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Characterisation of Hydrocarbon Reservoirs in Bonny Area of Niger- Delta, Using Probabilistic Approach

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Abstract- This work proposed a joint estimation of petro-physical properties which combines statistical rock physics and Bayesian seismic formulation. This work is to present a strategy for estimating the probability distributions of petro-physical parameters and litho-fluid classes from seismic. The estimation of the hydrocarbon reservoir properties and the associated uncertainty is performed in three steps: firstly, a rock physics model is established using well log data and seismic data to predict elastic attributes (velocities or impedances) from petro-physical properties, after which an elastic property from partially stacked seismic angle gather is estimated. Finally, the conditional probability of petro-physical variables and litho- fluid classes is calculated. The application of this reservoir study included two well data (well A and well B) and partially stacked seismic volume which provided the probability density of petro-physical properties and litho-fluid classes. This clearly demonstrates the applicability of the proposed statistical method. Results obtained showed that well A had effective porosity between 40% - 55%, clay content 34cm3 - 48cm3 and water saturation between 10cm3 - 20cm3 and well B had effective porosity between 20% - 25%, clay content between 54cm3 - 60cm3 and water saturation between 25cm3 - 40cm3. Due to this result, well A will have greater production that would last for years at a true vertical depth (TVD) of between 5720ft - 5855ft. It is therefore concluded that probabilistic method of estimating hydrocarbon reservoir works better in the near surface layer of the overburden, where the signal to noise ratio is high, rather than the lower layer where the signal to noise ratio is low.

Keywords: Statistical Rock Physics, Bayesian Seismic Formulation, Stacked Seismic Volume, Effective Porosity, Clay Content, Water Saturation, Hydrocarbon Reservoirs.

I. INTRODUCTION

It is well known that subsurface heterogeneity delineation is a key factor in reliable reservoir characterization. These heterogeneities occur at various scales, and can include variations in lithology, pore fluids, clay content, porosity, pressure, temperature e.t.c. Some of the methods used in reservoir characterization are purely statistical, based on multivariate techniques [1]. In reservoir characterization studies, statistical rock physics is normally used to combine statistical techniques with physical equations to generate different petro-elastic scenarios [2]. The goal of statistical rock physics is to predict the probability of petro-physical variables when velocities (or impedances) and density are assigned, and to capture the heterogeneity and complexity of the rocks and the uncertainty associated with theoretical relations. The technique adopted here is to combine a probabilistic approach with site-specific rock-physics relations between the rock properties and the elastic properties. In other words, uncertainty is draped on a deterministic model [3, 4].
Similar approaches have already been presented, with some assumptions and limitations about the form of the probability distributions, the size of the data and the type of dependencies considered. By means of more general parametric distributions, such as Gaussian Mixture Models (GMMs) [5, 2], or non-parametric statistical techniques such as Kernel Density Estimation (KDE) [1, 6] some limitations can be overcome by our approach. In addition, we take into account the up--scaling problem, in order to face the limited resolution and the greater uncertainty of seismic data compared to well log data and thereafter, we integrate this step within the probabilistic inversion framework. The rock physics model is a set of equations which transforms petro- physical variables in elastic attributes [7].

Geology of the study area
The field is sited in a middle Miocene deltaic sandstone-shale sequence. The sands of the middle Eocene Formation, the main reservoir rocks, was suspected to be formed in a deltaic sedimentary environment by distributary channels influenced by waves, and also having marshy and swampy

environment marked by shale/sand sequence [8]. The overlying shale section on top of the sand act as a seal for hydrocarbon entrapment. The structure of the field is a complex collapsed crest, elongated in the E-W direction. The study area is located south of Niger Delta sedimentary basin situated offshore Port Harcourt, Bonny Island, Rivers state, Nigeria. Bonny is located at the southern edge of rivers state in the Niger Delta of Nigeria near Port Harcourt. It is located on the continental margin in the Gulf of Guinea and extends in the equatorial West Africa. At the southern end of Nigeria bordering between the Atlantic Ocean of latitudes 4^027'36.15", longitude 7^08'23.06" and an altitude of 1387 feet [9].

