

POROSITY PREDICTION USING FUZZY CLUSTERING AND JOINT INVERSION OF WIRELINE LOGS: A CASE STUDY OF THE NAM CON SON BASIN, OFFSHORE VIETNAM

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Summary

Petrophysical properties such as porosity, permeability and fluid saturations are important parameters for reservoir characterisation, which can be determined by experimental constitutive equations between rock parameters and well logging data. Thus, the same rock properties might demonstrate different patterns, depending on the input and equations used. In this work, we used the cross-properties (a common set of rock properties) that influence different measurements to reduce the ambiguity of the petrophysical property definition. We present an approach of using fuzzy c-means clustering to classify the well logs and core data in clusters and then running inversion for each cluster. The obtained results allowed us to establish suitable parameters in constitutive equations, which usually vary with rock units that may relate to clusters. Testing data applied to the Nam Con Son basin show a square correlation coefficient of 0.66 between the predicted and core measurement, suggesting a reasonable matching of the testing data set.

Key words: Fuzzy c-means clustering, well logs, petrophysics, joint inversion, Nam Con Son basin.

1. Introduction

Porosity, permeability and saturation are the key petrophysical parameters for reservoir characterisation, which can be defined by means of rock physics modelling, experimental links [1, 2], and machine learning techniques [3, 4]. It is still the most difficult and challenging task in reservoir analysis since the prediction petrophysical parameters is generally affected by several factors and these parameters likely vary with rocks. Hence, the prediction might be better if we could divide the data sets into groups relating to rock units. Up to now, machine learning is considered as a promising tool to deal with the unknown reservoir properties because of its diversity. For example, Cuddy and Clover [5] applied ANN and fuzzy logic to estimate porosity in Mansouri oilfield, Iran; Ahmadi et al. [6] utilised the least square support vector machine (LSSVM), and fuzzy logic (FL) optimised by genetic algorithm (GA) was proposed to predict the permeability and

porosity of petroleum reservoirs in Persian Gulf, Iran. Nayak et al. [7] made an overview of fuzzy c-means to assist in clustering and classification. Hellman et al. [8] integrated the fuzzy c-means cluster analysis and joint inversion to achieve the most from the collected datasets such as DC resistivity and seismic profiling for dolerite dyke. Thus, enabling the methods to enforce each other is such a way that interpretation could be improved. The method has been employed successfully in near surface investigation. Therefore, it could be implemented in reservoir characterisation.

Dell'Aversana et al. [1] presented a joint inversion approach to define petrophysical properties from wireline logs. The results demonstrated that this approach is robust. However, they applied one set of constitutive equations for all data sets that may have different geological conditions or rock types. It should be more accurate if we can define the set of constitutive equations for each rock type. In this work, we use an unsupervised learning technique, fuzzy c-means (FCM) clustering [9], to classify well log data in clusters. Then we predict the porosity from well logs, including



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resistivity, sonic velocity, and gamma ray by means of the joint inversion method for each cluster.

2. Methodology

2.1. Constitutive equations

In this work, we use constitutive Equations (1), (2) and (3) that link rock properties with well-log measurements [2].

$$V_p = (1 - \phi)^2 V_0 + \phi V_f \quad (1)$$

$$R = \frac{1}{S_w^n \left(\frac{\phi m}{a R_w} + \frac{v_c}{R_c} \right)} \quad (2)$$

$$GR = (1 - v_c) GR_q + v_c GR_c \quad (3)$$

where V_p , GR , and R are p-wave velocity, gamma ray and resistivity, respectively; V_0 and V_f are the compressional wave velocities of the solid matrix and the pore fluid, respectively; ϕ is the porosity of the rock; v_c is the volumetric fractions of clay; S_w is water saturation; GR_q and GR_c are the specific values of gamma ray of quartz and clay; R_w is the resistivity of water; a is the tortuosity (we set a equal to 1.0 in this work); m is the cementation exponent (1.3 and 2.5 for most sedimentary rocks, and close to 2.0 for sandstones) and n is the saturation exponent (generally assumed to be 2 but can vary as well), thus we set m and n equal 2.0 in our process. The clay fraction in Equation (2) is calculated by using gamma ray logs (Equation 3).

