COBEM 99
XV Congresso Brasileiro de Engenharia Mecânica
15th Brazilian Congress of Mechanical Engineering
22 - 26 de Novembro de 1999 / November 22 - 26, 1999 Águas de Lindóia, São Paulo,

APPLICATION OF SEISMIC ATTRIBUTE FILTERING WITH FACTORIAL KRIGING TO ESTIMATE POROUS VOLUME: A CASE STUDY ON A BRAZILIAN EAST COAST OFFSHORE TURBIDITE RESERVOIR

Evaldo Cesário Mundim
PETROBRAS/CENPES, Rio de Janeiro, Brazil
mundim@cenpes.petrobras.com.br
Armando Zaupa Remacre
Universidade Estadual de Campinas, Instituto de Geociencias, Campinas, Brazil
armando@ige.unicamp.br
Paulo Roberto S. Johann
PETROBRAS/E&P, Rio de Janeiro, Brazil
johann@ep-petrobras.com.br

Abstract. *The estimation of a reservoir properties is a risky issue. Uncertainties come around; the number of wells (hard data) is often low and poorly distributed. Densely sampled, 3D seismic information (soft information) has been seen as a key to reducing interwell uncertainties. As it is well known, however, even after seismic processing, noises and sign distortions remain if not introduced by the processing itself. Moreover, inconsistency in horizons picking, during interpretation, worsens the quality of the obtained attributes with corresponding impact for its use as a predictive variable for reservoir mean properties estimation. In this paper, we discuss incorporation of seismic attributes filtered by Factorial Kriging via conditional simulation on reservoir porous volume estimation. The seismic attribute mean acoustic impedance obtained from a 3D seismic program with seismic stratigraphic inversion is considered. It shows itself to be well correlated to the porous thickness of the reservoir interval under consideration. A nested corregionalized model which presented two structures was fitted to the attribute. The small range associated to data noises was filtered by Factorial Kriging, which improved the correlation between the acoustic impedance and the porous thickness. The dispersion of the conditional simulation constrained by the filtered seismic attribute is lower than the dispersion of the conditional simulation constrained by the pre-filtering attribute, reducing the uncertainty of the reservoir porous volume estimation.*

Key word: *Factorial Kriging, filtering, simulation, reservoir characterization, seismic attributes*

1. INTRODUCTION

The integration of well data and seismic attributes using geostatistics has, nowadays, become more popular. Due to the limitations imposed by the seismic resolution, the reservoir mean proprieties are not correlated to seismic attribute volume, but to seismic attribute mean maps. It is well known, however, that, even after seismic processing, noises and sign distortions remain if not introduced by the processing itself. Moreover, inconsistency in horizons picking, during interpretation, worsens the quality of the obtained attributes with corresponding impact for its use as a predictive variable for reservoir mean properties estimation. It is also worth mentioning that monoattribute or mean maps may disguise the image of geologic features of different dimensions, hard to distinguish through conventional filtering techniques.

In this paper, we discuss incorporation of seismic attributes filtered by factorial kriging via conditional simulation on reservoir porous volume estimation. The next section provides the theoretical background assumed. Section 3 brings considerations about the data set used for the analysis. The attribute images before and after factorial kriging filtering are displayed in Section 4 as well as the description of the impact of its use for the reservoir volume estimation. Section 5 is the conclusion.

2. THEORETICAL BACKGROUND

Factorial kriging works in the spatial domain in a similar way to the spectral analysis in the frequency domain. Events which can not be distinguished in the Fourier transformed domain may be separated in a variographic analysis and filtered by factorial kriging.

Seismic attributes, contrary to well data, are densily sampled, and its integration in kriging or conditional simulations systems enhance the interwell estimations. The decisions about the seismic attribute feasibility is, in general, based in the correlation analysis between the attribute and the well data. Good correlations allow the attribute use. Nevertheless, applications to improve the attribute quality are not pursued.

