Relative permeabilities from simulation in 3D rock models and equivalent pore networks: critical review and way forward

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ABSTRACT

In the last 15 years, great progress has been achieved in the area of digital rock technology in the domain of 3D rock model generation using a range of techniques: sedimentation modeling, statistical methods and micro-CT imaging. In the context of sandstones, single-phase prediction from these 3D models or from the equivalent pore networks has become possible for static and, in some cases, for flow petrophysical properties. Nevertheless, according to Sorbie and Skauge [1], two-phase flow properties such as relative permeabilities cannot be predicted neither from the equivalent pore networks nor from the 3D models: in the first case, the input choices one has to make throughout the whole prediction workflow would greatly outnumber the actual system parameters; in the second, whilst the number of input parameters still remains too high, no technique is mature enough to produce calculations "that can be compared meaningfully with experiment". In this work we extend the observations of Sorbie and Skauge by actually simulating two-phase flow properties with a number of state-of-the-art pore network models and one Lattice-Boltzmann simulator. We begin the study by showing how the network extraction process, and not the distribution of the fluids in the pore network, might be at the origin of some recently published counterintuitive results on relative permeabilities, obtained by means of pore network simulation by another group. We then continue showing that the current physics embedded in network models, and the latest refinements to it, are less a concern than other issues such as rock representation and wettability characterisation. We conclude by comparing results from direct two-phase flow simulation in a micro-CT image and in the network model extracted from that image to focus on the issues that need to be addressed to establish these techniques as industry-ready tools.

INTRODUCTION

The Oil&Gas industry needs new technologies that can be able to provide accurate estimations of petrophysical properties of various types (permeability, capillary pressure, relative permeabilities, resistivity indexes and formation factors) or new insight into recovery mechanisms. Digital Rock Physics (DRP) has demonstrated great potential in the following 5 areas:

1. Help in tackling the deficiencies of macroscopic approach – use DRP when conventional simulation cannot be used with success [2,3].
2. Exploit digital images for enhanced understanding of oil recovery mechanisms: identification of pore-scale mechanisms, investigate wettability and fluids in 3D [4,5].

3. Perform otherwise impossible SCAL: TAR sands [6]; three-phase flow [7], blowdown at reservoir conditions [8].
4. « What if » sensitivity studies, interpolation and extrapolation of Lab datasets [8,9].
5. DRP as industrial LAB integration methodology: for some rocks, for some properties [10,11,12,13].

Regarding the last point, a debate has recently emerged whether multi-phase flow properties (Kr, Pc) can genuinely be predicted [1]. According to these authors this is not possible neither with network models due to the intrinsic limitations of the simulation approach that inherently goes through many "interpretation stages" nor through image-based simulation (again for the same reason but also because the technology is not yet mature). On the other hand, it is often stated in the literature that once network models are representative of the rock [14], then the workflow becomes automatically predictive (with the aid of the wettability tuning parameter). This approach seems quite debatable as:

- [7] predict even 3-phase relative permeabilities using a simple regular lattice network (therefore not representative of the rock as an extracted network).
- [15], using extracted network models, demonstrate that even in strongly water wet conditions, the same imbibition experiments can be reproduced (or "predicted") with quite different wetting parameters than [14] if the rest of the parametrisation (physics and network) is characterised differently.

In this paper, we show through simulation results, that if by prediction we mean the success of a validated model in reproducing an experimental trend or result without this being utilised/known during the "prediction" attempt, then, under these terms, the DRP technology as a whole cannot be considered predictive for relative permeabilities as a number of issues remain unresolved. In any case no global benchmark exists to date (where the performance of the various models is assessed on a given commonly agreed test case).

INTERPRETATION OF PORE NETWORK MODELLING RESULTS

A workflow embedded with parameters

It has long been known (although probably never formalized in a paper as in [1]) that the pore network modeling technique relies on some important assumptions and parameter choices. As an example, consider the implications of the empirical pore-filling models. Figure 1 shows an example on a Berea network (see [14], page 61, for the network properties and page 132 for a definition of the four models): it is observed that Blunt_2 and Øren_1 models produce very similar results. Øren_2, which adds the effect of the shape factor in the threshold capillary pressure produces a slightly different result with a bit more oil recovered (almost 5%). Blunt_1 produces lots more oil (at least 15% more). Since the reference experimental results on the strongly water wet Berea sandstone are more compatible with the first two models, one could make the choice to work with the simplest Blunt_2 model. Nevertheless such choice is not straightforward.

