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Principal Component Analysis Applied to 3D Seismic Data for Reservoir Property Estimation

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Abstract

We apply a common statistical tool, Principal Component Analysis (PCA) to the problem of direct property estimation from 3D seismic amplitude data. We use PCA in a novel way to successfully make detailed effective porosity predictions in a channellized sand and shale.

The novelty of our use of PCA (applied to a single-property: 3D-seismic amplitude) revolves around the sampling method: Our sampling technique consists of a small vertical sampling window, applied by sliding it along each vertical trace in a cube of seismic amplitude data. The window captures multiple, vertically adjacent, amplitude samples, which we then treat as a vector for purposes of the PCA analysis. All vectors from all sample window locations within the seismic data volume form the set of input vectors for the PCA algorithm.

Final output from the PCA algorithm can be a cube of assigned classes, whose clustering, is based on the values of the most significant Principal Components (PC's). The clusters are used as a categorical variable when predicting reservoir properties away from well control. The novelty in this approach is that PCA analysis is used to analyze covariance relationships between all vector elements (neighboring Amplitude values) by using the statistical mass of the large number of vectors sampled in the seismic dataset.

Our approach results in a novel and powerful signal analysis method that is statistical in nature. We believe it offers a data-driven objectivity for and a potential for property extraction not easily achieved in model-driven fourier-based time-series methods of analysis (digital signal processing).

We evaluate the effectiveness of our method by applying a cross-validation technique: Alternatively withholding each of the three wells drilled in the area, and computing predicted effective porosity (PHIE) estimates at the withheld location by using the remaining two wells as "hard" data. This process is repeated three times, each time excluding only one of the wells as a blind control case. In each of the three blind control wells, our method predicts accurate estimates of sand/shale distribution in the well, and the effective porosity-thickness product values. The method properly predicts a low sand-to-shale ratio at the blind well location, even when the remaining two "hard" data wells contain only high sand-to-shale ratios.

Good predictive results from this study area make us optimistic that this method is valuable for general reservoir property prediction from 3D seismic data, especially in areas of rapid lateral variation of the reservoir. We feel that this method of predicting properties from the 3D seismic is preferable to traditional, solely variogram-based, geostatistical estimation methods. Such traditional geostatistical methods have difficulty capturing the detailed distribution of the lithologies when limited by sampling bias of the hard data control. This problem is especially acute in areas where rapid lateral geological variation is the rule. Our method effectively overcomes this limitation because it provides a deterministic "soft" template for reservoir property distributions.

Introduction

Reservoir prediction from Seismic. The use of the reflection seismic attribute data for the prediction of detailed reservoir properties began at least as early as 1969[1]. Use of seismic attributes for reservoir prediction has accelerated in recent years, especially with the advent of widely available high quality 3D seismic data.

In practice, a seismic attribute is any property derived from the seismic reflection (amplitude) signal either during or after final processing. Any attribute (or attributes) may be compared to a primary reservoir property or lithology in an attempt to devise a method of attribute-guided prediction of the primary property away from well control. The method of prediction can vary from something as simple as a linear multiplier (single attribute) to multi-attribute analysis using canonical

correlation techniques[2], geostatistical methods[3] or fully non-linear, fuzzy methods[4].

The pace of growth in prediction methodologies utilizing seismic attributes seems to be outpaced only by the proliferation in number and types of seismic attributes reported in the literature[5]. As more researchers find predictive success using one or more new attributes, the list of viable reservoir – predictive attributes continues to grow. As evidence of the current proliferation of attributes, Chen and Sidney[6] have cataloged more than 60 common seismic attributes along with a description of their apparent significance and utility.

Despite the rich history of use of seismic attributes in reservoir prediction, the practice remains a difficult and uncertain task. The bulk of this uncertainty arises from the unclear nature of the physics connecting many of the demonstrably useful attributes to a corresponding reservoir property. Because of the complex and varied physical processes responsible for various attributes, the unambiguous use of attributes for direct reservoir prediction will likely remain a challenge for years to come.

In addition to the questions about the physical origin of some attributes, there is the possibility of encountering statistical pitfalls while using multiple attributes for empirical reservoir property prediction. For example it has been demonstrated that, as the number of attributes used in an evaluation increases, the potential arises that one or more attributes will produce a false correlation with well data[7]. Also, many attributes are derived using similar signal processing methods and can, in some cases, be considered largely redundant with respect to their description of the seismic signal. Lendzionowski, Walden & White[8] maintain that the maximum number of independent attributes required to fully describe a trace segment is a quantity 2BT, where B = bandwidth (Hz) and T = trace segment length (seconds). If this is supportable, it suggests most of the more common attributes are at least partially redundant. The danger of such redundancy is that of falsely enhancing statistical correlation with the well property. Doing so, may suggest that many seemingly independent seismic attributes display similar well property trends.

Finally, the utility of a particular approach using attributes involves at least a little bit of subjectivity and prior experience on the part of the practitioner, in order to be successful and reproducible. This is a source of potential error that cannot be quantified, but also, in most cases cannot be avoided. The most successful workers in the field of reservoir prediction from seismic, not coincidentally, are also the most experienced in the field.

Limiting Ambiguity: Our Approach. In this study we try to limit the potential for ambiguous outcomes caused by redundant attribute character. Our approach is designed with the expressed goal of deriving all meaningful seismic attributes in a single coordinated transformation. This transformation is followed by a calibration of the most significant of the attributes using reservoir data from the wells. The objective is to distill the amplitude signal into its most uniquely elemental components, essentially capturing all that is potentially descriptive of the signal character in a single transformation. At the same time, we desire that the transformation should optimize the mutual uniqueness of all derived attributes, limiting the possibility of overlapping redundancy.

Principal Component Analysis. To achieve this objective we need to employ a strategy capable of transforming the seismic trace into the unique multiple attributes that, as a group, are both comprehensive in their description of all that is unique in the signal, yet are as mutually independent as possible. To this end we employ principal component analysis (PCA). PCA is a long established statistical technique[9] historically used to transform and analyze multivariate datasets. Its behavior and our novel usage of it are described below.

Above, we defined the ideal seismic attributes to be "most completely descriptive of the signal" and "unique and mutually independent". In the parlance of PCA, these definitions conveniently translate to "maximally-variant" and "mutually-orthogonal" respectively.

Let us elaborate. A PCA procedure consists of first, computation of all the covariances for N-input components then, inversion of the covariance matrix so as to create a set of N-orthogonal eignvectors and corresponding eigenvalues. Taken together, each eigenvector-eigenvalue pair represents a distinct principal component (PC). All N-PC's are the uniquely and simultaneously determined from the set of input vectors. The inversion of the covariance matrix ensures the unique discovery of the "maximally-variant" component (highest eigenvalue PC). All subsidiary PC's, ranked in order of decreasing eigenvalue are mutually orthogonal (the eigenvector ensures this).

Thus, using PCA to derive a complete set of seismic attributes (in the form of PC's) achieves our paramount goals for attributes. Namely that the attributes are:

1. Maximally descriptive of the signal and
2. Mutually independent, and therefore maximally unique.

PCA on Seismic Amplitudes. PCA requires multivariate (N) inputs; yet we have earlier stated that we choose to apply PCA to only one input property, the seismic amplitude. However, we choose to analyze multiple adjacent amplitude values simultaneously. To do this, we use a sampling window.

Limitations of the Seismic Signal. The seismic method, by its physical nature, tends to disperse information generated by a localized reflector throughout a larger volume of recorded amplitude data. This "spreading" of information is a requirement of the fact that the propagating seismic impulse (called the wavelet) has a limited bandwidth of spectral components. Because of this bandwidth limitation, the wavelet is dominated by long wavelengths (low frequencies) causing the signal to be spread over a large part of the subsurface as it propagates. Because of this size, the recorded reflection signal is a compendium of overlapping wavelet

impulses that renders the observer unable to unambiguously resolve small, tightly-grouped features.

When an wavelet-impulse reflects from a layer-boundary, it returns to the surface as a filtered version of that feature. The filtering process caused by the wavelet, in effect, spreads information in the form of reflection signal both above and below the expected location of the reflector in terms of the final 3D-amplitude volume. This spreading of this information effectively mixes signals from many nearby reflectors together. Recovering the original geometry and reflection character becomes problematic because of this.

