Methodology for Integrating Analog Geologic Data in 3-D Variogram Modeling[1]

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ABSTRACT

Permeability estimation in three dimensions commonly suffers from inadequate horizontal data sampling. Thus, modeling the variogram in the horizontal plane and determining anisotropy ratios in the vertical direction is associated with substantial uncertainty. This uncertainty about spatial correlation of permeability is transferred into uncertainty in reservoir performance forecasting. Analog information, such as data borrowed from more extensively sampled fields or horizontal correlation measures derived from geologic process modeling, may be used to narrow this uncertainty. We present a compilation of published results of horizontal and vertical variograms of petrophysical parameters. A stepwise procedure describing a process to establish horizontal variograms for numerical geological modeling is developed based on the distinction between three different types of anisotropy. We also emphasize the challenge of meaningful combining data of varying volume support and the need for modeling decisions.

INTRODUCTION

Because subsurface flow takes place in three-dimensional (3-D) heterogeneous strata, constructing realistic 3-D numerical geological models that include petrophysical properties such as porosity and permeability is essential in reliably predicting the performance of a reservoir. Typically, reservoir dimensions are much larger horizontally than vertically; however, the greatest detailed resolution is vertical (e.g., geophysical well logs and lab analysis of cores). These well logs and lab analysis tools provide little information in the horizontal direction except in the rare case of horizontal wells; hence, there is a fundamental challenge to infer horizontal spatial statistics from limited site-specific information. Where data are sparse, inference of horizontal variograms can be complemented by the use of analog data deemed relevant to the site being considered. Analog data may come from other, more extensively sampled reservoirs, geological process simulation, or outcrop measurements. In all cases, expert judgment is needed to integrate "global" information from analogs with sparse local data.

The issue of permeability prediction becomes further complicated because generally permeability shows different spatial statistics in the horizontal and vertical directions. Thus, this anisotropy is spatially variable. Extensive vertical information cannot be used to directly infer horizontal structure. Horizontal and vertical variograms differ with respect to the magnitude of their short-scale spatial variability.

One important goal of numerical geological models of petrophysical parameters is input to fluid-flow modeling. Ignoring permeability anisotropy commonly leads to a poor prediction of actual flow.

In this paper, we address the problem of 3-D variogram inference and the consequence of having data with good vertical resolution but limited horizontal extent. After a short review of fundamental geostatistical definitions and variogram modeling practice, we present published data on vertical and horizontal correlation length of petrophysical parameters. Alternative methods to aid the modeling of the horizontal variogram are presented along with their limitations. Finally, to determine a 3-D variogram model, a stepwise procedure is presented. An appendix includes definitions of terms used in this paper.

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METHODOLOGY OF VARIOGRAM MODELING: A SHORT REVIEW

Geostatistical reservoir modeling focuses on layer- and lithofacies-specific data. The layers commonly are chosen to separate strata controlled by different geological processes, which result in different lithofacies, e.g., porous and permeable channel sandstones, lesser quality crevasse sandstones, and impermeable floodplain shales. Geostatistical techniques to model the spatial distribution of lithofacies can be subdivided into cell-based methods and object-based techniques. Within the cell or indicator methods the lithofacies are transformed to an indicator variable that is assigned the value 1 if a lithofacies is present at a given location and 0 otherwise. The subsurface architecture is then built by geostatistical modeling of such indicator variables. A more thorough discussion of cell-based methods can be found in Deutsch and Journel (1997) or Gomez-Hernandez and Srivastava (1989). The object-based modeling approach consists of establishing the spatial distribution of geo-objects (such as abandoned sand-filled channels, deltaic fans, or eolian sands) that are defined by geometric parameters, such as curvature or thickness. The geo-objects can be conditioned to well observations and sequence-stratigraphic interpretations. Tyler et al. (1992) and Deutsch and Wang (1996) provided a more complete discussion of object-based modeling.

Petrophysical parameters, including porosity and permeability, have to be assigned within each lithofacies. These parameters are modeled as continuous variables with the variogram describing their spatial distribution. The variogram is a geostatistical tool that relates geological variability to physical distance in the reservoir. The variogram for variable $z(\mathbf{u})$, where $\mathbf{u}$ is the location coordinate vector, is defined as

$$2\gamma(\mathbf{h}) = \left\{\left[Z(\mathbf{u}) - Z(\mathbf{u}+\mathbf{h})\right]^2\right\} \qquad (1)$$

for lag separation vector $\mathbf{h}$. The variogram is estimated by

$$2\gamma(\mathbf{h}) = \frac{1}{N(\mathbf{h})} \sum_{\alpha=1}^{N(\mathbf{h})} \left[z(\mathbf{u}_\alpha) - z(\mathbf{u}_\alpha+\mathbf{h})\right]^2 \qquad (2)$$

where $z(\mathbf{u}_\alpha)$ is a measured datum at location $\mathbf{u}_\alpha$, $\alpha = 1,\ldots,n$ indicating the n individual measurements. $N(\mathbf{h})$ denotes the number of pairs of data locations approximately a distance vector $\mathbf{h}$ apart.

EXPERIMENTAL CALCULATIONS

The calculation of the experimental variogram involves a series of decisions with respect to direction, lag increment, and their respective tolerances. The omnidirectional horizontal variogram provides a robust measure for initial data analysis. Depending on the characteristics of the omnidirectional variogram and the availability of data, directional variograms can be calculated. Usually, geological information will assist in determining the direction of maximum spatial continuity. Pooling together data with a large angular tolerance unfortunately reduces the distinction between the greatest and least continuous directions and hence reduces the anisotropy.

An experimental variogram typically can be described by three characteristic parameters: nugget, sill, and range (Figure 1). The range is defined as the distance at which the average squared difference between pairs of data values reaches the variance of the data. No spatial correlation exists between data points farther apart than the range. The plateau of $\gamma(\mathbf{h})$ values the variogram reaches at the range is called the sill and corresponds to the variance of the sampled data. The term "nugget effect" is used to describe the discontinuity at the origin of the variogram. The nugget effect describes the geological variability at scales smaller than the closest data spacing.

The lag separation vectors chosen depend on the number and spatial distribution of the data. The number of data pairs within a lag class (a pool of data pairs grouped together because of their similar separation vectors) should be of comparable magnitude within different classes. A typical choice for the lag tolerance is one-half the lag distance between two neighboring classes. When variograms do not result in interpretable shapes, alternative measures to describe spatial continuity exist: correlogram, covariance function, and several types of relative variograms. A detailed description of these functions can be found in Deutsch and Journel (1997) and Goovaerts (1997).

GEOMETRIC AND ZONAL ANISOTROPY

A variable is defined as anisotropic when its pattern of spatial variability changes with direction. By knowledge of the geological process or by experimental variogram calculations, the direction of greatest continuity (typically in the horizontal plane) may be determined. This direction is referred to as the major axis. The direction with the least continuity is called the minor axis. An anisotropy factor can be defined as the ratio of the range in the major and minor direction.

