Geostatistical shale models for a deltaic reservoir analog: from 3D GPR data to 3D flow modeling

Hongmei Li
Louisiana State University and Agricultural and Mechanical College

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GEOSTATISTICAL SHALE MODELS FOR A DELTAIC RESERVOIR ANALOG: FROM 3D GPR DATA TO 3D FLOW MODELING

A Thesis

Submitted to the Graduate Faculty of the Louisiana State University and Agriculture and Mechanical College in partial fulfillment of the Requirements for the degree of Master of Science in Petroleum Engineering

in

The Department of Petroleum Engineering

by

Hongmei Li
B.S., Jianghan Petroleum College, 1994
M.S., University of Petroleum (Beijing), 1997
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ABSTRACT

The effects of shales on fluid flow in marine-influenced lower delta-plain distributary channel deposits are investigated using a three-dimensional ground-penetrating radar (GPR) data volume from the Cretaceous-age Ferron sandstone at Corbula Gulch in central Utah, USA. Using interpreted GPR data, we formulate a geostatistical model of the dimensions, orientations, and geometries of the internal structure from the subaerial exposure surface down to about 12 m depth. The correlation function between GPR instantaneous amplitude and shale index is built after statistical calibration of the GPR attributes (amplitude) with well data (gamma ray logs). Shale statistics are computed from this correlation function. Semivariograms of shale occurrence for ten accretion surfaces indicate only slight anisotropy in shale dimensions. Sequential Gaussian Simulation stochastically maps shales on variably dipping stratigraphic surfaces. Experimental design and flow simulations examine the effects of semivariogram range and shale fraction on breakthrough time, sweep efficiency and upscaled permeability. Approximately 150 flow simulations examine two different geologic models, flow in all three coordinate directions, 8 geostatistical parameter combinations, and 5 realizations for each combination of parameters. Analysis of the flow simulations demonstrates that shales decrease the sweep, recovery and permeability, especially in the vertical direction.
CHAPTER 1. INTRODUCTION

1.1 Problem Statement

Many oil and gas reservoirs are contained in rocks formed by ancient deltas. Deltaic reservoirs often have complex internal architecture and properties (Barton, 1994). Many investigators have shown that shale properties often play a critical role in recovery in these reservoirs. Shales are the fundamental geologic control of the delta reservoir heterogeneity. Shales have variable effects in controlling reservoir behavior (White and Barton, 1999; Willis and White, 2000; White et al., 2001). They may affect vertical permeability (Begg and King, 1985), sweep efficiency and breakthrough time (Jackson and Muggeridge, 2001), and upscaled multiphase flow properties (Narayanan, 1999). However, shale properties are rarely measured because shales are typically not reservoir rocks. In addition, it is difficult to include realistic distribution of shales in reservoir models because of the wide spacing of wells and limited vertical resolution of seismic surveys. To better characterize reservoirs with abundant shales, methods to model shale distributions will be investigated in this research.

1.2 Geostatistical Models for Shales

One approach for improved shale modeling is to characterize the shale distribution statistically based on data from shale maps from an outcrop exposure of analogous deposit. Although many researchers have taken this approach to study shale distributions (Desbarats, 1987; Geehan and Underwood, 1993; Visser and Chessa, 2000; White and Willis, 2000), none of these studies addresses shale placement in a model with complex geometry such as point bar deposits, where the shales are deposited along accretion surfaces that have variable dip. In addition, many of these studies were confined to two spatial dimensions. Novakovic
et al. (in press) built 3-D stratigraphic framework based on 3-D ground-penetration radar data, and computed the shale distribution statistically based on the outcrop data of the Ferron Sandstone for use in analogous deltaic reservoir. However, they did not investigate the correlation between the lithology and radar responses; their variograms were based on nearby cliff exposures, which are of course two-dimensional. Because radar responses are caused by the physical property contrasts between sandstone and shale, the GPR reflections may provide useful information about the shale occurrence. It could be more accurate to combine ground-penetrating data with well data to simulate shale distribution.

Three-dimensional ground-penetrating radar (GPR) data set provides a unique source to examine the effects of fine-scale geologic variability in three dimensions, because the GPR reflection geometries are caused by contrasts in stratal properties, flow paths and barrier geometries are well-preserved. GPR data has provided high-resolution 3D images of fluvial reservoirs, and can be used to improve models of deltaic reservoirs. It would be particularly useful, for example, if GPR amplitude and frequency have some correlation with shale occurrence. If we can quantify this relationship, we can calibrate the GPR attributes with well data and to perform geostatistical estimates of the shale distribution in delta reservoir. To do this, data relationships will be investigated using linear or nonlinear regression (Montgomery and Peck, 1982; Gill et al., 1981) and other statistical methods. At the same time, the interpretation of GPR data volume and outcrop data set can be used to identify and describe the stratigraphic surfaces. It also can be imported into strata-conforming reservoir simulation grids to estimate effective properties and predict recovery behavior.
The study of reservoir analogs has progressed from one to two to three-dimensional (3-D) models of depositional systems (Miall and Tyler, 1991; Flint and Bryant, 1993). The long-term goal of such studies is to build accurate 3-D models of the internal structures of reservoirs for reliable simulation of fluid flow for evaluation of production strategies (Tomutsa et al., 1991; Tyler et al., 1992; Fisher et al., 1993a, b). 3-D outcrop reservoir models can improve our abilities to estimate the properties and behavior of analogous reservoirs. 3-D model development typically requires interpolation between outcrops or wells based on geometrical or statistical descriptions of the facies (Allen, 1979; Gundeso and Egeland, 1990; Haldorsen and Damsleth, 1990; Falt et al., 1991) because direct information is not available. Reservoir analog models can be improved by direct imaging of the internal structure by ground-penetrating radar (GPR) (Baker, 1991; Gawthorpe et al., 1993; Bridge et al., 1995). Although most GPR data collected over reservoir analogs are 2-D lines (Alexander et al., 1994; Bristow, 1995; Aigner et al., 1996; Rea and Knight, 1998), a few full 3-D surveys have been acquired (Beres et al., 1995; McMechan et al, 1997). These surveys reveal the dimensions, orientations, geometries, and connectivity of the internal sedimentological elements at the scale of meters or less.

Like seismic data, GPR attributes are derived from measurements of GPR traces. Nowadays, amplitude-derived attributes are the most commonly used for constraining stochastic reservoir simulations. There are two ways to integrate the GPR data with the well data and outcrop data. One is the direct method (Xu, 1992; Zhu, 1992; Yang et al., 1995; Tjolsen et al., 1995; Johann et al., 1996, Fichtl et al., 1997). Among the techniques allowing such a direct integration of GPR data, we can list for example the external drift, cosimulation or co-kriging methods, which make it possible to introduce a secondary variable
into the estimation or simulation process of a primary variable. These methods can be applied either to continuous variables or to categorical variables as indicators. The direct integration in reservoir simulations can also be performed a posteriori using inversion or simulation processes (Haas and Dubrule, 1994). Another way to integrate the GPR in reservoir simulations is to use indirect methods. These techniques require a preliminary calibration of the GPR attributes with the parameters to be simulated. In that case the GPR attributes are converted into local means on a given support of the studied parameters. The estimation phase that integrates the GPR information is then distinct from the simulation itself, which only integrates the soft constraint derived from GPR. The choice of the simulation methods to integrate GPR information into the reservoir simulations depends strongly on the type and the distribution of the variable to be simulated and also on its relationship with GPR data. The preliminary steps of the time to depth conversion, matching the data at wells with adjacent real traces, and calibration are also crucial in the process to ensure the consistency of the results. In this paper, we will use indirect methods based on the geostatistical methods (Kriging and Sequential Gaussian Simulation). These geostatistical methods provide a tool to integrate well data and calibrate GPR data, accounting for the correlation between well data and GPR data as well as the spatial correlation of the reservoir property to be modeled.

1.3 Assessing Effects of Shales on Fluid Flow

Reservoir simulation is widely used to investigate the effects of geological heterogeneity and engineering parameter variability on reservoir production performance (Willis and White, 2000). Because many geologic and engineering factors interact to affect recovery predictions, an exhaustive examination of recovery for all possible parameter
combinations is prohibitively time-consuming and expensive. The factors that most strongly influence production behavior should be identified to focus analyses and measurements. Experimental design has been used to conduct the reservoir simulation studies, including performance prediction (Chu, 1990), uncertainty modeling (Damsleth et. al., 1992), sensitivity studies (Willis and White, 2000), upscaling (Narayanan et. al., 1999), history matching (Eide et. al., 1994) and development optimization (Dejean and Blanc, 1999). And the response surface models can be used to summarize results of designed simulation sets (Willis and White, 2000). They can estimate how varying factors affect reservoir behavior using a relatively small number of reservoir simulation models. Response surface models can statistically test the relative importance of the factors in experimental designs. In this study, we will use experimental design methods to do designed fluid flow simulation, and the response surface methods will be used to examine the effects of shale.
2.1 Site Description

The study site of the deltaic reservoir analog used in this project is located south of Interstate 70 within the outcrop belt of the Ferron sandstone along the western margin of the San Rafael Swell in central Utah, USA (Figure 2-1). The Ferron sandstone was chosen because it has been used extensively in the past for reservoir studies and for industry training classes. The Ferron sandstone has been used as an analog for fluvial-deltaic reservoirs, especially for river-dominated systems of the U.S. Gulf of Mexico including the Frio sandstone (Barton, 1994). The chosen site, Corbula Gulch, has excellent stratigraphic control, outstanding surface and cliff face exposures, and a good setting for acquisition of GPR data. At this location we have access to a mesa top with a relatively flat bedding-parallel surface, there is little vegetation to interfere with the survey lines, and the GPR survey area is adjacent to cliff exposures of the sediments. Measurements at the site provide high-resolution images with features at scales that can be extrapolated with control from 1-D and 2-D sedimentary data obtained in boreholes, cliff faces, and surface mapping into the three-dimensional survey volume.