Capturing Detailed Features. If one hopes to recover all reflection information about a localized, finely-layered feature in the subsurface, then one must analyze the entire sub-volume that may reasonably contain the spread-out reflection information emanating from that feature.

This is the reason we choose to analyze a window of the seismic amplitude trace data, instead of the amplitude of each single point. To do so, we design a sampling window to be large enough to contain the entire "dispersed" signal resulting from a fine-scale feature in the subsurface, but small enough to exclude as much unrelated signal as possible.

All amplitude values within the window (N-samples) taken as an ordered set, or vector, create an N-dimensional vector that can be directly input to the PCA computation. By sampling the entire data volume with many uniformly sized windows, we can create the statistical mass of vector samples necessary for the computation of the covariances. This is followed by covariance matrix inversion.

The PCA identifies some elements of the signal that are common to the window (resulting from the wavelet) and others that are stationary with respect to the seismic cube (generated by the geology and fine-scale reflectors). The stationary components, those that correspond with the localized reflectors, are of most interest to us, but which components are which is not know implicitly, so we must calibrate the PC's against well data to recover this information.

We make effective use of the window-sampling concept for our PCA analysis. But windowing of seismic data for purposes of detailed signal analysis is an approach that has been used by many workers in the field of seismic signal analysis historically. Windowed analysis of seismic, (so-called "interval" approaches) have been reported in the literature at least as early as 1982[9,10] and have been commonly reported ever since[11].

Others have used PCA on multivariate seismic data, for example in Amplitude versus Offset (AVO) analysis[12]. The method has also been widely used in satellite-image processing[13]. Our PCA approach is different in that we concentrate using PCA to probe the "richness" of a single property sampled within a contiguous window, as opposed to evaluating diverse collocated data types. Previous workers' rationalization for the use of a sample/analysis window is similar to ours. Namely, doing so is the most straightforward way to capture all relevant signal emanating from the small-localized reflectors. In this study, we expand on the interval method, by applying it to the entire sampled volume and using PCA to further break down the windowed signal.

Calibration of the Principal Components The calibration of the PC's to the well data is our attempt to "collapse", as much as possible, the dispersed fine-scale information back to the original physical location of the reflectors, by comparison with the highly resolved reservoir property data at the wells. The ideal result is to achieve a highly resolved and unambiguous reservoir property description in 3D directly from the decomposed seismic signal. We choose to do the calibration of the seismic signal by first clustering the principal components. Then we compute a predicted reservoir property (effective porosity) on the grid, by using the statistics of the reservoir property at the wells for each cluster. These procedures are described in detail below.

Method: Principal Component Analysis

Computation of Principal Components. The PCA method requires as input a set of input N-dimensional vectors consisting of a population representative of the entire volume to be analyzed. The dimensionality of each vector sample is determined by the sampling window size, but the total number of sampled windows is dictated by the size of the volume chosen for analysis. In practice, the seismic volume contains many more sample windows than are required to achieve a reproducible PCA characterization. In order to improve computation time, we choose to sample the seismic data cube uniformly, yet decimate the number of sampled windows such that the total sampled dataset is limited to approximately 100,000 sample vectors. This number has been found to provide sufficient statistical mass to correctly characterize the more than 1.5 million window locations in the dataset used in this study.

The size of the sampling window is determined by specifying the number of grid samples above and below a relative reference point. The window reference point is at the center of each window and is designated as the locus of window-based attributes (such as PC's) which are assigned to the grid. The window sampling strategy is shown schematically on a synthetic seismic dataset in Figure 1.

In the studied volume, the seismic samples are arranged in a orthonormal 3D grid that is uniformly sampled along any given axis (X, Y, Z). The grid geometry intentionally coincides with the sample geometry of the original seismic survey. The data cube is analyzed with the vertical dimensions in two-way-travel acoustic travel time, in order to facilitate aspects of well-to-seismic alignment. Normally after the reservoir properties are defined in the time domain (as is done in this study), the volume is converted to depth for further reservoir study or flow simulation.

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The detailed mathematics of how the PC's are computed are described in Payrazyan[14]. For our purposes of this paper, it is sufficient only to state the following summary points.

1. PCA requires N inputs (determined by the dimensions of the sampling window) and returns N linearly transformed outputs (eigenvectors), called Principal Components.
2. PCA ranks the PC's according to their contribution to the total variance of the dataset (determined by descending eigenvalues). The first PC has the most information about the trace (highest eigenvalue), and each subsequent PC contains progressively less information about the trace and accounting for progressively smaller variance contributions of the total signal volume.
3. The principal components (PC's) are demonstrated to be mutually orthogonal, and as such, we consider them to be fully independent for purposes of further analysis. We will use this concept as the premise for clustering/classifying the population of transformed input vectors.

Sampling Window Size. For the purposes of this study, we have determined that the size of the window should be limited in the vertical dimension to approximately the seismic wavelet's mean-period (~34 milliseconds (ms) in this dataset). This choice of this sampling window is based on the knowledge that the seismic source signal has a finite duration in time, and therefore space. As this wavelet travels through the subsurface, it bounces back from many localized reflectors. The wavelet covers many fine scaled reflectors simultaneously, thus the sum total of information about each reflector is spread throughout this ~34 ms window. Once the wavelet has passed a given reflector, no significant signal from the reflector is produced. So we reason all relevant information about any one reflector (centered in the sampling window) is contained within the 34 ms limit.

Thus, by limiting the sampling window to the approximately the size of the impulse wavelet, we capture the signal that is directly related to any given reflector while minimizing the influence of signal generated by other unrelated reflectors. This is the logic for the window sampling strategy. In common practice, one would analyze a variety of windows, both larger and smaller to arrive at the optimum size for a given seismic dataset and study area.

The choice of sampling window shown in this study has proven to be effective but, it is not known whether our sizing technique is optimal. As a result, sizing of the sample window remains a subject of much experimentation, and research.

Clustering of PC's. In order facilitate the calibration of the computed PC's to the reservoir property data, we attempt to increase the uniqueness of the solution by reducing the dimensionality of the problem. As Kalkomey[7] points out, a greater number of attributes increases the likelihood of a false correlation. The mutually independent nature of the PC's, minimizes this risk, and we have reasoned that N PC's fully and completely describe the unique character of the amplitude signal, but this number of attributes also serves to make their calibration potentially more onerous, requiring a robust multivariate approach.

Although multivariate approaches are viable (we intend to pursue this area in future studies), in this study we choose to circumvent the use of such a method by reducing the relevant information contained in the PC's to a single categorical property. This is accomplished through the use of a clustering approach.

Clustering allows us to produce a volume of discrete classes that are computed directly, using all significant PC's in an objective way. These strategy combines the significant information contained in all the PC's with compactness of a categorical description. The clustering is done in an objective way in an attempt to limit any bias or the intrinsic contribution of any one PC.

Clustering method. Because the PC's are mutually orthogonal attributes, they necessarily exist in a universe of N orthogonal spatial dimensions (so-called principal component-space). Each sample vector can be located uniquely in this multidimensional space by knowing its eigenvector coefficients (computed by the PCA). With all sample vectors (seismic sample windows) containing unique loci in this PC-space, a proximity-based clustering scheme (K-means method[14]) can be employed. Such a clustering scheme jointly clusters and classifies each window of the seismic data. Sample vectors that are located proximal to one another in PC-space are likely to receive the same cluster index. Once cluster membership is determined for a given sample, the cluster index can be posted on the original seismic grid at each sample-window's reference point. The result is a cube filled with a unique categorical property, the PCA cluster index. An example of the physical appearance of a PCA clustered cube is shown on synthetic seismic data in Figure 2a.

Samples within the synthetic seismic cube belonging to the same PCA cluster receive the same index/color. The numerical value of the cluster property is simply an arbitrarily integer value that serves as a unique categorical "tag" for identifying all sample belonging to each specific cluster, but has no further significance.

