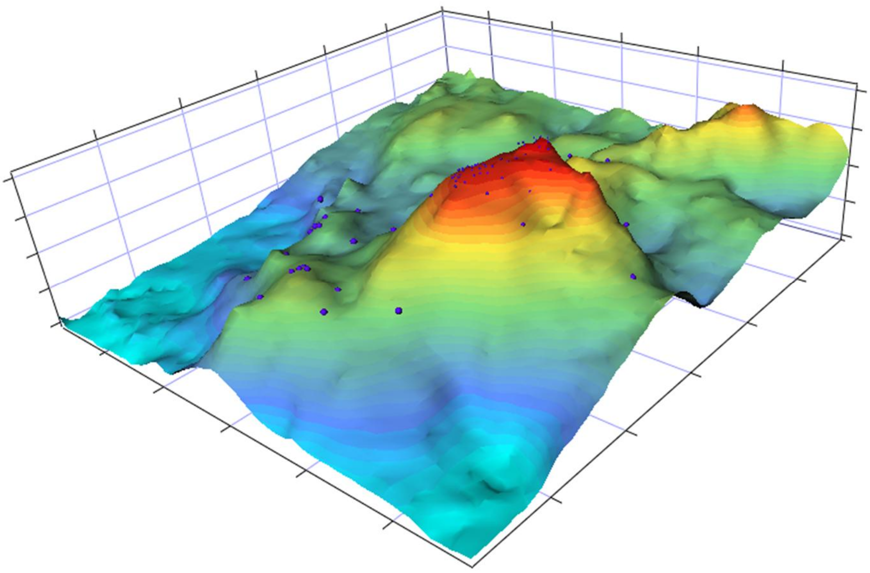
Geovariances

Where no one has gone before

White Paper



How to Capture Trend Uncertainty with Bayesian Kriging

How to Capture Trend Uncertainty with Bayesian Kriging

Taking into account secondary information is of key importance in numerous Oil & Gas workflows (e.g. combining seismic times with well picks, using acoustic impedance maps to predict porosity...). In the presence of trends**, kriging with Bayesian drift** bridges the gap between the traditional kriging with external drift (**KED**) and a simple kriging of the residuals (**SK**), allowing a better trend control.

Kriging methods are based on the dichotomy of the variable which can be written as the sum of a trend and a stationary residual. With **Bayesian kriging** (**BK**), the prior knowledge gained from similar fields or physical characteristics about the trend shape is used. This is very useful when the data are sparse and traditional geostatistical data analysis may lack robustness. The method enables control of the correlation between coefficients, as well as verification of the local posterior behavior of the trend coefficients when data are numerous. It has wide ranges of applications, notably in depth conversion workflows.

In the presence of trends, kriging with Bayesian drift bridges the gap between traditional Kriging with External Drift and Simple Kriging of the residuals.

Overview

Trend is a matter of scale. Geology can be stationary at regional scale but not at the local scale or field scale. There is frequently a trend in geology at the scale of the study (a dome, an anticline, etc.). External information about this trend is sometimes available, for instance from seismic. Classically, this external information can be integrated in two ways. First, linear regression can be used to derive a trend model and estimate residuals around it with **Simple Kriging** (**SK**). **Kriging** with **External Drift** (**KED**) provides an alternative which does not require the explicit distinction between trend and residuals. If there is an uncertainty on the drift model (e.g. due to too sparse data sampling) **Bayesian Kriging** (**BK**) approach can be used in order to account for prior knowledge about the trend. The **BK** result sits between the **SK** and the **KED** approaches. This paper shows how to include uncertainty in the drift model and how it affects both the estimate and its related uncertainty.

Methodology

Trend modeling

The idea of trend modeling is to find a polynomial function (linear, quadratic, etc.) from the observed data that would explain the "shape" of the main variable (figure 1). The trend parameters can be geographical (x, y, z) or external properties. In this latter case they are called external drifts. For instance a linear relationship between a variable v and a variable f1 means that it is possible to predict v from f1 or to use f1 as an external drift to predict v. This scenario is common in time to depth conversion where TVD can be predicted for instance from TWT (figure 1).