The Ferron sandstone was deposited in the Western Interior Seaway during Late Cretaceous (Turonian) time (Armstrong, 1968). It contains the preserved deposits of rivers, deltas, lagoons, shorefaces and associated deposits including coals. The deposits are divided into seven sandstone-rich tongues, each overlain by a coal (Figure 2-2; Ryer, 1983; Gardner, 1995). The study location, Corbula Gulch, is within stratigraphic cycle 7 of Gardner (1995). At the time of deposition, the delta shoreline was 15 to 20-km northeast of the study locality. It is interpreted to be marine-influenced point-bar deposits of distributary...
channels within the lower delta plain (Corbeanu, 2001). The deposits at Corbula Gulch include trough-cross-bedded and ripple-cross laminated sandstones, sandstones, mudstones, shale clast lags, and thin mud drapes.

**Figure 2-1 Location of Corbula Gulch Study Site**

The heterogeneities most likely to affect flow in this system are thin, discontinuous shale drapes associated with accretion surfaces of the point bar deposits. The combination of outcrop exposure and the high-resolution stratigraphic framework obtained from interpretation of ground penetrating radar studies allows systematic investigation of the effects of these surfaces in three dimensions.
2.2 Data Available

2.2.1 Ground-Penetration Radar (GPR) Data

Ground-Penetration Radar is analogous to the radar used in airport to track plane. A radar system comprises a signal generator, transmitting and receiving antenna, and a receiver that may or may not have recording facilities or hardcopy graphical output (Figure 2-3). The transmitter generates a pulse of broadband electromagnetic waves at a

---

**Figure 2-2** Section illustrating Ferron Sandstone Stratigraphy

**Figure 2-3** Simplified diagram of GPR survey system
frequency determined by the characteristics of the antenna; the antenna emits these waves into ground. The waves travel through the ground at high speeds (in air 300000km/s or 0.3m/ns). When they meet an object, parts of the waves will be reflected to the surface. A receiver picks up these reflections and records the travel times and reflection amplitudes.

The electromagnetic properties of materials are related to their composition and water content, both of which exert the main control over the speed of radiowave propagation and the attenuation of electromagnetic waves in materials. The speed of radiowaves in any medium is dependent on the speed of light in free space ($c=0.3m/ns$) and the relative dielectric constant $k$ (Equ.2-1)

$$V_m = \frac{c}{\sqrt{k}}$$  \hspace{1cm} (2-1)

The relative dielectric constant $k=\varepsilon/\varepsilon_o$, where $\varepsilon$ is medium permittivity and $\varepsilon_o$ is vacuum permittivity. It is the contrast in relative dielectric constant ($k$) between adjacent layers that gives rise to reflection of incident electromagnetic radiation. The greater the contrast, the greater will be the amount of radiowave energy reflected. The proportion of energy reflected, given by the reflection coefficient ($R$) is determined by the contrast in radiowave velocities (Equ.2-2), and more fundamentally, by the contrast in the relative dielectric constants of adjacent media (Equ.2-3). As a result, if the adjacent permittivities, a reflection can occur.

$$R = \frac{(V_1 - V_2)}{(V_1 + V_2)}$$ \hspace{1cm} (2-2)

$$R = \frac{\sqrt{k_2} - \sqrt{k_1}}{\sqrt{k_2} + \sqrt{k_1}}$$ \hspace{1cm} (2-3)
**Figure 2-4** shows the relationships between radiowave velocity and pore volume filled air and water. It can be seen that the radiowave velocity decreases with increasing soil moisture content (this implies that the relative dielectric permittivity increases). Because of the lower velocity, wetter materials have a better vertical resolution than dry materials, although the attenuation in wetter materials is greater than for dry so depth penetration is likely to be smaller. For Corbula Gulch study site, previous studies have identified that shale and sandstone contain different moisture contents, which indicates that ground-penetration radar method can generate reflections, and we can use these information to study shale distribution.

![Figure 2-4 Radar velocities vs. porosity plot](image)

*Figure 2-4 Radar velocities vs. porosity plot*  
*(After Reynolds, J.M., 1997)*
The traditional methods of GPR data collection and processing are similar to single-channel seismic reflection methods. One difference between GPR data and seismic reflection data is the range of 100MHz to 1MHz compared with 10-100 Hz for seismic methods (Davis and Annan, 1989). The frequency is inversely proportional to the pulse period. And the wavelength ($\lambda$) of the pulse is the product of the pulse period and the radiowave velocity. For the same rock, the higher the GPR frequency, the shorter wavelength. Vertical resolution is a measure of the ability to differentiate between two signals adjacent to each other. It can be taken as one-quarter of the wavelength, that is $(\lambda/4)$.

With high frequency, the vertical resolution of GPR data is increased (Table 2-1). Thin layers (thickness less than or equal one quarter of wavelength) may have strong reflections if the contrast of relative dielectric constant ($k$) is large enough. That is because the amplitude of the thin layer reflection is not only dependent on the thickness of the layer, but also on the Fresnel reflection coefficient for the rock. When the layer is much thinner than the pulse width the reflected pulse is the time derivative of the incident pulse. In other words, the high

| Table 2-1 theoretical vertical resolutions for Two geological materials at three frequencies |
|---------------------------------|--------|--------|--------|
|                                  | Antenna Frequency |
|                                 | (MHz)   |        |        |
|                                 | 120     | 500    | 900    |
| Soil                            |          |        |        |
| Wavelength(cm)                  | 62.5    | 15     | 8      |
| Resolution(cm)                  | 15.6    | 3.75   | 2      |
| Bedrock                         |          |        |        |
| Wavelength(cm)                  | 92      | 22     | 12     |
| Resolution(cm)                  | 23      | 5.5    | 3      |
frequency energy is strongly reflected and the low frequency is transmitted. So when the layer thickness is approximately equal to a quarter of wavelength, then a tuning effect occurs and quite a strong reflection will be observed. This phenomena is well known in the seismic industry (e.g., Yilmaz, 1987).

At Corbula Gulch, 28 2-D lines were collected (16 in the N-S direction and 12 in W-E direction; Figure 2-5). Each line is 100m long. Line spacing is 10m and sample or trace spacing along each line is 0.5m. The data were recorded at 100MHz frequency. The penetration depth is about 12m. The vertical resolution is about 0.1m.

Instead of the amplitude and frequency data, we use instantaneous amplitude (IA) and frequency (IF) to study the shale distribution. IA and IF are determined from the complex signal analysis. The concept of treating a seismic trace as the real part of a complex function of time has been used in recent years to interpret both earthquake signals
(Farnbach, 1975) and common-depth-point (CDP) reflection records (Taner and Sheriff, 1977; Sicking, 1978; Taner et al., 1979). Because a seismic trace is a causal time series, the imaginary part (also called quadrature or conjugate) of complex function can be computed directly from the seismic trace itself using a Hilbert transform. The real and imaginary parts are then the inputs, which can be used to determine specific properties of the complex function such as the instantaneous attributes of amplitude, phase and frequency. The advantage of this type of analysis is that the seismic signal is decomposed into functions, which distinguish the amplitude information in the original trace from the angular (phase and frequency) information.

Previous publications have addressed both the methodology of computing complex trace attributes and apparent relationships between features of attribute displays and physical properties of subsurface geologic sequences (Farnbach, 1975; Taner and Sheriff, 1977; Sicking, 1978; Taner et al., 1979). Complex trace analysis treats a seismic trace \( f(t) \) as the real part of an analytical signal or complex trace, \( F(t) = f(t) + f^*(t) \). The quadrature (also called imaginary or conjugate) component \( f^*(t) \) is uniquely determined from \( f(t) \). The use of the complex trace \( F(t) \) makes it possible to define instantaneous amplitude, phase and frequency using logical extensions of the definitions of these terms for simple harmonic oscillation. The real part \( f(t) \) can be defined for \( -\infty < t < \infty \), and be presented by the Fourier integral formula

\[
f(t) = \int_{-\infty}^{\infty} B(\omega) e^{iat} d\omega \tag{2-4}
\]

and

\[
f(t) = \int \left| C(\omega) \cos[\omega t + \phi(\omega)] \right| d\omega \tag{2-5}
\]

where \( C(\omega) = 2|B(\omega)| \) and \( \phi(\omega) = \arg B(\omega), \omega > 0 \). Then
\[ f^*(t) = \int \mathcal{C}(\omega) \sin(\omega t + \phi(\omega)) d\omega \]  \hfill (2-6)

and

\[ F(t) = \int \mathcal{C}(\omega) e^{i[\omega t + \phi(\omega)]} d\omega \]  \hfill (2-7)

The frequency-domain representations of a real trace and its complex trace equivalent are shown in **Figure 2-6**. The amplitude spectrum of the complex trace \( \mathcal{C}(\omega) \) vanishes for \( \omega < 0 \) and has twice the magnitude for \( \omega > 0 \). The phase \( \phi(\omega) \) is unchanged (except it is not defined for \( \omega < 0 \)). The complex trace can thus be found by (1) Fourier transforming the real trace, (2) zeroing the amplitude for negative frequencies and doubling the amplitude for positive frequencies, and then (3) inverse Fourier transforming.

