Logfacies modeling based on neutron pulsed logs and multivariate analysis

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Abstract

This work concerns logfacies modeling for an onshore oil field of Recôncavo Basin, Bahia state, Brazil. Data from geophysical logs and core description of only one well was used to model 33 wells that did not have core information, but have a suite of logging curves which includes neutron pulsed logs. Logfacies modeling was performed according to discriminant statistical rules, resulting in synthetics facies for all (34) wells. In order to check the efficiency of logfacies prediction on the 33 wells for which core description was nor available, the logfacies columns were compared with a hydrocarbon saturation curve derived from pulsed neutron data. A very good match was found for all wells, suggesting the used procedure as suitable for logfacies modeling, at least for this oil field.

Introduction

According to Soares (2005) the logfacies modeling, which uses statistical techniques, can be defined as the attempt to recognize the facies column of a well from its geophysical logs. This is an important activity that allows the construction of the geological model of the area, even in the absence of continuing cores.

The geological model can be constructed in many ways. A component that differentiates each of these ways is the input data used in the construction of the model affecting the responses in terms of uncertainty and resolution. A model created from core's description, for example, has desirable qualities, such as reliability and resolution. However, well core extraction is expensive and it is not always possible to recover the whole interval. Thus, the availability of cores is usually limited. On the other hand, the exploration area has, commonly, ample availability of geophysical logs data, which have variable degree of uncertainties and resolution. This work aims to apply the strategy of logfacies modeling described by Soares (2005) in an oil field in Recôncavo basin.

Method

This study uses a data package consisting of various geophysical logs from 34 wells and core description of just one well. Each well contains curves like gamma ray, caliper, resistivity, density, neutron, photoelectric factor, and several curves from pulsed neutron log.

For the logfacies modeling done in this study we used statistical techniques of discriminant analysis and clustering, which are the main statistical techniques used to determine logfacies (Souza Jr., 1992; Soares, 2005).

Using statistical techniques of supervised and non-supervised classification (Soares, 2005; Albuquerque *et al.*, 2004; Hair *et al.*, 2005), through successively applying of clustering and discriminant rule, best results for stratigraphical refinement of this field were achieved. SAS® statistical software was used to obtain these results.

Initially, a step-by-step discriminant analysis was used in order to choice the logs for logfacies modeling. As a result of this step, the curves ROHB (density log) and YCA (calcium yielding from neutron pulsed log) showed the most discriminating power, and they were therefore chosen.

Considering the diversity of original facies, 13 in total, it was decided to define an ideal number of synthetic facies for easy identification. Logs, in general, recognize smaller number of facies than those recognized by the geologist responsible for the core description. So, it is necessary to reduce the number of facies to be recognized through logfacies modeling.

Clustering analysis was done by average linkage and centroid techniques, using statistical indicators of the optimal number of groups, such as pseudo-F, pseudo-t^2 and CCC. For average linkage technique the pseudo-F statistics indicates good numbers of groups when this statistics shows high values. Thus, for our data, average linkage technique indicates 2 or 3 as a good number of facies to try identification (Figure 1). The pseudo-t^2 indicator shows high values for the number of facies immediately prior to the ideal number, in this case, good numbers would be 2 or 3 (Figure 2). For CCC, positive values greater than 2 or 3 are indicative of good numbers of facies, values between 0 and 2 values indicate potential number of facies, whereas high negative values are indicative of the presence of outliers, so, according to Figure 3 a good number of facies to be recognized would be 2. In the case of centroid technique of clustering analysis the numbers 4 or 5 would be ideal for the pseudo-F statistics (Figure 4), 3 for pseudo-t^2 statistics (Figure 5) and 1 for CCC indicator (Figure 6).

Based on an intersection between the values from the three statistics above, it was decided to recognize 3 facies: a non-reservoir, a good-reservoir facies and a reservoir with oil potential. It is important to remember that now the recognized facies aren't the same of the original facies from the core description. Thus, the main thirteen lithofacies from core description in the P08 well were subdivided into 3 facies: non-reservoir facies (green), reservoir facies (yellow) and a reservoir with oil potential (orange). This arbitrary division was based on geological knowledge.

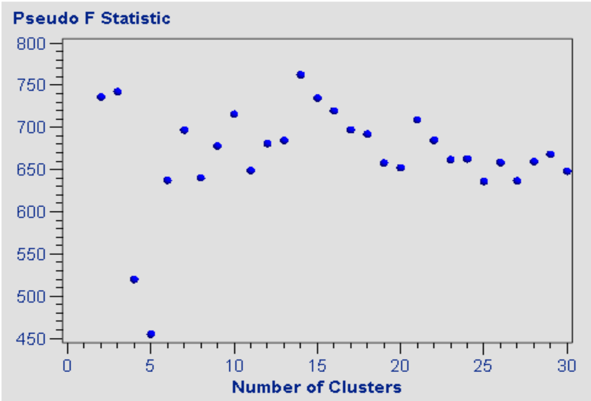

Figure 1 - Pseudo-F statistics for non-supervised average linkage classification.