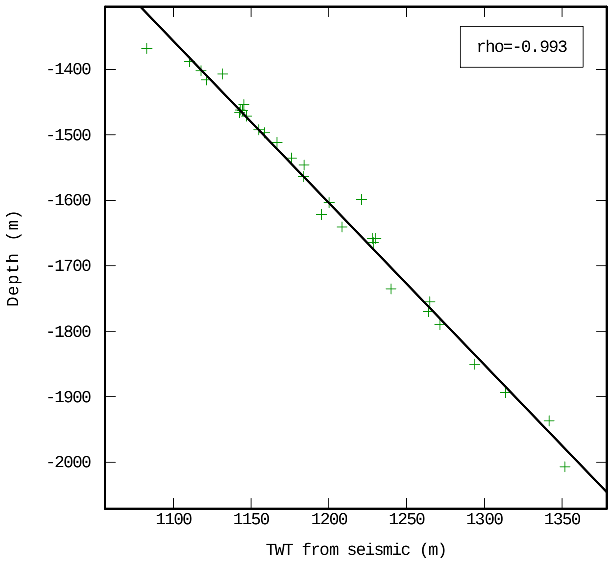


Figure 1: scatter diagram between Depth vs TWT at well locations.

To be meaningful, the relationship between the variables should rely on data points where both variables are known (i.e. at the well location).

Non-stationary geostatistics provides solutions to estimate data with trends.

Non-stationary modeling in Isatis provides a way of testing several trend scenarios and ranking them to help deciding which one might be the most appropriate choice.

Non-stationary geostatistics

To deal with non-stationarity the variable v(x) can be decomposed into a trend and a stationary residual r(x) zero mean.

$$v(x) = m(x) + r(x)$$

This decomposition is the one behind the **UK** system (Matheron, 1970).

In case the trend is modeled explicitly from the polynomial drift equation, residuals can be computed and estimated using **Simple Kriging** (**SK**). The trend has to be estimated using a unique neighborhood, resulting in constant trend coefficients. The variogram of the residuals can be modelled from the experimental variogram of the residuals or inferred by the user. Estimated residuals are added back to the trend to get a final result that ties to the wells.

In the **KED** case, the basis drift functions are defined externally through auxiliary variable f^l instead of monomials based on the geographic coordinates. In case of numerous data, using a moving neighborhood allows accounting for local variations in the trend. As for **SK**, **KED** requires the knowledge of the covariance or variogram part from the residuals and the drift terms f^l. For a unique neighborhood the residuals can be computed using Isatis Global Trend Modeling, but with a moving neighborhood the trend residual covariance needs to be inferred.

Computing a reliable trend may be difficult in the case of sparse data. **Bayesian kriging** (Omre 1987) allows accounting for prior knowledge in such cases. In this framework unknown coefficients a^l are considered as random variables A^l and assumed to have a Gaussian joint distribution. Within the Bayesian framework the distribution of these variables can be provided by the geoscientist (a Gaussian distribution defined by the mean and standard deviation of the A^l and the correlations between them). As for **SK** or **KED**, the drift functions and the covariance of the residuals have to be provided. The covariance is a challenging part as the trend is not yet known at this stage. It has to be inferred from prior knowledge.

Comparison of the techniques

Mathematically, there is a link between the three approaches presented here (**SK**, **BK**, **KED**). The **SK** approach is a Bayesian kriging with no uncertainty on the priors (standard deviation is 0 for each A^l). As can be seen from figure 2, the uncertainty only comes from the residuals spatial configuration and covariance. When the uncertainty on the priors is maximal (standard deviation goes to infinity) the **BK** system converges to the **KED** system. In any intermediate situation the **BK** gives an intermediate answer.