The categorical variable (cluster index) allows us to use a geostatistical method called a categorical cloud transform to produce multiple realizations of our property estimates based on the co-located well and cluster properties. This process is described in the section "Methods: Property Estimation Using a Cloud Transform".

In summary, the PC clustering step retains the characteristic uniqueness of all the PC's, but reduces the dimensionality of the problem by creating a single categorical variable that we use for calibration to well data.

Number of Clusters. When performing the PCA clustering, a choice must be made as to the number of clusters that will be created from the dataset. Ultimately we must calibrate the clusters by comparing them to spatially corresponding

reservoir property values at the wells, and the number of clusters retained will determine, in part, the success of this operation. Since the number of clusters is a specified parameter, we must we attempt to balance two competing objectives.

1. To produce as finely resolved a characterization as possible, in an attempt to capture fine reservoir detail. Following this objective will lead us to choose a higher number of clusters reducing the average sampled volume per cluster.
2. To calibrate the clusters with greater statistical weight by capturing as many well data points within each cluster as possible. Following this objective will lead us to choose fewer clusters increasing the sampled volume per cluster.

We find that objective 1 narrows the variance of hard-data sampled by a given cluster at the wells, but also weakens the statistical robustness of that sampled population. Both effects occur as a result of fewer individual well-samples being distributed to each cluster. Taking this to the limit by selecting a sufficiently large number of clusters could distribute only one well-based property value to each cluster. This would produce a very tight property distribution for each cluster (one-value, zero-variance), but would be prone to erroneous prediction.

On the other hand, decreasing the resolution of each cluster by choosing fewer of them serves to distribute more well-samples to each cluster, thereby strengthening the cluster statistics. But doing so also widens the population so as to make each cluster less predictive. In the limit, the choice of only one cluster would result in a strongly representative distribution (equal to the entire well-based property dataset), that would have little value in prediction. In fact doing so would eliminate the effect of using the seismic, at all!

After some experimentation, we chose 50 clusters as optimal to balance these two competing objectives. Experimentation and some subjective analysis is required to arrive at the optimal choice of cluster number, and usually retaining multiple choices of cluster numbers will serve to capture the uncertainty imposed by this step.

Number of PC's retained for clustering. PCA ranks the derived PC's in order of decreasing variance contribution (decreasing eigenvalue). In doing so, it defines the highest-ranking PC's as those that have the most overall information about the trace. In most cases, the lower ranked PC's do not contain much useful information about the signal. This logic can be used to justify reducing the number of retained PC's to a manageable number, without losing much descriptive value. For example our 34 ms sample window contains 17 sampled amplitude values. The PCA analysis dictates that 17 PC's must be computed, but we know that many of these PC's will contain little or no useful information about the signal.

Appropriately, the PCA ranking of variance leads us to assert that we can apply a cumulative variance cutoff which will collect the PC's in order of maximum descriptive capability, and reject those of lesser value. Beyond this cutoff, any PC's will be discarded and consequently, will not be used in the PC-space clustering step.

Exactly where to set the variance cutoff is a subject of experimentation, and is surely problem and data dependent, but the following steps are employed.

1. Observe the PC's by posting each as a separate attribute on the grid. Then observe each PC to determine whether what type of signal character (desirable or undesirable) is dominant within that PC.
2. Select a variance cutoff such that the maximum number of desirable PC's is retained and the minimum number of undesirable PC's are retained.

The terms desirable and undesirable are highly subjective. To identify what are desirable characteristics for a PC we look for localized diversity of features, both vertically and laterally (Figure. 3a). Such desirable characteristics indicate a PC with broad bandwidth and less noise. Undesirable characteristics are those shown in Figure 3b, where the signal is dominated by a narrow frequency range causing a vertically extensive pattern of "ringing" and lack of feature localization.

In this study, we chose to retain 80% of the total variance. This cutoff retains 4 of the 17 PC's. These 4 PC's are used to do the PCA clustering using the method described earlier. From 17 to 4 represents is a significant reduction in component dimensionality, but it serves the positive goal of filtering out high-noise components from the original data, while maintaining the high-signal components.

An example of the input and output for the PCA clustering flow in this study, is shown in Figure 4. Figure 4a shows the input amplitude data. Figure 4b shows the clustered result for the same slice through the cube. The gray tones in Figure 4a map the amplitude value, and the gray tones in Figure 4b are mapping the PCA cluster index property. Figure 4 serves to demonstrate how effectively the PCA clustering classifies the signal, capturing the essential elements of the geology within a categorical framework.

Methods: Property Estimation Using a Cloud Transform

The final procedure we apply in this study is a geostatistical estimation (simulation) technique known as a cloud transform. We use this technique to populate the seismic grid with effective porosity (PHIE) by using the PCA clusters as a guide.

A cloud transform is a stochastic estimation technique that is based on matching a cross-plot ("cloud") of points relating the two variables. The "cloud" is simply the physical bivariate plot of soft- *vs.* hard-data at the wells' sampling locations. In order to apply the transform everywhere, the soft-data must be located everywhere. The hard-data need only exist at the sampled well locations. The hard-data is the one that is intended for estimation over the entire grid, guided by the soft data. In this study, the PCA clusters are the soft-data and PHIE is the hard-data.

Cloud Transform and SGS. The Cloud transform is a derivative of the commonly used Sequential Gaussian Simulation (SGS or GSS) method of property estimation. The SGS algorithm is capable of producing any number of unique estimations of property values. All such estimated volumes obey the imposed spatial geostatistical model (variogram structure) and honor the hard-data. The details of implementation of SGS method are described fully by Deutsch and Journel[15], but a brief description of the process is warranted, because it is the underpinning of the cloud transform that we use in this study.

SGS creates a property estimate using the following of 5 steps:

1. A random travel path through the unpopulated cells of the grid is computed. Once this path is established, the first cell can be populated.
2. Computing the local kriging solution (conditional to the hard-data) populates the first cell on the path.
3. A random selection is made from the univariate gaussian population limited by the mean and variance for that location from step 2.
4. The value selected in step 3 is posted to the first grid location and becomes a member of the hard-data.
5. The algorithm then moves ahead to the next random-path location, repeating steps 1-4 until the entire grid is filled.

Because all simulated points are valid population selections, they obey the prescribed spatial model, and they honor the hard-data, each simulation can be considered to be an equally valid estimation of the hard data property.

We must recognize that because previously simulated points influence the subsequently simulated values, each choice of random path will necessarily produce a distinctly unique, yet equally valid, realization of the property.

Estimating PHIE from PCA Clusters. So how is an SGS used to estimate PHIE from the PCA cluster index? What is the Cloud Transform and how does it work with SGS?

First, using PCA clusters, let's look at what the "cloud" (cross-plot) looks like. When we cross plot an index-based (categorical) property like our PCA clusters against a continuous variable (like PHIE at the wells), we get a unique kind of "cloud". A hypothetical example is shown in Figure 5a. The figure shows that the cross-plot is really a set of individual univariate PHIE distributions, indexed by cluster value. The point of Figure 5a is to demonstrate that each cluster has its own unique distribution of PHIE values depending on which clusters are penetrated by the well. In fact, for purposes of our study, the "cloud" is really a collection of univariate "clouds", one for each cluster index. Figure 5b shows actual PHIE distributions for the first four (of 50 total) PCA cluster indices used in this study. Note the differences in the histogram character of each of the captured PHIE populations from the clusters. In our study, the use of 50 clusters results in each cluster capturing between 5 and 35 unique effective porosity (PHIE) values from the wells.

We use the unique PHIE distribution statistics for each cluster, in combination with SGS, to produce a suite of realizations of PHIE on the grid. We use SGS to simulate a probability field (p-field)[16] use the p-field to propagate PHIE values. The procedure is shown schematically in Figure 6, and summarized below.

Since we know each cluster has a PHIE probability distribution sampled at the well, this distribution can be expressed in the form of a cumulative density function (CDF) for each cluster. Given this specific relationship, the CDF value and its corresponding PHIE can be used interchangeably (for any given cluster).

If we post the CDF values to the grid as hard-data, we can use these points as hard data and let SGS infill the grid with a continuous field of probability (CDF) values.