Bonny is a progradational depositional complex within the Cenozoic formation of Southern Nigeria. The tectonic setting and geological evolution of Bonny Island goes beyond the post-eocene regressive clastic wedge that conventionally describe the later stage of delta development [10]. The tectonic framework of the continental margin along the West Coast of equatorial Africa is controlled by Cretaceous fracture zones expressed as trenches and ridges in the deep Atlantic [11]. The lithology in this area consists of unconsolidated loosely medium to coarse-grained cross-bedded sands occasionally pebbly with localized clays and shale [12].

Materials and Method

This chapter presents a methodology used to estimate petro-physical properties from well log data and seismic data in a given reservoir using the probabilistic method. The methodology has three main stages: firstly, a rock physics model is established using well log data and seismic data to predict elastic attributes (velocities or impedances) from petro-physical properties. Secondly, an elastic property from partially stacked seismic angle gather is estimated. Finally, the conditional probabilities of petro-physical variables and litho-fluid classes in multi properties using multi-scale model is calculated. To analyze the lateral variations of reservoir properties away from the boreholes and in inter-well regions, it was necessary to integrate reservoir properties derived from log data with seismic attributes. This was attempted when estimating the water saturation and effective pressure of the producing reservoirs using supervised neural networks. In the end, the results from the three stages are analyzed in other to estimate the petro-physical properties from the log in a given reservoir using probability method.

Data Used

The data used in this work are well log data (Fig. 1 and 2) and one multiple 3D post-stack seismic data (Fig. 3) from an offshore Niger Delta oil field provided by SPDC Port Harcourt. The data consist of suites of well logs from two wells (A and B), a base line seismic data acquired at different vintages whose calendar time was not known at the time of the work. These data were analyzed using Hampson- Russell (H-R) software. The well log data was evaluated. The seismic and rock attribute cross- sections were also created.

Well Log Data

The suite of wire-line log data comprises of gamma ray log, density log, resistivity log, porosity log, water saturation log and p-impedance log. This recorded suite of logs can be grouped into two categories: properties that affect seismic wave propagation (e.g., compressional- and shear- velocity) and properties of interest for reservoir characterization but which indirectly affect seismic- wave propagation (e.g., porosity, water saturation, and clay content). The zone of interest is typically a sand/shale/sand sequence. The wells are located at the north western region of the field and are used for statistical analysis.

Seismic Data

The seismic data used has a dominant frequency of 60 Hz. Crossline and inline ranges from 46333 to 59758. The seismic volume extends to 3400 milliseconds two way travel time (TWT), below which reflection continuity is generally poor (Fig. 3). The seismic volume is characterized by a series of parallel reflections offset and deformed by major normal faults and showing clay diapirs with collapse crestal faults in the overlying sediments. Major counter regional fault are evident in the cross line section through the volume and collapsed crest normal and roll over faults evident in the inline section through the volume. The normal faults can easily be traced. The clay diapirs itself is difficult to delineate. The character of the seismic record changes with depth. The basal part of the seismic record is disrupted by several zones with transparent to highly-discontinuous reflection patterns, which extend higher within the seismic volume under footwalls of major faults. Reflections within this region have moderate to good continuity and high amplitude variations. Reflections in the shallowest part of the seismic volume are parallel, nearly horizontal, and less continuous. Most wells of the field show logs that have uniformly low gamma ray values, which are characteristics of the fluvial Benin Formation. The study interval is defined by the first and last continuous reflections that could be traced throughout the seismic volume.

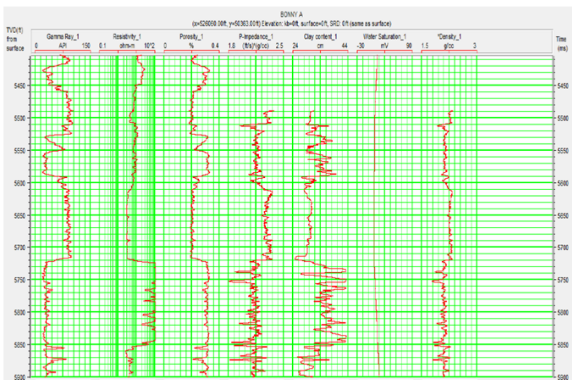

Fig. 1: Wireline log data for Well A showing markers (GRAY COLOUR) and suite of logs (RED COLOUR) including gamma ray log, resistivity log, porosity log, P-Impedance log, water saturation, Clay content and s-impedance log.