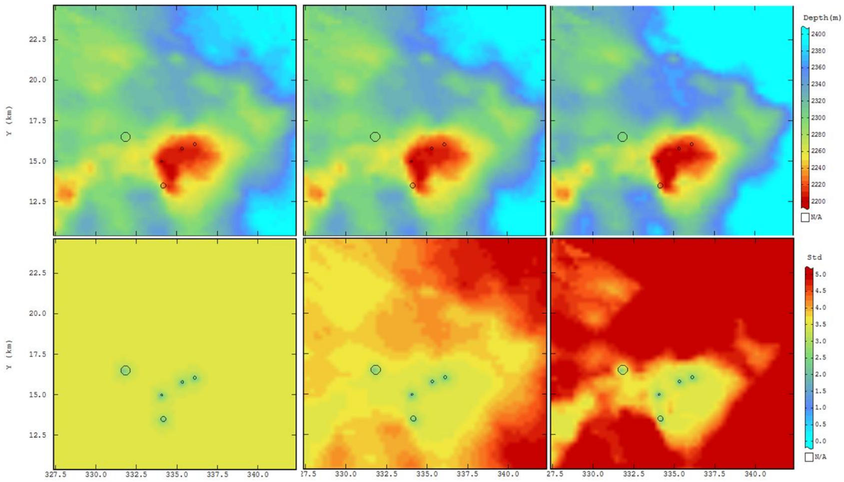


Figure 2: Depth estimation (top) and standard deviation (bottom) for three approaches: SK (left), Bayesian (middle) and KED (right). For the three scenarios the same residuals covariance, drift function and only 5 wells out of 87 are used. The prior for the trend coefficients are 1.4 and -850 with a medium standard deviation (0.05 for the slope and 100 for the intercept). The BK result gives an intermediate answer between the SK and the KED approach.

Simulations

The three systems can be simulated. The degree of uncertainty depends on the estimation error. In the **SK** approach, as full confidence is given to the trend, the uncertainty around the mean is small (compared to the other two). In the **KED,** as the trend coefficients are unknown the uncertainty is higher.

In the **BK** system the uncertainty on the drift can be estimated by deriving posterior distributions of drift coefficients. A serie of coefficients can be drawn from this distribution. They are used to compute the residuals which are then simulated. The drift is also computed over the whole field from the drawn drift coefficients and the final simulations obtained by adding the simulated residuals to it. As a consequence, the uncertainty about the trend coefficients might lead to an increased variability of the **BK** simulations.

Illustrations

Using a trend is a strong assumption as it would greatly reduce the overall uncertainty. It is therefore very important to ensure that all the data used to compute the trend are clean.

The illustration is taken from the Non Stationary & Volumetrics case study of Isatis. The dataset contains a seismic horizon in depth for the top structure, and 87 well markers for reservoir tops in depth. It contains also reservoir thickness at the well locations (figure 3). The correlation coefficient between the seismic attribute and the well is 0.984 which suggests that using the seismic depth to predict the true depth might be a good choice to make. Now using a trend is a strong assumption as it would greatly reduce the overall uncertainty. It is therefore very important to ensure that all the data used to compute the trend are clean. Any artifact, footprint, mispick would affect the quality of the conversion. Looking at possible outliers is recommended as it could impact the linear regression. This analysis shows that the points diverging the most from the trend line are local clusters and correspond to possible anisotropy or possible picking or migration issue. The divergence can sometimes reach 20m. This issue will be ignored in this tutorial as to resolve it would involve looking at the seismic and velocity field. Figure 4 shows the trend computed using the linear regression equation Well = 1.42*Seismic - 857.92. Also displayed are the residuals at the well locations, their histogram and experimental and model variogram.

With the variogram model of the residuals it is now possible to apply the 3 techniques described above (**SK**, **KED** and **BK**). For the **BK** system, as the 87 wells were used, the prior drift coefficients are taken to be very close to the ones estimated globally on the cross-plot; the slope and intercept are not allowed to vary much (only 6% and 1% respectively). This explains the similarity between the **SK** and **BK** approach. For all methods the same moving neighborhood is used. This allowed the **KED** to compute (or more precisely to filter) local drift. Artifacts can be noticed in the top right corner where the uncertainty is the highest (away from control points). Using a unique neighborhood leads to similar results between all three methods (the results are not presented here).

