Petrophysical characterization and permeability estimation using well log and core data from Namorado Oil Field, Campos Basin, Brazil.

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Abstract

The Namorado Oil Field, located off-shore Campos Basin, near the state of Rio de Janeiro, represents the beginning of oil exploration in Brazil in the 70's and is still target of re-exploratory researches. Because of turbidite sandstones significance in this Field and the huge general representativity of such reservoirs in Brazil's oil productivity, this study is aimed at petrophysical characterization of "Namorado Sandstone" with emphasis on permeability estimation from multiple linear regression. The Namorado Sandstone is the producer researvoir in the Namorado Field and consists of turbidite sand deposits, sedimented during the Albian - Cenomanian. The modeling, graphical generation and statistical analysis were performed with use of programming language matlab, version R2014a . Throughout this research, well log data from one vertical well were used, along with porosity and permeability data measured in laboratory from core samples extracted in this well. The well name is NA04, and was chosen because it has more core data overall. This approach was made because usually many wells are not cored, while others are not continuously cored for this process demand high costs and be quite slow. The greater effort on permeability estimation is justified because of its extreme importance on reservoirs quality and management analysis, along with its high complexity level from the point of view of obtaining it from empirical and/or semi-empirical equations. Such complexity is due to the fact that permeability is controlled by many parameters, both the microscopic and macroscopic level, and may even vary drastically in a matter of centimeters of rock.

Introduction

The knowledge of petrophysical characteristics within reservoir rocks is useful to set a suitable geophysical and geological interpretation, providing thus better prospects for reservoir operation forecast. Among the parameters that govern these properties, there are porosity, fluid saturation, shale content and permeability, which is the most difficult to be estimated given its high complexity and dependence on many parameters. Such measures, along with Net-pay are the most important from a commercial point of view and will be discussed in this paper using a simple and objective approach, for one well, located in Namorado Oil Field.

Permeability and porosity from core samples are the most close-to-reality way of obtain these rock properties. Though, according to Crain (2000), many wells are barely continuously cored, and even when they are, permeability measured in core samples may lead to questionable values, since in heterogeneous rocks, permeability can vary from 0 to 50 Darcies in a matter of centimeters.

A great amount of work was done by several investigators, such as Tixier (1949), Timur et al. (1968), Coates et al. (1973) and many others, in the attempt to grasp the complexity of permeability function into a model with general applicability. All these studies give a better understanding of the factors controlling permeability, but they also show that it is an illusion to look for an "universal" relation between permeability and other variables (Balan et al. 1995).

The regression approach, using statistical instead of "stiff" deterministic formalism, tries to predict a conditional average, or expectation of permeability, corresponding to a given set of parameters (wendt et al., 1986) and (Dubrule e Haldorsen, 1986). From this point of view this study will lean on obtaining some parameters from log data such as effective porosity (ϕ_e), shaleness (V_{sh}), water saturation (S_w) and Net-pay with an effort on predicting permeability also from well log data and from well-log-derived parameters, with use of multiple linear regression.

Method

This research was carried out in several steps, the first one being the lithological discrimination from curves ρ_b and GR using lithology data obtained from core samples, so that we could build a lithology column for the whole well. After that, cross-plots between log data were made to help in parameters selection such as ρ_m , GR_{max}, GR_{min}, ϕ_{Nsh}, ϕ_{Dsh} and R_{sh}, which will be explained later on. Then an anisotropy analysis of permeability was performed analyzing the $K_h \times K_v$ cross-plot, and $\phi_h \times \phi_v$, using Ordinary Least Square Regression (OLSR) and Robust Regression (RR); porosity $\times$ permeability relationships taken from core data and calculation of effective porosity (ϕ_e), water saturation (S_w), shale volume (V_{sh}) and Net-pay from the logs. Then, multiple linear regression analysis were performed with the logs as dependent variables and permeability as response variable which was denoted as K_{logs}. After that, a stepwise regression was carried out to eliminate the non-significant logs from K_{logs} regression, which was denoted as K_{SWR}. Finally a regression using the previously estimated parameters (ϕ_e and V_{sh}) as regression variables, and the response variable was denoted K_z. The results were plotted as "permeability logs", continuously with depth. All statistical analyses were performed in software matlab in the light of the t and F hypothesis tests as well as Coefficient of Determination (R^2), Adjusted Coefficient of Determination (R_a^2) and Pearson's Correlation Coefficient (R).

