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Stochastic seismic inversion & probabilistic estimate of reservoir facies - a case study from Upper Assam basin

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Summary

Assam-Arakan Basin, situated in north-east part of India is a proven sedimentary basin and several hydrocarbon fields are discovered historically in this region. The study area is in central basement high of the basin over a producing hydrocarbon field (Figure-01). This field was discovered during 1990s and Oligocene formation is the main producer along with Eocene formation. Presently, major contribution of hydrocarbon production of Upper Assam Basin comes from this field. The optimal exploitation of reservoir in cost effective fashion requires detailed understanding of distribution of pay sands and reservoir characteristics.

In order to understand the reservoir characteristic, extension and distribution of pay sands, knowledge of elastic attributes plays a vital role. Seismic inversion is a potent technique that aims to extract the elastic attributes from seismic data. Historically, all the inversion algorithms works in deterministic, and provides average impedance volumes; however, stochastic inversion algorithm uses well data (Variogram) to produce high resolution (beyond seismic bandwidth) impedance volumes. These inverted impedance volumes, on incorporation with well data provide detailed reservoir description in terms litho-type & fluid-type present.

Conventional methods of litho-type & fluid-type classification by defining the polygons in cross-plot space of elastic attributes uses sharp cut-offs, which is not always true in nature.

Supervised Bayesian classification is an alternate approach for facies classification, which is based on kernel techniques for multi-dimensional PDF computation. It produces a series of litho-probability cubes along with most probable facies volume, which gives us the not only extension & distribution of reservoirs, but also indicates probability of predicted facies. It is observed that the derived litho-facies provide a better understanding of reservoir extension & distribution of Oligocene reservoirs across the field in a probabilistic manner; and hence minimizes the risk of drilling dry wells.

Stochastic Inversion

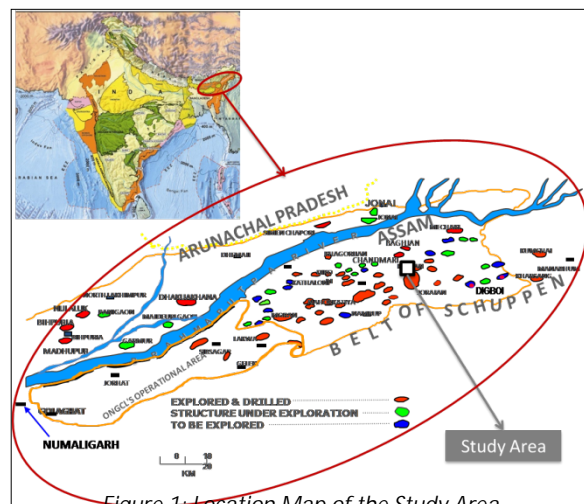


Figure 1: Location Map of the Study Area

Inversion techniques to estimate impedance from seismic are conventionally based on minimization of error between the forward convolution of the reflectivity from a prior impedance model and the seismic amplitudes. These inversion schemes are commonly referred as ‘deterministic’ inversion, and produces average impedance of the many possible non-unique solutions. In the stochastic considerations each non-unique solutions is referred is an individual realization with associated uncertainty. Stochastic inversion produces many possible, plausible solutions which average to the deterministic solution. In stochastic inversion, partial angle stacks are used along with the well logs for inversion. Based on well logs & comparison of synthetic partial stacks with the observed seismic, uncertainties & allowable deviation in inverted properties is

