Improving permeability prediction: A comparison rock typing and multilinear regression method in bioclastic carbonate reservoir

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Abstract
Carbonate rocks are known for high level heterogeneity due to syn-depositional and post-depositional process. Developing rock type scheme for reservoir rocks involves considering various factors, including rock fabric, pore types, and pore throat size distribution, and it requires the integration of multi-scale data to ensure its reliability and predictability in assessing reservoir properties and performance. Comprehensive understanding of the complex variations in pore geometry, as influenced by lithofacies, depositional, and diagenetic controls, is crucial for effectively managing and exploiting hydrocarbon reservoirs. Core data analysis plays a significant role in achieving this understanding and can help define distinct zones within the reservoir, aiding in reservoir management and optimization of hydrocarbon production. Permeability prediction is indeed a key component of reservoir characterization and evaluation. This study is expected to comparison and define more detail between two permeability prediction methods there are multilinear regression (MLR) and hydraulic flow unit in bioclastic carbonate reservoir. To estimate the rock type permeability value, a hydraulic unit approach is used by flow zone indicator. Whereas, to estimate multilinear regression value used by dependent variable (core permeability) and independent variable (porosity and shale volume). Petrographically from 60 core plugs concludes that the lithofacies in the Formation A is predominantly foraminiferal grainstone – packstone lithofacies and the diagenetic environment is marine phreatic. The Formation B is dominated by skeletal wackestone – packstone and the diagenetic environment is shallow burial or mixing zone. Petrography is a crucial role in the validation and comprehensive understanding of sedimentary rocks and their diagenetic history. It provides detailed insights into the mineralogy, texture, and structures of these rocks.

Keywords: Bioclastic carbonate rock, permeability, multilinear regression, hydraulic flow unit, rock typing

Introduction

Geologically, the carbonate rocks in the southern Banggai Basin consist of the Minahaki Formation and the Tomori Formation [1]. The Minahaki Formation is grainstone and Tomori Formation was dominated muddy carbonate [1, 2, 3]. Understanding how various factors, including lithofacies, depositional processes, and diagenesis, affect pore geometry is essential for improving the description and exploitation of reservoirs. Core data plays a key role in gathering information about these controls, which, in turn, helps in making informed decisions about resource extraction and management [4]. A comprehensive and systematic classification of reservoir rocks based on their rock fabric, pore types, pore throat size distribution, and other relevant properties. This classification can be invaluable for predicting how these rocks will perform as reservoirs and for making informed decisions in the field of petroleum exploration and production [5]. Carbonate rocks are known for high level heterogeneity due to syn-depositional and post-depositional process.

Due to these syn-depositional and post-depositional processes, carbonate rocks can exhibit a wide range of characteristics, including variations in lithology, porosity, permeability, and reservoir quality. This heterogeneity is of particular significance in geology, petroleum exploration, and environmental studies, as it can influence the behavior of fluids within these rocks and impact their suitability for various purposes. To predict permeability accurately, various methods and technologies are used, including core analysis, well logs, seismic data, and geological modeling [6]. Combining data from these sources allows to create a comprehensive reservoir description, including permeability distributions, which is vital for making informed decisions in the oil and gas industry. Various method to predict permeability based on pore and grain properties as table follow:

Prediction of Hydraulic Units

The hydraulic quality of a rock is a complex interplay of pore geometry, mineralogy, and texture. Geologists and hydrogeologists often study these factors to understand how rocks behave as aquifers or reservoirs for fluids like water, oil, or gas. A flow chart of the HFU permeability prediction shown on Fig 1.