The CDF value can be used with the PHIE- at any grid location to recover the appropriate PHIE value at that location by cluster value.

By using this method, each SGS probability realization will always match the well PHIE values. Because PHIE values are selected by CDF, all PHIE values throughout the grid will correctly reflect each PCA cluster's PHIE population as sampled at the wells.

Although SGS is driven by the underlying variogram, our use of this method is not overly sensitive to the variogram model. This is because the final PHIE is more heavily dominated by the PCA-cluster distributions. Because these distributions are for the most part narrow, the simulated value of CDF is of lesser importance to the determination of PHIE than is the cluster membership. But to run SGS we must provide a variogram. For this study we chose to create variograms by modeling the spatial distribution of categorical clusters by dividing them into multiple binary sets. Doing this tends to reinforce the primary fabric of the seismic. The variogram range using this approach was approximately 100 meters in the lateral dimensions (isotropic) and approximately 6 milliseconds in the vertical dimension for all clusters modeled.

Use of the SGS with Cloud Transform allows for multiple realizations of PHIE. Each of the realizations is true to both the hard data and the PCA cluster distribution. Twelve PHIE realizations were created for this study and analyzed probabilistically. A probabalistic treatment of multiple realizations further limits the impact of any specific variogram selection. Discussion and analysis of these results can be found in the "Results" section.

Datasets Used in This Study

Seismic Data. A subset of a large marine 3D seismic survey was used in this study. The data is multi-fold stacked and migrated amplitude traces with modest post stack resolution enhancement processing applied. The survey area is offshore, and was acquired using towed hydrophone array cables and

airgun sources. The data is high signal-to-noise and considered to be of excellent quality over the interval of interest at 1600 to 2000 milliseconds two-way travel time.

The subset of the grid used for this study is sampled areally at 25 X 25 meters and vertically at 2 milliseconds. The studied cube is 73 by 110 cells areally (1.8 km X 2.75 km) and 230 samples vertically for a total of 1.85 million cells.

An example of a vertical "slice" through the seismic amplitude cube can be seen in Figure 4a. The PCA-clustered result of this same slice is shown in Figure 4b.

Fluid/Hydrocarbon effects. Amplitude anomalies associated with both free gas and light oil in the sandstone sections can be observed within the data. These effects show up as high amplitude values on the right side of the amplitudes at the contacts (right side, Figure 4a). The presence of hydrocarbon related amplitude effects presents a problem for conventional attribute analysis, in that PHIE generally varies independently of hydrocarbon saturation. A characterization of PHIE that is affected by hydrocarbon saturation can be typically unreliable. Our results using PCA clusters seem to be largely unaffected by these hydrocarbon anomalies thanks to the calibration method that is used (see discussion in Results section).

Time to Depth: Alignment of the wells with the seismic. In this study, we choose to do all of our reservoir property estimation on a cube and well data that is in the time domain, however many workers prefer to convert the seismic to depth first in order to keep the hard-data at the wells in depth. Regardless of whether the analysis is done in depth or time, careful attention must be paid to getting proper alignment between wells and seismic when performing seismic attribute calibration.

Getting the proper well alignment may be the single most important and challenging element of using seismic attribute data to predict detailed reservoir properties. This is because even minor misalignments between the wells and the seismic can produce significant degradation of the seismic attribute to well data calibration. This is true regardless of what attribute or method is used. It is necessary that one repeatedly evaluate the quality of the time to depth transform at the wells in an effort to reach perfection.

In this study we use a two-phase approach for tying the wells to the seismic.

First we create a detailed layer-based velocity model based on measured well and seismic velocities. The methods employed in this step are beyond the scope of this paper, but the purpose of this first velocity solution is to provide an initial conversion of the well-depths to seismic times.

Secondly, we perform a property estimation using the flow described in the "Methods:.." sections above, without conditioning to the well data. We follow this with a cross correlation of the multiple PHIE estimations to the actual well values. By cross correlating we can determine whether any vertical shifts are required in order to produce a better fit between the wells and the seismic. If an appropriate shift is required, the estimation and cross-correlation steps can be rerun to verify the higher correlation. These steps may be repeated until a zero shift is verified.

Using this method, we determined that a -8 millisecond shift is required (wells move down 8 ms, relative to the seismic). Our final analysis is based on the use of the shifted well data.

Well Data. The well data consists of three wells. The wells contain mixed lithologies consisting of sands and shales from a deep-water turbidite depositional system. Many of the sands are highly localized in channels and tend to terminate abruptly against bounding shales. The highest porosity, most productive, oil sands are thought to be located within the channels, so a major objective of this study is to identify the lateral limits of all sands and estimate each sand's effective porosity (PHIE). PHIE curves are known for all wells indicating effective porosities ranging from 5% to over 40%. A sand-shale cutoff of 15% has been established based on petrophysical analysis of core. We will use this threshold to differentiate between predictions of shale and predictions of sand in our results.

Results

Analysis of multiple simulated PHIE Estimates. SGS with Cloud transform was used to create twelve distinct volumes of PHIE values. The following points apply to all.

1. Each PHIE volume exactly ties the PHIE values at the wells used as hard data.
2. Each PHIE volume uses a single set of PHIE-CDF, cluster-specific relationships from the wells to constrain the PHIE values.

The twelve estimated PHIE realizations allow us to perform probabalistic analysis of all PHIE estimates. By this, we mean that we can observe all PHIE estimates at each and every cell and determine the probability for each cell's PHIE falling within specified range of values.

Probability of exceedance. This form of analysis is called probability of exceedance. It's utility can be summarized in the following example:

The wells used in this study have an effective shale-sand cutoff 15% (PHIE). If we compute the probability that all realizations will exceed 15% using all twelve realizations, we will find that some cells will exceed 15% in more than 50% of the realizations, and the remainder of the realizations will not. Identifying the cells that exceed and those that don't, yields a sand-shale indicator flag. The result of doing this on the studied dataset is shown in Figure 7a in relation to one of the studied wells. The black areas in Figure 7a are identified as most probably sand. The white areas are most probably shale.

Having a number of realizations allows one to compute the mean value of all PHIE realizations on each cell. Although averaging PHIE realizations tends to narrow the overall distribution, it is useful to see the relative spatial distribution of high and low values. The mean PHIE results for all realizations are shown in Figure 7b at the same section

location as Figure 7a. For comparison, the amplitude data for this vertical section is displayed in Figure 8a along with the PCA clusters (Figure 8b).

Geologic features. Overall, the results are consistent with the known geology. Sands throughout the cube are expected to be localized in channels, like those sampled by the wells. This arrangement is what is dominantly observed in the PHIE realizations. The probabalistic summary of the realizations also predicts that one may find some sands that are arranged in more laterally-continuos layers but have not been penetrated by the well control.

The channel-like plan view distribution of the majority of the predicted sands can be observed in horizontal grid slices of the predicted-sand flag. A horizontal slice is shown in Figure 9a. The amplitude slice from the same location is shown in Figure 9b. Although the form of the channel can be seen in the amplitude slice (Figure 9b), the probability of exceedance sand indicator clearly defines the high sand abundance within the channel and its detailed distribution, within the channel. Although the shape of the channel is apparent from the amplitude slice (Figure 9b), there is no way to use this to predict the sand/no-sand distribution. The sand distribution is clearly shown in Figure 9a.

Fluid/Hydrocarbon effects. The results shown in Figure 7 serve to demonstrate the strength of our technique with regard to filtering of unwanted amplitude effects caused by variations in hydrocarbons. Most of the highest amplitudes seen in Figure 8a result from gas saturation in the sands at the top of the section or from oil saturation in the sands in the middle part of the section. Comparing Figures 7a and 8a visually may lead one to conclude that there is a systemic relationship between high amplitude values (Figure 8a) and sand indicator (Figure 7a). Although this appears to be the case, the calibrated clusters have the capability to exclude high amplitude when the entire PCA signature is not indicative of high PHIE. A good example of this is shown in the top quarter of the well in Figure 8a. In this location there is a “pod” of high amplitude (strong white over black---high energy) of which only the lower part calibrates to sand. Similarly, just this hgh amplitude is a zone of very low amplitude (grey—low energy), and this zone calibrates to mostly same. Because PCA cluster calibration step serves to evaluate all common PCA clusters with the appropriate distribution of PHIE values, no matter what the amplitude is, the method effectively filters against high amplitudes that correlate with anything other than high PHIE. The richness of the signal after PCA yields enough independent PC “attributes” such that subtle differences in signal attributable are identified. These subtle characteristic changes may correspond to fluid or rock property differences that can be selectively culled by the calibration step (cloud transform). The strength of separation of effects corresponding directly to rock/fluid/pressure properties affecting the signal has not yet been fully investigated.