The general theory of factorial kriging analysis (FKA) has been developed by Matheron (1979) and has been used in different areas such as soil sciences, hydrogeology, geophysics, petroleum prospecting, etc... to distinguish local structures from the background. Factorial kriging analysis was first used in geophysics by Galli, Gerdil-Neuillet & Dadou (1984), as a technique for magnetic anomalies separation. Yao, Mukerji, Journel & Mavko (1996) used factorial kriging analysis to filter out a seismic small scale structure which was considered unrelated to porosity. The filtered seismic data was used for porosity estimation.

Factorial kriging analysis relies on the assumption that a regionalized phenomenon can be seen as a linear sum of varied independent zero mean subphenomena acting at different scales, each of which presents its own variogram or covariance model which will, linearly summed up, compound the variogram or covariance model of the regionalized phenomenon. The components are separated by kriging. The factorial kriging system is similar to an ordinary kriging system except by the sum of weights which must be null so that the mean of the components be null as well, and the cross covariance between the data and the estimated point consider only the covariance associated to the component to be estimated.

Thus, a second-order stationary regionalized variable $Z(x)$ can be decomposed in a sum of its mean value $m(x)$, representative of $E[Z(x)]$, with s uncorrelated zero mean regionalized variables $Z_u(x)$:

$$Z(x) = Z_0(x) + Z_1(x) + \ldots + Z_u(x) + \ldots + Z_S(x) + m(x) \qquad (1)$$

The nested variogram will be the linear sum of the components variograms:

$$\gamma(h) = \gamma_o(h) + \gamma_1(h) + ... + \gamma_u(h) + ... + \gamma_s(h) \quad (2)$$

A component estimate $Z_u^*(x)$ is given by the linear combination:

$$Z_u^*(x_0) = \sum_{\alpha=1}^{n} w_\beta Z(x_\alpha) \quad (3)$$

The kriging system is solved in a neighborhood with *n* data points by:

$$\begin{aligned} &\sum_{\beta=1}^{n} w_\beta \gamma\left(x_\alpha - x_\beta\right) + \mu = \gamma^u\left(x_\alpha - x_0\right) \qquad \alpha = 1,...,n \\ &\sum_{\beta=1}^{n} w_\beta = 0 \end{aligned} \quad (4)$$

where μ is a Lagrange coefficient, w_β the kriging weights. The notation $\gamma(x_\alpha - x_\beta)$ describes the nested variogram between the data locations and $\gamma^u(x_\alpha - x_0)$ describes the component *u* of the nested variogram between each data location and the location where an estimate is sought.

If data exhibits a slight drift, it may be incorporated by the local mean m(x) in a moving neighborhood kriging system. For a more detailed presentation of factorial kriging, refer to Wackernagel(1995).

3. THE CASE STUDY DATA SET

In this paper, we show a porous thickness, Hϕ, estimation case study in the upper interval of a Cretaceous field in Campos Basin, Brazil. The reservoir is a canalized turbidite deposite in a paleocanyon scarved in a carbonatic plataform. The expected distribution of sand bodies in the upper unity is, according to Johann (1997), S-N with an inflection W-E in the central area. Reservoir producting sand presents mean porosity of 28% and is interbedded with mudstones and margs (fine turbidites). More detailed geological description can be found in Souza Jr.(1997).

The field area presents 45 wells, showing porous thickness values displayed in Figure-1, (notice the outlier associated to well 41). The bimodal shape of this distribution reflects the reservoir porous sand distribution. The lower moda is associated to the channel edge wells while the higher one is related to the wells inside the channel. The non-stationary feature of this distribution is not reflected in its variogram, Figure-2. Nevertheless, the porous thickness estimation obtained by ordinary kriging in a moving neighborhood – Figure 3 – due to the great number of wells, can be assumed to be a good approximation to the field reality.

This great number of wells does not reflect the usual hard data availability in a reservoir characterization since petroleum fields tend to be nowadays developed with a small number of wells. In such conditions the reservoir properties estimations become harder to obtain and the introduction of a soft information, such as seismic data, improves the results. In this paper, to simulate these conditions we consider in the estimations presented only the field first 11 wells so that its results may be validated against the estimation obtained with the complete dataset. We only present results obtained with the acoustic impedance for the upper interval of the reservoir. Mundim (1999) brings results obtained through the FKA for other attributes, extending it to the other intervals of the reservoir under discussion.

