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Integration of seismic interpretation in to geostatistical acoustic impedance

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Extended Abstract

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Abstract

In reservoir modelling and characterization different seismic inversion techniques are conditioned by the available existing data provided by seismic surveys and the subsurface petro-elastic properties obtained by wells, the inversion solution tries to provide a subsurface model that fits equally all the existing observed data. A geostatistical framework is a natural solution to integrate both data within the same framework while assessing the spatial uncertainty of the inverted property. The main objective of this thesis is to assess the performance of a new implementation within a known geostatistical seismic inversion methodology to retrieve subsurface elastics models (acoustic impedance) to characterize a non-stationary real reservoir. The new implementation of geostatistical seismic inversion algorithm consists in a regionalization by zones of the study area as interpreted form the existing data and the knowledge about the subsurface geology. The proposed methodology uses multi-local distribution functions based on direct sequential simulation algorithms. The case study presented in this thesis consists in the inversion of a real and complex partial-stacked seismic data where three wells are available. The results obtained by the proposed methodology are compared with those obtained by a conventional approach.

Key words: Geostatistical seismic inversion; seismic reservoir characterization; geostatistics; direct sequential simulation; direct stochastic simulations; Global stochastic inversion.

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1 Introduction

Among the tools to identify potential hydrocarbon reservoir, 3D seismic volumes allow exploring a huge volume of area of the subsurface helping oil and gas companies to obtain enough information regarding the geological structures and predict the best locations to drill wells. Depending on the existing data, there are different ways to build 3D models and different modeling techniques allow obtaining models with variable degrees of detail. However, independently of the methodology, all of them have some degree of uncertainty. Choosing the right modelling approach allow decreasing the risk level and consequently the costs related with a given hydrocarbon reservoir, and consequently allowing better management decisions (Doyen 2007; Caers 2011).

In petroleum applications, stochastic modeling of the reservoirs' internal properties, such as lithofacies and sand bodies, is normally done by using core and log data which locally provide detailed reservoir information but lack spatial information, therefore, these models have great level of uncertainly far from the wells locations. For this reason the integration of seismic reflection data, take into account the properties directly measured at the wells, allow inferring more reliable subsurface models with less uncertainty, i.e., better spatially constrained.

Normally seismic inversion methodologies take into account stacked seismic reflection data allowing the inference of acoustic and/or impedance models. Inferring the spatial distribution of impedance limits the identification of different litho-fluid facies of interest that could be obtained using pre-stack seismic data. The proliferation of high quality pre-stack seismic data allows us to obtain more reliable, with less uncertainty, reservoir models when compared with reservoir models derived exclusively from post-stack seismic reflection data.

The main objective of this thesis is the implementation on a real and challenging dataset of a new geostatistical seismic inversion that is able to deal with non-stationary geological environments. The results obtained are compared against those retrieved from conventional iterative geostatistical seismic inversion methodology.

The development of these algorithms was performed recurring to geostatistical toolboxes from CERENA/CMRP research group and Matlab. Petrel® (Schlumberger) was used for visualization of the results.

2 Methodology

2.1 Conventional Global Stochastic Inversion

The methodology used as the basis to develop the new methodology proposed under the scope of this thesis was the Global Stochastic Inversion (GSI, Soares 2007). The traditional GSI procedure uses a stochastic sequential simulation algorithm based on a single distribution function as estimated from the available well-log data and a single spatial continuity pattern as expressed by a variogram model for the entire study area. This methodology uses a global approach during the stochastic simulation stage and allows the inversion of fullstack seismic data for acoustic impedance (AI).

This iterative geostatistical methodology is based on two key main ideas: the use, at the end of each iteration, of a global optimizer based on cross-over genetic algorithm based on the trace-by-trace match between synthetic and the seismic data to ensure the convergence of the inversion procedure from iteration to iteration; and the perturbation of the inverted models with stochastic sequential simulation, the direct sequential simulation (DSS; Soares et al 2007).