**Figure 2-6**  Frequency domain representations of (a) real and (b) complex traces  (After Taner et al, 1979)
Reflection strength (amplitude of the envelope) is independent of the phase. High-reflection strength is often associated with major lithologic changes between adjacent rock layers. The instantaneous phase emphasizes the continuity of the events. It is a value associated with a point in time and thus is quite different from phase as a function of frequency, such as given by Fourier transform. Like instantaneous phase, instantaneous frequency is a value associated with a point in time. Frequency characteristics often provide a useful correlation tool. The character of a composite reflection will change gradually as the sequence of layers gradually changes in thickness or lithology. Variations, as at pinchouts and the edges of hydrocarbon-water interfaces, tend to change the instantaneous frequency more rapidly.

### 2.2.2 Borehole Data

Borehole data are critical to calibrate the GPR data with rock properties, effective reservoir properties, velocity model construction, and trying sedimentologic and stratigraphic boundaries to the GPR data for correlation and mapping of flow units, as well as conditioning the 3-D reservoir model. Four boreholes were drilled in study site. All of them are about 15 meters deep. Cores were collected every 0.1 meters for each well and were described in detail (for example Figure 2-7). The rock permeability was measured from the cores (for example Figure 2-8). Finally, gamma ray logs were collected from each borehole (Figure 2-8), which provide critical information to study the shale distribution. The gamma ray log is a measurement of the total gamma ray intensity in the wellbore. It includes the potassium, thorium and uranium contents. These radioactive elements tend to concentrate in clay minerals, which in turn, concentrate in shales. These data can be used to calculate the shale index or shale contents. The shale index, $I_{sh}$, is calculated from
where $\gamma_{\text{log}}$=gamma ray response in the formation of interest, $\gamma_{\text{cs}}$ =gamma ray response in clean, shale-free formations, and $\gamma_{\text{sh}}$=gamma ray response in shales. The shale content, $V_{\text{sh}}$, is calculated from $I_{\text{sh}}$ by some empirical equations. Determination of shale content with the total gamma ray log response assumes that all the radioactive minerals are associated with shale.

\[
I_{\text{sh}} = \frac{(\gamma_{\text{log}} - \gamma_{\text{cs}})}{(\gamma_{\text{sh}} - \gamma_{\text{cs}})} \tag{2-8}
\]

Figure 2-7    Lithologic Section of Well 6 (from UTD Corbula Gulch Project Database)
Figure 2-8  Section of core Gamma ray and permeability measurements of Well 6
(From UTD Corbula Gulch Project Database)
2.2.3 Photomosaic Section

The photomosaics of the cliff face give us direct information of the reservoir strata architecture. Detailed photomosaics show a series of offlapping, inclined interbedded sandstones and shales across the marine-influenced point-bar deposits (Corbeanu, 2000; Figure 2-9). These photomosaics can be used to condition statistical realizations of rock properties within GPR survey volume, and to perform flow simulations (Willis and White, 2000).

Figure 2-9 is the photomosaic of the south-facing outcrop at Corbula Gulch. Four erosive-based channel elements were mapped. The Lowermost channel element 1 overlies coal-bearing, delta-plain mudstones formed in a brackish swamp. The next overlying channel 2 consists of meter-thick sandstone beds floored by mudstone intraclast conglomerate. The internal architecture of channel 2 contains meter-thick dipping sandstone beds, draped with thin shales that show rare burrows. This indicates periodic marine incursion within a laterally accreting point bar. Channel 3 locally erodes into both channel 1 and 2 and consists of thick sandstone with thick mudstone intraclast conglomerates. Channel 4 lies at the top of the outcrop and contains medium-grained cross-bedded convolute stratified sandstone. The main object of this study is channel 2, a laterally accreting point bar deposits between surface C and B. In this zone, there are 10 accretion surfaces. All of them are inclined to the east. Some layers pinch out. Shales were deposited along these surfaces. This photomosaic provides 2D shale distribution. We will use geostatistics to study shale distributions along these surfaces in 3D.
2.3 Summary

To study shales distribution and examine shale effects on deltaic reservoir behaviors, GPR data, borehole data and photomosaic picture are collected. GPR data provide dense, three-dimensional, fine-scale reservoir analog information. Borehole data have high vertical resolution. We will use indirect methods to incorporate GPR data with borehole data to study shale distribution. Photomosaics can be used to help us check the quality of the surface model we created. With this understanding of the geologic setting and geophysical data, we are prepared to discuss the geostatistical tools used to model shales in this study.
CHAPTER 3. SOLUTION METHODS

This study focuses on imaging shale distribution and modeling flow in the laterally accreting point bar deposits in channel element 2 of the Corbula Gulch site (between surfaces B and C in Figure 2-9). To do this, we correlate GPR attributes (instantaneous frequency and amplitude) with shale occurrence as observed in the cores and displayed in gamma ray logs. Mapping instantaneous GPR attribute and shale relations throughout the GPR volumes allows us to place these ultralow permeability zones in a reservoir model.

The critical issue here is how to integrate GPR and borehole data. Data integration is difficult when the data volume support (i.e., the averaging volume of different measurements) varies widely, as it does for GPR, probe permeability, plug, and whole core measurements. This problem is closely related to estimation of rock properties from seismic attributes (e.g., Fitchl et al. 1997; Fournier et al., 2000; Gilbert and Joseph, 2000; Grijalba-Cuenca et al., 2000). In recent years, the use of geostatistical stochastic modeling techniques to generate 3-D reservoir models for simulation has been gained wider acceptance (Journel and Alabert 1990; Isaaks and Srivastava, 1989). Geostatistical techniques provide an integrated framework to incorporate reservoir data from different source at different scales (Isaaks and Srivastava, 1989; Journel and Huijbregts, 1978). Thus, geostatistics provides a tool to integrate GPR data and borehole data and calibrate GPR data. It takes into account the correlation between borehole data and GPR data as well as spatial correlation of the reservoir property to be modeled.

3.1 Geostatistical Methods

Geostatistical methods are based on the concepts of randomness and spatial correlation. Geostatistics is by nature mathematical and statistical. Several features set
geostatistics apart from ad hoc and manual approaches to local estimation. First of all, methods for estimation such as kriging use an explicit criterion of optimality requiring a model of spatial dependence. Second, parameters of this model are computed from data. Third, geostatistical methods such as kriging provide a measure of uncertainty in the estimation.

3.1.1 Semivariogram

The semivariogram is a function to quantify spatial continuity. It is defined as:

\[ 2\gamma(h) = E\{[Y(u) - Y(u + h)]^2}\]  \hspace{1cm} (3-1)

A straightforward way of measuring how a variable \(Y\) changes in value between site \(x\) and another site \(x+h\) units distant, say \(x+h\), is to compute the difference \(Y(x) - Y(x+h)\). If two points are continuous and \(|h|\) is small, one can expects the difference to be small. With increasing \(|h|\), the difference increases. Translating this intuitive notion into a formula, one would like to observe the behavior of

\[ \gamma(h) = \frac{\sum [Y(x) - Y(x + h)]^2}{2n} \]  \hspace{1cm} (3-2)

In words, the semivariogram is the expected squared difference between two data values separated by a distance \(h\). So the semivariogram is a measure of contrast as a function of distance. It increases as samples become more dissimilar. The covariance is a statistical measure of correlation:

\[ C(h) = E\{[Y(x) \cdot Y(x + h)] - m^2\} \]  \hspace{1cm} (3-3)

By definition, the covariance at \(|h|=0\), \(C(0)\), is the variance \(\sigma^2\). The covariance \(C(h)\) is 0 when the values \(|h|\) apart are not linearly correlated. The separation direction is often fixed, and the lag in that direction indicated as simply \(h = |h|\).
Expanding the square in **Equ. (3-1)** leads to the following relation between the semivariogram and covariance:

\[ \gamma(h) = C(0) - C(h) \quad \text{or} \quad C(h) = C(0) - \gamma(h) \]  

(3-4)

This relation depends on the modeling decision that the mean and variance are constant and independent of location. These assumptions are known as first and second order stationarity, respectively. These relations are the foundation for semivariogram interpretation. That is, (1) the “sill” of the semivariogram is the variance, which is the semivariogram value that corresponds to zero correlation; (2) range is the distance at which no spatial correlation exists; (3) the correlation between \( Y(x) \) and \( Y(x+h) \) is positive when the semivariogram value is less than sill, and (4) the correlation between \( Y(x) \) and \( Y(x+h) \) is negative when the semivariogram value exceeds the sill.