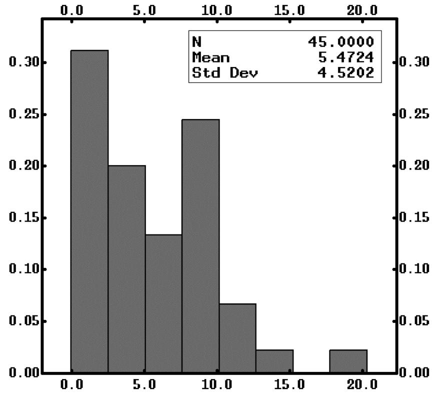

Figure-1: Porous thickness histogram (45 wells). The outlier is due to well 41

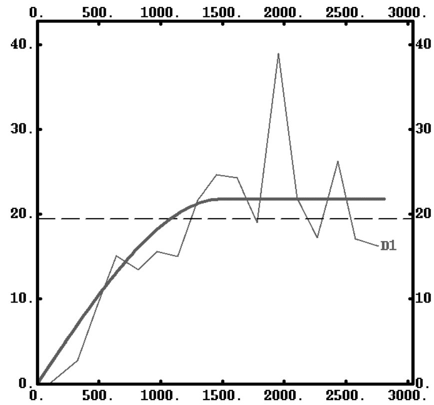

Figure-2: Porous thickness variogram. An isotropic spherical model with range 1500 m was fitted

A number of considerations, such as the non-stationary feature of the variable under consideration and the poorly sampled density of the 11 wells dataset, particularly in its east zone, as well as the fact that all the wells in this area are positioned in the channel edge, which may contribute to a subestimation of all its neighborhood, led us to run the porous volume analysis in a restricted area, which had been well estimated. The chosen area presented at least 4 wells in the kriging neighborhood. Well 41, which is located in the chosen area and shows Hϕ abnormal high values, was taken out from the estimation of the reference porous volume.

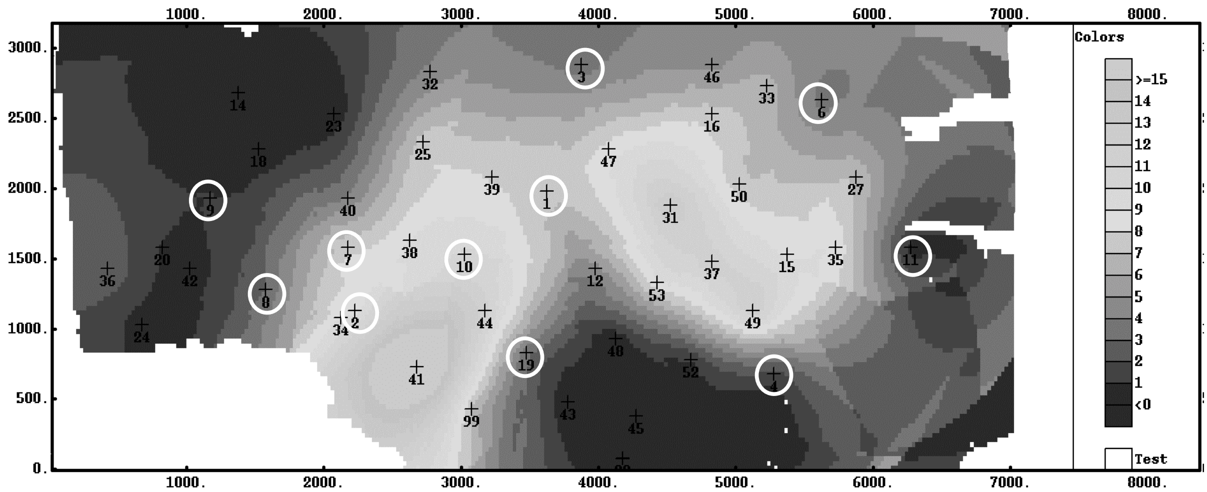

Figure-3: Hϕ ordinary kriging estimation with the complete dataset (45 wells). The blue circle wells correspond to the 11 wells dataset location.