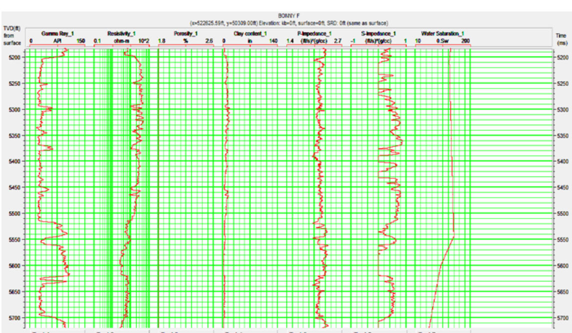

Fig. 2: Wireline log data for Well B showing markers (GRAY COLOUR) and suite of logs (RED COLOUR) including gamma ray log, resistivity log, porosity log, P-Impedance log, water saturation log, clay content and s-impedance log.

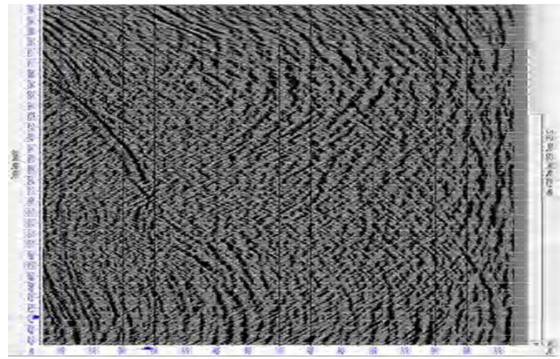

Fig. 3: Baseline seismic section for Inline 519138 and Crossline 46333 to 59758 in wriggle trace view mode showing clay diapirs with collapse crestal faults in the overlying sediments.

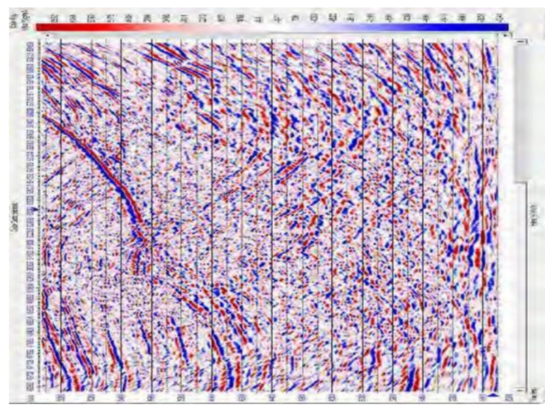

Fig. 4: Baseline seismic cross-section for Inline 519163 in variable density display, showing well path and the position of the reservoir in the seismic.

II. METHODOLOGY

Although this methodology is presented for an oil-saturated reservoir, it can be adapted to reservoirs with different saturation or lithological conditions by selecting an appropriate rock-physics model.

First of all, a rock physics model is calibrated at well location using velocity logs and petro-physical curves obtained in the formation evaluation analysis. The rock physics model can be written in the following formulation

(ρ, Vp, Vs) = f_RPM$(\emptyset, C, Sw) + \varepsilon$ ……eqn. 1

Where Vp and Vs are respectively P and S-waves velocities, ρ is the density, $\emptyset$ is the effective porosity, Sw is the water saturation, C is the clay content and ε is the error that represents the difference between model predictions and real data. The function f_{RPM}can be an empirical relation or a theoretical set of equations such as granular media models or effective media models [10].

Secondly we estimate elastic attributes from seismic data: we use a reformulation of the approximation of Zoeppritz equations by Aki-Richards [13] in terms of impedances, and we jointly estimate P and S-impedances and density following the Bayesian approach presented in [1].

Finally, we calculate the conditional probabilities of petro-physical variables conditioned by seismic following the methodology described below:

We assume a prior distribution of the petro-physical variables: in our case $P(\emptyset, C, Sw)$ is assumed as a trivariant GMMs to take into account the observed correlation between variables in each litho-fliud class; in this case the prior is the same at any vertical position.