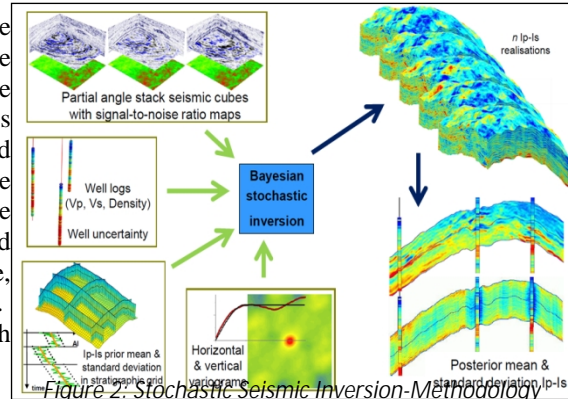
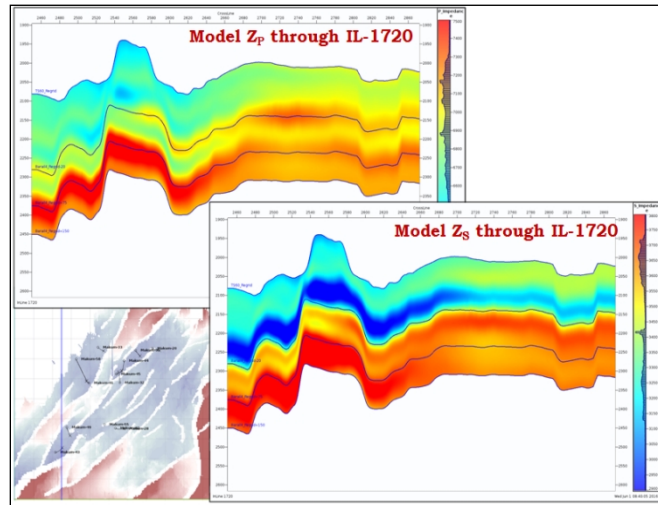
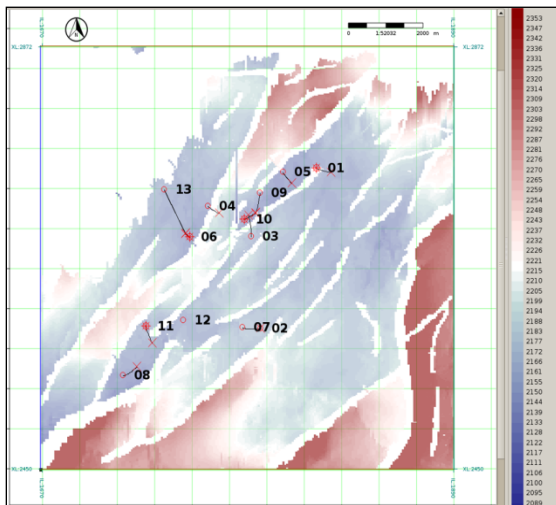


Figure 2: Stochastic Seismic Inversion Methodology

decided as hard constraint during Bayesian stochastic inversion. Horizontal and Vertical variogram are defined based on characteristics of seismic & well data. The working methodology /algorithm of stochastic inversion are illustrated in **Figure-02**.

In this present study, 3D seismic data over the field is inverted for acoustic impedance (Z_P), shear-impedance (Z_S) and V_P/V_S . First, an initial model has been constructed using 13 wells and key seismic horizons in the study area (**Figure-03**). The layer based gridding operation using Kriging method is performed for 3 macro layers (above reservoir, reservoir & below reservoir) are defined. Cross-section of finalized prior model through one in-line is shown in **Figure-04**.



Three partial stacks for near (30°-14°), mid (14°-25°) & far (25°-36°) is created by stacking angle gathers within respective incident angle ranges. The corresponding statistical (zero phase) wavelet is extracted for each of the partial angle stacks using 128 msec for wavelet length. The extracted statistical wavelets are upscaled using scaling operators calculated from initial model for each of the wavelets (**Figure-05**).

During stochastic inversion, a predefined deviation for Z_P and Z_S is used as hard constraint. In order to optimize deviation, synthetic seismic (near, mid & far angle stacks) is generated using scaled wavelets and compared with the observed seismic. Based on the average correlation between Z_P & Z_S at wells; deviation for Z_P & Z_S is optimized as 10 % & 12 % respectively, while uncertainty for seismic is optimized as 10 %, and for wells 5 % uncertainty is optimized.