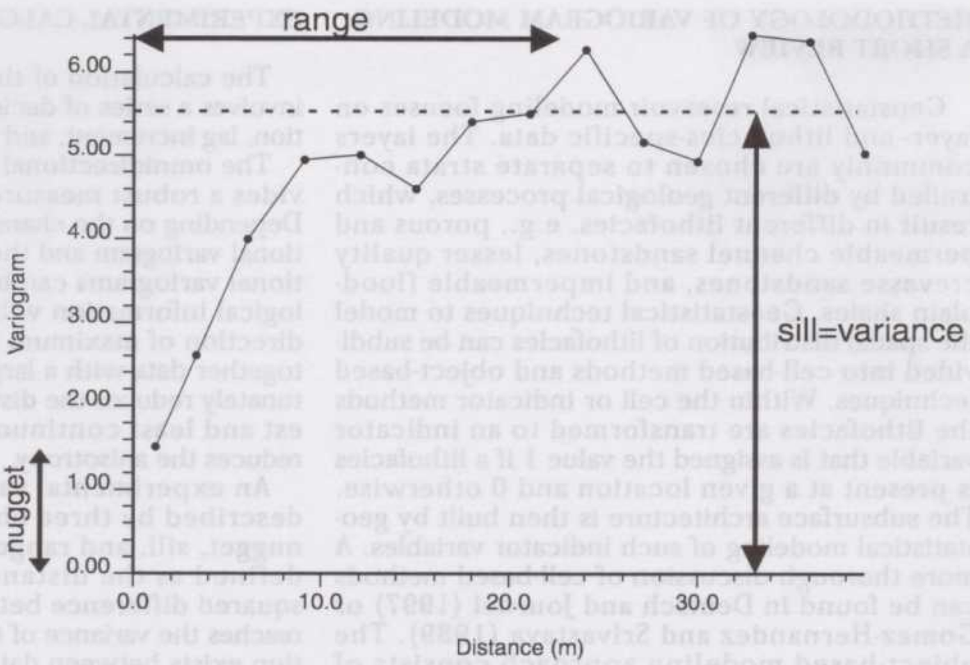

Figure 1—Typical shape of an experimental variogram (horizontal direction) and the parameters describing it.

Two basic types of anisotropy can be distinguished. Anisotropy is geometric when the directional variograms show the same shape and sill, but different range values. Figure 2A shows horizontal and vertical variograms with geometric anisotropy; the variograms reach the same sill, but the range in the vertical direction is 1/20 of the range in the horizontal direction.

In the case of zonal anisotropy, both sill and range values change with direction. Figure 2B and C shows two typical cases of zonal anisotropy.

In Figure 2B, the horizontal variogram reaches a lower sill (0.5) than the vertical variogram (sill of 1.0). The directional variogram parameters can be interpreted with various components (called nested structures) with the same sill parameters, but different correlation lengths (see the next section). The shown horizontal sill represents the variability within a single geologic stratum. The second of the nested horizontal structures cannot be seen in Figure 2B because it has a very large range beyond the distance scale. The scale of the structure indicates the variability between different geologic strata and may be related to laterally continuous sedimentary features (Anderson and Woessner, 1992).

Figure 2C portrays the influence of areal trends as the cause of zonal anisotropy. Here, the vertical variogram reaches a lower sill. Typically, the two types of zonal anisotropy can be found in any combination in the field, which complicates their identification. This entails uncertainty in interpreting those parts of the sill that can be attributed to stratification (interfacies variation), which part to areal trends, and which to the variability of the parameter under study (intrafacies variation).

VARIOGRAM MODELING

Because of the grouping of data pairs into classes of similar distances, the experimental variogram is specified only at these particular distances. To get a measure of spatial continuity for any distance, a theoretical model has to be fitted to the experimental variogram points (inference from the sample onto the entire population). This theoretical model can be any positive definite function. Positive definiteness ensures (1) existence of the solution of the kriging matrix, (2) uniqueness of the solution, and (3) that the variance of any linear combination of the data values will be positive. Various models, each describing the variable correlation for a component of the total variance, can be combined as nested structures. The most commonly used theoretical variogram models, which are known to be positive definite, are the nugget effect model (usually for a small fraction of the variance) and the spherical, exponential, Gaussian, and power models (Isaaks and Srivastava, 1989; Deutsch and Journel, 1997; Goovaerts, 1997).

ANALOG DATA FOR HORIZONTAL VARIOGRAMS

Ranges of Anistrophy: A Literature Overview

One choice to support modeling the horizontal variogram consists in looking at more extensively sampled sites that may serve as analogies to the

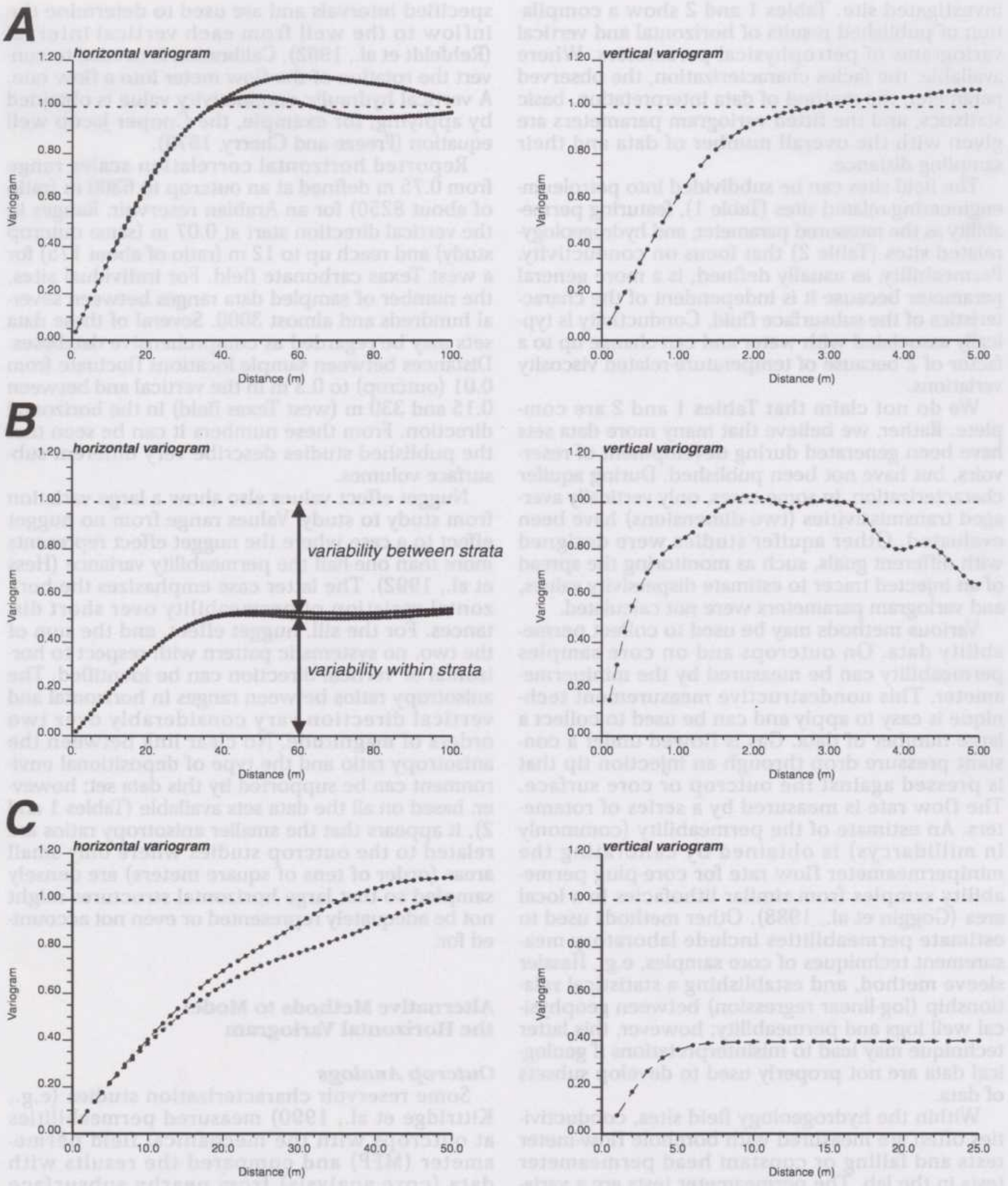

Figure 2—Horizontal (in longitudinal and transversal direction) and vertical variograms shown for three different synthetic cases of anisotropy: (A) geometric anisotropy, (B) zonal anisotropy due to stratification, and (C) zonal anisotropy due to areal trends. The *y*-axis shows standardized variogram value, and the *x*-axis shows distance in meters.