This methodology generates for an entire seismic grid a set of *Ns* impedance models using existing well-log data as experimental data. Each impedance model is then convolved for the wavelet to create *Ns* synthetic seismic volumes which are compared on a trace-by-trace basis against the observed seismic reflection data. With this approach the areas of low signal-to-noise ratio remain poorly matched at the end of the inversion process. Contrary to the trace-by-trace approaches, an ensemble of best-fit inverted models will always present high uncertainty, for those noisy areas where the signal-to-noise ratio is low (Figure 1).

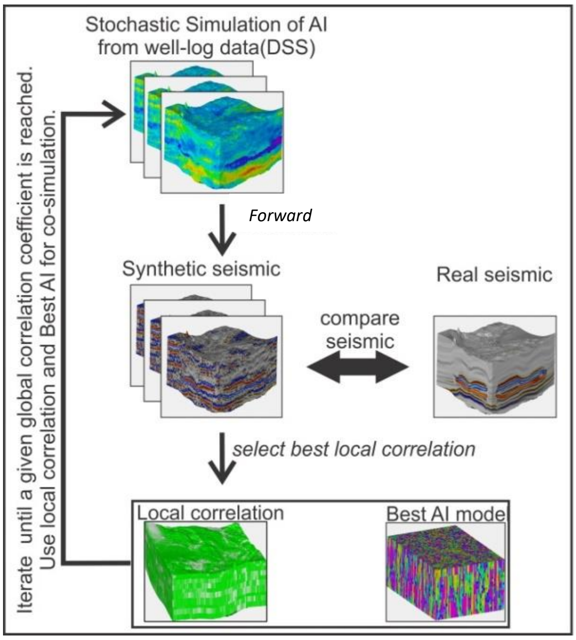

Figure 1- Schematic representation of GSI (from L.Azevedo 2013)

2.2 Global Stochastic Inversion for non-stationary geological environments

Here is introduces the proposed geostatistical seismic inversion methodology that is able to simultaneously integrate a regionalization model based in zones. The regionalization model may be created based on the simultaneous interpretation of seismic and well-log data and geological constrains from a priori knowledge of the geology. Each zone will be constrained by a given distribution function and his corresponding spatial continuity patterns as inferred from the experimental data (the available well-log given for each zone and a variogram model by zone).

The methodology can be summarized in the following sequence of steps (Azevedo et al. 2016):

- The first step comprises the generation of a geological model and the division of the entire study area into smaller zones which should be geologically consistent

- For each zone a histogram (one for each elastic property of interest) is assigned for each zone, the spatial continuity pattern of the property to be simulated is conditioned by the imposed variogram model for each zone individually.

- Taking into account the regionalization model, the available dataset is extracted from wells as a function of the zones thus obtaining each model for each zone.

- Generated of a random seed to define a random path over the entire simulation grid, u = 1, … , N, where N is the total number of nodes that compose the simulation grid and "u" is the current node location where the simulation is being performed.

- Estimation of the local mean and variance at x_u with simple kriging estimate [Z(x_u)*] (2) and the corresponding kriging variance ($\sigma^2(x_u)$) (3) to sample directly from the global conditional distribution function as estimated from the experimental data ($z(x_\alpha)$) located within a specific zone and the previously simulated data ($z(x_\alpha)^*$) within a neighborhood around u.

$$\frac{1}{n}\sum_{i=1}^{n} z(x_i) = [z(x_u)]^* \tag{2}$$

$$\frac{1}{n}\sum_{i=1}^{n} [z(x_i) - [z(x_u)]^*]^2 = \sigma_{sk}^2(x_u) \tag{3}$$

These global conditional distribution functions are going to be conditioned by the zones, however it is important nothing that, the simple kriging estimate and variance are computed taking into account point data that belong to different regions. The simple kriging estimate and variance are computed with all the point data within a given neighborhood that may cross different sub-regions. This is an important feature of the proposed approach since it avoids the generation of discontinuities at the boundaries of each region in the simulated models.

- Definition the interval of the Fz (z) (conditional distribution) to be sampled based on the simple kriging estimate and variance computed from the previous step Fz (z) corresponds to the probability distribution function of the variable to be simulated and estimated from the available experimental data that is located within that specific zone.

