Quantitative Use of Seismic Attributes for Reservoir Characterization

Richard L. Chambers* and Jeffrey M. Yarus**
Quantitative Geosciences, Inc.
Broken Arrow, Ok, U.S.A*
Houston, Texas, U.S.A**

Introduction

As industry consultants involved with reservoir studies, either directly, or typically as mentors, we are the benefactors, not the generators, of many data types. Often a client desires to use seismic attributes in a reservoir characterization study, or we find that seismic attributes are specified as general deliverables in projects up for competitive bid. Many times such requests are included as a project deliverable simply because it is fashionable, or there is a perception that "every one else is doing it."

Since the introduction of Complex Trace Attributes in the 1970s, literally hundreds of new seismic attributes have emerged from a variety of computational methods. Attributes may measure only one quality, termed "**Primitive**" attributes, or these primitive attributes may be combined through some statistical, neural network, or mathematical manipulation to form "**Hybrid**" attributes (**Taner**, 2001). The impetus behind the computation of so many attributes is the desire to use them as predictive variables in reservoir characterization projects. Most typical studies use attributes qualitatively, such as in seismic stratigraphic interpretations depicting internal bedding geometries and terminations, or to reveal spatial patterns related to depositional environments, faults or factures. However, the trend is towards the quantitative use of single or combined attributes to predict lithology, facies, porosity, or fluid type, for example.

This myriad of attributes poses a problem as few direct relationships are established between all the attributes and physical or geological characteristics. As pointed out by Barnes (2001), because many of the experts don't know what to make of all these attributes, it is no wonder that the rest of us are confused.

The purpose of this article is to review issues related to selecting and using seismic attributes quantitatively in reservoir characterization projects, rather than to describe or classify them. These latter tasks were lucidly presented in two recent CSEG *Recorder* articles by Barnes (2001) and Taner (2001).

Does the Seismic Data Warrant the Use of Attributes?

Before dashing headlong into the computation of numerous attributes, step back and look at quality of the data, determine the processing workflow, and ask what problems need to be solved. Too often we have seen that the data simply does not warrant use beyond a basic structural interpretation because of poor signal quality, low frequency content at the reservoir level, and improper processing. Data can be processed for structural interpretation using a minimum phase wavelet and a gain to enhance structural surfaces. However, the quantitative use

of seismic attributes dictates a different processing philosophy; what we term "stratigraphic" processing. Processing seismic data for stratigraphic and rock and fluid properties requires zero-phase, true amplitude, and migrated data, which is more costly and time consuming, but necessary if most attribute studies are to succeed. Perhaps geometrical attributes describing spatial and temporal continuity do not require such rigorous processing.

If for example, the purpose is acoustic impedance inversion, the data must be zero-phase, with true-amplitude recovery; otherwise the resulting impedance cube is meaningless for quantitative interpretation. AVO analysis examines the basics of amplitude variations with offset which result from contrasts in elastic rock properties. AVO analysis begins with unstacked data, generating hugh volumes of data, but may be combined with post-stack inversion techniques to infer rock properties. Again, success depends on zero-phase, true-amplitude seismic data.

What Seismic Measures and What We Require for Reservoir Characterization

The parameters measurable from the seismic data are (1) travel time, (2) amplitude, (3) the character of events, and (4) the patterns of events. From this information we often compute (**Sheriff, 1992**):

- Depth maps of important horizons ─ from traveltimes (and velocity information);
- Velocity ─ from differences in traveltime between source and receiver;
- Contrast in rock properties ─ from measurements of reflection amplitude;
- Locations of faults and stratigraphic changes ─ from discontinuities in reflection patterns.
- Dip and discontinuities ─ from differences in traveltimes along a surface

From this information it is often possible to infer:

- from velocity ─ lithology, fluid content, abnormal pressure, or temperature;
- from lateral amplitude changes ─ hydrocarbon locations, changes in porosity, lithology, or thickness;
- from seismic data patterns ─ depositional environments, or faults and fractures;
- from changes in measurement direction ─ velocity anisotropy, or fracture orientation;
- from time-lapse measurements (4D seismic) ─ locations of changes

2

For the flow simulation model the reservoir engineer needs:

- The amount and spatial (vertical and horizontal) distribution of porosity;
- Permeability
- The nature of the fluids and their saturations;
- Pressure
- Temperature
- Locations of barriers to flow (sealing and non-sealing faults, stratigraphic barriers, etc.)
- Locations of thief zones (high permeability layers)

Elastic Rock Properties

The following review is not addressed to the experienced AVO and rock property interpreter, but to those geoscientists and reservoir engineers who still have not been exposed to some of the basic theory on elastic rock properties. We need to know what information is contained in the seismic wavelet and how to extract it, before trying to use it quantitatively in reservoir characterization studies.

A rock's physical properties, such as rigidity (shear modulus, μ), incompressibility (bulk modulus,κ), porosity, pore fluid, clay content, gas saturation, and lithology affect how seismic waves travel through rocks.

Rocks have elastic properties and elasticity theory provides the expressions for the velocity of seismic P-waves and S-waves in terms of elastic rock constants for simple cases. Elasticity deals with deformation that vanishes completely upon removal of the stress which caused the deformation, such as from the passage of a seismic wave (**Sheriff**, 1973). The elastic media is determined from velocity and density (ρ) measurements. For isotropic media (**Sheriff**, 1992; **Hilterman**, 2001),

Compressional wave velocity = $V_p = \sqrt{[\lambda + 2\mu / \rho]}$ **Eqn. 1**

Shear wave velocity = $V_s = \sqrt{(\mu / \rho)}$ **Eqn. 2**

$$\frac{V_p}{V_s} = \left[\frac{1 - \sigma}{0.5 - \sigma}\right]^{0.5}$$ **Eqn. 3**

where σ is the Poisson ratio. Lamé's constant λ, an elastic parameter sensitive to fluid content, is related to μ and κ by $\lambda = \kappa - 2\mu/3$. These physical properties are related to the ability of rocks to propagate seismic waves. Our interest in P-wave and S-waves is that they travel through rocks differently depending on the fluid content and physical rock properties.

Further theory leads to the equations of **Gassmann** (1951) and **Biot** (1956) which relates seismic velocity to porosity and the rock and fluid properties.

Seismic velocity depends strongly on porosity and often a decrease in velocity with an increase in porosity is the principle controlling factor of velocity. We often use the time-average equation (**Wyllie et al**. 1956) to compute porosity from velocity through the following expression:

$$\frac{1}{V} = \frac{\phi}{V_f} + \frac{1-\phi}{V_m}$$ **Eqn. 4**

where ϕ is the porosity, V_f is the velocity of the interstitial fluid, and V_m is the velocity of the rock matrix.

When using attributes for the quantitative prediction of rock properties, it is important to remember the relations in the previous equations because they formulate the physical relationship between the seismic attribute and rock and fluid properties.

Seismic Attributes — Property Predictors or False Prophets?

