Geostatistical seismic inversion for frontier exploration

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Abstract

Numerical 3D high-resolution models of subsurface petroelastic properties are key tools for exploration and production stages. Stochastic seismic inversion techniques are often used to infer the spatial distribution of the properties of interest by integrating simultaneously seismic reflection and well-log data also allowing accessing the spatial uncertainty of the retrieved models. In frontier exploration areas, the available data set is often composed exclusively of seismic reflection data due to the lack of drilled wells and are therefore of high uncertainty. In these cases, subsurface models are usually retrieved by deterministic seismic inversion methodologies based exclusively on the existing seismic reflection data and an a priori elastic model. The resulting models are smooth representations of the real complex geology and do not allow assessing the uncertainty. To overcome these limitations, we have developed a geostatistical framework that allows inverting seismic reflection data without the need of experimental data (i.e., well-log data) within the inversion area. This iterative geostatistical seismic inversion methodology simultaneously integrates the available seismic reflection data and information from geologic analogs (nearby wells and/or analog fields) allowing retrieving acoustic impedance models. The model parameter space is perturbed by a stochastic sequential simulation methodology that handles the nonstationary probability distribution function. Convergence from iteration to iteration is ensured by a genetic algorithm driven by the trace-by-trace mismatch between real and synthetic seismic reflection data. The method was successfully applied to a frontier basin offshore southwest Europe, where no well has been drilled yet. Geologic information about the expected impedance distribution was retrieved from nearby wells and integrated within the inversion procedure. The resulting acoustic impedance models are geologically consistent with the available information and data, and the match between the inverted and the real seismic data ranges from 85% to 90% in some regions.

Introduction

Three-dimensional numerical reservoir models are approximations of the real subsurface geology built from several sources of knowledge, e.g., geophysical data, well-log data, analog sedimentary basins, or nearby fields. They intend to be a representation of the petroelastic subsurface properties that are directly related to the different existing rock types. These models are key tools to predict and estimate reservoir quality and architecture. However, rock properties are directly measured only at sparse well locations and unknown for the rest of the area of interest. Therefore, it is necessary to infer these properties for the rest of the reservoir area by understanding the spatial distribution pattern of the properties of interest to better predict potential hydrocarbon accumulation areas.

At early exploration stages, it is not only necessary to predict reservoir quality and its internal architecture but also to quantify risks and uncertainties. In these particular cases, it is of the utmost importance to integrate the geologic knowledge of the area with the existing geophysical and well-log data for reliable reservoir modeling and characterization. This is a particularly challenging task in frontier exploration areas, given the fact that there is a lack of direct measurements, such as well-log data, which makes the estimation of reservoir properties derived from traditional modeling procedures, for example, seismic inversion, difficult. In these cases, the estimation of reservoir properties derived from traditional modeling procedures is of high risk and associated with many uncertainties.

Seismic inversion methodologies are common techniques used to infer petroelastic subsurface properties, and they are useful for reservoir characterization. The most common elastic property resulting from seismic inversion is acoustic impedance Ip. The traditional geomodeling workflow uses the inference of related properties, for example, total porosity ϕ. Seismic inversion

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is based on the physical relationship between the seismic reflection data, i.e., seismic amplitude, and the elastic response of the subsurface geology. This response is intrinsic to the type of rock or facies and its correspondent characteristics. Seismic inverse problems have a nonunique solution, are nonlinear and ill-posed; therefore, any model resulting from seismic inversion is contaminated with noise that should be taken into account during the interpretation of the results (Tarantola, 2005).

There are two main ways to solve the seismic inversion problem: deterministic and probabilistic approaches. Deterministic procedures are based on optimization techniques that do not integrate explicitly available well-log data into its solution (i.e., existing well-log data are only used to build the a priori elastic models) and do not allow the uncertainty assessment of the inferred elastic model. However, probabilistic procedure, and particularly geostatistical seismic inversion methodologies, rely on the integration of the well-log data into the resulting inverse models and allow assessing the uncertainty of the inverted elastic models (Bosh et al., 2010).

