Uncertainty quantification in seismic reservoir characterization using geostatistical inversion

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ABSTRACT

Identifying and mapping of lithology or facies from inversion of seismic reflection data often encounters severe challenges due to overlapping elastic properties, especially data at different sampling rates. Probabilistic interpretation of elastic attributes derived from deterministic inversion based on Bayesian inference, provides a framework for quantification of the associated uncertainties in facies discrimination. In geostatistical inversion workflows, Bayesian inference, prior information with likelihood functions generate posterior probability density functions (pdfs). This facilitates experimenting with the two components of uncertainty, namely, bias and variance. By ranking multiple equiprobable realizations using suitable local criterion, it becomes possible to quantitatively measure uncertainty. Real-data examples from Gulf of Mexico, Gulf of Thailand, Malay Basin and Cooper-Eromanga Basin, Australia have been used to illustrate the process of uncertainty quantification in seismic reservoir characterization using deterministic and geostatistical inversion.

KEYWORDS

Uncertainty quantification, Bayesian inference, risk assessment, reservoir characterization

INTRODUCTION

In the context of hydrocarbon exploration and development, reservoir characterization refers to the determination of physical properties, such as porosity, permeability and water saturation, and their lateral and vertical distribution during the life cycle of one or more reservoirs in an oil or gas field. This process begins with the discovery of a field and continues through its development, production and eventual decline. A reservoir characterization study forms a crucial part of development of a predictive model of the subsurface reservoir. It is built by integrating multi-disciplinary data, often having different scales and resolutions. Ideally, a unified model of the reservoir should reconcile all available data - both surface and sub-surface. Surface data typically includes seismic reflection data, while subsurface data comprises borehole logs, core samples, drill cuttings and formation test results. This task of unified model building, though appears to be simple, is quite challenging. In practice, several reservoir models, e.g., petro-elastic model, geo-mechanical model, static and dynamic models etc. are built during various phases in the lifetime of an oil/gas field to meet different objectives.

Surface seismic data plays a crucial role in reservoir modeling due to their dense spatial coverage and relatively lower cost compared to drilling and subsurface measurements. Despite being band-limited, seismic reflection data provide valuable information about subsurface interfaces between layers with different elastic properties—namely P-wave velocity (V_P), S-wave velocity (V_S), and density (ρ). These seismic reflection data are transformed into subsurface layer properties through seismic inversion which formulates the problem as that of optimization in inverse theory. Current industry practices involve inverting both post-stack and pre-stack seismic data using two main types of tools, namely, deterministic and geostatistical inversion methods. While inversion of post-stack seismic data yields acoustic impedance of the subsurface layers consisting of the reservoir as well as the non-reservoir intervals, inversion of pre-stack data or simultaneous inversion of multiple offset/angle stacks yields the P-impedance, S-impedance, and density of these layers. It also enables the derivation of alternative subsurface elastic properties such as the ratio of velocities of P-wave and S-wave (V_P/V_S), Poisson's ratio (σ), Lambda-rho (λρ), Mu-rho (μρ). Deterministic inversion yields single model of elastic properties with resolution limited by the maximum frequency content of the seismic data, geostatistical inversion provides with highly detailed multiple realizations of the same properties. The choice of the data, whether post-stack or pre-stack as well as the choice of inversion tool, i.e., deterministic or geostatistical inversion is generally determined by the objective of the study and availability of data (Latimer et al., 2000).

Deriving an accurate subsurface model, whether elastic, petrophysical, or engineering, is one of key objectives of

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seismic inversion. This process involves integration of different data sets, e.g., measurements from wells, seismic amplitude, structural and stratigraphic interpretations and the depositional setup. As a result, the inversion model typically contains many unknown parameters, often exhibiting strong non-linear relations with the data. Thus, it is extremely challenging to build a single model that accurately captures all the information required for reservoir characterization. The limitations of available data including inaccuracies, insufficiencies, and inherent ambiguities, compound this challenge. The impact of such limitations on geophysical interpretation has long been discussed in the geophysical literature (Jackson, 1972). With multiple models, that can predict the observed data, one can provide a range of solutions to capture various possibilities in real field situations. In simpler words we can say that there is no single model which can explain all these disparate data perfectly. This gives rise to the notion of *uncertainty*.

To illustrate this, we present one real-world example from the Gulf of Mexico, demonstrating how Bayesian inference can be applied to quantify uncertainty in interpretation of deterministic inversion results. Further, we present two examples, one from Gulf of Thailand and the other from Cooper-Eromanga Basin, Australia covering exploration and development of oil/gas fields to elucidate how uncertainty quantification can be carried out using results from geostatistical inversion.

UNCERTAINTY

Uncertainty refers to the lack of surety about something, e.g., occurrence of some event, physical phenomenon, etc. All natural processes have some inherent randomness, whether big or small, leading to uncertainty in its prediction. Moreover, poor understanding of the nature of the process, approximations and assumptions in the model, noise in data and experimental errors, etc. contribute significantly to the overall uncertainty. Thus, uncertainty may be described by its two components, namely, variance and bias. Variance arises from some degree of randomness in the underlying processes. It is often called aleatory uncertainty or irreducible uncertainty in literature. Bias, on the other hand, consists of knowledge uncertainty such as lack of measured data, approximation of models and assumptions made to simplify complex models. This form of uncertainty is reducible if we have better quality data, sufficient data, more accurate models, and better understanding of the physics/mathematics of the problem and geology. Though bias constitutes the major component of total uncertainty, it is commonly neglected while assessing uncertainty.

