Geostatistical Simulation for Reservoir Characterization

John Pendrel, Miles Leggett, Peter Mesdag, Jason Geosystems, Calgary

Summary

Geostatistical Simulation, a technique with its origins in the hard-rock mining industry has become increasingly more commonly used as a reservoir characterization tool in the exploration for and production of hydrocarbons.   Its initial use was limited due to a total dependence on the requirement for a sufficient density of well information.   However, modern methods employing Geostatistical Inversion have forged a successful integration of high frequency logs and low frequency seismic information. In addition, the estimation of lithotypes between well locations can be implemented with Geostatistics.   Sequential Indicator Simulation can construct just such volumes, complete with uncertainty estimates.   The inputs to Geostatistics need no longer consists of traditional seismic reflection and log data. Indeed, we can simulate, for example, any output of AVO inversions, such as Vp/Vs or LambdaRho-MuRho.

We will illustrate the above comments with a review of some field examples, together with an explanation of how some of the more common Geostatistical techniques work.

Sequential Gaussian Simulation and Geostatistical Inversion

Geostatistical simulation is the process of estimating the value of a geophysical property at a grid point in space and time where it is unknown. Non-uniqueness is recognized by the procedure and accounted for by creating probability density functions (pdf's) at each grid point (ie voxel). It is from these pdf's that simulations are randomly drawn. The input statistics needed to construct the pdf's are first and second order in the form of means and variograms (spatial mis-correlations). This *a priori* information comes from well logs and spatial statistical property and lithology distributions. The logs are assumed to represent the correct solution at the well locations. It is useful to run a sparse spike inversion first, to establish this. Briefly, the procedure of Sequential Gaussian Simulation (SGS) consists of

1. Selection of a voxel where the reservoir property under investigation is unknown
2. Identification of neighbouring voxels where that property is known
3. The assignment of weights to the neighbours, depending upon their perceived relevance at the empty voxel
4. Construction of a local pdf at the empty voxel from the neighbour values
5. Extraction form the pdf of a single value to occupy the empty voxel
6. Random selection of another empty voxel
7. Proceed to Step 1 and repeat until estimations have been made at all empty voxels.

We use Geostatistical Inversion (GI) to constrain the simulations. This is especially valuable in regions out of range of the wells. The geostatistical inversion algorithm simply accepts or discards simulations at individual grid points, depending upon whether they imply synthetics which agree with the input seismic. The decision to accept or reject simulations can optionally be controlled by a simulated annealing strategy.   Previously simulated voxels are repeatedly re-assessed for updated values which might be in better accordance with the seismic data. The inversion option results in a tighter set of simulations, the variation of which can be used to estimate risk or make probability maps.
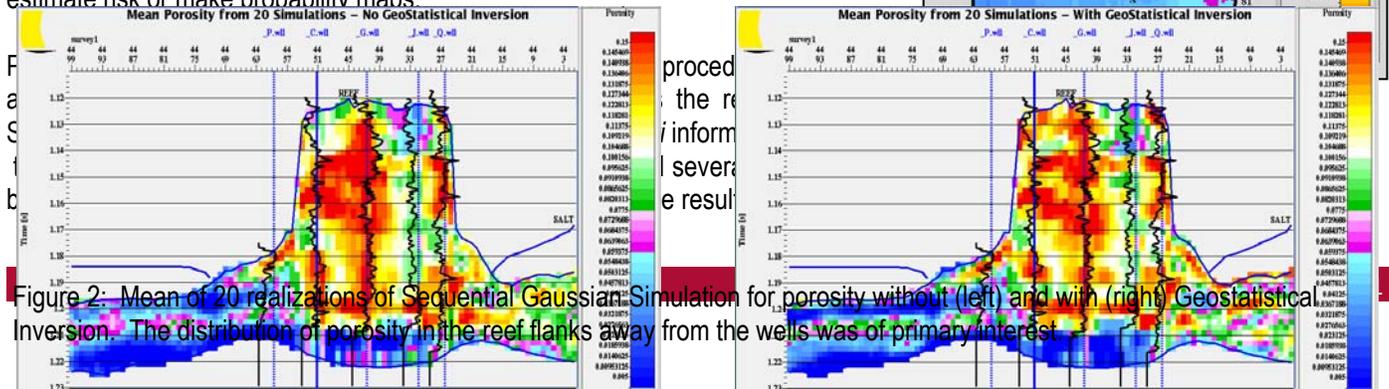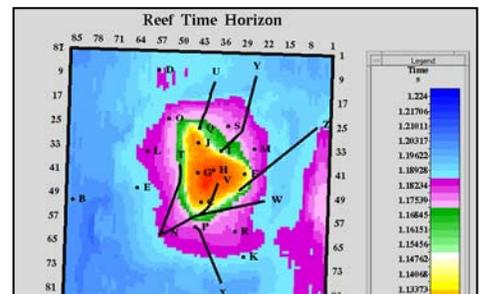
Figure 2: Mean of 20 realizations of Sequential Gaussian Simulation for porosity without (left) and with (right) Geostatistical Inversion. The distribution of porosity in the reef flanks away from the wells was of primary interest.