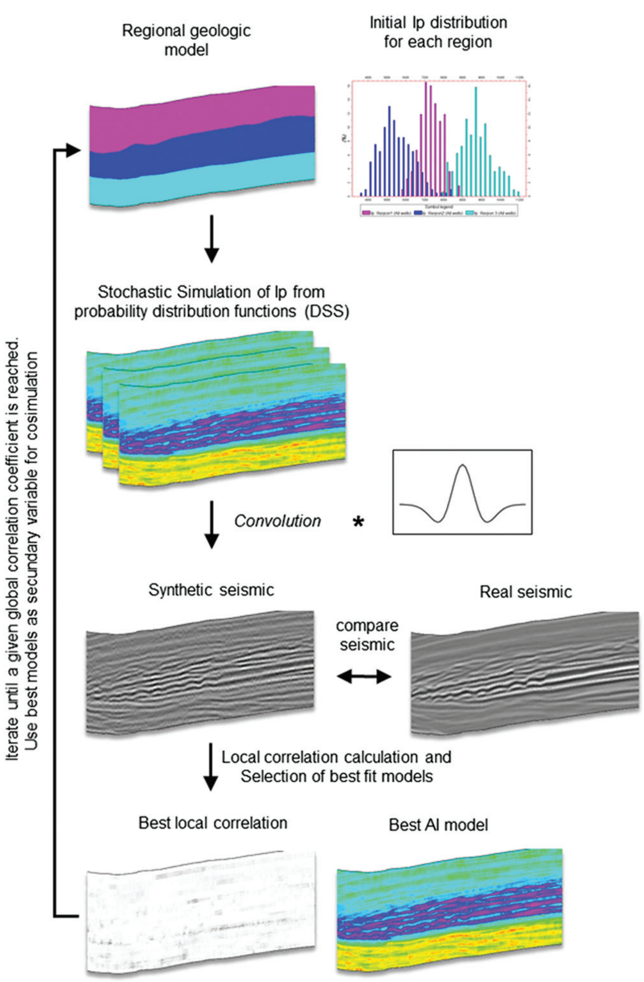

Figure 1. Workflow of the proposal geostatistical seismic inversion for frontier exploration.

In frontier exploration in which the available set of data are usually small and the risk and uncertainties are greater, creating a consistent and realistic reservoir models is not an easy task. In these situations, it is of special interest to create geologically constrained reservoir models. Due to the lack of data, one way several authors have identified is the use of analogs to constrain and integrate regional geologic knowledge into reservoir models (e.g., Grammer et al., 2004; Martinius et al., 2014). Analog fields, and/or sedimentary basins, can help to understand and predict the behavior of a reservoir because they are natural systems that may have similarity with the unknown area. In frontier exploration areas, it is of extreme importance to integrate geologic information to constrain the reservoir model to reduce uncertainties and risk. One of the valuable information that analogs can give to reservoir modeling is related to the geometry and the relationship between the different geologic units and its elastic properties. This information is normally obtained from outcrop studies and/or existing or expected depth trends (Howell et al., 2014).

For challenging exploratory environments, such as frontier basins, we propose herein the extension of a traditional geostatistical seismic inversion methodology to integrate data from analogs into iterative geostatistical seismic inverse procedures (Soares et al., 2007; Nunes et al., 2012; Azevedo et al., 2015). It is important to highlight that conventional geostatistical seismic inversion needs to be constrained locally by existing well-log data. Therefore, the proposed methodology surpasses this limitation. The analog information is provided by nearby well logs located outside the exploration area, but geologically related to the area of study.

The proposed seismic inversion procedure (Figure 1) is an iterative geostatistical seismic inversion methodology that integrates a priori knowledge from the regional geology and the information from analogs, such as nearby wells logs. The proposed procedure uses stochastic sequential simulation and cosimulation for nonstationary areas (Nunes et al., 2017) as the model perturbation technique and a global optimizer based on genetic crossover algorithms driven by the match between the real and synthetic seismic data produced during the inversion procedure. This methodology is presented in a real case study of a frontier basin offshore southwest Europe.

Methodology

The proposed iterative geostatistical seismic inversion technique allows increasing the geologic consistency of the resulting inverse models by incorporating the relationships between the rock and elastic properties of the subsurface geology from geologic analogs. We start with one of the mandatory steps of this procedure, by dividing the area of interest into regional geologic units based on traditional seismic interpretation (Figure 2). The interpretation of the available seismic reflection data should include interpreted seismic units consistent with the stratigraphy of the region. The regional geologic model of the area should be based not only on the available seismic reflection data, but it should also include information from outcrop analogs or the geologic knowledge of the sedimentary basin.

After defining the regional geologic model, we need to establish the correlation between each region and the expected elastic response inferred from the nearby wells or analog data. This is a critical step and should be done by integrating expertizes 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 (Figure 3). The resulting distributions should be representative of the elastic properties for a given region, and also of the relationship between the different geologic regions. Meaning that if there is a progressive transition between geologic regions (i.e., geologic transition in terms of facies), this relationship should be expressed in the distributions of each region.

Compared with a traditional iterative geostatistical seismic inversion methodology (e.g., global stochastic inversion; Soares et al., 2007), we propose the use of direct sequential simulation (Soares, 2001; Nunes and Almeida, 2010) for nonstationary environments as introduced by Nunes et al. (2017). In this way, we are able to incorporate within the inversion procedure each geologic region, resulting from the interpretation of the existing seismic reflection data, simultaneously using well-log data, and in the absence of wells, the a priori knowledge about the subsurface geology as expressed in terms of probability distribution functions of the petroelastic properties of interest (i.e., probability distribution functions of acoustic impedance built from geologic analog sedimentary basins or existing wells located in nearby fields).