2.2. Using fuzzy c-means clustering

Generally, various rock units formed in different geological conditions demonstrate some particular relationships between physical parameters. If a correlation between physical parameters can be defined correctly then the formulated set of petrophysical characteristics in a unit may represent a geological unit, which is distinguished from others in terms of geophysical properties by using clustering techniques. One of the powerful data analysis techniques is "fuzzy clustering", a method that separates data into subsets according to degrees of the measured similarity. Some studies using FCM to analyse geophysical data were conducted [10, 11].

2.3. Choosing optimal parameters for each cluster

To choose the optimal parameters in Equations (1), (2) and (3), we define the error between calculated values (Equations 1 and 2) and well logs data as follows:

$$Error = \sqrt{\frac{\sum (y_{cal} - y_{mea})^2}{N}} \quad (4)$$

where y_{cal} and y_{mea} are calculated and measured values, respectively; N is number of samples. When the Error is minimum, the parameters are supposed to be optimal.

2.4. Inversion

Forward modelling: The V_p and resistivity are linked to porosity and fluid saturation by using constitutive equations as seen in Equations (1) and (2).

Inversion: The objective function is defined as the sum of the L2 norms of the misfits between the measurements d^{mea} (V_p and electrical well logs) and the data d^{cal} from the coupled-models; the inverse problem solution \tilde{m} is obtained, at each depth location, by minimising the objective function within the domain Ω_m of the model parameters.

$$\tilde{m} = argmin_{m \in \Omega_m} \sum_{l=1}^{N_{lo}} w_l \|d_{lo}^{mea} - d_{lo}^{cal}\|_2 + \beta \|m - m_0\|_2 \quad (5)$$

where l_0 is the number of well logs used in the system of equations (in our case $l_0 = 2$ for V_p and resistivity) and w_l is the weight to scale the influence of each log due to different scales and noise levels of the well log measurements. β is the regularisation parameter and m_0 is the initial model parameters.

3. Case study of Nam Con Son basin

The Nam Con Son basin is one of the largest Tertiary sedimentary basins offshore Vietnam. It is situated in the southern

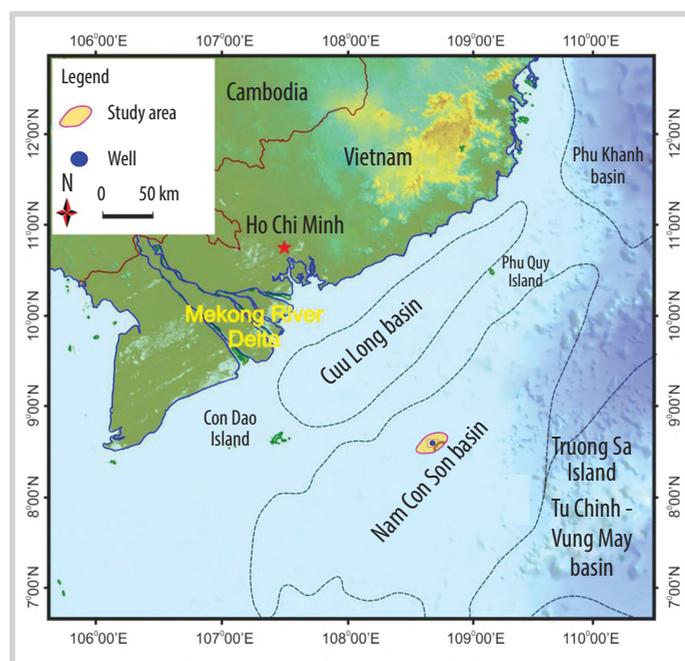


Figure 1. Location of the Nam Con Son basin within the East Vietnam Sea [12].