For our purposes we consider a seismic attribute as any seismically derived parameter computed from prestack or poststack data, before or after migration. Amplitude, phase, and frequency are fundamental parameters of the seismic wavelet and from these few all other attributes are derived, either singly or in combinations, and many of the new attributes duplicate each other because of the nature of the computations. For example, bi-variate scatter plots of amplitude variance, average energy, RMS amplitude, reflection strength, and average absolute amplitude show either a linear or parabolic relationship, but all these attributes contain the same information (Barnes, 2001)

With the proliferation of new attributes in the 1980s and into the 1990s, new methods arose to make sense of the many attributes lacking geological significance. There was a curious notation that if attributes didn't make sense individually, perhaps they might make sense in combination. One principle should be kept in mind when using attributes; the physical basis for the correlation with properties measured at the wells. For example, a high negative correlation between porosity and acoustic impedance has a physical basis, because velocity has an inverse relationship to porosity; as velocity increases, the porosity typically decreases. Unfortunately, there is a common practice of selecting attributes based solely on the strength of their observed correlations with properties measured at the wells, but with little thought given to the validity of the correlation, except that it looks good.

The Problem

Our problem is to identify and select which attributes to use, then to select a method to integrate them with properties measured at the wells. The three most common prediction methods used in our industry today are regression,

geostatistics and neural networks. Each method requires making an inference (prediction) from the seismic attribute(s) based on its relationship to much sparser information measured at well locations. We also make the assumption that the sample population (well data) is representative of the larger parent population (the reservoir). The basic data integration process is accomplished in five steps:

1. **Calibration**. Well data provide high-resolution, depth related local information, whereas 3D seismic data provide spatially dense, but vertically lower resolution, time related information. Calibration is the first and most critical step in the process as the data must be calibrated both vertically and areally.

2. **Choice of the seismic attribute(s)**. The primary objective is to identify the attribute(s) that works best as a predictor for the reservoir property of interest. However, care must be taken when choosing the seismic attribute, because it is not unusual to find spurious or false correlations that do not reflect any physical basis for the relationship. The probability of finding a false correlation increases with the number of seismic attributes considered and is inversely proportional to the number of data control points. This concept is discussed below.

3. **Prediction**. The areal distribution of the variable of interest is mapped by integrating the well data and the seismic attribute. This prediction step is typically done by either linear or non-linear regression models, neural networks, or using a geostatistical method like Colocated CoKriging.

4. **Cross-validation**. This is the systematic removal of wells, one-by-one, and re-estimating their values based on the model selected. Cross-validation is not always performed, but it does provide a means to validate the contribution of the secondary information to improve the prediction.

5. **Management Decisions**. Depending on the project objectives, management decisions based on the prediction may include location of in-fill wells, developing a depletion strategy, designing a secondary or tertiary recovery program. Perhaps the decision is more basic — are there enough in-place hydrocarbons to justify developing the prospect?

The basic process is simple, but the key is which attributes to use and how to perform the calibration.

Probability of observing a false correlation

Most of us are familiar with the correlation coefficient, r, which is a measure of the strength of the relationship between one or more variables. But, we must remember that for a given correlation coefficient, we should make some estimate of its validity. For example, is a correlation of 0.83 good or bad? Most practitioners are aware that the smaller the number of samples, the greater the uncertainty about the true value of the correlation. However, few of us know

5

about what statisticians call *experiment-wise error rates*. As we generate more seismic attributes, there is a greater chance of observing at least one large spurious (false) correlation value; a large correlation computed purely by chance. Kalkomey (1997) discusses the potential risks when using seismic attributes as predictors of reservoir properties and illustrates the impact of spurious correlations. The article is highly recommended reading, but for those lacking the time, we have taken the liberty of summarizing some of her work in the following paragraphs.

If we consider only one seismic attribute, acoustic impedance as a predictor of porosity for example, then the probability of observing the absolute value of the sample correlation coefficient, r, greater than some constant R, given the true correlation (ρ) is zero can be found from the following expression:

$$p_{sc} = P_r\left(|r| \geq R\right) = P_r\left(|t| \geq \frac{R\sqrt{n-2}}{\sqrt{1-R^2}}\right)$$
Eqn. 5

where *n* is the sample size or the number of locations (wells) where the reservoir property and the seismic attribute are measured, and *t* is distributed as a Student's *t*- critical value, with *n*-2 degrees of freedom.

The probability of a spurious correlation depends solely on R (the magnitude of the spurious sample correlation) and *n*, the number of well measurements, based on the assumption of random sampling. It is interesting that when data are spatially correlated, as is the case for the variables we work with in the petroleum industry, Eqn. 5 gives a conservative estimate of the probability of a spurious correlation. This is because the effective sample size is smaller than the actual sample size; and as n decreases, the probability of a spurious correlation increases (Kalkomey, 1997). Table 1 shows the probability of observing a spurious correlation for different levels of the sample correlation, R, and different sample sizes, *n*. This is the base case when only one seismic attribute is considered.

This table is used to assess the chance that the sample correlation, r, is actually false or uncorrelated with the reservoir property being predicted. For example, given 5 wells, and an r = 0.7, there is a 19% probability that the correlation is false. Perhaps we are willing to accept this risk, however there is another aspect of the correlation coefficient that should be considered — the confidence limits of the true correlation coefficient. For this example, the 95% confidence limits are from a minimum r of -0.48 (P97.5) and a maximum r of 0.98 (P2.5). Because the minimum r is negative, we cannot say with confidence that there is any correlation and we should reject this attribute as a predictor. Considering one seismic attribute and a sample correlation of 0.7, we need 9 samples before the minimum r is positive, but its value is only 0.07, with a 4% chance that the correlation is false.

Table 1. Probability of observing a spurious correlation between a reservoir property and a single seismic attribute (modified from Kalkomey, 1997, p 248)

Sample size

R	5	10	20	50	100
0.1	0.87	0.78	0.67	0.49	0.32
0.3	0.62	0.40	0.20	0.03	0.00
0.5	0.39	0.14	0.02	0.00	0.00
0.7	**0.19**	0.02	0.00	0.00	0.00
0.9	0.04	0.00	0.00	0.00	0.00

The problem of spurious correlations is only enhanced when considering more than one attribute at a time. Because many attributes contain the same information it is important to select independent attributes for multivariate analysis. Table 2 is similar to Table 1, except in this case 5 independent attributes are considered as the predictors (weighted, linear combinations) of a reservoir property. Returning to the example above for 5 samples and a correlation of 0.7, we see (Table 2) that there is a 65% chance that at least one of the 5 attributes is falsely corrected with the reservoir property measured at the wells. The confidence limits on the correlation coefficient remain the same as before.