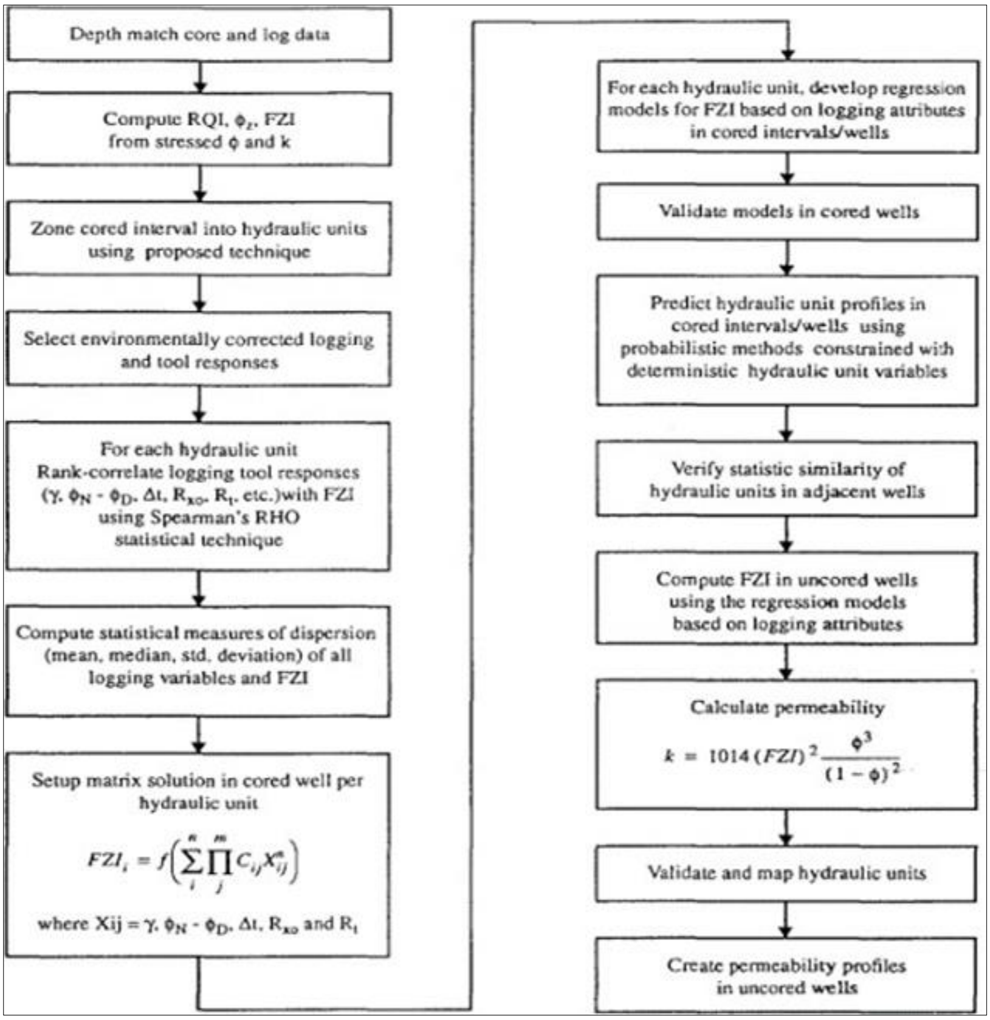

Fig 1: Workflow of permeability prediction (HFU) from core and log data [4]

The arrangement and characteristics of pores within a rock play a significant role in determining its hydraulic properties. Pore geometry refers to the size, shape, and connectivity of the pores. Rocks with well-connected, larger pores tend to have higher permeability, allowing fluids to flow more easily through them. In contrast, rocks with smaller, poorly connected pores have lower permeability. The type and abundance of minerals in a rock can affect its hydraulic quality. Some minerals are more porous than others, and the presence of certain minerals can create pathways for fluid flow or block them. Additionally, the morphology (shape) and location of minerals relative to pore throats can influence the ease with which fluids can move through the rock [7]. Hydraulic flow unit (HFU) is defined as the representative volume of total reservoir rock within which geological properties that control fluid flow are internally consistent and predictably different from properties of other rocks. HFU is an improved probabilistic technique to calculate permeability distribution in un-cored wells but logged well [8]. The Flow Zone Indicator (FZI) is a parameter used to characterize and discriminate between different pore geometrical facies or hydraulic units within a subsurface reservoir. The Reservoir Quality Indicator (RQI) method is a technique used in the field of petroleum reservoir characterization to classify reservoir data into distinct Hydraulic Flow Unit (HFU) based on the Fluid Flow Zone Index (FZI). This method helps in understanding and characterizing the heterogeneity of a reservoir [9]. By applying the concept of hydraulic flow units to wells with only well-log data, can gain valuable insights into the reservoir's heterogeneity and flow characteristics [10].

MLR Permeability Prediction

Multiple Regression Analysis is a valuable statistical technique to predict permeability and other dependent variables based on a set of independent variables or predictors, such as core and well log data. This technique helps establish relationships between the variables and provide valuable insights into the factors influencing permeability in a geological formation. The general purpose of multiple regression is to learn more about the relationship between several independent variables and a dependent variable. Multiple linear regression is a powerful statistical tool for understanding and predicting the relationship between multiple variables. Scale type for the dependent and independent log consist of linear, logarithmic, hyperbolic, and magnolia. In multiple regression analysis, the goal is to estimate a linear relationship between a dependent variable and two or more independent variables. The general form of the linear equation in multiple regression is:

$$Y = b0 + b1\ X1 + b2\ X2 + \ldots + bk\ Xk + \varepsilon$$

Where:

- Y is the dependent variable,
- X1, X2,…,Xk are the independent variables,
- b0 is the intercept (the value of Y when all independent variables are zero),
- b1, b2,…,bk are the regression coefficients (representing the change in Y for a one-unit change in the corresponding X),
- ε is the error term (captures the unobserved factors affecting Y),
- k is the number of independent variables

Data and Method

The primary data consist of 12 wells. Triple combo wireline log from 10 wells, 60 core plug samples from two wells. 25 samples from foraminiferal grainstone – packstone lithofacies and 35 samples from skeletal wackestone – packstone lithofacies. Wherein, four samples no permeability data, three mod, and five rubble. Quantitative petrophysical analysis uses deterministic methods to obtain VSh, total Porosity (PHIT), effective porosity (PHIE), hydraulic unit permeability (KHU), and multilinear regression permeability (K_MLR). Shale volume was obtained by the linear method calculating of the Gamma Ray index (IGR) based on gammaray log. Total and effective porosity were estimated using three methods that are density, neutron and density-neutron. The following equation is used to calculate total and effective porosity:

- Density Porosity (PHID)

$$\phi_d = \frac{\rho_{ma} - \rho_b}{\rho_{ma} - \rho_f}$$

- Neutron-density Porosity (PHIND)

$$PHIND = \frac{PHID + PHIN}{2}$$

- Effective porosity (PHIE) was obtained by correcting of the porosity value that estimated by neutron-density with total clay porosity (Vshl).

$$PHIE = PHIND - (V_{shl} * PHIT_{shl})$$

To estimate the permeability value, a hydraulic unit approach is used by Kozeny-Carmen. Kozeny derived the basic equation which describes the permeability relationship as a function of porosity and specific surface area. The quality of hydraulic rock is controlled by pore geometry which is a function of mineralogy (type, amount, morphology and position relative to pore throat) and texture (grain size, grain shape, sorting, packing). The variation in geological attributes indicates the presence of rock units with pore throat similarities. The concept of mean hydraulic unit radius is used to complete hydraulic units and the relationship between porosity, permeability and capillary pressure. The Kozeny-Carmen Permeability Equation can be written as follows:

$$\sqrt{\frac{k}{\phi}} = \frac{1}{s_{Vgr}\sqrt{K_T}}\left(\frac{\phi_e}{1-\phi_e}\right)$$

RQI = Reservoir Quality Index

$$RQI = 0.0314\sqrt{\frac{k}{\phi_e}}$$

FZI (μm) is defined as a flow zone indicator

$$FZI = \frac{1}{s_{Vgr}\sqrt{K_T}} \quad \log(RQI) = \log(\phi_z) + \log(FZI)$$

Result and Discussion

Shale Volume Calculation

To calculate shale volume using linear method, the value of GR clean/sand and GR shale is obtained using the histogram. GR clean for Formation A and B is 15 GAPI. GR shale is 90 GAPI (Figure 2).

