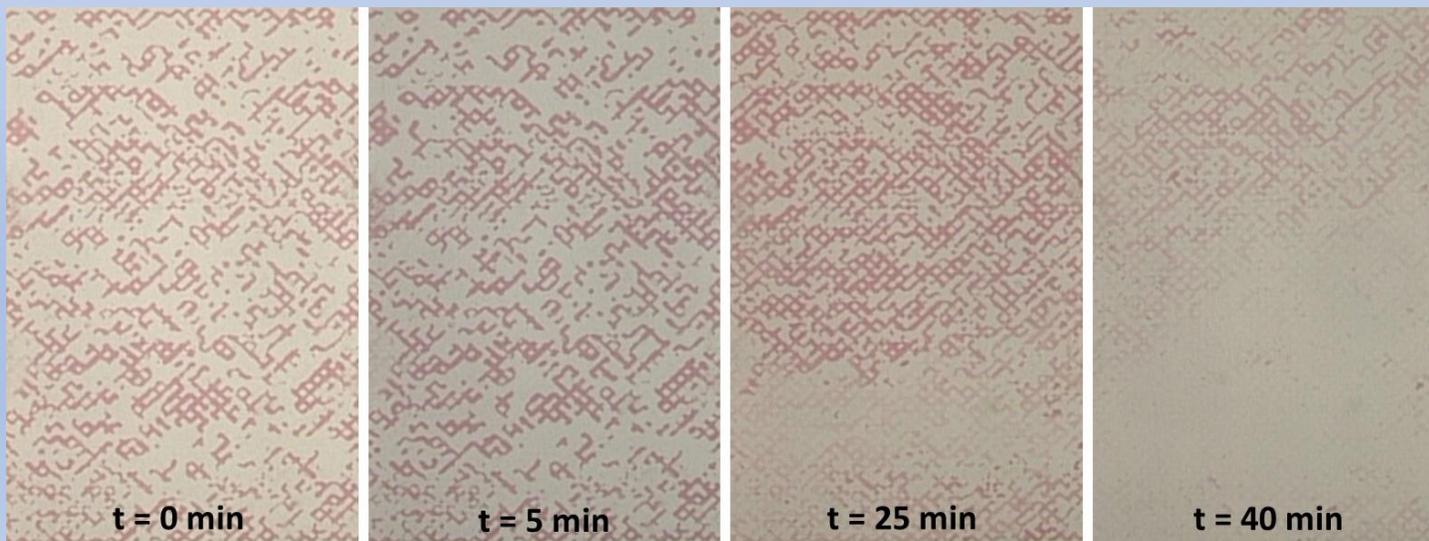
PREPARATION OF PNP-PICKERING EMULSIONS



OIL DISPLACEMENT BY PNP-STABILIZED EMULSIONS

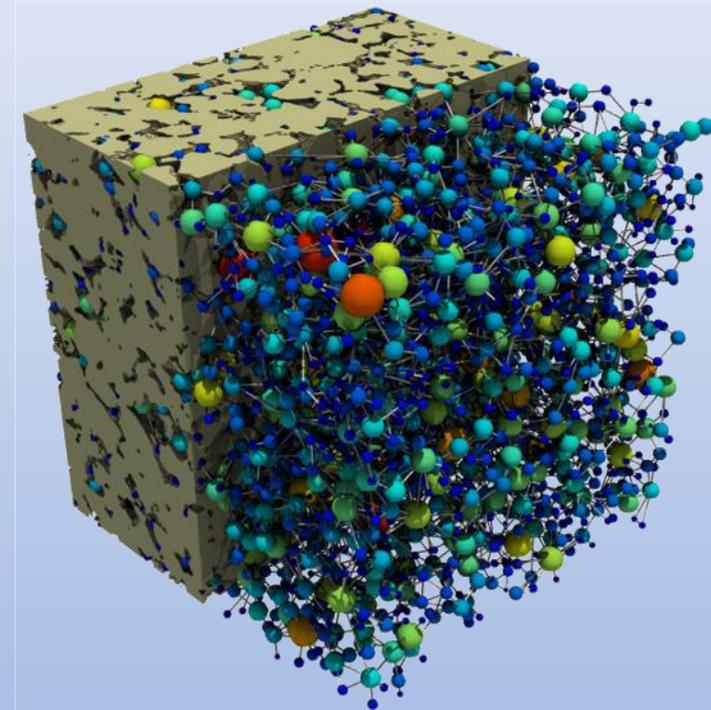
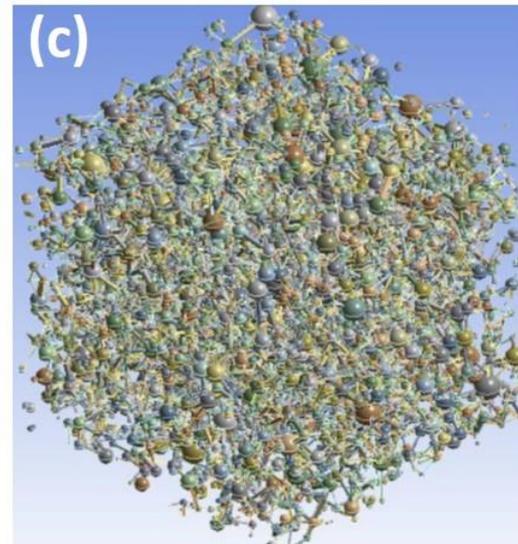
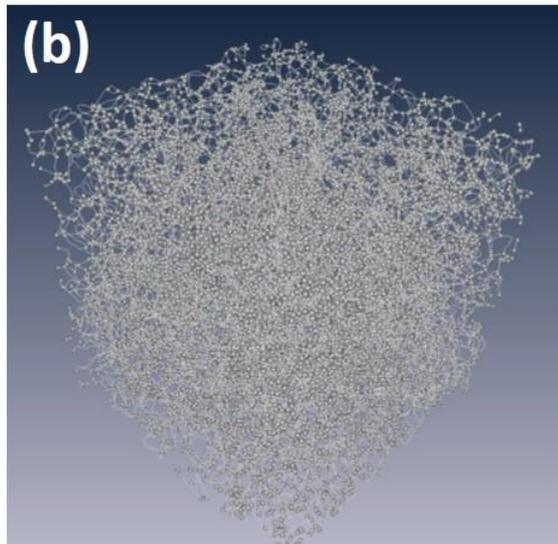
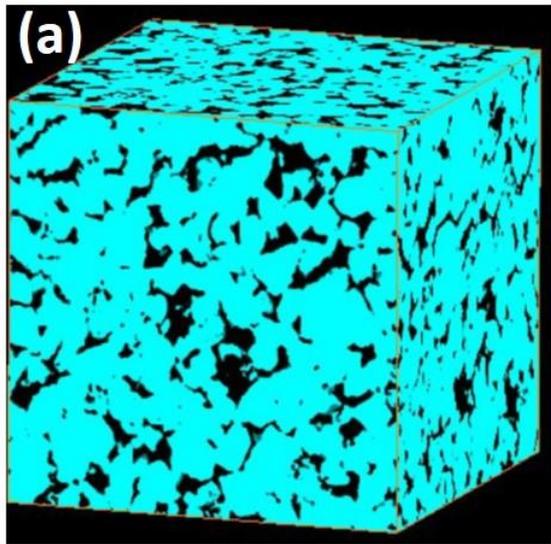


Displacement
of paraffin oil
by brine
(NaCl 1M)
 $S_{or}=0.447$



Displacement of
residual paraffin oil by
(SiO₂-AMPSA-DMA-
0.25% + NaCl 1M)
Pickering emulsion
 $S_{or}=0.157$

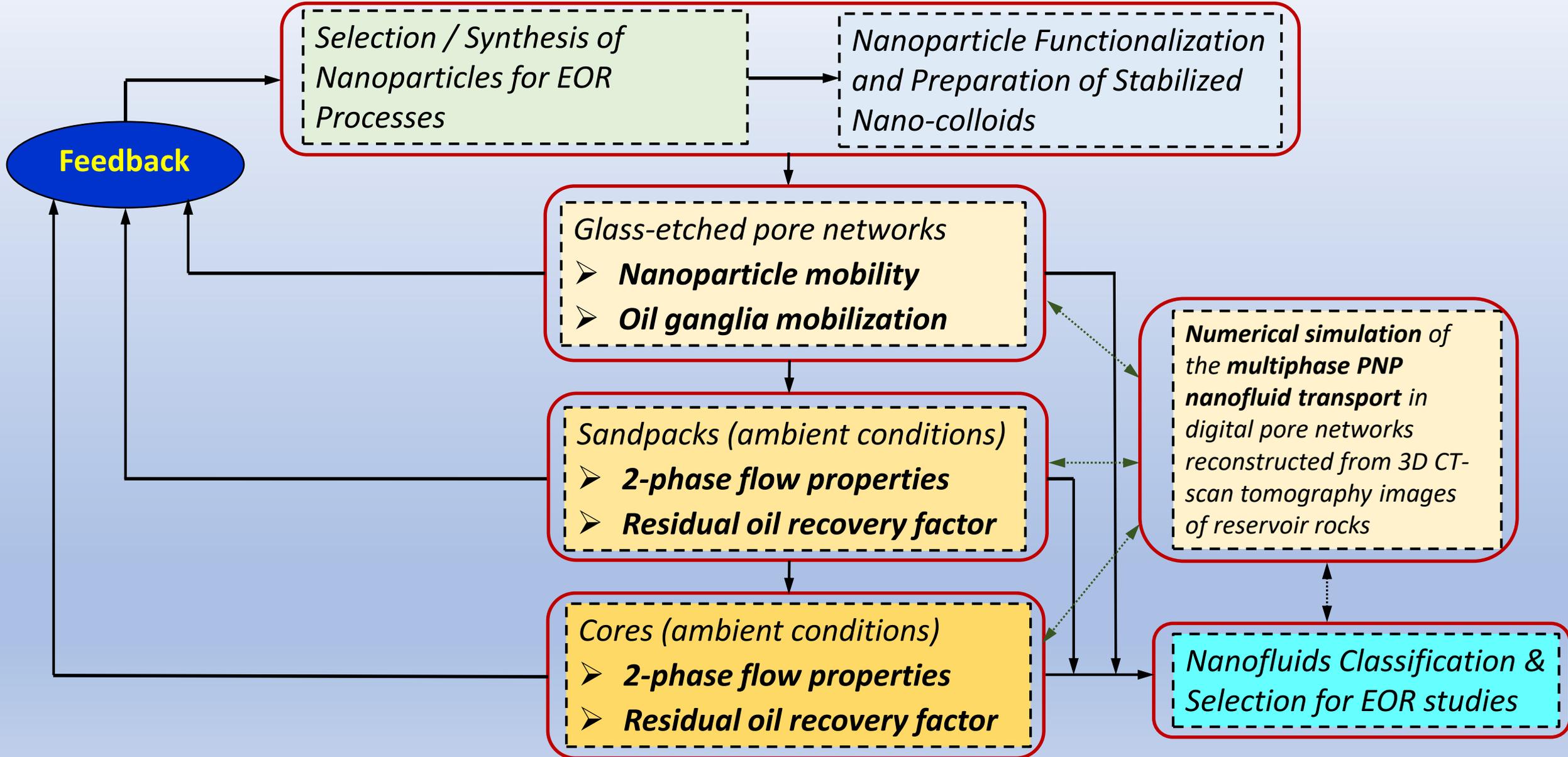
DIGITAL ROCK PHYSICS



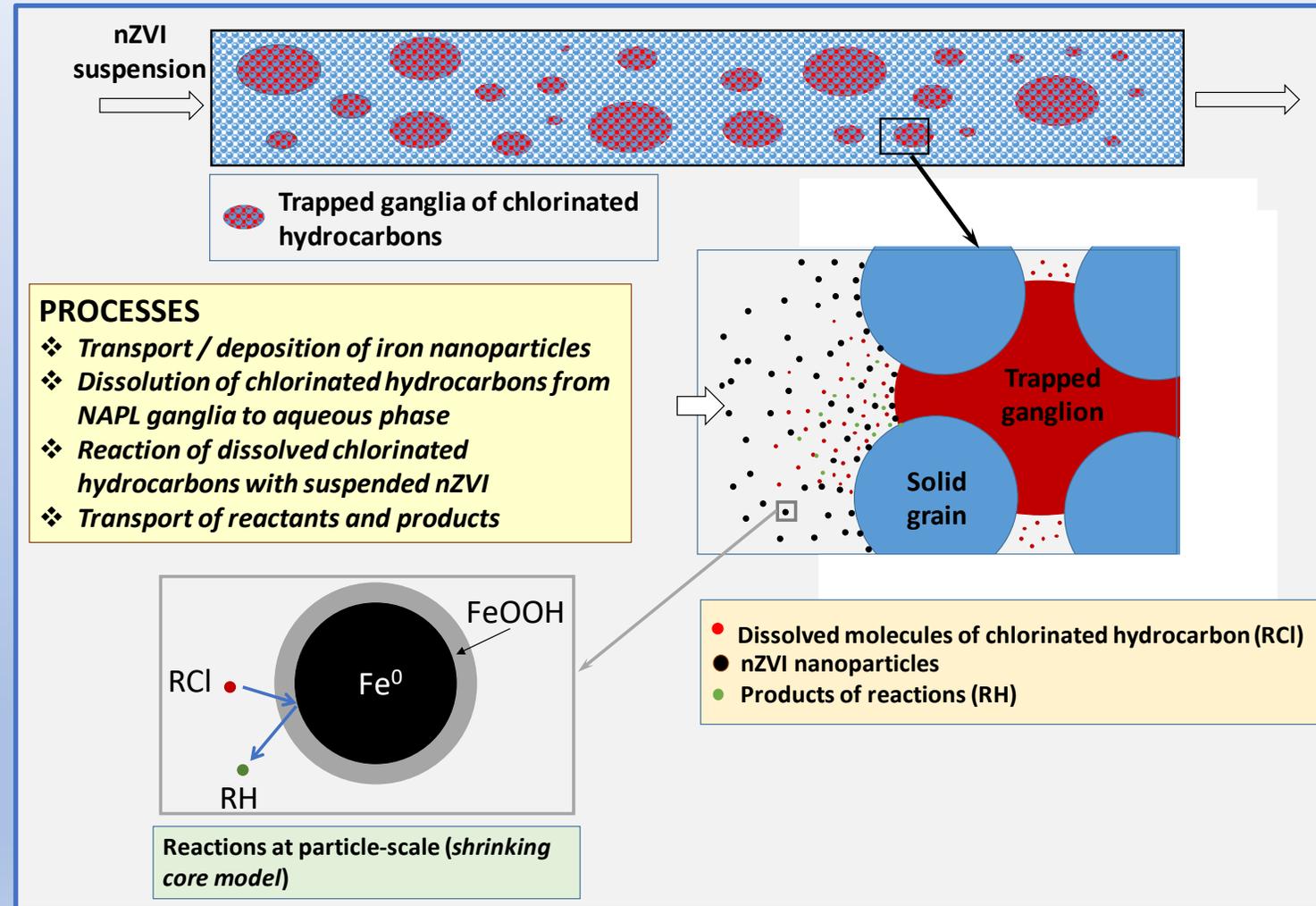
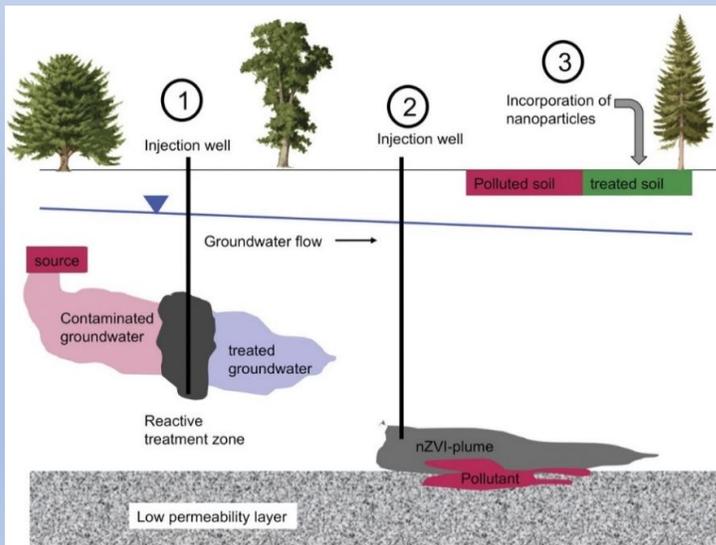
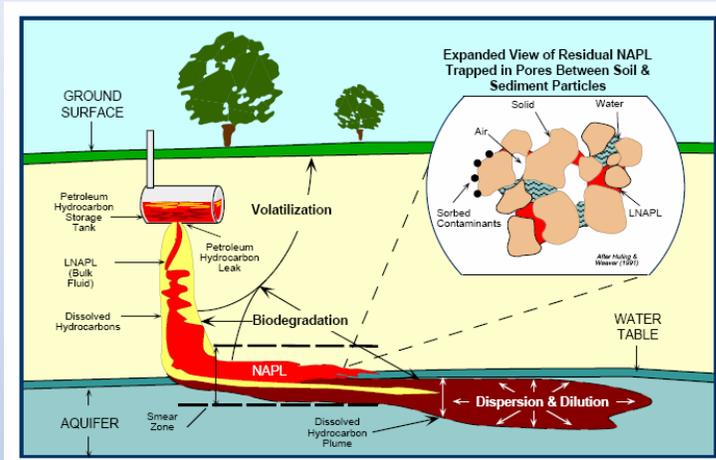
OpenPNM and PoreSpy software:

Tomorrow morning, you can bring your Laptop for training course on the use of software

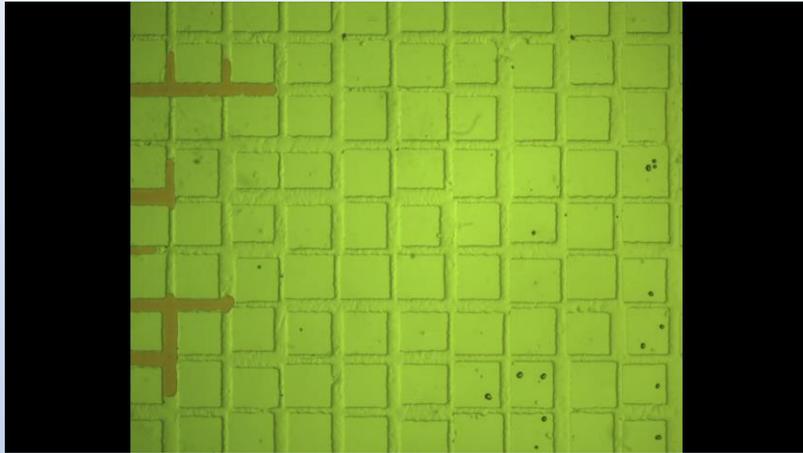
METHODOLOGY



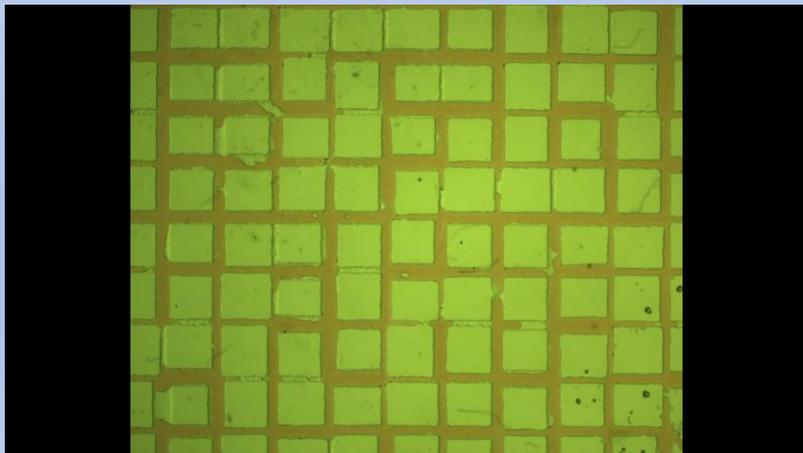
ENVIRONMENTAL APPLICATIONS: NANOREMEDIATION



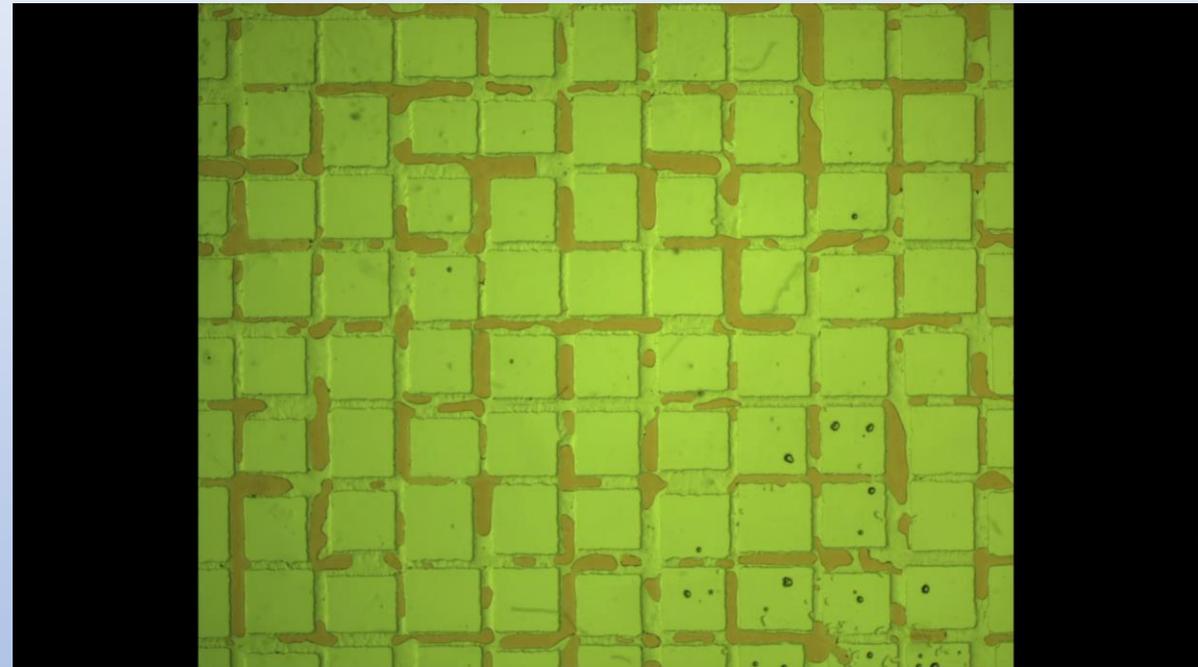
Drainage



Imbibition (secondary oil recovery)



Imbibition (tertiary oil recovery)



The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment (Project title: “Enhanced Oil Recovery by Polymer-coated Nano Particles - EOR-PNP», code: HFRI-FM17-361)

WORKSHOP AGENDA

Monday, 12 December 2022

14:30-15:00: Registration

Workshop I.

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ΠΑΝΕΠΙΣΤΗΜΙΟ
ΠΑΤΡΩΝ
UNIVERSITY OF PATRAS



Workshop, 12-13 December 2022
FORTH/ICE-HT, Patras

Advances toward the transport of nanoparticles in porous media and residual oil recovery applications

Synthesis and characterization of polymer-coated nanoparticles

Georgios Bokias, Professor
Zacharoula Iatridi, Post-doctoral Fellow

Patras, 12 December 2022



ΠΑΝΕΠΙΣΤΗΜΙΟ
ΠΑΤΡΩΝ
UNIVERSITY OF PATRAS



Advanced Polymers & Hybrid Nanomaterials Research Laboratory

<http://www.aphnrl.chem.upatras.gr/>

Department of Chemistry, University of Patras, Greece

<http://www.chem.upatras.gr/en>

Patras, 12 December 2022



**Department of Chemistry,
University of Patras, Rio, Greece**

<https://www.upatras.gr/en>



**Foundation for Research and Technology
Hellas, Institute of Chemical Engineering
Science (FORTH/ICE-HT), Patras, Greece**

<http://www.iceht.forth.gr/>



Advanced Polymers & Hybrid Nanomaterials Research Laboratory



Faculty Members

-  ▪ Joannis Kallitsis, Professor
-  ▪ Georgios Bokias, Professor
-  ▪ Chrysovalanto Deimede, Associate Professor
-  ▪ Aikaterini Andreopoulou, Assistant Professor

Postdoctoral Fellows

-  ▪ Dr. Charalampos Anastassopoulos
-  ▪ Dr. Zacharoula Iatridi
-  ▪ Dr. Georgia Lainioti

PhD Candidates

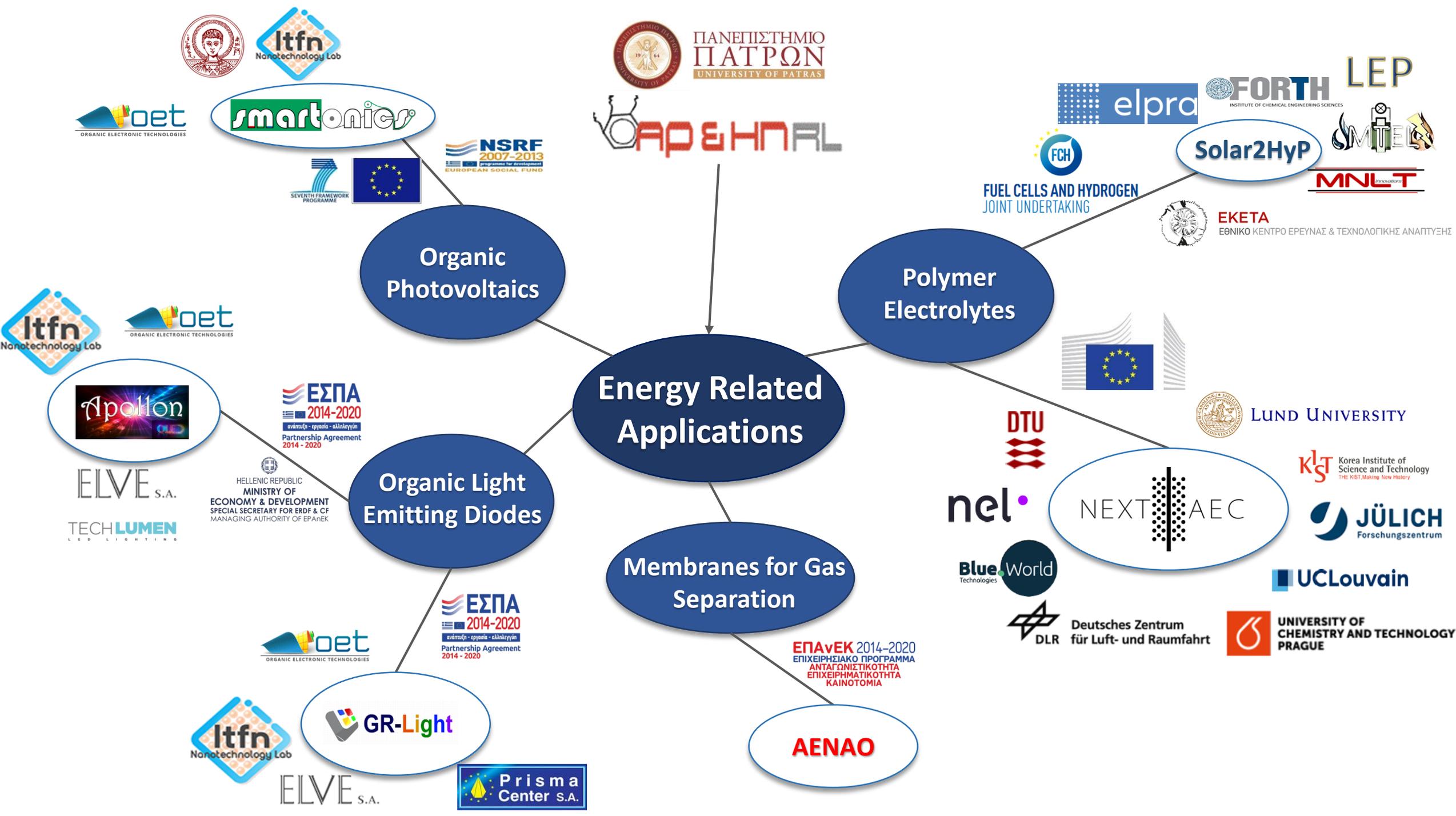
-  ▪ Mrs. Dionisia Druvari, MSc
-  ▪ Mr. Konstantinos Andrikopoulos, MSc
-  ▪ Mrs. Ioanna Tzoumani, MSc
-  ▪ Mrs. Efterpi Avdeliodi, MSc

Master students

-  ▪ Mrs. Paraskevi Loukopoulou
-  ▪ Mrs. Gjoshi Sara
-  ▪ Mrs. Koutsougera Maria-Filomeni
-  ▪ Mrs. Roufi Konstantina
-  ▪ Mrs. Tsolka Eftychia
-  ▪ Mrs. Stamatopoulou Eleftheria-Danae
-  ▪ Mr. Fotis Panagiotou

Pre-graduate students >15

- Secretary: Mrs. Evaggelia Kapota 
- Technical Support: Mr. Panagiotis Adamopoulos



Life Quality

Bionet

Τμήμα Αλλεργίας και Υδατοκαλλιεργειών

Τμήμα Γεωλογίας



Antimicrobial Applications

Serial



Environmental Applications

INCOMERA



Functional Materials for Optimization of Industrial Products



ΕΛVIFA - ΚΑΛΟΓΕΡΑΚΗΣ Η. ΜΙΧΑΗΛ ΑΕ

Chromasurf



ΕΠΑΝΕΚ 2014-2020 ΕΠΙΧΕΙΡΗΣΙΑΚΟ ΠΡΟΓΡΑΜΜΑ ΑΝΤΑΓΩΝΙΣΤΙΚΟΤΗΤΑ ΕΠΙΧΕΙΡΗΜΑΤΙΚΟΤΗΤΑ ΚΑΙΝΟΤΟΜΙΑ

ΕΣΠΑ 2014-2020

Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης



SELFNANO PUD

MEGARA RESINS ANASTASSIOS FANIS S.A.



SIAMIDIS

Thorax



ADAMANT



ΕΠΑΝΕΚ 2014-2020 ΕΠΙΧΕΙΡΗΣΙΑΚΟ ΠΡΟΓΡΑΜΜΑ ΑΝΤΑΓΩΝΙΣΤΙΚΟΤΗΤΑ ΕΠΙΧΕΙΡΗΜΑΤΙΚΟΤΗΤΑ ΚΑΙΝΟΤΟΜΙΑ

ΕΣΠΑ 2014-2020

Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης

Τμήμα Μηχανολόγων & Αεροναυπηγών Μηχανικών

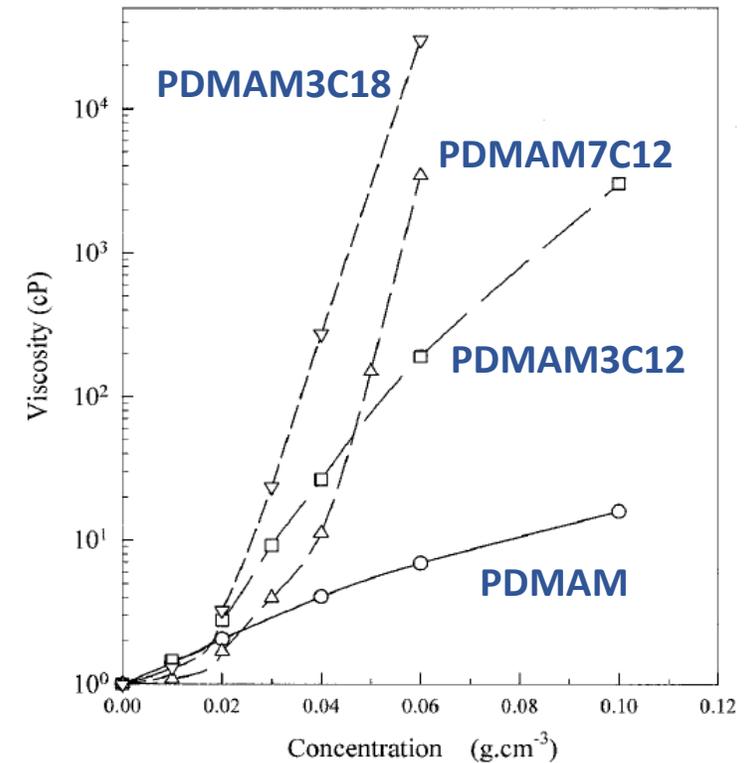
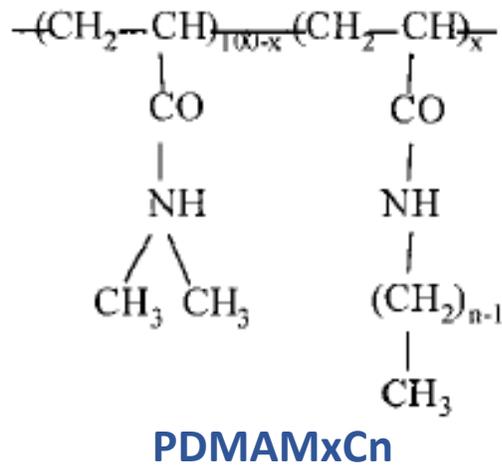
Hydrophobically modified water-soluble polymers

Main collaborators: Dr. Ilias Iliopoulos, Prof. Dominique Hourdet
ESPCI, France

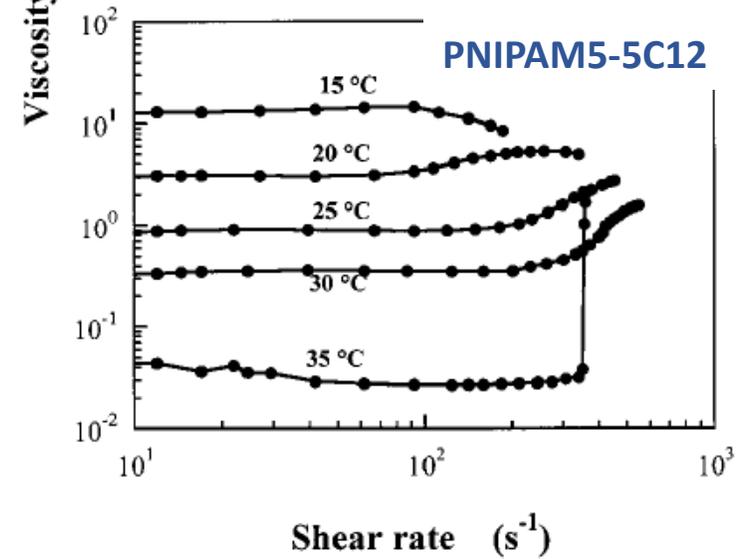
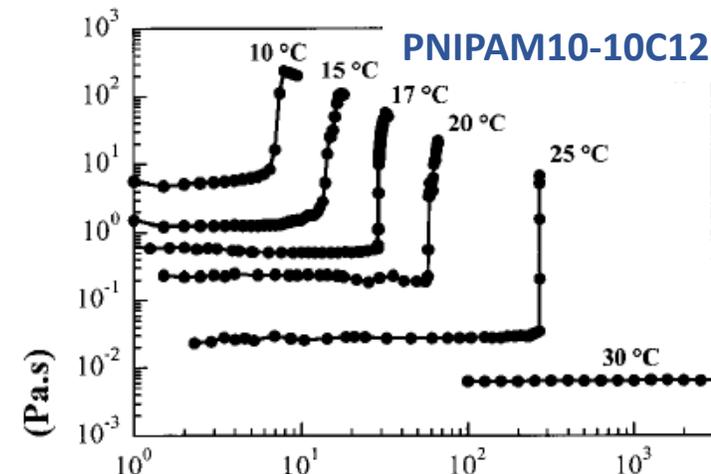
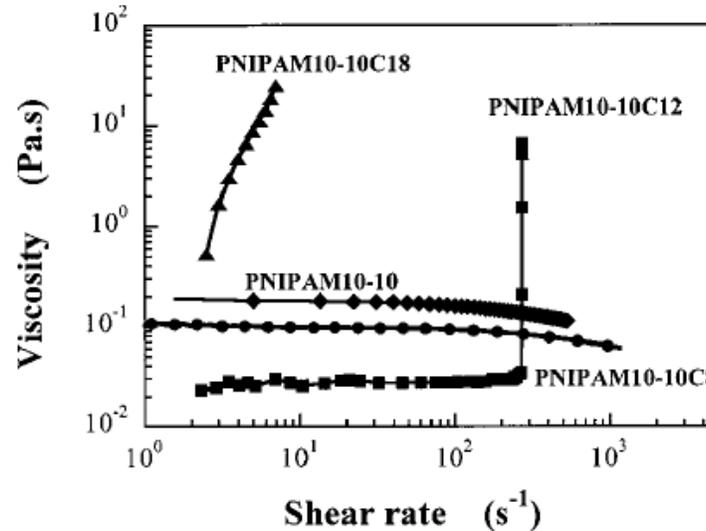
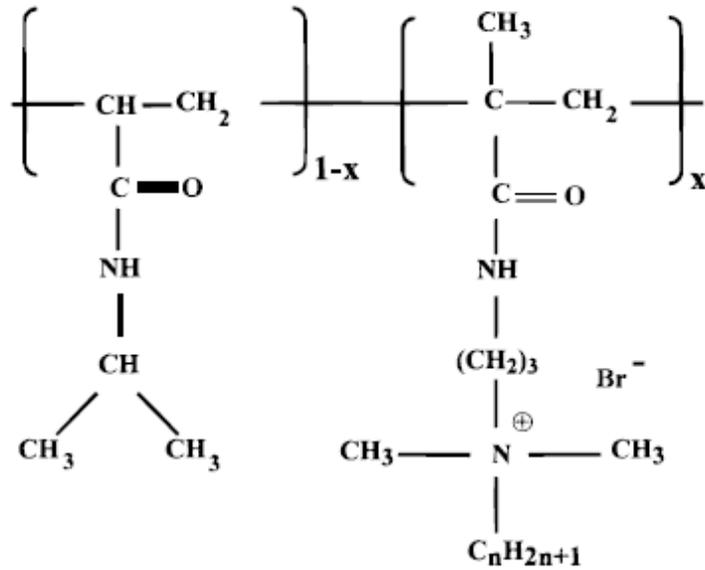


Examples

i) Hydrophobically modified PDMAM



ii) Cationic hydrophobically modified PNIPAM

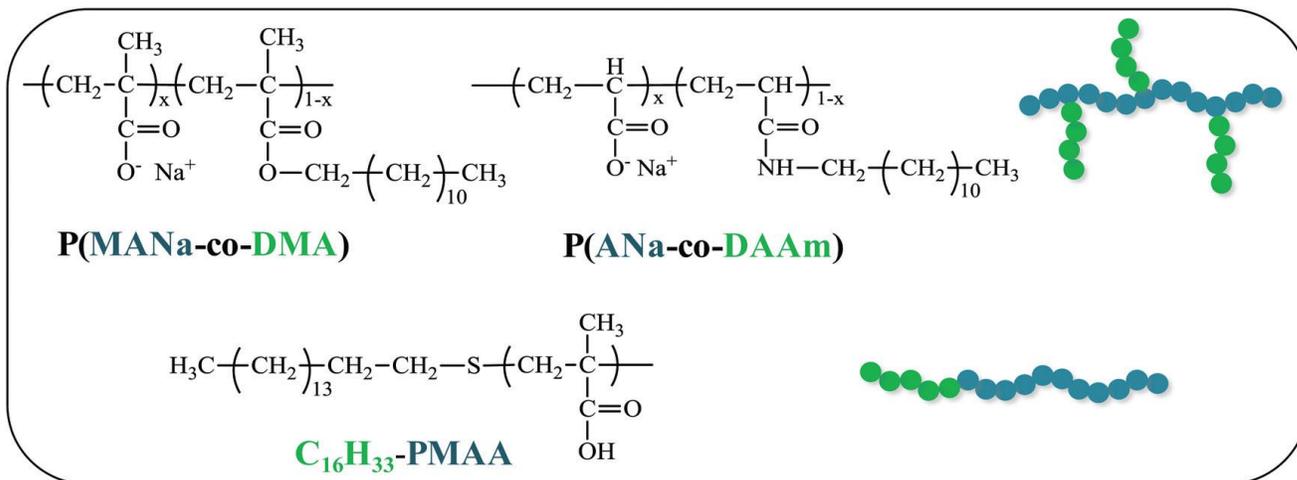


Amphiphilic Polymers - Transfer of Hydrophobic Magnetic NPs in Water

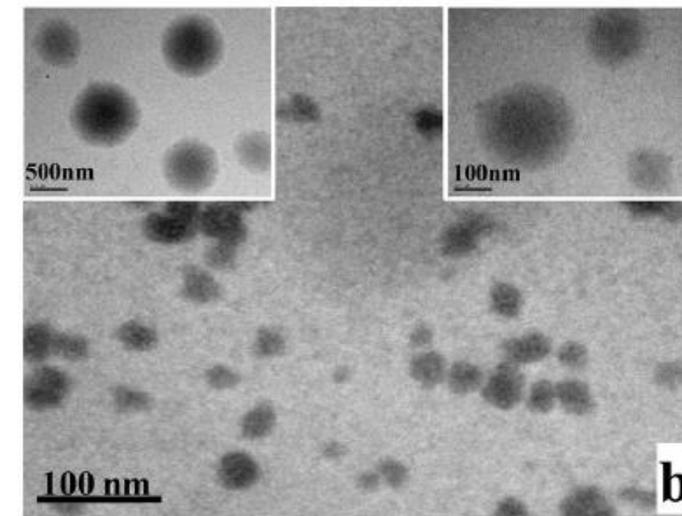


Main collaborator: Prof. Katherine Dendrinou-Samara, Chemistry Department, Univ. of Thessaloniki

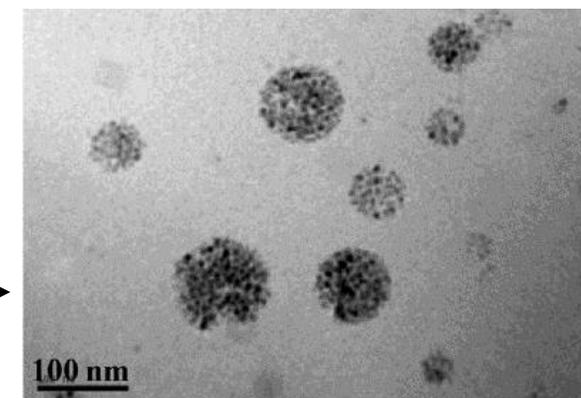
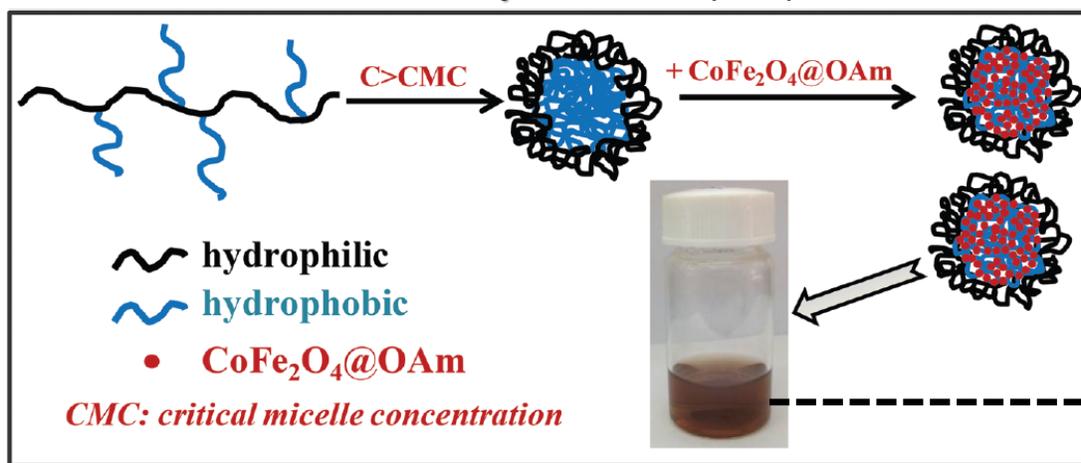
i. Use of hydrophobically modified polyelectrolytes



Self-assembly in
aq. media
Cpol > CMC

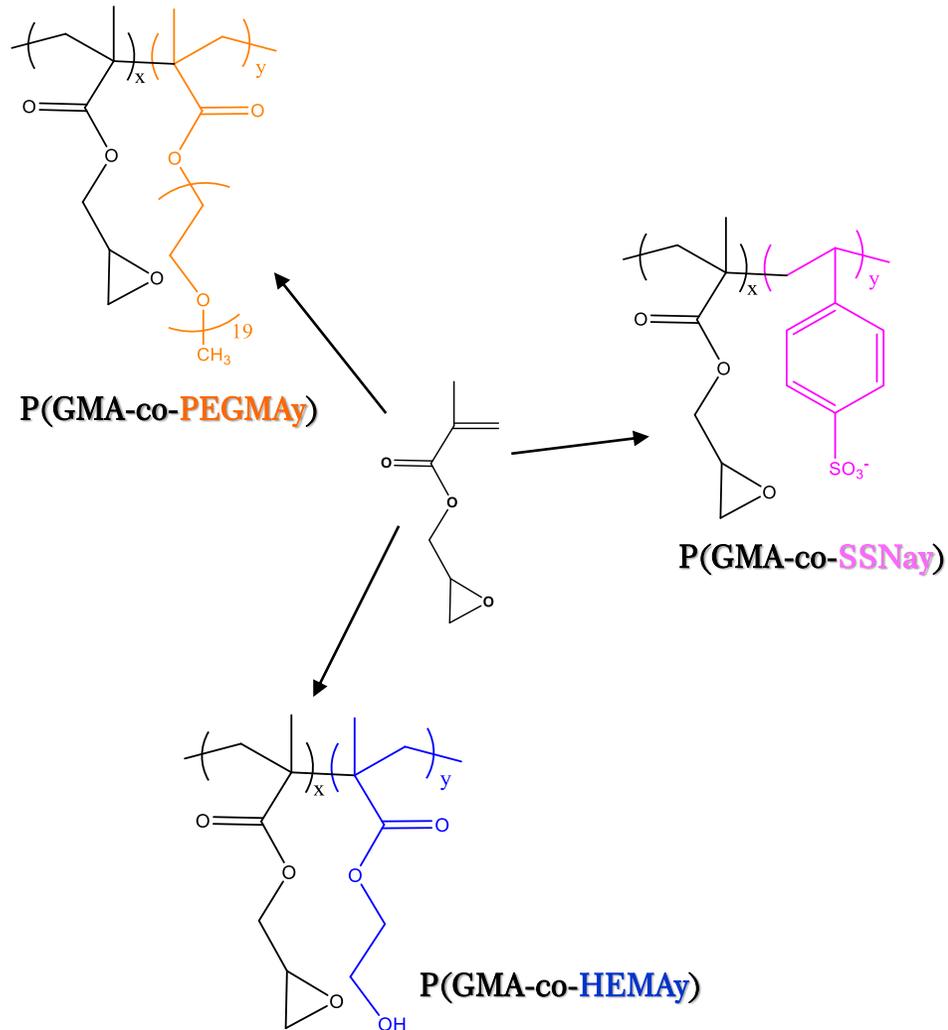


✓ dispersion of hydrophobic MNPs in aqueous media



GMA-copolymers with reactive functional groups - Self-healing properties

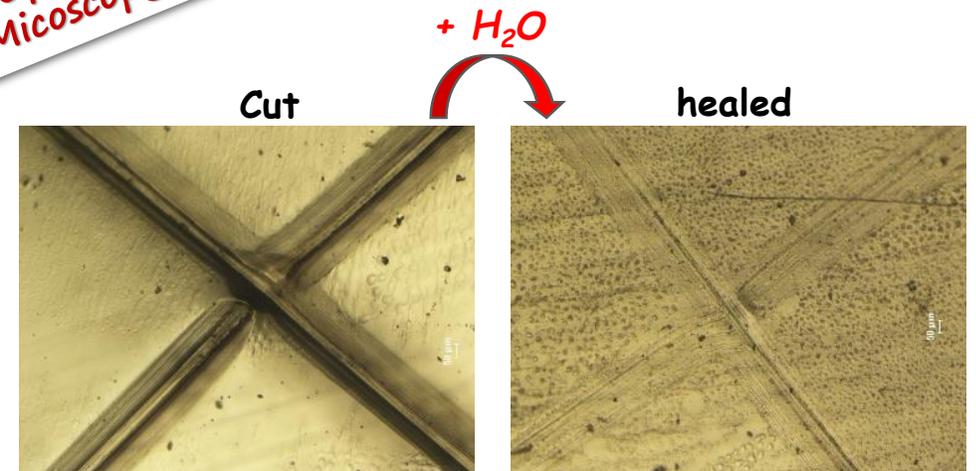
Main collaborator: Dr. P. Krassa, MEGARA Resins



Self-Healing Process

Polyurethane film containing
10 wt.% copolymer $P(\text{GMA-co-PEGMA})$

Optical
Microscopy





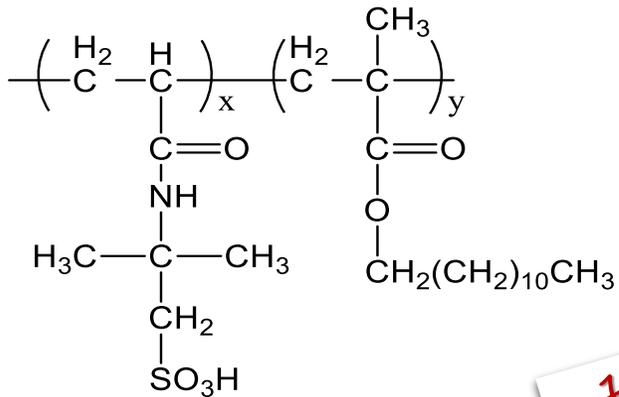
«Enhanced oil recovery by polymer-coated nanoparticles»

(Project Leader: Research Director Christos Tsakiroglou).



H.F.R.I.
Hellenic Foundation for
Research & Innovation

Water soluble amphiphilic copolymers



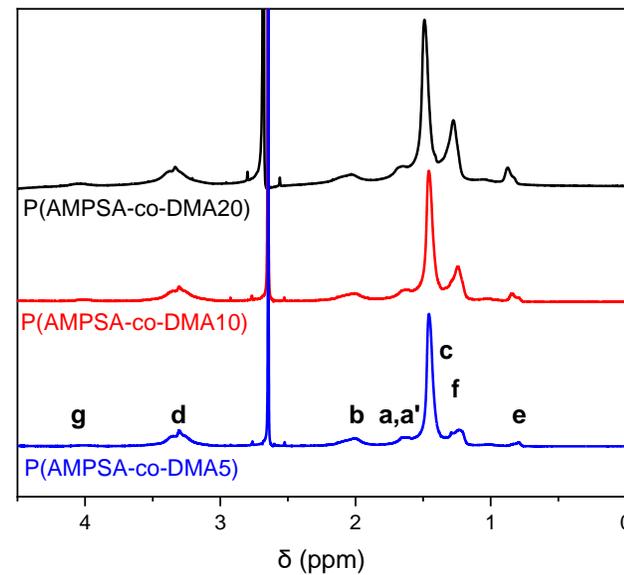
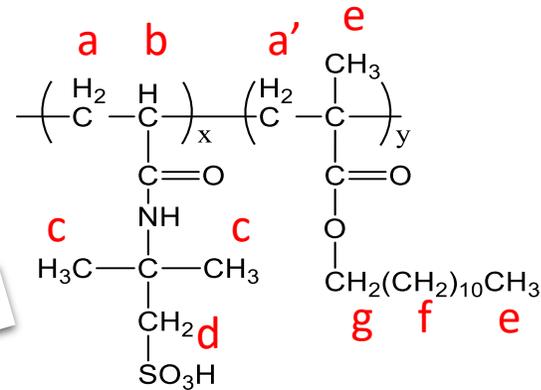
P(AMPSA-co-DMA_y)

x=95, y=5 %mol

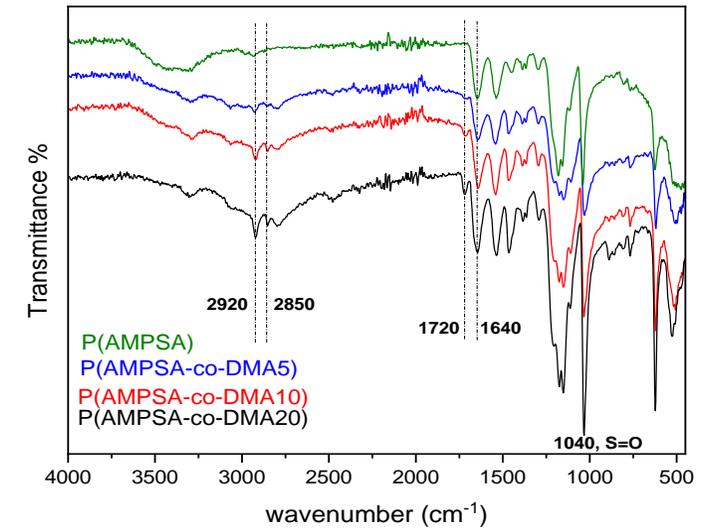
x=90, y=10 %mol

x=80, y=20 %mol

¹H NMR



ATR-FTIR

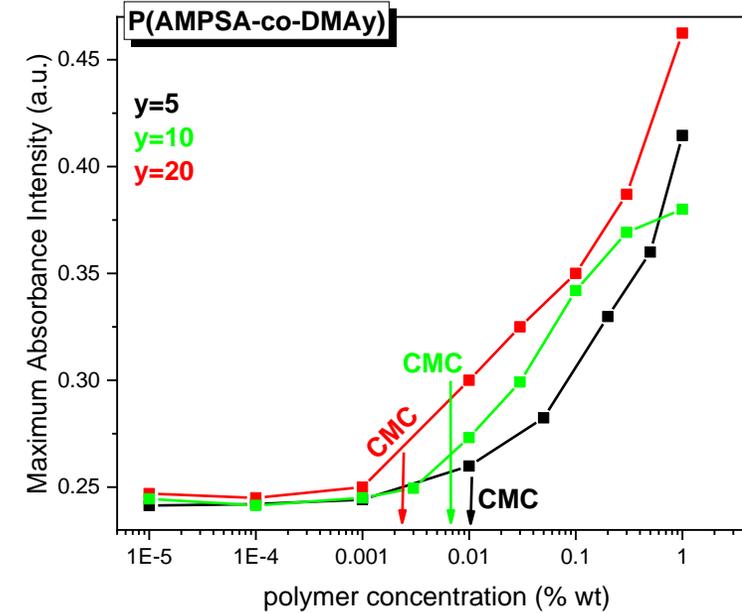
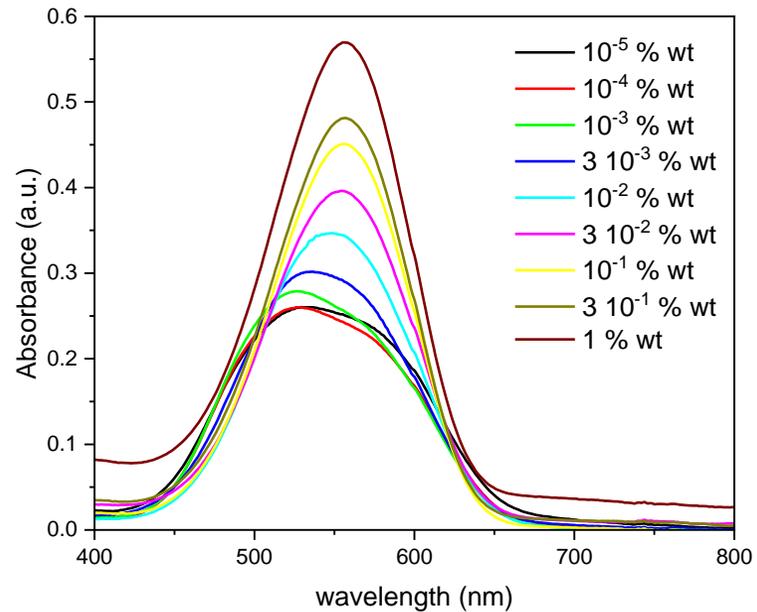


GPC (aq. LiNO₃)

polymer	M _n , g/mol	M _w , g/mol	PDI
P(AMPSA₉₀-co-DMA₁₀)	13700	22500	1.64
P(AMPSA₉₅-co-DMA₅)	16800	34200	2.04

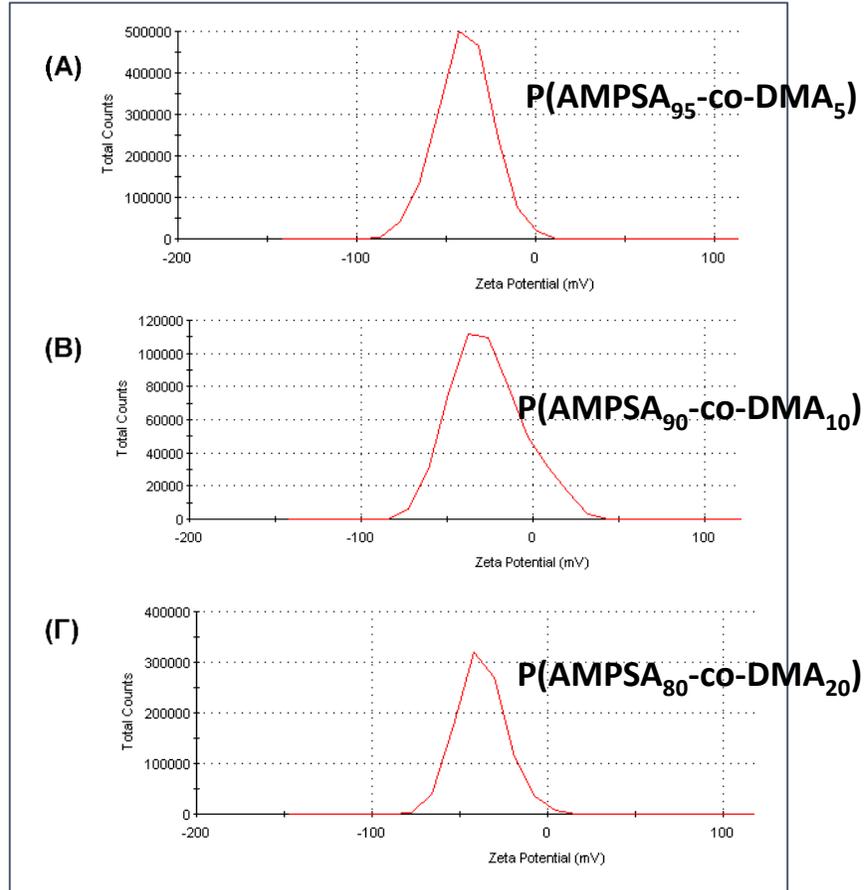
Self-organization in aqueous media

Nile Red probing for the determination of the **Critical Micelle Concentration (CMC)**

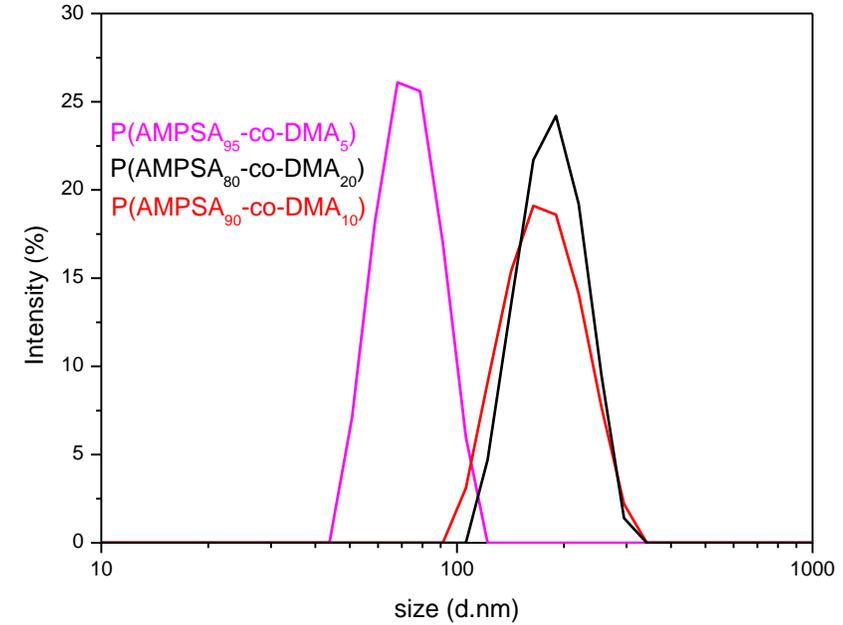


Self-organization in aqueous media

Zeta-potential



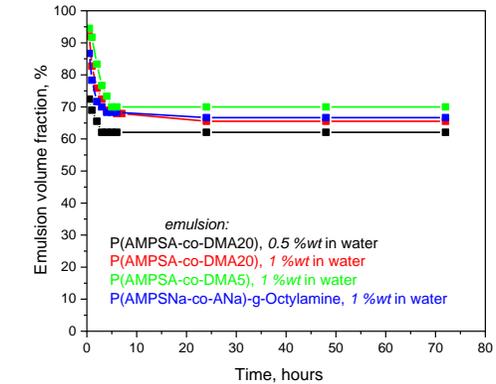
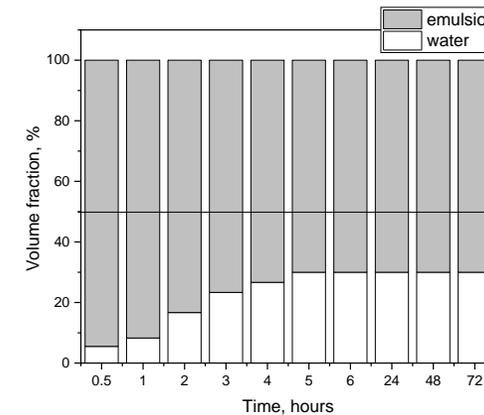
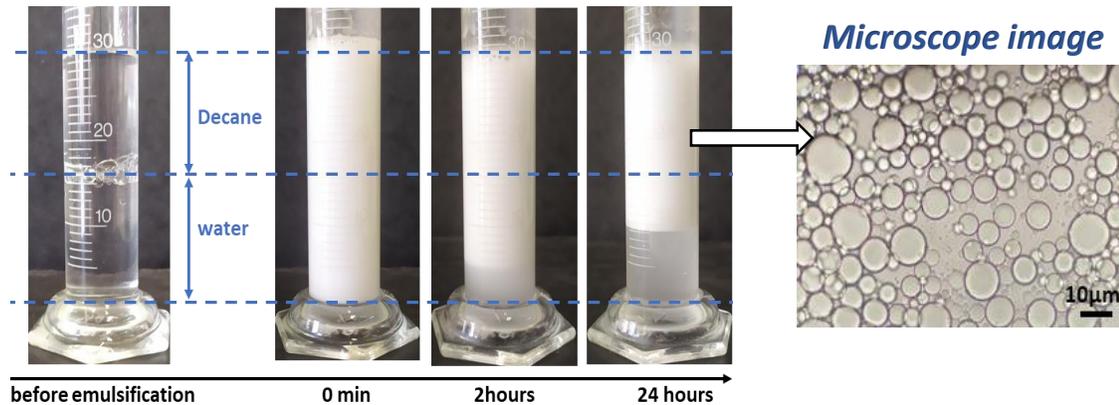
DLS



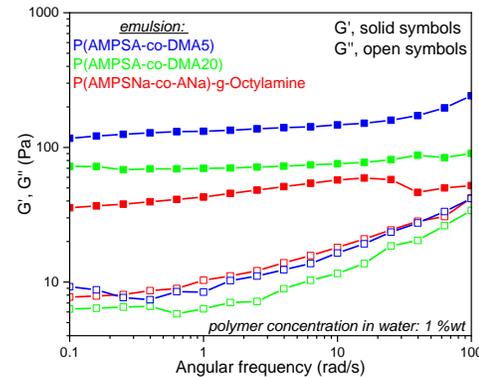
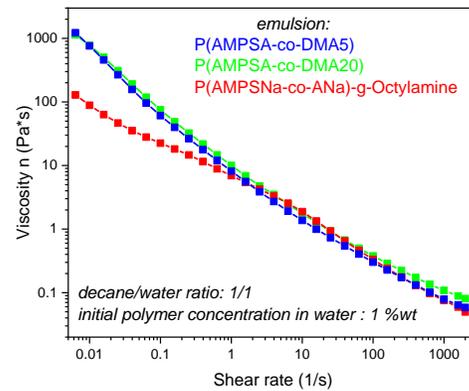
polymer	zeta(mV)	size: diameter (nm)		
		by intensity	by volume	by number
P(AMPSA ₉₅ -co-DMA ₅)	-39.8	74.1	67.7	61.5
P(AMPSA ₉₀ -co-DMA ₁₀)	-26.8	179.3	176.6	146.6
P(AMPSA ₈₀ -co-DMA ₂₀)	-37.8	188.1	187.9	78.8

Emulsifying Properties

Visual appearance of P(AMPSA-co-DMA) emulsions



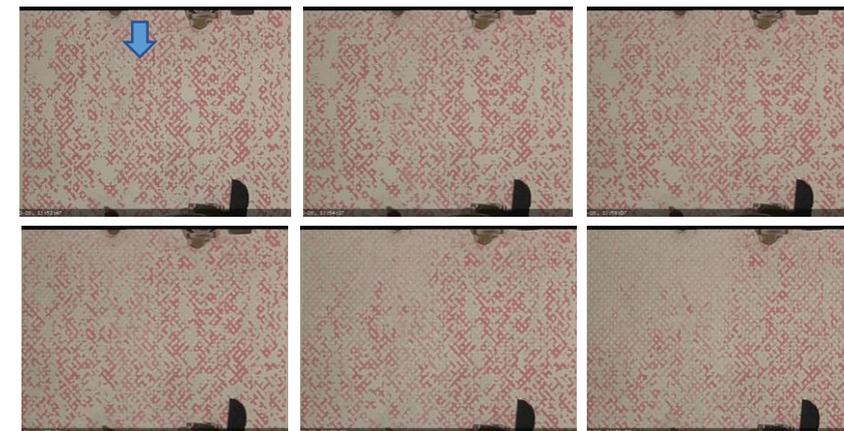
Rheology



✓ $G' > G''$: solid-like behavior

Non-Newtonian fluid type
Shear-thinning

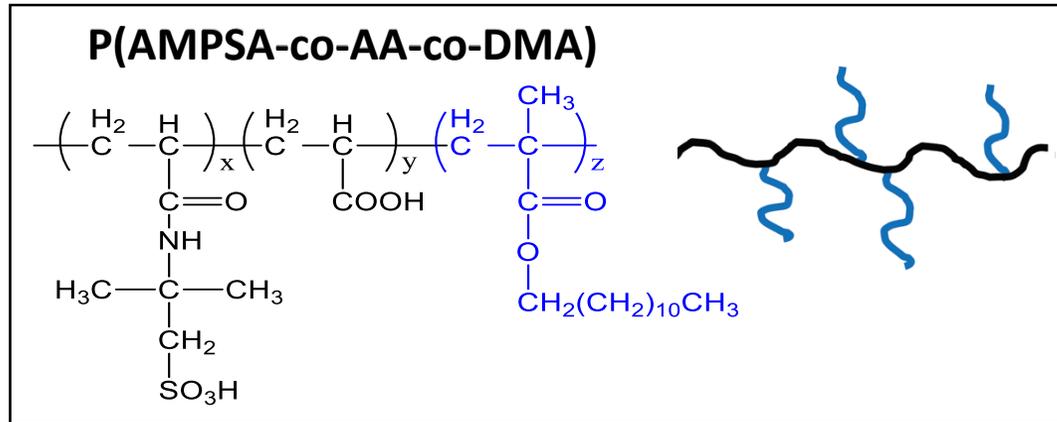
Displacement (secondary imbibition) of oil by emulsion



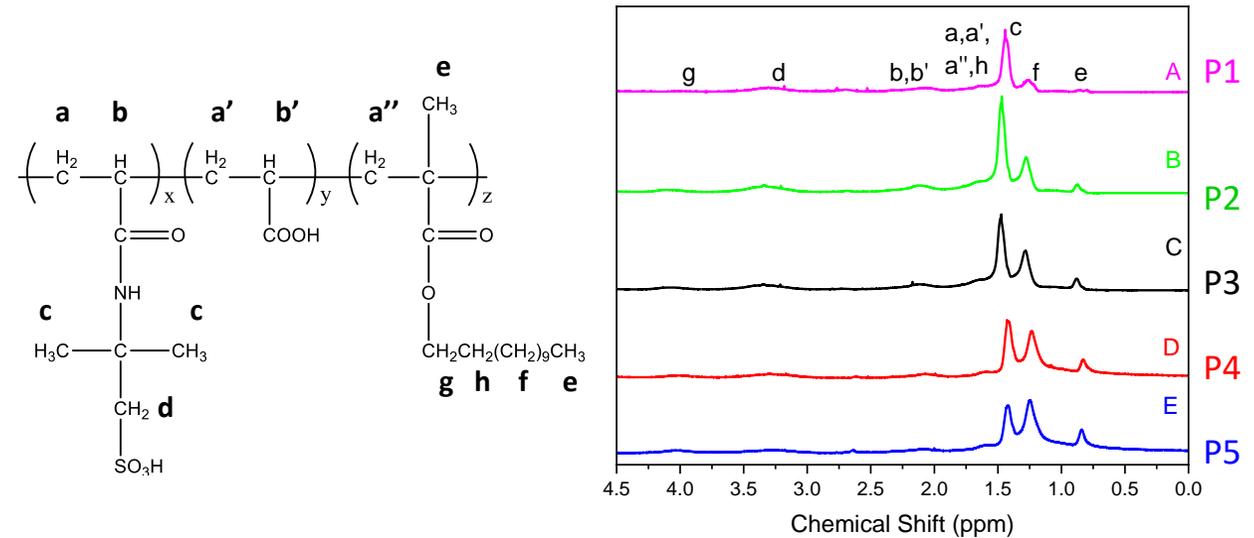
Gradual creation of a frontal drive that progressively mobilizes the majority of residual oil due to the high viscosity ratio

Successive snap-shots of the displacement of dodecane by emulsion prepared by mixing equal volumes (20mL:20mL) of decane with aq. dispersion of 1%wt P(AMPSA-co-DMA20)

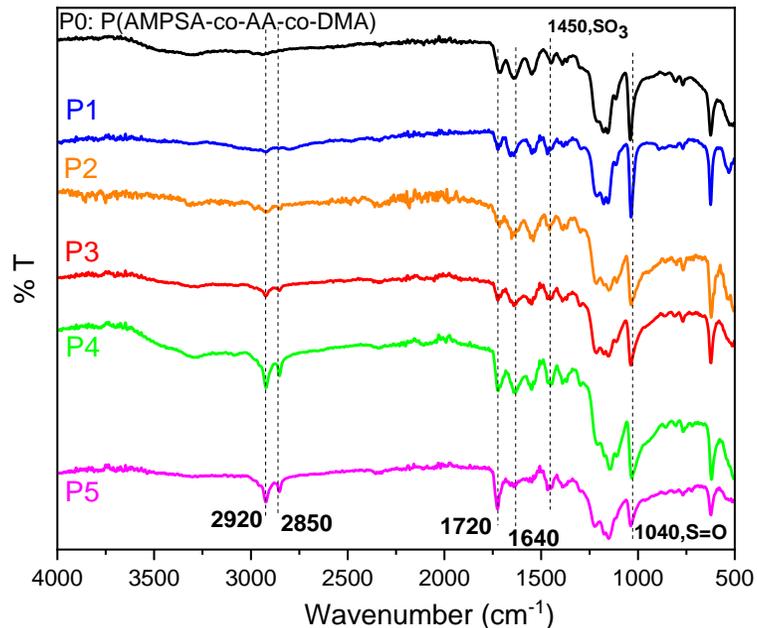
Water soluble amphiphilic terpolymers



1H NMR



ATR-FTIR

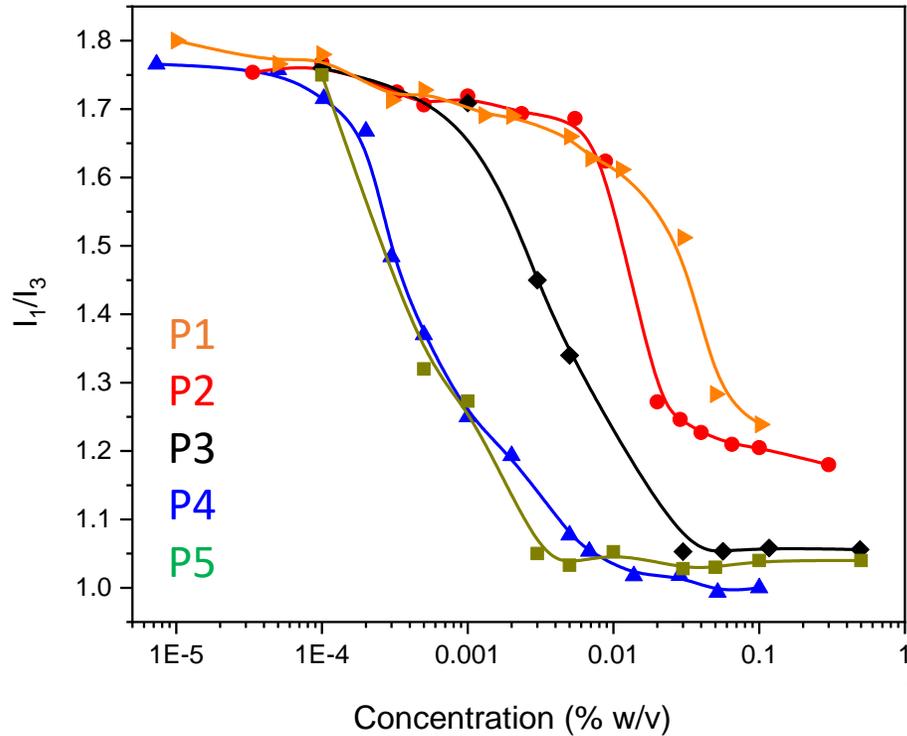


GPC

Polymer	Theoretical composition AMPSA/AA/DMA (% mol)	Composition from 1H NMR AMPSA/AA/DMA (% mol)	GPC		
			Mn (g/mol)	Mw (g/mol)	PDI
P1	65/30/05	60/37/3	17000	23400	1.38
P2	60/20/20	68/27/5	11310	15460	1.37
P3	68/22/10	66/22/12	12300	14450	1.17
P4	50/25/25	55/20/25	-	-	-
P5	40/30/30	39/33/28	-	-	-