investigated site. Tables 1 and 2 show a compilation of published results of horizontal and vertical variograms of petrophysical parameters. Where available, the facies characterization, the observed parameter, the method of data interpretation, basic statistics, and the fitted variogram parameters are given with the overall number of data and their sampling distance.

The field sites can be subdivided into petroleum-engineering-related sites (Table 1), featuring permeability as the measured parameter, and hydrogeology-related sites (Table 2) that focus on conductivity. Permeability, as usually defined, is a more general parameter because it is independent of the characteristics of the subsurface fluid. Conductivity is typically associated with water and can change up to a factor of 2 because of temperature-related viscosity variations.

We do not claim that Tables 1 and 2 are complete. Rather, we believe that many more data sets have been generated during development of reservoirs, but have not been published. During aquifer characterization, in some cases, only vertically averaged transmissivities (two dimensions) have been evaluated. Other aquifer studies were designed with different goals, such as monitoring the spread of an injected tracer to estimate dispersivity values, and variogram parameters were not calculated.

Various methods may be used to collect permeability data. On outcrops and on core samples permeability can be measured by the minipermeameter. This nondestructive measurement technique is easy to apply and can be used to collect a large number of data. Gas is flowed under a constant pressure drop through an injection tip that is pressed against the outcrop or core surface. The flow rate is measured by a series of rotameters. An estimate of the permeability (commonly in millidarcys) is obtained by calibrating the minipermeameter flow rate for core-plug permeability samples from similar lithofacies in a local area (Goggin et al., 1988). Other methods used to estimate permeabilities include laboratory measurement techniques of core samples, e.g., Hassler sleeve method, and establishing a statistical relationship (log-linear regression) between geophysical well logs and permeability; however, this latter technique may lead to misinterpretations if geological data are not properly used to develop subsets of data.

Within the hydrogeology field sites, conductivities often are measured with borehole flow-meter tests and falling or constant head permeameter tests in the lab. The permeameter tests are a variation of the classical Darcy experiment with different pressure conditions at the inflow and outflow end (Freeze and Cherry, 1979). Flow-meter tests measure the vertical flow in a pumping well at specified intervals and are used to determine the inflow to the well from each vertical interval (Rehfeldt et al., 1992). Calibration is needed to convert the rotation of the flow meter into a flow rate. A vertical hydraulic conductivity value is obtained by applying, for example, the Cooper-Jacob well equation (Freeze and Cherry, 1979).

Reported horizontal correlation scales range from 0.75 m defined at an outcrop to 6300 m (ratio of about 8250) for an Arabian reservoir. Ranges in the vertical direction start at 0.07 m (same outcrop study) and reach up to 12 m (ratio of about 175) for a west Texas carbonate field. For individual sites, the number of sampled data ranges between several hundreds and almost 3000. Several of these data sets may be regarded as comprehensive databases. Distances between sample locations fluctuate from 0.01 (outcrop) to 0.3 m in the vertical and between 0.15 and 330 m (west Texas field) in the horizontal direction. From these numbers it can be seen that the published studies describe very different subsurface volumes.

Nugget effect values also show a large variation from study to study. Values range from no nugget effect to a case where the nugget effect represents more than one-half the permeability variance (Hess et al., 1992). The latter case emphasizes the horizontal variation of permeability over short distances. For the sill, nugget effect, and the sum of the two, no systematic pattern with respect to horizontal or vertical direction can be identified. The anisotropy ratios between ranges in horizontal and vertical direction vary considerably over two orders of magnitude. No clear link between the anisotropy ratio and the type of depositional environment can be supported by this data set; however, based on all the data sets available (Tables 1 and 2), it appears that the smaller anisotropy ratios are related to the outcrop studies where only small areas (order of tens of square meters) are densely sampled so that large horizontal structures might not be adequately represented or even not accounted for.

Alternative Methods to Model the Horizontal Variogram

Outcrop Analogs

Some reservoir characterization studies (e.g., Kittridge et al., 1990) measured permeabilities at outcrops with the mechanical field permeameter (MFP) and compared the results with data (core analysis) from nearby subsurface reservoirs. The underlying idea of such analog studies is that the lithofacies are similar to those in the subsurface reservoirs, but the outcrops are much easier to access. Tomutsa et al. (1986)

concluded that the variance and correlation structure may be preserved but that a considerable decrease in the mean permeability of individual lithofacies from outcrop to subsurface is expected (see Table 1 for figures). In such cases, horizontal variograms derived from outcrop measurements may give some indication of the range, but not of the sill of subsurface horizontal variograms.

Horizontal Correlation Measures from the Geological Process Model SEDSIM

Geological-based process models simulate physical processes—such as sediment transport, deposition, and erosion—that induce subsurface structure over the time scale in which a reservoir evolved. Thus, the general character of reservoir heterogeneity can be inferred from limited well data (Davis et al. 1992; Webb, 1992). Essential features, such as the existence of preferential flow paths within the subsurface, may be revealed (Anderson, 1989). Geological process models are constrained by the geological variables that create the stratigraphic record, e.g., amount and type of sediment supply. Even if the observed location and geometry of facies units cannot be reproduced exactly with a geological process model, the continuous estimation of materials deposited within the flow system simplifies identifying those facies distributions that most affect subsurface flow (Ritzi and Dominic, 1993).

In the sedimentary simulation program SEDSIM®, the flow of water and the transport, erosion, and deposition of sediments is described by the Navier-Stokes equation for flow in open channels and the continuity equations for transported sediments and fluid mass. This set of equations is formulated in a Lagrangian framework and solved sequentially and explicitly for velocity, water depth, and sediment load. Water and sediment volumes are divided into fluid elements of finite volume that are tracked over a fixed grid. To fully describe sediment transport, deposition and erosion threshold conditions for sediment movement and sediment transport based on empirical relations (Meyer-Peter and Muller, 1948; Shields, 1936) are applied. Transfer of sediment between the overlying water column and the bed immediately beneath the water column is a function of flow conditions, the amount and type of sediment load, and composition of the bed.