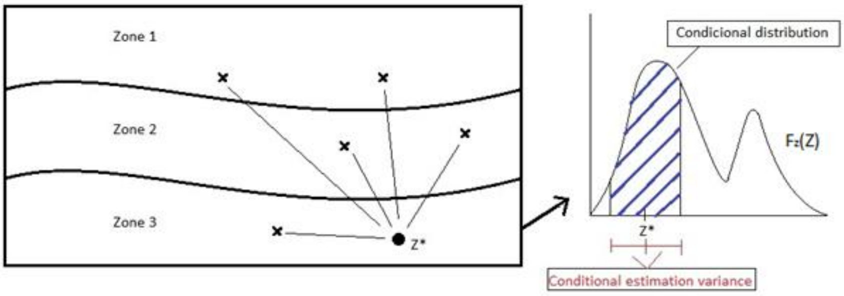

Figure 2 - Example of global cdf obtained from one zone with the conditional distribution centered by simple kriging and variance

- The simulated values Z^s $(x0)$ are drawn from an auxiliary Gaussian probability distribution function F_z'(z) which is built from the global cdf Fz (z), F_z'(z) is defined by selecting and interval over Fz (z) centered on the simple kriging estimate [Z(x_u)*] value with an interval range proportional to the kriging variance ($\sigma^2(x_u)$). Generate a value y^s from a Gaussian distributions $((x0)*, \sigma^2_{SK}(xu))$ Return the simulated value $zs(x0) = \varphi^{-1}(y^s)$

- Add the simulated value as conditioning for the simulation of the next location.

- Loop until all the *N* nodes of the simulated grid have been simulated.

In term of inverse procedure this work proposes replacing the traditional stochastic sequential simulation in the methodology summarized in (Figure 1) with the stochastic sequential simulation with multi-local distributions.

3 Results

The study area is an offshore turbidities environment. The available data set comprised partial seismic volumes of 794 inline by 1194 crossline with a sampling rate of 4 ms. The inversion grid was defined such as 398 x 598 x 200 and vertically delimited by within the interval of interest from 1100 ms to 1700 ms (Figure 3). A set of 3 wells with Vp, Vs and density logs was also available. A wavelet extracted from each partial angle stack individually was also made available. The simultaneous interpretation of the available properties logs for the different wells along with the seismic reflection data was used to divide the study area in eight vertical zones as showed the next figure.

