Available online at www.sciencedirect.com

ScienceDirect

Energy Procedia 4 (2011) 4354–4361

Energy Procedia

www.elsevier.com/locate/procedia

GHGT-10

Recent Progress in Predicting Permeability Distributions for History Matching Core Flooding Experiments

Michael Krause[a,1*], Jean-Christophe Perrin[b] and Sally Benson[a]

[a]Stanford University, 367 Panama St. Stanford, CA 94305 USA
[b]Laboratoire d'Energetique et de Mecanique Theorique et Appliquee, Nancy-University, CNRS, 2 Avenue de la Foret de Haye, BP 160, 54504 Vandoeuvre cedex, France

Abstract

Laboratory core flooding experiments coupled with CT scanning has been shown to be very useful for examining CO_2-brine displacement processes [1]. These experiments can be used to measure core average properties such as absolute and relative permeability, and also to examine sub core-scale saturation and porosity distributions. By examining the sub core scale fluid distributions during the displacement process, it is possible to study the displacement efficiency of CO_2-brine drainage processes, residual trapping and fluid saturation at the millimeter to sub-millimeter scale. One potentially useful tool for studying CO_2-brine systems is using numerical simulation to replicate and study these core flooding systems. This could be used to study the interactions and relative impact of different parameters such as capillary pressure, relative permeability and heterogeneity on brine displacement by CO_2 under various flow conditions.

One challenge to successfully conducting such numerical experiments has been accurate representation of the permeability distribution inside the core at the millimeter and sub-millimeter scale. Other simulation parameters can all be measured using laboratory experiments, but permeability must be derived from other properties at the core and sub core-scale. Previous work has shown that predicting sub core-scale permeability distributions based on porosity does not result in accurate representation of permeability at such a small scale [1]. To improve these predictions, a new method based on capillary pressure and was developed and used to accurately predict sub core-scale permeability distributions [1] in a relatively homogeneous Berea sandstone.

The work presented in this paper uses the same method to calculate permeability in a strongly heterogeneous sandstone core from the Otway Basin Pilot Project in Australia. Simulations show that the results are consistent with previous results in the homogeneous cores, with statistically significant capability to predict sub core-scale CO_2 distributions in the core. Due to the extreme heterogeneity of the core used in this study, the average match is not as good as for a relatively homogeneous rock core, however, a visual comparison shows that the results are still very good, and that the new method used to calculate permeability may still be valid even in the presence of strong heterogeneity.

© 2011 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.

Keywords: Permeability, Core Flooding Experiments, Carbon Capture and Storage, Relative Permeability, Capillary Pressure Permeability Method

1. Introduction

Laboratory core flooding experiments provide important absolute and relative permeability information about subsurface rock formations from recovered cores [2]. These measurements are routine in the oil and gas industry, and when combined with a CT scanning device, can be used to make sub core-scale measurements of rock porosity and fluid saturation [3]. If rock properties were accurately represented at the sub core-scale, it would be possible to numerically simulate the core flood under different flow and thermophysical conditions to study the resulting changes in fluid distributions, and saturation values. This ability would be very useful for many reasons, particularly because these experiments are very challenging and time consuming to conduct, and because many simulations can be conducted simultaneously.

* Corresponding author. Tel.: +1-650-725-0742; fax: +1-650-725-2099.
E-mail address: krausm2@stanford.edu.

doi:10.1016/j.egypro.2011.02.387

Until recently, such attempts at numerically simulating these experiments were primarily limited to matching core average properties such as average saturation and pressure drop across the core, or looking at purely qualitative qualities of the core flood. A recent method developed by Krause et al. [1] allows researchers to extend this to making quantitative predictions of fluid distributions at the sub core-scale by taking advantage of fluid saturation measurements from the experiment, to predict permeability, which cannot be measured at the sub core-scale. Results in Krause et al. [1] show that this method works to accurately predict the fluid saturation in the rock core at the sub core-scale for a relatively homogeneous Berea sandstone core, and this current work demonstrates the methods accuracy for certain heterogeneous cores.