Self-organization in aqueous media

Pyrene probing for the determination of the Critical Micelle Concentration (CMC)



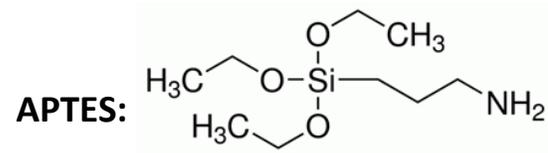
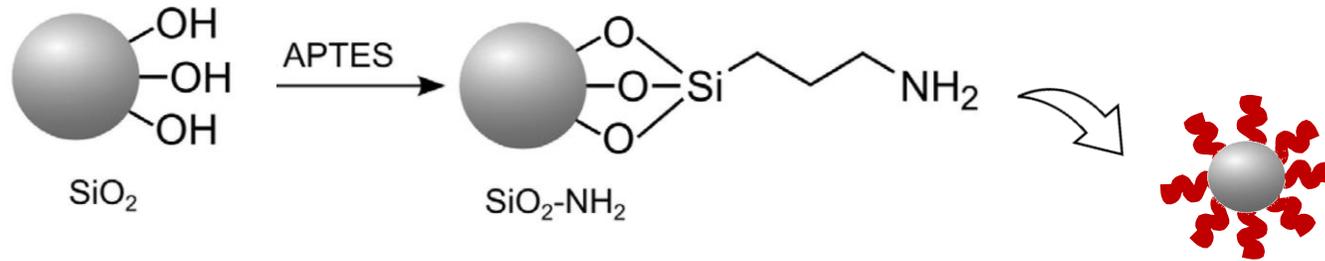
Polymer	CMC (% w/v)
P1: P(AMPSA60-co-AA37-co-DMA3)	0.04
P2: P(AMPSA68-co-AA27-co-DMA5)	0.02
P3: P(AMPSA66-co-AA22-co-DMA12)	0.008
P4: P(AMPSA55-co-AA20-co-DMA25)	0.002
P5: P(AMPSA39-co-AA33-co-DMA28)	0.001

Zeta-potential & DLS

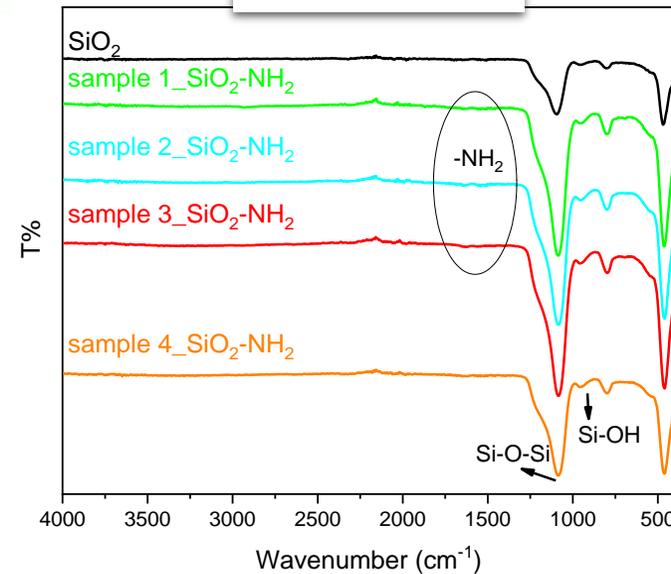
polymer	Zeta mV)	size:diameter (nm)		
		by intensity	by volume	by number
P(AMPSA ₅₅ -co-DMA ₂₀ -co-AA ₂₅)	-30.4	117.6	-	-
P(AMPSA ₆₈ -co-DMA ₂₇ -co-AA ₅)	-32.9	164.0	122.0	78.8
P(AMPSA ₆₀ -co-DMA ₃₇ -co-AA ₃)	-31.8	93.7	107.3	91.2

Polymer-coated nanoparticles (PNPs)

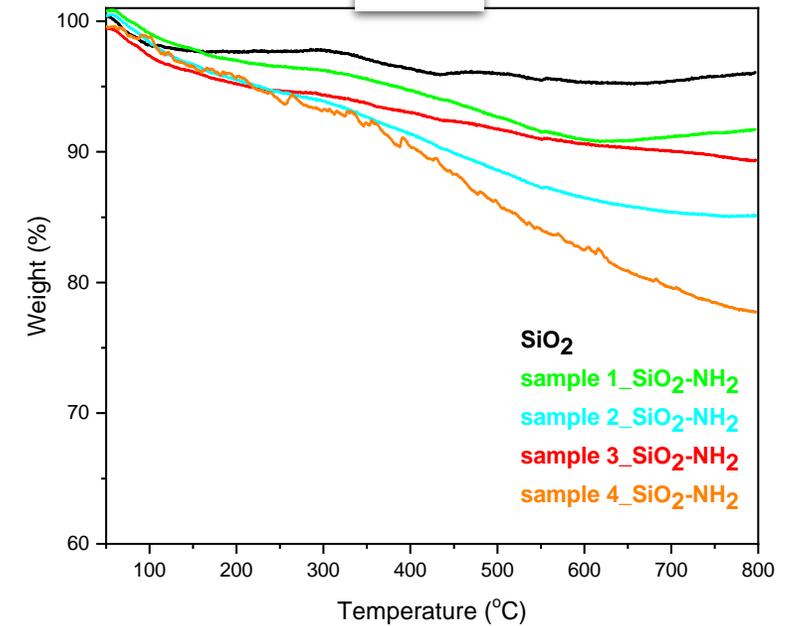
Step 1) Amine-functionalization of SiO₂ NPs with aminopropyltriethoxysilane (SiO₂-NH₂)



ATR-FTIR

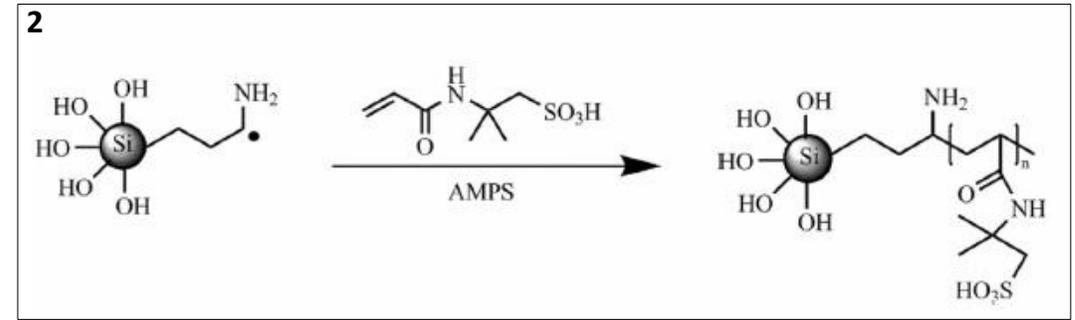
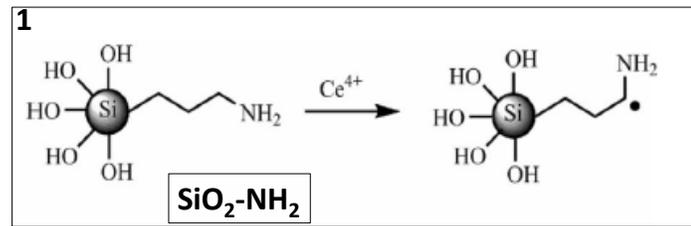


TGA

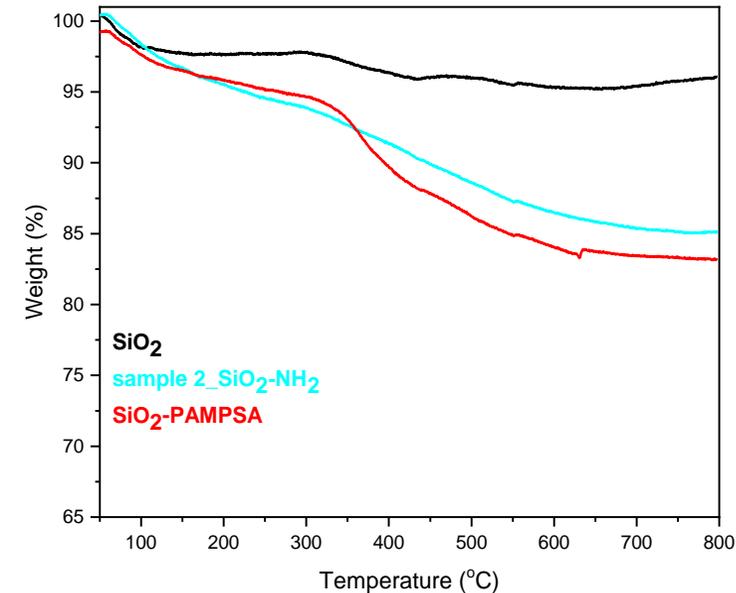
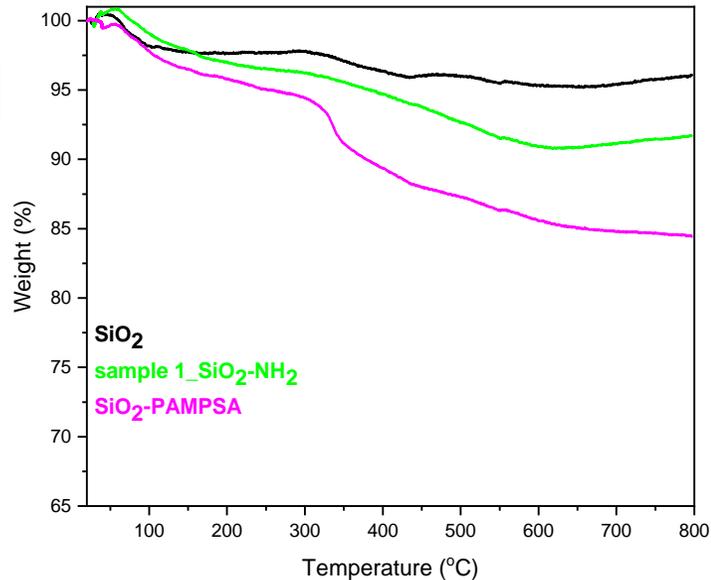


Polymer-coated nanoparticles (PNPs)

Methodology I) Polymerization of AMPSA onto the functionalized $\text{SiO}_2\text{-NH}_2$ NPs through Cerium (IV) ammonium nitrate oxidizing agent ($\text{SiO}_2\text{-PAMPSA}$)

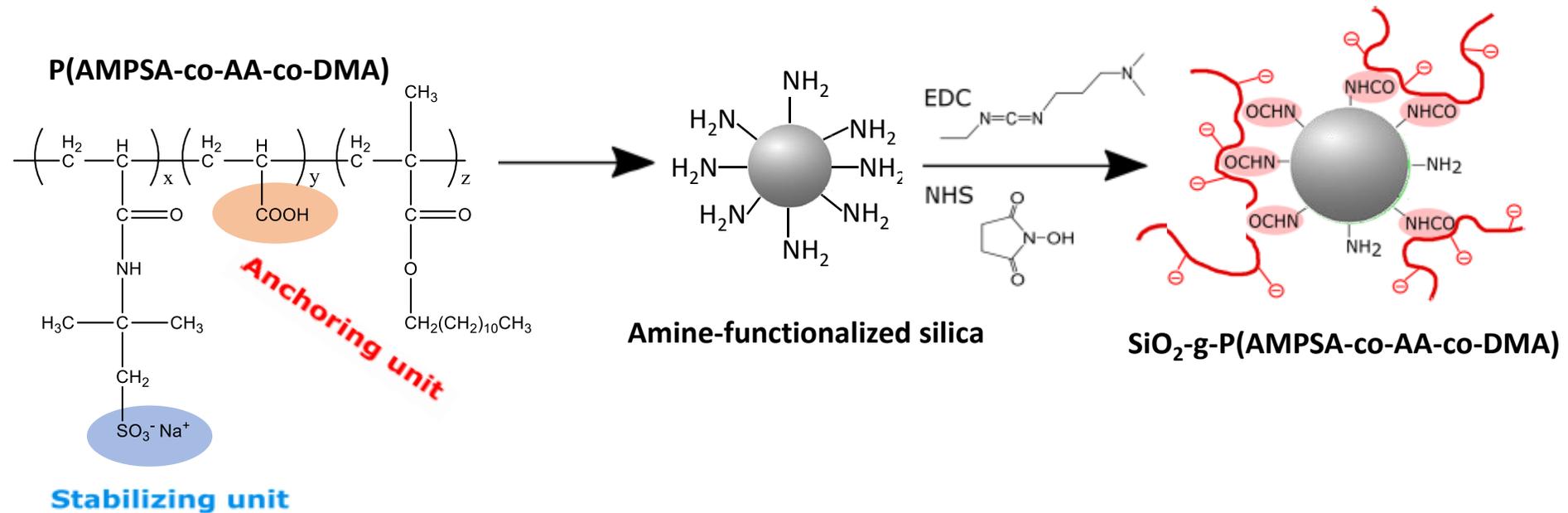


TGA



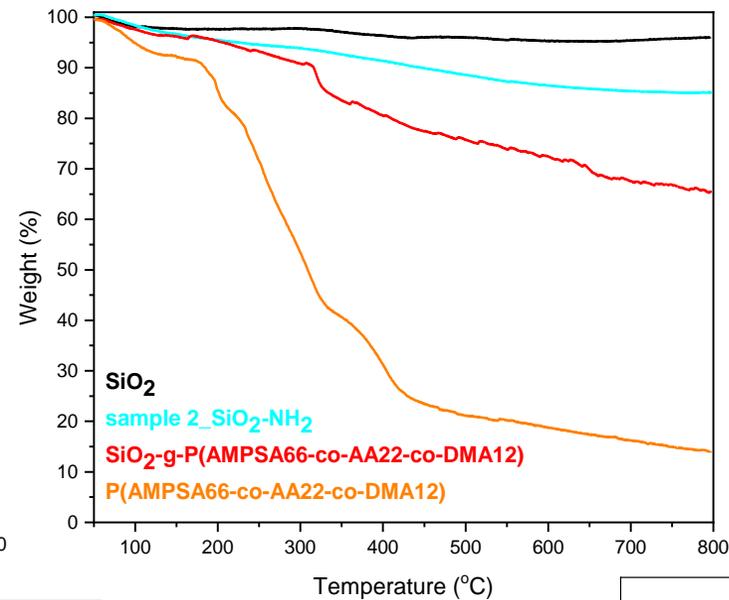
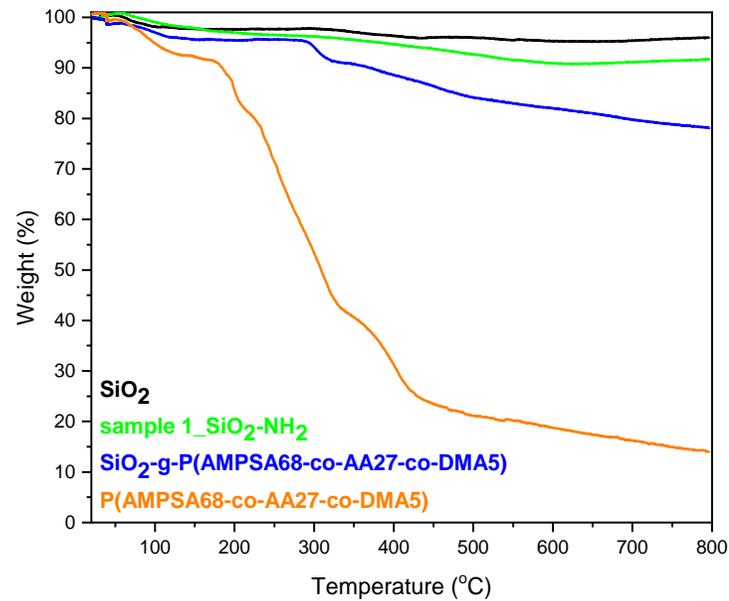
Polymer-coated nanoparticles (PNPs)

Methodology II) Post-grafting of terpolymers on $\text{SiO}_2\text{-NH}_2$ NPs by carbodiimide chemistry

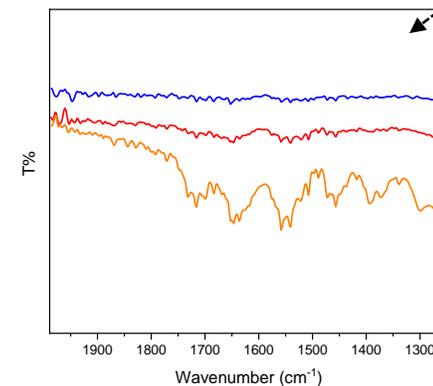
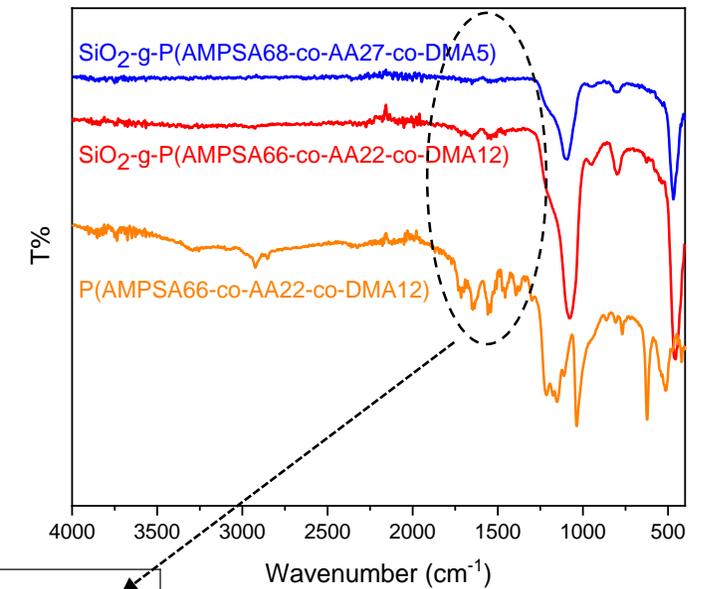


PNPs Characterization

TGA



ATR-FTIR



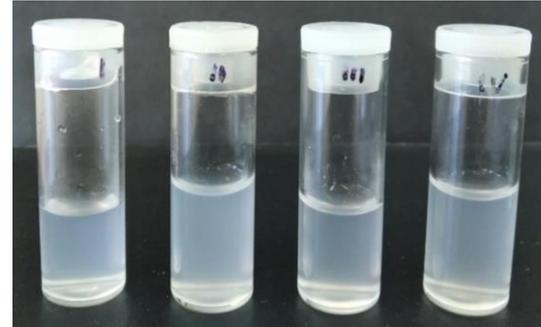
SiO₂-g-P(AMPSA66-co-AA22-co-DMA12) NPs
have more polymer content than
SiO₂-g-P(AMPSA68-co-AA27-co-DMA5)

The adsorption peaks of
the pure polymer are more evident
at the NPs with higher polymer content,
SiO₂-g-P(AMPSA66-co-AA22-co-DMA12)

Stability of polymer-coated SiO₂ particles in aqueous media

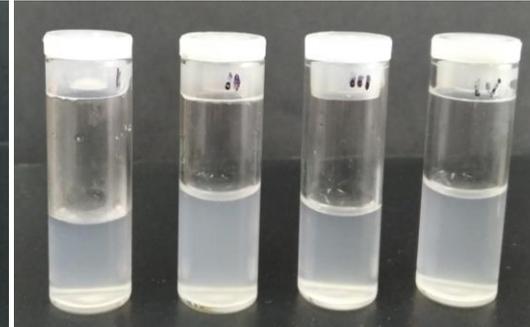
0.1 % w/v SiO₂-g-P(AMPSA66-co-AA22-co-DMA12) NPs

0 hours



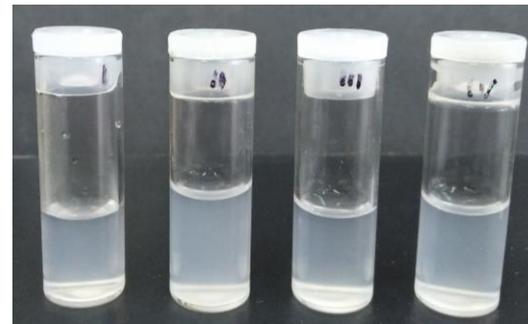
H₂O NaCl 1%wt NaCl 4 %wt NaCl 10 %wt

2 hours

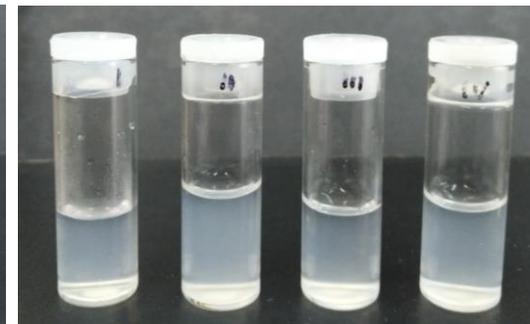


H₂O NaCl 1%wt NaCl 4 %wt NaCl 10 %wt

6 hours

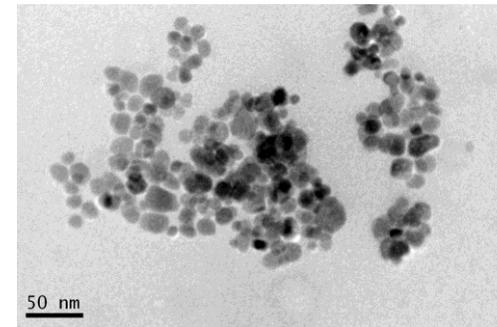


24 hours



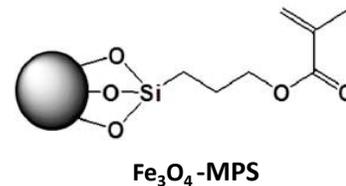
Iron oxide magnetic nanoparticles

Synthesis of iron oxide NPs (co-precipitation method)

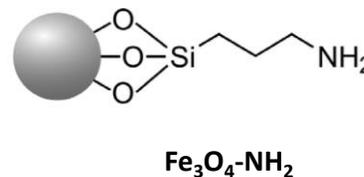


➤ Surface functionalization of Fe_3O_4 NPs with

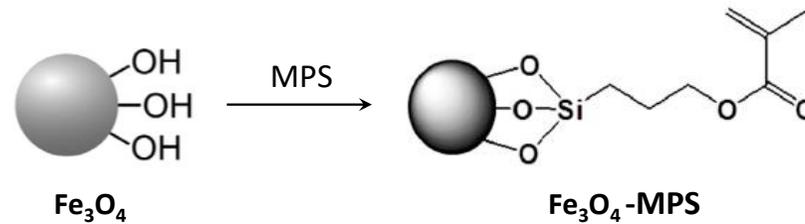
- **double bonds**



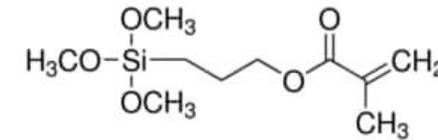
- **amine groups**



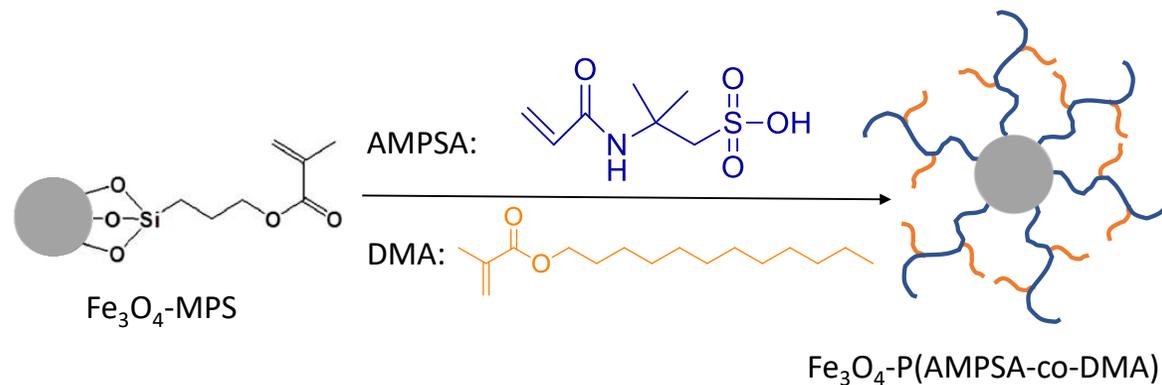
Functionalization with MPS



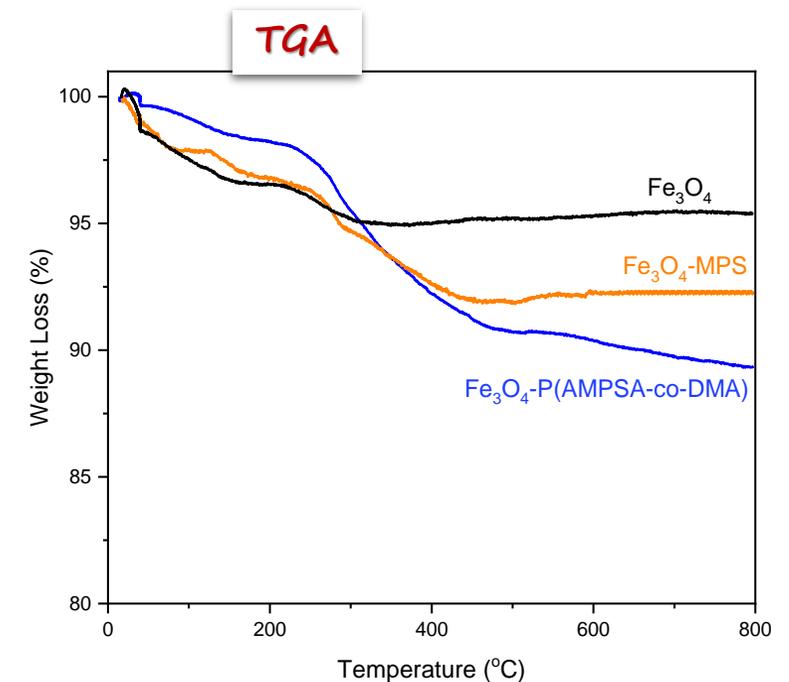
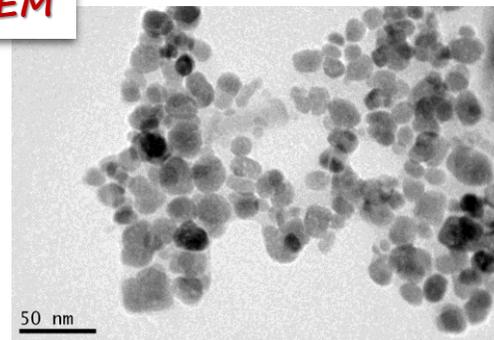
MPS :



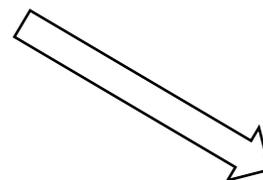
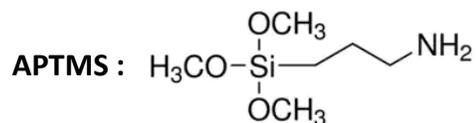
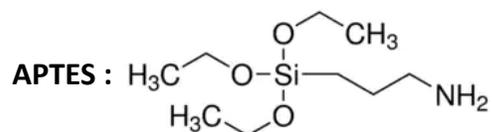
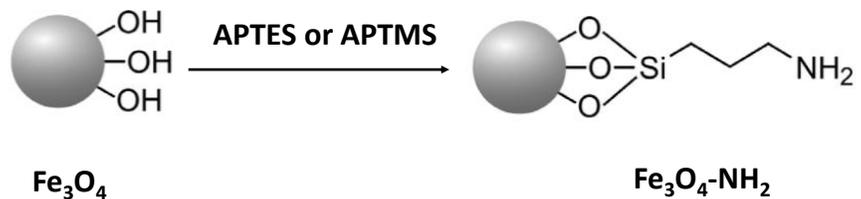
Polymerization of AMPSA and DMA monomers onto the functionalized $\text{Fe}_3\text{O}_4\text{-MPS}$ NPs



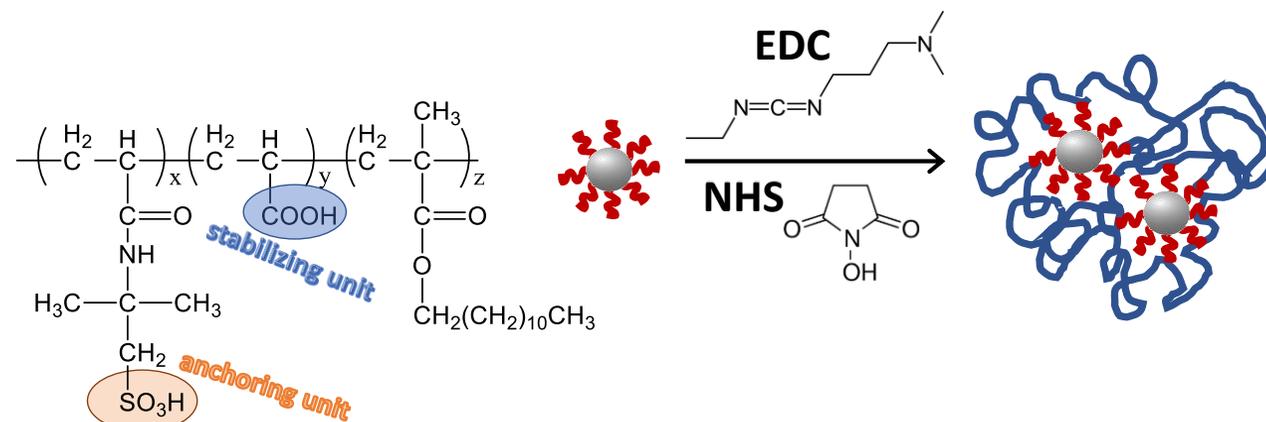
TEM



Amine-functionalization with APTES or APTMS

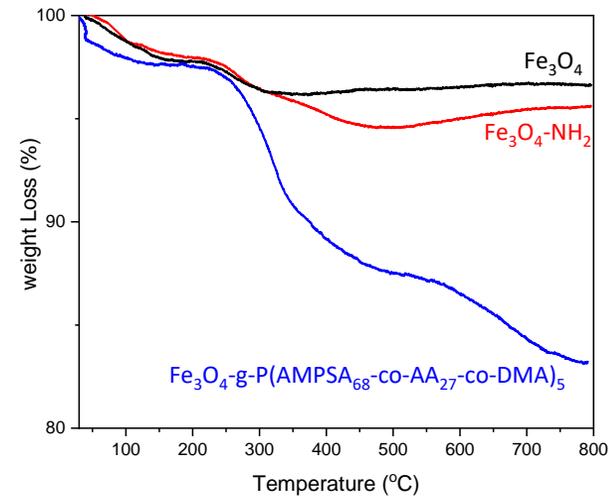
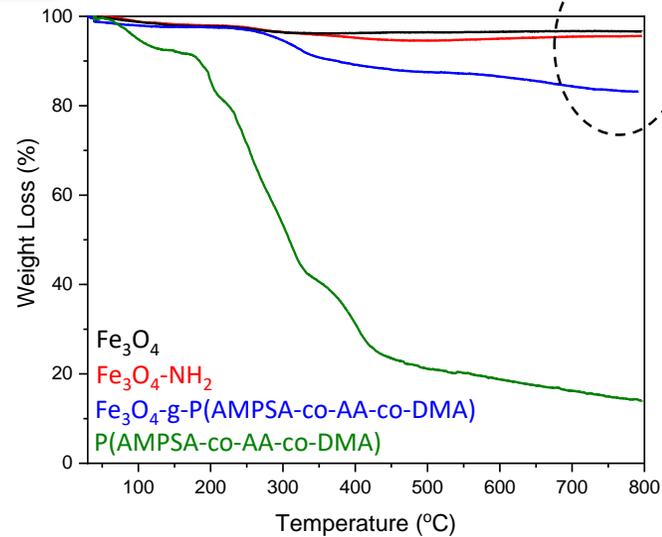


Post-grafting of terpolymers on $\text{Fe}_3\text{O}_4\text{-NH}_2$ NPs by carbodiimide chemistry

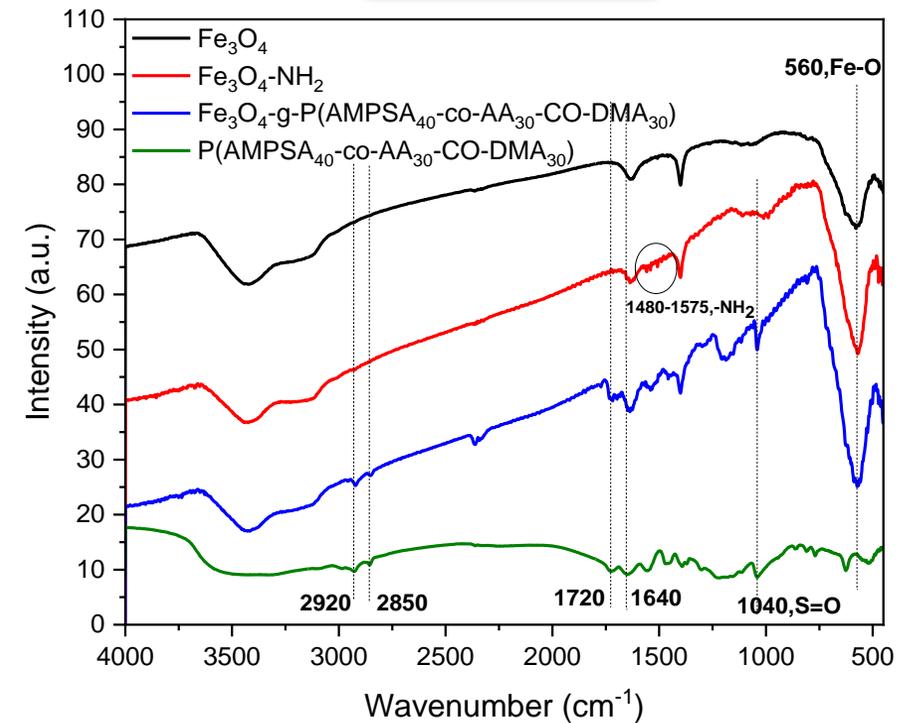


Polymer-coated nanoparticles (PNPs)

TGA

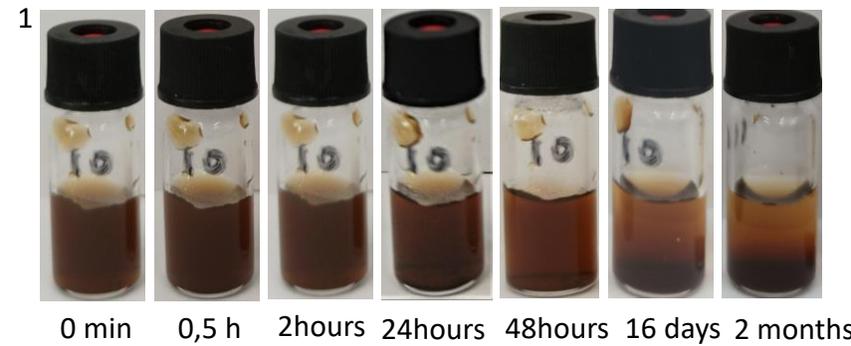


ATR-FTIR

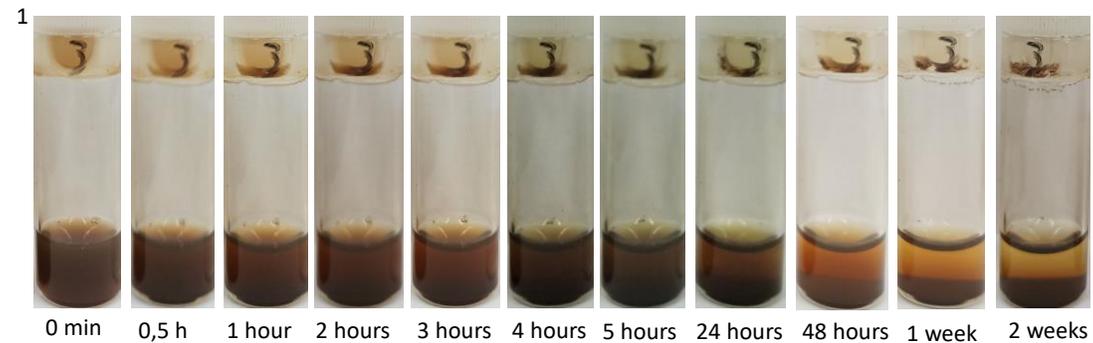


Stability of magnetic iron oxide particles in aqueous media

Fe_3O_4 -g-P(AMPSA₆₈-co-AA₂₇-co-DMA₅) in H_2O (C = 0,1 % w/v)



Fe_3O_4 -g-P(AMPSA₆₈-co-AA₂₇-co-DMA₅) in NaCl (C = 0,1 % w/v)



Conclusions

- Successful synthesis of **amphiphilic copolymers**
- Surface functionalization of SiO_2 or Fe_3O_4 NPs with **double bonds** or **amine** groups
- Synthesis of polymer-coated NPs by three methodologies:
 - **Free radical polymerization** of monomers on the acrylic-modified NPs surface
 - **Post-grafting** of terpolymers on amine-functionalized NPs, by **carbodiimide chemistry**
 - **Polymerization** of monomers through **Cerium (IV) ammonium nitrate** oxidizing agent
- Some polymer-coated NPs form **stable aqueous dispersions**

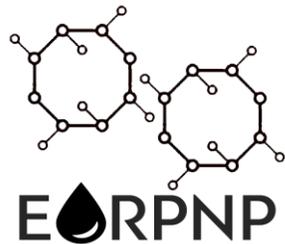




Acknowledgements



The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment (Project title: Enhanced Oil Recovery by Polymer-coated Nano Particles, acronym: «EOR-PNP», code: HFRI-FM17-361)



Thank you for your attention!

Nano-colloid interfacial properties, and emulsion stabilization

Christina Ntente

Foundation for Research and Technology Hellas, Institute of Chemical Engineering Sciences
(FORTH/ICE-HT), 26504 Patras, Greece

University of Patras, Department of Chemistry, 26504 Patras, Greece



Objectives

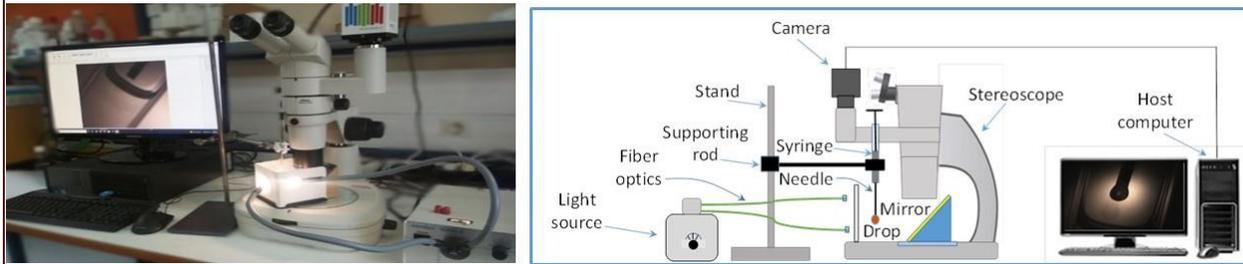
- ❑ Measurements of the ***surface and interfacial tensions*** of aqueous polymer and PNP – dispersions.
- ❑ Measurements of the ***contact angles (CA)*** on glass and PMMA surfaces.
- ❑ Preparation of the stabilized ***Pickering emulsions***.
- ❑ ***Rheology*** measurements of the Pickering emulsions.

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

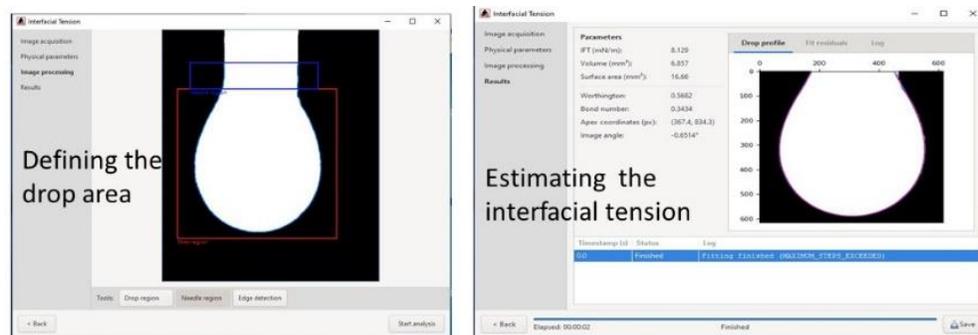
Surface Tension Characterization

Pendant Drop Method:

Dynamic Surface and Interfacial Tension measurements of nano-colloid suspensions.



Experimental setup of **pendant drop method**



Estimation of surface/interfacial tension by **OpenDrop software**

“Analyzing the recorded interfacial configurations with the open access OpenDrop software of inverse modeling of Young-Laplace equation”

Du Nouy ring Method:

Static Surface and Interfacial Tension measurements of nano-colloid suspensions.

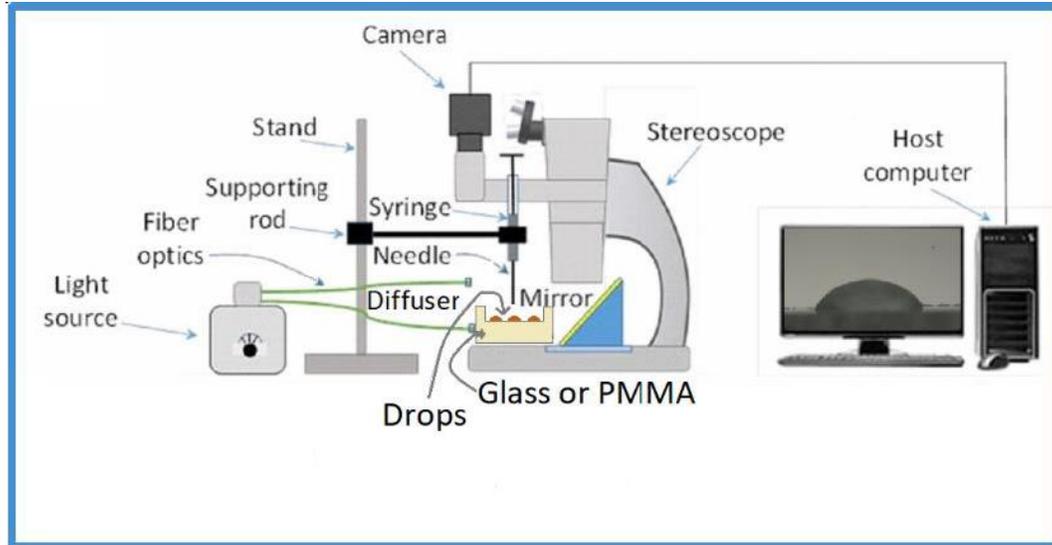


Tensiometer **Sigma -702**

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

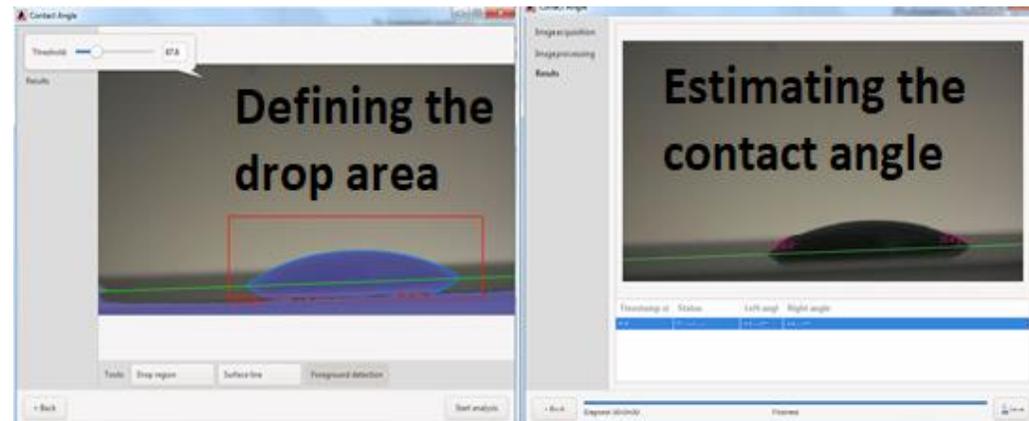
Wettability Characterization

Contact angles measurements of nano-colloid suspensions



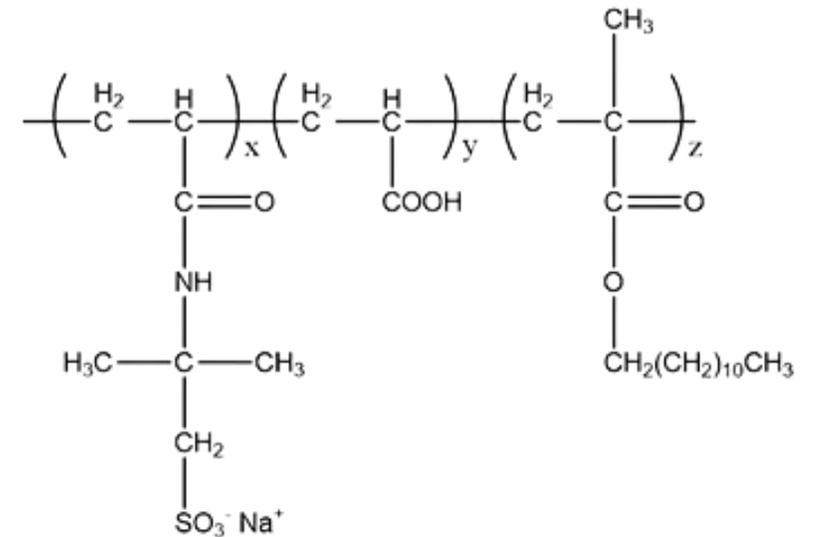
Experimental setup of **contact angles measurements**

“Analyzing the recorded contact angles configurations with the open access OpenDrop software”



Estimation of contact angle by **OpenDrop software**

Polymer Characterization



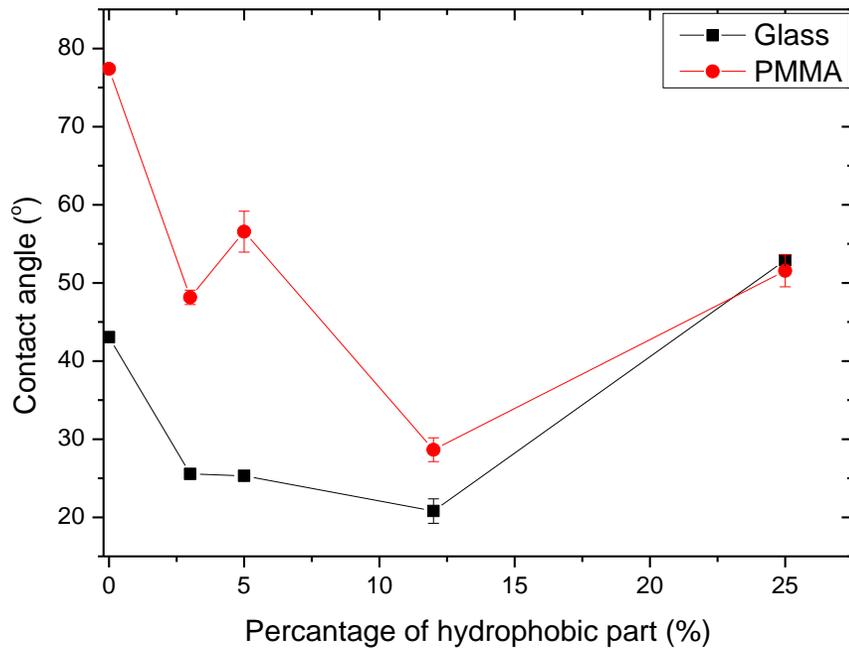
P(AMPS_x-co-AA_y-co-DMA_z):

Poly(2-Acrylamido-2-methylpropane sulfonic acid-co-acrylic acid-co-dodecyl methacrylate)

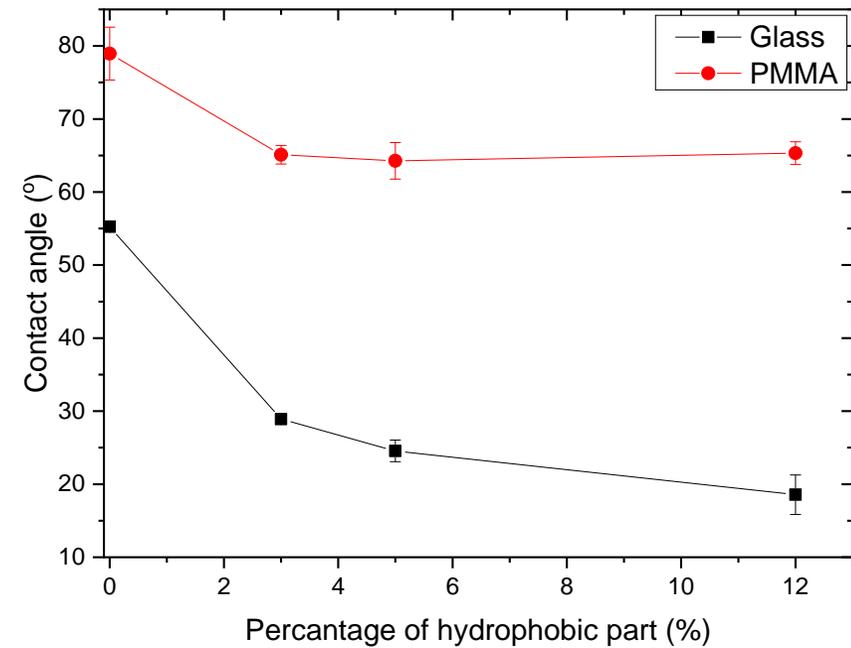
Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Wettability Characterization

CA as function of various types of polymers ($C_p = 0.25\%$ w/v), in air, on glass and PMMA surface.



CA as function of various types of polymers ($C_p = 0.25\%$ w/v), in oil ($n\text{-C}_{12}$), on glass and PMMA surface.



For all cases, $CA < 90^\circ$, so **polymers have moderate wettability**

- **Glass surface** shows further **hydrophilicity** for polymers with smaller percentage of DMA, in air.
- **PMMA surface** displays further **hydrophobicity** in the presence of higher percentage of DMA, in air and oil.

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Pickering emulsion

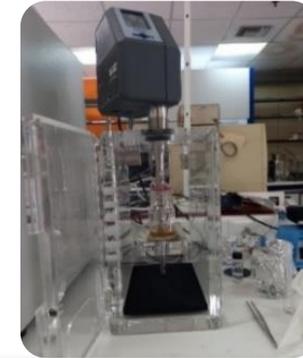
Formation of Pickering emulsions from different types of polymers in water and salt solutions

Static surface (ST) and interfacial tension (IT) with oil red n-C₁₂ for different types of polymer solutions

Types of polymers	ST ± STD (mN/m)	IFT with oil red n-C ₁₂ (mN/m)
66.22.12 (0.25% w/v – NaCl 1.0M)	47.46 ± 1.28	20.50
55.20.25 (0.25% w/v – water)	51.50 ± 1.45	24.46
55.20.25 (0.25% w/v – NaCl 1.0M)	40.77 ± 1.32	20.00

Preparation Process

Homogenizing dispersion with oil red n-C₁₂ (c=1500 ppm) (volume rate: 2/1) in an ultrasound probe for 10min.



Ultrasound probe UP400St (Hielscher Ultrasonics GmbH)



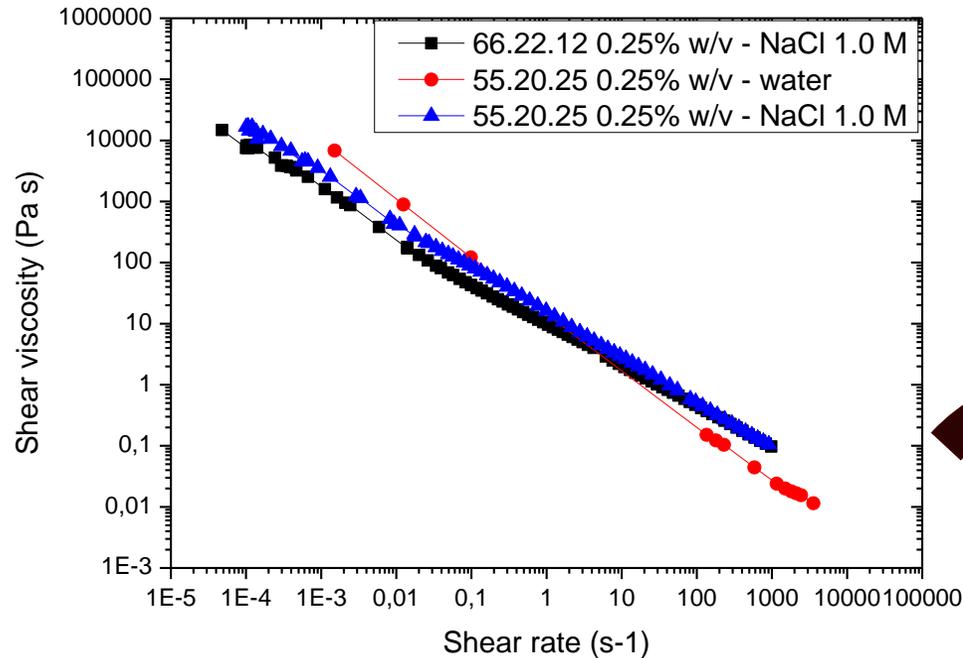
Immiscible phases



Pickering emulsion

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Emulsion Rheology



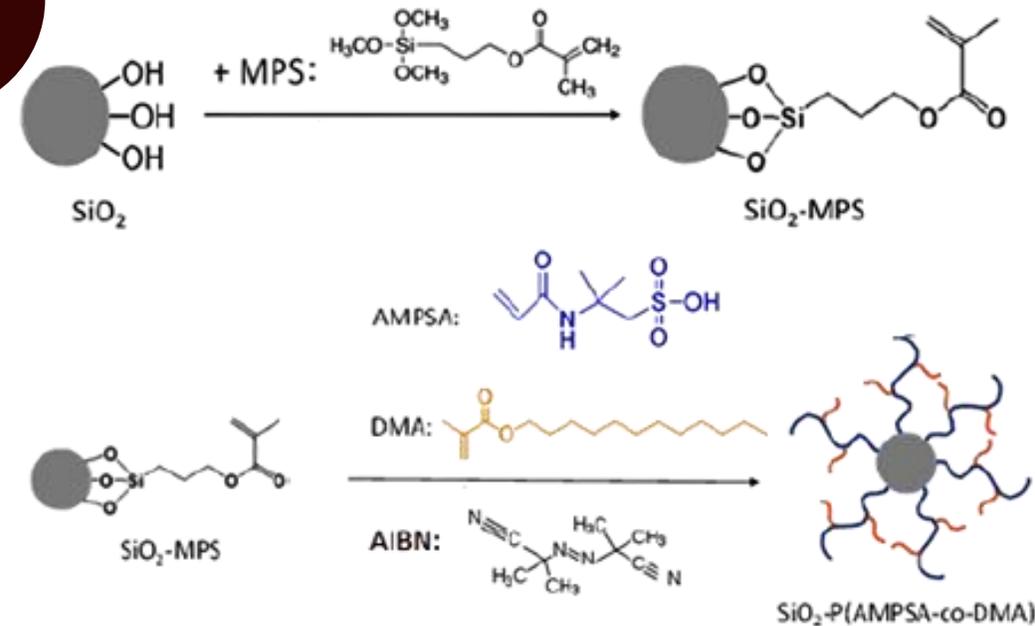
Power law model

$$\mu = \mu_0 \gamma^{n-1}$$

Emulsion	μ_0 (Pa s)	n
66.22.12 0.25% w/v - NaCl 1.0 M	17.44	0.20
55.20.25 0.25% w/v - water	15.00	0.09
55.20.25 0.25% w/v - NaCl 1.0 M	16.00	0.25

The *shear thinning rheology* of the Pickering emulsions was fitted satisfactorily with the *Power law model*

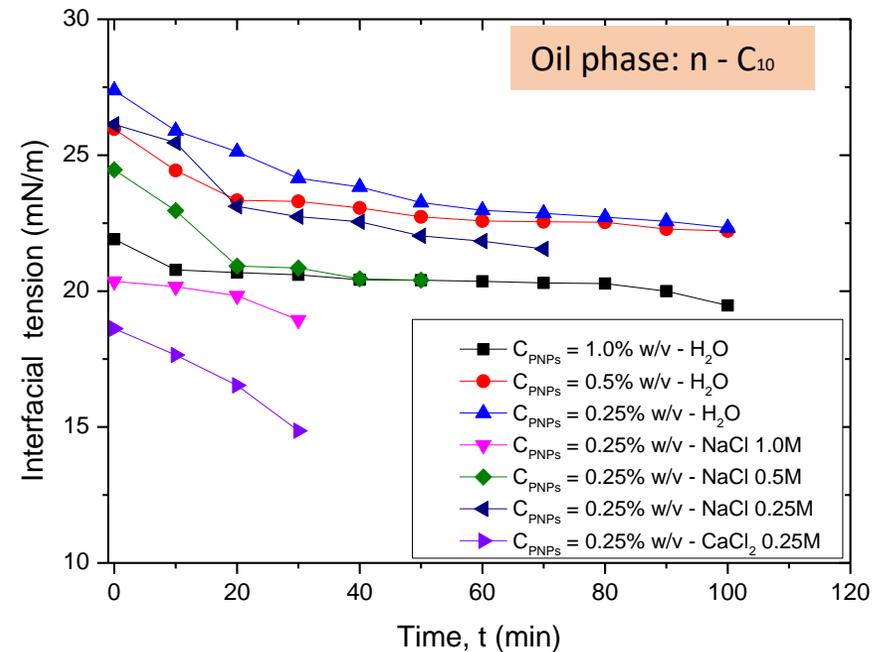
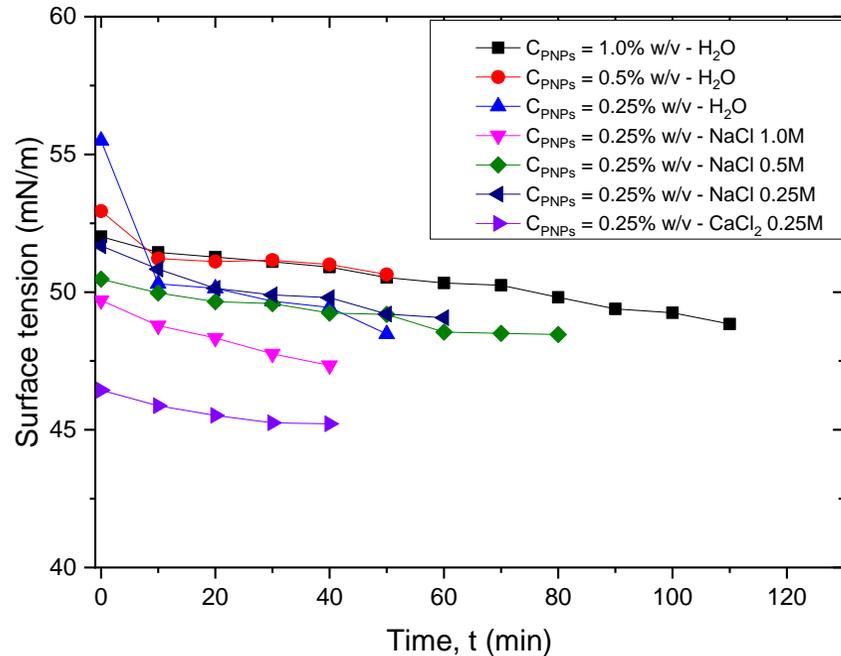
Polymer – coated nanoparticles (PNP) Characterization



Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Surface and Interfacial Tension Characterization

Dynamic surface (ST) and interfacial tension (IT) with $n\text{-C}_{10}$ as function of time for various concentrations of PNPs in water and salt solutions.

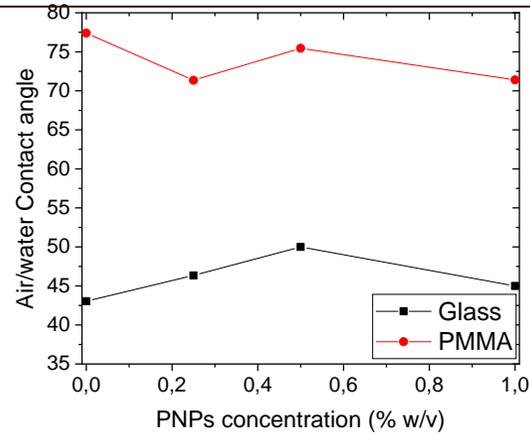


- Maximized reduction rate of ST, IT of $\text{SiO}_2\text{-P}(\text{AMPSA-co-DMA})$ NPs at PNP concentration equal to 0.25%.
- with the addition of NaCl, the ST, IT change weakly.
- with the addition of CaCl_2 , the ST, IT drop significantly, due to the stronger electrostatic interactions of the divalent CaCl_2 with the P(AMPSA-co-DMA) polyelectrolyte and increased ionic strength.

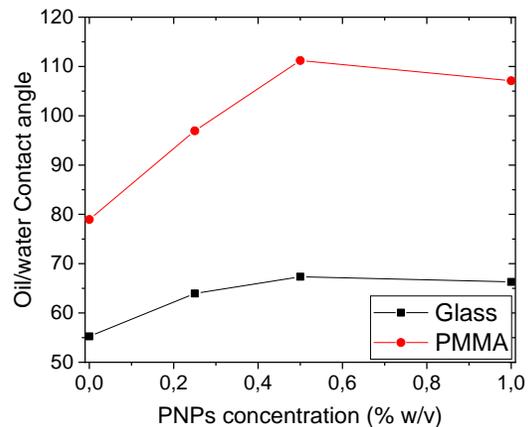
Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Wettability Characterization

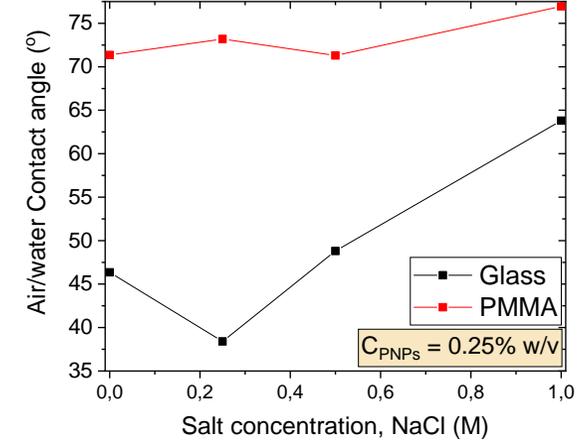
CA as function of various concentrations of PNP (- water), in air and oil, on glass and PMMA surface.



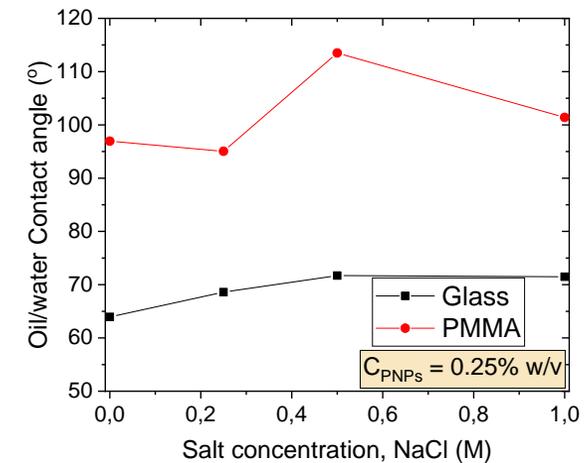
In the presence of PNP, *increasing PNP concentration decreases CA on glass surfaces and increases on PMMA surfaces.*



CA as function of various concentrations of salt solutions (NaCl) for PNP (0.25% w/v), in air and oil, on glass and PMMA surface.



The presence of *salts* does not particularly affect on CA.



PNP have *moderate wetting on glass surfaces (in the presence of air, oil) while they have even less wetting on PMMA surfaces.*

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Pickering emulsion

Formation of Pickering emulsions from nano-colloid suspensions and salt solutions

Static surface (ST) and interfacial tension (IT) with $n\text{-C}_{10}$ for PNP concentration 0.25% w/v at various salt concentrations

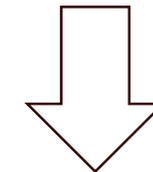
CPNPs = 0.25% w/v – salt	ST \pm STD (mN/m)	IFT PNPs $\mu\epsilon$ $n\text{-C}_{10}$ (mN/m)
NaCl 1.0M	53.07 \pm 0.46	26.88
NaCl 0.5M/CaCl ₂ 0.25M	55.40 \pm 0.21	33.25

Preparation Process

Homogenizing PNP – dispersion ($\text{SiO}_2\text{-P(AMPSA-co-DMA 0.25\%/salts solutions)}$) with $n\text{-C}_{10}$ (1:1) in an ultrasound probe for 10min.



Immiscible phases

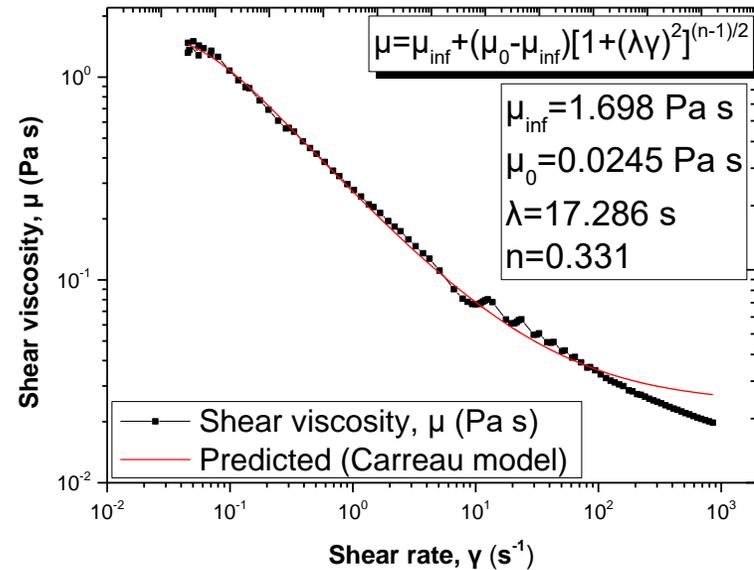


PNP – stabilized Pickering emulsion

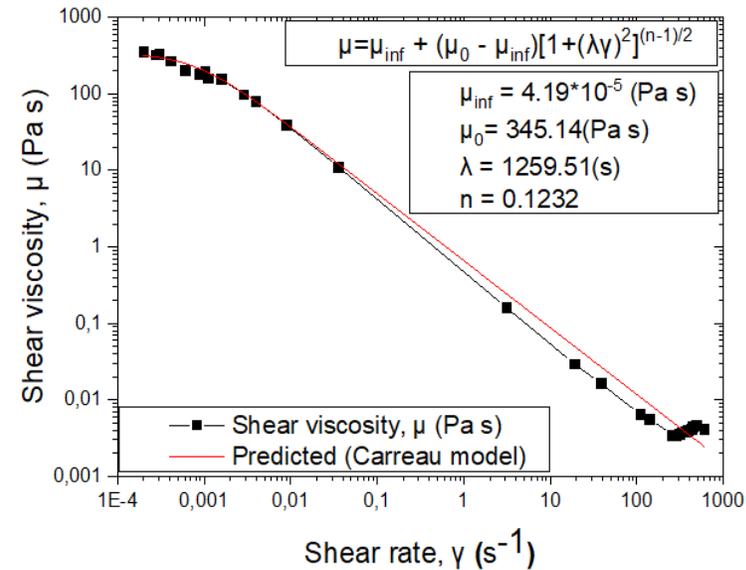
Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Emulsion Rheology

SiO₂-P(AMPSA-co-DMA) 0.25% - NaCl 0.5M / CaCl₂ 0.25M



SiO₂-P(AMPSA-co-DMA) 0.25% - NaCl 1.0M



The *shear thinning rheology* of the Pickering emulsion was fitted satisfactorily with the *Carreau model*

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

Conclusions

Polymers

- ✓ **Surface and Interfacial tension** depend on:
 - the *percentage of hydrophobic part DMA*.
 - the *presence of salt*.
- ✓ **Polymers** have
 - *good wettability on glass surface*.
 - *moderate wettability on PMMA surface*.
- ✓ Formation of **stable Pickering emulsions** was fitted satisfactorily with *the Power law model*.

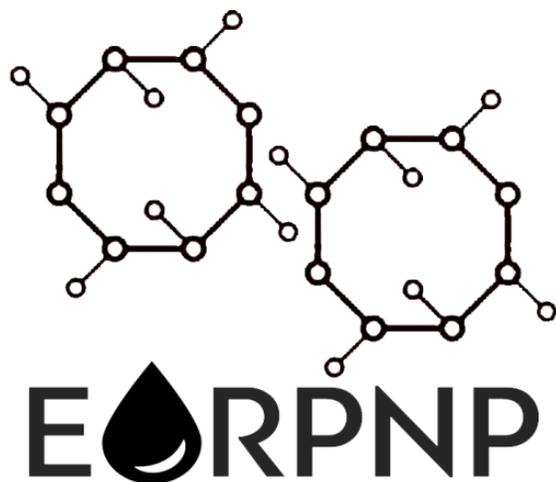
Polymer coated – nanoparticles (PNP)

- ✓ **Surface and Interfacial tension** depend on the *concentration of SiO₂-P(AMPSA-co-DMA) PNP*
 - with the addition of *NaCl*, the *ST, IT change weakly*.
 - with the addition of *CaCl₂*, the *ST, IT drop significantly*.
- ✓ **PNP** have
 - *moderate wettability on glass surface*
 - *even less wettability on PMMA surface*.
- ✓ Formation of **stable Pickering emulsions** was fitted satisfactorily with *the Carreau model*.

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)

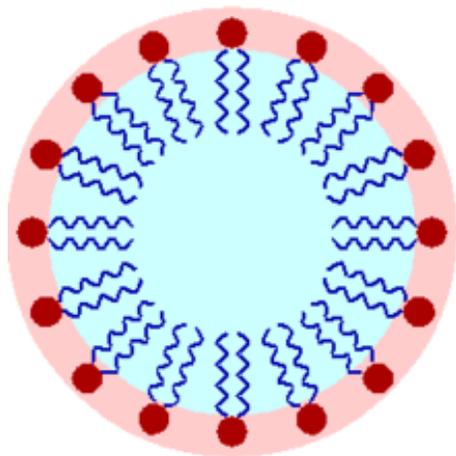
Acknowledgments

The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment” (Project Number: HFRI-FM17-361, Title: Enhanced oil recovery by polymer-coated nanoparticles, Acronym: EOR-PNP).

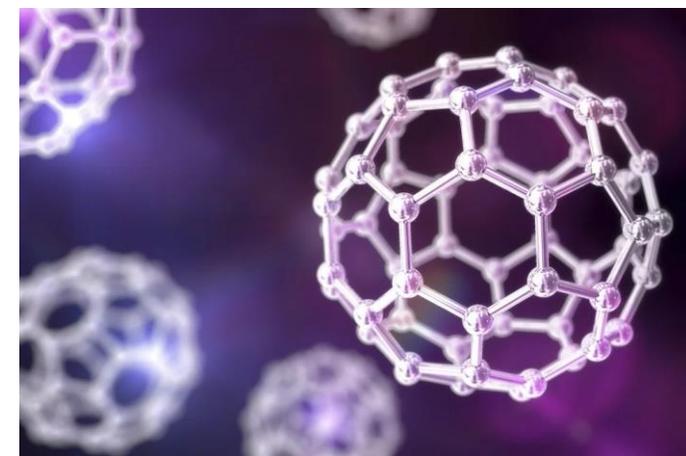
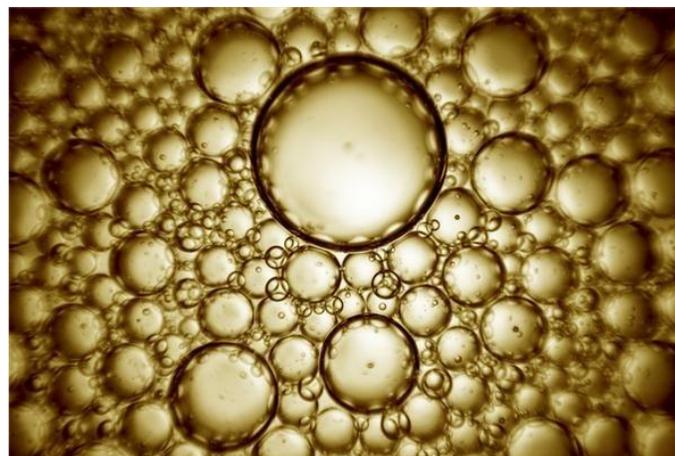
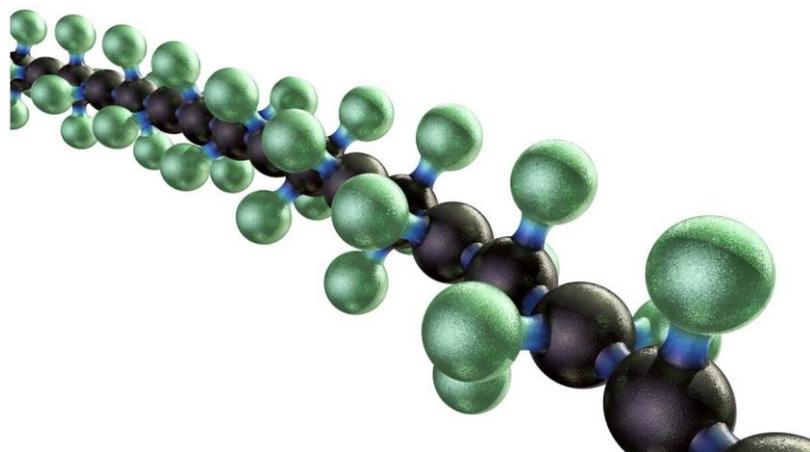


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Hellenic Foundation for
Research & Innovation

Enhanced oil recovery by polymer – coated nanoparticles (EOR-PNP)



Thank you for your attention!!!



