Collocated Cosimulation of Permeabilty in an Appalachian Oil Field

Michael Ed. Hohn
West Virginia Geological and Economic Survey
P.O. Box 879
Morgantown WV 26507-0879 USA
Tel. 304-594-2331

The importance of modeling permeability in petroleum geology and engineering is rivaled by the difficulty in obtaining sufficient data. In practice, two- or three-dimensional models of permeability that include spatial variation must depend on qualitative information or data from which permeability can be inferred through empirical relationships. For instance, a significant regression of permeability on porosity occurs in many reservoirs, and can be used to estimate permeability.

Collocated cosimulation is but one method for supplementing a primary data with a secondary variable such as porosity when generating equiprobable realizations of permeability. These methods rely on a secondary variable that is sampled more densely than the primary variable, and a measure of the dependency, expressed as the covariance or correlation coefficient between the two variables. Collocated cosimulation was originally proposed for use when the secondary variable is observed on a dense grid, such as with seismic data (Xu and others, 1992). Almeida and Frykman (1994) apply the method to situations where the grid of the secondary variable must be calculated from a set of observations.

The example shown here illustrates collocated cosimulation in an application that uses initial potential of oil to supplement permeability. Initial potential is measured soon after completion of a well, and represents that first rush of liquid to the well bore. It depends on permeability as well as other factors, including original oil in place and reservoir pressure.

Procedure

1) Transform primary and secondary to normal scores. GSLIB program *nscores* (Deutsch and Journel, 1992) was used in this example. Compute variograms from the normal scores and fit variogram models.

2) Calculate the correlation coefficient between primary and secondary variable.

3) If the secondary variable is not available at every grid node in the area or volume to be simulate, use sequential Gaussian simulation to generate a value of the

secondary variable at the exact grid locations to be used for simulating the primary variable. GSLIB program *sgsim* was used for all simulation.

4) Perform sequential Gauusian simulation of the primary variable, using the grid of the secondary variable, variogram model of the primary variable, and correlation coefficient.

Results

The variogram for permeability (Fig. 1) is not easily fitted with a model because of the sparse data distribution, which can also be seen from a map of permeability created with conventional sequential Gaussian simulation (Fig. 2). In contrast, many more values of initial oil potential occur in the study area (Fig. 3), and give rise to a variogram that is easy to fit with the following nested model:

$$\tilde{a}(h) = 0.63(1 - \exp(-h/50)) + 0.37(1 - \exp(-h/850))$$

Kriged estimates of initial potential display a strong north-south trend (Fig. 4) that a study of the field shows to be related to similar trends in the shapes of sedimentary units that make up the reservoir in this field, porosity, and cumulative oil production (Hohn and others, 1993). It seems reasonable that a model of permeability for use in flow simulation should mimic this trend.

The next step is to compute a conditional simulation of initial potential (Fig. 5). Note that the north-south trend is still present, even though the grid now lacks the typical smoothness of the Kriged estimates.

At this point, the practitioner must rely on experience and to make some decisions. The collocated cokriging algorithm embedded in this simulation method assumes the same variogram model for primary and secondary variables. Permeability data are too scarce to infer a variogram model reliably, although one was fitted for the purpose of creating the preliminary simulation in Figure 2. To meet the requirements of the collocated cokriging algorithm, the variogram model for initial potential was utilized, and in fact this model plotted on variogram for permeability looks reasonable (Fig. 6).

The correlation coefficient between permeability and initial potential determines the control that the secondary variable places on permeability during simulation. Unfortunately, both variables were observed in only one well; no previous studies were available to suggest reasonable values. Therefore, multiple simulations were generated using a range of values for the correlation coefficient (Figs. 7-9).

Discussion

Recall the sequential Gaussian simulation algorithm. At each step in the process, a node is selected, observed data and previously-simulated values are used to estimate the mean and variance of a local distribution of the primary variable, and this distribution is sampled. In conventional simulation, kriging is used to estimate this distribution from the conditioning data, which include only values of the variable being simulated.