Consider the problem of estimating lithology or facies from inversion of seismic amplitude or AVO, as an example. Both deterministic inversion and geostatistical inversion rely on Bayesian inference, but they differ in how they apply this principle within their workflows. In deterministic inversion, the inverted elastic properties are used as input to Bayes' theorem (equation 2) to estimate the posterior probability of expected lithology. Thus, Bayes theorem is used posterior to deterministic inversion to estimate probabilities of different lithologies. However, due to limitation in resolution of deterministic inversion results, the uncertainty in lithology discrimination, caused by the overlap of elastic properties, may pose challenges to map thin layers. Geostatistical inversion, on the other hand, provides a framework to integrate all available information from varied sources, e.g., wells, seismic interpretation, rock physics, geology and stratigraphy etc., giving rise to a robust workflow for joint inversion of lithology as well as elastic and petrophysical properties. It is interesting to note that highly detailed subsurface information available in the wells is tightly integrated with other information in geostatistical inversion within a Bayesian framework. This facilitates mapping of thin layers much below resolution of seismic data and deterministic inversion. Traditionally, many realizations are derived to capture both the variance and bias components of uncertainty. In general, the variance is captured through different realizations from the same set of model parameters. This can be viewed as drawing randomly from the same property distribution. On the other hand, bias is captured using different scenarios with different parameters. Simplistically, one can think of considering multiple distributions of elastic/ petrophysical parameters and having multiple draws from each of these distributions to capture the bias component of uncertainty. Finally, rankings of these multiple realizations based on a suitable criterion, e.g., net pay encountered in a well, estimate of reserve in a specified area, etc. help to select realizations with specified probabilities. Thus, a quantitative measure of uncertainty is captured in the process to help informed decision making.

UNCERTAINTY QUANTIFICATION

A model of the subsurface derived from a set of measured data is only one of several possibilities, maybe the most likely one, given our confidence on the process/ algorithm utilized. Interestingly, once we use terms like 'most likely', we acknowledge the presence of uncertainty in the model. In our mind comes the idea that variation in prediction from this model is not unlikely and we should assess it or even better- quantify it. Thus, providing an estimate of uncertainty becomes as important as providing the estimate of the most likely value so that risks associated with using the final products are assessed properly. Risks of a process can be identified qualitatively as well as quantitatively. Typically, in the oil and gas industry, only high-risk ventures are quantified! However, the scope of uncertainty quantification is much broader, as observed by Fournier et al. (2013). In an editorial note they commented that "Uncertainty quantification has many applications and is now becoming essential components of geosciences". They continued to add that the methods of uncertainty quantification play an important role in risk assessment and decision as well as policy making.

UNCERTAINTY AND RISK ASSESSMENT

A traditional way of qualitative risk assessment is preparation of a template that maps false positives and false negatives along with the correct predictions, namely, the true positive and true negative outcomes. This is conveniently represented in the form of a matrix called confusion matrix. The risk assessment process can mature with past experiences and lessons learnt from past successes and more importantly from past failures. Thus, the experience of an individual (an expert), a team (e.g., interpretation team) and a company (best practices, lessons learnt, etc.) as well as continual improvement of the practices are input for this risk assessment/mitigation process. The objective or the target for us is to make a template of this kind, where our predictions are such that the prospects for false positives and false negatives are reduced as much as possible. This way, we are now trying to quantify the risks.

In quantitative risk assessment, we attempt to answer questions like what can go wrong, how likely it can go wrong and what are the consequences of going wrong. As the consequences of going wrong can be devastating, we attempt to answer the other two questions confidently. We endeavor to clearly understand the assumptions in the process and the pitfalls associated in using the results to achieve a specified objective to answer the first question. How likely a process can go wrong is typically handled with probability theory (Oberkampf, 2005).

UNCERTAINTY QUANTIFICATION IN DETERMINISTIC INVERSION

Before proceeding to discuss how to quantify uncertainty in deterministic inversion, let us briefly review how we interpret deterministic inversion results quantitatively. One popular method of interpretation of deterministic inversion results is to use histogram range/ polygon based or seed based geo-body capture.

Consider the case of post-stack inversion where the derived property is acoustic impedance. This dataset used is from the Mississippi Canyon in the Gulf of Mexico (Figure 1), which has few wells that have been used to build the low frequency model and to calibrate the inversion results. Lithology was defined from petrophysical interpretation, identifying three primary facies, namely, shale, pay sand, and brine sand (Figure 2). An analysis of the distribution of acoustic impedance with lithology shows that pay sand can be discriminated against brine sand and shale, but significant overlap of acoustic impedance amongst these facies will introduce uncertainty in facies discrimination over and above those introduced by the quality of input data and inversion. Once deterministic inversion is performed, a traditional method of interpretation is histogram range-based capture of geo-bodies within the target zone, bounded by Red and Lime horizons in this example. We can see from the histogram of acoustic impedance, colored by lithology, that pay sand has lower acoustic impedance than brine sands and shale (Figure 2a). Visual inspection of the acoustic impedance histogram suggests a threshold of ~4.75 $\times10^{6}$ kg/m^{3}*m/s may be appropriate to map the pay sand with fair discrimination from brine sand and shale which we can see from the impedance panel shown in Figure 2b. If we intend not to capture any brine sand, we require revision of the threshold to a lower value of acoustic impedance, say 4.30 $\times 10^6$ kg/m^3*m/s. But as the panel in Figure 2c exhibits, this thresholding results in the possibility of missing out on the lateral continuity of the main pay sand. Besides, the pay sand just below the 'Red' horizon may not be captured using this lower threshold.

