An Initial Approach of Multiple Linear Regression in CO_2-water Relative Permeability Prediction for Carbon Storage Projects

Ying Yu*

Center for Economic Geology Research, School of Energy Resources, University of Wyoming. 1000 E University Ave, Laramie, Wyoming, USA, 82071.

*Corresponding author, Email: yyu3@uwyo.edu

The paper is a non-peer reviewed preprint submitted to EarthArXiv.

Abstract

This work discusses the feasibility of multiple linear regression in predicting water/CO_2 relative permeability using training and testing datasets from two nearby wells, separately, of the Lower Cretaceous Lakota Sandstone, Jurassic Hulett Sandstone, and Pennsylvanian Minnelusa Formation at the Dry Fork Station site. The outcome is promising as the predicted and measured relative permeability data are decently comparable. Yet, whether this approach could be generally applicable needs more delicate models and larger training datasets to be determined.

1. Introduction

Class VI well (EPA, 2013) requires site characterization and prediction of the extent of the injected CO_2 plume and associated pressure front, whichever is further defined as Area of Review. The Area of Review is identified via dynamic modeling, which is highly sensitive to the CO_2-water relative permeability of the injection formation. This work discusses the potential of the previously published relative permeability data of the injection formations (Yu et al., 2023) at one well to be applied to another nearby well. This approach might be useful for projects with limited sources of the special core data for dynamic modeling—relative permeability of the aquifer formations between water and CO_2.

2. Method

This work uses multiple linear regression to determine the dependent variable crosspoint saturation (CS_w) of water and CO_2 relative permeability curves from the irreducible water saturation (Sw_i) and true reference cross-point saturation (RCS). The first independent variable Sw_i is a decimal that has the range of 0–1. To constrain this range, another variable, true reference cross-point saturation (RCS) is also introduced. RCS has a physical meaning and is half of the dynamic space (Mirzaei-Paiaman, 2021):

$$RCS = 0.5 \times (1 - Sw_i) \qquad \textbf{\textit{(Eq. 1)}}$$

The multiple linear regression is defined as:

$$CS_w = w_1 \cdot Sw_i + w_2 \cdot RCS + b \qquad \textbf{\textit{(Eq. 2)}}$$

w_1, w_2, and b are fitting parameters. This work has limited core data from two CO_2 injection wells, PRB#1 and PRB#2, for three potential storage reservoirs — the Lower Cretaceous Lakota Sandstone, Jurassic Hulett Sandstone, and Pennsylvanian Minnelusa Formation—at the Dry Fork Station site, where PRB#1 data (Yu et al., 2023) is for training, and PRB#2 data is for testing. Both PRB#1 and PRB#2 relative permeability data were acquired with the unsteady-state method (Johnson et al., 1959). Modified Brooks and Corey model (MBC (Behrenbruch & Goda, 2006) is adopted for the relative permeability curve fitting:

$$krw = krw_{max} \cdot \left(\frac{S_w - S_{wi}}{S_{w_{max}} - S_{w_i}}\right)^{n\_water} \qquad \textbf{\textit{(Eq. 3)}}$$

$$krg = krg_{max} \cdot \left(\frac{S_{w_{max}} - S_w}{S_{w_{max}} - S_{w_i}}\right)^{n\_gas} \qquad \textbf{\textit{(Eq. 4)}}$$

Where $S_{w_{max}} = 1$ for the CO_2 injection into the aquifer scenario. For this application, the crosspoint CS_w serves to determine the index n_water and n_gas for the predicted curves. Thus, only the endpoint S_{wi} needs to be figured out for a certain core sample, which is the purpose and expectation of the work, while the limitations are concluded in the last section. Refer to the Appendix for the coding. Independent and dependent variables are tabulated in **Table 1**.

Table 1 Relative permeability data for training and testing.