The geostatistical seismic inversion for unexplored frontier areas may be summarized in the following sequence of steps: First, we defined a regional geologic model built from seismic interpretation; then, from the geologic analogs (i.e., nearby appraisal well-log data) probability distribution functions are built for the elastic property of interest and used as a priori; finally, a spatial continuity pattern is imposed as expressed by a variogram model assigned to each geologic region interpreted in the first step:

1) Define the main geologic units from traditional seismic interpretation to build the regional geologic model.
2) Assign a distribution function to each region based on a priori knowledge and information from geologic analogs, such as nearby well-log data. The distribution functions assigned to each region only need to reflect the geologic knowledge of the study area. These distributions may be overlapping from region to region (reflecting more uncertainty regarding the spatial distribution of *Ip*).
3) Generate a set (e.g., 32 simulated models) of acoustic impedance models using direct sequential simulation for nonstationary environments (Nunes et al., 2017). The resulting models are simultaneously conditioned at the wells location by existing wells and per region by the distributions generated in step 1. If no well data are available, the models will only be constrained by the distributions assigned to each region. In both cases, a spatial continuity pattern is imposed in terms of a variogram model per region.
4) Synthetic data are generated by convolving the reflection coefficients, derived from the acoustic impedance models generated in the previous step, with a known wavelet.

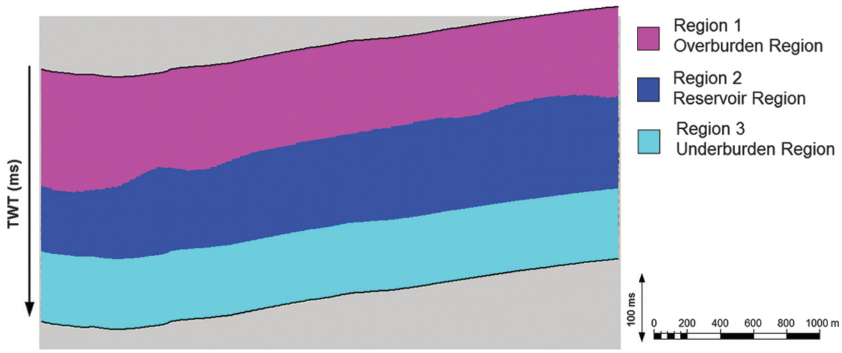

Figure 2. Regional geologic model, obtained from traditional seismic interpretation of the main seismo-stratigraphic units. Three main seismic units were defined: region 1 corresponds to the seismic unit above the interval of interest, the overburden region; region 2 is the region of interest of the potential hydrocarbon accumulation zone, the reservoir region; and region 3 corresponds to the underburden region of the interval of interest.

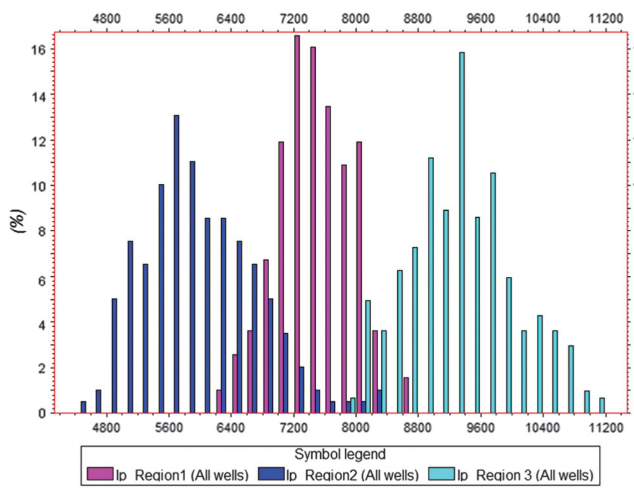

Figure 3. Initial a priori acoustic impedance distributions *Ip* for each region. These distributions were built based on the available nearby wells and published data (Figures 4 and 6). The colors represent each region as illustrated in Figure 2.

5) The correlation coefficient between the synthetic seismic and real seismic reflection data is computed on a trace-by-trace basis.
6) Select the acoustic impedance traces that produced the highest correlation coefficient at a given iteration. These traces are stored along with the corresponding correlation coefficients in two auxiliary volumes.
7) Generate a new set of Ip models using direct sequential cosimulation for nonstationary environments using the two auxiliary volumes generated in the previous step as auxiliary variables.
8) Return to step 3 and iterate until the global correlation coefficient between real and synthetic seismic data is above a certain threshold.

The resulting models after the convergence procedure is finished are able to honor the well-log data at the wells locations, if well data are available, the distribution functions assigned to each region individually and the spatial continuity pattern imposed by the variogram model for the stochastic sequential simulation. In a situation in which there is no experimental data (i.e., well-log data), the spatial continuity pattern might be inferred by modeling a variogram directly from the available seismic reflection data (i.e., seismic amplitude). The horizontal and vertical variogram models imposed for the inversion procedure should be coherent with the geologic knowledge of the area and consistent with the size of the expected sedimentary structures. We propose the use of the original seismic reflection data to estimate the horizontal spatial continuity pattern of the study. The resulting estimated ranges are expected to be overestimated due to the nature of the seismic reflection data (i.e., resolution limits). The vertical direction should represent a compromise on the expected variability of the geologic layers in the vertical direction and the sampling interval of the available seismic reflection data. In addition, the flexibility provided by the stochastic sequential simulation step allows the definition of different variogram models, with different anisotropy ratios and ranges, to each region individually.