In this study, the cross-validation seems to completely remove the gas effect. The oil-to-water transition is still partially visible, however (lower-most flat event in Figures 7 and 8). This filtering behavior may or may not be enabled in all rock types using our method, but this is not known at this time.

Calibration of other properties is possible using the same dataset and method. For example, if our objective was to predict fluid type and saturation, one could simply revise the calibration step, by changing the cloud transform scatter data to collect, the saturations, cluster by cluster, at the wells. Such a saturation-CDF could then be used in the cloud transform step and evaluated for accuracy. We have not yet attempted a saturation prediction with this dataset.

Cross Validation. We use a technique called cross-validation to objectively evaluate our true PHIE predictive accuracy at the wells. Cross validation involves the removal of a well from the “hard” data set followed prediction (in the absence of the withheld well) using SGS with Cloud Transform. The results of PHIE realizations are then evaluated against the well that was withheld resulting in a blind prediction of the withheld well PHIE.

We performed three complete cross validation tests consisting of three realizations each for each well. In each of the cross-validation tests, a different well was removed and then compared for accuracy of prediction.

The results of the cross-validation predictions are shown in Figure 10 a, b, and c. These displays show from left to right:

1. The original seismic trace.
2. The distribution of PCA cluster values.
3. The actual PHIE value at the well.
4. The blind predictions (mean of 3 realizations, then the actual realizations).

The curves in Figure 10 indicate that the PHIE predictions from PCA clusters accurately reproduce the known PHIE distributions observed in the well. There is good agreement between the predicted and actual positions of major shales and the overall sand-to-shale ratios. It is easy to correlate likely stratigraphic markers between well and predicted PHIE curves (gray correlation lines in Figure 10). It seems reasonable to assume that the difference in thickness of the well versus the seismic shale breaks (measured by the tilt of the correlation markers) may result from an incorrect estimate of well velocity function. Correction of the velocity inconsistencies followed by rerunning of the analysis would probably further improve these PHIE predictions.

Conclusions

The results reported here indicate that the procedure that we have outlined is an effective PHIE prediction methodology, at least when applied to the channelized turbidite sands in our study area.

The methods strength lies in the fact that it captures all relevant seismic character in a suite of mutually independent attributes (PC’s). The most information-rich of these PC’s are

used to classify the signal into diagnostic clusters that are easily calibrated using SGS with cloud transform.

The method performs well in cross-validation tests, by accurately predicting distributions and accurate values of PHIE, thereby allowing detailed 3D description of the lithology distributions.

Our results could probably be further improved, by refining the velocity functions used to create time-to-depth functions for the well data set used with in the analysis.

We feel that these results are sufficiently robust so as to suggest that the method may have general applicability to other areas, potentially even quite different lithologies than those tested here.

Ongoing research will continue to focus on methods for optimizing the selection of input parameters for the PCA analysis, including variance cutoff, sampling window size, and number of PCA clusters for general application.

Nomenclature

PCA = Principal Component Analysis
PC = Principal Components
PHIE = Effective Porosity
CDF = Cumulative density function
PDF = Probability density function
SGS = Sequential Gaussian Simulation

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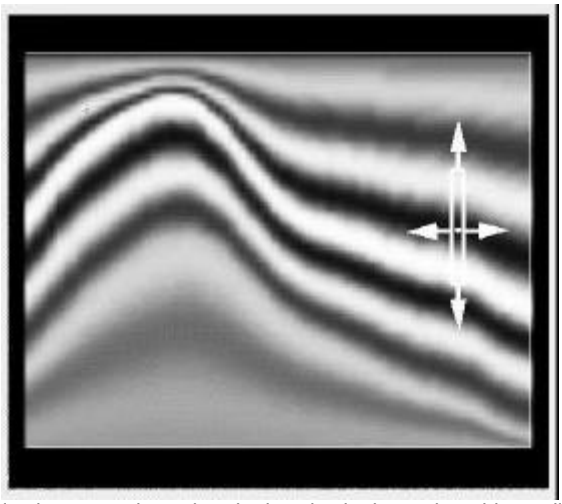
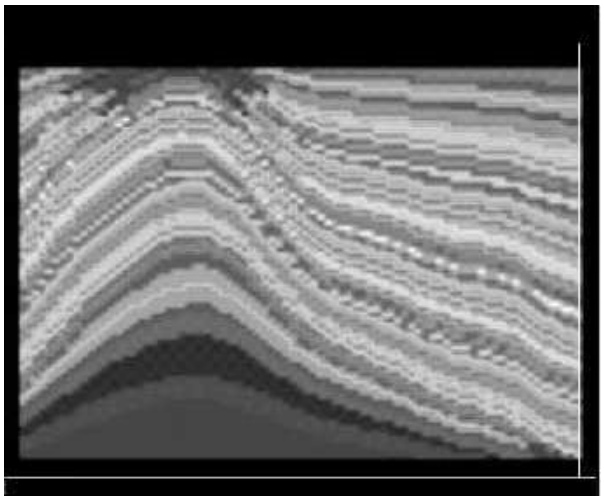


Figure 1. Example of Sampling window on Seismic Data Volume (synthetic seismic dataset). White outline represents typical sampling window, which captures many samples from the underlying data cube. Arrows indicate that the sampling window moves in all directions to sample many valid windows within the data cube. The white dot represents the reference point for the window. All window-derived data is posted to that window's reference point.

a. 

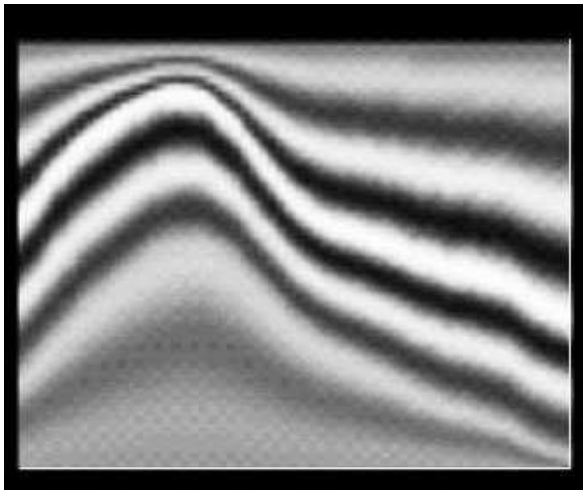
b. 

Figure 2. a)PCA cluster index property (synthetic seismic dataset). 40 clusters are chosen. The gray scale is randomly distributed according to cluster index. The cluster index has no numerical significance, except to serve as a "tag" for each cluster. b) Amplitude section from which the PCA clusters in a) were derived.