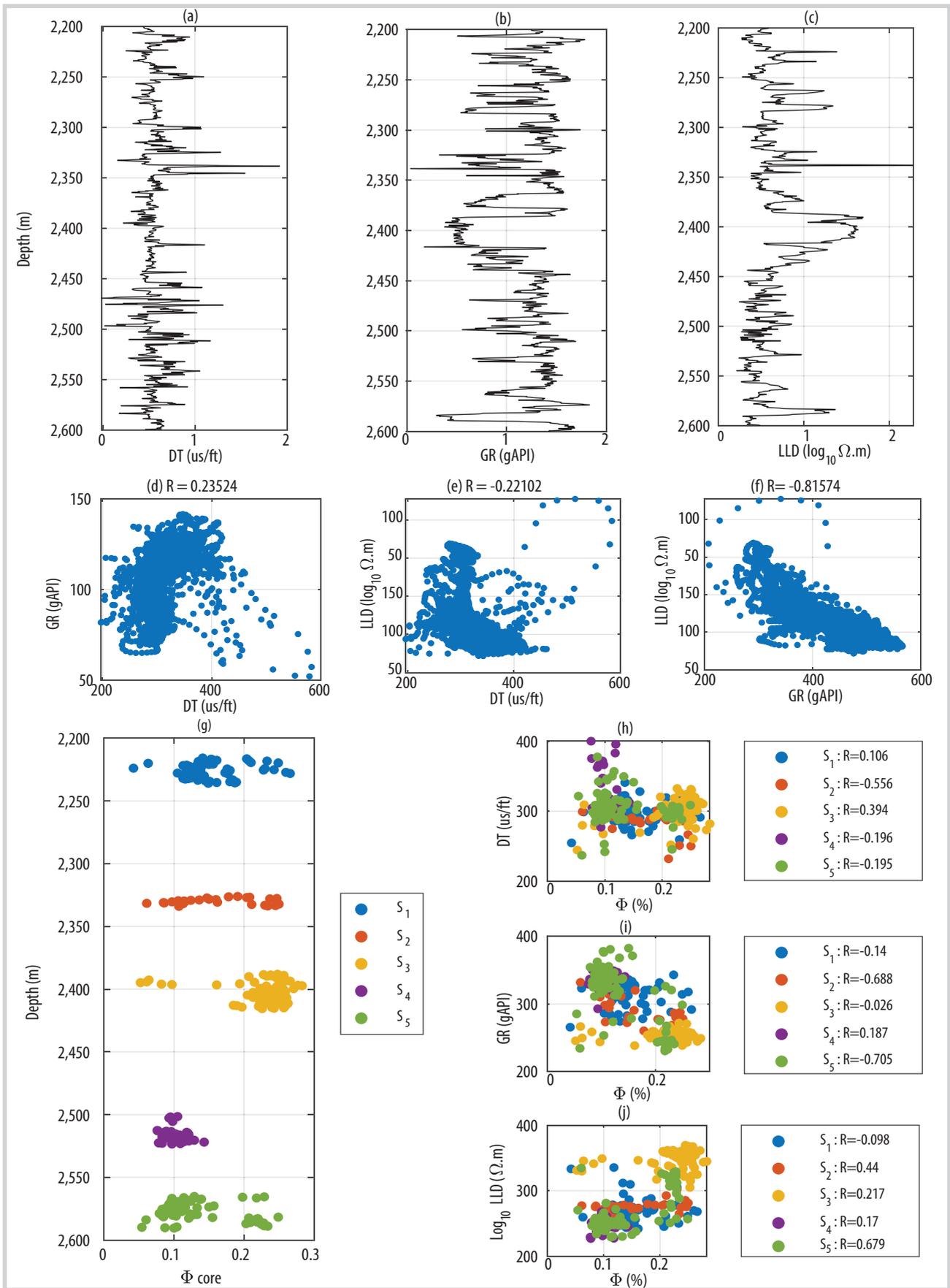


Figure 2. Well logs and core data: (a) p-wave travel time; (b) gamma ray; (c) resistivity; (d), (e), (f) correlation between well log curves; (g) porosity of core measurement at five depth sections: S₁, S₂, S₃, S₄, and S₅; and (h), (i), (j) correlation between well logs and porosity of core measurement with colour coded by depth sections.