$Well$	$Sample\ No.$	Sw_i	RCS	CS_w
PRB#1	Lakota 8031.4	0.540999	0.2295	0.770701
	Lakota 8035.4	0.580368	0.209816	0.787591
	Hulett 8307.7	0.46972	0.26514	0.74372
	Hulett 8325.8	0.579942	0.210029	0.817819
	Hulett 8332.6	0.526892	0.236554	0.712748
	Minnelusa 9366.8	0.406033	0.296984	0.652225
	Minnelusa 9464.2	0.416358	0.291821	0.747614
	Minnelusa 9529.3	0.491233	0.254384	0.725876
PRB#2	Lakota 8063	0.59199	0.204005	0.77327
	Hulett 8330	0.521616	0.239192	0.766865
	Minnelusa 9487	0.409992	0.295004	0.681677

3. Result and Discussion

The predicted CS_w is listed in **Table 2**. The mean absolute percentage errors (MAPE) of the samples Lakota 8063, Hulett 8330, and Minnelusa 9487 are 2.94%, 1.39%, and 1.67%, respectively, considered insignificant. Further, the relative permeability curve expression is displayed in **Figure 1**.

Table 2 Measured and predicted crosspoint saturation CS_w used for relative permeability expression.

$Well$	$Sample\ No.$	Sw_i	RCS	CS_w	$Predicted\ CS_w$
PRB#2	Lakota 8063	0.59199	0.204005	0.77327	0.79602105
	Hulett 8330	0.521616	0.239192	0.766865	0.75620107
	Minnelusa 9487	0.409992	0.295004	0.681677	0.69304051

The predicted CS_w and relative permeability expression are agreeably similar and feasible for dynamic modeling from a practical perspective. This suggests that the irreducible water saturation serves as a critical indicator for the rock's wettability, which dominates the fluid flow in porous media and might even neglect the petrophysical barriers of varying formations at the studied site. Yet, as the training and testing datasets used for this work are limited, this approach using irreducible water saturation (Sw_i) and reference crosspoint saturation (RCS) to predict the crosspoint saturation (CS_w) and further relative permeability curves of the injection formations at the nearby wells might only be applicable to this project. More delicate models and approaches should be quested for similar applications to assist the carbon storage projects efficiently and accurately.

