PCCE#09

Applications of Geostatistical Inversion for Detailed Reservoir Characterization

GEOIndia2022

Ranjit Kumar Shaw & Hemant Kumar Dixit

GeoSoftware

GeoSoftware™

www.GeoSoftware.com

Content

Session I :

- Geostatistical Inversion - the What, Where and Why?
- Role of Seismic Inversion in Reservoir Characterization.
- An overview of Deterministic Inversion and its Limitations.
- Benefits of Using Geostatistical Inversion in Seismic Reservoir Characterization.
- Workflows for Geostatistical Inversion Presently Used in O&G Industry.

Session II :

- How to Perform Geostatistical Inversion.
- Key Elements of Geostatistical Inversion. Bayesian Framework for Geostatistical Inversion.
- Variables and Parameters of a Geostatistical Model- Geostatistical Modeling.
- Bayesian Inference- Integrating multi-scale data and information to update knowledge about the subsurface.
- Methods to derive multiple realizations of subsurface properties and facies.

Content

- Quantifying uncertainty- characterizing natural variability of the underlying process and uncertainty due to data limitations/model approximations

Session III :

- Common Applications of Geostatistical Inversion in Reservoir Characterization
- Interpretation of Geostatistical Inversion Results-Ranking of Realizations as a Tool for Model Selection and Uncertainty estimation.
- Applications of Geostatistical Inversion for Mapping Thin Beds and for Well Planning- Examples from Clastic, Carbonate and Unconventional Reservoirs.
- Challenges and Benefits of using Geostatistical Inversion Results in Building Static Models and in Flow Simulation- case studies

Session IV :

- Evolving Trends
- Use of Machine Learning Techniques in Seismic Reservoir Characterization

Summary and Discussions

Geostatistical Inversion - the What, Where and Why?

GeoSoftware™

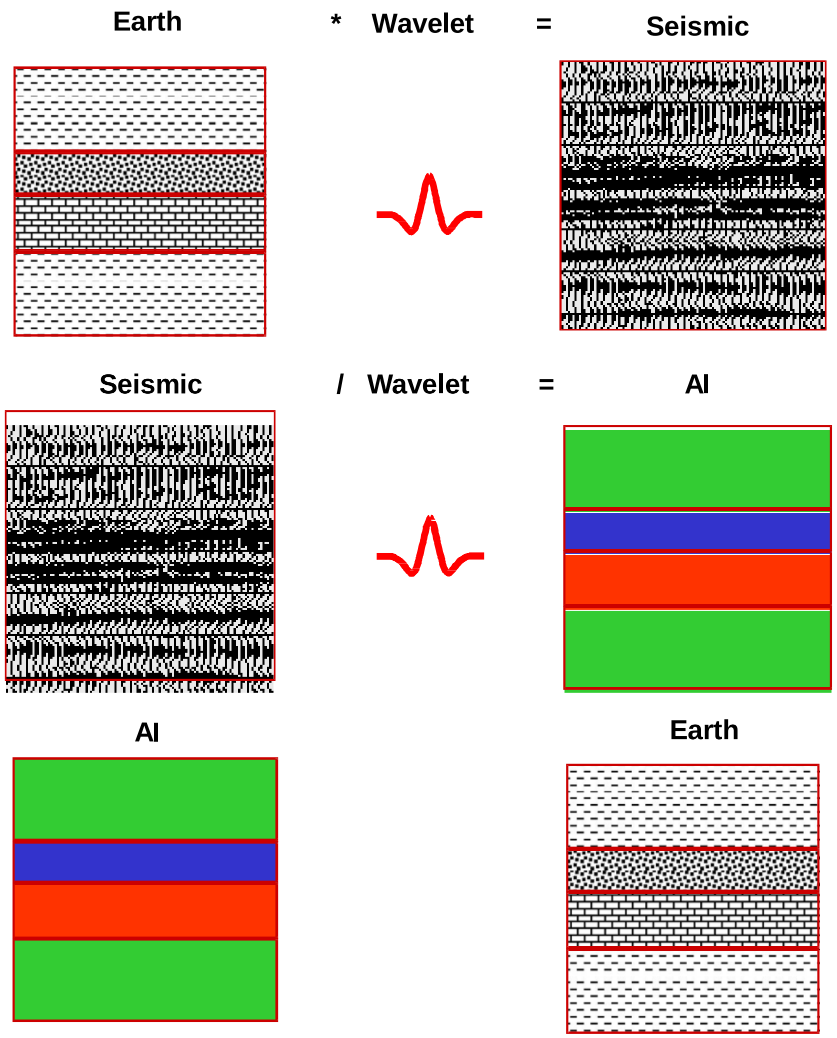
www.GeoSoftware.com

What is Seismic Inversion?

Reflection Seismic

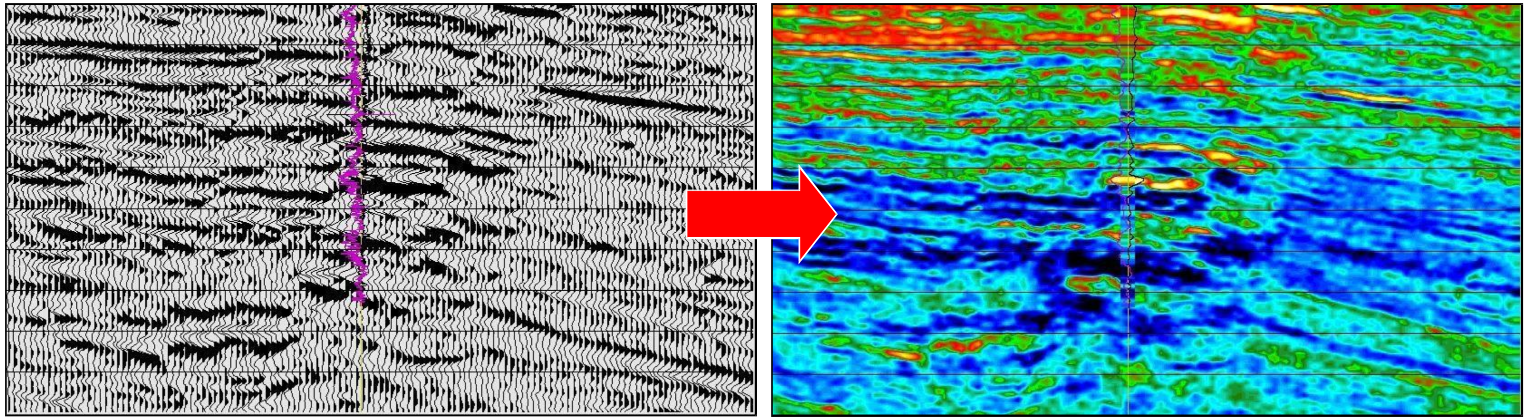
Seismic Inversion

Quantitative Reservoir Characterization



Seismic Inversion

- Integration of well logs and seismic data with geological information
- Transformation of seismic traces to acoustic impedance and other rock properties
- A description of the earth through rock properties



Seismic Data

Shows contrast between layers

Acoustic Impedance

Shows property value inside the layer

What Do We Gain?

Advantages

- Removal of wavelet effects
- Increased resolution
- Reduced noise
- Calibration with wells
- Relationships with reservoir properties

Challenges

Requires a Low Frequency Model (LFM)

…

Seismic Inversion: Methods

Attributes

AVO/AVA

Deterministic Inversion

Uncertainty Quantification

Geostatistical Inversion

4D Inversion

Multi Component

AVOAz

Full Waveform Inversion

Running Sum
Recursive Inversion
Colored Inversion

Elastic Impedance and its variants

Model Based Inversion

Sparse Spike Inversion

Simultaneous Inversion

Geostatistical Inversion

Bayesian Inversion

Seismic Inversion - Current Practices

Deterministic

- Post stack

Single Partial Stack (Elastic Impedance)

Multiple partial stacks (Simultaneous)

- Joint PP and PS inversion
- Uncertainty Quantification

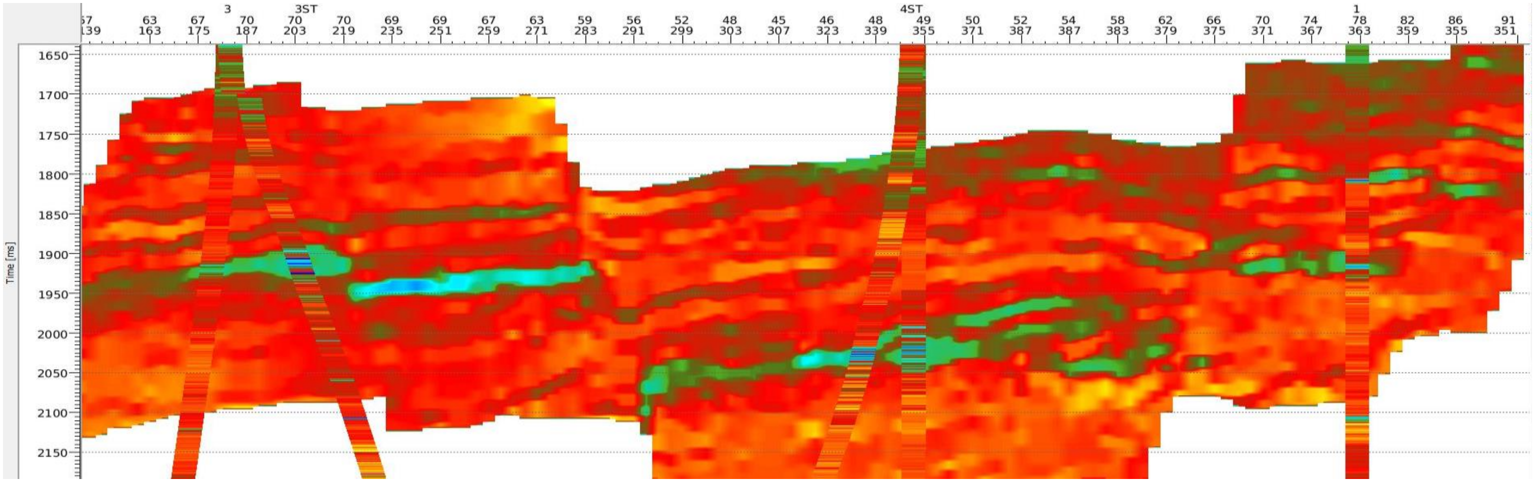
Stochastic

- Geostatistical inversion for high details

Limitations

Layer resolution is limited by highest seismic frequency

Rich information in wells are not fully utilized



Why Geostatistical Inversion?

The goal of geophysical inversion is to make quantitative inferences about the Earth from noisy, finite data.

The limitations of noise and the inadequacy of the data mean that geophysical inversion problems are fundamentally problems of ‘Statistical Inference”.

We do not invert data to find “models”,
Rather, we invert data to make inferences about the model.

There will be infinity of models that fit the data. Thus we must look to probability theory to help.

(Scales & Sneider, 1997, Geophysics) “To Bayes or Not to Bayes”

Why Geostatistical Inversion?

Subsurface petro-elastic models with high spatial resolutions (both lateral and vertical) are needed at different stages of field life of a reservoir, e.g. well planning, reserve estimation, flow simulation for predicting reservoir performance.

Geostatistical modeling using available well data is commonly used by modeler and reservoir engineers with occasional use of deterministic seismic inversion results.

None of geostatistical modeling or deterministic inversion fully qualify to provide the high resolution requirements of both lateral and vertical directions.

Geostatistical inversion subsumes benefits of geostatistical modeling and deterministic seismic inversion to provide highly detailed reservoir description.

Beyond Traditional Seismic Inversion …

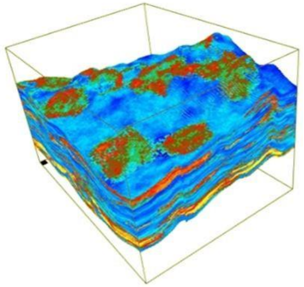
Generate scenarios of the reservoir with primary properties of interest

✓Facies

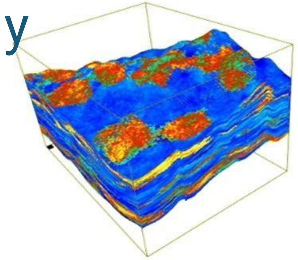
✓Porosity, Vclay, Sw, K, etc.

rather than intermediate elastic properties like Acoustic Impedance, Shear Impedance and Density

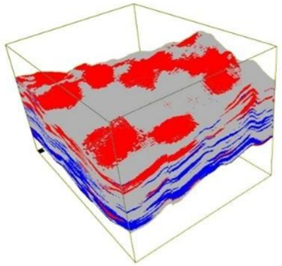
Vclay



Porosit
y



Facies



- Permeability
- Pressure

Shale

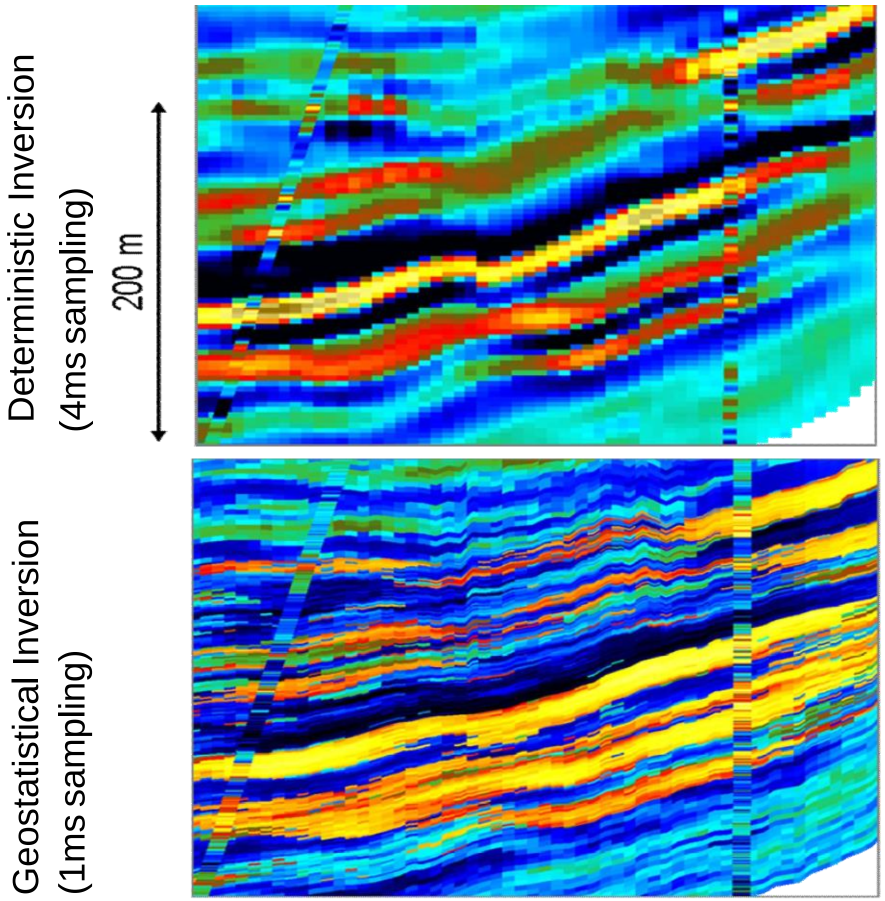
Channel sand

Cemented sand

When Do We Need Geostatistical Inversion?

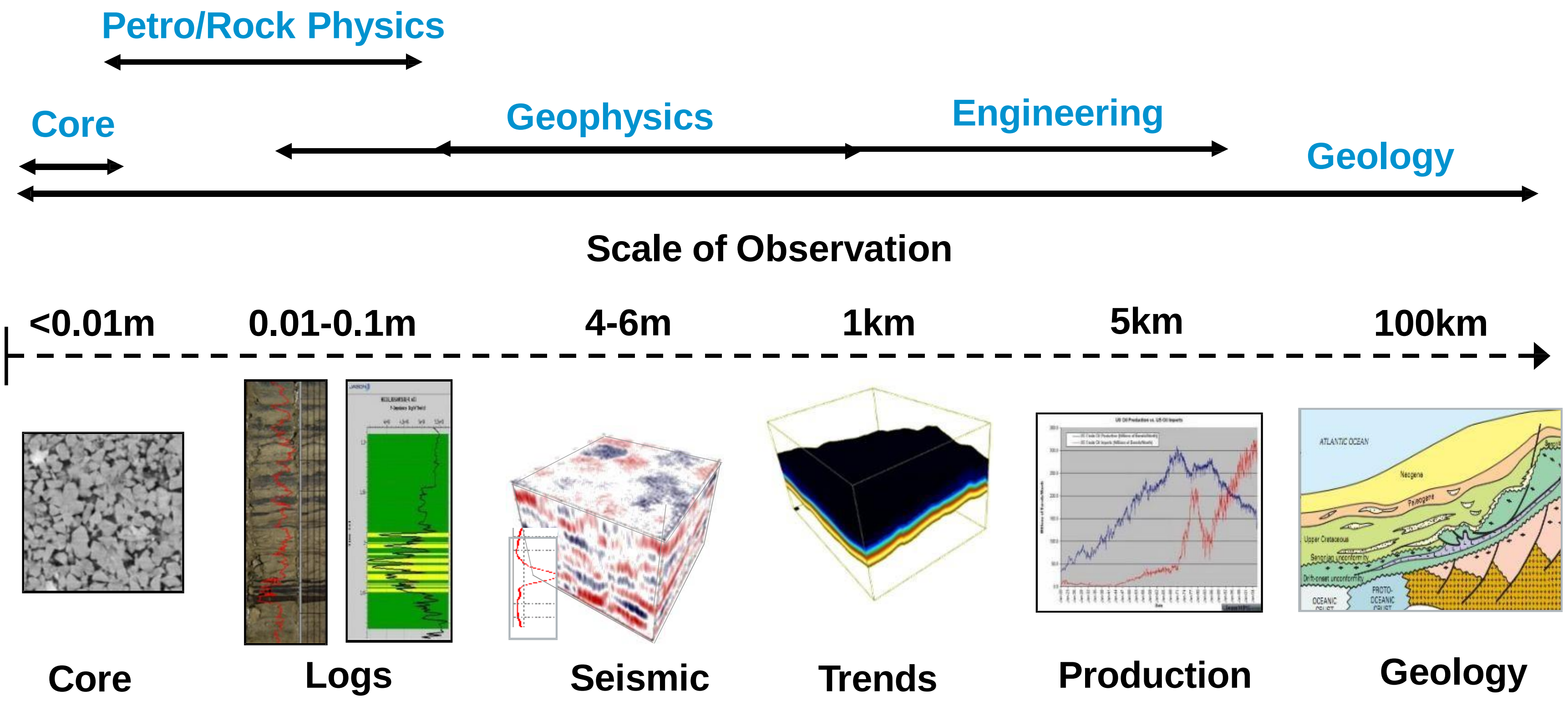
- Improved resolution
  - Depends on contrasts in elastic properties of different facies
- Data integration
  - Tighter and better integration as data scale issues are handled properly
- Capturing uncertainty
  - Reduces uncertainty due to variance
  - Allows for greater understanding of uncertainty due to bias
  - Require predictive reservoir model for flow
  - simulation and history matching.

For example, porosity co-simulated with acoustic impedance from geostatistical inversion of full stack data can serve as the porosity volume in static model.

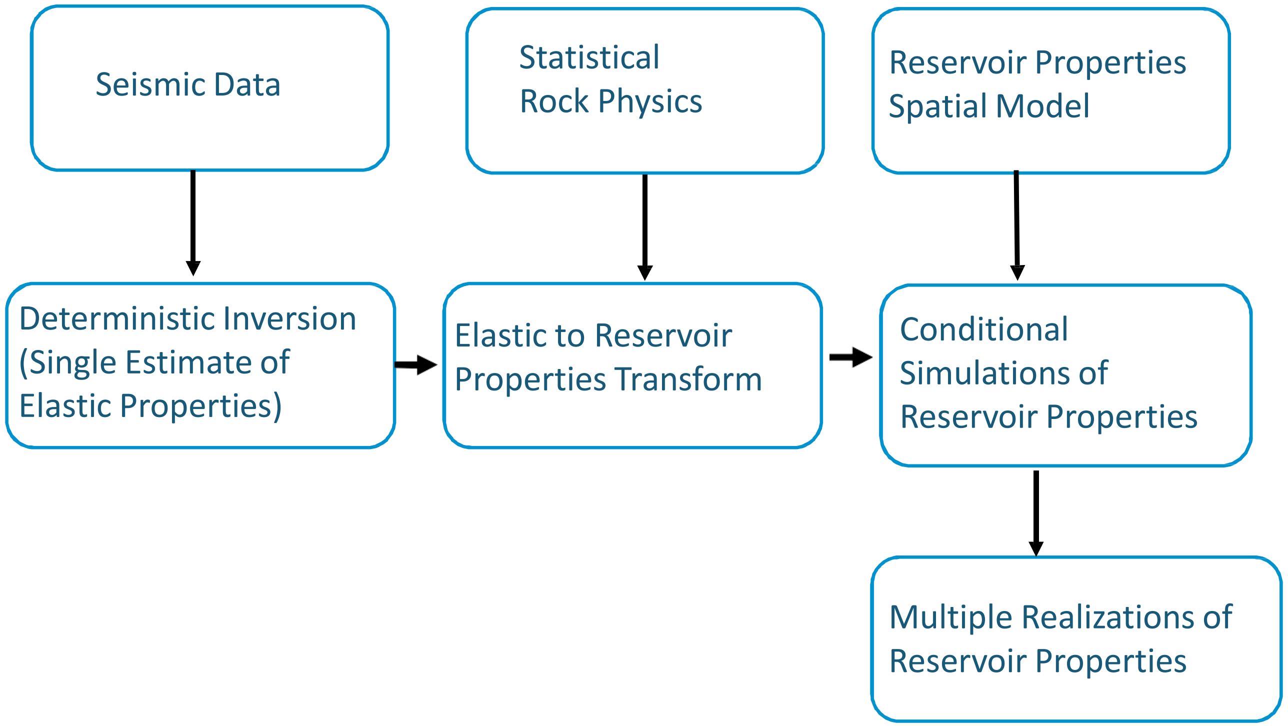


Create a Highly Detailed Reservoir Model by…

Tightly integrating all data in an unbiased manner

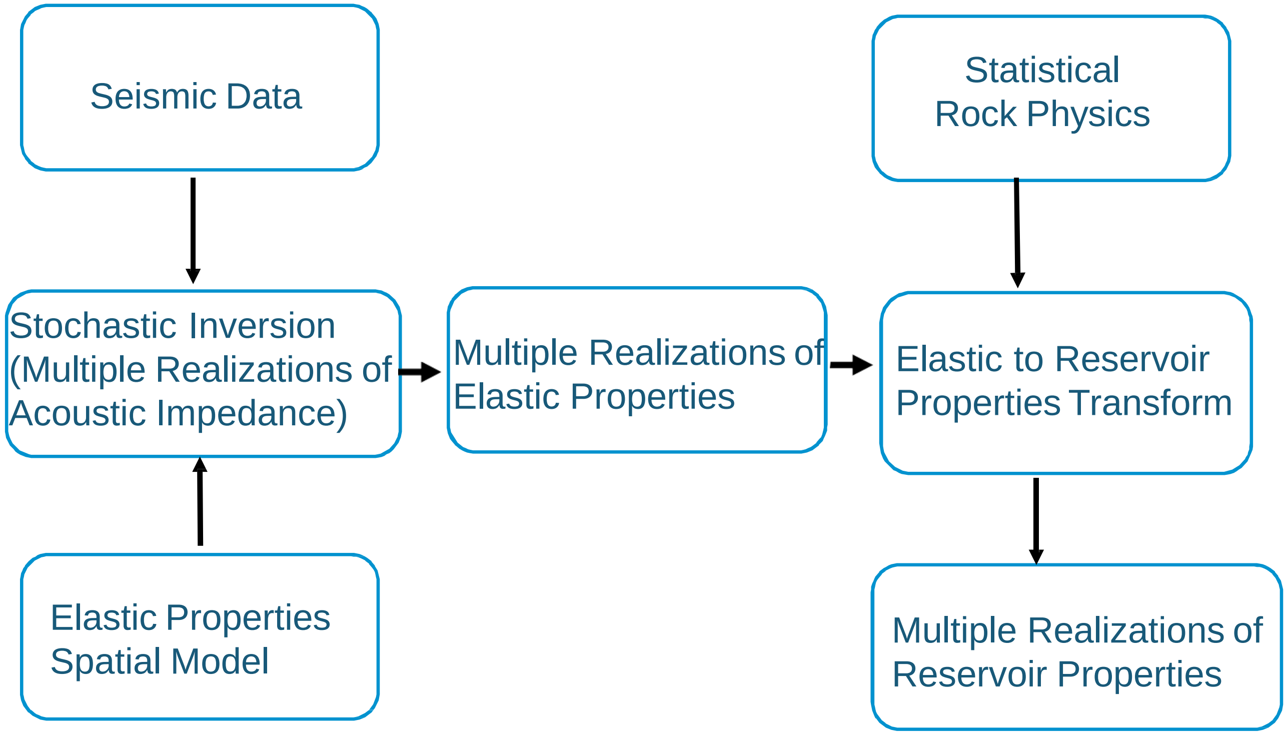


Workflows for Geostatistical Inversion: Scheme I



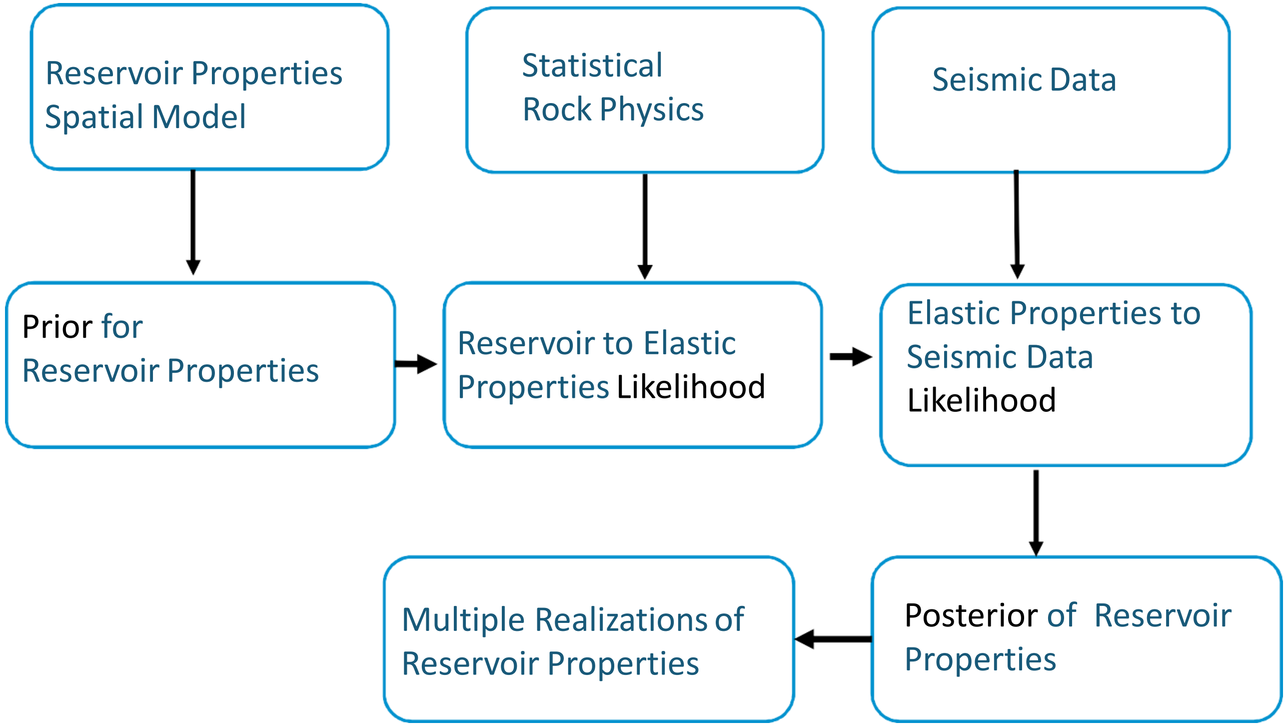
After Bosch, M., Mukerji, T. and Gonzalez, E. F, 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics, Geophysics, 75, A165-176.

Workflows for Geostatistical Inversion: Scheme II



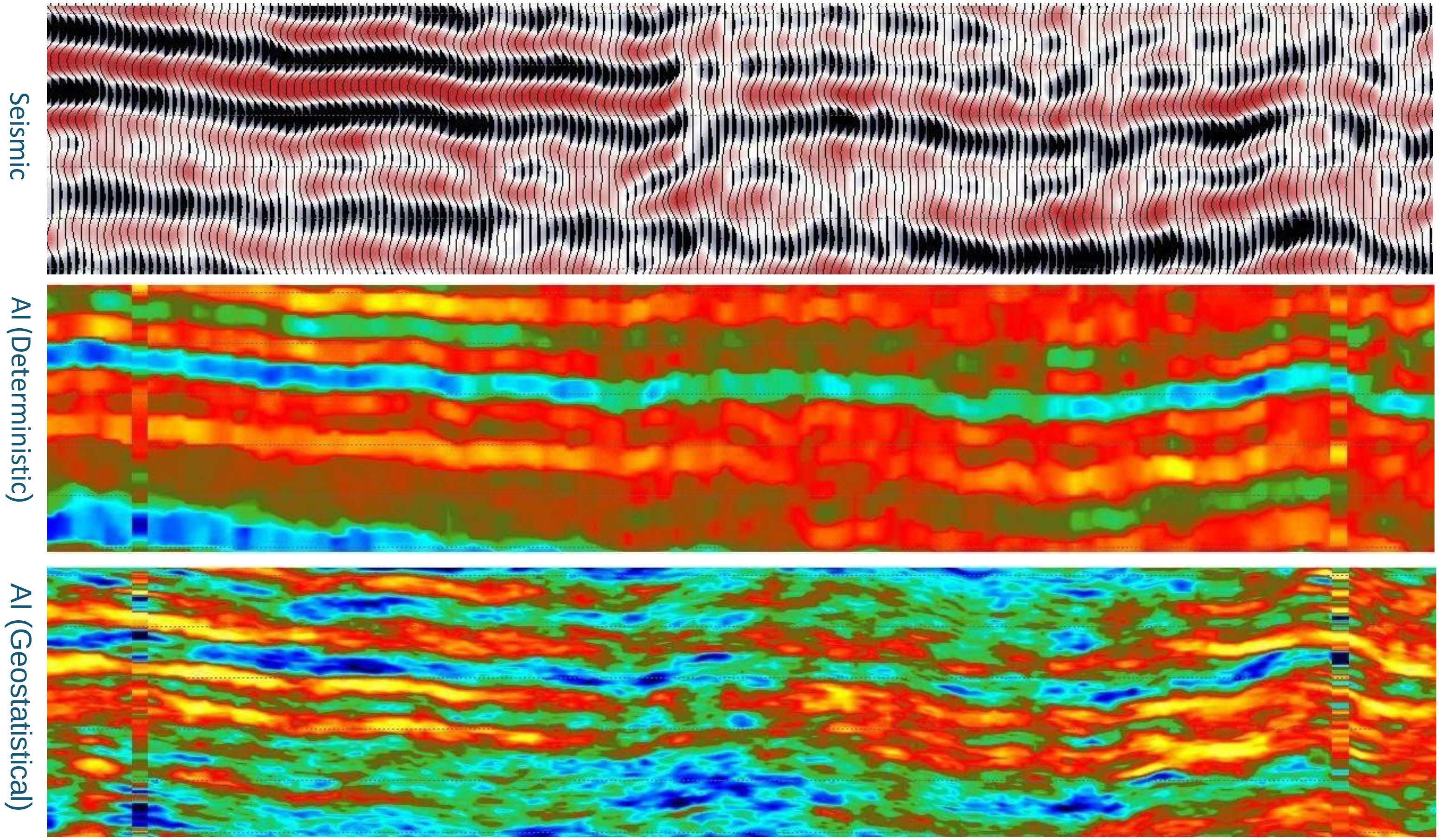
After Bosch, M., Mukerji, T. and Gonzalez, E. F, 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics, Geophysics, 75, A165-176.

Workflows for Geostatistical Inversion: Scheme III



After Bosch, M., Mukerji, T. and Gonzalez, E. F, 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics, Geophysics, 75, A165-176.

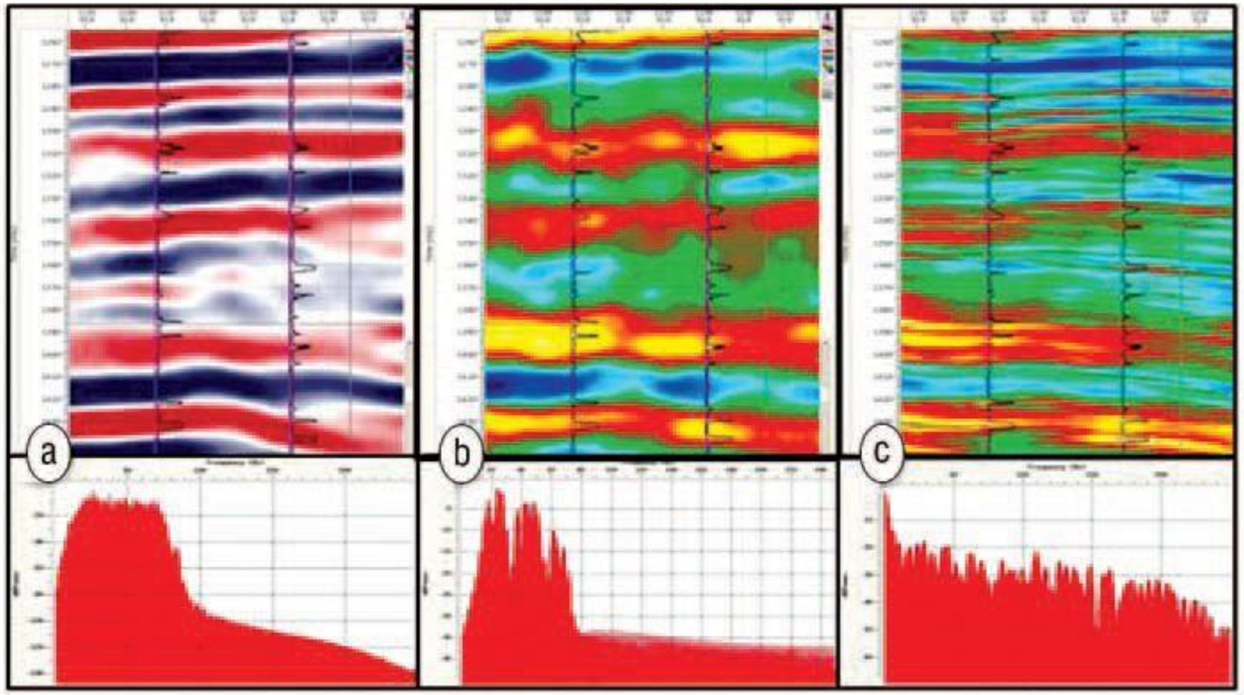
Deterministic Vs Geostatistical Inversions



Vernengo, L., Czeplowdozki, R. Trinchero, E., Sabate, A., Tsybulkina, E. and Morrillo, F., 2014 , Improvement of the reservoir characterization of fluvial sandstones with geostatistical inversion in Golfo San Jorge basin, Argentina, The Leading Edge, 33, 508-518.

Frequency Contents from Deterministic & Geostatistical Inversions

Frequency Contents from Deterministic & Geostatistical Inversions



Seismic AI (Deterministic) AI (Geostatistical)

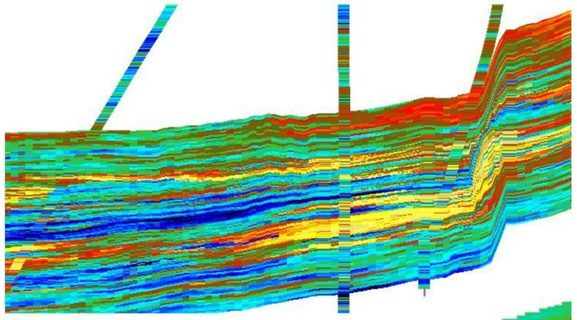
Vernengo, L., Czeplowdozki, R. Trinchero, E., Sabate, A., Tsybulkina, E. and Morrillo, F., 2014 , Improvement of the reservoir characterization of fluvial sandstones with geostatistical inversion in Golfo San Jorge basin, Argentina, The Leading Edge, 33, 508-518.

Benefits of Geostatistical Inversion

- Improved Resolution
  - Modeling at fine sampling interval (e.g. 0.5ms)
- Uncertainty Quantification
  - Bayesian inference integral part of the process
- Joint inversion of facies and elastic properties (P-impedance, Vp/Vs, Density)
- Results in stratigraphic grid
  - Transfers easily to Corner Point Grid
- Results directly in depth as well as in petrophysical/ engineering properties (Vclay, Porosity, Sw, etc.)

Geostatistical Reservoir Modeling, Deterministic Inversion & Geostatistical Inversion: A comparison

Geostatistical reservoir modeling



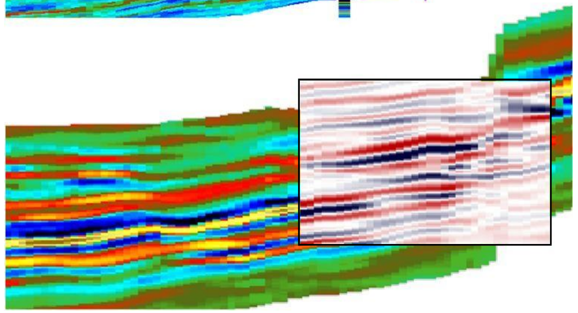
Interpolate between the wells

Plausible details ✓

Accurate near wells ✓

Not elsewhere ×

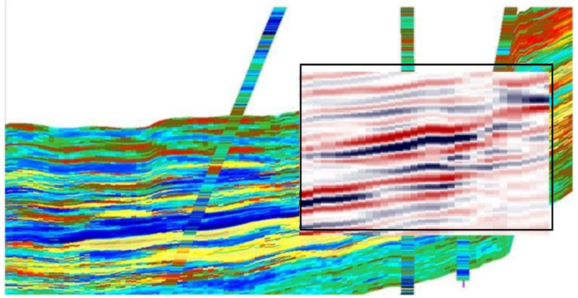
Deterministic inversion



Optimizes acoustic impedance to model seismic Accurate within seismic bandwidth ✓ Unrealistically smooth ×

Only one possibility ×

Geostatistical inversion



Subsumes geostatistical modeling and deterministic inversion

Does both simultaneously and in a statistically rigorous way

Multiple realizations at high detail (~ 1ms x 25 m)

Yet coherent 'interpretations' up to ~ km scale

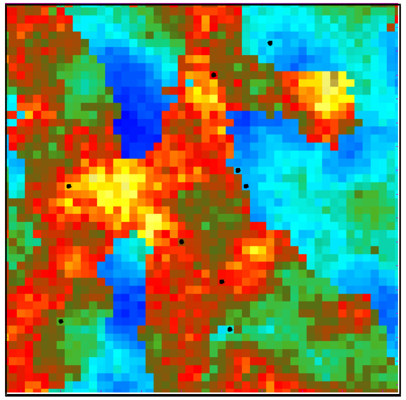
Geostatistical Modeling, Simulation & Inversion

Geostatistical Modeling: Estimation

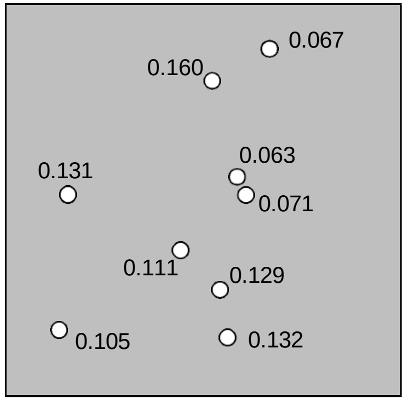
Geostatistical Estimation is a "best-guess" given the Measured Data:

- Aims to minimize local error, as this is most conservative estimate.
- Means there is only one solution and it is unrealistically smooth.
- No objective measure to quantify "how wrong" the solution may be.
- Analogous to choosing "3.5" when asked to predict the roll of a dice.

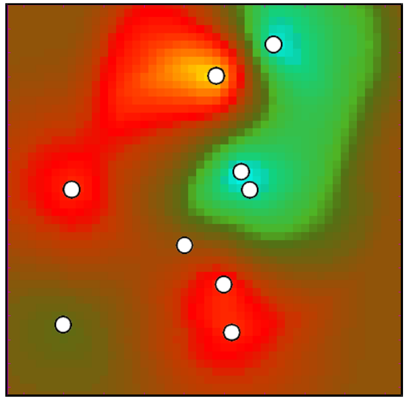
True Reservoir (Unknown)



Measured Data



Geostatistical Estimation

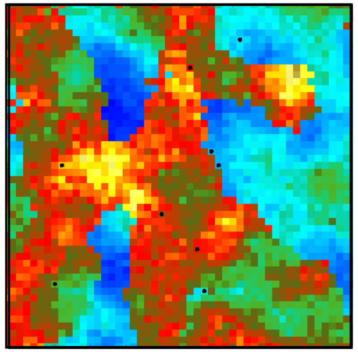


Geostatistical Modeling: Simulation

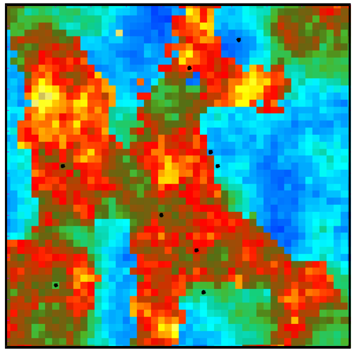
For reservoir characterization and modeling, a “best-guess” is not good enough:

- Need to have a model that is globally accurate and reflects geological patterns, not just local measurements.
- Willing to sacrifice some accuracy at any single location if it means globally have a more realistic model.
- Want multiple plausible solutions so that uncertainty in model may be quantified.

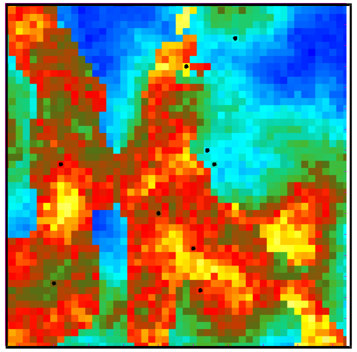
True reservoir



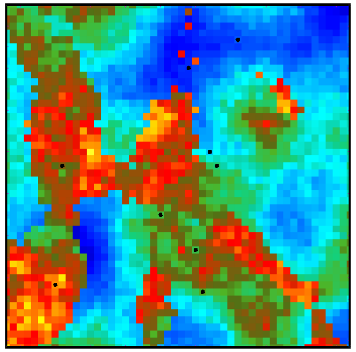
Simulation 1



Simulation 2



Simulation 3



Objectives

Find the parameters of geostatistical models, viz. pdfs and variograms that give the desired shapes and sizes in the simulation of discrete property types.

Uses geostatistical information from wells only, no information from seismic.

Geostatistical Model

Properties

- Discrete Properties (DP), e.g. Facies
- Continuous Properties (CP), e.g., P-impedance, Porosity

Probability Distribution Functions (pdf)

- DP proportions
- CP pdfs: univariate, bivariate or multi-variate

Variograms: For both DP and CP

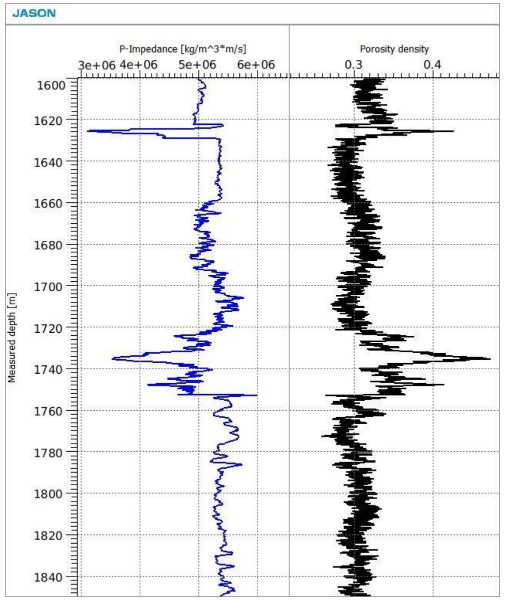
- Vertical Variogram - Type and parameters, e.g. exponential, range, nugget
- Lateral Variogram - Type and parameters including anisotropy azimuth

Probability Density Function (PDF)

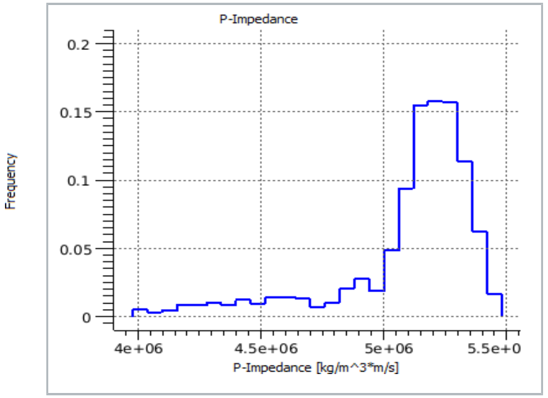
– From logs, we see that low values of Ip correspond to high values of Φ and vice-versa

– But this information is not discernable from the two corresponding Histograms

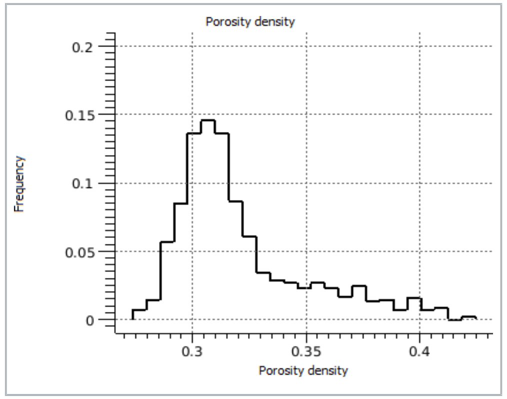
P-Impedance Porosity



P-Impedance



Porosity



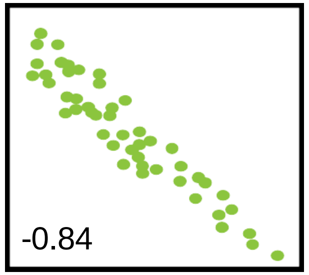
Correlation

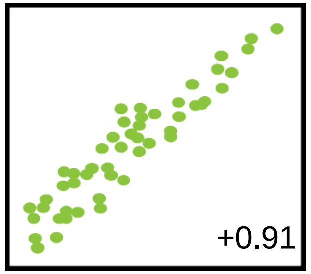
- Correlation between two properties is discernable from a crossplot
- The correlation coefficient characterizes the linear relationship between two properties

$$corr\left(Ip,\phi\right)=\frac{\frac{1}{N}\sum\left(Ip-\mu_{Ip}\right)\cdot\left(\phi-\mu_{\phi}\right)}{\sigma_{Ip}\cdot\sigma_{\phi}}$$

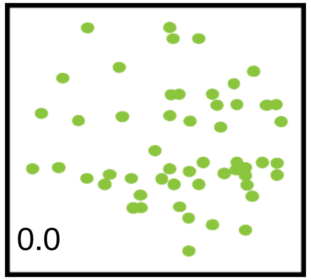
$$-1.0\leq corr\left(Ip,\phi\right)\leq+1.0$$

Good linear relationship

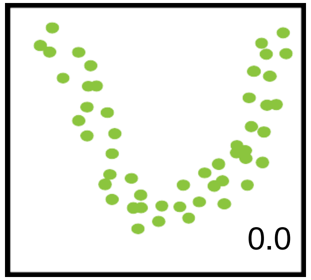




No relationship



No linear relationship



Spatial Continuity

All reservoir properties exhibit some degree of spatial continuity.