4. ACOUSTIC IMPEDANCE IMAGE FACTORIAL KRIGING

The acoustic impedance is a seismic attribute obtained from a seismic stratigraphic inversion and it is physically representative of the porous thickness. Despite the physical significance of the used seismic attribute, its image in the reservoir upper interval, Figure-4, does not show the expected geologic features, when compared to the image in Figure-3. A noise aligned in the direction E-W and a braided pattern affecting the data.

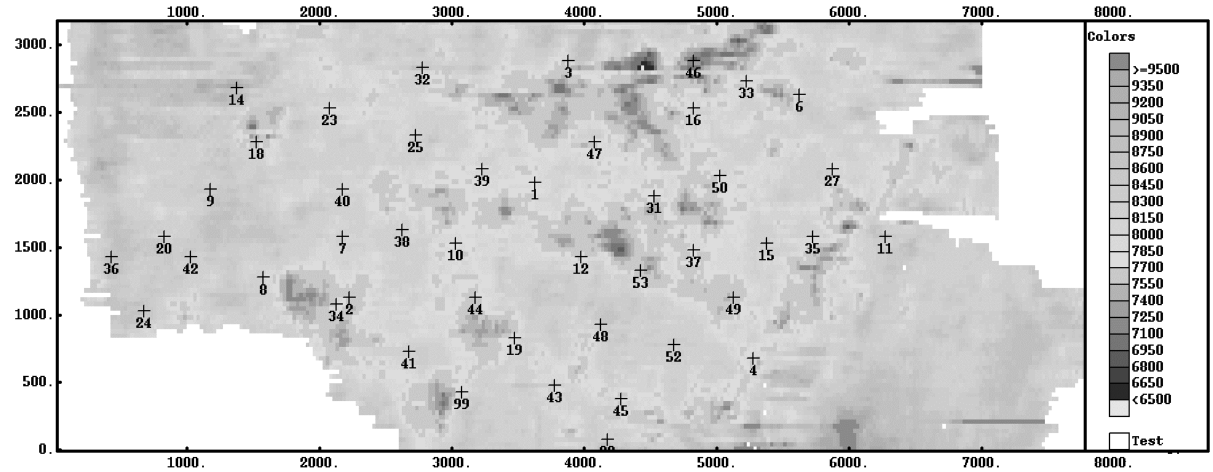

Figure-4: Raw acoustic impedance image from the upper reservoir interval.

The image's variogram, showed in Figure-5, is nested. We can see two structures, one with short range, anisotropic and the other with the long range, isotropic. The data show for lengths above 2500 m, a string drift in the N-S direction. A nested variogram with two structures - an exponential one and a linear one – each of which representing 50% of the image variance was fitted – Figure-5. The short range structure (the exponential one) is correlated to noises which disguise the attribute image, the long range structure is correlated to the geological features, such that it is possible to calculate a signal/noise ratio as being the variance relation between the long range structure divided by the short range one, which gives us 1 for the image under discussion. The data observed drift (for ranges above 2500 m) was not fitted, but once this drift is interpreted to be correlated to geological features, its fitting is not important because it will be preserved by factorial kriging.

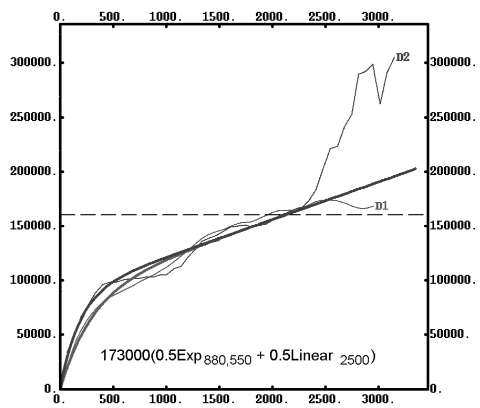

Figure-5: Raw acoustic impedance experimental variogram and the nested corregionalization model fitted.