Due to its importance within the proposed iterative geostatistical seismic inversion procedure, we briefly introduce the main steps of the direct sequential simulation algorithm for nonstationary environments. Nunes et al. (2017) present a detailed mathematical description of this stochastic sequential simulation algorithm. The definition of a regionalization model is one of the required steps for this stochastic sequential simulation technique. The regionalization model has the purpose of dividing the entire simulation grid into regions, where the assumption of stationarity of the main statistical moment for the property interest is more valid. Therefore, this regionalization model should be consistent with the geology of the region (i.e., geologically consistent regions). Each region can be defined with different shapes and sizes, and to each zone, a probability distribution function of the property of interest to be modeled and a spatial continuity pattern expressed by a variogram model needs to be assigned. The algorithm starts with the definition of a random path that visits all the cells of the grid, where at each location, the kriging estimate is calculated taking into account existing experimental data for the region and previously simulated cells locations, guided by the variogram model of the region where the estimation is being performed. Nevertheless, to avoid the generation of unexpected and unreliable discontinuities from region to region that do not have any geologic meaning, the estimation also takes into account experimental, or previously simulated samples, from different adjacent regions. For each region where the estimation is being performed, the values of the property of interest to be estimated are generated from a probability distribution function of the property by using a simple kriging estimate along with the corresponding kriging variance. The simulated value of the property of interest is assigned to that specific location, and it is considered as experimental data for the simulation of the next grid node following the predefined random path. This random path will be different for each time that this stochastic sequential simulation algorithm runs, and therefore the conditioning data at each location following the random path are going to be different. Consequently, the resulting models of the property of interest will be different, but all of the models are going to reproduce the global and regional distribution functions for the property of interest and the imposed variogram models per region.

The proposed methodology was successfully applied to a challenging real case study in an unexplored area, offshore Southwest Europe, where no well data were available within the area of interest and the distribution functions were borrowed from analog neighboring wells.

Case study

Data set description

The study area (Figure 4) is located in an offshore unexplored basin, where so far, there is no relevant exploration activity. In terms of exploration, the data regarding this basin comprise a 3D seismic reflection and three appraisal wells drilled during the past few decades (Figure 4). Despite the potential for hydrocarbon exploration, there are no proven accumulations. However, the existing appraisal wells show evidence that suggest hydrocarbon generation, migration, and possibly accumulation.

There is a promising prospect within this frontier basin associated with a clastic turbidite system. This promising feature is easily recognized and interpreted from the available seismic reflection data (Figure 5). The interpretation of the nearby well-log data (Figure 6) at the depth of interest suggests the presence of good-quality reservoir rocks. These data have similar sedimentary structures (i.e., turbidite sequences) for the geologic interval of interest as interpreted from the recorded seismic reflection data (Figure 5) suggesting a single regional sedimentary event.

The data available to perform this study consist of a 3D poststack seismic reflection data volume and three appraisal wells located outside the prospect area. The available full stack seismic volume was previously prestack migrated in time and has a sampling interval of 2 ms with an inline space of 18.75 and 12.50 m in the crossline directions. The average depth of the area considered for this application example is −1600 ms two-way traveltime (TWT). The seismic reflection data were interpreted, and three main geologic units were identified (Figure 2). These areas correspond to the potential reservoir region, the overburden, and the underburden. Then, for each region, distribution functions of Ip were built from published works about the region of interest and from the Ip logs available for the three analog wells (Figure 6) after a detailed interpretation of the existing logs and correlating the seismic and the well data.

In this particular case study, a representative wavelet of the time interval of interest was extracted using a commercial standard software package from the industry. The wavelet was also extracted exclusively from the available seismic reflection data using conventional wavelet extraction techniques based on statistical procedures (i.e., Weiner-Levinson filters). This procedure uses the autocorrelation of the seismic traces located within the interval of interest from where the amplitude spectrum of the autocorrelation is calculated. The wavelet amplitude spectrum is then equal to the square root of the autocorrelation amplitude spectrum. In addition, the wavelet phase is supplied taking into account the processing flow applied to the seismic reflection data.

A time window of 1000 ms was used as the extraction interval. Due to the lack of well data within the seismic grid, it was not possible to tie the extracted wavelet to the observed seismic. The procedure used for this particular case study oversimplifies the problem at hand by assuming no uncertainty for the extracted wavelet and that it is representative of the existing seismic. However, it is important to highlight that the reliability of the inverse petroelastic models is highly dependent on the quality of the extracted wavelet.