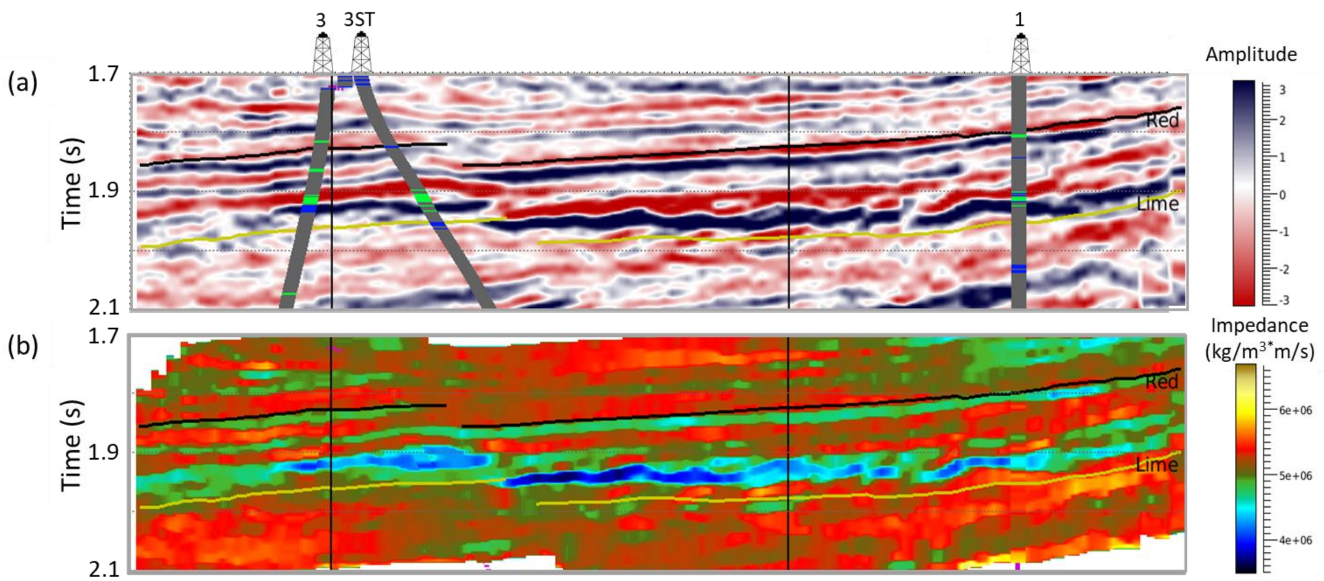

***Figure 1**: (a) An arbitrary line from stacked seismic data from Mississippi Canyon, Gulf of Mexico, and (b) the equivalent acoustic impedance inverted from the stacked data. Facies observed in the wells are overlaid in the seismic section, with shale exhibited in grey, brine sand in blue, and pay sand in green. On the acoustic impedance section, the impedance log is high-cut filtered to the maximum seismic frequency and overlaid. The main pay reservoir lies between the 'Red' and 'Lime' horizons shown in black and yellow respectively and can be broadly characterized by low acoustic impedances.*

While such methods are intuitively simple and convenient to use, there are some limitations in practical applications. For example, in polygon- or histogram-based classification, two neighbouring data points on either side of a facies boundary are assigned different facies due to the 'hard' classification criterion, i.e. a point either belongs to or does not belong to a defined facies class. This rigid approach can lead to abrupt and potentially unrealistic transitions. On the contrary, a probabilistic approach would assign comparable probability values to two competing facies for such neighbouring points, reflecting the inherent uncertainty more accurately. As mentioned earlier, the Bayesian inference framework, which maps prior probabilities using available data, enables a probabilistic interpretation of deterministic inversion results. This facilitates a quantitative assessment of uncertainty in facies classification, providing a realistic understanding of the subsurface.

BAYESIAN INFERENCE

Bayes Theorem (Bayes, 1763; Russell, 2024) deals with hypotheses and probabilities. It can answer questions like 'what is the probability that hypothesis (A) is true, given the information (B)' or it can go further to answer questions like 'how is the probability of an event (A) will get modified with the results of a new experiment (B)'. In simple mathematical terms, it can be written as,

$$P(A|B) = \frac{P(B|A).P(A)}{P(B)} \quad \ldots (1)$$

The experiment or the event we are discussing here is seismic inversion that converts seismic reflection amplitudes to acoustic impedance over a data volume.

