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Explorando nuevas fronteras energéticas

INSTITUTO ARGENTINO DEL PETROLEO Y DEL GAS

APPLICATION OF A STOCHASTIC WORKFLOW FROM SEISMIC AMPLITUDE AND VELOCITY TO GROSS ROCK VOLUME AND RESERVOIR GEOMETRY ASSESSMENT

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RESUMEN

La evaluación de prospectos de hidrocarburos históricamente ha sido una práctica común para estimar volúmenes y la posible geometría del yacimiento. Sin embargo, existe una gran incertidumbre en los volúmenes y sobre la extensión de las acumulaciones al estimar la capacidad de una trampa, especialmente cuando la evaluación se realiza de manera determinística, ignorando la incertidumbre asociada a estos procesos de evaluación. En este trabajo presentamos un método que busca caracterizar de manera consistente la incertidumbre, y propagarla a lo largo de todo el flujo de trabajo desde el análisis de datos hasta la estimación de volúmenes.
Nuestro método evalúa las incertidumbres provenientes de la interpretación sísmica y de las velocidades, para estimar estocásticamente la capacidad de las trampas estructurales y calcular una probabilidad del Volumen Bruto de Roca (GRV, por sus siglas en inglés). Tomamos como ejemplo un campo convencional maduro en Sudamérica para demostrar nuestro enfoque.
Como primer paso dentro de un flujo de trabajo estructural sólido, la cuantificación de la incertidumbre debe realizarse adecuadamente. En lugar de asumir rangos de confianza de manera arbitraria, definimos de forma consistente la incertidumbre a partir de los datos de entrada. En un proceso de conversión de tiempo a profundidad, la incertidumbre puede observarse en la interpretación en tiempo, en las fluctuaciones locales de velocidad, en las profundidades de los marcadores y en el propio modelo.
En nuestro caso, la incertidumbre en tiempo se basó en el análisis de la frecuencia sísmica y de la relación señal/ruido, definiendo así en cada punto del campo un intervalo de confianza alrededor del tiempo interpretado. La velocidad sísmica se utilizó para esta conversión a profundidad, aunque originalmente está optimizada con fines de procesamiento. Es necesario aplicar un acondicionamiento para que sea coherente con la conversión a profundidad, eliminando los artefactos de procesamiento que no son relevantes en este contexto, y evaluando simultáneamente la posible incertidumbre contenida en dicha velocidad sísmica.
Gracias a la técnica de Co-Kriging Bayesiano, seleccionamos el mejor modelo de velocidad posible para la conversión a profundidad, asegurando minimizar las discrepancias entre el modelo y las profundidades reales en los marcadores, evitando así sesgos sistemáticos y tendiendo a obtener la desviación estándar mínima de estas discrepancias. Todo este trabajo se realiza de manera multicapa, permitiendo una conversión a profundidad consistente con todos los datos disponibles y una caracterización robusta de la incertidumbre tanto en las entradas como en el propio modelo.
El tope y la base del yacimiento, que no corresponden a reflectores fuertes retenidos en la conversión a profundidad, se derivaron estocásticamente mediante una ley de espesores observada en los marcadores.
A partir de estas simulaciones, se generaron curvas de GRV para los distintos reservorios, así como mapas asociados, incluyendo mapas de probabilidad de presencia de reservorio para evaluar la geometría del mismo.

INTRODUCTION

Progress in acquisition techniques, on performance of processing and interpretation, don't prevent us from continuing to have uncertainty when we are dealing with reality that is kilometers below our feet. We should not fear these uncertainties but assess them as accurately as possible to correctly anticipate possible confidence intervals where our model and results of Structural workflow will land.
Using as an illustration a producing onshore field of South America where we are seeking the right GRV on 3 different reservoirs and prognosis for one future well, this paper will demonstrate strength of a proper stochastic structural workflow associated with right geophysical uncertainty quantification for having consistent and understandable results considering risk for any future development of the field.

Geostatiscal power through Bayesian co-kriging will help to gather all sources of Uncertainty, including the uncertainty of the velocity model itself in order to deliver not only a possible base case, but also a realistic depth confidence interval and multiple equiprobable realization of Depth inside for reservoir assessment.

GEOLOGICAL BACKGROUND

The sedimentary column of the study area is characterized by a marked repetitiveness of sandstones, limestones, and shales, possibly associated with eustatic sea-level fluctuations that occurred during the Cretaceous. This repetitiveness allows the succession to be subdivided into several sedimentary cycles. Each cycle begins with clastic deposits corresponding to proximal facies deposited during a Lowstand Systems Tract (LST), interpreted as estuarine channel sands, tidal channels, and estuarine sand bars. Subsequently, during a Transgressive Systems Tract (TST), finer-grained sediments appear as a consequence of environmental distalization, culminating in a maximum flooding surface where sedimentation is dominantly pelitic. The sequence concludes with the development of limestones corresponding to a Highstand Systems Tract (HST).

AVAILABLE DATA

Time interpretations are available on 30*30m grids from overburden to interesting deepest structures. 7 horizons will be used for the conversion and the two main reservoirs studied were between Layer 2 and 3 and between 3 and 4 (see figure 2). Interpretations are made on a good quality reprocessed Pre-Stack Time migration (PSTM) amplitude cube available every 2ms (twt).
Associated with amplitude, a seismic RMS velocity cube was available on the same gridding (Fig 1).
Well depth markers were also available as X, Y, Z information. According to the layers different wells are interpreted or not and used for the analysis:

- Layer 1: 83 markers
- Layer 2: 93 markers
- Layer 3: 93 markers
- Layer 4: 93 markers
- Layer 5: 92 markers
- Layer 6: 90 markers
- Layer 7: 40 markers