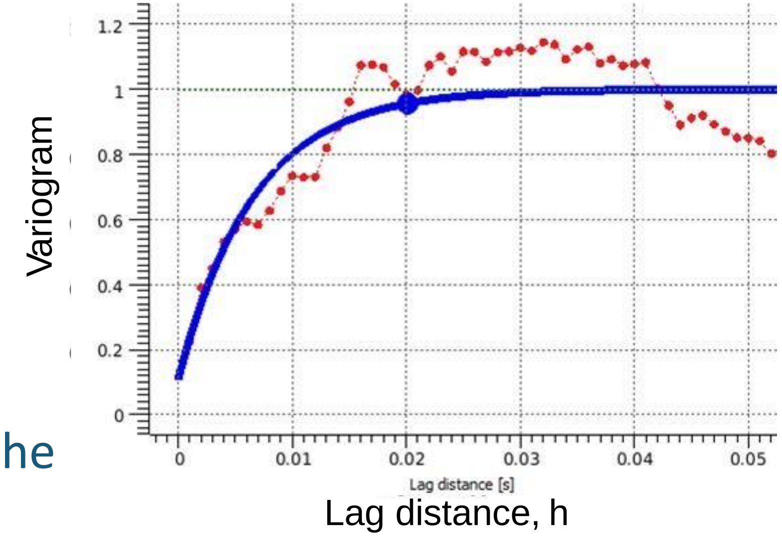
Realistic reservoir models require to:

– Quantify the spatial continuity of a property from measured data.

– Reproduce the same spatial continuity in a simulation.

Variograms are a tool to get this done.

– Relates to the variability of the property as a function of the



$$\gamma(h) = \frac{1}{2}\,\mathrm{var}\left[Z(u) - Z(u+h)\right]$$

h: lag distance between two spatial locations

Characteristics of Model Variogram

Shape: slope at the origin.

- Smoothness of values

Range: distance at which the variogram reaches plateau.

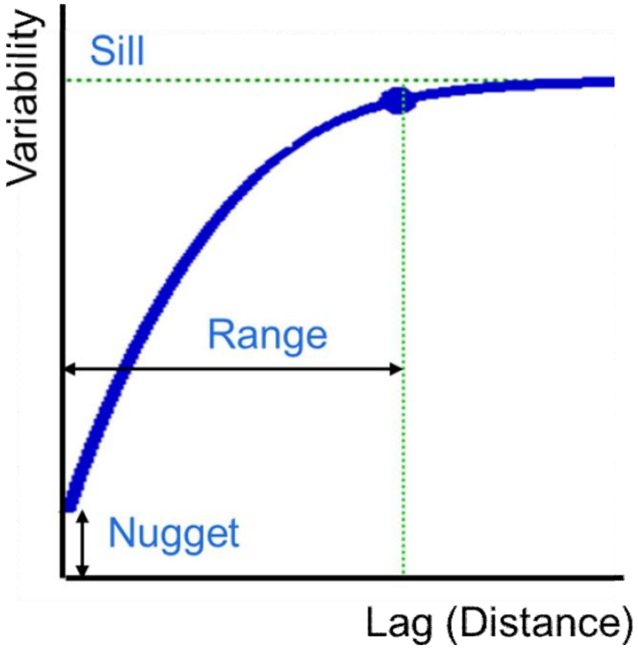
- Maximum distance at which two points are correlated.
- Might depend on the direction (anisotropy).

Sill: the plateau the variogram reaches at the range.

- The sample variance of the property.

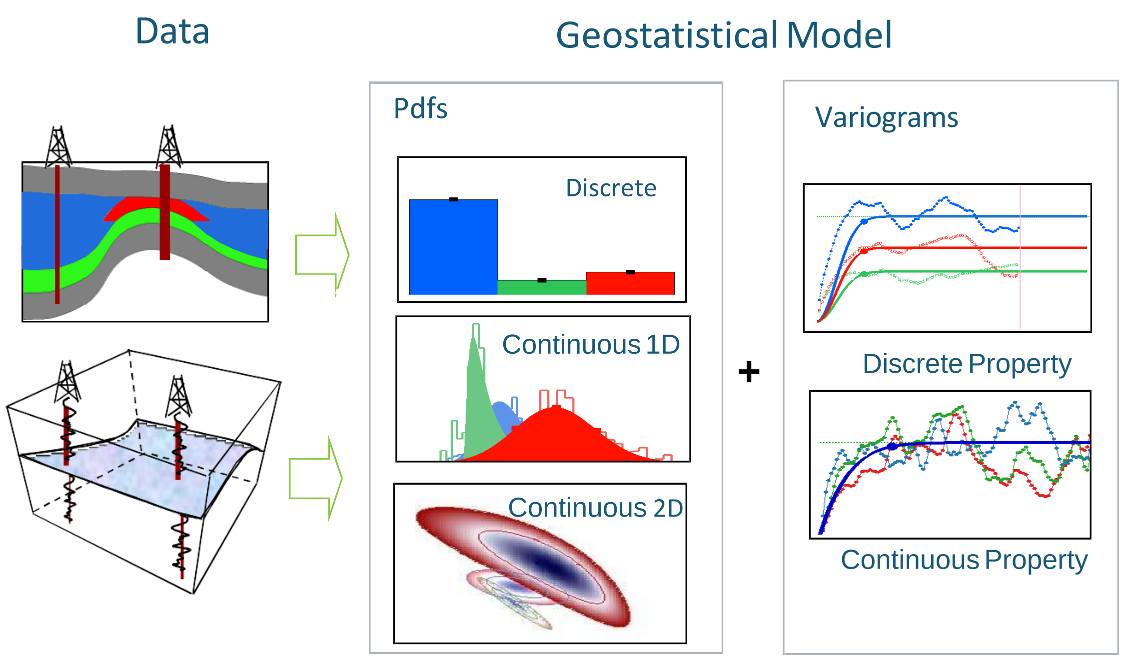
Nugget: discontinuity at the origin of the variogram.

- Micro-scale geological variation and measurement error.



Geostatistical Modeling

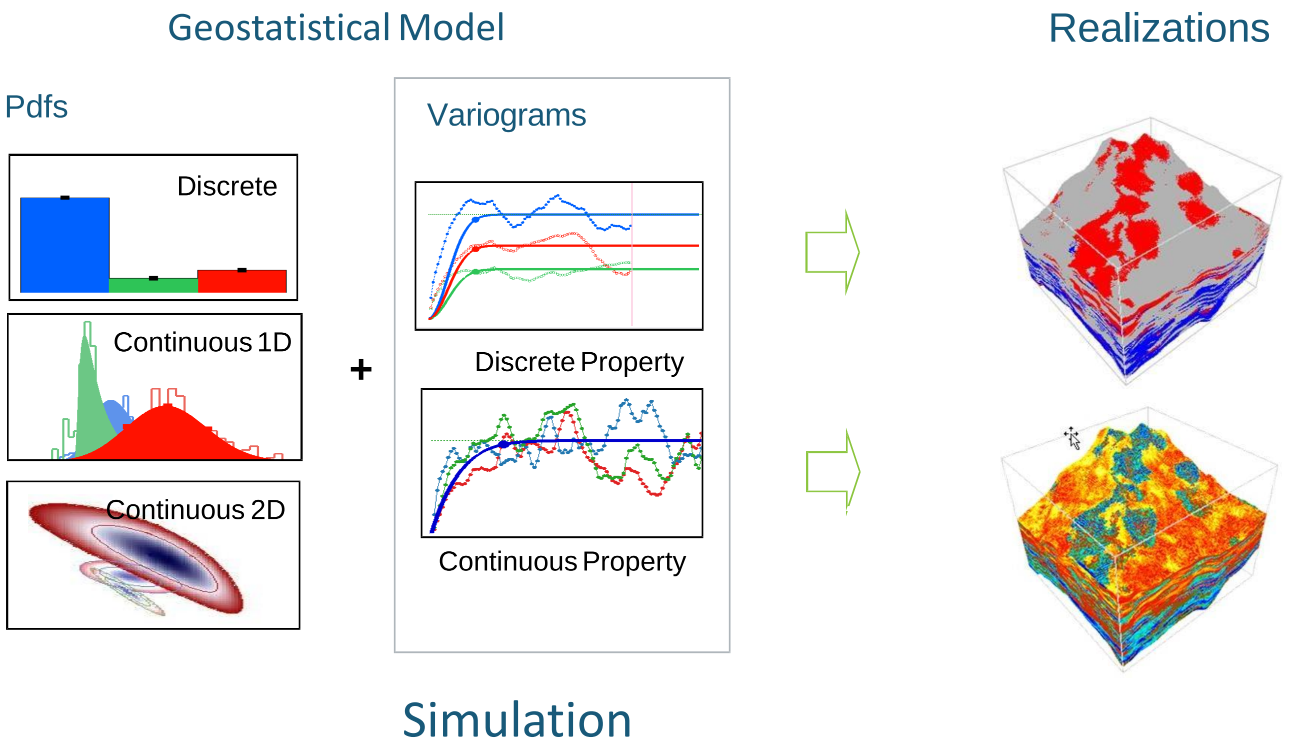
Geostatistical Modeling is done by fitting probability density functions (pdfs) and variogram models to histograms and experimental variograms computed on input data (well logs, attributes maps, trends, etc.).



Geostatistical Model Fitting

Overview of Geostatistical Modeling

Numerical (digital) reservoir models are realizations of the Geostatistical Model



Geostatistical Inversion Philosophy

Recognize that all input information contains uncertainties

- measured data like well logs, seismic stacks and velocity
- interpretations (petrophysics, horizons/faults, stratigraphy and
- models /hypothesis (rock physics, depositional system, hydrocarbon provenance etc.).

Phrase the problem in probabilistic terms and solve it using advanced statistical techniques.

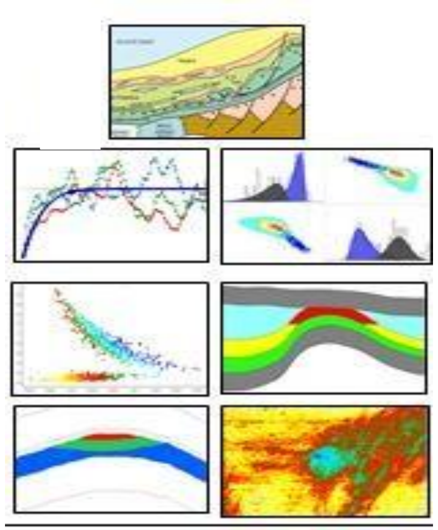
Generate multiple realizations that

- *Honor all input information.*
- *Reflect the multiple sources of uncertainty.*
- *Give insight into what is known and what is not known about the subsurface.*

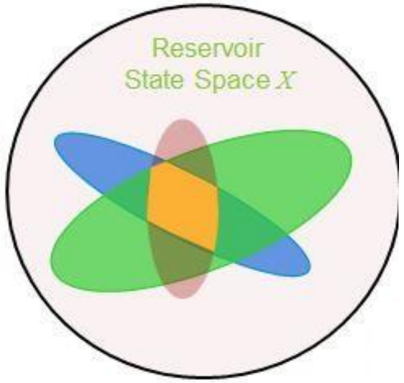
Components of Geostatistical Inversion

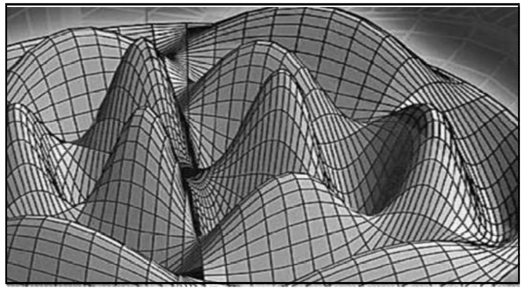
1. Geostatistical Modeling
2. Bayesian Inference
3. Sampling Posterior Probability Density Function

Rock Physics Geostatistics Geology



Fluid contact Seismic noise





Bayes' rule

Likelihood function

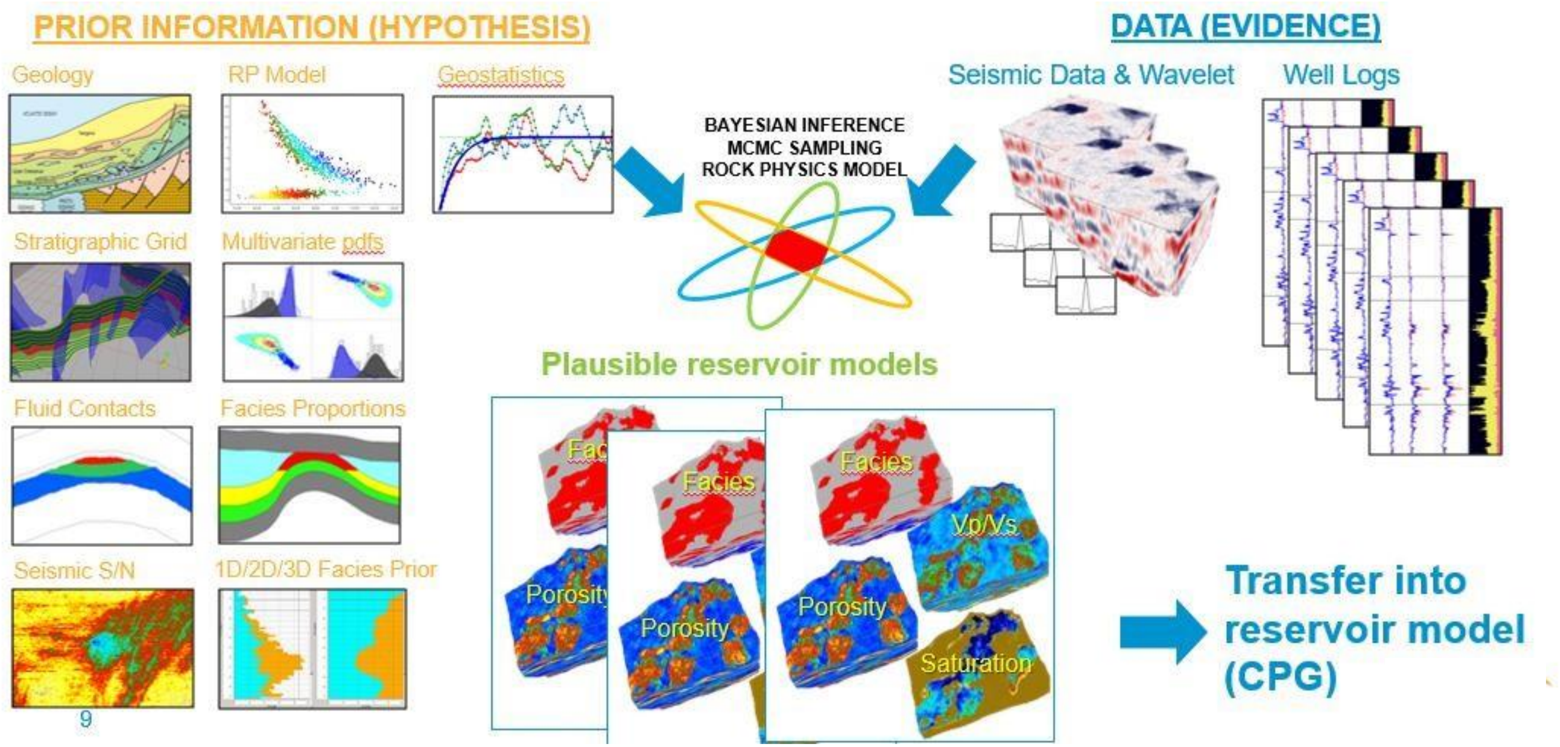
$$P(X|D,I) = \frac{P(D|X)P(X|I)}{P(D)}$$

Prior pdf

Posterior pdf

Workflow: Three Elements of Geostatistical Inversion

Geostatistical Modeling → Bayesian Inference → Sampling of Posterior Pdf



Types and Algorithms

All geostatistical inversion methods use geostatistical modeling and Bayesian inferences

Methods vary in using assumptions in geostatistical modeling and also in using the method for sampling posterior probability density function.

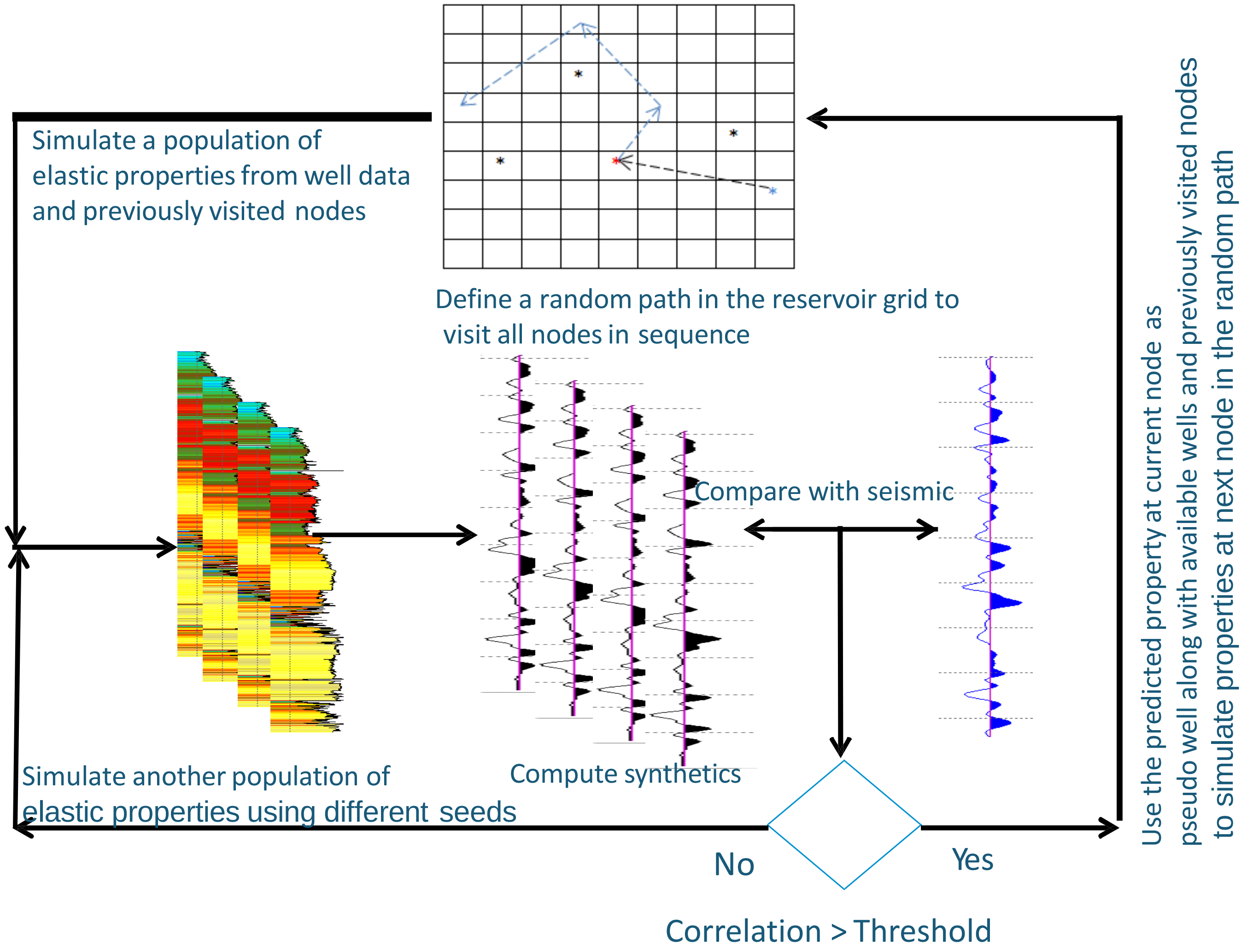
Commonly used methods of geostatistical inversion use :

Sequential Gaussian Simulation (SGS) and

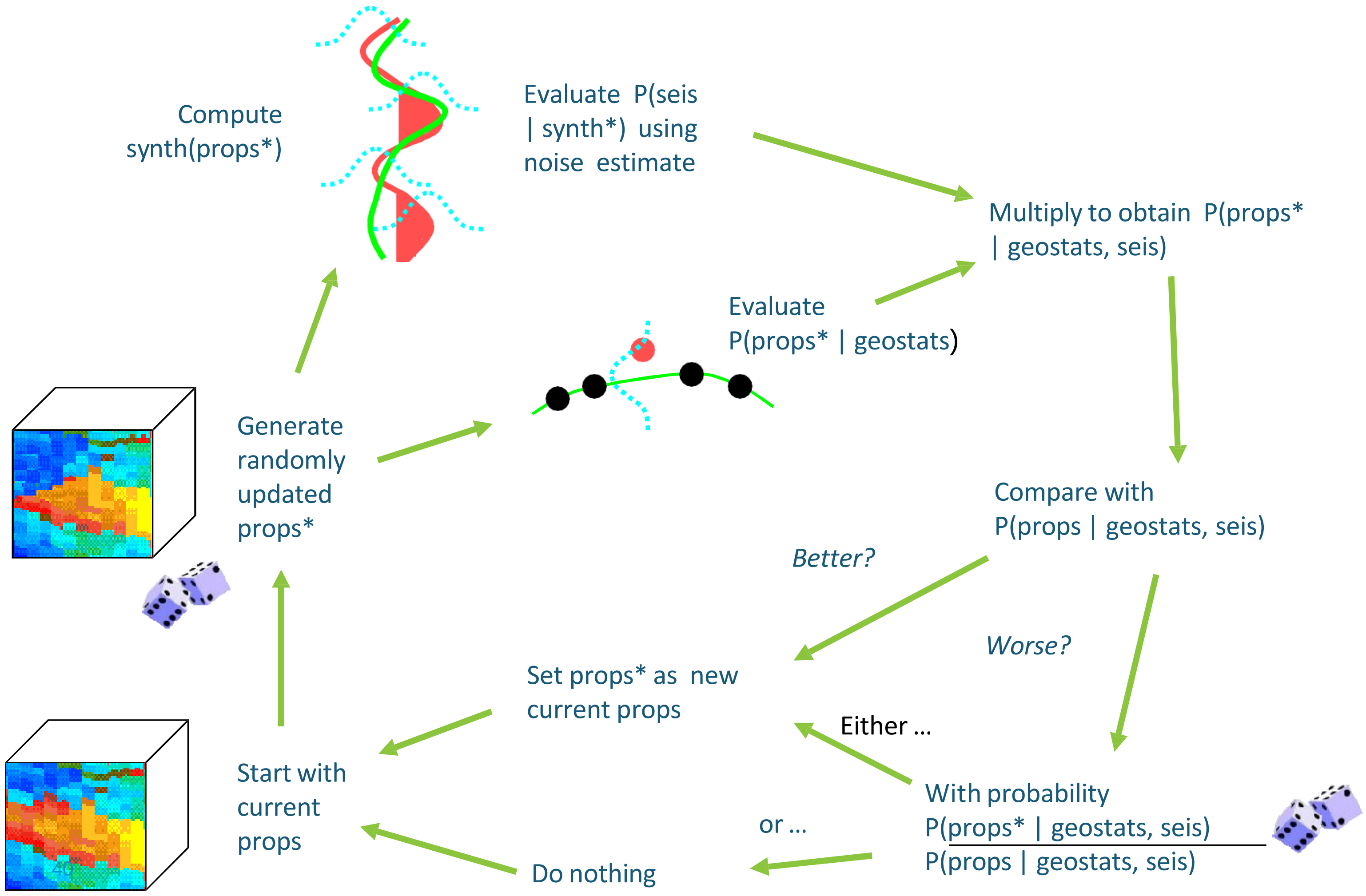
Markov Chain Monte Carlo (MCMC)

for sampling posterior pdf function obtained by combining the prior probability with the likelihood functions.

Geostatistical Inversion using Sequential Gaussian Simulation



Geostatistical Inversion using Markov Chain Monte Carlo Method



What is Good Geostatistical Inversion?

QC Geostatistical Inversion Results

An interplay of geostatistical model parameters, e.g.

i) Facies proportion,

ii) Property distribution per facies,

iii) Variogram type (exponential/Gaussian or non parametric)

iv) Variogram model (vertical and lateral ranges, anisotropy, nuggets, etc.) and

v) Seismic noise parameters

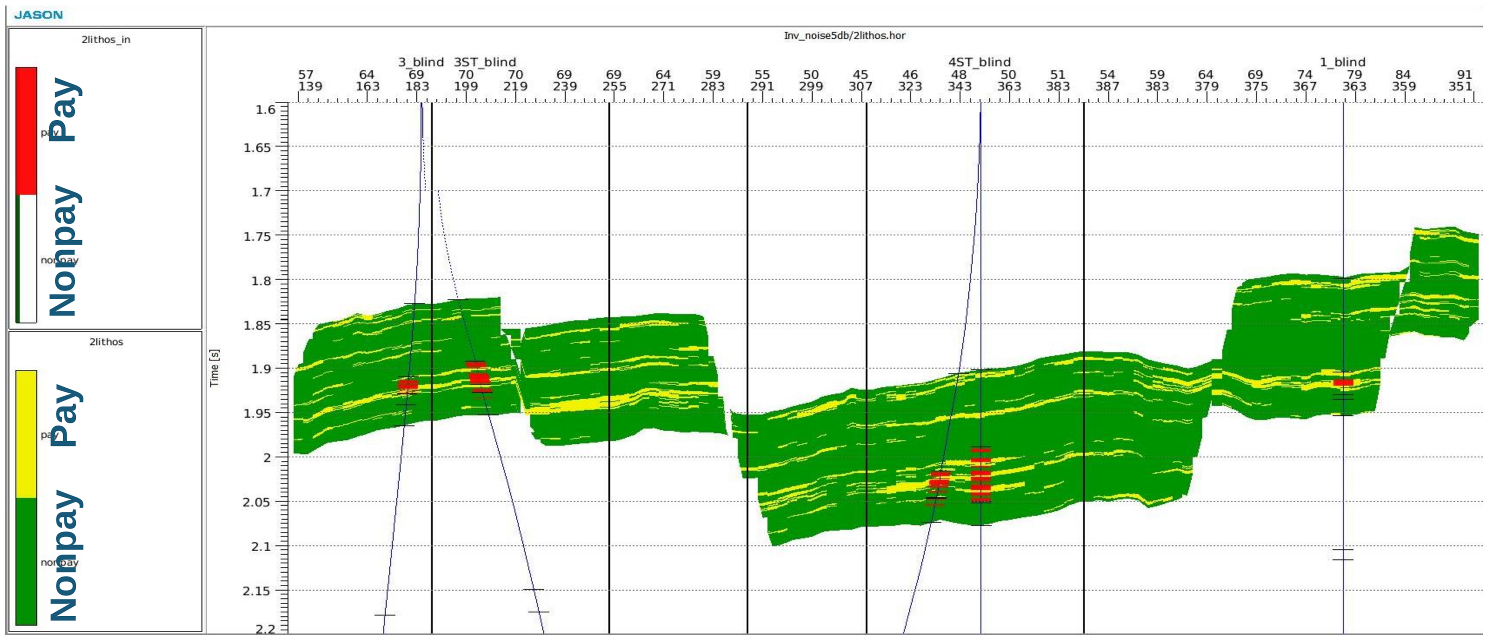
determine the quality of geostatistical inversion results.

Predict blind wells as closely as possible is one of the major objectives in parameter optimization of geostatistical inversion.

Blind Well Predictions

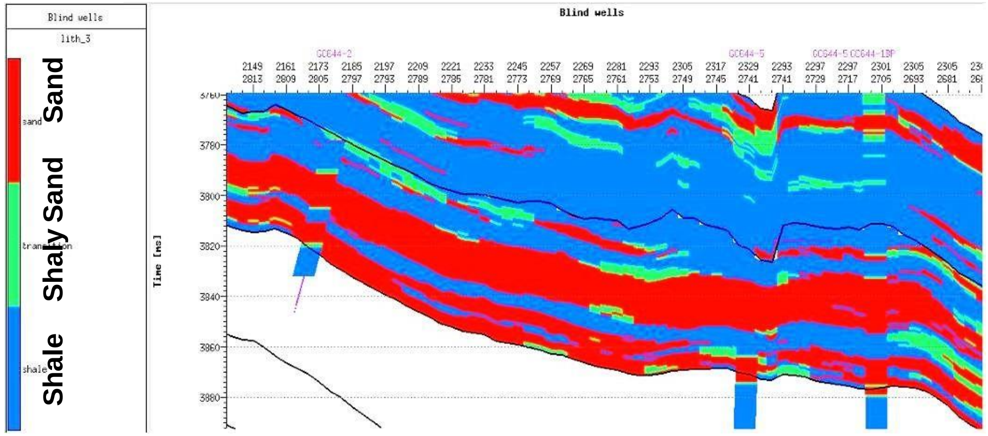
Select a discrete property section through blind wells and overlay the blind wells

Look out for good match for most of large scale features within seismic bandwidth and several of small scale features within seismic bandwidth.



Non-pay facies in the well has been masked for better comparison

Examples of Different Qualities of Blind Well Predictions



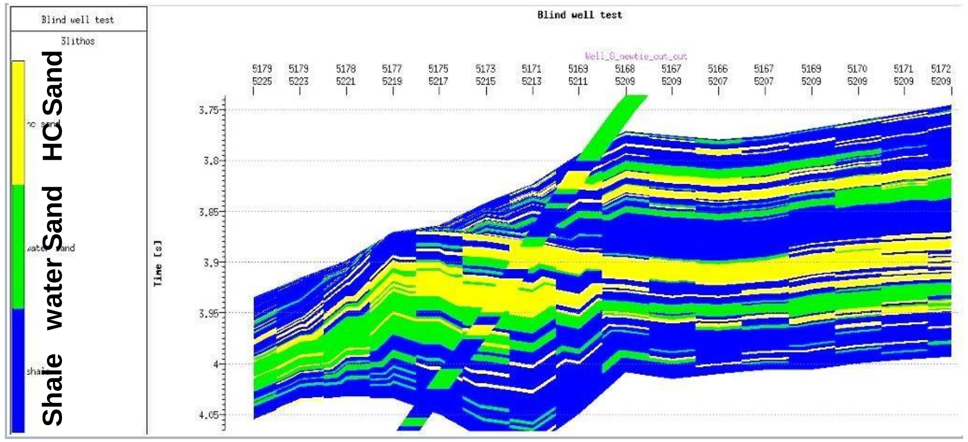
Very Good

Almost all features, large or small

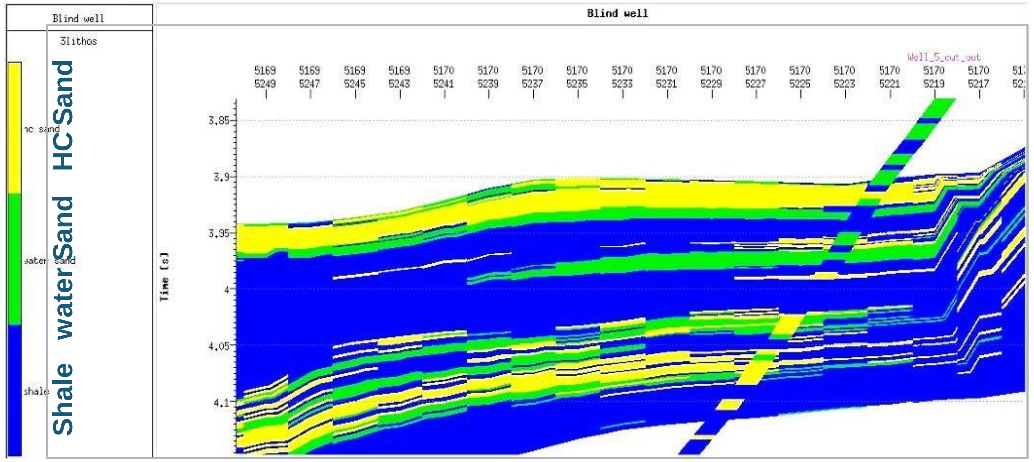
- a kind of an ideal situation!

Good

Most of large scale features and several small scale features match- features, large or small match- a kind of desired case with real data.



Examples of Different Qualities of Blind Well Predictions

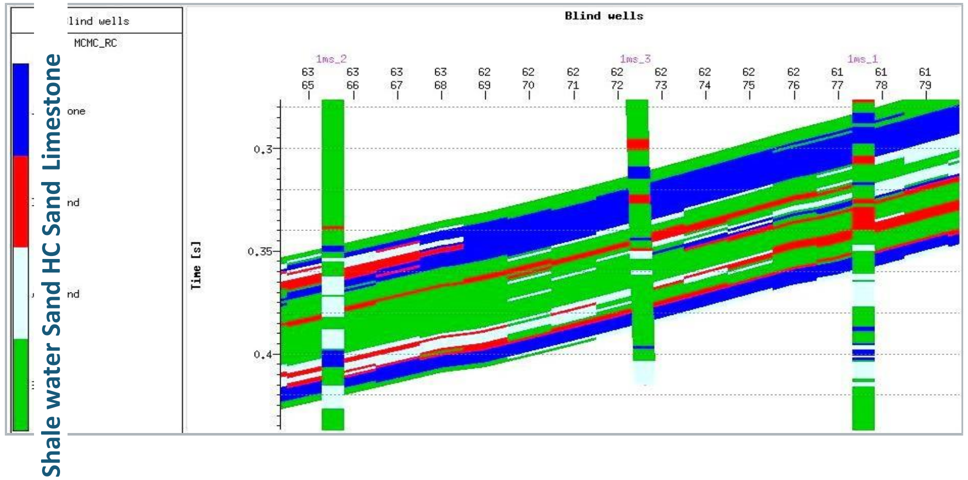


Poor

Only a few of large scale and small scale features match- a common situation during initial parameterization of a case with poor data quality or significant overlap of properties. Needs careful parameterizations.

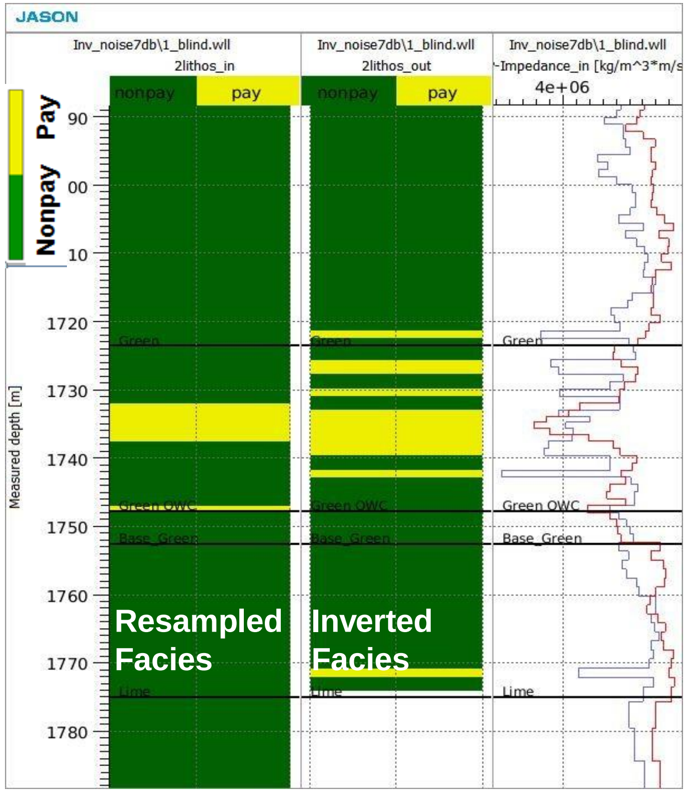
Unacceptable

Complete mismatch- something grossly wrong. May need to restart with a feasibility study and facies definition!

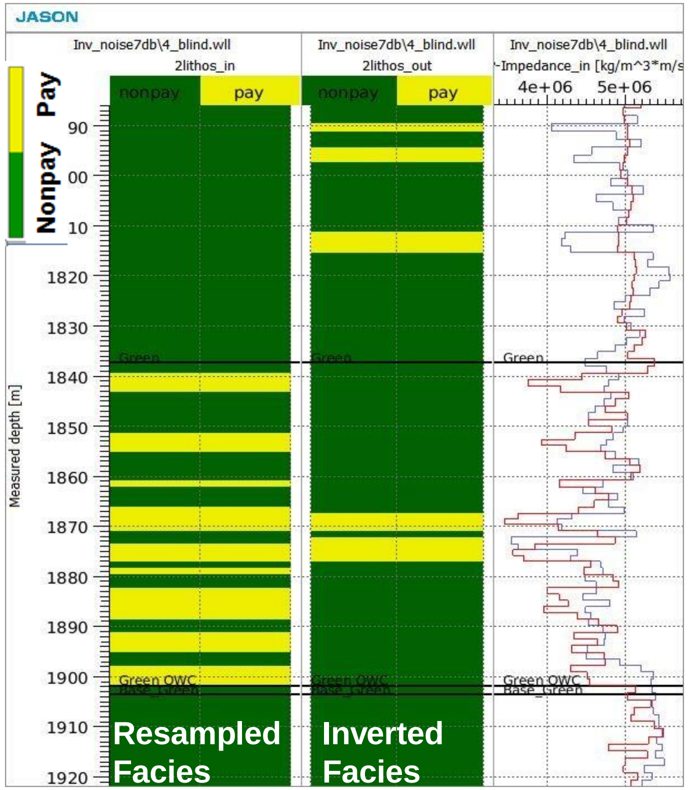


Blind Well Prediction – Match at Wells

Thick Beds



Thin Beds



P-Impedance resampled at well

P-Impedance from inversion at well

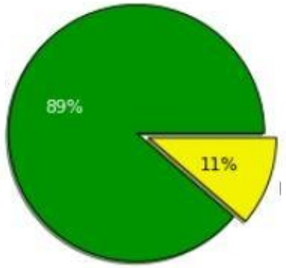
Compare results from realizations of different scenarios.

Thick sands should appear in all realizations but thin sand at any location may appear and disappear across realizations.

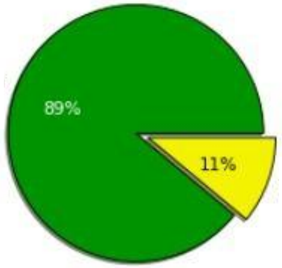
Match between Prior and Posterior Pdfs

Facies

Posterior



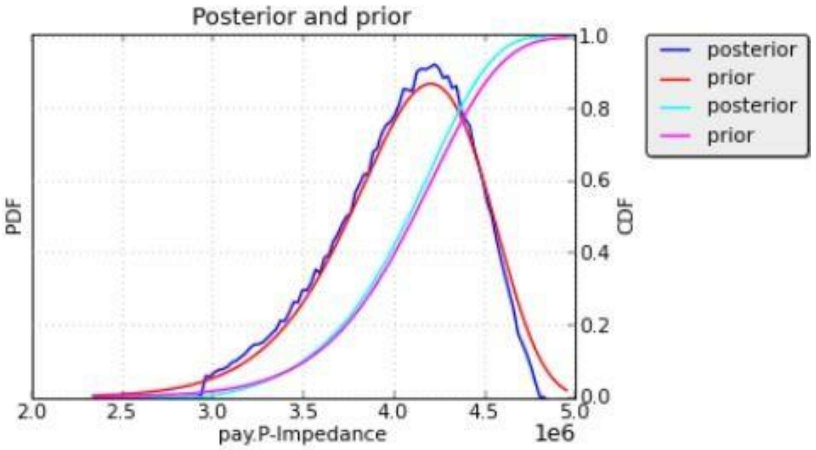
Prior



Good match between prior and posterior facies proportions

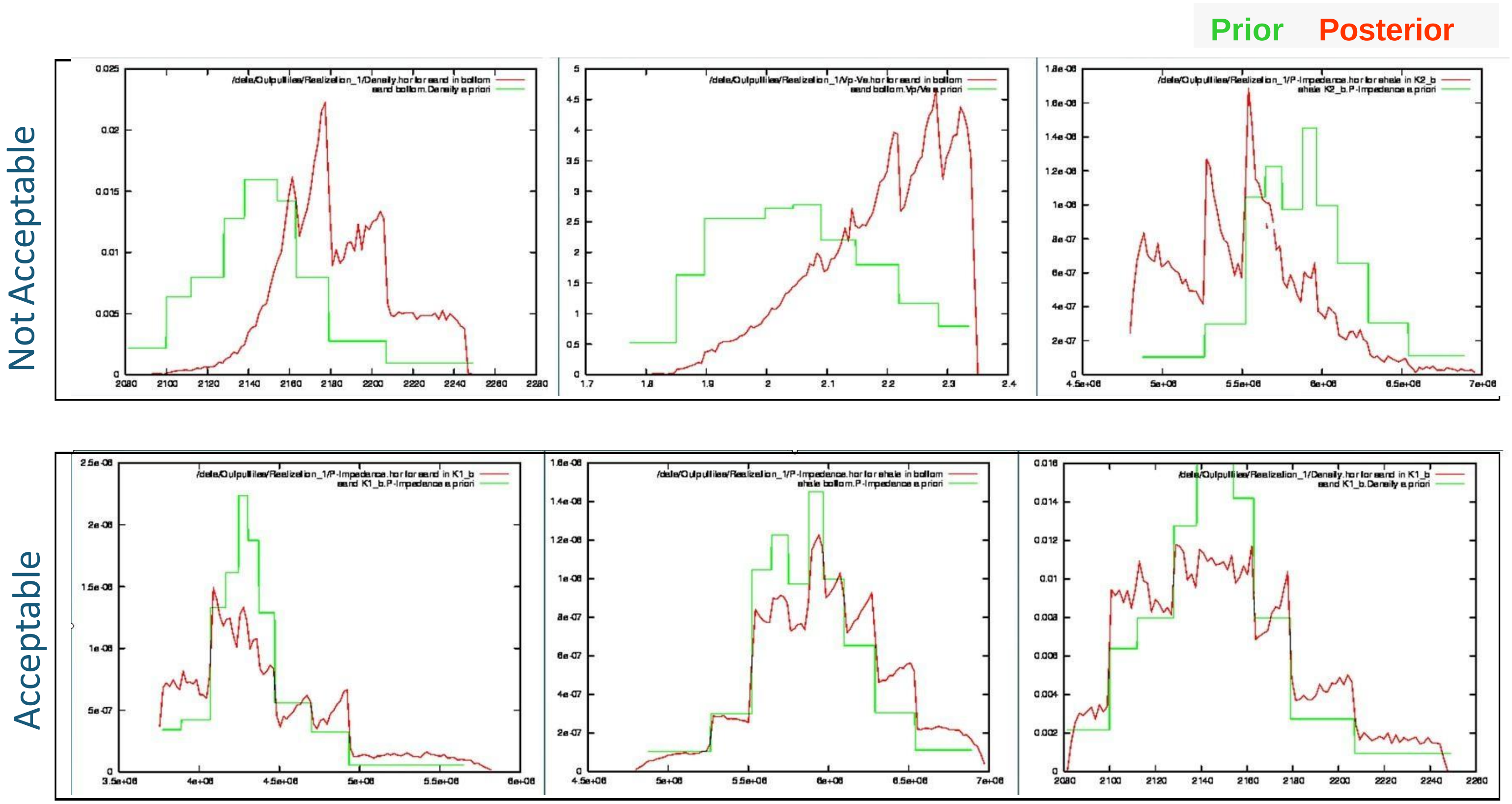
Prior and posterior pdfs of P-impedance of Pay facies

Good match between prior and posterior pdfs of elastic property

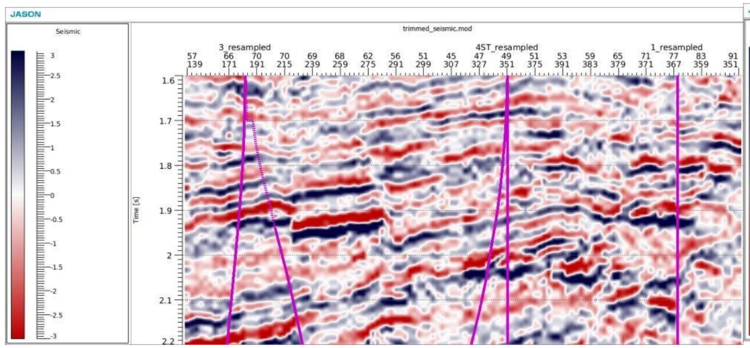


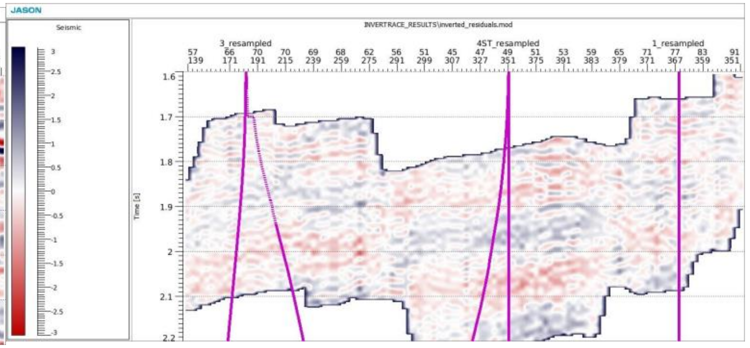
Examples of Prior/Posterior Match

Match between prior and posterior pdfs will imply that the shape of the two curves and the mean, the standard deviation and the asymmetry are close to each other.