Figure-4 image was filtered, which means that the short range structure, which was correlated to noises, was rejected by factorial kriging, resulting in the image in Figure-6. It is observable that the E-W aligned noises as well as the braided pattern were drastically attenuated. The lowest values of the acoustic impedance, which are correlated to Hϕ, in this field, allows the filtered image to clearly show a canalized body running SW-NE with an inflection W-E in the core area. A comparison between before and after impedance filtering images with the Hϕ map – Figure-3 – shows that the filtered image better reflects the field geological reality

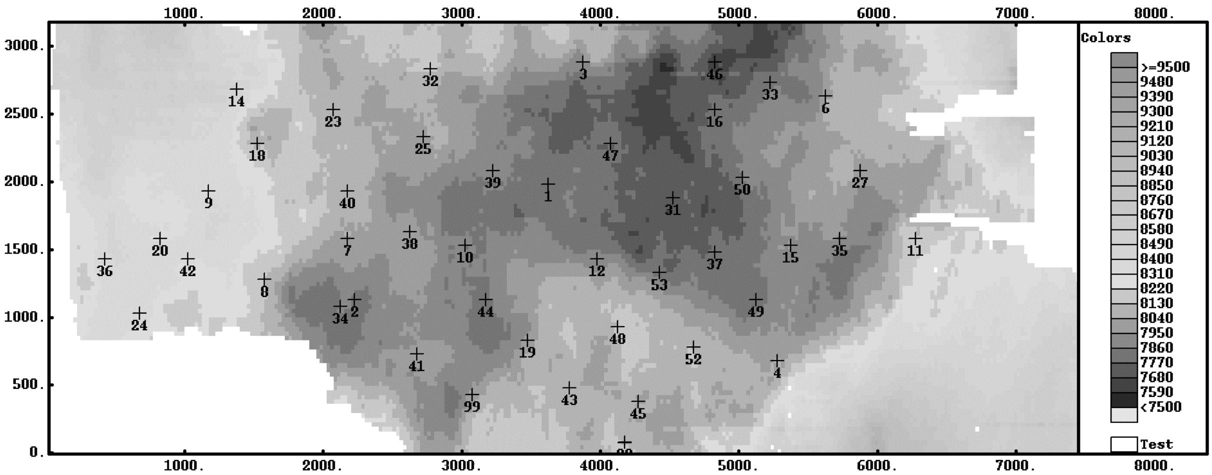

Figure-6: Filtered acoustic impedance image

4.1. Filtered Acoustic Impedance Use For Hϕ Estimation

As seen above, filtering improves the attribute image quality. Such improvement, however, does not warant its use as a predictive variable for the Hϕ in kriging systems. Notwithstanding, the correlation coefficient between Hϕ and impedance (based on the 45 wells) was improved from -35% to -80% after filtering. The Hϕ estimation for the 11 wells dataset by collocated cokriging using the pre-filtered impedance with collocated variable is presented in Figure 7. Such map shows the impedance aligned E-W noise. Besides that, one may see that the east part of the field was not well estimated (compare to Figure 3). On the other hand, the estimation obtained with the filtered attribute as collocated variable – Figure 8 – does not show the aligned noises, the east part of the field is better estimated and the sand area of the reservoir is more clearly delimited.