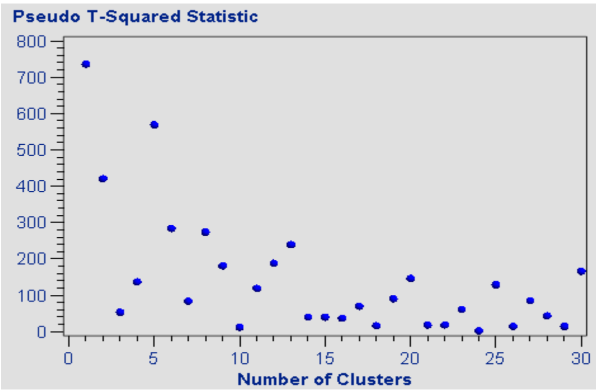

Figure 2 - Pseudo-t^2 statistics for non-supervised average linkage classification.

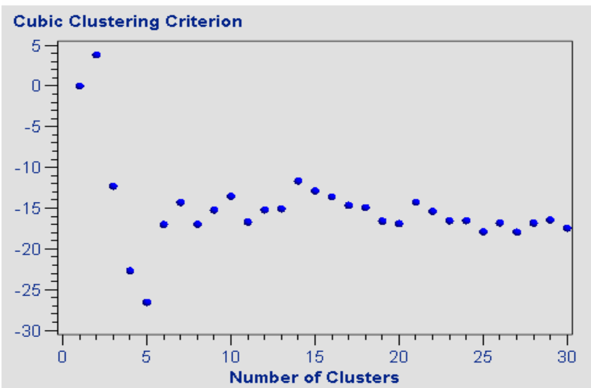

Figure 3 - CCC statistics for non-supervised average linkage classification.

Table 1 shows the original lithofacies grouping based on geological knowledge, grouping clay-rich rocks as non-reservoir facies, sandy facies as reservoir facies and shaly sand as potential reservoir.

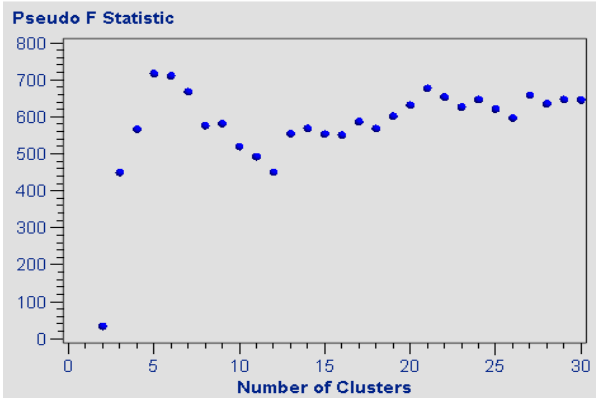

Figure 4 – Pseudo-F statistics for non-supervised centroid classification.

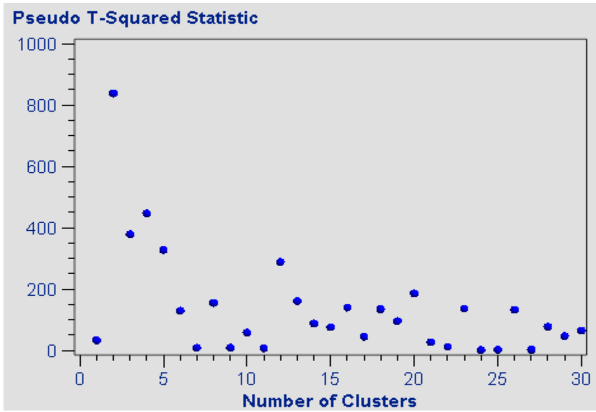

Figure 5 – Pseudo-t^2 statistics for non-supervised centroid classification.

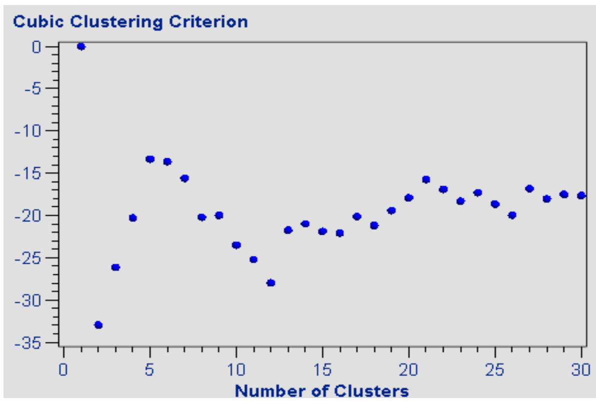

Figure 6 - CCC statistics for non-supervised centroid classification.