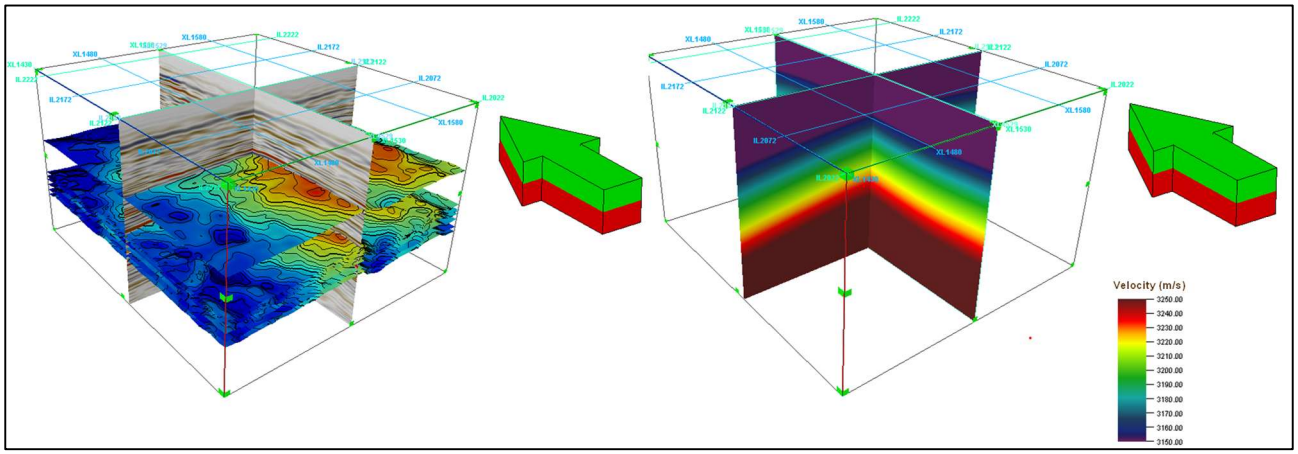


Figure 1: Slice between 1500 and 2000ms (twt) of available Amplitude (with interpretations) and Seismic velocity

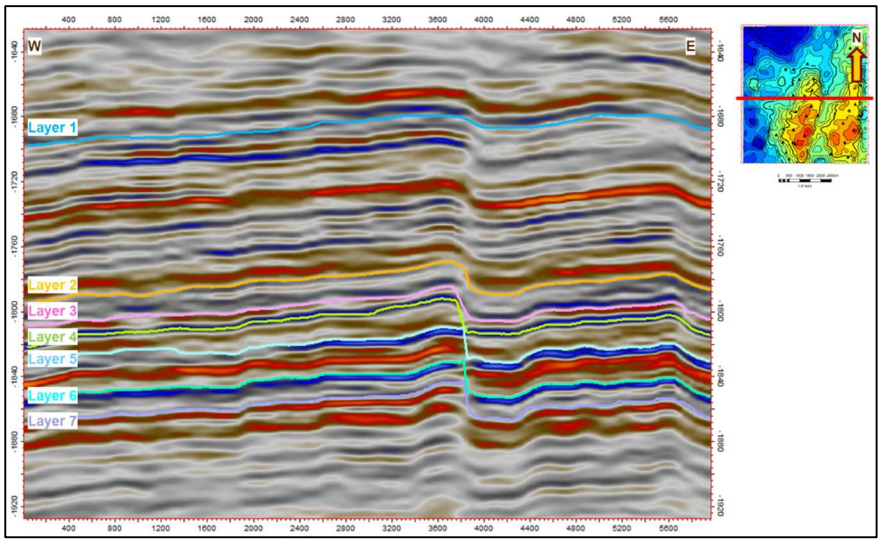


Figure 2: Time section (mstwt) with Amplitude and Interpreted Horizons

METHODOLOGY AND DATA ANALYSIS

Stochastic theory

Stochastic frameworks enable to transform incomplete deterministic geophysical processes into stochastic ones. Uncertainty in such process is determined at each step and propagated to systematically assess its magnitude, resulting in a final coherent margin of error. The margin of error between model value and true (unknown) is minimized thanks to kriging approach.

Theory of regionalized Variables, Matheron (1971)
This theory considers that the unknown (in our case subsurface value) may be represented by a random function Z, defined at a location (x) as a random variable Z(x):

$$Z(x)=m(x)+ R(x)$$

Where Z(x) represents the true (unknown) seismic signal or subsurface property at location (x);
m(x) s the average value of at location (x); R(x)= Z(x)-m(x) i.e., the residual of Z(x) around m(x) at location (x)

Based on scarce (well) and uncertain (seismic) data values is not possible to retrieve the true Z at each (x) location. But analyzing statistics on these data, it appears possible to determine m(x) and C(x,y) (the spatial covariance of R(x)). Assessing these two values cross with the kriging theory allow us to best estimate Z at any given location (x). Kriging provides the best unbiased linear estimator for Z while minimizing the error giving this estimated Z*(x0) for Z at location x0

$$Z^*(x0) = m(x0) + \sum_{i=1}^{N} \lambda_i R(x_i)$$

- $m(x0)$ represents the average value of $Z^*(x0)$ at location $x0$
- $\sum_{i=1}^{N} \lambda_i R(x_i)$ represents the linear combination of N neighboring available well data and seismic data values at location x_i

Kriging is unbiased as $E\{Z(x0) - Z^*(x0)\} = 0$ ie. the difference between the estimation of the kriging and the true (unknown) subsurface property value is 0. While minimizing the estimation variance $Var\{Z(x0) - Z^*(x0)\}$ and also providing a reliable confidence interval from the estimation variance

The kriging captures four aspects of the interpolation problem that exists in depth conversion:

1. The geometry of the sample points (and possible redundancy of the data)
2. The position of estimated points with respect to the data location

3. The lateral continuity of the phenomenon through the covariance/variogram model
4. The possible presence of a systematic location-dependent effect (trend with non-constant average value as a function of the location)

Time to depth conversion and Bayesian co-kriging

The core of the stochastic structural workflow is the time to depth conversion. As we've seen before kriging and in particular kriging with external drift (use of a non-constant average function of the location, in our case mainly function of the time interpretation) captures a large part of the issue link to the interpolation for a depth conversion. It allows to aggregate local hard data (well depth markers, considered most of the time with no uncertainty) to extended soft data (seismic time interpretation and/or seismic velocity coming with more uncertainty).
But depth conversion is a particular geophysical process where velocity follow rules control by geology (Water velocity is 1500m/s +/- 20m/s) and where position and number of hard data (wells) are controlled by the possible proximity of the reservoir and by the return of investment waited on drilling any new well (leading often to scarce and clustered wells on top of the structure).
This situation led to an important uncertainty of the model of velocity conversion that the Bayesian co-kriging can control. Indeed, Bayesian kriging can be seen as a generalization of the concept of kriging that stand in between simple kriging and kriging with external drift.
Bayesian Kriging hypothesis and mathematical expression with estimation of velocity parameters with associated uncertainties coming from prior parameters (can be a priori geophysical/geological knowledge on velocity) associated with uncertainties allow to:

- accounts for uncertainty on data
- accounts for uncertainty on model parameters
- accounts for prior knowledge on model parameters

Bayesian kriging converges to simple kriging in case of good knowledge of velocity parameters (low variance or narrow distribution of drift coefficients) and converges to kriging with external drift in case of very poor knowledge of the velocity parameters (big variance or large prior distribution of drift coefficient).