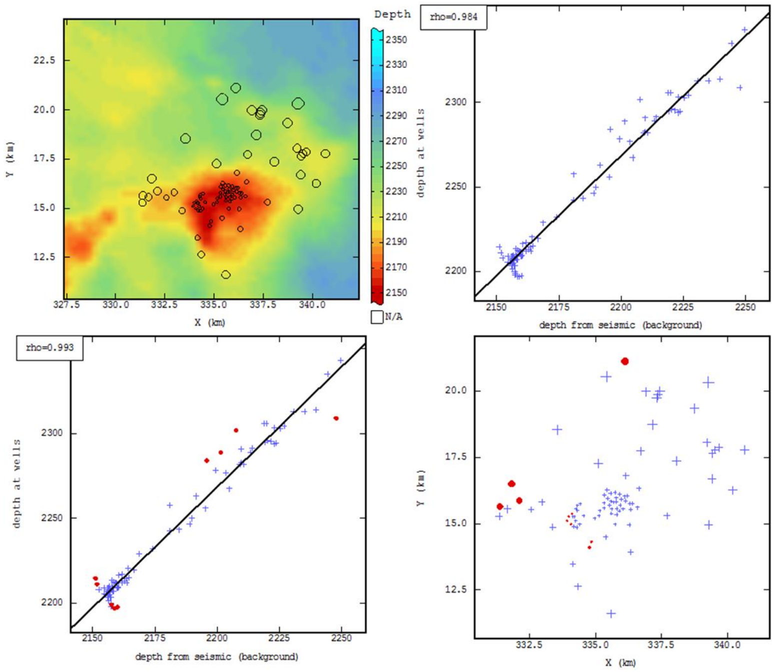


Figure 3: Seismic horizon depth (m) and well marker depth (m) of the top reservoir are displayed on the top left corner. The relationship between the two is displayed on the top right corner, showing a good linear relationship with a correlation coefficient of 0.984. Points away from the trend line are highlighted in red at the bottom, on the scatter plot (left) and basemap (right).

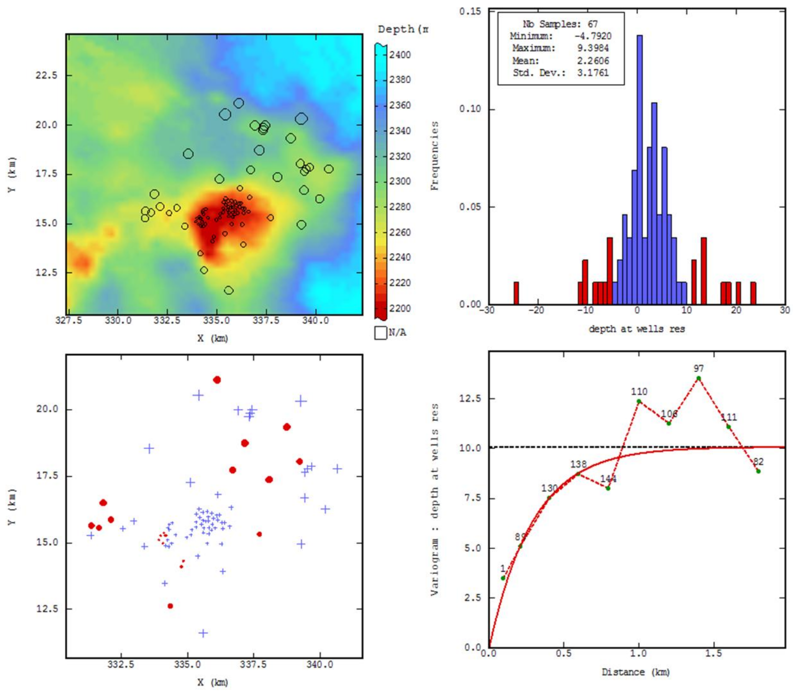


Figure 4: Trend computed using the linear regression equation Well = 1.42*Seismic -857.92 (top left corner). Also displayed are the residuals at the well locations (bottom left corner), their histogram (top right corner) and experimental and model variograms (bottom right corner).