Seismic Residuals: Assess Quality of Seismic Modeling


Seismic

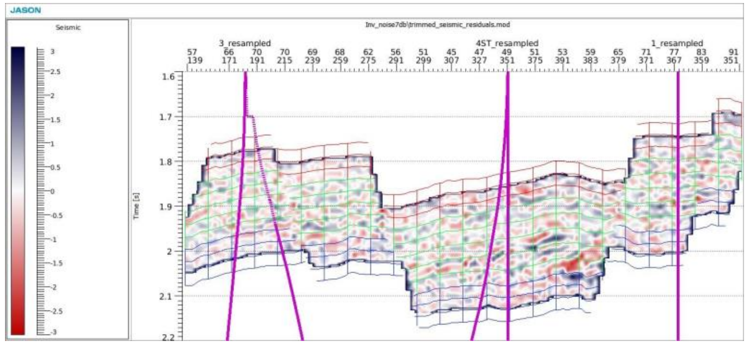

Deterministic Inversion Residuals

Geostatistical inversion (GI) residuals should be incoherent and patchy.

Always compare these residuals with those from deterministic inversion

GI residuals can be stronger than DI residuals depending on input noise level for geostatistical Inversion.

Coherent residuals may arise due to several factors, viz. in appropriate wavelet, lower level of SNR used as input or even inappropriate stratigraphic framework.

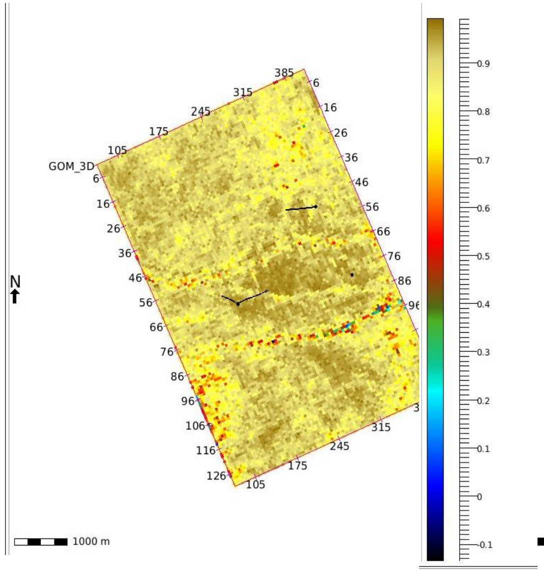

Geostatistical Inversion Residuals

Seismic Residuals: Assessing Quality of Seismic Modeling

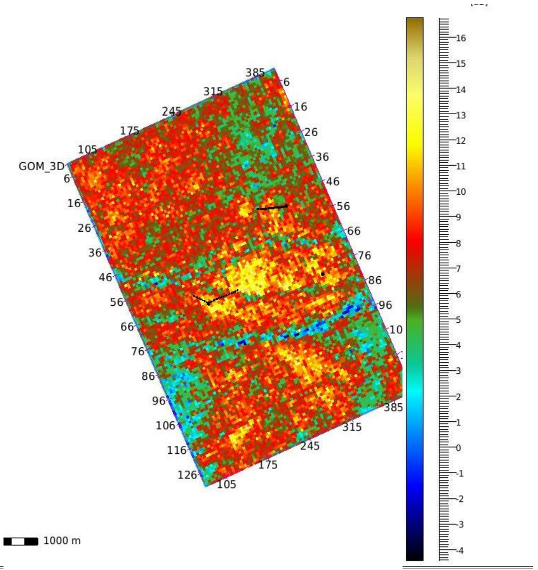
Look for presence of any geological shape which will mean that valuable information in seismic has not been modeled fully

Correlation values at well locations should be comparable to the corresponding values obtained during well to seismic tie and wavelet estimation

Cross Correlation



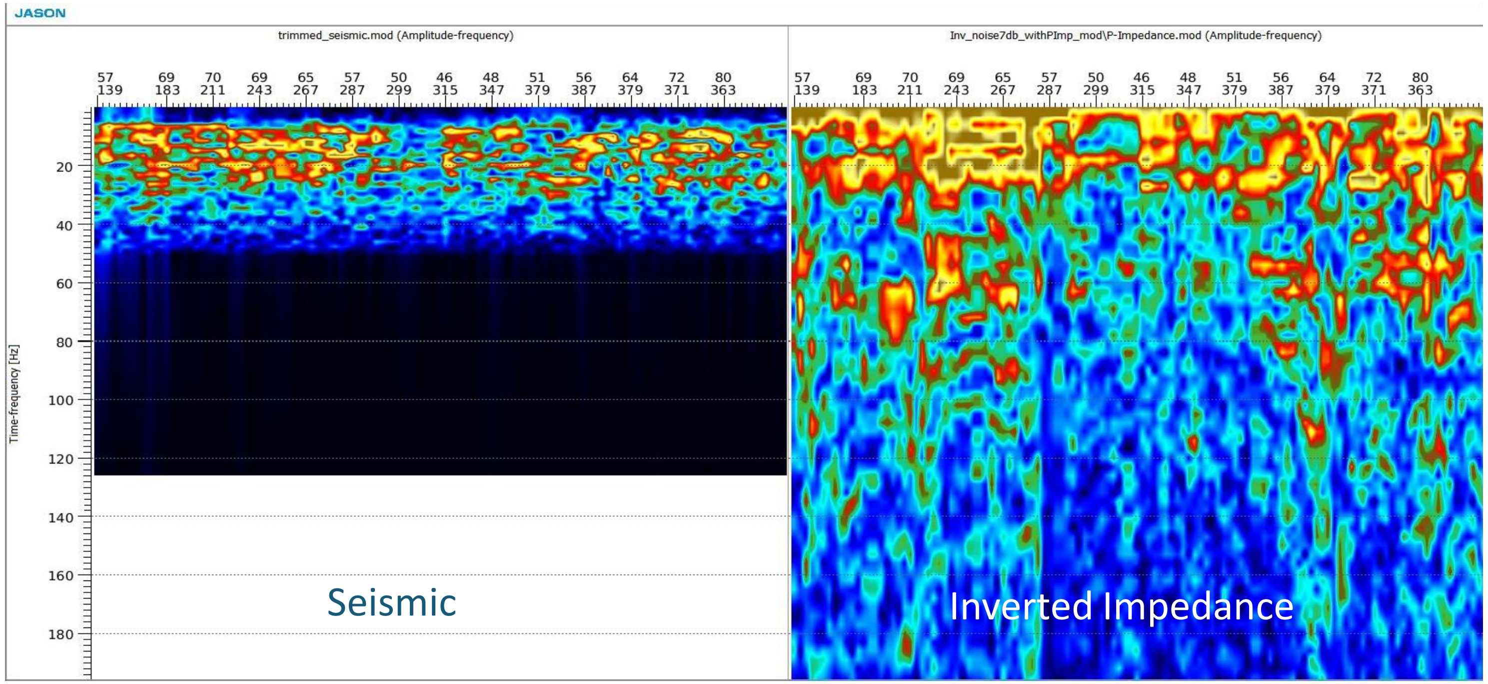
SNR (dB)



High Frequency Content in Geostatistical Inversion

Look for high frequency information above seismic frequencies derived in geostatistical inversion through geostatistical information, discrete properties etc.

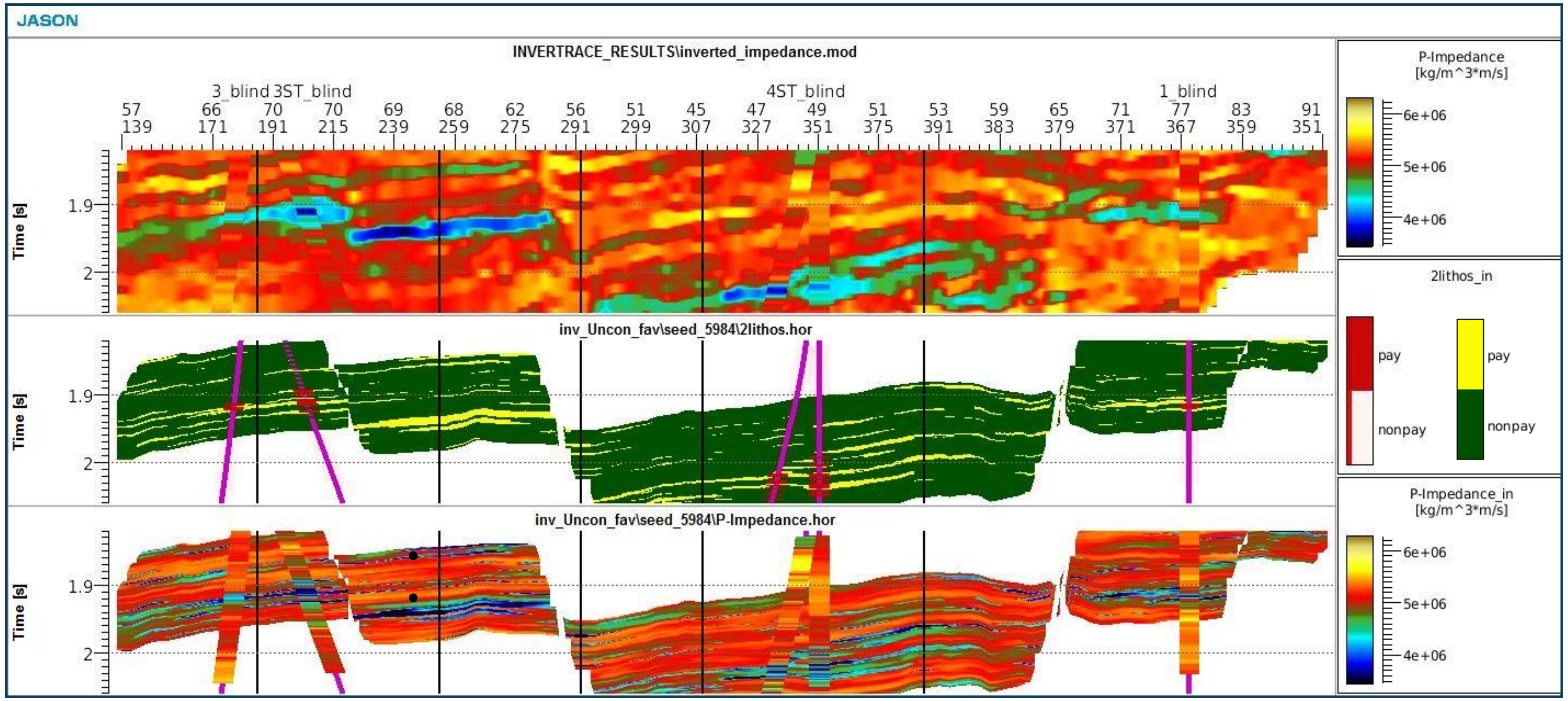
The high frequency part of the spectrum should not look random.



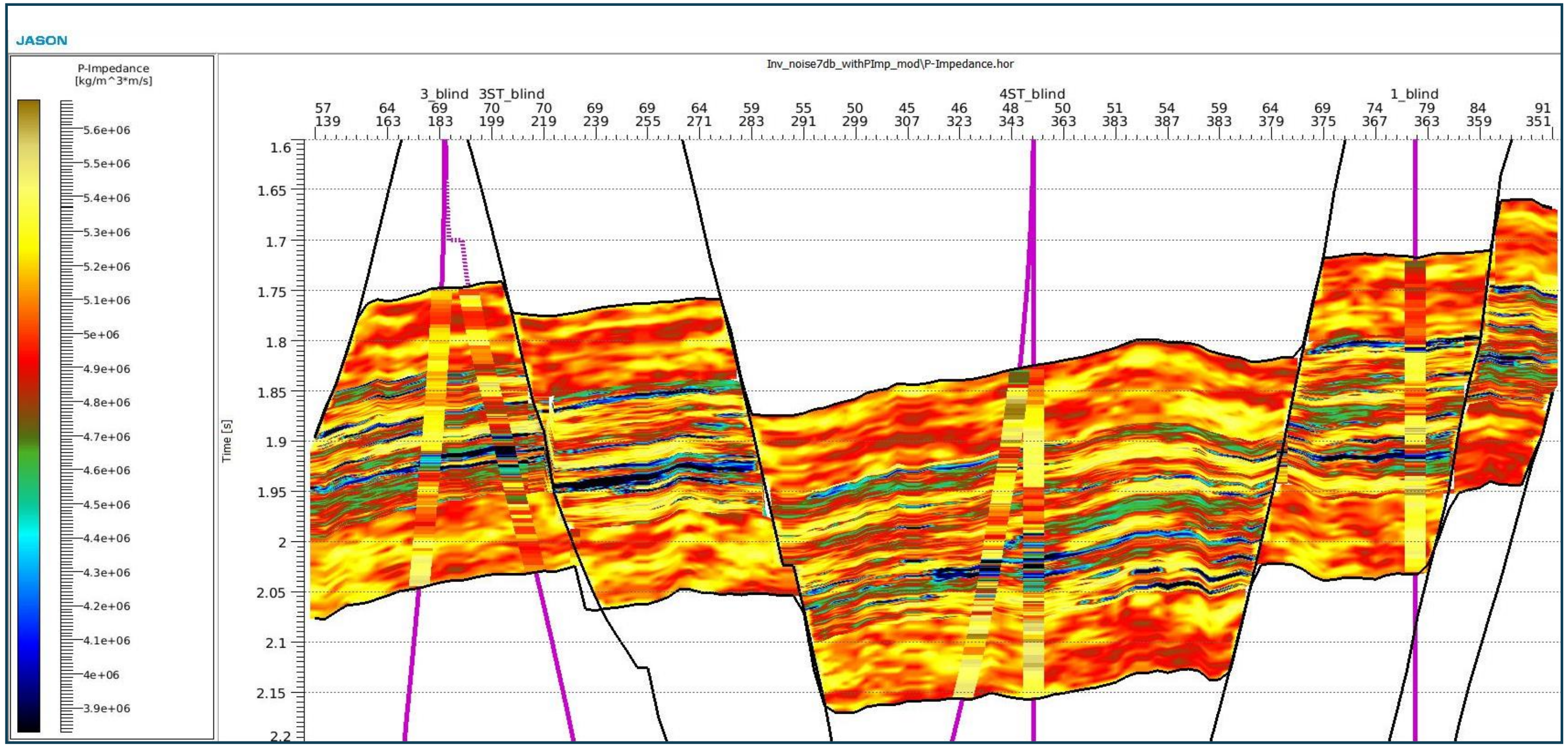
CSSI, Continuous and Discrete Properties

Compare with deterministic results to look for

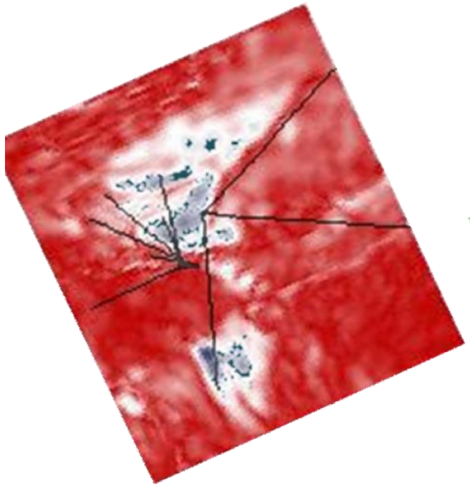
- proportion of different discrete properties
- location, shape and connectivity of sand bodies



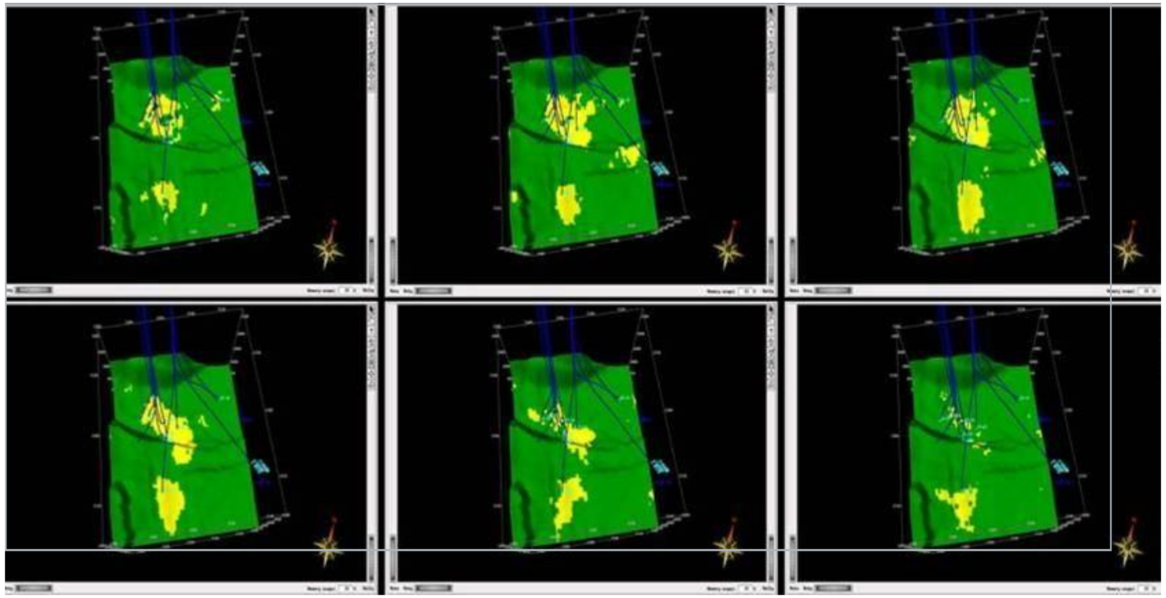
Continuous Property with Blind Wells



Look for Plausible Geological Shapes on Maps



RMS of seismic amplitude over reservoir layer



Geostatistical inversion derived seismic facies slices through the reservoir (6 slices shown here)

Look for plausible geological shapes. Shapes observed in seismic amplitude RMS maps should be clearly deciphered in geostatistical inversion results. Besides, subtle shapes and geometries not mapped in seismic attribute maps should also show up. Check for consistenc of these geometries with depositional setting.

Uncertainty Quantification

Uncertainty Quantification

GeoSoftware™

www.GeoSoftware.com

What is Uncertainty?

No single model is correct !

No single model exists that accurately captures all the information contained in all the disparate data used as input to reservoir characterization and modeling.

Providing estimate of the uncertainty of predicted rock property is *as important* as providing accurate estimate of its most likely value.

Interpretation of inaccurate, insufficient and inconsistent data
(Jackson, 1972, Journal of Royal Astronomical Society of London)

Sources of Uncertainty

Natural variability (variance)

- Inherent randomness of natural processes.
- Mathematical models cannot ever provide a perfect fit to natural phenomena.

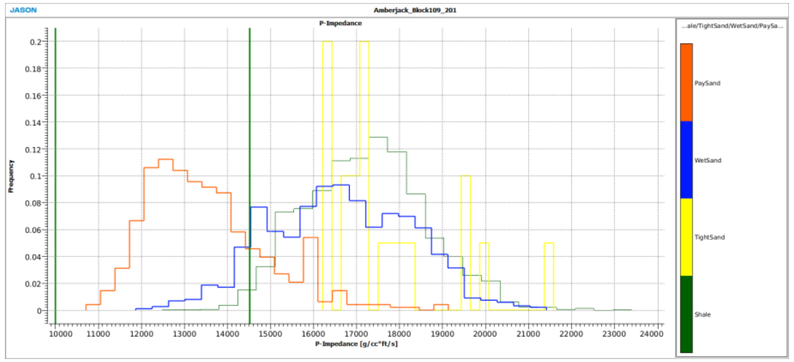
Knowledge uncertainty (bias)

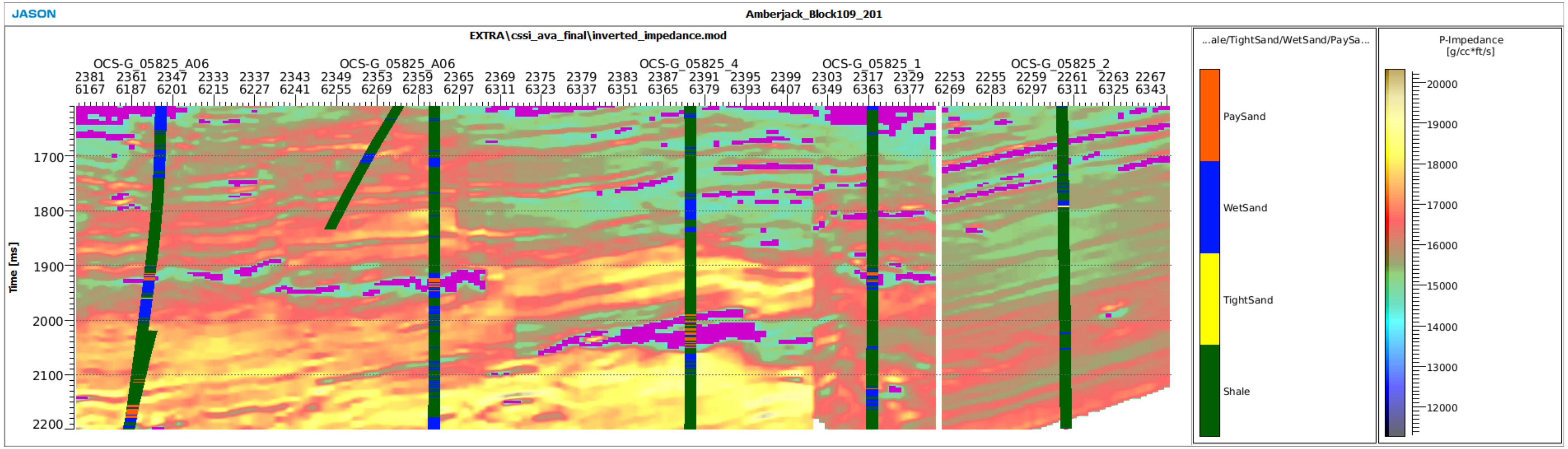
- Lack of measured data.
- Approximation of parameters.
- Assumptions and simplifications of theoretical models.

Uncertainty Estimation in Determining Inversion

Inverted acoustic impedance and/or Vp/Vs from deterministic inversion are often interpreted using histogram/polygon based body capture

- Thresholding on histogram if only one inverted property used
- Polygon based capture of bodies, if two inverted properties are used simultaneously.

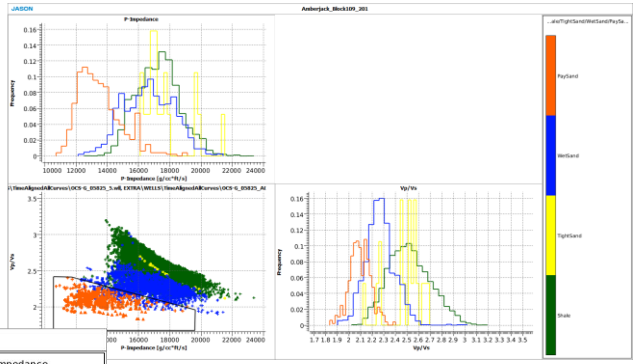


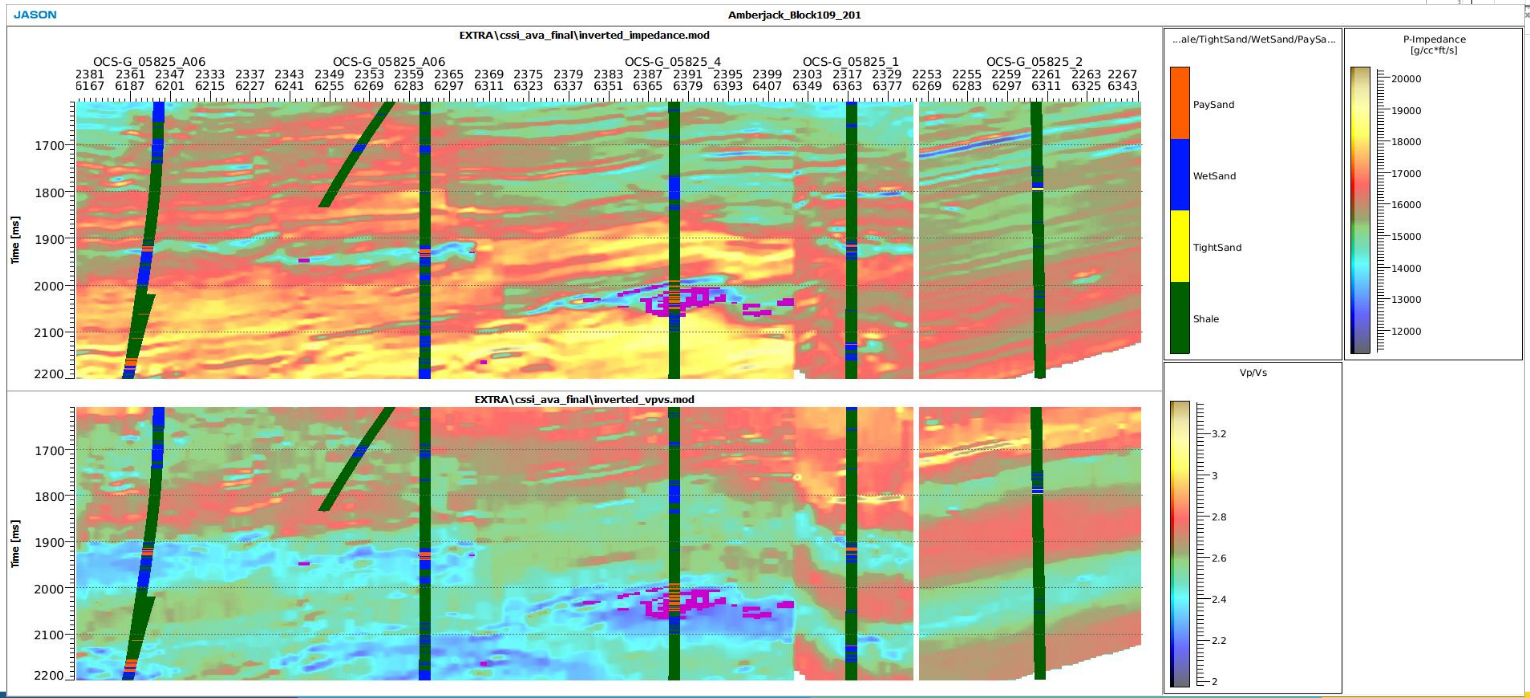


Uncertainty Estimation in Determining Inversion

Polygon based capture of bodies. Geo-bodies captured by polygon highlighting are shown in magenta in the section view

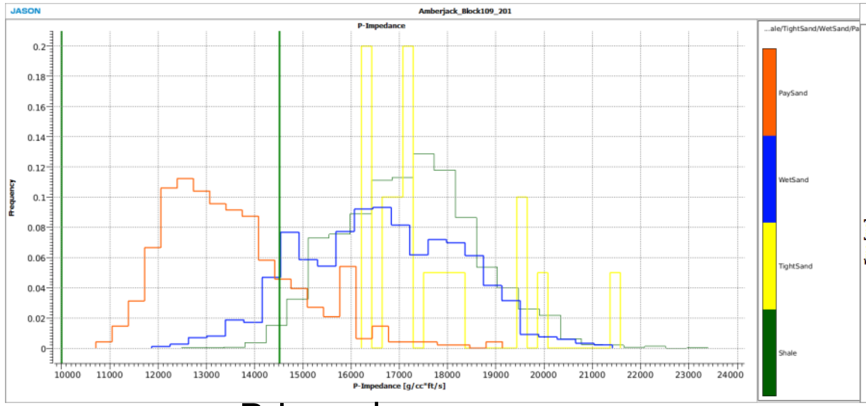
Captured body shape and size are sensitive to the range in histogram or polygon used to highlight the bodies.

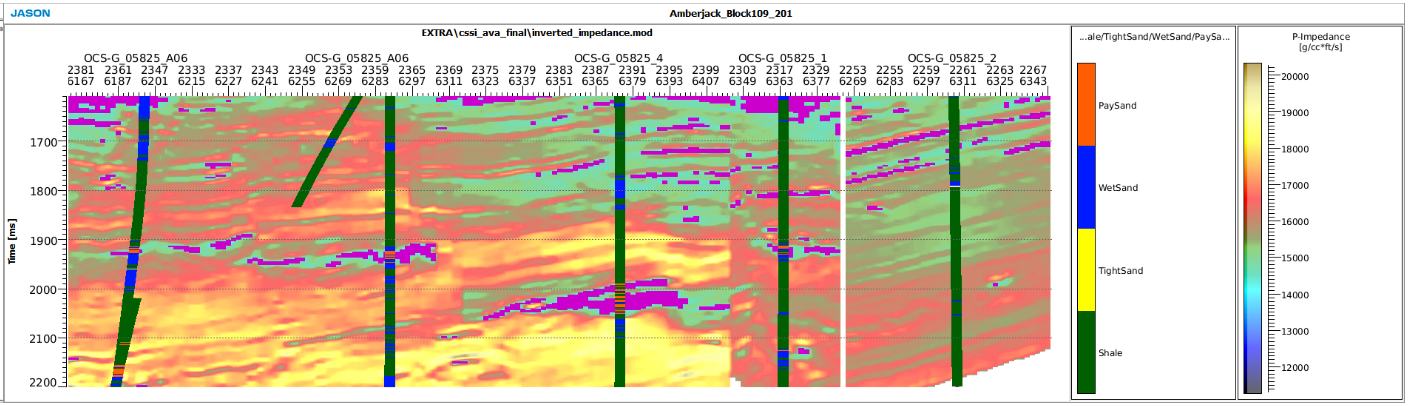




Threshold based Body Capture

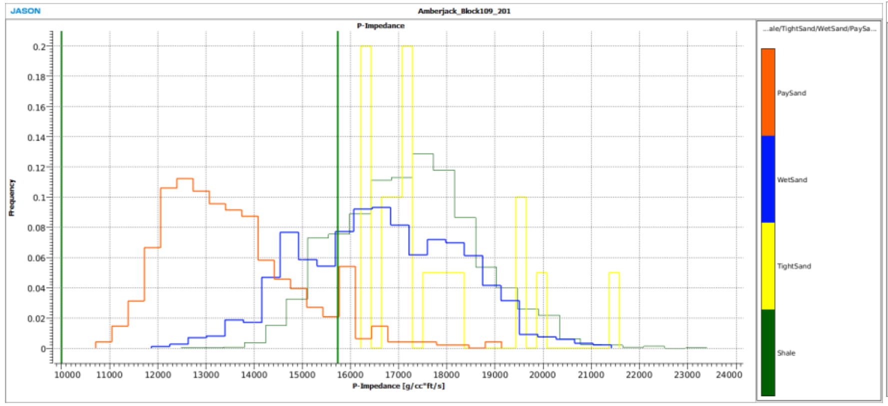
Frequency

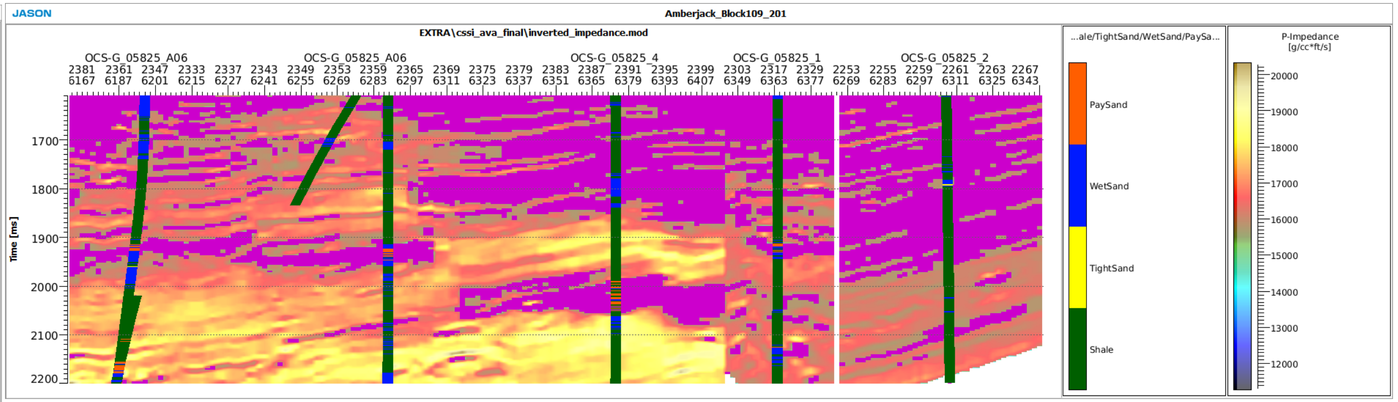




P-Impedance

Frequency





P-Impedance

Thresholding based on histogram range or polygon puts a hard boundary (barrier) to separate neighboring facies
Facies on either side of the boundary has a finite probability to belong to the other class.
This fact can be well recognized and handled through Bayesian classification

Bayesian Inference: The Theorem

If P(A) and P(B) represent probabilities of occurrence of events A and B respectively, then

The joint probability of occurrences of A & B is given by

$$P(A, B) = P(A \mid B).\, P(B)$$

$$= P(B \mid A).\, P(A)$$

which can be rearranged as

$$P(A \mid B) = \frac{P(B \mid A).\, P(A)}{P(B)}$$

Now think of ‘A’ as the Facies and ‘B’ as the Acoustic Impedance (AI).

Bayesian Inference: The Concept

Event / Experiment

Posterior

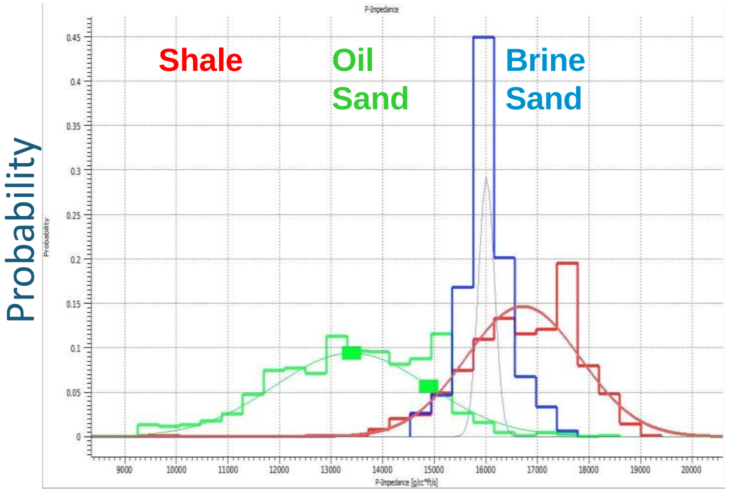
Prior

Likelihood

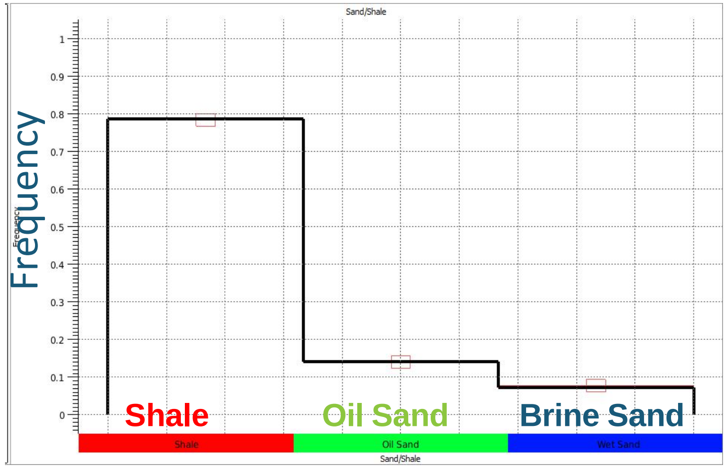
Prior Probability

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

Posterior Probability Density Function



Acoustic Impedance



Facies

Facies proportion (prior probability) can be derived from well measurements

Likelihood- given a facies, the distribution of property- can be derived from wells, petrophysics & rockphysics

Facies and Fluids Probabilities (FFP)

Facies and Fluids Probabilities (FFP) in Jason Workbench uses Bayesian inference to estimate facies (and fluid) probabilities from deterministic inversion results

The estimated facies probabilities include the uncertainties arising out of overlap of properties among different facies, limit of resolution of seismic data as well seismic noise

Uncertainty in the input data to FFP, e.g, the mismatch between measured and inverted P-impedance at well location can be easily incorporated

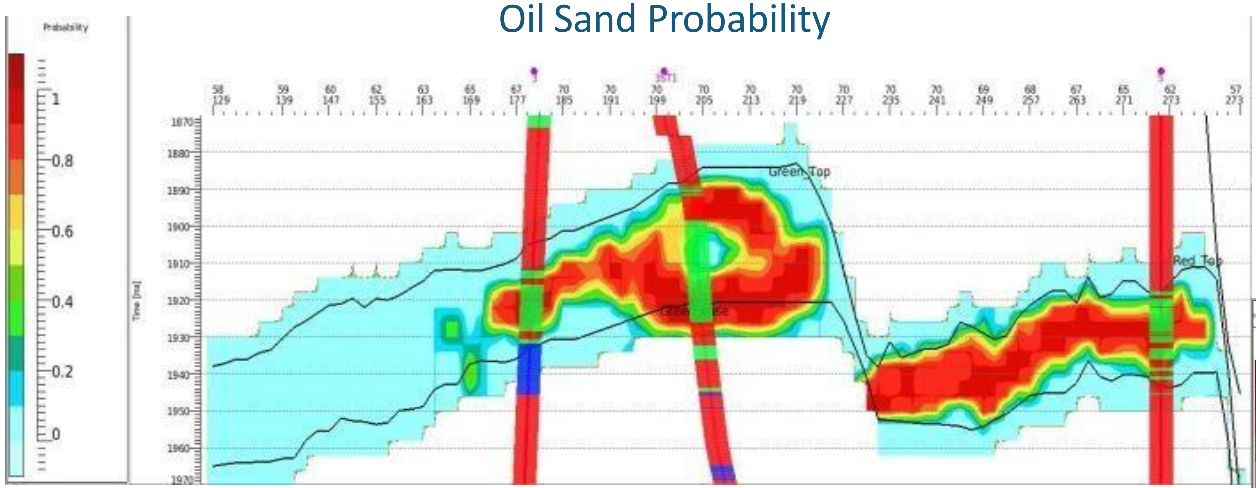
Uncertainty in prediction of facies from deterministic inversion results can be quantitatively assessed through Confusion Matrix

However, quantitative assessment of uncertainty are properly handled in geostatistical inversion which works on the premise that all the measurement, experiments as well as interpretation processes have inherent uncertainty

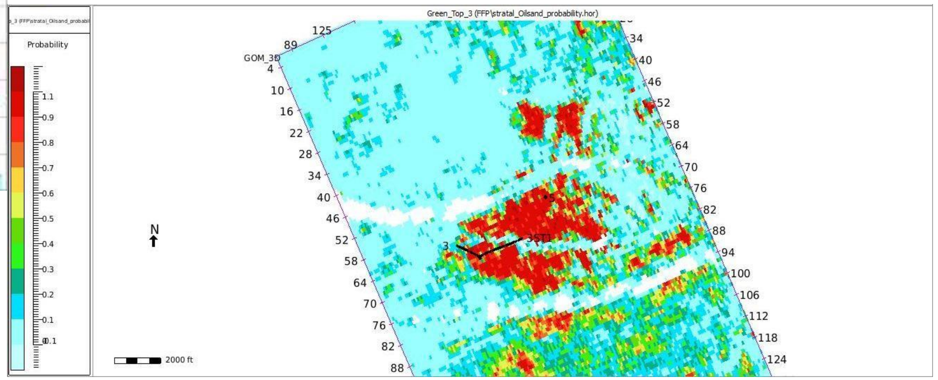
Results from FFP

Posterior probability density provides the probability of each facies at a subsurface point
From probability density per facies, the most probable facies can be derived using the best score

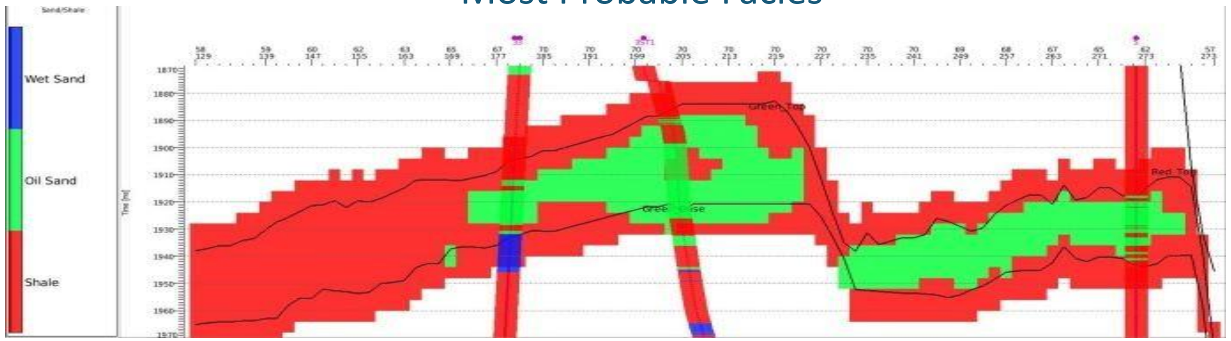
Oil Sand Probability



A Stratal Slice of Oil Sand Probability Volume



Most Probable Facies



Confusion Matrix: A Quantitative Measure of Uncertainty

Consider that we have two facies, Pay and Non-Pay to be estimated from deterministic inversion using Facies and Fluid Probabilities. Since we have facies logs already available in the wells in the area of study, we can count the number of a particular facies encountered along the well paths from FFP results and compare those with the real facies in the measured logs. There can be four different cases at any subsurface location as explained in the table below

Real Facies	Estimated Facies	
Pay	Pay	Non-Pay
Non-Pay	Non-Pay	Pay

Here, occurrence of Pay is a positive outcome and not encountering Pay is a negative outcome. Thus, we have the following nomenclature

Pay in reality estimated as Pay : True Positive (TP)

Non-Pay in reality estimated as Non-Pay : True Negative (TN)

Pay in reality estimated as Non-Pay : False Negative (FN)

Non-Pay in reality estimated as Pay : False Positive (FP)

Metrics of Confusion Matrix

Precision = $\frac{TP}{TP+FP}$

Recall = $\frac{TP}{TP+FN}$

Accuracy = $\frac{TP+TN}{(TP+FP)+(TN+FN)}$

F1-score = $\frac{2*(Precision * Recall)}{(Precision + Recall)}$;

$$\frac{2}{\text{F1}-\text{score}} = \frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}$$

Specificity = $\frac{TN}{(FP+TN)}$

Precision: is fraction of correctly identified positive cases out of total tested positive cases.

Recall: also called sensitivity is fraction of correctly identified positive cases out of total real positive cases.

Accuracy: is fraction of correctly identified cases out of total cases

F1-score: accounts for both precision and sensitivity

Specificity: is fraction of correctly identified negative cases out of total negative cases

Metrics of Confusion Matrix: Example

Effectiveness of facies estimation can be evaluated from various metrics of the confusion matrix

Precision = $\frac{TP}{TP+FP}$

Recall = $\frac{TP}{TP+FN}$

Accuracy = $\frac{TP+TN}{(TP+FP)+(TN+FN)}$

F1-score = $\frac{2*(Precision * Recall)}{(Precision + Recall)}$;

$$\frac{2}{\mathrm{F1{-}score}} = \frac{1}{\mathrm{Precision}} + \frac{1}{\mathrm{Recall}}$$

Specificity = $\frac{TN}{(FP+TN)}$

Well logs Facies	Facies Estimated from FFP	
	Pay	Non-Pay
Pay	0.88	0.12
Non-Pay	0.00	1.00

Metric	Pay	Non-Pay
Precision	0.30	1.00
Recall	1.00	0.88
Accuracy	0.89	0.89
F1-score	0.47	0.94
Specificity	0.88	1.00

How Do We Measure Uncertainty?

No such thing as a “true” uncertainty

It cannot be measured.

Best we can do is to capture the input uncertainties

Uncertainty in the data

- Measurement errors.

Uncertainty in the model

- Type of geological scenario.
- Parameters that defined a scenario.
- Limited amount of data.

Total Uncertainty = Variance + Bias

Variance = natural variability

- Range of possible solutions for fixed input.
- Usually minor component of total uncertainty.
- We try to reduce the variance component of total uncertainty by including as much data from different sources as we can (including the seismic data).

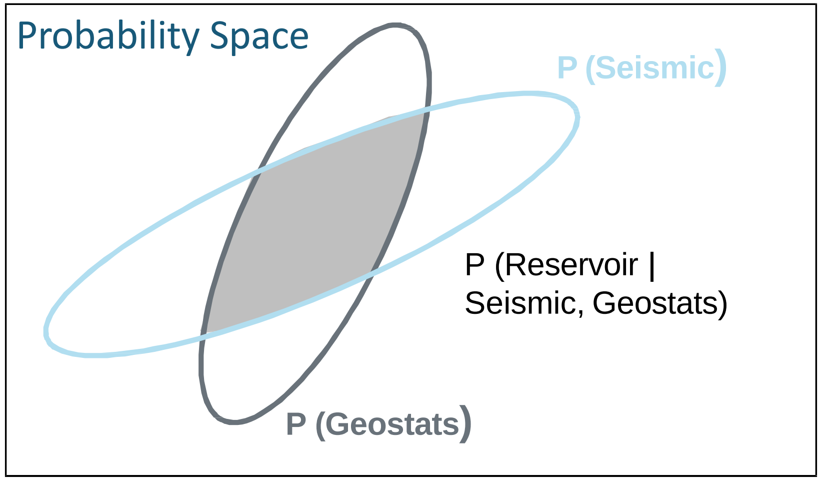
Bias = knowledge uncertainty

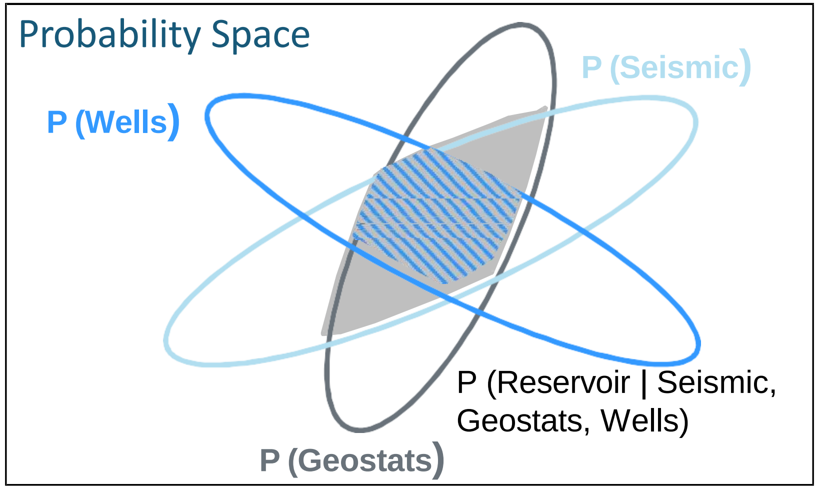
- Uncertainty induced by imperfections in the input
- Usually primary component of total uncertainty
- We try to capture the bias component of the uncertainty by trying different solid models, variograms, proportions, noise levels, wavelets, etc.