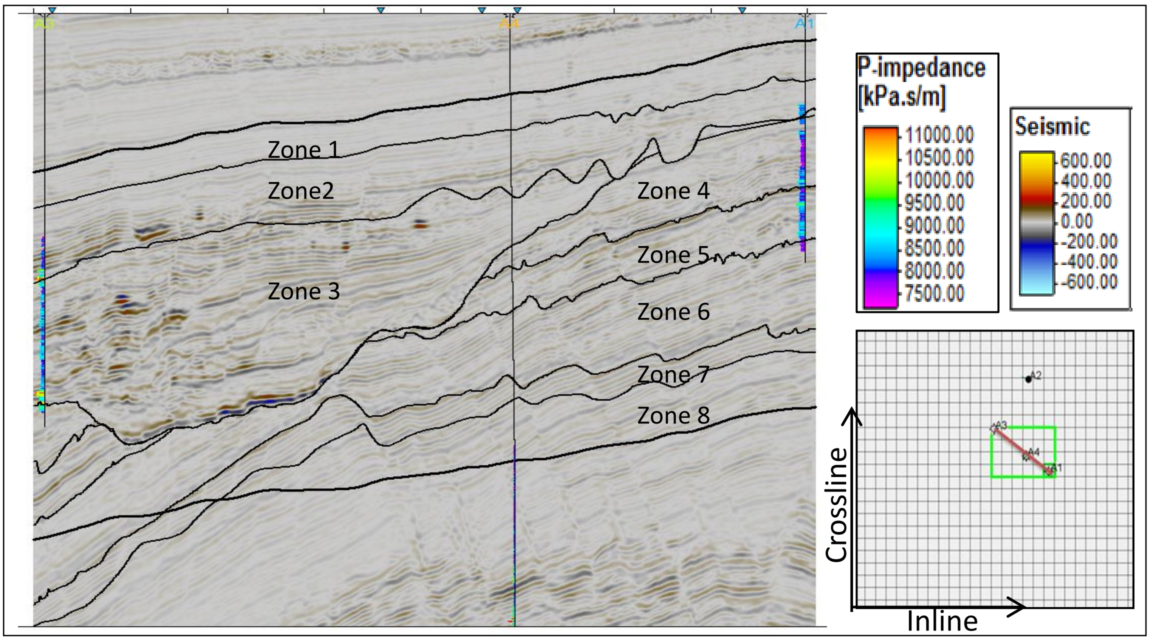

Figure *3* - Cross-section of model definition that will be used in the proposed methodology with a regionalization by zones within the seismic grid

3.1 Conventional Global Stochastic Inversion

In the methodology the spatial continuity pattern of AI property was inferred by modeling experimental variograms with SGeMs, the vertical variogram is computed from the upscaled well-log data and the horizontal direction from the real fullstack. (Table1)

Table 1: Ranges of variogram in Conventional Global Stochastic Inversion

	Max	Min	Vertical
Ranges	32	27	5

For this method was necessary to calculate the Acoustic impedance which one was used in the GSI to obtain the seismic inverted. This dataset described was successfully inverted with the geostatistical seismic GSI inversion algorithm (Section 2). The inversion methodology converged after six iterations, at each iteration, a set of 32 elastic models of Ip, were generated recurring to DSS (Soares 2001). The next models represent the best and mean model of AI computed from the ensemble of elastic models generated during the last iteration.