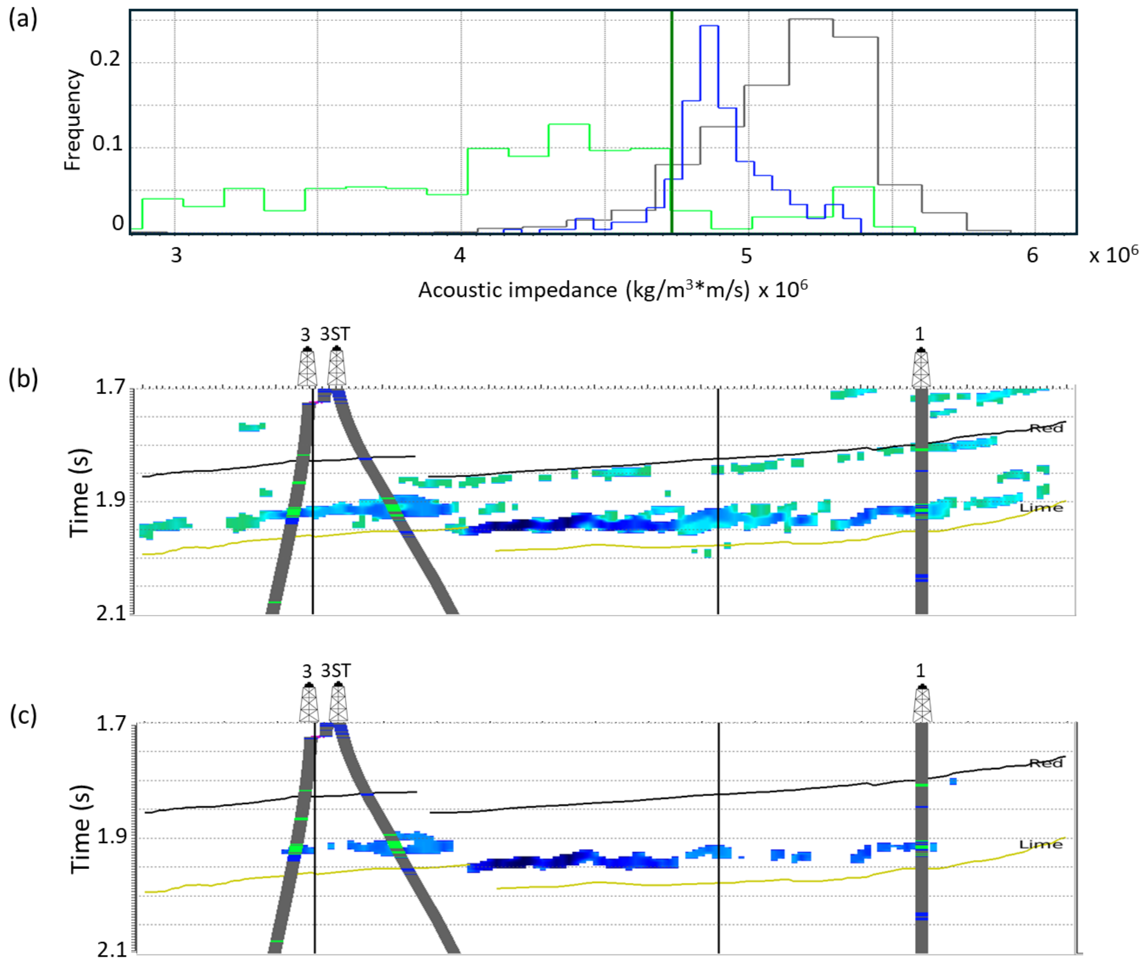

Figure 2: *(a) Frequency distribution (statistical) of acoustic impedance per facies measured in wells within the zone of interest. (b) Inverted impedance section showing values lesser than the selected threshold of 4.75 x 10^6 kg/m^3 * m/s representing the histogram range boundary shown as green vertical line. (c) same as figure (b) with acoustic impedance threshold of 4.30 x 10^6 kg/m^3*m/s.*

Any information on facies such as litho-facies or fluid facies available before inversion is considered as 'prior'. For example, we can estimate the probability of facies, P(Facies) from measurements in the wells and petrophysical interpretation that has been carried out before seismic inversion. Also, we can determine the distribution of acoustic impedance (AI) for a given facies from measurements of sonic and density logs in the interval of interest. Using these two pieces of information, we can write equation (1) as (Shaw and Sen, 2024),

$$P(\text{Facies}|\text{AI}) = \frac{P(\text{AI}|\text{Facies}).P(\text{Facies})}{P(\text{AI})} \quad ...(2)$$

which facilitates estimation of the probability of a given facies at a subsurface point using the value of AI from inversion. This helps us to know the most likely facies and probability of its occurrence! The underlying concepts are explained pictorially in Figure 3.

In the Mississippi Canyon example cited above, the primary reservoir lies between 'Red' and 'Lime' horizons. Based on measurements from a few wells in this block, the estimated probabilities for shale, pay sand and wet sands being 70%, 22% and 8% respectively. The acoustic impedance distributions for these facies can be reasonably modeled using normal and log normal distributions. Acoustic impedance data from wells filtered to seismic frequency, are overlaid on the acoustic impedance section as shown in Figure 1. There is a strong correlation between the measured and inverted values.