Proper assessment of the total uncertainty requires an understanding of the contributions of both variance and bias.

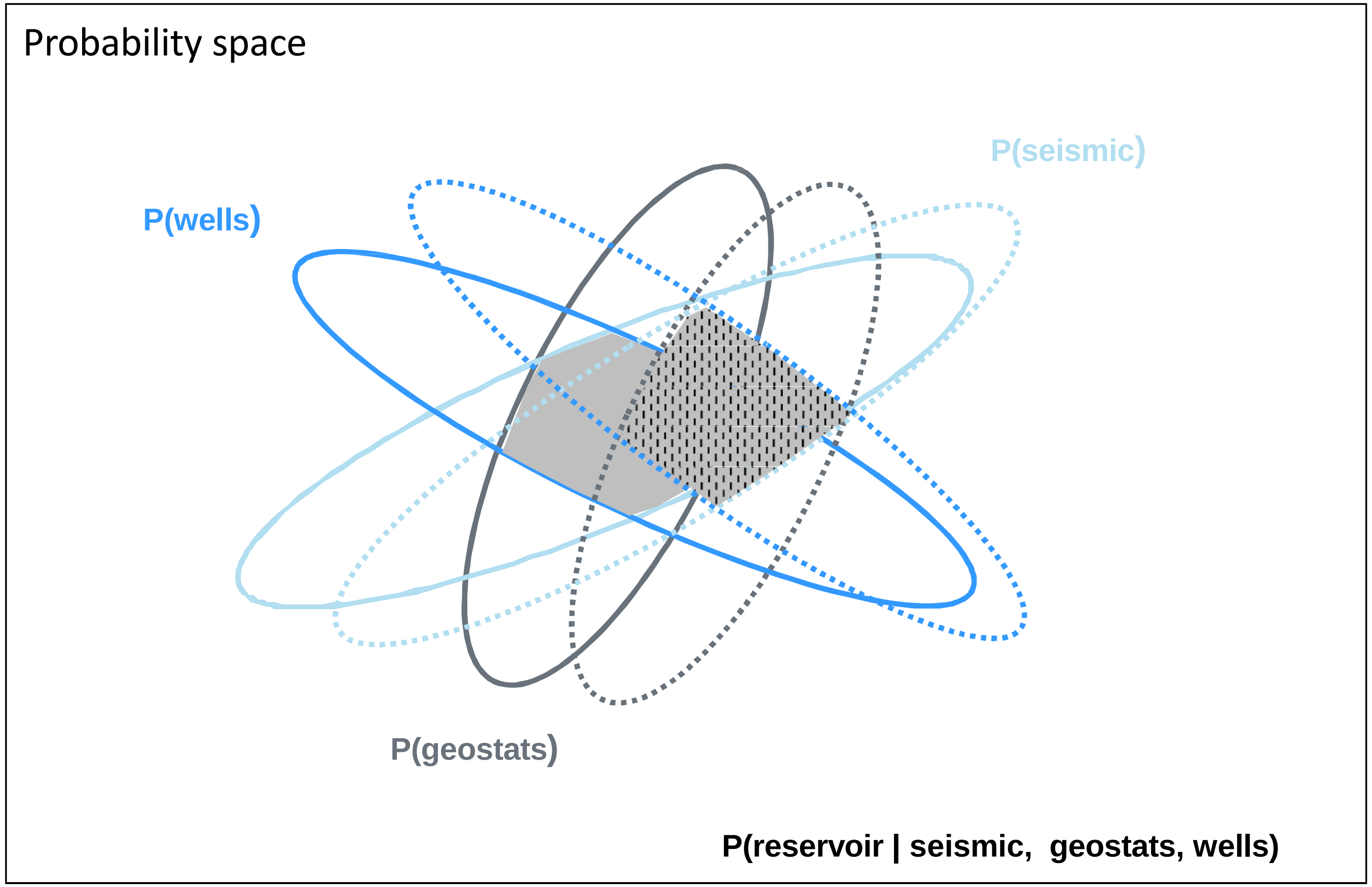
- Need to test not only different realizations, but more importantly different scenarios.

Uncertainty from Variance





Uncertainty from Bias



Experimenting with Variance and Bias

Variance

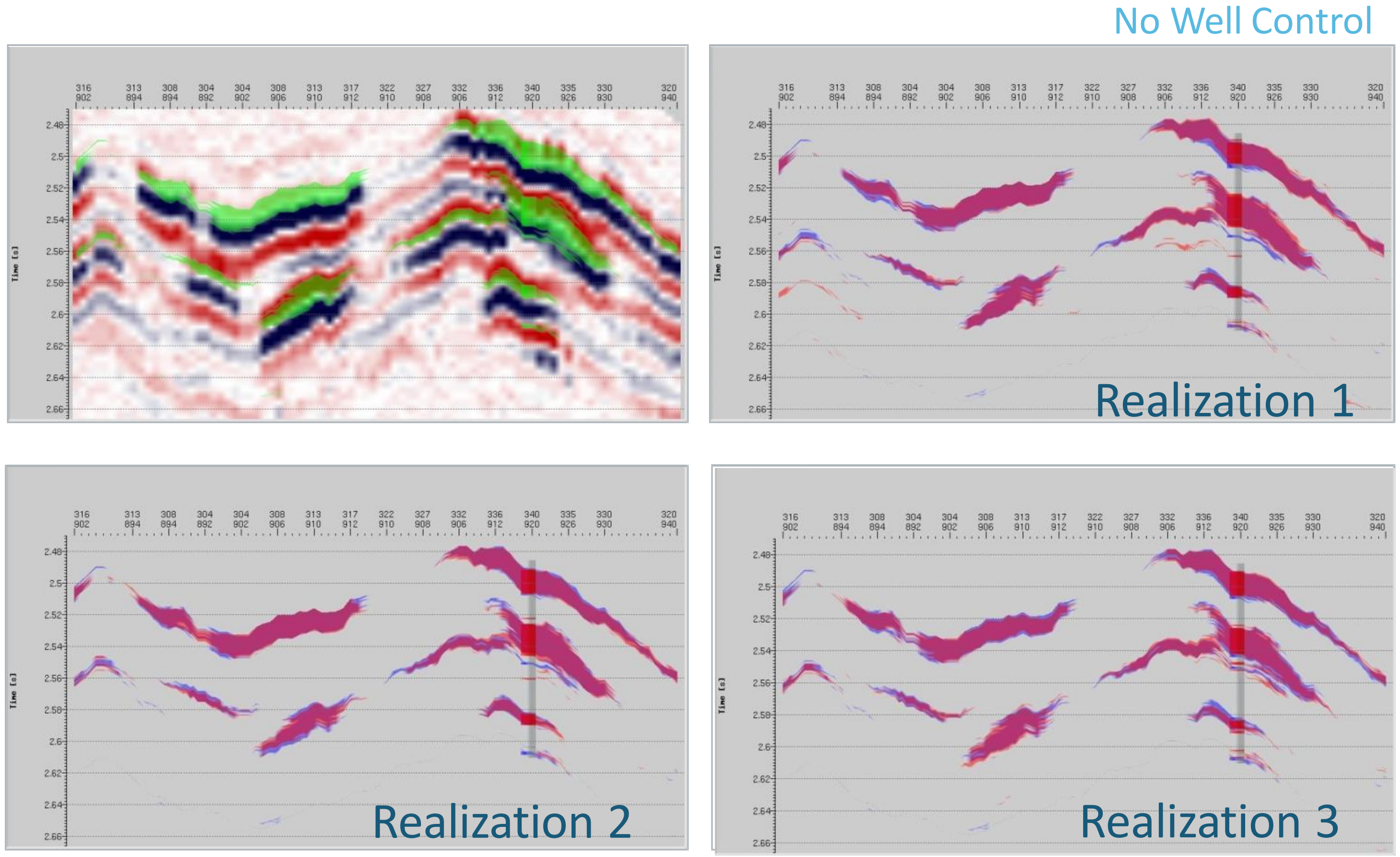
- Estimated by varying random seed

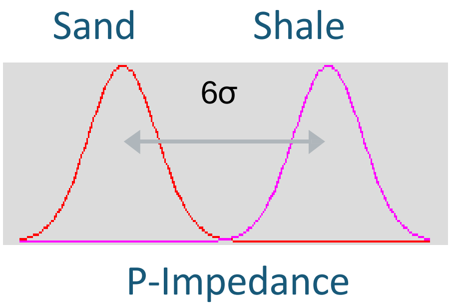
Bias

- Proportions of discrete property type
- Variograms of the discrete properties- type and parameters
- Definition of discrete property – vary number of types
- Noise level of the seismic data

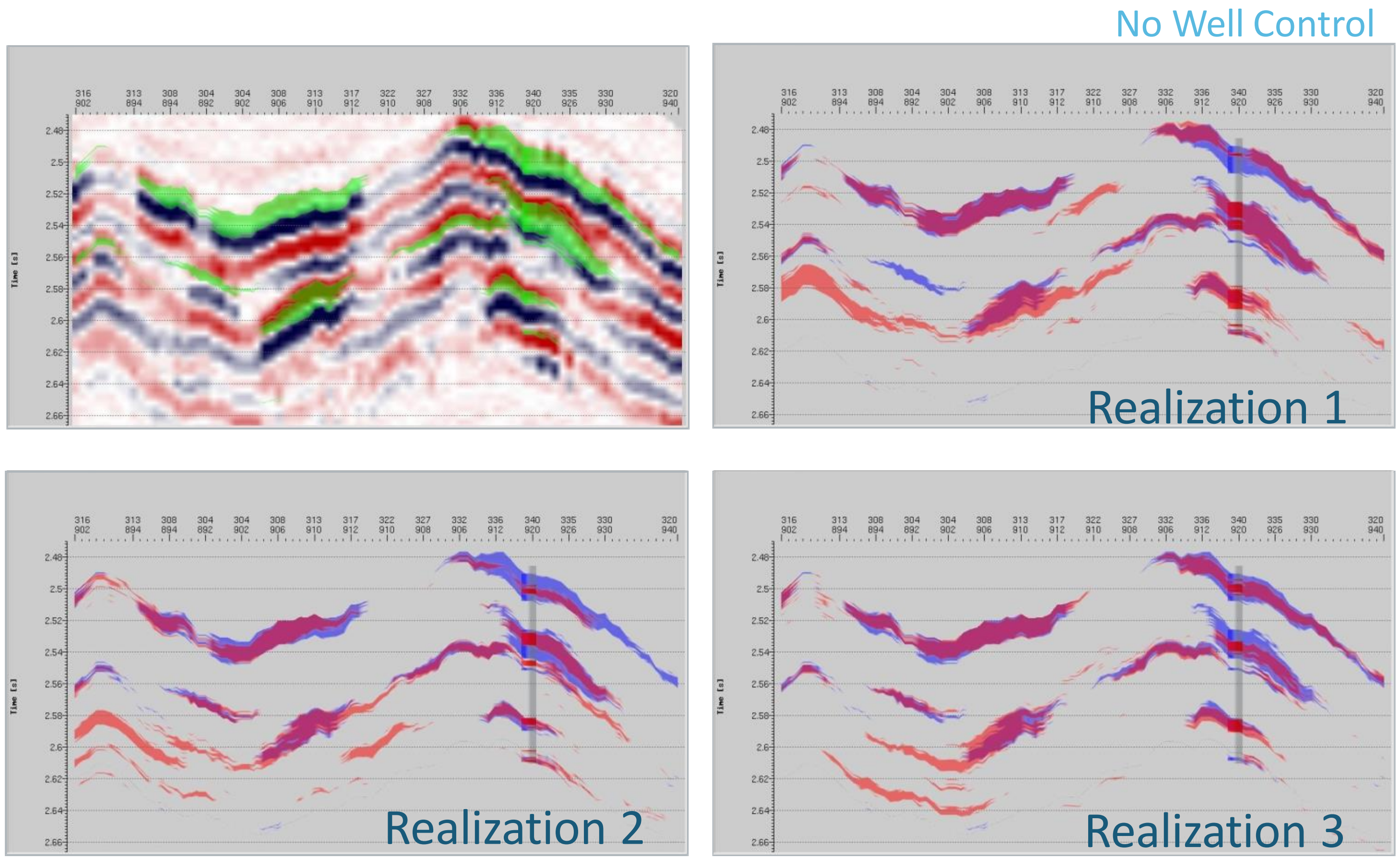
- Model – various horizon interpretation and number of layers
- Wavelet – different well combinations for multi well wavelets

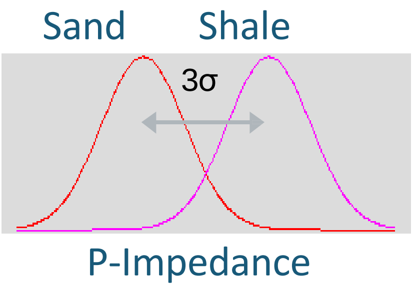
Variability: Clear Distinction of Sand/Shale in Acoustic Impedance





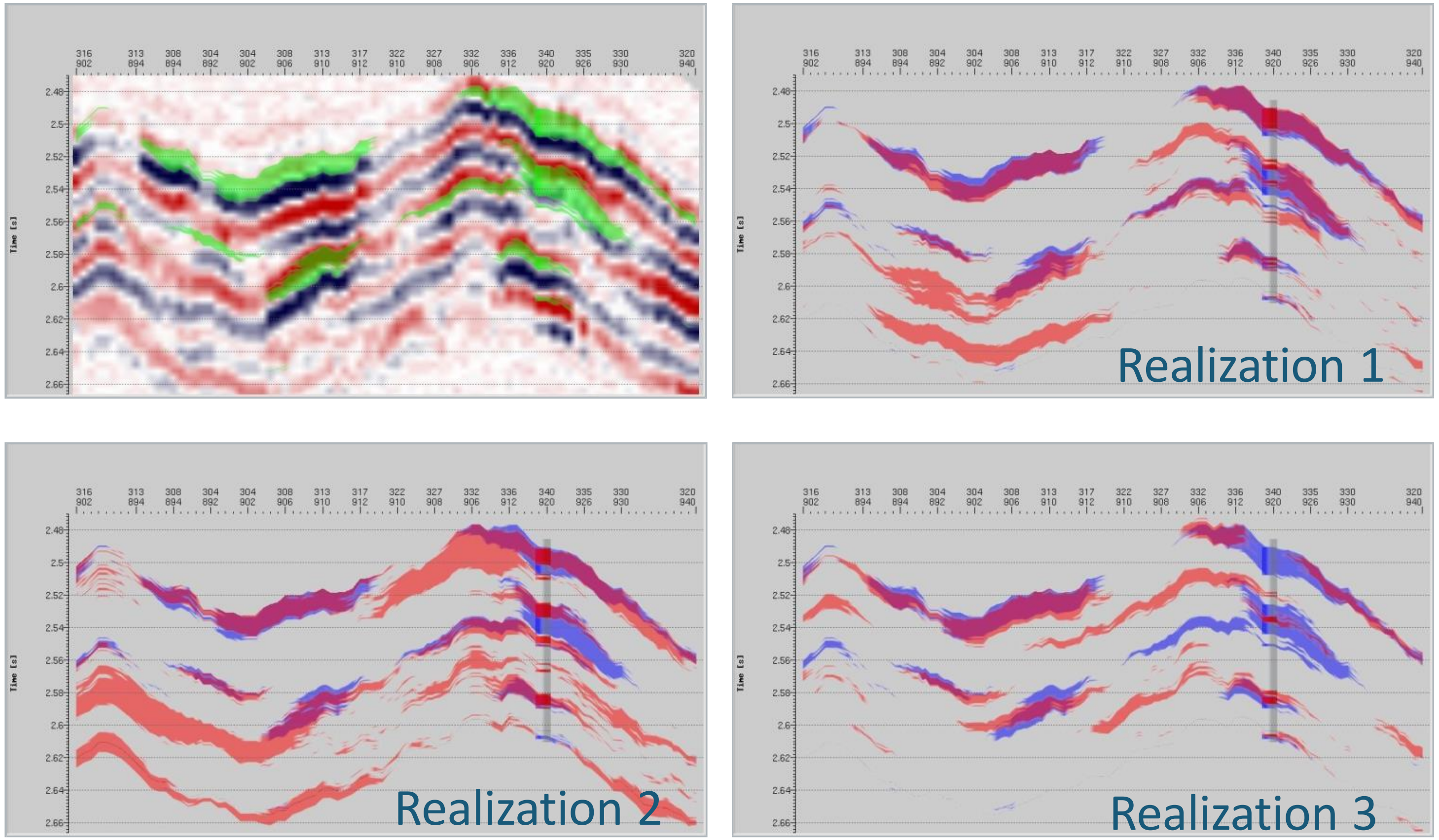
Variability: Good Distinction of Sand/Shale in Acoustic Impedance

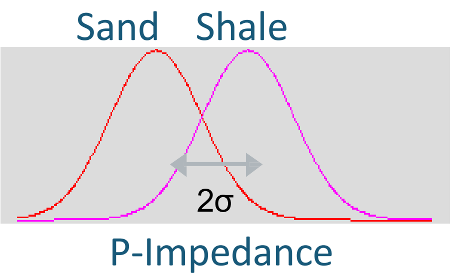




Variability: Poor Distinction of Sand/Shale in Acoustic Impedance

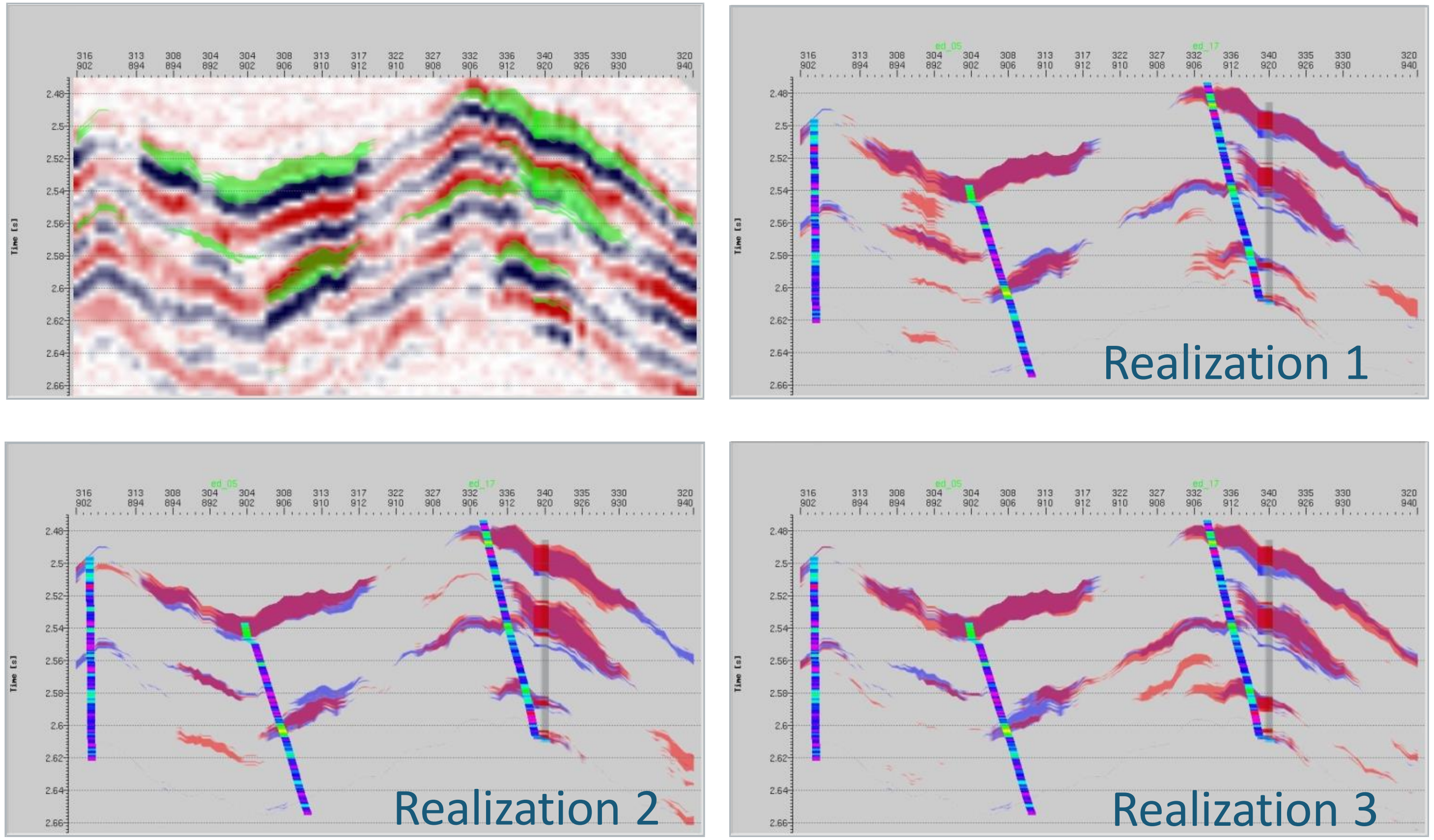
No Well Control



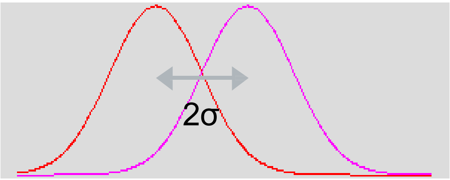


Variability: Poor Distinction of Sand/Shale in Acoustic Impedance

With Well Control



Sand Shale



P-Impedance

Summary

Determining estimates of uncertainty is as important as determining the estimate of the property of interest, itself.

Total uncertainty is composed of variance and bias. Multiple realizations give the variance and multiple scenario yields the bias.

Total uncertainty in E&P is dominated by bias, not variance.

Analysis and Interpretation of Geostatistical Inversion results

GeoSoftware™

www.GeoSoftware.com

Outputs from Geostatistical Inversion

Geostatistical inversion using StatMod/ RockMod results in multiple realizations (typical 30 or more) of discrete properties and elastic/petrophysical properties.

For analysis and interpretation of results, the following statistical attributes are used:

– Continuous properties

- Mean,
- Minimum,
- Maximum,
- Standard deviation.

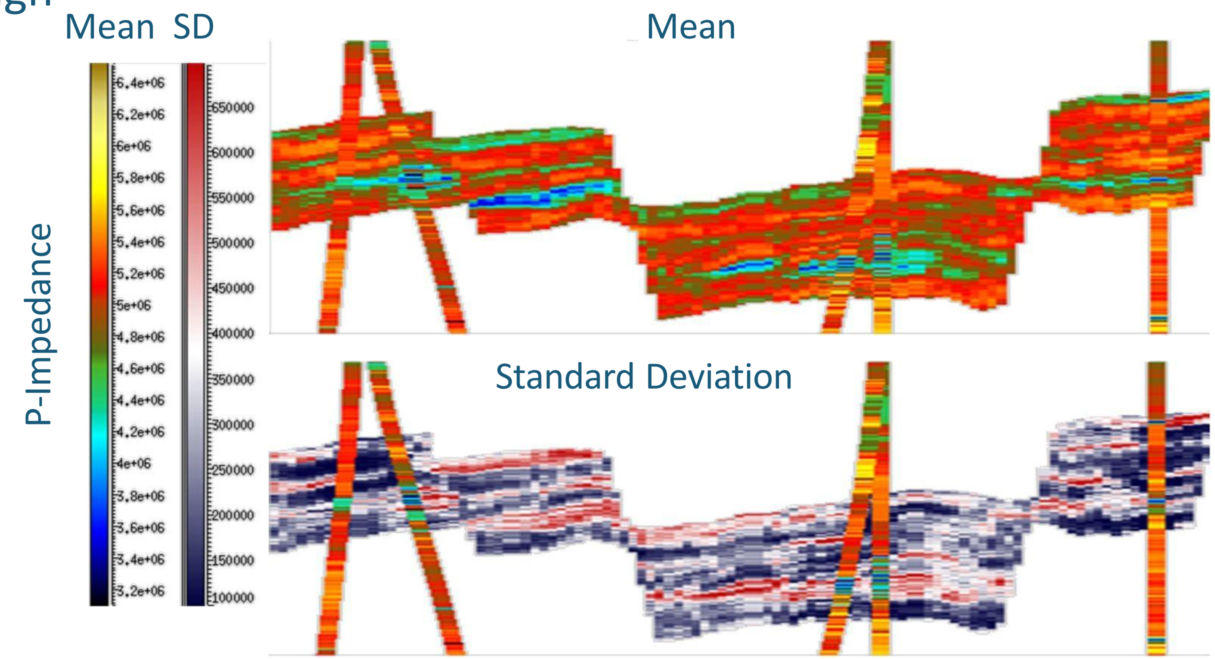
– Discrete property:

- Most probable discrete property type,
- Frequency of each discrete property type.

Continuous Properties: Mean and Standard Deviation

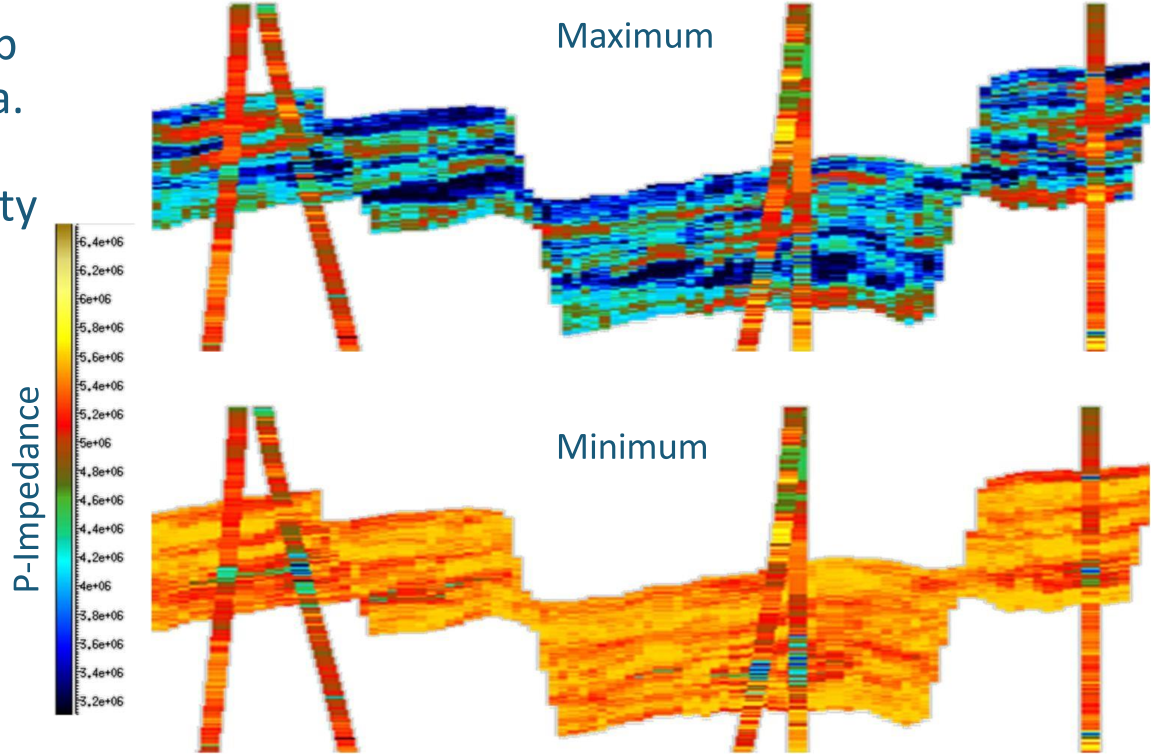
Mean (of all realizations) volume averages out the high details created in geostatistical inversion and can serve a reference to QC the geostatistical results against deterministic inversion results.

Regions with smaller standard deviation implies less uncertainty on the values compared to regions with higher standard deviation.



Continuous Properties: Minimum, Maximum and Range

Minimum and maximum attribute volumes help to recognize vertical or lateral trends in the data. Range volume (maximum minus minimum, not shown here) indicates total variation of property at a location.

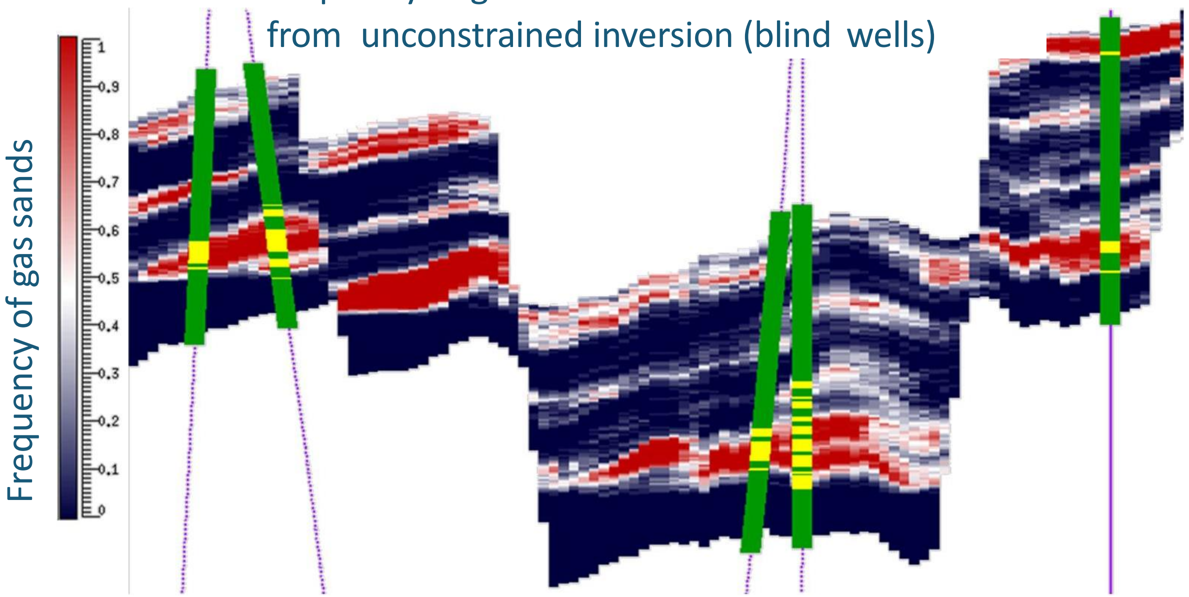


Discrete Property - Facies Probability

Frequency of a particular discrete property (facies) at any voxel can be computed from the ratio of number of occurrences of that facies to the total number of realization. If number of realization is large, this (sample) frequency can be interpreted as probability of occurrence of the facies at that voxel.

This provides valuable information to identify and map areas with high probability of occurrence of a desired facies, say hydrocarbon sand. Additionally, it also captures the uncertainty and associated risk.

Frequency of gas sands over 10+ realizations from unconstrained inversion (blind wells)



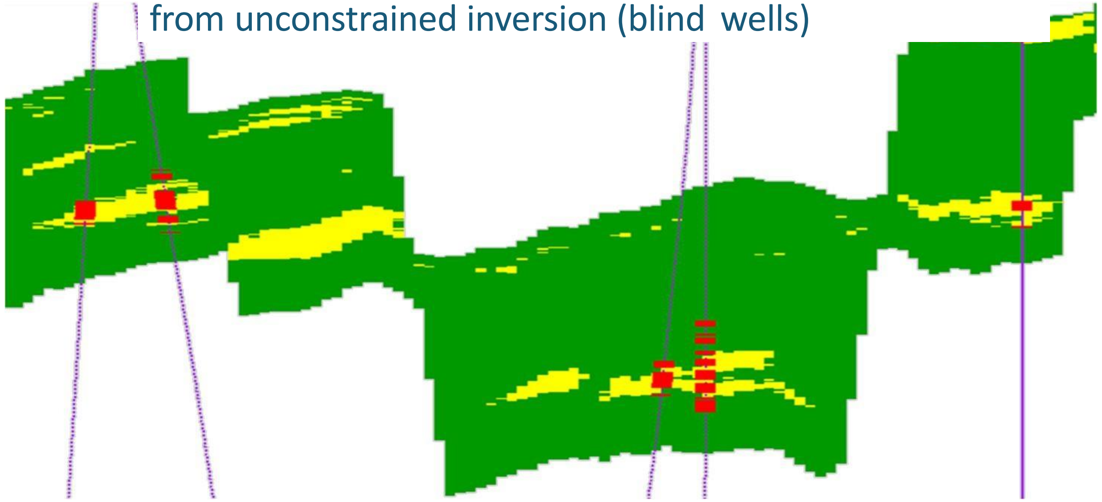
Discrete Property - Most Probable Facies

Most frequently occurring discrete property (facies) at any voxel is the facies that occurs maximum times at the voxel across all the realizations.

If number of realization is large, this (sample) can be interpreted as the most probable facies at that voxel.

This volume should always be interpreted alongside the frequency of facies for meaningful information and capturing the uncertainty.

Most frequently occurring facies over 10+ realizations from unconstrained inversion (blind wells)



Ranking: P10, P50 and P90 Realizations

We have so many realizations of property & Facies volumes, which one to use?

Ranking is a method for model selection and uncertainty quantification.

It provides a means to select few models from a large number of equally likely realizations.

A local and objective criterion is required for ranking so that can be a numerical value can be obtained from each realization, e.g.,

- Proportion of pay at proposed well location X,
- Volume of pay thickness within 200 meters of proposed location X,
- Average porosity within selected local area.

Two primary uses

- For exploration objectives: uncertainty quantification,
- For production objectives: model selection.

Ranking Procedure

- Define an criterion.
- Apply the criterion to all realizations and scenarios.
- Use the ranked results for uncertainty quantification and/or model selection.

What is a good criterion?

- Local measure of a key characteristic of the
- reservoir Expressible mathematically

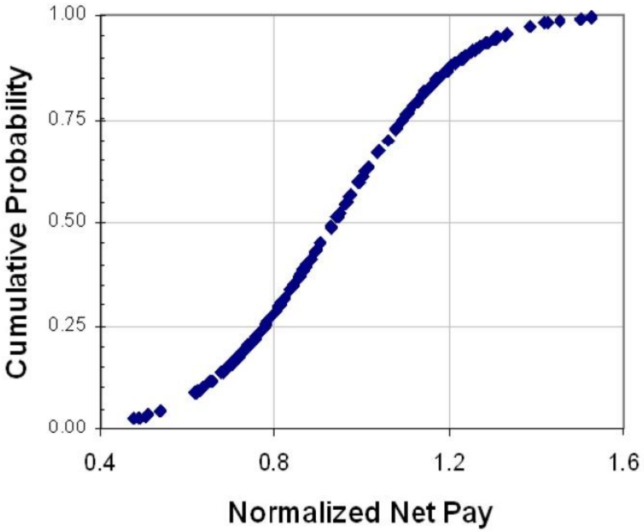
Examples

- Proportion of pay at proposed location X (What will my well encounter?).
- Volume of pay thickness within 200 meters of proposed location X (What will my well produce?).
- Average porosity within selected local area. (What is the reserve?)

Rank the Realizations

1. Compute the criterion value for each realization.
2. Compute the mean and standard deviation of the criterion values of all realizations.
3. Construct cumulative normal distribution function (CDF) given the mean and standard deviation.
4. Evaluate this normal CDF for each realization.
5. Plot the resulting normal CDF.

Scenario	netPay
thinGauss_noise_20db_pay10_seed0_vario_gauss_seed0	32.8
fatGauss_noise_20db_pay10_seed2_vario_gauss_seed0	39.0
fatGauss_noise_15db_pay10_seed0_vario_gauss_seed1	33.2
thinGauss_noise_20db_pay5_seed0_vario_expo_seed0	30.1
fatGauss_noise_20db_pay7_seed1_vario_expo_seed1	40.5
fatGauss_noise_20db_pay7_seed0_vario_expo_seed1	43.5
fatGauss_noise_20db_pay3_seed0_vario_sameAslp_seed1	24.5
fatGauss_noise_20db_pay3_seed1_vario_gauss_seed0	33.9
thinGauss_noise_20db_pay3_seed0_vario_gauss_seed0	29.6
fatGauss_noise_20db_pay7_seed0_vario_gauss_seed1	42.7
thinGauss_noise_15db_pay3_seed2_vario_expo_seed0	25.2
thinGauss_noise_20db_pay7_seed0_vario_expo_seed1	47.1
fatGauss_noise_15db_pay10_seed1_vario_gauss_seed1	50.9
fatGauss_noise_20db_pay7_seed1_vario_sameAslp_seed0	42.1
fatGauss_noise_15db_pay5_seed0_vario_sameAslp_seed1	30.2
thinGauss_noise_20db_pay7_seed0_vario_gauss_seed1	39.6
fatGauss_noise_15db_pay10_seed1_vario_expo_seed1	50.1



Ranking in Exploration – Quantify Uncertainty

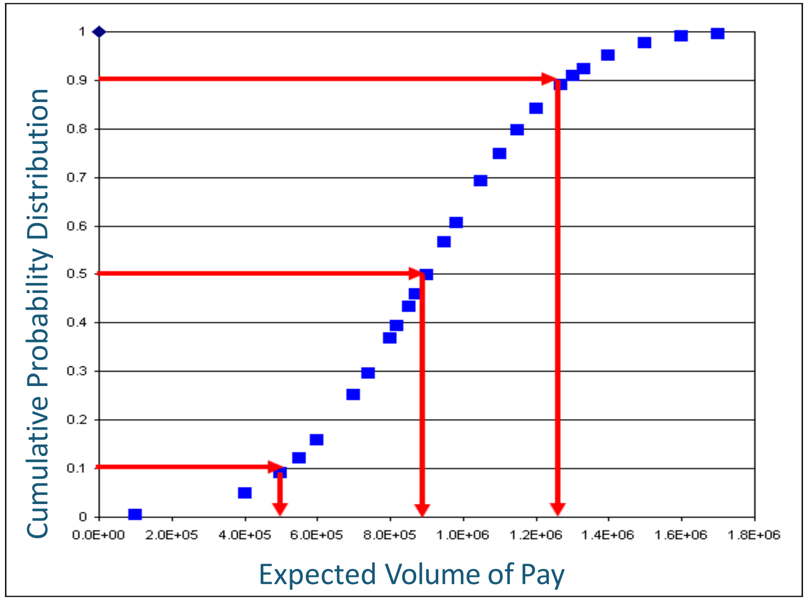
Question: What is the expected volume of pay connected to a well, and how precise is this expected value?

Answer(s):

The expected volume is 0.9 million barrels.

There is 90% probability that this volume is lower than 1.3 million barrels.

There is 10% probability that this volume is lower than 0.7 million barrels.



Ranking: Select Models

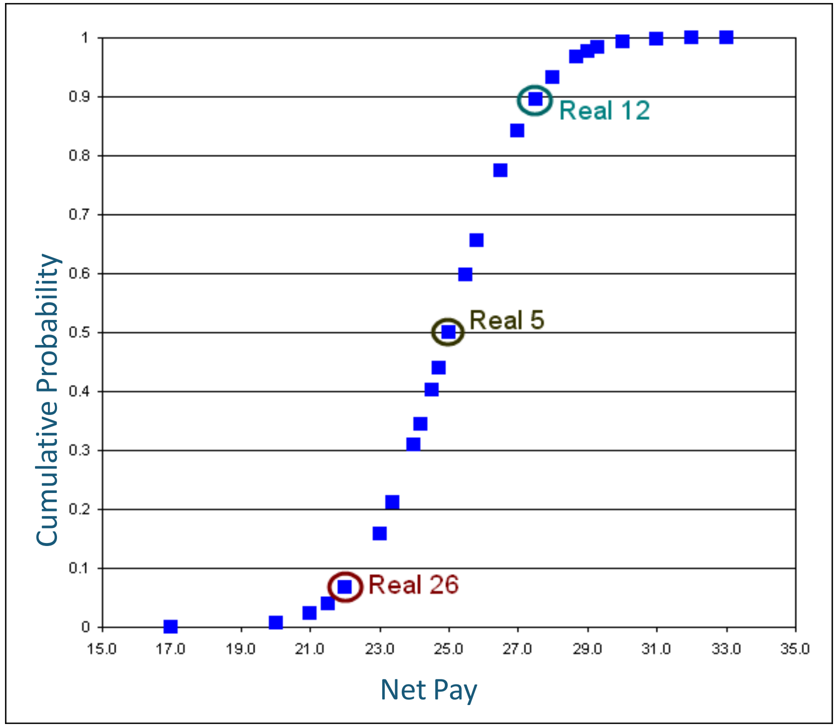
Question: Which realizations should we select for input to flow simulator, based on a net pay criterion?

Answer(s) : Selected three realizations are

P10: Conservative scenario- probability of getting net pay values less than that in realization #26 is 10% or alternately 90% of realizations encounter net pay values more than that in realization #26

P90: Optimistic scenario- probability of getting net pay value less than that in realization #12 is 90% or alternately 10% of realizations encounter net pay values more than that in realization #12

P50: Most likely scenario- realization #5 has a net pay value that is less than the value predicted by 50% of the realizations.



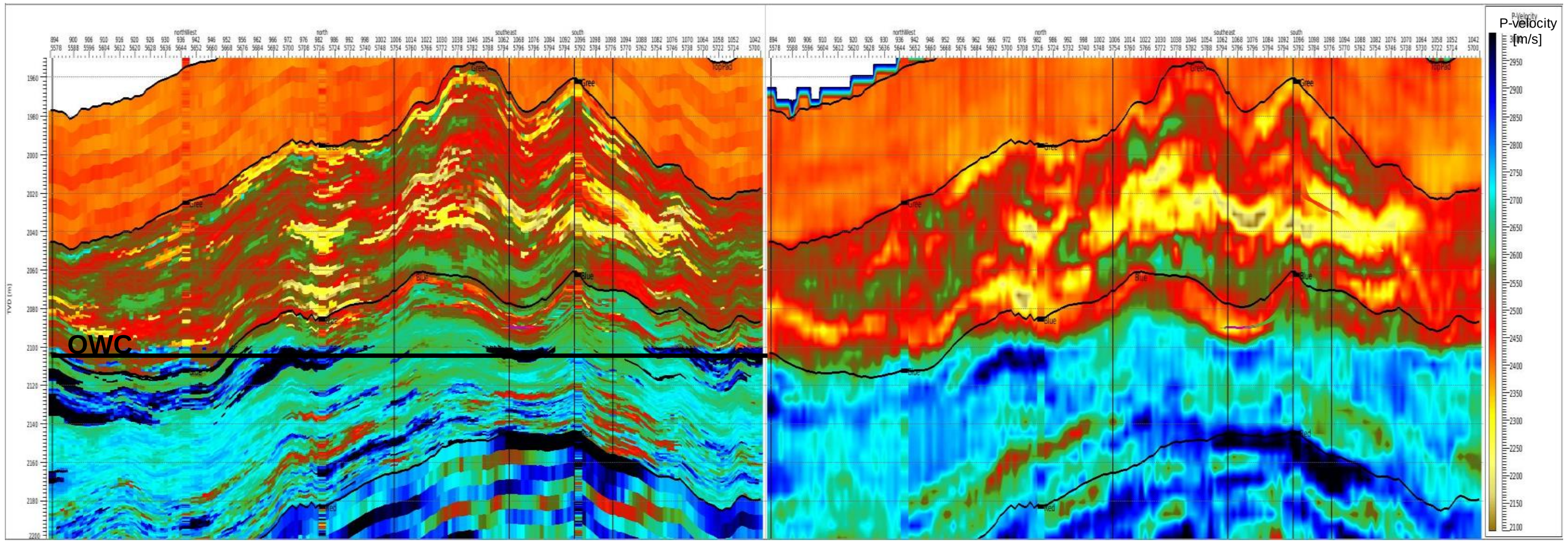
Applications of Geostatistical Inversion:
A Pictorial Tour

GeoSoftware™

www.GeoSoftware.com

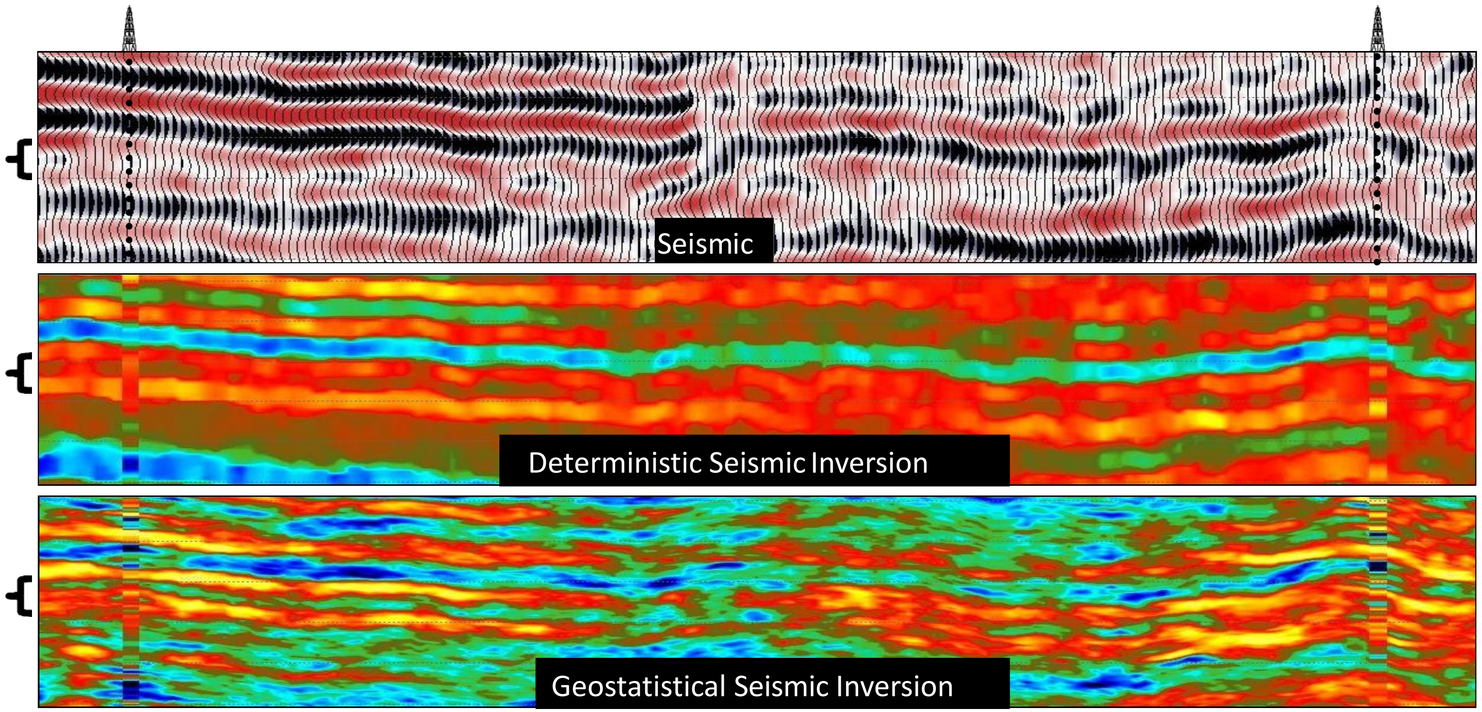
Detailed Reservoir Description

Inverted P-velocity (Geostatistical Inversion) Inverted P-velocity (Deterministic Inversion)



Marquez, D., et al., 2013, Incorporating Rock Physics into Geostatistical Seismic Inversion – A Case Study, EAGE London 2013.