Hypothesis Testing

The most frequent use of statistics is to test some hypothesis. Our hypothesis is that the reservoir property measured at the wells correlates with the seismic attribute. This hypothesis, call the *null hypothesis* (H_0) is the hypothesis under test. It is called the null hypothesis because we assume that the correlation between the seismic attribute and the well measurement is true. The alternative hypothesis (H_a) is that the correlation is not true. We may reject H_0 when, in fact it is true, or we may accept H_0 when it is false and some alternative hypothesis is true. These are type I and Type II errors, respectively. Table 3 illustrates a Decision Table and the goodness of a statistical test of a hypothesis is measured by probabilities of making a Type I or Type II error (**Sokal and Rohlf**, 1969)

Table 2. Probability of observing a spurious correlation between a reservoir property and five independent seismic attributes (modified from Kalkomey, 1997, p 248)

Samples

R	5	10	20	50	100
0.1	1.00	1.00	1.00	0.97	0.86
0.3	0.99	0.92	0.67	0.16	0.01
0.5	0.92	0.53	0.12	0.00	0.00
0.7	**0.65**	0.12	0.00	0.00	0.00
0.9	0.17	0.00	0.00	0.00	0.00

Table 3. A Decision Table for the Null Hypothesis

Decision	Property and attribute are uncorrelated	Property and attribute are correlated
Keep seismic attribute as a predictor	Type I Error	Correct Decision (no error)
Reject seismic attribute as a predictor	Correct Decision (no error)	Type II Error

The Decision Table illustrates the possible outcomes one must consider to assess the risk in selecting seismic attributes as predictors of reservoir properties.

- **Type I error**: We commit this error when the attribute is selected but the correlation is false. The prediction is less accurate, but more precise and the cost is an inaccurate predication with confidence.
- **Type II error**: This type of error occurs when a true correlation exists, but we fail to use the seismic attribute as a predictor. Now

we have less accurate and less precise prediction and the cost is more uncertainty than justified.

Kalkomey (1997) believes that for most cases the economic consequences of making highly confident, but inaccurate predictions (Type I error) are more severe than the consequence of a Type II error.

An Example

The previous discussion focused on aspects of the selection of a seismic attribute and the possibility that the correlation may be false. The following example illustrates some of these principles. The seismic attribute is acoustic impedance derived from zero-phase, true amplitude, and 58-fold 3D seismic data. Inversion to acoustic impedance followed the method of Lindseth (1979), using sonic and density logs from three wells to calibrate the inversion. Frequency content at the reservoir depth is 7-110 Hz between 1220-1370-m. The low frequency (0-7 Hz) contribution to impedance, due to density, was derived from the conversion of seismic stacking velocities to interval velocities, using a Gardner's relationship. The primary target was a siliciclastic interval 16-28-m thick, averaging 22-m (see **Chambers, et al**. 1994, for a detailed discussion of this example). The quarter-wavelet tuning thickness is about 13-m using 70 Hz as the dominant frequency and an average velocity of 3,650 m/s. The objective of this example is to use seismic acoustic impedance to predict porosity away from the wells.

Figure 1 shows a scatter plot of seismic acoustic impedance and porosity measured at 7 well locations. The sample correlation coefficient is -0.95, with only a 0.1% chance of a false correlation. The 95% confidence limits are -0.69 (P97.5) and -0.99 (P2.5). The negative correlation coefficient is expected because acoustic impedance (AI) varies inversely with the magnitude of porosity. Even with these high correlations, we assume that the pattern displayed by the seismic AI (Fig. 2) is related to the true distribution of porosity and that the high correlation isn't serendipitous. That is, there still may be a chance that the distribution pattern of the true porosity is quite different from the pattern displayed by the seismic attribute and that the well locations sampled the reservoir in such a manner creating a false, high correlation, thus we commit a Type I error.

Figure 1. Scatterplot of porosity percent and seismic acoustic impedance at 7 well locations.
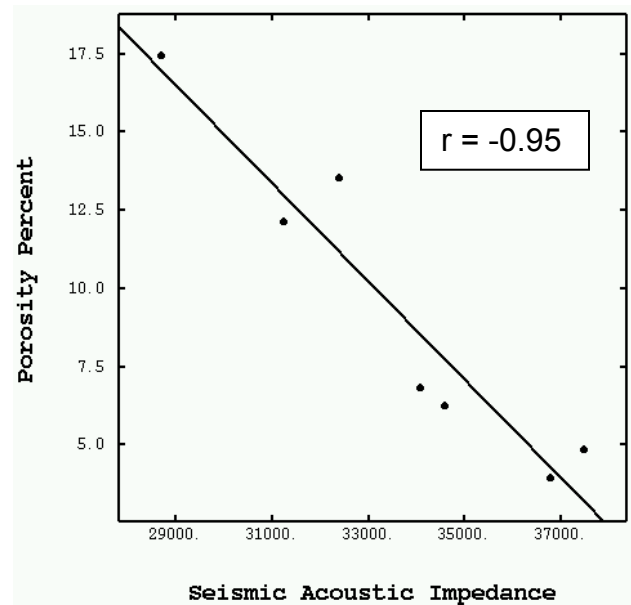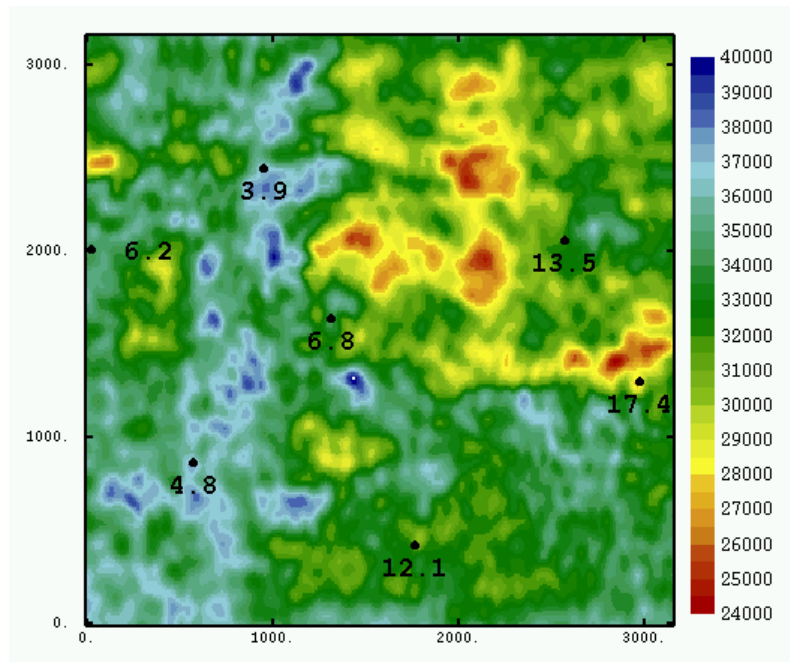

Figure 2. Map of seismic acoustic impedance and porosity percent at 7 well locations.

Data integration was by the Markov-Bayes approach to Colocated Cokriging. With only seven wells, computation of a variogram is not possible; therefore the variogram model (Fig. 3) was derived from the seismic acoustic impedance data (33,800 samples. Recall that in the Markov-Bayes method, the sill of the primary variogram is scaled based on the ratio of variances (seismic AI/porosity), using

10

the same scale lengths and anisotropy as the seismic AI model. The cross-covariance model has a "sill" based on the magnitude of the correlation coefficient.

