

Chapter 25

Geostatistics for Seismic Characterization of Oil Reservoirs



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Abstract In the oil industry, exploratory targets tend to be increasingly complex and located deeper and deeper offshore. The usual absence of well data and the increase in the quality of the geophysical data, verified in the last decades, make these data unavoidable for the practice of oil reservoir modeling and characterization. In fact the integration of geophysical data in the characterization of the subsurface petrophysical variables has been a priority target for geoscientists. Geostatistics has been a key discipline to provide a theoretical framework and corresponding practical tools to incorporate as much as possible different types of data for reservoir modeling and characterization, in particular the integration of well-log and seismic reflection data. Geostatistical seismic inversion techniques have been shown to be quite important and efficient tools to integrate simultaneously seismic reflection and well-log data for predicting and characterizing the subsurface lithofacies, and its petro-elastic properties, in hydrocarbon reservoirs. The first part of this chapter presents the state of the art and the most recent advances of geostatistical seismic inversion methods, to evaluate the reservoir properties through the acoustic, elastic and AVA seismic inversion methods with real case applications examples. In the second part we present a methodology based on seismic inversion to assess uncertainty and risk at early stages of exploration, characterized by the absence of well data for the entire region of interest. The concept of analog data is used to generate scenarios about the morphology of the geological units, distribution of acoustic properties and their spatial continuity. A real case study illustrates the this approach.

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25.1 Integration of Geophysical Data for Reservoir Modeling and Characterization

One of the main challenges regarding hydrocarbon reservoir characterization has been the integration of different types of data—geological conceptual models, well-log data, geophysical data, production data—for modelling the subsurface properties of interest while assessing the corresponding uncertainty and risk. Although well data provides certain ‘hard’ measures of the subsurface properties, given the usual lack of such data and, consequently, its limited spatial representativeness, the corresponding models normally provide little understanding of the complex and heterogeneous subsurface geology of the entire reservoir area. Since the eighties, Geostatistics has been a key discipline to provide a theoretical framework and corresponding practical tools to incorporate as much as possible different types of data for reservoir modeling and characterization, in particular the seismic reflection data (Dubrule 2003). One of the most important contributions of geostatistical methods for seismic data integration in reservoir modelling, has been the development of stochastic seismic inversion techniques.

Seismic reflection data, since it has high spatial representativeness, by covering the full spatial extent of the reservoir volume, is a different and privileged window for targeting the subsurface petro-elastic properties of interest. However, seismic reflection data represents an indirect measurement of these properties and has a poor spatial resolution along the vertical direction (temporal domain). This is translated in a much greater support compared with the well-log data and much greater uncertainty derived both from measurement errors and the nonlinear relationship between the recorded seismic signal and the subsurface properties one wishes to describe (Tarantola 2005). This has been the most serious limitation of direct use of seismic data as secondary information either in methods using it as local trends or in joint simulation methods (Dubrule 2003), or even accounting for the different support of both data (Liu and Journel 2009).

To overcome such limitations, an alternative approach has been widely used. Seismic inversion methods are based on the following rationale: subsurface petrophysical properties (such as facies, porosity and saturation), can have a relationship to other seismic attributes, such as acoustic and/or elastic impedances; hence, one wishes to know the model parameters \mathbf{r} (reflectivity coefficients derived from the subsurface elastic properties), which convolved with a known wavelet \mathbf{w} give rise to the known solution \mathbf{A} (i.e. the recorded seismic amplitudes):

$$\mathbf{A} = \mathbf{r} * \mathbf{w}. \quad (25.1)$$

The theoretical solutions for seismic inversion are stated in Tarantola (2005). The seismic inversion problem began to be tackled with deterministic methodologies (Lindseth 1979; Lancaster and Whitcombe 2000; Russell 1988; Coléou et al. 2005). Later, this framework was extended into a statistical domain. Among the many statistical inverse approaches, two different stochastic approaches for

solving the seismic inversion are worth mentioning. The first group of stochastic methodologies approach the seismic inversion as an optimization problem in an iterative and convergent process. This includes what are traditionally designated by iterative geostatistical seismic inversion methods, from the seminal work by Bortolli et al. (1993), until the most recent geostatistical inversion methods (Soares et al. 2007; Nunes et al. 2012; Azevedo et al. 2015; Azevedo and Soares 2017). The second group of stochastic seismic inversion algorithms is known by linearized Bayesian inverse methodologies. These are based on a particular solution of the inverse problem using the Bayesian framework and assuming the model parameters and observations as multi-Gaussian distributed as well as the data error, which allows the forward model to be linearized (Buland and Omre 2003). Several authors have recently contributed towards overcoming some of the limitations of this method, particularly the multi-Gaussian assumption, by using Gaussian Mixture Models (Grana and Della Rossa 2010).

This chapter summarizes some iterative geostatistical modeling techniques dealing with the integration of seismic reflection and well-log data, through seismic inversion procedures, for characterizing hydrocarbon reservoirs with high spatial resolution models of main properties of interest, such as lithologies, facies and fluid saturations.

Uncertainty and risk assessment at different stages of exploration are also important targets of the proposed methodologies approached in this chapter. Hence, this chapter finishes with the introduction of recent advances of geostatistical seismic inversion methods for the uncertainty and risk assessment at early stages of exploration.

25.2 Iterative Geostatistical Seismic Inversion Methodologies

The aim of seismic inversion is the inference of the subsurface elastic or acoustic properties from recorded seismic reflection data. The retrieved inverse models can be acoustic and/or elastic impedance for post-stack seismic data, or density, P-wave and S-wave models if the inversion algorithm is used to invert pre-stack seismic reflection data (Francis 2006).

Seismic inversion might be described as an ill-posed and nonlinear problem with multiple solutions that can be summarized by (Tarantola 2005):

$$\mathbf{d}_{\text{obs}} = \mathbf{F}(\mathbf{m}) + \mathbf{e}. \quad (25.2)$$

The goal is to estimate a subsurface Earth model, \mathbf{m} , that after being forward modelled, \mathbf{F} , produces synthetic seismic data showing a good correlation with the recorded seismic data, the observed data, \mathbf{d}_{obs} , which are normally contaminated by measurement errors \mathbf{e} . The match between observed and synthetic seismic is achieved by the maximization (or minimization) of an objective function measuring

the mismatch between inverted and real seismic. For example, the objective function can be as simple as the Pearson's correlation coefficient:

$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}, \quad (25.3)$$

where *cov* is the centered covariance between variables *X* and *Y*, which are the synthetic and real seismic volumes, respectively, and σ the individual standard deviations of each variable. More complex objective functions integrate Pearson's correlation coefficient with least-square errors calculated between the synthetic and the recorded seismic reflection data in terms of amplitudes.