Evidence of counter-intuitive trends…
A prediction workflow containing around 20 parameters [1], also has the consequence that it may be difficult to "understand" or interpret the simulated trends. Figure 2(a) shows a recent example from the literature [10] of relative permeability trends computed on network models for Amott wettability indexes going from strongly water wet (Iw-o=0.98) to strongly oil wet (Iw-o=-0.86). These simulations were performed on a pore network extracted from a digital image of a sandpack using the maximal ball algorithm [16] and show that Krw(water wet)>Krw(oil wet) and Kro(water wet)<Kro(oil wet). In particular Krw in oil wet conditions is extremely low and contributes in giving higher oil recovery in oil wet conditions. The same authors note that such trend is "counter-intuitive" as in oil wet conditions it would be expected that water invades the largest pores first (with higher conductance) and go on to propose an explanation based on the fact that, in those specific simulations, water would remain poorly connected in oil wet conditions up to very high water saturations. Figure 2(b) shows similar work carried out by our group on a network extracted from a Bentheimer rock model using a Voronoi diagram-based method for extraction (and a different pore network simulator): in this case Krw in strongly water wet conditions is also quite higher than in strongly oil wet conditions. According to the rationale expressed by [10], even in this case it could be speculated that, in oil wet conditions, water remains less connected.

…and interpretation efforts
We make here a different hypothesis: that these trends might instead be related to the rock representation itself, in this case the "extracted network". As it is known, a number of assumptions or approximations need to be made both at the stage of defining the topology of a network (defining the network backbone) or when partitioning the space in pore bodies and pore throats (where it is also needed to make decisions that will impact on the respective proportion of such elements, the dominant pore shapes, the length of the throats and so on). Once a network has been defined, it becomes a rather complex physical environment both on its own and when linked to the water-oil displacement model (think for example to the way snap off events might be enhanced by simply increasing the weights in the pore body filling model or by simply "choosing" to have more acute angles in the network).

As a simple exercise we studied the effect of combined pore volumes and wettability on relative permeabilities. To simplify, we decided to start with the simplest environment possible, that is, a regular cubic lattice composed of circular capillary elements where pore volumes are considered proportional to the radius raised to some power (say $V(r) \alpha r^{\nu}$ with $\nu \in [0,3]$, see [17]). The pore size distribution and connectivity of the regular lattice could easily be tuned to approximate the average connectivity and the ensemble of pore statistics of the irregular Bentheimer network mentioned above; waterflooding is then simulated in conditions of strong water wetness and strong oil wetness. It is found easily (Figure 3) that a pore volume exponent $\nu=1$ is sufficient to produce results of the "counterintuitive" type, whilst $\nu=2$ produces results of the "expected" type.

ISSUES WHEN PREDICTING Kr

The image-network extraction chain

It is known that the process of network extraction is non-unique and that different families of algorithms exist: Voronoi diagram-based, medial axis, maximal ball, watershed transform (see [16] for a comprehensive review). These algorithms inherently lead to different networks with some algorithms performing better on representing the pore space connectivity (medial axis), other better in identifying pores (maximal ball).

In this section, we set to show some important consequences on two–phase flow that emerge from different network models (extending the work of [18]). A small cylindrical end cut of a Clashach sample was cut in 4 parts: one piece was shipped to one DRP Group and two pieces were shipped to another DRP Group for a total of 3 micro-CT images. On these three samples (S1, S2, S3) in Table 1, different network extraction chains (N) were utilized: 1) a Voronoi diagram-based method (N1) implemented by Group 1, a watershed transform approach (N3) implemented by Group 2, and a watershed transform approach (N2) implemented by Group 2 where throat lengths are defined from the image using the same method as in N1. The experimentally measured properties of the Clashach sandstone are identical to the sample used by [18], i.e. permeability of 1000mD and porosity of 17%, although the imaging and processing was done 4 years later.