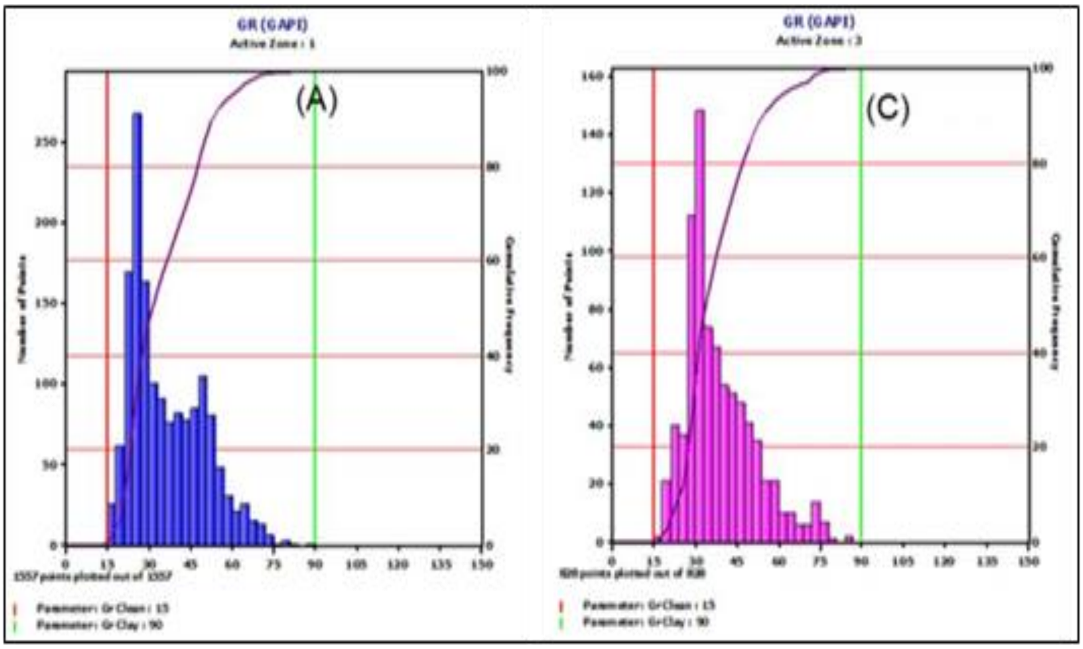

Fig 2: GR clean (red line) dan GR shale (green line) Formation Minahaki and Formation Tomori

Porosity Calculation

RHOB and NPHI crossplot are used to determine the neutron and density matrix (MA), shale (SH), and dry shale (Figure 3). These parameters are required to determine the total porosity value of clay in the calculation of effective porosity.

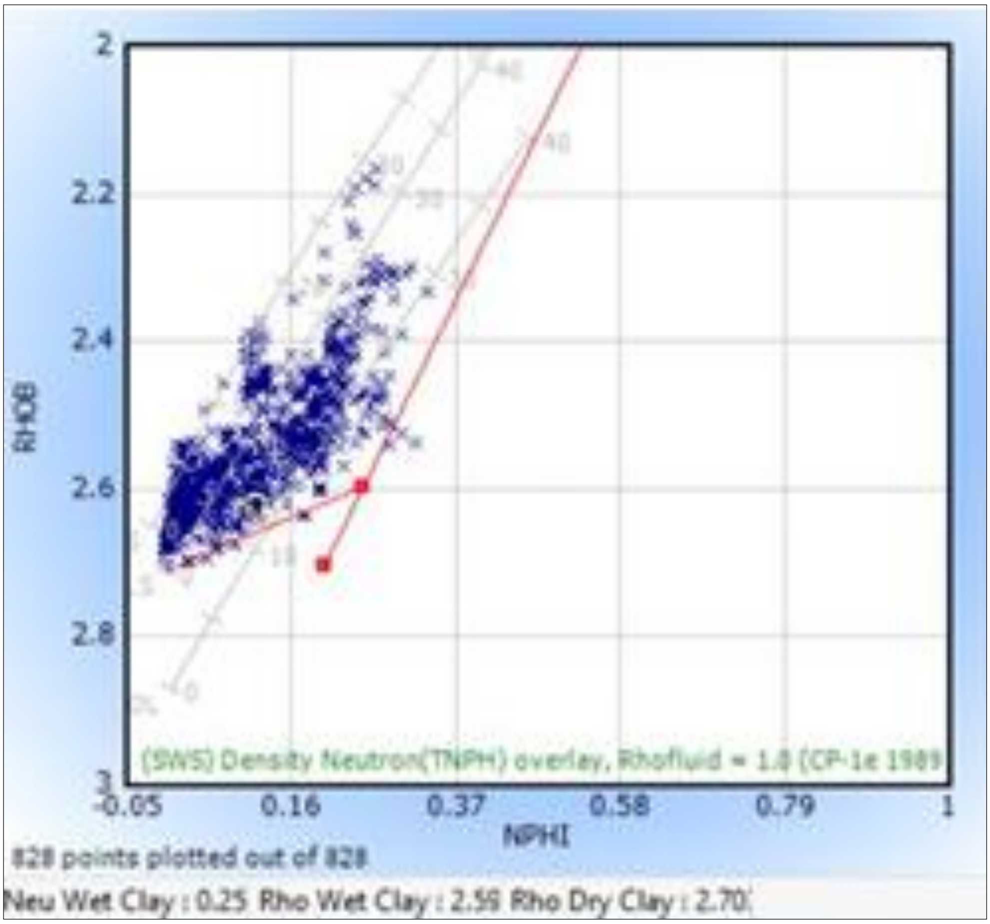

Fig 3: Neutron wet clay, density wet clay and density dry clay based on RHOB-NPHI crossplot

The porosity calculation results are validated by comparing of the porosity values with routine core analysis results (Figure 4).