Visualization EOR studies on glass-etched pore networks

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Introduction

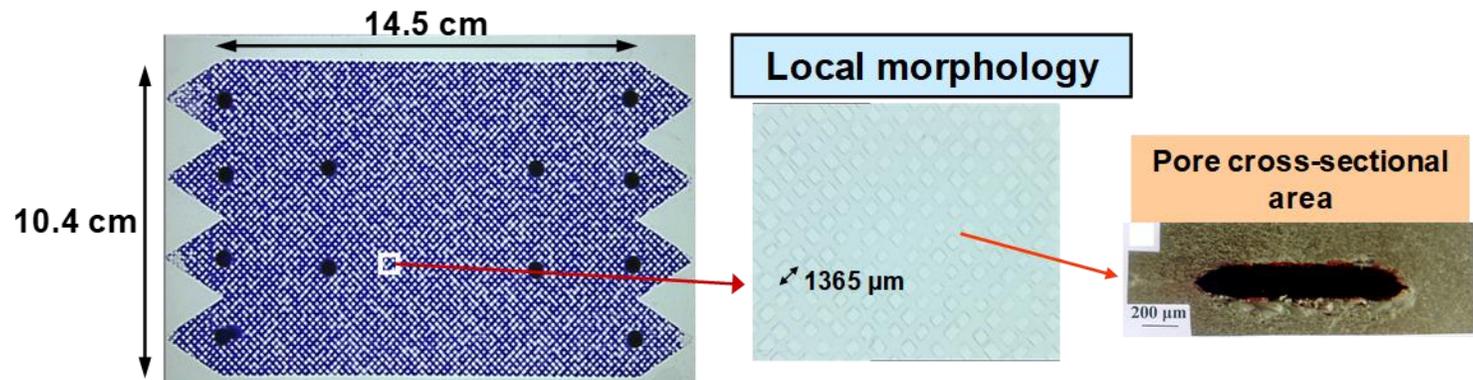
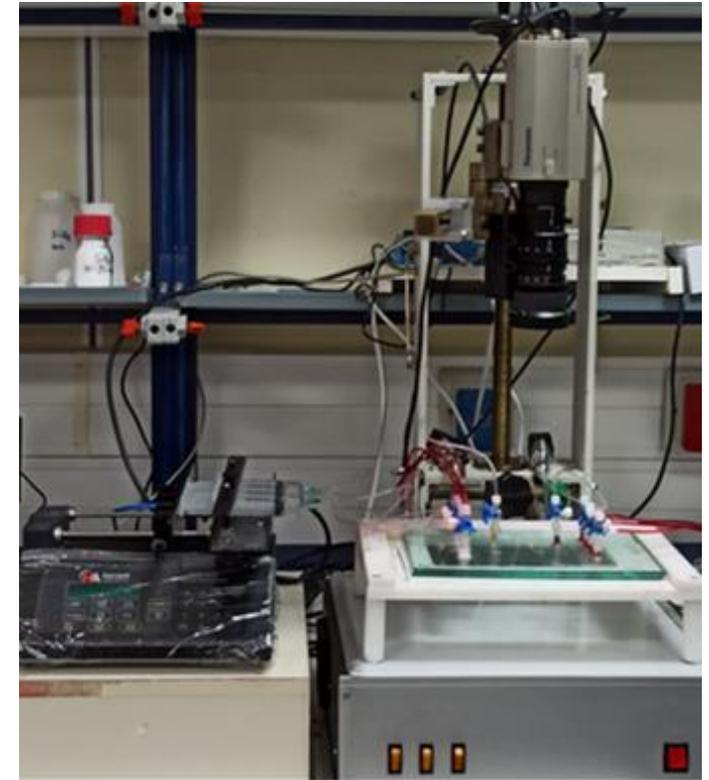
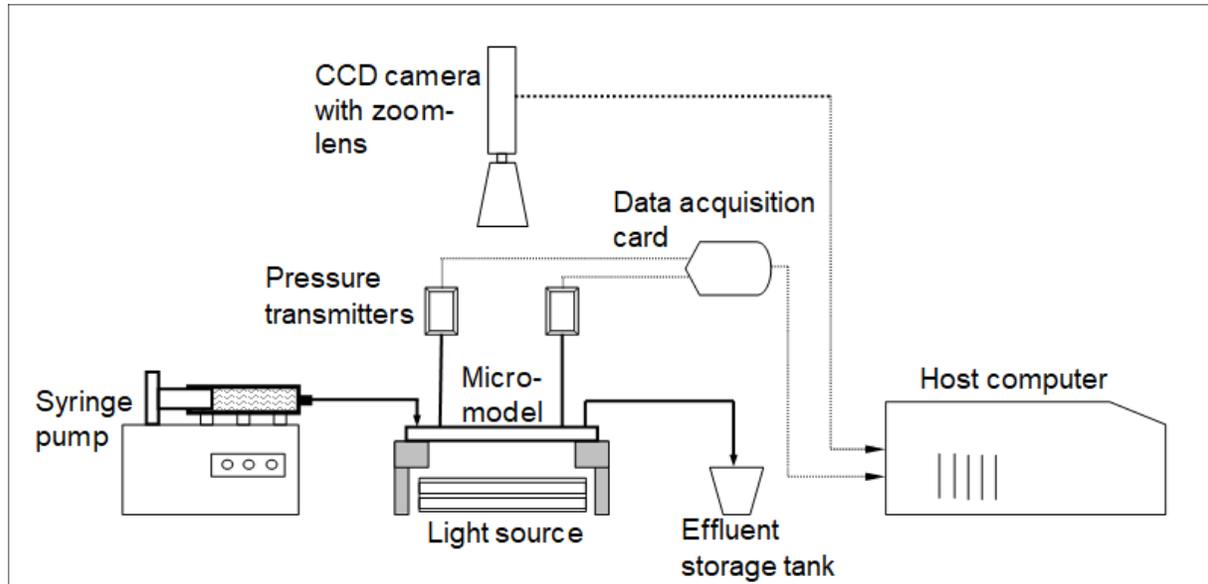
Problem

- Energy consumption worldwide is expected to increase by 50% relative to current levels by the end of 2030.
- This growth is unlikely to be met by renewable resources, and thus there is a strong and growing demand for oil as a predominant energy resource.

Objectives

- Globally the overall oil recovery factors for primary and secondary recovery range from 35% to 45%.
- A tertiary recovery method can enhance the recovery factor by 10-30%, which could contribute to energy supply.
- The use of nanoparticles in enhanced oil recovery (EOR) processes comprises an emerging and well-promising approach.

Experimental setup of visualization tests on transparent pore networks



Values of Ca and κ

$$\text{Capillary number } Ca = \frac{\mu_{displacing} U}{IT}$$

Ca pore scale $\rightarrow Ca_{L1} = Ca * \text{factor}$

$$\text{factor} = \frac{L_p r_H}{k}$$

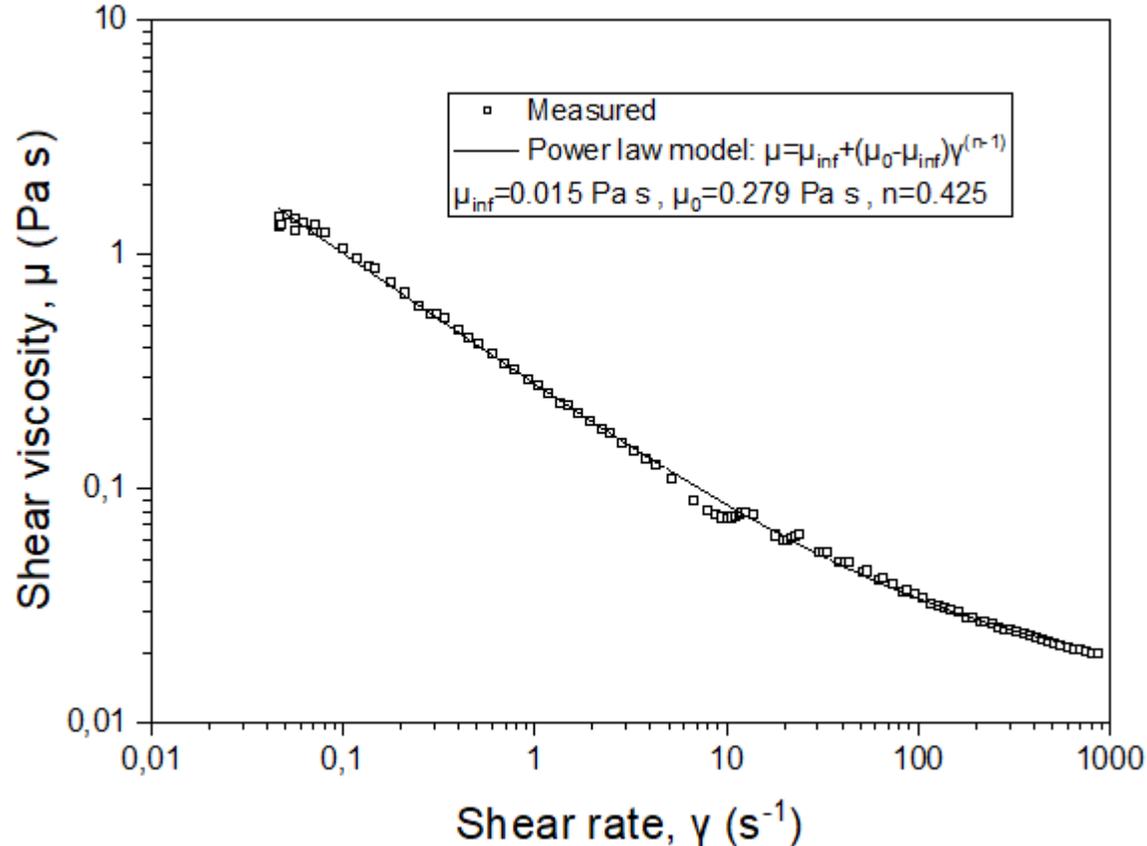
Ca network scale $\rightarrow Ca_{LN} = Ca_{L1} * L_N / L_p$

Tsakiroglou et al., AIChE J. 49, 2472 (2003)

$$\text{Viscosity ratio } \kappa = \frac{\mu_{displacing}}{\mu_{displaced}}$$

Shear viscosity of emulsions

$$\mu = \mu_{inf} + (\mu_1 - \mu_{inf})\dot{\gamma}^{n-1}$$



Rheology of **SiO₂-AMPSA-DMA-0.25%**
+ **NaCl 0.5M-CaCl₂ 0.25M** emulsion

Pore level to network scale:

$$\langle \mu \rangle = \mu_{inf} + \left(\frac{\mu_1 - \mu_{inf}}{n} \right) \gamma_w^{n-1}$$

$$\gamma_w = \left(\frac{8u_p}{4r_H} \right) \left(\frac{3n+1}{4n} \right)$$

$$u_p = \frac{u_0}{\varphi_V}$$

$$\varphi_V = \frac{\pi \langle W_p \rangle \langle D_p \rangle}{4L_p^2}$$

Values of Ca and κ

fluid	Flow rate($10^{-6}/60$) m ³ /s	U (10^{-5} m/s)	μ (Pa s)	IT (mN/m)	Ca (10^{-6})	κ
Old paraffin oil	0.08	0.94	0.02	30.5	6.1	20.0
New paraffin oil	0.08	0.94	0.1	40.76	23.0	100.0
NaCl 1M-old oil	0.2	2.35	0.001	34.96	0.67	0.05
NaCl 1M-new oil	0.2	2.35	0.001	27.76	0.84	0.01
<u>DISPERSIONS</u>						
SiO ₂ =AMPSA-DMA-0.25%+NaCl 1M	0.2	2.35	0.001	20.89	1.12	0.05
SiO ₂ =AMPSA-DMA-0.25% + NaCl 0.5M-CaCl ₂ 0.25M	0.2	2.35	0.001	30.51	0.77	0.05
AMPSA-55.20.25-0.25%-water	0.2	2.35	0.001	27.05	0.87	0.01
AMPSA-55.20.25-0.25% + NaCl 1M	0.2	2.35	0.001	12.65	1.85	0.05

Values of Ca and κ

fluid	Flow rate($10^{-6}/60$) m ³ /s	U (10^{-5} m/s)	μ (Pa s)	IT (mN/m)	Ca (10^{-5})	κ
Old paraffin oil	0.08	0.94	0.02	30.5	0.61	20.0
New paraffin oil	0.08	0.94	0.1	40.76	2.30	100.0
<i>EMULSIONS</i>						
SiO ₂ =AMPSA-DMA-0.25%+NaCl 1M	0.2	2.35	0.051	20.89	5.73	2.55
SiO ₂ =AMPSA-DMA-0.25% + NaCl 0.5M-CaCl ₂ 0.25M	0.2	2.35	0.077	30.51	5.93	3.83
AMPSA-55.20.25-0.25%-water	0.2	2.35	0.014	27.05	1.21	0.14
AMPSA-55.20.25-0.25% + NaCl 1M	0.2	2.35	0.014	12.65	2.60	0.7

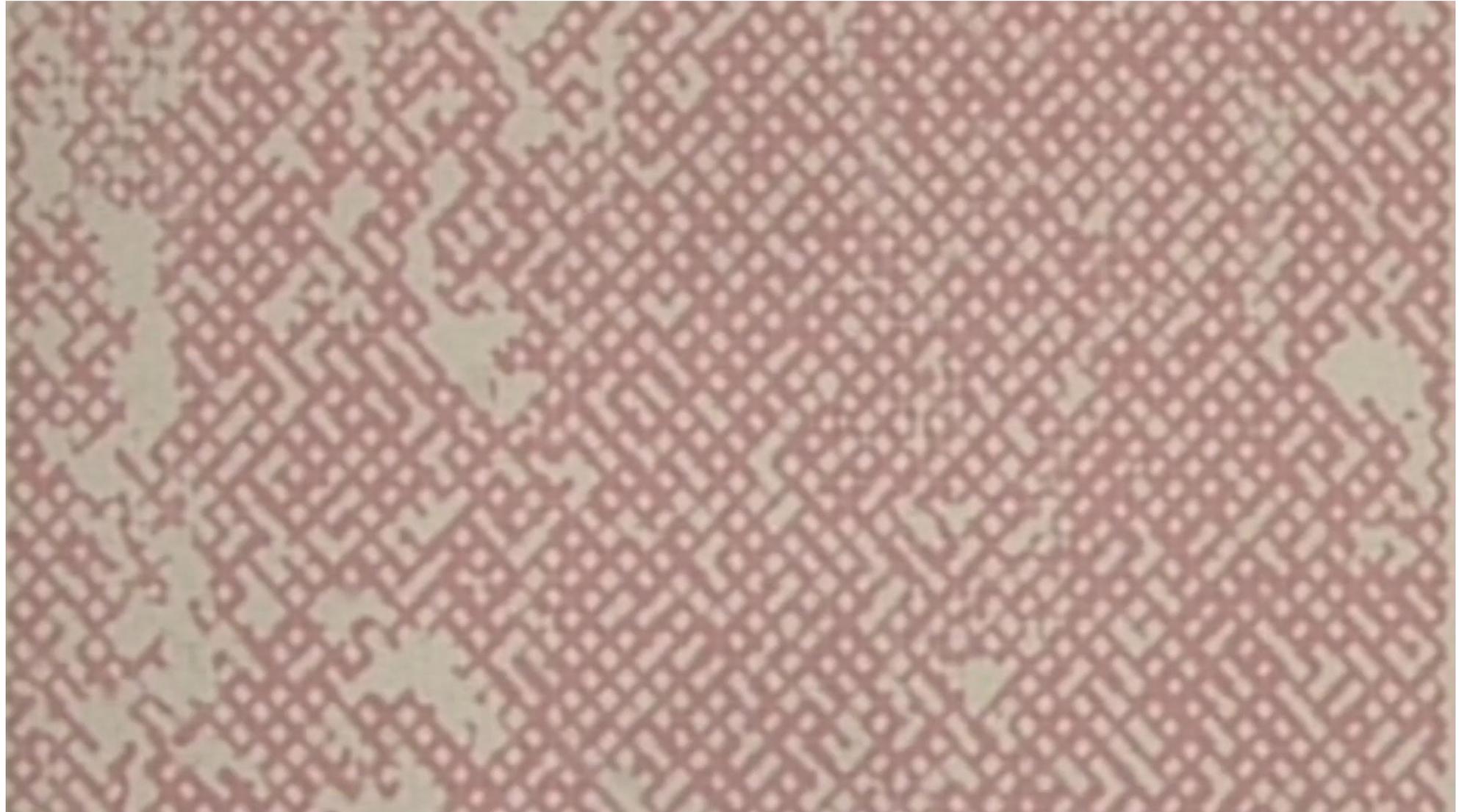
Ca to pore and network scale

fluid		Ca	pore scale Ca	network scale Ca
Old paraffin		6.1×10^{-6}	0.018	1.8
New paraffin		23.0×10^{-6}	0.069	6.9
NaCl 1M – old oil		0.67×10^{-6}	0.0020	0.2
NaCl 1M- new oil		0.84×10^{-6}	0.0025	0.25
SiO ₂ =AMPSA-DMA-0.25%+NaCl 1M	dispersion	1.12×10^{-6}	0.0033	0.33
	emulsion	5.73×10^{-5}	0.172	17.2
SiO ₂ =AMPSA-DMA-0.25% + NaCl 0.5M-CaCl ₂ 0.25M	dispersion	0.77×10^{-6}	0.0023	0.23
	emulsion	5.93×10^{-5}	0.178	17.8
AMPSA-55.20.25-0.25%-water	dispersion	0.87×10^{-6}	0.0026	0.26
	emulsion	1.21×10^{-5}	0.036	3.6
AMPSA-55.20.25-0.25% + NaCl 1M	dispersion	1.85×10^{-6}	0.0055	0.55
	emulsion	2.60×10^{-5}	0.078	7.8

Primary Drainage - Displacement with paraffin oil



Primary Imbibition – Displacement with NaCl 0.5M + CaCl₂ 0.25M



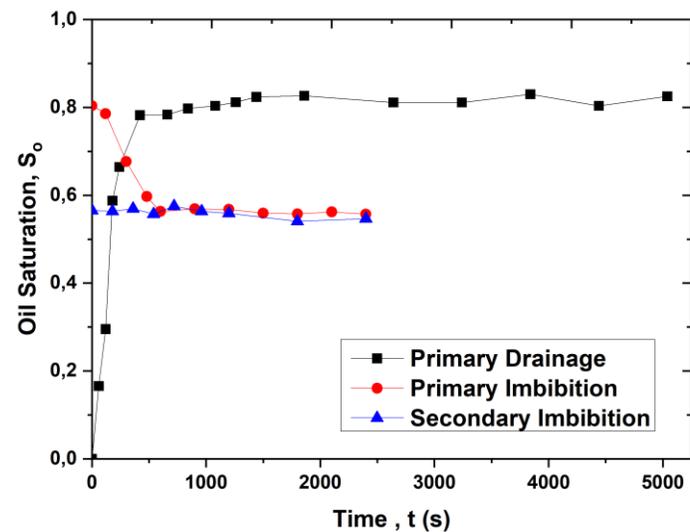
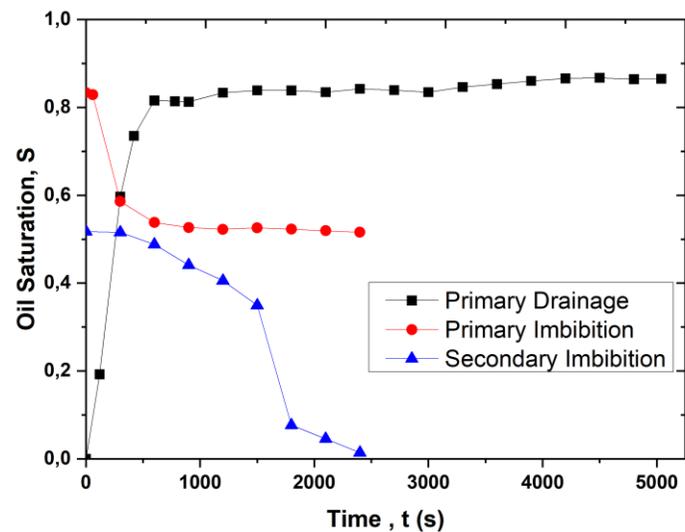
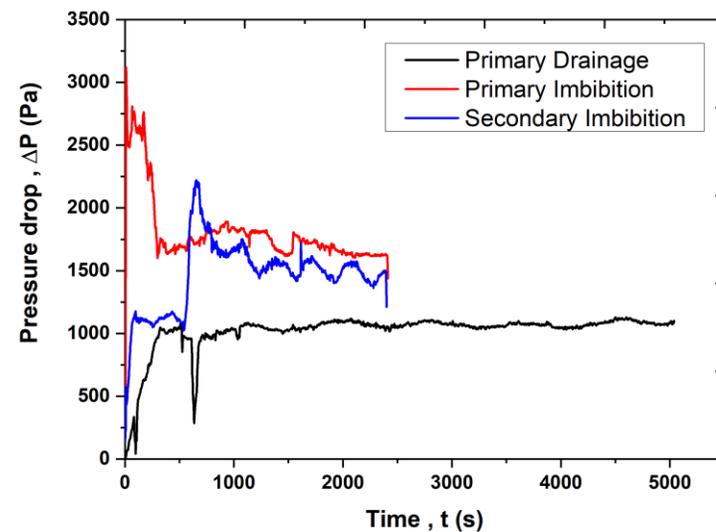
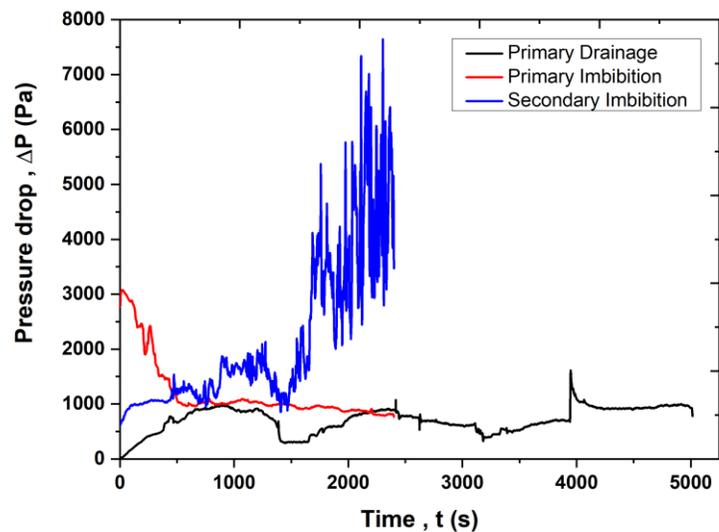
**Secondary Imbibition – Displacement with emulsion of
SiO₂-AMPSA=DMA 0.25% - NaCl 0.5M + CaCl₂ 0.25M**



SiO₂-AMPSA=DMA 0.25% -NaCl 0.5M+ CaCl₂ 0.25M

emulsion

dispersion



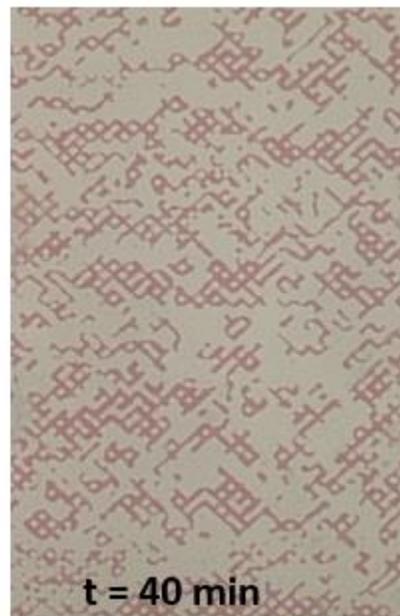
Results 1

SiO₂=AMPSA-DMA-0.25% + NaCl 0.5M - CaCl₂ 0.25M

Type of displacement	Displaced fluid	Displacing fluid	Flow rate (mL/min)	Injected volume (mL)	Oil saturation	Oil removal efficiency (%)
Drainage	NaCl 0,5M - CaCl ₂ 0,25M	-	0.08	8	0.82	-
Prim. Imbib.	Resid. paraffin oil	NaCl 0,5M - CaCl ₂ 0,25M	0.2	8	0.56	30.2
Sec. Imbib.	Resid. paraffin oil	Dispersion	0.2	8	0.55	1.7
Drainage	NaCl 0,5M - CaCl ₂ 0,25M	-	0.08	8	0.86	-
Prim. Imbib.	Resid. paraffin oil	NaCl 0,5M - CaCl ₂ 0,25M	0.2	8	0.52	39.5
Sec. Imbib.	Resid. paraffin oil	Emulsion	0.2	8	0.014	97.3

Secondary Imbibition **SiO₂-AMPSA=DMA 0.25% - NaCl 1M**

Dispersion

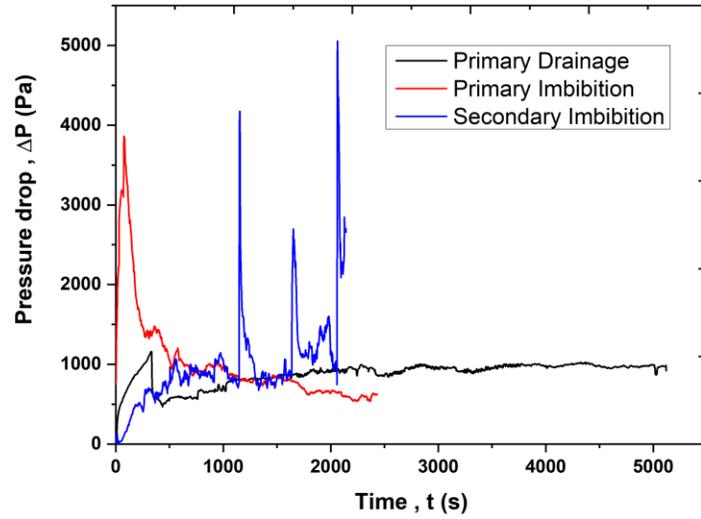


Emulsion

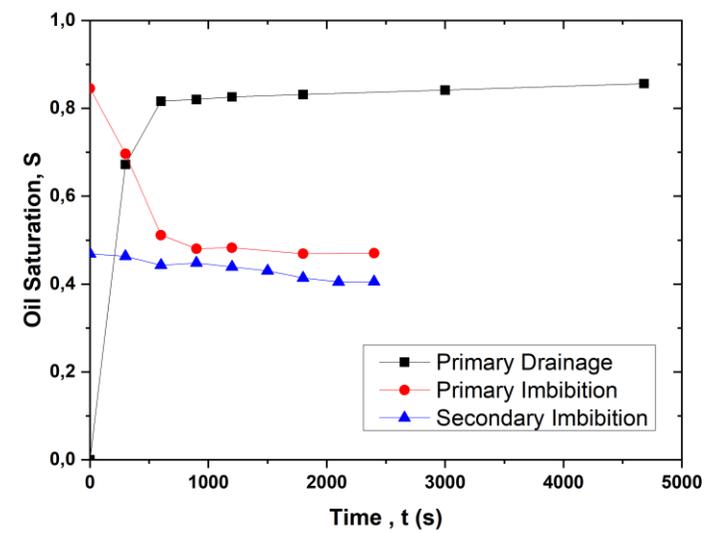
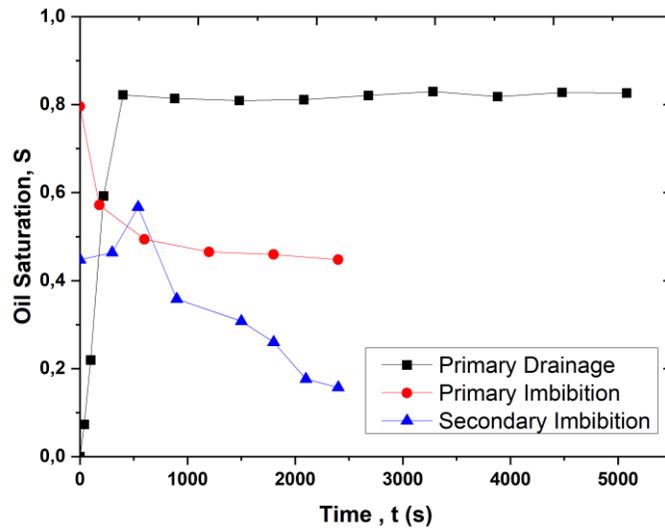
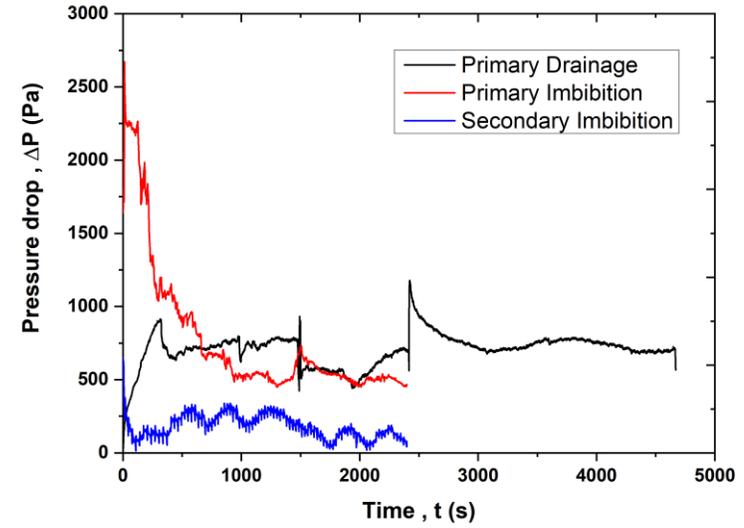


SiO₂-AMPSA=DMA 0.25% - NaCl 1M

emulsion



dispersion



Results 2

SiO₂=AMPSA-DMA-0.25% + NaCl 1M

Type of displacement	Displaced fluid	Displacing fluid	Flow rate (mL/min)	Injected volume (mL)	Oil saturation	Oil removal efficiency (%)
Drainage	NaCl 1M	-	0.08	7.6	0.86	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.47	45.3
Sec. Imbib.	Resid. paraffin oil	Dispersion	0.2	8	0.40	14.9
Drainage	NaCl 1M	-	0.08	8	0.83	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.45	45.8
Sec. Imbib.	Resid. paraffin oil	Emulsion	0.2	8	0.16	64.4

Secondary Imbibition

P(AMPSA-co-AA-co-DMA) 0.25%-water

Dispersion

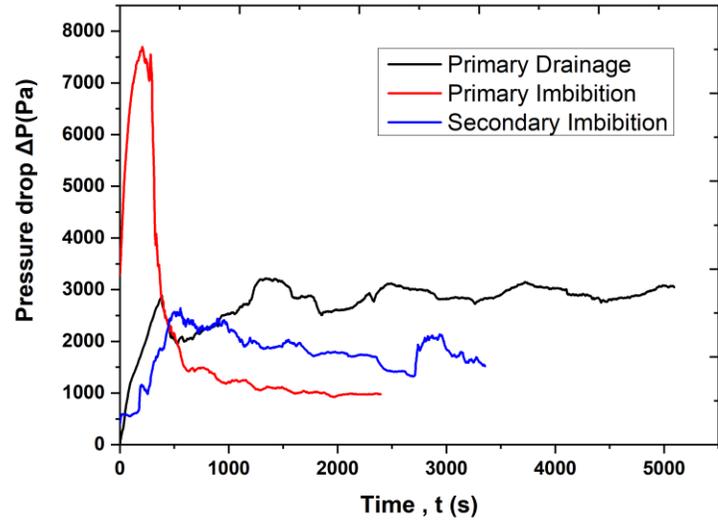


Emulsion

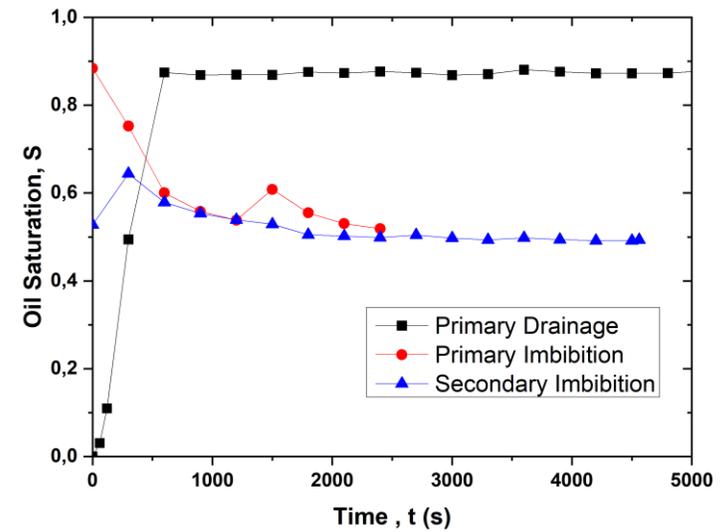
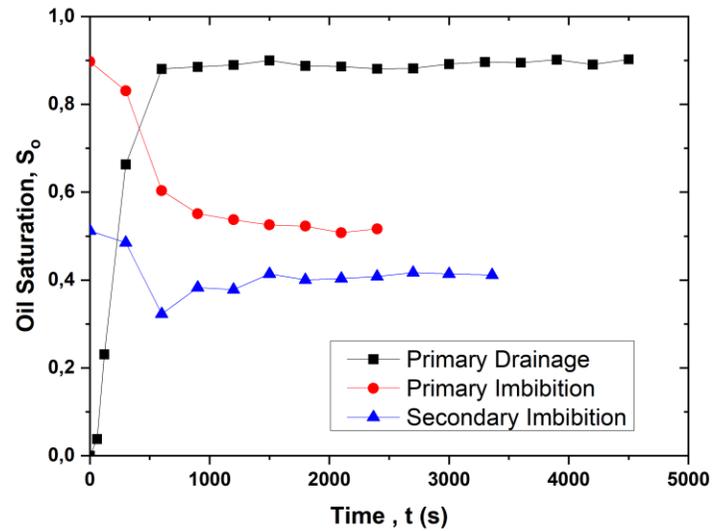
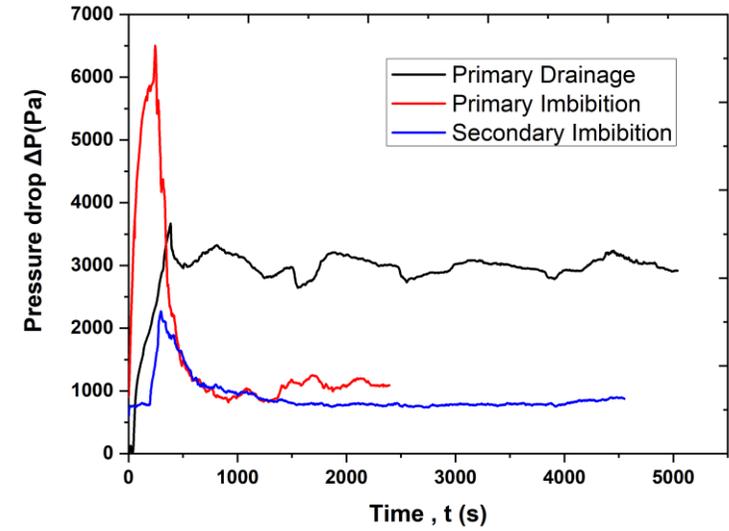


P(AMPSA-co-AA-co-DMA) 0.25%-water

emulsion



dispersion



Results 3

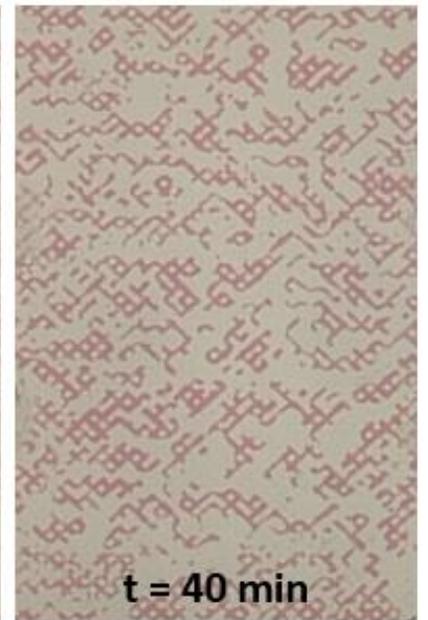
AMPSA 55.20.25 – 0.25% water

Type of displacement	Displaced fluid	Displacing fluid	Flow rate (mL/min)	Injected volume (mL)	Oil saturation	Oil removal efficiency (%)
Drainage	NaCl 1M	-	0.08	8	0.88	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.53	39.8
Sec. Imbib.	Resid. paraffin oil	Dispersion	0.2	8	0.50	5.7
Drainage	NaCl 1M	-	0.08	8	0.90	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.51	42.6
Sec. Imbib.	Resid. paraffin oil	Emulsion	0.2	11.2	0.41	20.5

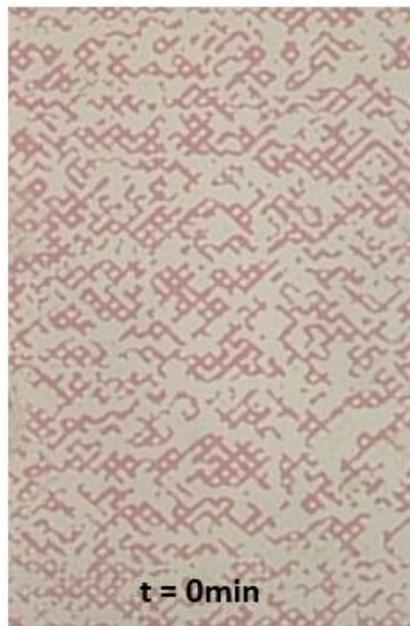
Secondary Imbibition

P(AMPSA-co-AA-co-DMA) 0.25%- NaCl 1M

Dispersion

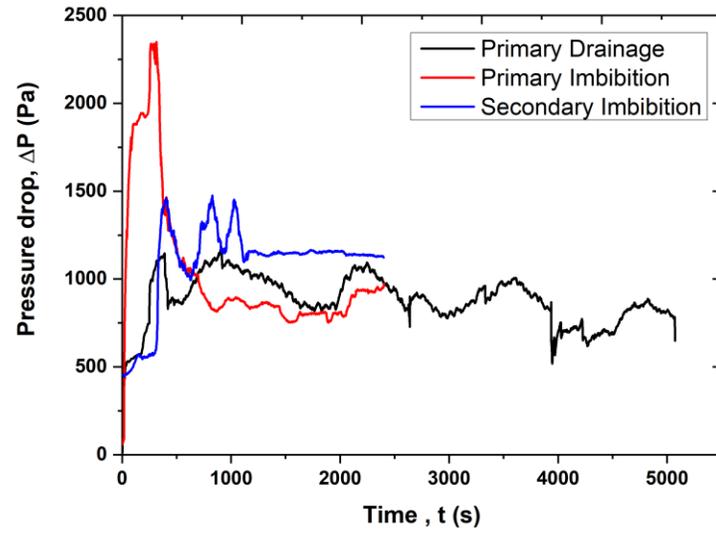


Emulsion

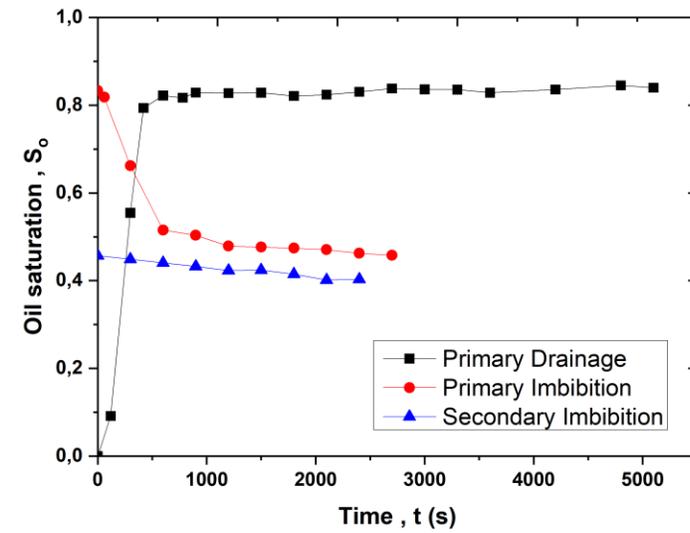
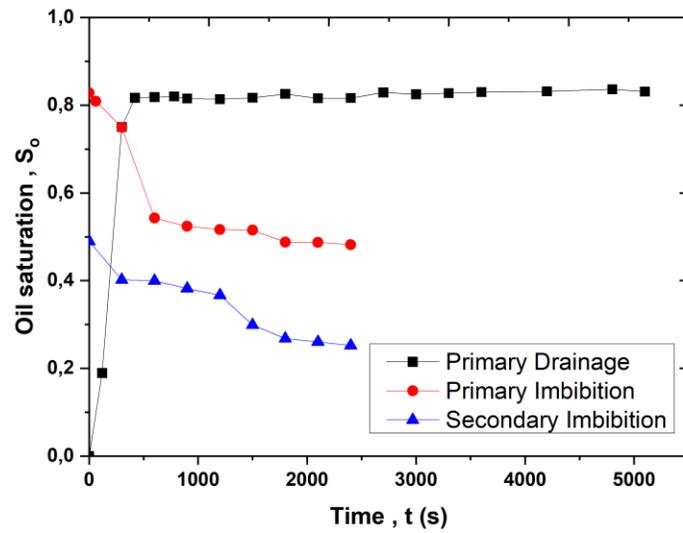
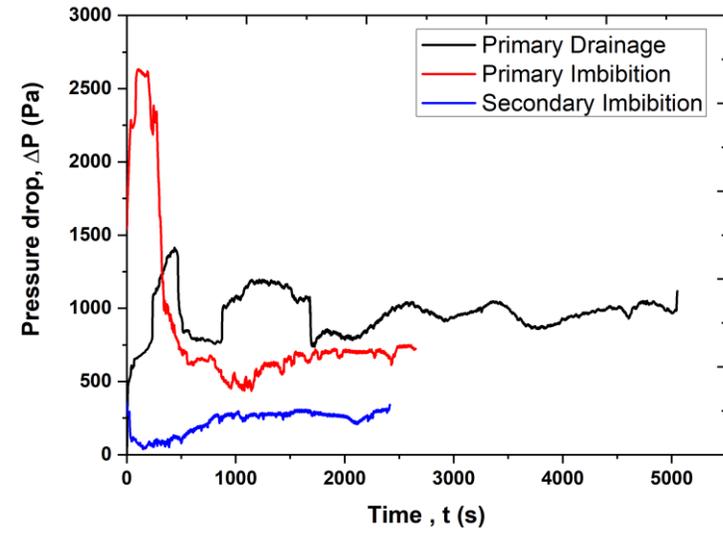


P(AMPSA-co-AA-co-DMA) 0.25% - NaCl 1M

emulsion



dispersion



Results 4

AMPSA 55.20.25 - 0,25% +NaCl 1M

Type of displacement	Displaced fluid	Displacing fluid	Flow rate (mL/min)	Injected volume (mL)	Oil saturation	Oil removal efficiency (%)
Drainage	NaCl 1M	-	0.08	8	0.84	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.46	45.2
Sec. Imbib.	Resid. paraffin oil	Dispersion	0.2	8	0.40	2.8
Drainage	NaCl 1M	-	0.08	8	0.83	-
Prim. Imbib.	Resid. paraffin oil	NaCl 1M	0.2	8	0.48	45.8
Sec. Imbib.	Resid. paraffin oil	Emulsion	0.2	8	0.25	47.9

Conclusions

- The potential to increase the residual oil recovery efficiency by injecting suspensions of polymer coated nanoparticles is investigated with visualization tests on a glass-etched pore network.
- The nanoparticles mobilize trapped oil by transferring it from upstream to downstream through a mechanism of successive steps of drainage (local increase of oil saturation) / imbibition (local decrease of oil saturation).
- It seems that the oil recovery efficiency of secondary imbibition tests is favored when using the SiO₂-AMPSA=DMA 0.25% suspension with the presence of NaCl 1M . On the other hand, the oil recovery efficiency increases respectably when using emulsions stabilized by SiO₂-AMPSA=DMA 0.25% with NaCl and CaCl₂.

Thanks for your attention

Acknowledgements



H.F.R.I.
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NANOPARTICLE INTERACTIONS WITH INTERFACES IN POROUS MEDIA: A MULTISCALE PERSPECTIVE

Marios Ioannidis, University of Waterloo



H.F.R.I.
Hellenic Foundation for
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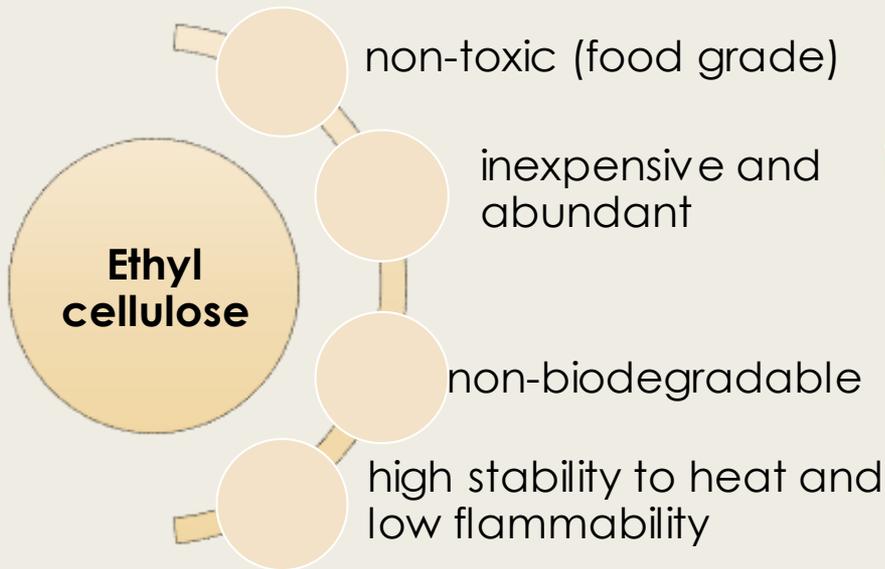
Workshop, 12-13 December 2022
FORTH/ICE-HT, Patras

**Advances Toward the Transport of
Nanoparticles in Porous Media and
Applications to Residual Oil Recovery**

Outline

- Need for a multiscale approach
 - *Surface forces*
 - *Diffusion and hydrodynamic dispersion*
- A case for using a model system
 - *Ethyl cellulose nanoparticles: Synthesis and characterization*
- Interactions between
 - *Nanoparticles in bulk: suspension stability*
 - *Adsorbing nanoparticles: dynamics of attachment*
 - *Adsorbed nanoparticles: maximum coverage*
- Nanoparticle transport in porous media
 - *Modeling hydrodynamic dispersion*
 - *Modeling retention at fluid-fluid interfaces*

A multiscale approach is required to establish applications.



**single
particle
scale**

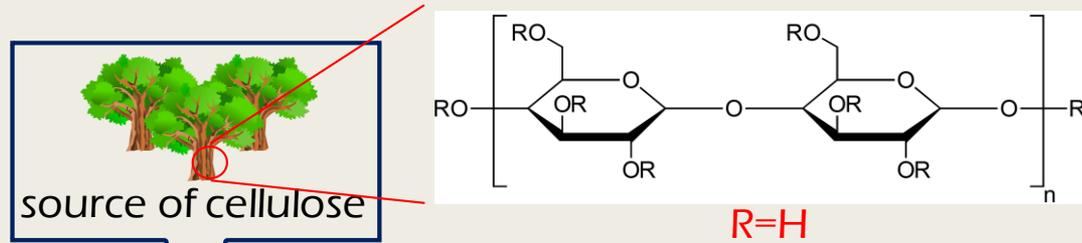
**single
interface
scale**

**multiple
interface
scale**

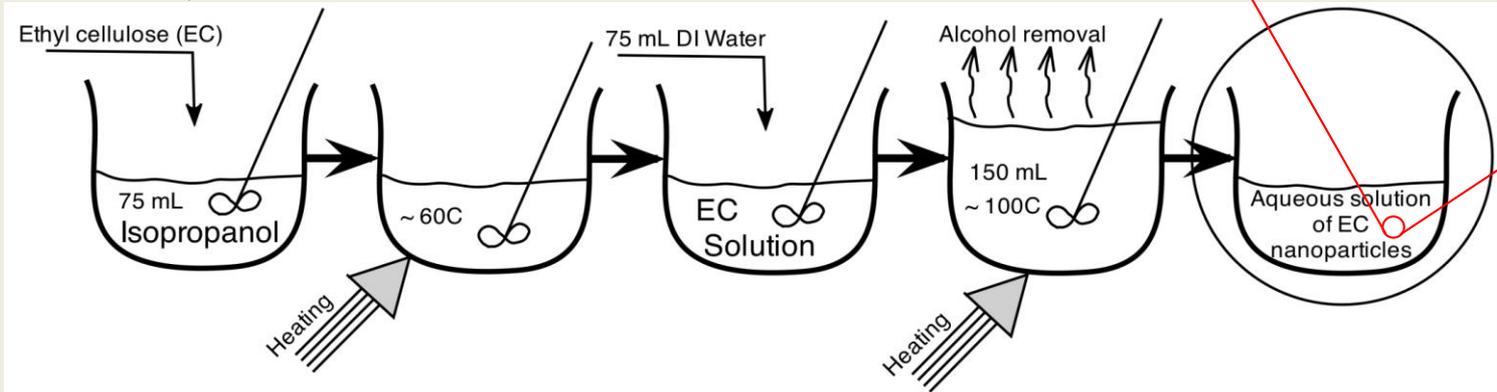
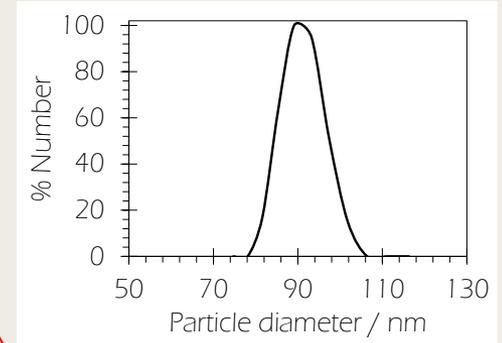
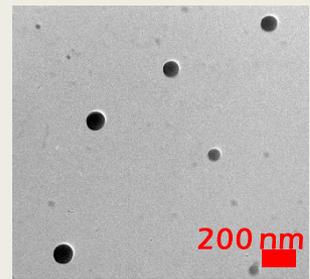
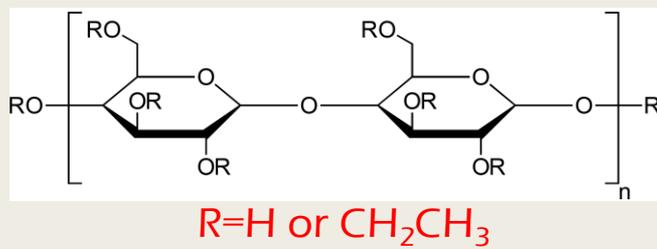


EC Nanoparticles are easily synthesized.

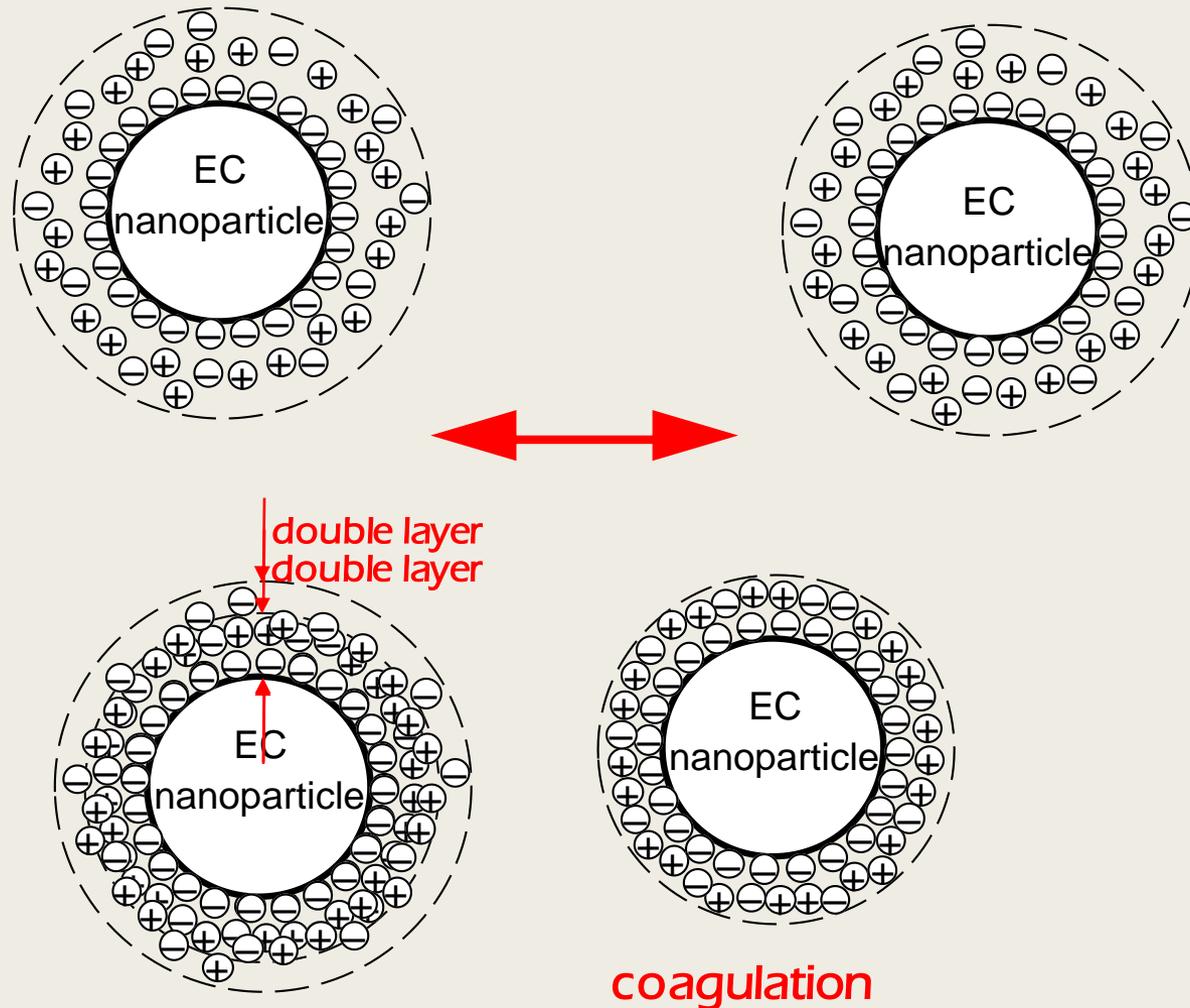
DLS results and TEM images of 89.1 nm EC nanoparticles.*



etherification process



Electrostatic repulsion stabilizes EC nanoparticle suspended in water.

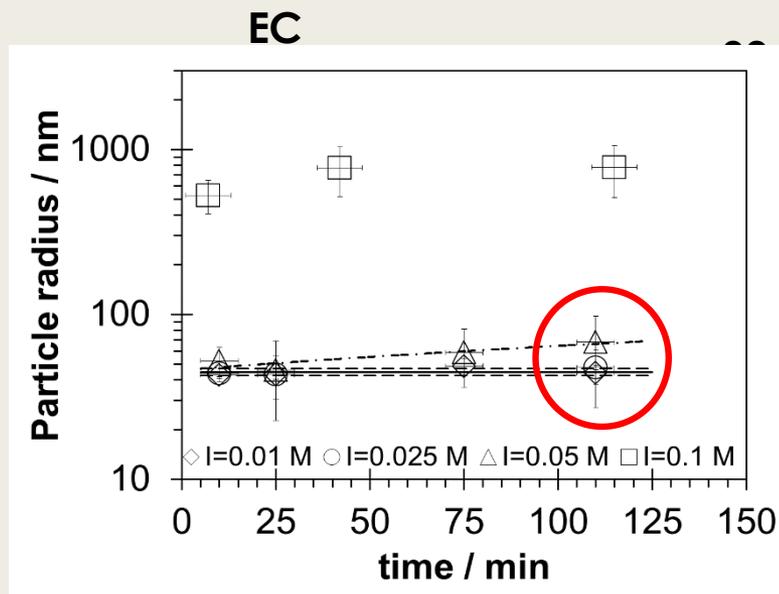


no salt

in the presence of
sufficiently large amount
of ions in solution

coagulation

Salt destabilizes the EC nanoparticle colloids.

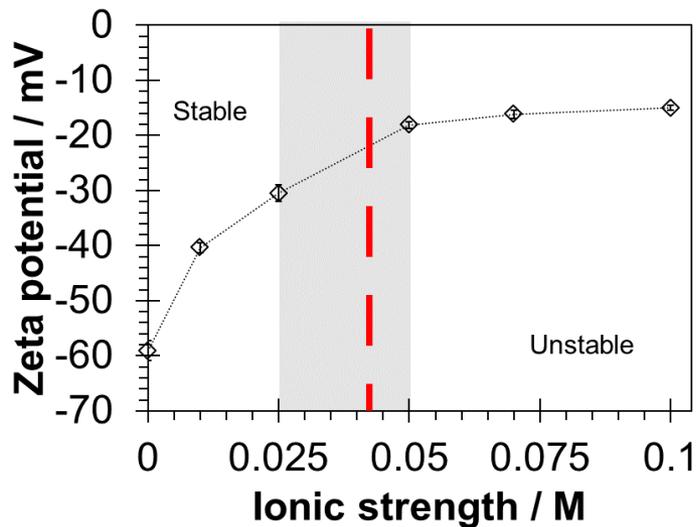


Changes in the hydrodynamic radius of EC nanoparticles over two hours at various ionic strengths and at EC nanoparticle concentration of 0.5 g L^{-1} .

Comparison pair EC 0.5 g L^{-1}	$t_{\text{obs.}}$	T_{critical} (from t-distribution table)	Conclusion
0.01 M vs. 0.025 M	0.83	2.78	1
0.01 M vs. 0.05 M	2.93		2
0.025 M vs. 0.05 M	2.90		

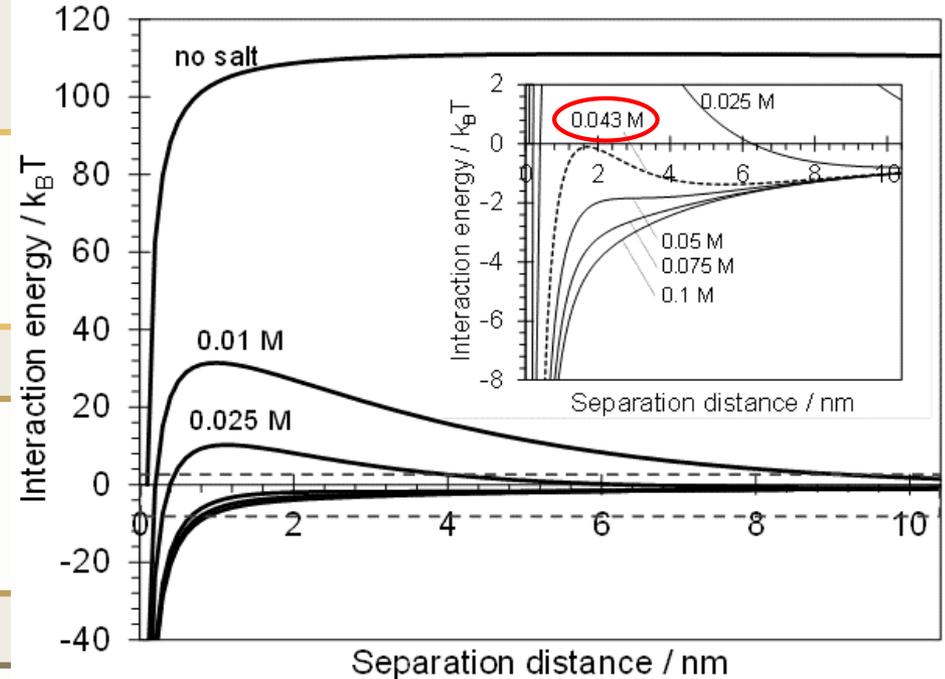
- $t_{\text{obs.}} < T_{\text{critical}} \rightarrow$ Fail to reject the null hypothesis
 \rightarrow There is no significant difference between the nanoparticle size.
- $t_{\text{obs.}} > T_{\text{critical}} \rightarrow$ Reject the null hypothesis
 \rightarrow There is a significant difference between the nanoparticle size.

Extended-DLVO calculations predict the critical coagulation concentration.



Zeta potential of EC nanoparticles in deionized water (neutral pH) as a function of ionic strength. The grey zone separates the conditions that result in a stable and unstable colloidal solution.

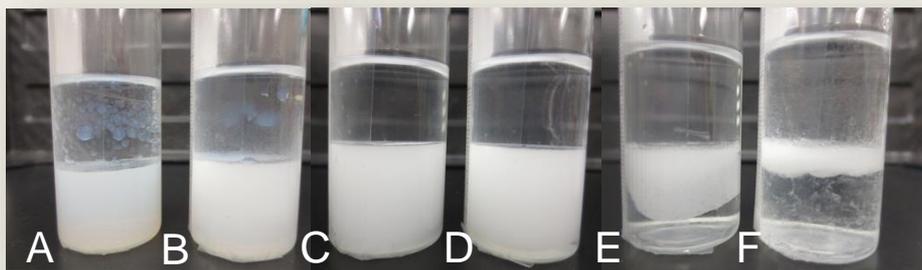
Interaction energies between two EC



Total interaction energy between two EC nanoparticles of the same size (radius 43.96 ± 4.92 nm) which is computed from extended-DLVO theory at various ionic strengths. The inset magnifies the dashed area.

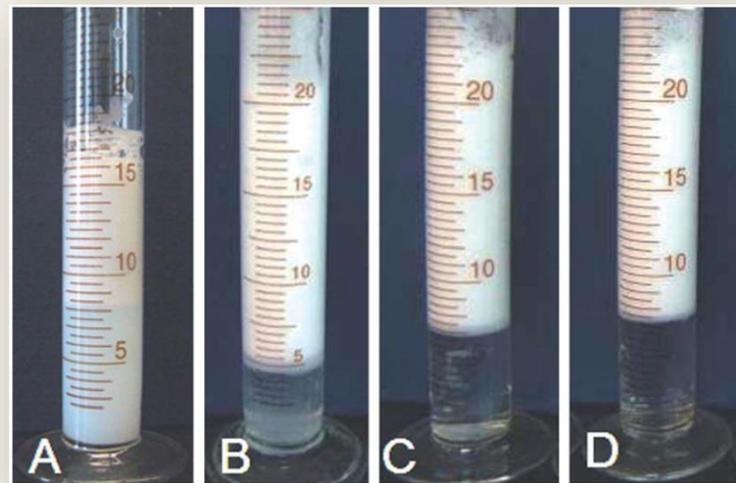
Stable emulsions and foams are made by EC nanoparticles.

EC nanoparticle-stabilized emulsion



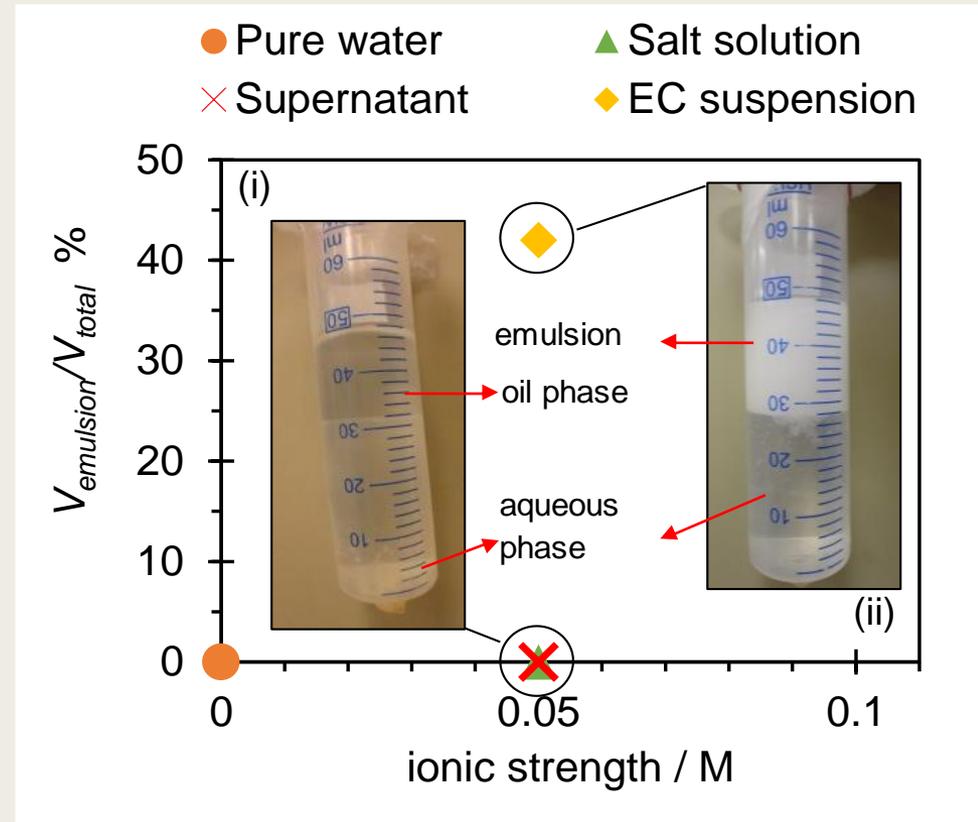
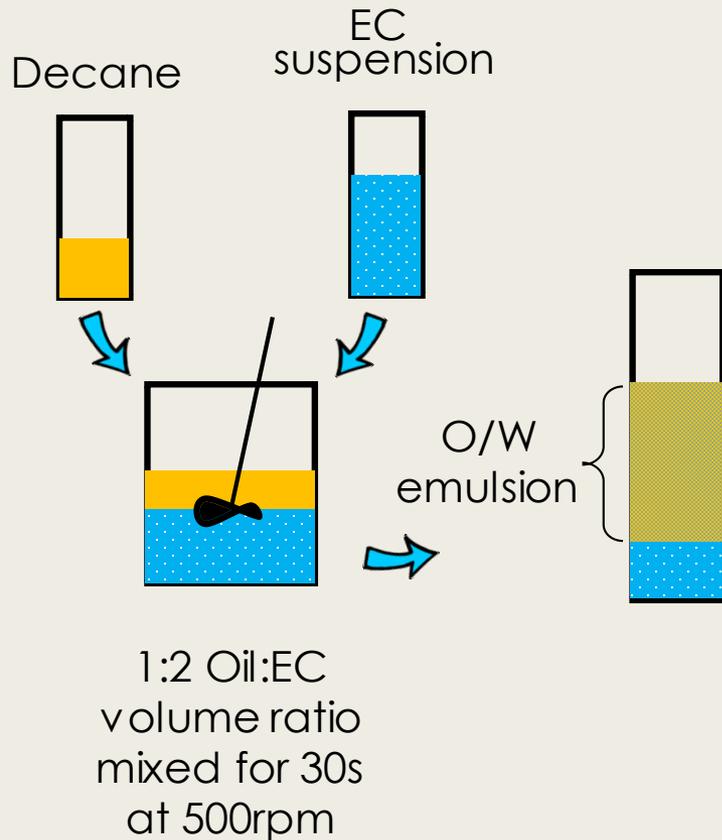
Pickering decane-in-water emulsions stabilized by EC nanoparticles at a concentration of 1 wt.% and ionic strength (I) of (A) 0 M, (B) 0.01 M, (C) 0.025 M, and (D) 0.05 M. (E) and (F) are emulsions made at EC 0.4 wt.% and $I=0.025$ M and 0.05 wt.% and $I=0.1$ M, respectively.

EC nanoparticle-stabilized foam



EC foam produced by hand-shaking for 2 min at different concentration of NaCl (A) 0M, (B) 0.01 M, (C) 0.05 M, and (D) 0.1 M. (pH of all samples being neutral).^[*]

Pickering emulsions are generated only in the presence of EC nanoparticles.



Adsorption is a necessary condition for emulsion/foam stabilization.



The adsorption of colloidal nanoparticles at fluid interfaces is irreversible – the process may be probed experimentally by measurements of the **dynamic surface or interfacial tension**.

Thermodynamic arguments enable application of RSA theory to dynamic surface/interface tension data.

$$\frac{dN_i}{dt} = -j|_{x \rightarrow 0^+} \quad \Rightarrow \quad \frac{d\Theta}{dt} = -\pi r^2 j|_{x \rightarrow 0^+}$$

$$\frac{d\Theta}{dt} = \pi r^2 \frac{dN_i}{dt}$$

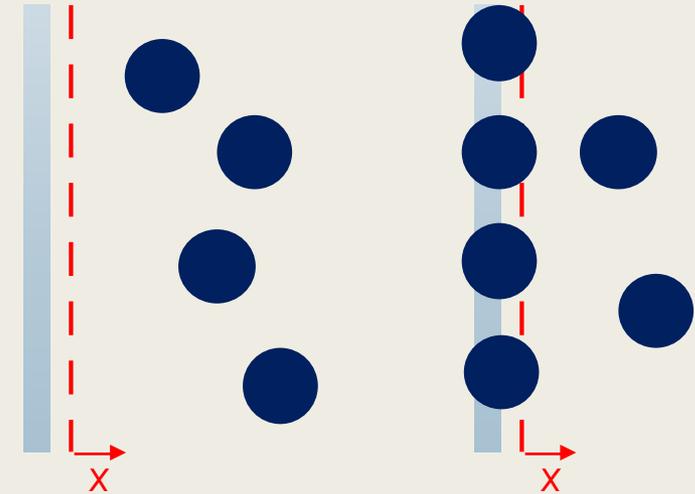
adsorption flux during the early stages of adsorption:

$$j|_{x \rightarrow 0^+} = -D \frac{\partial C}{\partial x} \Big|_{x \rightarrow 0^+} = -C_0 \sqrt{\frac{D}{\pi t}}$$

adsorption flux during the late stages of adsorption:

$$j|_{x \rightarrow 0^+} = -k_a N_A C_0 B(\Theta)$$

interface



state I

state II

$$\Theta = 2\pi r^2 N_A C_0 \left(\frac{Dt}{\pi} \right)^{0.5}$$

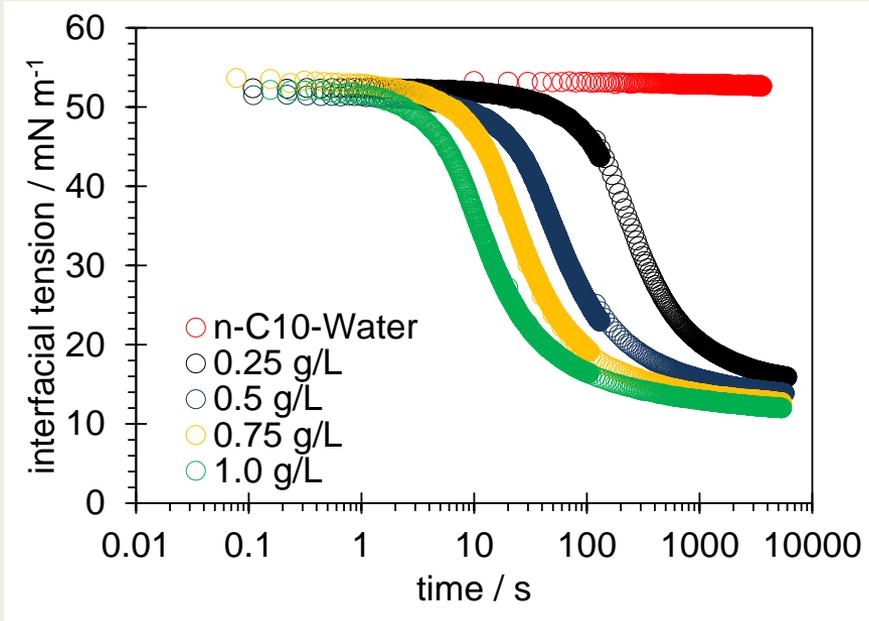
$$\Theta = \Theta_{\max} - \frac{K_l}{\pi r^2 N_A C_0} \left(\frac{1}{Dt} \right)^{0.5}$$

$$\Theta(t) = -\frac{(\gamma_0 - \gamma(t))\pi r^2}{\Delta E}$$

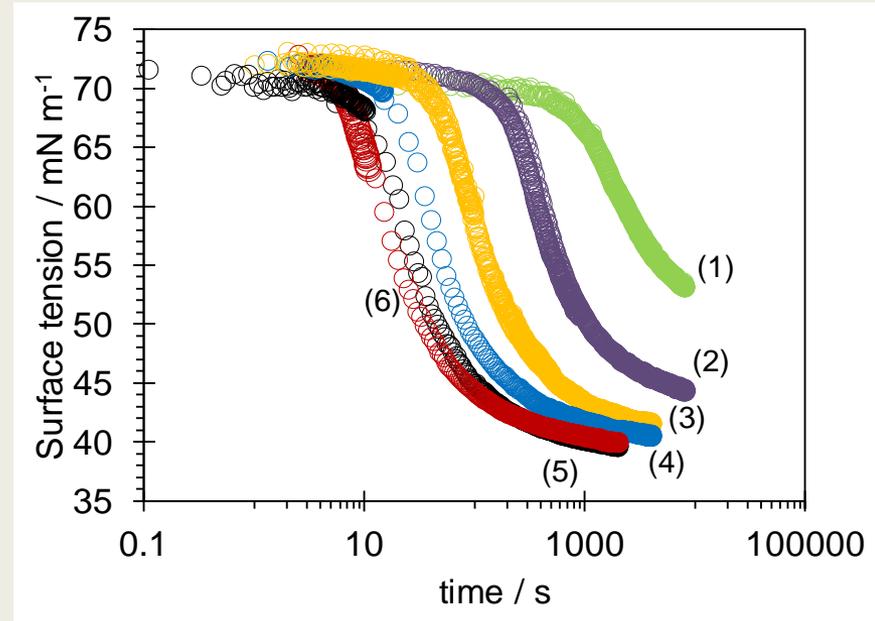
$$\gamma = \gamma_0 + 2N_A |\Delta E| C_0 \left(\frac{Dt}{\pi} \right)^{0.5} \quad t \rightarrow 0$$

$$\gamma = \gamma_\infty + \frac{K_l |\Delta E|}{(\pi r^2)^2 N_A C_0} \left(\frac{1}{Dt} \right)^{0.5} \quad t \rightarrow \infty$$

EC nanoparticles adsorb readily at fluid interfaces.