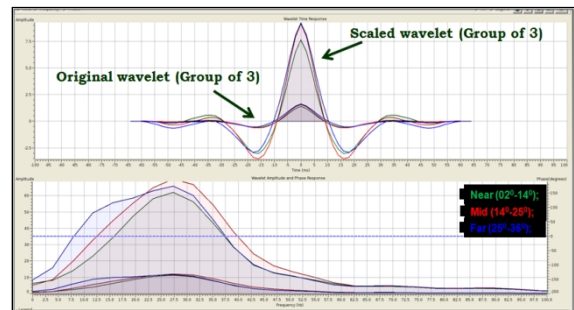


Figure 5: Scaled Seismic Wavelet

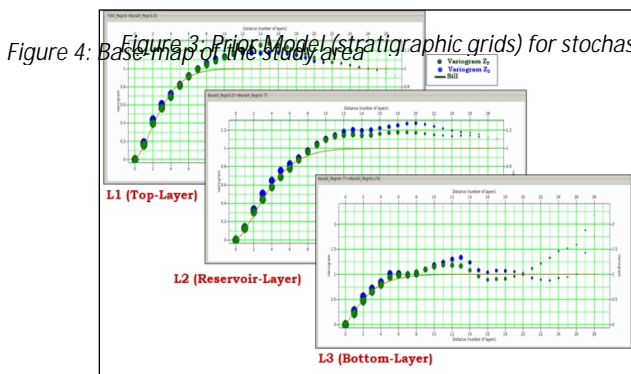


Figure 6: Vertical Variogram for each macro layer

During stochastic-inversion, variogram guides the property extension in vertical & horizontal directions. It is a critical parameter and largely influences the stochastic inversion results. After rigorous testing, number of layers and Alpha factor for vertical variogram are optimized as (07, 1.5), (09, 1.5) & (07, 1.2) respectively for the individual micro layers (**Figure-06**). The analysis of lateral continuity of structures in seismic amplitude maps concludes the range of horizontal variogram as 1500m.

A good concurrence among the inverted results and measured properties (Z_P , Z_S & V_P/V_S); and synthetic partial stacks & observed seismic is observed at the well locations (**Figure-07**). The results of stochastic inversion along In-line & cross-line passing through well-06 are shown in **Figure-08**.