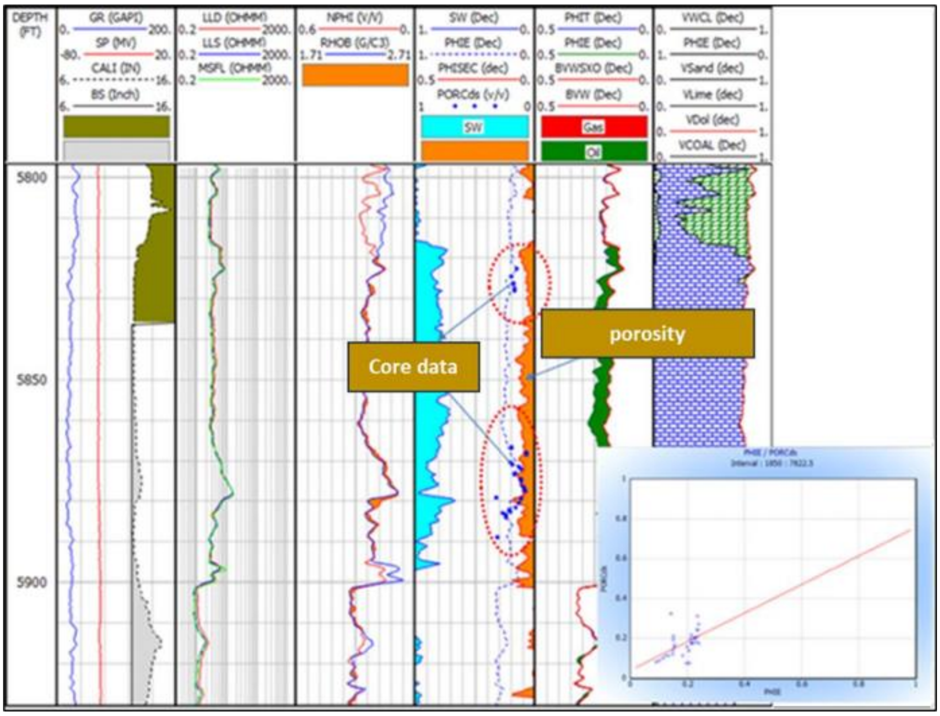

Fig 4: Total and effective porosity calculation and their validation with core porosity

Rock Typing Permeability Prediction

In the log plot RQI vs z all samples with similar FZI would be in a straight line with the same slope. The FZI value can be determined from the line intercept at the Z=1 where the sample that exactly on the same line has a similarity to the pore throat known as hydraulic unit. RQI, PORZ and FZI parameters are determined based on core data. Based on the RQI and PORZ plots (Figure 5), there are 6 different flow units where each flow unit has its own porosity and permeability relationship (Figure 6).