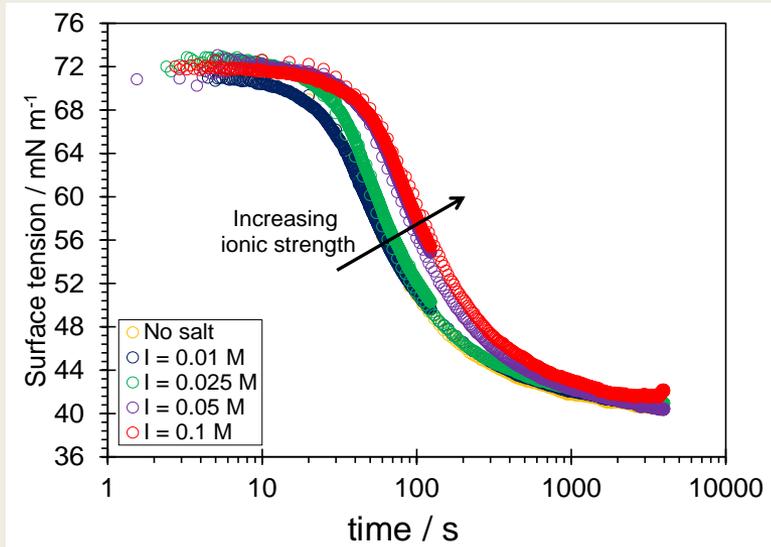


IFT measurements at different ionic strength for n-C10-water interface at the EC nanoparticle concentration of 0.5 g L^{-1} .

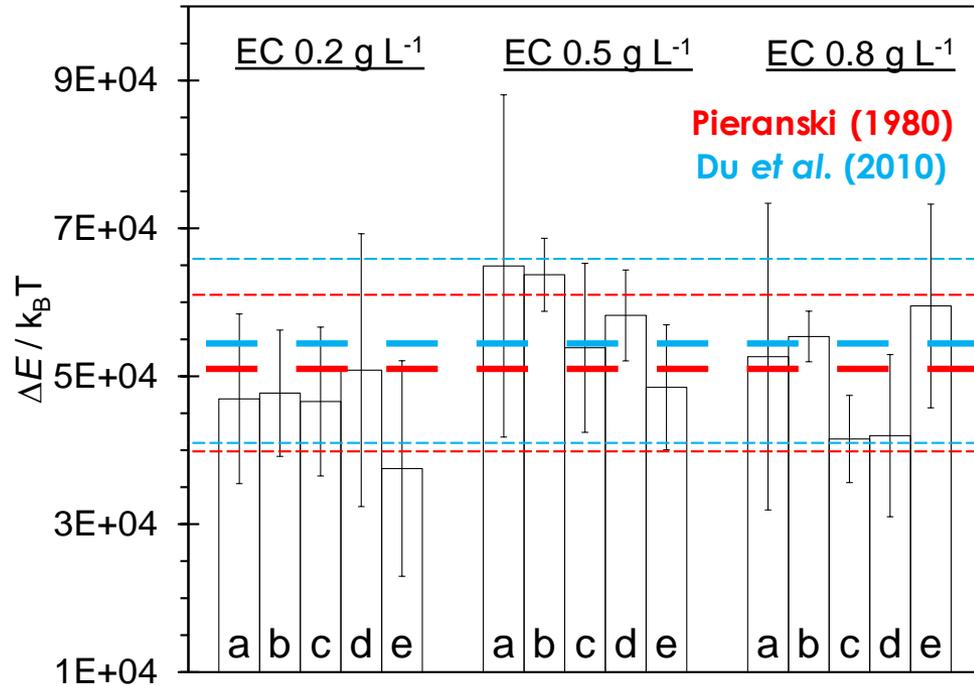


IFT measurements at different ionic strength for air-water interface at the EC nanoparticle concentration of (1) 0.1 g/L , (2) 0.2 g/L , (3) 0.4 g/L , (4) 0.6 g/L , (5) 0.8 g/L , and (6) 1.0 g/L .

Dynamic surface (interfacial) tension reveals irreversible adsorption of nanoparticles regardless of ionic strength.

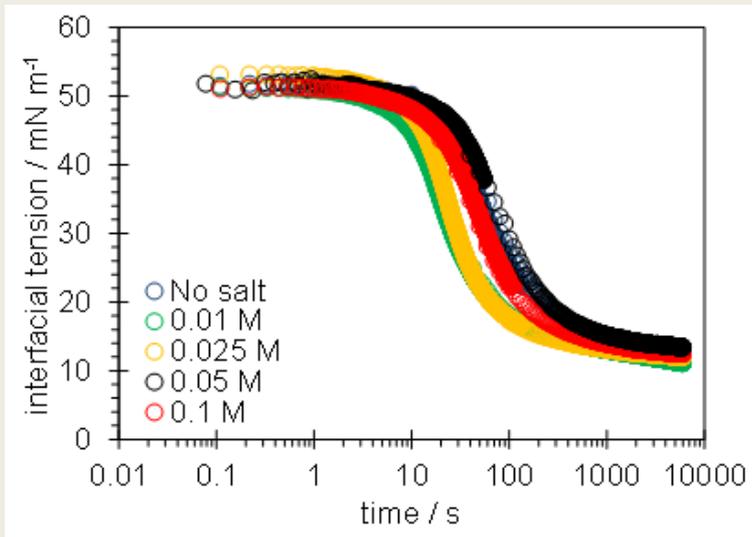


DST measurements of colloidal suspension of EC nanoparticles at the EC concentration of 0.5 g L⁻¹ and various ionic strength.



Adsorption energy at three levels of EC nanoparticle concentrations and at ionic strengths of (a) 0 M, (b) 0.01 M, (c) 0.025 M, (d) 0.05 M, and (e) 0.1 M.

Dynamic surface (interfacial) tension reveals irreversible adsorption of nanoparticles regardless of ionic strength.



IFT measurements at different ionic strength for n-C10-water interface at the EC nanoparticle concentration of 0.5 g L^{-1} .

Ionic strength (M)	iso-C8-water	n-C10-water
0.01	$(10 \pm 2) \times 10^4 k_B T$	$(8 \pm 3) \times 10^4 k_B T$
0.025	$(9 \pm 2) \times 10^4 k_B T$	$(7 \pm 3) \times 10^4 k_B T$
0.05	$(10 \pm 4) \times 10^4 k_B T$	$(8 \pm 3) \times 10^4 k_B T$
0.1	$(9 \pm 1) \times 10^4 k_B T$	$(6 \pm 2) \times 10^4 k_B T$
0.2	$(8 \pm 1) \times 10^4 k_B T$	–

Compare with $(7 \pm 1) \times 10^4 k_B T$ from Du *et al.*

Adsorption energy of EC nanoparticle at alkane-water interfaces at various ionic strengths. EC nanoparticle concentration is 0.5 g L^{-1} .

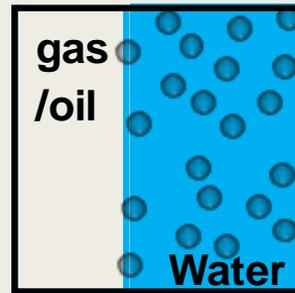
Adsorption flux decreases during the late stages of adsorption beyond the CCC.

ionic strength [M]	EC nanoparticle concentration [g L ⁻¹]	iso-C8-water	n-C10-water	air-water
0	0.5	85±21	98±12	90±10
0.01		62±11	83±5	100±10
0.025		54±4	57±1	90±20
0.05		54±5	107±7	120±70
0.1		61±2	84±11	140±40
0.2		64±4	-	-

$$\gamma = \gamma_{\infty} + \frac{K_l |\Delta E|}{(\pi r^2)^2 N_A C_0} \left(\frac{1}{Dt} \right)^{0.5} \quad \Rightarrow \quad \left. \frac{d\gamma}{dt^{-0.5}} \right|_{t \rightarrow \infty} = \frac{K_l |\Delta E|}{(\pi r^2)^2 N_A C_0 D^{0.5}}$$

Two possible scenarios for the adsorption of EC nanoparticles at fluid interfaces:

early stages of adsorption
($t \rightarrow 0$)

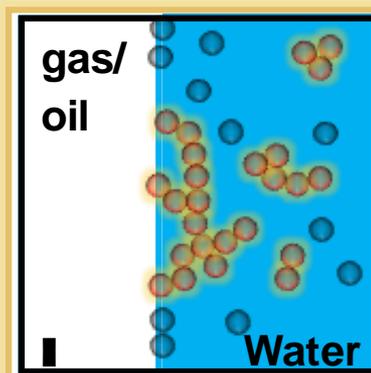


Nanoparticle flux at the interface

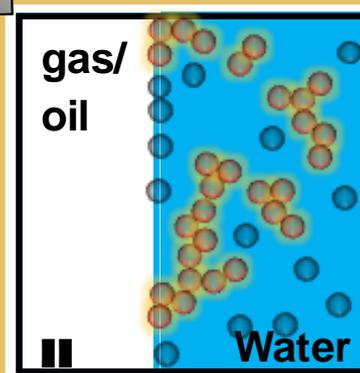
$$j|_{x \rightarrow 0^+} = -k_a C_0 B(\Theta)$$

$$B^{RSA}(\Theta) \cong 2.32 \left(1 - \frac{\Theta}{\Theta_\infty} \right)^3$$

late stages of adsorption ($t \rightarrow \infty$)
beyond CCC



nanoparticle aggregates formed in the bulk are adsorbed at the fluid interface alongside single nanoparticles.



only single nanoparticles are adsorbed at the fluid interface; nanoparticle aggregates at the interface are formed by the attachment on nanoparticles on already adsorbed ones

Extended-DLVO calculations are consistent with maximum surface coverage.

In Oil

$$\phi_{vdW}^O = -r\theta \frac{H_{121}}{12\pi h}$$

$$\phi_{elec}^O = \frac{(A_{po}\sigma_{po})^2}{8\pi r\epsilon_o\epsilon_o} \left\{ \frac{1}{\left(1 + \frac{h}{2r}\right)^2} - \frac{1 + \frac{h}{2r}}{(3 + \cos\theta)^2 + \left(2 + \frac{h}{r}\right)^2} \right\}$$

$$\phi_{d-d}^O = \frac{(\pi\sigma_d r^2 \sin^2\theta)^2}{32\pi\epsilon_o\epsilon_o \left(r + \frac{h}{2}\right)^3}$$

In Water

$$\phi_{vdW}^W = -r(\pi - \theta) \frac{H_{131}}{12\pi h}$$

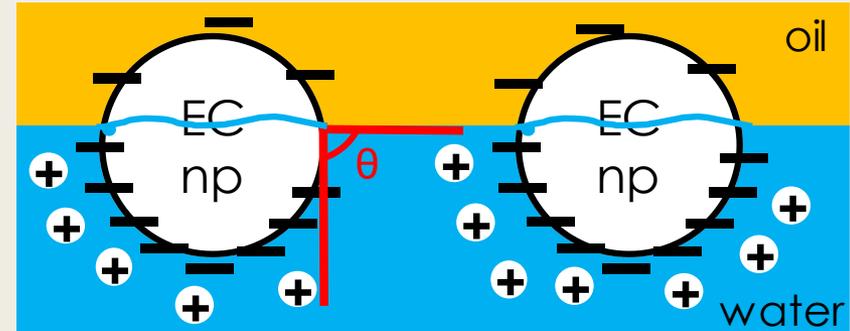
$$\phi_{hydro}^W = -r(\pi - \theta) \frac{K_{131}}{2\pi h}$$

$$\phi_{elec}^W = 4(\pi - \theta)\epsilon_o\epsilon_r r\psi_{pw}^2 \left(1 - \frac{r}{h+2r}\right) \ln \left[1 + \frac{\exp(-\kappa h)}{1 + h/r}\right]$$

$$\phi_{d-d}^W = \frac{(A_{pw}\sigma_{pw})^2}{16\pi\epsilon_o\epsilon_w^2\kappa^2 \left(r + \frac{h}{2}\right)^3}$$

Electrostatic repulsion through oil
Dipole-dipole repulsion through oil

Van der Waals attraction through oil



Van der Waals attraction through water
Hydrophobic attraction through water
Capillary attraction due to undulation

Electrostatic repulsion through water
Dipole-dipole repulsion through water

Capillary attraction a negligible impact on the net interaction energy between particles adsorbed at the interface.

monopole capillary

$$Bo = \frac{\Delta\rho gr^2}{\gamma} = O(10^{-10}) \quad \text{negligible}$$

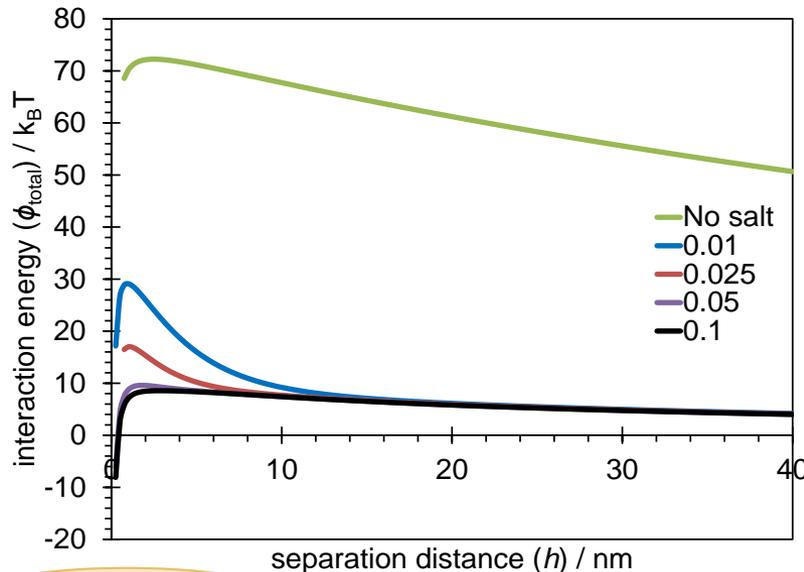
Extended DLVO calculations for adsorbed EC nanoparticles at n-decane-water interface considering quadrupolar capillary attraction.

quadrupole capillary

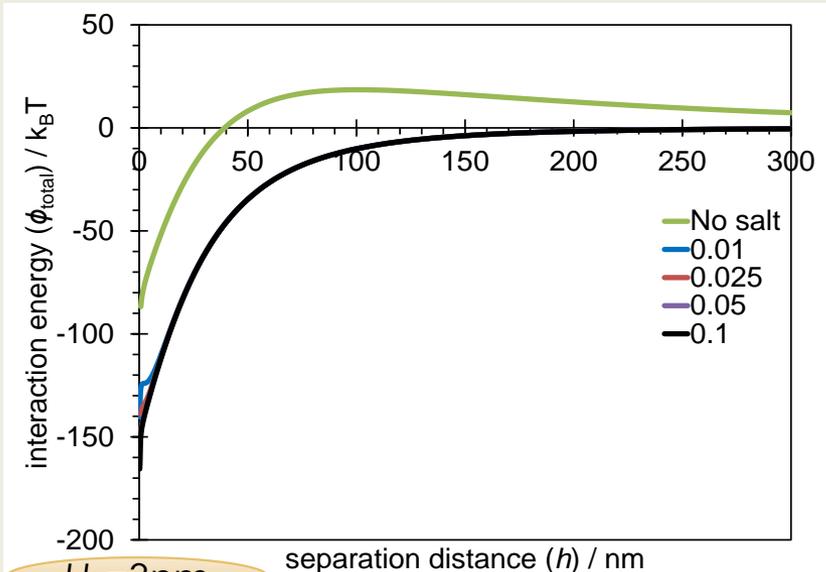
$$\Delta\phi_{Qcap}(h) = \phi_{Qcap}(h) - \phi_{Qcap}(\infty)$$

$$\phi_{Qcap}(h) = \pi\gamma H_2^2 (2S(\delta) - G(\delta))$$

$$\phi_{Qcap}(\infty) = 2\pi\gamma H_2^2$$

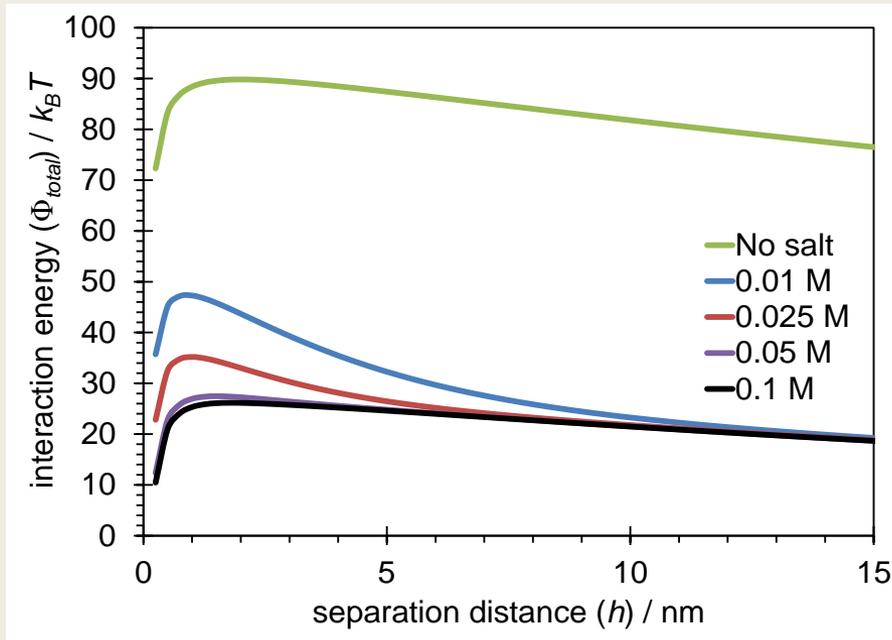


$H_2 = 1 \text{ nm}$

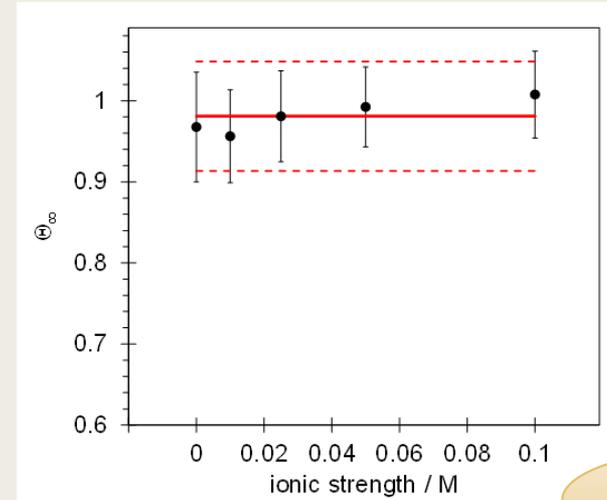


$H_2 = 3 \text{ nm}$

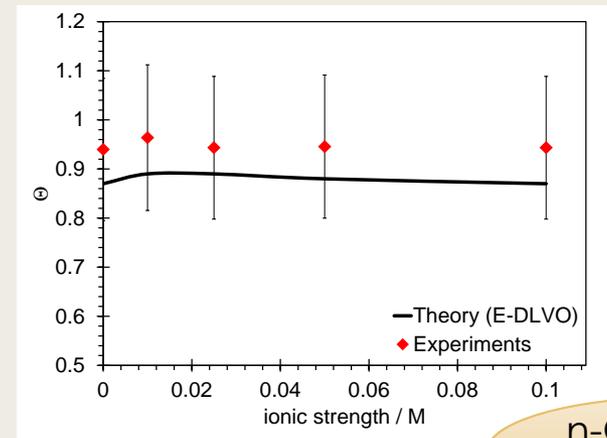
Extended-DLVO calculations predict maximum surface coverage at the interface.



DST measurements of colloidal suspension of EC nanoparticles at the EC concentration of 0.5 g L^{-1} and various ionic strength.

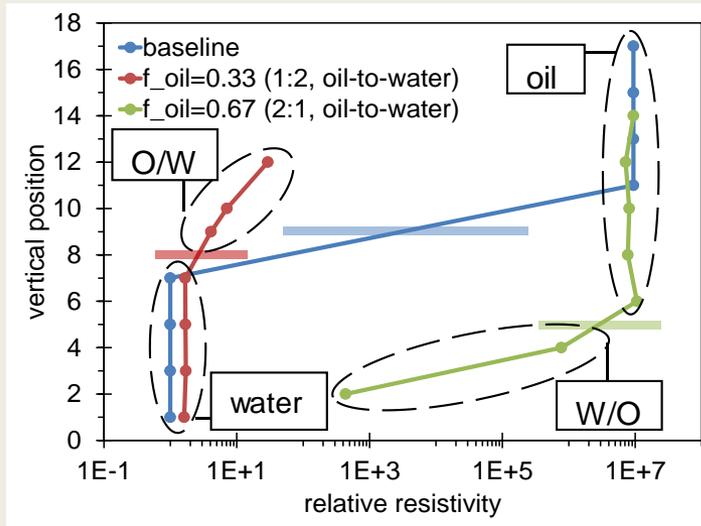
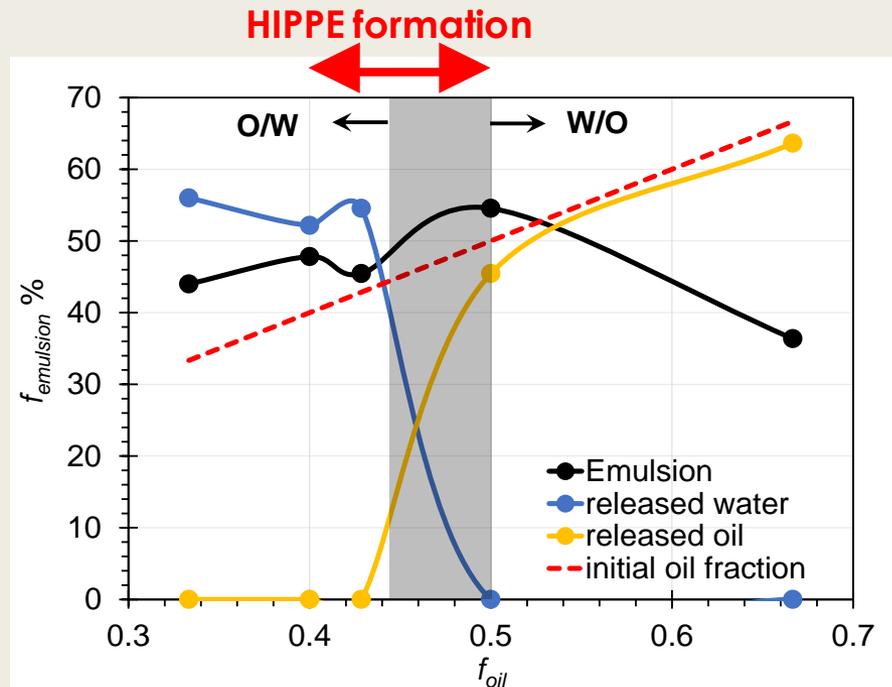
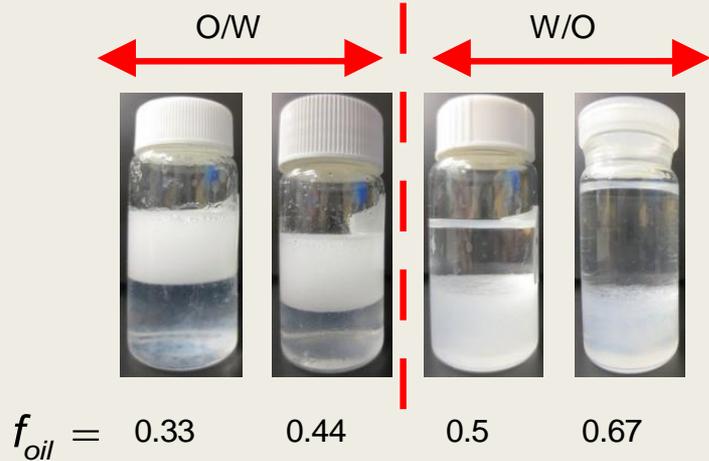


air-water interface



n-C10-water interface

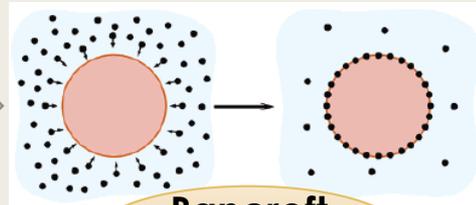
Oil volume fraction decides the type of Pickering emulsion generated with EC nanoparticles.



The O/W Pickering emulsions are enriched in oil as f_{oil} as increased and at $f_{oil} \geq 0.4$, where the dispersed phase occupied at least 74% of the volume of emulsion, **high internal phase Pickering emulsions** (HIPPEs) formed.

(anti-)Bancroft-type Pickering emulsions are generated depending on the oil volume fraction.

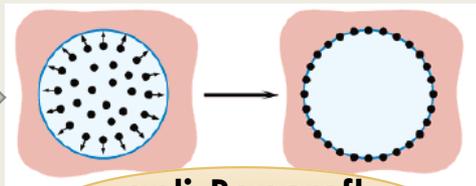
Emulsifier dispersed in continuous phase



Bancroft emulsion

$$D_{32}|_{f_{oil} < 0.5} = \frac{8r\rho_p\Theta}{\rho_0} \frac{f_{oil}}{1-f_{oil}}$$

Emulsifier dispersed in dispersed phase

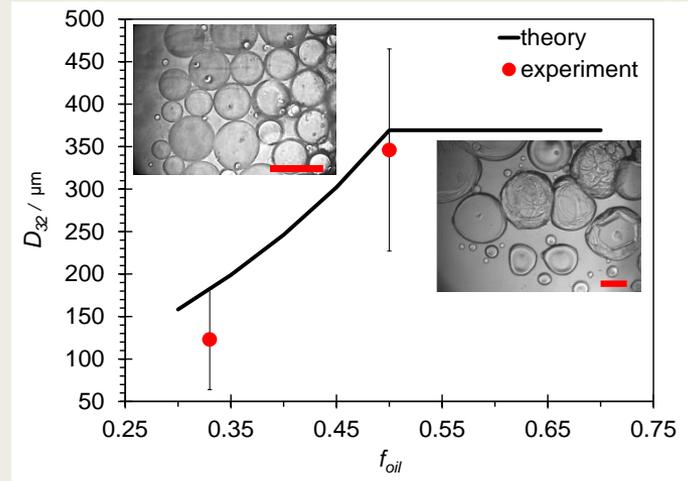


anti-Bancroft emulsion

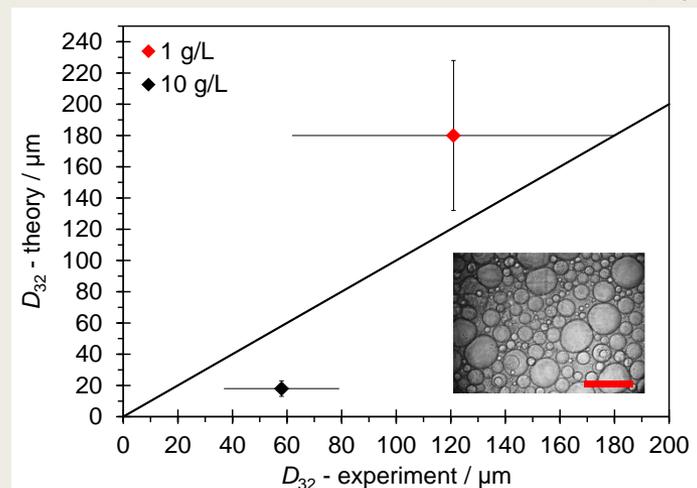
$$D_{32}|_{f_{oil} \geq 0.5} = \frac{8r\rho_p\Theta}{\rho_0}$$

Analyses on the drop size distribution further support the conclusion that the fluid interface is densely covered to its maximum limit (i.e. 91%).

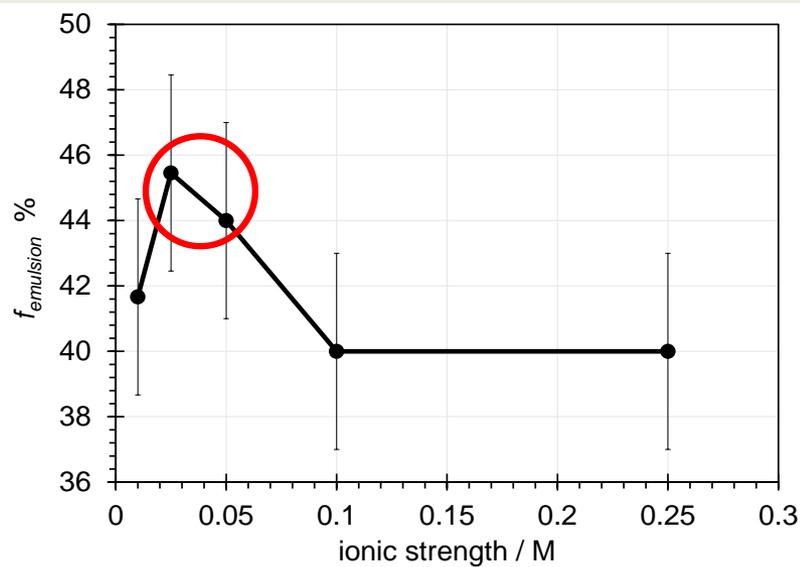
effect of f_{oil}



effect of ρ_0

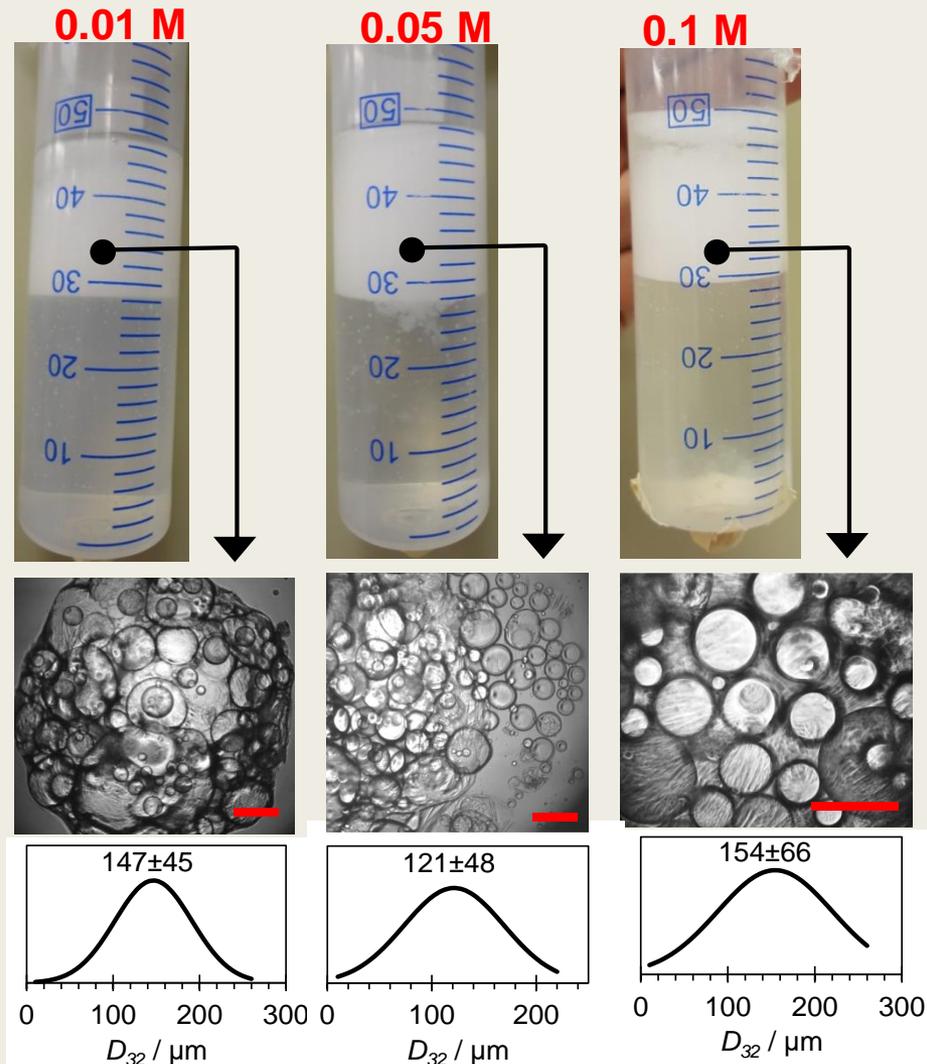


The most stable Pickering emulsion could be obtained when the ionic strength is close to the CCC.

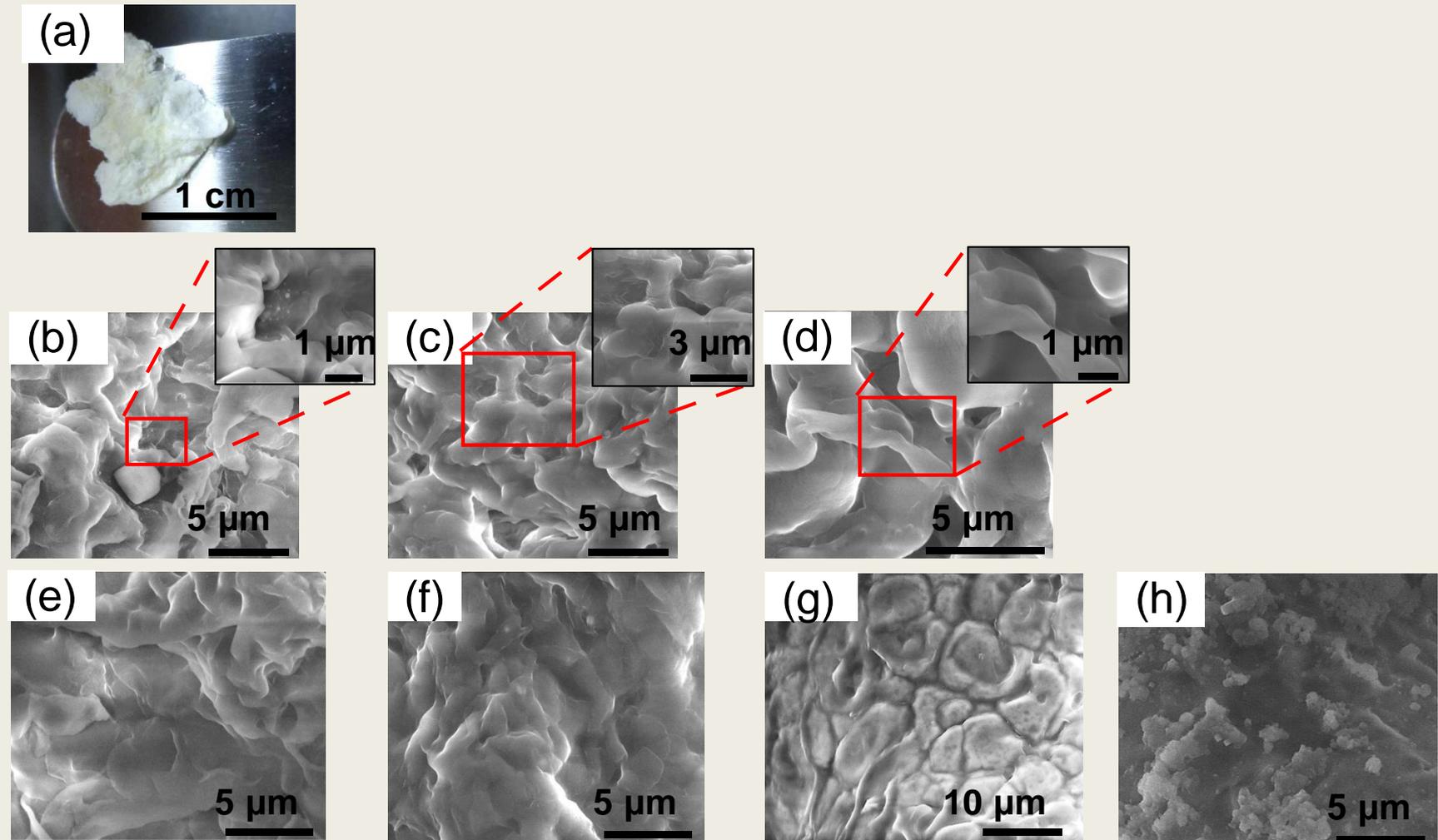


Salt has no significant effect on the volume fraction of emulsion or mean size of oil drops.

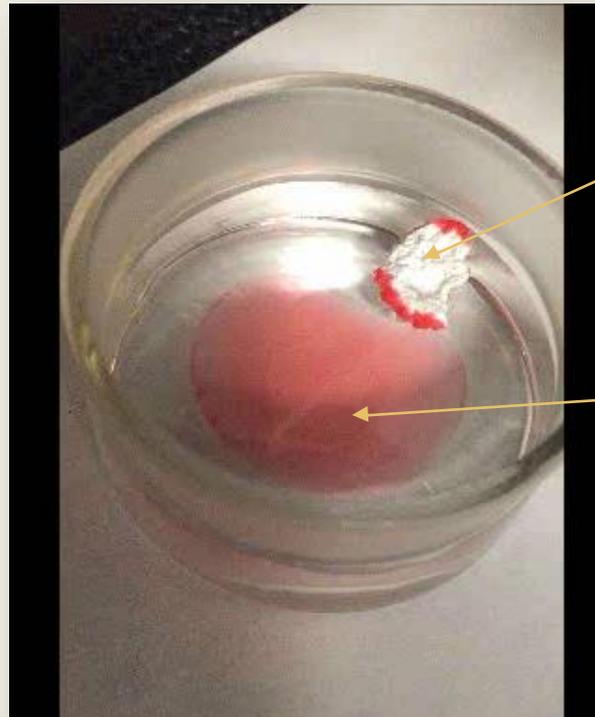
However, the largest volume for Pickering emulsions could be obtained when ionic strength is between 0.025 M and 0.05 M.



High internal phase Pickering emulsions serve as a template for porous material fabrication.



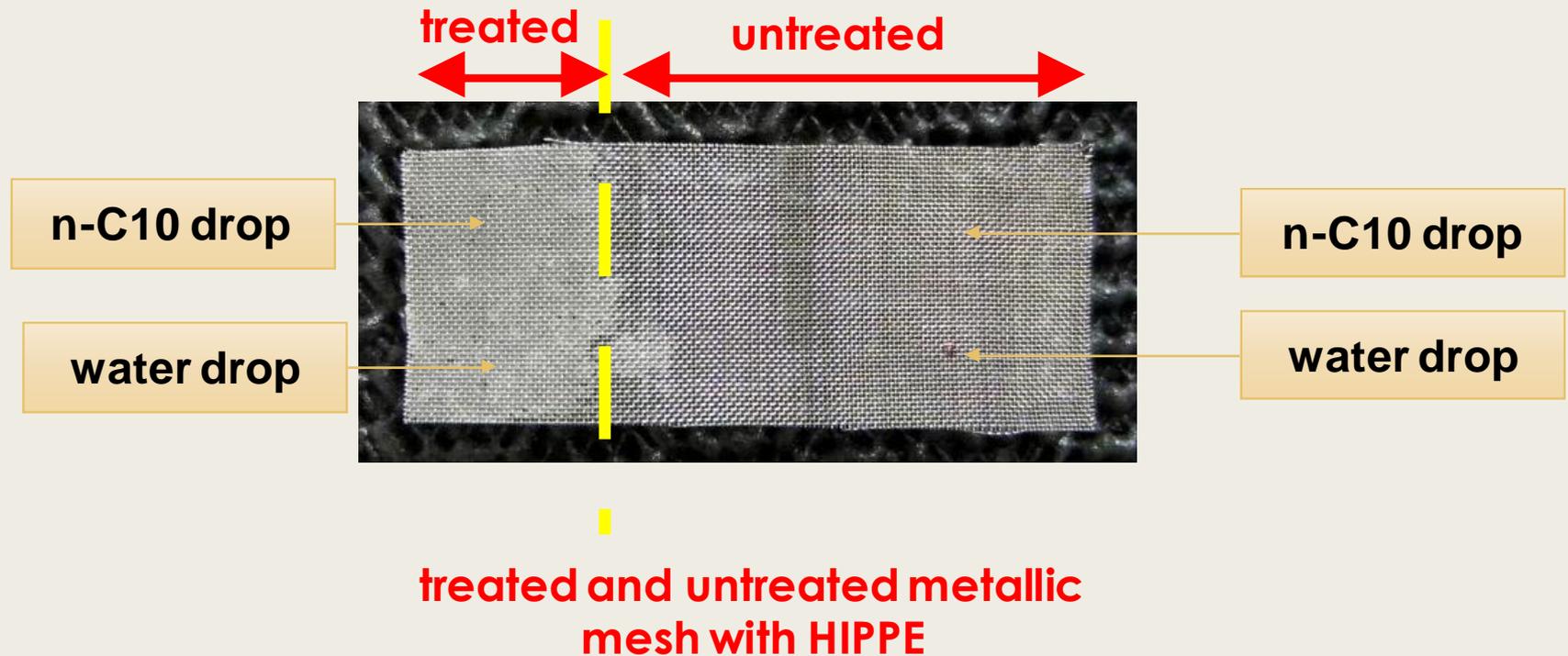
Oil spill is successfully removed.



**dried
Pickering
emulsion**

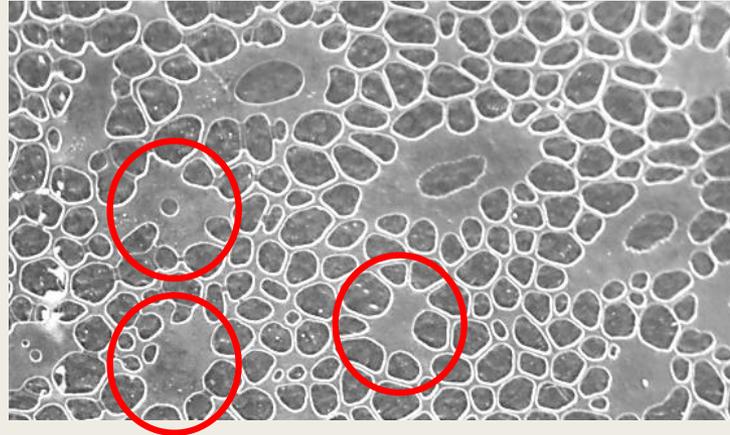
**Red-dyed
decane spilled
on the surface
of water**

Wettability is controlled.



Foam can be generated *in situ* by co-injecting gas and np suspension.

Injecting water at ionic strength of 0.05 M

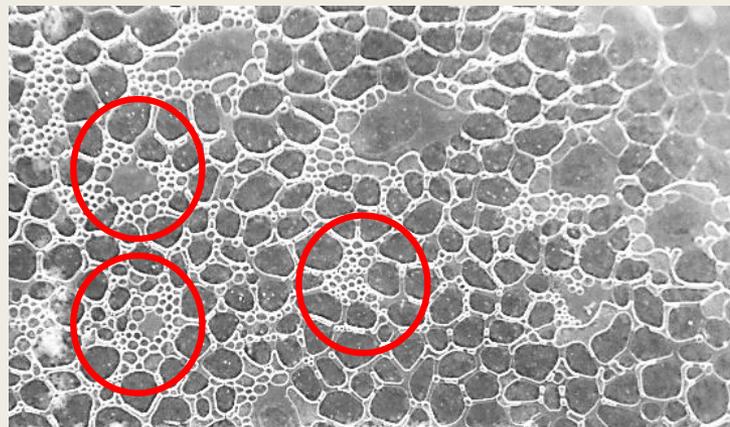


100% water-saturated
(ionic strength = 0.05 M)

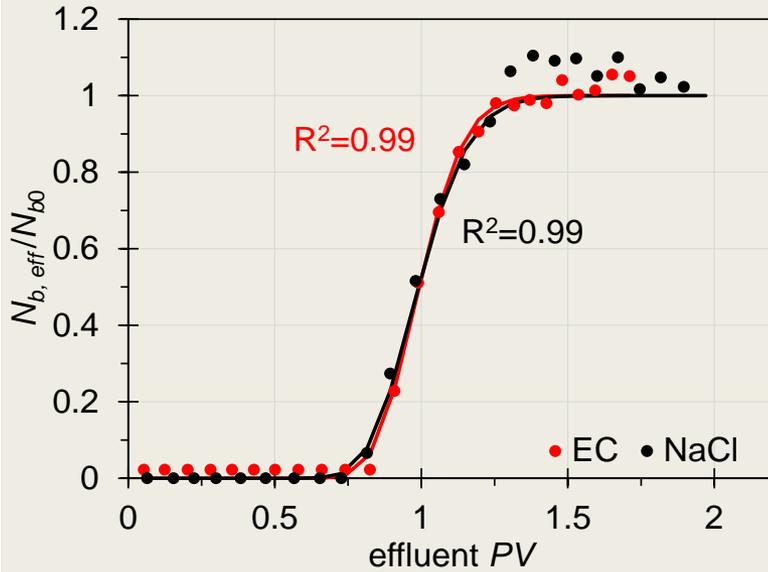
nitrogen stream



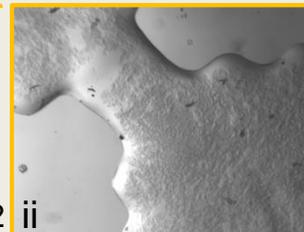
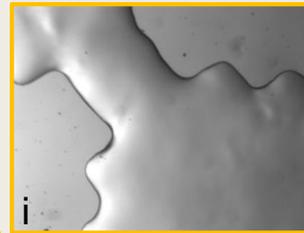
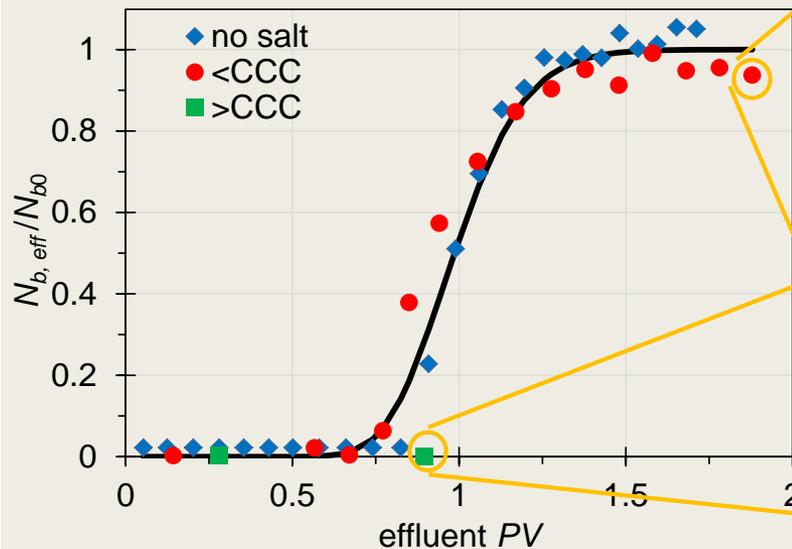
EC nanoparticle suspension at 0.05 M



EC nanoparticles are transported as a conservative tracer in porous media.

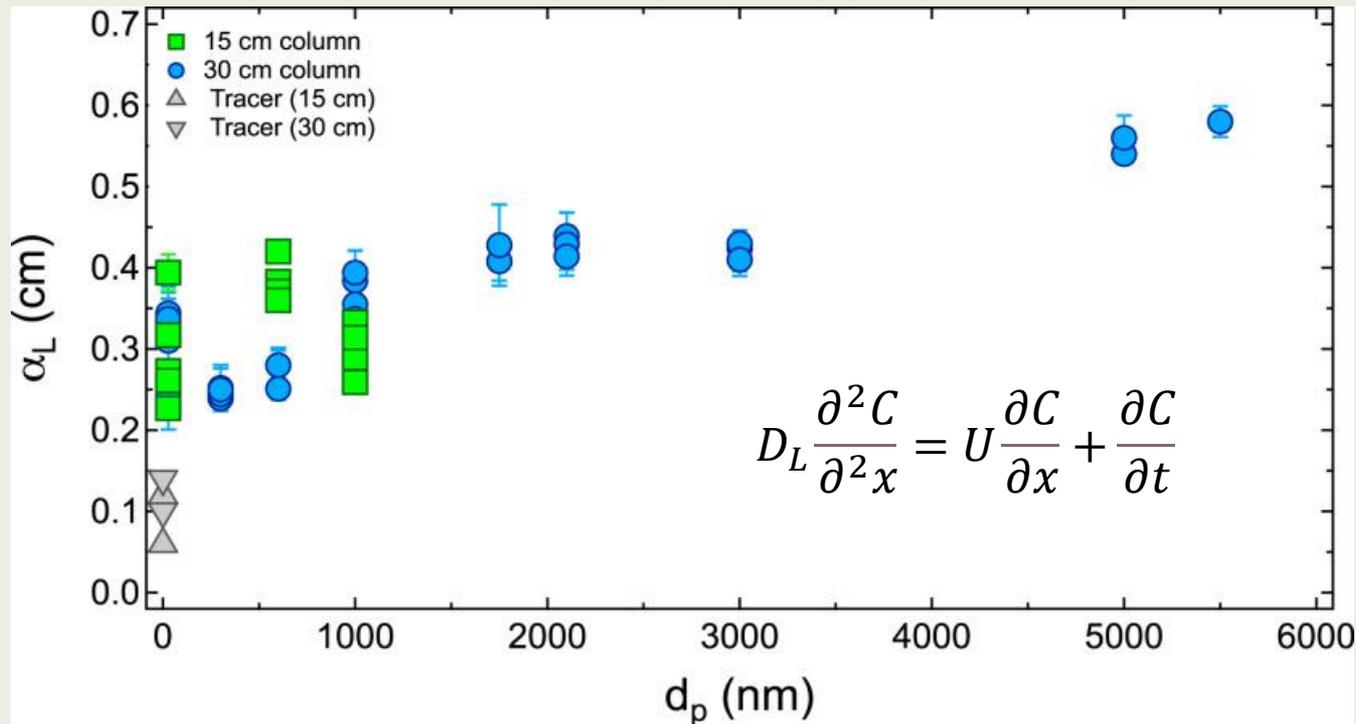


Transported species	Ionic strength (M)	α_L (cm)	D_h (m^2/s)	Pe
NaCl	1.52	0.3 ± 0.1	$(4 \pm 2) \times 10^7$	104 ± 61
EC np	0	0.2 ± 0.1	$(3 \pm 1) \times 10^7$	135 ± 44
EC np	0.01	0.4 ± 0.1	$(6 \pm 1) \times 10^7$	70 ± 19
EC np	0.1	-	-	-



Pore network modeling of nanoparticle transport in porous media

- A testbed for multiphysics
 - *Is dispersivity particle size-dependent?*



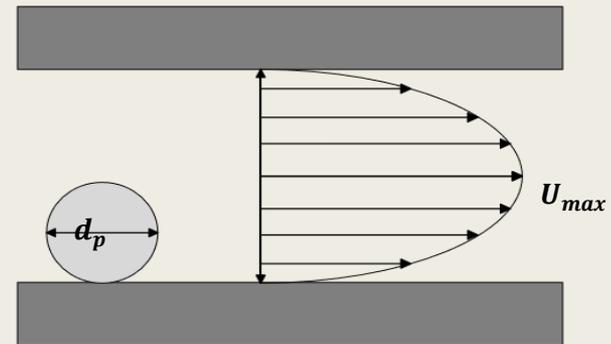
Chrysikopoulos and Katzourakis, *Water Resources Research*, Volume: 51, Issue: 6, Pages: 4668-4683, First published: 21 May 2015, DOI: (10.1002/2014WR016094)

Hydrodynamic dispersion of nanoparticles in porous media: is there a size effect?

- Velocity profile exclusion:

$$U_{EPV} = \bar{U} \left[1 + \frac{d_p}{R} - \frac{1}{4} \left(\frac{d_p}{R} \right)^2 \right]$$

$$D_{ETD} = D + \frac{1}{192} \frac{U_{max}^2 R^2}{D} \left(1 - \frac{d_p}{R} \right)^6$$



- Hindered diffusion:

$$D_{HD} = D_{AB} F_1(\varphi) F_2(\varphi)$$

$$F_1(\varphi) = \frac{\text{Flux area available to solute}}{\text{total flux area}} = \frac{\pi(d_{pore} - d_p)^2}{\pi d_{pore}^2} = (1 - \varphi)^2$$

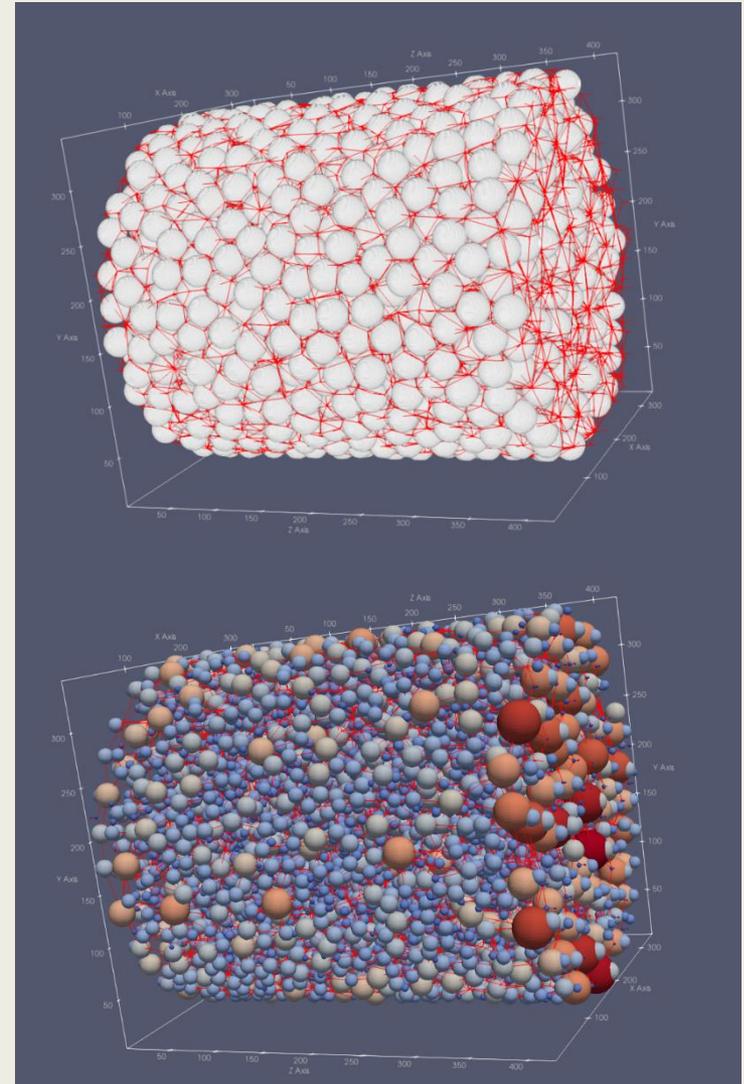
$$F_2(\varphi) = 1 - 2.104\varphi + 2.09\varphi^3 - 0.95\varphi^5$$

Pore network model extraction

- Replicate the experimental system of Chrysikopoulos & Katzourakis (2015)

Extracted pore networks with $L_c = 15$ cm, $D_c = 2.5$ cm, and $D_b = 2$ mm

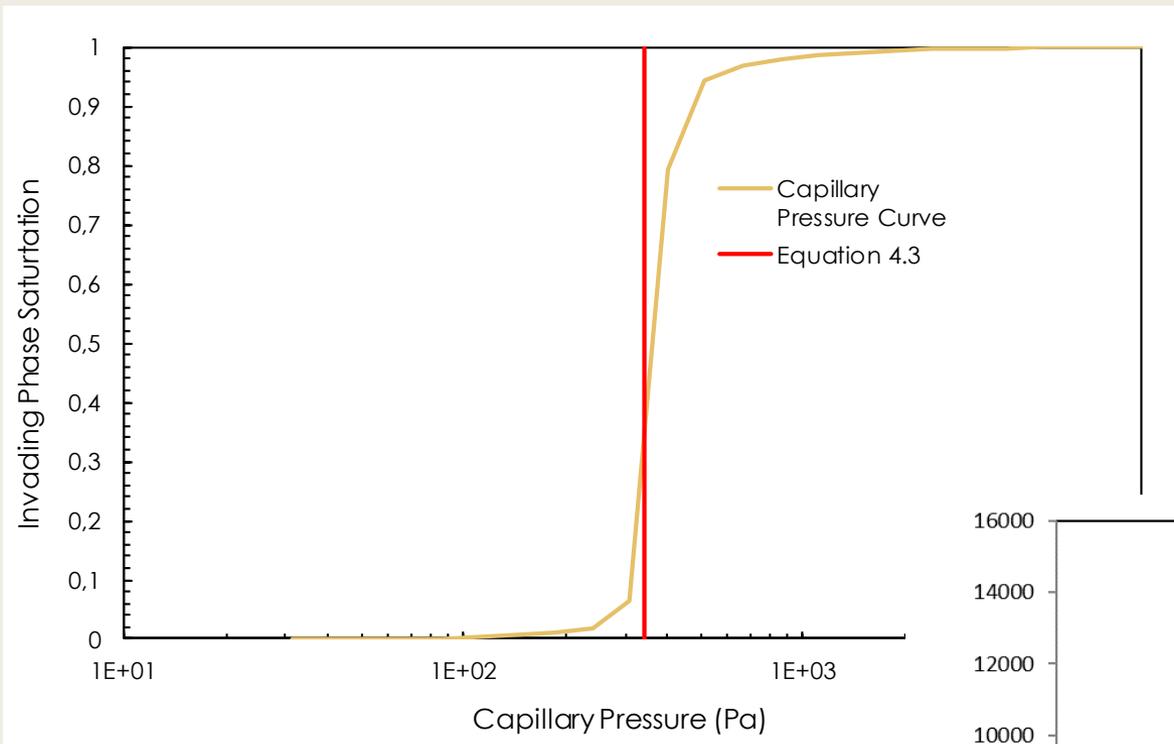
	Column #1	Column #2
Bead Count	10916	10918
ε	0.390	0.390
k_S (D)	3598	3607
k_{KC} (D)	4072	4173
τ	1.43	1.42



Pore network models at different scales extracted from column #1.

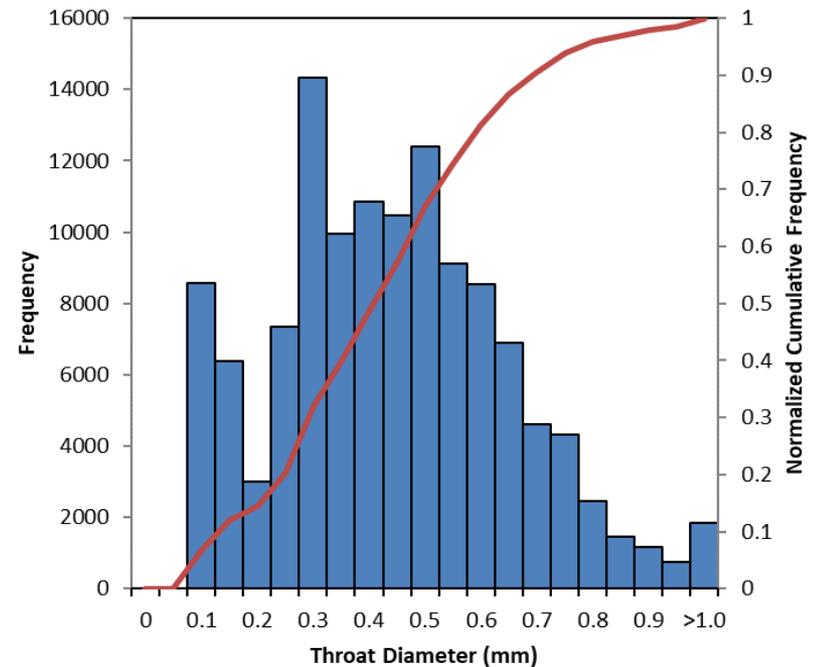
	Ratio to Column #1	d_b (mm)	k_s (D)
Column #1	1	2	4072
Column #3	0.1	0.2	40.72
Column #4	0.04	0.08	6.51
Column #5	0.02	0.04	1.63
Column #6	0.01	0.02	0.407
Column #7	0.002	0.004	0.0163

Pore network model validation



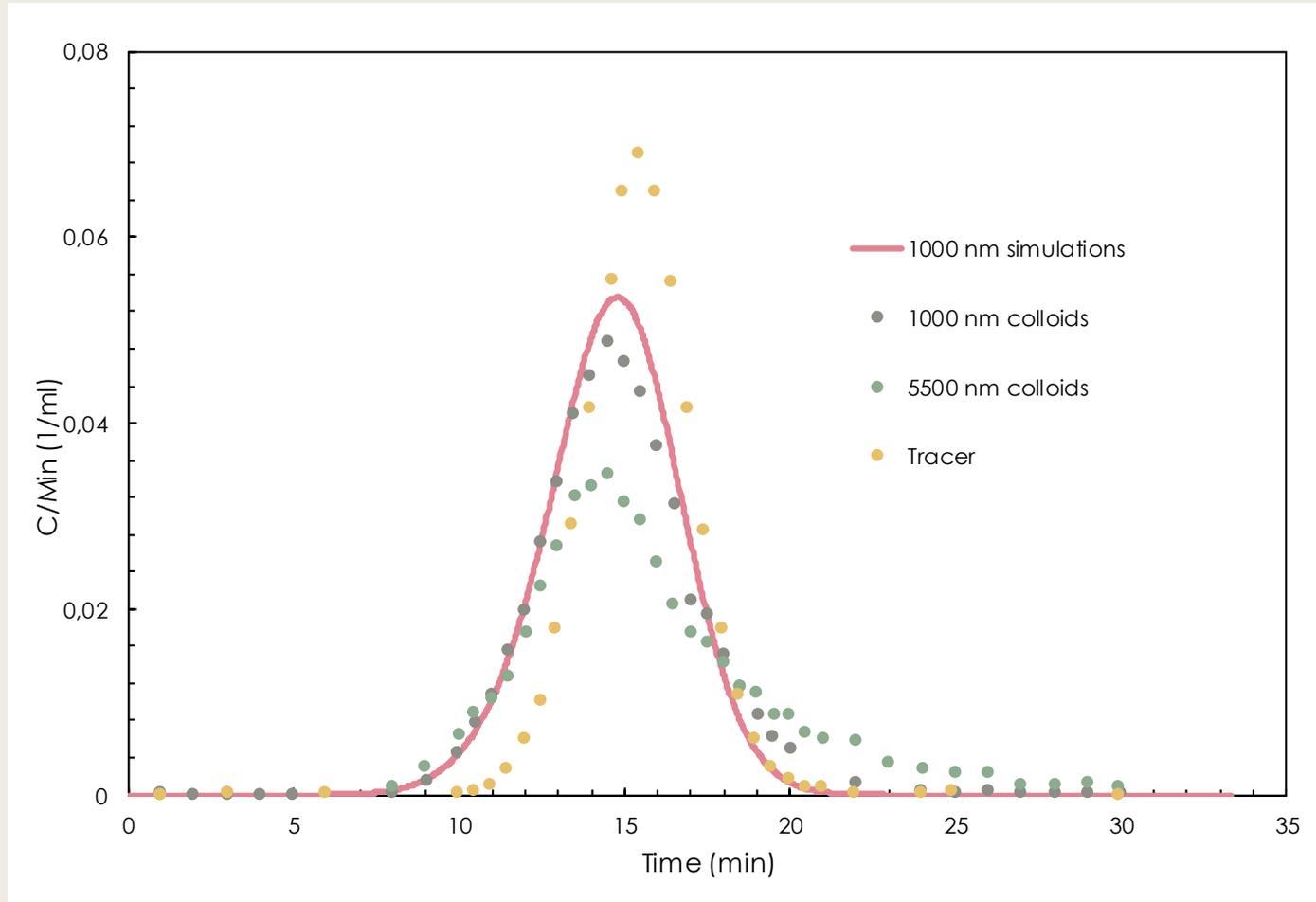
$$p_c^o = \frac{2\gamma_{air-water}}{R_t^o}$$

$$R_t^o = 0.21d_b$$

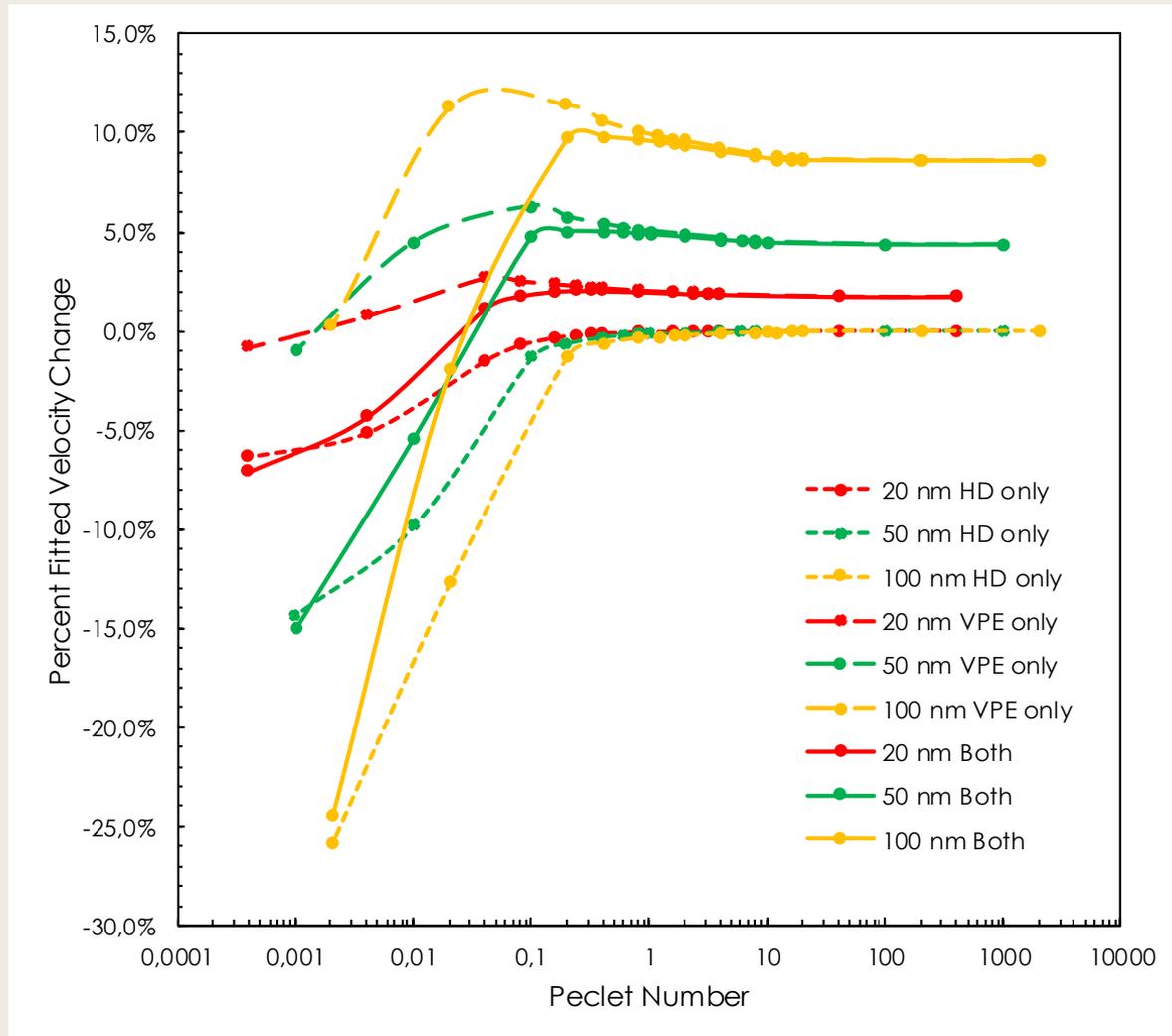


Comparison to experiments

- PNM challenges the conclusions of Chrysikopoulos & Katzourakis (2015)

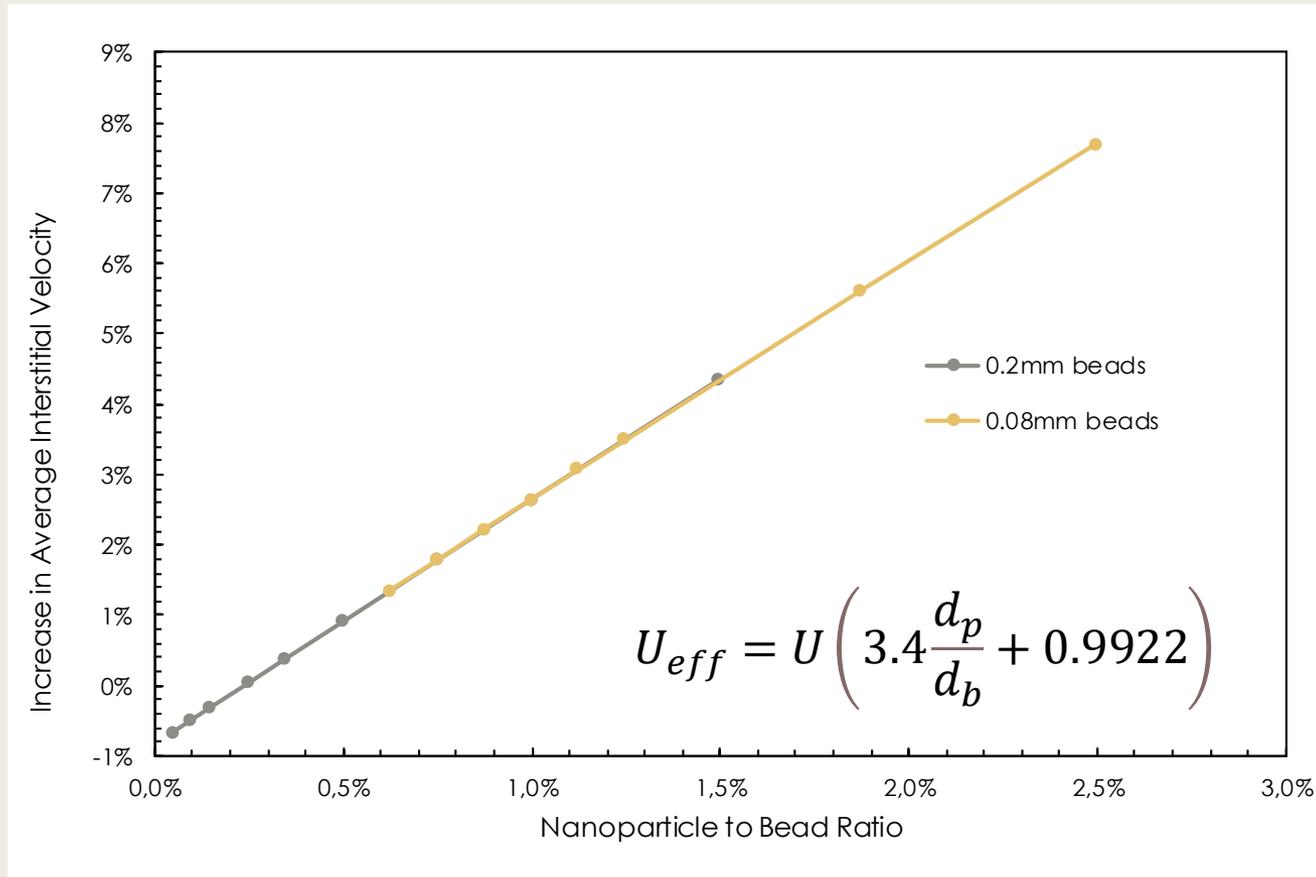


Anticipated effect is real but small

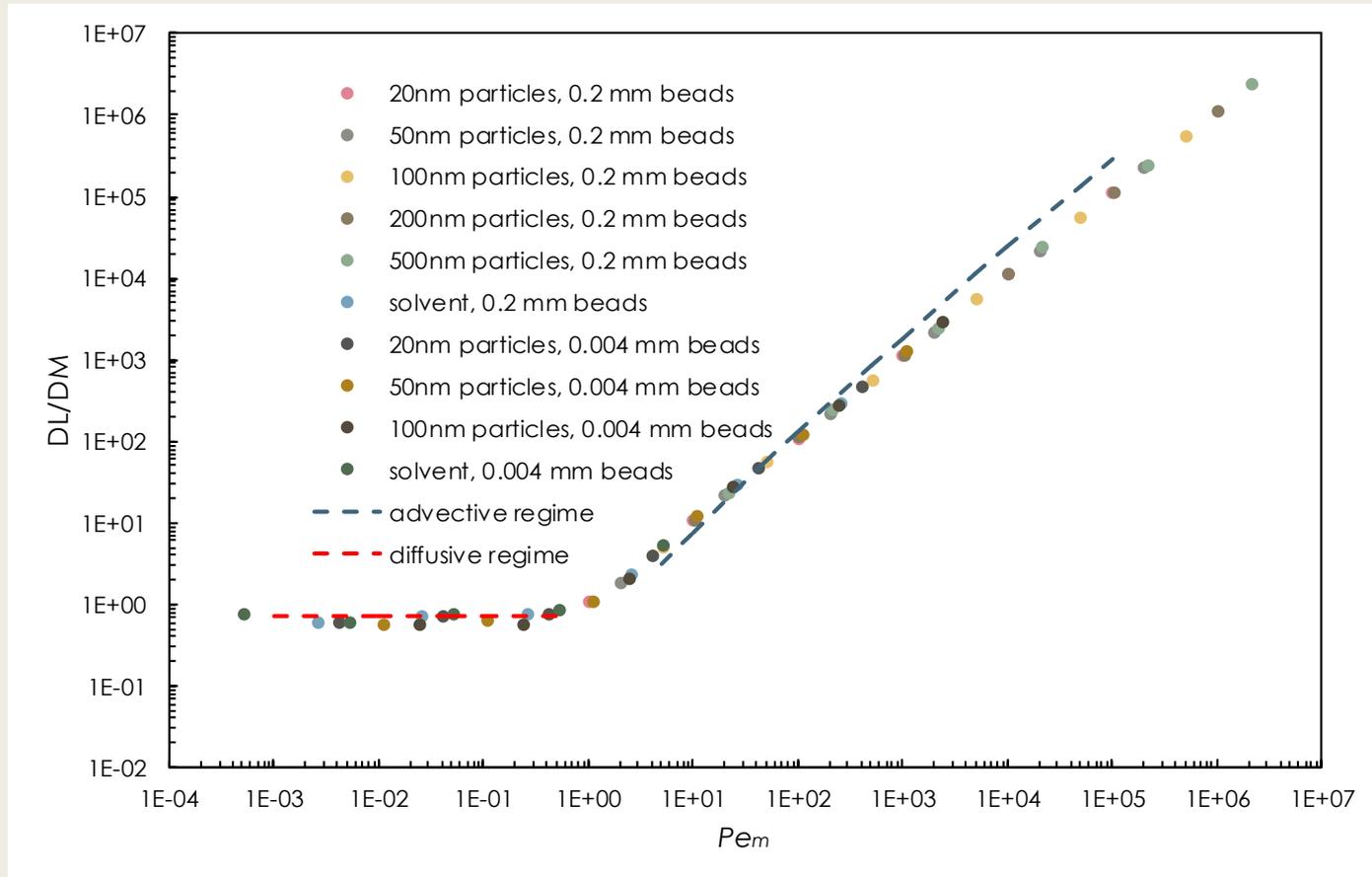


$$d_b = 0.004 \text{ mm}$$

Anticipated effect is real but small

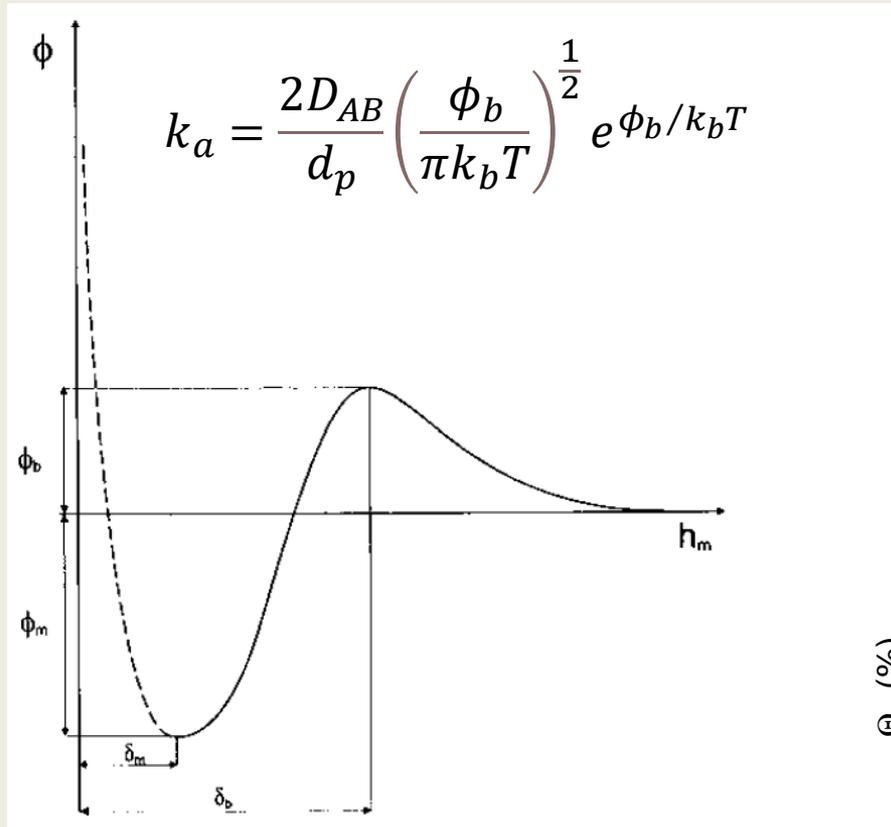


PNM predictions of the dispersion coefficient follow established trends



$$\frac{D_L}{D_m} = \frac{Pe_m}{6\tau} \left[\ln \left(\frac{3}{2} Pe_m \right) - \frac{1}{4} \right], \quad \text{valid for } \frac{Pe_m}{\tau} \gg 1$$