Figure 3. Anisotropic variogram model of seismic acoustic impedance. Dashed lines are the experimental points and the solid lines are the nested model. Vertical units are variance and the horizontal units are meters.
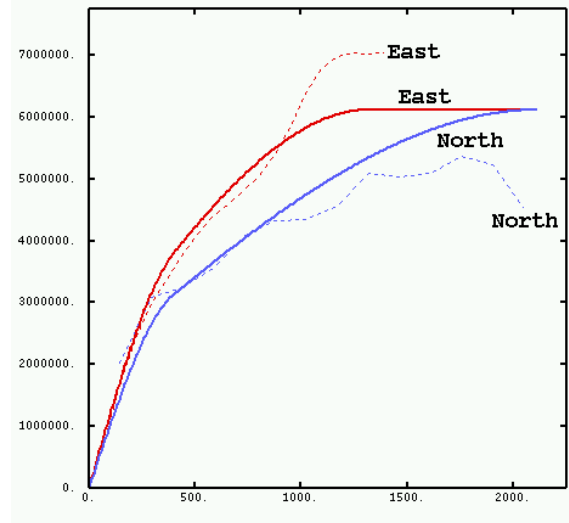

Figure 4 illustrates the colocated cokriging results using the minimum correlation (-0.69, Fig. 4A), the sample correlation (-0.95, Fig 4B), and the maximum correlation (-0.99, Fig 4C). Because of the high correlation and only 7 wells, the footprint of the seismic attribute is very pronounced. The difference between Figures 4B and 4C are imperceptible, whereas differences can be seen when these figures are compared to the image in Figure 4A. The zone of intense red is not as broad in Figure 4A as it is in the other two images. From past experiences, suppose the operator knows that wells encountering ≥ 9% porosity, within this reservoir interval, are good producers. If the purpose of the study was to locate in-fill drilling locations, we could use any of the maps shown in Figure 4 to make such a decision, assuming that we did not make a Type I error (using an attribute when the correlation is false). Before selecting a final location, it may be prudent to run conditional simulations with each correlation coefficient and create a risk map showing probability that porosity is ≥ 9%. Figure 5 illustrates a risk map based on 100 conditional simulations with an r = -0.95. The only wells satisfying the ≥ 9% condition are the three shown with a white asterisk (*) with porosity values of 12.1, 13.5, and 17.4 percent (see Fig. 2)
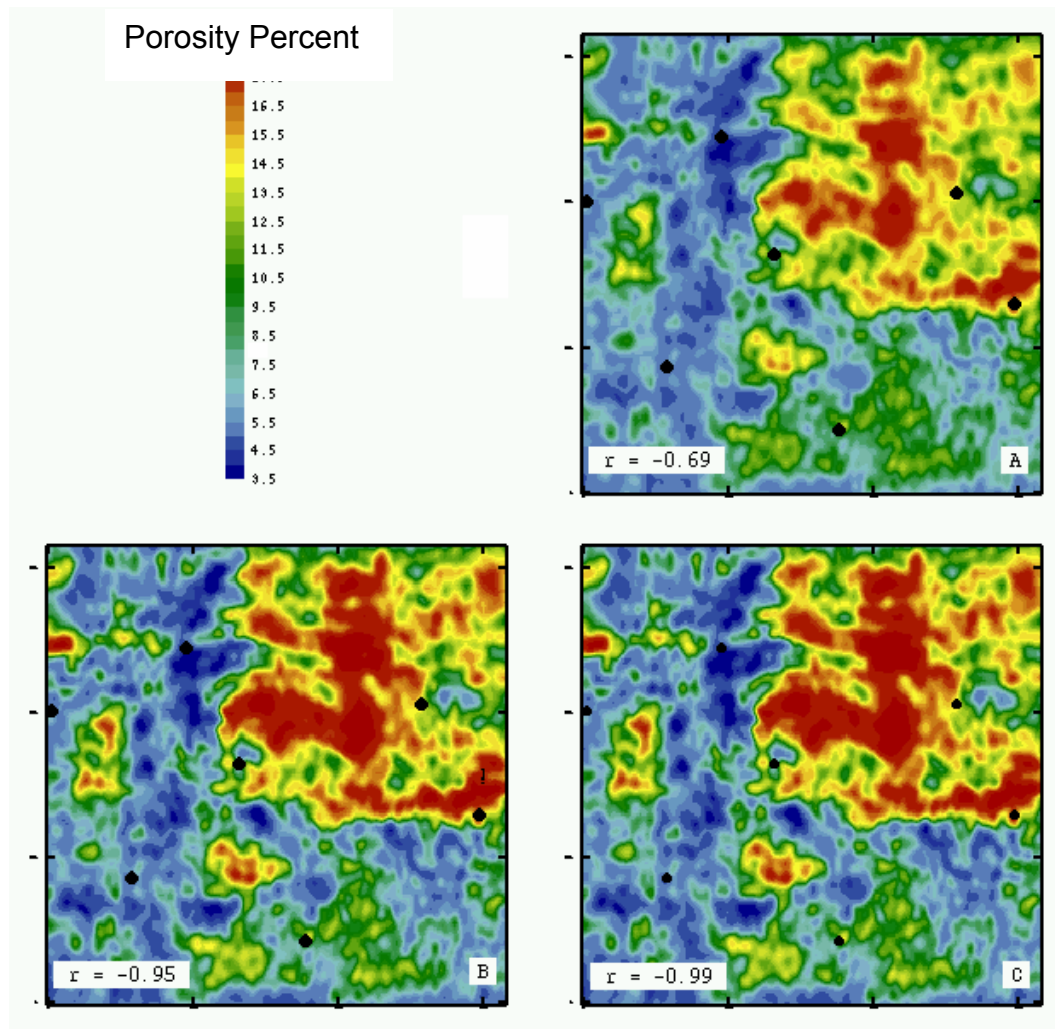
Porosity Percent

Figure 4 illustrates the colocated cokriging results using the minimum correlation (-0. 69, Fig. 4A), the sample correlation (-0.95, Fig 4B) and the maximum correlation (-0.99, Fig 4C).

The 55 well locations, shown in Figure 6, were the true well density (40-acre, 5-spot) at the time of this study. The map is based on kriging 55 porosity values using an anisotropic variogram. Compare this map to the maps shown in Figure 4 based on 7 wells and seismic acoustic impedance used as the predictor variable. The large scale features shown in the map, based on kriging porosity data only, are similar in appearance to those in Figure 4, but the map lacks the higher frequency heterogeneity added by the use of the seismic attribute.