We generate pseudo logs of petro-physical properties from the prior distribution with a realistic vertical correlation, in two step. We firstly create a pseudo-fluid class profile, for example using a markov chain download model and then we generate in each litho-fliud class petro physical properties vertically correlated using a variogram estimated on well data.

$$=\Pr(X_n=x_n \mid X_{n-1}=x_{n-1}, X_{n-2}=x_{n-2} \ldots\ldots X_1=x_1) = \Pr(X_n=x_n \mid X_{n-1}=x_{n-1}, X_{n-2}=x_{n-2} \ldots\ldots X_{n-m}=x_{n-m}) \quad \ldots\ldots \text{eqn. 2}$$

We apply the rock physics model f_{RPM} to the petro-physical pseudo logs to obtain the corresponding elastic attributes and we add a random error ε; then we compute fine scale impedances

Using the random samples generated in step b) and c), we estimate the joint probability $(I_P^f, I_s^f, \emptyset, C, S_w)$ and we derive the conditional probability of petro-physical properties conditioned by impedances $P(\emptyset, C, S_w | I_P^f, I_s^f)$ at fine scale.

We upscale the elastic properties applying sequential Backus averaging on a running window whose length is found by estimating the wavelength from the seismic bandwidth and the average velocity. We then compute the conditional probabilities at coarse scale:

$$P(\emptyset, C, S_w \mid I_P^c, I_s^c) = \iint \left[P(\emptyset, C, S_w \mid I_P^f, I_s^f) P(I_P^f, I_s^f \mid I_P^c, I_s^c) \right] dI_P^f, I_s^f \quad \ldots\ldots \text{equ. 3}$$

This last conditional probability is then combined by means of Chapman-Kolmogorov equation [10] with the probability of elastic properties coming from linearized Bayesian inversion $(I_P^f, I_s^f | S_z)$, to obtain the posterior probability of petro-physical properties

$$P(\emptyset, C, S_w \mid S_z) = \iint \left[P(\emptyset, C, S_w \mid I_P^f, I_s^f) P(I_P^f, I_s^f \mid S_z) \right] dI_P^c, I_s^c \quad \ldots\ldots \text{equ. 4}$$

Results and Discussion

The results of the petro-physical properties estimation are in three different conditions: at fine scale, at coarse scale and conditioned by seismic data using well log data coming from well A and a synthetic seismic trace to verify the applicability and the validity of the method. Thereafter, the corresponding correlation coefficients between estimated petro-physical properties and real data at well A and well B location were determined and the difference in each rock attribute were investigated in order to map out regions in the field that is favourable for greater production.

Well Log Analysis

We apply the rock physics model f_{RPM} to the petro-physical pseudo logs to obtain the corresponding elastic attributes and we add a random error ε; then we compute fine scale impedances.

Using the random samples generated in step b) and c), we estimate the joint probability $(I_P^f, I_s^f, \emptyset, C, S_w)$ and we derive the conditional probability of petro-physical properties conditioned by impedances $P(\emptyset, C, Sw|If, If)$ at fine scale.

We upscale the elastic properties applying sequential Backus averaging on a running window whose length is found by estimating the wavelength from the seismic bandwidth and the average velocity. We then compute the conditional probabilities at coarse scale:

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analysis are porosity, water saturation and clay content for well A and well B. The true vertical depth (TVD) of investigation ranges from 5450ft (1661.1m) to 5900 ft (1798.3m) for well A and 5200 ft (1585.0m) to 5700 ft (1737.4m) for well B. The wells exhibit a dominantly shale/sand/shale sequence typical of the Niger delta formation.

In the first step, we take into account only the uncertainty related to the rock physics model at fine scale, without considering the uncertainty associated to coarse scale and to seismic. In order to estimate the conditional distribution $(R|mf)$, the EM algorithm has been applied assuming three mixture components (one component for each litho-fluid class) combined with the analytical expression of Gaussian Mixtures. In Fig. 5a, we display the marginal conditional probabilities of effective porosity, clay content and water saturation extracted from $(R|mf)$ at fine scale. Since the rock physics model is accurate, the uncertainty propagated here is quite small and the petro- physical properties estimation honours the actual curves of effective porosity, clay content and water saturation derived from the log interpretation. In Fig. 5b, we show the results of the probability estimation (Eqn. 3) conditioned by the upscale impedances obtained by applying sequential Backus averaging to rock physics model predictions: the probabilistic up scaling step allows us to take into account the uncertainty associated to the scale change. The comparison between Fig. 5a and Fig. 5b, clarifies the impact of coarse resolution on uncertainty, which is as expected, larger in the second case $(R|mc)$ especially for water saturation. Finally we combined the results of the statistical rock physics model performed with the Bayesian approach, by means of Eqn. 5, in order to obtain an estimation of the petro-physical properties conditioned by seismic data $(R|Sz)$. In fig. 5(a)(b), The background colour is the conditional probability. Black lines are the actual petro-physical curves, red dotted lines represent P10, median and P90.