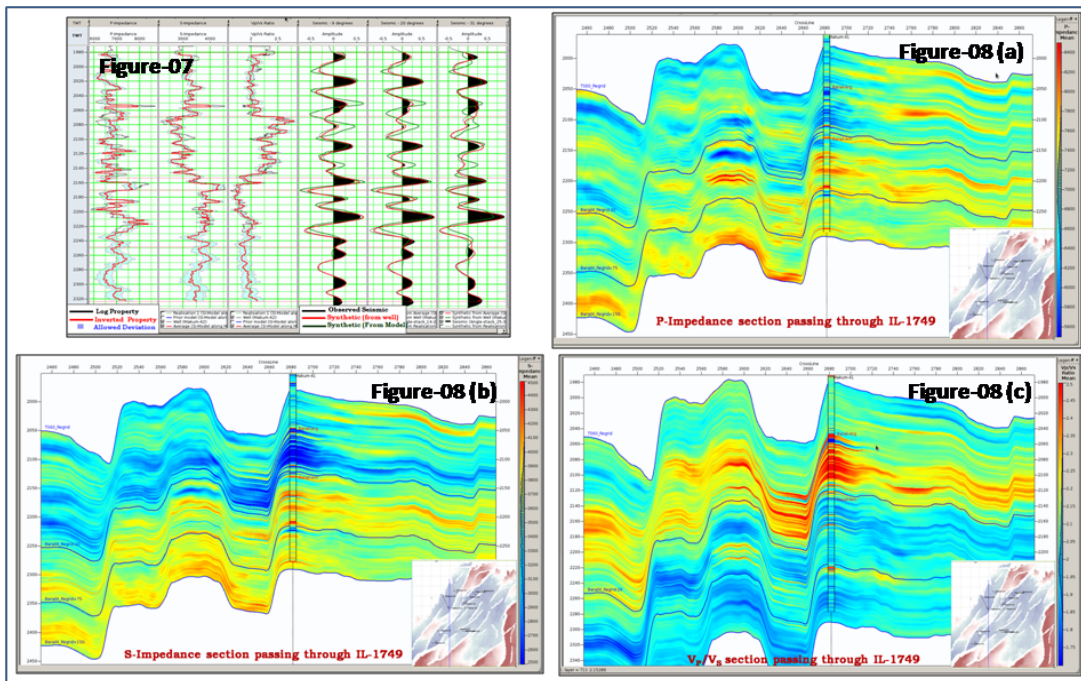


Figure 7: Inversion QC at well 06; Figure 8: Inversion results at Inline passing through well-06

Litho-facies Classification

The inverted elastic properties (Z_P , & V_P/V_S volumes) are further used for facies classification using Supervised Bayesian approach. This method is based on kernel techniques for multi-dimensional PDF computation. It produces a series of litho-probability cubes along with most probable facies volume, which gives us the not only extension & distribution of reservoirs, but also indicates probability of predicted facies. The detailed methodology/algorithm of supervised Bayesian classification approach for litho-facies classification is illustrated in Figure-09.

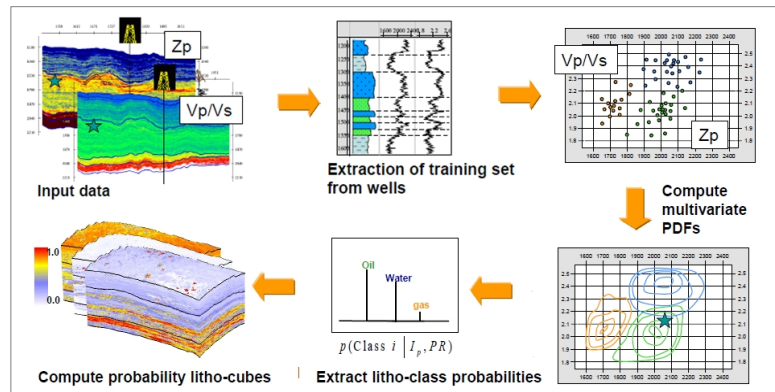


Figure 9: Facies classification using Supervised Bayesian approach

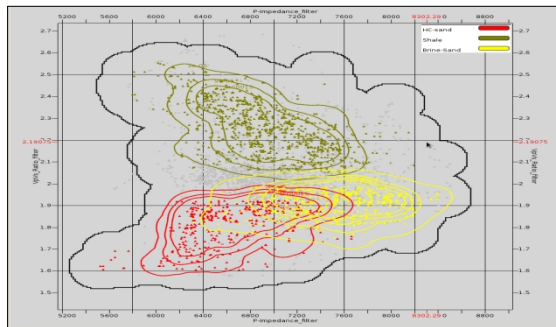


Figure 10: PDF definition for individual Facies

The cross-plot analysis of well-log data indicates that P-Impedance and V_P/V_S together are very sensitive to the reservoir characteristics & provide a good separation among the three facies viz. shale, brine-sand & hydrocarbon-sand. First, litho-log for each facies is created at using the zone definition in P-Impedance vs. V_P/V_S cross-plot space. These lithofacies are used as training dataset and probability distribution is calculated using histograms of individual facies (Figure-10).

In order to QC the PDFs, these PDFs are applied to individual logs, and classified facies is created. The classified facies were compared with the original facies wells and a good match is observed between the classified & original facies. In order to analyze the efficacy of defined PDFs for accurate classification, confusion matrix at well location were analyzed. It is observed that, at most of the wells the PDFs are able to predict facies accurately, with very less no. of mis-classified samples. The QC section for classified & original facies along with confusion matrix is shown in Figure-11. The finalized PDFs are applied on the volume using Z_P & V_P/V_S volumes (derived after stochastic inversion). The individual PDFs creates the probability volumes for each of lithofacies i.e. shale brine-sand hydrocarbon-sand. On the basis of probability volumes for each facies, volume of most probable facies is derived. A cross section of probability cubes (for shale, brine-sand hydrocarbon-sand) along with most probable facies passing through In-line 1749 is shown in Figure 11.