In this work, a steady-state core flooding experiment using CO_2 and brine is conducted to measure relative permeability and to obtain a high resolution dataset for studying the factors controlling the CO_2 saturation distribution. The heterogeneous sandstone core used in this study comes from the Waare C formation at the Otway Basin Pilot Project in Australia, and was specifically selected because of its high degree of heterogeneity. The experimental core flooding system uses a series of pressure transducers and a CT scanner to calculate the core average permeability and relative permeability, the CT scanner is used to measure sub core-scale porosity and CO_2 saturation distributions within the rock core [4] during the experiment.

Using these experimental data, numerical simulations are conducted by creating a discretized grid of the core and assigning porosity values from measurements made using the CT scanner. Permeability of each element in the grid is then calculated using the methods provided in Krause et al. [1], briefly described in this paper. Simulations of the core flood experiment are conducted at the same conditions as the experiment. The CO_2 saturation distribution determined by each simulation is then compared to the experimentally measured distribution to determine how well the simulations predict the measured saturation.

2. Experimental and Simulation Procedure

Experimental Apparatus and Procedure

The core flooding experimental apparatus and procedure is described in detail in Perrin and Benson [4]. The experiment is conducted at reservoir pressure of 12.41 MPa and a temperature of 63 ˚C, at which CO_2 is a supercritical fluid. The core is very heterogeneous, and is 8.33 cm long and 5.08 cm in diameter. The experiment includes a set of high precision pressure transducers to measure the pressure drop across the core, and uses a CT scanner to measure sub core-scale porosity and saturation distributions during the experiment. The experiment uses constant injection rate of 2.44 ml/min and a constant outlet pressure boundary condition of 12.41 MPa. Relative permeability is measured using a single core steady state method as described in Perrin and Benson [4].

Porosity and saturation are indirectly measured by taking a series of four CT scans of the core at the desired resolution. The first image is the dry core, the second image is the CO_2 saturated core at the experimental pressure and temperature, the third is the brine saturated core, all taken before the experiment begins and in the given order. Lastly, images of the core are obtained during the core flooding experiment after steady state has been reached, which is defined as the time when saturation and pressure drop across the core have stabilized. The porosity and saturation in each grid element of the core image can then be calculated using methods presented in Akin and Kovscek [2]. The measured porosity and CO_2 saturation at 100 percent fractional flow of CO_2 in the core are shown below in Figure 1 and Figure 2 respectively, the figure data has been upscaled by volume averaging from the original CT grid size of 0.254 mm x 0.254 mm x 1 mm to the simulation grid size of 1.52 mm x 1.52 mm x 2 mm.

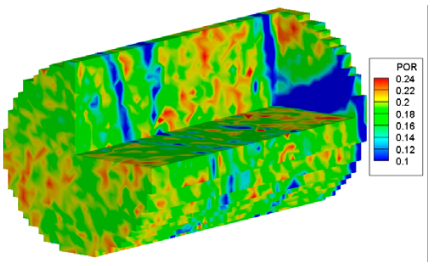


Figure 1. Measured core porosity (grid element size is 1.52 mm x 1.52 mm x 2 mm)