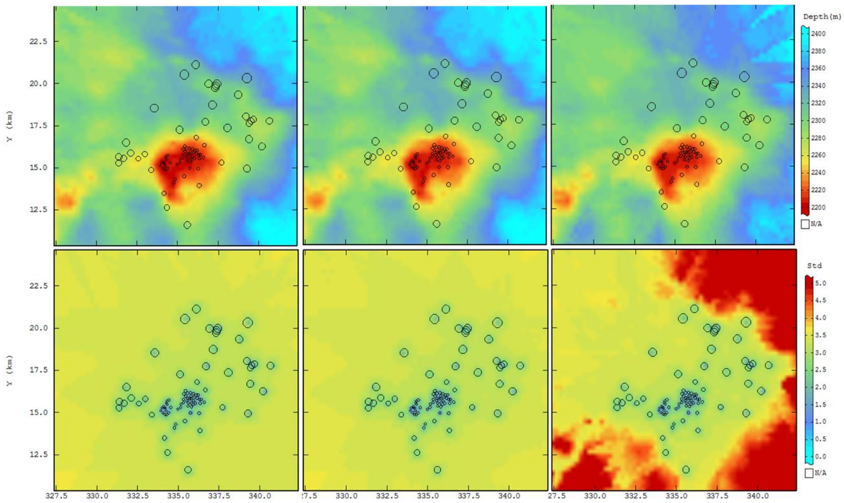


Figure 5: The estimation (top) and the standard deviation (bottom) are shown for three methods: SK (left), BK (middle) and KED (right). For the BK system, as the 87 wells were used, the prior drift coefficients are taken to be very close to the ones estimated on the cross-plot; the slope and intercept are not allowed to vary much (only 6% and 1% respectively). This explains the similarity between the SK and BK approach. For all methods the same moving neighborhood is used.

Another interesting test is to check what happens when the well information is sparse. To do that we take the same dataset but only select 5 wells out of 87. Two scenarios are tested, one where the sampling can still be informative about the "real" trend and one where it is not (figure 6). With a so sparse data sampling the variogram is meaningless and needs to be inferred.

This result is intuitive and shows how prior knowledge can be used and blended with the observed information using a BK approach.

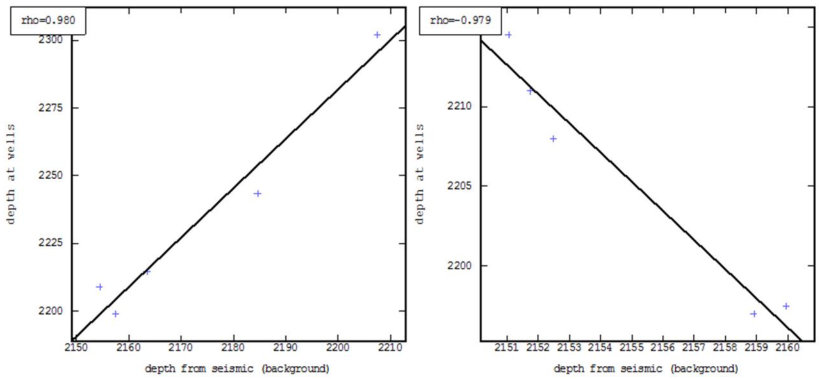


Figure 6: Two test scenarios: one where the trend can be considered as moderately informative (left) and one where it is not informative at all (right).

Figure 7 shows the estimation results. Obviously with so few data a unique neighborhood need to be selected. The covariance part is the same as the one used previously. In reality it would have to be inferred from prior knowledge. The drift coefficients chosen for the priors are -1500 for the intercept and 1.4 for the slope which is consistent with the field information using all 87 wells. The prior coefficients are sometimes selected to be moderately uncertain (an STD of about 15% of the coefficient value) or uncertain (an

STD of about 50% of the coefficient value). When the trend is informative and consistent with the priors, the results converge to the 87 wells scenario for both types of prior uncertainties. When the trend is non-informative, the results converge to the 87 wells scenario only if the prior are accurate and set with certainty. This result is intuitive and shows how prior knowledge can be used and blended with the observed information using a **BK** approach.