The sedimentary process model SEDSIM (Tetzlaff and Harbaugh, 1989) has been successfully applied in nearshore marine environments to describe hydraulic conductivity fields of aquifers (Koltermann, 1993; K. Tuttle and J. Wendebourg, 1996, personal communication). Our paper presents SEDSIM results for two different geological environments. Figure 3 shows horizontal and vertical variograms of conductivities and permeabilities. These values have been statistically inferred from simulated grain-size distributions based on correlations between measured conductivities (and permeabilities) and grain-size distributions at common data locations. The geologic environments comprise the upper Drau valley in Austria (Figure 3) as a braided alpine river (unpublished data) and the Pleistocene Tulare Formation at South Belridge field (western San Joaquin basin, California) interpreted as a progradational fluvial-deltaic sequence (Wendebourg, 1994).

For the braided river case (Drau valley, Figure 3) it can be seen that in the horizontal direction a high nugget effect exists and that the variogram does not reach a sill, but continuously increases for the indicated distances between data pairs. This feature, although ambiguous, can be interpreted as a long-range horizontal structure. The horizontal variogram of the deltaic sequence (Belridge field, Figure 3) shows similar characteristics.

The differences in the vertical variograms for the two cases can be explained by the differences in the geologic environments. The deltaic setting displays an inferred nested zigzag structure that can be interpreted as a vertically layered structure. In contrast, the high-energy braided river environment is inferred to result in a smoother vertical variogram with a range of about 6 m and a Gaussian-type shape.

For both case studies the general geological character of their subsurface formation can be quantified in terms of variogram parameters. Because these parameters are based on the modeling of geologic processes, they provide valuable information to support the characterization of a reservoir given only sparse direct permeability data.

LIMITATIONS OF USING ANALOG DATA

Given the sparsity of permeability measurements in the horizontal direction, we must use analog (inferred or borrowed) information to supplement the estimation of permeability distributions; however, some limitations of using analog data have to be recognized.

Permeabilities may have been calculated using a number of different measurement devices and a varying density of samples. Core analysis data represent only a small volume (on the order of cubic centimeters) that can be regarded as a point value with respect to the dimensions of a reservoir, whereas single or multiple well tests might sample volumes on the order of 100 m^3. Integration of data of the same parameter obtained using different measurement techniques into one variogram is not a straightforward task. Downscaling or upscaling

Table 1. Horizontal and Vertical Variograms of Petrophysical Parameters for Petroleum Engineering Sites Investigating Permeability

Reference	Facies Characterization	Parameter Observed	Measurement Technique	Mean*	Variance, cv**	Type of Variogram	Nugget (md²)	Sill (md²)	Range	Ratio of Correl.	Sampling Interval
Benkendorfer et al. (1995)	Limestone	Perm. (large scale)	Open-hole flow meter	(log d) 0.67	(log d) 1.12	Horiz.		0.897	6300 m†		(918 data)
						Vert.		0.89	42.0 m†	150.0	
Chu et al. (1991)	Alternating dolomites & sandstone	Perm.	Well log	5.78	149.0	Horiz.	Impossible to model	100	2100 m		(1705 data) 330 m
						Vert.	20†	60† 90†	3.6 m 12 m	175.0	
Dimitrakopoulos and Desbarats (1993)	Sandstone	Perm.	Core measurements	(log md) 1.39	(log md) 4.04	Horiz.	0.0	4.0	900 m		(587 data)
						Vert.	0.0	4.0	6 m	150.0	
Fogg et al. (1991)	Dolomitic carbonate rocks deposited in subtidal environment	Perm.	Core measurements in lab; wireline geophysical log data			Horiz. (high perm.)		1.2	600 m		300 m
						Vert. (thick beds)		1.3†	3.8 m	151.9	
						Horiz.		1.2	300 m		
						Vert. (thin beds)		0.4†	1.5 m	200.0	0.3 m
Goggin et al. (1988)	Eolian sandstone; highly ordered heterogeneity	Perm.	MFP§	20.8 L/min	56.2 (var) 0.36 (cv)	Horiz.	8.0	44.0	14 m		(200 data) ~30 m
						Vert.	15.0	37.0	10 m	1.4	
Goggin et al. (1992)	Sandstone (eolian formation)	Perm.	MFP§	5.82 μm²	0.6 (cv)	Horiz.	17% of sill		4.5 m		(100 data) 0.25 m
				4.25 μm²	0.55 (cv)	Vert.	0.5 (25%)	1.19	1.55 m	2.90	0.01 m
Kittridge et al. (1990)	Outcrop of grainstone, dolomite	Perm.	MFP§	22.2 md	1820 md²	Horiz.	0.5††	0.93††	0.75 m††		(15 data) 0.15 m
				48.7 md	2440 md²	Horiz.	2.5††	8.0††	0.07 m††		0.01 m
				33.9 md	9160 md²	Vert.	0.28	1.32	3.3 m	0.23	0.05 m
	Subsurface of dolomitized packstone and sandstone	Perm.	Whole core			Horiz.	0.16††	0.16††	2.6 m††		(167 data) 0.3 m
						Vert.	0.24	0.24	2.7 m	0.94	(165 data)
						Horiz.	0.22††	0.16††	3.5 m††		(122 data)
						Vert.	0.38	0.19	3.0 m	1.15	(122 data)

Table 1. Continued.

Reference	Facies Characterization	Parameter Observed	Measurement Technique	Mean*	Variance, cv**	Type of Variogram	Nugget (md^2)	Sill (md^2)	Range	Ratio of Correl.	Sampling Interval
Lund et al. (1995)	(Muddy) sandstone	Perm. & gamma ray	Portable probe permeameter, gamma-ray spectrometer	535 md	0.225 (cv)	A: horiz.	0.02†	0.02†	3.0 m†		(242 data) 0.4 m
				71.2 md	1.776 (cv)	a: vert.	1.3†	(trend) 1.9†	5.4 m†	0.56	(169 data) 0.9 m
				532.5 md	0.36 (cv)	c: horiz.	0.02†	(trend) 0.1†	9.0 m†		(297 data) 0.4 m
				225.3 md	0.97 (cv)	c: vert.	0.25†	0.7†	2.1 m†	4.3	0.9 m
Senger et al. (1992)	Outcrop; carbonate ramp deposit; tight mudstone & wackestone beds	Perm.	MFP§	Facies dependent; bar facies 1.1 log (md)		Horiz. short range	0.35 md^2	0.12†	9.0 m	10.0	(1584 data) 1.5 m
						Horiz. long range	0.35†	0.2†	120 m	133.0	7.5–90 m
						Vert.	0.15 md^2	0.25	0.9 m		
Stalkup (1986)	Sandstone of fluvial & shallow-marine origin	Perm.				Horiz.	0.5	(d^2) 0.4 1.0	(trend) 1.8 m 7.2 m		0.6–1.2 m
						Vert.			Erratic		0.3 m
		Perm.	Air driven core tool	850 md	340 md (sd)	Horiz.	0.025	0.1	4.5 m		
						Vert.	0.07	(d^2) 0.06	1.2 m	3.75	
Tyler et al. (1991)	Outcrop of fluvial sandstone; contorted bedding	Perm.	Mini-permeameter	88 md		Horiz.	24.0	8.0	1.2 m		0.6 m
				145 md		Horiz.	13.0	16.3	3.6 m		0.6 m
				308 md		Horiz.	33.0	42.0	5.5 m		0.6 m
						Vert.			0.6 m	5.7	

*Arithmetic mean if not noted otherwise.
**cv = coefficient of variation, sd = standard deviation.
†Variogram parameters measured by hand from printed variogram.
††Measurements in two perpendicular horizontal directions have been available; displayed values represent the arithmetic average.
§Mechanical field permeameter.