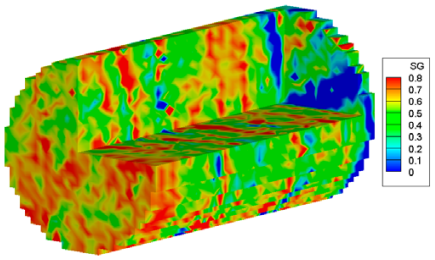


Figure 2. Measured core CO_2 saturation at 100 percent fractional flow of CO_2

Simulation Procedure

To conduct the simulations, the compositional integral finite-difference simulator TOUGH2-MP with the ECO2N module is used [5], [6], [7]. TOUGH2-MP solves a discretized form of the mass and energy balance equations for non-isothermal compressible multiphase flow. ECO2N incorporates an accurate equation of state for supercritical CO_2 and NaCl brine. The simulations are parallelized on 16 processors using domain decomposition to reduce run time, simulations are fully implicit, and are conducted using the same thermophysical conditions as the experiment. The core grid shown below in Figure 3 has 712 cells in each slice with a total of 41 slices, which includes one additional inlet and one additional outlet slice to create the boundary conditions. The inlet slice is designed to simulate the constant flux injection used in the experiment, and each cell has the same generation (injection) rate, such that the sum equals 2.44 ml/min. The permeability of the inlet slice is adjusted to mimic the role of the diffuser plate in the experiment by setting the vertical and horizontal directions to a very large value (6,300 md). This approach has been shown to best simulate the core inlet conditions in the experiment. The outlet slice cells have infinite volume and the capillary pressure gradient between the last slice in the core and the outlet is set equal to zero, which has been shown to most reliably simulate the constant pressure outlet condition from the experiment. Initially, the core is filled with CO_2 saturated brine.

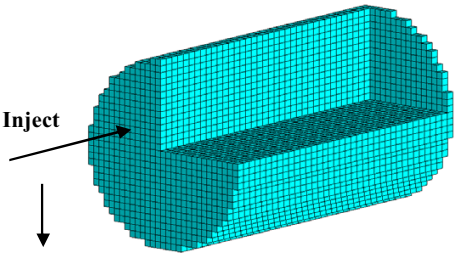


Figure 3. Simulation grid (grid element size is 1.52 mm x 1.52 mm x 2 mm)

A summary of the thermophysical conditions in the experiment and simulation, as well as core and gridding information, is shown below in Table 1. The simulations are conducted until steady state is achieved by injecting CO_2 until the pressure drop across the core and the core average saturation stabilized, injecting a total fluid volume of 14 pore volumes in each simulation. The injected CO_2 is saturated with brine to prevent dry-out, as in the experiment.

Table 1. Summary of simulation and injection conditions

Simulation Conditions		Thermophysical Data		Injection Conditions		Simulation Grid Data	
T (˚C)	63	Dissolved CO_2^{init} (mass fraction)	0.04106	$q_{CO2\text{-}Gas}$ (kg/s)	1.743E-05	Simulation Cells	27768
P (MPa)	12.41	ρ_{CO2} (kg/m^3)	429.90	$q_{CO2\text{-}Aq}$ (kg/s)	0.00E+00	Cell Length (mm)	2
x_{NaCl} (ppm)	6500	ρ_{H2O} (kg/m^3)	986.95	$q_{H2O\text{-}Gas}$ (kg/s)	1.106E-07	Cell Width (mm)	1.52
φ_{ave}	0.180	$\sigma_{CO2\text{-}Brine}$ (N/m)	0.0285	$q_{H2O\text{-}Aq}$ (kg/s)	0.00E+00	Longitudinal Upscaling	2:1
k_{ave} (md)	62.3	Injection Rate (ml/min)	2.44	q_{NaCl} (kg/s)	0.00E+00	In-Slice Upscaling	6:1

Core Average Absolute Permeability and Relative Permeability

Core average permeability and relative permeability are calculated in the experiment using Darcy's law. Absolute permeability (k) is calculated by injecting only brine, setting the flow rate (q) and measuring the core dimensions (area (A), length (L)) and pressure drop (ΔP) and using the correlation of Philips et al. [8] to calculate brine viscosity (μ).

Using this method, a core average absolute permeability of 62.3 md is calculated. Once absolute permeability is determined, relative permeability can be determined by injecting increasing fractional flows of CO_2 and brine, and using Darcy's law for multiphase flow, shown in Eq. 1, solve for $k_{r,i}$ once pressure has stabilized at each fractional flow. The drainage relative permeability data is shown in **Error! Reference source not found.**, along with curve fits used to calculate relative permeability in the simulator. Saturation along the x axis is normalized to residual wetting phase saturation, assumed to be 0.20.