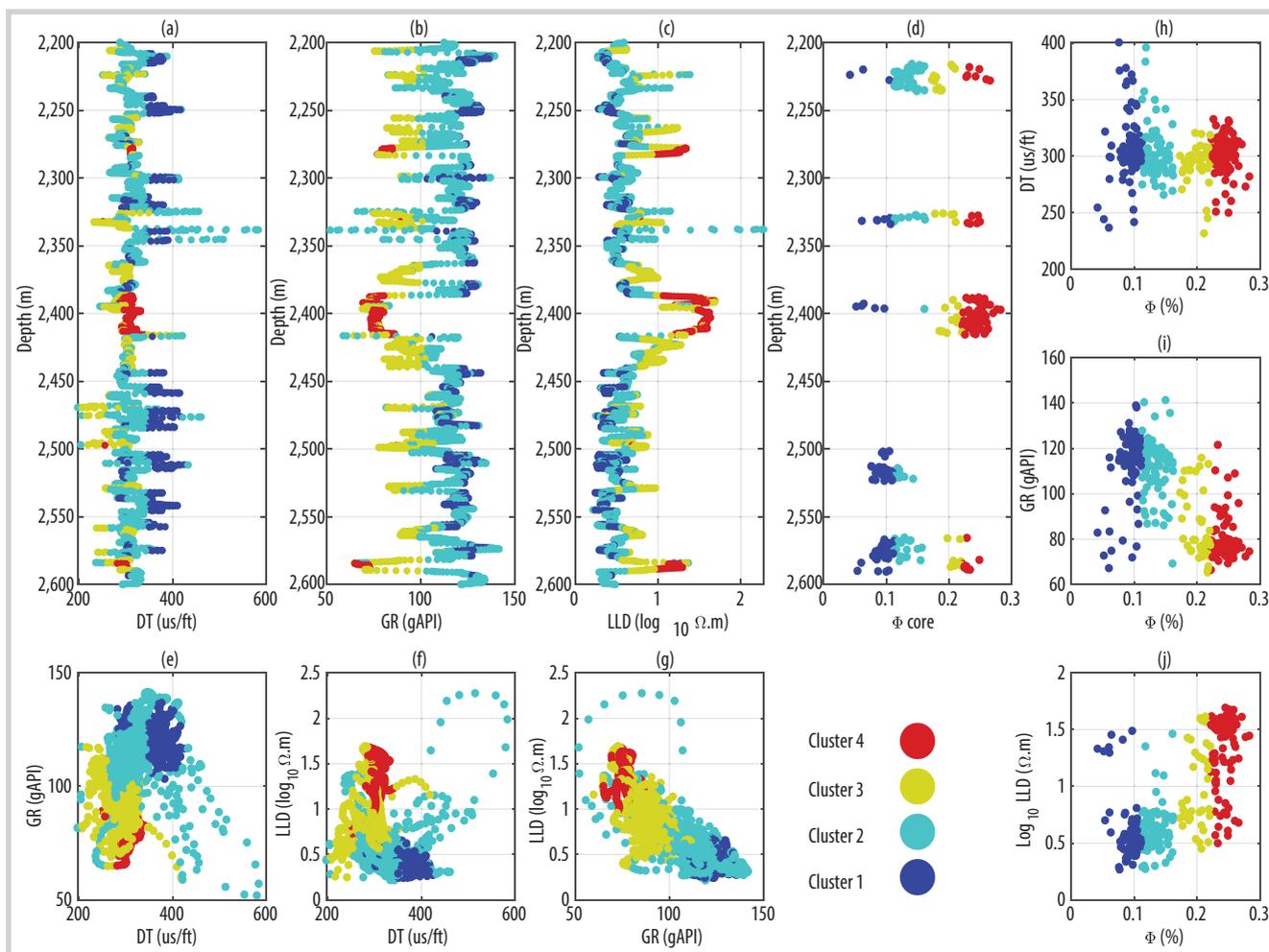


Figure 3. Clustering results. The cluster numbers are defined by data analysis and geological conditions.