Table 2. Horizontal and Vertical Variograms of Petrophysical Parameters for Hydrogeology Sites Investigating Conductivity

Reference	Facies Characterization	Parameter Observed	Measurement Technique	Mean*	Variance, cv**	Type of Variogram	Nugget	Sill	Range	Ratio of Correl.	Sampling Interval
Byers and Stephens (1983)	Torrifluvent with channel deposit features	Conductivity	Metal ring sampler	0.0019 cm/s (0.018)	0.00014 cm/s (0.00005)	Two horiz. transects (1 d) cm/s	Auto-correlation (ln space)	0.275	1.8 m		(200 data) 15 cm
				0.0013 cm/s	0.00008 cm/s	Vertical transect (1 d)	Auto-correlation (ln space)		~0.75 m	2.5	(71 data) 7 cm
Hess et al. (1992); Eggleston et al. (1996)	Sand & gravel aquifer	Conductivity	Flow-meter; (perm. analysis of cores)	(geom.) 0.11 cm/s	0.24	Isotropic horiz.	0.13	0.11	24.24 m		(668 data) vert.: 15 cm, horiz.: 0.9–24 m
						Vert.	0.13	0.11	1.14 m	21.3	
Hufschmied (1986) cited in Hess et al. (1992)	Alpine fluvial deposit	Conductivity	Single-well pump test & flow-meter	0.36 cm/s (geom.)	2.15 cm/s (ln space)	Horiz.			15–20 m (correlation scales)		
						Vert.			0.05–0.06 m	318.0	
Rehfeldt et al. (1992)	Heterogeneous alluvial aquifer (deposited by meandering stream)	Conductivity	Borehole flow-meter	Facies dependent at 0.0054 cm/s	ln (k) 4.5	Horiz.	0.0	4.5	38.4 m		(2187 data) ~10 m
						Vert.	0.0	4.5	4.8 m	8.0	15.24 cm
Schad and Teutsch (1990)	Braided river environment (poorly sorted sand & gravel)	Conductivity	(Permeameter) sieve analysis	(Geom.) 0.052 cm/s	0.097 cm^2/s	Horizontal			(erratic) ~10 m		(200 data)
						Vertical			0.30 m	33.3	0.05–0.25 m

Table 2. Continued.

Reference	Facies Characterization	Parameter Observed	Measurement Technique	Mean*	Variance, cv**	Type of Variogram	Nugget	Sill	Range	Ratio of Correl.	Sampling Interval
Schafmeister and Pekdeger (1992)	Alternating layers & lenses of fine & medium sands	Conductivity	Grain size analysis	0.034 cm/s	0.04 (cv)	Horiz.	0.025	0.115	14 m		2.5 m
						Vertical	0.025	0.115	1.5 m†	9.33	0.25–0.5 m
				0.062 cm/s	0.05 (cv)	Horizontal	0.0	0.186	1 m		(216 data) 0.1 m
						Vertical	0.1	0.086	0.25 m	4.0	
Smith (1981)	Pleistocene Quadra Sand	Conductivity		0.055 cm/s	0.01 (sd)	Horiz. line (1d)	Auto-correlation		1.8 m		(100 data) 0.3 m
				0.044 cm/s	0.022 (sd)	Vert. line (1d)	Auto-correlation		0.6 m	3.0	(100 data) 0.3 m
				0.052 cm/s	0.016 cm/s	X-Z plane					(100 data)
Woodbury and Sudicky (1991); Sudicky (1986)	Sand aquifer	Conductivity	Analysis of 32 cores	(Geom.) 0.00975 cm/s	ln(k) of 0.38	AA′ horiz.	0.118	0.304	21.45 m		(800 data) 1.0 m
						AA′ vert.	0.027	0.218	0.48 m	44.69	0.05 m
						BB′ horiz.	0.097	0.17	8.37 m		(520 data) 1.0 m
						BB′ vert.	0.063	0.291	0.756 m	11.07	0.05 m

*Arithmetic mean if not noted otherwise.
**cv = coefficient of variation.
†Variogram parameters measured by hand from printed variogram.

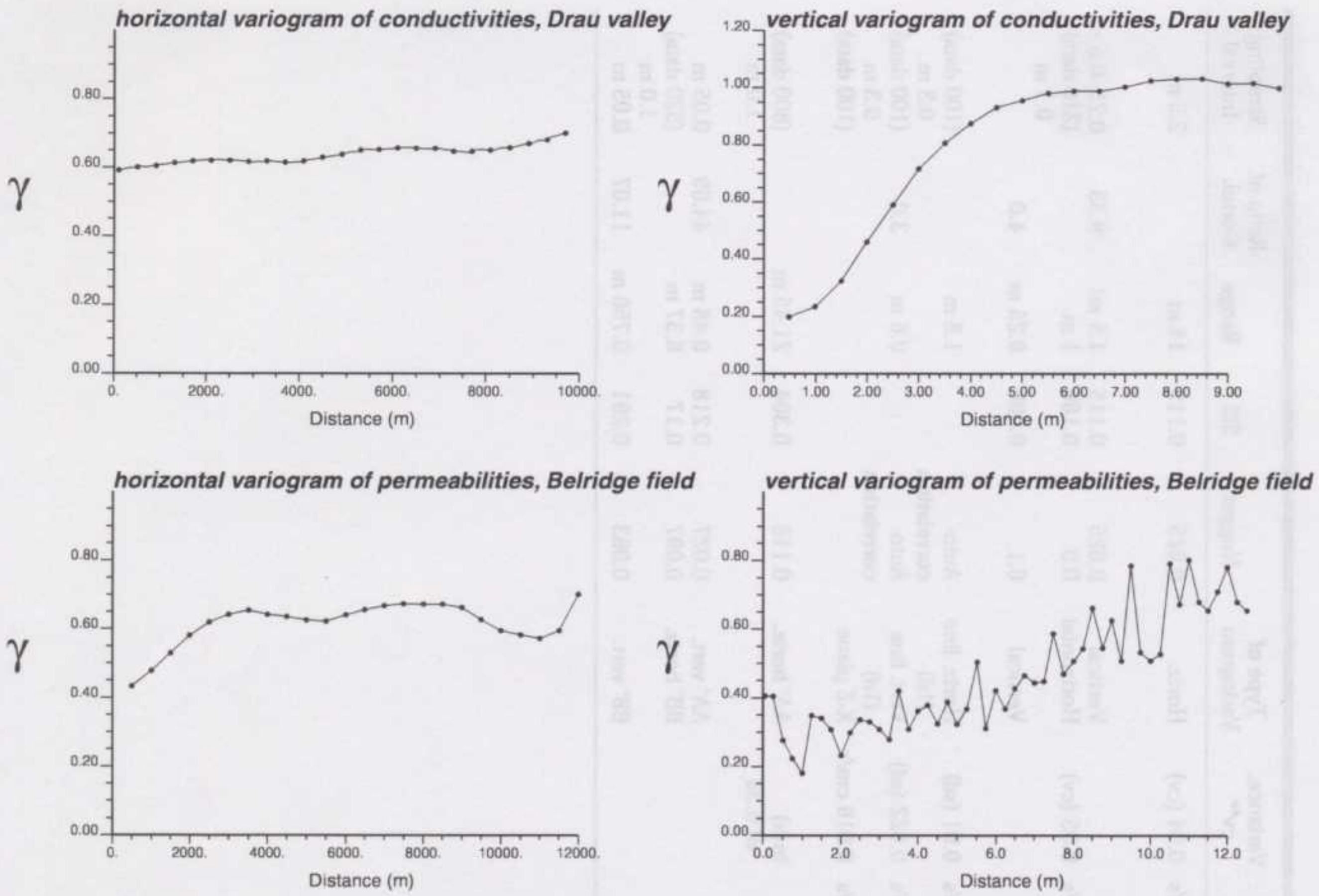

Figure 3—Experimental horizontal variograms (left column) and vertical variograms (right column) derived from SEDSIM simulations. At the top are conductivities in the upper Drau valley, Austria. (Bottom) Permeabilities in the Belridge field, California. The y-axis shows standardized variogram value, and the x-axis shows distance in meters.

techniques, depending on the particular situation, may have to be applied, which will result in different (with respect to the measured data) representative values due to inherent assumptions. A more thorough discussion of this issue is beyond the scope of this paper.