From Table 1, it can be seen that the networks are quite different in their statistics. Furthermore, the effect of modifying the definition of throat lengths from the skeleton produces networks with "average throat length to radius ratio" 5 times higher for N3-type networks than for N2.

It might be possible to state that S1_N1 reproduces better the experimental K/ϕ characteristics (which were known to Group1 but not to Group 2). On the other hand nothing can obviously be concluded on which parametrisation is the best regarding the proportion of triangular (TR), square (SQ) and circular (CR) or on other pore geometry statistics not reported here. We show in Figures 4(a),(b),(c) simulations done on 3 of these networks for:

- Oil drainage with oil-water contact angle set to 0.
- Water imbibition for oil-water contact angle set to 30 degrees.
- Water injection for oil-water contact angle set to 150 degrees.

Figures 4(d) and 3(f) show the ratios Krw/Kro for the waterfloods. It can be verified that:

- Large variations in both water and oil relative permeabilities are observed that would induce very different oil production forecasts.
- The relative permeability to the wetting phase is much less robust with respect to the network utilized.

Figures 5(a),(b),(c) report the comparison between simulations done in water wet and oil wet conditions for the networks S1_N1, S2_N2 and S3_N3 respectively. In this Figure, WW stands for strongly water wet conditions (oil water contact angle equal to 30 degrees) and OW stands for strongly oil wet conditions (oil water contact angle equal to 150 degrees). Figures 5(d),(e),(f) show the results in semi-log coordinates. It is seen that:

- Network S1_N1 returns a conventional trend: Krw_WW<Krw_OW and Kro_WW>Kro_OW.
- Network S2_N2 returns a "counterintuitive trend" of the type reported in [10]: Krw_WW>Krw_OW and Kro_WW<Kro_OW.
- Network S3_N3 returns an intermediate trend where: Krw_WW>Krw_OW and Kro_WW>Kro_OW.

These results would lead to think once more that the results of [10] could be "counterintuitive" due the specificities of the network model (or network extraction algorithm) they have used. Figure 6(a) show Kr calculations done in strongly water wet conditions (oil water contact angle equal to 30 degrees) on N2 and N3 and should be compared with Figure 6(b) which shows the same type of simulations carried out with N2 on Samples 2 and 3 of the 1000mD Clashach sandstone. It is shown that, in this particular case, applying two different network extraction algorithms (even if almost identical apart from throat length definition) on the same image has much bigger consequences than applying the same algorithm on two different images.

In view of the above quite general observations and results, the authors would agree with the observation from [19], that "little quantitative work has been done to understand the influence of different network structures on modelling" and would themselves conclude the following:

- the influence of different network structures on relative permeabilities has not yet being given enough attention (and important differences exist between different approaches).
- because the workflow for network model simulation is over parameterized, the interpretation of a simulation exercise can be far from trivial.

Regarding the decision of whether a given network extraction scheme is better than another, [19] think that this might perhaps never be made on a general basis and conclude that the correctness of a given network might eventually depend on the application for which it is used.

Physics and wettability

Very recently, a number of researchers have included more sophisticated physical models [20, 21], namely full thermodynamically-based oil layer existence and collapse models. The objective is to model the existence and collapse of the oil layers (as proposed by the Kowscek pore wettability model) with the "correct physics" and not only through simplistic geometrical layer collapse models (as in [14] for example). The first reports [21] of implementation of these criteria imply these make indeed a difference in the simulation exercise for residual oil, for example.

In our case we set to investigate whether such differences are as important as those observed in the previous section. We consider one simulator of the old (with geometric criteria only, GC) generation and one of the new generation (thermodynamic criteria, TC): the two simulators come from different research groups and could differ from each other

also in other specificities (pore body filling model for example). Nevertheless we run the two simulators on the same network (the Berea network used in [14] in both strongly water wet (oil-water contact angle of 30 degrees) and strongly oil wet conditions (oil-water contact angle of 150 degrees): although the impact due to the thermodynamic criterion cannot be isolated on its own, the aim is to check whether very large discrepancies can be expected in relative permeabilities. Figure 7 shows that the differences appear to be mild for this Berea network even in the oil wet case, where oil layers sandwiched between water in the corner and water in the bulk are effectively affected by the thermodynamic criteria. Differences exist in the prediction of residual oil of less than 5%.