Solutions for Thin Sands – Highly Detailed and Realistic 3D Model

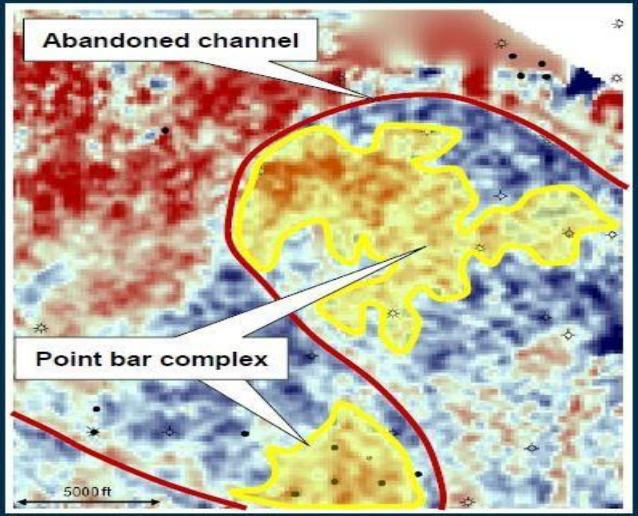


- Thin (20-40’) Upper Morrow sands were identified from geostatistical simultaneous AVO inversion.
- High-detailed inversion results reflected the complex nature of fluvial reservoirs.
- Inversion results created “bottom line value” with successful drilling of additional wells and statistically significant correlation to blind wells.

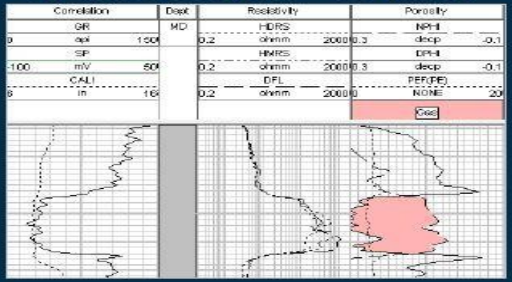
Solution for Thin Sands Mapping

Mid-Continent Upper Morrow Sandstones

- Upper Morrow fluvial sandstones of the Mid-Continent are prolific oil and gas producers
- Fluvial sandstones (20-40' thick) are challenging to image on seismic data
- Geomorphic shapes on stacked seismic data suggest various fluvial environments



21' thick sandstone, IP = 10+ mmcfd

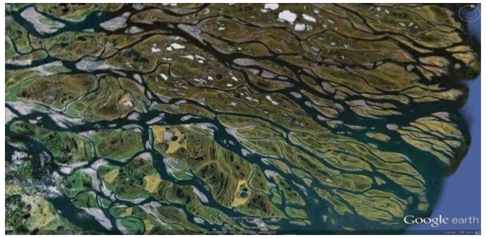


Zawila, J., et al., 2010, A case study for detecting thin Upper Morrow fluvial sands in the United States Mid-continent from geostatistical simultaneous AVO inversion, SEG Expanded Abstract

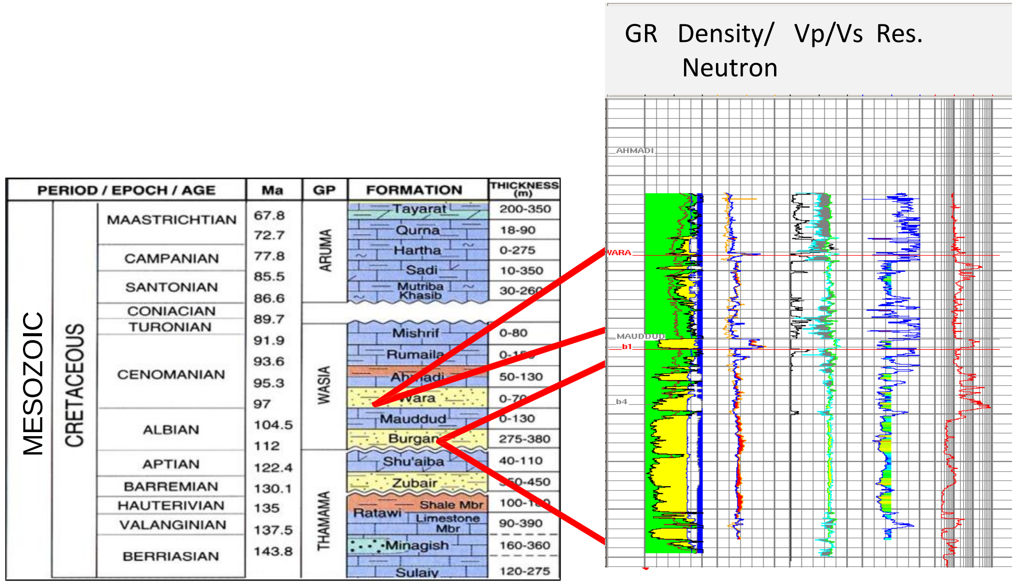
Solution for Thin Sand Units – Wara Formation

The Wara sandstone is composed of fine grained quartzose sands which are not well sorted and associated with fine- grained siltstones and shales. The lower part of the Wara consists of gray, glauconitic and lignite shale with occasional fine grained glauconitic sand.

The zone of interest is 150-200 feet thick with individual sand units being 3-50 feet thick.



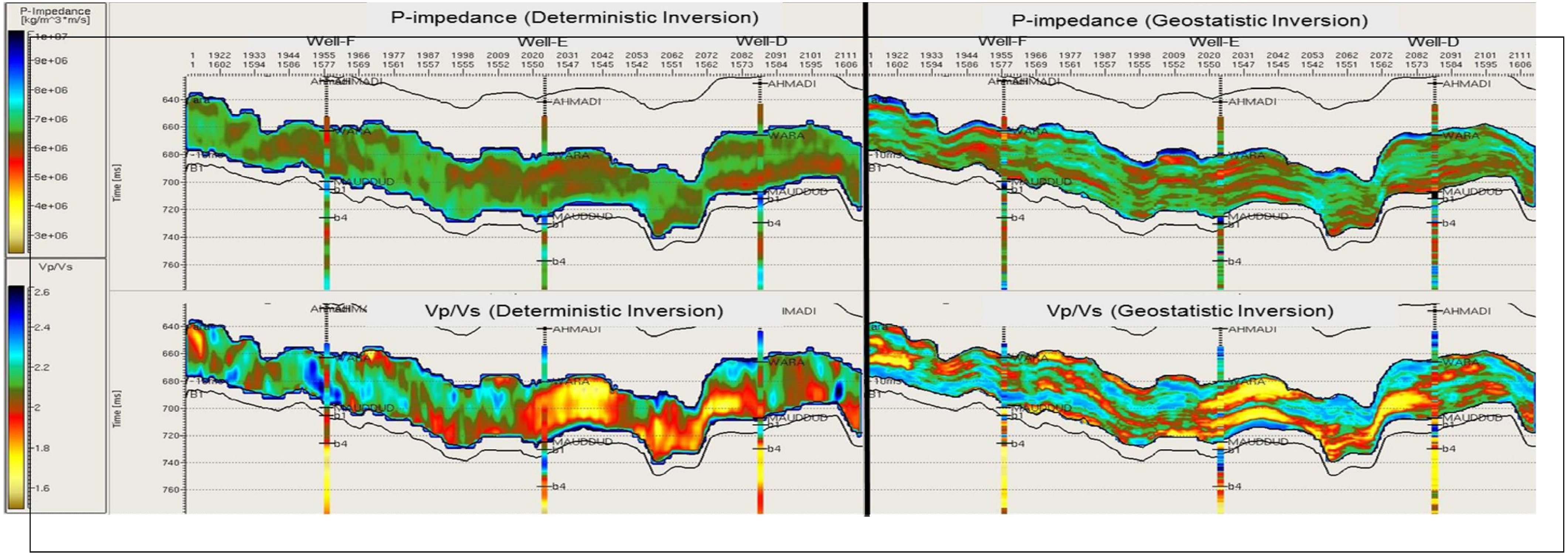
Analog Depositional Environment



Al-Khaled, O., et al., 2012, Geostatistical Inversion in Carbonate and Clastic Reservoirs: Oilfield Case Studies from Kuwait, GeoConvention, Expanded Abstract.

Solution for Thin Sand Units – Wara Formation

Bungan Field (Wara Sandstone)

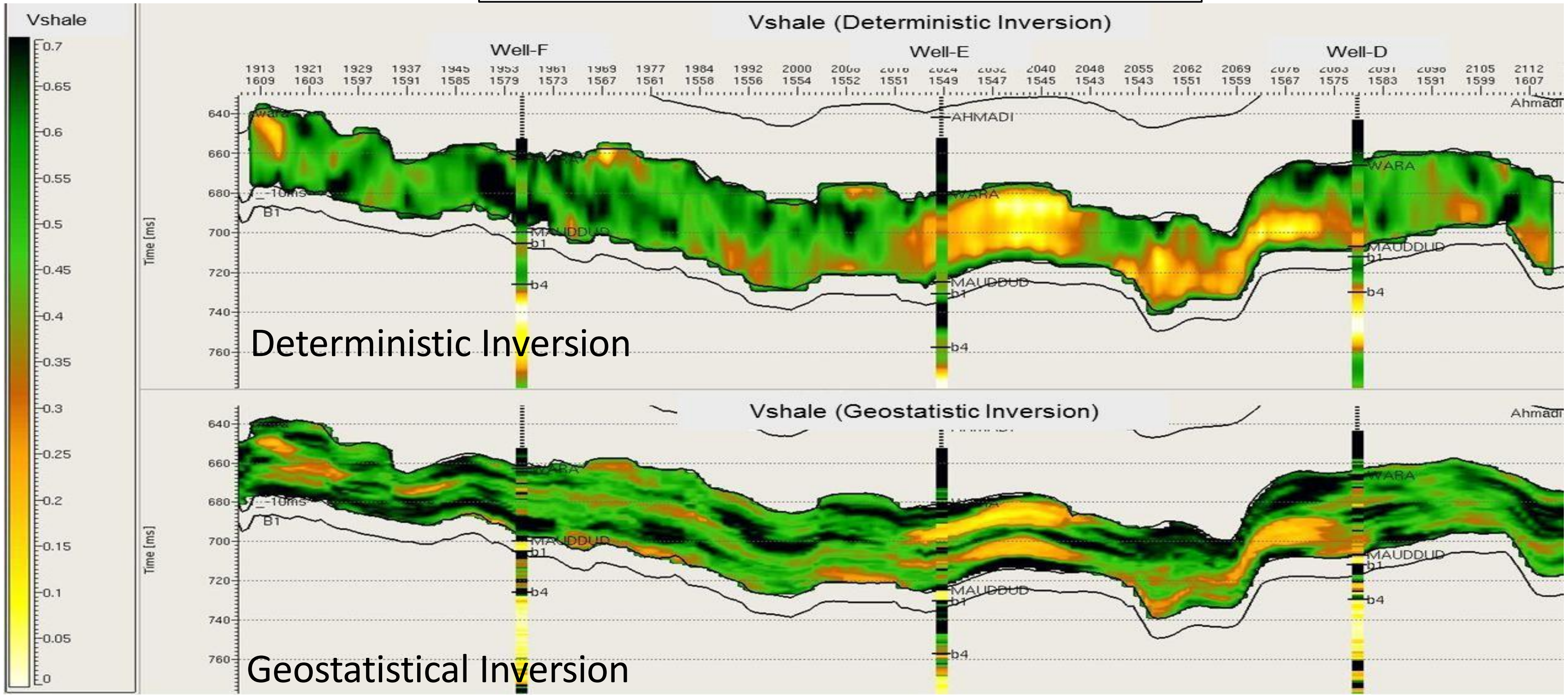


Deterministic Inversion

Geostatistical Inversion

Solution for Thin Sand Units – Wara Formation

Bungan Field (Wara Sandstone)

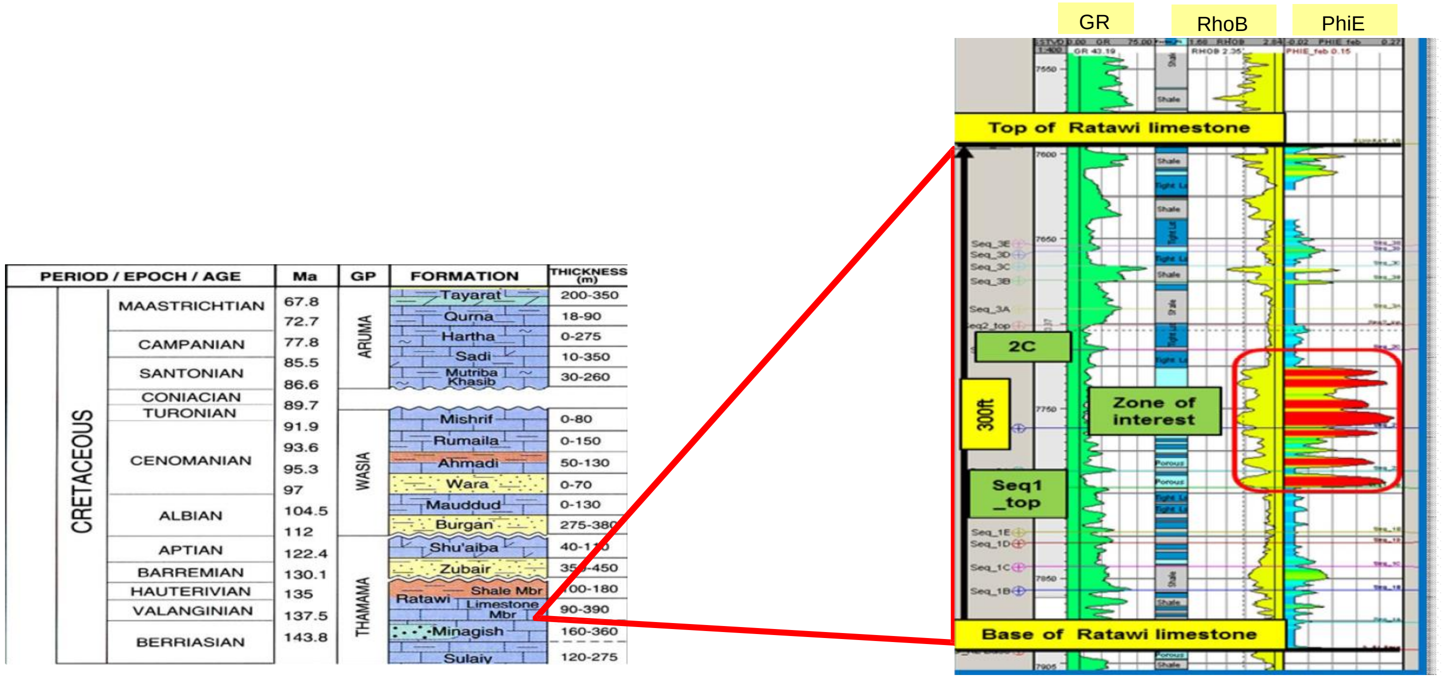


Vshale from geostatistical inversion shows greater details compared to deterministic inversion

Solution for Thin Porous Limestone Units – Ratawi Limestone

The Ratawi Limestone is composed of argillaceous mudstone to clean packstone to wackestone with some bioturbation. Deposition was in a shallow shelf environment. With the reservoir thought to be developed in emergent shoals, banks and bars.

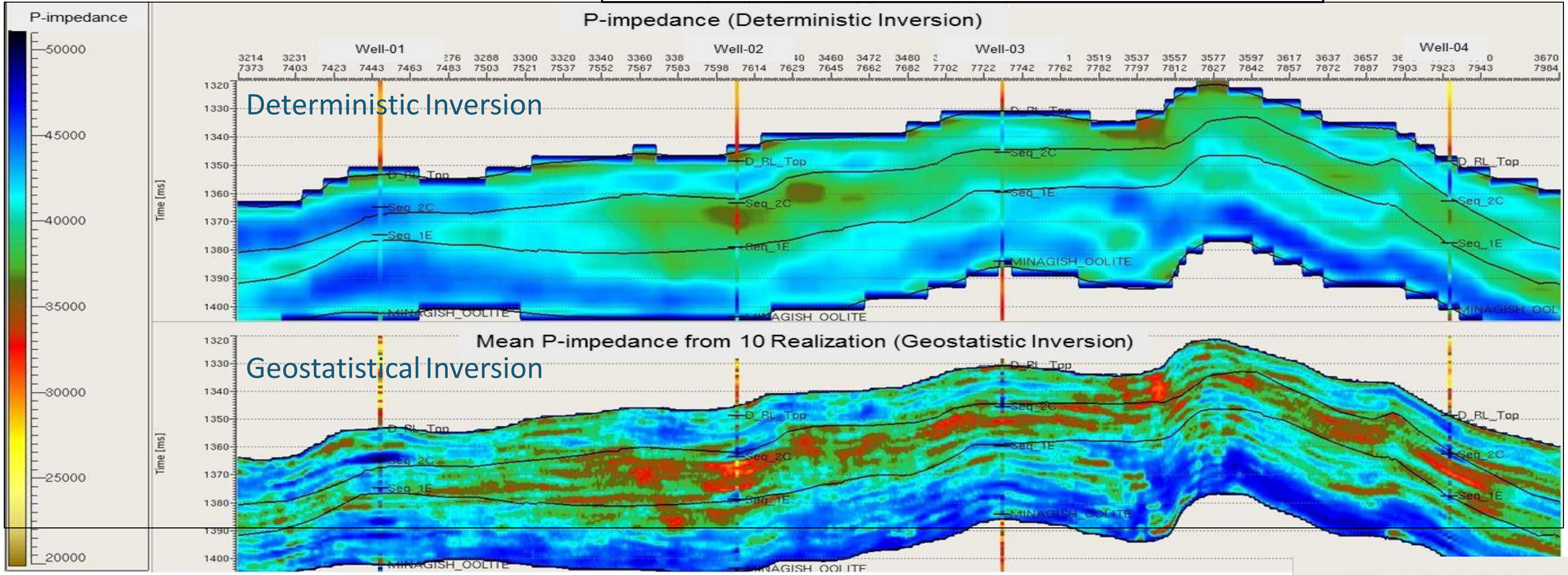
The zone of interest is approximately 70 feet thick with individual porous units being 10-20 feet thick.

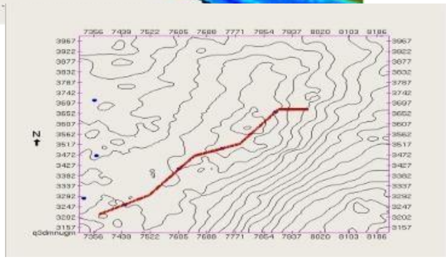


Al-Khaled, O., et al., 2012, Geostatistical Inversion in Carbonate and Clastic Reservoirs: Oilfield Case Studies from Kuwait, GeoConvention, Expanded Abstracts.

Solution for Thin Porous Limestone Units – Ratawi Limestone

Umm Gudair Field (Ratawi Limestone)

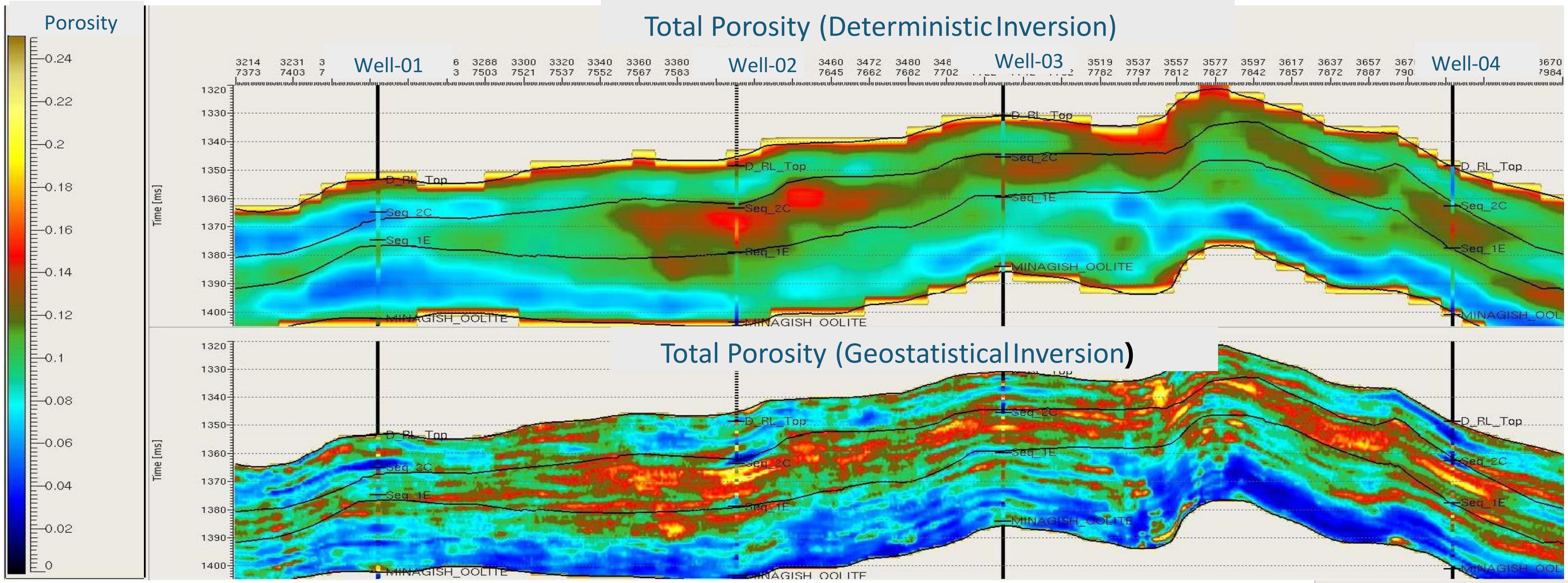


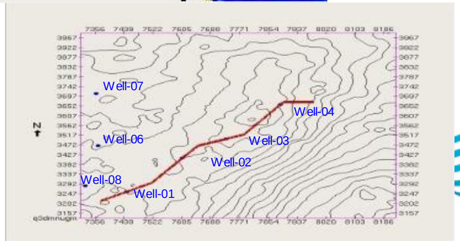


Geostatistical inversion produces highly detailed results of P-impedance

Solution for Thin Porous Limestone Units – Ratawi Limestone

Umm Gudair Field (Ratawi Limestone)



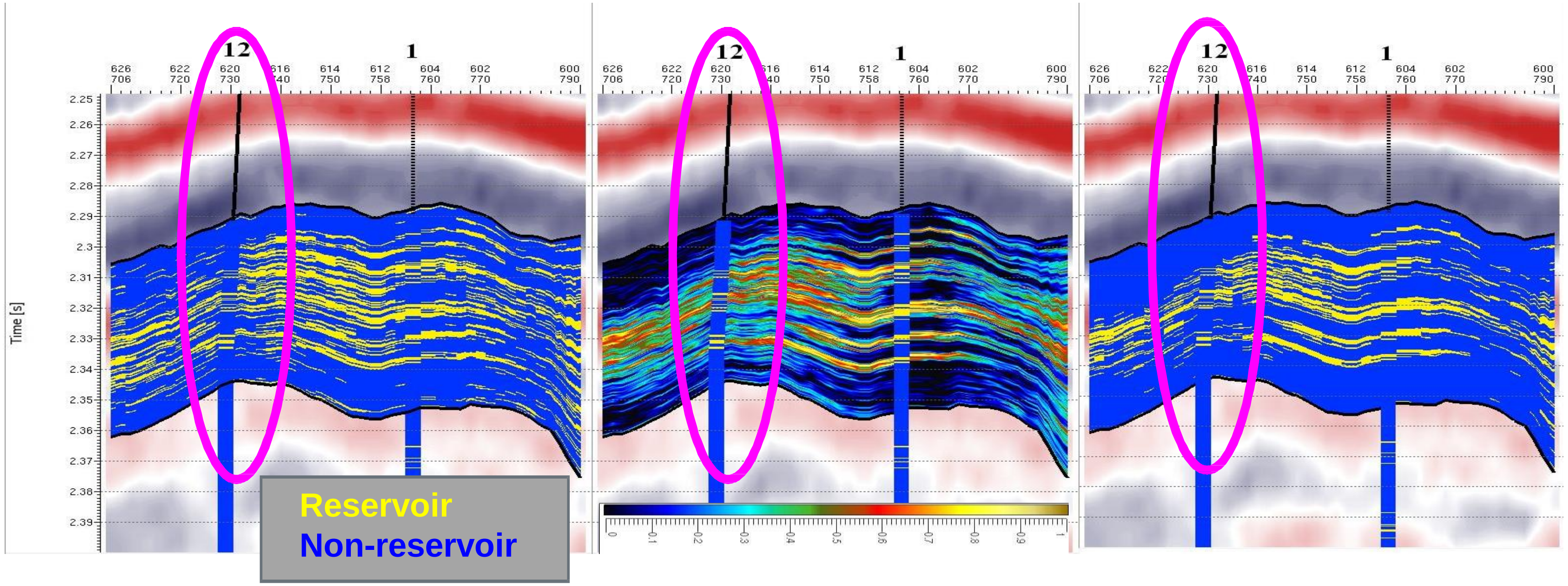


Accurate Net Pay Prediction (Carbonate Reservoir)

Single realization

Reservoir Probability from 20 realizations

Most probable (P50) lithology types distribution based on 20 realizations

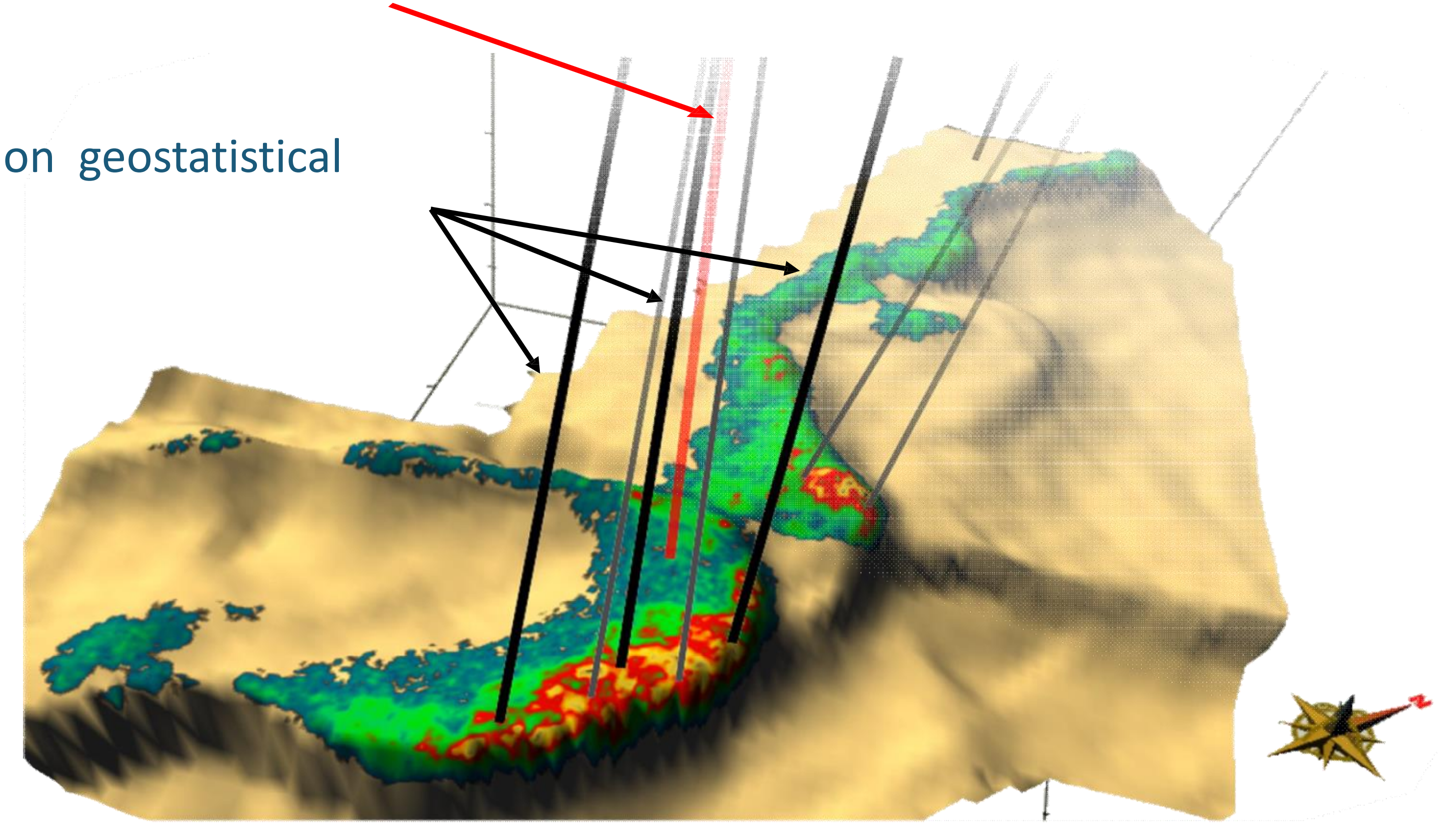


Filippova, K., et al., 2011, Detailed geological model of Devonian reefs based on geostatistical inversion, 73th EAGE Conference & Exhibition, Vienna.

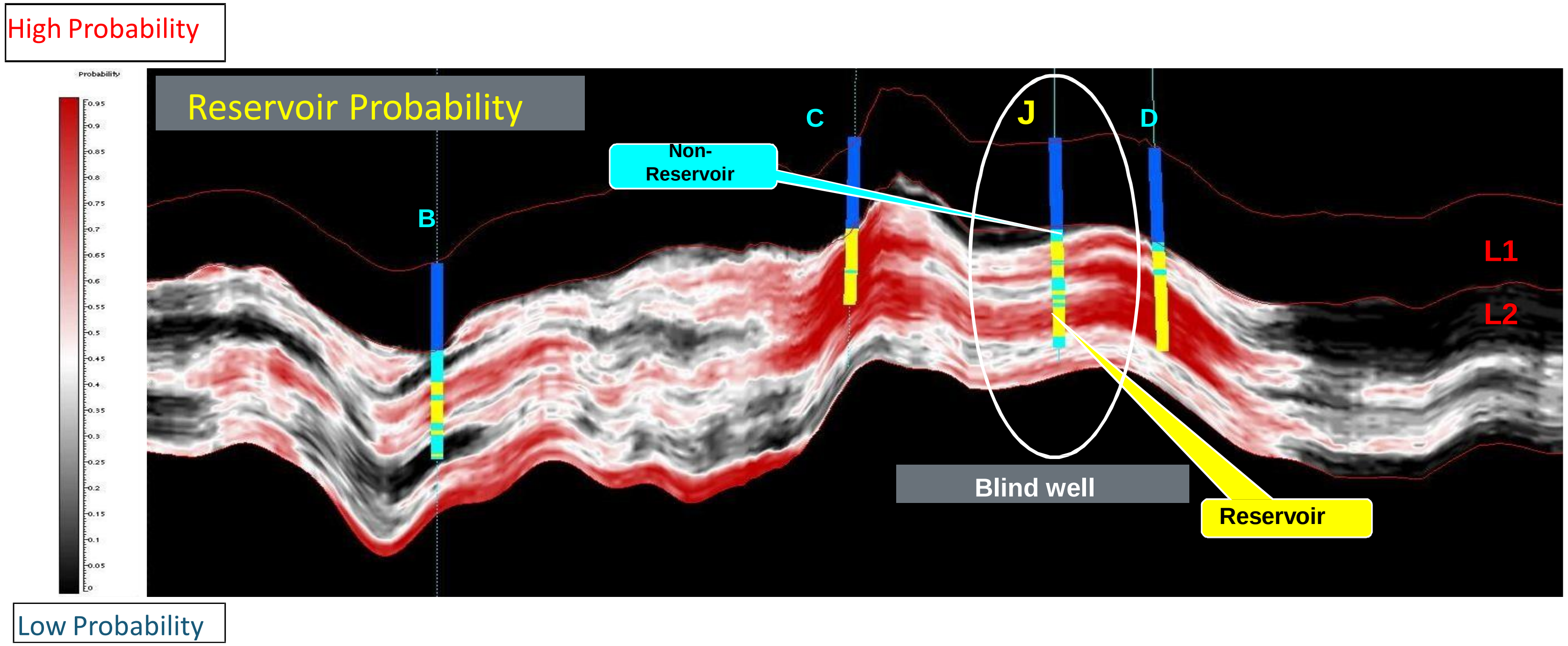
Well planning

Unsuccessful wells drilled on other results

Successful wells drilled on geostatistical inversion results

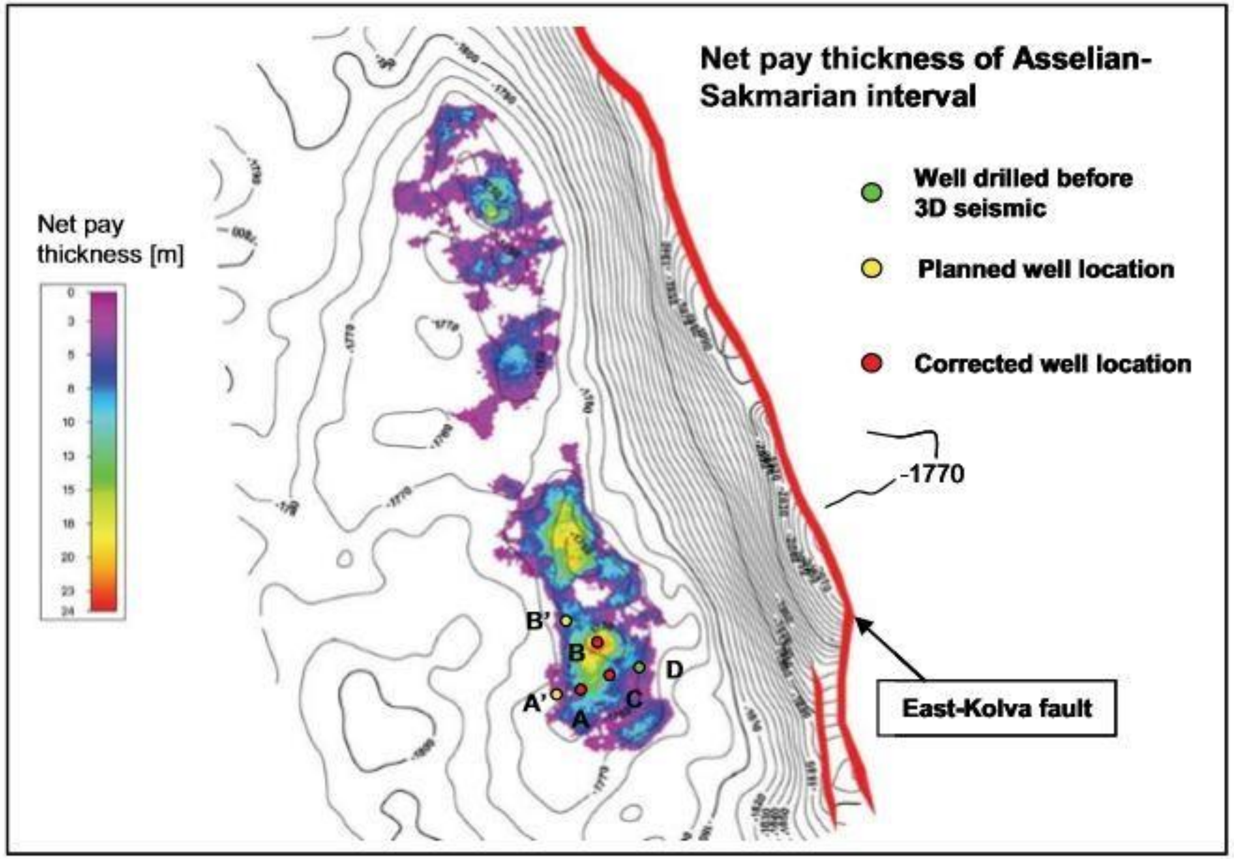


Successful Blind Well Test – Reservoir L2



Rodina, O., et al., 2008, Detailed geological model of carbonate reservoir based on geostatistical AVA-inversion - A Case Study: 73th EAGE Conference & Exhibition, Rome.

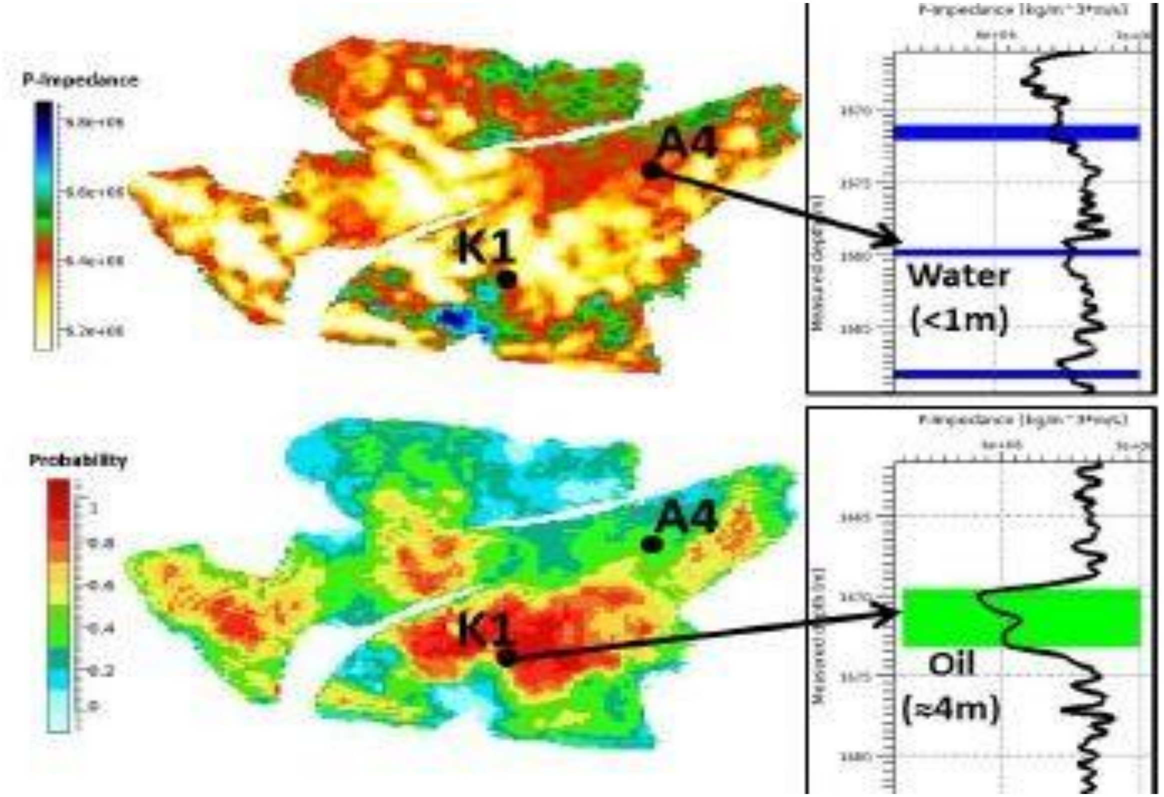
Accurate Net Pay



Reservoir Distribution and Connectivity

Mean P-impedance from Deterministic Inversion

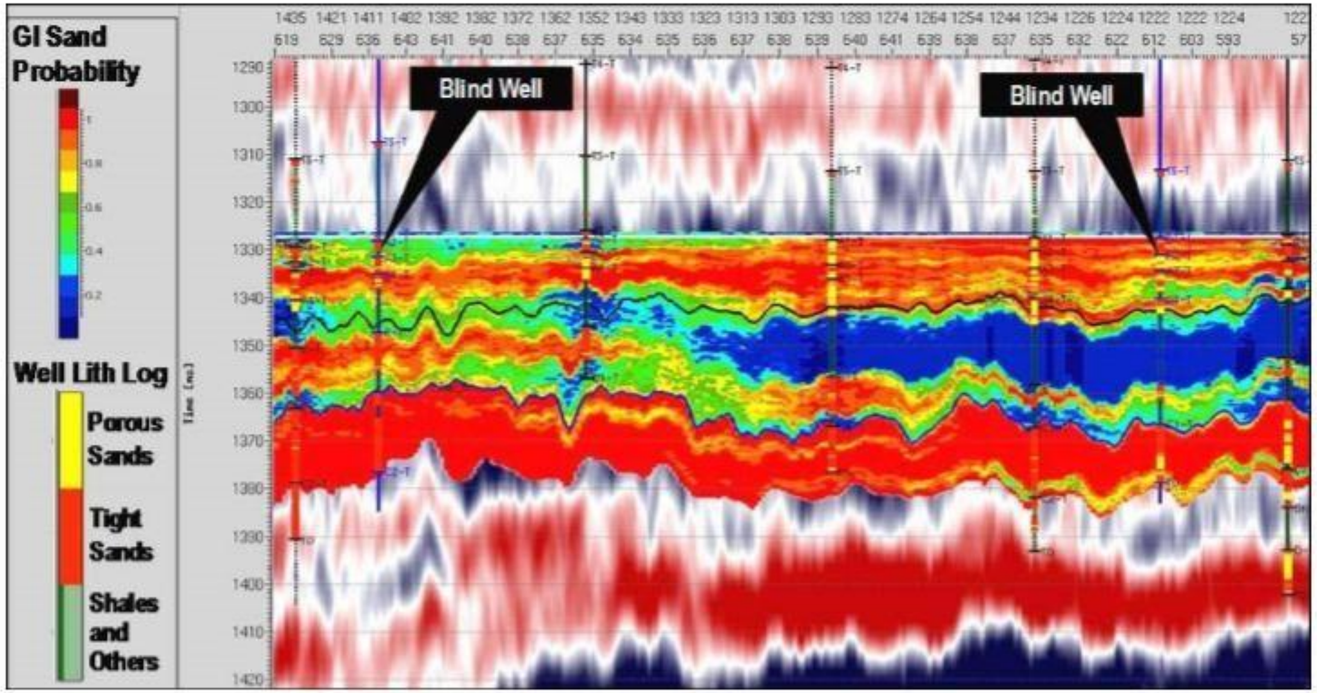
Oil Sand probability from Geostatistical Inversion



Reservoir boundary and connectivity are better delineated in geostatistical inversion compared to deterministic inversion reducing the risks of the prospects.

Vernengo, L., et al. 2014 , Improvement of the reservoir characterization of fluvial sandstones with geostatistical inversion in Golfo San Jorge basin, Argentina, The Leading Edge, 33, 508-518.

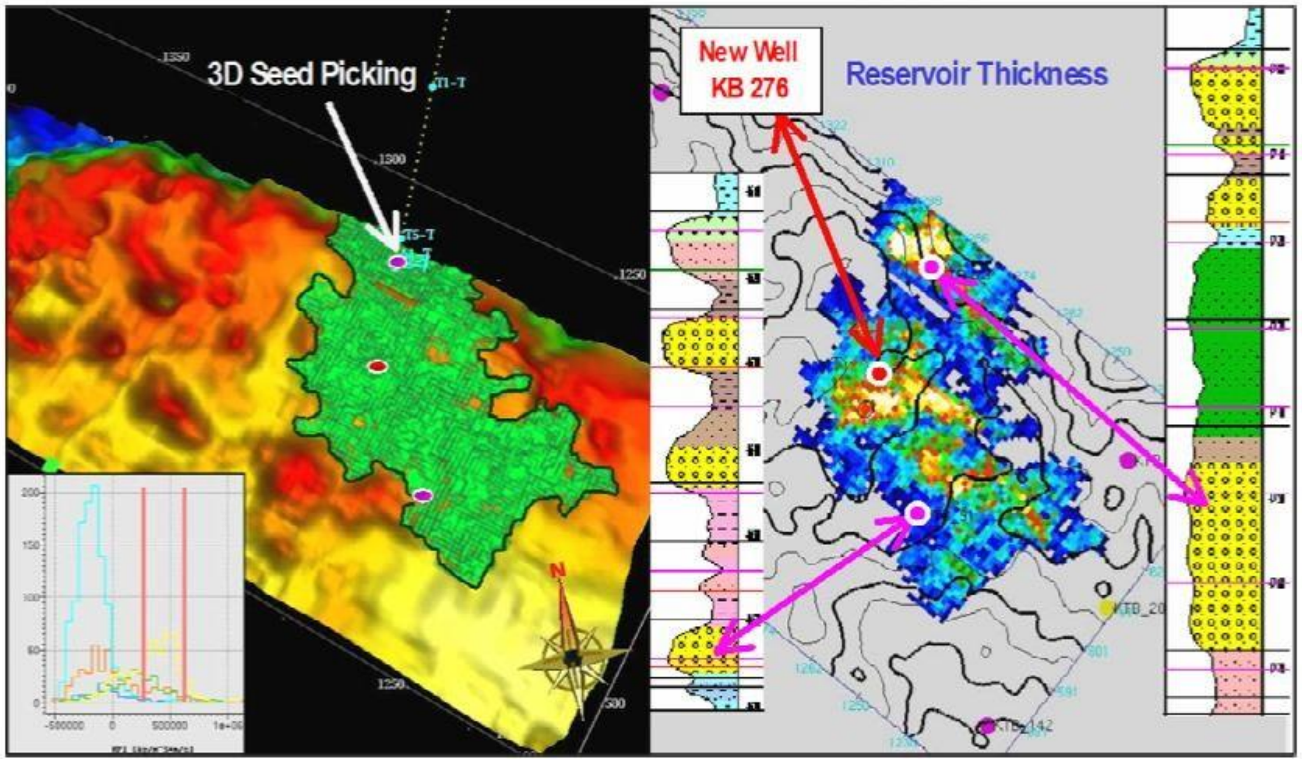
Sand Probability from Geostatistical Inversion



Very good correlation of high probability of sand at two blind wells that were not used as constraints in geostatistical inversion building high confidence in using the results.