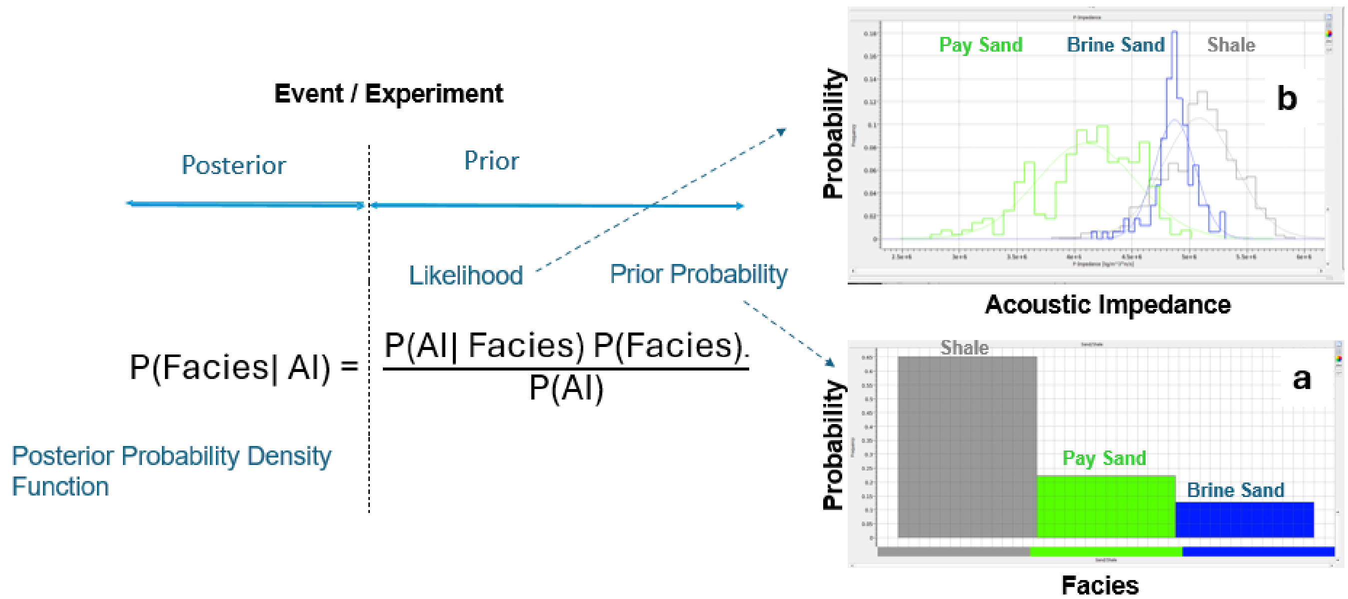

Figure 3: *Pictorial illustration of Bayes' theorem representing the interrelation of prior and posterior probabilities. The dotted vertical line represents the event/experiment that created new data/information. (a) The prior probability of facies estimated from wells, (b) the likelihood function-distribution of acoustic impedance per facies.*

By applying Bayes' theorem, we can estimate both the most probable facies and their associated probabilities. As shown in Figure 4, there is a good agreement between the measured and predicted facies at Well 3 and Well 3ST. However, predictions at Well 1, where several thin sand layers are present, are fewer. The equivalent panel showing the probability of pay sand is shown in Figure 4b. A stratal slice through the main reservoir highlights areas associated with pay sand probability, which are consistent with the structure and depositional framework of the region (Mayall et al., 1992; Latimer et al., 2000).

With the above approach our confidence in identifying potential pay zones and understanding the associated uncertainty is enhanced. Two important points to note here are that uncertainty quantification is carried out after seismic inversion, and we are talking about uncertainty in interpretation of the inverted acoustic impedance in terms of lithology; not the inversion process itself.

UNCERTAINTY QUANTIFICATION IN GEOSTATISTICAL INVERSION

In contrast to deterministic inversion workflow, geostatistical inversion incorporates uncertainty quantification, as Bayesian inference forms its integral component. The other two components of geostatistical inversion are i) geostatistical modeling, and ii) sampling of posterior probability density function (pdf). In view of complexity of the multi-dimensional posterior pdf, advanced sampling methods, e.g. Markov Chain Monte Carlo (MCMC) are used to build many equiprobable realizations. With a fundamental insight from geostatistical modeling and inversion, it can be said that no unique solution exists for a given set of data, prior knowledge, and assumptions. In fact, a range of values of different parameters can be consistent with all the observations. Typically, several scenarios are created by applying small perturbation (10%-20%) to the sensitive parameters, depicting various possibilities, e.g., lithology proportion, variogram type and ranges, signal-to-noise ratio of seismic data, etc. The resulting realizations generated from such multiple scenarios capture the 'bias' component of the uncertainty. The variance component is captured by selecting several random seeds for each scenario.

As multiple realizations of the subsurface properties are generated through geostatistical inversion, the quality control (QC) and interpretation of the results are also carried out in terms of statistical measures. For continuous properties, such as elastic, petrophysical or reservoir properties, besides the mean of a large number