Figure 5. A risk map based on 100 conditional simulations with an r = -0.95 showing the probability that porosity is ≥ 9%.
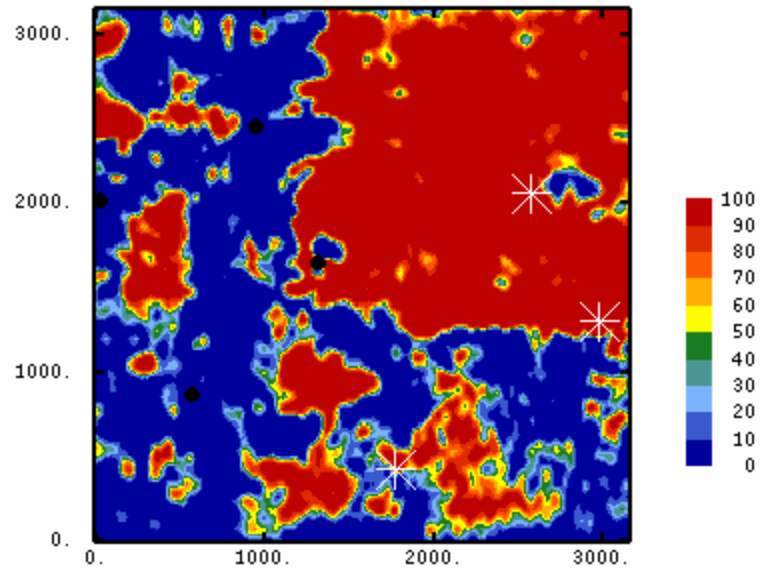

Figure 6. A map of porosity based on kriging 55 values. The wells indicated by the black asterisk are the locations of the 7 wells shown in figures 2, 4, and 5.
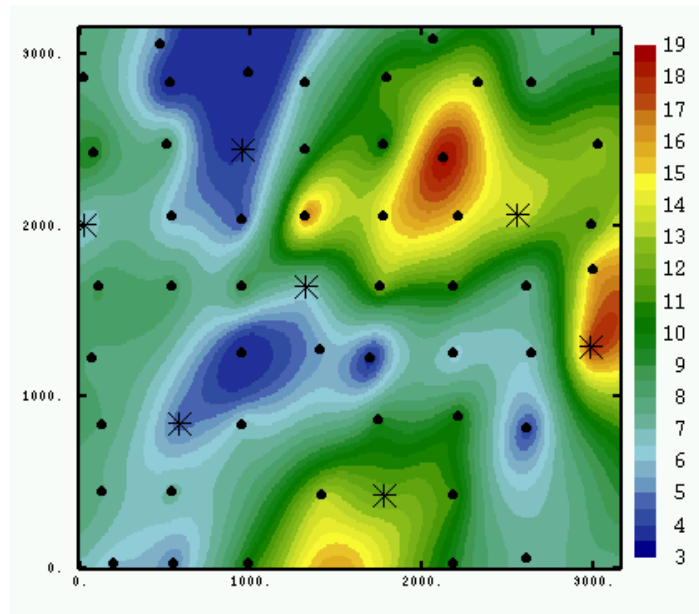
Figure 7 illustrates the value of integrating a seismic attribute when mapping porosity using only 7 porosity values. For this study we had the advantage of knowing the porosity values at 48 other well locations, thus we can test the accuracy of using the seismic attribute as a predictive variable. Of the 48 'new' locations, only 9 were misclassified using the criterion of finding porosity ≥ 9 percent. The wells shown as open circles are the values for the 7 wells and are predicted perfectly, because colocated cokriging is an exact interpolator, like kriging (the red line shows the perfect line of correlation).

13

The additional 48 wells were part a typical west Texas 40-acre 5-spot drilling pattern. If seismic data had been available when designing the original in-fill program, we can see that many wells should not have been drilled using the porosity cutoff criteria.

Figure 7. Scatter plot of measure porosity (Y-axis) versus predicted porosity (X-axis). Nine wells were misclassified out of the 48 'new' wells.
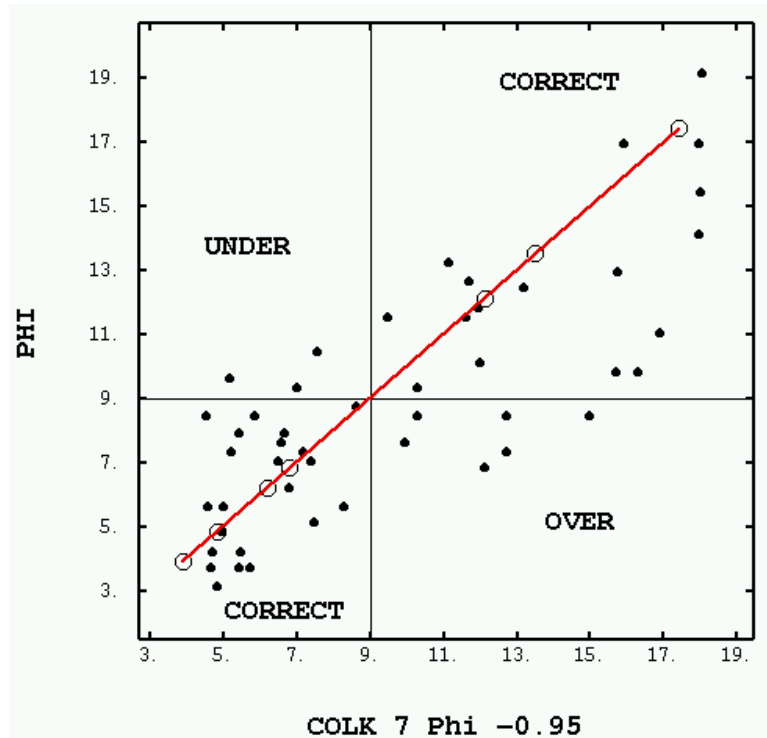
What about using Linear Regression?

Reviewing the scatterplot shown in Figure 1 and recalling that the correlation coefficient is -0.95, it would seem logical to simply use linear regression to predict porosity from seismic acoustic impedance. The map can be made using the following regression equation: Y= c-bX.

$$Porosity = 62.13 - (0.00157 * AI) \qquad \textbf{Eqn. 7}$$

where c is the intercept and b is the slope.

The map of porosity based on a regression relation is shown in Figure 8. At first glance this porosity map looks very similar to a map made using colocated

14

cokriging (Figure 4). However, the range of porosity in Figure 5 is greater than the predicted porosities in Figure 4; there is nothing wrong with this, except that the regression method predicted negative porosities. Compare Figures 7 and 9 illustrating scatter plots between the measured and predicted porosity from colocated cokriging and regression. The most obvious difference is the inability of the regression method to predict the porosity values used to compute the regression equation (the open circles). The number of underestimations is the same as colocated cokriging, but there are 4 additional locations that over estimate porosity. The fundamental problem with such an application is that we just, inappropriately, turned a point estimation method into a spatial estimator. Traditional regression methods use only data available at the target location and fail to use existing spatial correlations from additional secondary data control points and the primary attribute to be estimated (Journel, 1989). The fact that regression uses only one data point during the estimation is valid, because traditional regression assumes data independence. Although the results seem fine, the b term (slope of the function) imparts a spatial linear bias (trend) in the estimates during the mapping process. The bias becomes apparent in an analysis of the residuals shown (Figure 10) as a scatter plot of measured porosity versus residual porosity, where residual porosity is measured porosity minus porosity predicted by linear regression at the 55 well locations. The correlation coefficient is 0.69.