A geostatistical seismic inversion framework consists on an iterative procedure in which a set of realizations of parameters, **m**, are generated by using stochastic sequential simulation methods (Deutsch and Journel 1996) and optimized until the match of the objective function reaches a given user-defined value, or a certain number of fixed iterations. Geostatistical inversion techniques are based on the use of stochastic sequential simulation as the model perturbation technique, ensuring in this way the reproduction of the main spatial continuity patterns and the joint distribution functions of the acoustic and/or elastic properties of interest as retrieved from the existing well-log data in all the models generated during the iterative procedure, while simultaneously allowing access to the uncertainty attached to the retrieved inverse models.

Within this framework there are two traditional approaches for integrating seismic reflection and well-log data for hydrocarbon reservoir modeling.

25.3 Trace-by-Trace Geostatistical Seismic Inversion

Geostatistical seismic inversion was introduced by the seminal papers of Bortoli et al. (1993) and Haas and Dubrule (1994). These authors proposed a sequential trace-by-trace approach in which each seismic trace, or location within the inversion grid, is visited individually following a pre-defined random path within the seismic volume. At each step along the random path a set of *N_s* realizations of one acoustic impedance trace is simulated using sequential Gaussian simulation (Gómez-Hernández and Journel 1993; Deutsch and Journel 1996), taking the well-log data and previously visited/simulated nodes into account. Then, for each individual simulated impedance trace, the corresponding reflection coefficient is derived and convolved by a wavelet, resulting in a set of *N_s* synthetic seismic traces. Each of the *N_s* synthetic traces is compared in terms of a mismatch function with the recorded/real seismic trace. The acoustic impedance realization that produces the best match between the real and the synthetic seismic traces is retained in the reservoir grid as conditioning data for the simulation of the next acoustic impedance trace at the new location following the pre-defined random path. One of the main drawbacks of trace-by-trace stochastic seismic inversion methodologies concerns those areas of

the record seismic reflection data with low signal-to-noise ratio. In areas of poor seismic signal, the sequential trace-by-trace approaches impose inverted models fitting the observed noisy seismic reflection data. As the simulated trace is assumed to be ‘real’ data for subsequent steps, this can lead to the spread of unreliable impedance values that are related with noisy seismic samples. Noisy areas should be interpreted as high uncertainty areas with very low influence throughout the inversion process. More recent versions of trace-by-trace models try to overcome this drawback by avoiding noisy areas in the early stages of the inversion procedure (Grijalba-Cuenca and Torres-Verdín 2000).

25.4 Global Geostatistical Seismic Inversion Methodologies

To overcome these limitations, Soares et al. (2007) introduced the global stochastic inversion methodology that, contrary to trace-by-trace approaches, uses a global approach during the stochastic sequential simulation stage of the inversion procedure: at each iteration a set of N_s impedance models is generated at once for the entire inversion grid. The general outline of this family of geostatistical inversion algorithms is depicted in Fig. 25.1. Briefly, this group of iterative inverse approaches uses the principle of cross-over genetic algorithms as the global optimization technique driving the convergence of the procedure from iteration to iteration, while the model perturbation is performed using direct sequential simulation and co-simulation (Soares 2001). The global optimizer uses the trace-by-trace correlation coefficients between the different simulated synthetic seismic data and the real model as the affinity criterion to create the next generation of models for the next iteration, by using stochastic sequential co-simulation. The iterative procedure continues until a stopping criterion is reached: frequently the global correlation coefficient between real and inverted seismic reflection data.

In global iterative geostatistical seismic inversion procedures, areas of low signal-to-noise ratio remain poorly matched throughout the entire iterative inversion

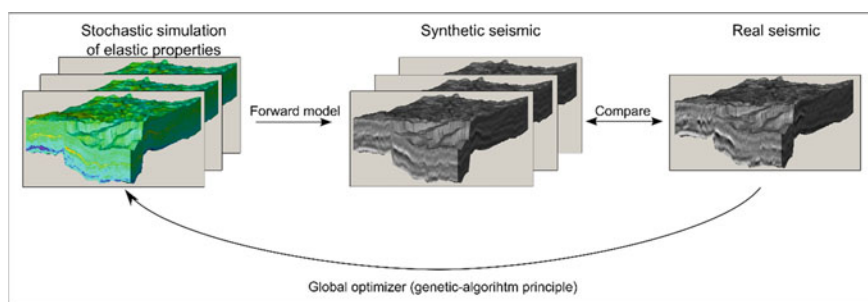


Fig. 25.1 General outline for global iterative geostatistical seismic inversion

procedure: an ensemble of best-fit inverted models will always present high variability, or high uncertainty, for those noisy areas where the signal-to-noise ratio is low.

This framework was generalized for the inversion of seismic reflection data for acoustic and elastic impedance, direct inversion of petrophysical properties and seismic AVA inversion. These methods are introduced with more detail in the following sections.

25.4.1 Global Geostatistical Acoustic Inversion

The global stochastic inversion (GSI; Soares et al. 2007; Caetano 2009) is one of the existing methods to invert fullstack seismic reflection data for acoustic impedance (I_p) models. The general outline of this iterative geostatistical methodology can be described in the following sequence of steps, summarized in Fig. 25.2:

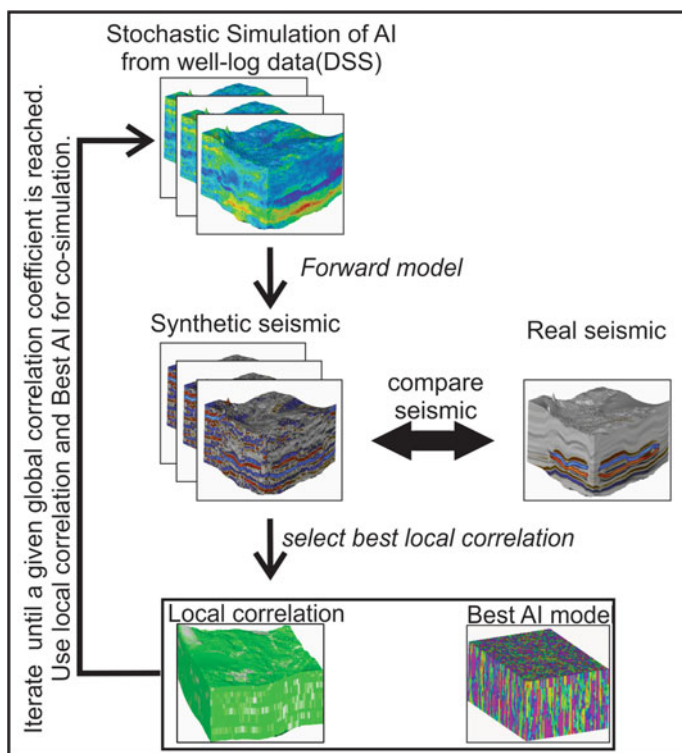


Fig. 25.2 Outline of geostatistical acoustic inversion (adapted from Azevedo and Soares 2017)

- (1) Simulate with direct sequential simulation (Soares 2001) for the entire seismic grid a set of N_s acoustic impedance models, conditioned to the available acoustic impedance well-log data and assuming a spatial continuity pattern as revealed by a variogram model;
- (2) From the impedance models simulated in the previous step, derive a set N_s synthetic seismic volumes by computing the corresponding normal incidence reflection coefficients (RC) (Eq. 25.4):

$$RC = \frac{Ip_2 - Ip_1}{Ip_2 + Ip_1}, \quad (25.4)$$

where the indexes 1 and 2 correspond to the layer above and below a given reflection interface.

- (3) The resulting RC are convolved by an estimated wavelet for that particular seismic dataset in order to compute synthetic seismic volumes (Eq. 25.1).
- (4) Each seismic trace from the N_s synthetic seismic volumes is compared in terms of correlation coefficient against the real seismic trace from the same location. From the ensemble of simulated Ip models, the acoustic impedance traces that produce synthetic seismic with the highest correlation coefficient are stored in an auxiliary volume along with the value of the correlation coefficient.
- (5) These auxiliary volumes, the one with the best acoustic impedance traces and the other with the corresponding local correlation coefficients, are used as secondary variables and local regionalized models for the generation of the new set of acoustic impedance models for the next iteration. The new set of N_s acoustic impedance models is built using direct sequential co-simulation (Soares 2001) conditioned to the available acoustic impedance well-log data, and using the best Ip volumes as secondary variable and local correlation coefficients to condition the co-simulation.
- (6) The iterative procedure stops when the global correlation coefficient between the full synthetic and real stacked seismic volumes is above a certain threshold.

Synthetic and real case applications of geostatistical acoustic inversion can be found in several studies; for example, Soares et al. (2007) and Caetano (2009). A summary of a real application example, using a fullstack seismic volume acquired offshore Brazil, illustrates herein the method (a detailed description of the dataset is available in Azevedo et al. 2015). The best-fit Ip model (Fig. 25.3) was retrieved after 6 iterations where on each iteration an ensemble of 32 realizations of Ip were generated. The use of stochastic seismic inversion allows retrieving high resolution (with high variability) acoustic impedance models. The synthetic full-stack seismic data computed from this model (Fig. 25.4) do match the observed seismic reflection data in both the spatial extent of the main seismic reflection and its amplitude content. This is of great importance for this case study since the reservoir areas are related with those spatially constrained amplitude anomalies

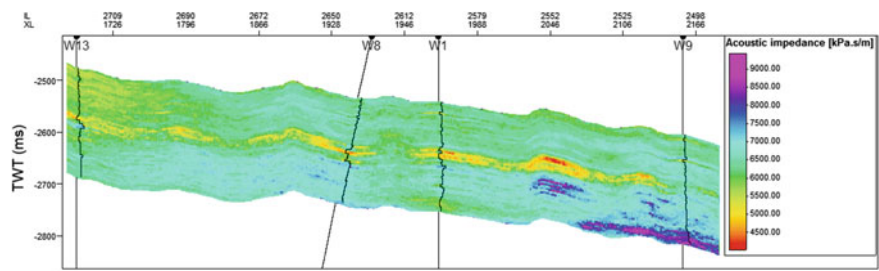


Fig. 25.3 Vertical well-section extracted from the best-fit P-impedance volume retrieved from the global stochastic inversion after six iteration with thirty-two realizations generated at each iteration

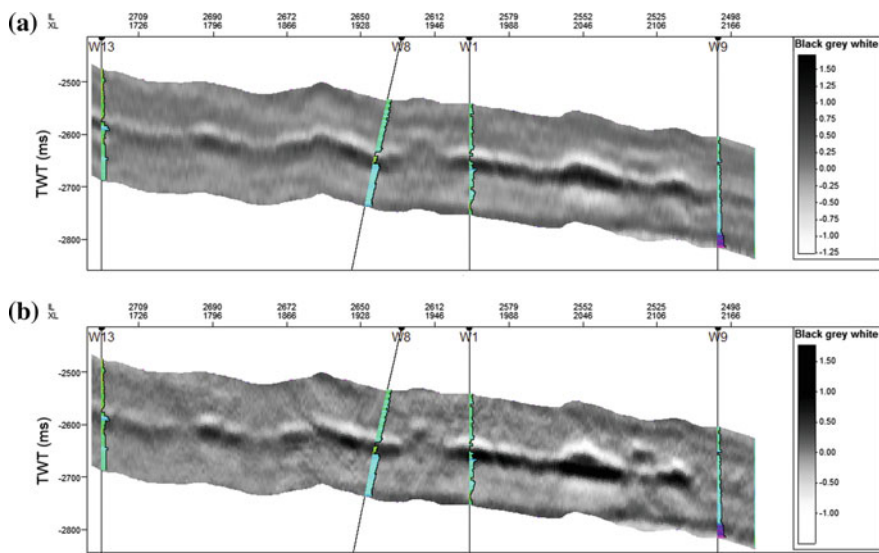


Fig. 25.4 Comparison between vertical well sections extracted from: **a** synthetic seismic reflection data computed from the best-fit inverse I_p model shown in Fig. 25.3 and **b** real seismic volume. The log curve plotted on top of the seismic data represents I_p (same color scale as shown in Fig. 25.3)

observed in the real seismic volume. The global correlation between the inverted and the real seismic volumes is 87%.