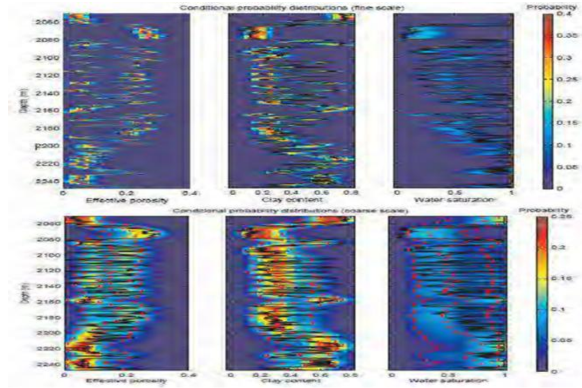

Fig. 5: (A) Petro-physical properties estimation conditioned by high resolution impedances, extracted from $(R|mf)$, (B) Petro-physical properties estimation conditioned by up-scaled data, extracted from $P(R|mc)$.

Seismic Data Analysis

The results at seismic scale obtained with Gaussian Mixture Models (Fig. 6) shows that the top of the reservoir is characterized by a thick high porosity oil sand layer and it is well detected. In this application, Gaussian Mixtures Model is an appropriate solution and it provides a good result because the litho-fluid classification of well data (which identifies the components of the mixture) allows for a good discrimination of petro-physical and elastic properties. Also in fig. 6, Black lines are the actual petro-physical curves and the red dotted lines represent P10, median and P90. Though the linear correlation coefficients cannot be used as a full quantitative measure of the posterior quality in the case of multimodal distributions, we tried to evaluate the quality of the match between the posterior results and real data computing the correlation coefficients between the estimated petro-physical properties and the actual curves (Table 1).

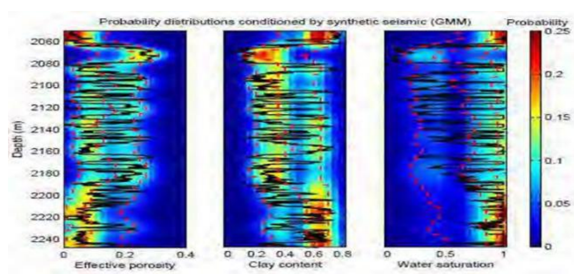

Fig. 6: Petro-physical properties estimation conditioned by synthetic seismic data at well A location.

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Table 1: Correlation coefficients between estimated petro-physical properties and real data at well A location.

	Correlation coefficient of effective porosity	Correlation coefficient of clay content	Correlation coefficient of water saturation
Conditioned by fine scale data	0.95	0.89	0.87
Conditioned by coarse scale data	0.55	0.67	0.63
Conditioned by synthetic seismic (GMM)	0.58	0.55	0.64

Finally, we applied the methodology to the whole reservoir level using real seismic data in order to obtain 3D volumes of petro-physical properties with the associated uncertainty. First of all we performed a Bayesian formulation on a small 3D volume including well A used for rock physics model calibration and well B used for methodology validation. The seismic volume contains about 10000 traces in a time window corresponding to a depth interval of approximately 250 m. In Fig. 7, we display two seismic sections (related to the partial angle stacks 20o and 44o), passing through the two wells.

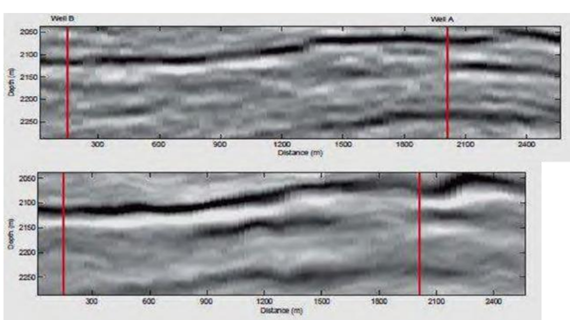

Fig. 7: 2D seismic sections passing through well A (on the right) and well B (on the left): (A) angle stack 20o; (B) angle stack 44o.