To remind that wettability distribution in the simulated pore space is greatly approximated or assumed, Figure 8 reports the effect of wettability on the same simulations of Figure 7: in the GC model we distribute contact angles in a 20 degrees range centred on 30 and 150 degrees but we distribute them with some level of correlation (Hurst exponent=0.75; correlation length=6 pores). Instead in the TC model, the contact angles are set randomly in the same interval. This simple exercise shows that the mild differences observed in Figure 7 are now greatly enhanced.

Kr FROM 3D IMAGE AND NETWORK MODEL

Computation of relative permeability in digital images mostly acquired through non-destructive x-ray micro-CT technology (and therefore skipping the network extraction step) is fast gaining ground as the next promising approach in digital rock technology. Four main simulation categories exist today:

Navier-Stokes solvers. These solve continuum based partial differential equations which account for conservation of mass, energy and momentum. To utilize Navier-Stokes in 3D images of porous media, these equations need to be solved in systems with highly irregular fluid-solid boundaries, notoriously a very difficult task. The solution of the equations for the evolution of the interfaces (level set, volume of fluid) present a big computational challenge and no reliable example of application in representative digital images seems to exist in the literature.

Pseudo-particle methods. In this category, Lattice-Boltzmann is today considered the most promising approach for the simulation of 2-phase flow in 3D images of porous media (basically as simulations can run faster than the previous method). In these approaches, pseudo-particles can be thought of as average particles: they do not represent single atoms or molecules, but rather clusters of atoms or molecules. Each pseudo-particle carries the position and momentum of coarse grained fluid elements: even in this case the simulation of fluid interfaces remains computationally very challenging and computation times to carry out simulation at the size of a network model (already quite small) and at representative capillary numbers are prohibitive. Furthermore there is still a very limited amount of work in the literature where the performance of the many 2-phase Lattice-Boltzmann methods (colour gradient model, pseudo-potential, free energy,...) used on binarized images of porous media is validated against experimental data. There are also

concerns on the resolution that the lattice needs to have to capture the wetting films on the pore wall.

Maximal inscribed sphere and capillary drainage transforms (CDT). In this case fluid distributions are simulated depending only on capillary pressure as explained by [22]. More complex wettability scenarios cannot be tackled as well as the effect of saturation history: this approach is indeed simplistic. Effective permeabilities can be computed through a single-phase flow LBM solver or a Laplace solver (without the need to simulate interfaces).

Experiment + single-phase simulation. Micro-CT imaging can be conducted at different steps of a 2-phase flow experiment, the images can be treated and the phases segmented; single-phase simulation can be performed on each phase separately to compute the effective permeabilities. The procedure to conduct this type of work is quite heavy but in practice possible and cases for primary drainage have been reported recently [22].

In this paper we focus on Lattice-Boltzmann and CDT. Regarding the first method, a colour gradient model for interface separation is used which appears identical to the one in [23]. The code was run on a 500x250x250 rock model of Clashach (Sample_2 discussed above) with a voxel size of 5.2μm (original image was downsampled by a factor of 2) and using periodic mirror boundary conditions. To compute one single relative permeability using the steady-state method (see [23] for details), 4 simulations are run at Sw=20%, 40%, 60%, 80%. Fluid parameters are identical to those of [23]. In Figure 9(a) the oil-water contact angle is chosen to be again either 30 or 150 degrees and the simulations are run at a capillary number of 10^{-5} which makes the simulation exercise very challenging due to the huge number of iterations that is needed to achieve convergence (not all simulation might have converged in this Figure). The simulations do probably suffer from finite size effects too: nevertheless Krw(WW)<Krw(OW) and Kro(WW)>Kro(OW) as it would be expected. In Figure 9(b) we check the effect of running the simulations at a much higher capillary number than Nca=10^{-5}: the simulation have now fully converged and the results are quite similar to the case presented above (which is not in line with the results of [23], who in fact do find a Nca effect on Kr when going from Nca=10^{-5} to Nca=10^{-4}). Figure 10(a) shows the same exercise as Figure 9(a) by using instead the CDT method on a 500x500x500 sample of S2: again Krw(WW)<Krw(OW) and Kro(WW)>Kro(OW). Finally Figure 10(b) shows a comparison of the drainage image-based Kr (in this case, oil is introduced in big pores both in LBM and CDT) and the network based Kr: it can be seen that image-based Kro computations have no resemblance with network based Kro computations, whilst relevant similarity is observed for Krw.