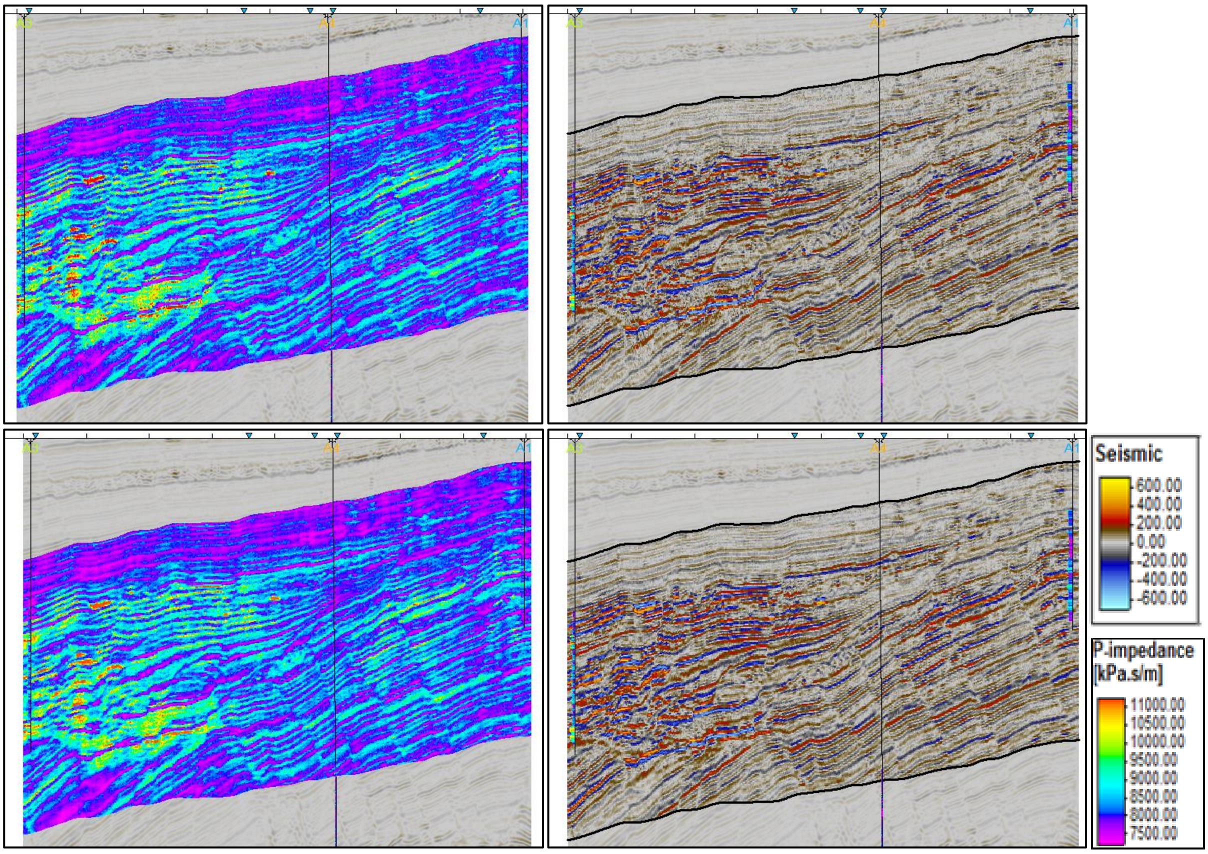

Figure 4 - Comparison between vertical sections extracted from (on the left) elastic models computed from the ensemble of models simulated during the last iteration and (on the right) synthetic seismic data. From top to bottom: best AI model, mean AI model. For profile location see Figure 3.

It is important to highlight that the elastic inverted models from Figure 4 reproduce the spatial distribution of the original elastic properties but at the same time are able to reproduce its values and their relative variation within the areas of interest with amplitude values higher than real seismic volume. The small-scale details are extremely important for reliable reservoir characterization. All inverted models shows large and small detail of interest and are constrained by the corresponding well-log data at their locations

The convergence of the inverse methodology can also be assessed by the interpretation of the standard deviation (Figure 5) that represents the distribution respect to the mean. The next model represent also the local correlation coefficient volume, calculated on a trace-by-trace basis between the real seismic and the synthetic seismic volumes.

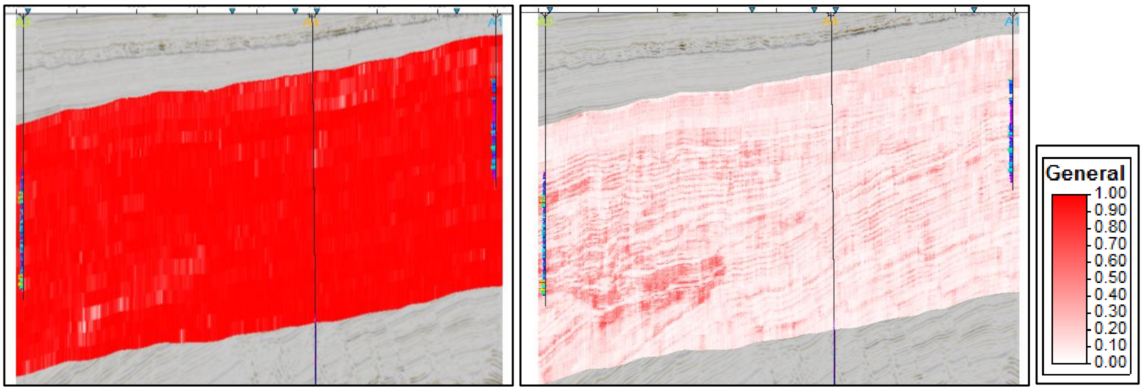

Figure 5 - Local correlation coefficient volume (left) and Standar deviation (right)

3.2 GSI by zones

In the proposed methodology the simulation area is subdivided by zones (Figure 3). From the experimental data obtained from each zone is defined a spatial continuity pattern given a data distribution function and a regional variogram (one for each zone). In this case due to the lack of well data and limited data in certain zones it was imposed for each zone a variogram with the same ranges as in the traditional methodology (Table 1).

For the application example with the proposed methodology due to the lack of well-log data in each zone individually, in this case, in the zones 1 and 7 it was introduced the entire original distribution of acoustic impedance as conditioning distribution. Moreover in the zones 6 and 8 there are some experimental data but not enough samples to infer a distribution used to simulate. Therefore, the distribution as inferred form the entire dataset of acoustic impedance was used.

The integration of the proposed technique by zones within the inversion procedure allows that the constrained distribution function may be populated with nearby data in concordance with the expected geology. The proposed methodology of stochastic sequential simulation by zones has the benefit of smoothing the zone transition between zones preventing the creation of discontinuities.