In the presence of secondary information, estimating a local distribution can be conditioned to additional data through cokriging, but at a price. Full cokriging requires variograms for primary and secondary variables, and crossvariograms. The resulting system of equations can be unstable. Computing the variogram suite can be tedious, perhaps even difficult. On top of this, if the primary variable is seriously undersampled, the variogram modeling step does not seem to deserve the effort; in fact the easiest way to ensure the admissibility of the resulting variogram model is to use the same model throughout, with appropriate scaling of the variance terms.

The collocated cokriging approach utilizes two simplifications of the cokriging variogram model, and exploits two observations:

1) When the secondary variable is present on the same grid as the simulation, the value of the secondary variable at a location being simulated effective shields the surrounding values of the secondary variable.
2) In many cases, crossvariograms can be represented by the variogram of the primary variable multiplied by a constant.

The first observation is a consequence of the system of equations solved to obtain the local means and variances. We can turn the second, empirical observation around to say that if variograms and crossvariograms are not at least reasonably similar, such that any one can approximately substitute for the other with appropriate variance adjustment, then we would wonder whether the secondary variable is useful at all! Of course, in this example, it was necessary to go one step further and ignore the variogram model fitted for permeability, and adapt the one for the secondary variable. Almeida and Frykman (1994) did the same in their simulation of permeability from limited permeability data and much more numerous porosity data.

Data

File gccorp3.eas includes permeability data; file gcoip.eas has the initial potentials.

References

Almeida A. S. and P. Frykman, 1994, Geostatistical Modeling of Chalk Reservoir Properties in the Dan Field, Danish North Sea. in Yarus, J. M. and R. Chambers (eds.), *Stochastic Modeling and Geostatistics*, American Association of Petroleum Geologists, Tulsa, OK, 143-157.

Deutsch, C. V. and A. G. Journel, 1997, *GSLIB: Geostatistical Software Library and User's Guide*, Oxford University Press, New York, 369p.

Hohn, M.E., D.L. Matchen, A.G. Vargo, and R.R. McDowell, 1993, *Petroleum geology and reservoir characterization of the Big Injun Sandstone (Price Formation) in the Granny Creek field, Clay and Roane counties, WV*. West Virginia Geological and Economic Survey, publication B-44, p. 91.

Xu, W., T. Tran, R. M. Srivastava, and A. G. Journel, 1992, Integrating Seismic Data in Reservoir Modeling: the Collocated Cokriging Alternative. *Proceedings of Society of Petroleum Engineers Technical Conference*: 833-842.

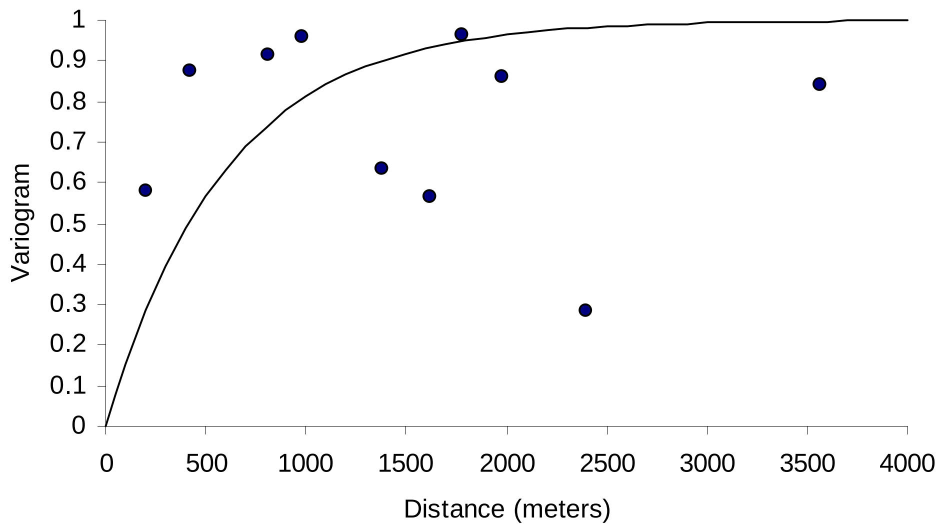


Figure 1. Variogram and exponential model of normal scores of average permeability in the producing sandstone, Granny Creek oil field, West Virginia.