Hoehn, M.H., et al. 2005, Combined Geostatistical Inversion and Simultaneous AVA inversion: Extending the life of a mature area, Kotabatak field, Central Sumatra basin, Indonesia: Indonesian Petroleum Association (IPA)

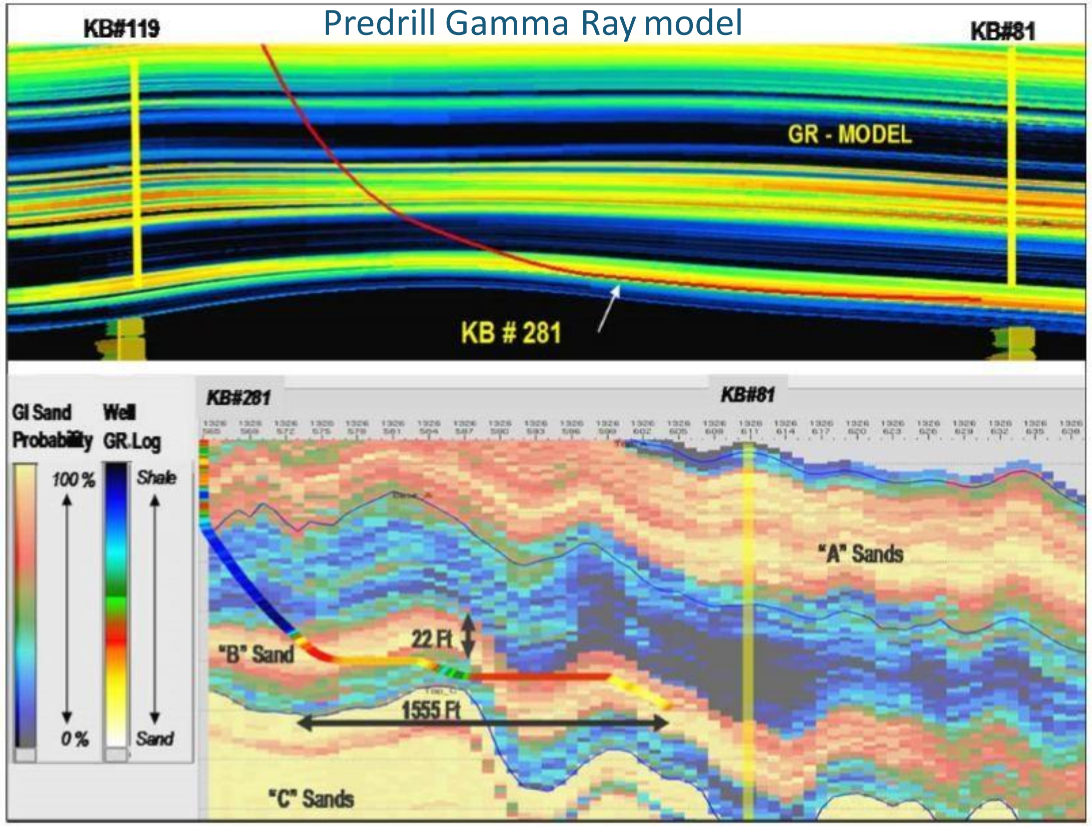
Geostatistical Inversion Maps Thin Sands



3D seed picking from ranked P50 volume based on realizations of porosity index, delineates Good quality channel sands (~25ft) confirmed by drilling.

Hoehn, M.Het al., 2005, Combined Geostatistical Inversion and Simultaneous AVA inversion: Extending the life of a mature area, Kotabatak field, Central Sumatra basin, Indonesia: Indonesian Petroleum Association (IPA).

Using GI Results in Drilling Horizontal Well



Post drill results show good match between KB 281 well gamma ray logs and predrilled sand probability from geostatistical inversion.

Hoehn, M.Het al., 2005, Combined Geostatistical Inversion and Simultaneous AVA inversion: Extending the life of a mature area, Kotabatak field, Central Sumatra basin, Indonesia: Indonesian Petroleum Association (IPA).

Applications of Geostatistical Inversion to Infer Reservoir Connectivity & Pressure Depletion in Reservoirs (Case Studies)

GeoSoftware™

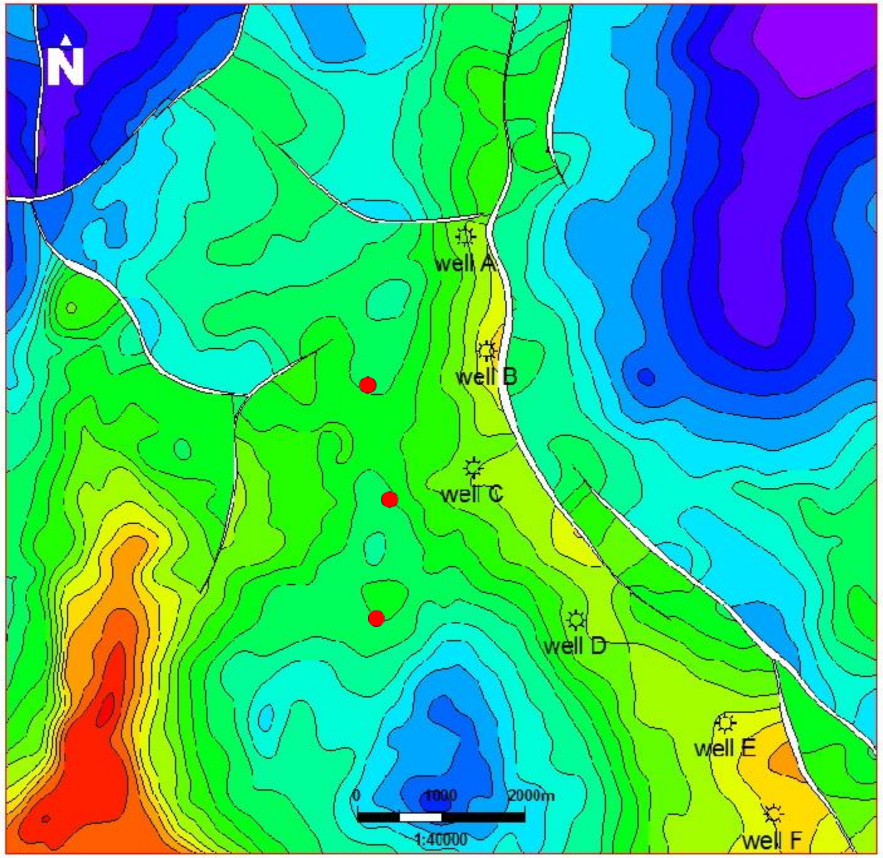
www.GeoSoftware.com

Geostatistical Inversion: Integrating seismic and well data into highly detailed reservoir model

GeoSoftware™

Area of Study

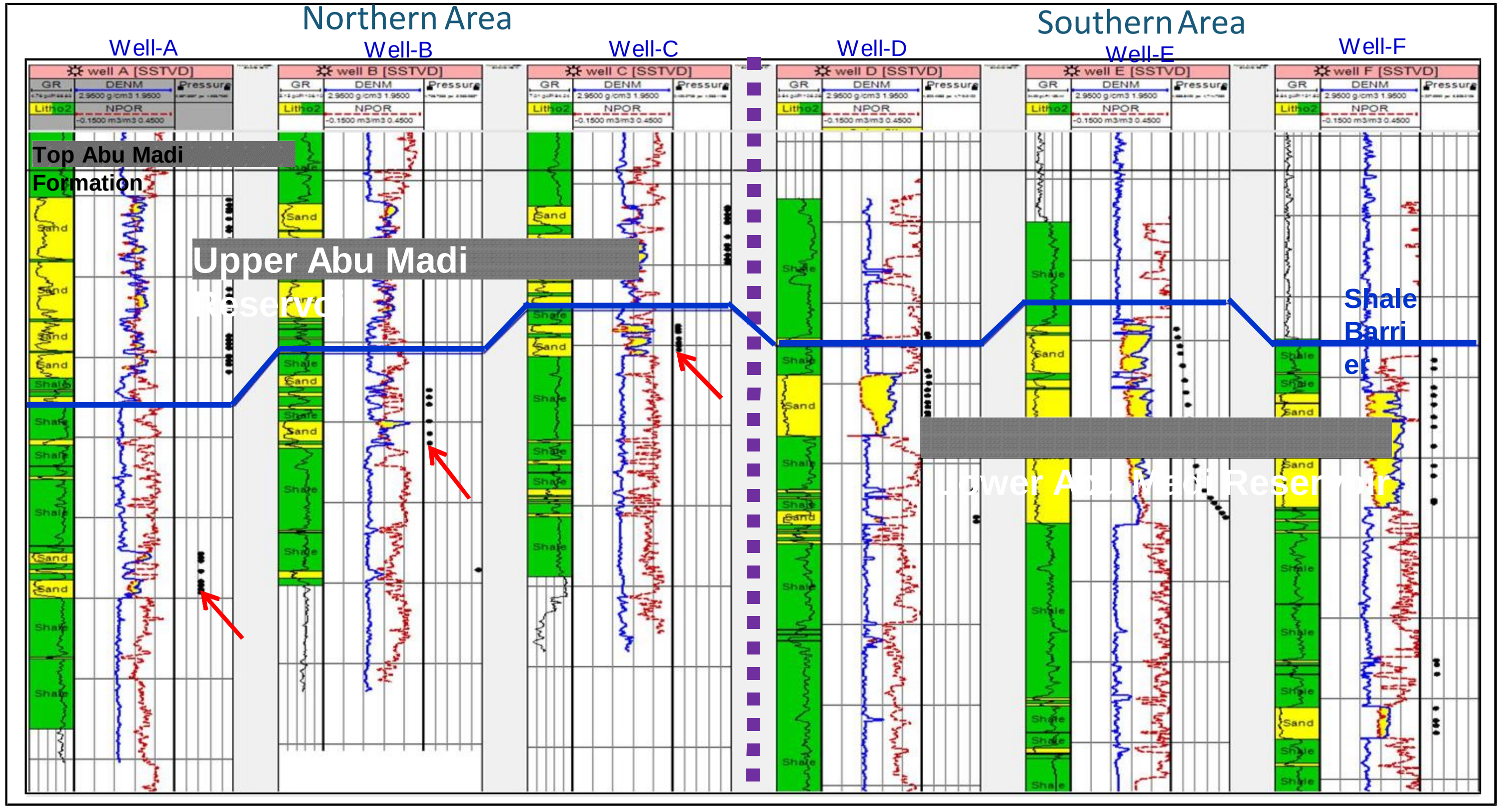
- Gas field, located Central Nile Delta ~150 km north of Cairo.
- Field characterized N-S to NW-SE trending 3-way dip structure.
- Late Miocene (Abu Madi Formation) lacustrine turbidite sheet sand and shales.
- Reservoir zones are Upper Abu Madi (UAM) in northern closure and Lower Abu Madi (LAM) in Sothern closure.
- Well B: drilled Oct 2008. Net pay = 33m, Av. Sw = 40%, NTG = 54%. Original reservoir pressure ~4750 psi.
- Well A: appraisal well to north - drilled in May 2010. Upper Abu Madi (UAM) pressure was at near original pressure. Lower Abu Madi (LAM) was depleted by ~1600 psi and water wet.
- Well C: appraisal to south - drilled in Aug 2011. UAM pressure was at near original pressure. LAM was depleted by ~2000psi with gas bearing.



Hot colors = shallow depth

Challenges

Lower Abu Madi (northern area), pressure being depleted. Why?

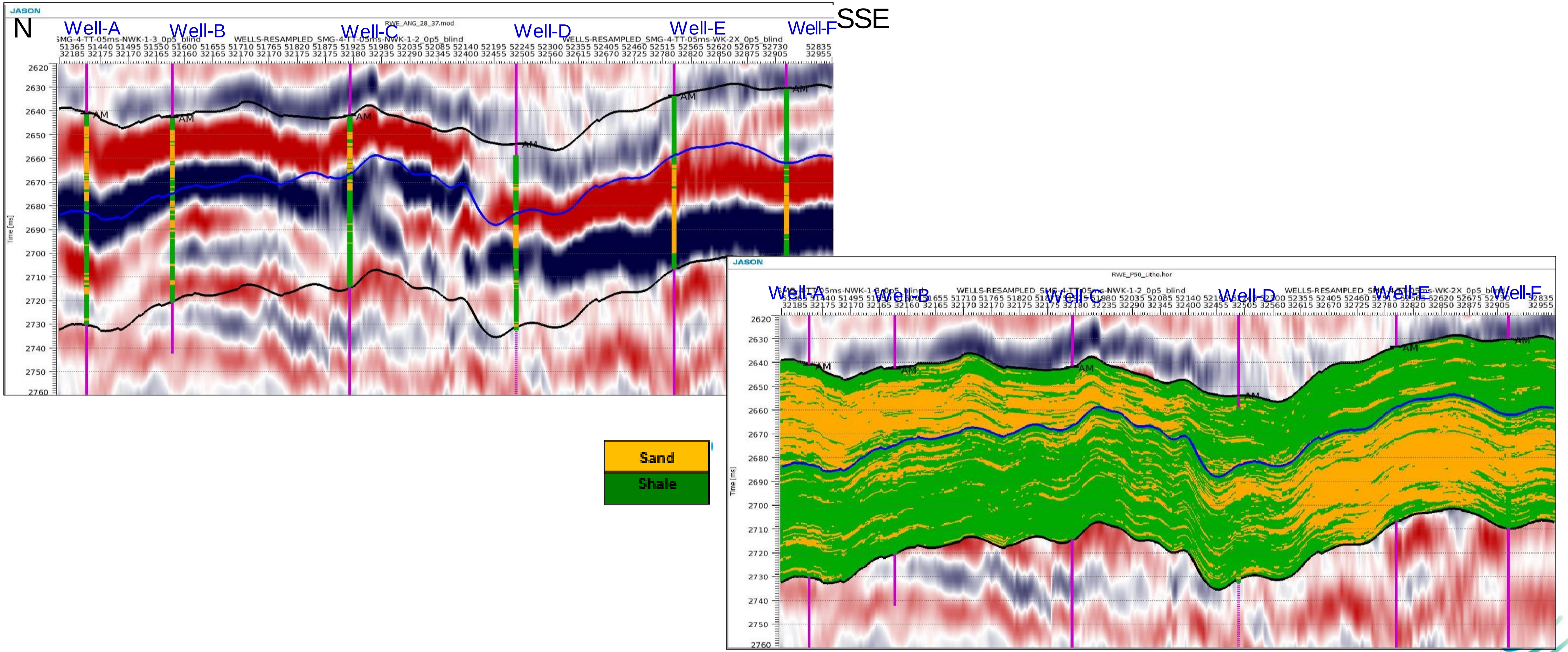


Hypothesis: potentially Lower Abu Madi in Northern area connected to Southern area

Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Challenges

How to integrate seismic, well, and horizon into highly detail geological model?



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Challenges

Generate highly detailed geological model by integrating seismic, well, core, and horizon data through petrophysics, rock physics modelling and geostatistical inversion in order to understand reservoir connectivity and pressure depletion of the field.

Data Set

Reprocessed seismic data 2012 produces six partial angle stacks,

(5-15, 10-20, 16-26, 22-32, 28-37, 33-42 deg.).

There are 6 wells processed through a consistent petrophysical analysis and

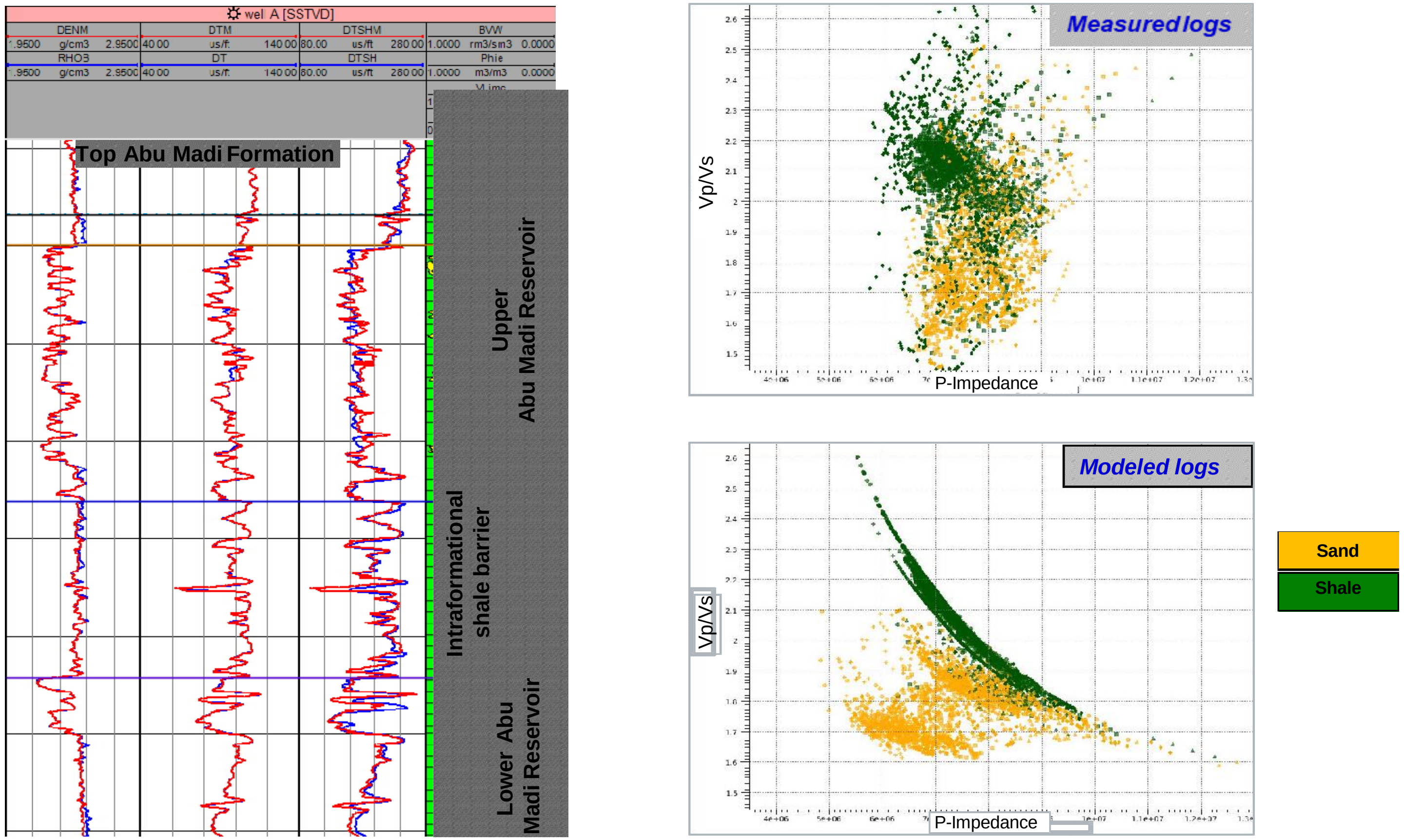
rock physics modelling.

Key horizons: Upper Abu Madi, Lower Abu Madi, Shale barrier.

Integrated Petrophysics and Rock Physics

A consistent elastic modeled logs achieved by integration of petrophysics and rock physics modelling.

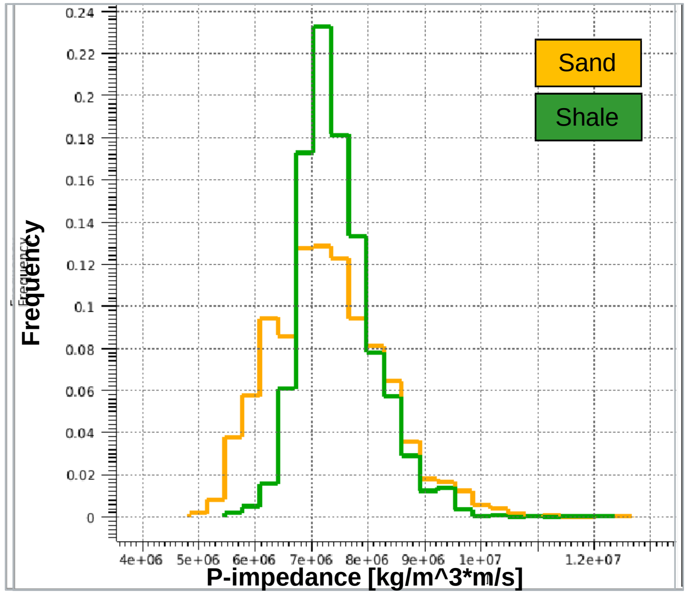
Measured logs
Modeled logs

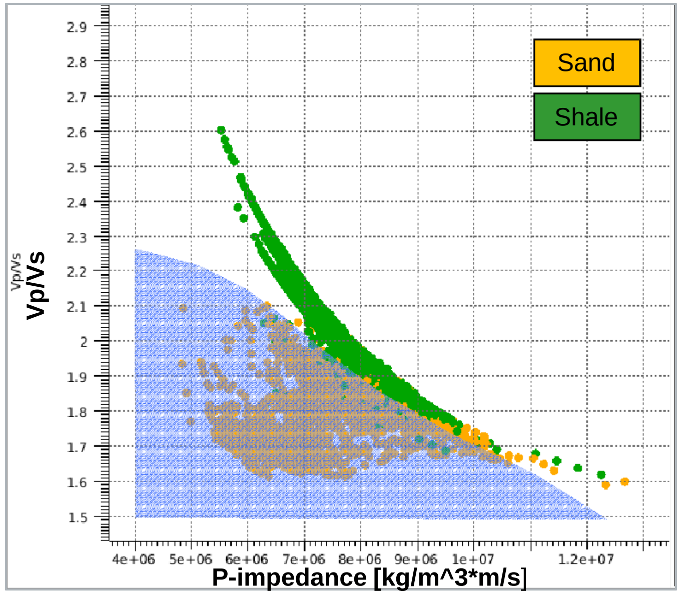


Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Data Analysis – Which Elastic Parameters?

P-impedance and Vp/Vs discriminate sand and shale





Single stack seismic inversion produces P-impedance only, unable to discriminate sand and shale

Multiple partial stacks seismic (simultaneous) inversion produces P-Impedance, Vp/Vs and Density able to discriminate sand and shale

Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

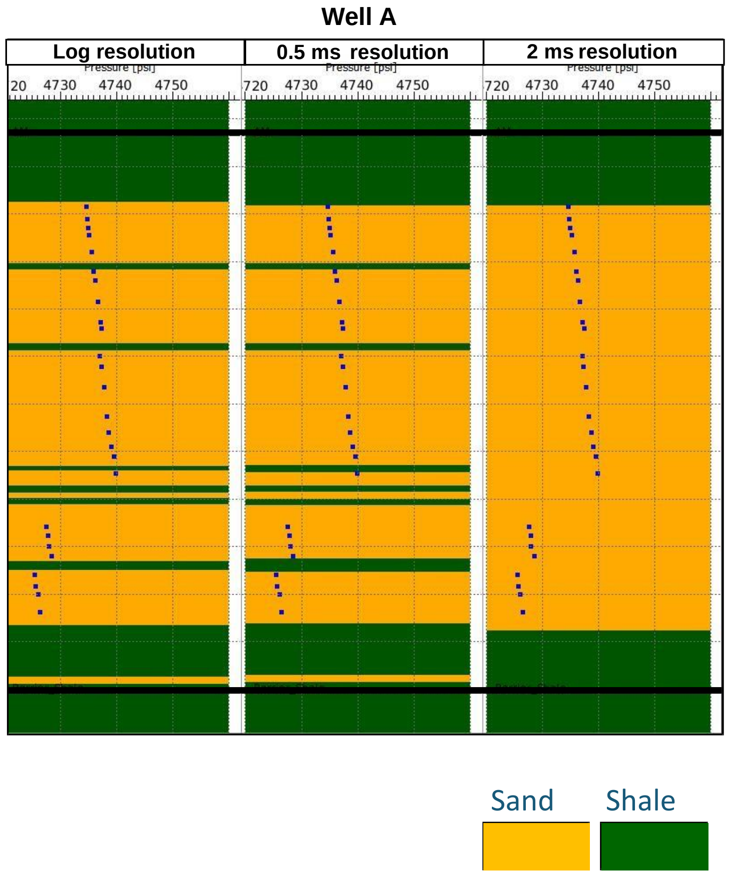
Analysis – Degree of Details

Log resolution (0.5 ft resolution) shows thin sand and shale layers.

Deterministic Inversion provides results at the seismic resolution and at 2 ms sample interval, and unable to capture thin shale layer.

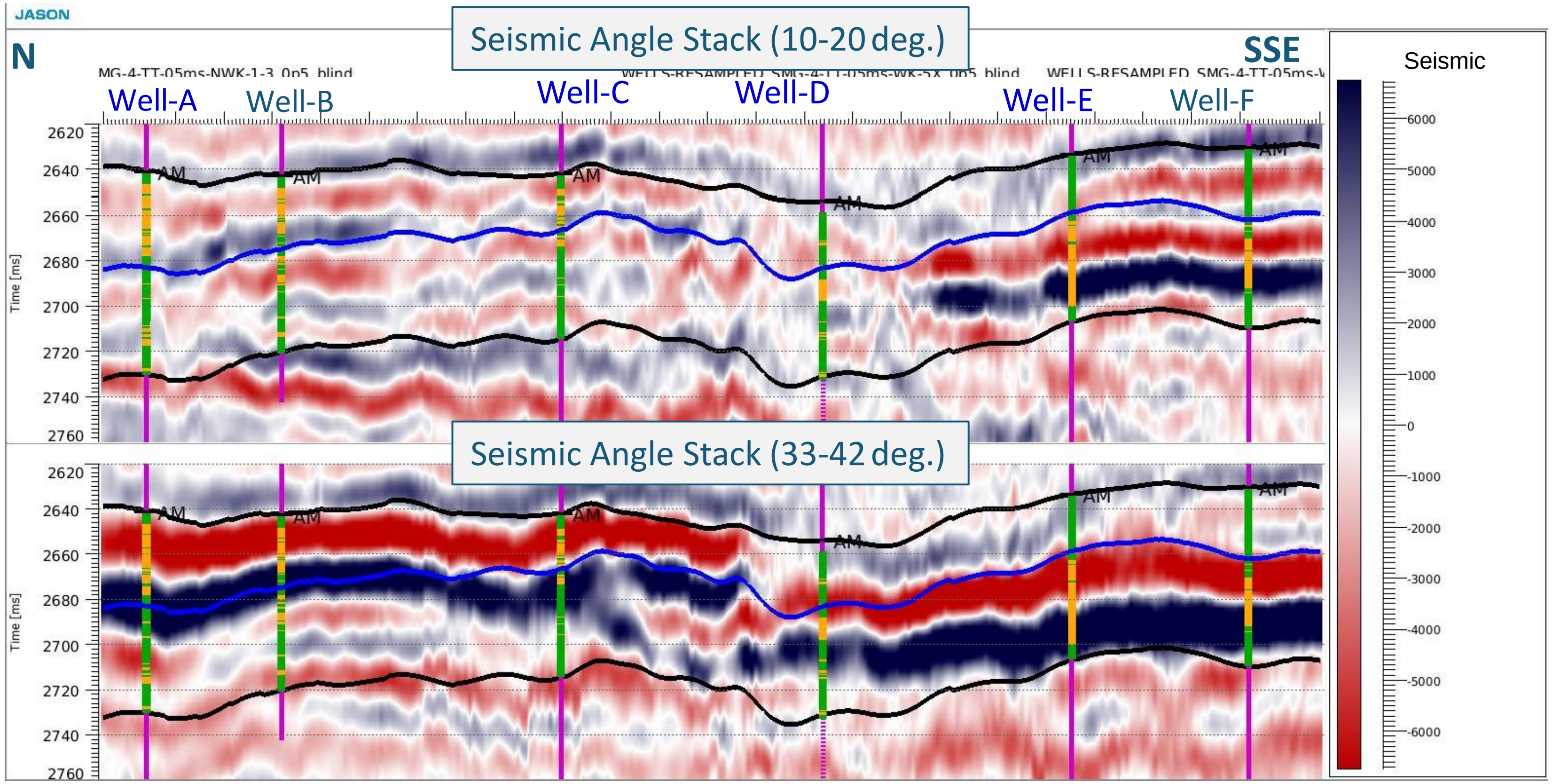
Final results need to be at 0.5 ms sample interval, to enable modeling sand and thin shale layer.

Geological model CPG (1-1.5m x 50m x 50m)



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

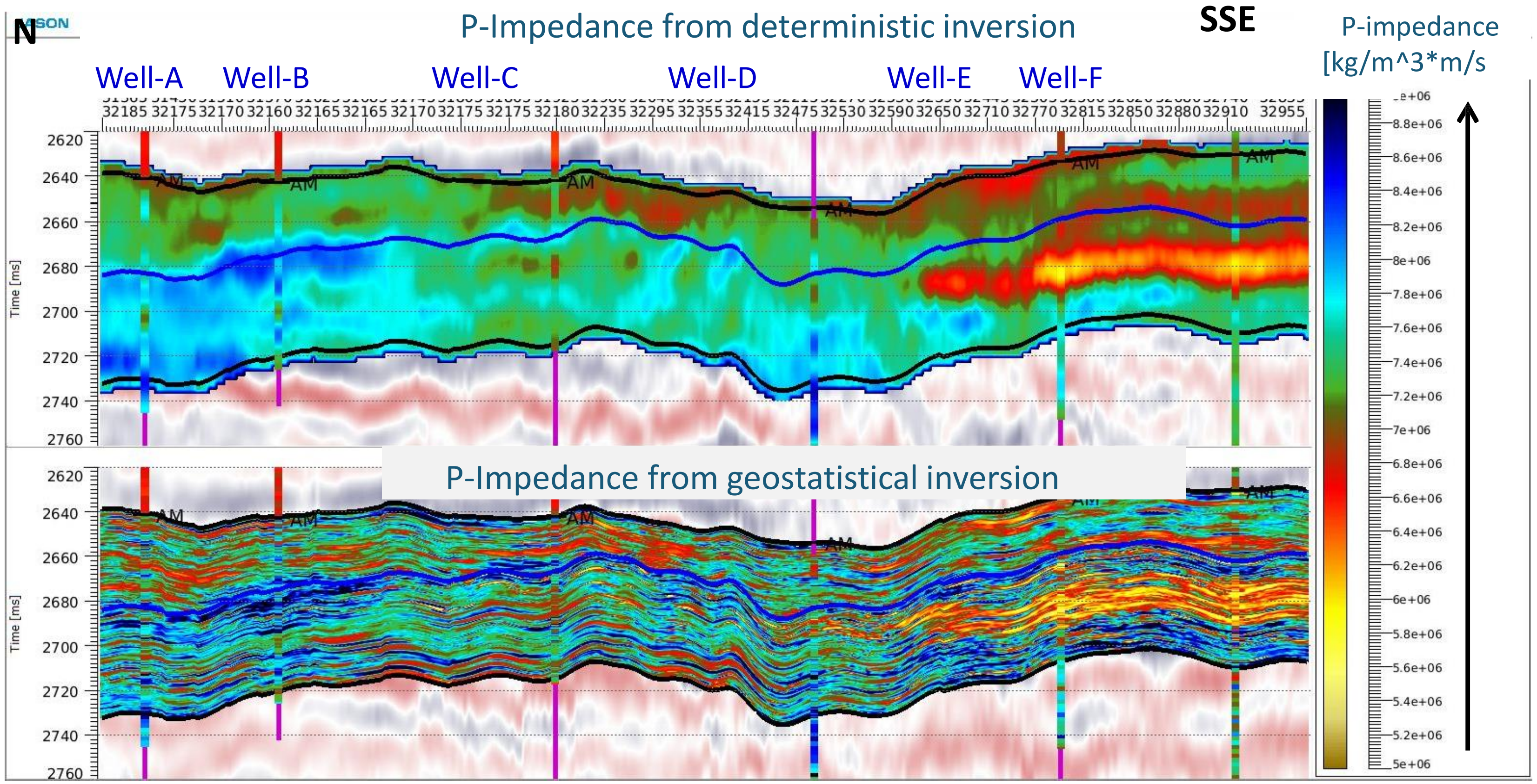
Input - Seismic Data



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Results - Deterministic vs. Geostatistical

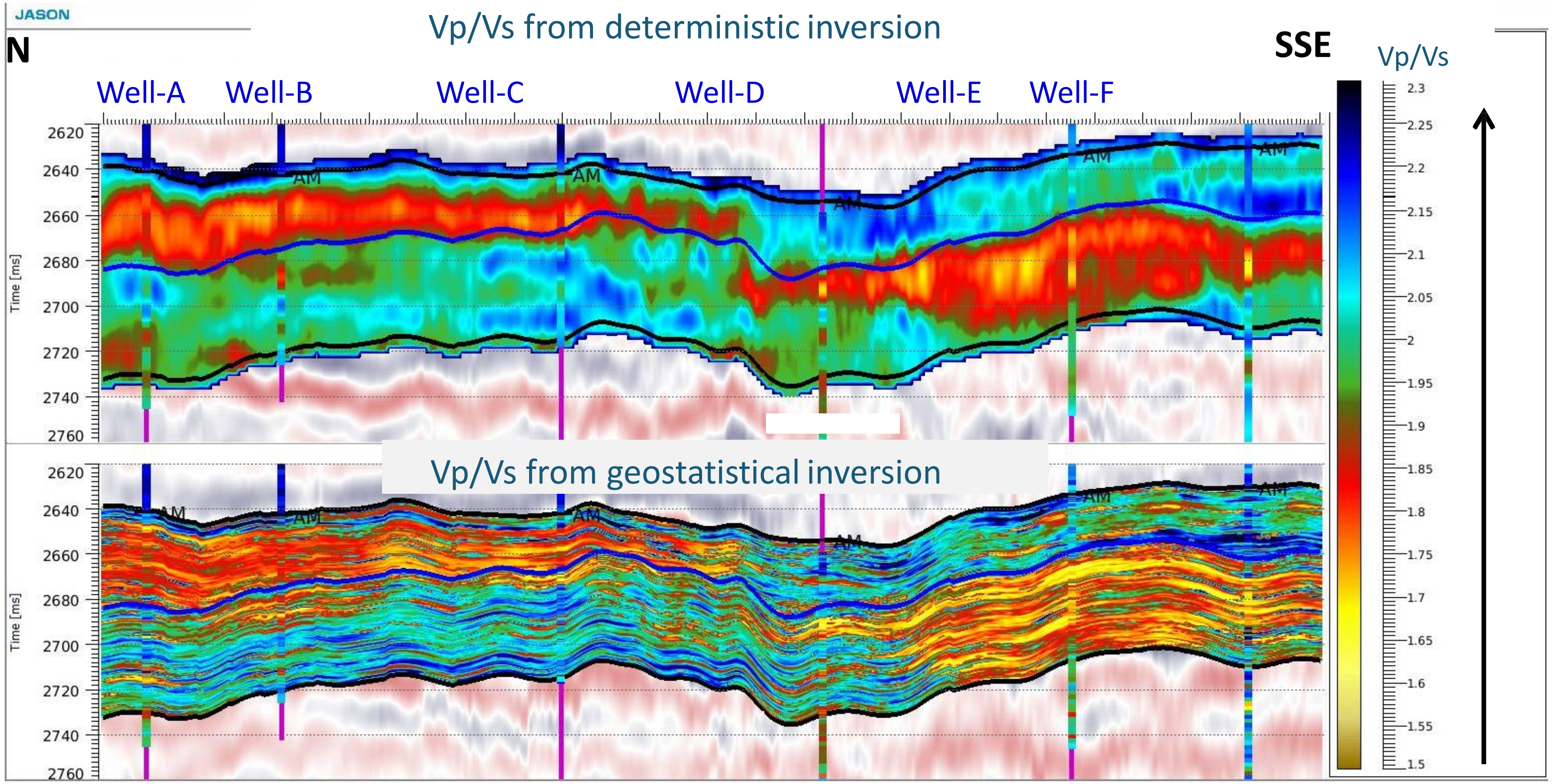
Comparison of P-Impedance from deterministic and geostatistical inversion



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Results - Deterministic vs. Geostatistical

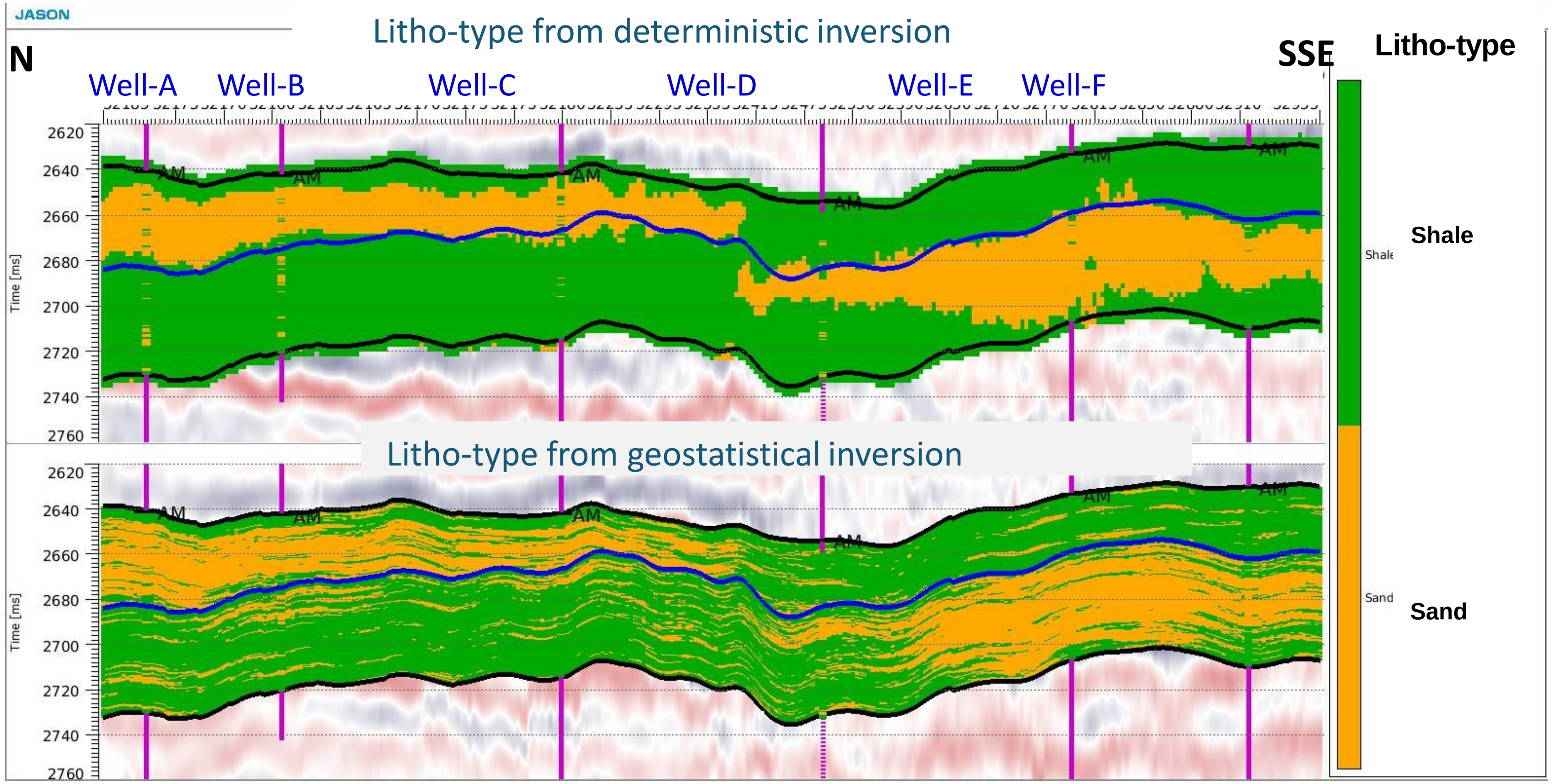
Comparison of Vp/Vs from deterministic and geostatistical inversion



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Results - Deterministic vs. Geostatistical

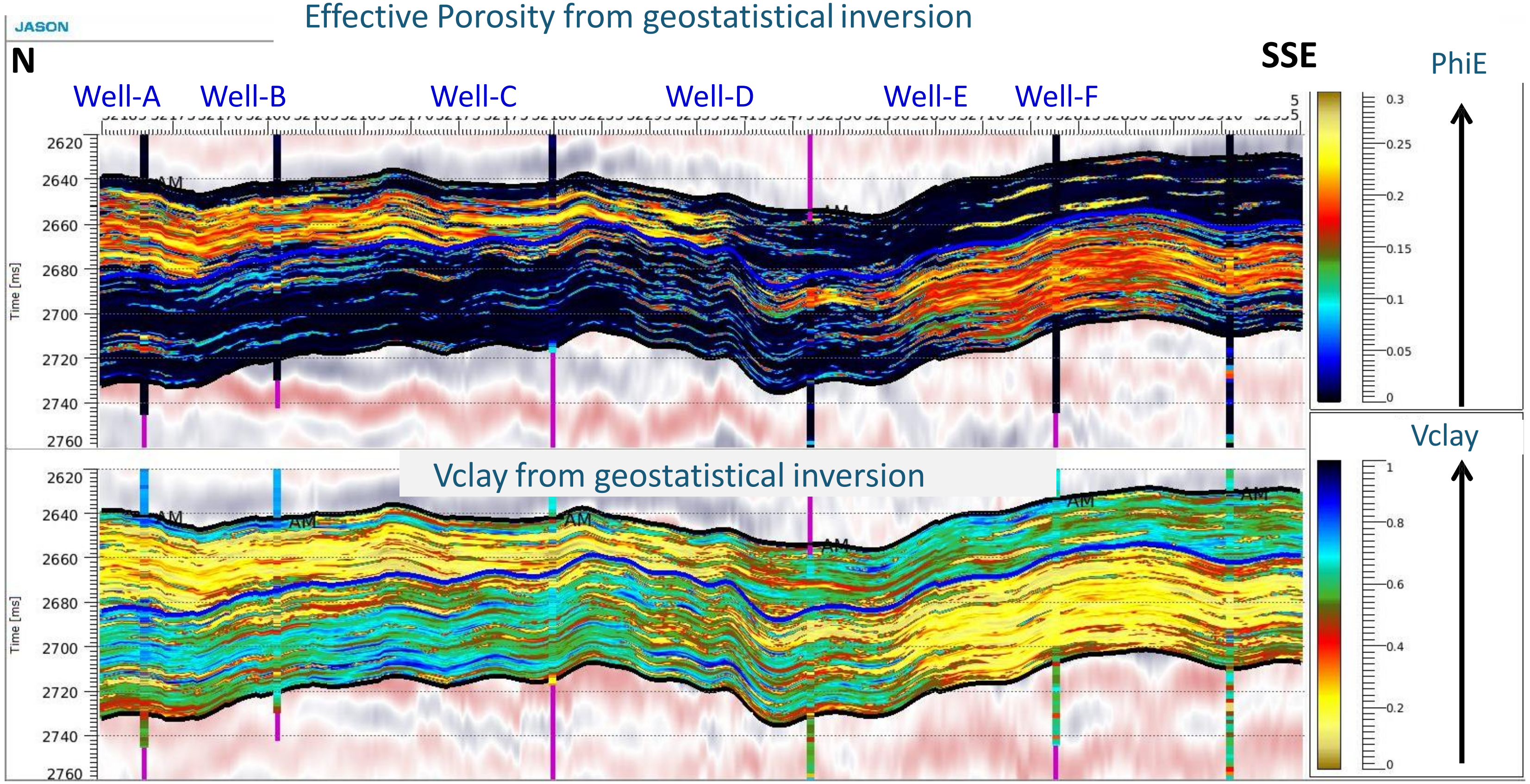
Comparison of litho-type from deterministic and geostatistical inversion



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

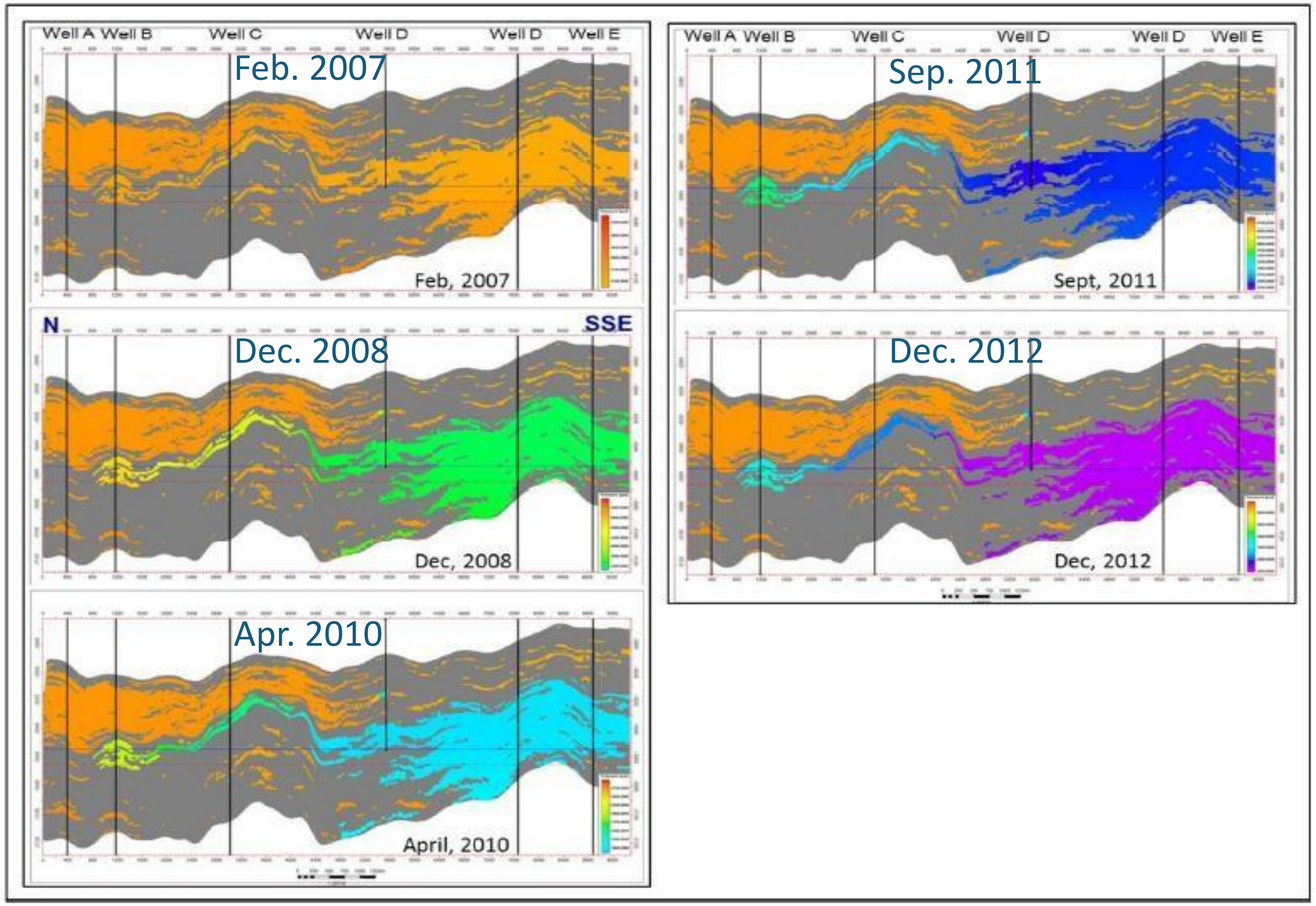
Results - Co-simulation

Geostatistical inversion results co-simulated into engineering properties



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Flow Simulation with P50 Realization



Sulistiono, D., Vaughan, R., Ali, M. and Rasoulzadeh, 2015, Integrating Seismic and Well data into highly detailed reservoir model through AVA geostatistical inversion,: ADIPEC, Abu Dhabi.