Ensemble approach

Usage of a Bayesian co-kriging lead to an accurate estimation of the velocity model and estimated depth of the different layers used for the conversion associated with confidence intervals.
These estimations and confidence intervals are important to answer several questions linked to a structural analysis. These values are expected for a regional basin study, for a driller who need to know where he will encounter the different interface with an associated confidence interval to prevent any issue *etc*… However, when dealing with reservoir estimation the single estimation cannot be used to sort a relevant value for GRV or reservoir extension. Reservoir assessment can be seen as a nonlinear computation due to the cutting of the surfaces delimiting the reservoir by hydrocarbons contacts.
As a "smooth" version of the reality (best realization with one single set of data and one model), estimated surfaces cannot successfully represent the full spatial uncertainty contained in his estimation.
When traditional methods rely on deterministic estimation of the traps to produce afterwards GRV by simple fluctuations of the base case (Figure 3), Ensemble methods (Figure 4) are techniques that create multiple models that can be combined to produce improved results. In this workflow, multiple models are generated via Bayesian simulation, which accounts for all sources of uncertainty to produce a set of equiprobable solutions around the estimation inside the confidence interval (under gaussian assumptions: 94.4% of realization between +/- 2* Standard deviation).
Bayesian approach also has this advantage not to just simulate value around a base case but to simulate the trend itself for each realization in the confidence interval around the different velocity parameters.
This ensemble of simulation is then used to produce multiple reservoir estimations as GRV that can be ranked in order to figure out coherent P10/P50/P90 value associated with data and model uncertainty.