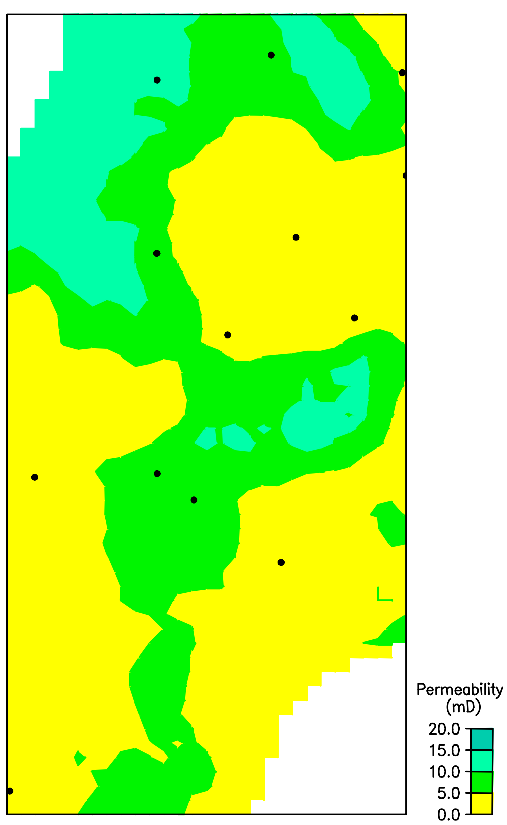


Figure 2. Conditional simulation of average permeability.

Figure 3. Variogram and exponential model of normal scores of initial oil production.

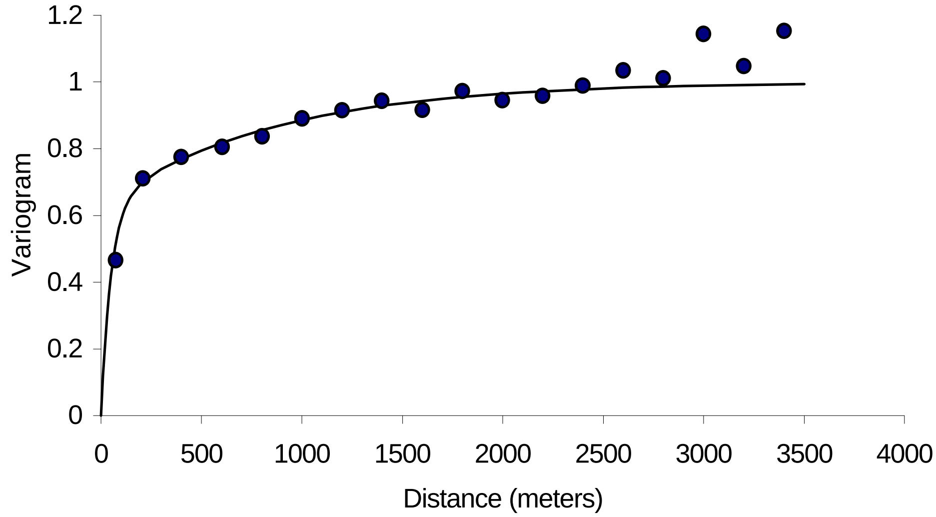
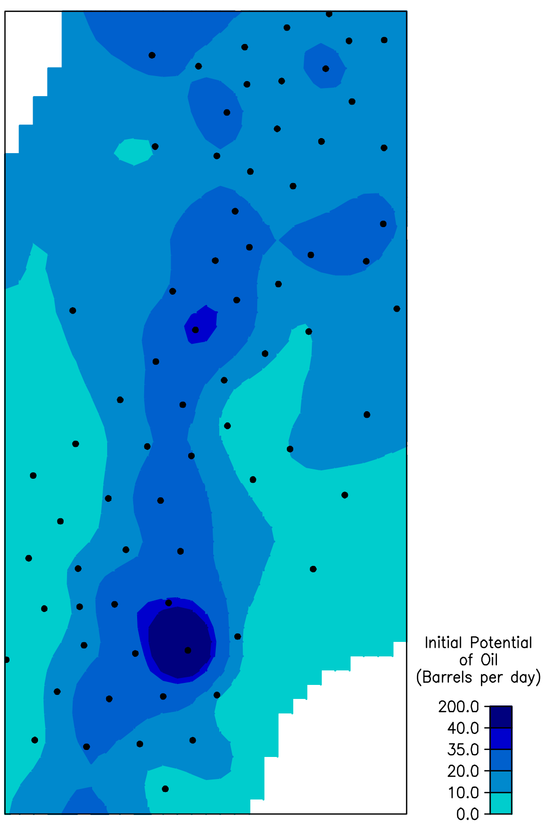


Figure 4. Initial flow of oil in Granny Creek field, West Virginia, mapped with ordinary kriging.