Table 1 – Lithofacies grouping based on geological knowledge. Clay-rich facies are grouped as non-reservoir facies, sandy facies as reservoir facies and shaly sand facies as potential reservoir.

No.	Litofácies	Descrição
1	AGT	folhelho maciço
2	ARN/AGO	arenito argiloso
3	ARN/FLH	intercalação arenito / folhelho
4	ARNCGL	arenito conglomerático
5	ARNECAC	arenito com clastos de folhelho
6	ARNECBA	arenito com laminação cruzada transladante
7	ARNECGP	arenito fino, cimentado e argiloso
8	ARNEOND	arenito fino com laminações cruzadas subcríticas
9	ARNEPP	arenito cimentado com estratificação plano-paralela
10	ARNLCONV	arenito argiloso com deformação por escape de fluido
11	ARNMAC	arenito maciço
12	CGL	conglomerado maciço argiloso
13	SLT	silte

Results

Once defined three as the number of facies to be recognized, a non-supervised procedure was applied in the training well (P08) according to K-means method (Soares, 2005). The column of facies resulting from the non-supervised classification by the K-means technique was given as data input for supervised classification by quadratic discriminant rule (RDQ). The efficiency of this process can be assessed by comparing the facies column generated by the discriminant rule with the original lithological column (Figure 7).

The next step was the generation of discriminant rule that was used in all other stages of logfacies modeling. Thus, the facies column resulted from the non-supervised classification by k-means technique was given as data input for supervised classification by Quadratic Discriminant Rule (RDQ). Thus, the rule was applied to the well and the response was compared with core description and indications of cementation, shaly and hydrocarbon occurrence (Figure 8).

At this point, evaluating the efficiency of the process, it is observed that the column of logfacies generated by the discriminant rule concerning the main features of the original lithological column is very satisfactory, allowing, therefore, the generated rule to be used in the validation data. Thus, we applied the same discriminant rule (RDQ) defined for P08 data in other wells which did not have core description in order to create the final product which is the logfacies modeling of the field. As there was core description only for P08 well, a method to evaluate the consistency of logfacies modeling in other wells of the field was to compare the logfacies column of each well with its hydrocarbon saturation curve (SHCEFFCO, derived from pulsed neutron curves), since the saturation curve is an indicator of the reservoir occurrence, and also compare the logfacies column with the set of curves in each well. Figure 9 is an example of results obtained for borehole P01. There is an excellent correlation between sandy facies (yellow and orange) and areas of high oil saturation and also between clay facies (green) where the hydrocarbons saturation generally ceases. Same level results were achieved for all 33 wells of this oil field.

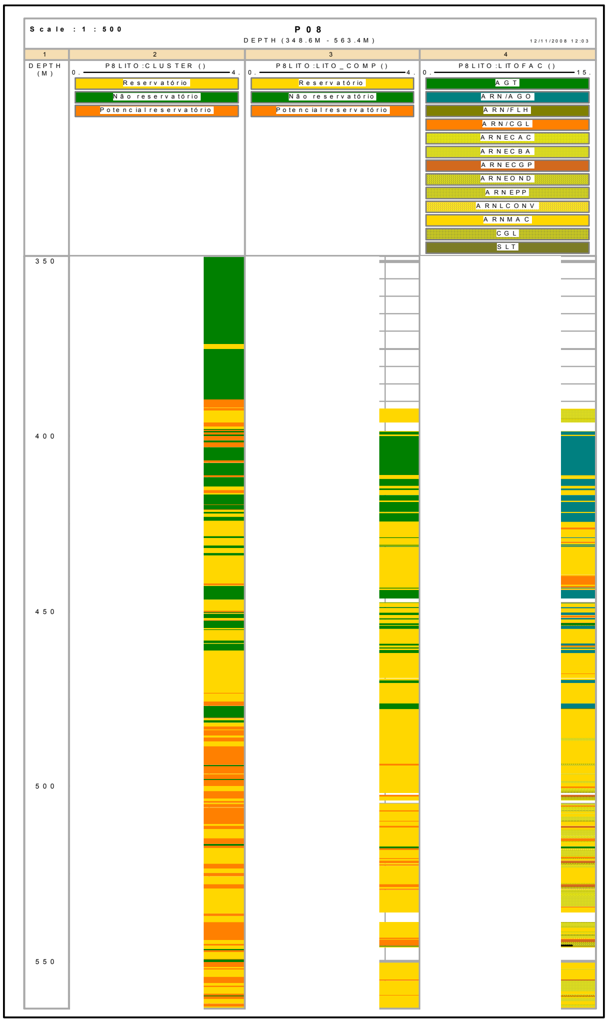

Figure 7 - Comparison among the classification result by K-means method (left), composite facies (center) and core description (right).