The indicator semivariogram is computed on a specially defined indicator variable. This requires the specification of a continuous variable and cutoff to create the indicator transform. For the cutoff \( z_k \) and datum value \( x_i \), the indicator transform \( i_k(x_i) \), is defined as:

\[
i_k(x_i) = \begin{cases} 
0, & \text{if } z(x_i) \leq z_k \\
1, & \text{otherwise}
\end{cases}
\]  

(3-5)

There are many types of theoretical semivariogram models. Three commonly used models are the spherical model, the exponential model and the Gaussian model. The spherical model is often used. The equation of a spherical model as follows:

\[
\gamma(h) = C \left[ \left( \frac{3h}{2a} \right) - \left( \frac{h^3}{2a^3} \right) \right] \quad \text{for } \ h \leq a
\]  

(3-6)

\[
\gamma(h) = C \quad \text{for } \ h > a
\]

where \( C=\text{sill} \) and \( a=\text{range} \).

The exponential model has the following equation:
\[
\gamma(h) = C \left[ 1 - \exp \left( -\frac{h}{a} \right) \right] \tag{3-7}
\]

And Gaussian model is:

\[
\gamma(h) = C \left[ 1 - \exp \left( -\frac{h^2}{a^2} \right) \right] \tag{3-8}
\]

Because the semivariogram is a measure of “geological variability” versus distance, it plays an important role in reservoir modeling. It can be used to check the nugget effect, geometric and zonal anisotropy, geologic trends and cyclicity, and so on. Thus the semivariogram is needed for geostatistical interpolation and for stochastic modeling of surfaces and petrophysical properties. Geostatistical model-building algorithms such as sequential Gaussian simulation, sequential indicator simulation, and truncated Gaussian simulation use a semivariogram model to create a model constrained to local data and the semivariogram model. The semivariogram can be an important tool for creating reservoir models because of the sparseness of data available in petroleum reservoirs.

### 3.1.2 Ordinary Kriging

Kriging is a method of calculating estimates of a regionalized variable at a point, over an area, or within a volume, and uses as a criterion the minimization of an estimation variance. Assume that the regionalized variable under study has values \( z_i = z(x_i) \), each representing the value at a point \( x_i \). Also assume that this regionalized variable is second-order stationary, with expectation

\[
E\{z(x)\} = m \tag{3-9}
\]

A centered covariance

\[
E \{ Z(x+h)Z(x) \} - m^2 = C(h) \tag{3-10}
\]

And a semivariogram
\[ E \{ [Z(x+h) - Z(x)]^2 \} = 2\gamma(h) \]  
(3-11)

A kriged estimator \( z_k^* \) is a linear combination of a values of the regionalized variable:

\[ z_k^* = \sum_{i=1}^{n} \lambda_i Z_i \]  
(3-12)

Weights \( \lambda_i \) are calculated according to these criteria:

1. The estimate is unbiased
2. The estimation variance is minimized.

Estimates using these criteria are “BLUE,” or best linear unbiased estimators. The first criterion is satisfied by requiring weights to sum to one, thus ensuring that

\[ E(z_k^*) = m \sum_i \lambda_i = m = E(Z_v) \]  
(3-13)

and \( E(Z_v - z_k^*) = 0 \)

The second criterion says that estimation variance:

\[ E\{ [Z_v - z_k^*]^2 \} \]  
(3-14)

is to be minimized. Writing estimation variance as

\[ E\{ [Z_v - z_k^*]^2 \} = E\{ Z_v^2 \} - 2E\{ Z_v Z_k \} + E\{ Z_k \} \]  
(3-15)

it is calculated from:

\[ \bar{C}(V, V) - 2\sum_i \lambda_i \bar{C}(V, v_i) + \sum_{ij} \lambda_i \lambda_j \bar{C}(v_i, v_j) \]  
(3-16)

where \( \bar{C}(A, B) \) is the average covariance between each point in an area A, and each point in an area B.

The ‘kriging system’ is a set of \( n+1 \) linear equations with \( n+1 \) unknowns, obtained by setting equal to zero each of the partial derivatives:
Where the \( n \) weights \( \lambda_i \) are to be calculated, and \( \mu \) is a Lagrange parameter. The system of equations can be written in terms of covariances, in terms of the semivariogram function. The first instance gives the following system of equations to be solved:

\[
\sum_{j=1}^{n} \lambda_i \bar{C}(v_i, v_j) + \mu = \bar{C}(v_i, V) \quad \text{for all } i = 1, \ldots, n \quad (3-18)
\]

\[
\sum_{j=1}^{n} \lambda_i = 1 \quad (3-19)
\]

Estimation variance can be rewritten as follows:

\[
\sigma_k^2 = -\bar{C}(V, V) - \mu - \sum_{j=1}^{n} \lambda_i C(v_i, V) \quad (3-20)
\]

With the exception of the first term, all terms in this equation are computed in the course of setting up and solving the system of equations. This way of calculating estimation variance avoids the double summation term and having to save a duplicate \( n \) by \( n \) array of \( \bar{C}(v, v) \) terms.

The system of equations is perhaps more easily visualized in matrix form. Defining

\[
[\lambda] = \begin{bmatrix}
\lambda_1 \\
\lambda_2 \\
\vdots \\
\lambda_n \\
\mu
\end{bmatrix}
\]
Each entry in matrix $[W]$ is a sample-to-sample covariance. The distance between well site $i$ and well site $j$ is calculated to give $h_{ij}$ along with the direction of vector described by the two samples if an anisotropic model is to be used. The value of $\gamma(h_{ij}) = \gamma(v_i, v_j)$ is calculated from the semivariogram model, to give the covariance $C(v_i, v_j) = C(0) - \gamma(v_i, v_j)$.

### 3.1.3 Sequential Gaussian Simulation (SGS)

In sequential simulation, a simulated value at each location $x$ is drawn from a probability distribution function computed from observed and previously simulated values in the neighborhood of this location. The algorithm begins with a randomly selected location, and progresses sequentially across the grid representing the area to be simulated.
The order of this progression is not specified by theory, but a random sequence is usually followed (Isaaks, 1990).

At each location, the computer searches for points in a user-specified neighborhood; these points can include both data input to the program, and points that have been simulated in earlier steps. A probability distribution is computed from these points by way of one of a number of methods. How one computes this probability distribution distinguished between types of sequential simulation.

Sequential Gaussian simulation method computes a conventional kriged estimate and estimation variance from data transformed to normal scores. This approach requires a single semivariogram model based on transformed data. Once simulation at every node is complete, results are back-transformed to the original units. The entire procedure is the following:

(1) Transform the sampled data to be Gaussian. The most common technique is the normal scores technique. This is a natural precursor to any Gaussian technique.
(2) Assign each of the (J-I) unconditioned cell values to be equal to those at the nearest conditioned cells. The values in the conditioned cells do not change in the following.
(3) Define a random path through the field such that each unconditioned cell is visited once and only once.
(4) For each cell along the random path, locate a prespecified number of surrounding conditioning data. This local neighborhood, which may contain data from previously simulated cells, is selected to roughly conform to the ellipse range on the semivariogram model.
(5) Perform ordinary Kriging at the cell using data in the local neighborhood as conditioning points. This determines the mean of the Gaussian distribution (the kriged estimate) and the variance at the point (the kriging estimation variance). The local cumulative distribution function (CDF) is now known since the mean and variance completely determine a Gaussian distribution.

(6) Draw a random number in the interval \([0,1]\) from a uniform distribution. Use this value to sample the Gaussian distribution in step 5. The corresponding transformed value is the simulated value at each cell.

(7) Add the newly simulated value to the set of “known” data, increment I by 1, and proceed to the next cell as in step 4.

### 3.1.4 Experiment Design

Experimental design allows us to select a small set of simulations to run from the large sets that we could run. By choosing an appropriate design, we minimize the number of runs that need to be made to obtain the required results—whether the required results are uncertainty estimates, sensitivity coefficients, upscaled properties, parameter estimates. The methods are used to select a set of experiments that allow the analyst to make definitive statements about the effects of variables, interactions of variables, and estimates of errors.

The three parts of an experiment are the factors to be varied, the responses to be measured, and the design or combinations of factors at which the experiment is to be carried out. Factors are input variables. In classic experimental design, these were the experimental conditions, which were varied. In reservoir simulation, the factors can be controllable (like injection rate) or stochastic (like shale fraction). The factors will be systematically varied in the simulation study to assess their effects. Responses are system outputs. In the example
used for factors, corresponding responses might be such things as recovery efficiency, breakthrough time, and average permeability. Designs are lists of different experimental conditions (or combinations of factors) at which experiments will be performed.