General expression of multiple linear regression with $p-1$ regression variables:

$$Y_i = \alpha_0 + \alpha_1 X_{i1} + \alpha_2 X_{i2} + ... + \alpha_{p-1} X_{i,p-1} + \varepsilon_i, \quad i \in N^* , \quad (1)$$

where $\alpha_0,\ \alpha_1,\ \alpha_2 ... \alpha_{p-1}$ are the regression coefficients (α_0 is also called intercept); the function Y_i represents a response surface, describing an hyperplane in the p-dimensional space of input variables X_i.

To minimize outliers influence (which are values that "lies outside" or are much smaller or larger than most of the other values in a set of data), linear robust regression can be performed.

Robust regression works by assigning a weight to each data point. Weighting is done automatically and iteratively using a process called *iteratively reweighted least squares*. In the first iteration, each point is assigned equal weight and model coefficients are estimated using ordinary least squares. At subsequent iterations, weights are recomputed so that points farther from model predictions in the previous iteration are given lower weight. Model coefficients are then recomputed using weighted least squares. The process continues until the values of the coefficient estimates converge within a specified tolerance.

The F-test of the overall significance used here is a specific form of the F-test. It compares a model with no predictors to the model that you specify. A regression model that contains no predictors is also known as an intercept-only model. If the P-value for the F-test of overall significance test is less than the significance level (the value used here is 0.05) you can reject the null-hypothesis and conclude that your model provides a better fit than the intercept-only model.

In linear regression The t-test works the same way as the F-test, with the difference that it can assess only one regression coefficient at a time. The hypothesis test on coefficient i tests the null hypothesis that it is equal to zero - meaning the corresponding term is not significant - versus the alternate hypothesis that the coefficient is different from zero. If the P-value for the t-test is lower than 0.05 (significant level used here) for variable, say, i, than one can reject the null hypothesis and this variable is significant on the model, otherwise it is not.

The steps to calculate the petrophysical parameters were mostly taken from Nery (2013).

Getting started with the linear gamma ray index (I_{GR}):

$$I_{GR} = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} , \quad (2)$$

where GR_{log}, GR_{min} and GR_{max} are respectively, the gamma ray reading at the depth of interest, the minimum gamma ray reading (usually the mean minimum through a clean sandstone or carbonate formation) and the maximum gamma ray reading (usually the mean maximum through a shale or clay formation).

The V_{sh} based on the I_{GR} is then calculated as follows:

Clavier equation:

$$V_{sh_{Cla}} = 1,7 - \sqrt{3,38 - (I_{GR} + 0,7)^2} \quad (3)$$

Larionov equation for older rocks (Cretaceous Period):

$$V_{sh_{Lar}} = 0,33 \cdot (2^{2 \cdot I_{GR}} - 1) \quad (4)$$

As the Namorado Formation is composed by arcosean sandstones the V_{sh} estimation from conventional Gamma ray logs is overestimated. In order to overcome this problem, another shale volume indicator was used, taken from curves ρ_b and ϕ_N:

$$V_{shND} = \frac{\phi_N - \phi_D}{\phi_{Nsh} - \phi_{Dsh}} , \quad (5)$$

where ϕ_N is the neutron porosity corrected to the matrix of reservoir rock, ϕ_D is the porosity estimated from ρ_b curve, ϕ_{Nsh} and ϕ_{Dsh} the shale apparent porosity, from both ϕ_N and ρ_b curves.

After calculating the V_{sh}'s above it was chosen the smallest value among the three, at each depth of interest, like this:

If $V_{shND} < 0$ we used the smallest between equations (3) and (4), otherwise we used the smallest among (3), (4) and (5), which was then labeled as $V_{sh_{minor}}$. Besides $V_{sh_{minor}}$, an average V_{sh} was performed from equations (3) and (4), which was labeled as $V_{sh_{med}}$.

Steps for ϕ_e calculation:

$$\phi_D = \frac{\rho_m - \rho_b}{\rho_m - \rho_f} , \quad (6)$$

where, ρ_b, ρ_m and ρ_f are respectively, the bulk density reading at the depth on interest, the bulk density of matrix mineral and the bulk density of fluid.