Conclusions

- Simultaneous geostatistical inversion produced multiple plausible models, enabled assessing uncertainty and further ranking (P10, P50 and P90) the models for static reservoir description.

- Tight integration of petrophysical analysis, rock physics modelling and geostatistical inversion produced a highly detailed consistent geological model that predicted pressure depletion in Lower Abu Madi sand very well.

Geostatistical Inversion as a Tool for Accurate Updates of the Hydrodynamic Models

GeoSoftware™

www.GeoSoftware.com

Study Area

The oil field is located in the Western-Siberia oil and gas province, discovered in 1986 and in production since 2003.

Up-to-date of this study, more than 10 exploration and 30 production wells have been drilled in the area.

Oil saturated reservoir. $BC10_{2+3}$ (neokomian interval) is one of the main production unit.

It is a clastic reservoir, net pay varies from 5 to 18 meters and porosity from 15 to 17%.

The Reservoirs and the Challenges

Scheme of $BC10_{2+3}$ reservoir bodies delineated from pre-stack geostatistical inversion.

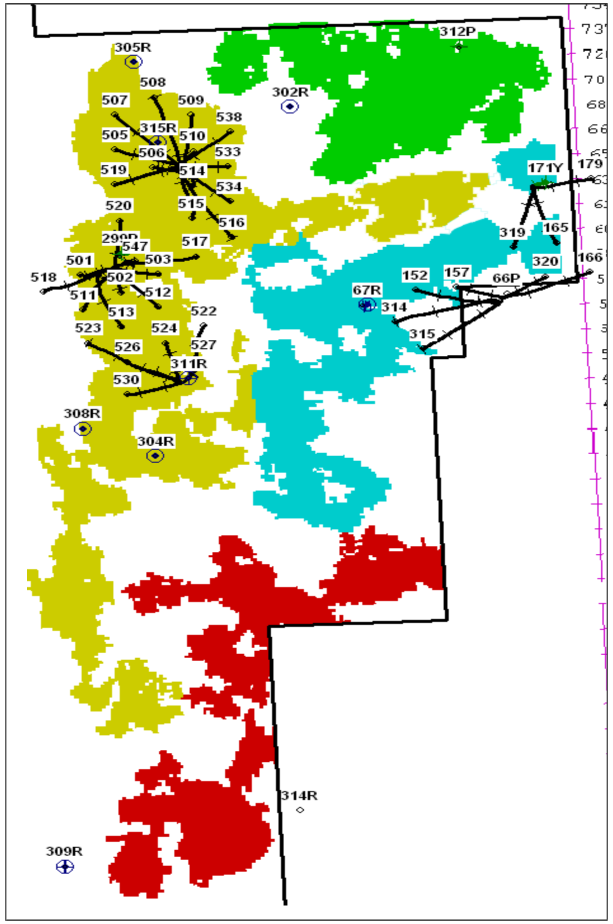
Four isolated bodies in layer $BC10_{2+3}$ have been identified.

Main BC102+3 reserves are in the Western zone (shown in yellow) and is connected to the east with the feeding channel.

The second reservoir in the Eastern zone (shown in blue) is being actively developed as part of the neighboring oil field.

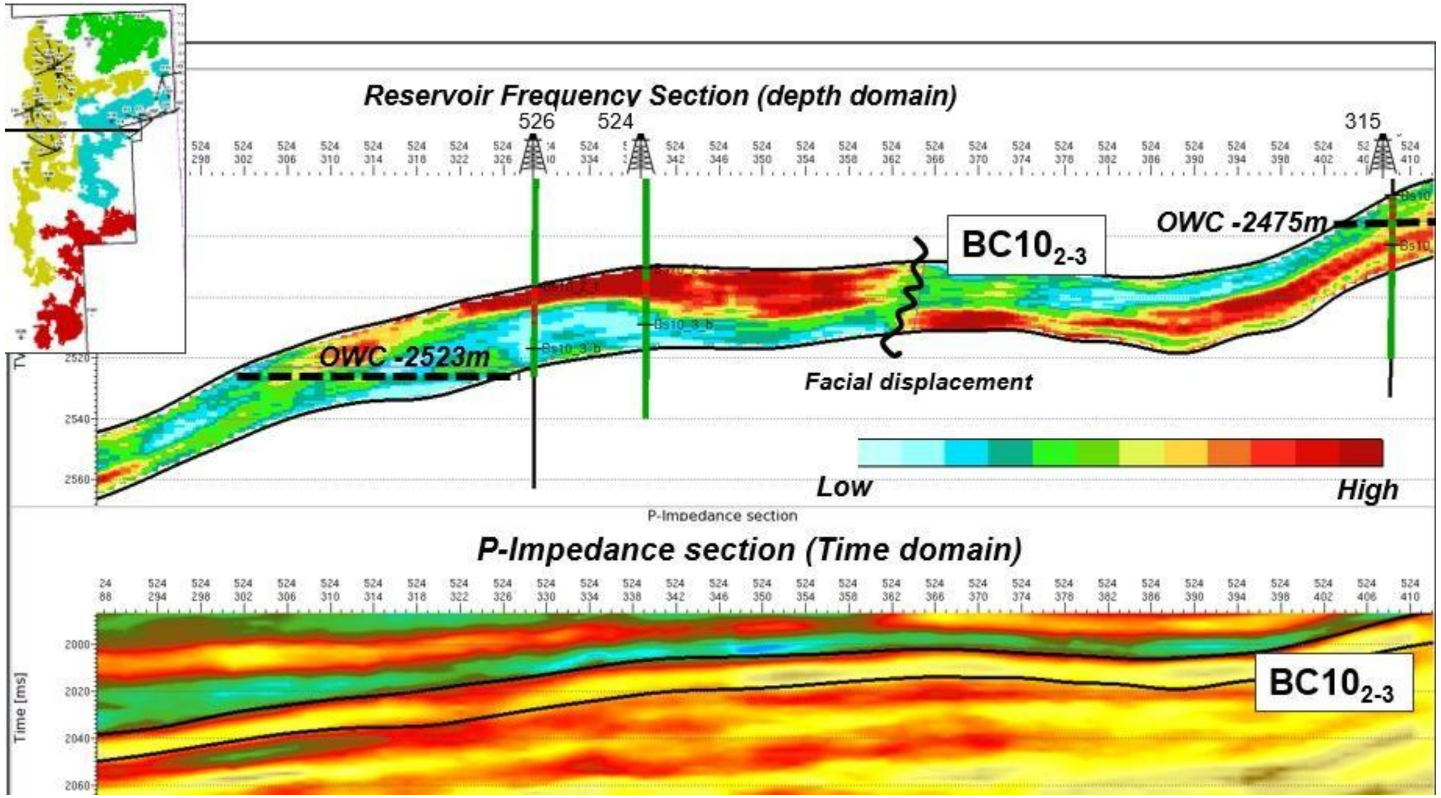
No drilling done in other two reservoirs (Green and Red) in view of high risk associated with their occurrence in structurally low area.

Geological model for flow simulation build and tested for the main reservoir.



Filippova, K., et al., 2013, Geostatistical Inversion as a Tool for the Accurate Updates of the Hydrodynamic Models – Case Study: 75th EAGE Conference & Exhibition, London.

$BC10_{2+3}$ Reservoir Frequency Volume



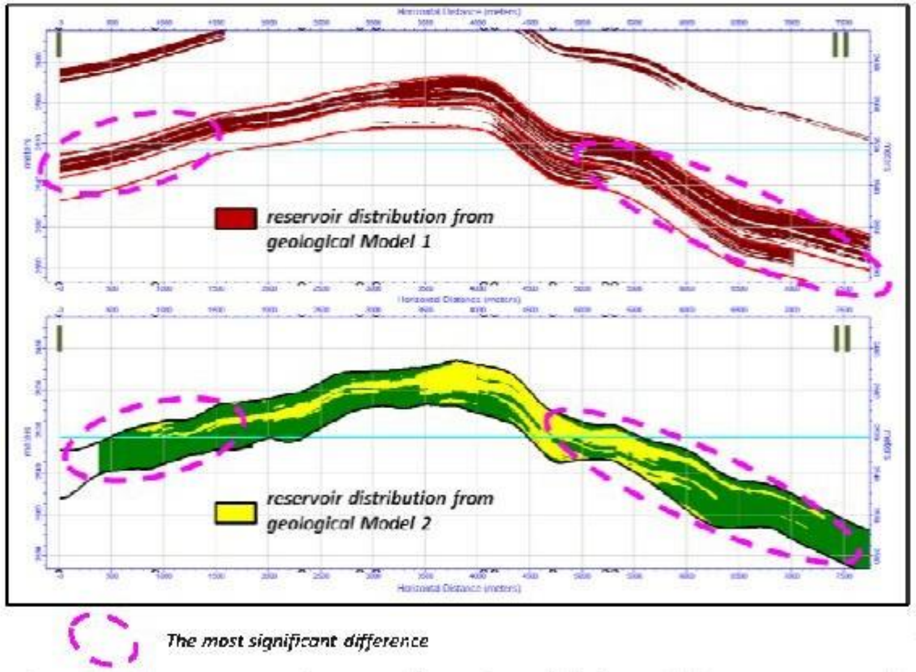
This section intersect yellow and blue reservoir bodies with different OWC levels. It shows that $BC10_{2+3}$ reservoir has a tiled structure not shown in seismic or P-Impedance from deterministic inversion

Filippova, K., et al., 2013, Geostatistical Inversion as a Tool for the Accurate Updates of the Hydrodynamic Models – Case Study: 75th EAGE Conference & Exhibition, London.

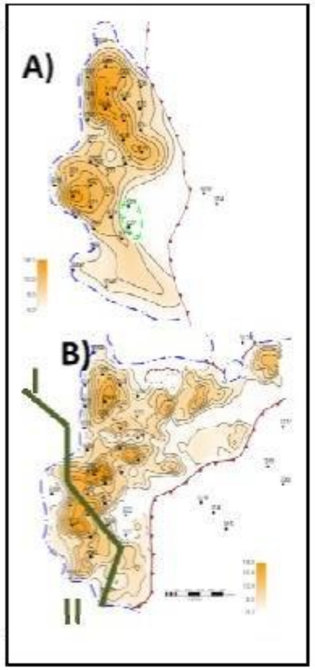
Geological Models

Model 1: Build mainly based on well log data and general geological concepts in view of large number of wells.

Model 2: Fully driven by results from pre-stack geostatistical inversion



Net pay



Filippova, K., et al., 2013, Geostatistical Inversion as a Tool for the Accurate Updates of the Hydrodynamic Models – Case Study: 75th EAGE Conference & Exhibition, London.

Geological Models

Differences between Model 1 (traditional) & Model 2 (Geostatistical Inversion)

Structural Framework: Results of deterministic inversion were used to update interpretations of top and bottom of the reservoir and structural framework for Model 2 was refined accordingly.

Areas away from the wells highlighted by purple circles exhibits major differences between Models 1 & 2. Whereas Model 1 has minimal input from seismic (only horizons), Model 2 is fully integrated with seismic data through geostatistical inversion.

The net pay map from the seismic driven model demonstrates a high degree of lateral heterogeneity in the reservoir in the inter well space. Additionally, the reservoirs extend further towards east providing the scope of identifying new locations to place horizontal wells.

Flow Simulations

Two hydrodynamic modelling were built based on Model 1 & Model 2.

For Model 2, facies obtained from geostatistical inversion was directly used.

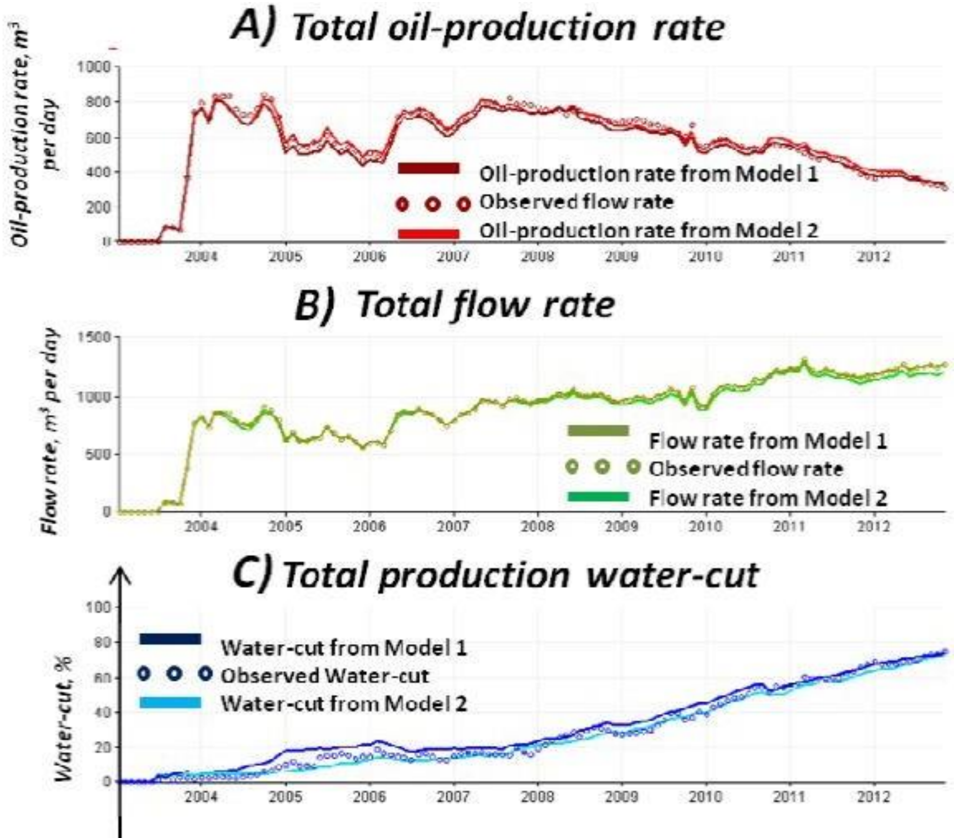
Porosity was co-simulated from inverted P-impedance and lithology volume.

Permeability was obtained through regression with porosity.

For non reservoir section permeability was set to zero.
No additional modifiers were used for NTG and porosity.

Permeability modifiers were used as required but were much smaller in Model 2 compared to Model 1.

Simulated values of total flow rate, total oil & water cut from Model 2 match better with the observed historical data compared to predictions from Model 1.



Filippova, K., et al., 2013, Geostatistical Inversion as a Tool for the Accurate Updates of the Hydrodynamic Models – Case Study: 75th EAGE Conference & Exhibition, London.

Summary & Discussions: Benefits, Pitfalls and Limitations

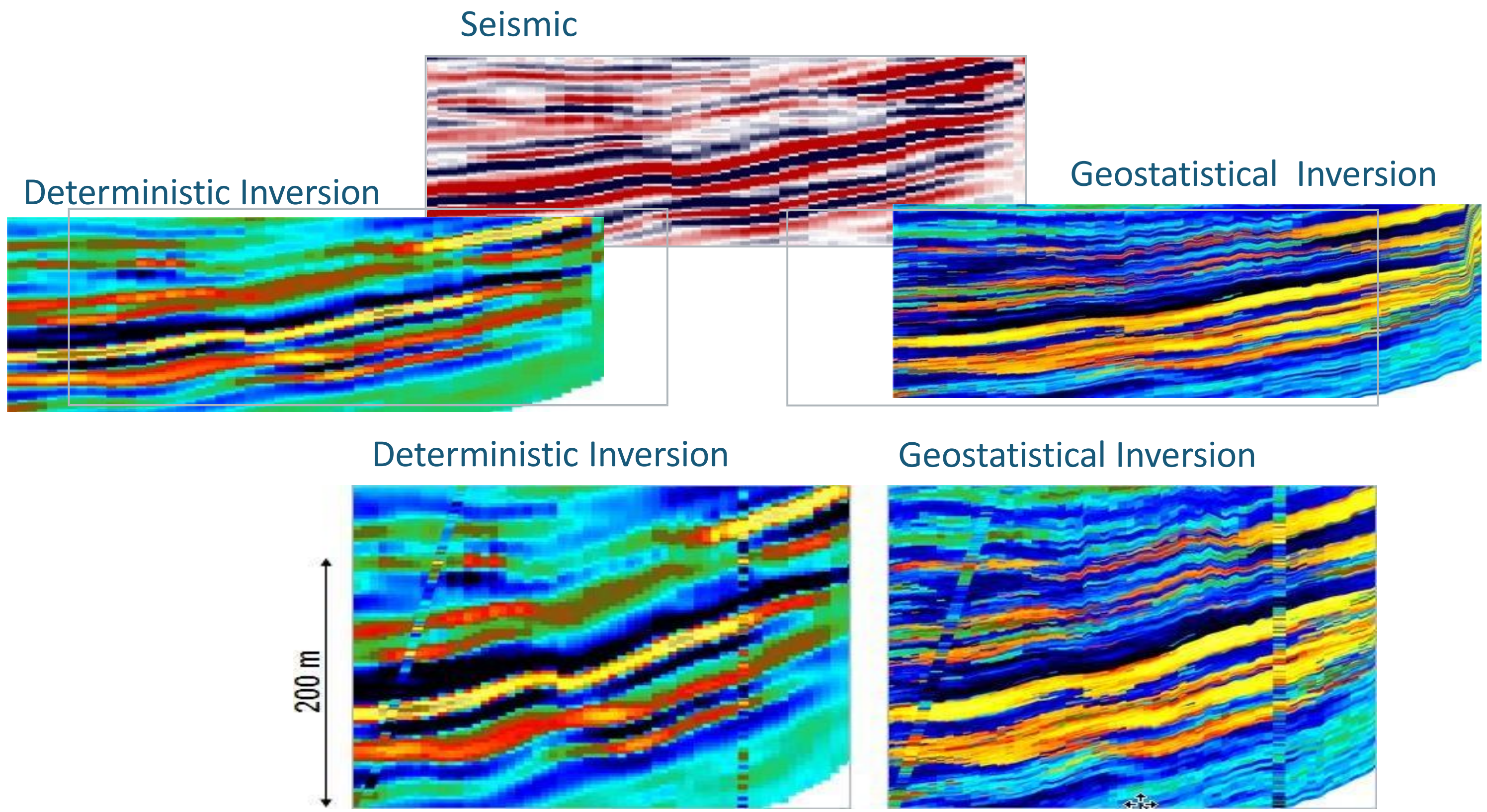
Benefits

Benefits of a generic geostatistical inversion

- Highly detailed outside the seismic bandwidth.
- Geologically plausible shapes in reservoir properties.
- Estimates of uncertainty for risk assessment.

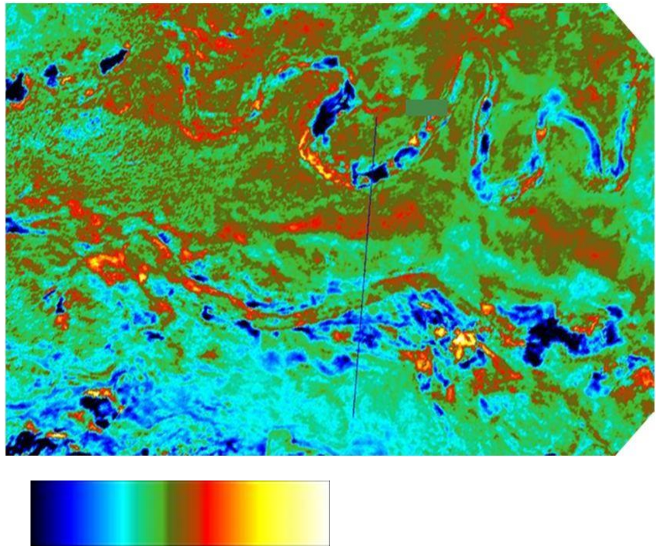
Benefits: Details Beyond Seismic Bandwidth

Within seismic bandwidth both deterministic and geostatistical inversion agree but beyond seismic bandwidth high details arises from geostatistical model

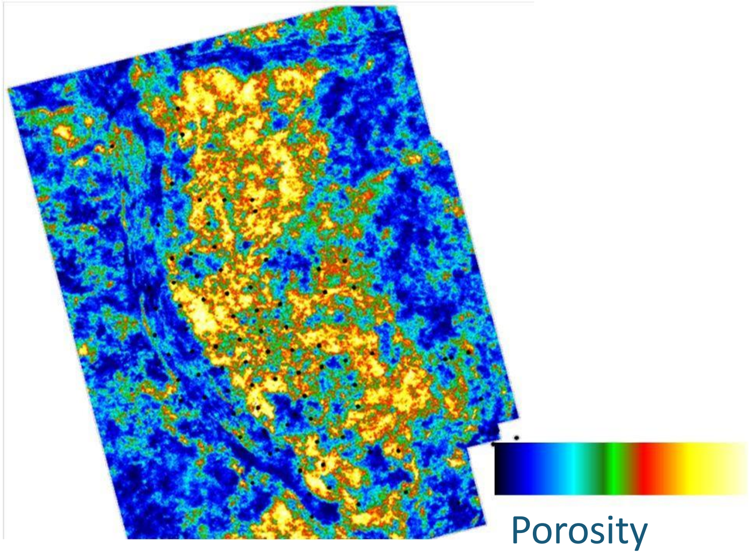


Benefits: Plausible Geological Shapes

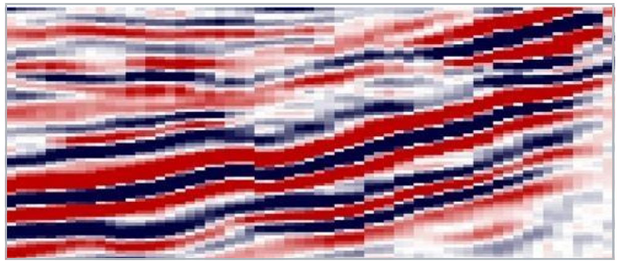
Channels clearly visible

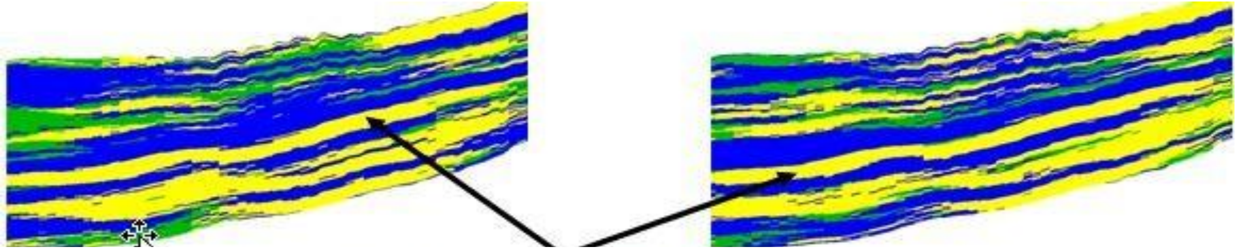


Porosity through reservoir consistent with depositional features

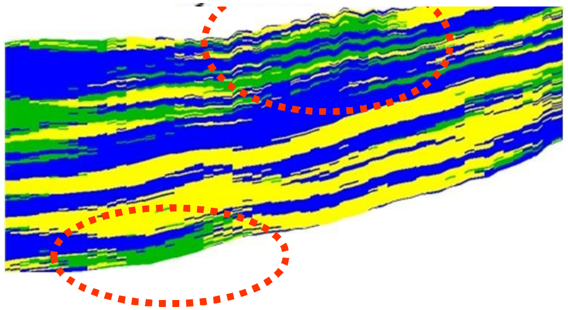


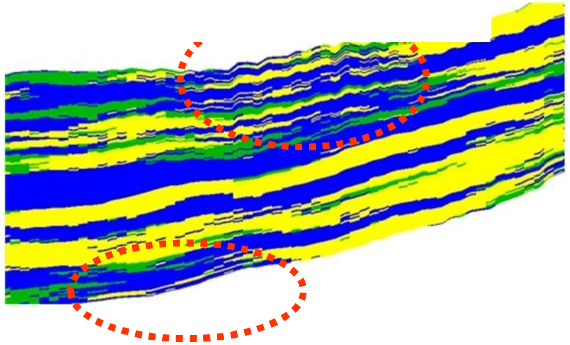
Benefits: Estimating Uncertainty





Large-scale features are similar across different realizations, showing less uncertainty as constrained by seismic.





Very thin features come out slightly different across realizations, capturing the associated uncertainty.

Benefits

Additional benefits of geostatistical inversion using StatMod/RockMod

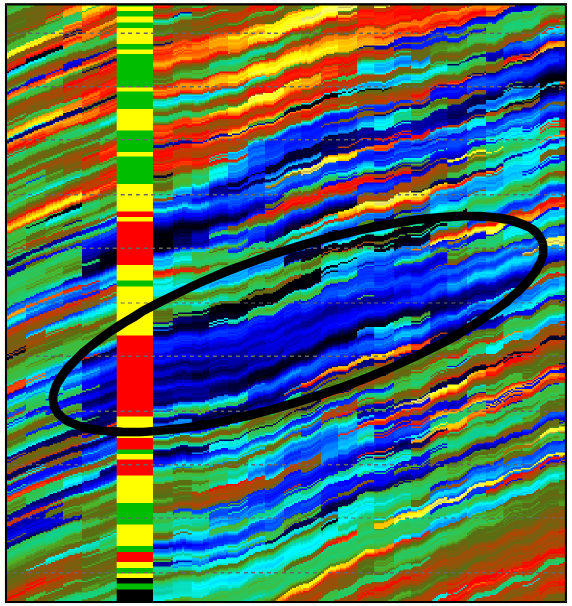
– Joint inversion of impedance and lithology
– Unbiased integration of data coming from disparate sources including vertical/ lateral as well as 3D facies trend as prior
– Quick QC of a large number of realizations

Benefits: Joint inversion of Facies and Properties

The distribution of lithology within a reservoir is a major source of uncertainty in modeling reservoir properties.

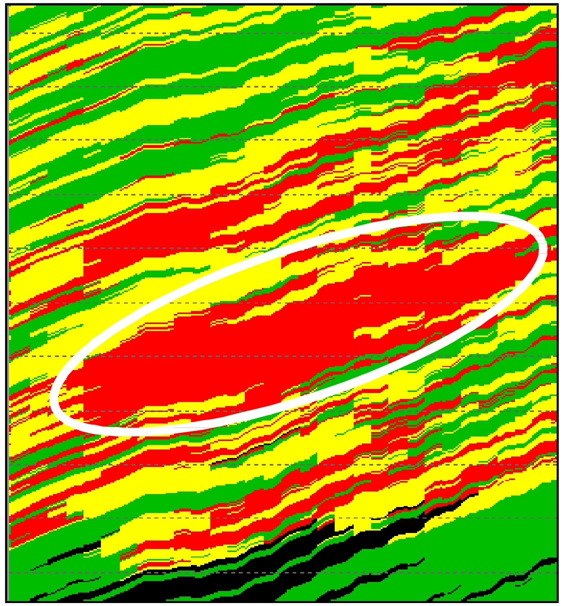
Joint inversion of facies and elastic properties ensures consistency between the two.

Inverted P-impedance



+

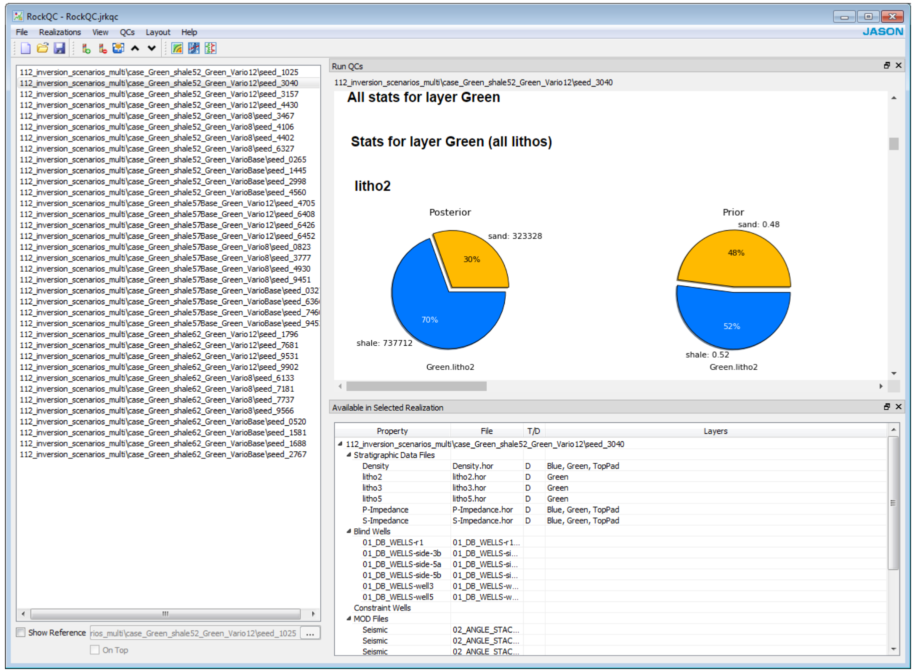
Inverted Lithology

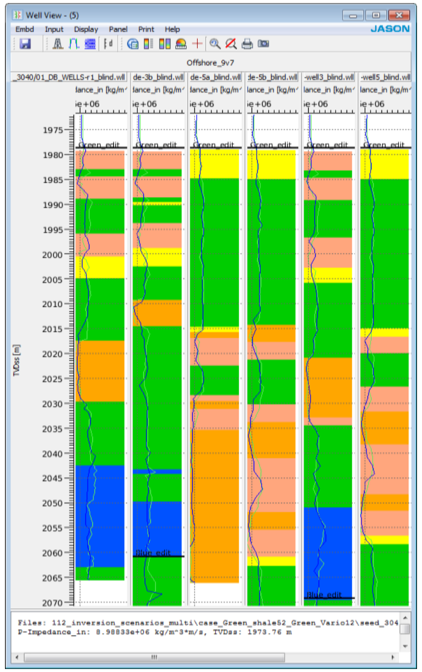


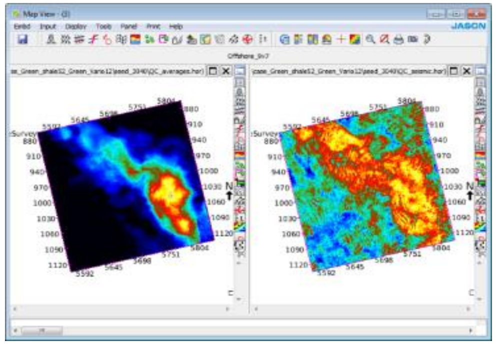
RockQC: Quickly Analyse Multiple Realizations

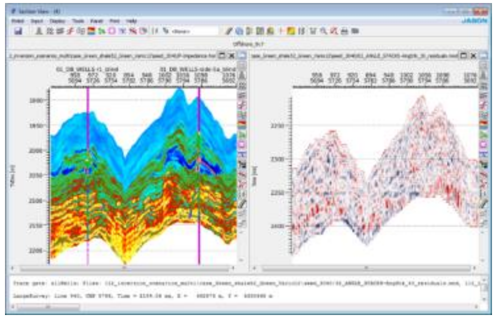
Create template for QC, e.g. prior & posterior facies proportions, log views of facies, section view of properties and properties in stratigraphic slices

Scroll through realizations and QC the results.









Pitfalls of Geostatistical Inversion

Using poor quality well data

Bias can be introduced in petrophysical interpretation due to changes in i) log responses due tools of different generation or companies, ii) different processing parameters, e.g. using different matrix densities for density estimation, sand/shale base lines for calculating volume of shale, different water resistivity for Sw estimation. This can result in poor integration of well and seismic data.

Noise in seismic data

Even though used as soft information and overall seismic data quality can be high, local issues like multiples, acquisition foot prints, poor stacking or migration velocities can create bias restricting quality of geostatistical inversion.

Inadequate well information

Number of wells or their distribution could be inadequate to capture the true geostatistical character of the whole area. This can create bias in favor or against a particular facies. This may lead to estimation of high proportion of preferred facies when applied to whole volume.

Pitfalls of Geostatistical Inversion

Outliers in data

Outliers in data (samples outside 2-3 times standard deviation from the mean) may have major impact in defining the probability density function and spatial correlation resulting in estimation of wrong parameters. Important to recognize data outlier or samples from other population.

Trends in reservoir property

Presence of trend in the data violates the basic requirement of stationary statistical process which demands mean of the data to be same if sampled from different regions Trend in properties should be recognized and removed from the data before geostatistical modeling and then added back.

Wrong geostatistical model

Correct geostatistical model comprising spatial variograms, prior pdfs and likelihood functions are key to success of any geostatistical inversion algorithms. Results derived from wrongly selected geostatistical model, if not recognized and rectified, may lead to incorrect interpretation of results.

Pitfalls of Geostatistical Inversion

Amplitude & AVO pitfalls

Geostatistical inversion uses seismic amplitude or AVO information. As a consequence, several of pitfalls in interpreting seismic amplitude and AVO will apply to geostatistical inversion, too.

Evolving Trends

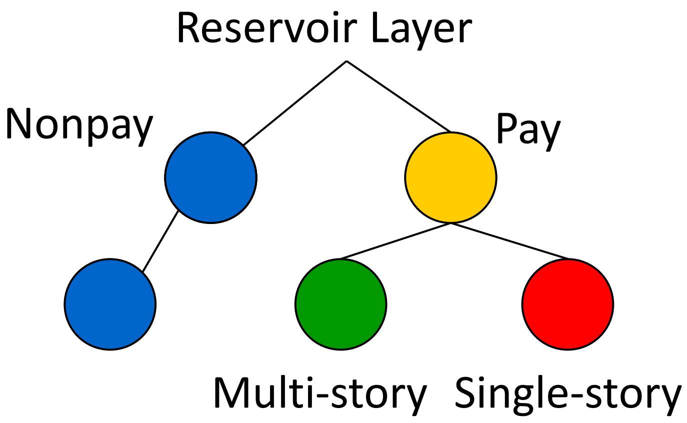
Advanced Features of Geostatistical Inversion

GeoSoftware™

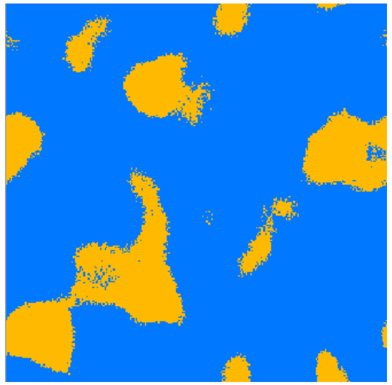
www.GeoSoftware.com

Facies Ordering and Associations

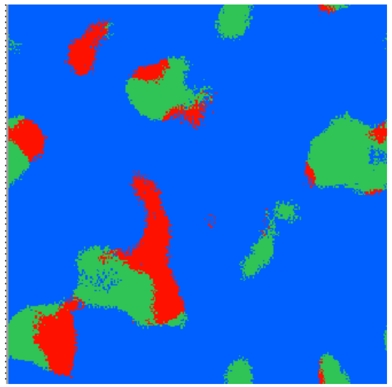
Multi-level hierarchical facies



Level 2

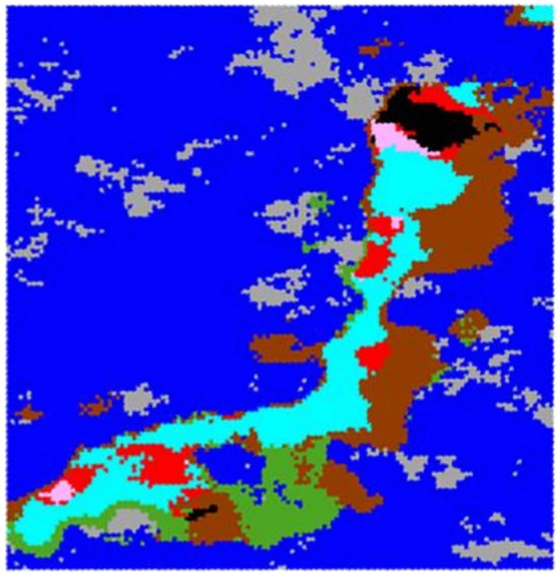


Level 3



Nested facies

Honor sequential ordering of the facies, e.g.



<u>Channel</u>
Light oil
Heavy oil
Gas
Brine

<u>Levee</u>
Tight
Loose

<u>Overbank</u>
Shale
Muck

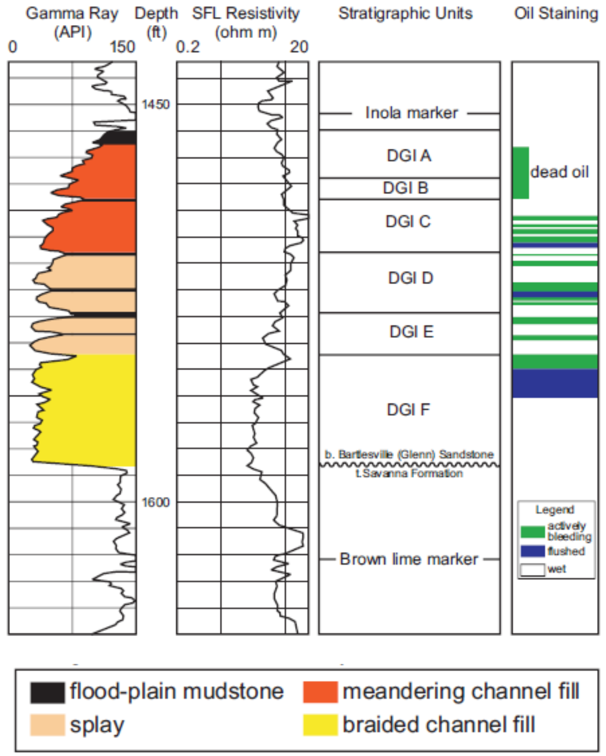
Geological Trends

Incorporate geological trends

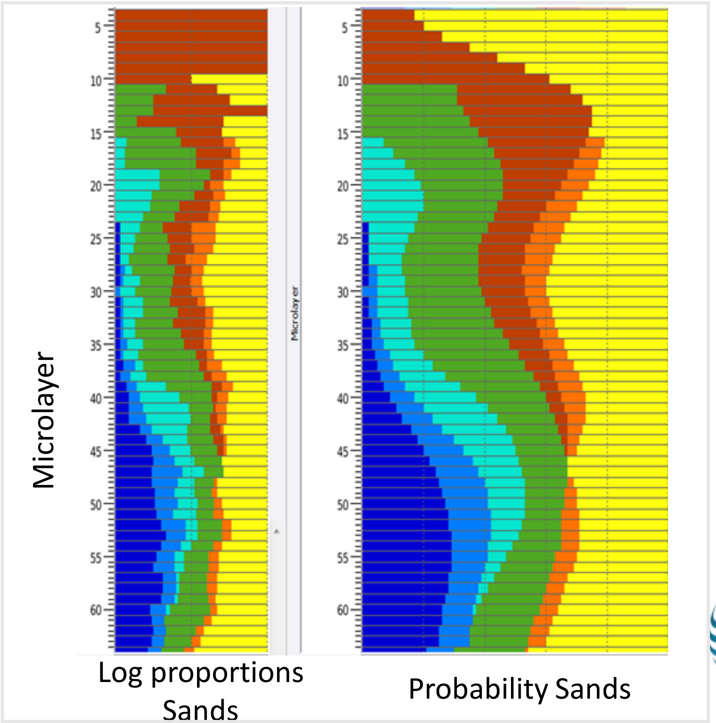
- Vertical Trends
- Lateral Trends
- 3D Trends

Vertical probability trends built from the input facies logs to model depositional changes

Depth Trend – Fining Upwards



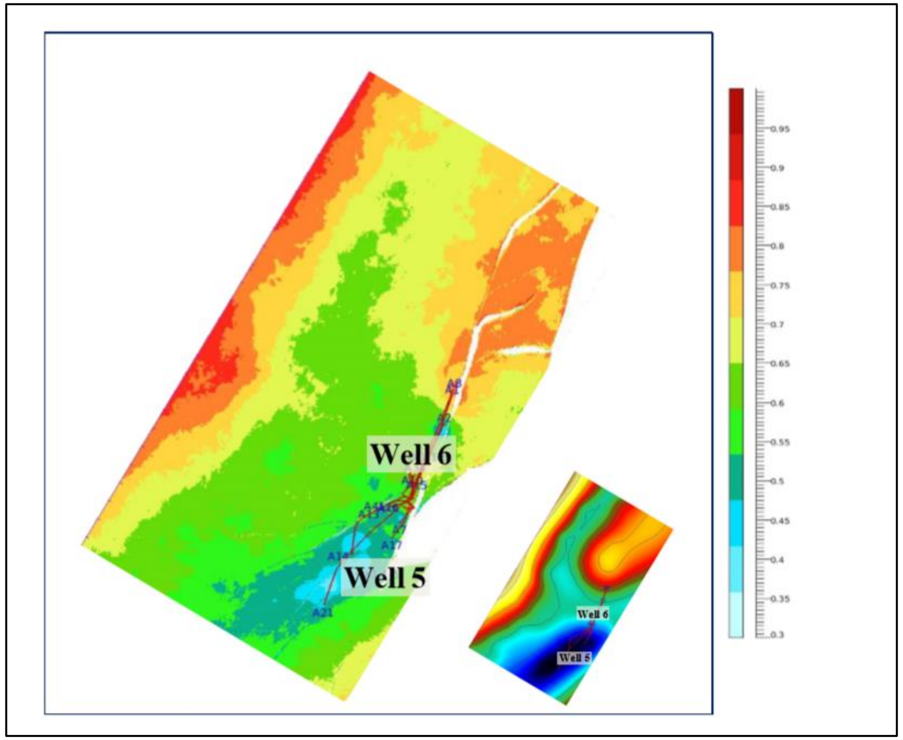
Vertical probability trend curves

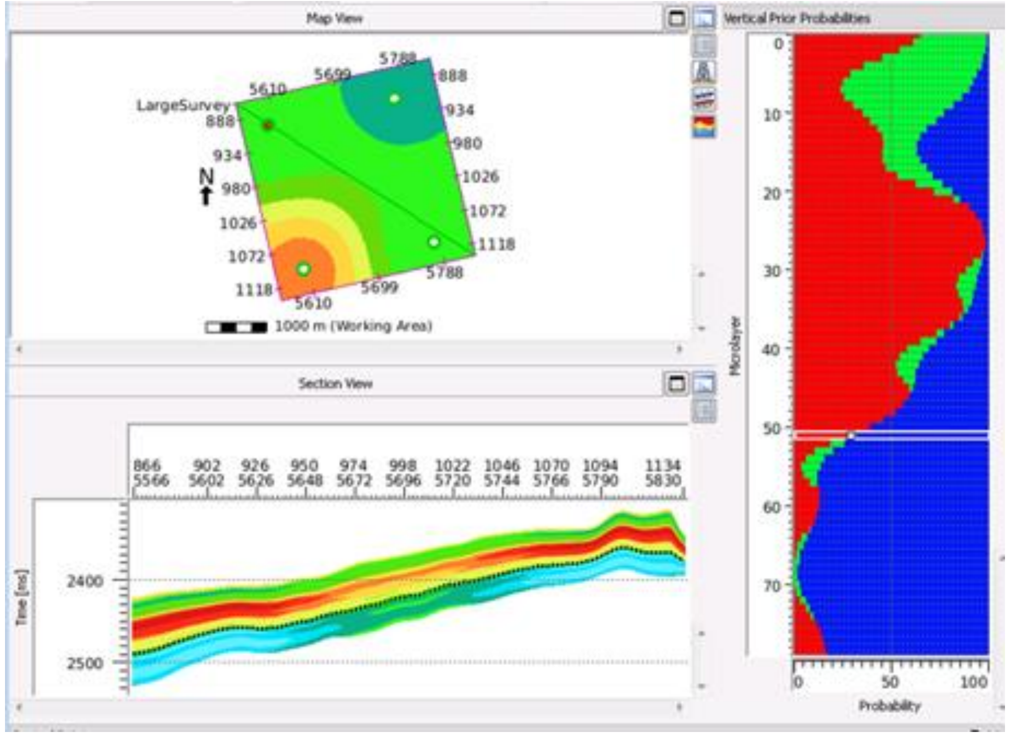


2D & 3D Trends

- Wells are usually drilled in good zones and proportions purely from wells can be biased
- Incorporating geological prior information may help in these cases