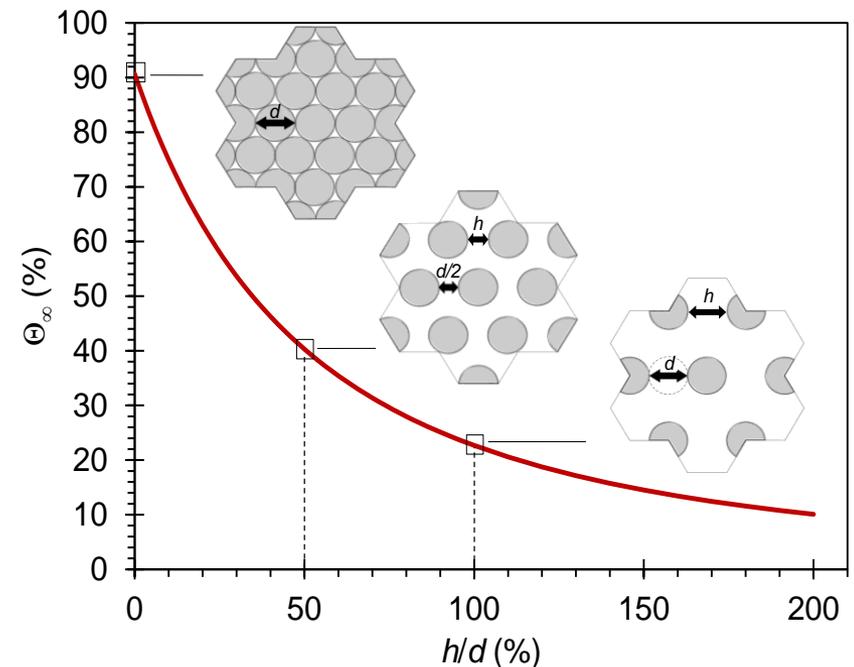
Pore network modeling of nanoparticle transport in porous media: attachment at interfaces



$$-\vec{j} = \frac{1}{S} \frac{d\theta}{dt} = k_a C \bar{B}(\theta)$$

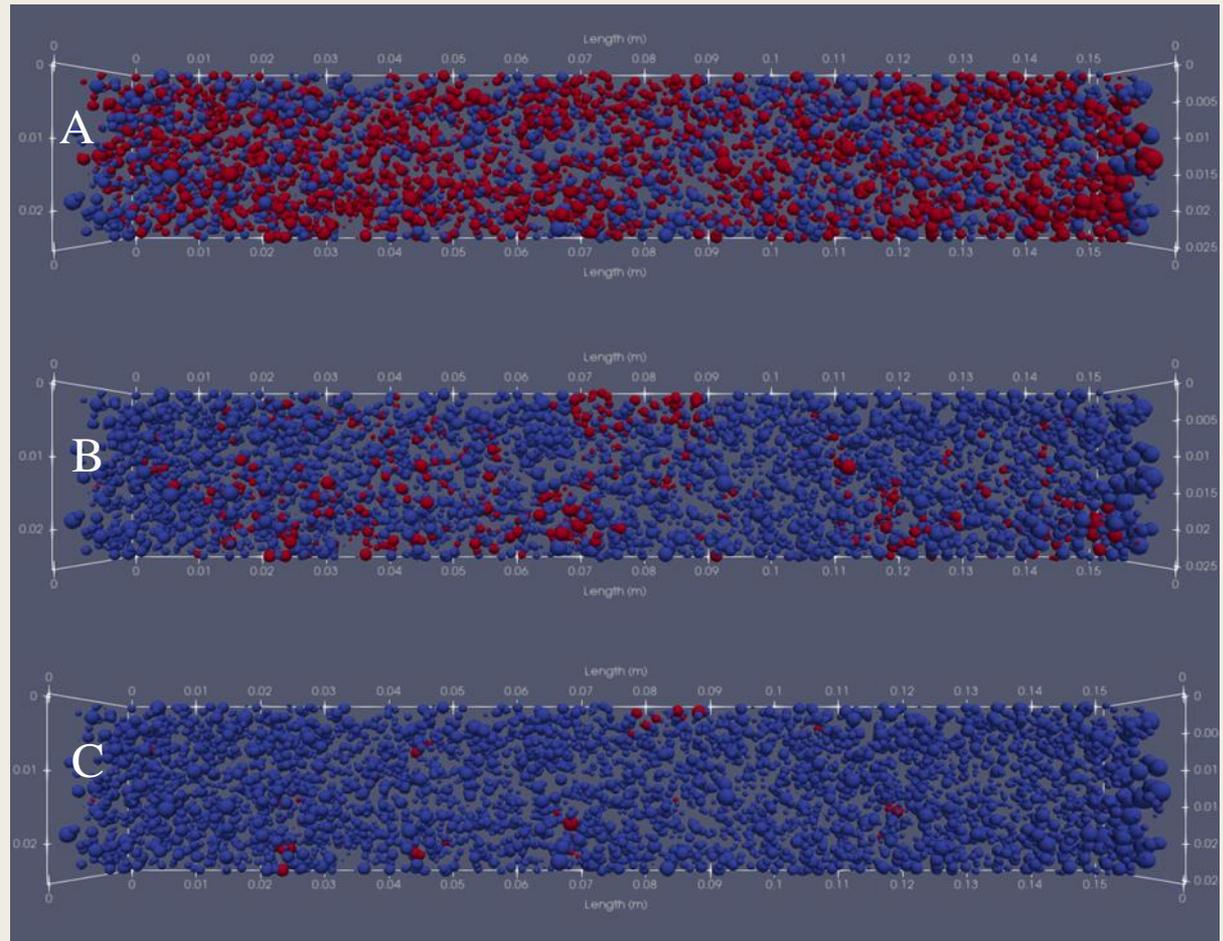
$$\theta = \frac{S n_{ads}}{A_{ads}}$$

$$\bar{B}(\theta) = 2.32 \left(1 - \frac{\theta}{\theta_{max}} \right)^m$$



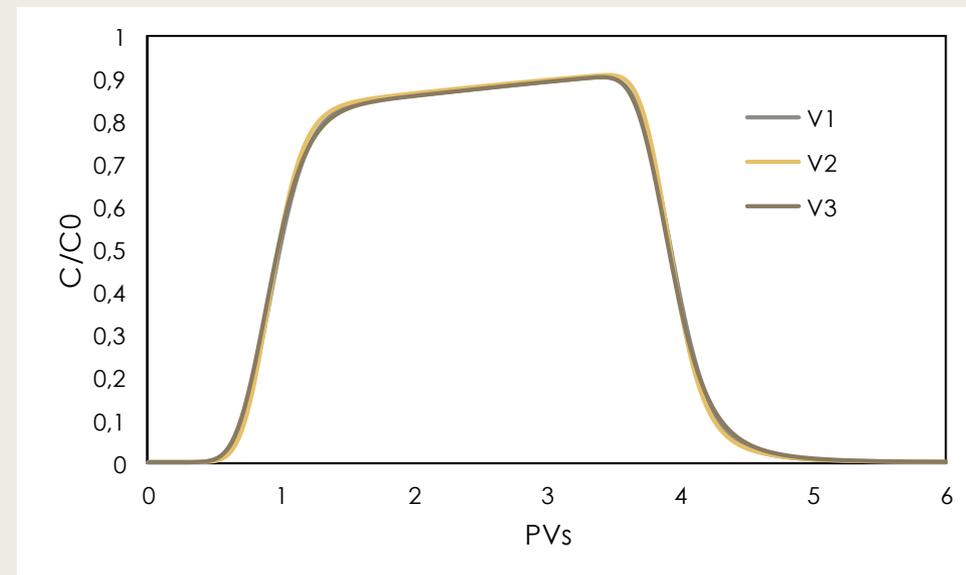
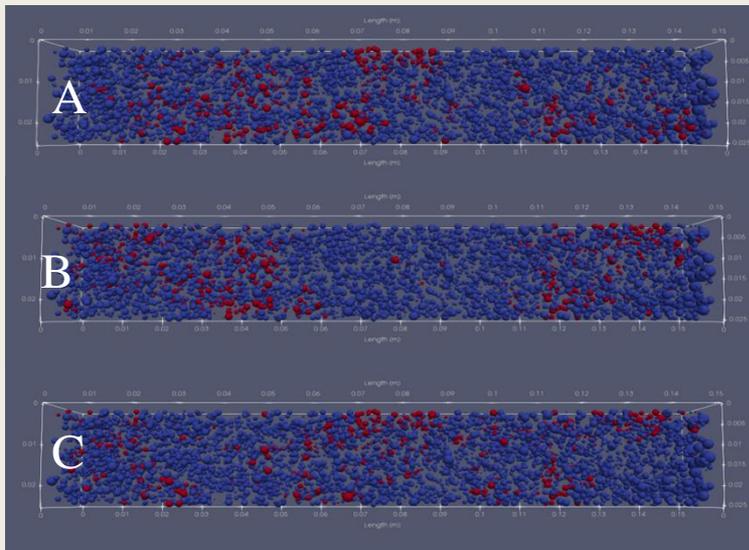
Pore network modeling of nanoparticle transport in porous media: attachment at interfaces

Pore network extracted from a 15-cm packed column with water phase shown in blue and NWP shown in red where $S_{NWP} = 0.5$ in (a), $S_{NWP} = 0.1$ in (b), and $S_{NWP} = 0.01$ in (c).



Pore network modeling of nanoparticle transport in porous media: Reproducibility

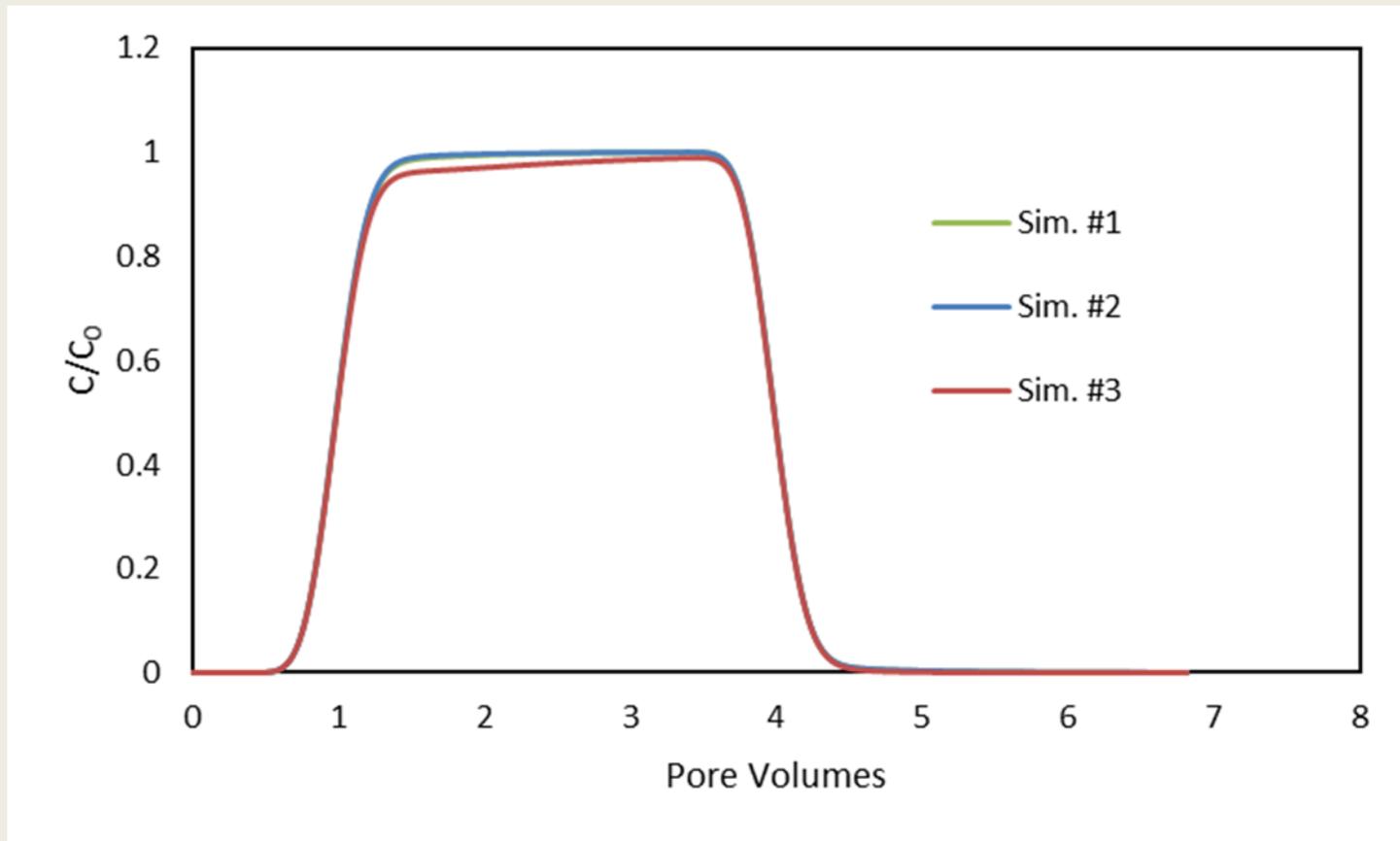
Pore Network	L	M1	M2	M3	H
S_{NWP}	0.01	0.1	0.1	0.1	0.5
$S_{NWP,calc}$	0.013	0.115	0.115	0.115	0.588
ϵ_{eff}	0.391	0.350	0.350	0.350	0.163
$A_o (m^2)$	0.0018	0.0140	0.0139	0.0140	0.0561
$a_o (m^{-1})$	62.4	535.4	531.3	534.6	3850.6



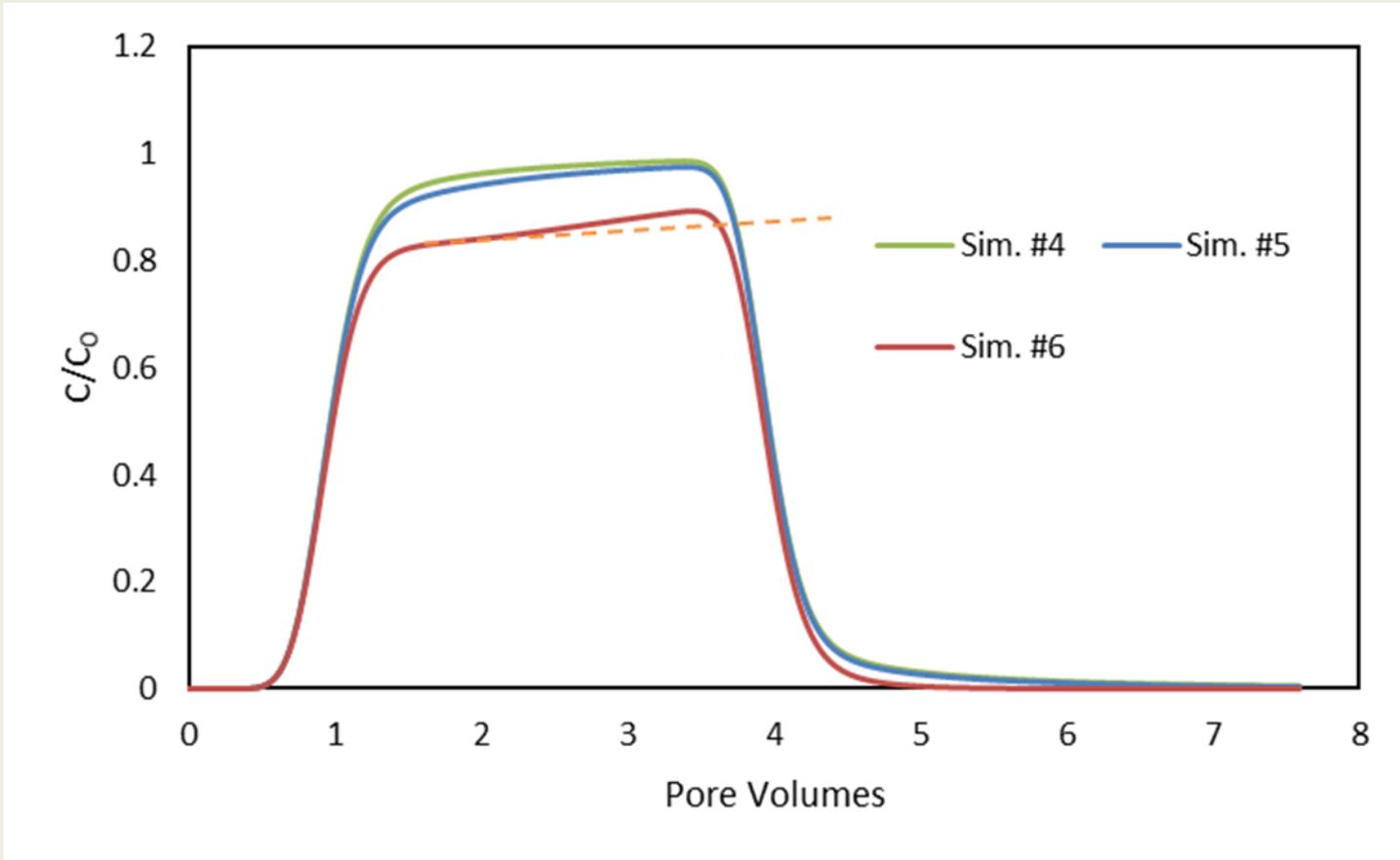
Pore network modeling of nanoparticle transport in porous media: Parametric study

Simulation Number	S_{NWP}	ϕ_b/k_bT	Φ_V	M_r	θ_{total}
1	0.01	50	10^{-4}	1.000	0.000
2	0.01	8	10^{-4}	0.999	0.889
3	0.01	8	10^{-5}	0.980	0.772
4	0.1	50	10^{-4}	0.998	0.000
5	0.1	8	10^{-4}	0.978	0.875
6	0.1	8	10^{-5}	0.871	0.530
7	0.5	50	10^{-4}	0.947	0.000
8	0.5	8	10^{-4}	0.856	0.613
9	0.5	8	10^{-5}	0.684	0.150

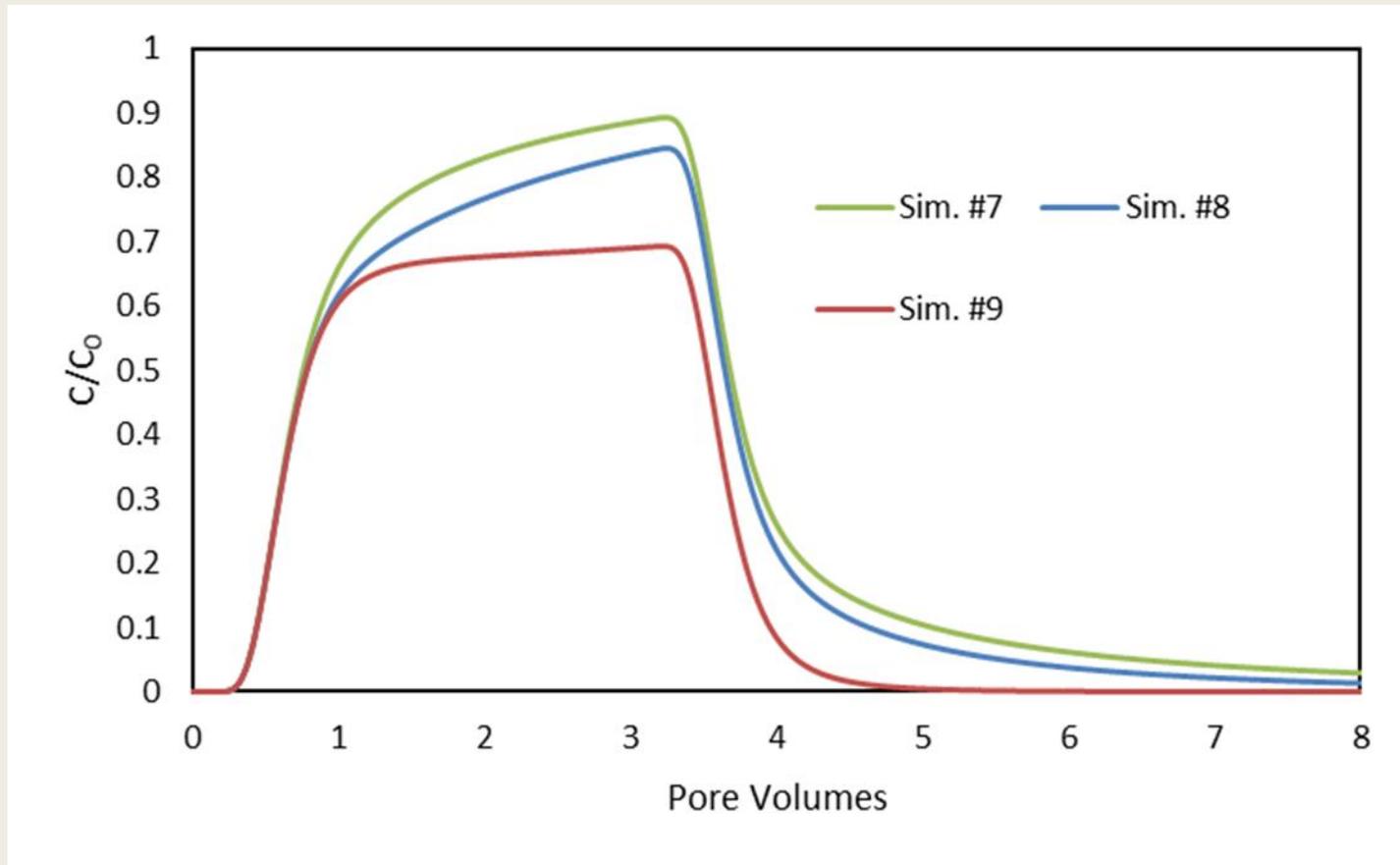
Pore network modeling of nanoparticle transport in porous media: $S_{NWP} = 0.01$



Pore network modeling of nanoparticle transport in porous media: $S_{NWP} = 0.10$



Pore network modeling of nanoparticle transport in porous media: $S_{NWP} = 0.50$



Continuum scale modeling of nanoparticle transport in porous media: Theory

- 1-D advection, dispersion and irreversible attachment

$$\frac{\partial \bar{N}_b}{\partial \bar{t}} = \frac{\partial^2 \bar{N}_b}{\partial \bar{x}^2} - Pe \frac{\partial \bar{N}_b}{\partial \bar{x}} - D_{aI} \bar{N}_b \underbrace{B_i(\theta_i)}$$

Blocking function on fluid interface

$$\frac{\partial \theta_i}{\partial \bar{t}} = \frac{k_i L^2}{D_h} N_{b0} \pi r^2 \bar{N}_b B_i(\theta_i) = A_r D_{aI} \bar{N}_b B_i(\theta_i)$$

$$\bar{x} \equiv \frac{x}{L}, \bar{N}_b \equiv \frac{N_b}{N_{b0}}, \bar{t} \equiv \frac{D_h t}{L^2}$$

Area ratio

$$A_r = \frac{N_{b0} \pi r^2}{a_0}$$

Initial concentration

Particle radius

Interfacial area

Damköhler number

$$D_{aI} = \frac{k_i L^2 a_0}{D_h}$$

Adsorption constant

Porous medium length

Péclet number

$$Pe = \frac{v_p L}{D_h}$$

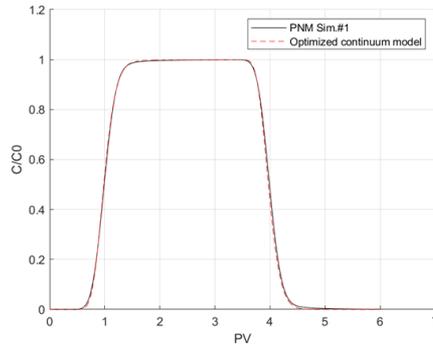
Pore velocity

Dispersion coefficient

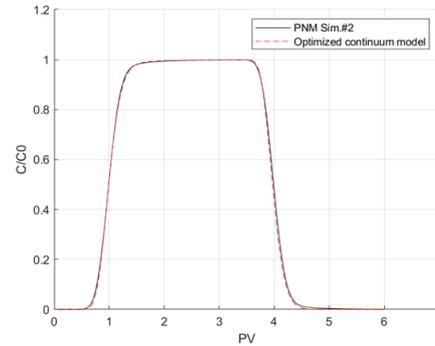
Pore network vs. continuum-scale model: Upscaling

$S_{nwp} = 1 \%$

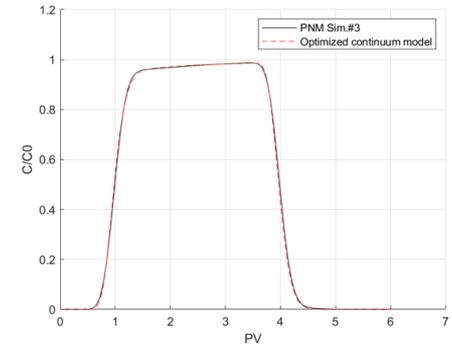
$Nb_0 = 2.4 \times 10^{19}$ particles/m³



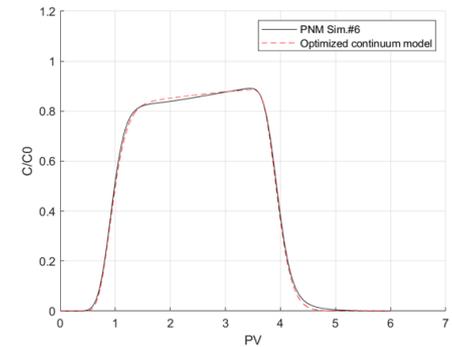
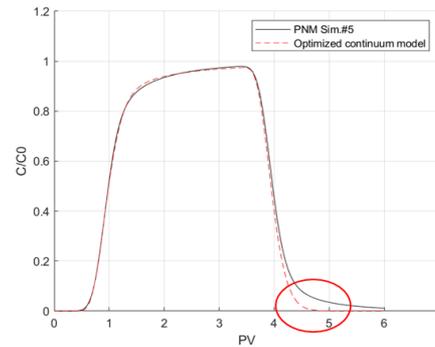
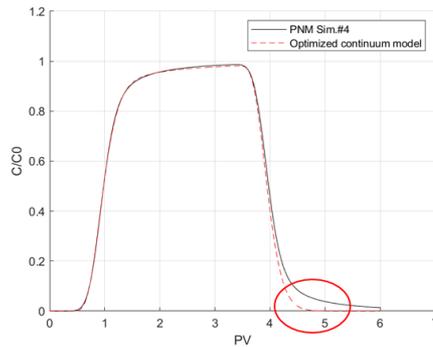
$Nb_0 = 2.4 \times 10^{19}$ particles/m³



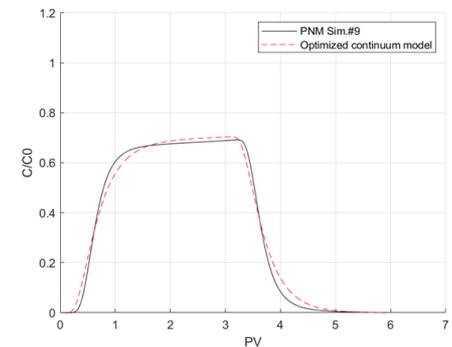
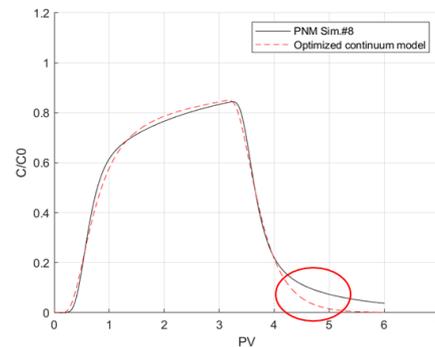
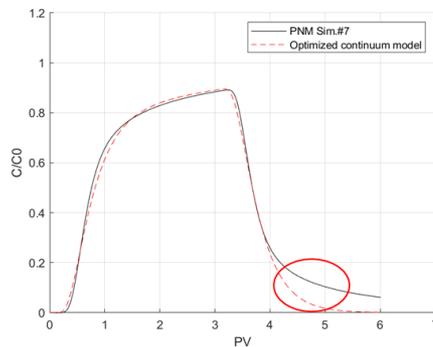
$Nb_0 = 2.4 \times 10^{18}$ particles/m³



$S_{nwp} = 10 \%$



$S_{nwp} = 50 \%$

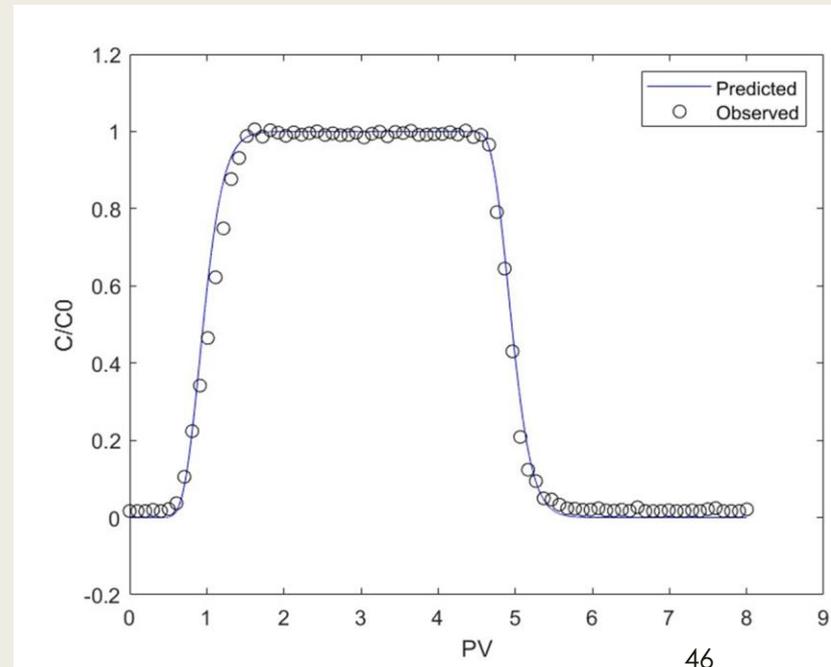
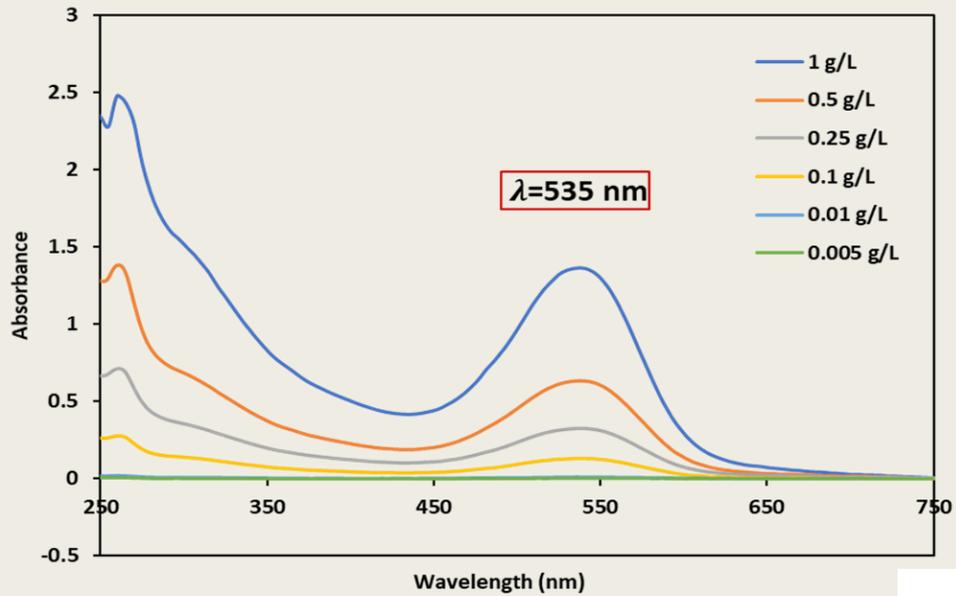


Pore network vs. continuum-scale model: Upscaling

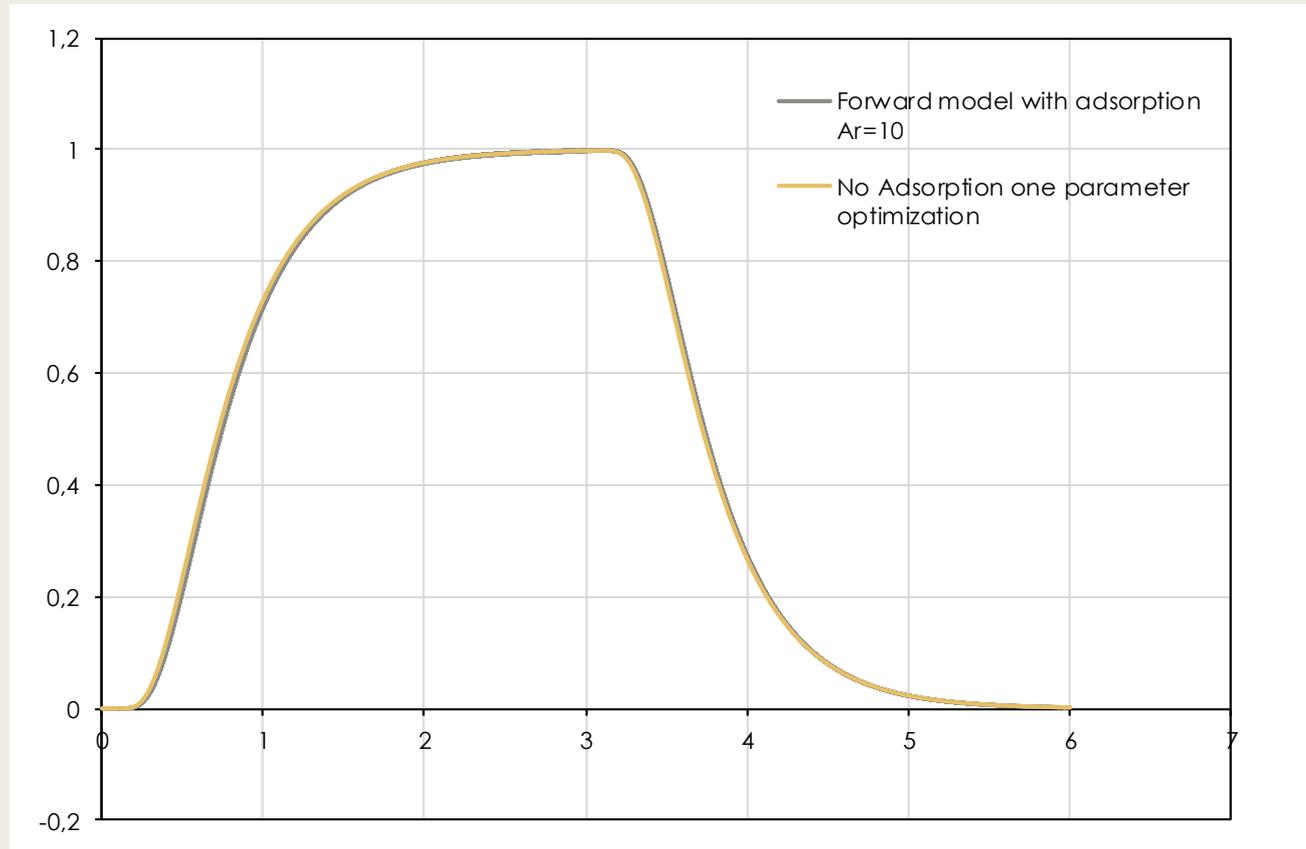
simulation number	a0 (1/m)		k (m/s)		ki (m/s)		a0*ki (1/s)		Dh (m ² /s)	Pe	Da	Ar	
	PNM	Continuum	PNM	Continuum	PNM	Continuum	Continuum	Continuum	Continuum	Continuum	Continuum	Continuum	PNM
1	63.53	145.5	2.18E-24	1.93E-08	1.38E-22	2.80E-06	5.95E-09	64.52	10.59	51.53	118.04		
2	63.53	299.5	1.52E-06	7.12E-09	9.66E-05	2.13E-06	5.85E-09	65.68	8.20	25.04	118.04		
3	63.53	151.9	1.52E-06	2.98E-09	9.66E-05	4.52E-07	5.65E-09	68.01	1.80	4.94	11.80		
4	551.9	1940.3	2.18E-24	5.78E-10	1.20E-21	1.12E-06	1.10E-08	38.98	2.30	3.86	13.59		
5	551.9	2655.8	1.52E-06	6.00E-10	8.39E-04	1.59E-06	1.12E-08	38.20	3.20	2.82	13.59		
6	551.9	1898.9	1.52E-06	8.80E-10	8.39E-04	1.67E-06	1.04E-08	41.01	3.60	0.39	1.36		
7	4742	13000.4	2.18E-24	4.00E-10	1.03E-20	5.20E-06	1.46E-07	6.30	0.80	0.58	1.58		
8	4742	19576.7	1.52E-06	3.73E-10	7.21E-03	7.30E-06	1.51E-07	6.11	1.09	0.38	1.58		
9	4742	23891.7	1.52E-06	3.67E-10	7.21E-03	8.76E-06	1.76E-07	5.23	1.12	0.03	0.16		

Experimental validation

UV-vis spectra of ECNR nanoparticles



Observability of continuum-scale model parameters



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Stephen Dauphinais (MAsc) – Prof. J. Gostick (co-supervisor)

Youssra Rahham (PhD)

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Department of Chemical Engineering



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FORTH

INSTITUTE OF CHEMICAL ENGINEERING SCIENCES



ΕΛΙΔΕΚ.
Ελληνικό Ίδρυμα Έρευνας & Καινοτομίας

Computational Fluid Dynamic models inside 3D digitally represented rocks and soils

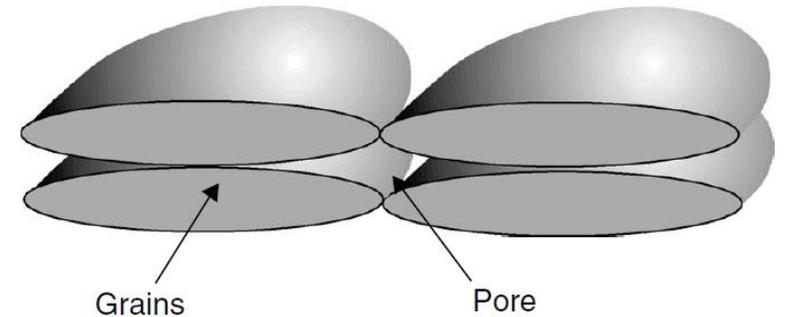
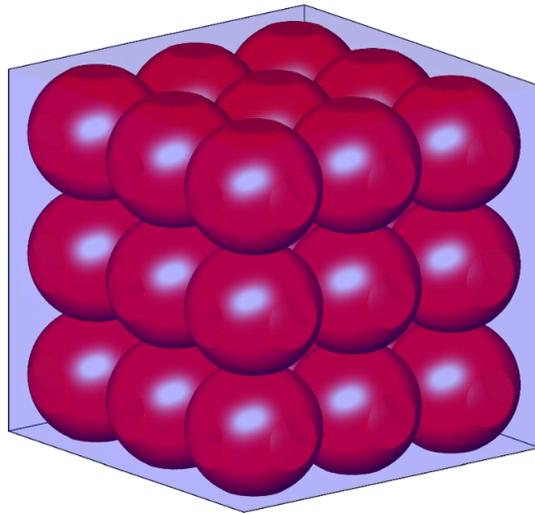
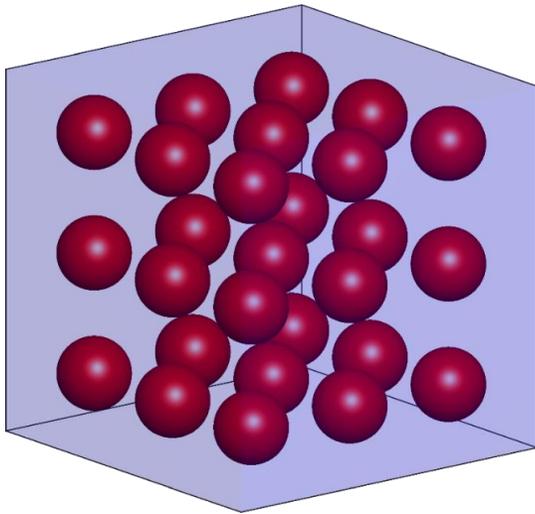
Nadia Bali

Outline

- Structures characteristics
- Numerical reconstruction
- 3 different computational fluid dynamic problems
- Effective properties
- Simulations inside real reconstructed geometries

Structure characteristics

- Pore structure and packing



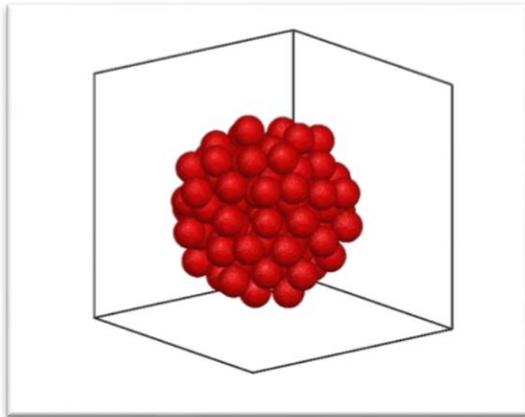
- Single arrangement of spherical particles
- FCC structure lead to minimum porosity 0.48

Ellipsoid packing -clay

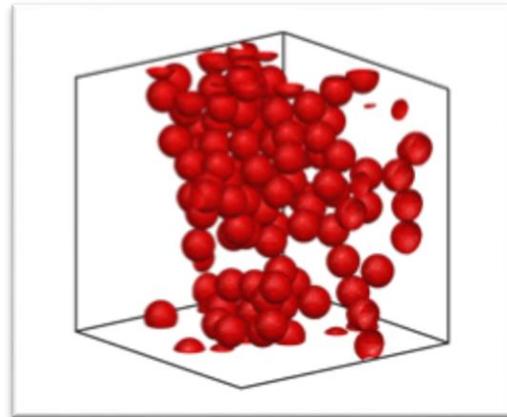
Structures characteristics

- Pore size
- Porosity
- Grain size distribution
- Tortuosity

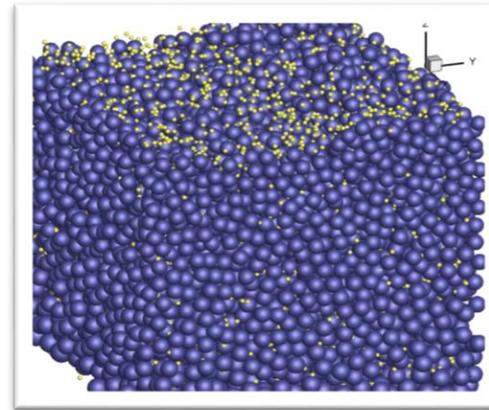
$$\varepsilon_p = 1 - NV_{sp}/V_{tot}$$



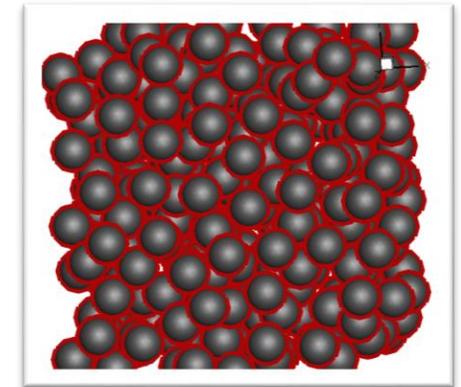
Ballistic Aggregation



1 point contact-
Randomized structure
with 2-symmetrical
constrains



Ballistic Deposition of 2
different spheres' size

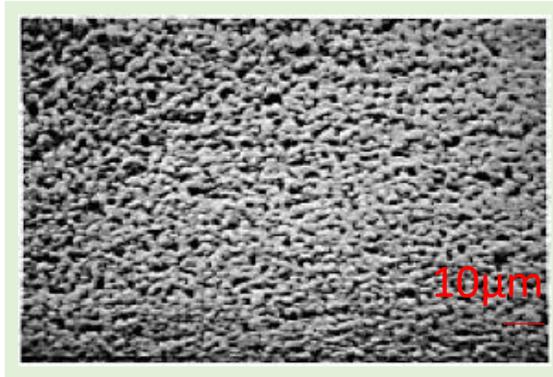


Ballistic Deposition
with a spherical cover
(overlapping ring)

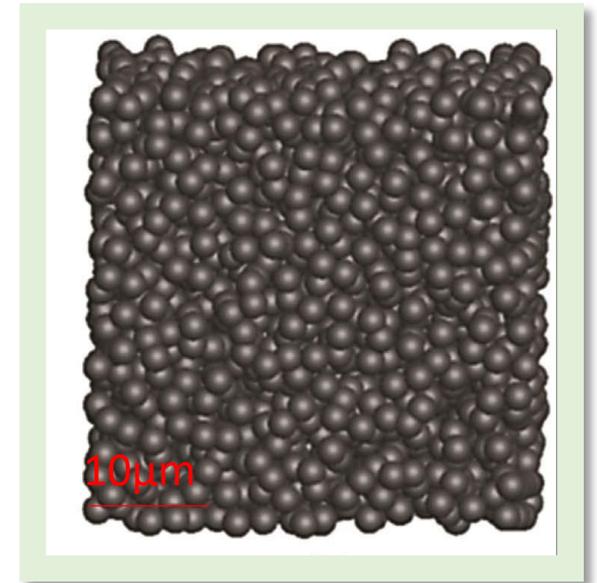
Numerical reconstruction

- Setting the goals:

1. Porosity value
2. Particles density
3. Optically resemblance

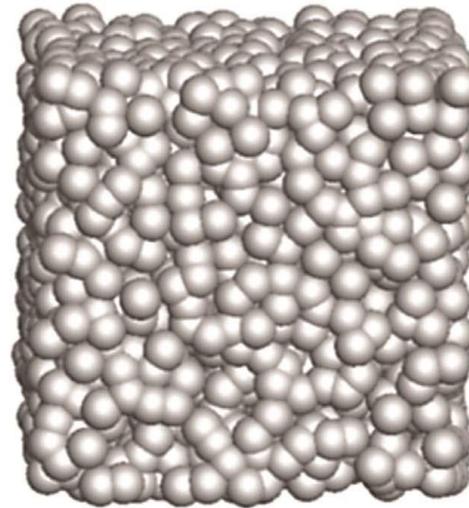


SEM image 10µm
Porosity=0.2

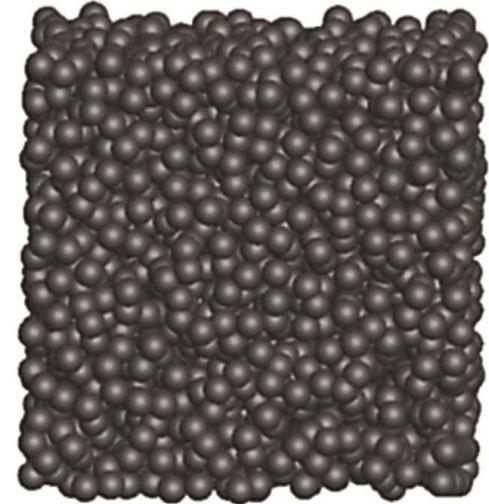


Algorithms

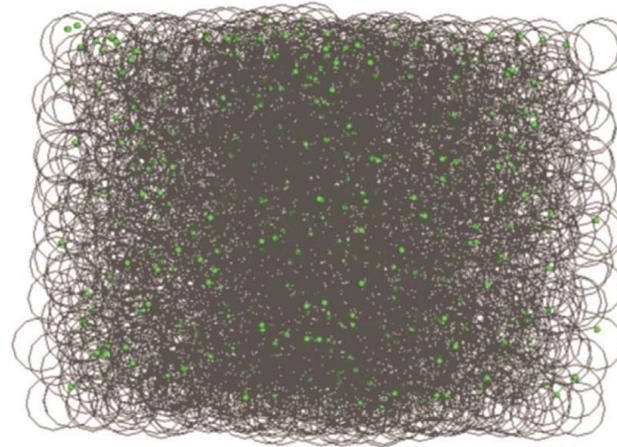
- Stochastic algorithms
 - a) Monte Carlo free
 - b) Monte Carlo cherry-pit
 - c) Ballistic deposition



(a)



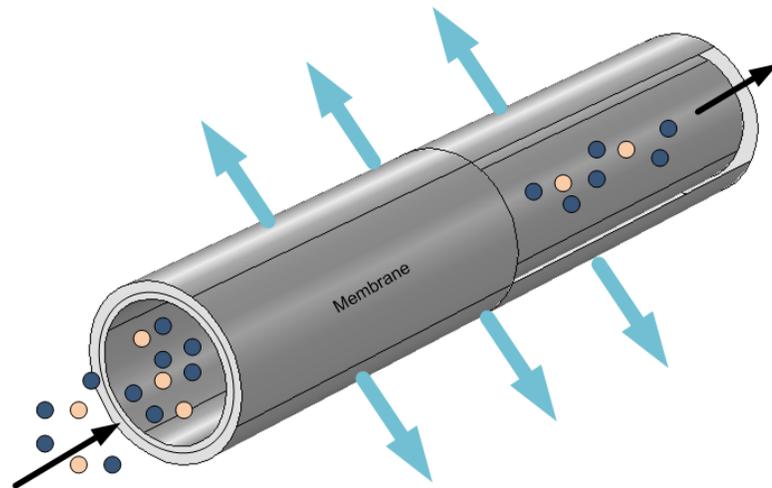
(b)



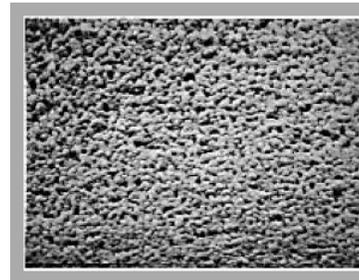
(c)

Example 1: Problem of lactose transport inside porous membrane

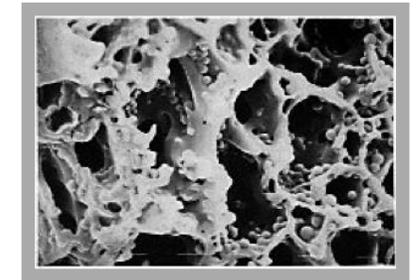
- Problem of lactose free milk=> conversion of lactose



Dense layer $\epsilon=0.2$



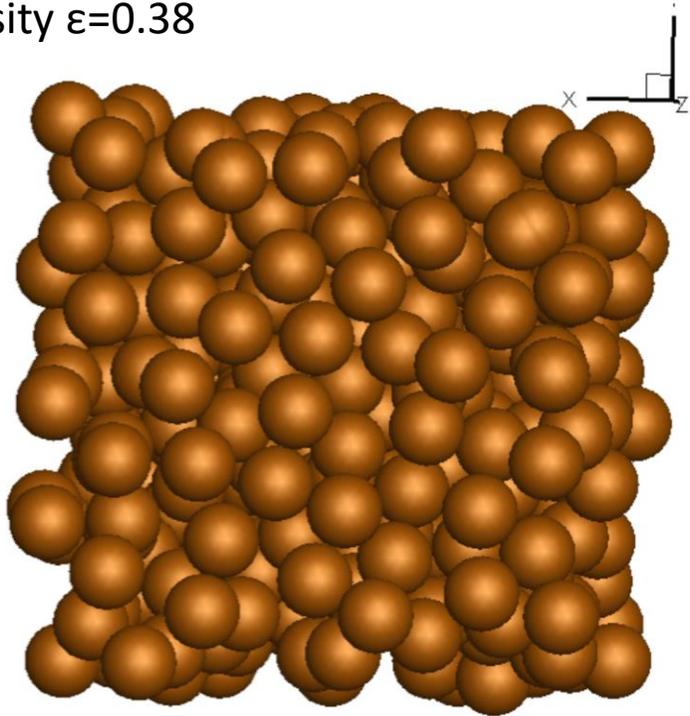
Spongy layer $\epsilon=0.67$



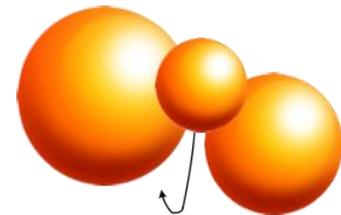
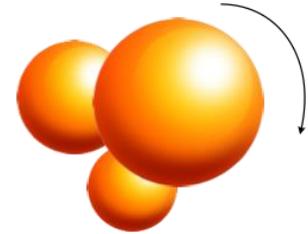
N. Bali, A. Petsi, E. Skouras, V. Burganos, Three-dimensional reconstruction of bioactive membranes and pore-scale simulation of enzymatic reactions: The case of lactose hydrolysis, *Journal of membrane science* 524 (2017) 225-234.

Ballistic Deposition

Porosity $\epsilon=0.38$

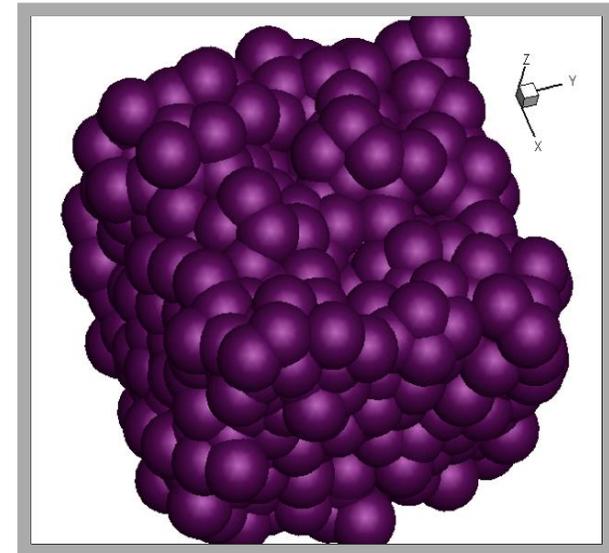
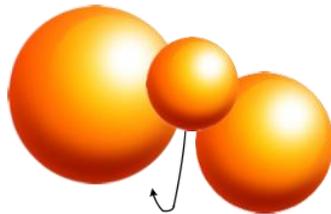
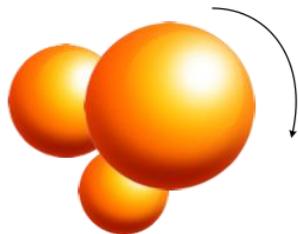
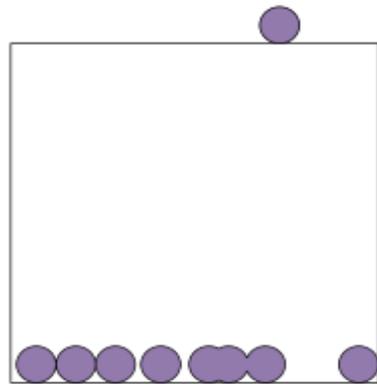
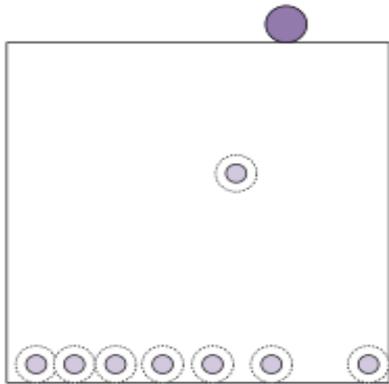


- Non-overlapping spheres
- Porosity=0.38



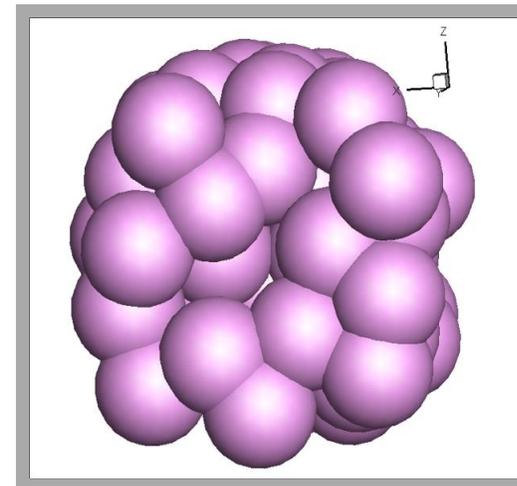
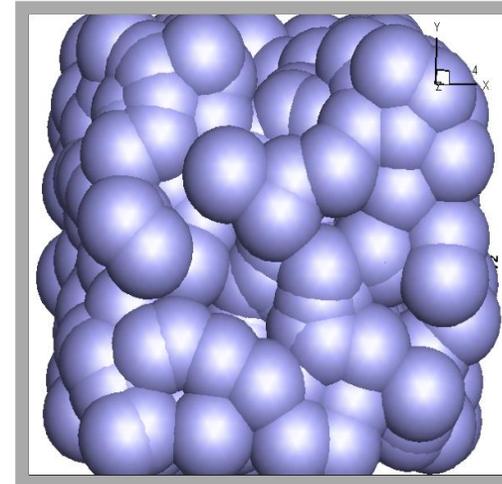
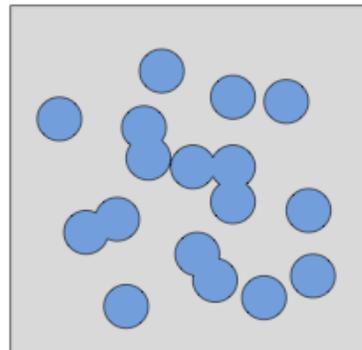
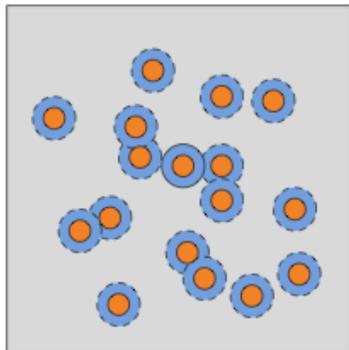
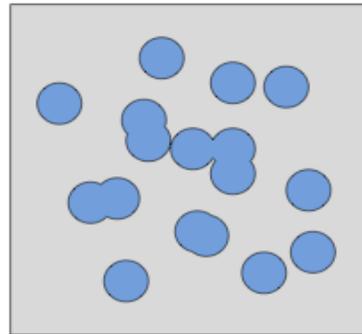
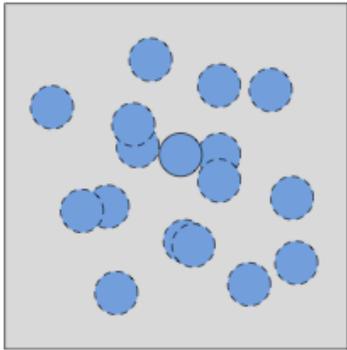
Modified Ballistic Deposition algorithm

- For the dense layer of the membrane a modified ballistic method can be used

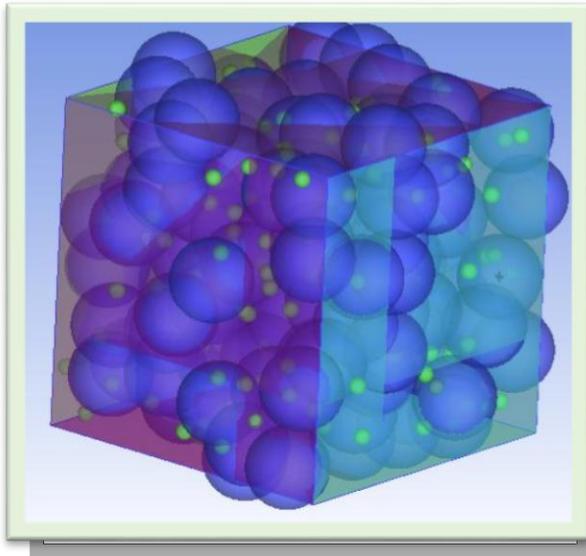


Monte Carlo algorithm

- Monte Carlo cherry pit
- Free Monte Carlo



Transport properties



Mem layers	Effective diffusivity (m ² /s)	Effective permeability (m ²)
Layer1	2.236 10 ⁻¹¹	2.3 10 ⁻¹⁹
Layer2	3.796 10 ⁻¹⁰	8.1 10 ⁻¹⁵

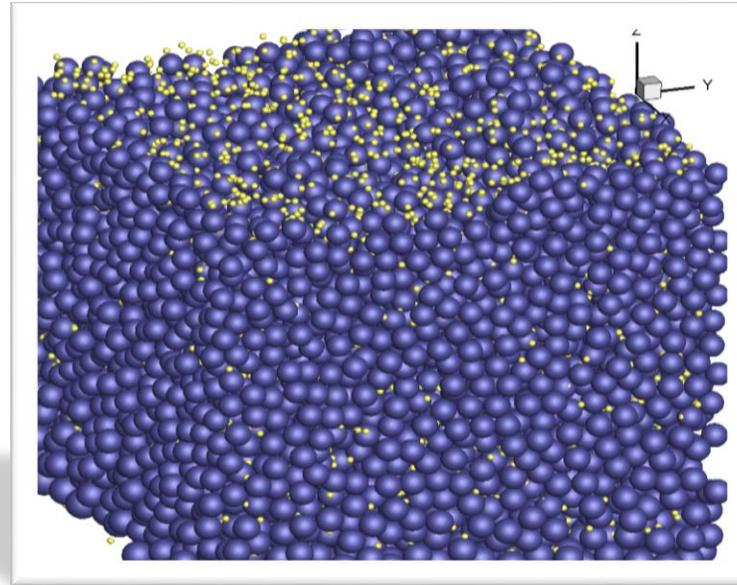
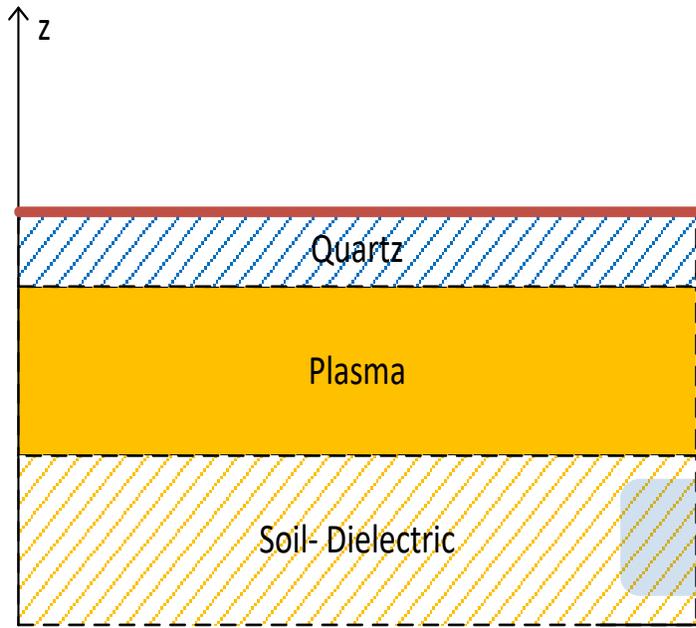
$$D = \frac{\iint_A NdA}{A_{tot}} \frac{1}{C_{out} - C_{in}}$$

$$K = \frac{\iint_A udA}{A} \frac{\mu L}{(P_{out} - P_{in})}$$

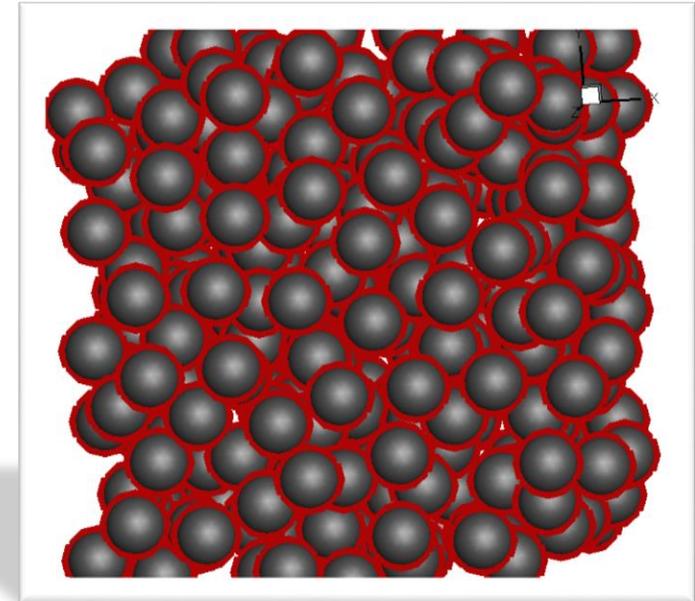
$$K_{exp} = 6.7 \cdot 10^{-18} \text{m}^2$$

$$K_{sim} = 6.3 \cdot 10^{-18} \text{m}^2$$

Example 2: Soil structure during plasma discharges

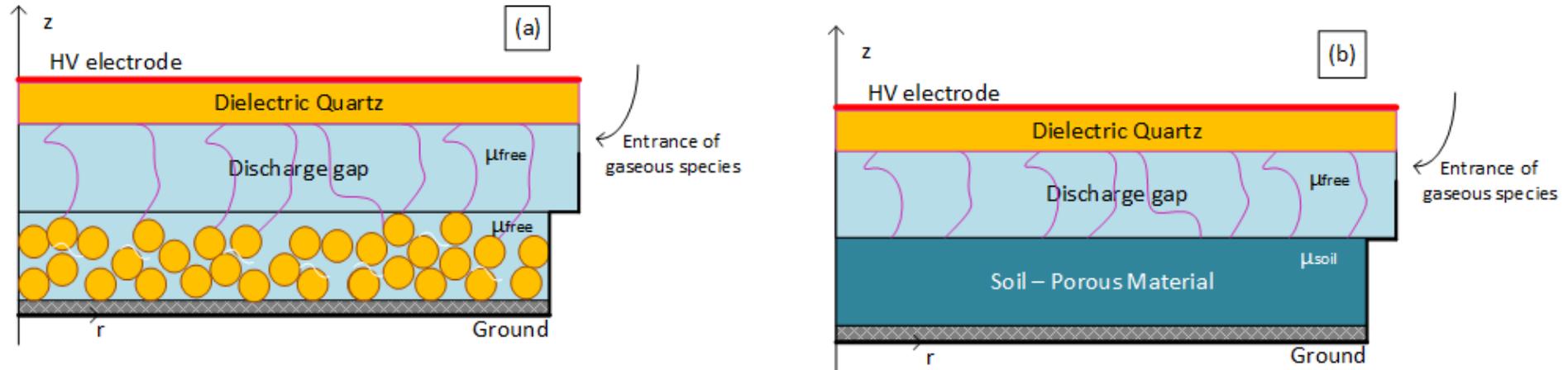


Non-wetting



Wetting

Example 3: Mobility transport

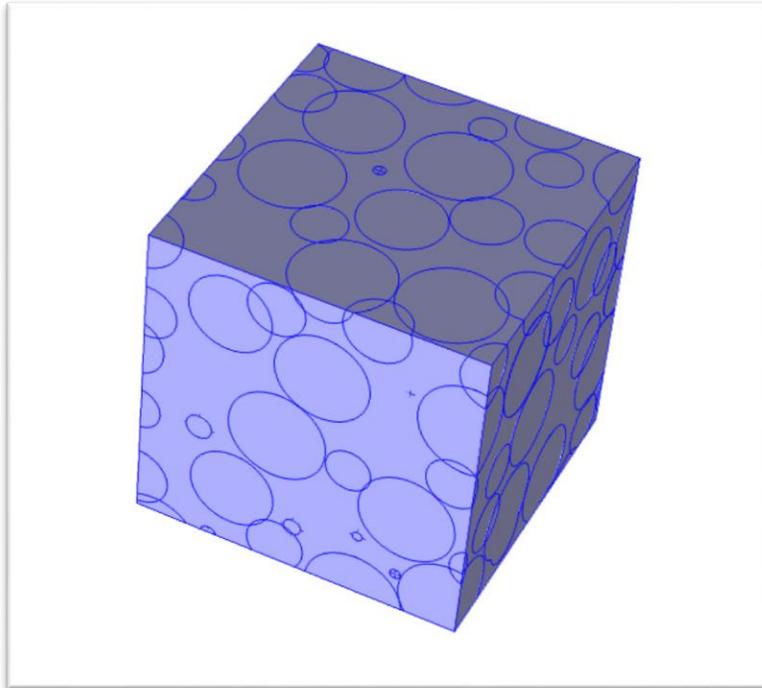


- Modified equations:
 - μ (mobility factor that describes the movement of electrically charged particles) its effective value can be obtained by:

$$m_{soil} = \frac{e_p}{t} m_{free}$$

Bali, N.; Aggelopoulos, C.; Skouras, E.; Tsakiroglou, C.; Burganos, V., Modeling of a DBD plasma reactor for porous soil remediation. *Chemical Engineering Journal* **2019**, 373, 393-405.