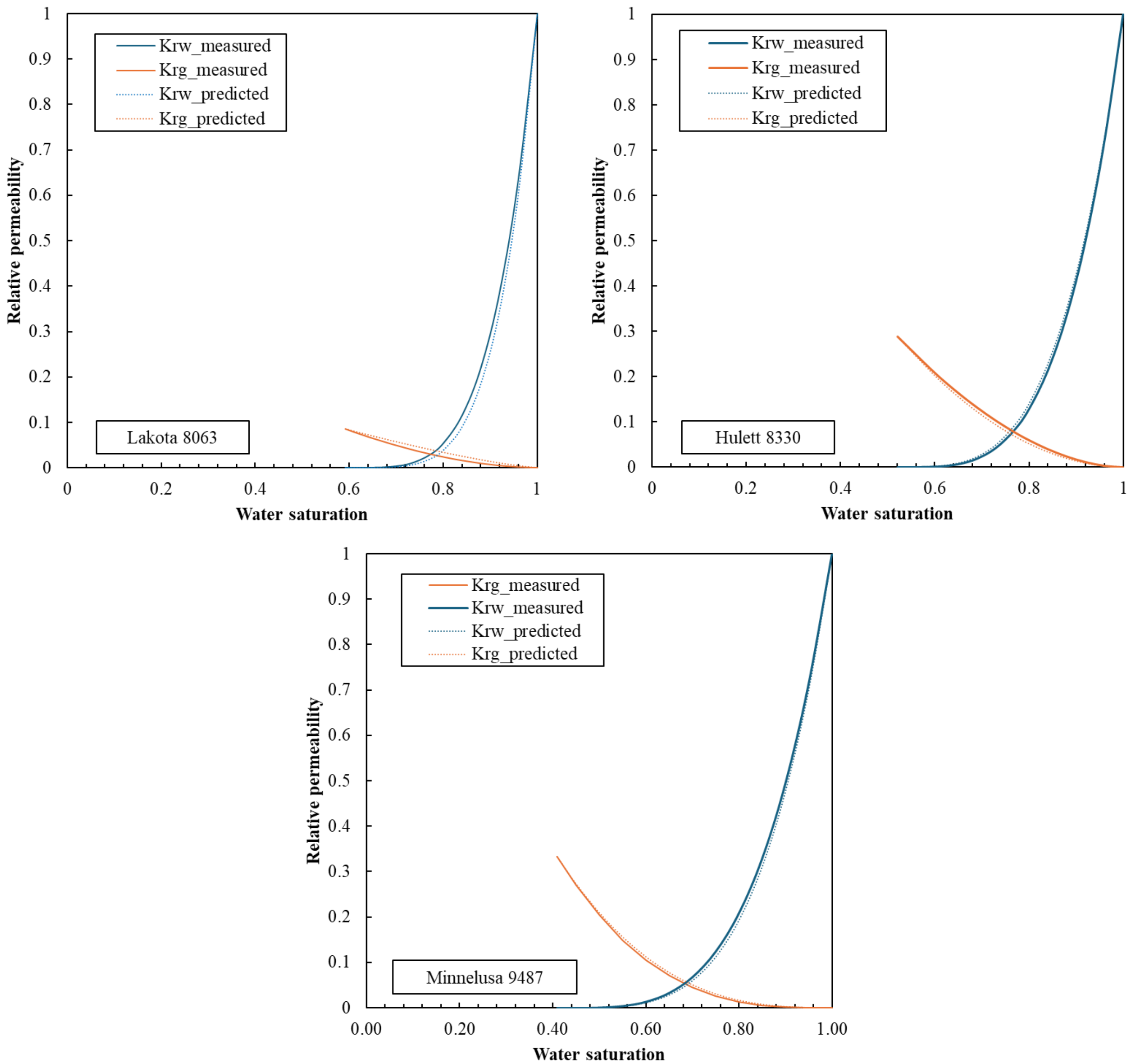

Figure 1 Measured and predicted relative permeability comparison.

4. Conclusion

This work discusses the feasibility of multiple linear regression in predicting water/CO_2 relative permeability using training and testing datasets from two nearby wells, separately, of the Lower

Cretaceous Lakota Sandstone, Jurassic Hulett Sandstone, and Pennsylvanian Minnelusa Formation at the Dry Fork Station site. The outcome is encouraging as the predicted relative permeability data is usable for dynamic modeling from a practical standpoint at the study site. Meanwhile, whether this approach could be generally applicable needs more delicate models and larger training datasets to be determined.

Appendix

Multiple linear regression code is published on GitHub (https://github.com/yuyu84310/MLR-for-CCUS-relative-permeability-prediction).

Reference

Behrenbruch, P., & Goda, H. M. (2006). Two-phase relative permeability prediction: A comparison of the modified Brooks-Corey Methodology with a new carman-kozeny based flow formulation. *Proceedings - SPE Asia Pacific Oil and Gas Conference and Exhibition 2006: Thriving on Volatility*, *2*, 810–827. https://doi.org/10.2118/101150-ms

EPA. (2013). *Geologic Sequestration of Carbon Dioxide Underground Injection Control (UIC) Program Class VI Well Area of Review Evaluation and Corrective Action Guidance*. http://water.epa.gov/type/groundwater/uic/wells_sequestration.cfm.

Johnson, E. F., Bossler, D. P., & Bossler, V. O. N. (1959). Calculation of Relative Permeability from Displacement Experiments. *Transactions of the AIME*, *216*(01), 370–372. https://doi.org/10.2118/1023-g

Mirzaei-Paiaman, A. (2021). New methods for qualitative and quantitative determination of wettability from relative permeability curves: Revisiting Craig's rules of thumb and introducing Lak wettability index. *Fuel*, *288*(November 2020), 119623. https://doi.org/10.1016/j.fuel.2020.119623

Yu, Y., Farzana, S., Nye, C., Bagdonas, D., Waghmare, P. R., Jiao, Z., & McLaughlin, J. F. (2023). Wettability variation and its impact on CO2 storage capacity at the Wyoming CarbonSAFE storage hub: An experimental approach. *Fuel*, *344*(February), 128111. https://doi.org/10.1016/j.fuel.2023.128111