Shale probability map used as 2D trend





Li, et al., SEG 2019

Direct Inversion in Engineering Properties in Depth

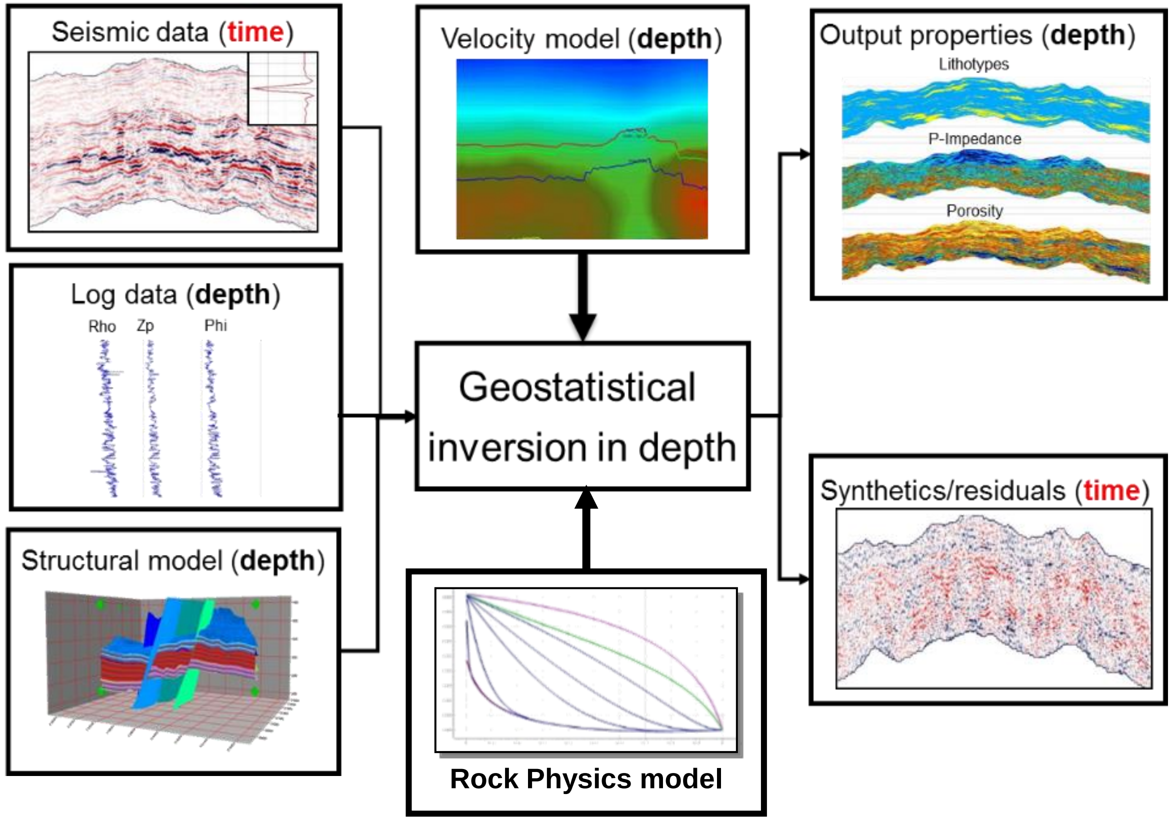
Benefits of working in depth:

More intuitive

- Depth is natural domain for modeling and simulation
- Easier to share information with geologists and reservoir engineers who ultimately own the reservoir model

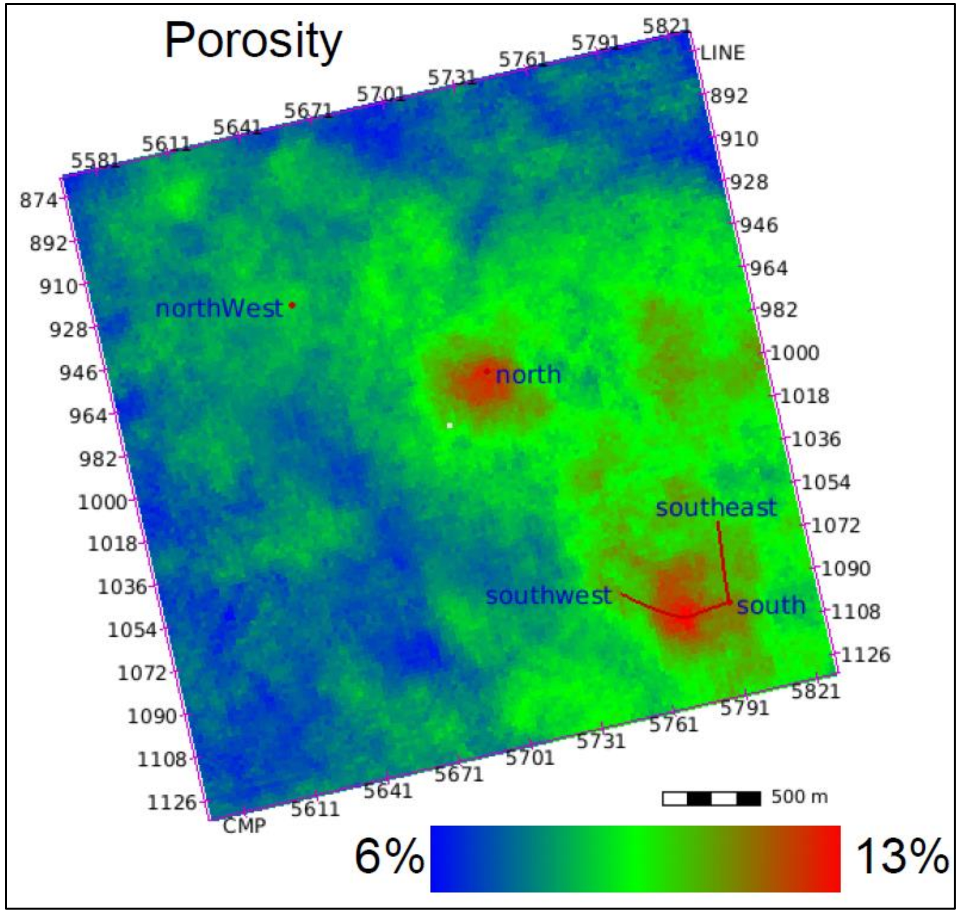
More realistic facies features

- Resampling discrete properties from time to depth can introduce artifacts and discontinuities

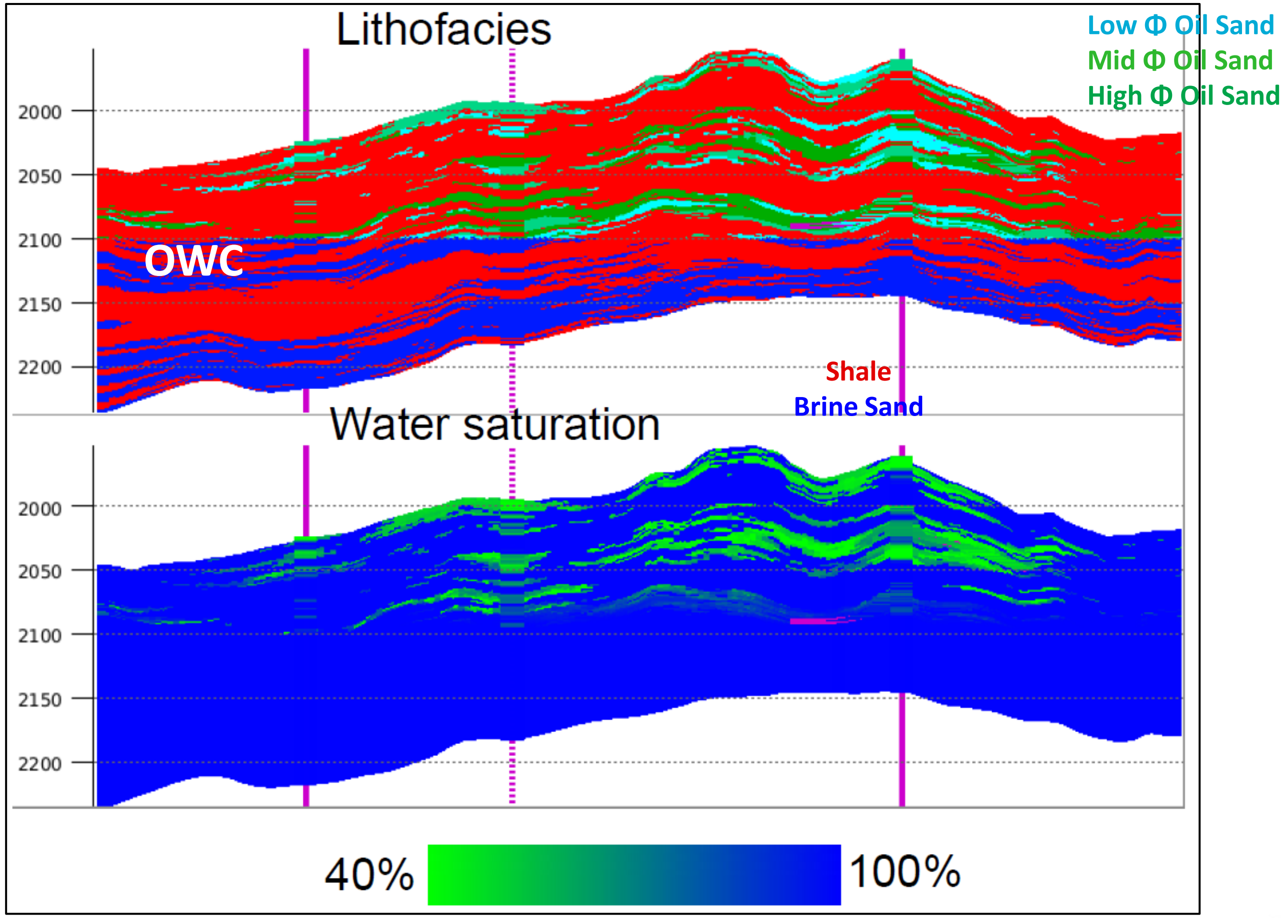


Integration of Rock Physics in Inversion Workflows

Mean Porosity Map over the Reservoir Layer



Lithofacies and Water Saturation Sections in Depth



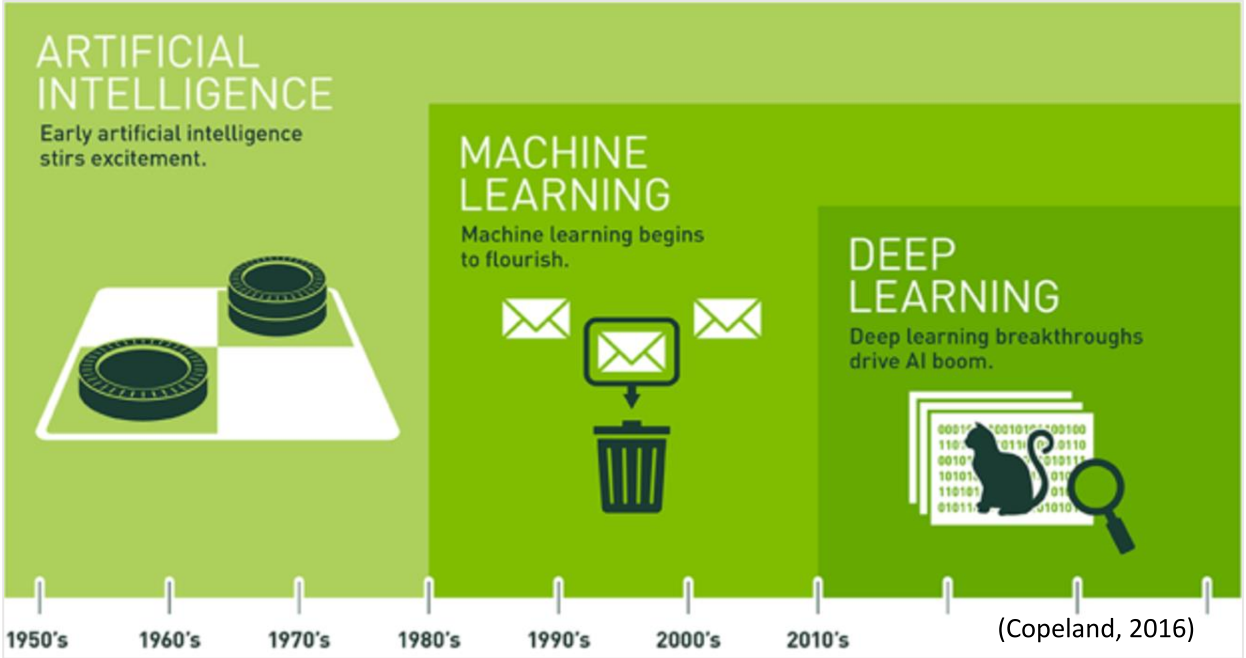
Marquez., et al., 2013, Incorporating rock physics into geostatistical inversion: 75th EAGE Conference & Exhibition, London.

Evolving Trends

Use of Machine Learning Techniques in Seismic Reservoir Characterization

Deep Learning Driving Artificial Intelligence Boom

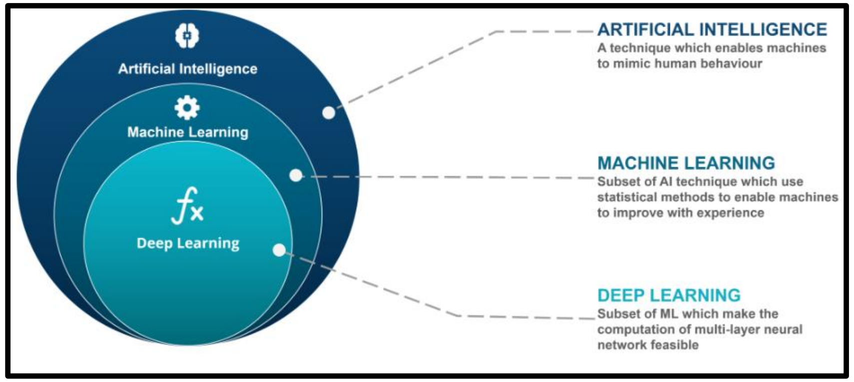
- The concept of **Artificial Intelligence (AI)** was first introduced by Turing in 1950. But it was the uptake in the interest in **Machine Learning (ML)** that began in the 1980s had helped its popularity and especially adoption in geophysics
- Starting 2010s, **AI** has boomed due to the **Deep Learning (DL)** or **Deep Neural Network (DNN)** breakthroughs
- Especially after 2015, **AI** has exploded due to availability of hardware (i.e., use of GPUs) and software (i.e., open-source libraries: Tensorflow, PyTorch, XGBoost, etc.)



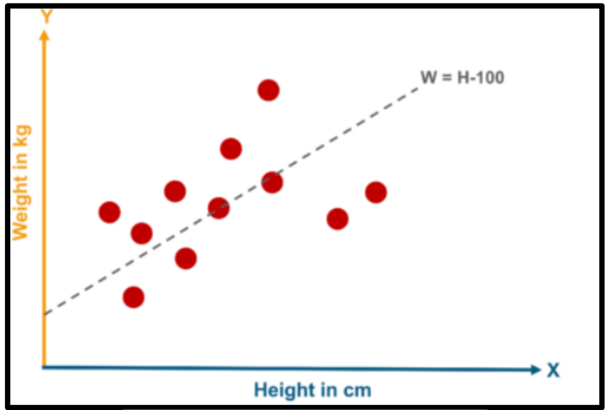
(Copeland, 2016)

Copeland, M., 2016, What's the Difference Between Artificial Intelligence, Machine Learning and Deep Learning: Nvidia website.)

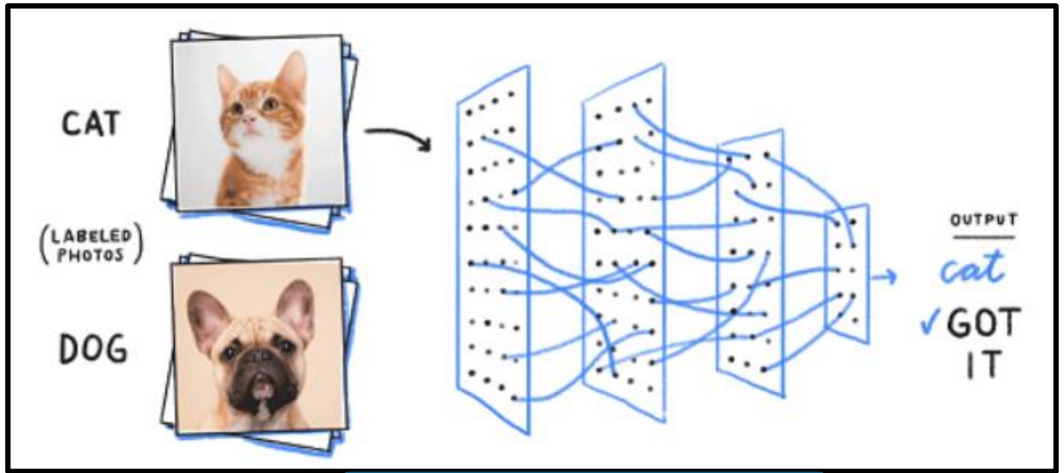
What is Deep Machine Learning



AI



Machine Learning



Deep Machine Learning

https://www.edureka.co/blog/ai-vs-machine-learning-vs-deep-learning/

Recent Use Cases of ML/DL Applications in Oil & Gas Industry

Petrophysics	Rock Physics	Geology	Seismic Imaging	Seismic Interpretation	Quantitative Interpretation	Reservoir Modeling	Reservoir Engineering	Production / Monitoring
• Well Log Data QC & Conditioning • Missing Log Prediction • Petrophysical Evaluation: Vcl, N/G, Phi, Sw, Perm., etc. • Facies Classification • Missed Pay Prediction in E&P • NMR & FMI Processing	• P- & S-wave Velocity Prediction • Pore Pressure Prediction • Geomechanics	• Geological Tops Picking & Correlation • Stratigraphic Sequence Interpretation • Borehole Image Interpretation • Lithotype Interpretation from drill cuttings	• Preprocessing: Bad Data Detection • Velocity Picking • Velocity Modeling • Image Processing & Enhancement • Increase Resolution • De-noise • De-multiple	• 3D Fault Extraction • Horizon Picking, Top & Base of Salt Picking • Seismic Facies Analysis • 3D Geobody Capture: Salt, MTD, Channels, etc. • Microseismic Analysis	• Seismic Facies Classification (Map, Vol.) • Petrophysical Property, TOC, Facies Probability Prediction (Amp., Inv.) • Seismic Inversion • Probabilistic Facies Inversion with RP Model • Seismic & Well Integration	• Reservoir Property Modeling: Sw, Effective Phi, Pressure, etc.	• History Matching & Forecasting • Formation Testing Operation • Artificial Lift Selection	• Economics • Reservoir Performance Analysis • HSSE

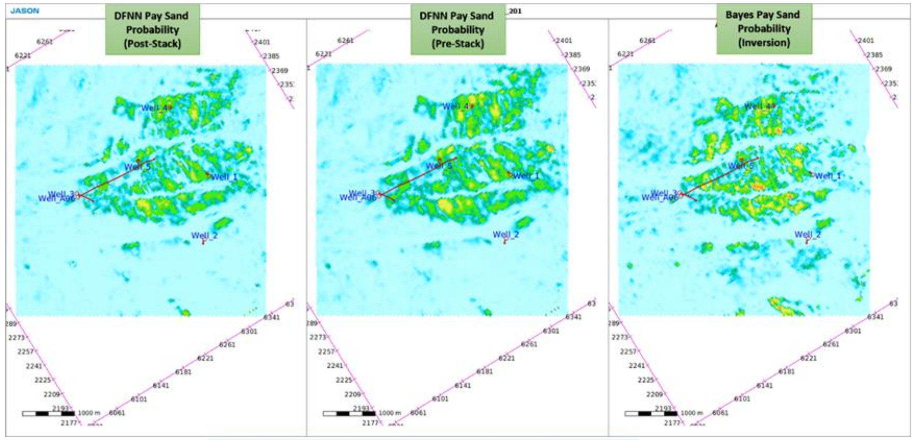
- In addition, **ML** is also applied in unstructured data extraction and interpretation

Recent Use Cases of ML/DL Applications in Oil & Gas Industry

Quantitative Interpretation

- Seismic Facies Classification (Map, Vol.)
- Petrophysical Property, TOC, Facies Probability Prediction (Amp., Inv.)
- Seismic Inversion
- Probabilistic Facies Inversion with RP Model
- Seismic & Well Integration

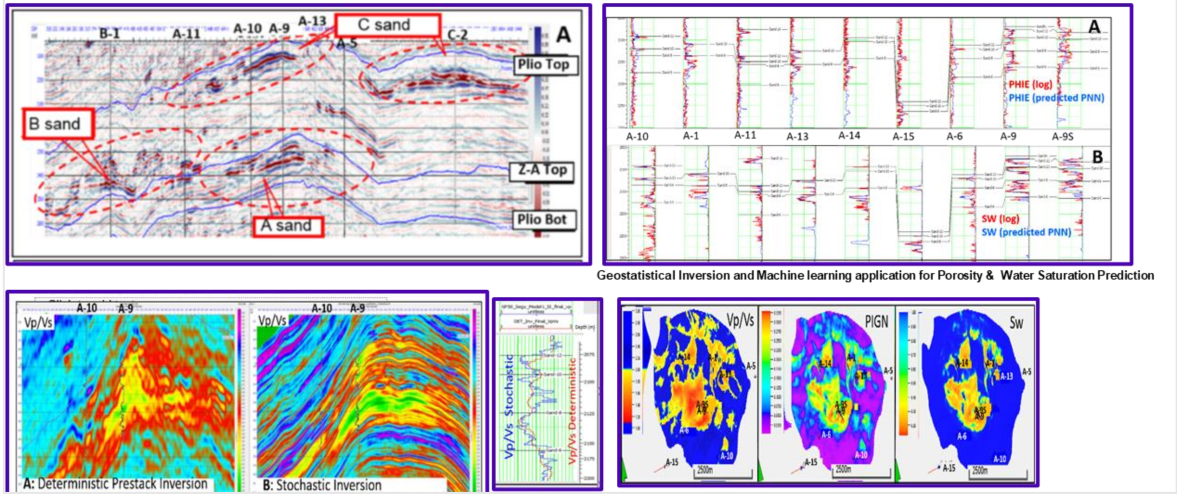
Comparison of Facies Probability Maps from DL and Simultaneous Inversion



(Bekti, 2020)

RMS attribute of Pay Sand Probabilities near Reservoir Interval

Stochastic Inversion + ML: Detailed Porosity & Water Saturation Prediction in KG-Basin, India



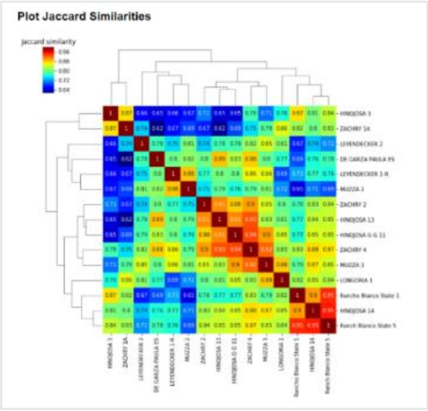
Geostatistical Inversion and Machine learning application for Porosity & Water Saturation Prediction

Mekup et al., 2017, Stochastic seismic inversion for static reservoir modeling, Annual conference and Exhibition of Society of Petroleum Geophysicists, Jaipur

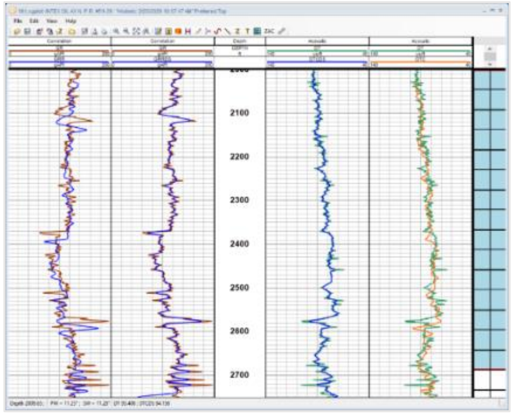
Recent Use Cases of ML/DL Applications in Oil & Gas Industry

Petrophysics

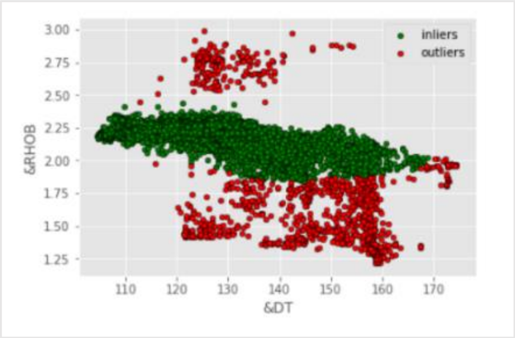
- Well Log Data QC & Conditioning
- Missing Log Prediction
- Petrophysical Evaluation: Vcl, N/G, Phi, Sw, Perm., etc.
- Facies Classification
- Missed Pay Prediction in E&P
- NMR & FMI Processing



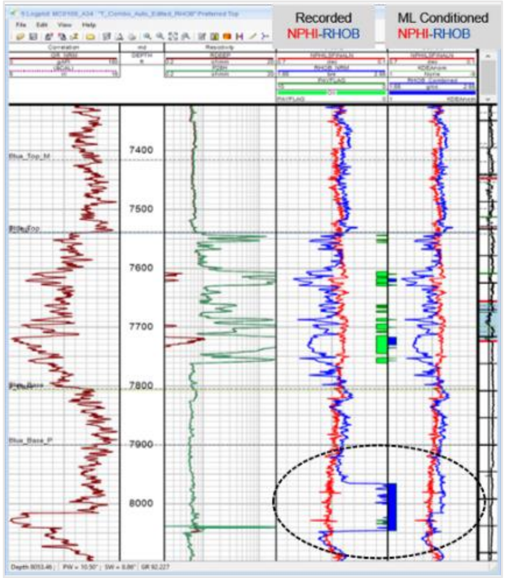
Data QC: Similarity Analysis



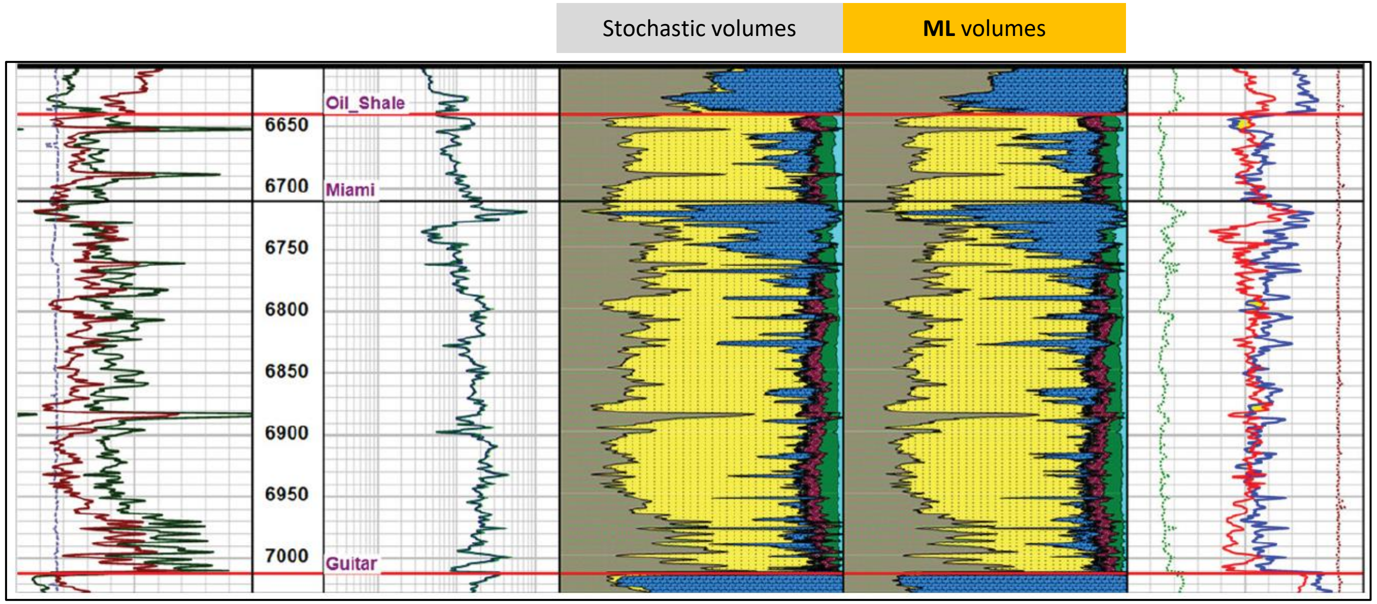
Automated Depth Matching



Outlier Detection



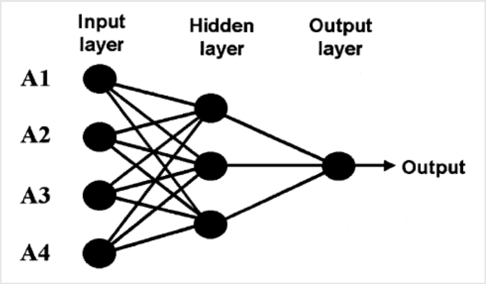
Curve Patching



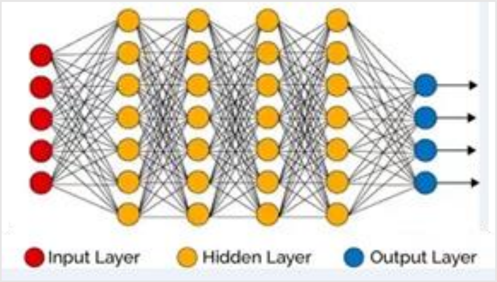
Comparison of stochastic modeling results versus machine learning results on a blind well showing very good agreement

Jensen, F., 2021, Machine learning for predicting stochastic fluid and mineral volumes in complex unconventional reservoirs, World Oil, pp. 45-47.

QI Technology Evolution from Linear Regression to Deep Learning



(Hampson et al., 2001)



1997/98

Single & Multiple Linear Regression

1999/2001

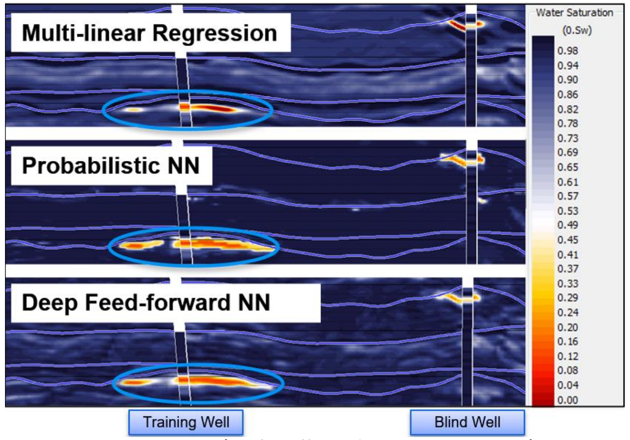
MLFNN

RBFNN

PNN

2018

DFNN

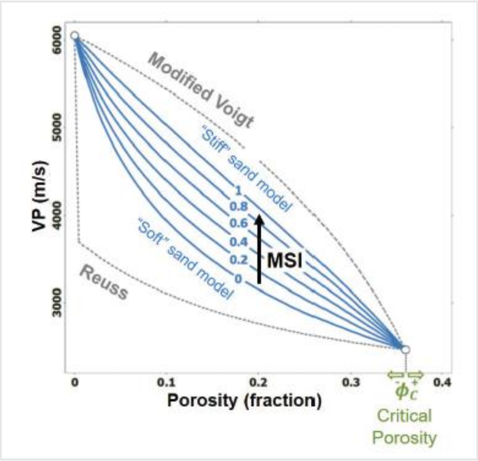


(Colwell and Kjøsnes, 2018)

2021

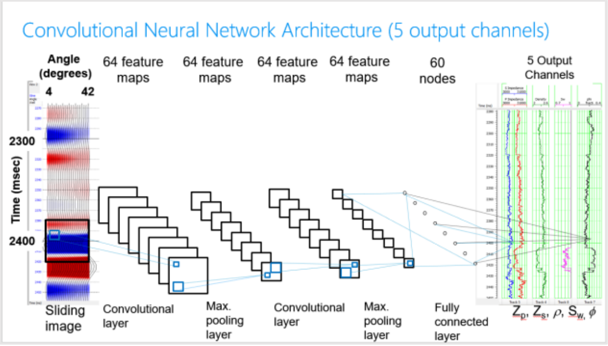
TGDS-based RP and DFNN

(Downton et al., 2020)



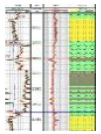
2022

CNN

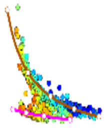


Hampson, D. P. et al., 2001, Use of multiattribute transforms to predict log properties from seismic data: Geophysics, 66, 220-236.

Hybrid Theory-Guided Data Science (TGDS)-based Method for Reservoir Characterization

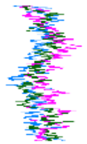


PETROPHYSICS



ROCK PHYSICS

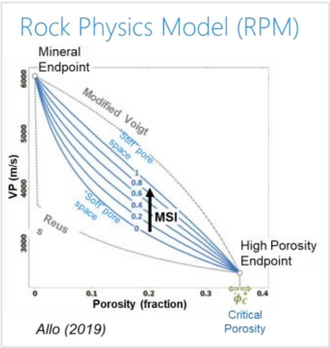
STATISTICS

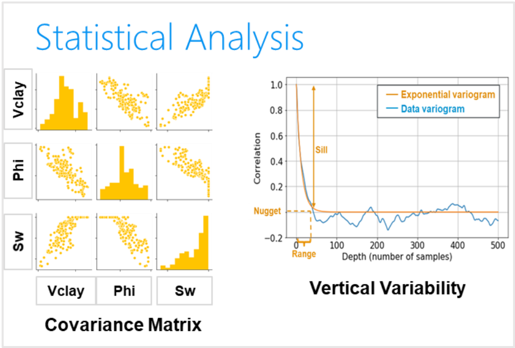


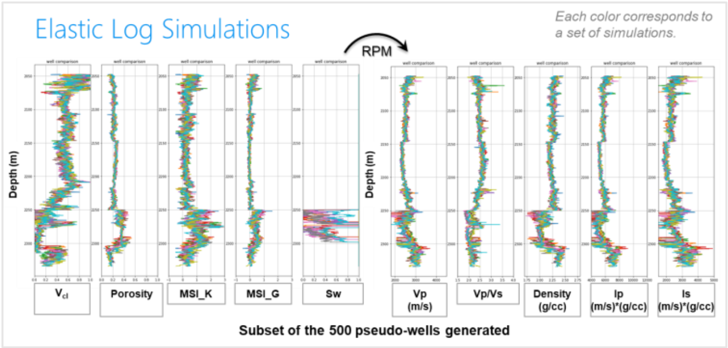
SIMULATIONS

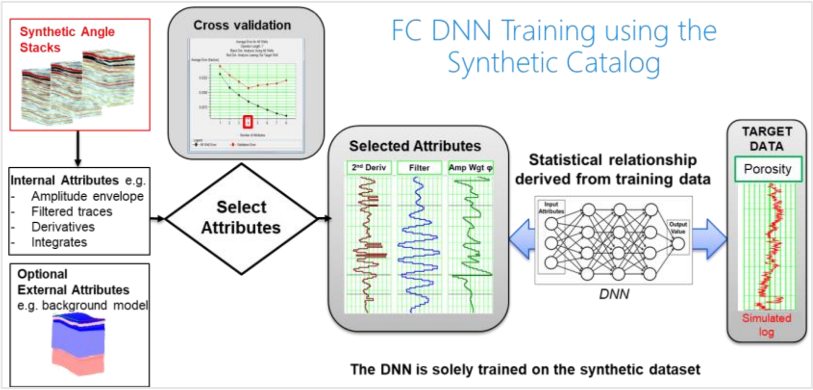
SYNTHETIC MODELLING

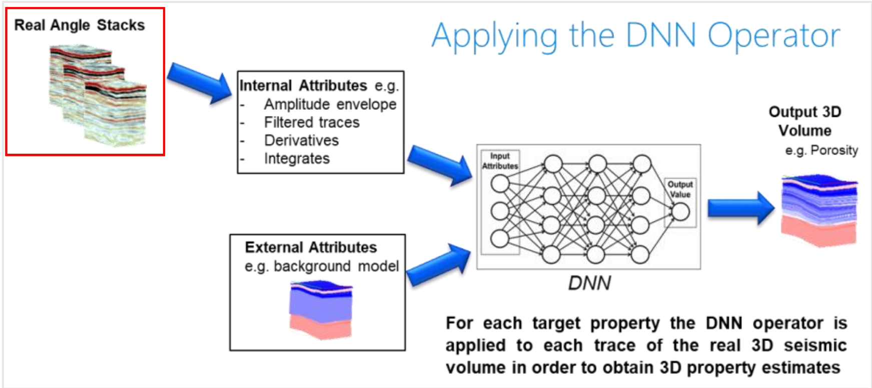
NEURAL NETWORK

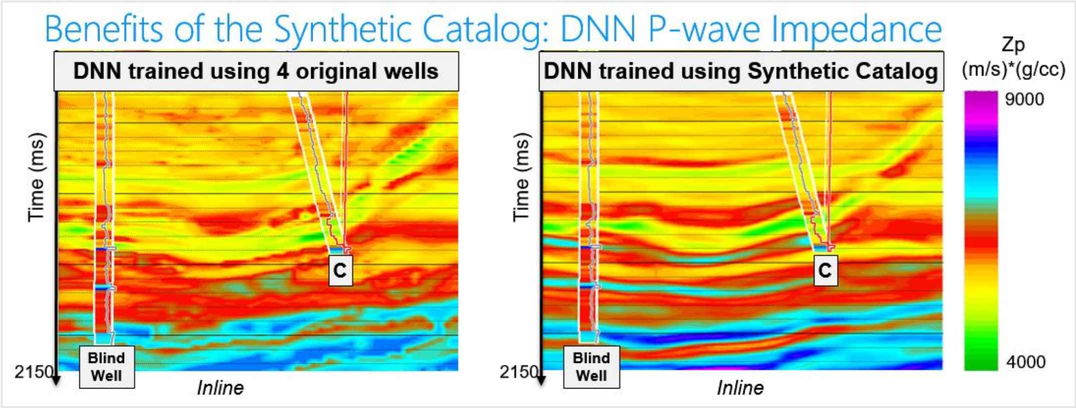








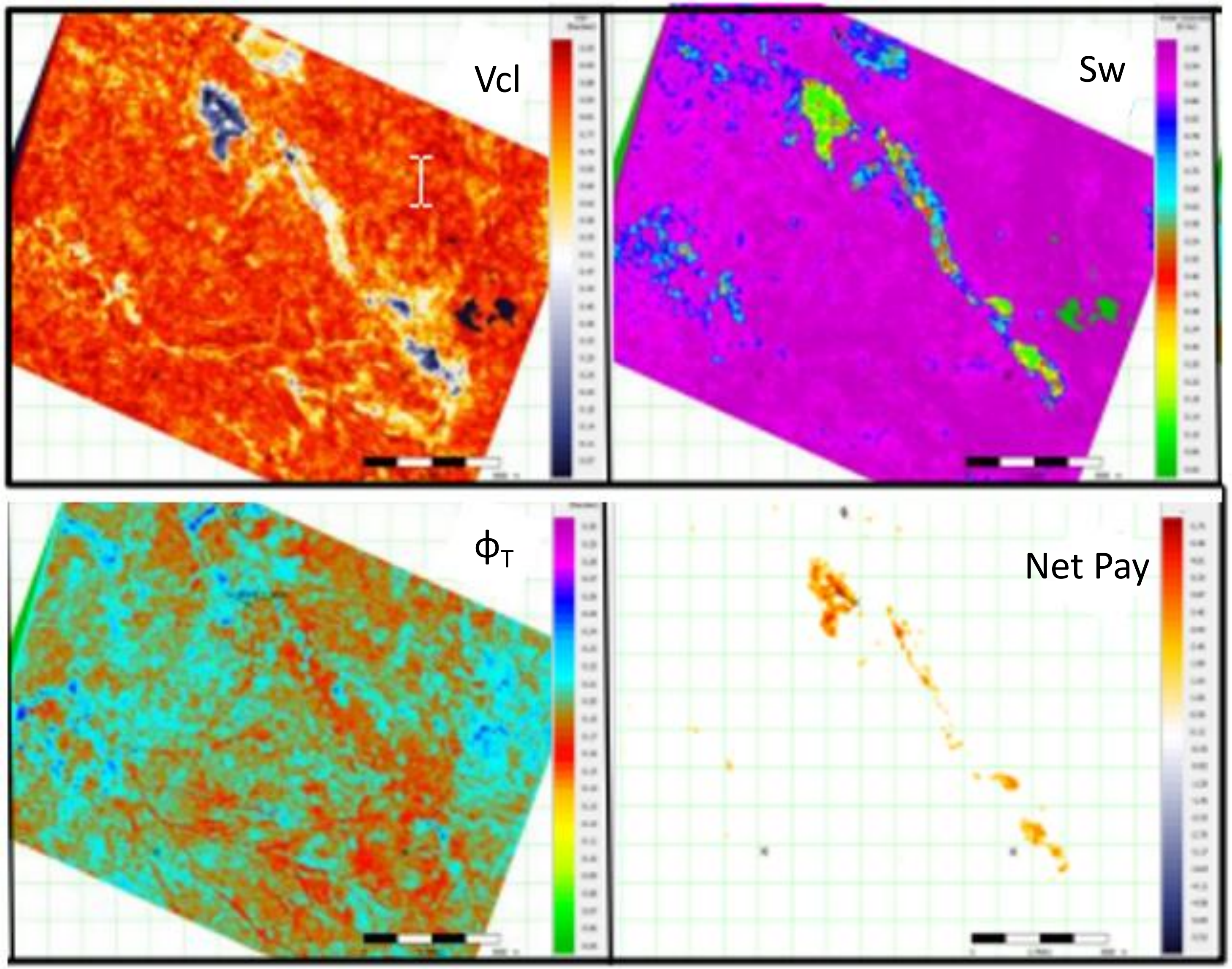




Prediction of Petrophysical Properties

Accuracy of prediction by Deep Neural Network is higher compared to first generation Machine Learning methods

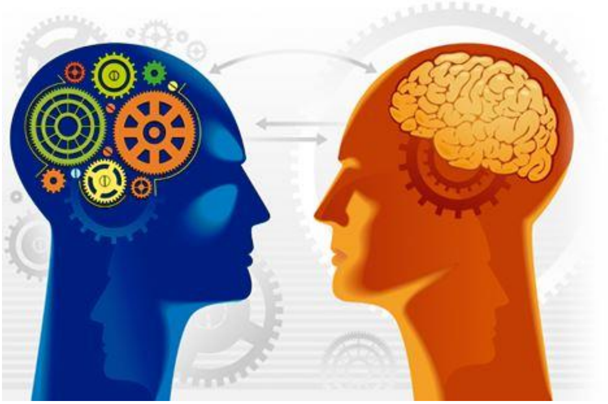
	Training		Validation	
Porosity	Error	Correlation	Error	Correlation
MLR	0.028	0.69	0.032	0.59
PNN	0.023	0.82	0.036	0.50
DFNN	0.019	0.86	0.030	0.70



MLR : Multi-linear regression
PNN : Probabilistic Neural Network
DFNN: Deep Feedforward Neural Network

Proposed Approach for Deep Learning Applications

- Comprehensive data preparation: QC and validation, using various available algorithms
- Test and select the optimal algorithms, we do not know the true model!
- Review the output data and *iterate*
- Validate the results with data from other domains e.g., geology, production, etc.
- Assess the limitations and risks of the output data before using them for follow on studies
- Use **DL** especially theory-guided to *supplement* physics-based methods to optimize extraction of information and value addition from all available data
- Human supervision is the *key to success* of **DL** application!



https://jpt.spe.org/statistical-modeling-vs-machine-learning-whats-difference

References

Al-Khaled, O., Y. Al-Zuaiby, K. Edwards, M. Hafez, and D. Sulistiono, 2012, Geostatistical inversion in carbonate and clastic reservoirs: Oilfields case studies from Kuwait: GeoConvention Extended Abstract.

Bosch, M., T. Mukerji, and E. F. Gonzalez, 2010, Seismic inversion for reservoir properties combining statistical rock physics and geostatistics: A review:Geophysics, 75, A165-A176.

Colwell, T. and Kjosnes, O., [2018], Comparative study of deep feed forward neural network applications for seismic reservoir characterization: First EAGE/PESGB Workshop on Machine Learning 29-30 November 2018, London, UK

Copeland, M., 2016, What's the Difference Between Artificial Intelligence, Machine Learning and Deep Learning: Nvidia Blog.

Downton, J., O. Collet, D. Hampson and T. Colwell, 2020, Theory guided deep learning for reservoir characterization, 87th EAGE Annual conference and Exhibition.

Filippova, K. E., Z. I. Gazaryan, A. A. Kozhenkov, P. G. Ponomarenko and a. A. Alabushin, 2011, Detailed geological model of Devonian reefs based on simultaneous geostatistical partial stack inversion, 73rd EAGE Conference and Exhibition, Vienna.

Filippova, K., P. Ponomarenko, Z. Gazaryan, S. Molkanov, V. Vingalov V. Shkondatrov, 2013, Geostatistical inversion as a tool for the accurate updates of the hydrodynamic models- Case study:75th EAGE Conference and Exhibition, London.

Hampson, D. P., J. Schuelke and J. Quirein, 2001, Use of multiattribute transforms to predict log properties from seismic data: Geophysics, 66, 220-236.

Hoehn, M. H., I. Arif, C. Welch, F. H. Sidi, D. Rubyanto, R. van Eykenhof, M. Sams, Y. Prasetyo, 2005, Combined geostatistical inversion and simultaneous inversion: Extending the life of a matured area, Kotabatak field, Central Sumatra basin, Indonesia: 30th Annual Convention and Exhibition, Indonesian Petroleum Conference, 25-37.

Jackson, D.D., 1972, Interpretation of inaccurate, insufficient and inconsistent data, Geophysical Journal of Royal Astronomical Society, 28, 97-109.

Jensen, F., C. Ranganathan, and T. Holden, 2021, Machine learning for predicting stochastic fluid and mineral volumes in complex unconventional reservoirs, World Oil, pp. 45-47.

References

Marquez, D., D. Saussus, R. Bornard, and J. Jimenez, 2013, Incorporating rock physics into geostatistical inversion: 75th EAGE Conference and Exhibition, London.

Roden R., M. Forrest, and R. Holeywell, 2012, Relating seismic interpretation to reserve/ resource calculations: Insights from a DHI consortium, The Leading Edge, 31, 1066-1074.

Rodina, O., A. Rabay, L. Makarova, D. Neudachin, and J. Corballo., 2008, Detailed geological model of carbonate reservoir based on geostatistical AVA inversion- A case study: 70th EAGE Conference and Exhibition, Rome.

Scales, J. A. and R. Sneider, 1997, To Bayes or not to Bayes?: Geophysics, 62, 1045-1046.

Sulistiono, D., R. Vaughan, M. Ali, and S. Rasoulzadeh, 2015, Integrating seismic and well data into highly detailed reservoir model through AVA simultaneous inversion: Abu Dhabi International Petroleum Conference and Exhibition, Abu Dhabi.

Vernengo, L., R. Czeplowdozki, E. Trinchero, A. Sabate, E. Tsybulkina, and F. Morrillo, 2014, Improvement of the reservoir characterization of fluvial sandstones with geostatistical inversion in Golfo San Jorge basin, Argentina, The Leading Edge, 33, 508-512.

Zawila, J., H. Titchmarsh, J. Pendrel, A. Valdez, 2010, A case study for detecting thin upper Morrow fluvial sands in the United Sates Mid-continent from geostatistical simultaneous inversion, SEG Expanded Abstracts, 363-367.

Thank you

GeoSoftware™

www.GeoSoftware.com

Follow our LinkedIn for our latest technology, training and webinar

GeoSoftware