Thermal transport problem



- Thermal transport equations:
(pseudo-steady state)

$$\rho_i C_{p,i} \frac{\partial T}{\partial t} + \nabla k_i \nabla T = 0$$

- Conductivities for each phase:

$$k_{eff} = - \frac{\iint_A N_{therm} dA}{A_{tot}} \frac{\Delta L}{T_{out} - T_{in}}$$

Time t (s)	Saturation S	Conductivity k_{eff} (W/m/K)	Conductivity k_{bref} (W/m/K)
0	0.33	0.155	0.172
180	0	0.128	0.146

Effective properties

- Permeability value
- Diffusivity
- Thermal conductivity
- Mobility
- ..etc

Maxwell

$$\frac{k_{eff} - k_f}{k_{eff} + 2k_f} = f_p \frac{k_p - k_f}{k_p + 2k_f}$$

Bruggeman

$$f_p \frac{k_p - k_{eff}}{k_p + 2k_{eff}} + (1 - f_p) \frac{k_f - k_{eff}}{k_f + 2k_{eff}} = 0.$$

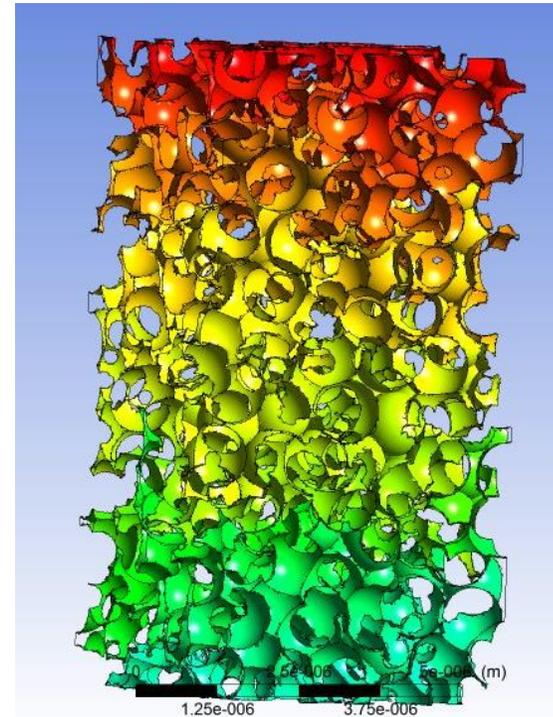
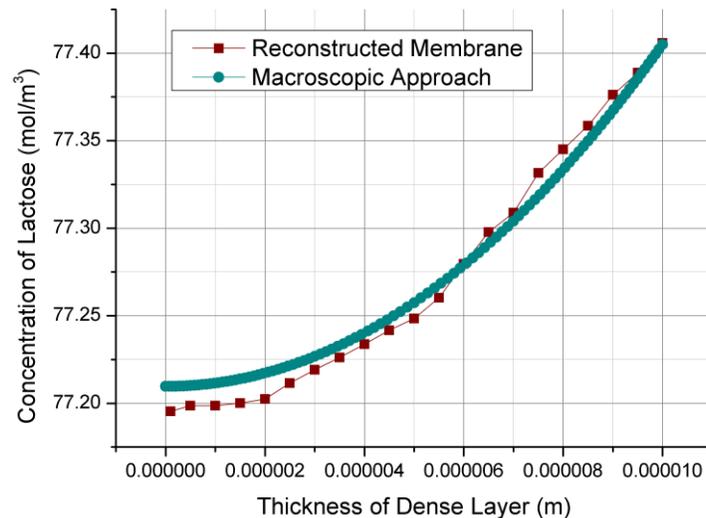
Bruggeman DEM

$$\frac{k_p - k_{eff}}{k_p - k_f} \left(\frac{k_f}{k_{eff}} \right)^{1/3} = 1 - f_p.$$

- Advantages of calculating these values numerically:
 - Avoid artifacts and other errors that introduced through the approximation of the structure (its numerically generated)
 - Less computational cost (the problem have less mesh elements) difficulties in structures
 - More robust solutions

Numerical reconstructions and “black box”

- Solving in numerical reconstructed domain
- Solving in a “black box”



N. Bali, A. Petsi, E. Skouras, V. Burganos, Three-dimensional reconstruction of bioactive membranes and pore-scale simulation of enzymatic reactions: The case of lactose hydrolysis, Journal of membrane science 524 (2017) 225-234.

Numerical reconstructions and EMT

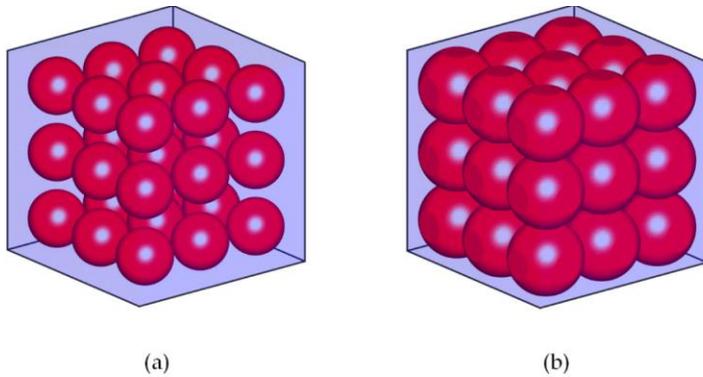


Figure 8. Single arrangement of spherical particles. (a) $f_p = 0.3$, (b) $f_p = 0.7$.

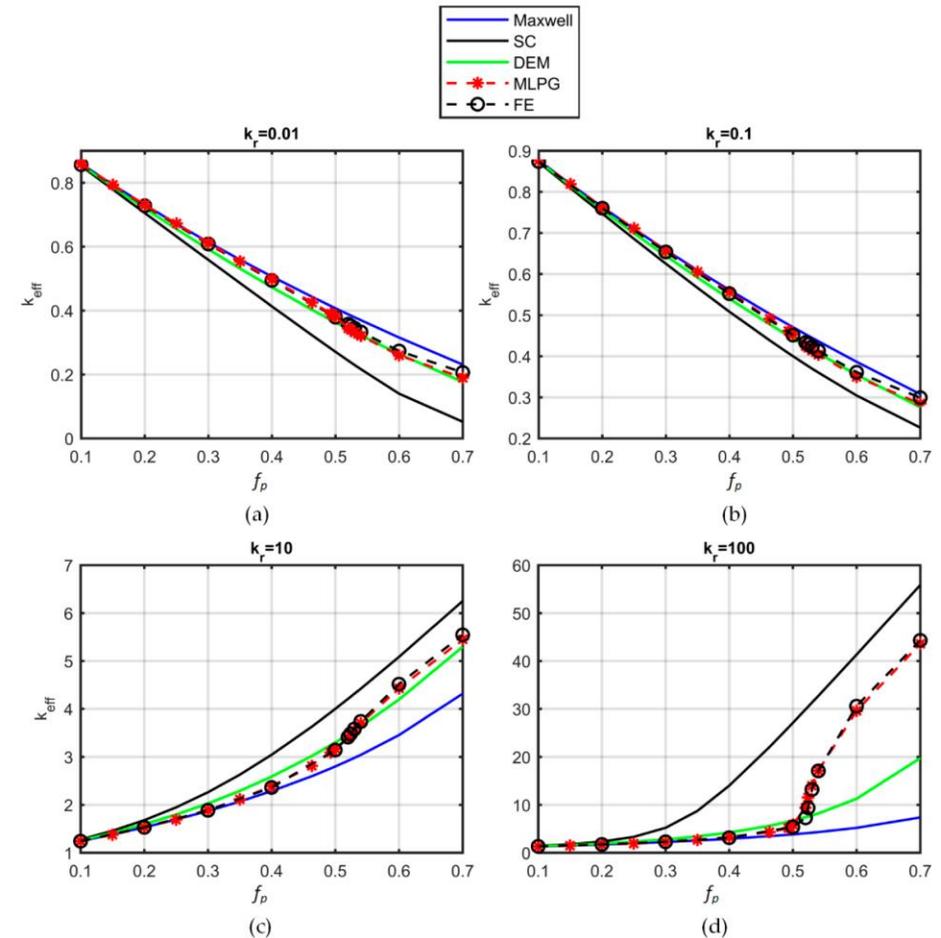
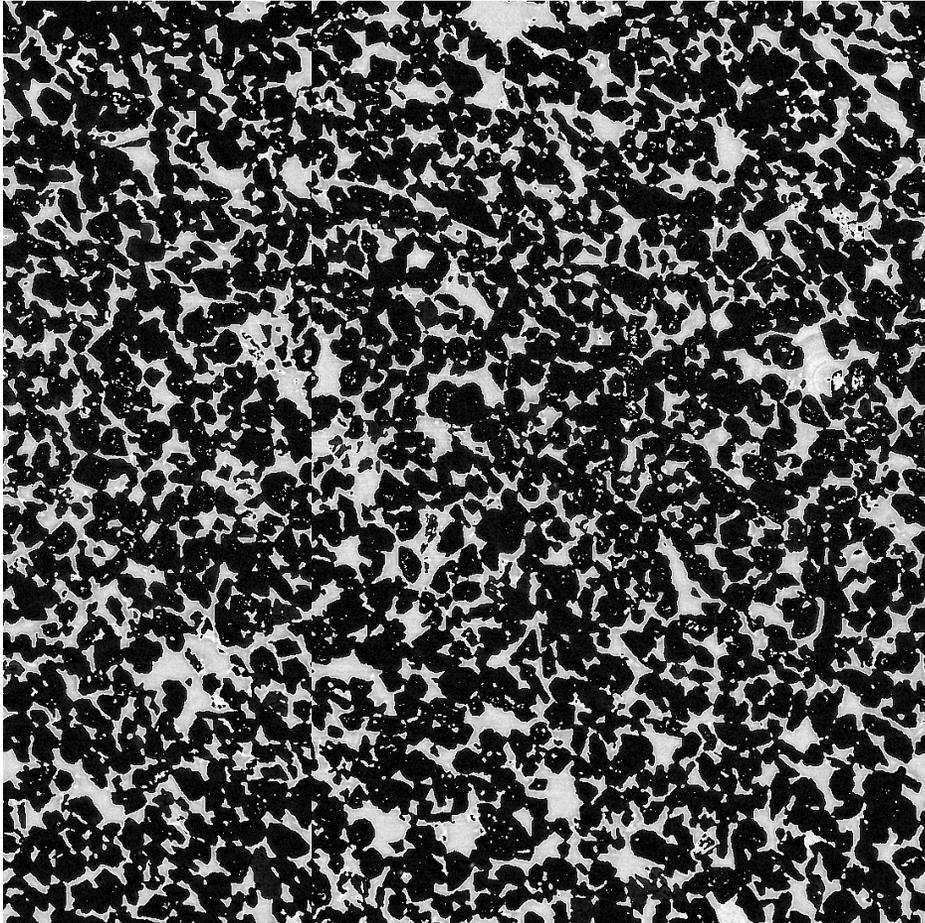


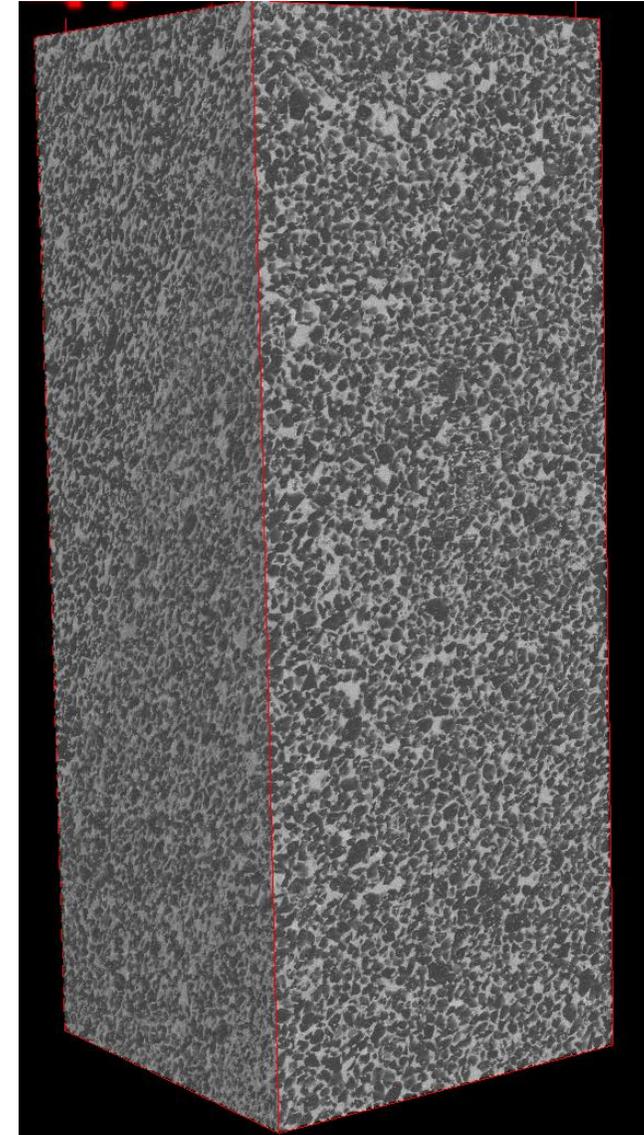
Figure 9. Effective thermal conductivity of the single arrangement as a function of the volume fraction of the inclusions for four different conductivity ratios (k_r), (a) 1/100, (b) 1/10, (c) 10, (d) 100. Continuous lines: analytical expressions. Blue lines: Maxwell. Black lines: SC. Green lines: DEM. Dashed lines: simulations. Red: MLPG. Black: FE. Abbreviation; SC: self-consistent approximation, DEM: differential effective medium approximation MLPG: meshless local Petrov-Galerkin, FE: finite element.

P. Karagiannakis, N.; Bali, N.; D. Skouras, E.; N. Burganos, V., An efficient meshless numerical method for heat conduction studies in particle aggregates. *Applied Sciences* **2020**, 10, 739.

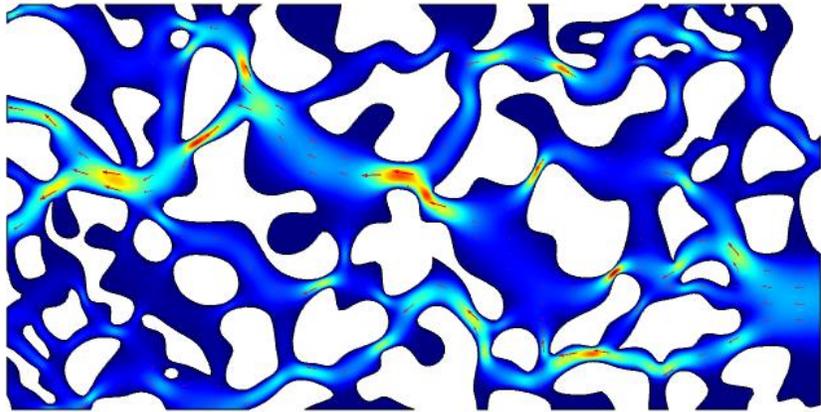
New era: Transport phenomena in real structures



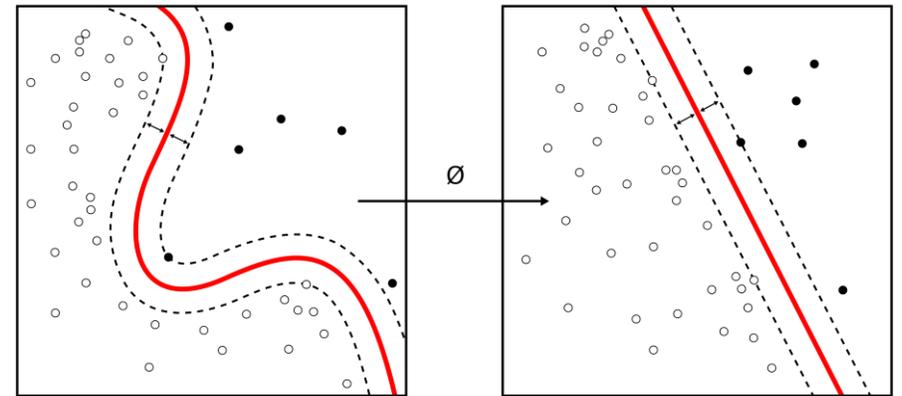
The results of
~3000 scanned
images



Transport phenomena in real structures: future goals



Solving in 2D vertical images to CT scanned



Convolutional Neural Networks



The research project is supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “1st Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment (Project title: Enhanced Oil Recovery by Polymer-coated Nano Particles, acronym: «EOR-PNP», code: HFRI-FM17-361)

THANK YOU

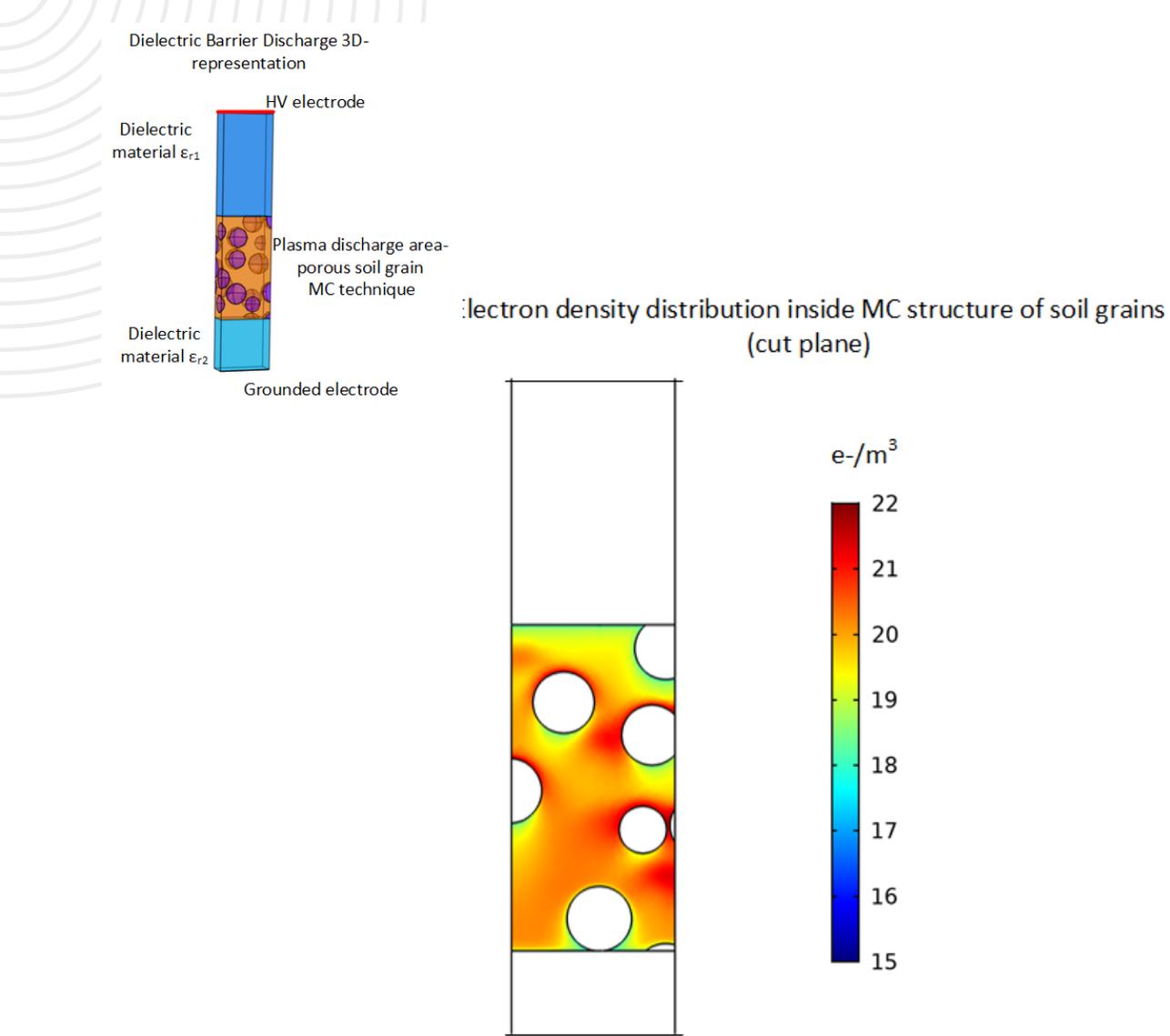


Figure 7. Plasma distribution inside Monte Carlo (MC) randomly placed spheres domain

Electron density distribution inside grid-placed soil grains (cut plane)

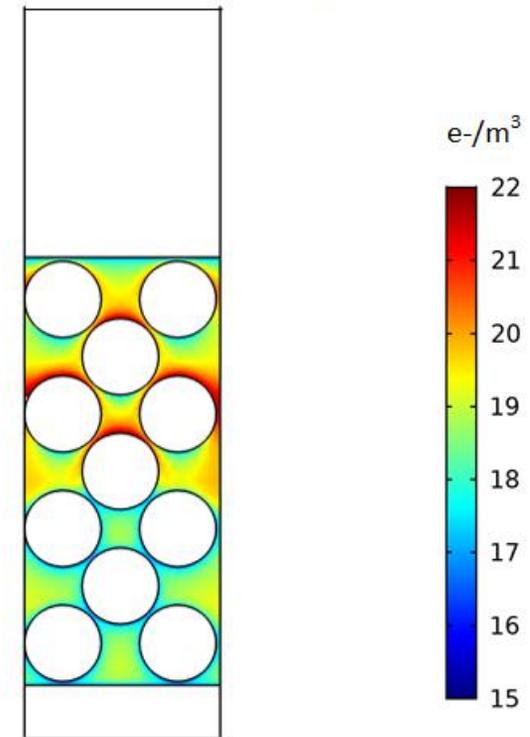
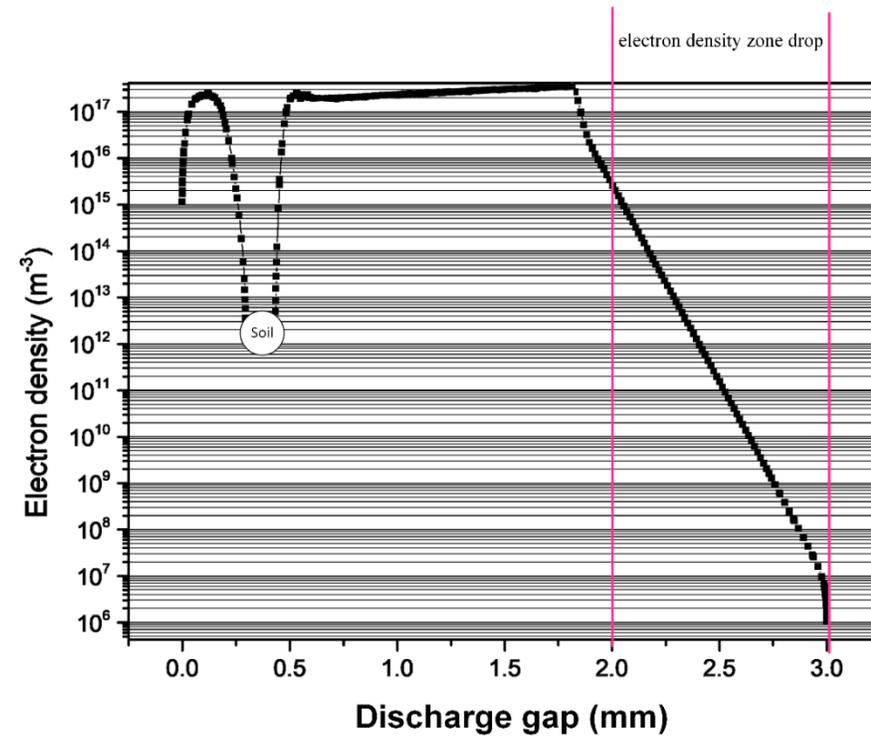
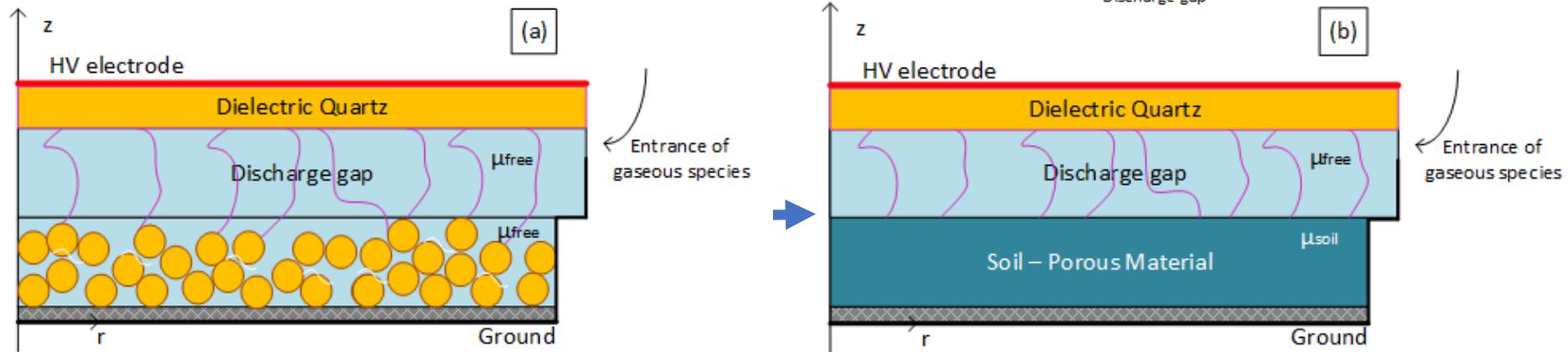
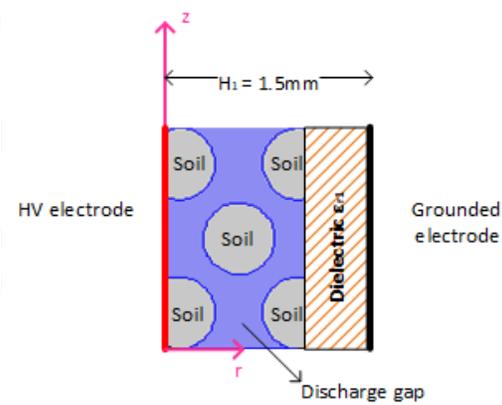


Figure 6. Plasma distribution inside cubic spheres arrangement (FCC)



Μοντελοποίηση πλάσματος στο εκκένωσης +)



- Τροποποιημένες εξισώσεις:

- ως προς τα μονοπάτια των αντιδράσεων (θερμοκρασία 300K – ψυχρό πλάσμα) 100 αντιδράσεις
- μ (συντελεστής ευκινησίας ηλεκτρικά φορτισμένων σωματιδίων) η ισοδύναμη τιμή μέσα στο χώμα δίνεται από:

$$m_{soil} = \frac{e_p}{t} m_{free}$$

- Αντίστοιχα αλλάζουν και οι συντελεστές διάχυσης των συστατικών του πλάσματος στο χώμα

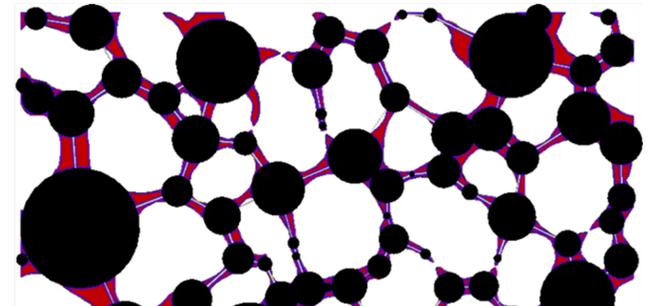
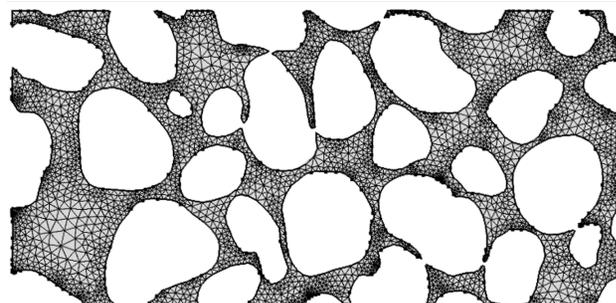
Thanks to Dr. Christos Tsakiroglou and the FORTH Institute, and the EORPNP consortium

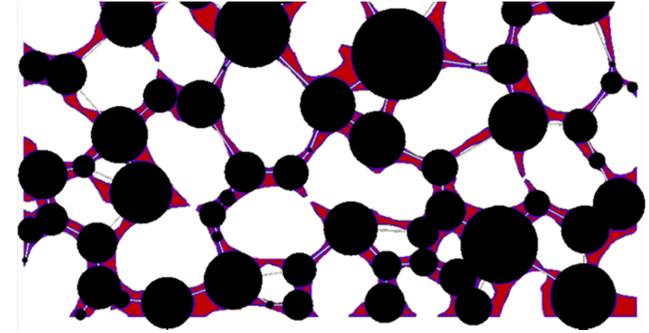
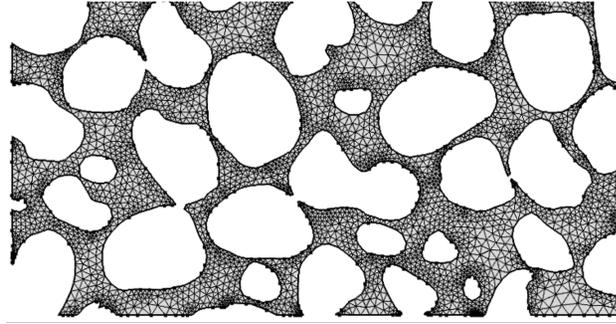


Introduction to Pore Network Modeling

Pore network modelling in one sentence:

PNM is based on the recognition that the interconnected voids of a real porous material can be mapped onto an equivalent net convenient mathematical analysis



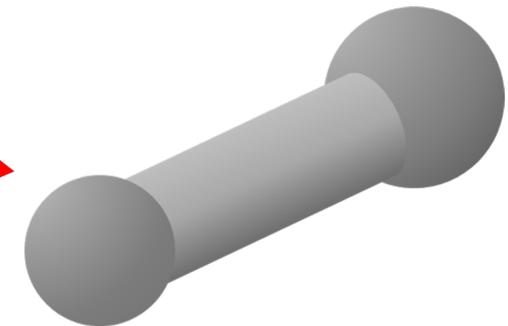
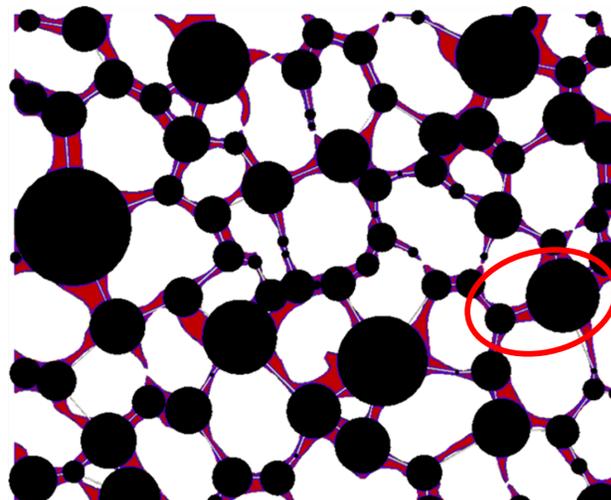


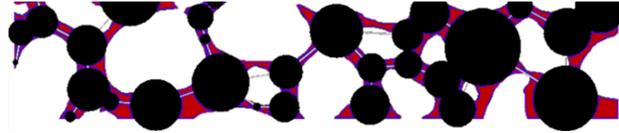
Pore Network Modelling, or PNM, offers several advantages or capabilities:

- It allows "pore-scale" modeling of transport processes in porous materials with computational ease
 - This permits the study of the "structure-performance" relationship in materials like electrodes, filters, catalysts, ...
- It enables multiphase flow predictions through percolation theory
 - This permits the study of multiphase transport processes like relative permeability and resistivity index

Some Definitions and Terminology

- A *pore* is a cavity or opening in the voids
- A *throat* is a constriction between two cavities
- A throat plus *half* of each pore on either end define a *conduit*



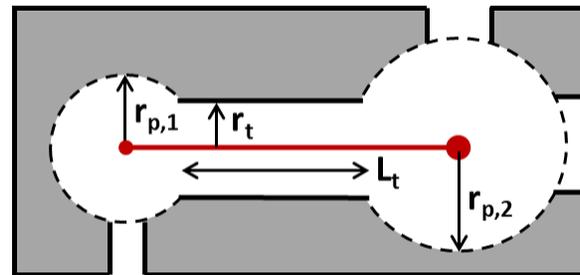


Accurate pore network predictions require that the pore space is correctly mapped, this means two things:

1. The *topology* of the network is mapped correctly
 - Each pore is connected to the correct neighboring pores
 - The spatial locations of each pore is known
2. The *geometry* of each pore and throat are determined correctly
 - Image analysis tools (e.g. PoreSpy) are used to measure the size of each pore cavity and throat constriction

Using a Simplified Geometry

We often represent pores by spheres and throats by cylinders, as shown below, but this is completely flexible:

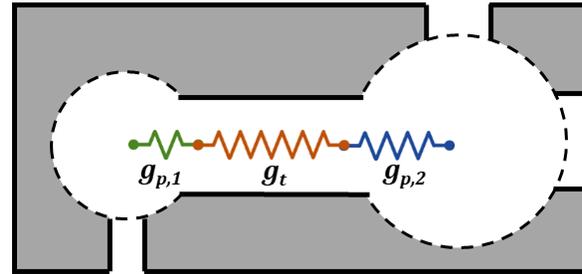


Whatever physical law and geometrical simplification are used, they must be representable as a form of Ohm's law:

$$n_{i,j} = D_{AB} \frac{\pi R_t^2}{L_t} \Delta C_{i,j} = g_D \Delta C_{i,j}$$

Converting to an Equivalent Conductance

We can be more or less detailed about how we find g_D , but ultimately the pore-throat-pore conduit is a set of resistors (or conductors)



$$\frac{1}{\sigma_p} = \frac{1}{\sigma_{p,1}} + \frac{1}{\sigma_t} + \frac{1}{\sigma_{p,2}}$$

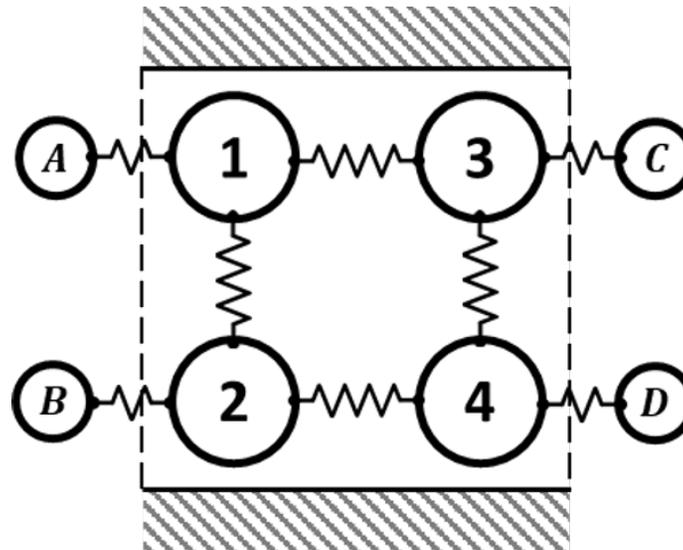
Resistor Network Calculations

Performing a mass balance on each pore gives the net rate of material entering or exiting that pore:

$$N_j = \sum g_{D,i-j} \Delta C_{i,j} = b$$

where b would be 0 for a non-reactive, internal pore, or $b = \text{const}$ for a constant rate boundary condition, etc.

The pore network is a fully connected network where the mass balances between pores are all coupled to their neighbors:

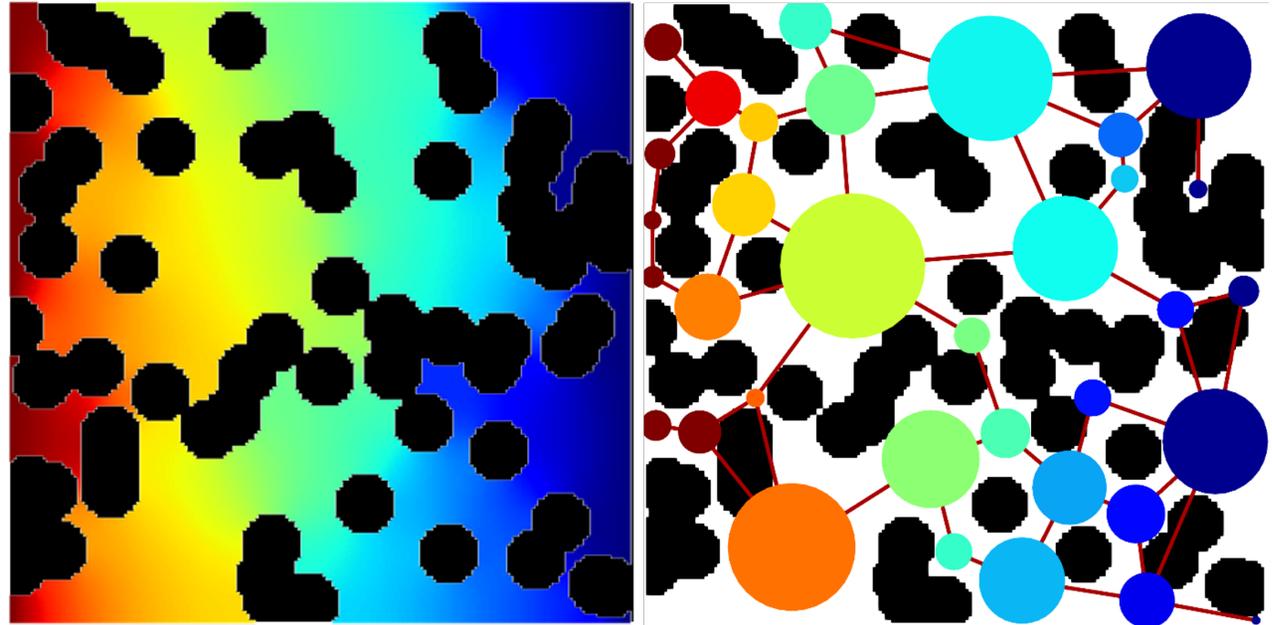


This gives a system of equations that can be solved to find the quantity of interest (i.e. concentration, pressure, etc):

$$C_i = A^{-1}b$$

Calculating Species Distributions

The result is that we can solve for the quantity in each pore, which we can compare to full DNS calculation:



Overview of OpenPNM

OpenPNM is a framework for conducting *Pore Network Modelling* studies (i.e. **PNM**).

The name **Open** refers to the fact that the code is 100% open-source and available on Github (<https://github.com/PMEAL/OpenPNM> ([/PMEAL/OpenPNM](https://github.com/PMEAL/OpenPNM)))

It includes functionality like generating networks, computing thermodynamic properties of phases, and solving the numerical problems.

In this workshop we'll cover each aspect of the package to provide an overview of OpenPNM's capabilities and how to access them.

OpenPNM is Organized in Several Modules

The main modules are described below:

- `network` : Contains the `Network` class and numerous generators. The network objects are dictionaries that contain the topologic properties of the network.
- `phase` : Contains the `Phase` class, as well as several other classes for mixtures. The phase objects are also dictionaries that contain transport properties of the fluid.
- `algorithms` : Contains all the classes used for performing simulations, including flow, diffusion, dispersion, percolation, drainage,
- `models` : A library containing 'pore-scale' models which are used to compute the properties of each pore and throat.

It also contains several helper modules such as:

- `io` : Functions for reading and writing data between formats
- `visualization` : Small set of functions for basic visualization
- `topotools` : Functions for editing and querying the network topology
- `solvers` and `integrators` : Classes for steady-state and transient solving of the equations
- `core` : Mostly used internally
- `utils` : Mostly used internally

OpenPNM is Object-Oriented

- An OpenPNM simulation is quite a bit more complicated than some image analysis with PoreSpy for instance.
- There is a lot more data to deal with and a lot more things that can be done with the data.
- Because of this added complexity, it is necessary (and helpful!) to use objects .
- The main object used in OpenPNM is the Python `dict`

Refresher on the `dict`

The `dict` is a highly versatile data container that allows access to the data by name:

```
In [11]: ▶ d = dict()
          d['bob'] = 1.0
          d['fred'] = [1, 2, 3]
          print(d)

          {'bob': 1.0, 'fred': [1, 2, 3]}
```

In OpenPNM, the data being stored are the pore and throat properties, like diameter and volume:

```
In [12]: ▶ net = dict()
          net['pore.diameter'] = [2, 1.5, 1]
          net['throat.length'] = [0.75, 1.5]
          print(net)

          {'pore.diameter': [2, 1.5, 1], 'throat.length': [0.75, 1.5]}
```

We'll explore this data storage scheme in more depth later.

The key to note here is that there are 3 pores and 2 throats.

One *massive* benefit of using a `dict` is that we can *subclass* it. This allows us to add our own custom functionality to the `dict` .

This is done as follows:

```
In [13]: ▶ class Network(dict):  
  
    def num_pores(self):  
        return len(self['pore.diameter'])  
  
    def num_throats(self):  
        return len(self['throat.length'])
```

And we can use it like this:

```
In [14]: ▶ net = Network()  
net['pore.diameter'] = [2, 1.5, 1]  
net['throat.length'] = [0.75, 1.5]  
print(f'The network has {net.num_pores()} pores')  
print(f'The network has {net.num_throats()} throats')
```

```
The network has 3 pores  
The network has 2 throats
```

Hopefully the class definition above gives you as sense of the power of object-oriented programming.

The main point is:

The `net` object behaves as a generic `dict` PLUS we have added some functions that are *very specific* to our use case. The designed to work on the data within the `dict` .

And the motivation for tell you this:

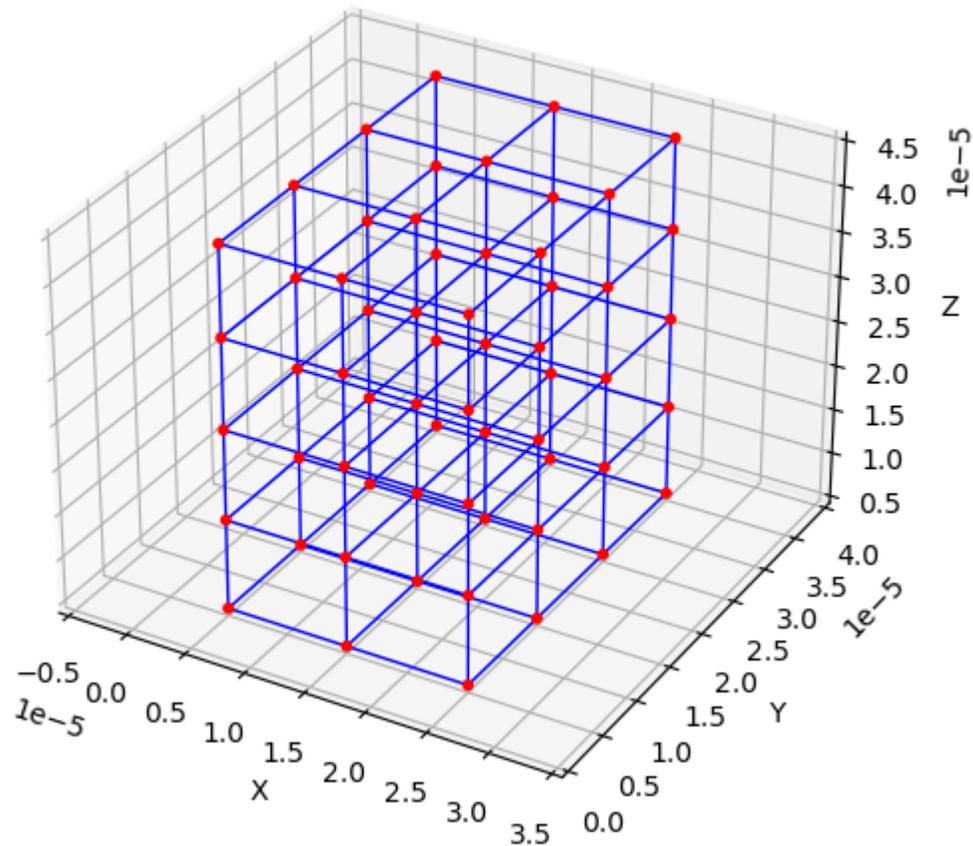
OpenPNM uses this technique quite extensively

A First Look at Using OpenPNM

Let's look quickly at using OpenPNM. Don't try to code this, we'll revisit it in the next tutorial:

```
In [15]: ▶ import openpnm as op
```

```
In [16]: ▶ pn = op.network.Cubic([3, 4, 5], spacing=1e-5)  
ax = op.visualization.plot_connections(pn)  
ax = op.visualization.plot_coordinates(pn, ax=ax);
```



In [17]: `print(pn)`

```
net : <openpnm.network.Cubic at 0x1ab78dfcd10>
```

#	Properties	Valid Values
2	pore.coords	60 / 60
3	throat.conns	133 / 133

#	Labels	Assigned Locations
2	pore.surface	54
3	throat.surface	104
4	pore.left	20
5	pore.right	20
6	pore.front	15
7	pore.back	15
8	pore.bottom	12
9	pore.top	12

Adding Geometrical Properties

Note that this network does not yet have any geometrical properties. We have to add these explicitly, which is how we declare our preferred size distribution, and so forth.

We'll use a predefined collection of models, which gives everything we need (and more!):

```
In [18]: ▶ pn.add_model_collection(op.models.collections.geometry.spheres_and_cylinders)
print(pn)
```

```
net : <openpnm.network.Cubic at 0x1ab78dfcd10>
```

#	Properties	Valid Values
2	pore.coords	60 / 60
3	throat.conns	133 / 133
4	pore.coordination_number	60 / 60
5	pore.max_size	60 / 60
6	throat.spacing	133 / 133
7	pore.seed	60 / 60
8	pore.diameter	60 / 60
9	throat.max_size	133 / 133
10	throat.diameter	133 / 133
11	throat.cross_sectional_area	133 / 133
12	throat.hydraulic_size_factors	133 / 133
13	throat.diffusive_size_factors	133 / 133
14	throat.lens_volume	133 / 133
15	throat.length	133 / 133
16	throat.total_volume	133 / 133
17	throat.volume	133 / 133
18	pore.volume	60 / 60

#	Labels	Assigned Locations
2	pore.surface	54
3	throat.surface	104
4	pore.left	20
5	pore.right	20
6	pore.front	15
7	pore.back	15
8	pore.bottom	12
9	pore.top	12

Calculating Thermodynamic Properties

And let's create an `Air` object then do a diffusion simulation:

```
In [19]: ▶ air = op.phase.Air(network=pn)
print(air)
```

```
phase_01 : <openpnm.phase.Air at 0x1ab79683220>
```

#	Properties	Valid Values
2	pore.temperature	60 / 60
3	pore.pressure	60 / 60
4	pore.density	60 / 60
5	pore.molar_density	60 / 60
6	pore.diffusivity	60 / 60
7	pore.thermal_conductivity	60 / 60
8	pore.viscosity	60 / 60

#	Labels	Assigned Locations
2	pore.all	60
3	throat.all	133

Computing Transport Properties

The diffusive conductance of a conduit, the pore-throat-pore connection, is a function of the geometric sizes and thermodynamic properties

$$N = D_{AB} \frac{A}{L} \Delta C = g_D \Delta C$$

```
In [20]: ▶ air.add_model_collection(op.models.collections.physics.basic)
air.regenerate_models()
print(air)
```

```
[15:07:51] WARNING throat.entry_pressure was not run since the following property is missing: _mo
'throat.surface_tension'
```

```
phase_01 : <opennm.phase.Air at 0x1ab79683220>
```

#	Properties	Valid Values
2	pore.temperature	60 / 60
3	pore.pressure	60 / 60
4	pore.density	60 / 60
5	pore.molar_density	60 / 60
6	pore.diffusivity	60 / 60
7	pore.thermal_conductivity	60 / 60
8	pore.viscosity	60 / 60
9	throat.hydraulic_conductance	133 / 133
10	throat.diffusive_conductance	133 / 133

#	Labels	Assigned Locations
2	pore.all	60
3	throat.all	133

With the pore sizes, phase properties, and transport models defined, we can do the simulation:

```
In [21]: ▶ fd = op.algorithms.FickianDiffusion(network=pn, phase=air)
fd.set_value_BC(pores=pn.pores('top'), values=1.0)
fd.set_value_BC(pores=pn.pores('bottom'), values=0.0)
fd.run()
```

The algorithm writes the results of the simulation into it's own dictionary:

In [22]: `print(fd)`

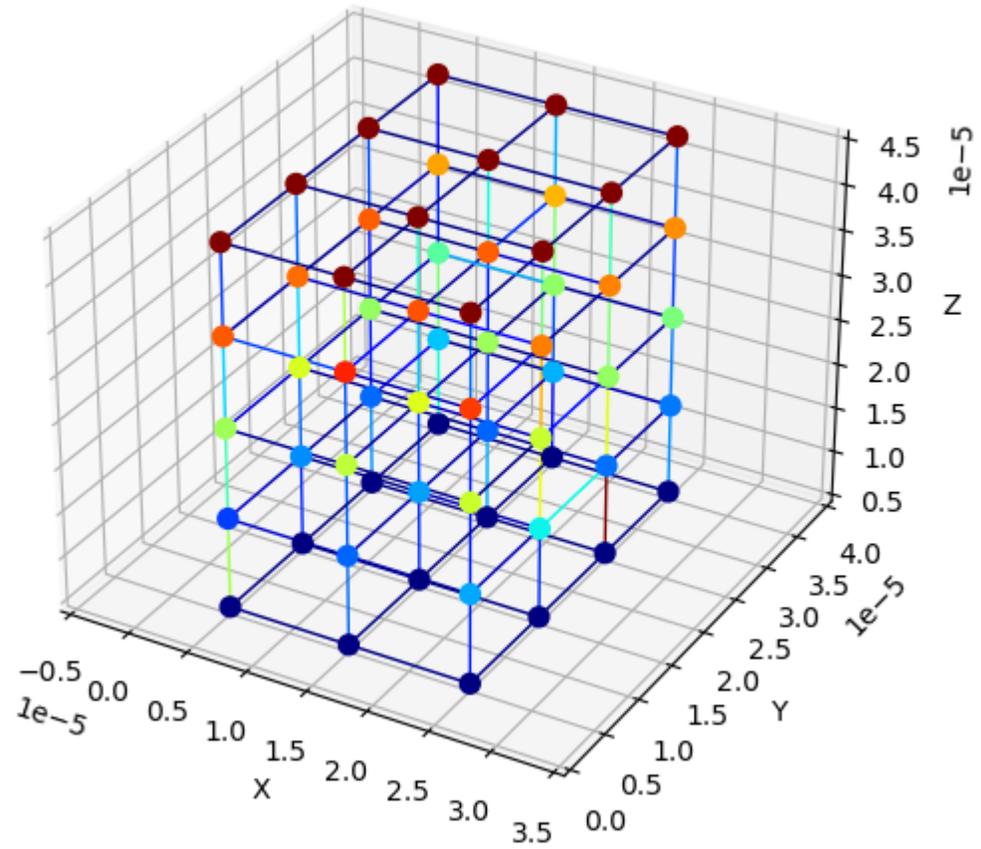
```
fick_02 : <openpnm.algorithms.FickianDiffusion at 0x1ab0176dd10>
```

#	Properties	Valid Values
2	pore.bc.rate	0 / 60
3	pore.bc.value	24 / 60
4	pore.concentration	60 / 60
5	pore.initial_guess	60 / 60

#	Labels	Assigned Locations
2	pore.all	60
3	throat.all	133

We can re-visualize the network, but chose to color the nodes according to their concentration, and the throats according to the mass f

```
In [25]: ▶ ax = op.visualization.plot_connections(pn, color_by=fd.rate(throats=pn.Ts, mode='single'))
ax = op.visualization.plot_coordinates(pn, markersize=50, color_by=fd.x, ax=ax)
```



Compute Network Permeability

There are three main stages of an OpenPNM simulation.

1. Create a network topology and define geometric properties
2. Create a phase object and define pore-scale transport properties
3. Create an algorithm object, assign boundary conditions, and run it

Let's proceed as though we're going to do a single phase flow simulation to compute the permeability of the network.

One common conductance model for flow through a tube is the Hagan-Poiseuille model:

$$Q = \frac{\pi R^4}{8\mu L} \Delta P = g_H \Delta P$$

From this we can see that our simulation will need the diameters and lengths of pores and throats, as well as the fluid viscosity.

Network Generators

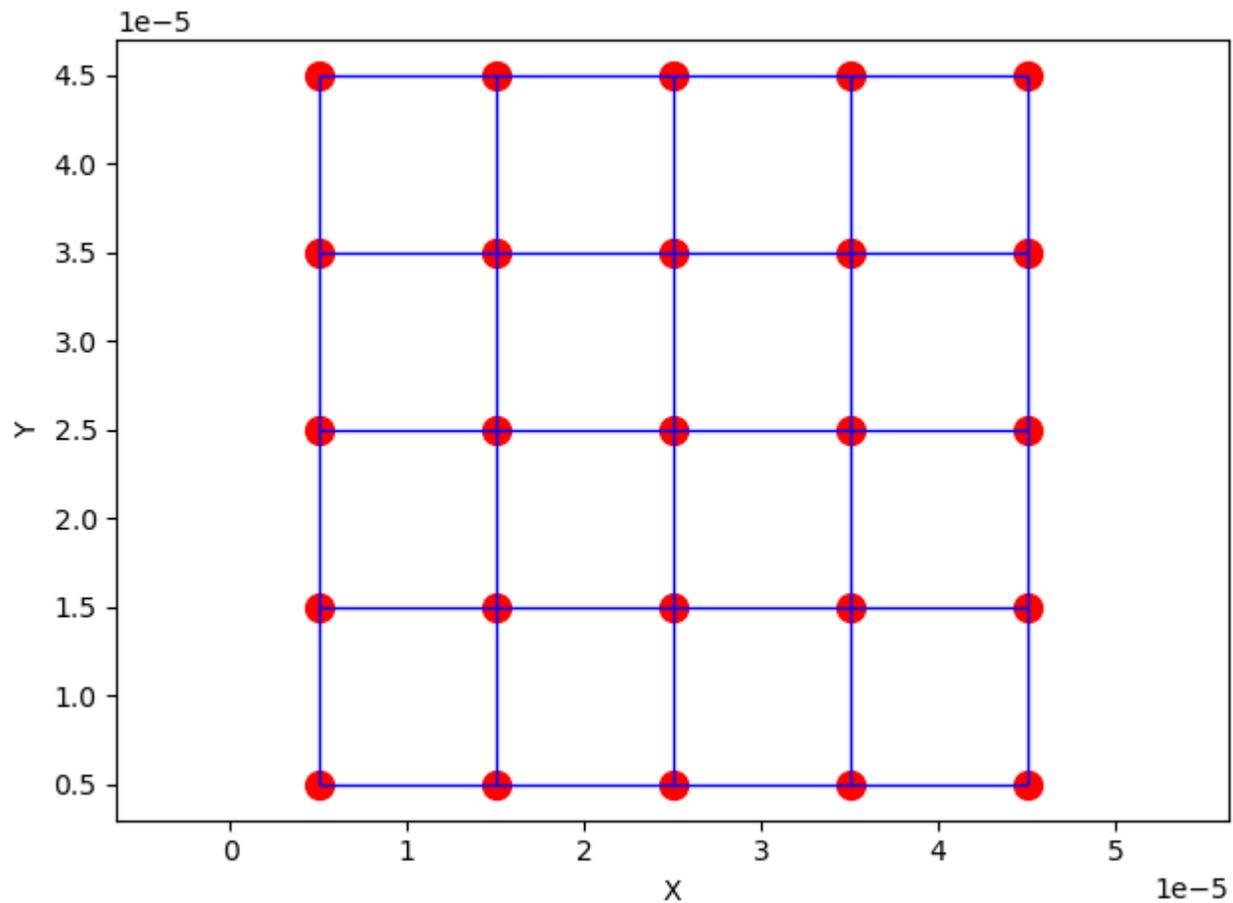
OpenPNM includes a number of ways to [generate networks \(https://openpnm.org/modules/generated/openpnm.network.html#module-regular_lattices_and_random_networks\)](https://openpnm.org/modules/generated/openpnm.network.html#module-regular_lattices_and_random_networks):

```
In [56]: ▶ import openpnm as op
          for item in dir(op.network):
              if not item.startswith('_'):
                  print(item)
```

```
BodyCenteredCubic
Cubic
CubicTemplate
Delaunay
DelaunayVoronoiDual
Demo
FaceCenteredCubic
Network
Voronoi
```

Let's use the Cubic generator, and stick to 2D, for simplicity:

```
In [57]: ▶ pn = op.network.Cubic(shape=[5, 5, 1], spacing=1e-5)
ax = op.visualization.plot_connections(pn)
ax = op.visualization.plot_coordinates(pn, s=100, ax=ax)
```



Data Storage

Let's print the network and see what data is created during the generation:

In [28]: `print(pn)`

```
net : <openpnm.network.Cubic at 0x2761b786ea0>
```

#	Properties	Valid Values
2	pore.coords	25 / 25
3	throat.conns	40 / 40

#	Labels	Assigned Locations
2	pore.surface	16
3	throat.surface	16
4	pore.left	5
5	pore.right	5
6	pore.front	5
7	pore.back	5

Key things to note:

1. Each item listed above is an entry in the `pn` dictionary, like `pn['pore.coords']`
2. Items starting with the word 'pore' are obviously "pore data" and 'throat' indicates "throat data"
3. Each item is a numpy array with one element for each pore or throat...this network has 25 pores and 40 throats
4. 'pore.coords' lists the [x, y, z] coordinates of each pore
5. 'throat.conns' lists the [head, tail] of each throat, meaning which pore is on each end
6. The things referred to as "Labels" are boolean arrays (i.e. True/False) where True indicates where that label is applied. (These applying boundary conditions).
7. Geometrical data is missing, but we'll add that next

Define Geometry

To conduct our simulation we need:

- The diameter of pores and throats

- The length of throats

Pore Diameters: The easy way

Let's assign pore diameters from a uniform distribution, remembering that the pores are spaced 10 um apart and they should not overlap.

```
In [86]: ▶ import numpy as np
pn['pore.diameter'] = np.random.rand(pn.num_pores())*1e-5
print(pn['pore.diameter'])

[7.62352084e-06 4.18667497e-07 2.78986473e-06 8.57960414e-06
 3.69039996e-06 8.98991875e-06 2.89097831e-06 3.80323481e-06
 1.09373393e-06 8.14624611e-06 9.33485442e-06 1.83107189e-06
 3.11198567e-06 6.74704043e-06 7.91010422e-07 3.27239943e-07
 3.26575619e-06 3.86612194e-06 5.48967345e-06 5.52931172e-06
 3.30127174e-06 4.25651101e-06 2.51856859e-06 2.02635132e-06
 7.77525513e-06]
```

Throat Lengths: The hard way

First, let's do this by hand:

We'll use the 'throat.conns' array to index into the 'pore.diameter' array to get the diameter of the pore on each end then we'll subtract half of each diameter from the known pore spacing, with the remaining amount being the throat length

```
In [59]: ▶ D1, D2 = pn['pore.diameter'][pn['throat.conns']].T
Lt = 1e-5 * D1/2 + D2/2
print(Lt)

[3.38614765e-06 2.66129569e-06 2.68908581e-06 6.21639964e-06
 6.77185282e-06 6.01354562e-06 5.27774603e-06 4.47143498e-06
 5.42389468e-06 7.11133557e-06 5.28112350e-06 1.37637822e-06
 3.18933525e-06 3.12918888e-06 2.74284317e-06 2.70295620e-06
 5.95339764e-06 2.11642329e-06 5.28608824e-06 8.91380333e-06
 3.34892736e-06 6.80907310e-06 1.86576821e-06 6.10106364e-06
 4.58677099e-06 4.67340213e-06 7.52234536e-06 5.60253583e-06
 4.95633370e-06 8.91479500e-07 4.15921814e-06 4.45401178e-06
 5.78651267e-06 2.23745401e-06 1.84188042e-06 5.81224492e-06
 3.33048797e-06 1.91512421e-06 6.11380720e-06 5.50295233e-06]
```

Throat Lengths: The "pore-scale model" way

Calculations like the one above are common, so OpenPNM offers pre-defined ways to do them.

`openpnm.models` is a library of prewriting functions for computing many things.

The library is further organized by the type of thing being computed, such as `openpnm.models.geometry` and `openpnm.models.ph`.

```
In [75]: ▶ mod = op.models.geometry.throat_length.squares_and_rectangles
pn.add_model(propname='throat.length', model=mod)
pn.regenerate_models()
print(pn['throat.length'])

[3.38614765e-06 2.66129569e-06 2.68908581e-06 6.21639964e-06
 6.77185282e-06 6.01354562e-06 5.27774603e-06 4.47143498e-06
 5.42389468e-06 7.11133557e-06 5.28112350e-06 1.37637822e-06
 3.18933525e-06 3.12918888e-06 2.74284317e-06 2.70295620e-06
 5.95339764e-06 2.11642329e-06 5.28608824e-06 8.91380333e-06
 3.34892736e-06 6.80907310e-06 1.86576821e-06 6.10106364e-06
 4.58677099e-06 4.67340213e-06 7.52234536e-06 5.60253583e-06
 4.95633370e-06 8.91479500e-07 4.15921814e-06 4.45401178e-06
 5.78651267e-06 2.23745401e-06 1.84188042e-06 5.81224492e-06
 3.33048797e-06 1.91512421e-06 6.11380720e-06 5.50295233e-06]
```

Throat Diameters: The "pore-scale model" way

Calculating throat diameters by hand is also tedious because we'd like to ensure they are not larger than their neighboring pores.

Luckily there is a pore-scale model for that:

```
In [76]: ▶ mod = op.models.geometry.throat_size.from_neighbor_pores
pn.add_model(propname='throat.diameter', model=mod)
pn.regenerate_models()
```

Compute Phase Properties

There are several ways to compute phase properties, but for the sake of this tutorial we'll just do it the quick and easy way.

```
In [79]: ▶ water = op.phase.Phase(network=pn)
water['pore.viscosity'] = 0.001 # Pa.s
water['throat.viscosity'] = 0.001
```

Things to note:

- We assigned a scalar value (0.001), but internally OpenPNM applies it to all pores and throats so that each has its own value
- We have assigned values to both pores *and* throats, but OpenPNM would have automatically interpolate one if it only had the other

Compute the Hydraulic Conductance

For simplicity, we will assume that all the pressure drop occurs in the throats, so we will not consider the contribution of the pores.

So:

$$\frac{1}{g_H} = \frac{1}{g_{p,1}} + \frac{1}{g_t} + \frac{1}{g_{p,2}} = \frac{1}{\infty} + \frac{1}{g_t} + \frac{1}{\infty} = \frac{1}{g_t}$$

```
In [81]: ▶ R = pn['throat.diameter']/2
L = pn['throat.length']
mu = water['throat.viscosity']
water['throat.hydraulic_conductance'] = np.pi * R**4 / (8 * mu * L )
```

Run the Simulation

Now we create a `StokesFlow` object, assign boundary conditions and run it.

Note that the `StokesFlow` algorithm automatically looks for values of `'throat.hydraulic_conductance'` on the `Phase` object.

```
In [82]: ▶ sf = op.algorithms.StokesFlow(network=pn, phase=water)
```

Applying Boundary Conditions Using Labels

The labels mentioned above will now be of great help. They allow us to choose pores on the desired faces for inlet and outlet boundaries.

We can ask the network to return the indices of the pores which have been labelled "left":

```
In [83]: ▶ print(pn.pores('left'))
[0 1 2 3 4]
```

Now we use these to specify boundary conditions:

```
In [84]: ▶ sf.set_value_BC(pores=pn.pores("left"), values=200_000)
sf.set_value_BC(pores=pn.pores("right"), values=100_000)
```

And finally we are ready to run it:

```
In [85]: ▶ sf.run()
```

Determine Darcy Permeability of the Network

The simulation performed above is equivalent to the experiment that one would conduct on a real sample.

We just need to ask OpenPNM what was the total flow rate across the network, then we can find K from:

$$Q = \frac{KA}{\mu L} \Delta P$$

```
In [92]: ▶ L = 5*1e-5  
A = (5 * 1) * (1e-5)**2  
mu = 0.001  
DeltaP = 100_000
```

```
In [93]: ▶ Q = sf.rate(pores=pn.pores('left'), mode='group')
```

```
In [95]: ▶ K = Q * mu * L / (A * DeltaP)  
print("The Darcy permeability is: ", K, "m^2")
```

```
The Darcy permeability is: [1.35291722e-13] m^2
```

Simulating Capillary Pressure Curve on an Extracted Network

In this tutorial we will dive into the process of extracting a network from an image, then we'll compute the capillary pressure curve using and compare to the image-based drainage simulation in PoreSpy.

As usual, let's import the needed packages:

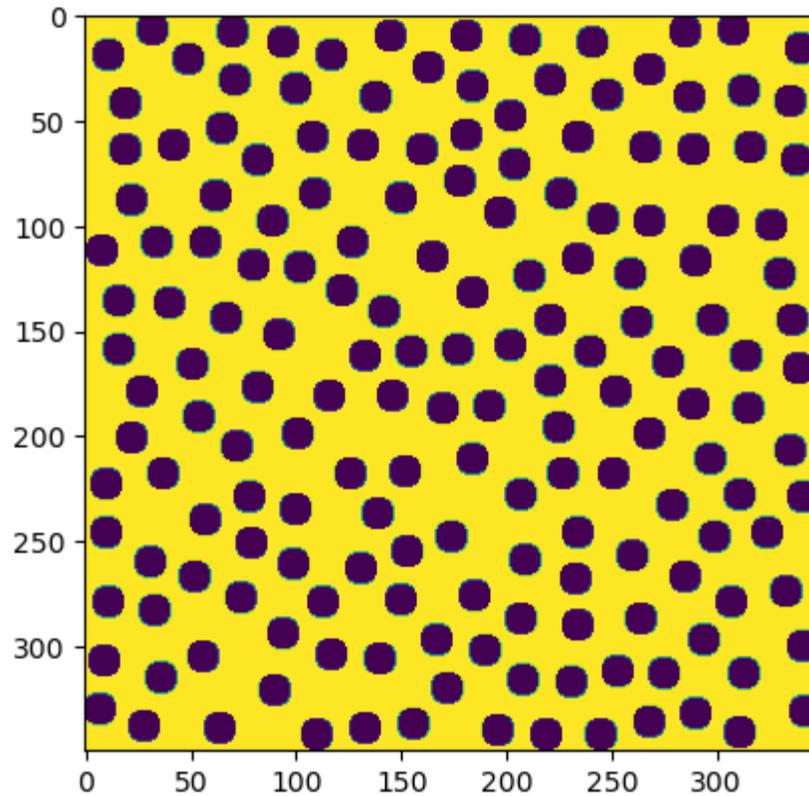
```
In [79]: ▶ import porespy as ps  
import openpnm as op  
import matplotlib.pyplot as plt  
import numpy as np
```

Generate an Image

Let's use a 2D generated image, for quicker processing and easier visualization:

```
In [99]: ▶ im = ~ps.generators.rsa([350, 350], r=8, clearance=3)
plt.imshow(im);
```

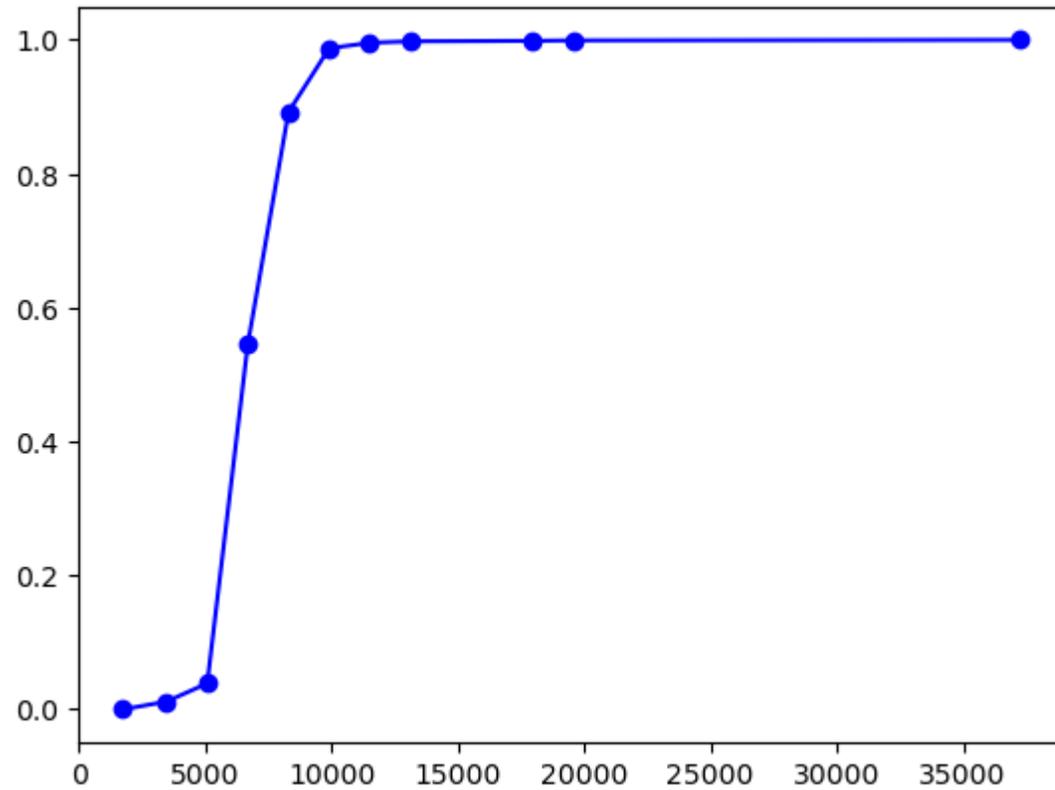
```
Out[99]: <matplotlib.image.AxesImage at 0x289a89e1460>
```



Perform Drainage on Image

```
In [100]: ▶ inlets = ps.tools.get_border(shape=im.shape, mode='edges')
drn = ps.simulations.drainage(im, inlets=inlets, sigma=0.480, theta=140, voxel_size=1e-5)
```

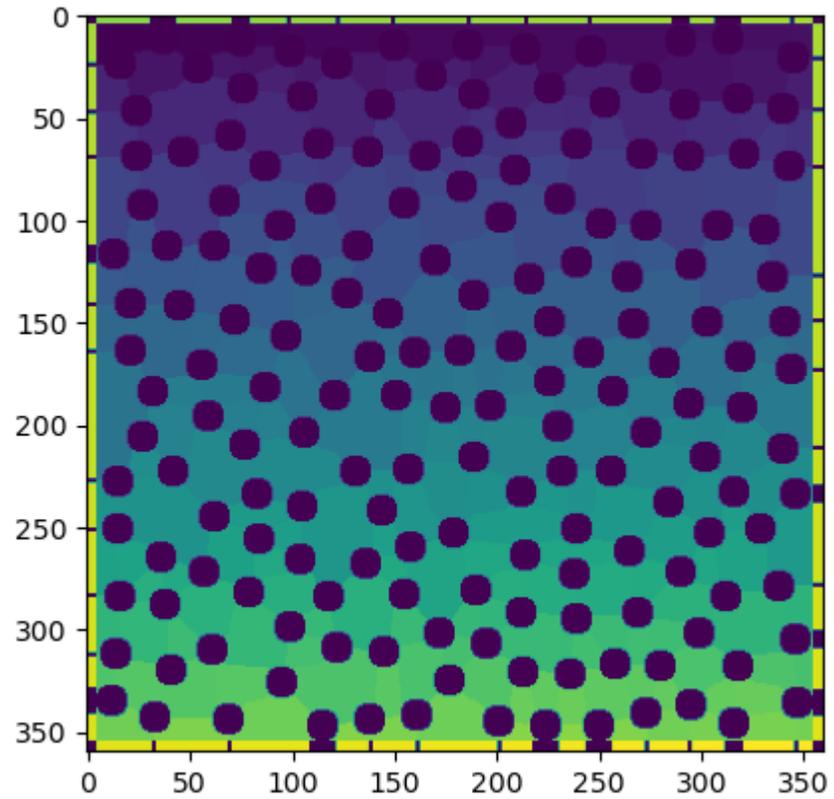
```
In [101]: ▶ plt.plot(drn.pc, drn.snwp, 'bo-');
```



Extract the Network

We'll use the `snow2` function in PoreSpy:

```
In [102]: ▶ snow = ps.networks.snow2(im, boundary_width=5, voxel_size=1e-5)
plt.imshow(snow.regions);
```



```
In [103]: ▶ pn = op.io.network_from_porespy(snow.network)
print(pn)
```

```
net : <openpnm.network.Network at 0x289a9da38b0>
```

#	Properties	Valid Values
2	throat.conns	440 / 440
3	pore.coords	274 / 274
4	pore.region_label	274 / 274
5	pore.phase	274 / 274
6	throat.phases	440 / 440
7	pore.region_volume	274 / 274
8	pore.equivalent_diameter	274 / 274
9	pore.local_peak	274 / 274
10	pore.global_peak	274 / 274
11	pore.geometric_centroid	274 / 274
12	throat.global_peak	440 / 440
13	pore.inscribed_diameter	274 / 274
14	pore.extended_diameter	274 / 274
15	throat.inscribed_diameter	440 / 440
16	throat.total_length	440 / 440
17	throat.direct_length	440 / 440
18	throat.perimeter	440 / 440
19	pore.volume	274 / 274
20	pore.surface_area	274 / 274
21	throat.cross_sectional_area	440 / 440
22	throat.equivalent_diameter	440 / 440

#	Labels	Assigned Locations
2	pore.all	274
3	throat.all	440
4	pore.boundary	49
5	pore.xmin	12
6	pore.xmax	13
7	pore.ymin	12
8	pore.ymax	12

Define Pore and Throat Sizes

PoreSpy returns many different pieces of size information, but does not make any choices about *which* ones to use in OpenPNM.

For instance, there are 3 different value of pore diameter, but none are 'pore.diameter'. We must choose.

```
In [110]: ▶ pn['pore.diameter'] = pn['pore.inscribed_diameter']
pn['pore.volume'] = pn['pore.region_volume']
pn['throat.diameter'] = pn['throat.inscribed_diameter']*2
pn['throat.volume'] = 0.0
```

Define Thermodynamic and Capillary Properties

We need to create a Phase object to represent the mercury, with its surface tension and contact angle.