Figure 8. The map of porosity based on a regression relation.
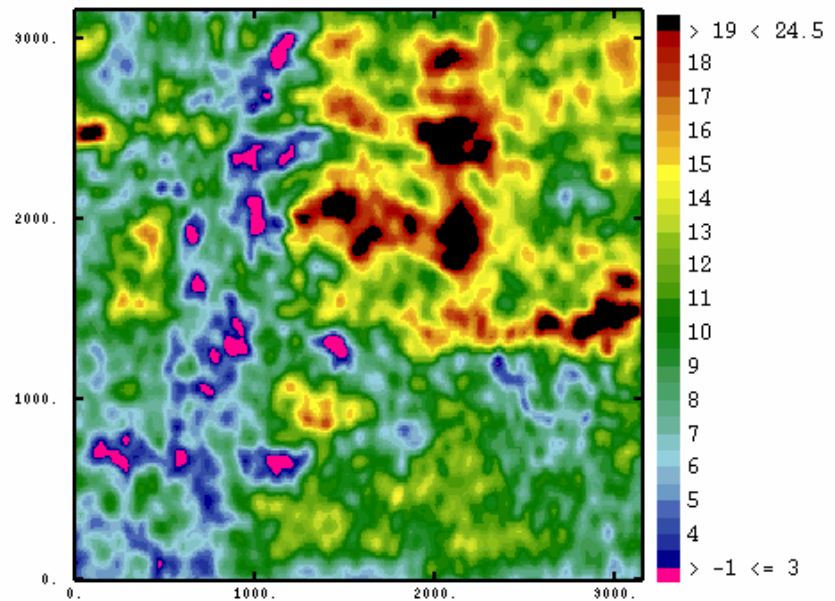
Figure 9. Scatter plot of measure porosity (Y-axis) versus predicted porosity (X-axis) using a linear regression model (Eqn. 7).
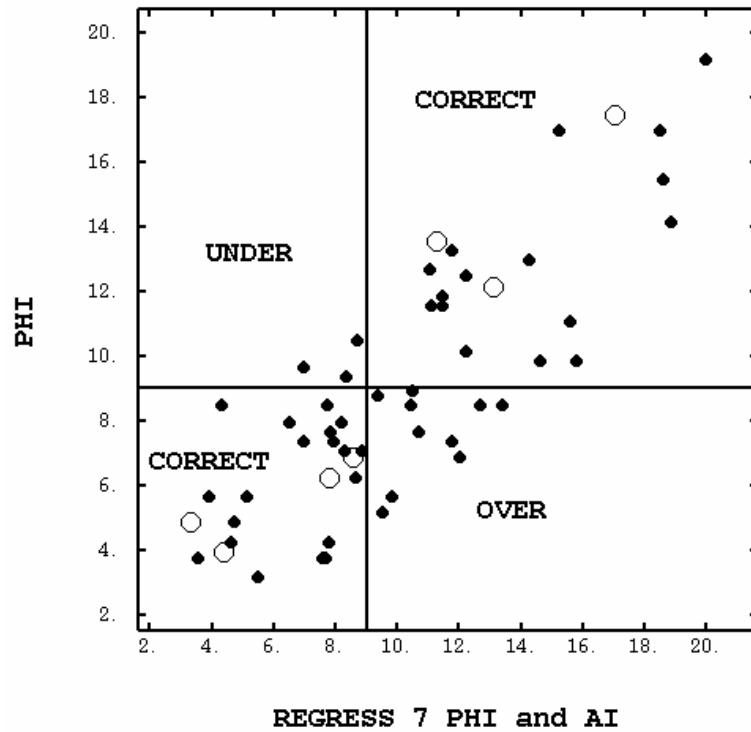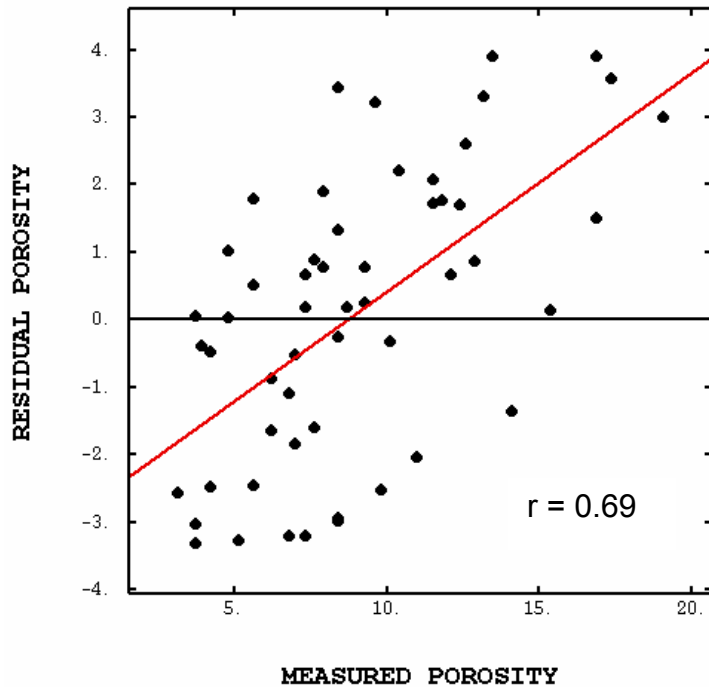

Figure 10. Scatter plot of measured porosity versus residual porosity. Residual porosity is measured porosity minus porosity predicted by linear regression at the 55 well locations.