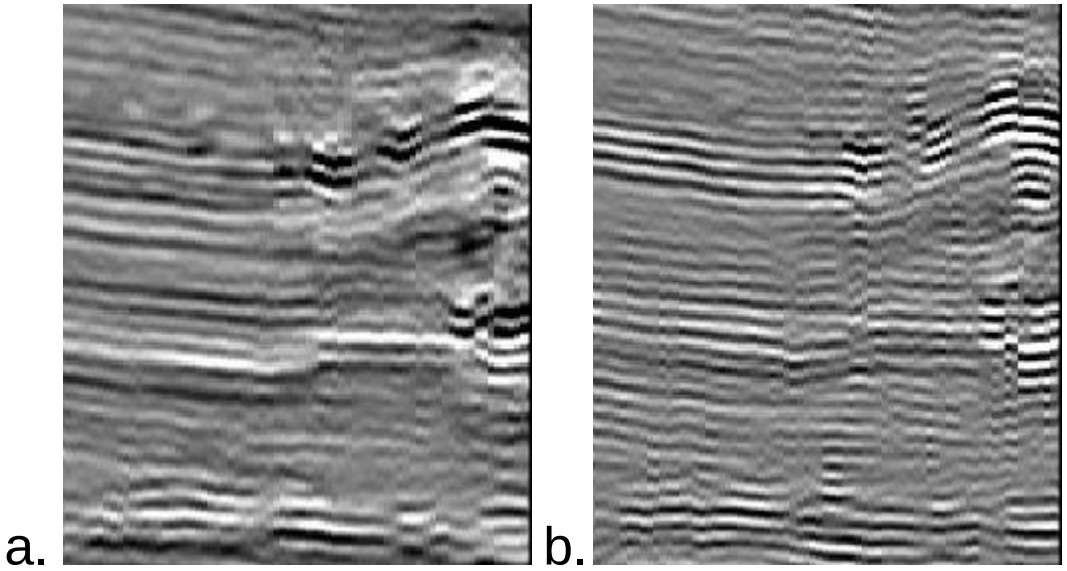


Figure 3. a)Example of desirable PC characteristics (from this study's seismic dataset). Desirable characteristics include localized vertical features and diverse reflection character. b) Example of undesirable character for a PC's. Undesirable characteristics include signal dominated by a narrow frequency bandwidth (commonly called ringing), and a non-localized or non-diverse reflection character.

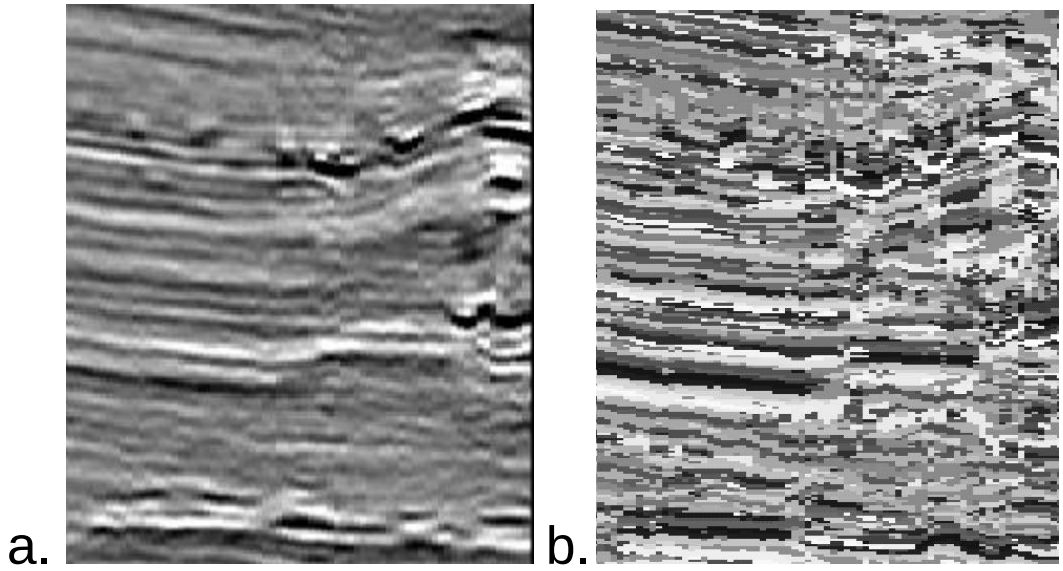


Figure 4. a) An example of vertical a line of section from the seismic amplitudes from the studied 3D survey. The sand-channel dominated part of the section is on the right side of the image. Channels trend in and out of the page. b) Example of PCA clusters (50 clusters). The cluster index has no numerical significance, except to serve as a "tag" for each cluster.

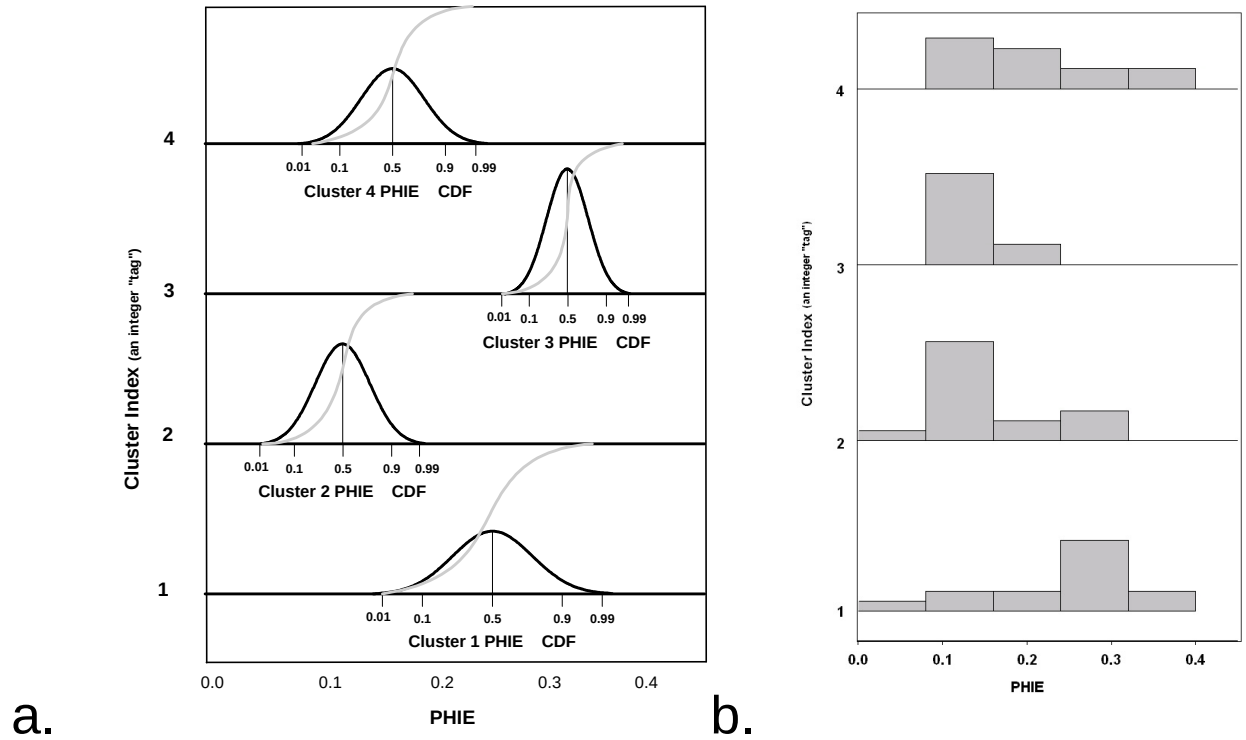


Figure 5. a) Hypothetical "cloud" cross-plot of categorical PCA cluster vs. PHIE. Note that each PCA cluster has its own unique distribution of co-located PHIE values. The cumulative density function CDF (gray curve, and number scale) for each cluster constrains the probability of selected values that can be distributed to the grid where that cluster is present. b) Actual PHIE PDF distribution "clouds" for clusters 1-4 (of 50, total) from this study dataset. Note the differences in the distributions between clusters. The tighter the distribution of each cluster, the stronger the influence of the seismic on the final computed PHIE results.