We also need to define the physical law for capillary entry pressure:

```
In [111]: ▶ hg = op.phase.Mercury(network=pn)
hg.add_model(propname='throat.entry_pressure',
             model=op.models.physics.capillary_pressure.washburn)
```

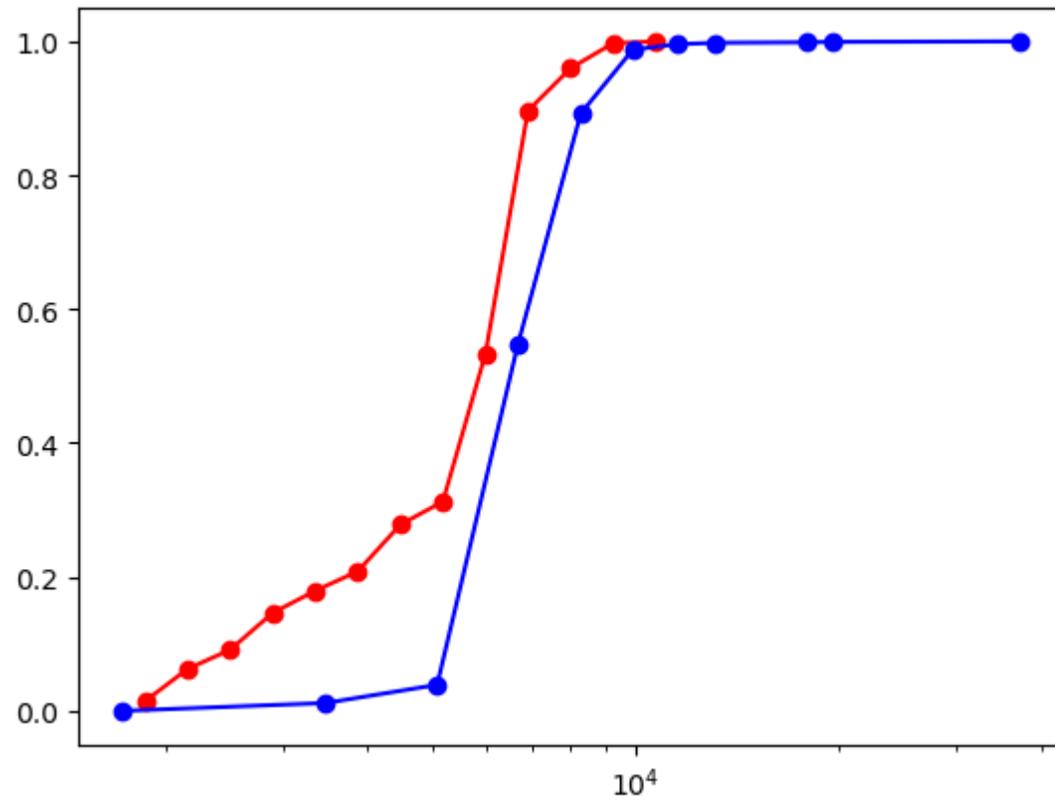
Create Drainage Algorithm

```
In [112]: ▶ mip = op.algorithms.Drainage(network=pn, phase=hg)
mip.set_inlet_BC(pores=pn.pores(['xmin', 'xmax', 'ymin', 'ymax']))
mip.run()
```

Performing drainage simulation: 100%

25/25 [00:00<00:00, 323.57it/s]

```
In [113]: ▶ data = mip.pc_curve()  
plt.semilogx(data.pc, data.snwp, 'ro-')  
plt.semilogx(drn.pc, drn.snwp, 'bo-');
```



Introduction to Scientific Python

Python has become a very popular choice for scientific applications for a few reasons:

- It's free, unlike the main alternative Matlab which is free for students but very expensive for industry
- It's easy to learn and use
- It's very powerful and general purpose, so you can learn Python for numerical studies but use it for making a website
- It has a huge ecosystem of existing packages, creating ever more momentum for the addition of new packages

Python is not without it's downsides though:

- It is actually terrible at numerical stuff!
- It is very slow

These downsides have been mostly addressed by the package called [Numpy \(https://numpy.org\)](https://numpy.org) which provides Python with a new data type (array) and a set of mathematical functions (Trigonometric, Transforms, ODE solvers, etc). In fact, many packages have sprouted up around Numpy/Scipy, which are collectively called the "Scipy Stack" (Pandas, scikit-learn, etc).

The bottom line is that you need to install both Python and the "Scipy Stack" packages. This is most conveniently done using the [Anaconda Distribution \(https://www.anaconda.com/products/distribution\)](https://www.anaconda.com/products/distribution). This distribution is maintained and distributed by a company called Anaconda, which is by the original authors of Numpy. They make money by providing advanced versions of Anaconda to companies, but they offer a free version of the package for free.

Doing Math in Python: The Wrong Way

Let's quickly look at using pure Python to do some basic math. Start by putting some numbers into a `list` :

```
In [5]: ▶ a = [1, 2, 3, -2, 0.5]
```

Now let's multiply each number by 2:

```
In [6]: ▶ a = a * 2  
print(a)
```

```
[1, 2, 3, -2, 0.5, 1, 2, 3, -2, 0.5]
```

OOPS! That is not what we wanted. This illustrates that Python is really not math focused. Let's do it inside a for-loop:

```
In [7]: ▶ for i in range(len(a)):  
        a[i] = a[i] * 2  
print(a)
```

```
[2, 4, 6, -4, 1.0, 2, 4, 6, -4, 1.0]
```

OK, that worked. But there is one more problem...Python let's us put ANYTHING into lists :

```
In [8]: ▶ a = [1, 1.0, True, 'one']
```

Here we have an integer, a float, a boolean, and a string. Trying to do make on this mixed bag will have problems:

```
In [9]: ▶ for i in range(len(a)):  
        a[i] = a[i]*2  
print(a)
```

```
[2, 2.0, 2, 'oneone']
```

This did as expected for the integer and float, but it converted the boolean to a integer and did the 'doubling' trick on the string. What h: Python performed the multiplication of each element differently depending on the type of element. This required Python to stop and ins element, making it slow.

Doing Math in Python: The Numpy Way

The slowness of Python comes from the fact that it must inspect each element in a the `list` to get its type, then apply the the correct avoids this by offering a new type of `list` where all elements are forced to be the same type. This `list` is actually called an `ndarray`. Let's see it in action:

```
In [10]: ▶ import numpy as np
a = np.array([1, 2, 3, 4.0, True], dtype=float)
print(a)

[1.  2.  3.  4.  1.]
```

Here we have told Numpy that this `array` should be of type `float`, so it converts all values to `float` for us. Now we can do some

```
In [11]: ▶ a = a*2
print(a)

[2.  4.  6.  8.  2.]
```

All operations in Numpy as done in a 'vectorized' way, meaning everything list done 'element-wise'. There is no need to use a for-loop t elements, since Numpy will essentially do this for us:

```
In [12]: ▶ a = 2*a*a + a + 3
print(a)

[ 13.  39.  81. 139.  13.]
```

Python's Data Containers

Python's ease of use is one it's main appeals. This ease of use comes from Python's ability to mix and match data of different types wit such as the `list` we saw above. In addition to the `list`, there is also the `dict` and `tuple`. The differences are:

- `list` let's you read and write elements using numerical indices
- `dict` let's you access elements by name
- `tuple` let's you read elements by index, but forbids you from writing.

There is one additional way to collect data into a bundle: as `attributes` of an `object`.

Let's quickly explore each of these below:

```
In [13]: ▶ e = list()
e.append(np.array([1, 3, 4], dtype=int))
e.append(1.0)
e.append('two')
print(e)
```

```
[array([1, 3, 4]), 1.0, 'two']
```

```
In [14]: ▶ d = dict()
d['dave'] = 1.0
d['bob'] = 1
d['fred'] = True
d['george'] = 'one'
print(d)
```

```
{'dave': 1.0, 'bob': 1, 'fred': True, 'george': 'one'}
```

```
In [15]: ▶ t = tuple(e)
print(t)
```

```
(array([1, 3, 4]), 1.0, 'two')
```

And finally, let's look at the object :

```
In [16]: ▶ class NewTypeOfObject:
pass
```

```
In [17]: ▶ obj = NewTypeOfObject()
obj.bob = np.array([1, 3, 5], dtype=float)
obj.dave = 1.0
```

Overview of Volumetric Images

Comparison of 2D and 3D Images

We are all used to 2D digital pictures. When zooming tightly on such an image we are familiar with seeing the "pixels" of the image. As images are just a stack of 2D images, and the pixels are usually called "voxels" indicating they are a "volume element".

Color 2D images are just a massive array of pixels, each containing a numerical value indicating its color. In fact, color images are a 3 each one indicating the intensity of the Red, Green, and Blue (RGB) at each location. When these 3 colors are mixed together they can produce all possible colors. So even 2D images are actually 3D arrays.

```
In [74]: ▶ import numpy as np
import matplotlib.pyplot as plt
from skimage import data
```

```
In [75]: ▶ im = data.coffee()  
plt.imshow(im);
```

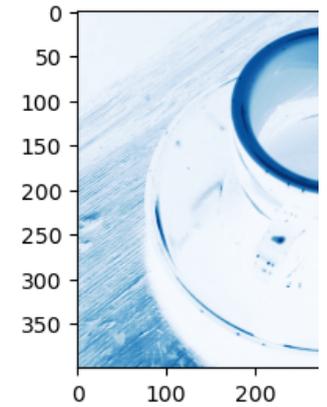
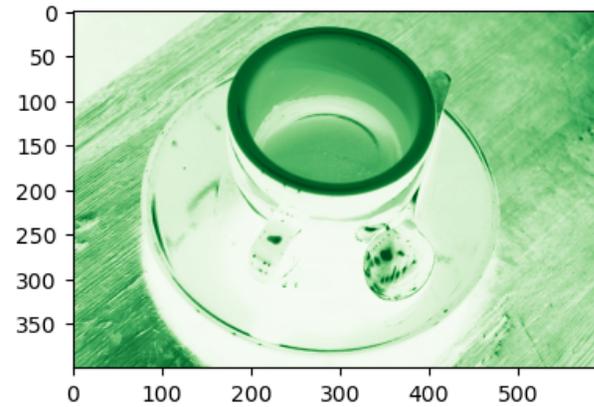
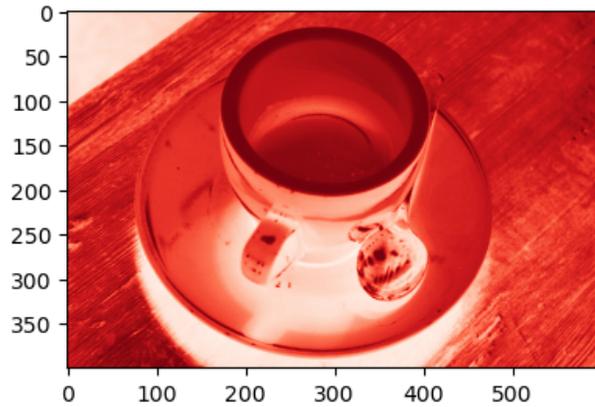


Color Images

As mentioned, color images are actually 3 images stacked together:

```
In [76]: ▶ print(im.shape)  
  
(400, 600, 3)
```

```
In [77]: ▶ fig, ax = plt.subplots(1, 3, figsize=[15, 5])
ax[0].imshow(im[... , 0], cmap=plt.cm.Red)
ax[1].imshow(im[... , 1], cmap=plt.cm.Green)
ax[2].imshow(im[... , 2], cmap=plt.cm.Blue);
```

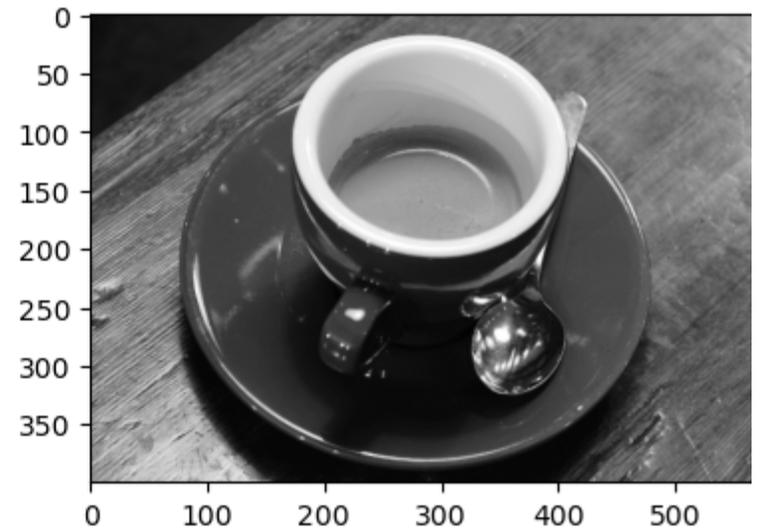
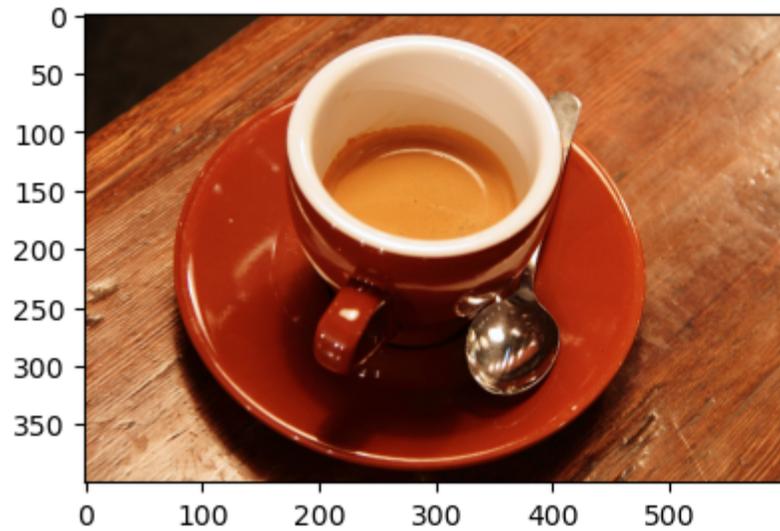


Grayscale Images

When dealing with 'technical' or 'scientific' images, we usually only want 'grayscale' images where the color information is discarded at some scalar intensity value at each location.

```
In [78]: ▶ from skimage.color import rgb2gray
fig, ax = plt.subplots(1, 2, figsize=[10, 5])
ax[0].imshow(im)
im2 = rgb2gray(im)
print(im2.shape)
ax[1].imshow(im2, cmap=plt.cm.gray);
```

(400, 600)



Zooming in closely to a spot in the 2D grayscale images reveals the pixels, which contain scalar values:

```

In [79]: ▶ from skimage.color import rgb2gray
import matplotlib as mpl
import matplotlib.patches as patches
mpl.rcParams['text.color'] = 'red'

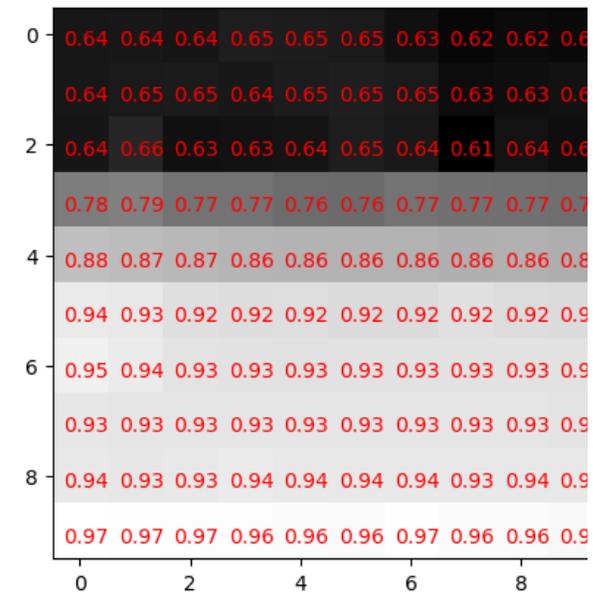
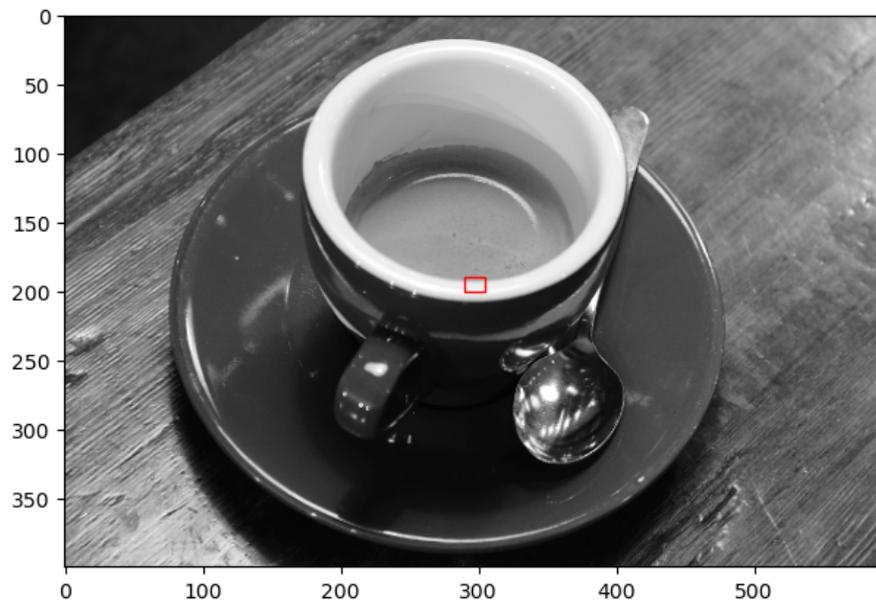
fig, ax = plt.subplots(1, 2, figsize=[16, 8])

ax[0].imshow(im2, cmap=plt.cm.gray)
rect = patches.Rectangle((290, 190), 15, 10, linewidth=1, edgecolor='r', facecolor='none')
ax[0].add_patch(rect)

temp = im2[190:200, 290:305]
ax[1].imshow(temp, cmap=plt.cm.gray)

x, y = np.meshgrid(range(temp.shape[0]), range(temp.shape[1]))
x = x.flatten()
y = y.flatten()
for i, j in zip(x, y):
    ax[1].annotate(np.around(temp[i, j], decimals=2), xy=(j-0.3, i+0.2))

```



3D or Volumetric Images

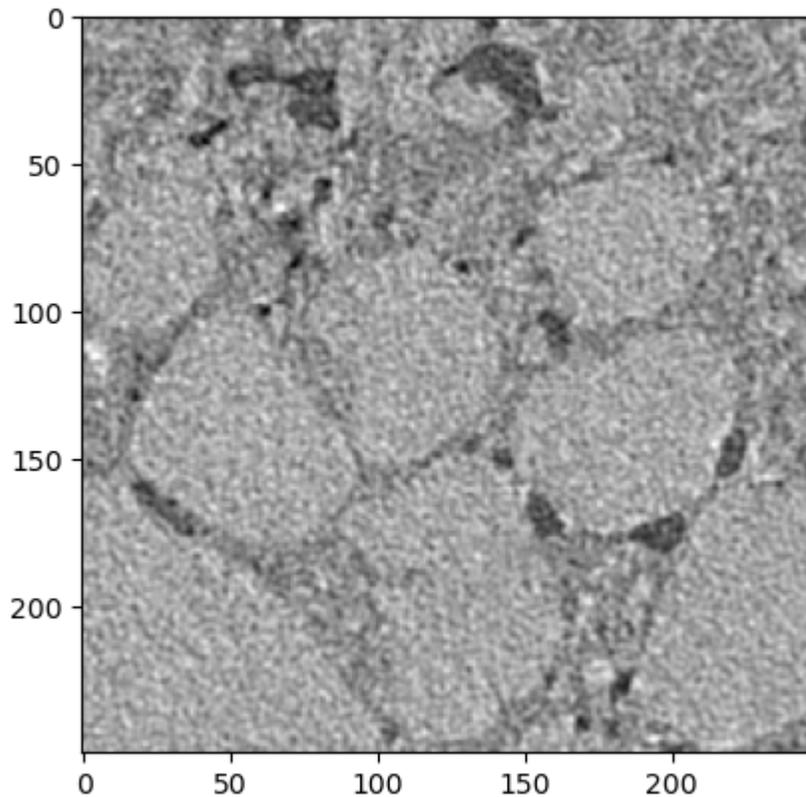
Now let's look at a 3D image. The `imageio` package is very helpful for reading in different file types. Volumetric images are often stored since these natively support multiple layers and are universally recognized as an image format. A small section of a sandstone is included

```
In [87]: ▶ import imageio
         im = imageio.volread('images/sandstone.tif')
         im.shape
```

```
Out[87]: (250, 250, 50)
```

When viewing a 3D image using tools normally meant for 2D images, be sure to extract a single slice:

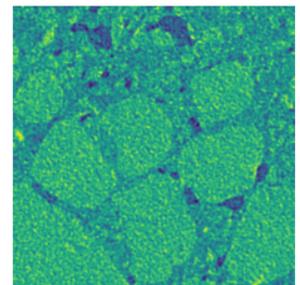
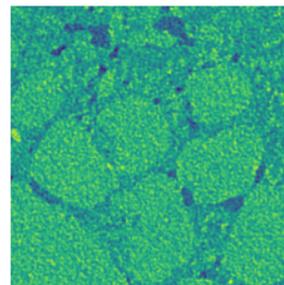
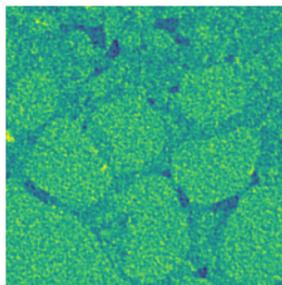
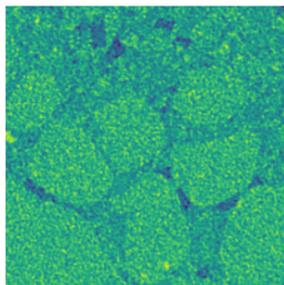
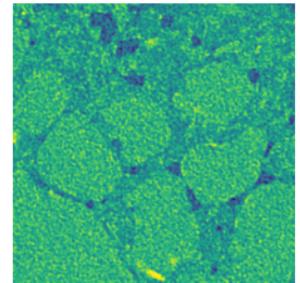
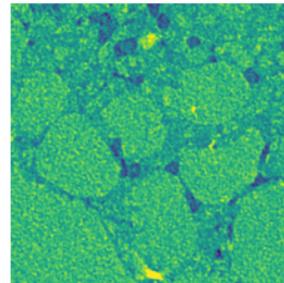
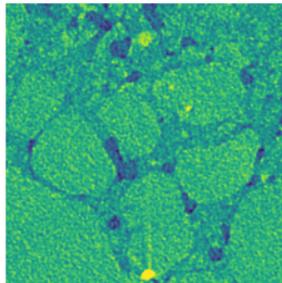
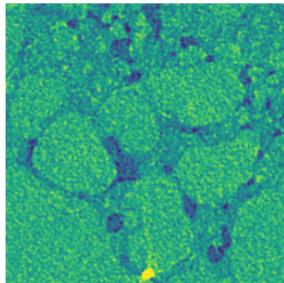
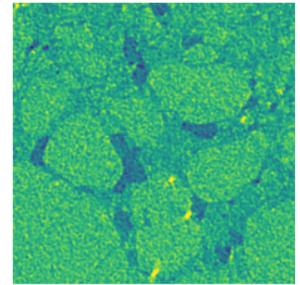
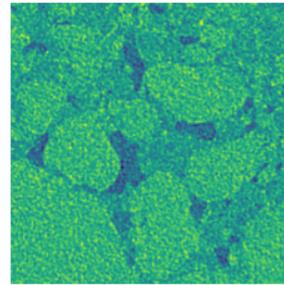
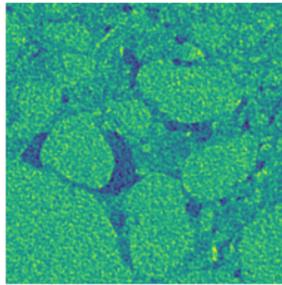
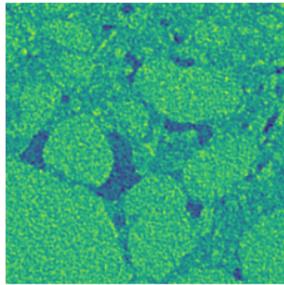
```
In [88]: ▶ plt.imshow(im[... , 25], cmap=plt.cm.gray);
```



Here we can see solid grains, dark voids, and some intermediate intensity material which is probably clay. This is classified as "unresolved" because we can't see the pores but we know they are there.

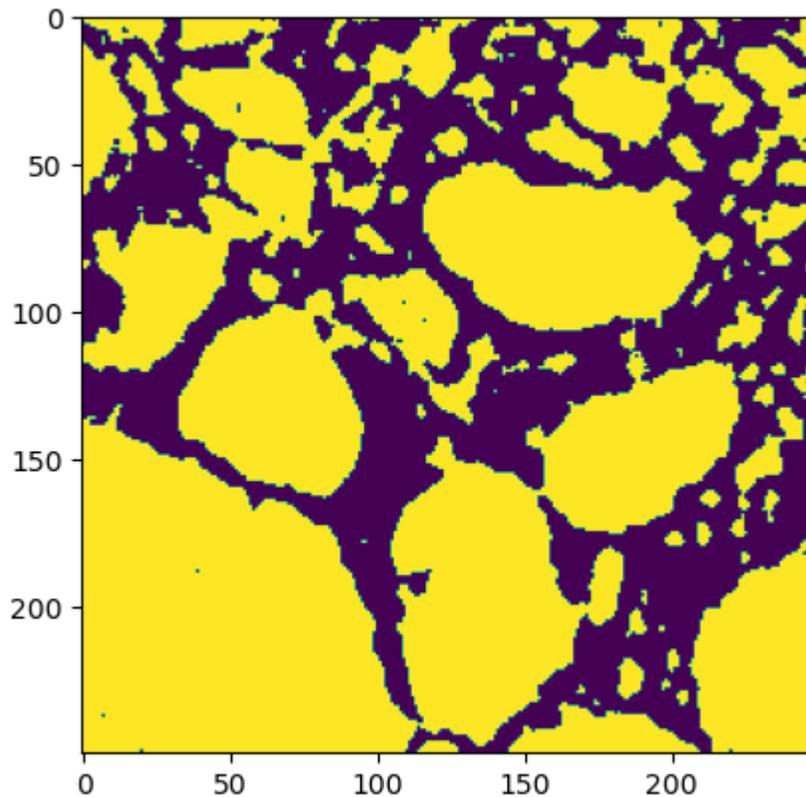
The above image is slice 25 from a stack of 50 slices. There is not a simple way to visualize 3D images in Jupyter notebooks, so we will

```
In [89]: ▶ import porespy as ps
N, M = 3, 5
fig, ax = plt.subplots(N, M, figsize=[20, 10])
k = 0
for i in range(N):
    for j in range(M):
        ax[i][j].imshow(im[...], k)
        ax[i][j].axis(False)
        k += 2
```



One of the most important yet challenging steps is the filtering of noise from the greyscale images obtained experimentally. As can be seen inside the solid grains are generally brighter than the other phases, but this is only an average and there are lots of dark voxels in the pores. Some averaging can be applied to remove or smooth the noise. For the sake of a simple demonstration, let's apply a median filter.

```
In [91]: ▶ import scipy.ndimage as spim
im2 = spim.median_filter(im, 5)
plt.imshow(im2[...], 0] > 158);
```



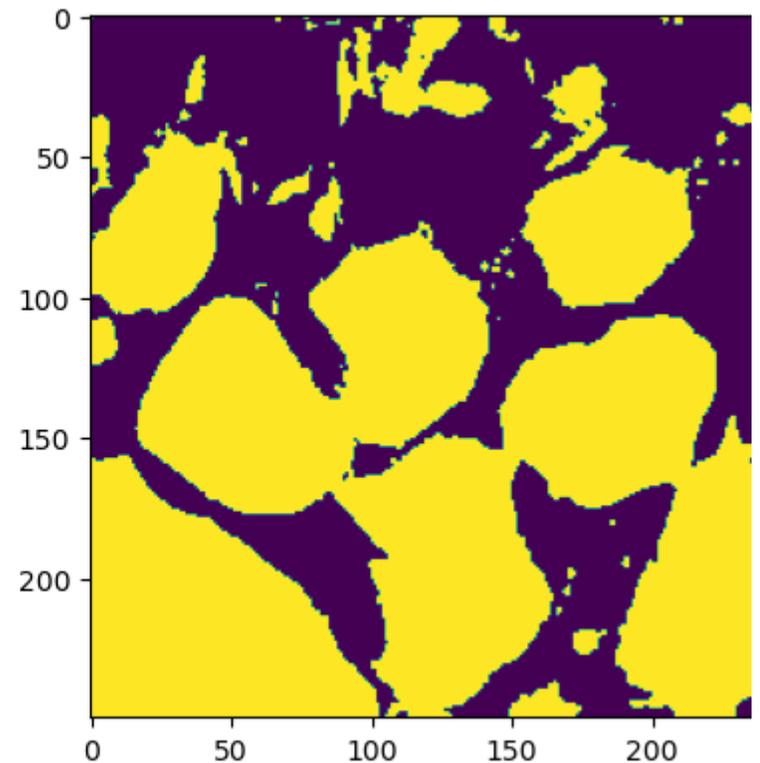
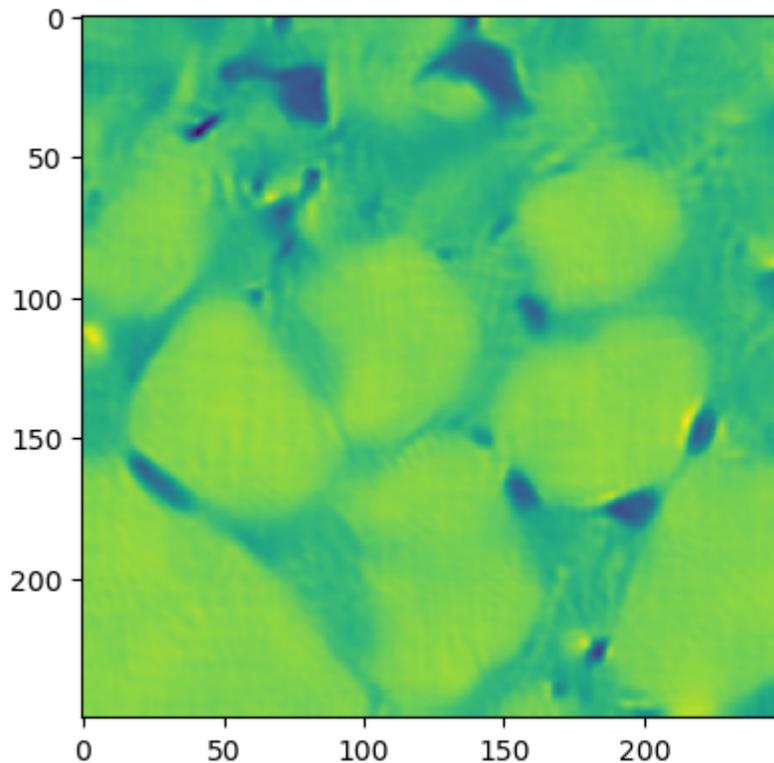
After applying the `median_filter` we can find (by trial and error) that all voxels with a value higher than 158 belong to solid.

Of course, a better filtering process should have been applied to really reduce the noise and aid this process. It's important to get the single stray voxel in the middle of a pore will drastically alter any quantitative analysis.

```
In [92]: ▶ from skimage.restoration import non_local_means, estimate_sigma
im3 = (im - im.min())/(im.max() - im.min())
im3 = im3[... , 25]
```

```
In [93]: ▶ s = estimate_sigma(im3)
im4 = non_local_means.denoise_nl_means(im3, sigma=s, patch_size=11, patch_distance=9, h=0.1)
im4 = (im4 - im4.min())/(im4.max() - im4.min())
```

```
In [94]: ▶ fig, ax = plt.subplots(1, 2, figsize=[10, 5])
ax[0].imshow(im4)
ax[1].imshow(im4 > 0.73);
```



Using PoreSpy for Quantitative Image Analysis

Finally we are ready to start analyzing images. The `porespy` package has many functions that are custom built for the study of porous media. It includes tools for calculating pore sizes, obtaining tortuosity, analyzing anisotropy and more.

PoreSpy is organized into the following modules:

- `generators` : Functions for generating artificial images useful for testing and validation
- `filters` : Functions for manipulating images to replace voxel values with some computed values
- `metrics` : Functions for analyzing images to extract quantitative information
- `simulations` : Functions for performing physical simulations directly on images
- `networks` : Functions for extracting pore networks from images for use in OpenPNM
- `visualization` : Functions for performing basic visualizations of 3D images
- `io` : A small set of functions for converting between various formats
- `tools` : Functions mostly used within PoreSpy itself

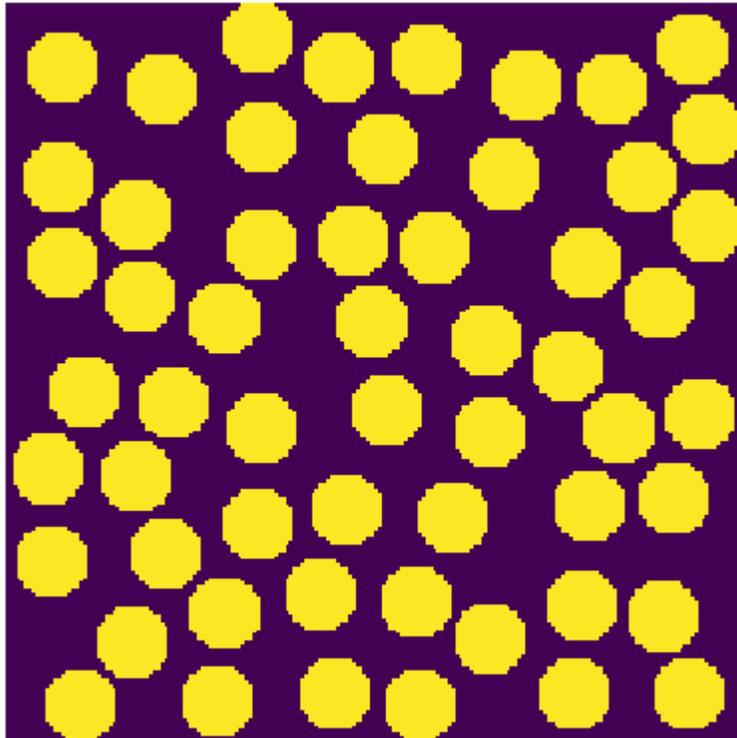
```
In [1]: ▶ import porespy as ps
import matplotlib.pyplot as plt
import numpy as np
from edt import edt
import scipy.ndimage as spim
```

Generating an Image for Demonstration

Let's start by generating an image of non-overlapping spheres using the 'random sequential addition' algorithm.

Note that all demonstrations will be done with 2D images to conserve CPU time and aid visualization

```
In [2]: ▶ im = ps.generators.rsa([200, 200], r=10, clearance=1)
plt.imshow(im, interpolation='none', origin='lower')
plt.axis(False);
```



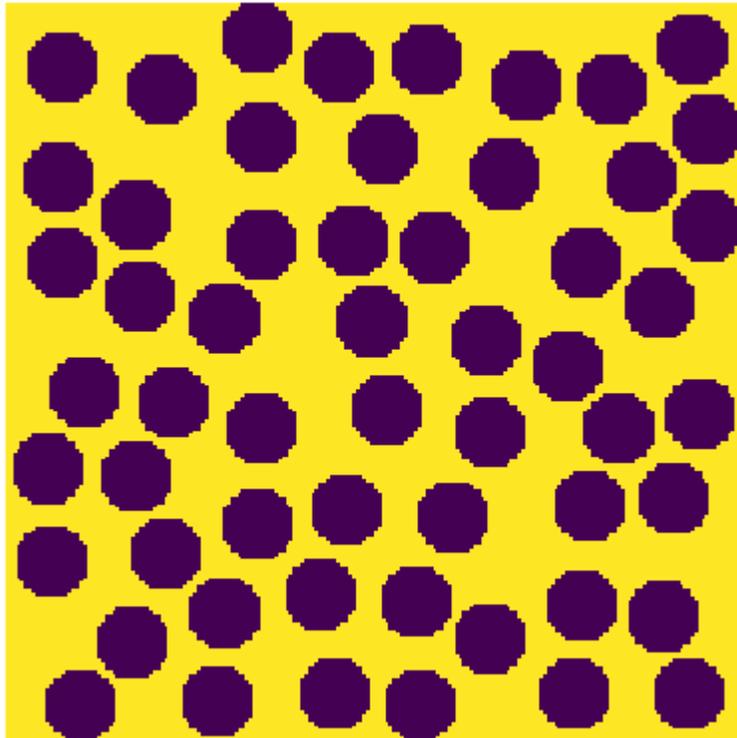
Defining the Image "Foreground"

The *foreground* or the *phase of interest* in PoreSpy is always the voxels marked `True` .

The `rsa` function has labelled the spheres as `True` . If we want the spheres to be solid grains then the we must invert the image.

This is very simple:

```
In [3]: ▶ im = ~im
plt.imshow(im, interpolation='none', origin='lower')
plt.axis(False);
```



Porosity

The most basic property of an image, and a sample of porous media in general, is the porosity.

This is defined as the ratio of void volume to bulk volume.

In terms of an image this means the number of "yellow" pixels divided by the total number of pixels in the image:

```
In [4]: ▶ porosity = np.sum(im)/np.size(im)
print(porosity)
```

```
0.573
```

Pore Size Distributions

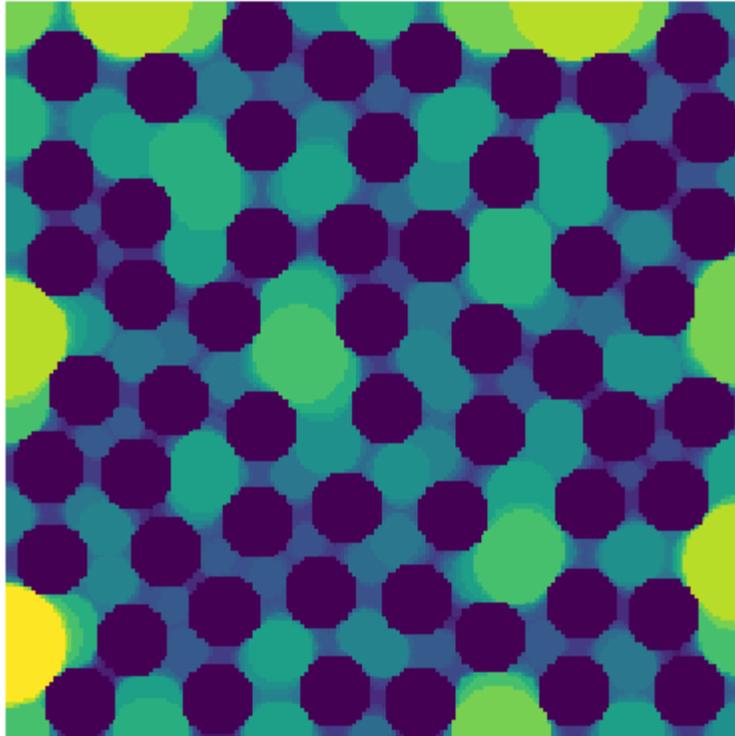
The spheres above all have a radius of 10 voxels, but the spaces between the spheres are distributed due to their random placement.

One of the common ways to estimate pore sizes is using the "local thickness".

PoreSpy has a `local_thickness` function, which draws the largest possible spheres in all the *foreground* pixels, and indicates the size voxel value it inserts into the image:

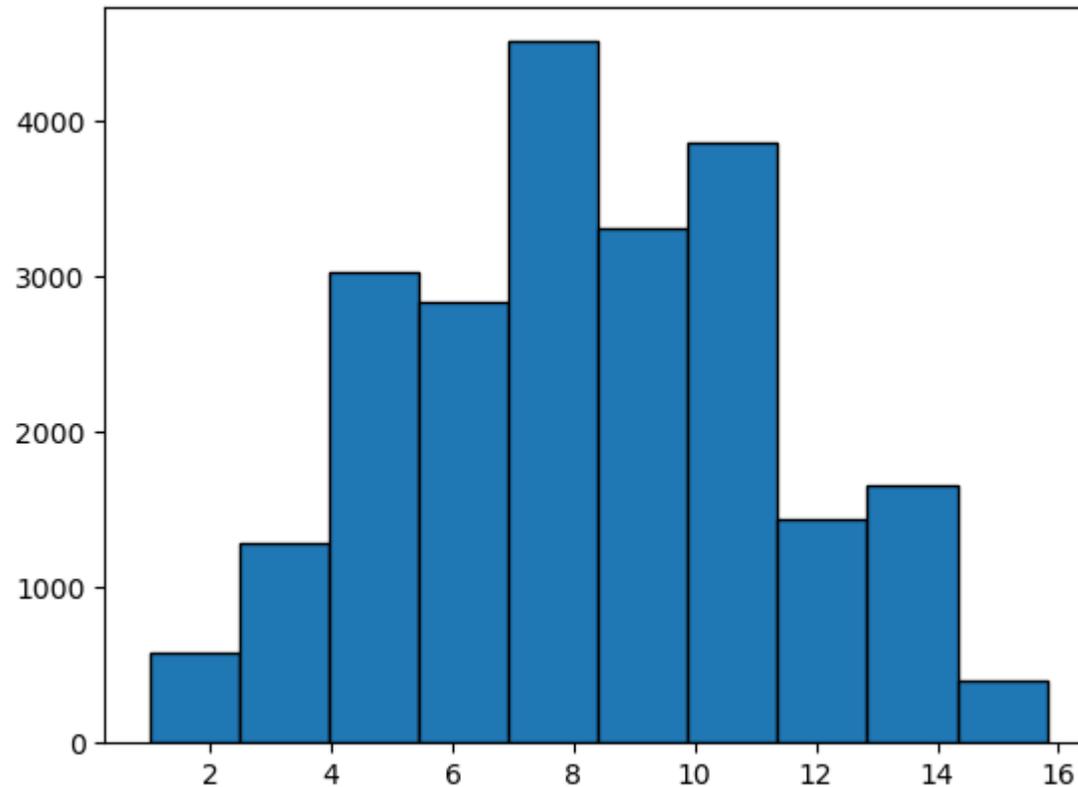
```
In [5]: ▶ lt = ps.filters.local_thickness(im)
plt.imshow(lt, interpolation='none', origin='lower')
plt.axis(False);
```

```
0%|          | 0/25 [00:00<?, ?it/s]
```



We can get a quick look at the pore size distribution by creating a histogram of the voxel values:

```
In [6]: ▶ plt.hist(lt[l<0].flatten(), bins=10, edgecolor='k');
```



The previous curve showed that the average pore radius is around 8 voxels. PoreSpy offers a more rigorous way to analyze this output module. In this case the results of the `local_thickness` filter are passed to the `pore_size_distribution` function:

```
In [7]: ▶ psd = ps.metrics.pore_size_distribution(lt, bins=15, log=False)
```

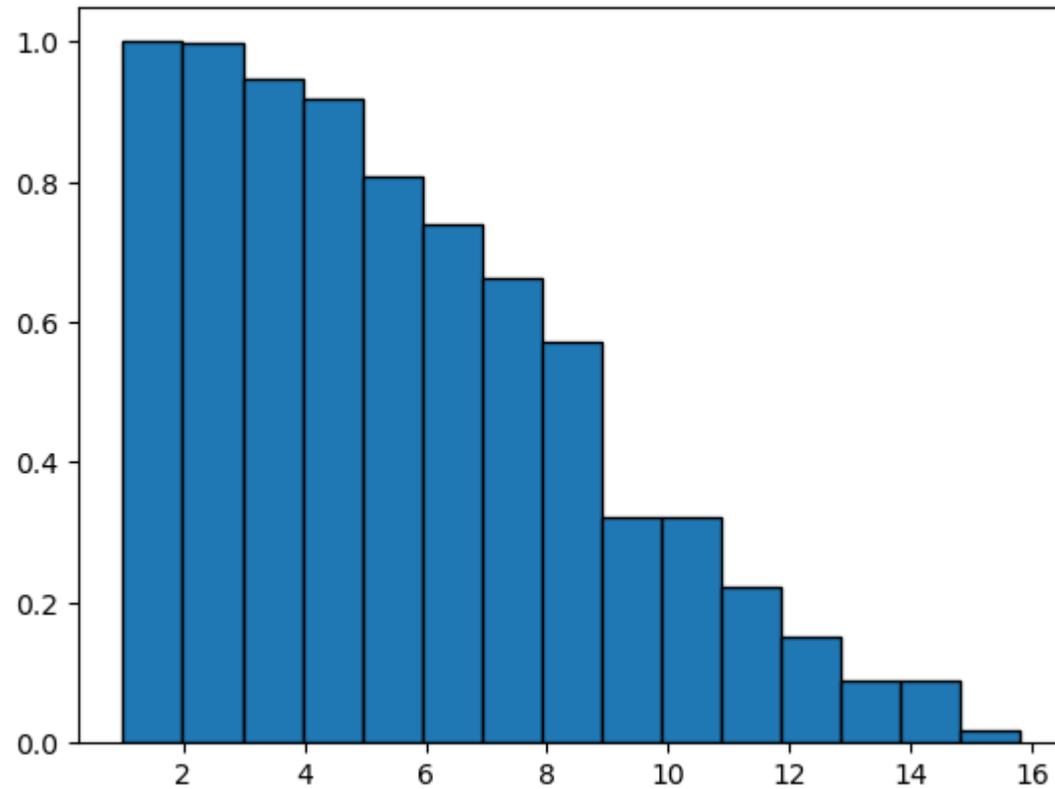
The `psd` object that is returned has various data stored as "attributes". This object can be printed to inspect these values:

In [8]: `print(psd)`

Item	Description
R	Array of size (15,)
pdf	Array of size (15,)
cdf	Array of size (15,)
satn	Array of size (15,)
bin_centers	Array of size (15,)
bin_edges	Array of size (16,)
bin_widths	Array of size (15,)

Using these values we can plot the cumulative distribution as follows:

```
In [9]: ▶ plt.bar(x=psd.R, height=psd.cdf, width=psd.bin_widths, edgecolor='k');
```

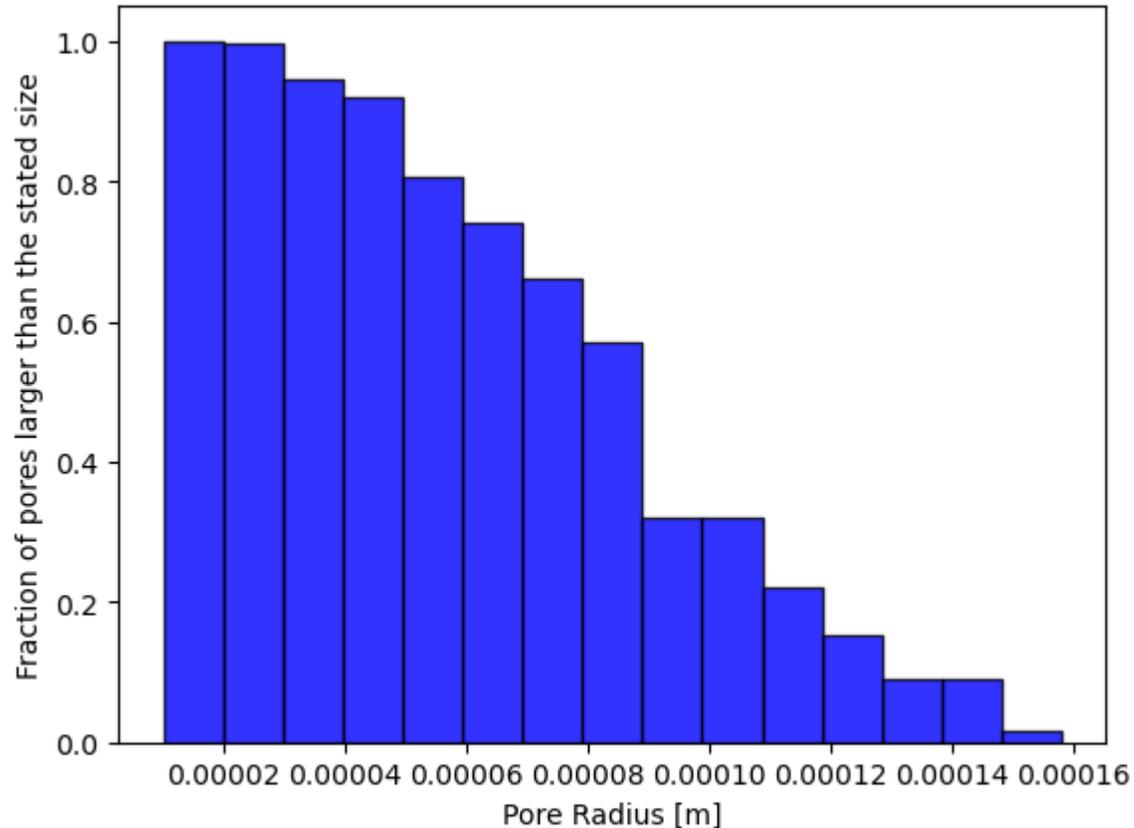


Setting Voxel Size

The above analysis was conducted in units of voxels. It is usually the case that physical sizes are desired, and moreover, all imaging te voxel size.

The above few steps can be re-run but with the voxel size specified (assume 10 um/voxel):

```
In [10]: ▶ psd = ps.metrics.pore_size_distribution(lt, bins=15, log=False, voxel_size=1e-5)
plt.bar(x=psd.R, height=psd.cdf, width=psd.bin_widths, edgecolor='k', color='b', alpha=0.8)
plt.xlabel('Pore Radius [m]')
plt.ylabel('Fraction of pores larger than the stated size');
```

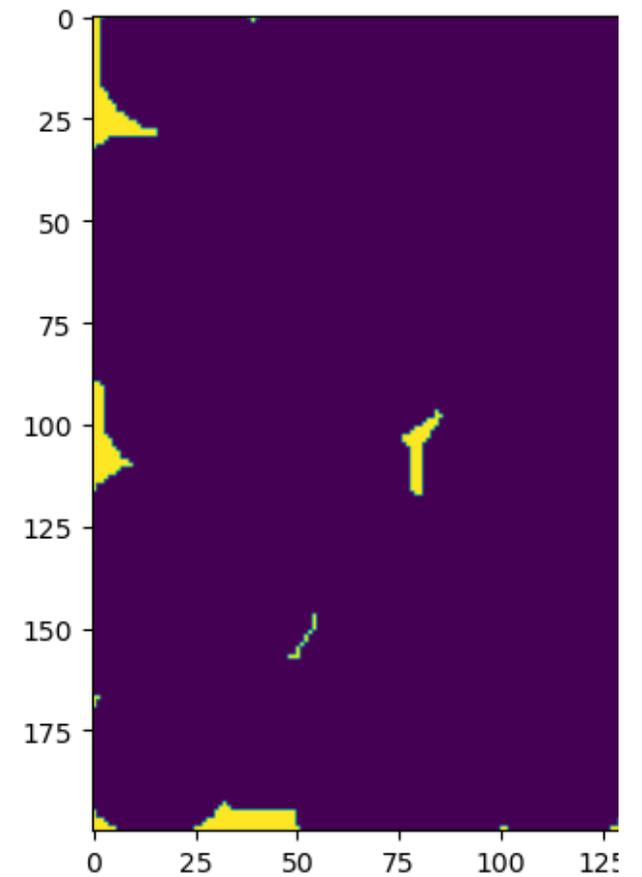
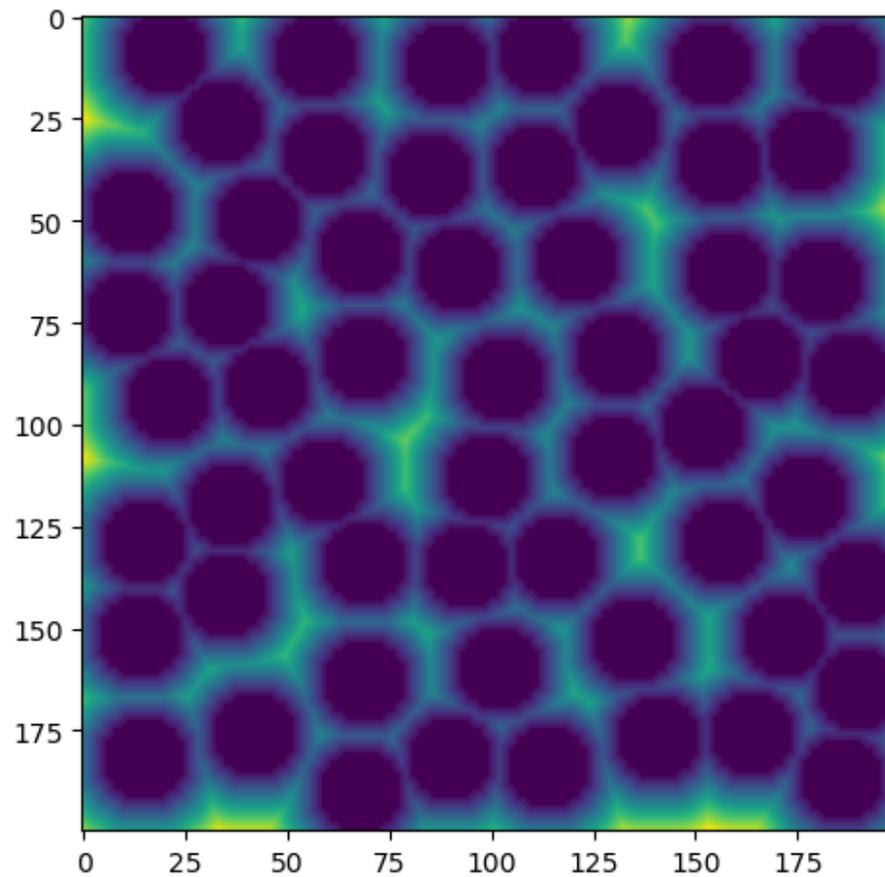


Background on How Local Thickness is Computed

It is instructive to look at how the local thickness is calculated, since this involves some elementary image operations which are used with dilation and erosion.

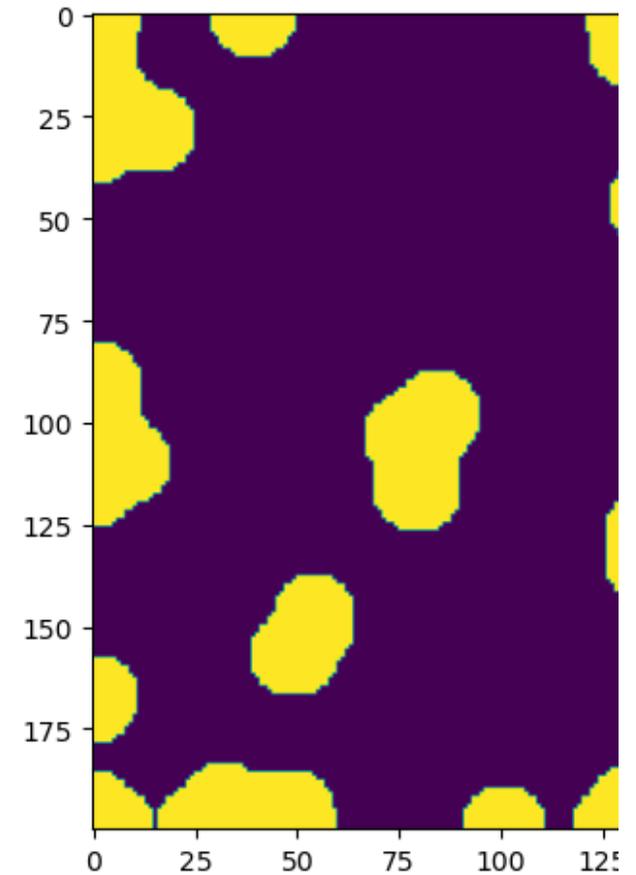
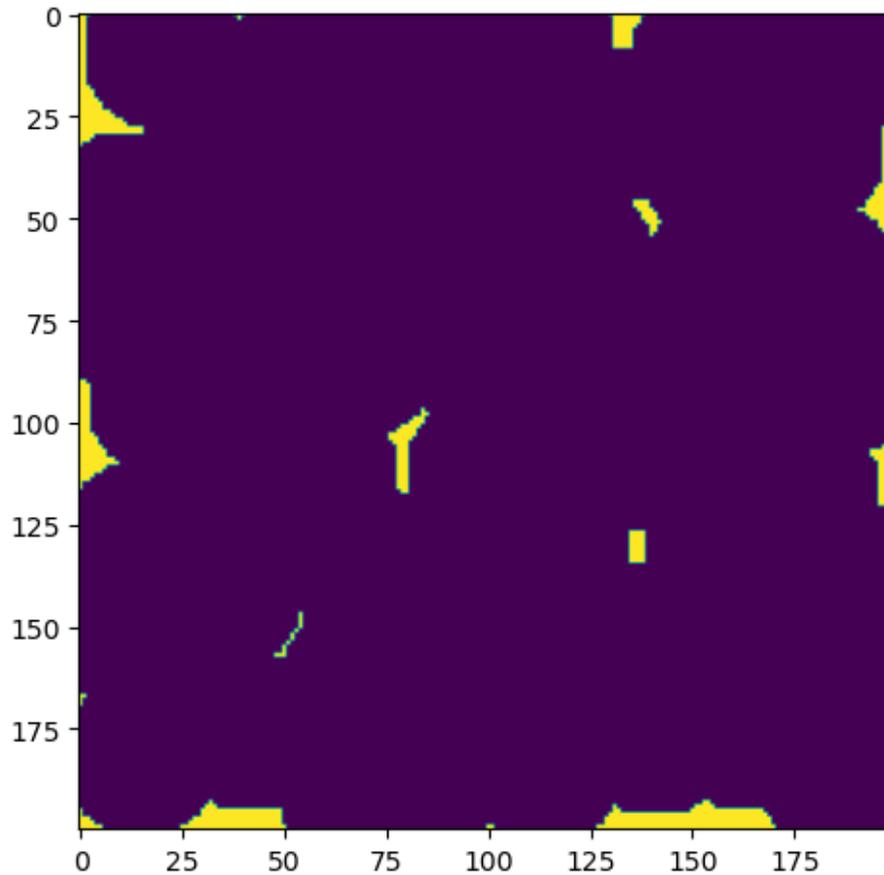
Step 1: Find all void voxels on which a sphere of size R can be drawn using a distance transform

```
In [11]: ▶ lt = np.zeros_like(im, dtype=int)
R = 10
dt = edt(im)
fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(dt)
ax[1].imshow(dt >= R);
```



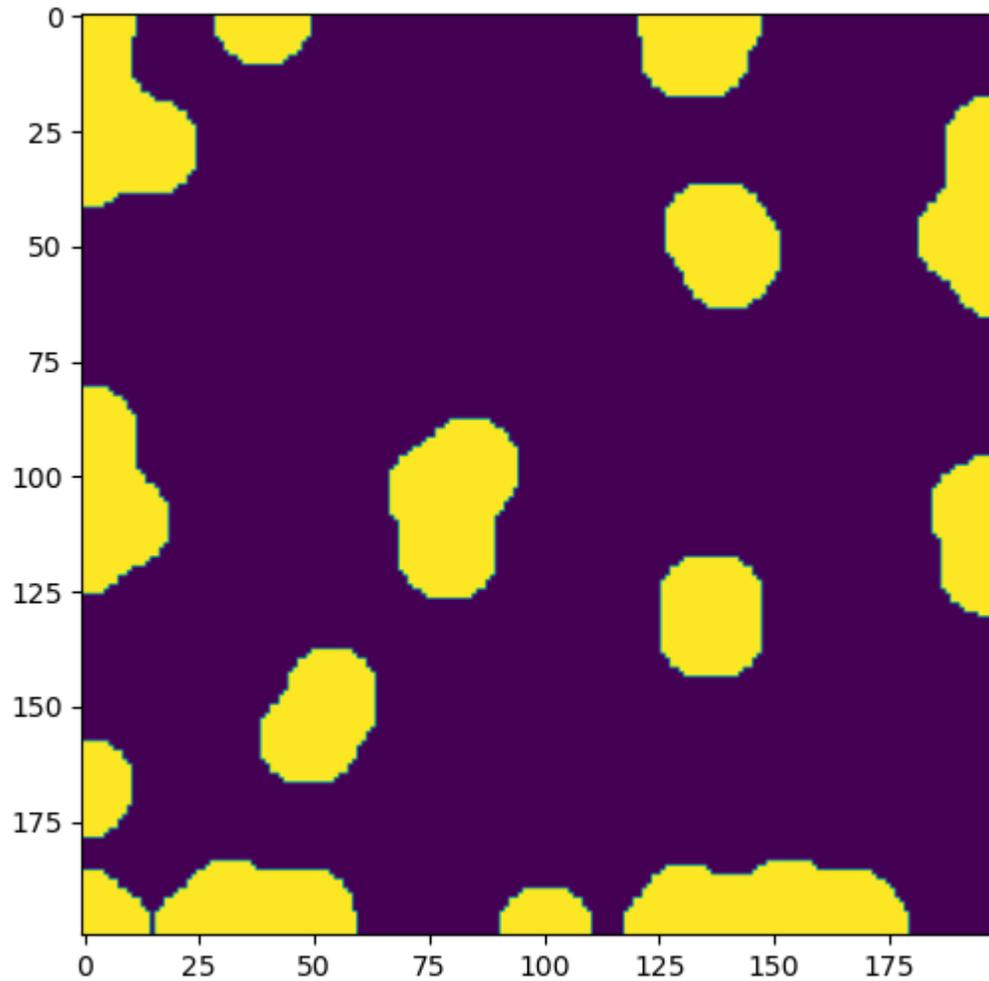
Step 2: Dilate the surviving voxels by R

```
In [12]: ▶ temp = spim.binary_dilation(dt >= R, structure=ps.tools.ps_round(r=R, ndim=2))
fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(dt >= R)
ax[1].imshow(temp);
```



Step 3: Mark these locations with the radius, unless they already have a larger value

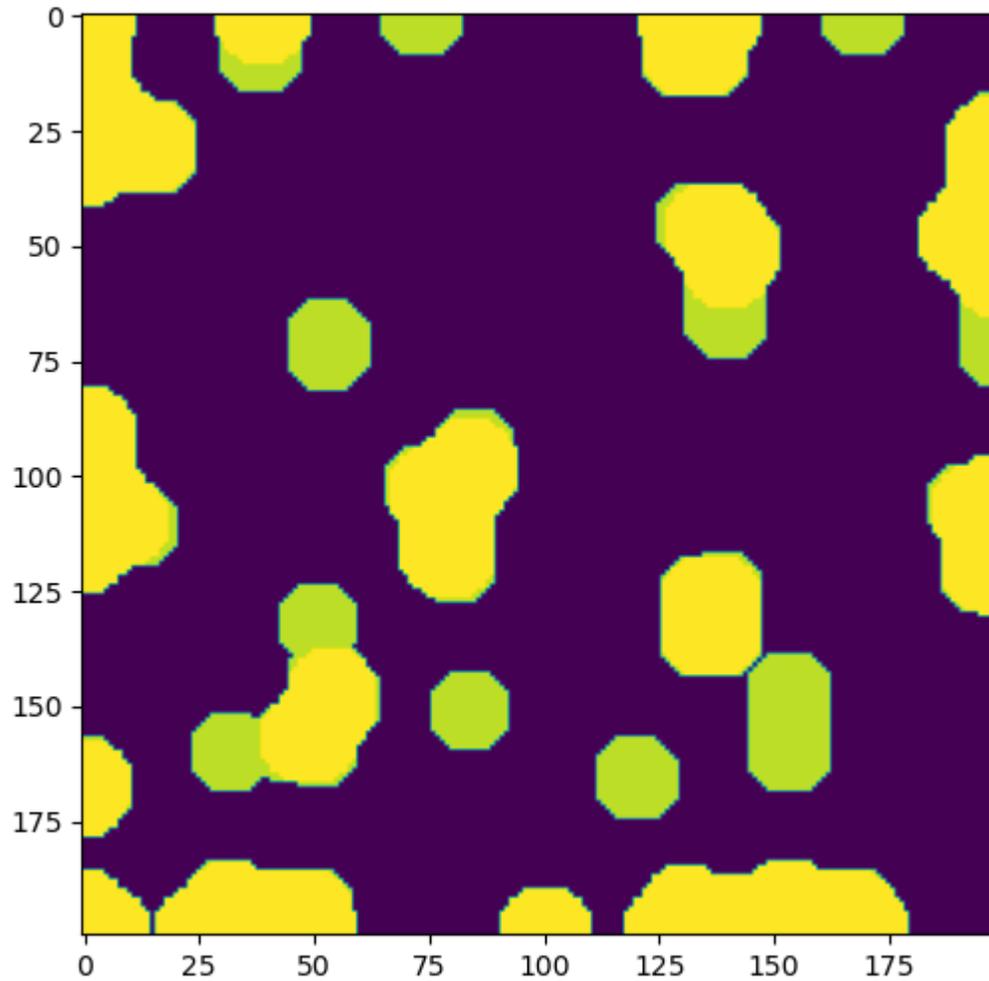
```
In [13]: ▶ lt = lt + R*temp*(lt == 0)
fig, ax = plt.subplots(1, 1, figsize=[6, 6])
ax.imshow(lt);
```



Step 4: Repeat with R=9

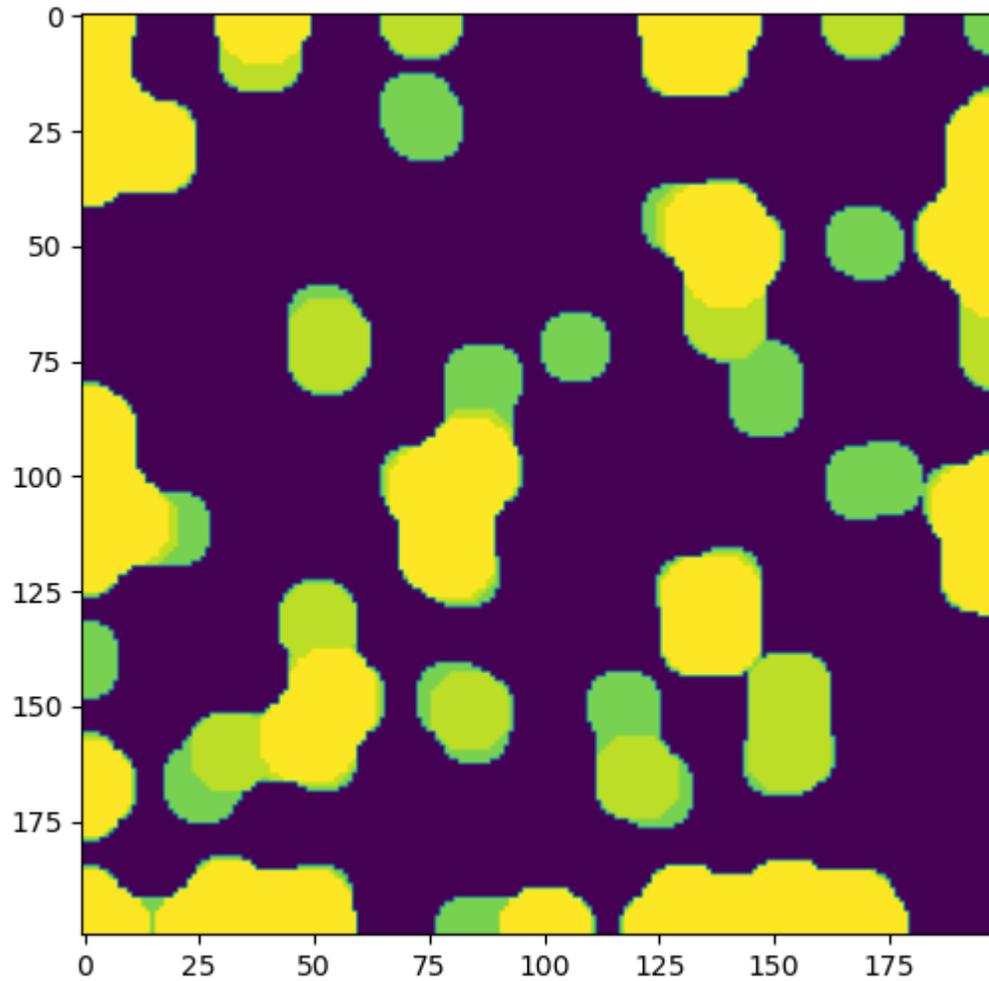
Now repeat steps 1 to 3 with a smaller value of R:

```
In [14]: ▶ R = 9
temp = spim.binary_dilation(dt >= R, structure=ps.tools.ps_round(r=R, ndim=2))
lt = lt + R*temp*(lt == 0)
fig, ax = plt.subplots(1, 1, figsize=[6, 6])
ax.imshow(lt);
```



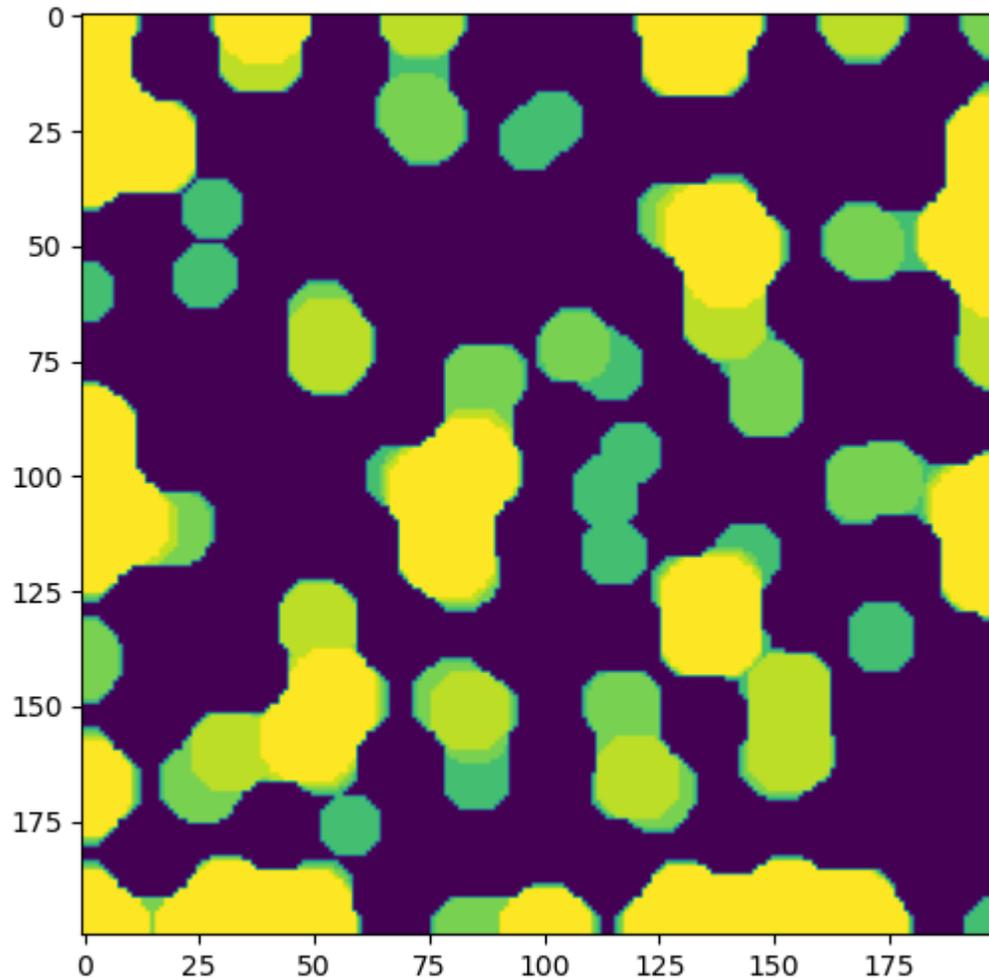
Repeat with $R=8$

```
In [15]: ▶ R = 8
temp = spim.binary_dilation(dt >= R, structure=ps.tools.ps_round(r=R, ndim=2))
lt = lt + R*temp*(lt == 0)
fig, ax = plt.subplots(1, 1, figsize=[6, 6])
ax.imshow(lt);
```



Repeat with $R=7$

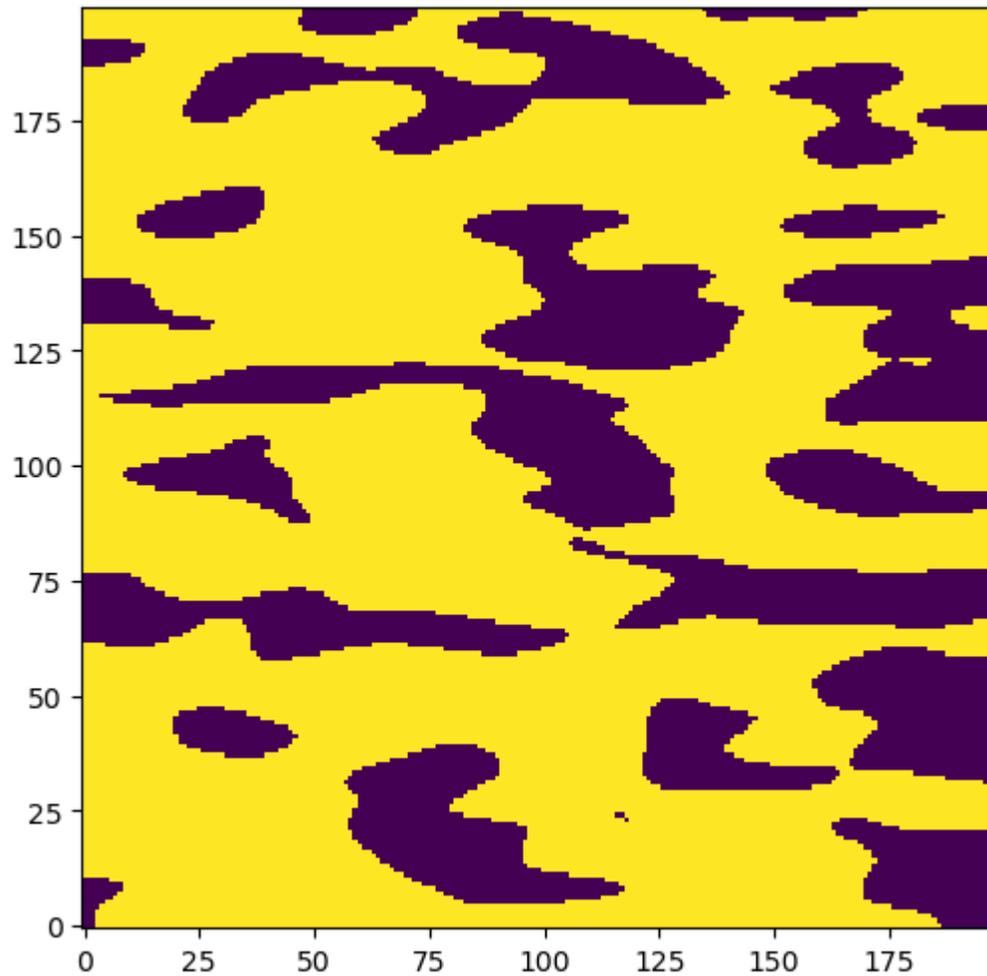
```
In [16]: ▶ R = 7
temp = spim.binary_dilation(dt >= R, structure=ps.tools.ps_round(r=R, ndim=2))
lt = lt + R*temp*(lt == 0)
fig, ax = plt.subplots(1, 1, figsize=[6, 6])
ax.imshow(lt);
```



Chord Length Distributions

Chords are lines drawn across the void space, spanning from one side of a pore to the other. Their length therefore indicates the pore :
They can be drawn in random directions, but the real power of chords is to detect anisotropy: pores that are elongated in one direction.

```
In [17]: ▶ im = ps.generators.blobs([200, 200], blobiness=[1.5, 0.5], porosity=0.7)
fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow(im, interpolation='none', origin='lower');
```



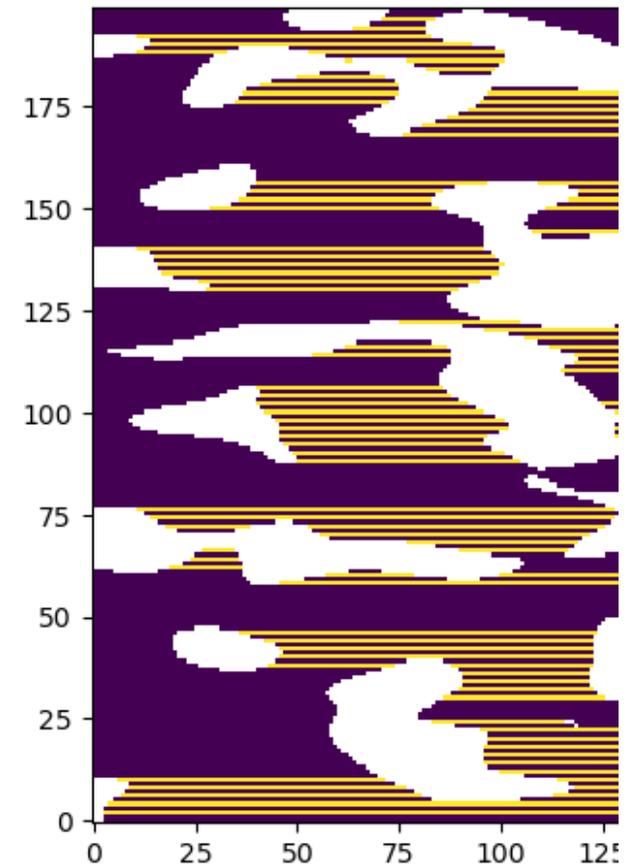
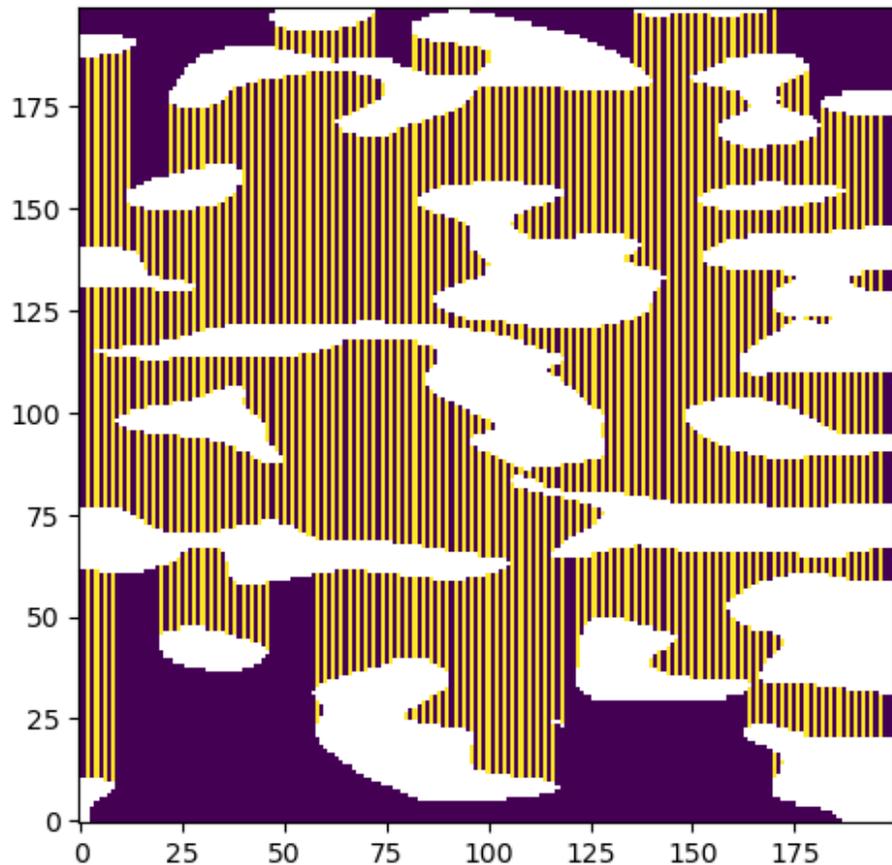
Draw Chords

The `filters` module contains 2 functions for drawing chords:

- `apply_chords` will add chords to the image, all in the same direction
- `apply_chords_3D` draws chords in all three principle directions, which only works for 3D images

```
In [18]: ▶ crds_x = ps.filters.apply_chords(im, axis=0)
         ▶ crds_y = ps.filters.apply_chords(im, axis=1)
```

```
In [19]: ▶ fig, ax = plt.subplots(1, 2, figsize=[12, 6])
         ▶ ax[0].imshow(crds_x/im, origin='lower', interpolation='none')
         ▶ ax[1].imshow(crds_y/im, origin='lower', interpolation='none');
```



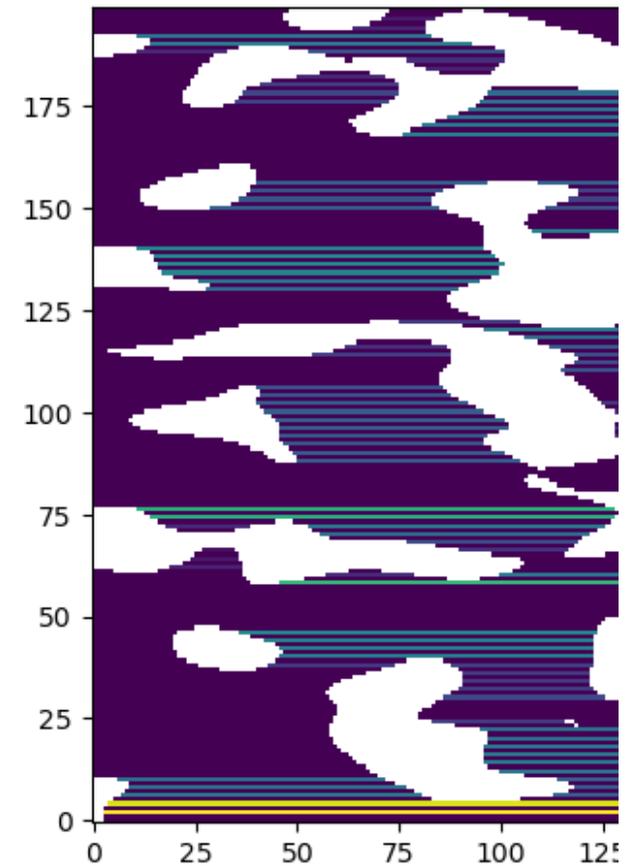
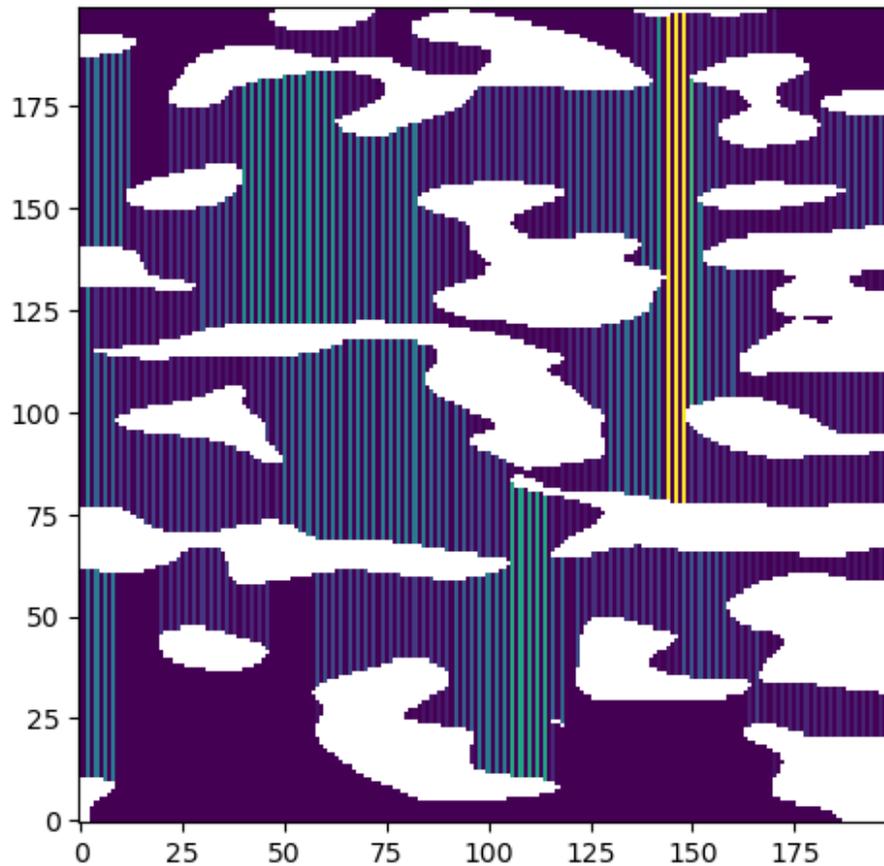
Note that chords touching the image boundary have been removed since these would be artificial shortened.