simulation are shown in Figure 2. The influence of the seismic data has created more lateral variability in the simulation with Geostatistical Inversion. We note here and below that it is the collection of many simulations which adds the power of uncertainty estimation to Geostatistics. In Figure 3, we show the standard deviation from 20 such simulations. Note the smaller standard deviations when Geostatistical Inversion has been used. This smaller, subset of simulations has the unique property that each is consistent with the input seismic.
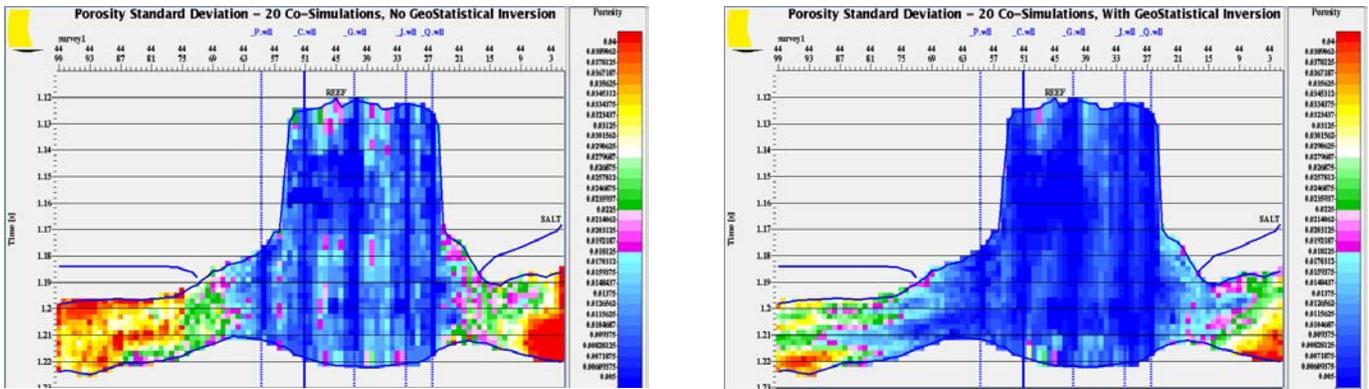
Figure 3: Standard deviation of 20 realizations of Sequential Gaussian Simulation for porosity without (left) and with (right) Geostatistical Inversion. Note how GI produces a tighter set of simulations, each of which is in agreement with the input seismic data. Estimation of porosity is also more consistent in the reef flanks.