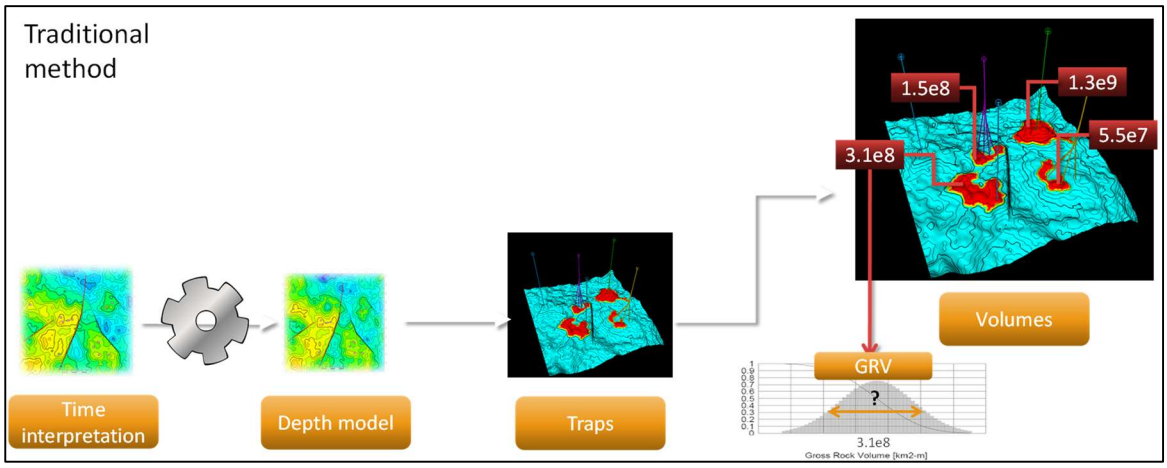


Figure 3: Deterministic method for reservoir assessment

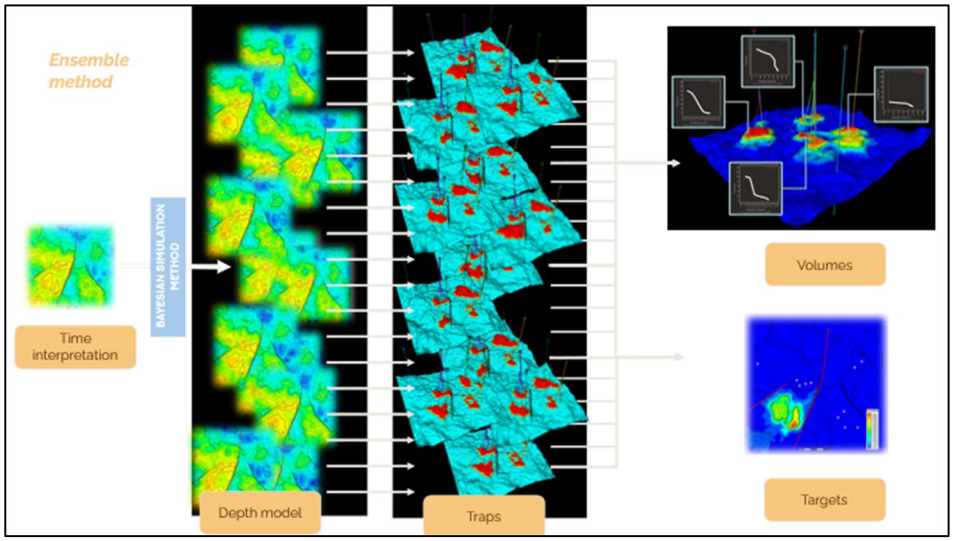


Figure 4: Ensemble method for reservoir assessment

Data analysis: Time interpretation uncertainty

Drilling, seismic acquisition, processing and interpretation to obtain well depth markers and subsequent time-to-depth conversion come with many uncertainties at all stages mainly due to the distance between the true measured object and the geological/geophysical data set.
Properly assessing the uncertainty associated with all the different data involved in the time-to-depth conversion process will help to fully characterize the final structural uncertainty.
Seismic interpretation is an important stage for the structural workflow comprehension and for establishing the structural framework of the studied reservoir. However, uncertainties are inherent in generating the final maps used for the depth conversion. Seismic acquisition and processing workflows, structural complexity associated with environment of the reservoir and possible unclear overburden -to name a few- as well as difference of interpretations that are interpreter dependent make sometimes uncertainties assessment a very tedious work with many inputs to incorporate.
To avoid this challenging work, we can base our computation linked to time uncertainty on Ramos Pinto et al. (2017) that presents a methodology to capture this seismic and interpreted related uncertainty.
Uncertainty quantification on a particular surface passe here by the creation of a wavelength map that brings ideas about possible data resolutions and represents the minimal uncertainty of seismic data. These maps are built from the extraction of the dominant frequency at the surface and weighted by a normalized RMS amplitude. Indeed, RMS amplitude is a valuable tool to measure the level of incoherent noise as it's directly proportional to the signal-to-noise ratio. Where RMS amplitudes decrease the seismic quality degrade.

From this map of uncertainty (figure 5), we can build a confidence interval around the seismic time (Figure 6). From this view, uncertainty can be adjusted by a penalty factor to increase/decrease the confidence interval to fit possible priori knowledge of the geophysicist.

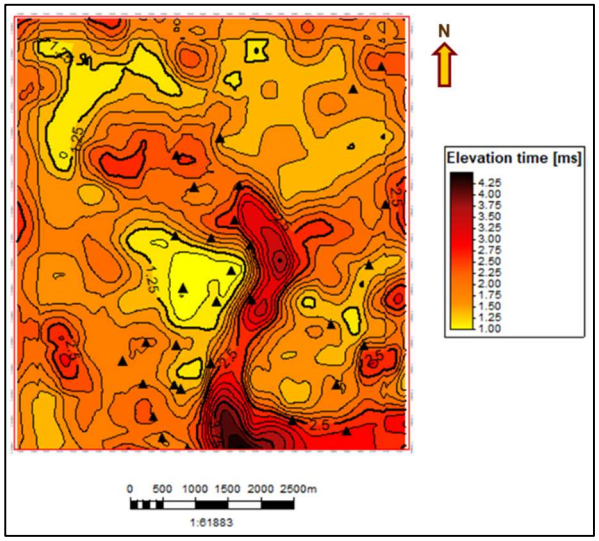


Figure 5: Near reservoir map time uncertainty

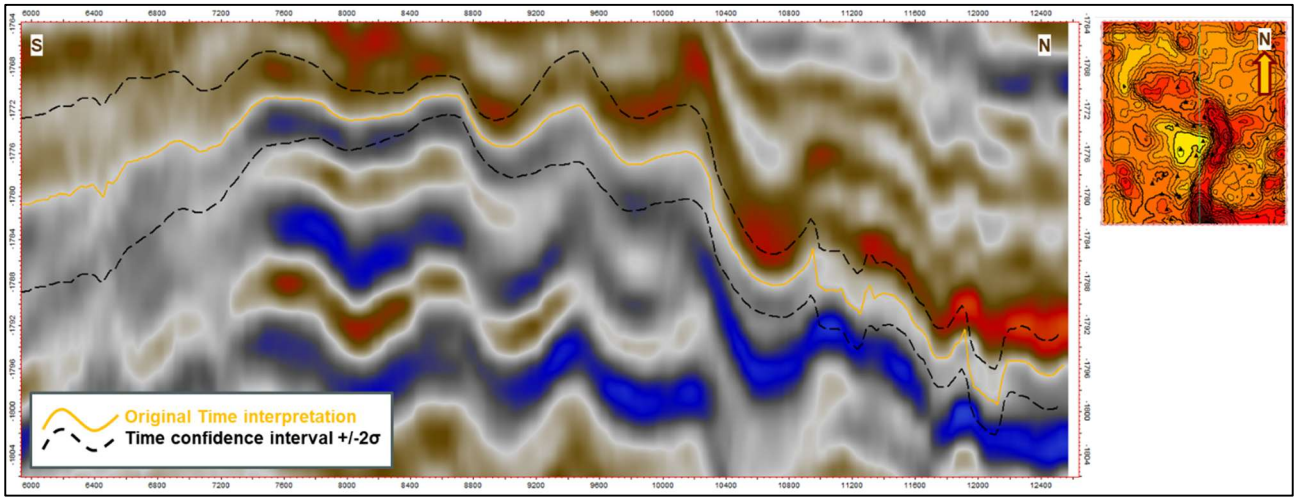


Figure 6: Zoom on cross Section of Near reservoir layer in time with confidence interval

Data analysis: Seismic Velocity Uncertainty

If the more precise velocity analysis comes from the wells (Checkshot or Sonic) seismic velocity can be a useful tool for bringing added information and perform a good time to depth conversion far from the wells. However seismic velocity is not optimized for depth conversion but more for processing purposes, either Pre-stack Time Migration (PSTM) for flattening the gather or Post-Stack Depth Migration (PSDM) for depth imaging. Due to these processing optimizations, seismic velocity contains processing artefacts that are not relevant for time-to-depth conversion purposes.

Sandjivy & Al (2016) propose a possible methodology for filtering unwanted lateral variations of seismic velocity associated with an estimation of the seismic velocity confidence interval from 2 statement, that considered seismic time interpretation as granted and that any local velocity variations should have an impact on seismic travel time.

Using the filtering properties of factorial Kriging, it's possible to split original seismic velocity into a consistent seismic velocity for depth conversion and an artefact that represents all local variations that are not coherent between time and velocity. These incoherencies could be associated with processing.

To properly filter the velocity, we must compare seismic time and velocity, so the process is done on a layer-by-layer basis and not directly on the 3D seismic cube.