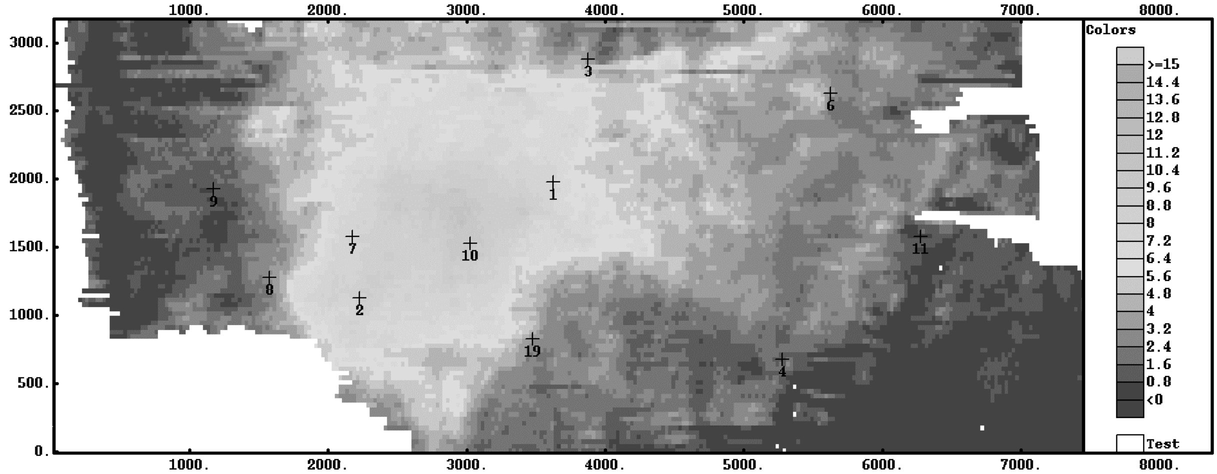

Figure-7: Hϕ maps estimated by collocated cokriging with original acoustic impedance and the 11 wells dataset

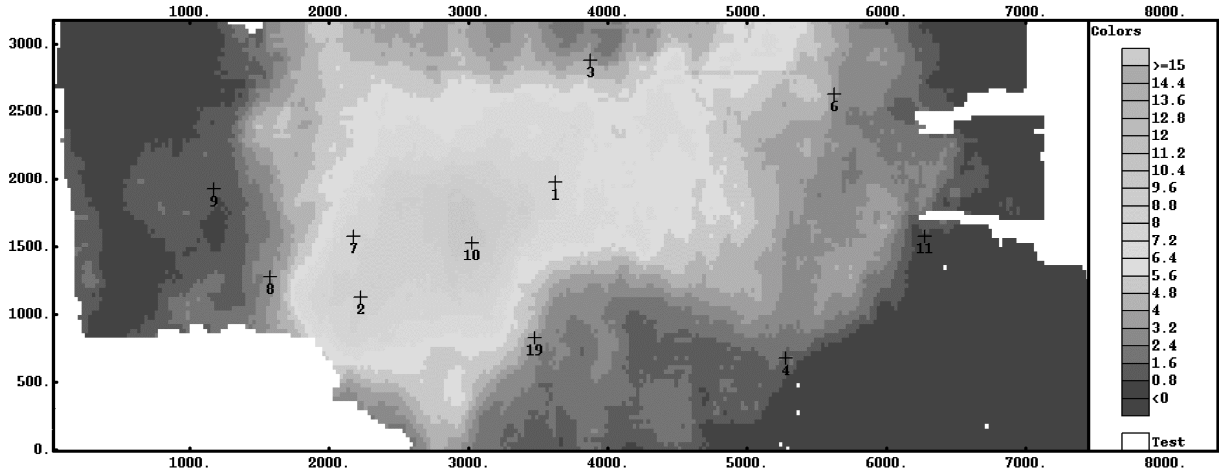

Figure-8: Hϕ maps estimated by collocated cokriging with the filtered acoustic impedance and the 11 wells dataset

4.2. Porous Volume Estimation

The reservoir porous volume (VP) could be well estimated in the krigged Hϕ map by the sum of grid nodes plus the grid area. The value estimated by this methodology is representative of the porous volume mathematical expectation, but we can not take any information about their probability distribution.

The use of stochastic simulation, as long as each estimation represents a realization of the regionalized variable VP(x,y) constrained by the well data, allows the inference of the distribution of this variable probabilities laws, and consequently the involved error inference, that is, it is possible to measure the uncertainty range of the estimated value. Similarly to the kriging approach, the stochastic simulation can also be constrained by well data (hard data) as well as soft data such as seismic attributes.