The simplest experimental designs are factorials. Factorial designs are widely used in experiments involving several factors where it is necessary to investigate the main effects and interactions of the factors (Myers and Montgomery, 1995). A complete factorial design in k factors is obtained by choosing \( n_1 \) levels of factor 1, \( n_2 \) levels of factor 2, \ldots, \( n_k \) levels of factor k, and then selecting the \( n = n_1 \times n_2 \times \ldots \times n_k \) runs obtained by taking all possible combinations of levels selected. The most common designs are two-level designs. In these designs, each factor is set to either its maximum or minimum value. These designs require \( 2^k \) experiments, where k is the number of factors being examined. As example, a \( 2^3 \) factorial design shown in the following Table 3-1, where 1 and –1 stand for the coded levels of the factors.

<table>
<thead>
<tr>
<th>Run</th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>2</td>
<td>+1</td>
<td>-1</td>
<td>-1</td>
</tr>
<tr>
<td>3</td>
<td>-1</td>
<td>+1</td>
<td>-1</td>
</tr>
<tr>
<td>4</td>
<td>+1</td>
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</tr>
<tr>
<td>5</td>
<td>-1</td>
<td>-1</td>
<td>+1</td>
</tr>
<tr>
<td>6</td>
<td>+1</td>
<td>-1</td>
<td>+1</td>
</tr>
<tr>
<td>7</td>
<td>-1</td>
<td>+1</td>
<td>+1</td>
</tr>
<tr>
<td>8</td>
<td>+1</td>
<td>+1</td>
<td>+1</td>
</tr>
</tbody>
</table>

These designs are simple to use. However, when there are many factors the number of experiments required becomes large. Also, these designs can estimate first-order effects and interactions only. They cannot be used to estimate quadratic effects.
3.2 Summary

These techniques—variography, Kriging, Sequential Gaussian Simulation, surface modeling, and experimental design—will be used to construct and critique models for shales, and examine shale effects on reservoir behaviors in the following chapters. We will use semivariogram to quantify the layer elevations’ spatial variability, and then use deterministic kriging method to create a surface model. An indirect geostatistical method will be used to calibrate GPR attributes to well data. Based on the surface model, the Sequential Gaussian Simulation method will be used to estimate shale distribution along the surfaces. Then the experimental design will be used to design the fluid flow simulation.
CHAPTER 4. GEOSTATISTICAL MODELS OF SHALE

4.1 Surface Grid Construction

To study the reservoir internal architecture and shale distribution, a surface grid model should be built. There are three reasons. First, most of the shales were deposited along these accretion surfaces; second, the accretion surfaces define the point bar sand body geometry, once we build the surface model, the internal architecture and geometry of sand bodies are determined; third, in GPR volume, the line spacing is 10m and sampling spacing is 0.5m, this scale and the anisotropic sample spacing is not feasible for reservoir and fluid flow simulation.

Based on this surface model, the shale distribution will be studied statistically and this regular model will be transferred into corner-point grid for fluid flow simulations. In this study we use 1m by 1m gridblock in surface grids, thus there are 150 gridblocks in \( x \) (west-east) direction, 110 gridblocks in \( y \) (north-south) direction. In \( z \) (top to bottom) direction, there are 10 gridblocks based on 10 GPR interpreted layers.

4.1.1 Semivariogram Models

As mentioned before, the first important step in all geostatistical modeling exercises is to quantify the spatial variability of the data. The semivariogram is a critical input to geostatistical studies. Furthermore, the semivariogram reflects our understanding of the geometry and continuity of reservoir properties and can have an important effect on predicted flow behavior.

To understand the semivariogram behavior, \( x \)- and \( y \)-directional semivariograms must be considered simultaneously. The experimental semivariogram points are not used directly in subsequent geostatistical steps; a parametric semivariogram model is fitted to the
experimental points. There are a number of reasons why experimental variogram must be modeled: (1) the semivariogram function \( \gamma(h) \) is required for all distance and direction within the search neighborhood of subsequent geostatistical calculations; however, we only calculate the semivariogram for specific distance lags and directions. There is a need to interpolate the semivariogram function for \( h \) values where too few experimental data pairs are available. (2) there is also a need to introduce geological information regarding anisotropy, trends, sampling errors and so on in the model of spatial correlation. As much as possible, we need to filter artifacts of data spacing and data collection and make the semivariogram represent the true geological variability. (3) we must have a semivariogram measure \( \gamma(h) \) for all distances and directions that has the mathematical property of positive definiteness, that is, we must be able to use the semivariogram, or its covariance counterpart, in kriging and stochastic simulation. For these reasons, geostatisticians have fit semivariograms with specific known positive definite functions like spherical, exponential, Gaussian and hole-effect semivariogram models.

To build the surface grids, first the thickness of each layer is calculated. Then the base semivariograms are computed (using \texttt{gamv} in \texttt{GSLIB}) based on the GPR interpreted base elevations (\textbf{Figure 4-1}). In \textbf{Figure 4-1}, the experimental semivariogram in the west-east directional (square shape line) keeps increasing with increasing lag. In simple terms, this means that as distances between data pairs increase, the differences between elevation data values also systematically increases. The presence of a trend makes the elevation variable nonstationary, that is, it is unreasonable to expect the mean value to be independent of location. Residuals from some simple trend model are easier to consider stationary. Thus this trend must be modeled and removed before semivariogram modeling and geostatistical
simulation. Semivariogram analysis and all subsequent estimations or simulations are performed on the residuals. The trend is added back to estimated values at the end of study. A linear trend was fitted to the elevation profile (Figure 4-2) and then removed from the data. The resulting residuals constitute the new property of interest. The variogram of the residuals is shown in Figure 4-3, which now exhibits a clearer structure reaching the sill at about 50m range. The parameters of model are given in Table 4-1. There are no indications

![Figure 4-1 Base elevation semivariograms with a clear horizontal trend](image1)

![Figure 4-2 Fitted linear trend model of base elevation](image2)

33
of anisotropy for the base model.

![Base Semivariogram](image)

**Figure 4-3** Base elevation semivariogram without trend

<table>
<thead>
<tr>
<th>Structure</th>
<th>W-E range (m)</th>
<th>N-S range (m)</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nugget</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Gaussian</td>
<td>15</td>
<td>15</td>
<td>0.2</td>
</tr>
<tr>
<td>Spherical</td>
<td>55</td>
<td>55</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 4-1 Base semivariogram model parameters

The layer thickness semivariograms and their models are shown in Figure 4-4; the parameters are given in Table 4-2. Based on the calculated layer thickness data, the semivariograms of thickness for each layer are calculated. The semivariograms for all layers (10 layers) are pooled to obtain these experimental semivariograms. Similar to the conclusion for the base elevation semivariograms, the layer thicknesses are isotropic.

### 4.1.2 Surface Grid Building

The models of base elevation semivariograms and layer thickness semivariograms provide quantitative information about reservoir geometry’s special variability. Putting this information into GSLIB 3-D kriging program (KT3d), the base elevation data are kriged on
to the regular grid we created before. Then the trend is added back to the base grid. Layer thicknesses are estimated by the same methods. Based on the base elevation grid, each layer thickness is added up from bottom to top., the result is the surface grid model (Figure 4-5). Figure 4-5 shows the strata architecture we observed from the outcrop. This 3-D surface model defines the elevation for each gridblock. So it quantifies the internal reservoir architecture. This quantitative surface model provides a good basis to study shale distribution.
4.2 Correlation Estimation

In the field of reservoir modeling, the integration of data from different sources and of different types leads to more accurate models, for fluid simulations and production decision-making. Stochastic simulation techniques have become popular as they are well suited to image uncertainty in the reservoir models and to integrate data of various types and at different scales. In this study, we use an indirect method to integrate GPR data and well data in reservoir simulation. This technique requires a preliminary calibration of the GPR attributes with the parameters to be simulated; a calibration function between GPR attributes and shale occurrence (shale index calculated from gamma ray) will be built. This function is built in the vicinities of wells where log and GPR information are both available. Then the spatial distribution of the shale is quantified by the experimental semivariograms. These are
fitted by theoretical models in order to obtain simulation parameters for the future simulation.

### 4.2.1 GPR Data Qualification

GPR data provide valuable spatial information that well data cannot furnish because of relatively large well spacing. However, to use GPR data for mapping reservoir properties requires that the GPR data reflect the relative change of that reservoir properties from location to location. If we want the GPR data to help us identify the shale occurrence in a reservoir zone, then the GPR amplitude or other attributes in that zone should vary according to the different reservoir rocks. If the GPR data had been normalized to have about the same attribute, for example, amplitude, we cannot learn anything about the lithological variation. For this reason, the GPR data qualification is checked before the calibration study. **Figure 4-6** is borehole 4 data file, (a) is the synthetic offset GPR traces (central group) with corresponding field data traces (right and left). The synthetic traces are produced by finite-difference modeling. All traces are plotted with automatic gain control (AGC) scaling; (b) is the core log, and (c) clay profile calculated from gamma ray; (d) is GPR interval velocity profile, and (e) median fluid (nitrogen) permeability profile. (c), (d) and (e) are blocked averages, not the raw measurements (Szerbiak, et al, 2000). This figure shows that the GPR velocity decreases as the clay fraction increases, in part because clay retains both bound and intrapore water. This is the basis of the assumption we made in this study that the GPR reflections are produced primarily by clay/sand interfaces. Based on this reasonable assumption, the GPR amplitudes reflect the variation of reservoir lithology, and can be used to study the shale distribution.
4.2.2 Calibration GPR Data to Well Data

In this study, 4 boreholes were drilled. The core data were collected every 0.05 m, gamma ray logs were recorded every 0.1 ft; GPR data were collected with 0.1 m vertical resolution. To accurately calibrate the GPR attributes with shale occurrence (here indicated by gamma ray value), two things must be checked. One is checking and editing geomarkers (or shale occurrence) locations. Relating GPR reflectors to geological markers seen in boreholes is a critical step. Inaccuracy of a fraction of a meter may completely change the results. After the well tie, based on velocity model, it is important to be able to fine-tune the intersections interactively. Thus, the core data and borehole GPR amplitudes data are checked. Because the GPR reflections are produced primarily by shale/sand interfaces, the
strong reflections (high amplitude value) should correspond to the shale/sand interfaces. Following this rule, the GPR amplitudes data are slightly adjusted to calibrate to core data, assuming core data is more direct measurements of reservoir vertical lithology variation.