The size of the sampled area influences the correlation scale in the sense that the sampled area might actually be too small to capture a large-range structure. The issue of scale dependence of the correlation length is discussed in more detail by Schafmeister and Pekdeger (1992) and Gelhar (1986), who showed that the correlation length increases with increasing scale of the investigated area. In agreement with Gelhar's (1986) discussion, it can be inferred from Tables 1 and 2 that the correlation length is not an absolute property of the subsurface, but that it is related to the size of the investigated area. Because the horizontal correlation length is an integral part of the anisotropy ratio we also see that larger model scales lead to increased anisotropy. Generally, comparing modeled correlation scales and ranges of anisotropy has to be done with caution.

Transferring results from a more detailed sampled field has to be done on a site-specific basis because of the influence of different local geological environments. No correlation between the geologic environments and the anisotropy ratios could be established from data presented in Tables 1 and 2. Thus, better sampled fields, which seem comparable, should be used only as guidelines to limit variogram parameters for the study site instead of using the same variogram parameters from the better sampled field. Lowry and Raheim (1991) gave an illustrative example with data collected within a fluvial delta setting. They provided descriptive statistics (mean, standard deviation, minimum, and maximum data values) that could be used to infer ranges of corresponding variogram parameters for distributary mouth-bar sandstone bodies.

The geological process-modeling case studies applying SEDSIM show that the general character of the geologic environment can be reproduced, but that these studies lack local precision. Part of the reason for this imprecision may lie in the fact that the assumptions within SEDSIM do not fully apply to the individual study area.

If geophysical measurements such as seismic impedance are used to infer permeability, a number of additional problems arise that make their application strongly subjective (e.g., nonunique relation, low correlation). Establishing a correlation at one site might not be applicable at a different field site. In general, the successful integration of additional information (i.e., geophysical measurements) into the estimation of permeability distributions can be documented only by comparing measured parameters with values simulated by a numerical flow model.

Increasingly, wells are being drilled horizontally with the goal of improving well productivity. The analysis of a pump test in a horizontal well requires model assumptions that entail substantial uncertainty (e.g., Horne, 1995) mainly due to the definition of the influenced area. Cores with horizontal spacing are normally not taken and only limited geophysical logs are available; furthermore, horizontal wells are rarely truly horizontal, that is, they do not follow the stratigraphic horizons. Thus, despite their information potential, their benefit for horizontal variogram modeling has yet to be demonstrated.

STEPWISE 3-D VARIOGRAM DETERMINATION

Figure 4 summarizes the process of determining a 3-D variogram model. At the beginning of the process of determining a 3-D variogram model, summary statistics, such as the mean and variance, are used to characterize the data set. A more comprehensive picture of the data set is obtained by the histogram (Figure 4A) or the cumulative frequency distribution. These two measures may reveal outliers or the dominance of a particular range of values that can determine the proceeding data analysis. For example, outliers may lead to noisy variograms that are hard to interpret. Those values need to be treated consistently throughout the data analysis.

Depending on this prior data analysis, geologic knowledge, and the goal of the reservoir characterization, one has to choose a modeling approach, that is, continuous or categorical variable and object-based or cell-based approach. Basic considerations are whether the variable of interest can be treated as a continuous parameter or whether geologic evidence suggests that there are several lithofacies types with distinct petrophysical properties whose shapes and distributions should be modeled first. Is the existence of flow barriers or flow paths of primary concern? The following discussion assumes that the variable of interest can be modeled as a continuous parameter, that is, the lithofacies are of minor importance or have already been determined.

Because of data availability, it is a convenient and common practice to first calculate the vertical variogram (Figure 4B). Transforming the data to a standardized normal distribution (i.e., zero mean and unit variance) simplifies data handling and eases comparison to different data sets. A conceptual geologic model of the study area is necessary to meaningfully interpret the vertical variogram. For example, the vertical variogram may not reach the unit sill, which can be related to areal trends of the investigated variable, or the vertical variogram may depict nested structures indicating geologic processes at different scales.

Given that horizontal variogram parameters most often have to be inferred from variogram values at only a few distance classes, geological principles may provide valuable guidance to model the horizontal variogram. At times, geologic field-work interpretations may suggest that stratification (interfacies variation) constitutes a major feature of the reservoir and an appropriate anisotropy model should be adopted. Figure 4 provides an overview of the principal shape of the horizontal and vertical variogram presumed for different cases of anisotropy. Three different types of anisotropy are illustrated: (1) zonal anisotropy due to areal trends (Figure 4C), (2) zonal anisotropy due to stratification (Figure 4D) and (3) geometric anisotropy (Figure 4E). Each case corresponds to a different geological interpretation. One must decide on the anisotropy model that best fits all the available information.

The lack of data in the horizontal direction commonly requires a large search angle to calculate the horizontal variogram. This causes the directional ranges to be blurred and leads to computed anisotropy ratios that are not representative of the anisotropy of the underlying phenomenon; consequently, relevant additional information has to be looked for to complement the available horizontal data. For instance, analog information, such as outcrop data or results from geologic process simulation of the investigated region, can be used as qualitative data to aid computation of the variogram.

Thus, the horizontal variogram is subject not only to observed data but also to decisions by the modeler about the integration of the additional data. Those decisions need to be clearly documented and checked to ensure that the original data are still honored; furthermore, the decisions must be consistent throughout the modeling process.