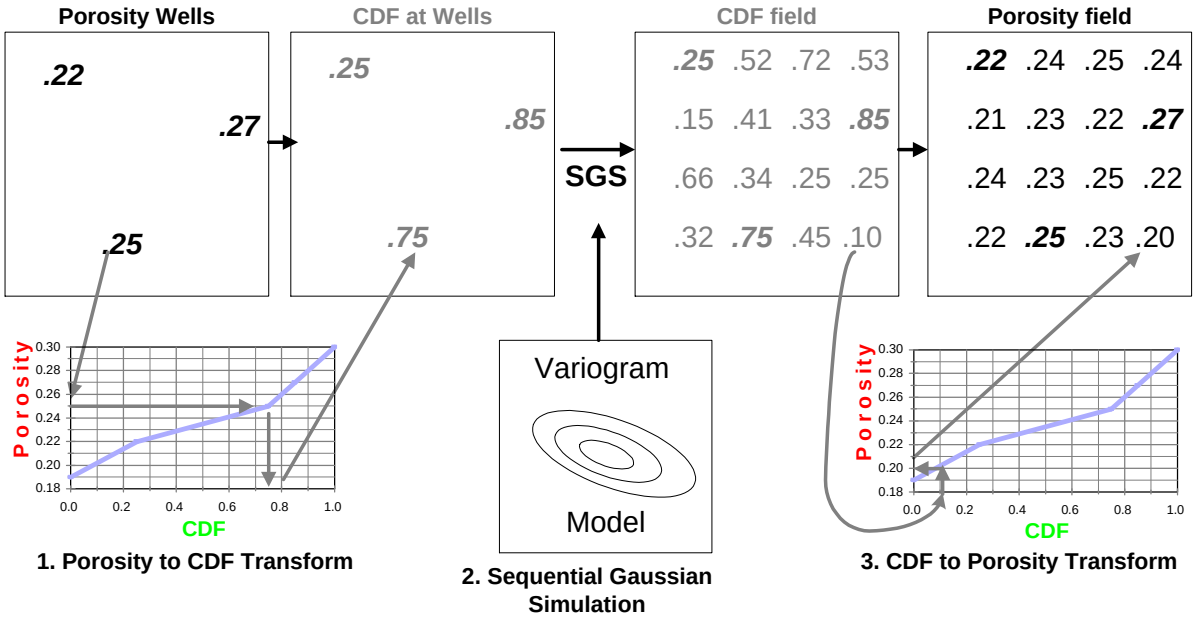


Figure 6. Simulation of porosity based on Sequential Gaussian Simulation (SGS) of the underlying CDF (probability) field. The Cumulative density function is used as the key to transforming the PHIE value to CDF (lower left) and later transforming the Simulated CDF value back to PHIE (lower right). SGS is used to fill in the grid with CDF values, based on the CDF values from the "hard" data at the wells.

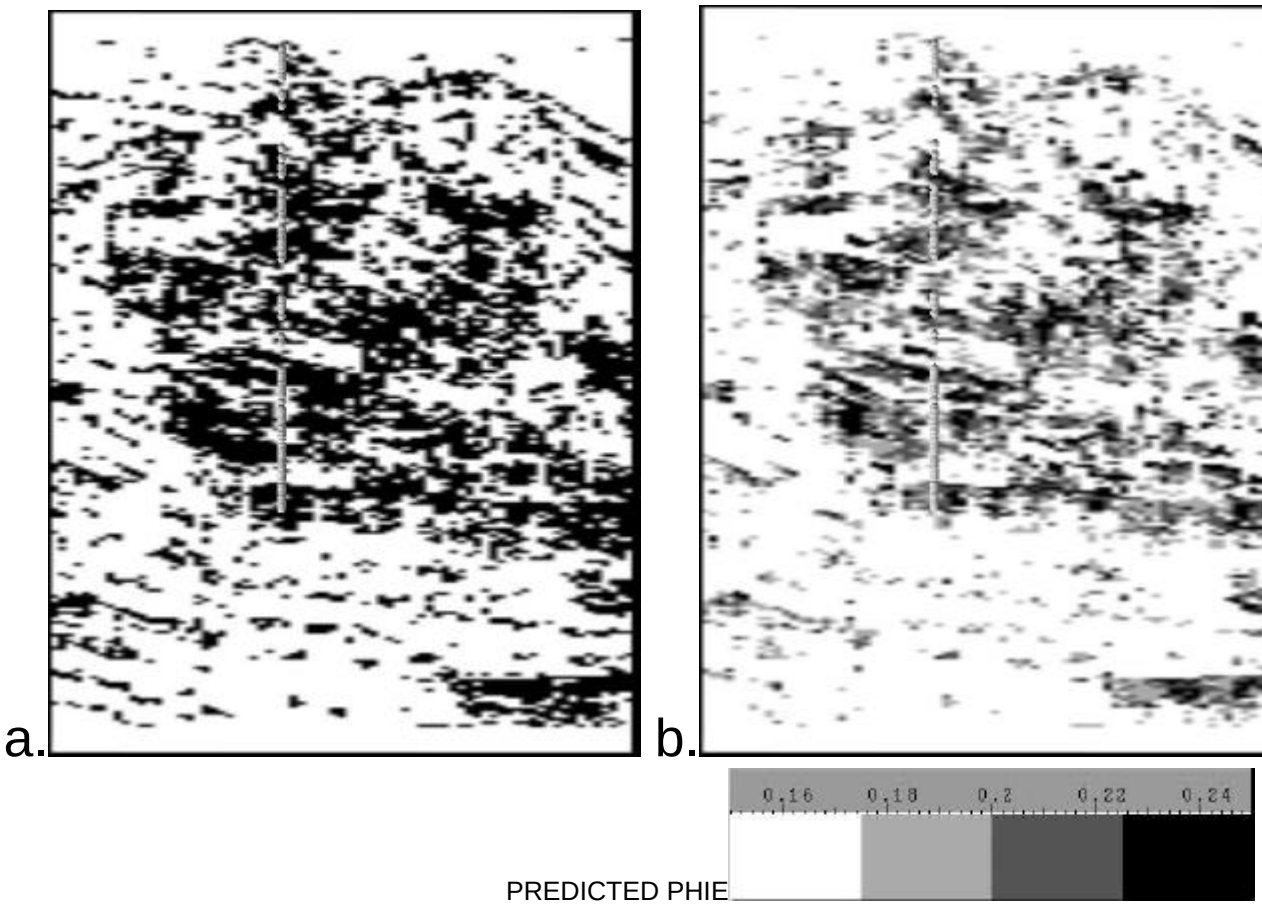


Figure 7. a) Sand indicator on vertical seismic section. The indicator was computed by finding when 50% or more of the PHIE realizations exceeds the shale cutoff of 15% PHIE (black). b) Average PHIE from the first three realizations shown on the same section displayed in a. PHIE scale is shown. Small gray spheres are shown along the wellbore indicating the presence of sand in the well. The vertical gray bar at the right is approximately 250 milliseconds or about 1000 feet (300 meters).