The iterative geostatistical seismic inversion GSI data regionalized by zones was concluded after 6 iteration where set of 32 elastic models of Ip, were generated recurring to DSS geostatistical sequential simulation (Soares 2001).

From all individual simulations obtained at the end of the methodology, the best-fit and the mean model from the ensemble of elastic models generated during the last iteration. Here again all the models resulting from the last iteration produce synthetic seismic very well correlated with the real one, notice that the synthetic seismic data resulting is a bit better conditioned in term of amplitude content compared with the traditional method, as the location of the main reflectors retrieve by both methodologies is similar. To each zone the models shows coherent and continuous layers as interpreted from the real seismic reflection data (Figure 7).

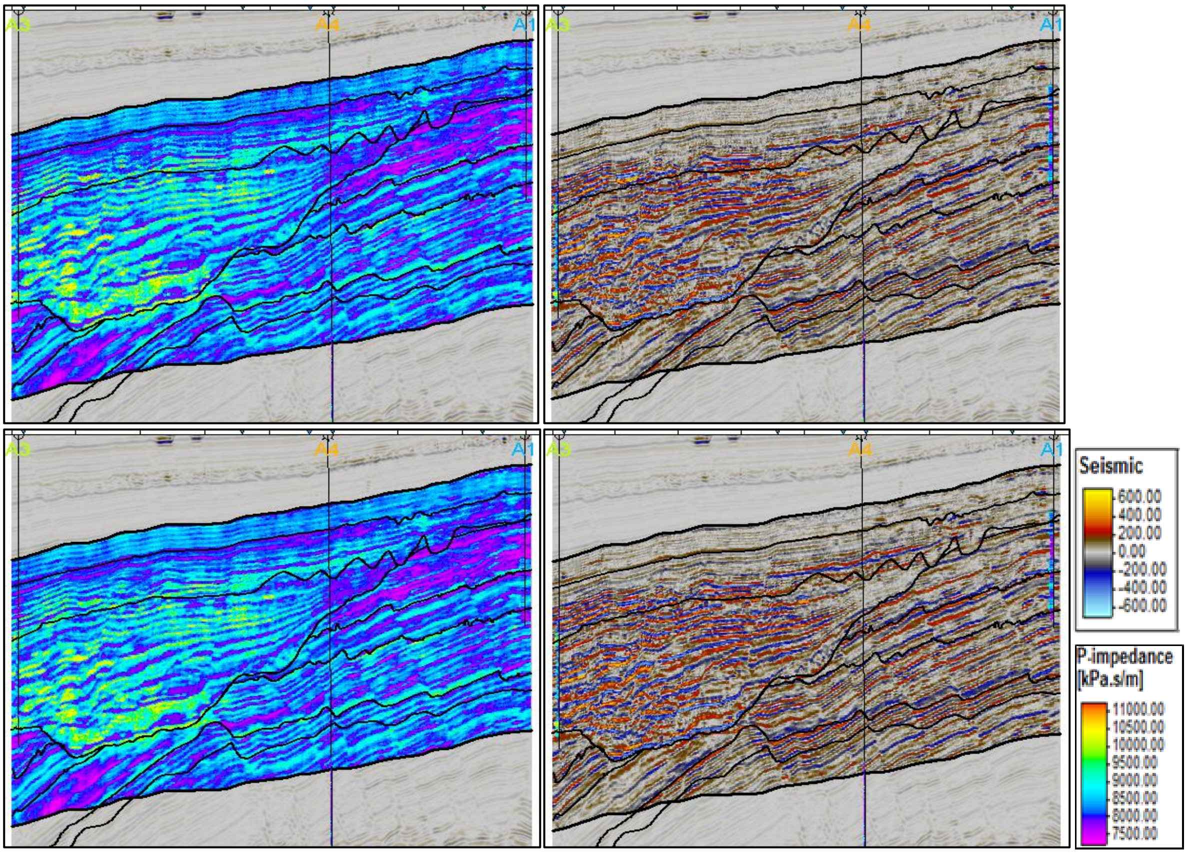

Figure 7 - Comparison between vertical sections extracted from (on the left) elastic models computed from the ensemble of models simulated during the last iteration and (on the right) synthetic seismic data. From top to bottom: best AI model, mean AI model. For profile location see Figure 3

Next model represent the standard deviation and local correlation coefficient calculated trace by trace basis between the real seismic and the synthetic seismic volumes. The local correlation coefficient is high for most of the trace locations although a little bit lower that the traditional method without zones.