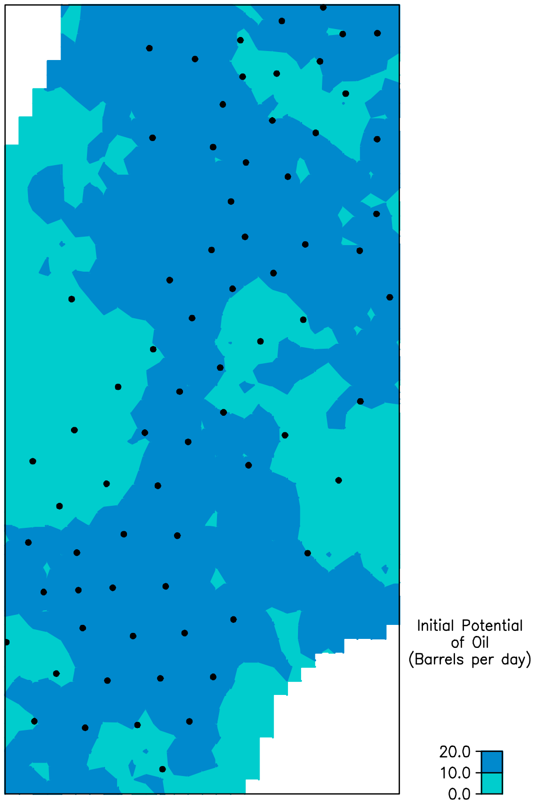


Figure 5. Conditional simulation of initial oil potential.

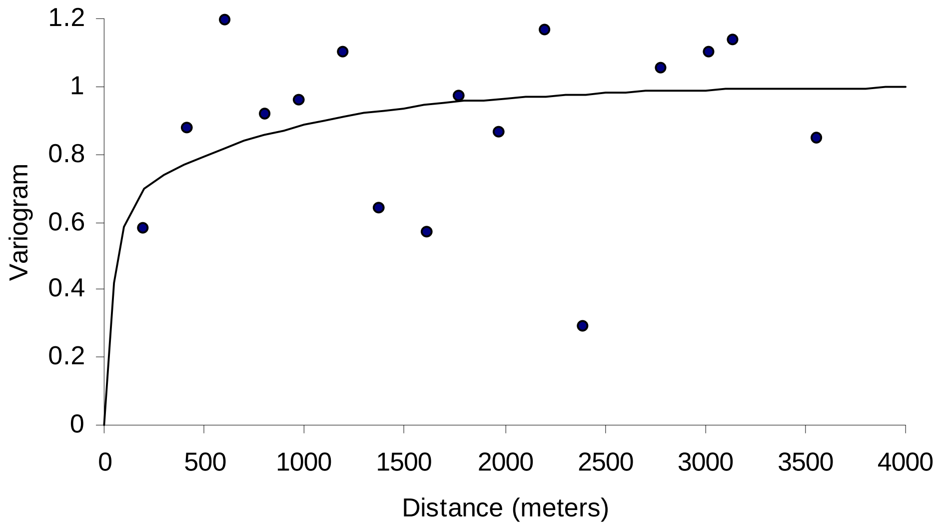


Figure 6. Variogram model of initial oil potential superimposed on variogram of average permeability.