The inversion grid was defined around the prospect of interest in a grid with $198 \times 279 \times 190$ cells in the i-, j-, k-directions, respectively (Figure 4). The geostatistical seismic inversion procedure ran with six iterations, in which each set of 32 realizations of Ip were generated conditioned simultaneously by the regionalization model (i.e., the three main seismic units resulting from seismic interpretation [Figure 2]) and the individual Ip distributions as inferred from the nearby analog wells and published data (Figure 3).

Results

The seismic inversion converged after six iterations (Figure 7) 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% (Figure 8). The synthetic seismic data were able to reproduce the real observed seismic reflection data in terms of the location and spatial distribution of the main geologic features of interest (Figure 9). Although reproducing the location and extent of the seismic events is of outmost importance, the synthetic seismic data also need to reproduce the values of the original recorded amplitudes of the seismic reflection data. The residuals between real seismic and synthetic seismic are shown in Figure 10.

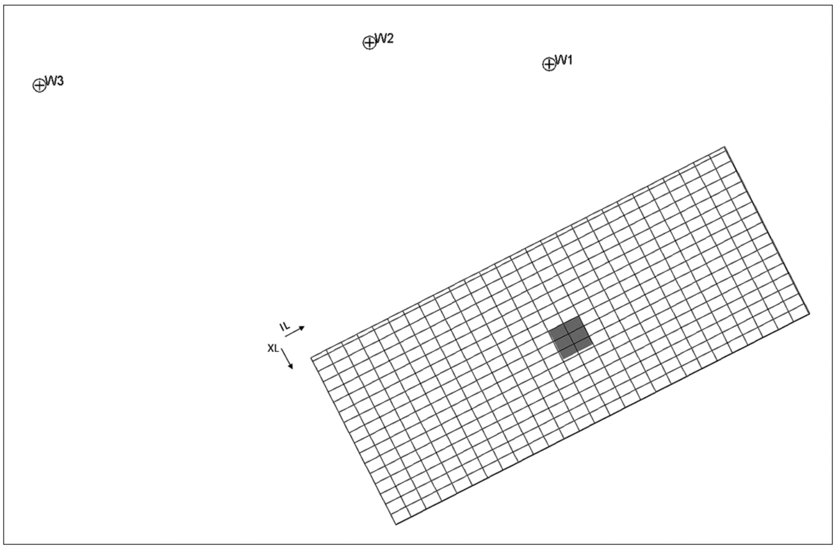

Figure 4. Available data located within the unexplored basin. The gray seismic grid corresponds to the entire seismic volume. The distance between the inlines and crosslines is 18.75 and 12.5 m, respectively.

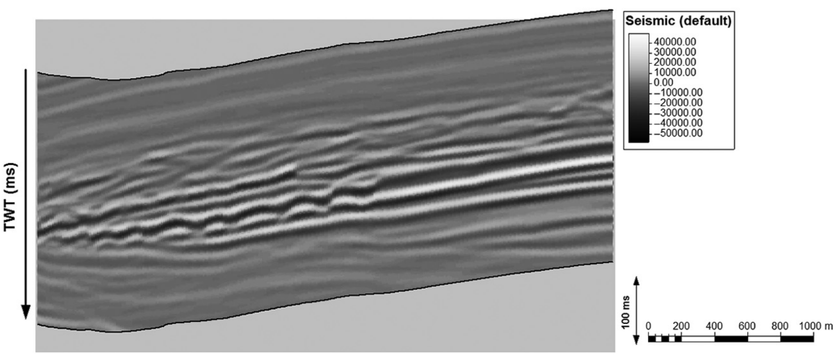

Figure 5. Real seismic data for the area of interest showing the seismic signature of the prospect of interest. The lighter values indicate positive polarity, and the darker values indicate negative polarity.

The best-fit inverse Ip model (Figure 11) allows the interpretation of the turbidite feature in the vertical and horizontal slices. It also shows a reasonable spatial continuity pattern, in which it is possible to identify 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 Ip values. In this way, we are constraining the spatial distribution of the simulated values. Because the regionalization of the area of interest is done using a geologic criteria, the resulting best-fit inverse models are therefore geologically consistent with the geologic knowledge.