25.4.2 Global Geostatistical Elastic Inversion

The acoustic inversion algorithm was extended for the inversion of partial angle stacks directly, and simultaneously, for acoustic and elastic impedance (I_s) models

(Nunes et al. 2012; Azevedo et al. 2013b). The main purpose of this development was the integration of more information, related with the elastic domain (I_s), to enrich the final elastic reservoir models allowing better lithofacies prediction. Two main differences compared with acoustic inversion summarize this elastic inversion method (Azevedo and Soares 2017):

- (i) Acoustic and elastic impedances, I_p and I_s , are jointly simulated (step 1) of previous outline and co-simulated (step 5) by using the direct sequential simulation with joint distributions of probability (Horta and Soares 2010). This simulation method succeeds in reproducing the bivariate distribution function (I_p , I_s) as it was estimated from the experimental log data.
- (ii) The reflectivity coefficients (step 9) are obtained with the N_s pairs of I_p and I_s , simulated at each iteration, using the approximation outlined in Fatti et al. (1994) (Eq. 25.5) for the calculation of the corresponding angle-dependent reflection coefficient volumes:

$$\begin{aligned}
 R_{pp}(\theta) &\approx (1 + \tan^2 \theta) \frac{\Delta I_p}{\Delta I_s} - 4 \left(\frac{I_s}{I_p} \right)^2 \sin^2 \theta \frac{\Delta I_s}{2 I_s}, \\
 \Delta I_p &= I_{p2} - I_{p1}, \\
 I_p &= \frac{I_{p2} + I_{p1}}{2}, \\
 \Delta I_s &= I_{s2} - I_{s1}, \\
 I_s &= \frac{I_{s2} + I_{s1}}{2}.
 \end{aligned} \tag{25.5}$$

The index 1 refers to the vertical location in which the calculation of the reflection coefficient is carried out, the layer above the reflection interface; and 2 refers to the sample immediately below, the layer below the reflection interface.

Detailed application examples of this method can be found in the following studies: Nunes et al. (2012), Azevedo et al. (2013b), Azevedo and Soares (2017). For illustrative purpose, here we show the application of this methodology to the same case study shown in the previous section. The best-fit I_p and I_s models that jointly produce the highest value of correlation coefficient between synthetic and real seismic reflection data are shown in Fig. 25.5. Comparing the I_p models derived from the acoustic and elastic inversion it is clear that the introduction of more information using different angles of incidence brings more detail for the retrieved inverse model. The comparison between real and synthetic seismic reflection data derived from the best-fit elastic models is shown in Fig. 25.6.

Due to the use of direct sequential simulation with joint probability distributions (Horta and Soares 2010) the relationship between I_p and I_s as observed in the well-logs is reproduced for all pairs of models generated during the inversion procedure (Fig. 25.7). Besides the richness of the inverted models, this is a key step of the proposed inversion technique since it allows, for example, more reliable facies classification, and consequently a better reservoir description, over the inverted elastic models.

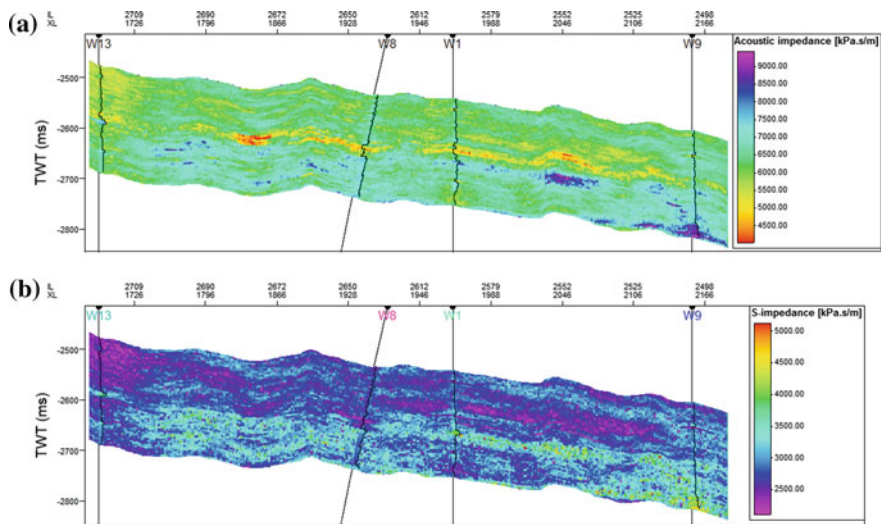


Fig. 25.5 Comparison between vertical well sections extracted from: **a** best-fit I_p model and **b** best-fit I_s model

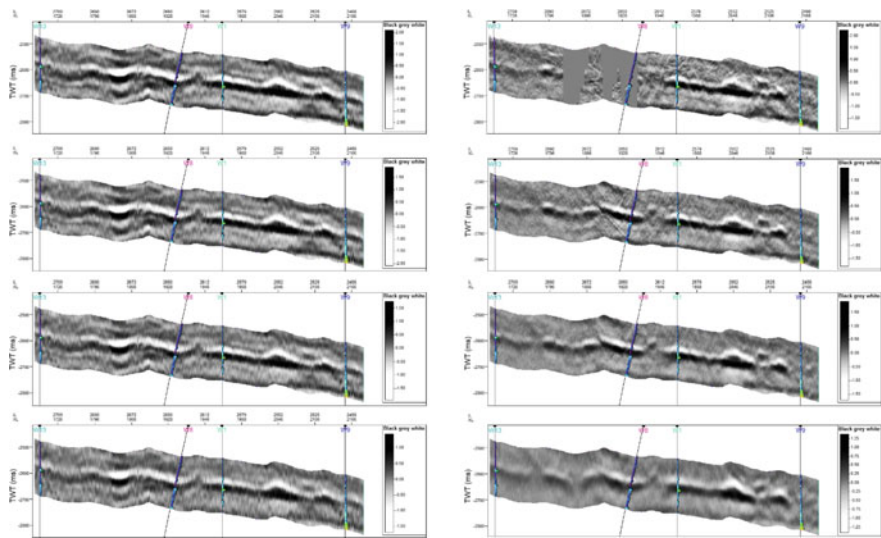


Fig. 25.6 Comparison between vertical well sections extracted from: (left) synthetic seismic reflection data computed from the best-fit inverse I_p and I_s models and (right) real seismic volume. From top to bottom: nearstack, near-mid stack, far-mid stack and farstack. The log curve plotted on top of the seismic data represents I_s (same color scale as shown in Fig. 25.5)