Thanks to artefact estimation it is possible to derive a possible seismic velocity uncertainty by estimating the local standard deviation of the magnitude of the artefact.
An example of this process can be found in figure 7, for the first layer of the depth conversion.

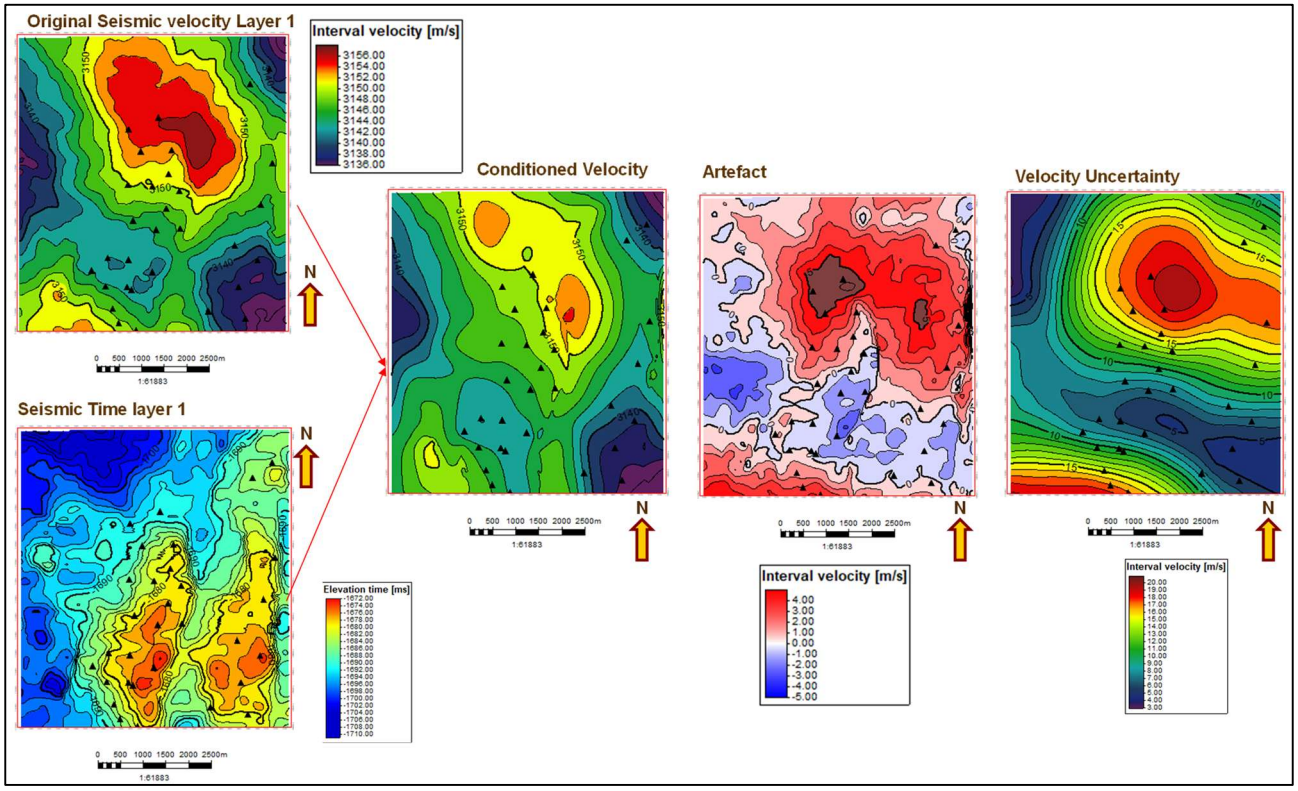


Figure 7: Seismic velocity conditioning and Uncertainty estimation (Example on 1 layer).

Time to depth conversion

Stochastic frameworks enable us to transform incomplete deterministic geophysical processes into stochastic ones. Bayesian co-kriging algorithm allows the best estimation of the velocity laws parameters (Either rescaling of maps, interval velocity or model of linear increase of velocity with depth as V0/K) to minimize all mismatches (between untied estimations and markers) of all the layers in a unique mathematical framework. The final map is tied from the best untied estimation using the kriging algorithm within the range of the variogram. Using this true multi-layer approach optimizes data usage as all information will be used to constrain all layers.
Attached to this depth estimation, uncertainty on input time interpretations and local velocity variation aggregate to a reliable mathematical confidence interval (kriging standard deviation) that is null around well location (if no Well depth uncertainty) and increase far from it (Figure 8).

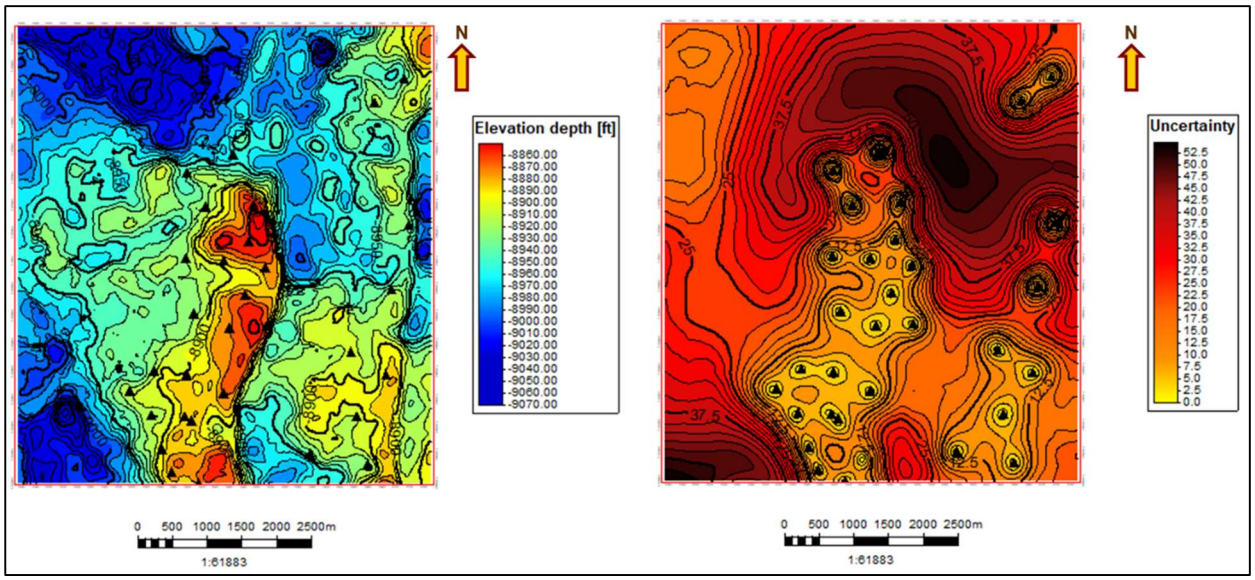


Figure 8: Main target Depth Maps (left) and associated Standard deviation (Right).