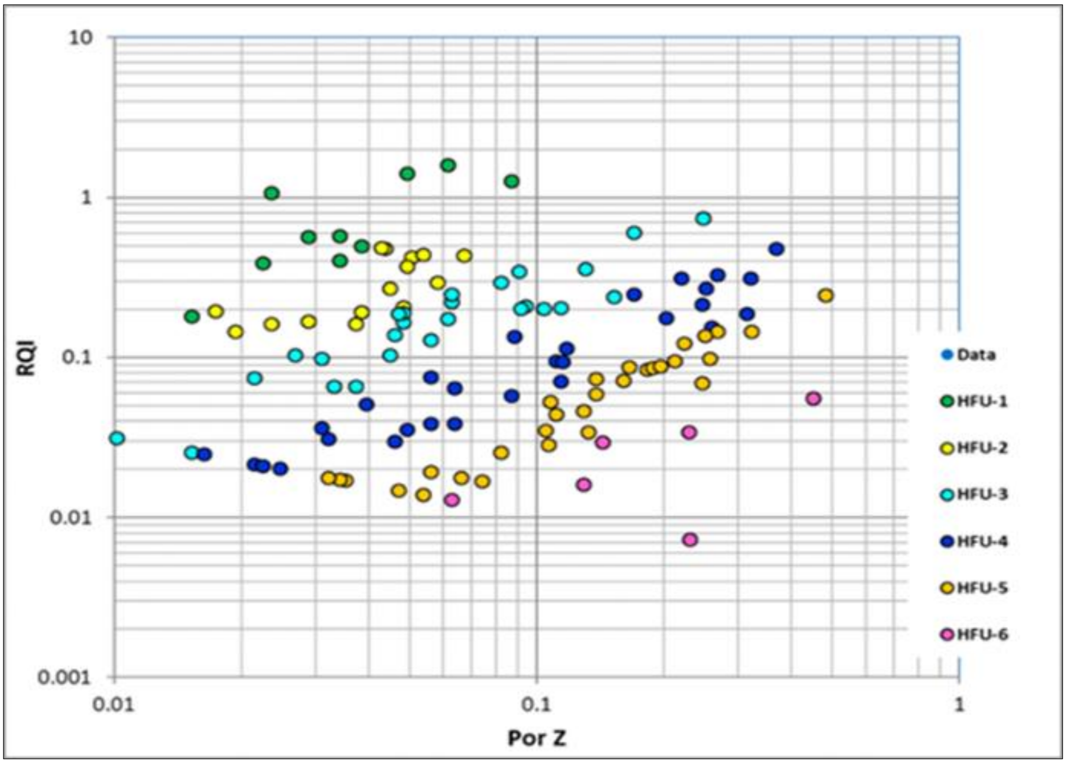

Fig 5: The flow units from PORZ vs RQI

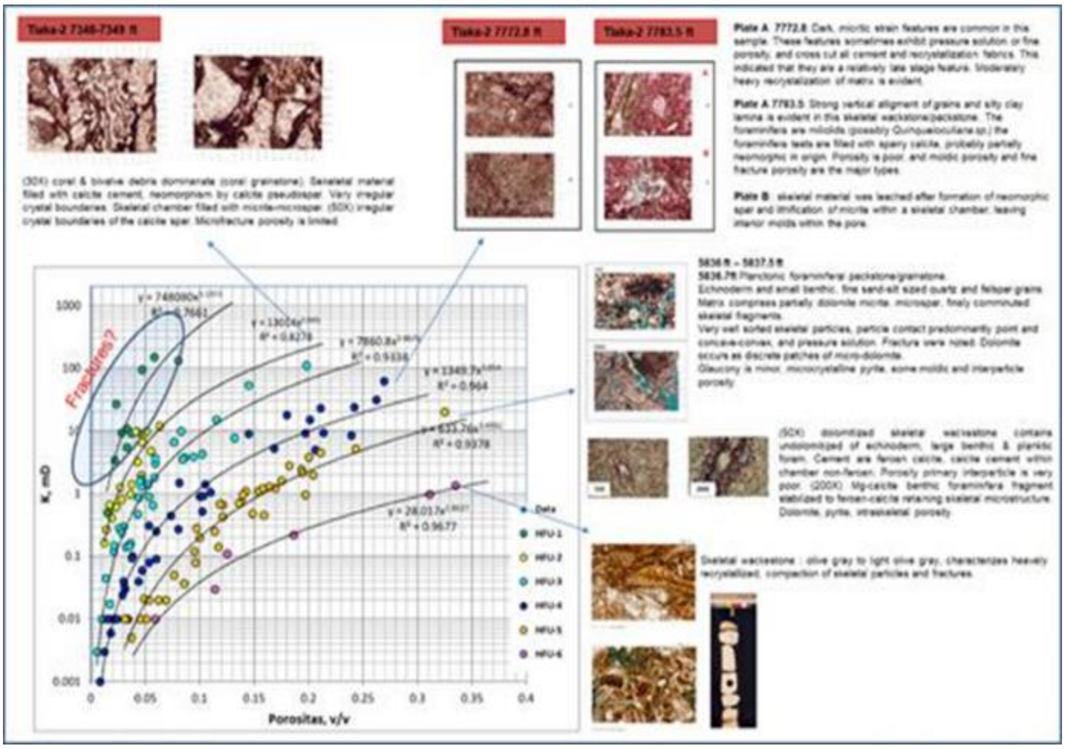

Fig 6: Porosity-Permeability transform and petrography

To estimate the permeability value on un-core well is conducted by generate of RQI, PORZ, and FZI based on core data. The results of log analysis (VSH and porosity) with statistical methods (neural-network). Furthermore, hydraulic unit has determined in each depth interval. Permeability for each hydraulic unit was predicted by the equation obtained from the relationship of porosity versus permeability (Figure 7).

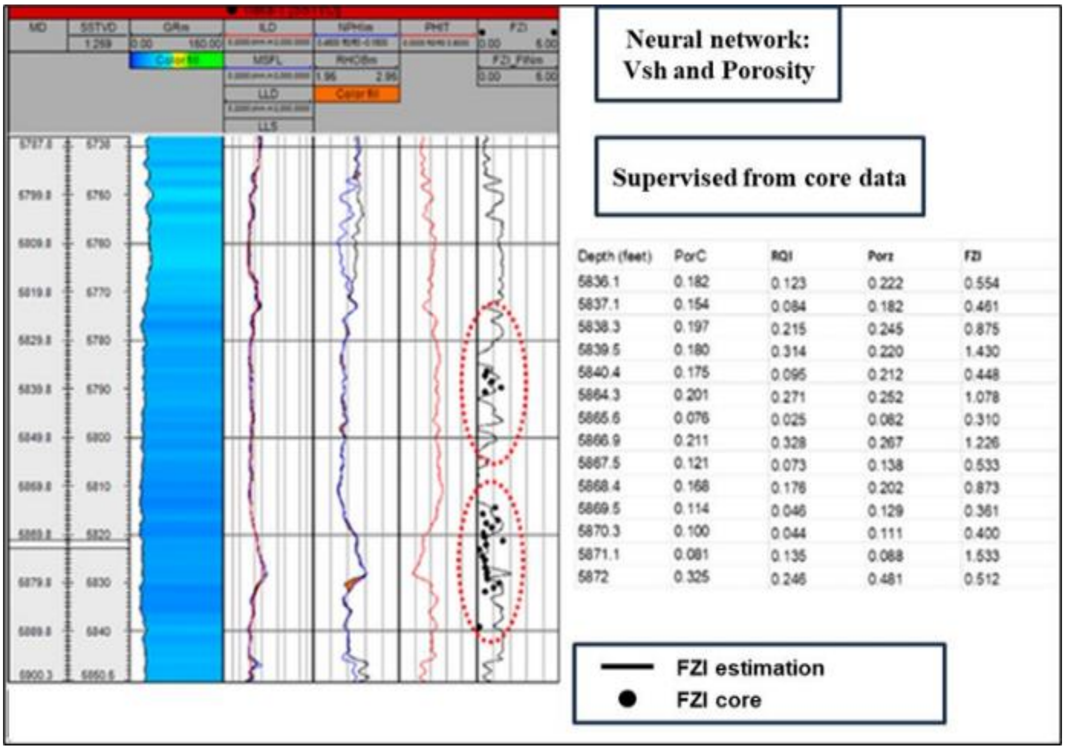

Fig 7: FZI estimation dan validation based on core data

Permeability for each hydraulic flow unit is predict using an equation obtained from the relationship between porosity and permeability (Figure 8). Correlation coefficient of rock type permeability prediction and core permeability of TK-1 in the Minahaki Formation is 0.8211 and Correlation coefficient of permeability prediction and core permeability of TK-4 in the Tomori Formation is 0.7693 (Figure 9 and Figure 10).