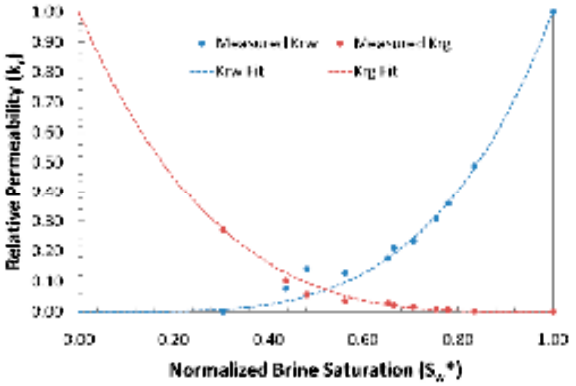


Figure 4. Relative Permeability Data (dots) and Curve Fit Used in Simulations (lines)

$$q_i = \frac{k k_{r,i} A}{\mu_i} \cdot \frac{\Delta P}{L} \tag{1}$$

Capillary Pressure

Capillary pressure is measured using mercury intrusion up to 228 MPa with a Micromeritics Autopore IV 9500 mercury porosimeter on small core samples cut from an adjacent core from which the experimental core was cut. This data was then converted to a capillary pressure curve for the brine-CO_2 system using Eq. 2, where σ is the interfacial tension and θ is the contact angle between the two phases. Interfacial tension was assumed to be 485 dynes/cm for Hg-Air and 28.5 dynes/cm for CO_2-brine [9] and contact angle was assumed to be 130° for Hg-Air and 180° for CO_2-brine.

$$\frac{P_{c,CO_2-brine}}{P_{c,Hg-Air}} = \frac{\sigma_{CO_2-brine} \cdot \cos(\theta_{CO_2-brine})}{\sigma_{Hg-Air} \cdot \cos(\theta_{Hg-Air})} \tag{2}$$

Capillary pressure is calculated from a curve fit. Additionally, the Leverett-J function is used to scale the measured capillary pressure data to the porosity and permeability of each grid element, given by Eq. 3 [10], [11].

$$P_{c,i} = \sigma_{CO_2-brine} \cos(\theta_{CO_2-brine}) \sqrt{\frac{\phi_i}{k_i}} J(S_w) \tag{3}$$

$J(S_w)$ is the J-Function and is simply a dimensionless function of normalized wetting phase saturation used to fit to a single measured capillary pressure curve from a sample of known porosity and permeability. The J-Function typically has several fitting parameters which are determined empirically to give the best curve fit to the experimental data. The J-Function used in this study was developed by Silin et al. [12] and is shown in Eq. 4

$$J(S_w) = A\left(\frac{1}{S_*^{\lambda_1}} - 1\right) + B\left(1 - S_*^{\lambda_2}\right)^{1/\lambda_2} \tag{4}$$

A, B, λ_1 and λ_2 are empirical fitting parameters and S_* is the wetting phase saturation normalized to residual liquid saturation. Eqs. 3 and 4 are then used to determine the fitting parameters to match the measured data using the experimentally measured porosity of the core of 0.180, and permeability of 62.3 md. The fit to the measured data is shown in Figure 5 using the curve fitting parameters of 0.01 for A, 0.04 for B, 2.0 for λ_1 and 1.9 for λ_2. Due to the unique shape of the capillary pressure curve, an exact fit to the data using an equation is not possible.

Once the fitting parameters are determined, they are assumed not to change because it has been shown that $J(S_w)$ is the same function for rocks of similar origin, but different permeability and porosity [10], [11]. For cores with variable

rock types, this assumption may not be accurate, but different fitting parameters could be easily incorporated if capillary pressure data on the different rock types were available. Therefore, once porosity has been measured and permeability calculated for each unique grid element, a unique capillary pressure curve can be created for each grid element in the simulation using Eq. 3. This is done automatically in the simulator.