This effort of searching for additional relevant information is justified, compared to the alternative

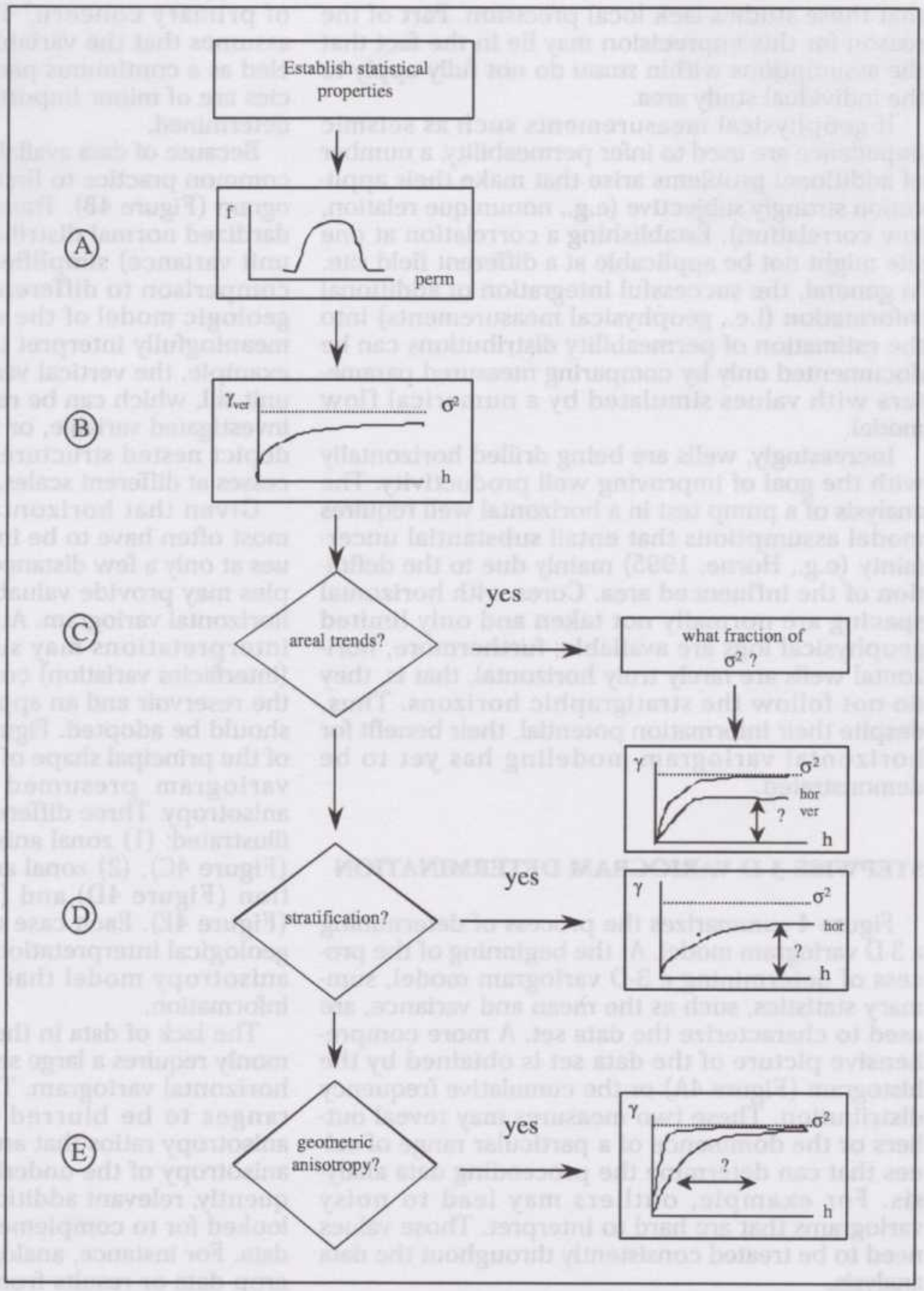

Figure 4—Flow chart displaying the choices in determining the three-dimensional variogram model based on three different types of anisotropy. See text for discussion.

of accepting even larger uncertainty in the horizontal distribution of reservoir parameters. A sensitivity study of the obtained variogram parameters can be performed to illustrate the impact of the choices on flow modeling results. Quantifying this impact provides a sense for the importance of the variogram.

As an example consider Figure 5, which shows eight vertical variograms of measured porosities in different stratigraphic intervals of the same fluvio-deltaic reservoir. These variograms are of the standardized (normal score transform) data; the histogram of porosity is different in each stratigraphic layer. The variograms show different features: (1) layers 1 and 8 show evidence of cyclicity; (2) layers 2 and 7 show evidence of a vertical trend; (3) layers 3, 5, and 6 show evidence of areal variations in average porosity; and (4) layer 4 shows nothing remarkable.

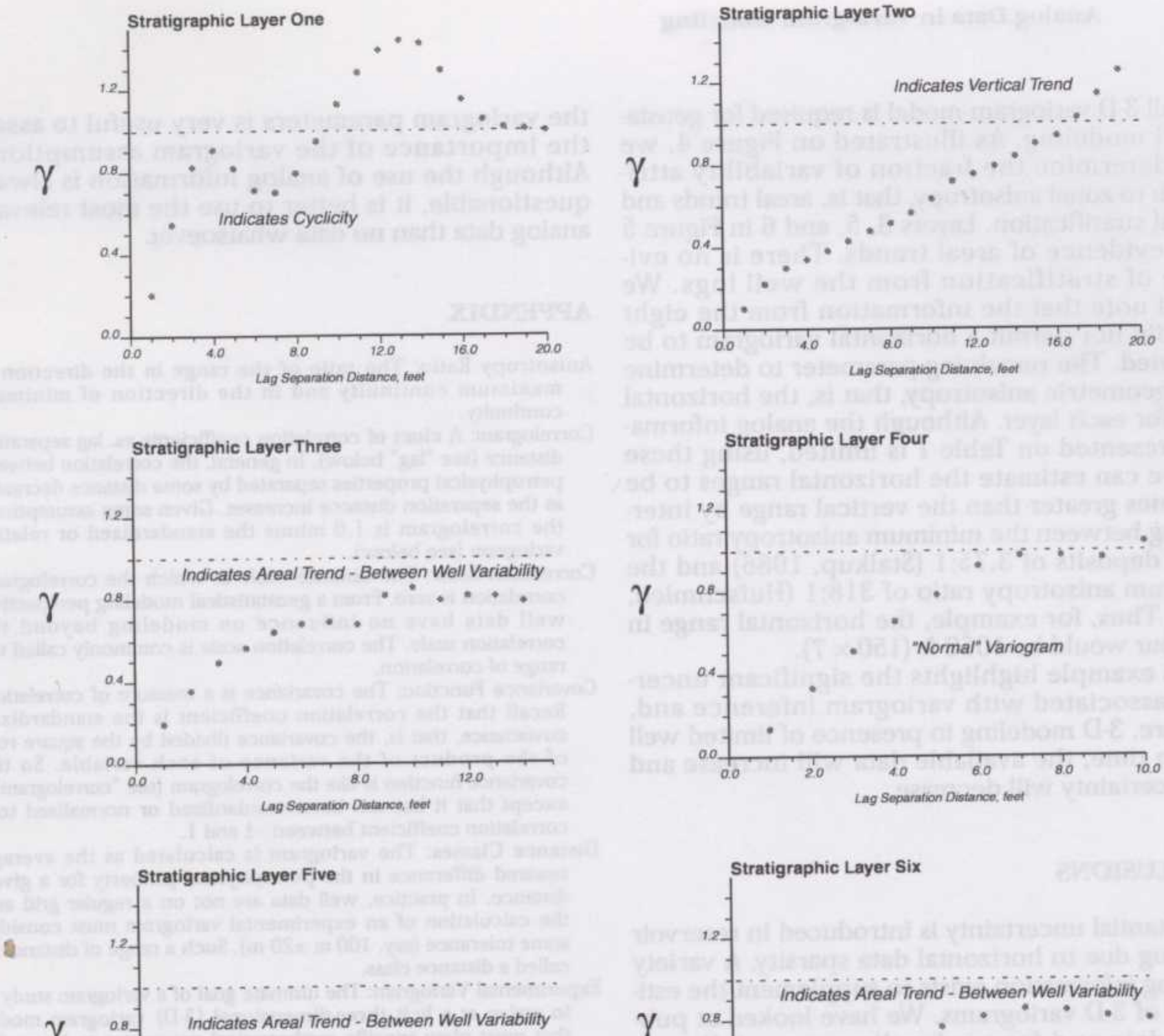

Figure 5—Eight vertical variograms in eight different stratigraphic intervals of the same fluvio-deltaic reservoir. See text for discussion.