Then, a correction was performed to remove the shale influence on both, ϕ_D and ϕ_N:

$$\phi_{Dc} = \phi_D - \phi_{Dsh} \cdot V_{sh_{minor}} \quad (7)$$

$$\phi_{Nc} = \phi_N - \phi_{Nsh} \cdot V_{sh_{minor}} \quad (8)$$

And finally, if $\phi_{Nc} < \phi_{Dc}$, Gaymard-Poupon equation is used to calculate ϕ_e:

$$\phi_e = \sqrt{\frac{(\phi_{Nc})^2 + (\phi_{Dc})^2}{2}} \quad (9)$$

else, we use the equation below:

$$\phi_e = \frac{\phi_D \cdot \phi_{Nsh} - \phi_N \cdot \phi_{Dsh}}{\phi_{Nsh} - \phi_{Dsh}} \quad (10)$$

For the Water saturation determination we used a modified expression of Simandoux equation (1963), firstly introduced this way by Bardon and Pied (1969):

$$\left(\frac{\phi_e^m}{a \cdot R_w}\right) \cdot S_w^2 + \left(\frac{V_{sh_{minor}}}{R_{sh}}\right) \cdot S_w - \frac{1}{R_t} = 0 \qquad (11)$$

which would return for the positive root:

$$S_w = \frac{a \cdot R_w}{2 \cdot \phi_e^m} \cdot \left[\sqrt{\left(\frac{V_{sh_{minor}}}{R_{sh}}\right)^2 + \frac{4 \cdot \phi_e^m}{a \cdot R_w \cdot R_t}} - \frac{V_{sh_{minor}}}{R_{sh}}\right] \qquad (12)$$

where R_w is the formation water resistivity, R_{sh} the resistivity of the shale, R_t being the true resistivity of the rock saturated with brine and hydrocarbon, a the tortuosity index and m the cementation factor.

Results

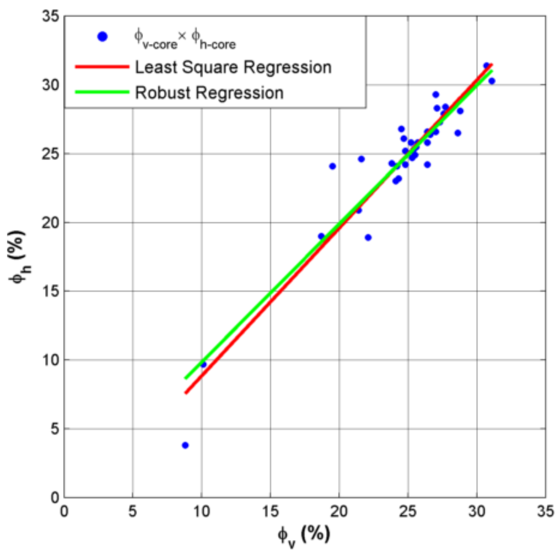

Figure 1: Vertical vs horizontal porosity shows the scalar nature of porosity.

Table 1: Results for regressions in figure 1.

OLSR	$\phi_h = 1.074 \cdot \phi_v - 1.86;\ \ R^2 = 0.90$
RR	$\phi_h = 1.006 \cdot \phi_v - 0.21;\ \ R^2 = 0.94$

Based on a judicious analysis with the help of cross-plots between the log data, it was found the parameters as follows for the well-log-based calculation of petrophysical properties: $\rho_m = 2,68\ g/cm^3$; GR_{min} = 45 API and GR_{max} = 104 API; $R_{sh} = 2\ \Omega.m$, $\phi_{Nsh} = 0,26$ and $\phi_{Dsh} = 0,10$, $m = 2$, $a = 1$ and $R_w = 0.025\ \Omega.m$. The results are shown in table 4 and in figure 4.

In figure 3 ϕ_v was used instead of ϕ_h because it had more data available, although using ϕ_h would lead to the same result as porosity doe not depend on the measuring direction (figure 1).