The second thing is to check the amount of potassium, thorium and uranium. Generally, high thorium content indicates high clay content. But for the case that potassium, uranium contents are high, using total gamma ray may lead to overestimate the shale fraction. This is because formation waters that contain dissolved radioactive salts or volcanic, granite wash present in the analyzed formation can cause potassium, uranium contents high. After checking the 4 borehole gamma ray logs, we found that at most locations where gamma ray value are high, thorium values are also high, whereas potassium and uranium values are low. Thus, we can use total gamma ray log to get a reasonable shale fraction. To get the correlation function, gamma ray values are picked from the depth where the shale/sand interfaces exist or variation of amplitude is large, and the GPR relative instantaneous amplitudes are calculated at corresponding depth. Because some sandstones contain minerals which generate high gamma ray values, it is more realistic to filter out these sandstones. Thus we also pick the high gamma ray value points which correspond to sandstone. Using Equ. 2-8, shale index ($I_{sh}$) is calculated. All of these values are included in Table 4-3. In Figure 4-7, 14 of 15 shale points fall into the zone of $I_{sh}>0.75$ and $DIA \geq 3000$. It also shows that there is a high correlation between shale index and amplitudes. A linear regression is performed on available data and a linear calibration function for $I_{sh}$ and GPR amplitudes is determined:

$$I_{sh} = 0.0002(\Delta IA)+0.194 \quad (4-1)$$
<table>
<thead>
<tr>
<th>Well</th>
<th>Core</th>
<th>Depth(m)</th>
<th>Psh</th>
<th>DIA</th>
<th>amma(cp)</th>
<th>Ish</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0</td>
<td>2000</td>
<td>1400</td>
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<tr>
<td></td>
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<td>1600</td>
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<td>800</td>
<td>0.00</td>
</tr>
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<td>4500</td>
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<td>1400</td>
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<td>1000</td>
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<td>0</td>
<td>2000</td>
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<tr>
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<td>1550</td>
<td>0.91</td>
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<td>800</td>
<td>0.27</td>
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<td>sand</td>
<td>15.75</td>
<td>0</td>
<td>3000</td>
<td>1200</td>
<td>0.82</td>
</tr>
</tbody>
</table>
Ish vs. Delta IA

\[ y = 0.0002x + 0.194 \]

\[ R^2 = 0.7117 \]

Figure 4-7  Regression line between shale index (Ish) and amplitude (DIA)

Psh vs. Ish

Psh=0(sandstone)  Psh=1(shale)  Ish=0.75

Figure 4-8  Psh and Ish plot for 4 boreholes
The relationship between shale index and the core data is checked, and find that all the shale indexes for shale are greater than 0.75, most of the shale indexes for sandstone are less than 0.75 (Figure 4-8). Linear calculation is adequate when relationships are linear. This calibration function is estimated at well locations. It is then applied everywhere the attribute are given.

4.3 Shale Distribution Model Construction

The correlation function is critical for shale distribution study. It provides the feasibility to combine GPR data with well data to do reservoir modeling. To build the shale distribution model based on GPR data, the relative instantaneous amplitudes in 3D volume are calculated, and each accretion surface in surface grid created before are assigned corresponding relative instantaneous amplitudes. Using the correlation function (Equ. 4-1), shale index is calculated for each surface from the amplitude values. These shale index values will be used to study shale distribution. The semivariograms of shale index will be calculated. And the semivariogram parameters are used with sequential Gaussian simulation to get the shale index for each surface. Based on the relationship showing in Figure 4-8, sand will be filtered out from the simulated data (Ish<0.75).

4.3.1 Shale Index Semiarograms Calculation

After data checking and data transform, we can apply geostatistical methods to estimate shale distribution. As stated before, we will use stochastic simulation to estimate shale distribution. For stochastic simulation, first the data spatial continuity should be measured. Here we still use gamv program in GSLIB to calculate shale index semivariograms. The computed semivariograms and their models are shown in Figure 4-9; the parameters are given in Table 4-4. The semivariograms for all surfaces are pooled
together to obtain these experimental semivariograms. There are indications of anisotropy. The N-S semivariogram indicates slightly less correlation in this direction.

4.3.2 Sequential Gaussian Simulation

The shale index semivariograms (Figure 4-9) are used with a sequential Gaussian simulation algorithm (Deutsch and Journel, 1998) to simulate shale index along the surfaces. In this study, we use sgsim program in GSLIB to do simulation. The geocellular grids has 110,752 active gridblocks. Because the number of gridblocks is too large for multiple reservoir simulation runs, the grids are resampled at intervals of 2m horizontally.

![Shale Index Semivariogram](image)

**Figure 4-9** Shale index semivariograms

<table>
<thead>
<tr>
<th>Table 4-4 Shale index semivariogram model parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structure</strong></td>
</tr>
<tr>
<td>Nugget</td>
</tr>
<tr>
<td>Spherical</td>
</tr>
<tr>
<td>Exponential</td>
</tr>
</tbody>
</table>
Thus, there are 75 gridblocks in west-east ($x$-) direction, 55 gridblocks in north-south ($y$-) direction, and 10 blocks in vertical ($z$-) direction. Once we the $I_{sh}$ values for each gridblock, the cutoff line showing in Figure 4-8 is used to filter out the sandstone deposited along the surface. After that we get the shale distribution for each surface. Example of simulated surface 4 from bottom is shown in Figure 4-10. The average shale coverage of the accretion surfaces is about 30 percent. And most of the shales are preserved on the west part, where the elevation of surface is relatively high. Because of the low shale coverage and the distribution trend, there are many opportunities for “leaks”.

![Figure 4-10 Shale image on accretion surface 4](image)

4.4 Summary

A reservoir model has been prepared, based on stratigraphy and geostatistical models of shale distribution inferred from GPR and borehole data. We are now preparing to investigate the flow behavior of the model.
CHAPTER 5. FLOW MODELING

The objective of this point bar reservoir analog characterization is to assess the shale effects. Keeping that objective in mind, fluid flow simulation is performed on the reservoir models provided by \texttt{sgsim} in \texttt{GSLIB}. Reservoir simulation data sets are constructed with different images of shale distribution. Flow is simulated through these models in all three coordinate directions, aligned with the grid of GPR surveys. Several flow responses are considered for each flow simulation:

1. the time at which the produced tracer concentration exceeds 1 percent (often called breakthrough time, $\tau_{BT}$);
2. the fraction of the model contacted by injected fluid after 1 pore volume of injection (sweep efficiency, $N_{pD}$), and
3. the upscaled permeability ($k$).

These flow responses are examined with linear sensitivity analysis of the two-level factorial (Myers and Montgomery, 1995). This approach ranks the effects and characterizes interactions between factors statistically (e.g., Kjønsvik et al., 1992).

5.1 Analysis Approach

Experimental design is a method to select combinations to assess the effects of process factors (Box et al., 1978). In this study, 3 factors are selected (\textbf{Table 5-1}). The selected design is a full two-level factorial. Thus, 8 sets of factors ($2^3=8$) are considered (\textbf{Table 5-2}). Two-level full factorials are simple to design and to analyze (Box et al., 1978). The three factors considered are (\textbf{Table 5-1}):
1. D, the variogram range in the dip (west-east) direction. The inferred variogram ranges for all structures (Table 4-4) are used for the low case, and all ranges are doubled for the high case.

2. S, the variogram range in the strike (north-south) direction. It is varied in the same way as D.

3. F, the mean fraction of the accretion surfaces covered by shale. The low value of F is the mean shale fraction (0.3) simulated on the condition of D and S with low case, and the high value of F is twice the simulated mean shale fraction.

These are the same factors examined by Novakovic et al. (in press) in their smaller-scale study of shales at Corbula Gulch.

<table>
<thead>
<tr>
<th>Table 5-1 Factorial designs</th>
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</thead>
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<tr>
<td>Factor name</td>
</tr>
<tr>
<td>Dip range</td>
</tr>
<tr>
<td>Strike range</td>
</tr>
<tr>
<td>Shale coverage</td>
</tr>
</tbody>
</table>

*Multiplier for ranges in Table 4-4

<table>
<thead>
<tr>
<th>Table 5-2 Factor combinations for flow simulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Set number</td>
</tr>
<tr>
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</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
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<td>6</td>
</tr>
<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
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</table>
Because the experimental factors are parameters for a stochastic model for shale distributions, multiple realizations must be considered for each combination. In this study, 5 realizations are created for each combination of geostatistical parameters. Thus, 40 stochastic models are prepared for flow simulations in each direction. For each combination of geostatistical parameters, the mean responses and variances among realizations are computed. These responses are then examined with sensitivity analysis.