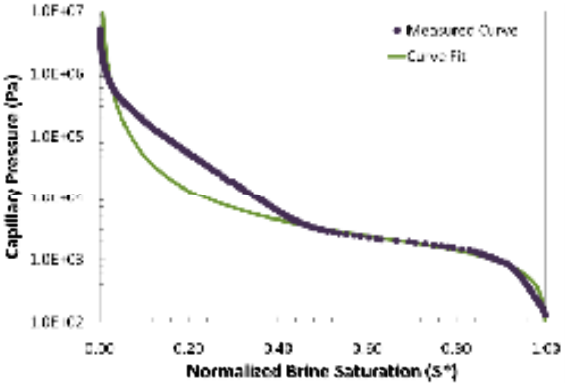


Figure 5. Sample 1 measured capillary pressure data and curve fit J-Fit 1

Sub Core-Scale Permeability

With these assumptions, the only independent parameter required to conduct the simulations is the sub core-scale permeability, all other input has been measured experimentally. The method is relatively complex, and the reader is referred to Krause et al. [1] for further reference, but a summary of the method is given here. The method begins by first assuming that at steady state, for viscous dominated flow systems, a capillary equilibrium exists within the core, once this assumption is made, it must be true that $P_{c,i}$ in Eq. 3 is equal for every grid block in the core. (Note: that we relax this assumption in one of the simulations provided below.) We can see now in Eq. 3, that the only unknown is k, because $J(S_w)$ has the same fitting parameters for every grid block, and every grid block has a measured saturation value from the experiment, which can be input into Eq. 4 to calculate a value for $J(S_w)$. At steady state, this is a fundamental property of Leverett scaling, as shown by Leverett [10], [11]. Since porosity is also measured and the interfacial tension is known from Chalbaud et al. [9], we can now rearrange Eq. 3 into Eq. 5 and solve for permeability, where is the capillary pressure as determined from Figure 5 for the core average saturation.

$$k_i = \frac{1}{P_c^2}\phi_i\left[J\left(S_{w,i}\right)^2\right]\cdot\left(\sigma\cos\left(\theta\right)\right)^2 \tag{5}$$

3. Simulations

A total of three simulations are conducted using Eq. 5 to calculate permeability. In simulation 1, the curve fitting parameters from Figure 5 are used to calculate the values of $J(S_{w,i})$ in Eq. 5. Simulation 2 uses the discretely measured capillary pressure data to calculate permeability, rather than a curve fit. This is possible because the curve fit is only required for the simulation, and a spline fit to the actual data can easily be used to calculate permeability directly by using Eq. 3 to solve for a discrete set of points for $J(S_w)$ using the measured data and core average permeability and porosity. Simulation 3 also uses the discretely measured P_c curve to calculate permeability, but instead of using one value for the average capillary pressure, , it is assumed that there is a capillary pressure gradient across the core, as some researchers have shown to be possible [1], [13], therefore, is calculated for each slice in the core using the slice average saturations, and applied to the corresponding grid elements in each slice. The core in this simulation has 39 unique values for .

It is also important to point out that since the measured sub core-scale CO_2 saturation ranges from zero to one, a residual liquid saturation of zero must always be used when calculating the J-Function values used in Eq. 5 to calculate permeability in each grid element, not doing so would result in non-physical permeability values. Changing the residual liquid saturation does not change the accuracy of the J-Function fit however, because it is a dimensionless function of normalized saturation. It is also evident from the curve fit in Figure 5 that at very low wetting phase saturations, the calculated permeability will be very large; therefore the maximum permeability is arbitrarily limited to 2,000 md.

Simulations Results

The results for these simulations are shown in Table 2, which shows only one slice for visual comparison. Slice 12 was selected because its properties are similar to the core average, and because it has strong heterogeneity which

enhances the spatial variations in CO_2 saturation, however, results are consistent across all slices. The permeability distribution in the slice is primarily dominated by regions of high and low permeability. The permeability distributions for each simulation are similar, although there is some difference between simulation 1 which uses the curve fit to calculate permeability, and the other simulations, which use discrete data.