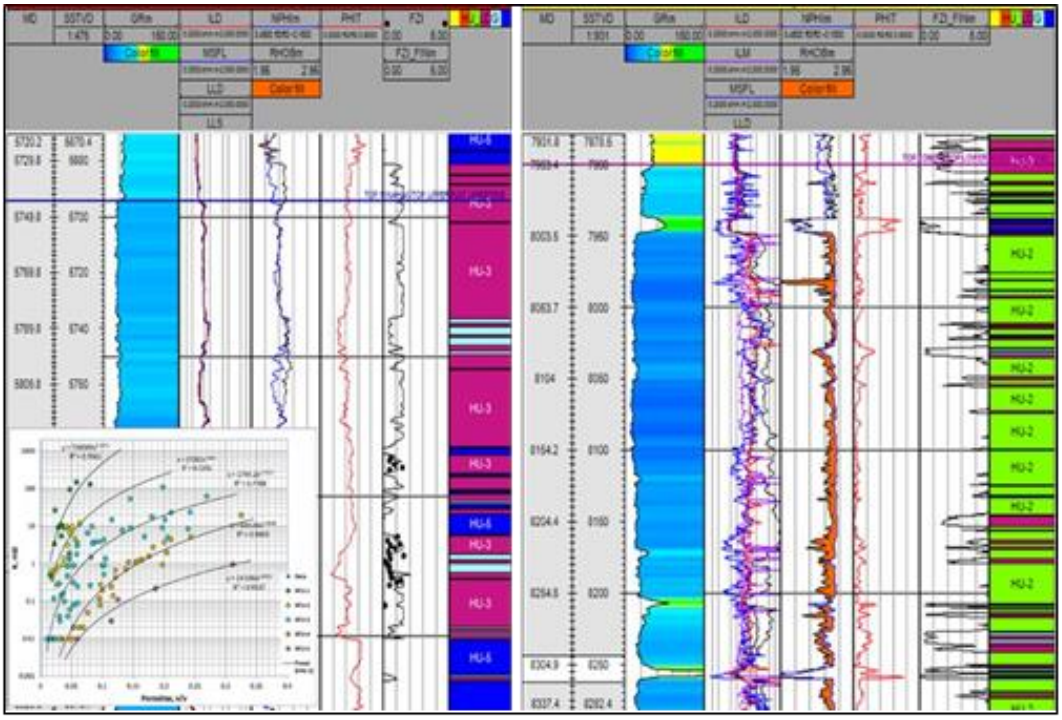

Fig 8: HFU distribution of un-core interval

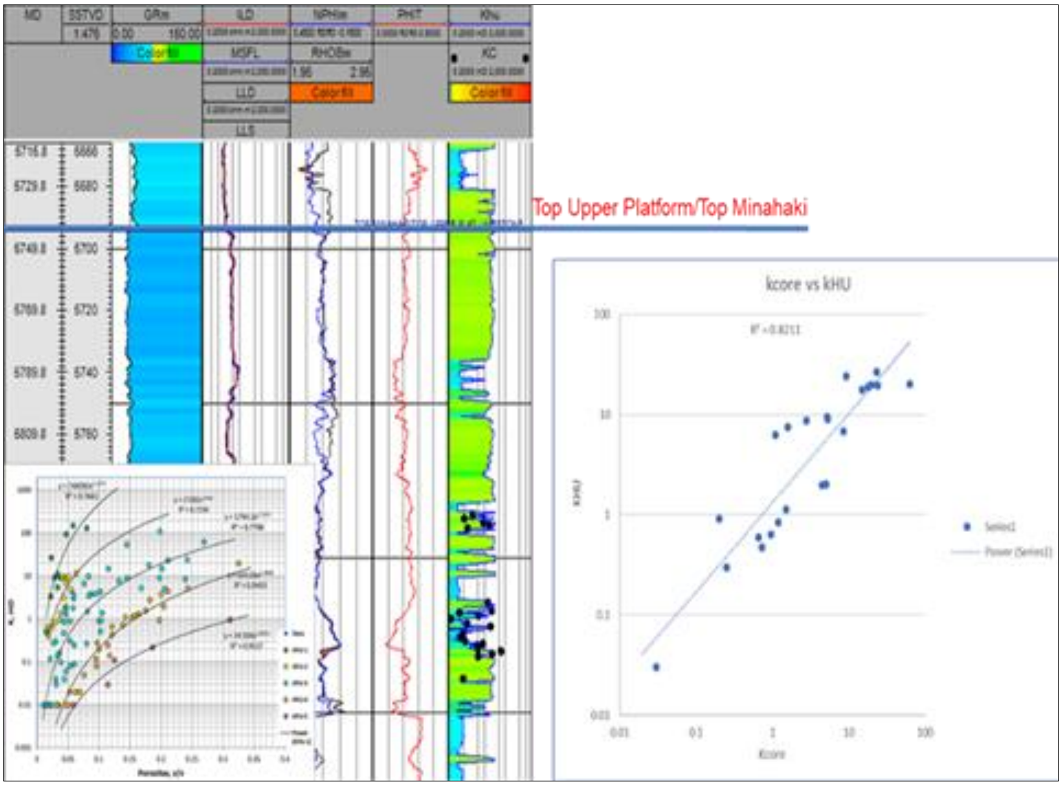

Fig 9: Rocktyping permeability prediction and core-log validation of Minahaki Formation in TK-1