Analyze Chord Length

One of the benefits of drawing chords only along the principle axes is their length is equal to the number of voxels, which is easy to count.

```
In [20]: ▶ crds_x = ps.filters.region_size(crds_x)
          crds_y = ps.filters.region_size(crds_y)
```

```
In [21]: ▶ fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(crds_x/im, origin='lower', interpolation='none')
ax[1].imshow(crds_y/im, origin='lower', interpolation='none');
```

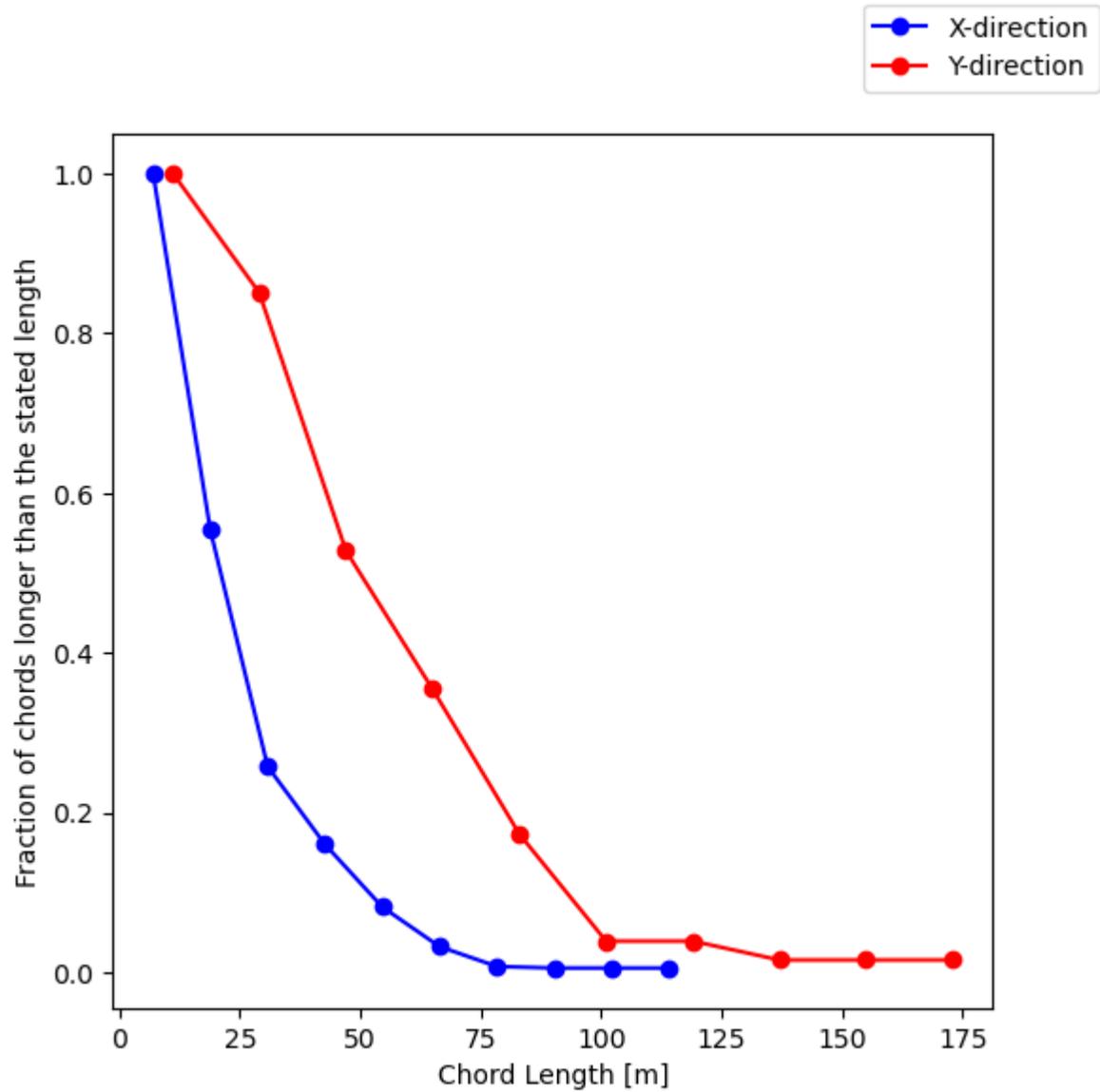


Get Chord Length Distributions

The `metrics` module contains a function for converting the chord lengths into property statistical distributions:

```
In [22]: ▶ cld_x = ps.metrics.chord_length_distribution(crds_x, bins=10)
cld_y = ps.metrics.chord_length_distribution(crds_y, bins=10)
```

```
In [23]: ▶ fig, ax = plt.subplots(figsize=[6, 6])
ax.plot(cld_x.L, cld_x.cdf, 'b-o', label='X-direction')
ax.plot(cld_y.L, cld_y.cdf, 'r-o', label='Y-direction')
ax.set_xlabel('Chord Length [m]')
ax.set_ylabel('Fraction of chords longer than the stated length')
fig.legend();
```



Survey of Other Available Analysis Tools in PoreSpy

The *porespy.org* website has extensive documentation

- Here is a [list \(https://porespy.org/_examples/filters/index.html\)](https://porespy.org/_examples/filters/index.html) of functions in the `filters` module
 - Here is a [list \(https://porespy.org/_examples/metrics/index.html\)](https://porespy.org/_examples/metrics/index.html) of functions in the `metrics` module
-

Determining Transport and Capillary Properties from Images

It is becoming increasingly common to perform simulations directly on an image, using the voxels as the computational mesh.

PoreSpy offers some limited functionality in this area:

- Effective diffusivity, aka formation factor or tortuosity
- Drainage simulations, aka mercury intrusion porosimetry
- Invasion percolation

PoreSpy currently does *not* have (but are working on):

- Permeability (Navier-Stokes equations e much harder than the Laplace equation)
- Imbibition

```
In [17]: ▶ import porespy as ps
import matplotlib.pyplot as plt
import numpy as np
```

Tortuosity

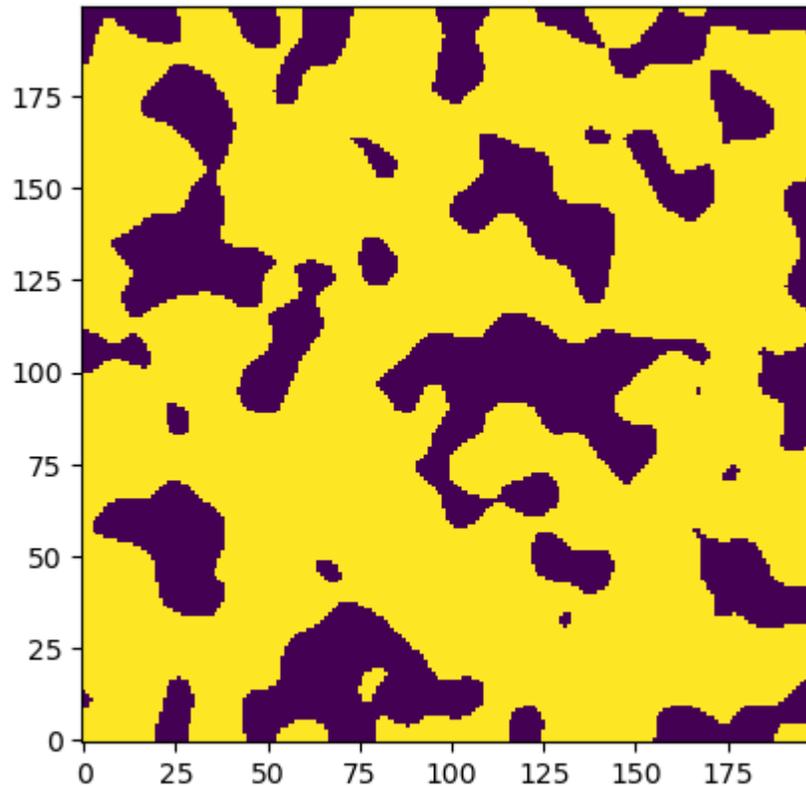
Tortuosity is a fitting factor to account for the reduction of diffusion rate beyond the effect of porosity. It is defined as:

$$\frac{D_{eff}}{D_{bulk}} = \frac{\epsilon}{\tau}$$

- D_{eff} is some fraction of coefficient in open space (i.e. $D_{eff}/D_{bulk} < 1.0$)
- The reduction in D_{eff} is *at least* equal to the reduced pore volume (i.e. $D_{eff}/D_{bulk} < \epsilon$)
- But there is an additional reduction since the diffusing molecules are not able to move *directly* across the domain
- This additional resistance is called *tortuosity*

Let's generate a 2D test image

```
In [18]: ▶ np.random.seed(0)
im = ps.generators.blobs([200, 200], porosity=0.7)
plt.imshow(im, origin='lower', interpolation='none');
```



Preparing the Image

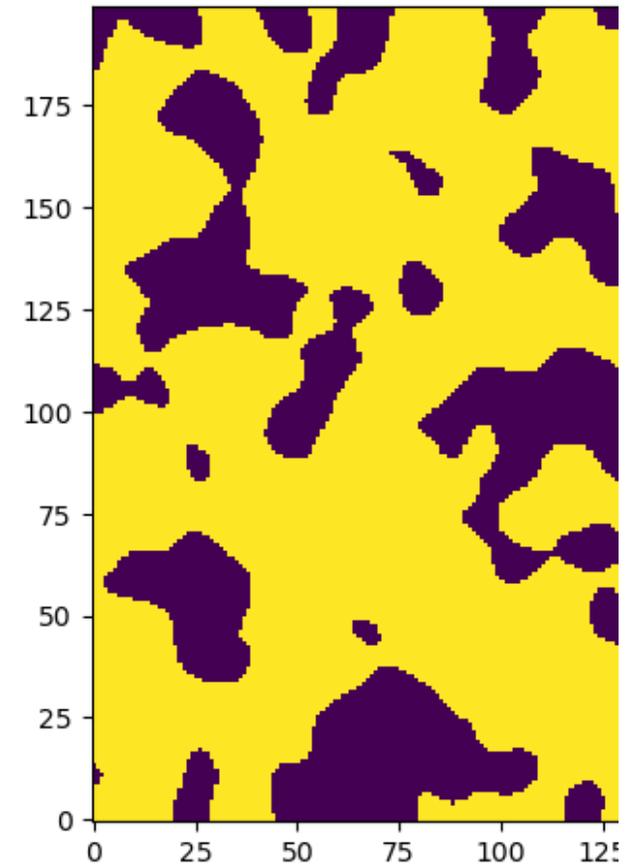
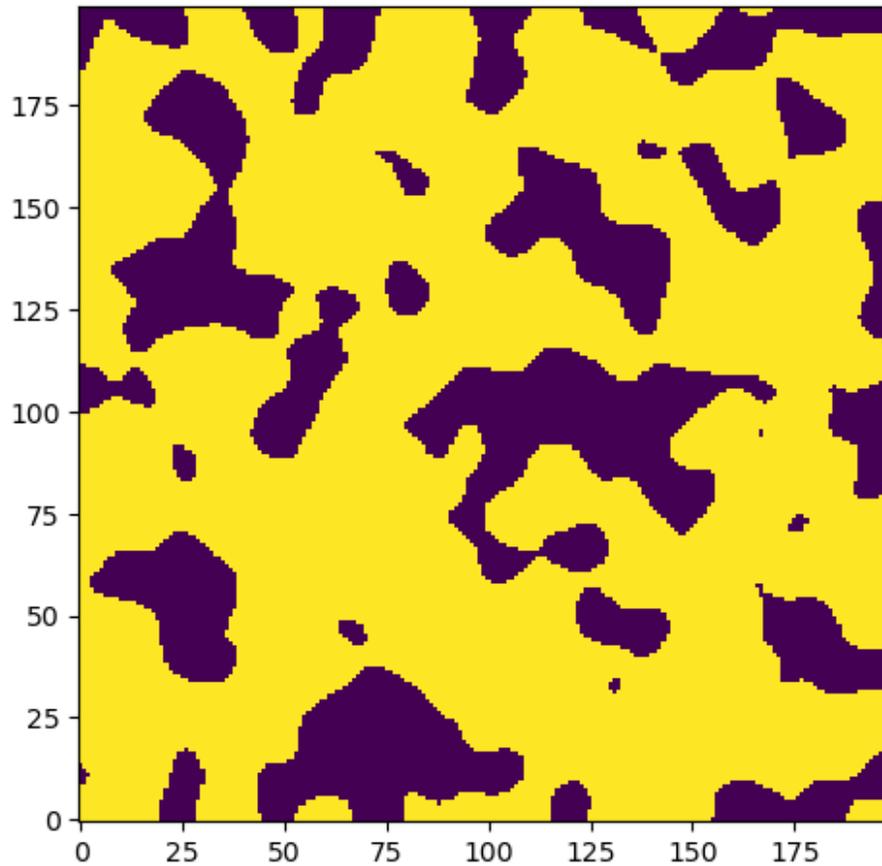
A few problems with this image:

- There are several 'blind pores' which will cause problems for the numerical solver
- There are also several pores on the edges which are not connected to the main percolating path

OpenCV has functions for cleaning this up:

```
In [19]: ▶ im1 = ps.filters.fill_blind_pores(im)
fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(im1, origin='lower', interpolation='none')

im2 = ps.filters.fill_blind_pores(im, surface=True)
ax[1].imshow(im2, origin='lower', interpolation='none');
```



Calling the Function

```
In [20]: ▶ tau_x = ps.simulations.tortuosity_fd(im2, axis=0)
tau_y = ps.simulations.tortuosity_fd(im2, axis=1)
```

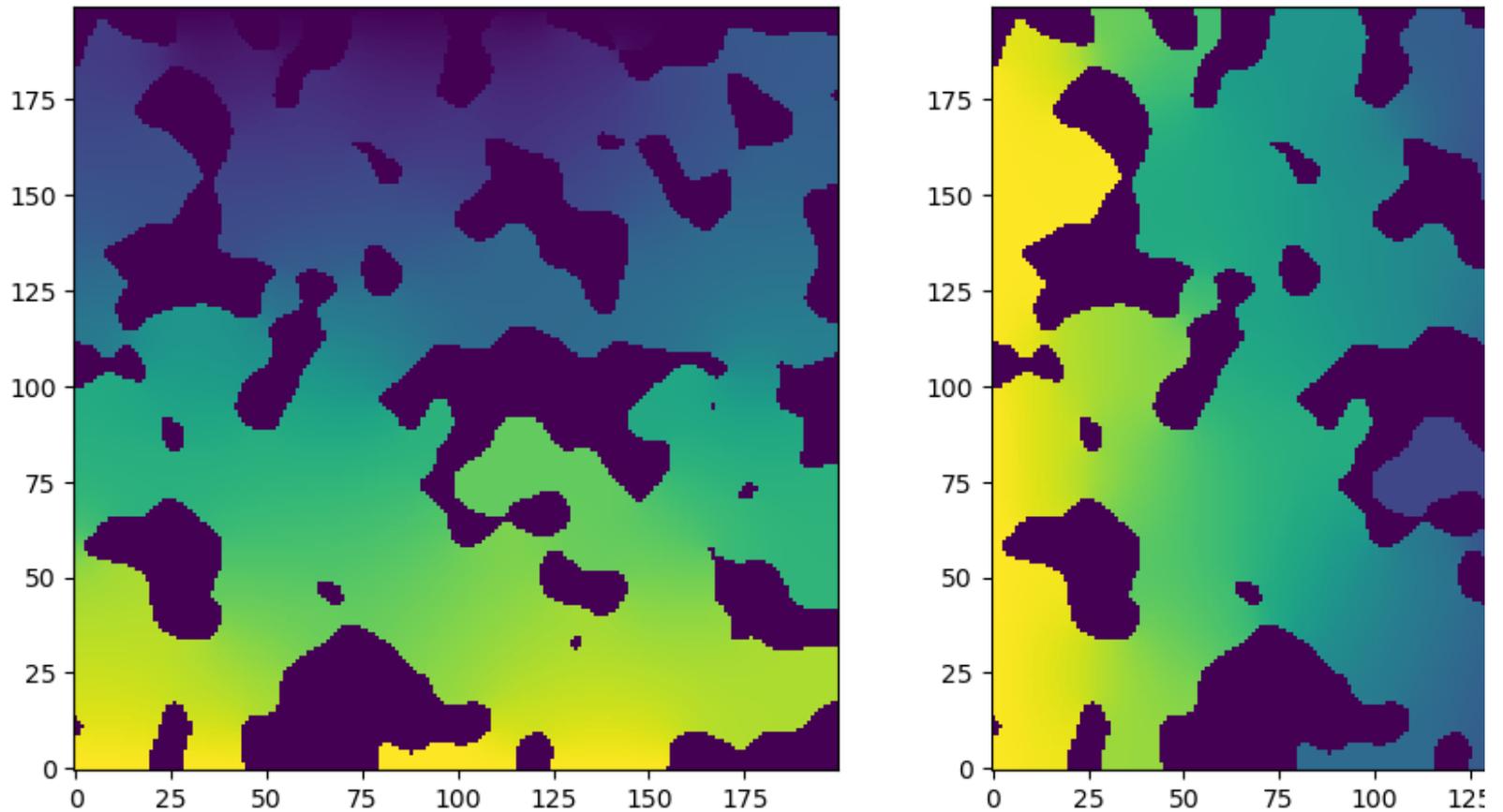
The returned objects contain several pieces of data as attributes, including the calculated tortuosity value, which we can inspect by print

```
In [21]: ▶ print(tau_x)
```

Item	Description
im	Image of size (200, 200)
tortuosity	1.8569242614864547
formation_factor	2.6298318389554662
original_porosity	0.7061
effective_porosity	0.7061
concentration	Image of size (200, 200)

And we can inspect the concentration distribution:

```
In [22]: ▶ fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(tau_x.concentration, origin='lower', interpolation='none')
ax[1].imshow(tau_y.concentration, origin='lower', interpolation='none');
```



Drainage and Porosimetry

The invasion of a non-wetting fluid can be simulated by drawing spheres with a radius corresponding to the applied capillary pressure:

$$R = -2\sigma \frac{\cos(\theta)}{P_C}$$

This allows us to insert spheres of size R to determine where the fluid will be invaded at a given P_C .

```
In [23]: ▶ mip = ps.simulations.drainage(im, sigma=0.465, theta=140, voxel_size=1e-5)
print(mip)
```

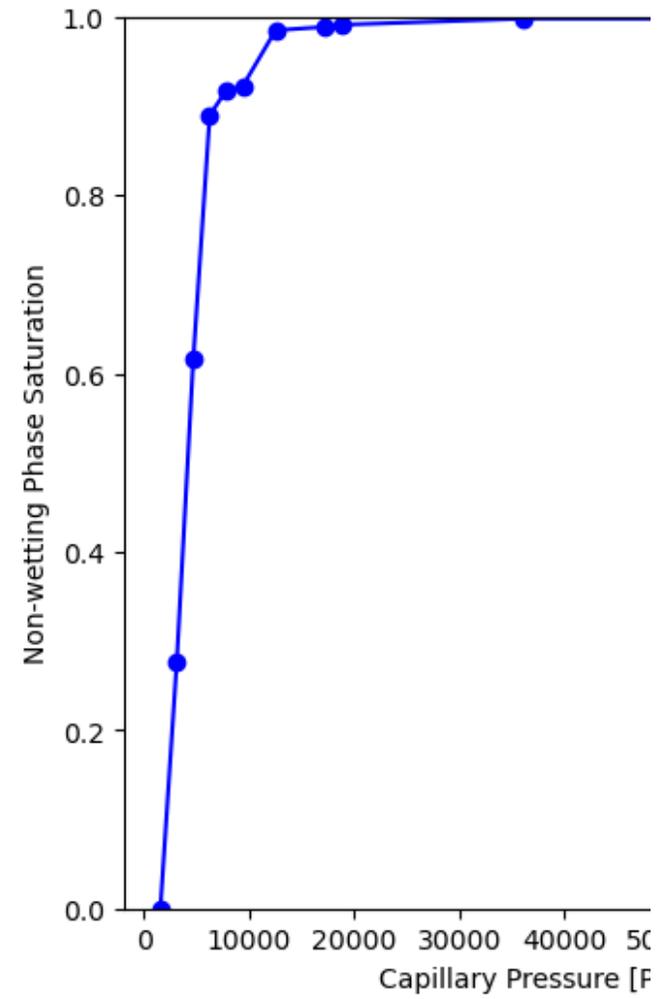
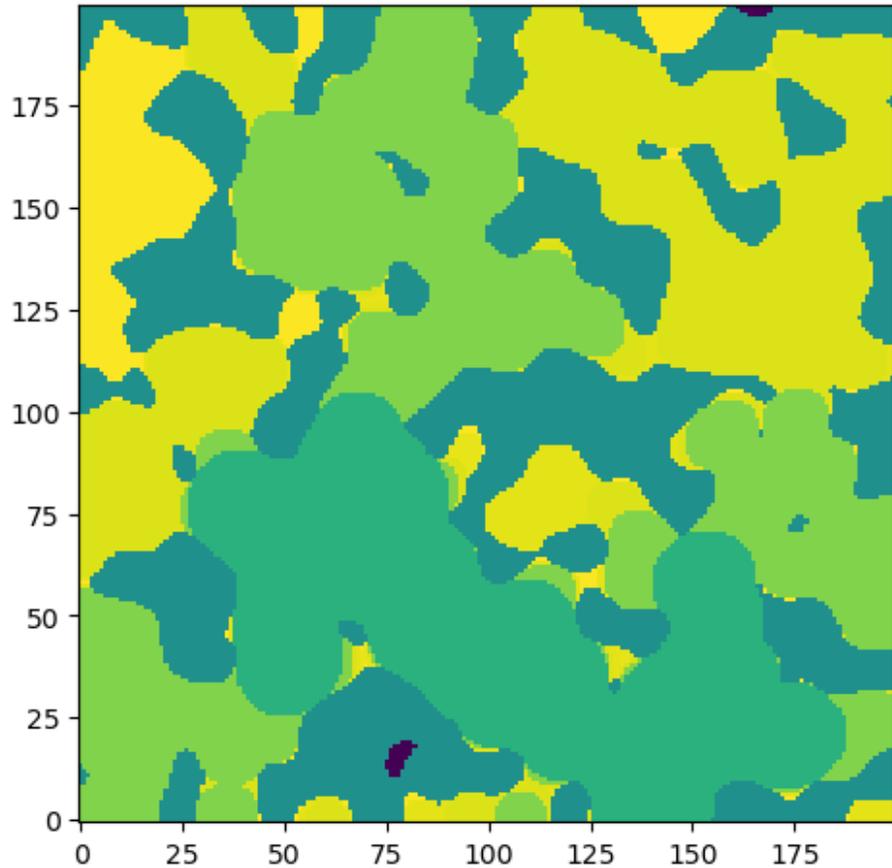
```
0%|          | 0/25 [00:00<?, ?it/s]
```

```
0%|          | 0/11 [00:00<?, ?it/s]
```

Item	Description
im_satn	Image of size (200, 200)
im_pc	Image of size (200, 200)
im_trapped	None
pc	Array of size (11,)
snwp	[0.0, 0.2760524742376816, 0.6157633735448247, 0.889318749340555, 0.91731438821612391, 0.9847360461435656, 0.9884992790067879, 0.9909260366475574, 0.9977490943621848, 0.9977490943621848]

And we can plot the results as follows:

```
In [24]: ▶ fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(mip.im_satn, origin='lower', interpolation='none')
ax[1].plot(mip.pc, mip.snwp, 'b-o')
ax[1].set_ylim([0, 1.0])
ax[1].set_xlabel('Capillary Pressure [Pa]')
ax[1].set_ylabel('Non-wetting Phase Saturation');
```

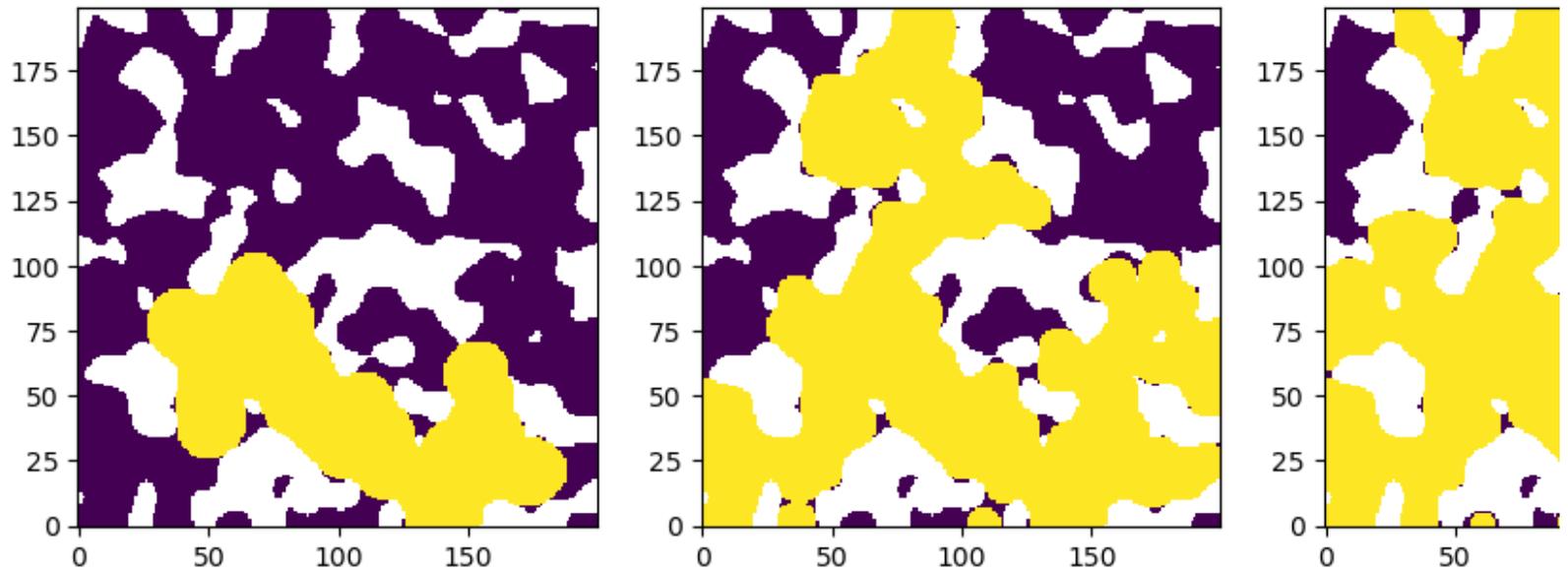


Obtaining Fluid Configurations

The `im_satn` array returned by the `drainage` function is designed so that all fluid configurations are contained in the same image. A configuration for a desired saturation can be obtained quickly as follows:

```
In [25]: ▶ s1 = (mip.im_satn < 0.3) * (mip.im_satn >= 0)
s2 = (mip.im_satn < 0.7) * (mip.im_satn >= 0)
s3 = (mip.im_satn < 0.9) * (mip.im_satn >= 0)

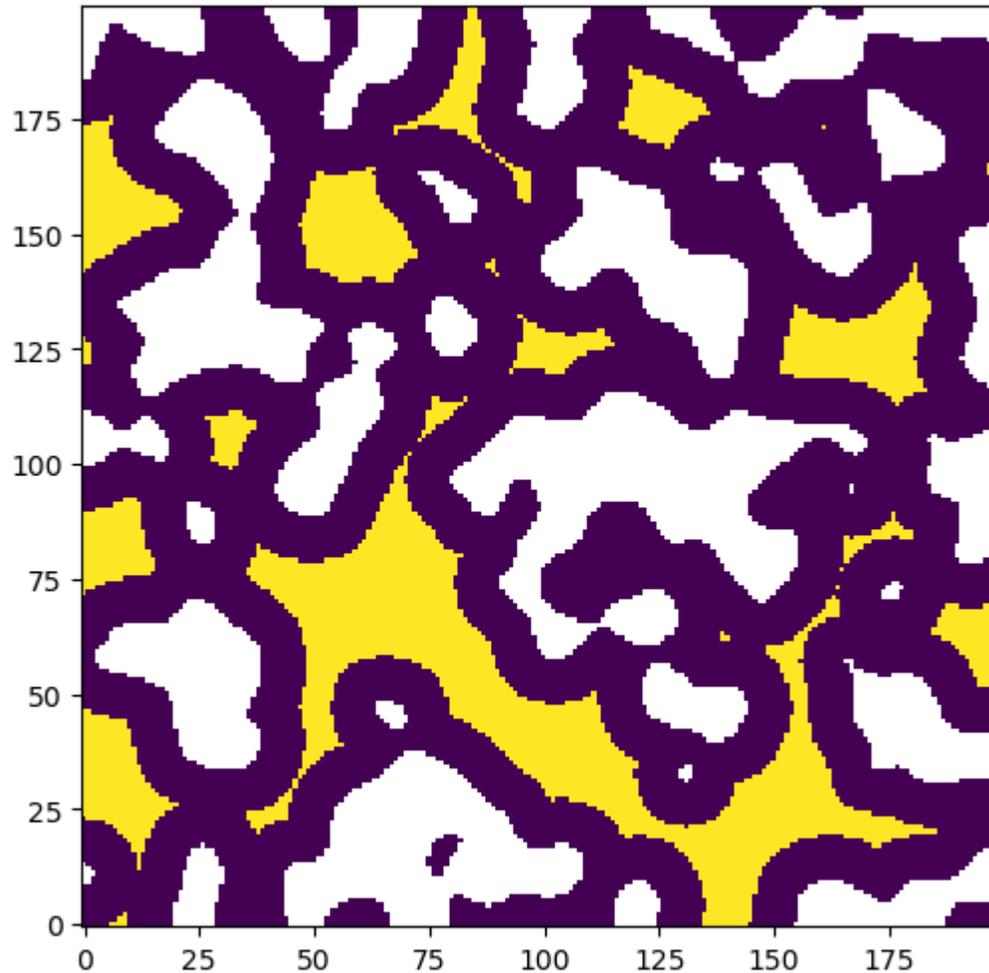
fig, ax = plt.subplots(1, 3, figsize=[12, 6])
ax[0].imshow(s1/im, origin='lower', interpolation='none')
ax[1].imshow(s2/im, origin='lower', interpolation='none')
ax[2].imshow(s3/im, origin='lower', interpolation='none');
```



Background Simulating Drainage

Like the local thickness filter, the drainage simulation is done by progressively adding smaller spheres, but there is one difference: any to the inlet are removed. This is outlined below:

```
In [26]: ▶ from edt import edt
dt = edt(im)
fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow((dt > 10)/im, origin='lower', interpolation='none');
```



Each yellow voxel is a location where a sphere of radius 10 *could* be drawn. But before we do that we should trim voxels that are not c

We can do this by:

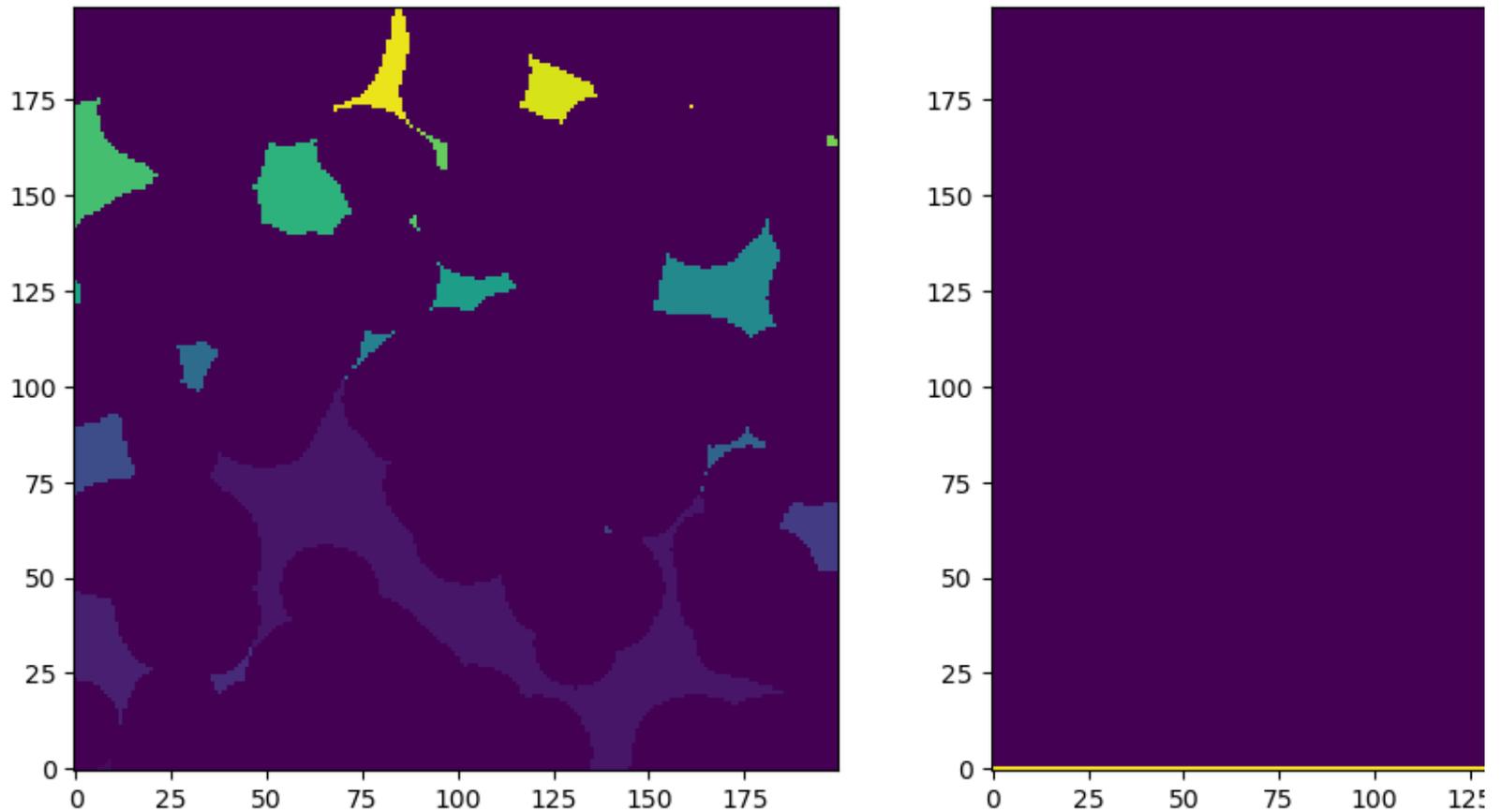
- Creating an image with `True` values indicating the inlets

- Labeling the clusters
- Removing all voxels whose label does not appear in the inlets

```
In [29]: ▶ import scipy.ndimage as spim
labels, N = spim.label(dt > 10)
inlets = np.zeros_like(im)
inlets[0, :] = True

fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(labels, origin='lower', interpolation='none')
ax[1].imshow(inlets, origin='lower', interpolation='none');
```

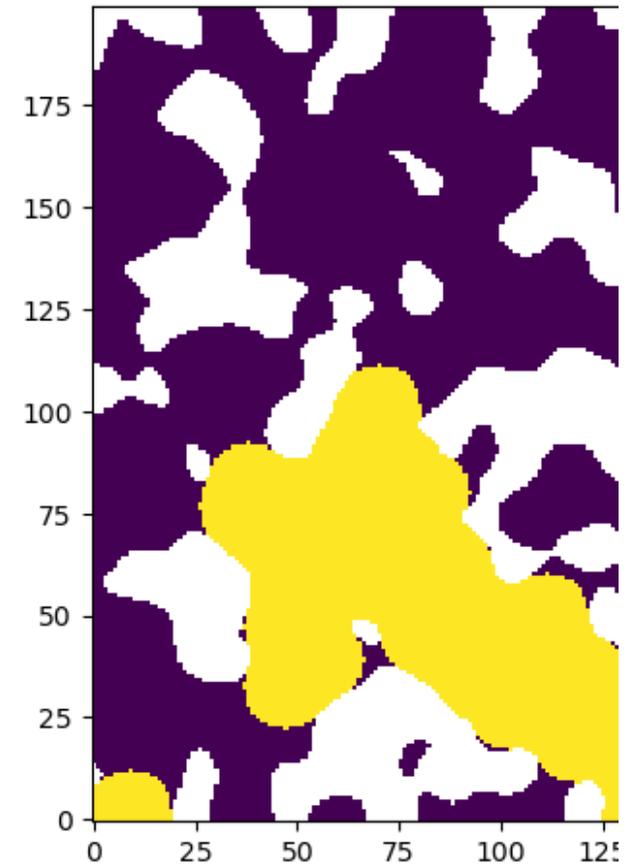
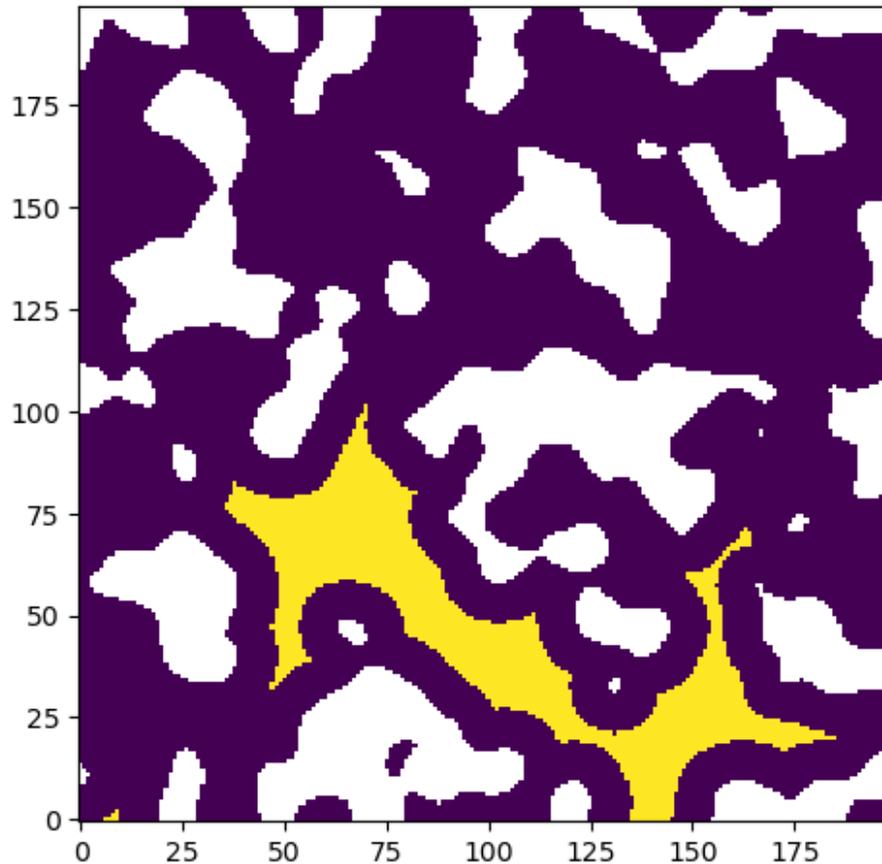
Out[29]: <matplotlib.image.AxesImage at 0x20041b0ebe0>



Using a bit of fancy logic and boolean masks, we can drop all voxels whose label number does not appear on the inlet:

```
In [38]: ▶ keep = np.isin(labels, labels[inlets])*(labels > 0)

fig, ax = plt.subplots(1, 2, figsize=[12, 6])
ax[0].imshow(keep/im, origin='lower', interpolation='none')
fluid = spim.binary_dilation(keep, structure=ps.tools.ps_round(10, ndim=2, smooth=False))
ax[1].imshow(fluid/im, origin='lower', interpolation='none');
```



Multiphase Flow Simulations

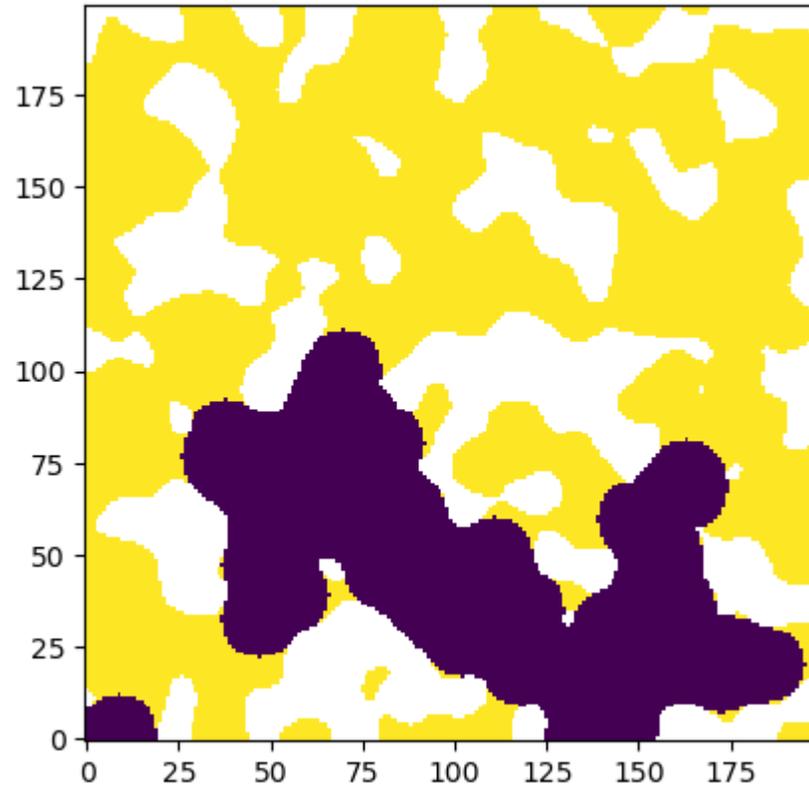
Aside from simulating capillary pressure curves for comparing to experimental data, the `drainage` algorithm can also be used to obtain

corresponding to different saturations. This can be used to compute relative effective diffusivity (or resistivity index).

Given the fluid configuration computed above, let's find the effective diffusivity across the domain, perpendicular to the invasion face.

```
In [41]: ▶ im2 = im*(~fluid)
          plt.imshow(im2/im, origin='lower', interpolation='none');
```

```
Out[41]: <matplotlib.image.AxesImage at 0x2003f9b75b0>
```

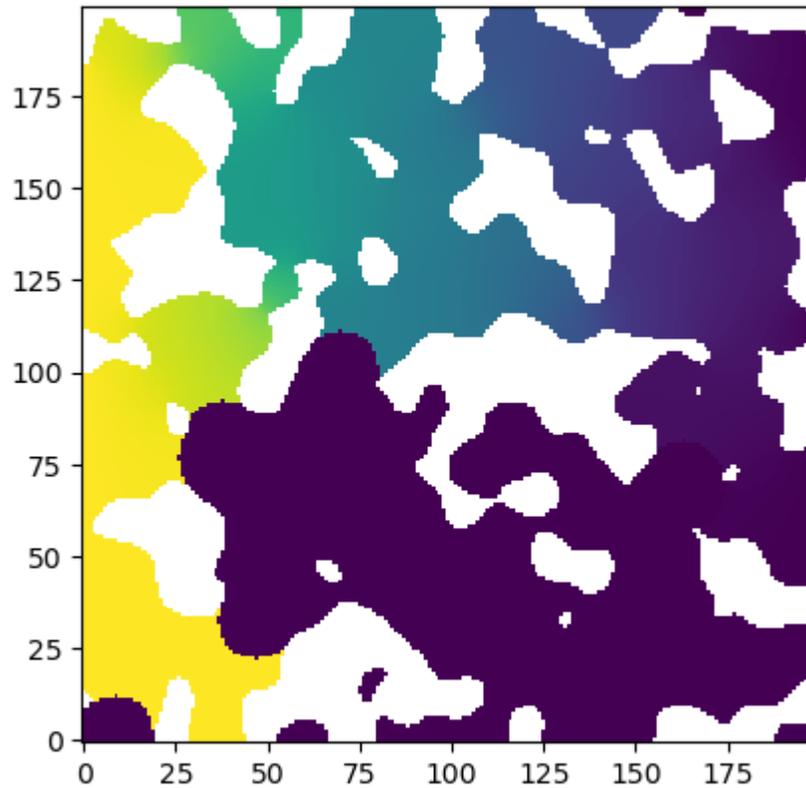


Now lets apply `tortuosity_fd` along the y-axis:

```
In [44]: ▶ deff_y = ps.simulations.tortuosity_fd(im2, axis=1)
plt.imshow(deff_y.concentration/im, origin='lower', interpolation='none');

[20:28:34] WARNING Found non-percolating regions, were filled to percolate
```

```
Out[44]: <matplotlib.image.AxesImage at 0x2003f904d60>
```



Let's print the `deff_y` object to see what the tortuosity was:

In [45]: `print(deff_y)`

Item	Description
im	Image of size (200, 200)
tortuosity	2.828969370086357
formation_factor	6.342269633642769
original_porosity	0.490325
effective_porosity	0.44605
concentration	Image of size (200, 200)

Now let's check the `tau_y` object to see the tortuosity through the dry image:

In [46]: `print(tau_y)`

Item	Description
im	Image of size (200, 200)
tortuosity	1.8336360644542187
formation_factor	2.596850395771447
original_porosity	0.7061
effective_porosity	0.7061
concentration	Image of size (200, 200)

So the presence of the invading fluid increase the tortuosity by 50%.

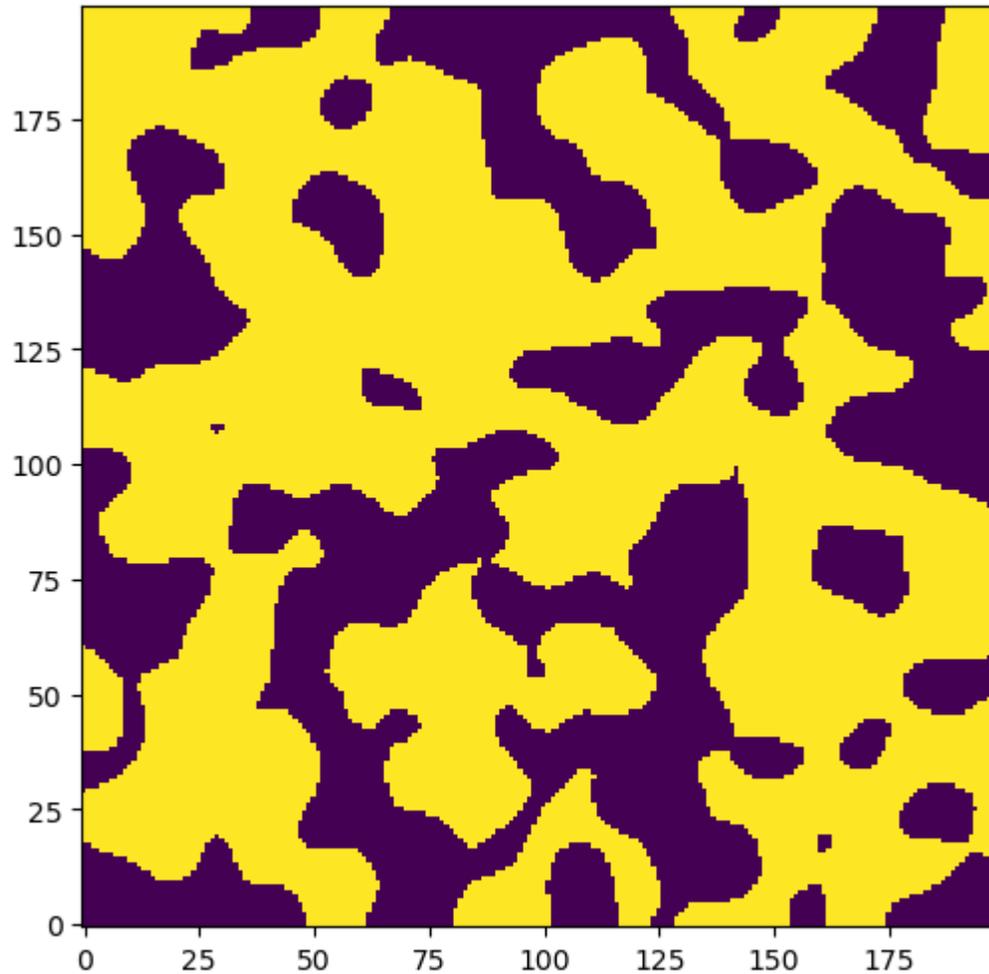
Note: This 'tortuosity' value is already account for the reduced pore volume due to the presence of invading fluid, so this a real tortuosity, above and beyond the effect of just pore blockage.

Network Extraction

One of the more interesting and powerful tricks that can be done to a volumetric image is extracting a network representing the void sp

```
In [1]: ▶ import porespy as ps  
import numpy as np  
import matplotlib.pyplot as plt
```

```
In [5]: ▶ im = ps.generators.blobs([200, 200], porosity=0.6)
fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow(im, origin='lower', interpolation='none');
```



Applying the SNOW Algorithm

PoreSpy V2 includes the `snow2` function, which is an evolution of the original function with the following features:

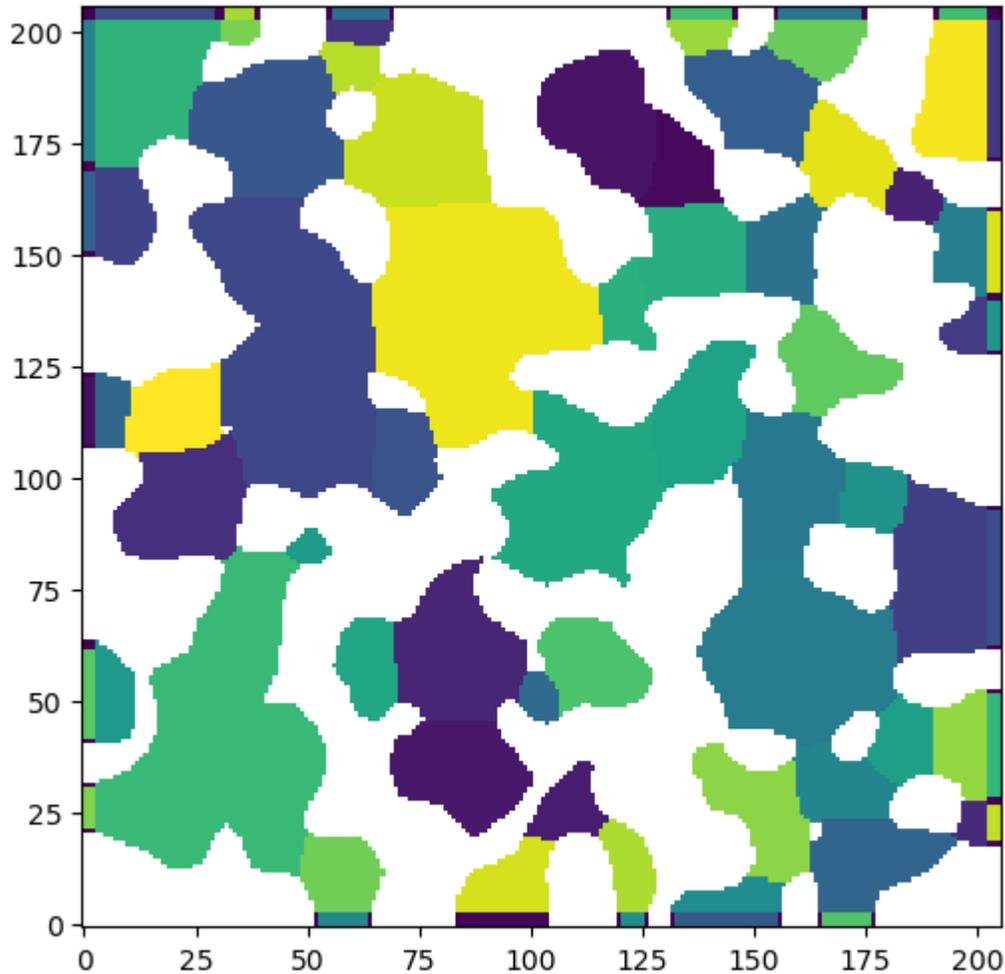
- Simple addition of boundary pores

- Unlimited number of phases
- Parallelized watershed step for improved speed

Using the defaults gives:

```
In [31]: ▶ sn = ps.networks.snow2(im)
0it [00:00, ?it/s]
0it [00:00, ?it/s]
0it [00:00, ?it/s]
0it [00:00, ?it/s]
Extracting pore and throat properties: 0%|          | 0/74 [00:00<?, ?it/s]
```

```
In [60]: ▶ fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow(ps.tools.randomize_colors(sn.regions)/(sn.phases > 0), interpolation='none', origin='lower');
```

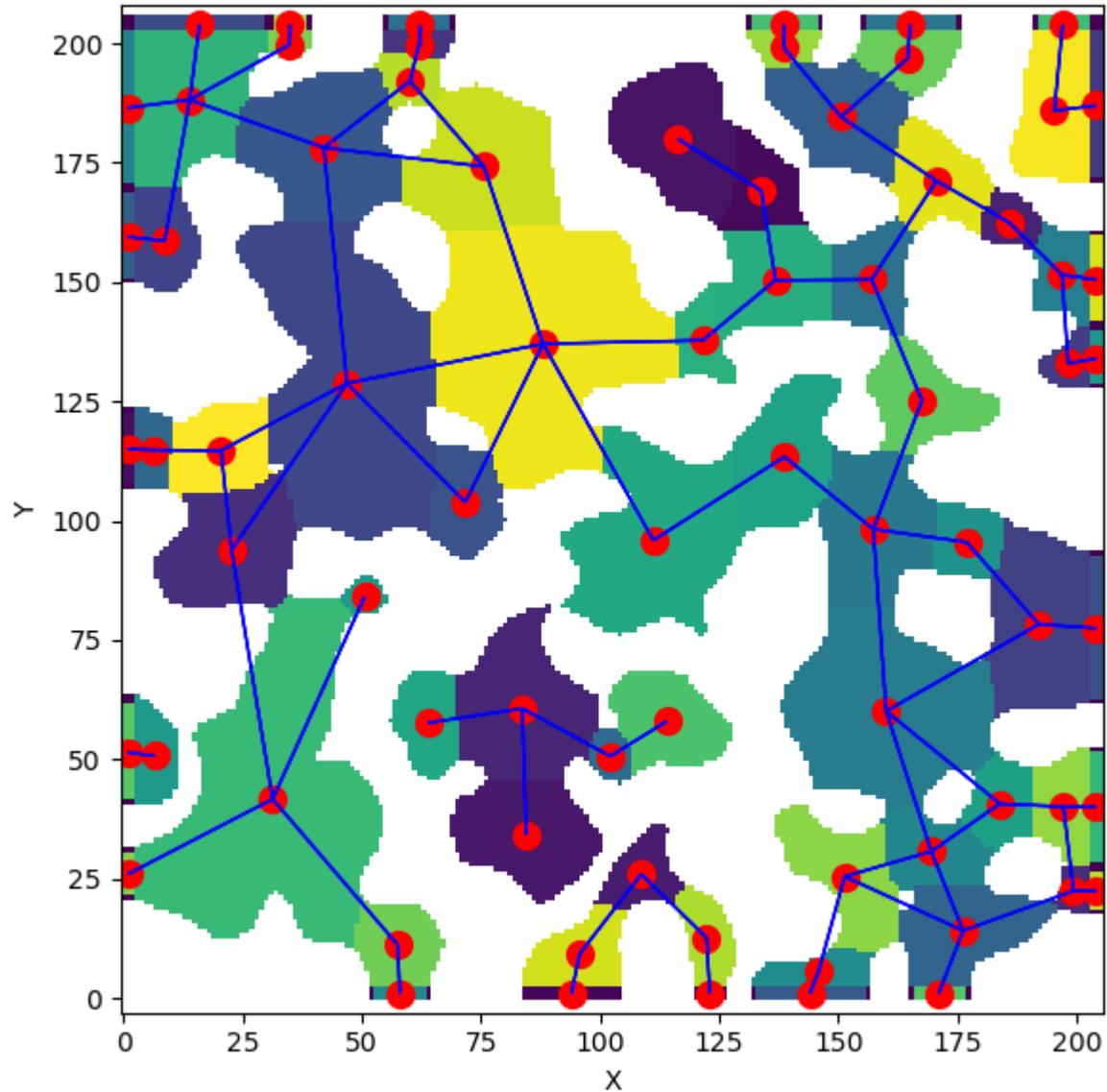


Overlay Image and Pore Network

Without covering pore network modeling too much, it's possible to overlay the extracted network on top of the image

```
In [63]: ▶ import openpnm as op
pn = op.io.network_from_porespy(sn.network)
pn['pore.coords'] = pn.coords[:, [1, 0, 2]]
ax = op.visualization.plot_connections(pn, ax=ax)
ax = op.visualization.plot_coordinates(pn, s=100, ax=ax)
fig
```

Out[63]:



Applying to Multiple Phases

One of the most interesting feature of `snow2` is the ability to do 'multiphase' extractions.

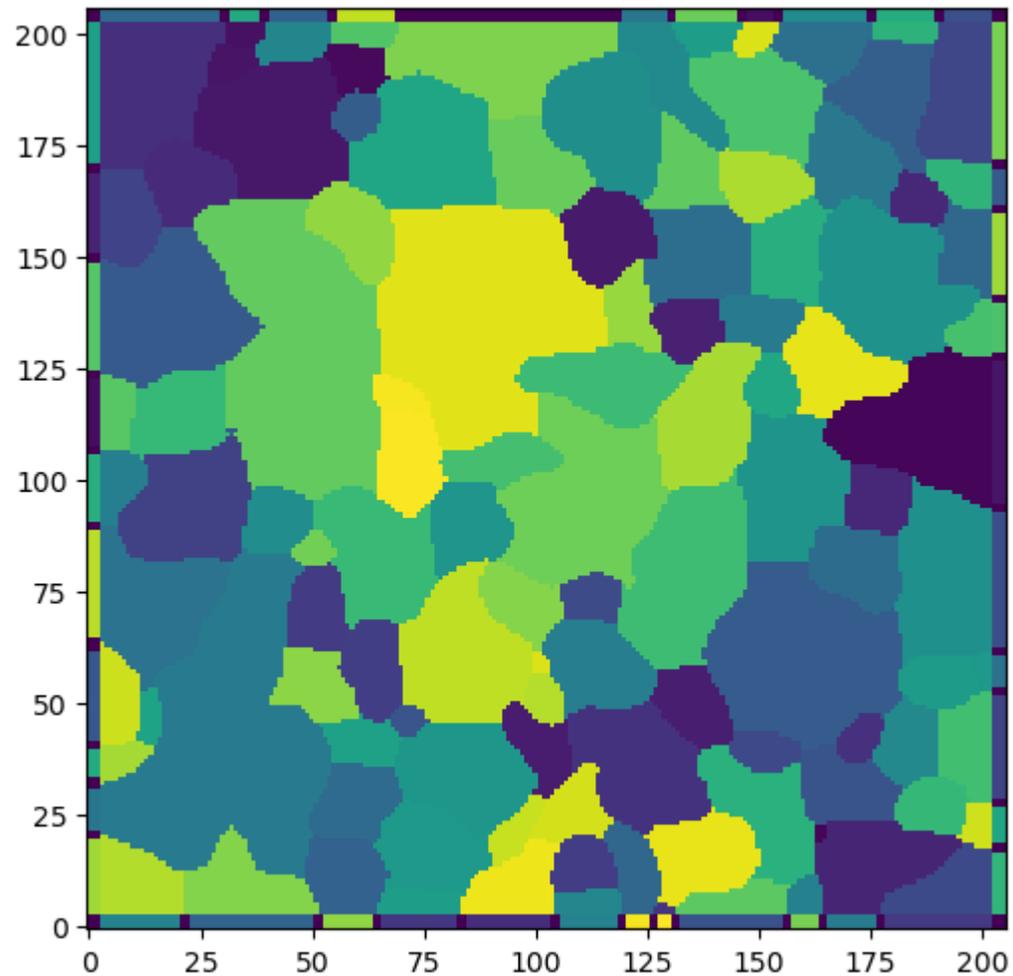
- This is essential for electrochemical devices since solid phase transport is crucial
- Has also been used for 'multiscale' modeling where the 2nd phase is unresolved pore space (i.e. clay) and treated as continuum n

```
In [64]: ▶ sn2 = ps.networks.snow2(phases=im.astype(int)+1)
```

```
0it [00:00, ?it/s]
```

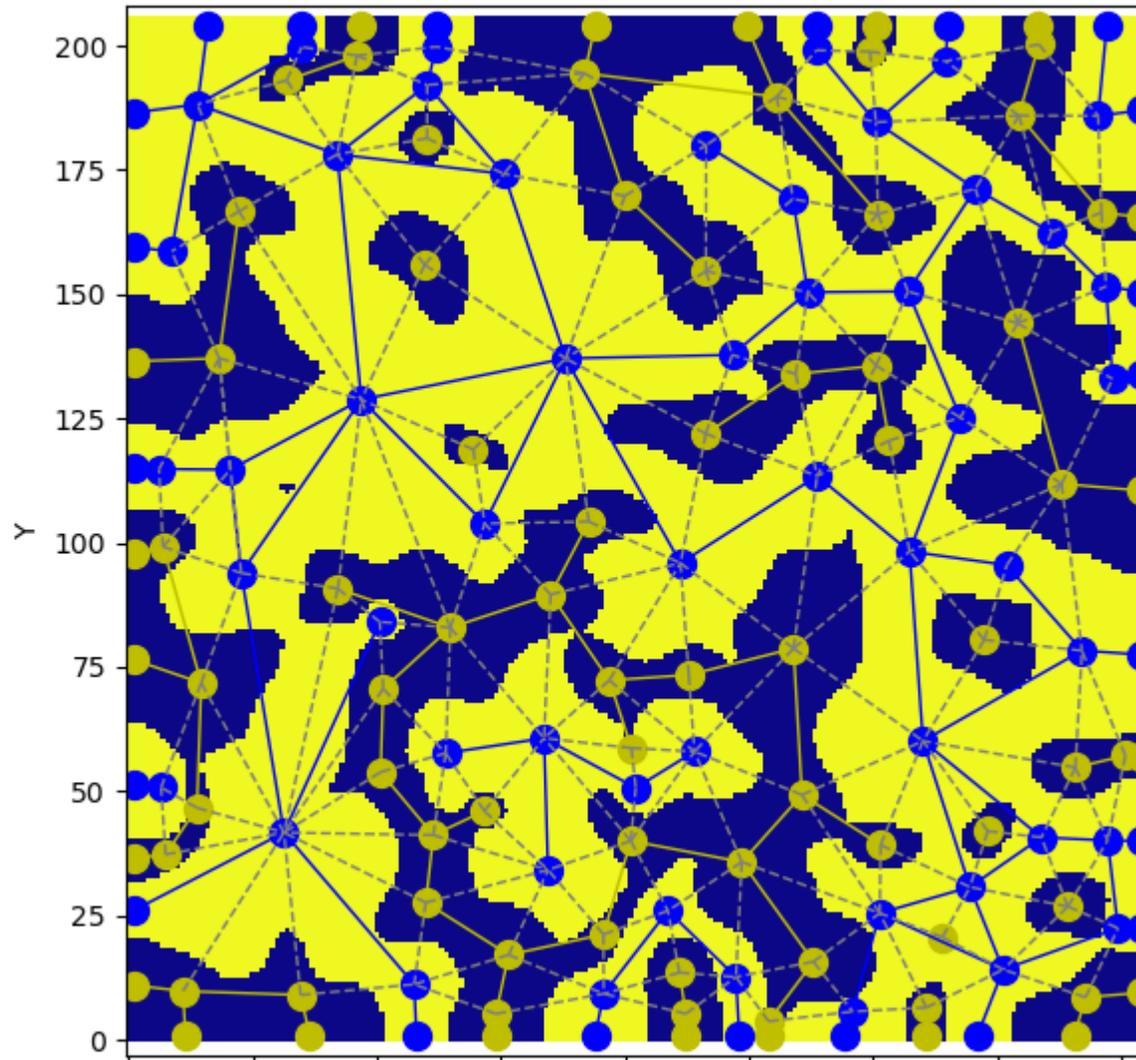
```
Extracting pore and throat properties: 0%|          | 0/155 [00:00<?, ?it/s]
```

```
In [72]: ▶ fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow(ps.tools.randomize_colors(sn2.regions), interpolation='none', origin='lower');
```



Overlaying Both Networks on the Multiphase Image

```
In [85]: ▶ pn = op.io.network_from_porespy(sn2.network)
pn['pore.coords'] = pn.coords[:, [1, 0, 2]]
fig, ax = plt.subplots(figsize=[6, 6])
ax.imshow(sn2.phases, cmap=plt.cm.plasma, interpolation='none', origin='lower');
ax = op.visualization.plot_connections(pn, throats=pn.throats('phase1_phase1'), c='y', ax=ax)
ax = op.visualization.plot_connections(pn, throats=pn.throats('phase2_phase2'), c='b', ax=ax)
ax = op.visualization.plot_connections(pn, throats=pn.throats('phase1_phase2'), linestyle='--', c='gray')
ax = op.visualization.plot_coordinates(pn, pores=pn.pores('phase1'), c='y', s=100, ax=ax)
ax = op.visualization.plot_coordinates(pn, pores=pn.pores('phase2'), c='b', s=100, ax=ax)
```



0 25 50 75 100 125 150 175 200
X