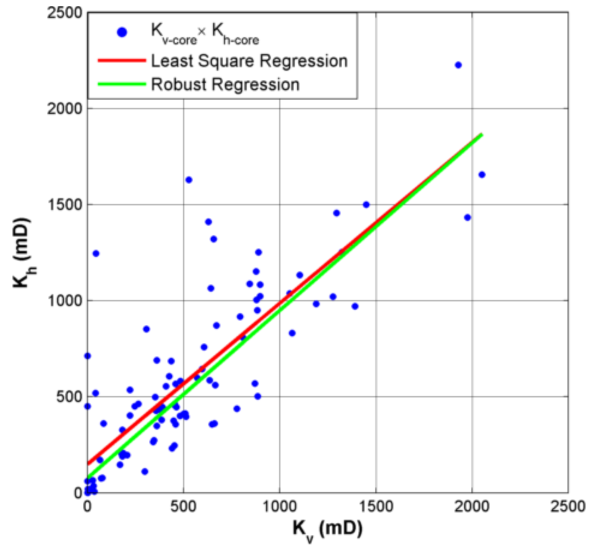

Figure 2: Vertical vs horizontal permeability shows the tensorial nature of permeability.

Table 2: Results for regressions in figure 2.

OLSR	$K_h = 0.84 \cdot K_v + 150;\ \ R^2 = 0.68$
RR	$K_h = 0.87 \cdot K_v + 78.3;\ \ R^2 = 0.80$

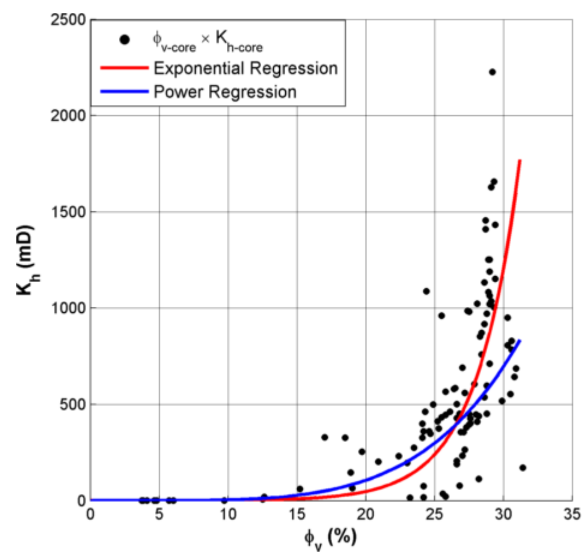

Figure 3: poro-perm graphics showing that porosity and permeability have a non-linear relationship with strong exponential and power correlation.

Table 3: Results for regressions in figure 3.

Exponential	$K = 0.076 \cdot e^{0.3224 \cdot \phi}\ ;\ \ R^2 = 0.84$
Power Law	$K = 0.0001 \cdot \phi^{4.632}\ ;\ \ R^2 = 0.876$

Although the core data shows 10 different facies for this well, they were grouped into 4 great domains, and the following logic was used to create the lithology column:

$45 \leq GR \leq 70$ and $\rho_b \leq 2.35 \Longrightarrow$ sandstone;
$45 \leq GR \leq 60$ and $2.40 \leq \rho_b \leq 2.60 \Longrightarrow$ clayey silt, marl, and/or shale;
$GR \geq 70 \Longrightarrow$ shale;
$GR \leq 45$ and $\rho_b \geq 2.50 \Longrightarrow$ limestone.

Of course this is not a cluster analysis technique, but rather, a simple way of representing the main lithologies continuously with depth, since the cored interval represents only a fraction of the wellbore.

Table 4: Netpay with the average values of effective porosity, shaleness and water saturation in the net-pay zone.

V_{sh} **(fraction)**	S_w **(fraction)**	ϕ_e **(fraction)**	Netpay (m)
0,09	0,22	0,228	69,6