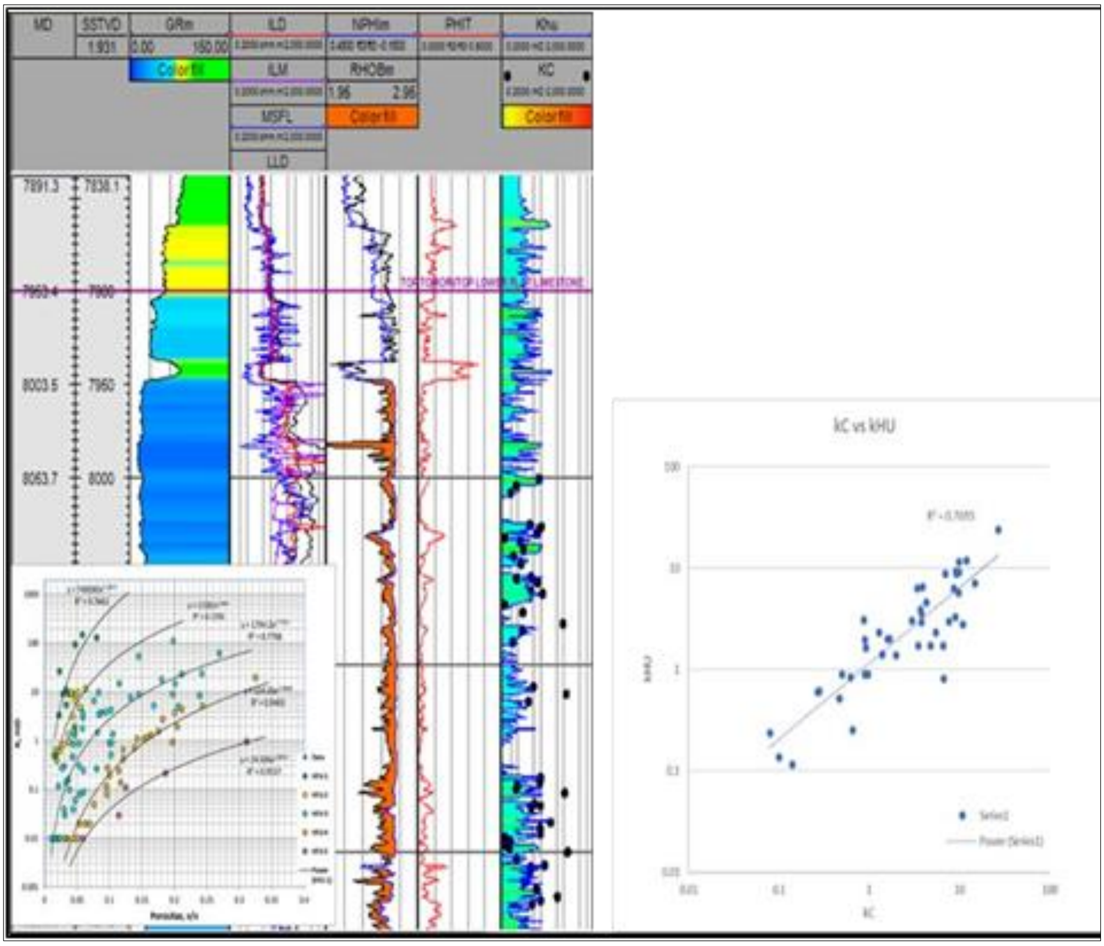

Fig 10: Rocktyping permeability prediction and core-log validation of Tomori Formation in TK-4

Multilinear Regression Permeability Prediction

On the other hand, multilinear regression used to predict permeability and compared which the most appropriate with core data. Statistically, multilinear regression predicting the relationship between core permeability, porosity, and shale volume. Total porosity (PHIT) and shale volume (VSH) as the independent logs. Whereas, core permeability as dependent log. Correlation of dependent log and the independent logs are PHIT = 0.13724 and VSH = 0.03032 summary of the regression coefficients can be seen in the table below:

Table 1: Regression coefficients of independent logs

LOG	COEFFICIENT	STD. DEV.	T STATISTIC	BETA COEF.
CONSTANT	-0.41914	0.18870	-2.22115	-0.03561
WIRE_EVAL.PHIT	8.19838	1.68845	4.85558	0.41814
WIRE_EVAL.VSHX	-1.31781	0.44865	-2.93727	-0.25294

Variance of the regression is 0.99086, standard deviation of the regression is 0.99542, coefficient of determination is 0.19894, adjusted coefficient of correlation is 0.44603. Based on multi regression statistics, the following equation is obtained:

PERM MLR = 10**(-0.419136 + 8.19838*PHIT - 1.31781*VSH)

Correlation coefficient of multi linear regression permeability prediction and core permeability of TK-1 in the Minahaki Formation is 0.4670 and Correlation coefficient of permeability prediction and core permeability of TK-4 in the Tomori Formation is 0.37330 (Figure 11 and Figure 12).