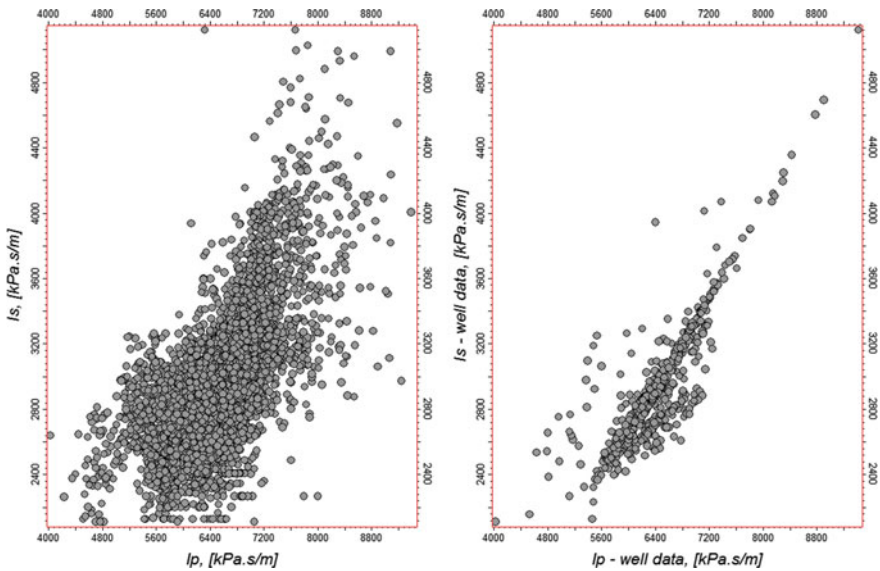


Fig. 25.7 Comparison between the joint distribution of I_p and I_s as retrieved from the best-fit inverse pair of I_p and I_s and from the well-logs

25.4.3 Geostatistical Seismic AVA Inversion (Pre-stack Inversion)

During the last decades, the quality of seismic reflection data has increased tremendously, together with the decreasing of its acquisition costs. Pre-stack seismic data with high signal-to-noise ratio and high fold number is nowadays a reality, increasing this data's use in seismic reservoir characterization even within early exploratory stages. The better subsurface characterization using pre-stack seismic data is achieved by interpreting the changes of amplitude versus the offset (AVO), or with the angle of incidence (AVA; Castagna and Backus 1993; Avseth et al. 2005). The use of pre-stack seismic reflection data allows the inference of density, P-wave and S-wave velocity models, instead of the traditional impedance models. The availability of the three properties individually is a clear enhancement in what reservoir modelling and characterization are concern with.

Stochastic seismic inversion methodologies for pre-stack seismic data, commonly called seismic AVA inversion, are being proposed based on different assumptions and frameworks (Mallick 1995; Ma 2002; Buland and Omre 2003; Contreras et al. 2005). Here we refer to geostatistical seismic AVA inversion (Azevedo et al. 2013a), which relies on the same general framework of global iterative geostatistical seismic inversion methodologies but with the following main characteristics of pre-stack inversion (see outline of Fig. 25.8; Azevedo and Soares 2017):

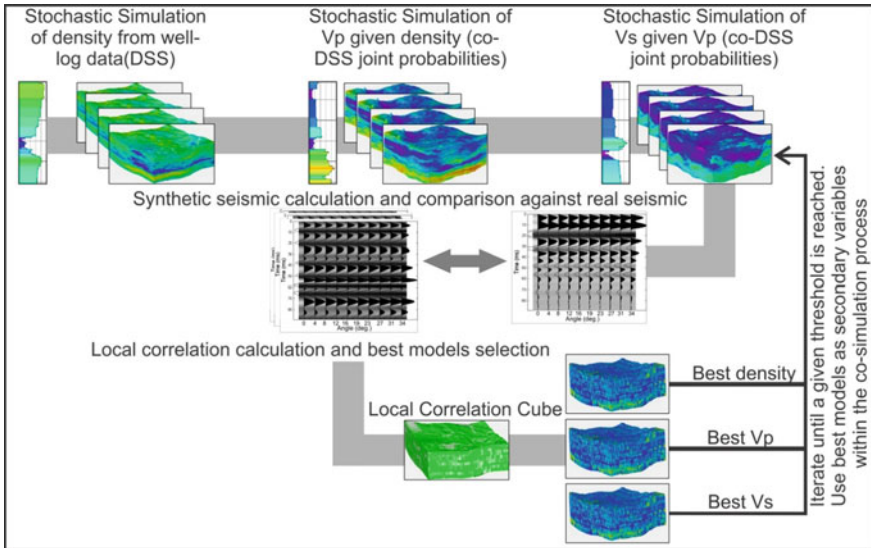


Fig. 25.8 Schematic representation of the global iterative geostatistical seismic AVO inversion methodology (adapted from Azevedo and Soares 2017)

- (i) the perturbation of the model parameters for density, P-wave and S-wave velocities is performed sequentially using stochastic sequential co-simulation with joint distributions (Horta and Soares 2010);
- (ii) forward modeling is computed using an angle-dependent approximation when computing the reflection coefficients that can be modified according to the complexity of the subsurface geology;
- (iii) the mismatch evaluation between the observed and the inverted seismic data and selection of the conditioning data for the generation of the next set of elastic models during the next iteration by multi-variable optimization.

In this approach, each elastic property is generated sequentially. Density is first simulated because it is the property associated with a higher degree of uncertainty since its contribution to the recorded seismic reflection data is small, i.e. the component of the seismic reflection data related with density is low and mostly related to the signal received at the far angles (Avseth et al. 2005). Also, density is the most spatially homogeneous variable and consequently most convenient to be used as secondary variable for the co-simulation with joint probability distributions of Vp. The resulting Vp models are then used as auxiliary variable for the co-simulation with joint probability distributions of Vs. At the end of the iterative inversion procedure, the reproduction of the joint distribution densities, Vp and Vs, allows a distinction to be made between any litho-fluid facies previously identified from the original well-log data within the inverted set of elastic models. As well as the spatial interpretation of these litho-fluid facies, the stochastic approach allows the assessment of the spatial uncertainty related with each facies of interest.