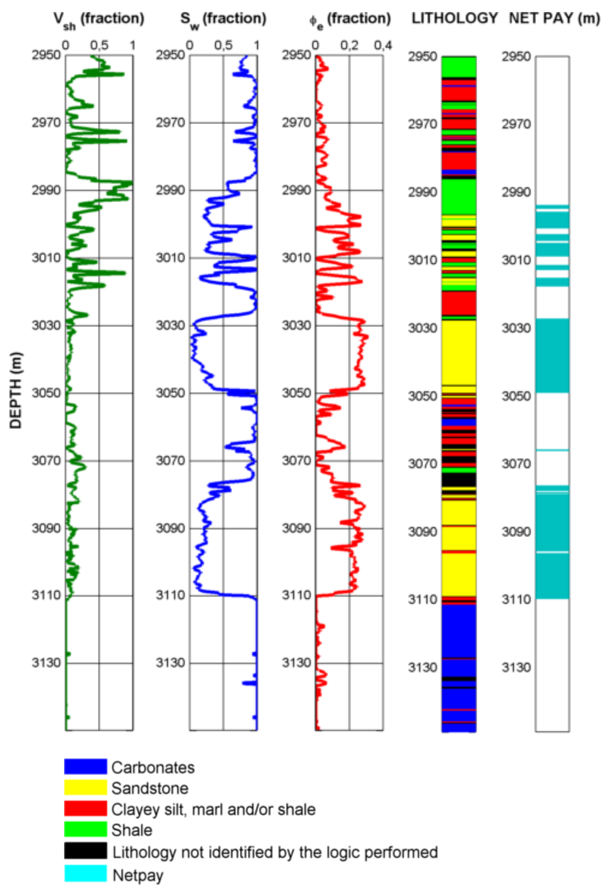

Figure 4: Petrophysical parameters plotted continuously with depth, being the net-pay cutoffs: $V_{sh_{minor}} < 0.30$; $S_w < 0.55$ and $\phi_e > 0.10$.

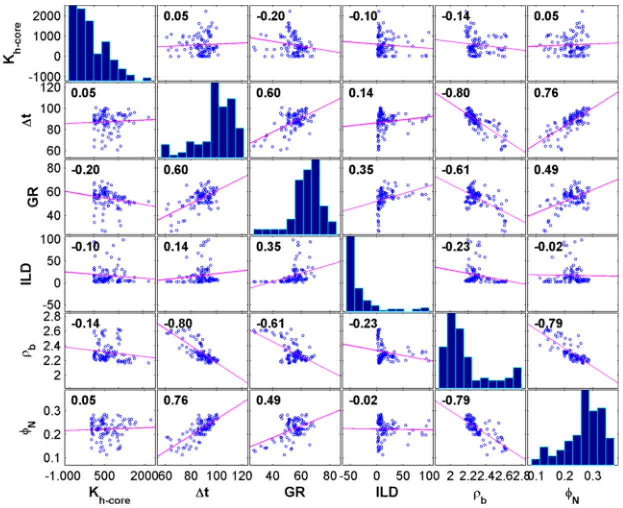

Figure 5: The main diagonal shows the variables histogram, while the other matrix entries shows the Pearson's Correlation Coefficient between the vertical and respective horizontal variable.

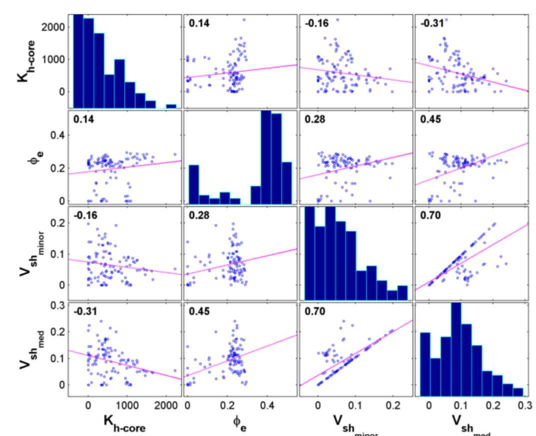

Figure 6: Correlation Coefficient between K_{h-core}, ϕ_e, $V_{sh_{minor}}$ and $V_{sh_{med}}$.

Table 5: Coefficients and statistical parameters obtained for K_{perfis} regression.

Variable	**Coef.**	**t$_0$**	**p-value (t stat.)**
intercept	7353.88	3.3231	0.0012484
Δt	1.35	0.15339	0.8784
GR	-26.17	-3.5695	0.00055354
ILD	-1.69	-0.75309	0.45318
ρ_b	-2118.37	-3.1425	0.0022102
ϕ_N	-2435.35	-1.2522	0.21345
R^2	R_a^2	**t**	**p-value (F stat.)**
0.173	0.132	$\pm$ 1.984	0.00181

Table 6: Coefficients and statistical parameters obtained for K_{SWR} regression.

Variable	Coef.	t_0	p-value (t stat.)
intercept	16335	3.5337	0.00061968
GR	-240.42	-2.6753	0.0087107
ρ_b	-5946.1	-3.1574	0.0020992
$GR \times \rho_b$	88.419	2.3742	0.019478
R^2	R_a^2	t	p-value (F stat.)
0.203	0.18	$\pm$ 1.984	0.0000393

Table 7: Coefficients and statistical parameters obtained for K_z regression.