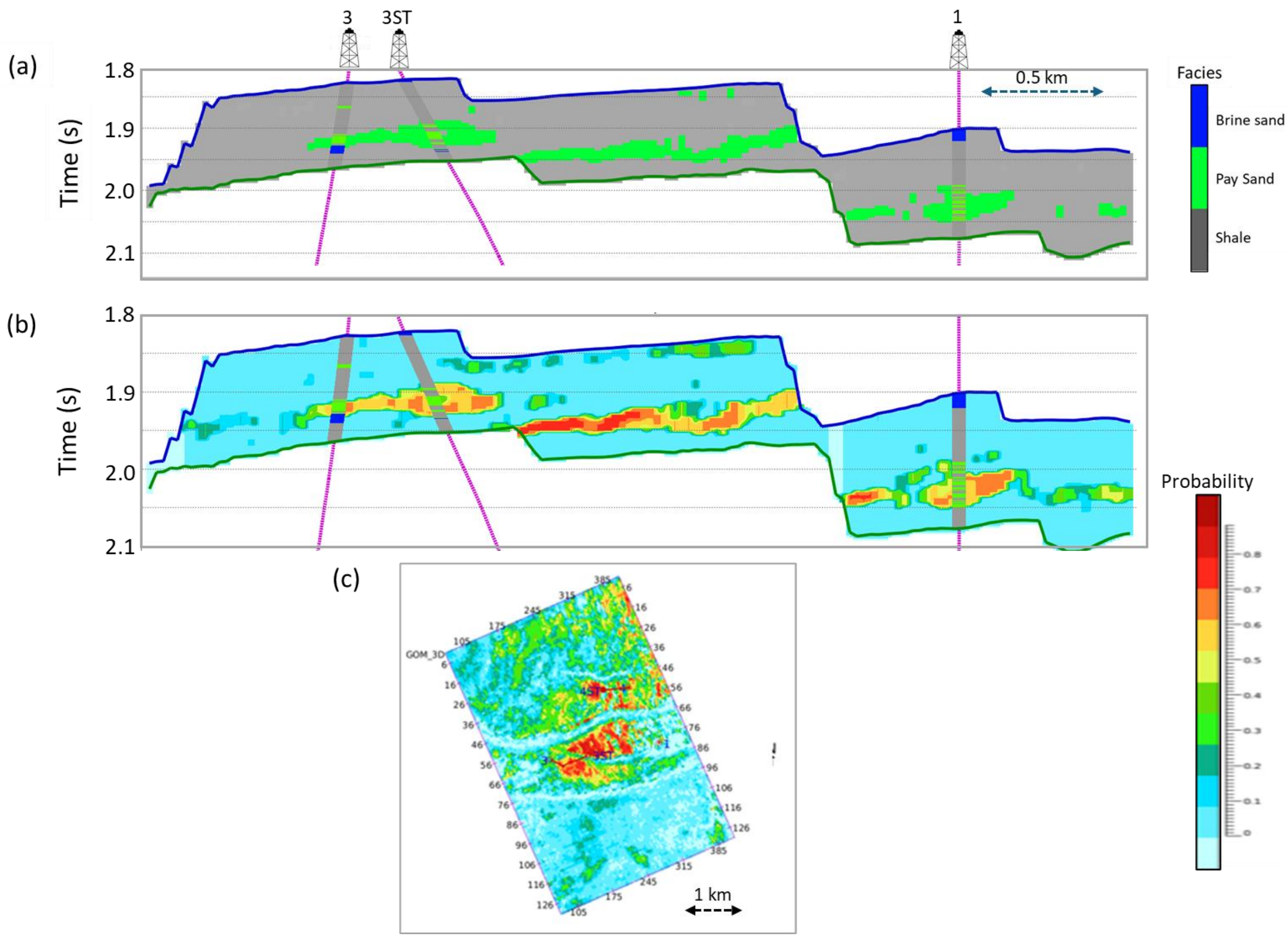

Figure 4: *An arbitrary line section exhibiting the (a) most probable facies, and (b) probability of pay sand derived from deterministic inversion results. (c) Map representing a stratigraphic slice of pay sand probability through the main reservoir.*

of realizations, maximum/ minimum or range as well as standard deviations provide good measures for characterizing the uncertainty. The mean of multiple realizations loses the fine details and approaches towards deterministic inversion results- quite often used as QC of geostatistical inversion results. Range (maximum-minimum) and standard deviation represent the associated uncertainty. Consider a scenario with two facies, namely, shale and sand, and a geostatistical inversion is run yielding 100 realizations. If a particular voxel contains sand in 80 out of 100, then the most probable facies is sand with frequency of occurrence 80%. At another voxel, if sand appears 52 times and it is 48 times for shale, then sand remains the most probable facies, but only with 52% frequency. Thus, our confidence in predicting sand at the first location is much higher than that at the second location. Therefore, combining the most probable lithology with its frequency of occurrence provides a more stable quantitative measure of uncertainty in lithofacies identification and distribution.

Further, as all realizations from geostatistical inversion are considered equally probable, specific criterion can be applied to evaluate and rank them on localized attributes of interest. These criteria may include, for example, net pay thickness in a vertical interval (zone) at a proposed well location, or the estimated oil/ gas reserves within a reservoir volume bounded by selected top and bottom horizons. By ranking the realizations based on such a criterion, we can derive statistical percentiles, typically P10, P50 and P90, for quantifying uncertainty. In this context, P50 means the probability that the expected value would be greater (or lesser) than 50%. Similarly, P10 and P90 denote the probability of the predicted value to be lesser than 10% and 90% of the population respectively. Note that there is no equivalence of such probability values in deterministic inversion results. P10-P50-P90 values taken together quantify the associated uncertainty in a much clearer way. A word of caution here is on the usage of the terminology- the terms P10 and P90 have been used differently by different disciplines. Depending upon the ordering of the ranking variable in defining its cumulative distribution function, viz. increasing or decreasing order of values, the P10 and P90 values can swap. However, for a specific ranking criterion the P50 value of the population remains the same irrespective of the scheme of ordering, though it may be different for different ranking criteria.

FIELD EXAMPLES

Bongkot Field, Gulf of Thailand

An example of uncertainty quantification is presented using the results of geostatistical inversion of pre-stack seismic data over the Bongkot field, Gulf of Thailand, North Malay Basin, which is the biggest gas and condensate producing field of Thailand (Promrak et al., 2016). In this study, petrophysical properties have been co-simulated using their statistical relationship with elastic properties and net pay was subsequently calculated at 15 blind well locations. The results were compared with the pre-drill prognosis obtained through conventional analysis (Figure 5). To evaluate the uncertainty, two parameters were defined:

i) *pay prediction precision*, defined as how often the actual net pay lies within prediction range of P10-P90

ii) *pay estimation uncertainty*, defined as the difference in percentage between predicted P50 and actual net pay

It was found that geostatistical inversion results improved the pay prediction precision from 40% to 83% compared to pre-drilled prognosis. On the other hand, pay estimation uncertainty reduced from 72% to 43% suggesting that, geostatistical inversion workflow better suited to delineate the pay sands in such thin-bedded and randomly distributed sands in the area, not only in terms of mapping but also in characterizing the uncertainty in pay estimation.