CONCLUSIONS

The objective of this paper is to convey the ideas from the authors that prediction of multi-phase flow properties using DRP technology is not possible in general terms. We have shown that the most established technique for Kr computation (pore network modelling) can produce results which are in some cases difficult to interpret due to the high number of

parameters involved in the simulation workflow, that the representation of the rock (the network model) is still a weak point and we have reminded that wettability is just a tuning parameter. Nevertheless pore network models have important applications and represent the short term tool of preference for R&D purposes, but not for predicting relative permeabilities. Direct simulation in 3D images represents the medium and long term future: for the moment only Lattice-Boltzmann methods allow simulations in multi-million voxels samples in various wettability conditions. Nevertheless the progress of the technique in terms of thorough published physical validation on large petrophysical datasets appears to be slowed down by computational issues (in any case, very few comprehensive studies exist). Independently of the methodology, "genuine prediction" of multi-phase flow properties will remain not credible until important progress is achieved in the area of wettability characterisation at the pore scale (a physically-based pore-scale wettability model based on crude oil-water-rock interaction).

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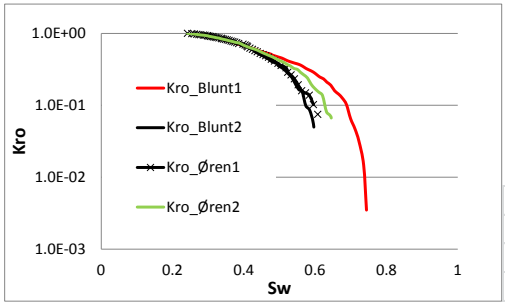
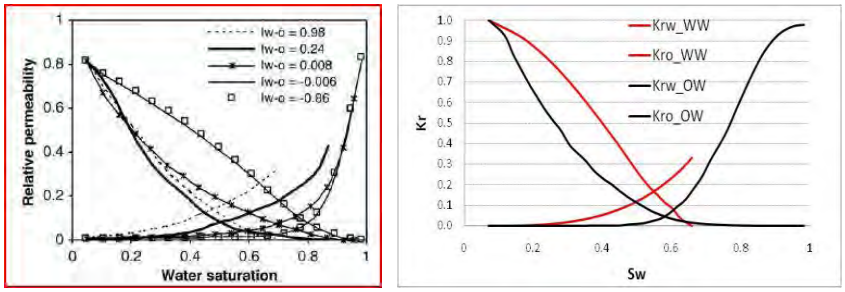
Table 1: Statistics of irregular networks derived from μ-CT images utilised in this paper (average connection number, number of pore and throat elements, median throat length to radius ratio, percentage of triangular, square and cylindrical elements, net porosity and permeability).

		Z	Npores	Nthroats	Th_l/Th_r	% TR	% SQ	% CL	Net f	K(mD)
Group 1	**S1_N1**	3.42	36446	63082	8.90	0.97	0.03	0.00	0.16	780
Group 2	**S2_N2**	3.02	49880	76611	2.20	0.65	0.23	0.12	0.19	2456
Group 2	**S2_N3**	3.02	49880	76611	11.00	0.65	0.23	0.12	0.19	3563
Group 2	**S3_N2**	2	88851	89938	2.23	0.55	0.20	0.25	0.18	1889
Group 2	**S3_N3**	2	88851	89938	11.10	0.55	0.20	0.25	0.18	2504