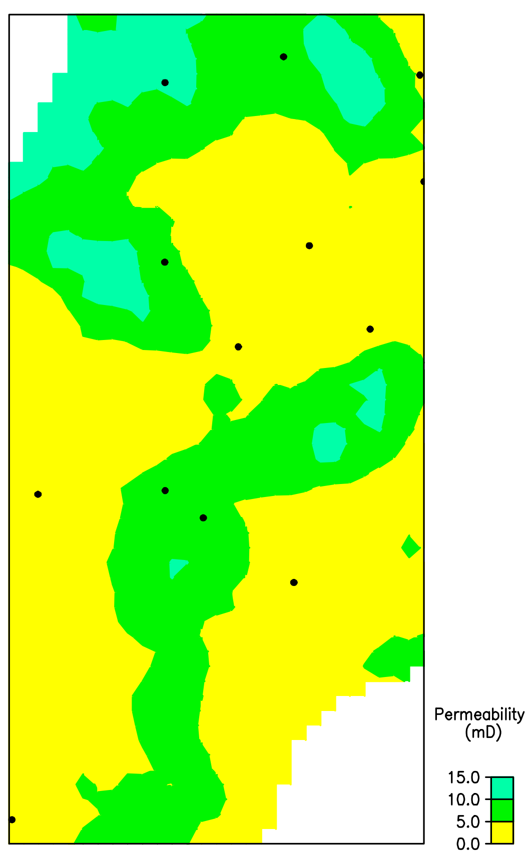


Figure 7. Conditional collocated cosimulation of average permeability, using initial potential as the secondary variable and a correlation coefficient of 0.2.

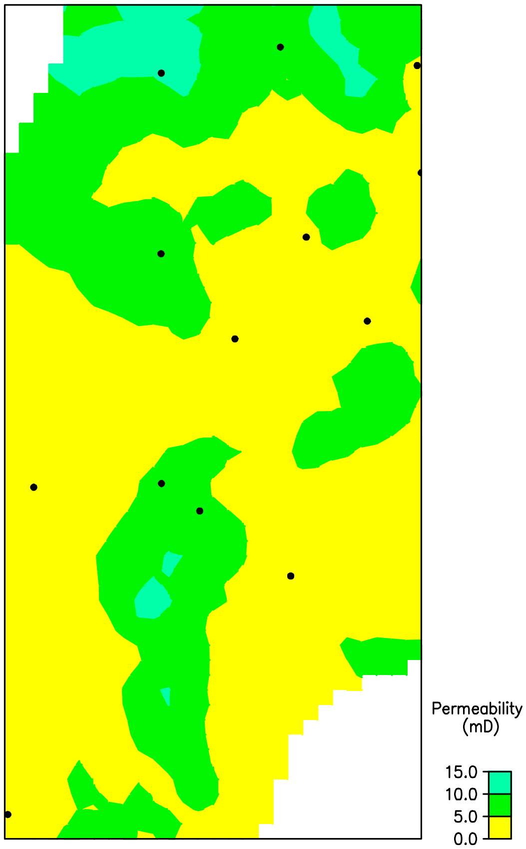


Figure 8. Conditional collocated cosimulation of average permeability, using initial potential as the secondary variable and a correlation coefficient of 0.6.

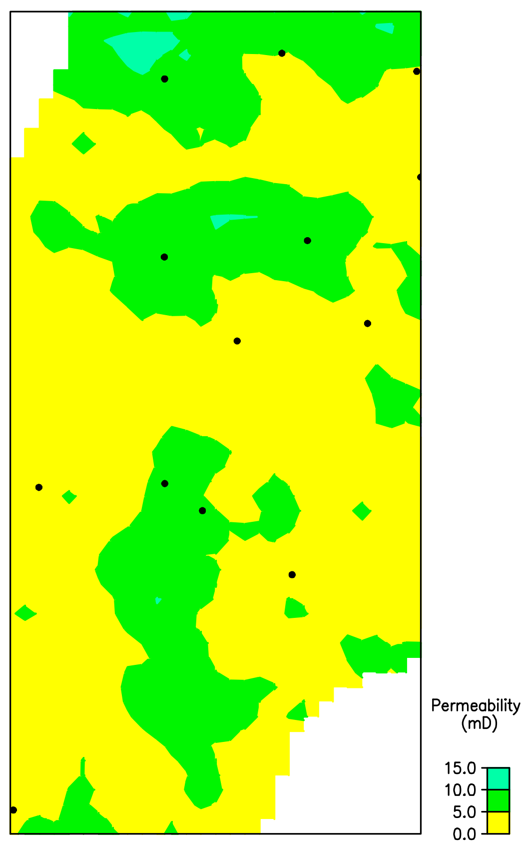


Figure 8. Conditional collocated cosimulation of average permeability, using initial potential as the secondary variable and a correlation coefficient of 0.9.