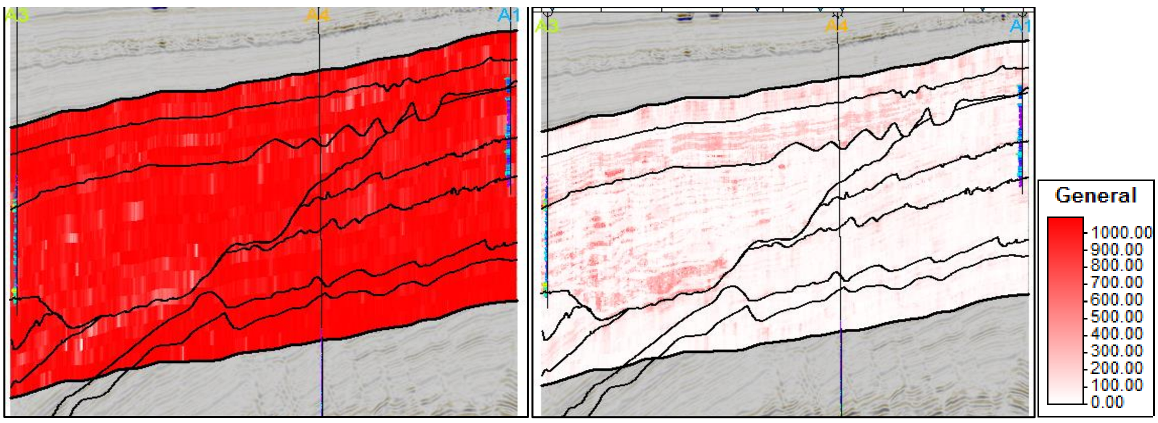

Figure 8 - Local correlation coefficient volume (left) and Standar deviation (right)

4 Discussion and Conclusion

As interpreted from the available well-log data the best fit inverse Ip model retrieved from the proposed inversion technique by zones shows that for example in the zone 1 there are highs AI values that agrees better with the available seismic reflection data.

In the real seismic volume (Figure 3) we cannot distinguish any geological layers, amplitude content or any structure within the first seismic unit. However, the best-fit inverse model from the traditional GSI shows low and high values of AI and a fine layering. The model resulting from the proposed methodology shows higher Ip values and more homogenous distributions. In fact, the standard deviation model obtained for the proposed methodology (Figure 8) shows smaller values of standard deviation, meaning a lower spatial uncertainty. When considering the rest of the zones, note that in the real seismic volume there is strong amplitude content and all zones present certain homogeneity and continuity.

Now if zone 4 in the elastic model retrieve is observed, the result in both methodologies is different with less degree of continuity and lower values of AI per zones in the proposed methodology. Observing the available well log data in well A1 allows distinguishing low Ip values in almost all that zone that not matches considerably well in term of amplitude content, and does not make sense with the final model retrieve with the traditional GSI without zones for this specific area, where it is observed continuity and higher values of AI.

Interpreting the standard deviation in Figure 8 the proposed methodology by zones achieves a lower variance, this means that the model is closer to the real seismic volume and therefore reach the final target of this methodology since the methodology generates models as close as possible in zones where the real seismic volume is good and therefore with lower degree of standard deviation

As conclusion the proposed technique was successfully applied to evaluate the implementation of multi-local distribution function to a real case study within a geostatistical framework. The elastic model was computed over the entire ensemble of simulated AI models resulting from the dataset. The results showed that the retrieve inverse impedance model are able to reproduce synthetic seismic reflection data more correlated with the observed one and the synthetic volume have better amplitude content when compared with the real seismic and model are reliable and converged toward the global solution real AI model.

Besides, the proposed technique may also be used within other different seismic inversion algorithms in order to improve the uncertainly characterization and flexibility allowing complex spatial regionalization and more number of scenarios to be tested.

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