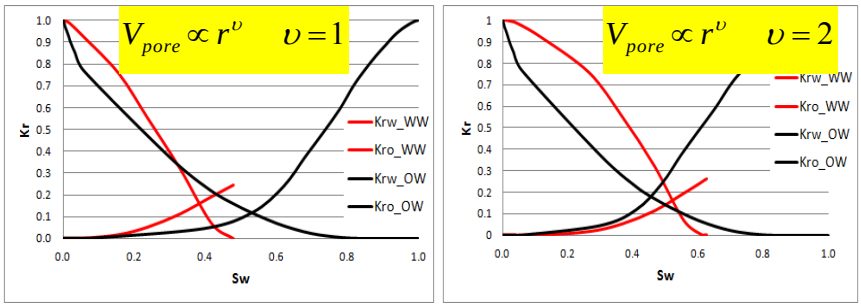
Blunt_1	0	0.5	1	2	5
Blunt_2	0	30000	30000	30000	30000
Øren_1	0	0.5	1	2	5
Øren_2	0	0.5	1	2	5

Figure 1. Kro computed on the Berea network model of Valvatne (2004) with four different models for pore body filling.



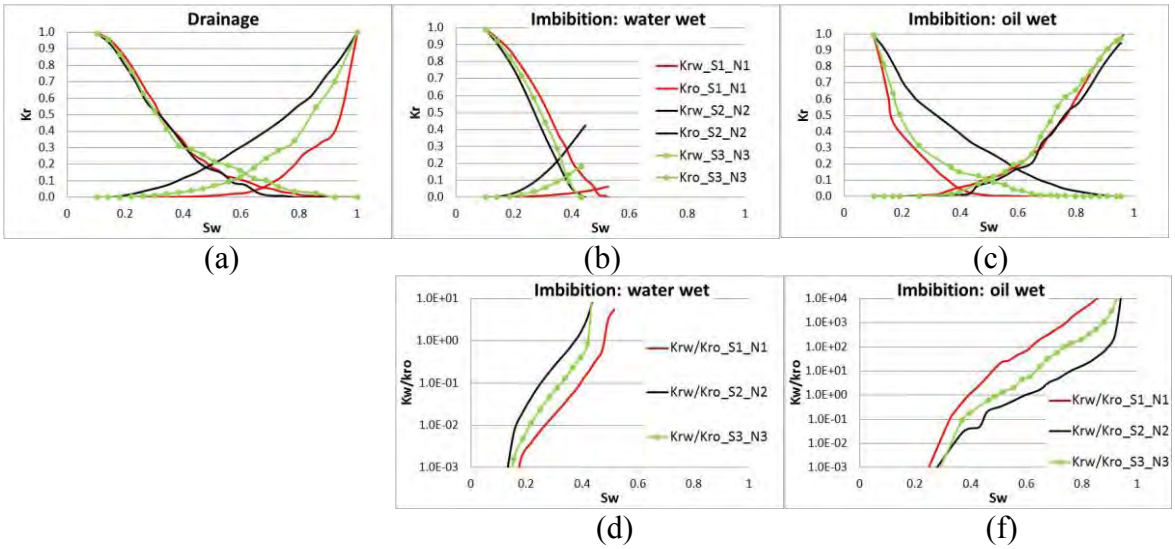
(a) (b)

Figure 2. (a) "Counterintuitive" trends reported by Zhao et al. (2010) on a sand pack network model; (b) Trends found by the authors on a Bentheimer network model: contact angles are in the range 20-40 (WW) and 140-160 (OW).



(a) (b)

Figure 3. Krw can move from "counterintuitive" trends (Krw_WW>Krw_OW) in (a) to expected trends (Krw_WW<Krw_OW) in (b) by associating different volume laws to the pore elements of a network.



(a) (b) (c)

(d) (f)

Figure 4. (a), (b), (c) Kr computed on networks extracted from 3D µ-CT images of Clashach sandstone; (d), (f) Ratios Krw/Kro for the waterflooding simulations.