Non-stationary geostatistics systems can be simulated to quantify the uncertainty in the model.

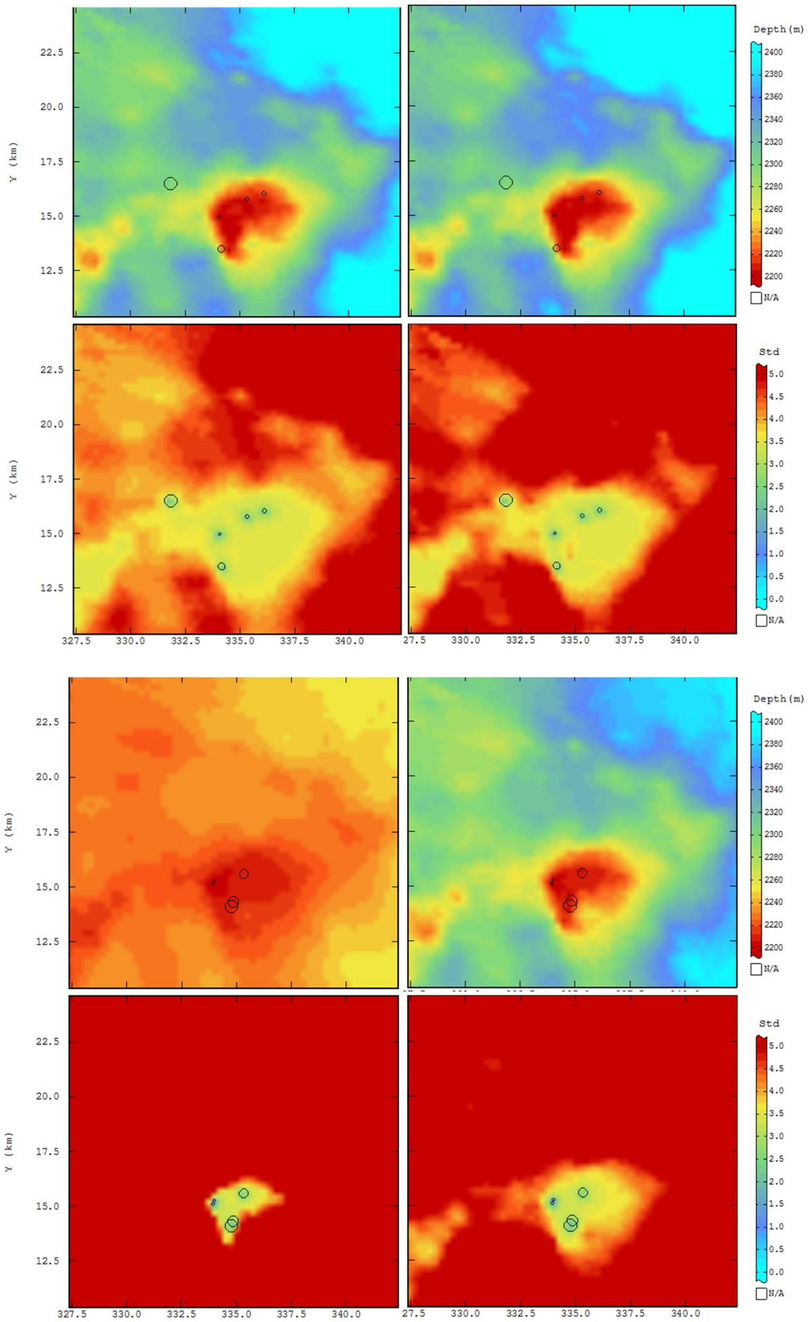


Figure 7: Estimation results (first row) and estimation error (second row) for the informative trend case scenario. Estimation results (third row) and estimation error (fourth row) for the non-informative trend case scenario. The first column is for moderately uncertain priors and the second for uncertain priors. Prior values and covariance are chosen to be in good agreement with the field information.