After the sequential simulation of N_s elastic models, density, V_p and V_s , an ensemble of synthetic pre-stack seismic volumes are calculated. The angle-dependent RC ($R_{pp}(\theta)$) may be calculated, for example, following Shuey's (1985) three-term approximation:

$$R_{pp}(\theta) \approx R(0) + G \sin^2 \theta + F (\tan^2 \theta - \sin^2 \theta), \quad (25.6)$$

with the normal incidence, $R(0)$, reflection as defined by:

$$R(0) = \frac{1}{2} \left(\frac{\Delta V_p}{V_p} + \frac{\Delta \rho}{\rho} \right),$$

and the variation of the reflectivity versus the angle, the AVO gradient, G :

$$G = R(0) - \frac{\Delta V_p}{V_p} \left(\frac{1}{2} + \frac{2\Delta V_s^2}{V_s^2} \right) - \frac{4\Delta V_s^2}{V_p^2} \frac{\Delta V_s}{V_s},$$

and F , the reflectivity at the far angles (reflection angles higher than 30°), defined as:

$$F = \frac{1}{2} \frac{\Delta V_p}{V_p}.$$

Each elastic property is defined on each side of the interface where the reflection is happening as follows:

$$\begin{aligned} \Delta V_p &= V_{p2} - V_{p1}, \\ V_p &= \frac{V_{p2} + V_{p1}}{2}, \\ \Delta V_s &= V_{s2} - V_{s1}, \\ V_s &= \frac{V_{s2} + V_{s1}}{2}, \\ \Delta V_\rho &= V_{\rho2} - V_{\rho1}, \\ V_\rho &= \frac{V_{\rho2} + V_{\rho1}}{2}. \end{aligned}$$

Indexes 1 and 2 have the same meaning as in Eq. 25.4.

Each angle gather is composed by n seismic traces, equal to the number of reflection angles considered. The N_s angle-dependent reflection coefficient traces are convolved by estimated angle-dependent wavelets for each particular incident angle θ (Fig. 25.9) to obtain N_s synthetic angle gathers. The best elastic models, created at the end of each iteration, are composed by the portions of the elastic traces from the ensemble of density, P-wave and S-wave velocity models simulated at the current iteration, that jointly produce synthetic seismic reflection data with the highest correlation coefficient compared with the real seismic volume. Hence, the

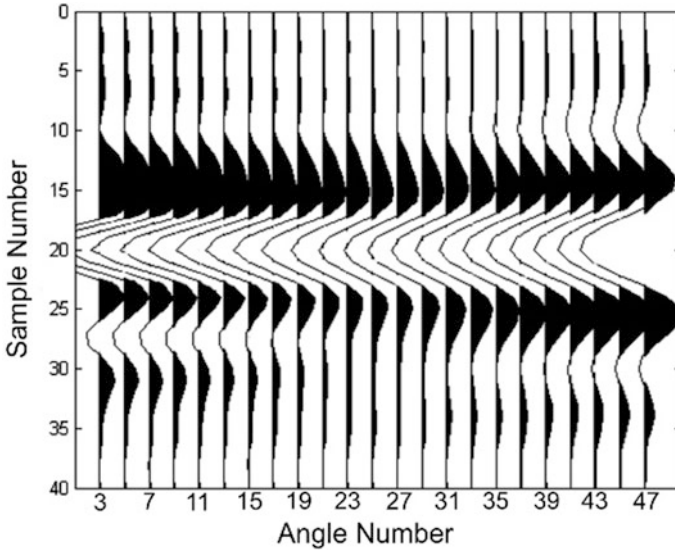


Fig. 25.9 Example of an angle-dependent wavelet, for 23 angles, used for the convolution of the angle-dependent reflection coefficients ($R_{pp}(\theta)$) to generate pre-stack seismic reflection data

best models are selected by using a multivariate (traces for each angle) objective function (Azevedo and Soares 2017 illustrate an example of multivariate objective function).

As an application example, Fig. 25.10 shows vertical well sections extracted from the triplet of elastic models that produced synthetic pre-stack seismic reflection data with the maximum correlation coefficient during the iterative procedure. The inverted density, Vp and Vs models show high variability and agree with the expected spatial extent of the anomalies of interest as inferred from previous studies (Azevedo et al. 2015).

By comparing the inverse elastic inversion, shown in the previous sections for the different geostatistical seismic inversion techniques (Figs. 25.3, 25.5 and 25.10) it is clear that introducing more information within the inversion procedure, i.e. moving from the fullstack into the pre-stack domain, allows retrieving more detailed and variable inverse models. Usually, such models allow for a better understanding of the reservoir and identify and assess the main uncertainties related with its subsurface properties.

25.4.4 Recent Developments of Iterative Geostatistical Seismic Inversion

The global iterative geostatistical inversion techniques presented in the previous sections have been extended to allow inferring the subsurface petrophysical

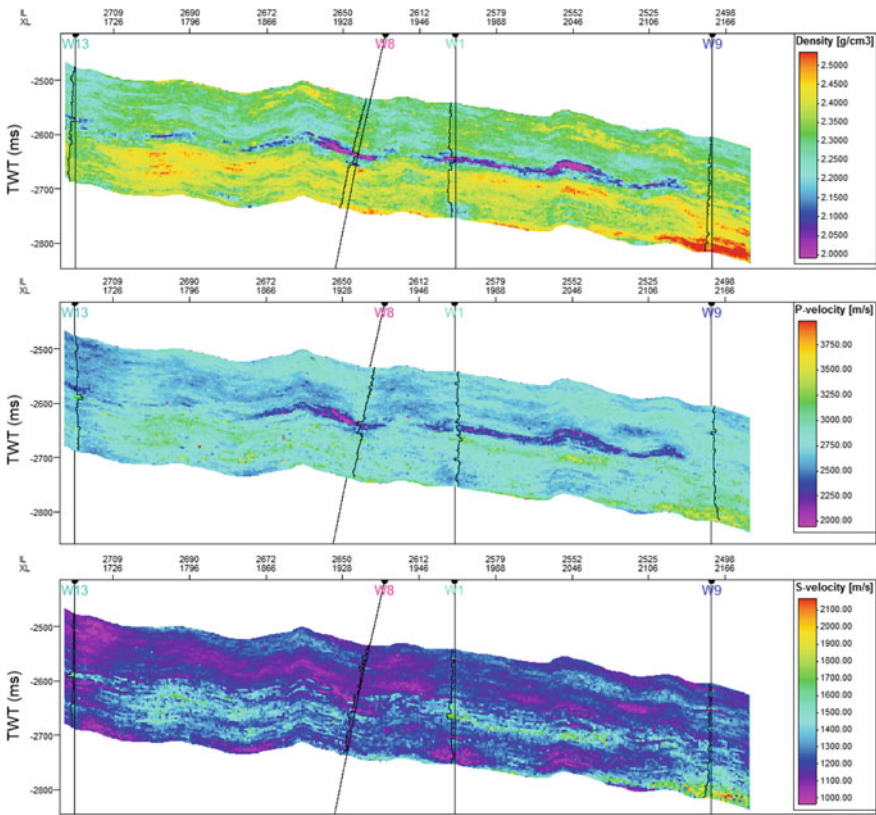


Fig. 25.10 Vertical well section extracted from the best-fit models of: (from top to bottom) density, V_p and V_s