We simulated 3 sets of 100 Hϕ realizations in the selected area, the first of which constrained only by the well data, the second one constrained by the well data and the raw acoustic impedance, and the last one constrained by the well data and the filtered acoustic impedance. Calculated distributions are presented in Figures-9-a to 9-c and Table- 1.

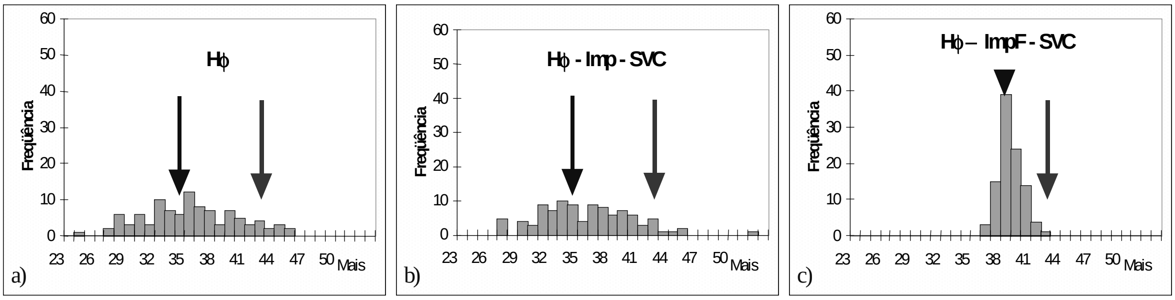

Figure-9: Histograms of a 100 volume stochastic simulations constrained by well data (a), by well and raw acoustic impedance (b) and by well and filtered acoustic impedance (c). The blue arrow point to the distribution mean and the red arrow to the reference value.

Table-1: 100 Simulations Statistics (hϕ im millions of m3).

	Constrained by	Mean	σ	RU	RRU %
Hϕ	Wells	34,67	4,62	10,55	15,21
	Wells + impedance	34,91	4,62	9,37	13,42
	Wells + filtered impedance	37,95	1,18	2,29	3,02

Figure-9a shows that the distribution of the porous volume obtained from the simulations constrained only by the well data presents a great dispersion. The mean value (the most probable one) of this distribution, which could be chosen as the estimated volume for the reservoir, is associated to a great uncertainty. However, Figure-9b shows that constraining a stochastic simulation to a seismic attribute does not always imply that uncertainties associated to the estimations will be reduced. The simulations were constrained by the well data and the raw acoustic impedance but, even so, the uncertainties associated to the estimations were still high. The attribute is affected by a noise and presents low correlation coefficient to Hϕ (-35%), which reduces its significance as a constrained variable so that the volume distribution obtained does not differ significantly from the previous one.

On the other hand, as it was mentioned earlier, the factorial kriging filtering attenuates the noises affecting the acoustic impedance image, optimizing its correlation coefficient. Figure-9c shows that a higher quality attribute, which better reflects the petrophysical variable under consideration, when used for constraining the simulation, reduces significantly the dispersion of the distribution. The obtained porous volume value presents, due to the distribution characteristics, a higher degree of certainty.

The impact of the incorporation of a filtered attribute can be better seen in Figure-10, where Figure-9 histograms are presented in the form of decreasing acumulated histograms, or volume risk curves. Such curves allows the quantification of the uncertainties, as proposed by Dimirmen (1998). Two indices can be defined by the volume risk curves: the uncertainty range (RU) and the relativized uncertainty range (RRU). The former is the difference between the percentis 85% e 5% and the latter is seen as the ratio between RU/(2* central value), that is, it measures the percentage of the error around the central value, which, in this study, is taken as the mean value.

As it can be seen in Table-1, the simulations constrained by the filtered attribute reduced the RRU from 15% to 3%.

A comparison between the mean volume values obtained by the three sets of simulations – Table-1 – shows that the use of the filtered acoustic impedance implies higher values for the distribution means, which are closer to the reference value - 42,58 millions of m^3, obtained with the complete dataset. That is compatible with the historical process of reservoir quantification, when the availability of greater information leads to estimated volume values significantly different.