Comparing the saturation to the permeability, it is obvious that saturation correlates well with permeability, which is a result of using this method to calculate permeability, since saturation is an input. Comparing the visual match between the simulations and the experiment, the correlation is clear for all of the simulations. Looking at the histograms however, it is apparent that the match is not exact. This is largely due to a numerical artefact, whereby a residual liquid saturation of 0.2 was imposed in the simulations, whereas CO_2 saturations greater than 80 percent were measured in the core at the sub core-scale. Work is ongoing to address this discrepancy. Absent that artefact however, the histogram for simulation 1 appears to match the experiment very well, with the others having a somewhat different characteristics, which is primarily due to using discrete capillary pressure data to calculate permeability, and a capillary pressure curve fit in the simulations. If a better curve fit were possible, or tabular data could be used for capillary pressure in the simulation, the match would improve. In terms of the range of values predicted by the simulation, simulation 2 and 3, which use discrete data to calculate permeability, have a standard deviation about the mean saturation which is closest to the experimental value.

Spatial Correlation

The table shows the qualitative match between the simulations and experiment, however, to quantitatively show the quality of the match, a plot of the predicted CO_2 saturation from the simulations vs. the experimental measurement is shown in Figure 6. The figure shows a clear spatial correlation between the experimentally measured saturation and the numerical prediction, although the correlation does not exactly follow the perfect correlation line in dark blue, the match is still clear. The figure also shows distinctly different characteristics for simulation 1, using a curve fit to calculate permeability, and the other simulations, which used discrete data. This is due in part to using discrete data to calculate permeability using Eq. 5, and a curve fit for capillary pressure in the simulations for simulations 2 and 3, whereas simulation 1 uses the same curve fit for calculating permeability and in the simulations.

Table 2. Simulation results for Slice 12 of the Heterogeneous Waare C Core

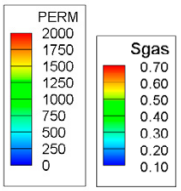
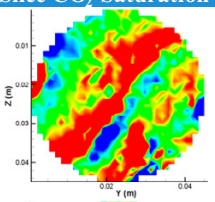
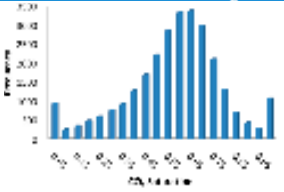
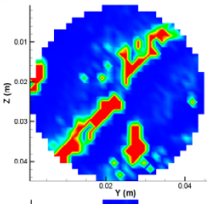
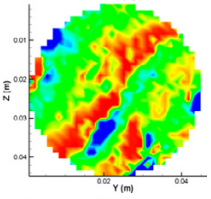
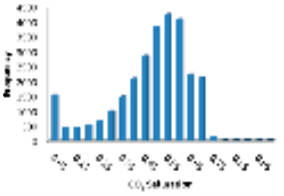
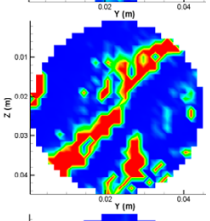
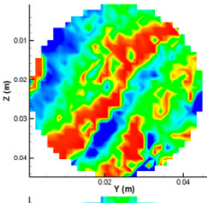
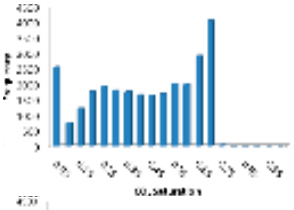
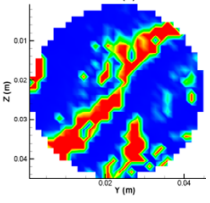
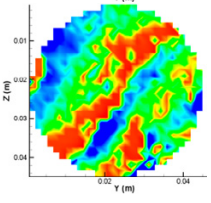
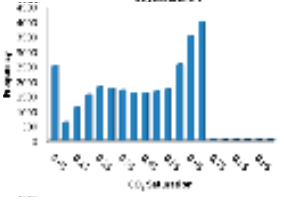
Description	Slice Permeability	Slice CO_2 Saturation	Core Saturation Histogram
Experimentally Measured Saturation Grid Element Dim. (2x1.52x1.52 mm) CO_2 Saturation Std. Dev. 0.343			
Simulation 1 Eq. 5 $J(S_w)$ – Curve Fit - Single Core Average CO_2 Saturation Std. Dev. 0.173			
Simulation 2 Eq. 5 $J(S_w)$ – Discrete - Single Core Average CO_2 Saturation Std. Dev. 0.218			
Simulation 3 Eq. 5 $J(S_w)$ – Discrete - Unique for each Slice CO_2 Saturation Std. Dev. 0.217			