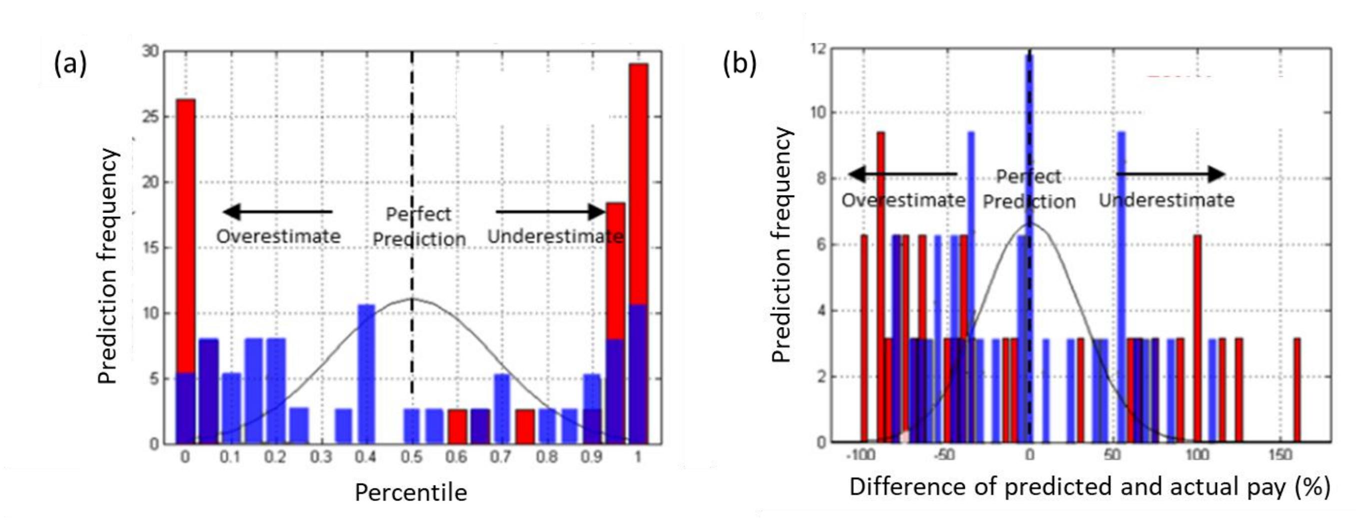

Figure 5: *Comparison of conventional pre-drill prognosis (red) and geostatistical inversion (blue). (a) Net pay estimation precision, and (b) uncertainty in pay. (Modified after Promrak et al. 2016). Compared with conventional pre-drill prognosis, geostatistical inversion approach reduces pay estimation uncertainty from 72% to 43% and enhances prediction precision from 40% to 83% at blind wells.*

Vertical wells	Reservoir sand thickness (ms) at the well	Sand thickness (ms) from ranking of 81 realizations		
		P10	P50	P90
Growler_1	10	7	11	14
Growler_3	12	8	10	13
Growler_4	11	5	8	11
Growler_5	10	4	8	13
Growler_6	11	8	11	14
Growler_7	12	9	12	15
Growler_8	13	8	10	14
Growler_9	10	6	9	13
Growler_11	11	6	10	12

Figure 6: *Quantitative estimation of uncertainty through ranking. Net pay at 9 vertical well locations were estimated from 81 realizations of geostatistical inversion and ranked. Actual pay encountered in these wells are found to lie close to P50 values (After Mannini et al., 2023).*

Growler Field, Cooper-Eromanga Basin

Another example demonstrating uncertainty quantification comes from geostatistical inversion of multi-stack seismic data where uncertainty primarily arises from (i) substantial overlap of elastic properties, namely, P-impedance and V_P/V_S between the reservoir facies, (ii) presence of carbonaceous shale, which can lead to misinterpretation of amplitude variation with offset (AVO), and (iii) noisy seismic data that mask weak AVO anomalies (Mannini et al., 2023). Geostatistical inversion was carried out after proper conditioning of both well logs and seismic data. Three facies, namely, reservoir, non-reservoir and carbonaceous shale were mapped. Geostatistical inversion delineates point bars with medium range porosity in the target interval of the core area of the field surrounded by low porosity flood plains. Geostatistical inversion was run for 3 different values, viz. low, mid and high of 3 most sensitive parameters, namely sand proportion, vertical and lateral variogram ranges resulting in 3^3 (=27) scenarios. For each scenario, 3 realizations were created using random seeds, thus generating 81 realizations, in total. Gross bulk volume of the sand in the core area was used as the criterion to rank these realizations to capture both bias and variance components of uncertainty. Figure 6 shows the results from a ranking process at 9 vertical wells in the core area, which were kept completely blind in the geostatistical inversion process. P10, P50 and P90 values of estimated sand thickness are shown in the figure alongside the corresponding thicknesses measured at the respective wells to represent the efficacy of uncertainty quantification. Wells highlighted with green colour indicate that sand thickness encountered in these wells falls within P30-P70 ranges and can be considered as good prediction. Sand thickness lying beyond this range but within P10-P30 or P70-P90 values are coloured in orange, indicative of moderate quality of prediction. The red colour indicates poor prediction of sand thickness. It is encouraging to note that actual sand thickness in 5 out of 9 blind wells lie within P30-P70 ranges while the other 4 wells lie within P70-P90 values. In none of these 9 wells, the actual sand thickness lied below P10 or above P90 values. A radar plot (spider plot) of these results (Figure 7) exhibits that P50 values represented by the green curve (P50) follows closely with the black curve- the actual values. These results convincingly show that advanced geostatistical inversion workflow can be effectively used for quantifying uncertainty in seismic reservoir characterization.