References:

- Matheron, G (1970), The theory of regionalized variables and its applications: Centre de Géostatistique de l'Ecole des Mines de Paris, Les Cahiers du Centre de Morphologie Mathématique. Fasc. 5.
- Omre, H (1987), Bayesian kriging – merging observation and qualified guesses in kriging, Math Geol. 19(1), 25-39.

Who is Geovariances?

Geovariances is a specialist geostatistical software, consulting and training company. We have over 45 staff, including specialist oil consultants and statisticians.

Our software, Isatis, is the accomplishment of 25 years of dedicated experience in geostatistics. It is the global software solution for all geostatistical questions.

Other technical specialties

Geovariances is a world leader in developing and applying new and practical geostatistical solutions to oil operations. We have strong experience in applying geostatistics from seismic data QC to reservoir characterization and have gained trust from some of the biggest international companies.

Lastly all methods can be simulated and used to compute GRV uncertainty. As an example 100 Bayesian drift simulations using the same settings as the ones used in figure 5 are run. 100 simulations of the reservoir thickness are also run. Isatis Volumetrics and spill point module is used to report the GRV PDF within the green polygon and output a map of the mean reservoir thickness (figure 8).

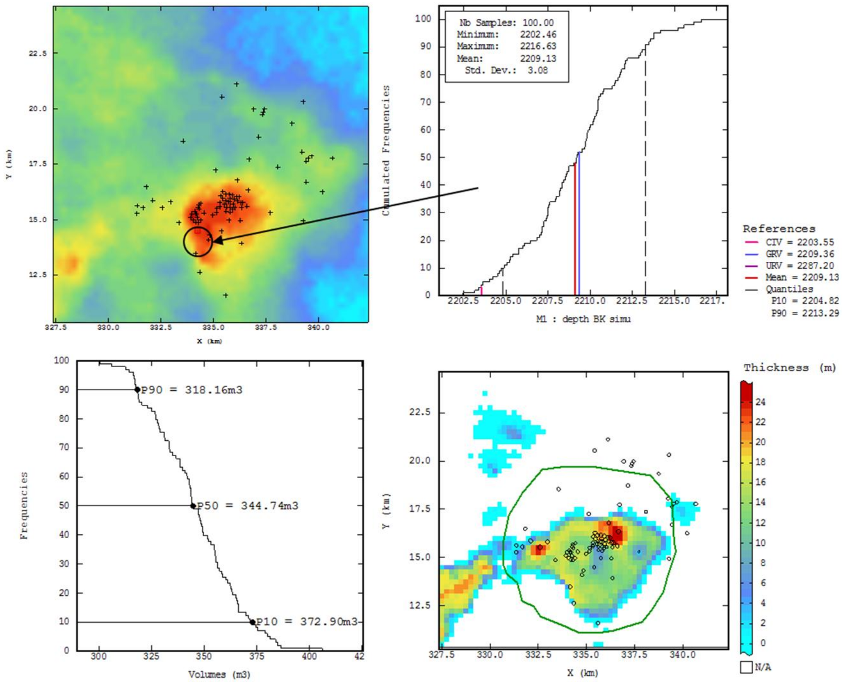


Figure 8: First realization with Bayesian drift out of 100 (top left corner). Converted depth CDF of the top reservoir for a point located in the middle of the black circle (top right corner). GRV PDF (bottom left corner) within the green polygon and map of the mean reservoir thickness (bottom right corner) computed from Isatis Volumetrics and spill point module.

Our expertise

Geovariances has more than 15 years' experience in geostatistical time to depth conversion projects. Numerous studies have been carried out for major Oil & Gas companies. We can provide a unique expertise through both our French and Australian offices.

For more information

Let us help you in your time to depth conversion workflow.

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