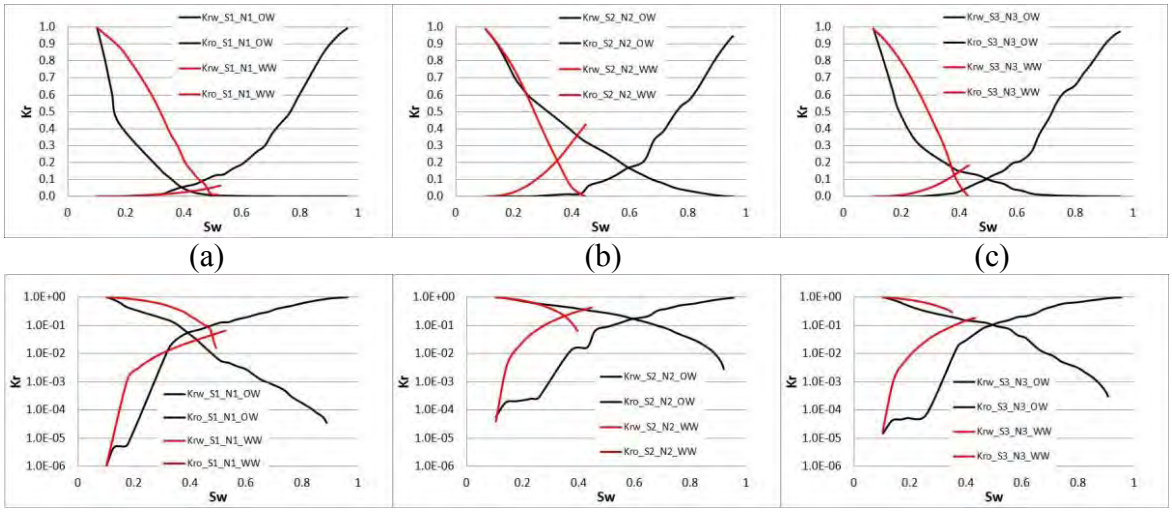


Figure 5. Effect of wettability on relative permeabilities for three different networks. Bottom figures show the semi-log plots.

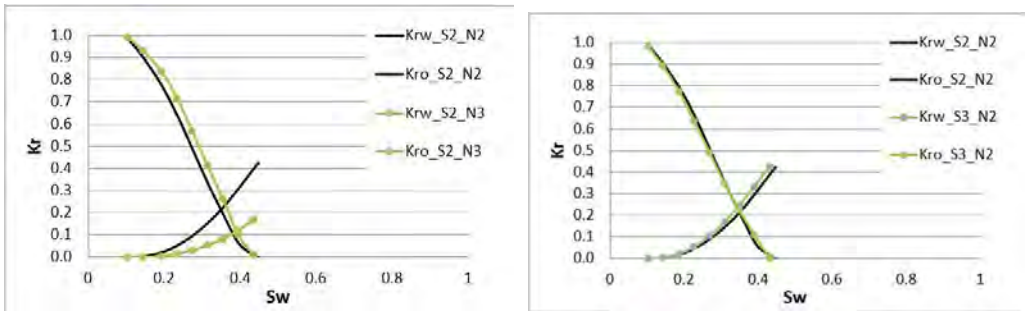


Figure 6. Effect of changing one assumption (definition of throat length) during the network extraction parameter (a) compared to the effect of changing sample location (b).