Sequential Indicator Simulation

A very useful outcome of Geostatistics is Sequential Indicator Simulation (SIS) – the estimation of lithotypes at each voxel. Initially, key lithotypes must be chosen in the context of the reservoir properties of interest. For example, should the outcome of SGS be P Impedance, it would make sense to simulate for shale, tight sandstone and porous sandstone, as long as they were somewhat separable with respect to P Impedance. An SIS workflow would involve….
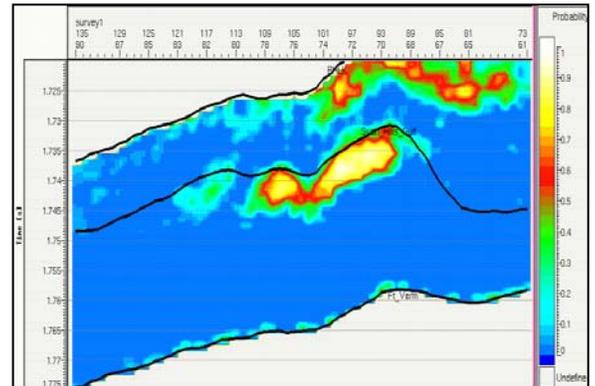
1. Selection of a voxel where the lithotype is unknown
2. Identification of neighbouring voxels with known lithotypes
3. The assignment of weights to the neighbouring points
4. Construction of a local cumulative distribution function (cdf) for lithotype probability from the neighbour lithotypes
5. Extraction form the cdf of a single lithotype to occupy the empty voxel
6. SGS (see procedure above) to assign a reservoir property to the voxel
7. Random selection of another empty voxel
8. Proceed to Step 1 and repeat until estimations have been made at all empty voxels.
9. Implement Geostatistical Inversion to ensure accordance with the seismic data.

This technique was used successfully by Torres-Verdin et al. (1999) to simulate porous sandstone packages in the San Jorge Basin of Argentina. The Geostatistical workflow used was SGS for density with GI and SIS for porous sandstones, tight sandstones and non-sandstones (mostly shales). Although individual sandstones were beyond seismic resolution, the influence of sandstone packages was not. Figure 4 shows an example of one SIS realization. The exploration strategy was to drill through the regions containing the thickest packages. Initial results showed increased sandstone penetration by a factor of 3.
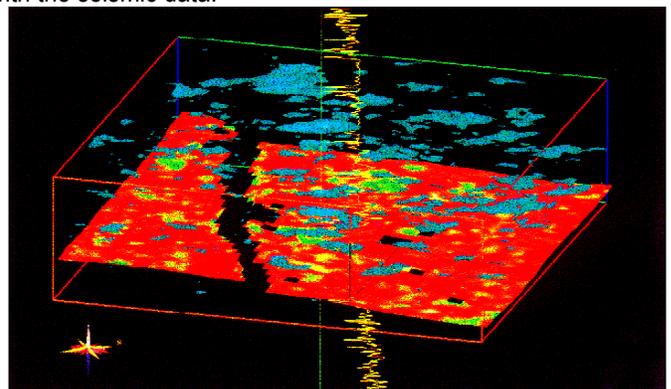
Figure 4: Porous sandstone bodies for a single realization of SGS for Density with GI and SIS. From Torres-Verdin et al., 1999.

Estimation of Uncertainty

A set of property volumes can be used to make property probability density functions (pdf's) at each voxel in 3D space.

The pdf's are then integrated to determine the probability that the property in question lies in a certain acceptable range of values. For example we could be interested in the probability that porosity met or exceeded some minimum value. These probabilities are then posted into a probability volume. This volume can be automatically interpreted to map the likely areas of enhanced porosity and reduced risk. With this approach reservoir risk can be quantified and directly used to guide drilling decisions.