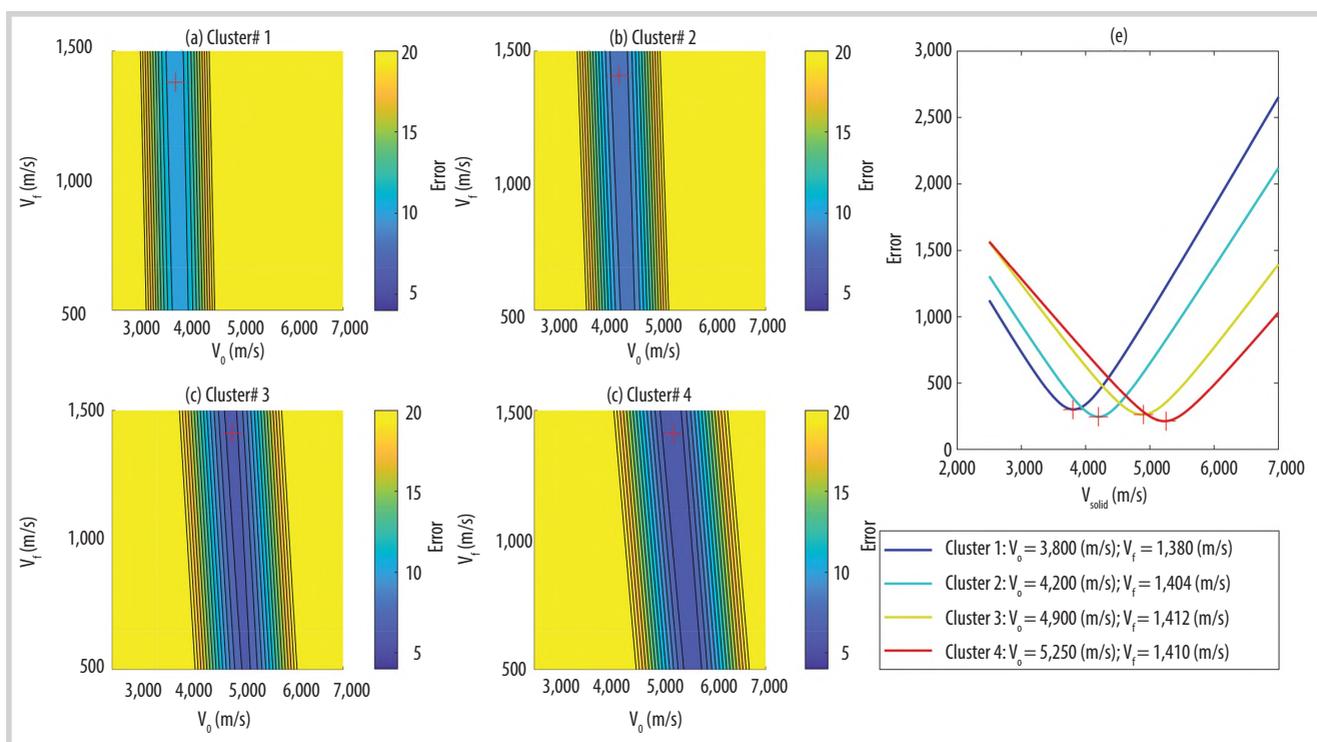


Figure 4. Error between the calculated and measured V_p for each cluster. We choose the optimal pair values of V_0 and V_f for each cluster (marked by red cross).