The quantification of confidence intervals associated with depth conversion allows us to derive a set of stochastically simulated depth maps (figure 9). These maps are derived using the same Bayesian probabilistic model engine using all uncertainty inputs (time, local velocity, parameters) to build a set of equiprobable maps not as “smooth” as the estimated one but containing uncertainties on their estimations. This set of simulations is the only one valid to assess reservoir with for example Gross Rock Volume (GRV) computations and sort the expected P10/P50/P90 values that are 10/50/90 % probabilities chance to recover at least the corresponding volumes. Each of these values are attached to a specific simulation that is producing this number.
If assuming a gaussian distribution for the unknown probability law of the estimation error, we can say that 95.4% of these simulations will be contained in a confidence interval of +/- 2 times the associated standard deviation computed for each depth map.

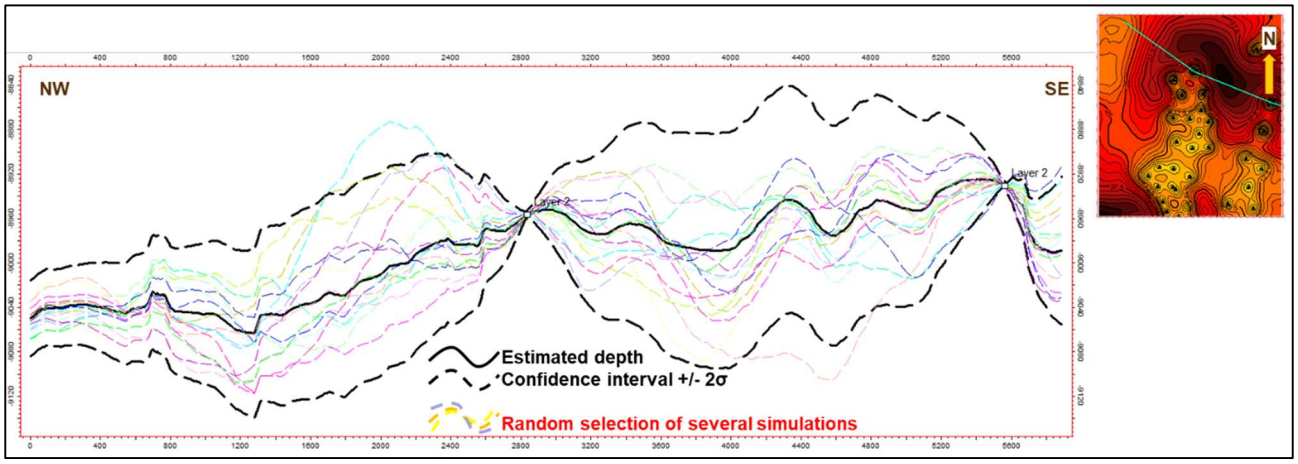


Figure 9: Cross Section of simulated depth maps for main target.

Actual top and base of the reservoir haven’t been seismically interpreted as they are not good reflectors. But it was possible to interpret from well logs so only depth markers were available. Top and base are so not part of the time to depth conversion.
As many wells have well depth markers information, it’s possible to analyze a statistical law for the thickness between the closest converted horizons and Top of the reservoir and between top and base of the reservoir (see figure 10).

To obtain simulated depth for top and base of the reservoir, we can simply derive simulated constant thickness that we'll add to the reference horizons and tie this simulation to the well markers with the same variogram ranges than the reference.