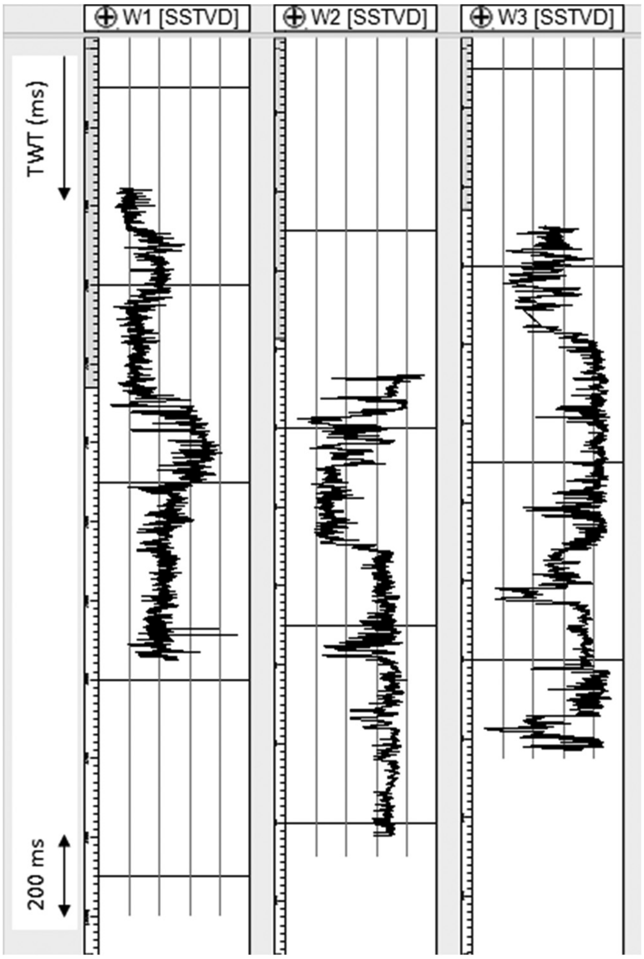

Figure 6. Acoustic impedance Ip well logs of the tree appraisal wells outside the area used as analogs to extract the initial a priori Ip distribution function (Figure 3).

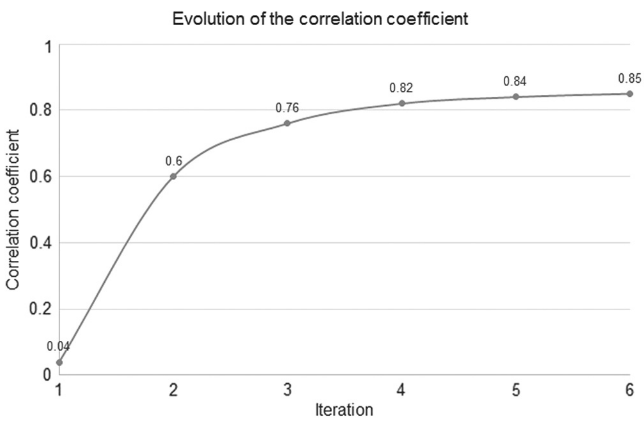

Figure 7. Evolution of the correlation coefficient along the six iterations. It is possible to see the algorithm converge at the end of sixth iteration.

Finally, as a geostatistical seismic inversion procedure, we are able to assess the uncertainty associated with the inverted property. This uncertainty may be assessed by computing the variance (Figure 12) between the Ip models generated during the last iteration. During the last iteration, all the cosimulated Ip models result in synthetic seismic volumes globally highly correlated with the real one. However, there are local areas where the inversion procedure struggled to converge. These areas will show a higher variance value, and the inferred Ip values are associated with a higher uncertainty.

Discussion

We introduce herein an iterative geostatistical seismic inversion methodology for unexplored areas that surpasses the need of existing well data at the area of interest while allowing the direct integration of geologic knowledge within the inversion procedure.

This technique was successfully applied to a real case study over a prospective area allowing retrieving 3D models of Ip and assessing the spatial uncertainty of the inferred models. The geologic model used in this example was derived from traditional seismic interpretation, and the a priori Ip distributions were generated after a detailed interpretation of existing nearby wells complemented by information from analog basins and published data. The synthetic seismic reflection data generated during the last iteration have a global correlation coefficient when compared against the observed one at greater than 85%.

One question that the present state of this inversion technique does not address, as illustrated by the real case study, is how uncertainties related with the extracted wavelet affect the results of the inversion. The quality and reliability of the inverse elastic models will greatly depend on the representativeness of the estimated wavelet. To assess the robustness of the inverse Ip models and the impact of the wavelet extraction procedure, we suggest the use of different wavelet extraction techniques with different parameterizations. In fact, this procedure allows the generation of an uncertainty space built from possible Ip models (those that generate highly correlated synthetic seismic data) inferred using different wavelets.

Another concern related with the wavelet is scalar applied to it. This issue was addressed when selecting the distribution function of Ip for each region, making them plausible, and comparing the amplitude values of the synthetic seismic against the observed one. By matching the recorded amplitude values with the inverted synthetic seismic, it allows inferring that at least