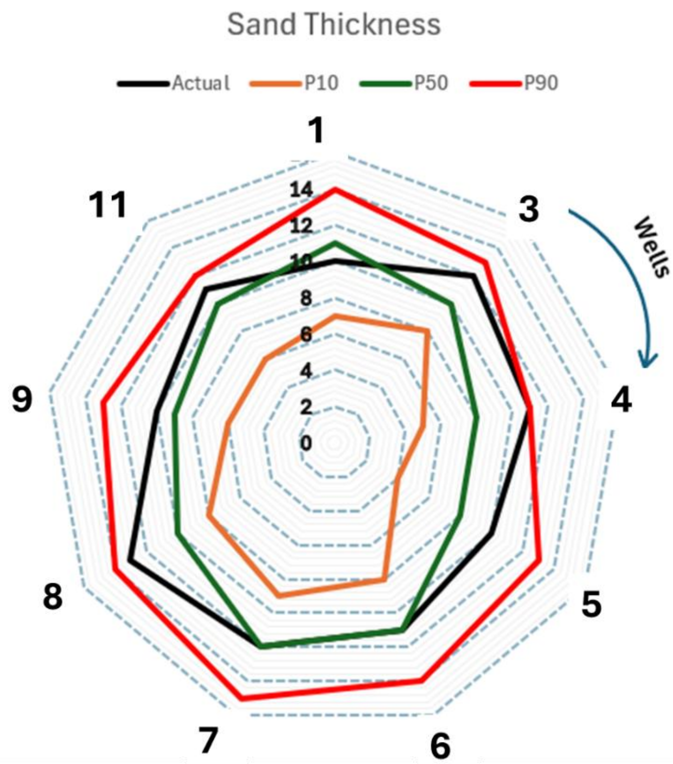

Figure 7: Radar plot (spider plot) of the results shown in Figure 6. Numbers at the circumference represent blind wells. The dotted contours represent the net pay thickness in time (in ms) increasing radially outward. The figure clearly shows that P50 value of the net pay predicted for all 9 wells are close to the corresponding actual values.

CONCLUSIONS

Principle of Bayesian inference provides a framework for quantification of uncertainty in interpretation of both deterministic and geostatistical inversion results. This approach helps in risk assessment and promotes informed decision-making in subsurface evaluation. The cited example from Gulf of Mexico illustrates how uncertainty in the delineation and mapping of pay sands can be quantitatively estimated by deriving the most probable litho-facies and probability of pay sands from deterministic inversion results. Further, an analysis of geostatistical inversion results from Bongkot field, Gulf of Thailand established the improvement in pay uncertainty and pay prediction accuracy compared to traditional prognosis tools, which could be quantitatively assessed. Finally, the reservoir sand thickness estimated from 81 equiprobable realizations from geostatistical inversion at 9 blind well locations from the Growler field, Cooper-Eromanga Basin showed that the P50 value turns out to be close to the actual value encountered at the respective wells.

Thus, advanced workflows for geostatistical inversion provides a robust tool for uncertainty quantification in seismic reservoir characterization capturing both the bias and variance components of uncertainty. Ranking of a large number of equiprobable realizations using a local criterion and analyzing P10-P50-P90 values together quantify the associated uncertainty in a clear way.

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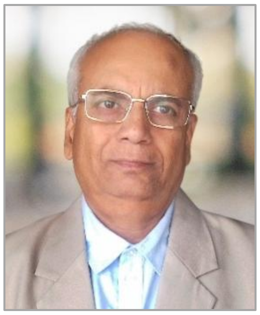
BIOGRAPHIES



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Jimmy Ting received his B.Sc. in applied geology from the University of Malaya in 1991, completing a thesis on the study of limestone and paleogeographic interpretation. After graduation, he joined Sarawak Shell Berhad (SSB) as a seismic imaging geophysicist for three years, followed by another three years as a special studies/quantitative interpretation geophysicist.

Since 1997, Jimmy has been with GeoSoftware for over twenty-eight years, serving in various technical, product R&D, and commercial roles. His expertise spans seismic imaging, rock physics, quantitative seismic reservoir characterization, and seismic fracture interpretation across clastic, carbonate, and unconventional reservoirs. Over the years, he has delivered technical training classes, educational series, pre-conference workshops, and continuing education courses. Together with his team, Jimmy has developed several customized Action-Based Learning courses tailored for exploration geoscientists.

He is an active member of SEG, EAGE, ASEG, the Board of Geologists Malaysia (BOG), and a life member of SEAPEX (Southeast Asia Petroleum Exploration Society).

Siew Jiun Yap graduated from University Science of Malaysia with a bachelor's degree in applied science (geophysics). From 1996 to 2006, she served as a seismic processor at WesternGeco, specializing in 2D/3D seismic data processing. Transitioning to quantitative interpretation (QI) in 2006, she joined Fugro-Jason which is now GeoSoftware, where she currently holds the role of geoscience custodian.

As geoscience custodian, Siew conducted project services across the Far East region, with customized workflows to resolve clients' technical challenges and optimize subsurface solutions. She actively collaborates with clients to ensure effective utilization of GeoSoftware's technologies, enhancing operational value and decision-making. Additionally, Siew delivers technical training programs for both internal teams and external customers, fostering knowledge transfer and advancing geoscience applications. With over two decades of industry expertise spanning seismic processing, QI, and client-centric advisory roles, she continues to contribute to innovative geoscientific practices and client success in exploration and reservoir characterization.