Variable	Coef.	t_0	p-value (t stat.)
intercept	569.76	5.6233	1.6438e-07
$V_{sh_{med}}$	-3853.1	-4.7042	8.0277e-06
ϕ_e	1802.1	3.5403	0.00060387
R^2	R_a^2	t	p-value (F stat.)
0.195	0.179	$\pm$ 1.9835	0.000016

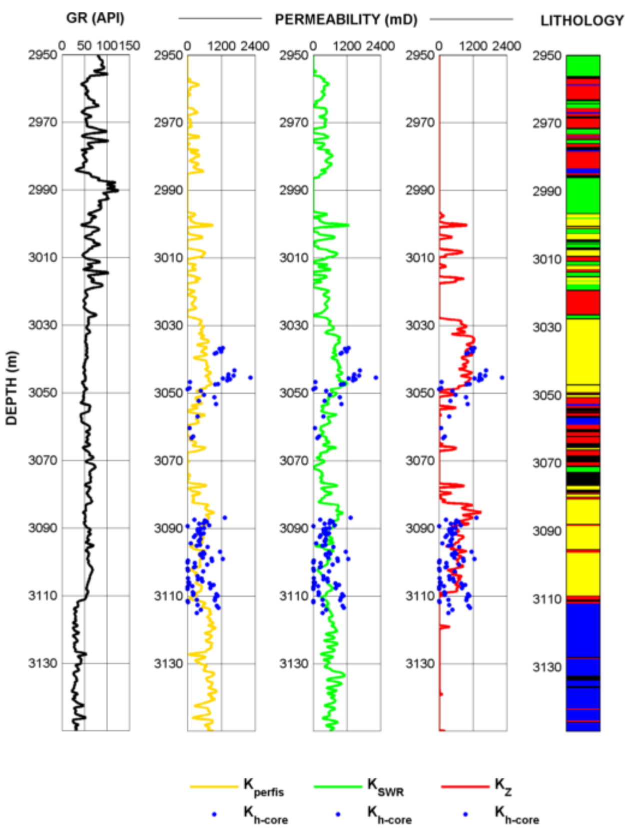

Figure 7: Graphical result for the three multiple linear regressions performed.

Conclusions

In this paper it is proposed a methodology for reservoir characterization using well logs and core data. It's clear that porosity does not depend on the measuring direction as shown in figure 1. On the other hand, permeability shows a tensorial characteristic, exhibiting a greater dispersion (figure 2), that is, varying with direction. The Namorado Sandstone though, exhibits low permeability anisotropy, as can be seen for both, the OLSR and RR regressions. The RR regression suffers less influence on outliers, thus converging to the origin point (0,0), as expected.

It is also shown that permeability and porosity have a direct relationship (figure 3), meaning that the greater the porosity the greater the permeability, which makes sense. Going beyond that, it is shown that it is a rather exponential or a power law relationship. Tixier (1949), Timur et al. (1968) and Coates et al. (1973) obtained empirical equations relating permeability, porosity and irreducible water saturation, where in all of them permeability is a power-law function of porosity. The exponential relationship obtained here is visually better than the power law relation, although the R^2 points out to a better power law correlation between the variables (table 3).

Besides, permeability have little relationship with the conventional well log data used in this paper. The ones who show better correlation are curves ρ_b and GR as can be seeing by both, the figure 5 and the table 5, exhibiting greater R and the smallest p-values for t-statistic. It might be because curve ρ_b is better related to the real porosity of the formation in comparison to ϕ_N (highly influenced by the pore-filled fluid) and GR be related to the shaleness, since dispersed shale reduces the effective porosity of the rock which also reduces permeability (GR and K_{h-core} exhibit inverse relationship seen also in figure 5).

In regression K_z, the well-log-derived parameters ϕ_e and $V_{sh_{med}}$ Shows an expected pattern. K_z grows with ϕ_e and decreases with $V_{sh_{med}}$, as shown by the respective coefficients in table 7. Although $V_{sh_{minor}}$ was used to calculate ϕ_e and S_w, $V_{sh_{med}}$ shows a way better correlation to permeability (figure 6). Might be because $V_{sh_{med}}$ used here depends only on GR curve, while $V_{sh_{minor}}$ depends on curves GR, ρ_b and ϕ_N.

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