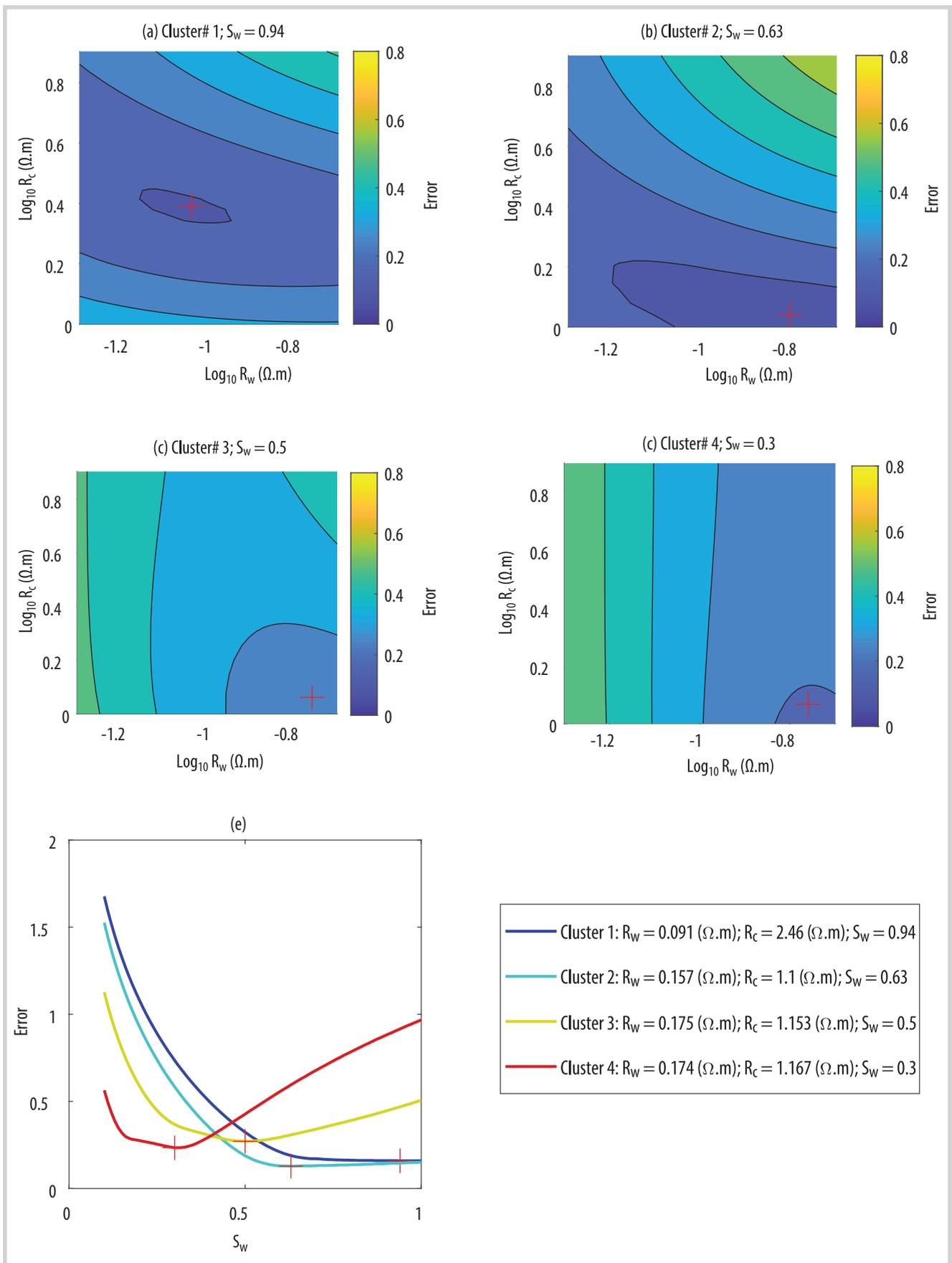


Figure 5. Error between the calculated and measured resistivity for each cluster. We choose the optimal values of R_w , R_c and S_w for each cluster (marked by red cross).