Conclusions

The comparison between the results of logfacies modeling and the logging curves for each well, shows that the lithological variation observed in estimated logfacies, although generated by a statistical discriminant rule with data from only one well (P08), is compatible with variation observed in the logs. The saturation curve, the resistivity log and the density-neutron plot confirm the result of the discriminant rule.

Accordingly, it is observed that although logfacies modeling reduces the number of original facies, almost always it reproduces the most representative facies very well. This result is a desirable feature in terms of reservoir engineering, because, in general, it is not concerned with small variations, but major lithological intervals for flow simulation.

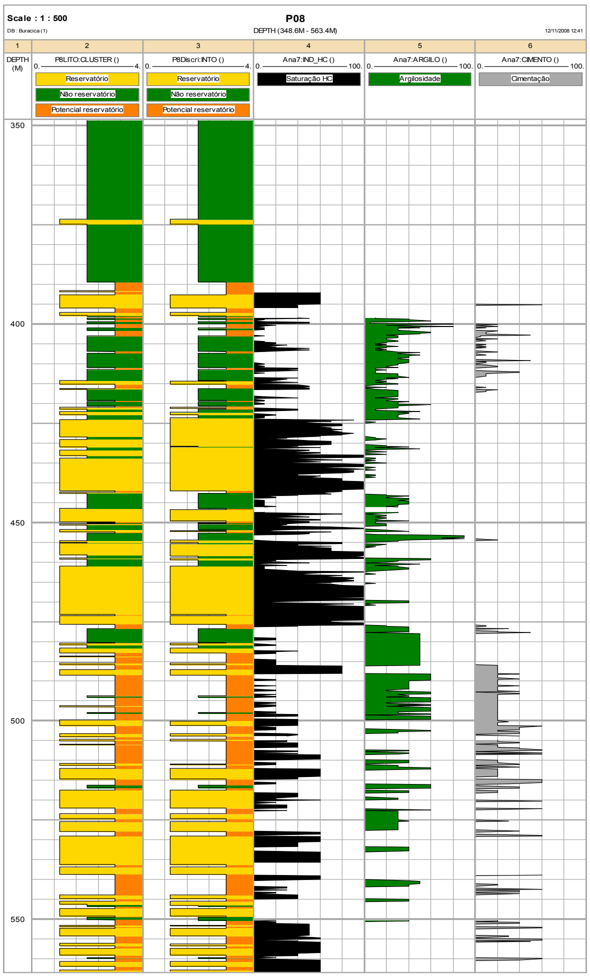

Figure 8 - Comparison among quadratic discriminant rule, core description, occurrence of hydrocarbon, clay content and cementing indication in the training well P08.

Acknowledgments

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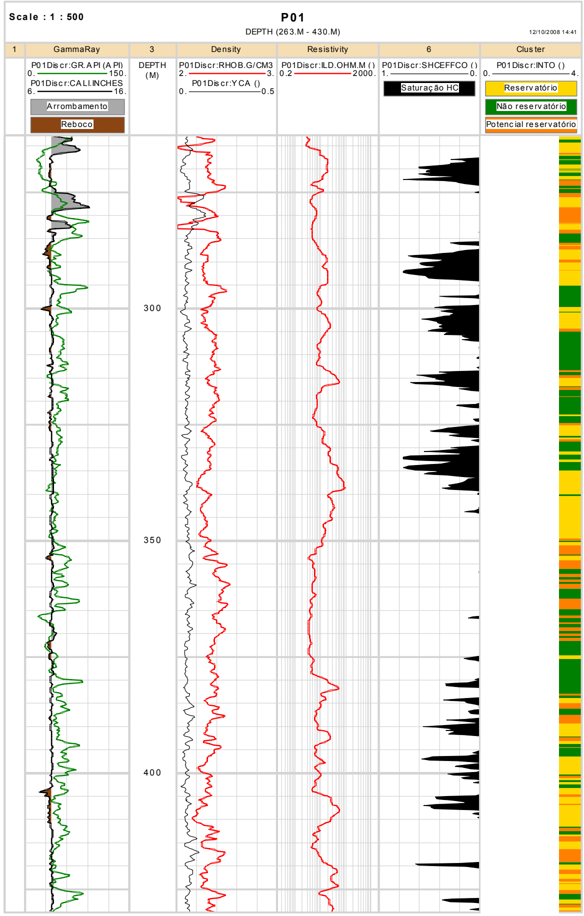

Figure 9 – Comparison among logging curves, oil saturation curve derived from neutron pulsed log and logfacies column obtained by discriminant rule for borehole P01.

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