16

The displays in Figure 11 illustrate the spatial distribution of the estimation errors based on a cross-validation using colocated cokriging (Fig. 11 A) and linear regression (Fig. 11 B). The open circles represent under-estimates of porosity, whereas solid circles are locations of over-estimates of porosity. The desired pattern would be a random distribution of open and solid circles, indicating no bias in the estimation error. Comparing the two results, Figure 11 B shows much more clustering of the two symbols when using linear regression — the southwestern quadrant is almost always over-estimated, and there is more under-estimation of the measured porosity in the northwestern quadrant, which is an undesirable attribute in an estimator algorithm. The colocated cokriging error distribution is more random, honoring the unbiasedness trait of the system of kriging algorithms.
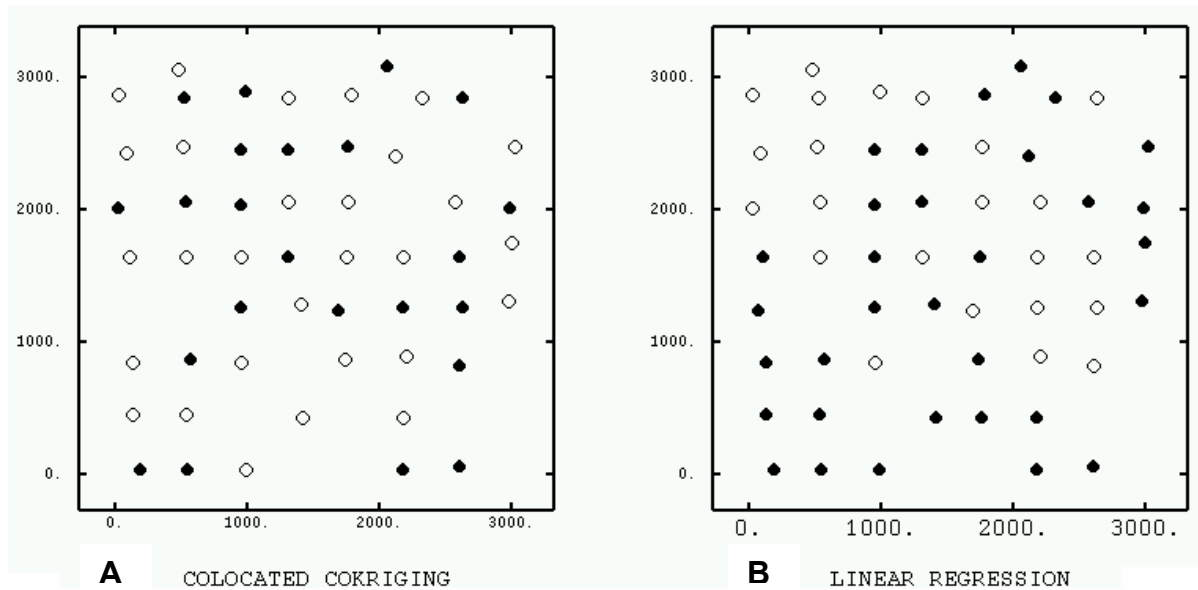

Figure 11. The spatial distribution of the residual errors based on a cross-validation using colocated cokriging (A) and linear regression (B).

Integrating Geometrical Attributes

Geometrical attributes depict spatial and temporal patterns related to bedding geometries, discontinuities such as faults and fracture swarms, bedding similarity, bedding dips, event characteristics, and can be used to quantify features related to depositional patterns, and related lithology (Taner, 2001).

Traditional geostatistics uses the variogram model to capture spatial continuity by measuring the degree of variability or conversely correlation/continuity between any two locations in space. Because the variogram is based only on two-point statistics, it cannot easily model curvi-linear features, such as channels, nor can it model strongly contiguous patterns, such as fractures.

17

The incorporation of geometrical features, like channels, deltas, reefs, etc. into reservoir models is typically accomplished using object-based (Boolean) geostatistical methods. Reservoir models build using objects is appealing to the geologists because they look realistic, that is, channels look like channels. However object-based methods have their limitations in that the algorithms require numerous input parameters describing the geometrical dimensions, such that object modeling becomes nearly deterministic, especially when many wells are used as conditioning information. However, when many wells are used, object modeling often fails because the parametric conditions imposed by the modeler cannot honor the conditioning well data.

A new method, called multiple-point statistics has been introduced that allows geological patterns integration through the framework of pixel-based modeling (**Journel, 1997, 2002; Caers, 2000; Strebelle, 2000**). Training images rather than variograms models are used to depict the prior geological conceptual model, then a sequential-based simulation algorithm is used to generate multiple realizations, with each realization honoring the well data and the multiple-point statistics (patterns) derived from the training images.

Figure 12 illustrates the integration of geological features using multiple-point statistics to infer spatial patterns. The image on the left represents a time slice through a 3D seismic amplitude cube. The image shows the presence of channel-like features, which are to be included in the reservoir model. The seismic data image is sampled, and the resampled data are used in the data integration step. The center image depicts a conceptual model of the channels, in this case, a meandering channel system, with a user specified wavelength, sinuosity, etc. The right image is one of many possible pixel-based simulations. The simulation honors the statistics of the channel morphology shown in the center image, and reproduces the shapes, locations, and orientations of the channel-like features in the seismic amplitude data (left image). The multiple-point statistics works in 2D and 3D.

The advantage of this method is the easy implementation and conditioning to well data, regardless of the number of wells, unlike object-based modeling. The training image could be much more complex with the incorporation of cross-cutting features, such as a fracture system normal to the channel orientation. Two immediate issues to consider are the choice of the training image(s) and the conceptual geological model, i.e., meandering or braided channels, for this example can make a significance difference in the connectivity. Some current problems with the multiple-point statistics method are: 1) how to evaluate the relative contributions (weight) of the training image and the soft data, especially when they are somewhat inconsistent; 2) how to select samples from the training image, i.e., randomly, or on a Cartesian grid with an equal sampling interval, for example; and 3) it is not always possible to preserve the non-stationarity of the information in the final results, if non-stationarity is present in the seismic data, or the conceptual model.
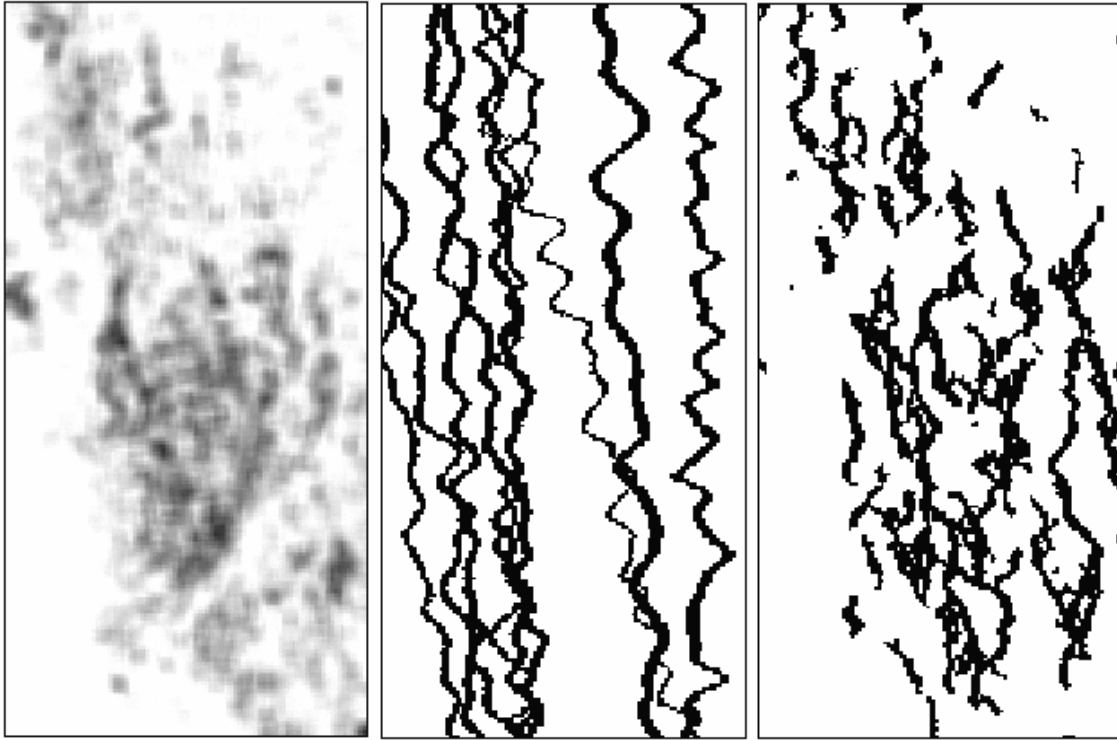
Figure 12. These images illustrate the integration of geological features using multiple-point statistics to infer spatial patterns. The left image is seismic amplitude data showing channel-like features, the center image is the conceptual model, and the right image is one pixel-based realization (modified from Caers, 2002).