properties of interest, directly from the existing seismic reflection data: direct geostatistical seismic inversion to porosity (Azevedo and Soares 2017); and integration of rock physics into geostatistical seismic AVA inversion for simultaneous characterization of facies (Azevedo et al. 2015). In addition, the potentiality of these methodologies is enormous in what concerns the very different data integration like for example the electromagnetic data (CSEM). Application example of the joint inversion of seismic and electromagnetic data is illustrated in the study of Azevedo and Soares (2014).

The integration of dynamic production data with seismic data is another important and very promising field of application of these methodologies. In fact the integration of dynamic production data in reservoir modelling (commonly designated as history matching) is an even more complex inverse problem (e.g. Oliver and Chen 2011; Oliver et al. 2008; Mata-Lima 2008; Demyanov et al. 2011; Caeiro et al. 2015). If this is approached by a geostatistical iterative outline, the integration of both inverse methods can lead to a very rich model able to

characterize geological complex structures and, simultaneously, reproduce the geological conceptual model, the seismic data and the dynamic data at the production wells (Marques et al. 2015; Azevedo and Soares 2017).

25.5 Uncertainty and Risk Assessment at Early Stages of Exploration

This section introduces a recent development of using seismic inversion for uncertainty and risk assessment at early stages of reservoir exploration characterized by the lack of well data. The idea of the proposed methodology is to account with the concept of geological analog data to define possible geological models of a given target, such as the geometry of different geological units, and also the a priori probability distributions for the elastic property of interest. An a priori uncertainty space is first built from plausible geological scenarios, generated from different sources of knowledge about the area of interest. For each scenario the corresponding elastic properties are computed and existing seismic reflection data is integrated, through a geostatistical seismic inversion, giving rise to an uncertainty space of petro-elastic properties. The first steps towards this direction correspond to the case study presented below.

25.5.1 Characterization of Different Scenarios with Analogue Data

Due to the lack of data, several authors use analog data to constrain and integrate regional geological knowledge into reservoir models (e.g. Martinus et al. 2014; Grammer et al. 2004). The use of analog fields, and/or sedimentary basins, can help understand and predict the behavior of a reservoir since they are natural systems that may have similarity with the unknown study area. For example, one of the most valuable information that analogs can give to reservoir modelling, normally obtained from outcrop studies (Howell et al. 2014), is related to the geometry and the relation between the different geological units and their elastic properties.

This section proposes the extension of a traditional geostatistical seismic inversion methodology to integrate data from analogs (Pereira et al. 2017). In this application example the analog information is provided by well-logs located very far from the exploration area but somehow geologically related with the area of study. This iterative geostatistical seismic inversion methodology integrates a priori knowledge from the regional geology and the information from analogs, such as existing well-logs far from the region of interest (illustrated in Fig. 25.11).

One of the mandatory steps of this procedure, consists in dividing the area of interest in regional geological units based on conventional seismic interpretation

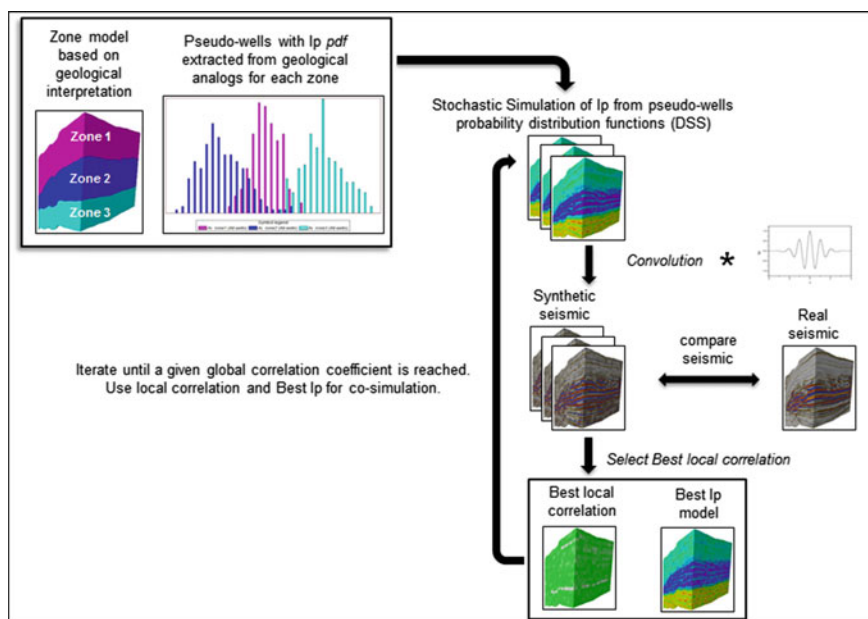


Fig. 25.11 Schematic representation of the workflow to integrate geological analogue data into geostatistical seismic inversion, for each scenario

and the current knowledge of the prospect under study. The interpretation of the available seismic reflection data should be such that the interpreted seismic units are consistent with the stratigraphy of the region. The geological regionalization model of the area of study should be based not only on available seismic reflection data but include information from outcrop analogs or based on the geological knowledge of the sedimentary basin.

After the definition of the geological regionalization model, one needs to establish different scenarios, for each geological unit, about its elastic responses. These can be inferred from for example analogue data. This critical step should be done by integrating expertises from different fields. The correlation between the elastic and rock properties should result in probability distribution functions of the elastic property of interest per region. The resulting distributions should be representative of the elastic properties of the geological region, and also of the relationship between the different geological regions. Meaning that if there is a progressive transition between geological regions (i.e. geological transition in terms of facies), this relationship should be expressed in the distributions of each region.