5.2 Model Description

The flow simulations use a stratigraphic cornerpoint grid (King and Mansfield, 2000) and a commercial reservoir simulator (Schlumberger Technology Co., 1997). The reasons of choosing cornerpoint grid are: (1) cornerpoint grid can accurately preserve the reservoir geometry, which allows shale to be placed exactly on grid block faces, thus shale effects in flow models can be accurately and efficiently represented (White and Baton, 1999; Willis and White, 2000) and (2) cornerpoint grid requires fewer gridblocks than Cartesian models and can therefore be run in less time. For feasible multiple reservoir simulation runs, the block count should be moderate (with a Pentium III or 4 processor, $10^4$ to $10^5$ blocks). At the same time, in order to adequately represent the shale distribution, the grid block sizes in $x$- and $y$- direction should less than shale correlation ranges. Keeping these points in mind, we choose 75 gridblocks in the $x$-direction, 55 in the $y$-direction, and 10 in the $z$- direction, for a total of 21,140 active gridblocks (Figure 5-1). Statistics of the grid are given in Table 5-3.

<table>
<thead>
<tr>
<th>Table 5-3 Three-dimensional flow models</th>
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<tbody>
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<td>Model dimensions</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>X length (m)</td>
</tr>
<tr>
<td>150</td>
</tr>
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</table>
The displacement process for the fluid flow simulation is ideal tracer flow. There are no buoyancy, capillary, relative permeability, or viscosity contrast effects (Calhoun, 1968). There are several reasons for choosing a tracer displacement rather than a water-flood as the model process (Novakovic et al., in press): the tracer displacements are quicker to simulate, they isolate the effects of permeability heterogeneity (simplifying interpretation), fewer factors influence responses, and truncation errors can be reduced for these fully miscible systems (Rubin and Blunt, 1991). On the other hand, tracer simulations cannot investigate effects of gravity with reduced vertical permeability caused by shale, relative permeability and capillarity.

Figure 5-1 Corner-point grids for flow simulation

Flow is simulated in the x-, y- and z-directions. The models are initially saturated with tracer-free water at constant potential. The models are very similar to those described by Novakovic et al. (in press). For x-direction flow, the x=0 and x=150m faces are held at different and constant pressures throughout the simulation. The other faces are considered impermeable, which corresponds to a no-flux boundary condition on the y- and z-faces.
Fluid is injected and produced at a constant rate of 0.001 pore volume per day (here, 137.3 bbl/d). The injected fluid is marked with an ideal tracer at unit concentration. The pressure and rate are managed via the reservoir simulator well model. Each “well” is a set of connections to gridblocks that span the entire face of the grid perpendicular to the flow direction (Figure 5-2). Because these stratigraphic grids have some layers that pinch out, there are many void blocks in these grids. Therefore, the well-to-grid connections are described explicitly rather than using automatic well-completion features in the flow simulator. This is especially important for vertical flow (Novakovic et al., in press), where the tops and/or bottoms of the grids are defined by gridblocks in 10 simulation layers. The simulations for y- and z-directional flow are carried out similarly (Figure 5-3 and 5-4).

![Figure 5-2](image)

The vertical scale is magnifies 3 times; Threshold =0.55, blocks with tracer concentration <0.55 are blank

**Figure 5-2  x-direction fluid flow simulation model**
The vertical scale is magnified 3 times; Threshold = 0.55, blocks with tracer concentration < 0.55 are blank

**Figure 5-3**  \(y\)-direction fluid flow simulation model

The vertical scale is magnified 3 times; Threshold = 0.35, blocks with tracer concentration < 0.35 are blank

**Figure 5-4**  \(z\)-direction fluid flow simulation model
Since our objective is to examine shale effects, the analysis is simpler with a simple reservoir model. We assign the reservoir same permeability in x-and y-direction (30md), and \(k_x/k_z\) is assumed to be 10. Sandstone porosity averaged 19 percent. The volume of shale bodies is neglected. However, when shale occurs, it is modeled as vertical transmissibility barriers (White and Barton, 1999). The results of each simulation are used to calculate three responses: upscaled permeability, breakthrough time, and sweep efficiency. The upscaled permeability is computed directly from the flow rate and the pressure drop between the wells. The breakthrough time is defined as the time at which the produced fluid contains more than 1 percent tracer. Sweep efficiency is the fraction of initial fluid in place that is recovered after one volume of injection.

5.3 Analysis of Responses

Two models are considered to evaluate the effect of shales on flow responses. One is the model without shale (\(M_b\)). This model is relatively homogeneous, with no stochastic shales, and it is deterministic. The other one includes stochastic shales (\(M_s\)). As described before, 8 different combinations of factors (D, S, F) are considered for flow in the models with shales (\(M_s\)). Flow is also simulated through the model without shale (\(M_b\)). The latter one is deterministic and has no variable factors.

The mean responses (based on 5 realizations) for all models are presented in Table 5-4. The parameter combination corresponding to the factor values is (D, S, F)=(-1, -1, -1), where –1 indicates the low value for each factor. This factor setting corresponds most closely to the geostatistical parameters inferred for Corbula Gulch. All responses reported in Table 5-4 are for this factor combination. T-tests (with 95% significance level) (Table 5-5) give us the probabilities that we make a type I error to reject the null hypothesis. The
probabilities for three responses in three directions are very low, thus we can reject the null hypothesis conclude that the base model is drawn from different population than the stochastic model. Shales make these two models different.

<table>
<thead>
<tr>
<th>Model</th>
<th>Direction</th>
<th>Response or mean response</th>
<th>(t_{BT}^{(pv)})</th>
<th>(NpD^{(pv)})</th>
<th>(k) (md)</th>
</tr>
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<tr>
<td>Mb, no shale</td>
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<tr>
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<table>
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<th>Model</th>
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<th>(NpD^{(pv)})</th>
<th>(k) (md)</th>
</tr>
</thead>
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<td>0.967</td>
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<td>Z</td>
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<td>0.732</td>
<td>1.88</td>
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</table>

### Table 5-4 Mean responses from flow models

### Table 5-5 t-test comparing base and stochastic case

Risk of Type I error, \(a\), in rejecting Ho: base case drawn from same population as stochastic case (percent)

<table>
<thead>
<tr>
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<th>(NpD)</th>
<th>(K)</th>
</tr>
</thead>
<tbody>
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<td>0.11</td>
</tr>
<tr>
<td></td>
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</table>

Differences between base and stochastic responses (percent)

<table>
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<th>Direction</th>
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<th>(NpD)</th>
<th>(K)</th>
</tr>
</thead>
<tbody>
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</tr>
<tr>
<td></td>
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</tbody>
</table>

After compared the stochastic model with the base model, we found that the largest differences in responses are for \(z\)-direction flow, which is expected because of the large cross-area of shale in this direction. In \(x\)-and \(y\)-direction, breakthrough time is more sensitive than any other responses, and in \(z\)-direction, permeability is more sensitive.
5.4 Factor Importance Assessment

The contribution of each of the geostatistical factors (D, S, F) are examined by the least square method (PROC GLM in SAS). To assess the main effects of these factors and their interactions, the first-order model is chosen. In the first-order model, the significant terms are the factors that contribute significantly to the response variable, which means the higher the coefficient, the more important the factor. The factors or interactions without significant contributions are left blank. These models seem to have good fit between response variable and input factors because of the high $R^2$ values (Table 5-6).

From Table 5-6 we can see the semivariogram factors (D and S) have little effects on breakthrough time and sweep efficiency (low coefficients). And the shale fraction (F) is the most statistically significant factor. It has an especially significant effect on the upscaled permeability for all the models. These results suggest that reasonable estimates of tracer flow behavior will be obtained if the shale coverage is estimated correctly. Variogram parameters are less important than coverage fraction.

<table>
<thead>
<tr>
<th>Direction</th>
<th>Response</th>
<th>Factor coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>F</td>
</tr>
<tr>
<td>X</td>
<td>$t_{BT}$</td>
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</tr>
<tr>
<td>Y</td>
<td>$t_{BT}$</td>
<td>0.0750</td>
</tr>
<tr>
<td>Z</td>
<td>$t_{BT}$</td>
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</tr>
<tr>
<td>X</td>
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<tr>
<td>Z</td>
<td>K</td>
<td>1.9335</td>
</tr>
</tbody>
</table>
CHAPTER 6 DISCUSSION

6.1 Hydraulic Effects of Shales

The shale effects are not large in this system. The largest change is about 30% in vertical permeability, the most sensitive response. The fraction of the surfaces covered by the shales (F) is the most significant factor. The small effect for the variogram factors (D and S) is partly due to the low coverage of the shale. Fundamentally, the Corbula Gulch system is not especially sensitive to the details of the shale distribution because of the low shale coverage. The interactions between shale fraction and variogram factors have small but statistically significant effects on the responses. The effects of these factors and their combinations on reservoir responses are quite complex. For example, the coefficient of dip range (D) is negative (-0.0022 for x-direction $\tau_{BT}$), and the F*D also has negative value (-0.0056 in this case, see Table 5.6). In this case, the effects of shale ranges increase with shale fraction increase. But if D coefficient is positive (0.0929 for x-direction K, see Table 5.6), and F*D is negative (-0.6047), shale effect will decrease as D increase. In this case, the effect of shale range at first decreases (in absolute value) as shale fraction increases, but later increases (because FD > D).