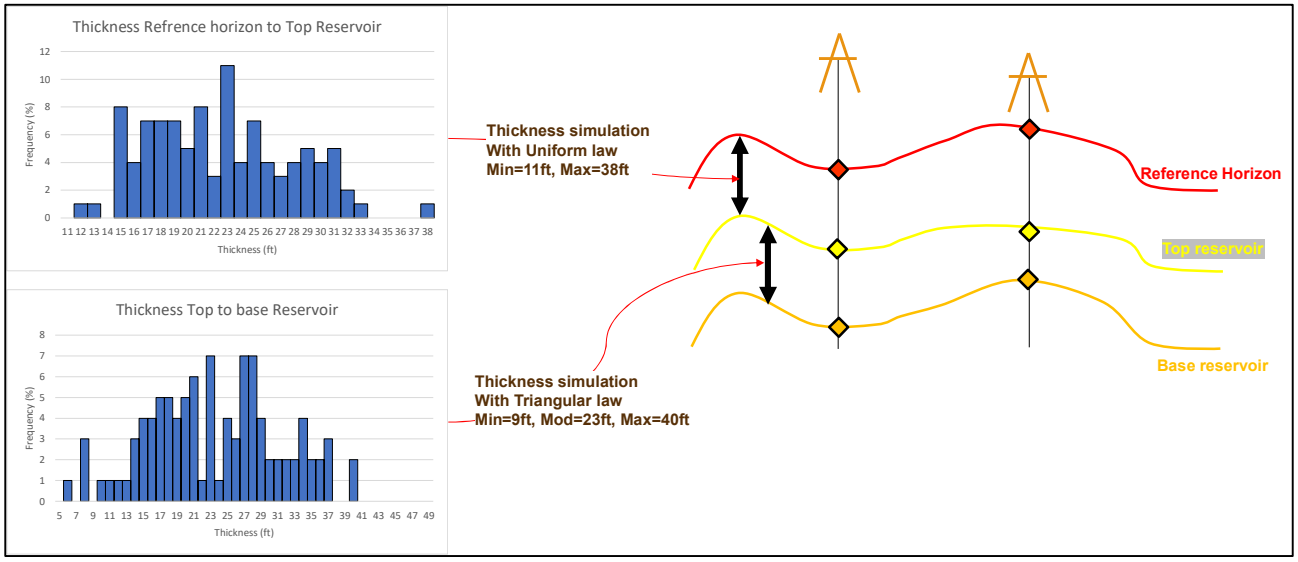


Figure 10: Statistical analysis for simulating Top and Base Reservoir

RESULTS AND DISCUSSION

For the depth conversion model, the first scenario was constructed using the simplest model for every interval, a constant interval velocity. Subsequently, seismic velocity was added to evaluate potential model improvements. Analyzing at the Standard deviation of the mismatches reveals that the best model possible is to use only seismic velocity for the first two intervals. This approach reduces the standard deviation from 39 ft to 29 ft on Layer 2, which corresponds to the first reservoir top. Analysis of mismatches can be done with table recording statistics on them for all layers (Figure 11). Consistency of the model is also analyzed trough the final estimated parameters of the velocity law (Orange number in Velocity table).

	HORIZON	DEPTH	VELOCITY
1	...uts\Time_Horizons\Layer 1	...APER\Stratigraphy\Layer 1	A.Vseis + B
2	...uts\Time_Horizons\Layer 2	...APER\Stratigraphy\Layer 2	A.Vseis + B
3	...uts\Time_Horizons\Layer 3	...APER\Stratigraphy\Layer 3	V0
4	...uts\Time_Horizons\Layer 4	...APER\Stratigraphy\Layer 4	V0
5	...uts\Time_Horizons\Layer 5	...APER\Stratigraphy\Layer 5	V0
6	...uts\Time_Horizons\Layer 6	...APER\Stratigraphy\Layer 6	V0
7	...uts\Time_Horizons\Layer 7	...APER\Stratigraphy\Layer 7	V0

Statistics table

		Mean		RMSD			Extremum	
	Samples	Prior trend	Post trend	Prior trend	Post trend	Model	Prior trend	Post trend
Layer [1]	83	-354 ft	-2.13 ft	355 ft	28 ft	32.3 ft	-445 ft	-89 ft
Layer [2]	93	-397 ft	-7.09 ft	398 ft	28.9 ft	33.3 ft	-493 ft	-95.2 ft
Layer [3]	93	-398 ft	-9.86 ft	399 ft	29.8 ft	31.3 ft	-556 ft	-161 ft
Layer [4]	93	-388 ft	-2.09 ft	389 ft	32.5 ft	32.7 ft	-580 ft	-188 ft
Layer [5]	92	-393 ft	-5.43 ft	395 ft	33.1 ft	31.9 ft	-612 ft	-216 ft
Layer [6]	90	-397 ft	-6.1 ft	398 ft	28.6 ft	32.2 ft	-586 ft	-188 ft
Layer [7]	40	-395 ft	-5.93 ft	397 ft	39.8 ft	31.8 ft	-604 ft	-208 ft

Velocity table

	Velocity law	Parameter	Prior trend	Post trend
Layer [1]	A.Vseis + B	A	1	0.9882
			σ(0.5)	σ(0.0868)
		B	0 m/s	-90.28 m/s
			σ(1000 m/s)	σ(271.52 m/s)
Layer [2]	A.Vseis + B	A	1	0.5904
			σ(0.5)	σ(0.1833)
		B	0 m/s	1344.2 m/s
			σ(1000 m/s)	σ(707.64 m/s)
Layer [3]	V0	V0	3535.7 m/s	3609.6 m/s
			σ(152.4 m/s)	σ(66.695 m/s)
Layer [4]	V0	V0	4998.7 m/s	5192.5 m/s
			σ(152.4 m/s)	σ(91.872 m/s)
Layer [5]	V0	V0	3730.1 m/s	3641.4 m/s
			σ(152.4 m/s)	σ(57.696 m/s)
Layer [6]	V0	V0	2804.2 m/s	2722.5 m/s
			σ(152.4 m/s)	σ(49.71 m/s)
Layer [7]	V0	V0	3535.7 m/s	3598.9 m/s
			σ(152.4 m/s)	σ(77.39 m/s)

Figure 11: Optimized velocity model with velocity estimation & Statistics on mismatches

Using this conversion model, we obtain for each layer a depth estimation and an associated uncertainty estimate (see figure 8) that can be used to extract, at any point of the studied area, crucial information for drillers on next well operations (Figure 12).

		Mean (ft)	Sigma (ft)
Layer 2	Position 1	-8072,4	12
	Position 2	-8102,5	18
Layer 3	Position 1	-8165,3	11
	Position 2	-8196,0	15
Layer 4	Position 1	-8250,8	12
	Position 2	-8249,4	17

Figure 12: Well prognosis for three layers on 2 positions

We can also obtain, derive from the velocity model, a set of equiprobable realizations (300 realizations here) that are containing uncertainty in order to assess reservoir.
As an anonymized case, the results above will be done on a dummy scenario of a possible reservoir, however the final result is the same.
We consider between layer 3 and 4 a possible reservoir that is known on 4 wells (W1, W2, W3 & W4 see figure 13) with an Oil Down To (ODT). On the north, W6 & W7 have a shallower contact and, on the south, W5 appears to be dry. Using these contacts information it's possible to determine possible GRV and reservoir extension using an automatic spill point detection.
For each realization, the depth of the maximum Free Water Level (FWL) including in a same close structure W1/W2/W3/W4 without W5/W6/W7 is determined. Averaging these closure results lead to a probability map of Reservoir that illustrates:

- Northern wells W1/W2/W3 have 100% chance to be in the reservoir
- W4 can be part of the same structure with a remaining 80% chance
- Extension of the reservoir is possible at West of W2 (Around 200m) but limited on East of W3 (Due to the fault)

