Enhanced Shale Permeability Estimation Based on Statistical Rock Physics Analysis : A Midland Basin Wolfcamp Shale Case Study

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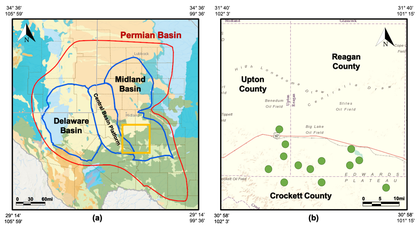
1. Introduction

1. An accurate estimation of the shale permeability (k) is essential to understand heterogeneous organic-rich shale rocks and predict the complexity of pore fluid transport in the rocks.
2. However, predicting the shale matrix permeability by traditional models, such as Kozeny's equation and Herron's method, is still challenging because they require information often measured from core measurements.
3. In this study, we estimate shale matrix permeability by a combined exploratory data analysis (EDA) and nonlinear regression estimation from the wireline logs. As a result, a cubic logarithmic function of porosity significantly improves the estimation of the permeability values, better than the traditional methods.

2. Study Area

- **University Lands in the Midland Basin (eastern part of the Permian Basin, TX)**
- **Well logs and core measurements**

(a)



(b)

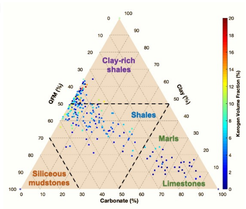


Figure 1. (a) Study area and well locations in three counties, the southern part of the Midland Basin. (b) Mineralogic ternary diagram of the core measurements.

3. Traditional Methods

- **Kozeny's equation (Kozeny, 1927)**
  - Using porosity and specific surface area of solid grains
  - $k = c\frac{\phi^3}{S^2} \approx a\phi^3$, $c = \frac{1}{(4\cos(\frac{1}{3}\arccos(\phi\frac{64}{\pi^3}-1)+\frac{4}{3}\pi)+4)}$
  - However, it is difficult to characterize the specific surface area values or grain sizes in the well logs.

- **Herron's method (Herron, 1987)**
  - Based on the mineral contents provided by well log data in quartz-rich sandstone rocks
  - $k = A_f\frac{\phi^3}{(1-\phi)^2}e^{(\sum B_i M_i)}$
  - However, the predictive accuracy is low due to the different pore network structures of the shales.

4. Exploratory Data Analysis (EDA)

- **Three-phase statistical shale rock physics model (Lee & Lumley, 2019)**
  - $Y = a_1\phi + a_2V_{Clay} + a_3TOC + a_4$
  - Porosity shows the strongest correlation with the shale matrix permeability.
    → The porosity can be an efficient indicator to estimate the permeability.

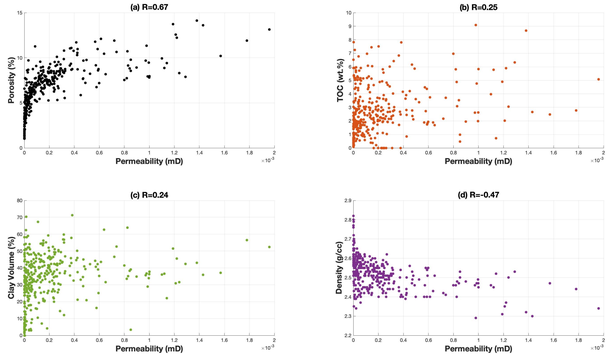


Figure 2. Crossplots of the permeability and four rock properties from the core data: (a) porosity (ϕ), (b) total organic carbon (TOC), (c) clay volume (V_{Clay}), and (d) bulk density (ρ_{bulk}).

	k	ϕ	TOC	V_{Clay}	ρ_{bulk}
k	1.00				
ϕ	0.67	1.00			
TOC	0.25	0.30	1.00		
V_{Clay}	0.24	0.49	0.22	1.00	
ρ_{bulk}	-0.47	-0.74	-0.71	-0.40	1.00

Table 1. Bivariate correlation values between the permeability and four rock properties.

6. Multivariate Linear Regression (MLR)

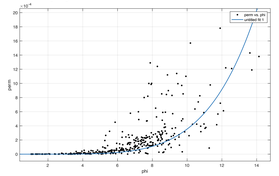
- $k = a_1\phi + a_2V_{clay} + a_3TOC + a_4$ (R^2 = 0.46, RMSE = 0.00023)
- Porosity is the most influential factor on the permeability estimation. Therefore, porosity can be a better indicator to predict the permeability.
- Due to the nonlinearity between two variables, we can derive a nonlinear permeability function with a better fit to the permeability data than the traditional methods.

	a_1	a_2	a_3	a_4
Coefficient	0.0000857	-2.56e-06	0.000011	-0.0002961
SRC	0.71	-0.12	0.06	
Shapley	87.9%	11.2%	0.9%	

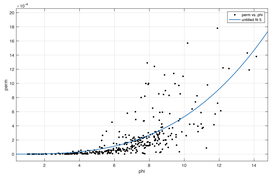
Table 2. MLR analysis with regression coefficient, standardized regression coefficient (SRC), Shapley values between the permeability and three rock properties.

7. Results

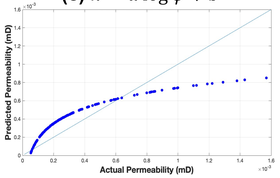
(a) Herron's method



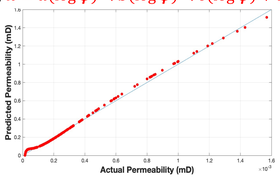
(b) Modified Kozeny's equation



(c) $k = a\log\phi + b$

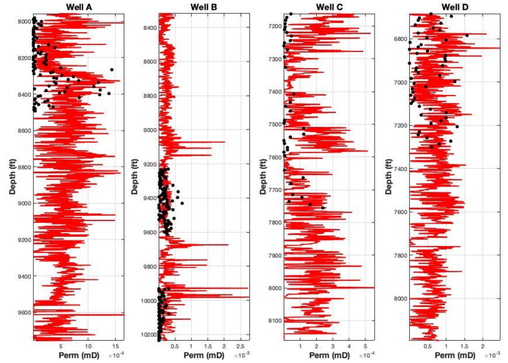


(d) $k = a(\log\phi)^3 + b(\log\phi)^2 + c(\log\phi) + d$



	R^2	RMSE
(a)	0.40	2.4×10^{-4}
MLR	0.46	2.3×10^{-4}
(b)	0.56	2.1×10^{-4}
(c)	0.67	2.0×10^{-4}
(d)	0.99	2.5×10^{-5}

Figure 3. Predicted versus actual permeability plots for four estimation functions.



Deriving a nonlinear function of porosity to permeability from the core data

Calibrating the porosity logs with the core porosity measurements

Generating the permeability logs from the calibrated porosity logs

Figure 4. Synthetic permeability logs from the calibrated porosity logs with the core permeability measurements (black dots).

8. Conclusions

- First, we conduct a bivariate correlation analysis for permeability and rock properties in core measurements. We find that permeability change has a significant effect on the variation in porosity.
- Second, we derive a nonlinear polylogarithmic estimation function of porosity to permeability, comparing it to the traditional methods and the MLR model. As a result, a cubic logarithmic function of porosity significantly improves the fitting performance of the permeability values better than the traditional methods.
- We successfully generate the permeability logs from the calibrated porosity logs, and this approach can also help to understand the pore systems in shales and improve the fluid flow modeling.