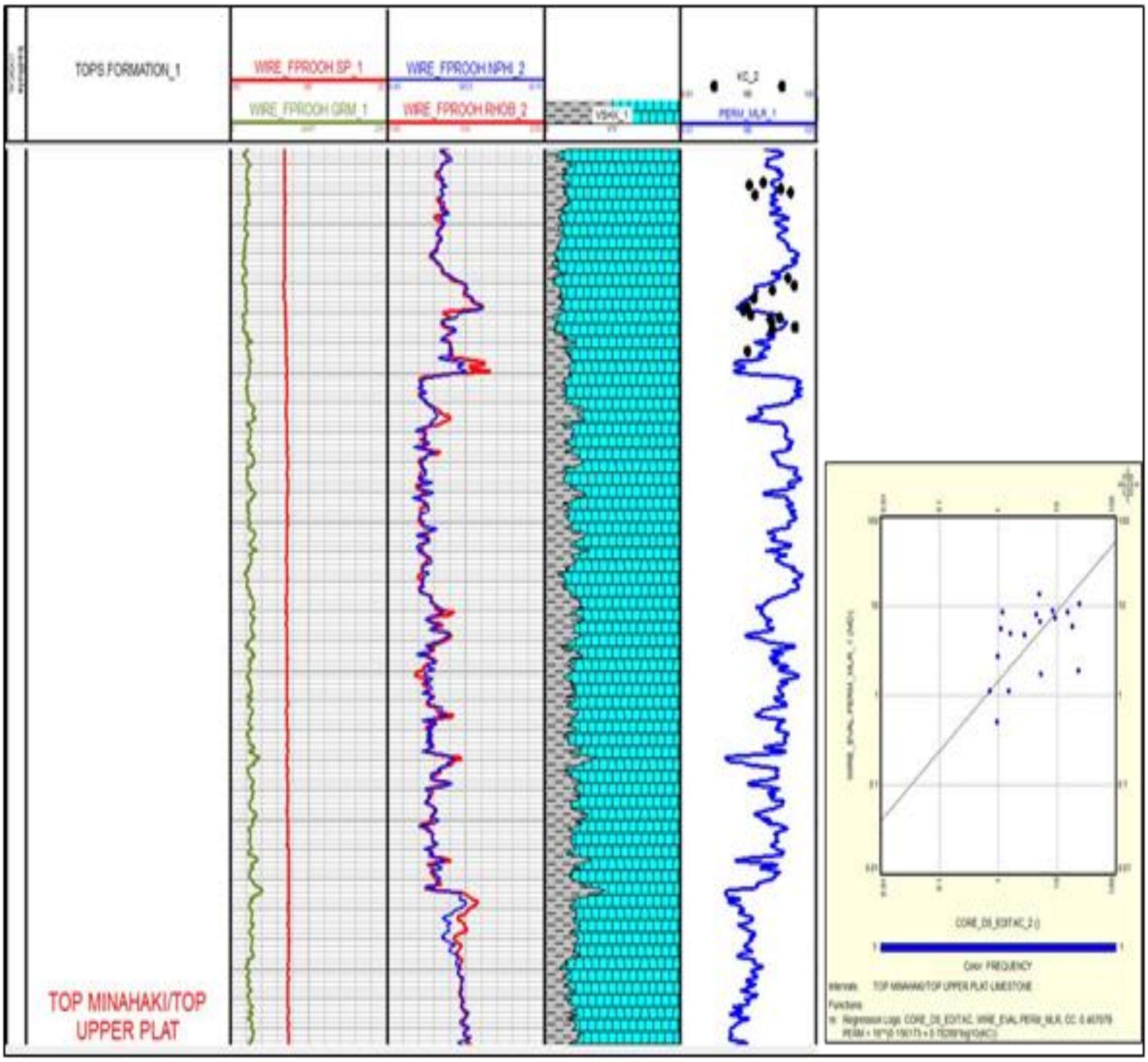

Fig 11: Multi linear permeability prediction and core-log validation of Minahaki Formation in TK-1

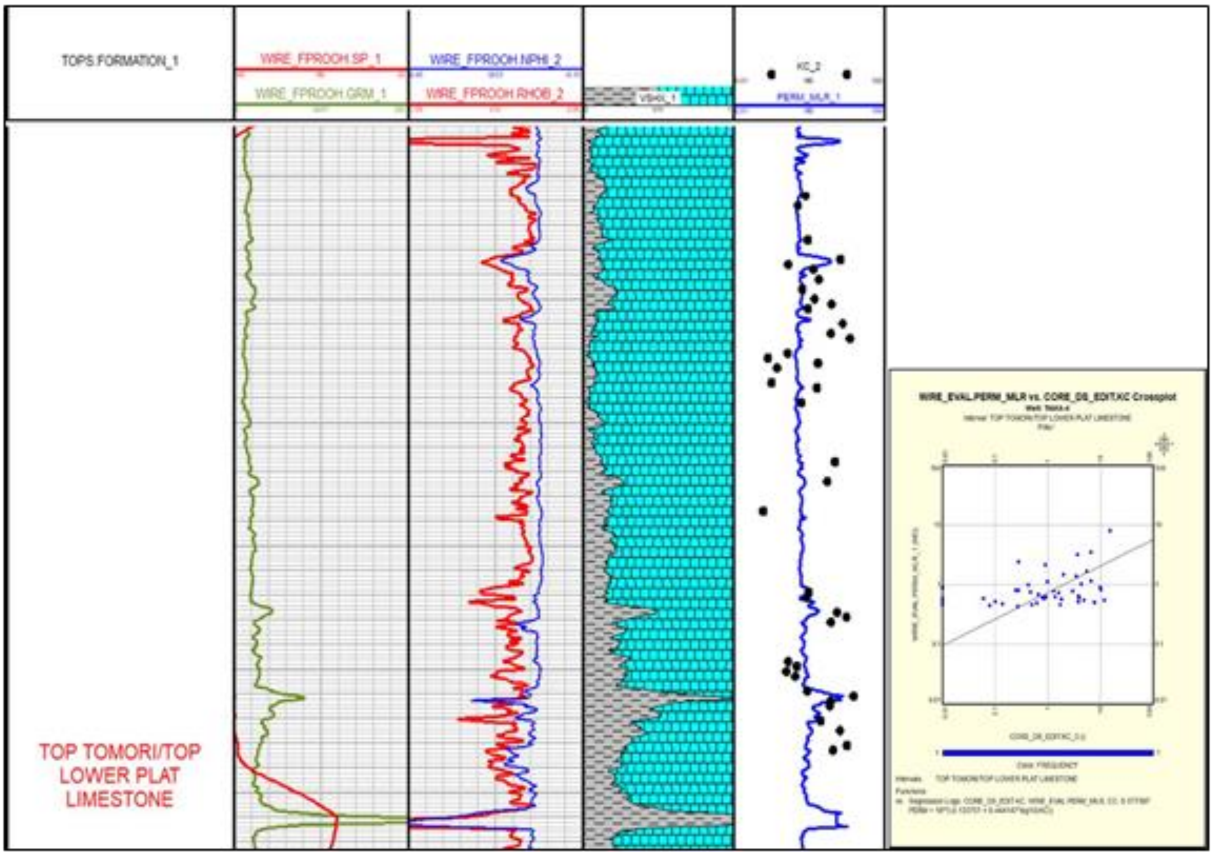

Fig 12: Multi linear permeability prediction and core-log validation of Tomori Formation in TK-4

Conclusion

Based on the correlation coefficient of two permeability prediction methods, it was concluded that the rock typing (HFU) permeability prediction method is more reliable. The shale volume does not have significant effect on calculating permeability in the carbonate rock reservoirs. The most important role in permeability calculating are matrix pores and diagenetic pores, pore geometry refers to the size, shape, and connectivity of the pores.

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