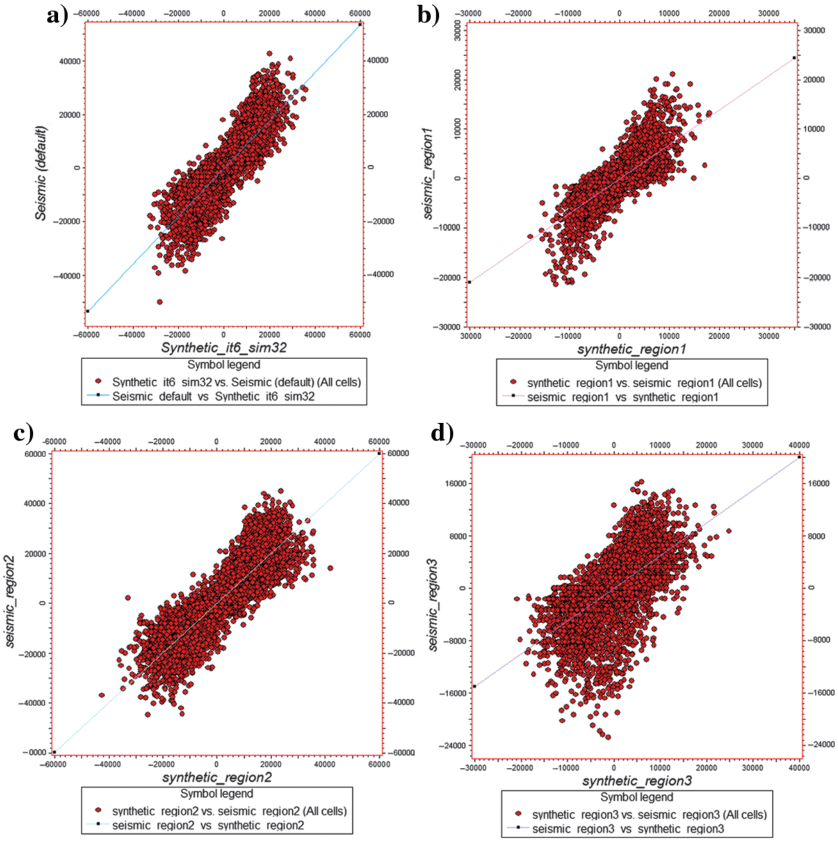

Figure 8. Scatterplot between the real seismic full stack versus the synthetic volume resulting after the inversion procedure finished. (a) The global correlation coefficient between both volumes is 85%. (b) The correlation coefficient between the seismic and synthetic for region 1; the overburden region was 80%. (c) The correlation coefficient between the seismic and synthetic for region 2; the potential reservoir region was 89%. (d) The correlation coefficient between the seismic and synthetic for region 3; the underburden region was 70%.

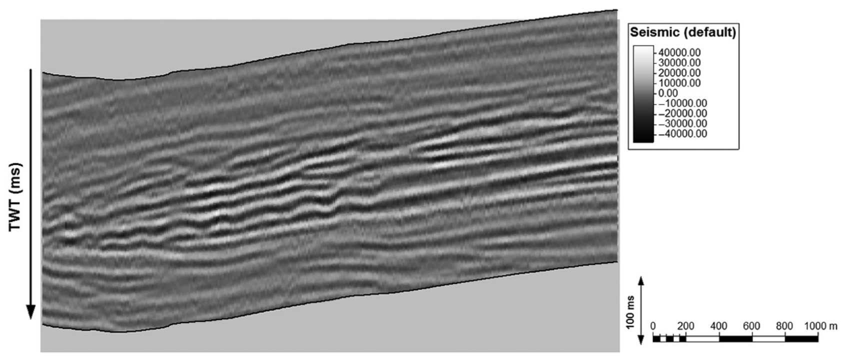

Figure 9. Synthetic seismic obtained from the best-fit inverse Ip model (Figure 11) inferred at the end of the iterative procedure. The synthetic seismic volume matches the real seismic in the spatial extent of the seismic event and its amplitude content.

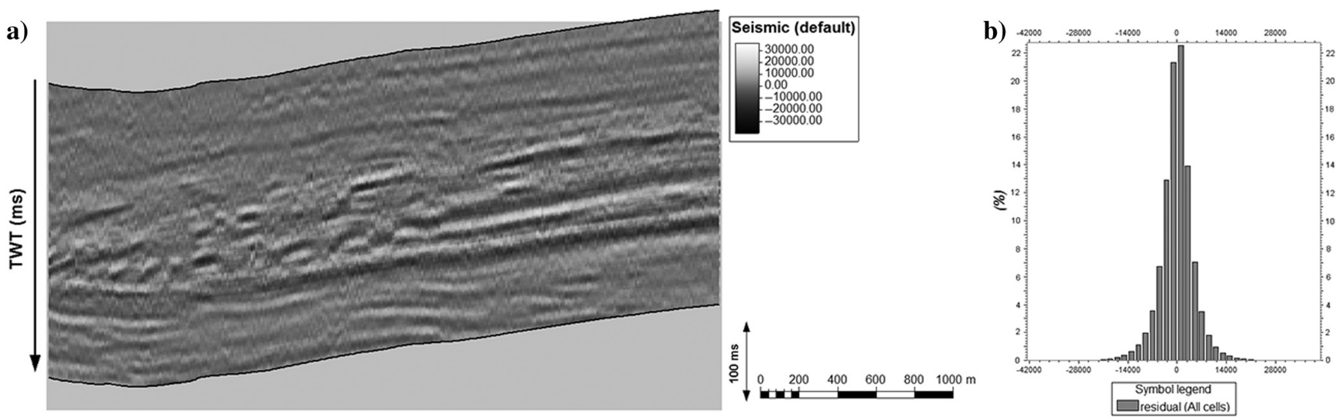

Figure 10. (a) Residuals between the real seismic and synthetic seismic and (b) the correspondent distribution function.