This approach is illustrated here with a real case study located in an offshore unexplored basin. The available data of this basin comprises a 3D seismic reflection and three appraisal wells drilled outside the main region of interest. The existing appraisal wells show evidences that suggest hydrocarbon generation, migration and possibly accumulation. Within this unexplored basin a promising prospect was

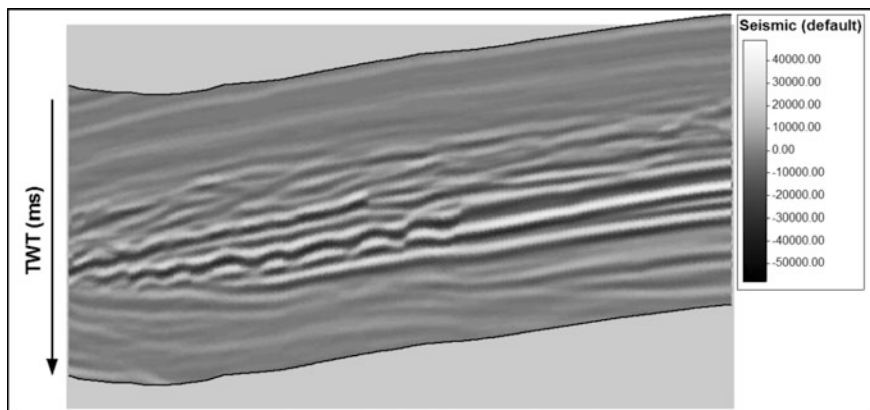


Fig. 25.12 Real Seismic data for the area of interest showing the seismic signature of the prospect of interest. Lighter values indicate positive polarity and darker values indicate negative polarity

identified associated with a turbidite system, corresponding to a classic clastic sedimentary unit. This can be recognized and interpreted from the available seismic reflection data (Fig. 25.12). A detailed description about the geology of this basin can be found in Pereira et al. (2017).

The interpretation of the existing seismic reflection data resulted in three main geological units. For each region, probability distribution functions of I_p were assumed, taking into account the geological knowledge of the region of interest and from the I_p -logs available at the three neighbor wells. A representative wavelet of the time interval of interest was extracted exclusively from the available seismic reflection data using conventional wavelet extraction techniques based on statistical procedures (i.e. Weiner-Levinson filters). One of the main difficult steps of this methodology is the validation of the wavelet scale. A possible approach to tackle this issue can be selecting the distribution function of I_p for each region, making them plausible, by comparing the amplitude values of the synthetic seismic against the observed one.

25.5.2 Geostatistical Seismic Inversion of Each Scenario

The previous step of this approach results in a set of geological models that represent the uncertainty about the prospect to be modelled. In order to reduce this space, the purpose of this step is based in the following rationale:

- (i) for each one of the a priori chosen scenarios, in terms of geological regionalization model, one intends to access the models of acoustic and/or petrophysical properties, that match the known seismic, by running a conventional iterative geostatistical seismic inversion;

- (ii) The match of each scenario synthetic seismogram with the real seismic can be used to validate or falsify them and build an uncertainty space of those properties.

Here, we show an example for one of the scenarios considered. The iterative geostatistical seismic inversion ran with six iterations, where on each sets of thirty-two realizations of I_p were generated conditioned simultaneously by the regionalization model (i.e. the three main seismic units resulting from seismic interpretation (Fig. 25.12)) and the individual I_p distributions as inferred from the nearby analog wells and published data.

The seismic inversion converged after six iterations when a global correlation coefficient between real seismic and synthetic seismic reflection data reached 85%. For region 1, the overburden region the correlation coefficient was 80%; for region 2, the potential reservoir region the correlation coefficient was 89% and for region 3, the underburden region the correlation coefficient was 70%. The synthetic seismic data was able to reproduce the real observed seismic reflection data in terms of the location and spatial distribution of the main geological features of interest.

The best-fit inverse I_p model (Fig. 25.13) allows the interpretation of the turbidite feature of interest in both vertical and horizontal slices. It also shows a reasonable spatial continuity pattern where it is possible to identify both large and subtle features of potential interest when appraising an unexplored sedimentary basin. Moreover it is clear that each region of the inversion grid is constrained individually by a given distribution function of I_p values. In this way we are constraining the spatial distribution of the simulated values. Since the regionalization of the area of interest is done using a geological criterion, the resulting best-fit inverse models are therefore geological consistent with the geological knowledge.

Uncertainty and risk of this unexplored area could be accessed by doing identical exercise but for different scenarios regarding the geometry of different geological units (regions) and, as well as, the I_p distributions for each one of them.

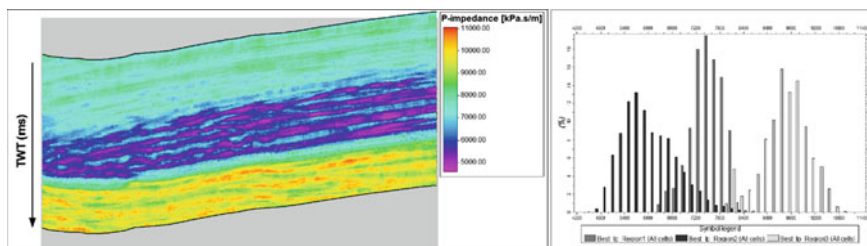


Fig. 25.13 Best-fit inverse model of I_p retrieved after 6 iterations (left). It is possible to identify the turbidite system of interest corresponding to lower acoustic impedance values (purple). At right is the distribution function of the Best-fit inverse model of I_p , which reproduces the initial distribution function of I_p

25.6 Final Remarks

This chapter presents the state of the art and the most recent advances in geostatistical seismic inversion. The promising results of presented and also referenced case studies clearly show an evident maturity of these methods as privileged instruments for the integration of different types of data, particularly seismic reflection data, for the characterization and modeling of hydrocarbon reservoirs.

Very recent studies, regarding the integration of electromagnetic data and production data, show the inversion methodologies as important new paths on geostatistical tools for modelling complex geological structures.

The methodology introduced for the characterization of uncertainty and risk in early stages of exploration integrates two important components: (i) the use of analog data to generate scenarios of uncertainty regarding the morphology of geological units and the distribution of acoustic and petrophysical properties; (ii) the stochastic inversion methodologies evaluate the most probable images within each scenario and also validate (or falsify) these scenarios regarding the known seismic reality.

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