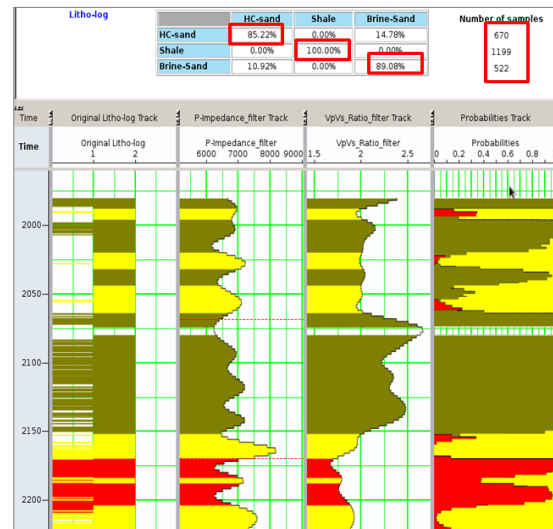


Figure 11: PDF derived facies with original log facies

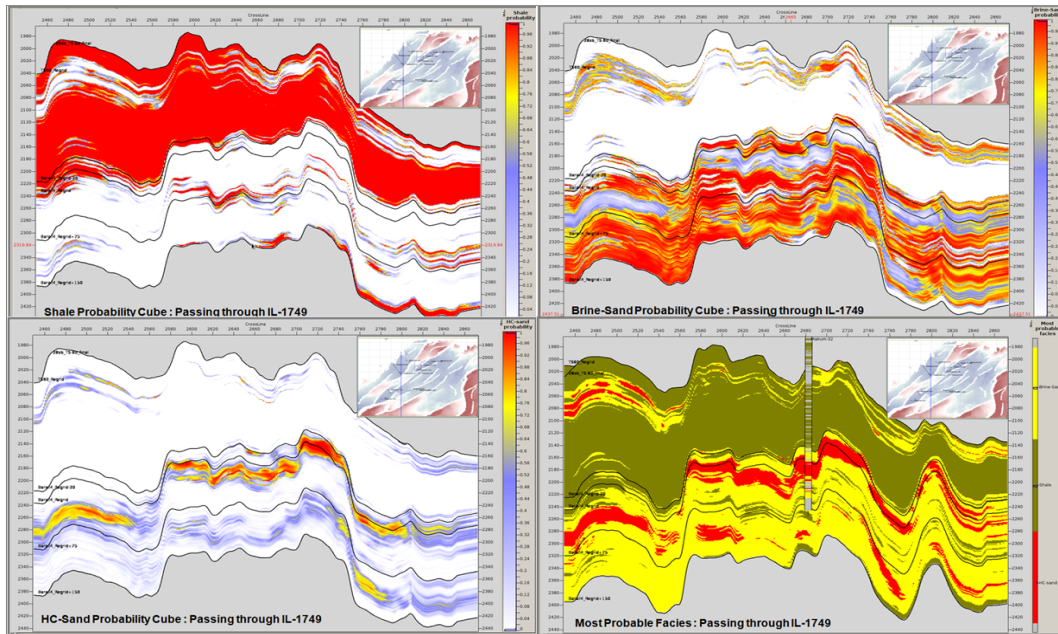


Figure 12: cross section of probability cubes (for shale, brine-sand hydrocarbon-sand) along with most probable facies

Results and Discussions

Elastic attributes on incorporation with well provides greater understanding the extension & distribution of sand along with its fluid content. Stochastic seismic inversion enables the accurate and high resolution elastic attributes. Lithofacies classification using the estimated elastic attributes based on kernel techniques for multi-dimensional PDF computation provided the probabilistic estimates of shale, brine-sand hydrocarbon-sand facies in the reservoir. It is envisaged that the lithofacies cubes of the individual facies aids value n providing a better insight not only in terms of understanding the reservoir extension & distribution but also probabilistic approach of decision making of drilling successful wells.

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