Van der Laan and Pendrel (2001) have implemented this procedure for data over a Swan Hills reef. Maximum porosity thickness is 25 m and there are 65 wells within the survey. Impedance is directly related to porosity. This was confirmed through log cross-plots and by doing a standard constrained sparse spike inversion. Twenty simulation sets of porosity were computed from transformed impedance simulations. The porosity simulations were modelled by a Normal probability density function at each voxel. From these, volumes could be constructed giving the probability that the porosity lay within a specified range. Figure 5 shows an example of this for porosities equal to or greater than 10%. This volume was then viewed in 3D perspective and probabilities less than 60% were set to be transparent (Figure 6). The tops and bottoms of the viewable remainders were identified and picked automatically. The corresponding thicknesses were then mapped (Figure 7). The colours represent the thickness, within which, the probability of 10% or greater porosity exceeds 60%. From plots such as these, uncertainty can be formally measured and input directly into risk management analyses.
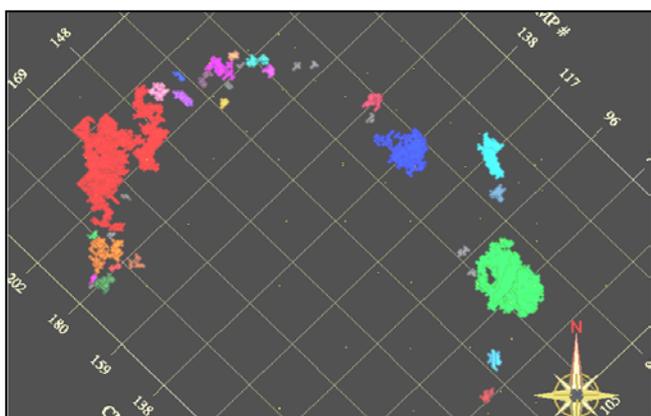
Figure 6: The porosity probability volume was viewed in 3D perspective and the probability values below 0.6 set to be transparent. The remaining visible regions are the results of implementing a "body Capture" procedure.
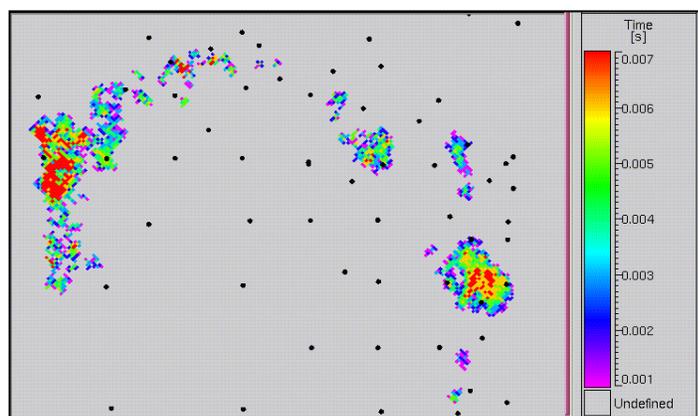
Figure 7: The high probability bodies in Figure 6 were automatically interpreted and their thicknesses mapped. The colours represent the thickness within which the probability of finding porosity greater than or equal to 10% is 60% or greater.

Figure 5: The set of 20 porosity simulations was modelled to make a unique porosity probability density function (pdf) at voxel. The area under the pdf's above 10% porosity was used to form a porosity probability volume.

Conclusions and the Road Ahead

The examples above demonstrate, in our view, that there is a growing role to play for Geostatistics in the exploration for oil and gas. The integration of logs and seismic in an intelligent way can lead to more accurate estimates of reservoir properties and estimations of the distributions of key lithotypes. We foresee an even greater integration of geostatistics in traditional Post-stack and AVO Inversion wherein the two will happen simultaneously within a single algorithm. Additionally, better ways will emerge in which to pass the results of Geostatistics to other processes such as reservoir simulation.

References

Pendrel, J., Van Riel, P., 1997, Using seismic inversion and geostatistics to estimate porosity – A Western Canadian reef example, CSEG Ann. Mtg. Abs.

Torres-Verdin, C., Victoria, M., Merletti, G. and Pendrel, J., 1999, Trace-based and geostatistical inversion of 3-D seismic data for thin-sand delineation: An application in San Jorge Basin, Argentina: THE LEADING EDGE, **18,** no. 9, 1070-1077.

Van der Laan, J. and Pendrel, J., 2001, Geostatistical simulation of porosity and risk in a Swan Hills reef, 71st Ann. Internat. Mtg: Soc. of Expl. Geophys., 1588-1591.