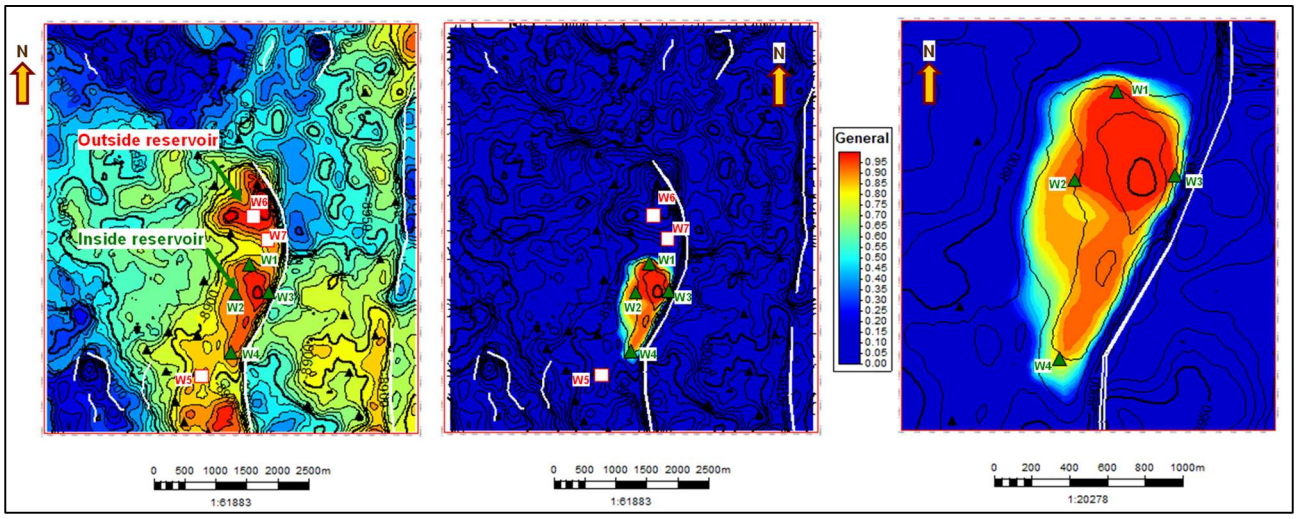


Figure 13: Depth maps with reservoir constraint, probability maps of reservoir and details of it.

GRV estimations on all simulations using depth of the spill as a contact give us a cumulated distribution curve where at any point, we can have the probability to at least encounter on the reservoir a minimum GRV (Figure 14). From this curve, we'll extract the meaningful value of P10/P50/P90 where at least we have 10/50/90% probability that the quantities actually recovered will equal or exceed the High/best/Low estimate. We can see here that we have an equilibrate estimation between P90 and P10 with around 81Mft3 between P10 and P50 while 65Mft3 are between P90 and P50.

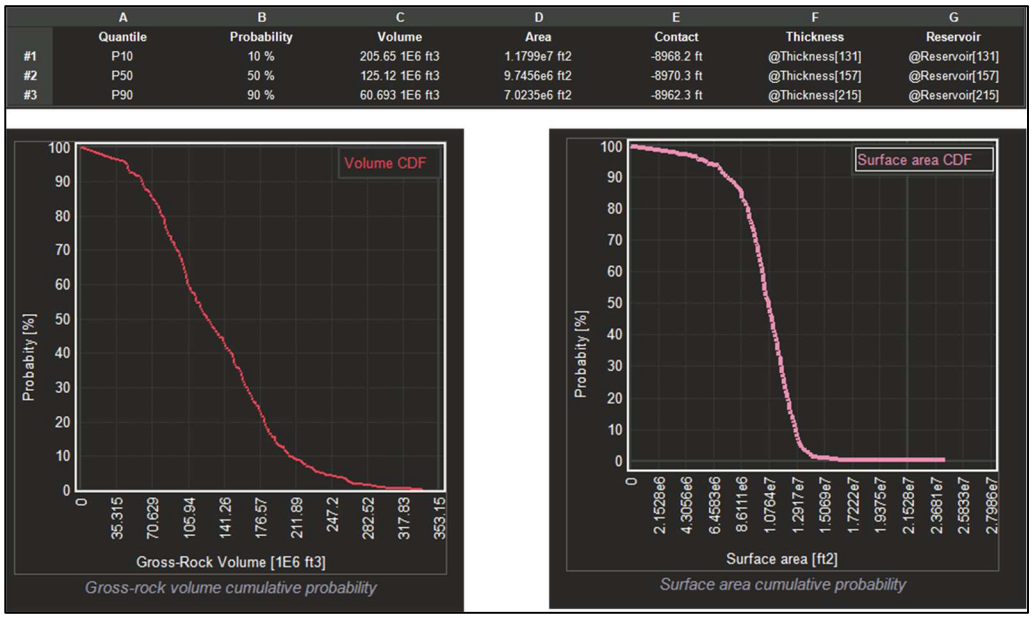


Figure 14: Volume estimations of reservoir

CONCLUSIONS

Stochastic geophysical workflow consistently propagates uncertainty from data analysis to the reservoir assessment through the Depth conversion itself. Compared to a traditional deterministic method, uncertainty exists at each workflow stage and is inherited from the previous step to obtain a consistent uncertainty characterization that is easily replicable and updatable throughout the life of the field where you can have constant update with improved and/or new data. By the generation of multiple realizations, that are all equiprobable model around the estimation within the confidence interval defined by the uncertainty, we can acknowledge clearly the risk associated with possible recoverable GRV, probable reservoir geometry and possible inter-connectivity between wells to enhance the comprehension of the reservoir configuration at the structural stage. The robustness of the approach can be seen lastly with the most probable structural map resulting from the stochastic depth conversion that is consistent with the markers from two blind wells that were not used in the workflow and served as quality control. For one of the control wells, the differences between the structural surfaces and the corresponding markers ranged between 1 and 15 feet, whereas for the other well, the differences were approximately between 9 and 24 feet.
Likewise, in the case of a new well drilled after completion of this study, the maximum difference between the prognosis derived from the stochastic conversion and the well markers was approximately 16 feet.
Furthermore, the uncertainty maps of the most probable structural surfaces showed maximum uncertainties of approximately 20 feet, a value consistent with the differences observed between the prognoses and the actual markers for several wells drilled within the study area.
Stochastic geophysical workflow is a straightforward approach that is easily repeatable and can appear somewhere automatic. However, careful hindsight on the data is needed and fortunately exists for the Geoscientist community of expertise that we can rely on.

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