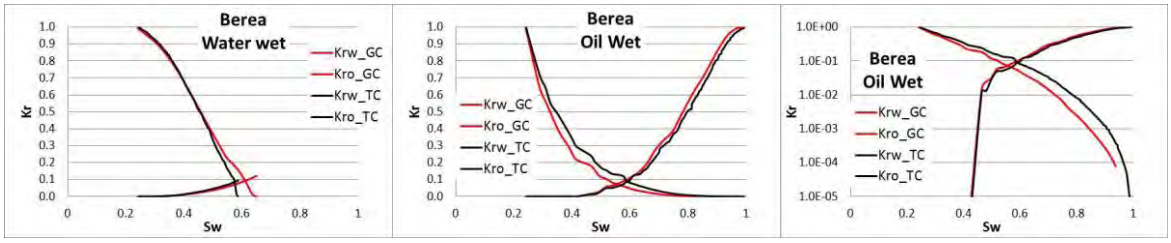
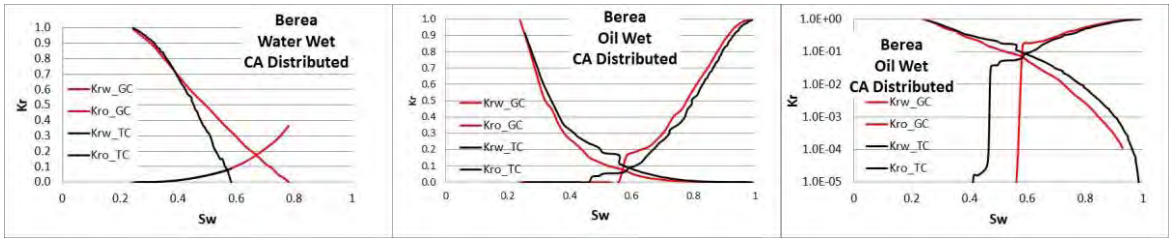
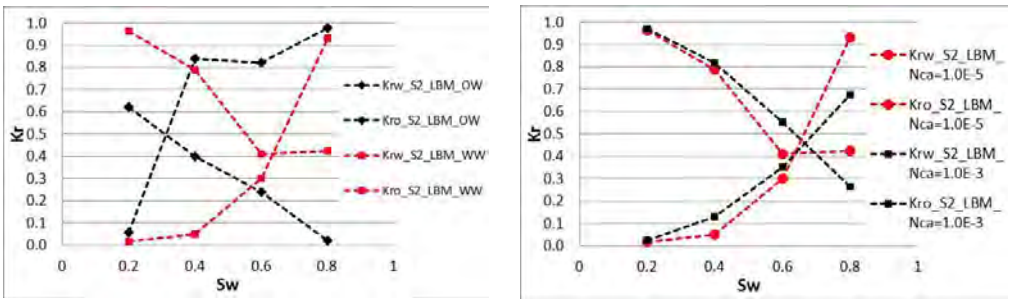


Figure 7. Effect of using codes based on geometric (GC) and thermodynamically-based (TC) entry thresholds for (a) water wet; (b) oil wet; (c) oil wet semi-log.



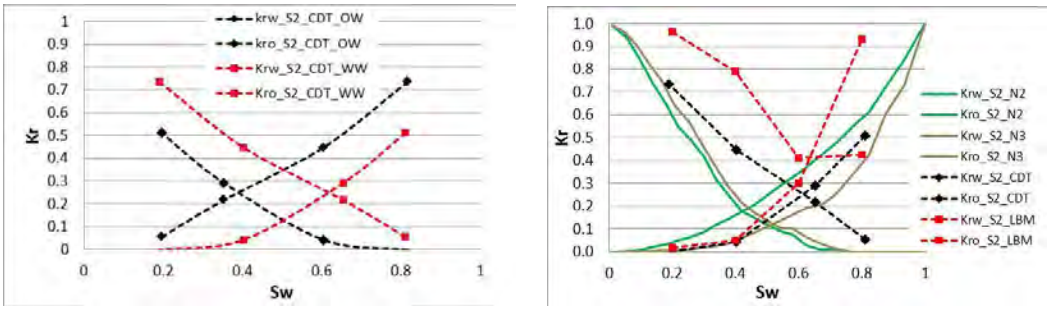
(a) (b) (c)

Figure 8. Same as in Figure 7, but now contact angles are distributed in 20 degrees intervals centred on 30 and 150 degrees.



(a) (b)

Figure 9. (a) Kr computed with 2-phase Lattice-Boltzmann simulator in water wet and oil wet conditions at Nca=10^{-5} on a 500x250x250 Clashach digital rock (S2); (b) Effect of capillary number.



(a) (b)

Figure 10. (a) Kr computed with single phase Lattice-Boltzmann simulator on fluid distributions simulated by CDT in water wet and oil wet conditions on a 500x500x500 (S2); (b) Comparison of drainage relative permeabilities with various methods.