Summary

Seismic attributes can be important qualitative and quantitative predictors of reservoir properties and geometries when correctly used in reservoir characterization studies. It is critical when using attributes as quantitative predictors of reservoir properties to consider: 1) how the seismic data were processed; 2) the physical basis of the correlation; 2) the possibility of false correlations when the number of well data are few, and/or when the number of attributes are many; 3) when using multiple attributes, the attributes must provide independent information about the reservoir property; 4) and, although, easily applied, linear regression is not recommended because the results will be biased. Geostatistical data methods, such as colocated cokriging and colocated cosimulations, offer attractive means to integrate seismic attribute and well information, without an estimation bias, and account for the scale (support) differences between the two data types. Geometrical seismic attributes probably require less rigorous data processing. Integration of geometrical information in

reservoir model is not as straight forward as the "rock property" attributes, however, the new multiple-point statistics methods have good promise.

References

Barnes, A. E., 2001, Seismic attributes in your facies, pp. 41-47, September Issue

Biot, M. A., 1956, Theory of propagation of elastic waves in a fluid-saturated porous solid, J. Acoustic. Soc. Am., 28, pp. 168-191.

Caers, J., 2000, Modeling facies distributions from seismic using neural nets, Stanford Center for Reservoir Forecasting Annual Report, No. 13, Vol.1.

Caers, J., 2002, History matching under training-image based geological model constraints, Stanford Center for Reservoir Forecasting Annual Report, No. 15, Vol.1.

Chambers, R. L., M. A. Zinger and M. C. Kelly, 1994, Constraining Geostatistical Reservoir Descriptions with 3-D Seismic Data to Reduce Uncertainty, *Stochastic Modeling and Geostatistics*, J. M. Yarus and R. L. Chambers, Eds. AAPG Computer Applications in Geology, No. 3, pp. 143-58.

Gassmann, F., 1951, Elastic waves through a packing of spheres, Geophysics, 16, pp. 673-685.

Hilterman, F. J., 2001, Seismic Amplitude Interpretation, 2001 Distinguished Instructor Short Course Series No. 4, sponsored by the Society of Exploration Geophysicists, European Assoc. of Geoscientists and Engineers, Houston, TX, p. 2-24.

Journel, A. G., 1989, *Fundamentals of Geostatistics in Five Lessons*, Short course in Geology, Vol. 8, American Geophysical Union, 40 p.

Journel, A. G., 1997, Deterministic geostatistics: a new visit, in Baffi, E. and Shofield N. eds., Geostatistics-Wollongong, 1, Kluwer Academic Press, Dordrecht, pp. 174-187.

Journel, A. G., 2002, Combining knowledge from diverse information sources: an alternative to Bayesian analysis, in press, J. Mathematical Geology.

Kalkomey, C. T., 1997, Potential risks when using seismic attributes as predictors of reservoir properties. *The Leading Edge*, March., pp. 247-251.

Lindseth, R. O., 1979, Synthetic sonic logs – a process for stratigraphic interpretation, Geophysics, 44, pp. 3-26.

Sheriff, R. E., 1973, Encyclopedic Dictionary of Exploration Geophysics, Society of Exploration Geophysicists, Tulsa, OK, p. 69.

Sheriff, R. E., 1992, Basic petrophysics and geophysics, in Reservoir Geophysics, R. E. Sheriff, ed., Investigations in Geophysics No. 7, Society of Exploration Geophysicists, Tulsa, OK, pp. 37-49.

Sokal, R. R. and J. F. Rohlf, 1969, *Biometry*, W. H. Freeman and Co., San Francisco, pp. 155-173.

Strebelle, S., 2000, Sequential simulation drawing structures from training images, Stanford Center for Reservoir Forecasting Annual Report, No. 13, Vol.1.

Taner, M. T., 2001, Seismic attributes, CSEG Recorder, pp. 48-56, September Issue.

Wyllie, M. R. J., Gregory, A. R., and Gardner, L. W., 1956, Elastic waves in heterogeneous and porous media, Geophysics, 21, pp. 41-70.

Richard L. Chambers is co-owner of Quantitative Geosciences, Broken Arrow, Oklahoma, U.S.A. He earned BA and MS degrees in geology from the University of Montana, and then attended Michigan State University, earning a PhD in geology, with an emphasis on quantitative sedimentology and statistical applications. He worked for the Great Lakes Environmental Research Laboratory, NOAA, U.S. Department of Commerce for 8 years before joining Phillips Petroleum Company, where for 8 years his activities included research in high-resolution P- and S-wave seismic imaging and developing exploration plays and lease acquisition strategies as a member of a regional basin studies team. In 1988, he joined the Amoco Production Company Research Center where he worked for 9 years in various technical and management capacities related to the application of geostatistical methods for exploration and production problems. In 1997, he became a consultant providing training and geostatistical modeling expertise to the petroleum industry. His professional activities include publishing, consulting, lecturing and offering applied training courses in reservoir characterization and geostatistical applications. In late 2001, he co-founded, with Jeffrey M. Yarus, Quantitative Geosciences, with offices in Broken Arrow, Houston, and London.

Jeffrey M. Yarus is co-owner of Quantitative Geosciences, Houston, Texas. While attending the College of Wooster, he received a scholarship to study geology for one year at the University of Durham, England, before earning his BA at Wooster. He earned his MS and PhD degrees in geology from the University of South Carolina where he refined his interests in computer mapping and numerical and statistical analysis. He joined Amoco Production Company in New Orleans, Louisiana, as a production geologist for the Gulf Coast Region. He left Amoco, to work as an independent for 8 years on a variety of domestic basins in the Rockies, mid-continent and Appalachian regions. He joined Marathon Oil Company's Petroleum Technology Center, in 1988, where he was instrumental in instituting desktop computer mapping and geostatistical technology. Before co-founding Quantitative Geosciences, with Richard L. Chambers, he held various managerial positions with GeoGraphix, Geomath, Roxar (formerly Smedvig Technologies) and Knowledge Reservoir. His professional activities include publishing (in AAPG's first volume on computer applications in1992), consulting,

lecturing and offering applied training courses in reservoir characterization and geostatistical applications. He has been an adjunct professor at the University of Colorado, Denver and a visiting professor at the Colorado School of Mines.

Yarus and Chambers are co-editors of *Stochastic Modeling and Geostatistics,* AAPG Computer Applications in Geology, No. 3, published in 1994. The second volume, with a new collection of papers, should be published in the AAPG Computer Application in Geology Series by late 2002.