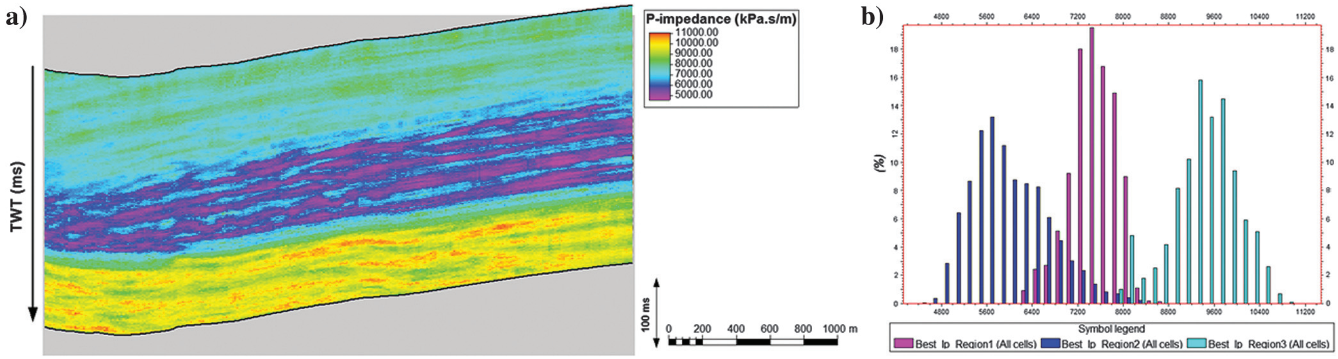

Figure 11. (a) Best-fit inverse model of Ip retrieved after six iterations. It is possible to identify the turbidite system of interest corresponding to lower acoustic impedance values (purple). (b) The distribution function of the best-fit inverse model of Ip, which reproduces the initial distribution function of Ip.

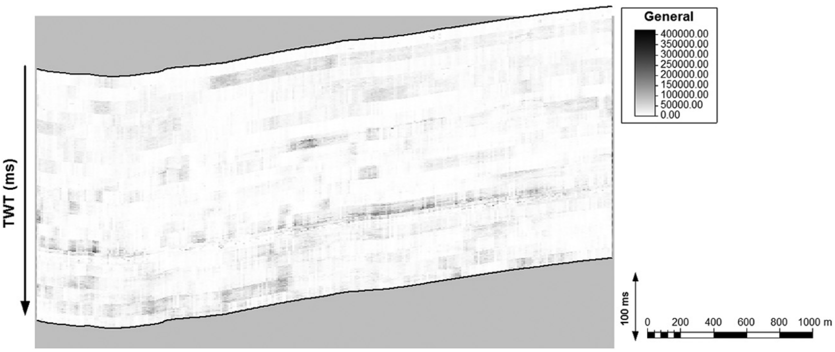

Figure 12. Variance between the Ip models generated during the last iteration. The higher variance value means the inferred Ip values are associated with a higher uncertainty.

the contrast between Ip values along the vertical direction should be close to the real geology. The reproduction of the recorded amplitudes values is a crucial aspect of the proposed methodology. If the Ip distributions assigned to each region are not close enough to the real subsurface elastic property, then the amplitude values of the inverted seismic do not match the real one. In one way, we may consider that the reproduction of amplitudes is a proxy to validate the results of the proposed methodology in the absence of direct measurements, i.e., well-log data.

The resulting elastic models of the proposed methodology are inferred exclusively from seismic reflection data, as in deterministic approaches, but, on the other hand, they have higher resolution when compared with deterministic solutions and allow assessing the uncertainty associated with the inverted properties. Assessing uncertainty is of outmost important particularly at this early exploration stages.

Conclusion

The global and regional statistics are reproduced at the end of the seismic inversion procedure. In addition, the relation between the acoustic impedance distributions for each region is also maintained, respecting the transition between the different geologic regions.

The proposed geostatistical seismic inversion procedure has shown good results for reservoir modeling. Constraining the seismic inversion to a regional geologic model that is representative of the subsurface geology and to a priori distribution functions of elastic properties of interest obtained from geologic analogs (i.e., nearby wells), it generates a more consistent and reliable geologic subsurface model and helps to better predict the behavior of the reservoir. This method integrating the geologic knowledge and geologic analogs in the seismic inversion procedure can be very useful for reservoir modeling and uncertainty assessment, especially in early stages of exploration or in frontier exploration areas, where normal well-log data are absent or sparse.

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