The final result of the study is the posterior probability of petro-physical properties on the whole 3D volume. . In Fig. 8, we display the posterior probabilities of effective porosity, clay content and water saturation.

In the upper part of the section, we can clearly detect the overcap clay and the top of the reservoir characterized by high porosity sand filled by oil; in the lower part the thin layers observed in the well logs are not detected and the uncertainty associated to the petro-physical properties increases.

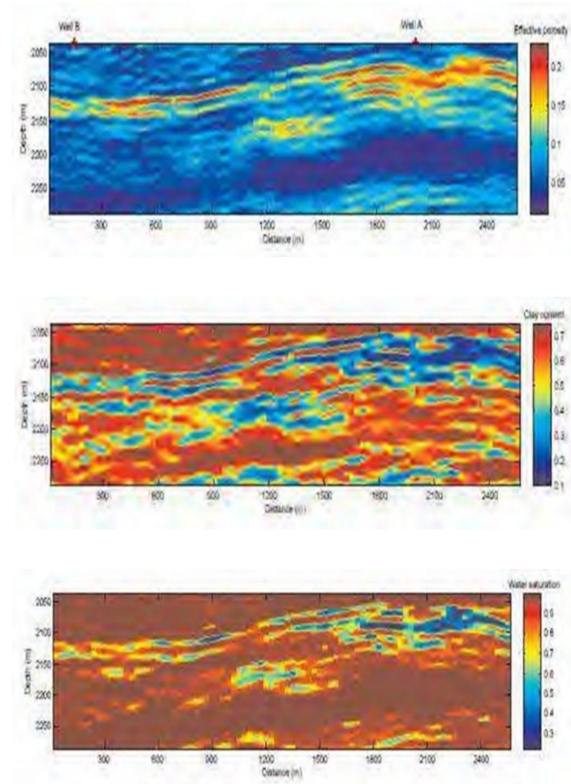

Fig. 8: Estimation of effective porosity (top), clay content (middle), and water saturation (bottom) in the 2D section obtained from the mode of the posterior distributions.

Discussion

The real case application, that is, integrating well data and seismic data pointed out that the results are quite satisfactory as long as the quality of seismic is acceptable. In particular the use of Gaussian Mixture model seems to be a better approach for the classification of petro-physical and categorical parameters, which can be applied to real cases with reduced computational time. Gaussian Mixture Models is a suitable solution because of their analytical convenience, especially when the distributions of petro-physical and elastic attributes describe different litho-fluid classes' features.

The application of the rock physics model is not computationally demanding but the estimation of the conditional probability in a Bayesian framework can be quite hard to obtain because it requires the estimation of joint distribution. The main simplification we adopted in our approach is the overlooking of the spatial correlation of petro-physical variables for the estimation of the conditional distributions, in order to reduce the dimension of the probability space. In order to perform the final step from continuous petro- physical variables to litho-fluid classes modeling, Gaussian Mixture Models seem to be an appropriate approach as they can express the multimodal features of the petro-physical variables in the different litho-fluid classes.

CONCLUSION

The method presented in this work aims to propagate the uncertainty from seismic to petro- physical properties, including the effect of scale change, the seismic noise error and the degree of approximation of the physical models. Statistical rock physics, combined with the probabilistic approach adopted for seismic formulation, is proposed in order to assess the uncertainty. The main result of this method is the probability distributions of the estimated petro-physical parameters that can be used to assess the reliability of reservoir properties estimation. In order to obtain the posterior distribution of the petro-physical properties, we point out that one of the key points of our method is the use of Gaussian Mixture Models and the identification of the weights of the mixture as the indicator probability of the litho-fluid classes.

In the application case, the method works better in the upper layers, where the signal to noise ratio is high, rather than in the lower layers, where the signal to noise is low. In conclusion, where the signal to noise is acceptable, the probabilistic petro- physical evaluation on the real case shows the applicability of the method and that the reliability of the seismic data is evenly propagated to the petro- physical properties prediction.

This proposed method can be applied to any reservoir where elastic characterization of petro- physical properties is possible and where the physical link can be described by a suitable rock physics model.

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