Figure 6. Plot showing simulation CO_2 saturation by grid element vs. corresponding experimental measurement in slice 12

4. Statistical Comparison

To make a quantitative comparison between the different simulations, the coefficient of determination, or R^2, of the sub core-scale saturation prediction can be compared for each simulation. This is calculated for slice 12, shown in Table 2, and also for the entire core for each simulation; the values are shown in Table 3. The R^2 values in the table are all significant for the selected slice, however the core average is lower, but still positive. The average is lower because slices with a great deal of heterogeneity, especially farther from the inlet, have a lower average R^2, this is especially true in simulation 2, where a capillary pressure gradient is assumed to be true when calculating permeability. Despite the lower statistical match in simulations 2 and 3, the qualitative visual match to remains quite good for most slices.

The table shows that the core average saturation error is relatively large, but this is primarily due to imposing a residual liquid saturation of 0.20 in the simulations, which was derived from a relative permeability history match to the measured data. Similar results were obtained for a homogeneous core in [1], and is still a large improvement over simpler methods used to calculate permeability. Allowing a lower value for the residual liquid saturation would increase the core average saturation and the standard deviation. Research is ongoing to reconcile the relative permeability data with the lower residual saturation needed to obtain a better match to the sub core-scale saturation distribution.

Table 3. Statistical comparison of simulation results

Simulation	Slice 12 Saturation R^2	Core Saturation R^2	Average CO_2 Saturation	Saturation Error (%)	CO_2 Saturation Std. Dev.	Std. Dev. Error (%)
1	0.815	0.539	0.449	-20.1	0.173	-49.6
2	0.741	0.152	0.395	-42.4	0.218	-36.5
3	0.715	0.253	0.406	-27.8	0.217	-36.7

5. Discussion of Results

The results from these simulations show that a good qualitative match to experimentally measured sub core-scale saturation distributions is possible using the method in Krause et al. [1] to calculate permeability. The results in this study are consistent with results on homogeneous cores in the previous study in Krause et al. [1]. Despite advances over previous methods used to calculate permeability, using this method does not result in a perfect correlation to the experimental results. There are several factors which contribute to this.

In the experiment, saturation values range from zero to one at the grid element scale, however, a residual liquid saturation of 0.20 was specified for these simulations, lowering the residual liquid saturation to zero will remove the artificial ceiling this places on the maximum CO_2 saturation, but may also results in higher error in the relative permeability history match. A second factor which will affect the saturation distributions is the capillary pressure fit used in the simulations, since the fit in Figure 5 is not exact, the capillary pressure will not be accurate at some saturations; a better fit would be desired, but is difficult to achieve because of the shape of the measured data curve.

Another factor which will have a strong effect on the maximum CO_2 saturation is relative permeability. Based on the input data, residual liquid phase saturation and relative permeability are the only whole core rock properties used in these simulations; porosity, permeability and capillary pressure are all unique to individual grid elements. In strongly

heterogeneous rocks, it may be more accurate to assign one observed rock type one relative permeability correlation, and another rock type a different correlation. Since relative permeability is measured for the whole core, this would be difficult however, without curves measured on samples of each pure rock type present in the heterogeneous core. This also extends to capillary pressure curve fitting parameters, where more than one set of parameters may be required.

6. Conclusions

This work has shown that in order to use sub core-scale experiments and simulations to study multiphase flow behaviour, accurate representation of geological properties is paramount for making quantitative conclusions about the processes controlling sub-core scale saturation distributions. Since these systems can be studied in such detail, they are very useful for understanding how fluid properties and geological parameters govern multiphase flow and influence the behaviour and distribution of CO_2 under different conditions and flow regimes. Therefore, in order to maximize the usefulness of these experiments and the previously developed method used to calculate permeability [1], the objective of this work was to validate the method on highly heterogeneous cores typical of reservoir rocks.