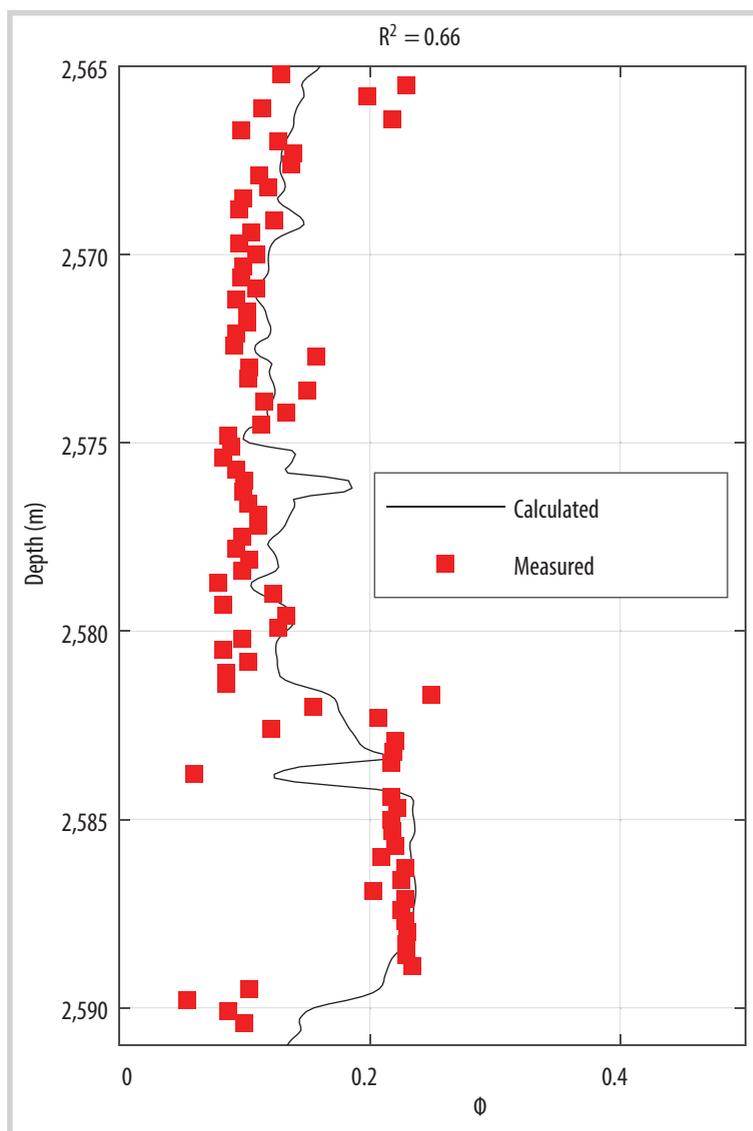


Figure 6. Estimation of porosity of testing data set, S5.

East Vietnam Sea (Figure 1), where numerous wells have been drilled for oil and gas exploration and production purposes.

The well log data tested in this study is taken from the Nam Con Son basin, which is located in the southern Vietnam continental shelf (Figure 1). The basin has an area of about 110,000 km². Hydrocarbons were discovered in the Nam Con Son basin in three different types of reservoirs: pre-Cenozoic weathered and fractured basement, Oligocene - Miocene clastics and Miocene carbonates.

We applied the process to a well log data set containing p-wave velocity, resistivity, gamma ray and core measurement (Figure 2) for a clastic reservoir interval from 2,200 m TVD to 2,600 m TVD of a well in the Nam Con Son basin. The core data are available for five depth ranges: S1 (66 samples), S2 (26 samples), S3 (91 samples), and S4 (41 samples) for data analysis; S5 (83 samples) for the final test.

The well logs and core data were employed in the FCM cluster-

ing process, and the results are presented in Figure 3. The Error (Equation 4) was used to define the optimal parameters in Equations (1) and (2). The error between the calculated p-wave velocity (using Equation 1) and the measured p-wave velocity defines the optimal pair of values V_0 and V_f (Figure 4). The error between the calculated resistivity (using Equation 2) and the measured resistivity (LLD logs) defines the optimal values of R_w , R_c and S_w (Figure 5). The inversion of testing data, S5 is presented in Figure 6, showing a good correlation between the inverted and measured porosity values. Noting that this data set is excluded in any previous FCM analysis process.

4. Conclusions

We present an approach of using fuzzy c-means clustering to classify the well logs and core data in clusters and then running inversion for each cluster. The basic idea of doing this is to set suitable parameters in the constitutive equations, which usually vary with rock units that may relate to clusters. We demonstrate the process by using well logs and core data of one well in the Nam Con Son basin, Vietnam. The prediction shows reasonable results for testing data set, S5. The square correlation coefficient between the predicted and core measurement is 0.66.

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