A full 3-D variogram model is required for geostatistical modeling. As illustrated on Figure 4, we must determine the fraction of variability attributable to zonal anisotropy, that is, areal trends and vertical stratification. Layers 3, 5, and 6 in Figure 5 show evidence of areal trends. There is no evidence of stratification from the well logs. We should note that the information from the eight wells did not permit a horizontal variogram to be calculated. The remaining parameter to determine is the geometric anisotropy, that is, the horizontal range for each layer. Although the analog information presented on Table 1 is limited, using these data we can estimate the horizontal ranges to be 150 times greater than the vertical range by interpolating between the minimum anisotropy ratio for fluvial deposits of 3.75:1 (Stalkup, 1986) and the maximum anisotropy ratio of 318:1 (Hufschmied, 1986). Thus, for example, the horizontal range in layer four would be 1050 ft (150×7).

This example highlights the significant uncertainty associated with variogram inference and, therefore, 3-D modeling in presence of limited well data. In time, the available data will increase and this uncertainty will decrease.

CONCLUSIONS

Substantial uncertainty is introduced in reservoir modeling due to horizontal data sparsity. A variety of analog information exists to supplement the estimation of 3-D variograms. We have looked at published data and forward sediment modeling as sources of analog data. Analog information may range from minipermeameter measurements in a related outcrop (centimeter spacing) to geological process modeling addressing general geological characteristics. Horizontal wells, unavailable for this study, promise to provide valuable additional information in the future. Analog information can be used to infer bounds for variogram parameters or as supplementary data when too few measurements are available. The major challenges exist in meaningful combining data of varying volume support representing different subsurface features.

To account for anisotropy between the horizontal and vertical correlation structure of a reservoir three different types of anisotropy can be considered, each referring to a different conceptual geologic model: (1) zonal anisotropy due to stratification, (2) zonal anisotropy due to areal trends, and (3) geometric anisotropy. For each type of anisotropy, the relation between sills and correlation lengths differ with changing direction. Thus, modeling the horizontal variogram relies not only on data but also on a series of decisions that have to be consistently followed. A sensitivity analysis of the variogram parameters is very useful to assess the importance of the variogram assumptions. Although the use of analog information is always questionable, it is better to use the most relevant analog data than no data whatsoever.

APPENDIX

Anisotropy Ratio: The ratio of the range in the direction of maximum continuity and in the direction of minimum continuity.

Correlogram: A chart of correlation coefficients vs. lag separation distance (see "lag" below). In general, the correlation between petrophysical properties separated by some distance decreases as the separation distance increases. Given some assumptions, the correlogram is 1.0 minus the standardized or relative variogram (see below).

Correlation Scale: The distance scale at which the correlogram/correlation is zero. From a geostatistical modeling perspective, well data have no influence on modeling beyond the correlation scale. The correlation scale is commonly called the range of correlation.

Covariance Function: The covariance is a measure of correlation. Recall that the correlation coefficient is the standardized coviariance, that is, the covariance divided by the square root of the product of the variance of each variable. So the covariance function is like the correlogram (see "correlogram"), except that it has not been standardized or normalized to a correlation coefficient between −1 and 1.

Distance Classes: The variogram is calculated as the average squared difference in the petrophysical property for a given distance. In practice, well data are not on a regular grid and the calculation of an experimental variogram must consider some tolerance (say, 100 m ±20 m). Such a range of distance is called a distance class.

Experimental Variogram: The ultimate goal of a variogram study is to arrive at a licit three-dimensional (3-D) variogram model that must obey specific mathematical properties to be useful in further studies. Experimental variogram points for specific distance classes (see "distance classes") are calculated from the available well data before fitting such 3-D variogram models. They are called experimental in the sense that they precede the determination of an ultimate variogram model.

Facies: In this paper, facies simply may be considered as different rock types or groupings of data that share certain properties. For example, limestone and dolomite would be considered two different facies. A variogram study would have to be conducted within each significant facies.

$\gamma(\mathbf{h})$ or gamma($\mathbf{h}$): See the text for a formal definition of the variogram. We should note that $\gamma(\mathbf{h})$ is technically the semivariogram, whereas $2\gamma(\mathbf{h})$ is the variogram.

Gaussian Variogram: Depending on the context there can be two meanings: (1) a continuous petrophysical property such as porosity or permeability commonly is transformed to a Gaussian or normal distribution prior to variogram calculation; the experimental variogram in this case is sometimes referred to as a Gaussian variogram or (2) more commonly, there is an analytical function that is used to fit experimental variograms known as a Gaussian variogram model. This analytical function is called Gaussian because it has an "exponential-squared" term, which is the same as the Gaussian probability distribution.

Lag Increments: When the experimental variogram is calculated, the data pairs are grouped into classes of similar distances. Any of these classes is also called a lag, and the difference between the average distance of the data pairs in one class and the average distance of the data pairs in the subsequent class is referred to as the lag increment.

Lag Separation Vector: The vector that describes the change of direction and average distance between one lag and the subsequent lag is called a lag separation vector.

Lag Tolerance: To rigorously define a distance class, the two parameters lag increment and lag tolerance are used. If the distance of a data pair falls into the distance range described by the lag increment plus or minus the lag tolerance, the data pair is sorted into this distance class. The most common choice for the lag tolerance is one-half the lag increment.

Nested Structure: The experimental variogram that is defined only at discrete distances is modeled by an analytical function called the theoretical variogram. The theoretical variogram can be composed of a sequence of individual analytical functions each of which describes only the dissimilarity between data pairs within a particular distance interval. In this case, the theoretical variogram is said to have a nested structure. The term "structure" refers to each analytical subcomponent.

Normal Score Transform: The transformation of the given data so that their cumulative distribution function corresponds to a standard Gaussian cumulative distribution function with zero mean and unit variance.

Positive Definiteness: Each analytical function that can be used to model the experimental variogram has to be positive definite. Positive definiteness is a mathematical condition that ensures (1) existence of the solution of the kriging matrix, (2) uniqueness of the solution, and (3) that the variance of any linear combination of the data values will be positive.

Relative Variogram: The relative variogram measure is computed as one-half of the squared difference between two data standardized by the squared mean of the data used for the lag. This standardization distinguishes the relative from the traditional variogram (see equation 1 in the text).

Sensitivity Study: If a model consists of several parameters that need to be determined, it is useful to figure out those parameters that influence the model result the most. Typically, the parameter values are varied, and the model response is monitored. The model is most sensitive to parameters where a little change causes a significant different model result. This procedure is called a sensitivity study.

Stratification: In this paper, stratification refers to the sequence of different facies in the vertical direction. Interfacies variation, in this context, is considered as the variation of facies properties from one facies to the next facies.

Vertical Trend: A variable is said to have a vertical trend if the variation of data within a neighborhood (vertical direction) can be described as a smoothly varying function of the coordinates.

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