Simulations in this work have shown that the method gives results for heterogeneous cores which are consistent with results in previous work [1] for relatively homogeneous cores, although with some reduction in accuracy. The whole core saturation distribution match as given by the R^2 value is not as good as for homogeneous cores in previous work, but it is still a statistically significant improvement over simple porosity based methods previously used to calculate sub core-scale permeability. This is to be expected, as highly heterogeneous systems pose a significantly greater challenge to match to a high degree of accuracy as compared to relatively homogeneous systems. The simulations in Table 2 show that a qualitative visual match to the experiment is achieved, and Figure 6 shows that a definite correlation exists between the simulation CO_2 saturation results, and the experimental measurements.

Although the method gives accurate results, there are some limitations which future work will address. The effect of avoiding the imposition of a residual liquid saturation in the simulations is ongoing. In addition, we hope that future modification of the simulation code is possible to allow a more accurate representation of measured capillary pressure curves. Finally, future work will also test the uniqueness of the calculated permeability distribution.

7. Acknowledgements

The authors would like to gratefully acknowledge the financial support of the Global Climate and Energy Project.

8. References

[1] Krause, M., Perrin, J.-C., Benson, S. M. Modeling Permeability Distributions in a Sandstone Core for History Matching Coreflood Experiments. SPE Journal 2010; In Publication

[2] Honarpour, M., Koederitz, L., Harvey, A.H. Relative Permeability of Petroleum Reservoirs. Boca Raton, Florida USA: CRC Press. ISBN 0-8493-5739-X; 1986.

[3] Akin, S., and Kovscek, A. R. Computed Tomography in Petroleum Engineering Research. In Mees. F., Swennen, R., Van Geet, M., & Jacobs, P., editors. Applications of X-ray Computed Tomography in the Geosciences, 23-38. London: Special Publication 215, Geological Society; 2003.

[4] Perrin, J.-C. and Benson, S.M., An Experimental Study on the Influence of Sub core-scale Heterogeneities on CO_2 Distribution in Reservoir Rocks. Transport in Porous Media 2010; 82(1), 93-109.

[5] Pruess, K. ECO2N: A TOUGH2 Fluid Property Module for Mixtures of Water, NaCl and CO_2. Berkeley, California: Lawrence Berkeley National Labs Report LBNL-57952, Earth Science Division, University of California, Berkeley 2005.

[6] Pruess, K., Oldenburg, C., and Moridis, G. TOUGH2 User's Guide Version 2.0. Berkeley, California: Lawrence Berkeley National Labs Report LBNL-43134, Earth Science Division, University of California, Berkeley 1999.

[7] Zhang, K., Y-S, Wu., and Pruess, K. User's Guide for TOUGH2-MP – A Massively Parallel Version of the TOUGH2 Code. Berkeley, California: Lawrence Berkeley National Labs Report LBNL-315E, Earth Science Division, University of California, Berkeley 2008.

[8] Philips, S. L., Igbene, I., Fair, J. A., Ozbek, H., and Tavana, M. A Technical Databook for Geothermal Energy Utilization. Berkeley, California: Lawrence Berkeley National Labs Report LBL-12810, Earth Science Division, University of California, Berkeley 1981.

[9] Chalbaud, C., Robin, M., Lombard, J.-M., Martin, F., Egermann, P., and Bertin, H. Interfacial Tension Measurements and Wettability Evaluation for Geological CO_2 Storage. Advances in Water Resources 2008 32; (1): 98-109

[10] Leverett, M. C. Dimensional-Model Studies of Oil-Field Behavior. Trans. AIME 1942; 146: 175-193

[11] Brown, H. W. Capillary Pressure Investigations. Trans., AIME 1951; 192: 67-74

[12] Silin, D., Patzek, T., and Benson, S. M. A Model of Buoyancy-Driven Two-Phase Countercurrent Fluid Flow. Transport in Porous Media 2009; 76: 449-469

[13] Richardson, J. G., Krever, J. K., Hafford, J. A., and Osaba, J. S. 1952. Laboratory Determination of Relative Permeability. Trans., AIME 1952; 195: 187-197