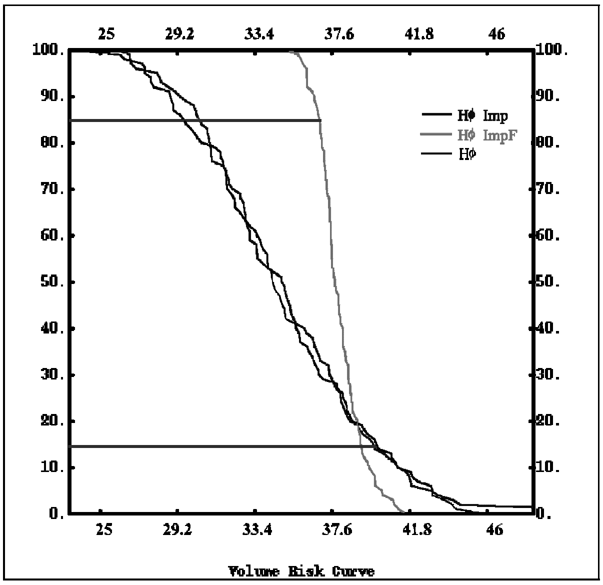

Figure-10: Volume risk curves from 100 simulations constrained by well data (black curve), by well data and raw acoustic impedance (blue curve) and by well data and filtered acoustic impedance (green curve).

5. CONCLUSION

The filtering of seismic attributes by factorial kriging analysis proves to be an efficient tool for noise removal in seismic attribute images, which after treated by such technique present clearer geological features and optimized correlations to petrophysical data.

This case study shows that simulations constrained by filtered attributes may provide a better prospective view of the field under investigation. Stochastic simulations constrained by the filtered attributes allowed the reservoir calculus of porous volume with a reduced range of uncertainty. The approach used led to a porous volume estimation closer to the actual one (the reference volume value) in a “initial phase of the field development”, since only the first 11 wells were taken into account.

ACKNOWLEDGEMENT

The authors would like to thank PETROBRAS S/A for permission to publish this paper.

6. REFERENCES

DEMIRMEN, F. Reserves uncertainty: some historical trends and wider implications. *First Break*, v.16, n.5, 1998, p.143-149.

GALLI, A., F. GERDIL-NEUILLET. & C. DADOU Factorial Kriging Analysis: A substitute to Spectral Analysis of magnetic data. In: G. Verly, M. Davis, A. G. Journel & A. Maréchal (eds), *Geostatistics for Natural Resources Characterization, Part 1*, D Raidal Publishing Company, 1984, p.543 – 557.

JOHANN, P. *Inversion Sismostratigraohique et Simulations Stochastiques en 3D: Réservoir Turbiditique, Offshore du Brésil,* Thèse de doctorat soutenue à l’Université de Paris VI, 1997, 352 p.

MATHERON, G. Pour une analyse krigeante des donnés régionalisées. *Publication N-732,*

MUNDIM, E. C. (1999) *Avaliação da krigagem fatorial na filtragem de atributos sísmicos: um filtro geoestatistico aplicado à caracterização de reservatórios*. Dissertação de mestrado, UNICAMP, Brasil, 136 p.

SOUZA Jr., O. *Stratigraphie séquentielle et simulations probabilistes d'un cône sous-marin, champ de Namorado*. Thèse de doctorat soutenue à l'Université de Paris VI, 1997, 368 p.

WACKERNAGEL, H. *Multivariate Geostatistics.* Berlin, New Yok: Springer, 1995, 256 p.

YAO, T. , T. MUKERJI, A. G. JOURNEL & G. MAVKO (1996) Factorial kriging and Simulation for integrating seismic data. *Stanford Center for Reservoir Forecasting (SCRF),* Report 9.

YAO, T. , T. MUKERJI, A. G. JOURNEL & G. MAVKO (1996) Seismic data filtering with factorial kriging. *Stanford Center for Reservoir Forecasting (SCRF),* Report 9.