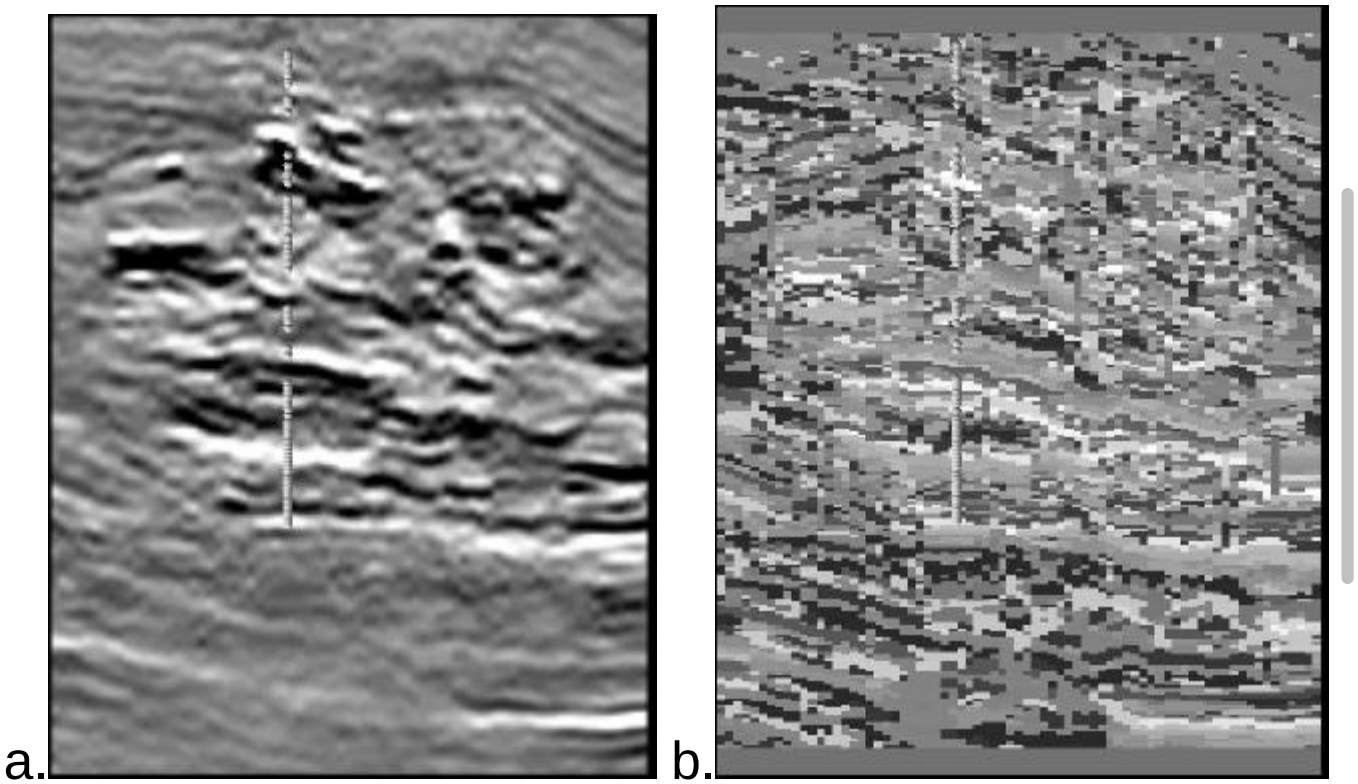


Figure 8. a) Amplitude of the original Amplitude property on the same section shown in Figure 7. b)The PCA cluster data from the same slice in a. and in figure 7. The well data display is the same as that in Figure 7. The vertical bar is approximately 250 milliseconds or about 1000 feet (300 meters).

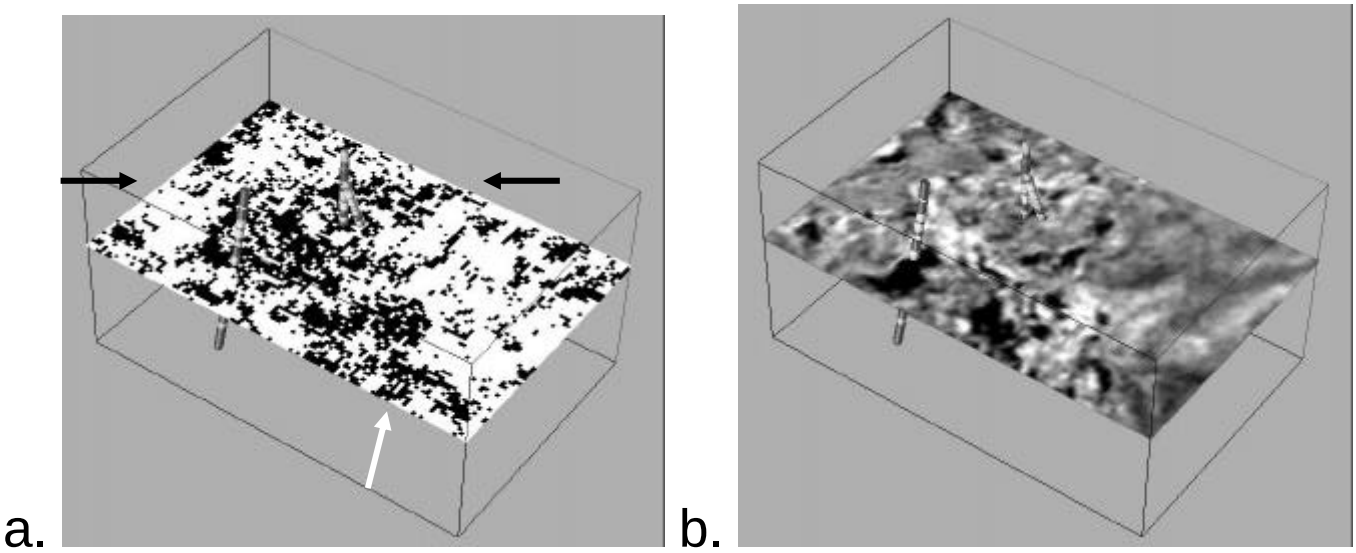
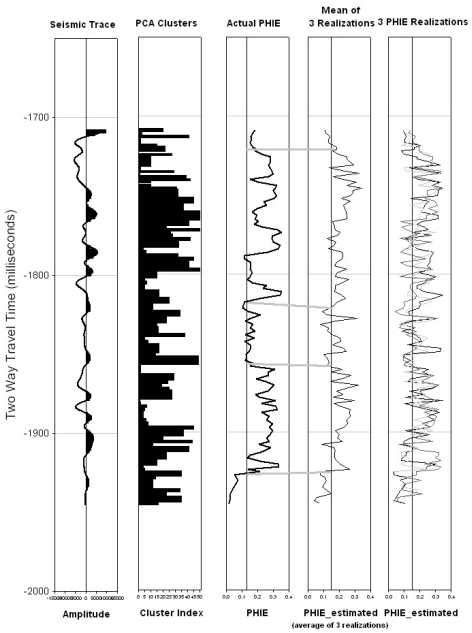
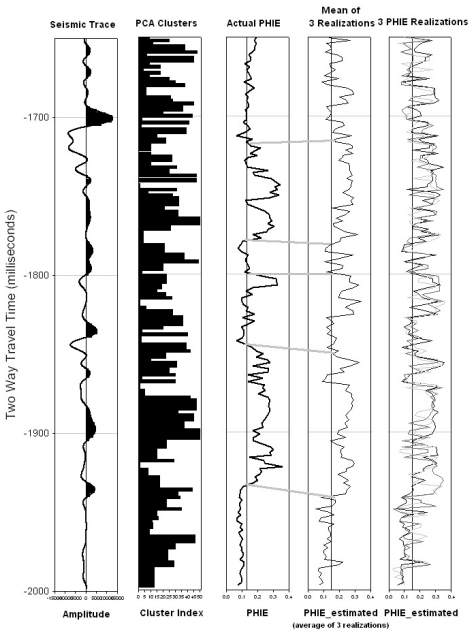


Figure 9.a) Probability of exceedance based Sand indicator (Sands are black, shales are white), shown on a horizontal slice through the cube. Note the meandering channel character starting in the lower-central corner of the slice (white arrow) and continuing upward and to the left. The termination in the upper third of this slice is due to fault truncation. The fault runs horizontal across the view (between the black arrows). The three control wells are shown in multi-gray tones penetrating the horizontal slice. b) Amplitude slice of the data on the same slice as shown in a) for comparison.



a.



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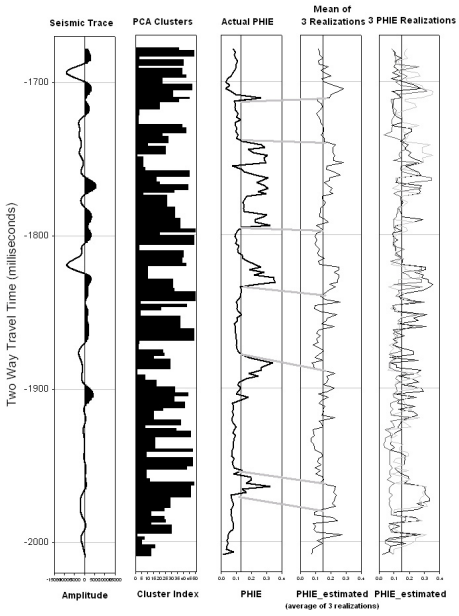

c.

Figure 10. Graphs displaying (from left to right): Amplitude trace, PCA Cluster index, Actual PHIE (well data), Mean of 3 PHIE realizations from SGS with Cloud Transform, and three realizations of PHIE from SGS with Cloud Transform. The vertical reference line on the PHIE graphs represents 15% PHIE (Shale cutoff). Results are shown for a) Well 1, b) Well 2, and c) Well 3. All PHIE realizations were performed using cross-validation. The subhorizontal gray lines highlight likely correlating stratigraphic breaks on the predicted and actual PHIE curves.