This model is different from the models of Novakovic et al. (in press). First, this model is larger scale (150m×110m×7m), and 8 layers pinched out in the grid. Novakovic et al.’s models are smaller (51.5m×28m×11.91m for grid B, 27m×31m×11.65m for grid A). In his model, all the layers except the topmost strata extend all the way across the grid. As a result, the hydraulic effects of shales are larger in our model compared with than Novakovic et al.’s model (30% compared to 20%). Because many layers pinched out in the grid, the shale on the surfaces separating the strata is a greater impedement to horizontal flow as
Novakovic et al. predicted. Another reason that this model has larger shale effect is that this model has higher shale coverage (30 to 60 percent here versus 21 to 42 percent in Novakovic et al.). Further, the models in this study have fewer blocks in vertical direction. Novakovic’s model used 66 (grid A) and 108(grid B) gridblocks in vertical direction, whereas we just use 10 gridblocks based on ten layers. Novakovic et al. (in press) used models with $k$ and $\phi$ inferred from GPR responses rather than using uniform $k$ and $\phi$ as was done in this study. On the other hand, theses models have many similarities: they are three dimensional models, the grids are stratigraphic, shale placement is stochastic, shale dimensions and the stratigraphic frameworks are anisotropic, and the anisotropies of shale dimensions are all slight.

6.2 Applications

The study of reservoir analogs not only can improve our abilities to estimate the properties and behavior of analogous reservoirs, but also can provide results or methods to study the analogous reservoirs.

For this reservoir analog study, the variograms we calculated can be used in the analogous reservoirs that do not have such fine-scale data. For example, we can use shale variograms to model the shale distribution in analogous reservoirs. If a stratigraphic framework is created, well data can condition semivariogram-based geostatistical models of shale distribution. These models can then be used for performance prediction.

The correlation of reflector amplitude to flow barrier may be useful in other contexts. Seismic data are similar to GPR data. Thus, an examination of seismic amplitudes and well data may reveal correlations between seismic amplitude and flow barrier occurrence. The
reservoir modeling team could use these data to create variograms of shale occurrence, and then to model shale distribution in the reservoir.

The variogram-based cornerpoint grid might be used for construction of complex models for reservoirs, just as it was used for this reservoir analog. Reservoir geometry provides important controls on the prediction of reservoir performance (Xie, 2001). However, it is difficult to accurately preserve the geometry when it is complex. This study provides a method to improve the complex model construction. In this method, the surface model is created geostatistically. The shape, extent, height, and orientation of the surfaces are controlled by the GPR interpreted data (seismic data can be used instead). The addition of each surface is based on sedimentological rules. Once the surface model is finished, it is transferred into cornerpoint grid. This cornerpoint grid can be used to do reservoir simulation.

For simple analysis, we used an ideal tracer flow model. As a result, tracer simulations cannot investigate effects of gravity, relative permeability and capillary. For reservoir simulations in which these effects are expected to be important, a two- or three-phase simulation model can be used to upscale multiphase flow properties. The analysis methods can be similar to those used in this study or in the upscaling work of Narayanan (1999).

6.3 Future Work

The correlation between GPR instantaneous amplitude and borehole data is critical to study shale distribution. To improve the shale distribution model, more wells should be drilled and cored. This will yield a more reliable correlation between instantaneous amplitude and shale index. It is better to drill wells in the west side, where most of the shales
were deposited, thus there are more chances to meet shales, and get more calibration data. Another useful method to get more accurate shale distribution model is using high frequency GPR survey to measure borehole section. This will help us identify thin shale (thickness <0.1m), and examine the relationship between thin shales and GPR reflections. Although in our study the thicknesses of 15 shale intervals within four boreholes are above GPR resolution (0.1m), we cannot say all of the shale thicknesses are beyond the GPR resolution. Adding thin shale in the simulation model no doubt is more realistic.

If we can combine the outcrop information into shale model, that could improve the model predictions. One way of the combination could be as follows: calculate shale ranges from the outcrop observations and measurements, then compare these ranges with ones we get from the GPR data and well data (shale index). If these two sets parameters are similar or same, we can say the calibration of GPR attribute with well data, the correlation between GPR attributes with borehole data are feasible. If they have big differences, we have to check the calibration and correlation processes.

For this study, we use 3-D GPR-derived shale index to calculate shale correlation ranges (integral ranges of 22.1m in $x$-direction, 15.7m in $y$-direction). Compared to shale ranges Novakovic et al. (in press) estimated from outcrop data (7.6m in $x$-direction, 5.75m in $y$-direction), these models have similarity, that is, the $x$-direction range is larger than $y$-direction range; the difference is our ranges are nearly 3 times larger. The main reason that makes these differences may be the different study location. Even both of these studies are at Corbula Gulch, Novakovic et al. data comes from the more east part (Figure 2-5 grid A and B) than our data. In this distributary environment, most of shales were deposited on the west side, which cause west side shale were more continuous than east side. The differences
could also be caused by the sparse well data in our study site which causes the correlations between GPR attributes and gamma ray values did not completely reflect the real case. That is, our shale index $I_{sh}$ may be more continuous spatially than the true shale indicator (observed in outcrop) is. This issue is best addressed using additional well data and higher-resolution GPR to better map thin shales in three dimensions.

In simulation model, we set all the gridblocks uniform porosity and permeability. For point-bar deposits in distributary channels, the porosity and permeability become poor gradually from bottom to top. In order to get a realistic simulation model, it is better to get these information from core data, and assign these features to simulation models.

In this study, GPR attributes were used to study shale distribution. Constrained by GPR vertical resolution, it is inevitable to miss some thin shales in our shale model. However, based on our study, it is higher shale fraction and correlation ranges that have significant contributions to the reservoir responses. Thin shales often have small distribution on the accretion surfaces, as a result they do not have big influences on the reservoir behaviors. That is, the thin shales we have not characterized are likely to have smaller effects on flow compared with the larger shales that we can resolve with GPR.

### 6.4 Implications For Reservoir Models

The flow models for the point bar deposits at Corbula Gulch demonstrate that the effects of shales on horizontal flow are relatively low (maximum is about 3%). The shale effects on vertical properties are relatively large, especially permeability. The fraction of accretion surfaces covered by shale is the most significant factor. These results can guide researchers in constructing models for shale distribution in similar depositional settings. For analogous reservoirs, data acquisition should focus on estimating the shale fraction with
lesser emphasis on ranges. For simulation model construction, the block size should be less than the shale variogram ranges, yet large enough to run simulations feasibly. In our models, the variogram range was at least 7 times the horizontal grid dimension; this should resolve the shale geometry adequately. More work would be required to relate the maximum grid size to the variogram range for the shale indicator.
CHAPTER 7. SUMMARY AND CONCLUSIONS

Information on the 3-D geometry of point bar deposits contained in 3-D GPR data can be used for 3-D reservoir characterization of reservoir analogs. The 3-D kriging method is used to regrid the accretion surfaces for shale distribution study.

GPR and well data were integrated to characterize the shale distribution. GPR information is incorporated after a step of statistical calibration, which prevents constraining the simulation to noise or information inconsistent with the shale occurrence. Discriminant analysis is used to calibrate GPR amplitude with gamma ray data. A significant correlation between relative instantaneous amplitude and shale index is found, and a statistic linear model is built.

Shale distributions within the point-bar deposits at Corbula Gulch are described via variograms. The analysis uses GPR data and core data. A slight anisotropy is observed in all shale statistics, but this anisotropy was not proved to be statistically significant. Sequential Gaussian Simulation is an effective geostatistical technique to characterize the reservoirs while incorporating variograms information. It reproduces the spatial correlation of shale on the accretion surfaces. Shales are placed on the accretion surfaces that are interpreted from the ground penetrating radar surveys. This approach is different from most previous shale models, in which shales are placed either horizontally or with constant dip.

Stochastic flow models based on ground-penetration radar surveys data demonstrate that for the sand-rich rocks at Corbula Gulch the effects of thin shale on flow behavior are statistically significant. Vertical flow is the most affected, with shales decreasing breakthrough time (approximately 4 percent), sweep efficiency (approximately 2 percent), and vertical permeability (approximately 29.59 percent). Shale distributions have little effect
on breakthrough time and sweep efficiency but have significant effects on vertical permeability. However, the details of the shale distribution are relatively unimportant: only the shale fraction ($F$) is practically significant in terms of the magnitude of the effect.

Although this study is based on near-surface sandstone, the results and methods are useful for reservoirs in marine-influenced distributaries. The variograms we calculated can be used in the analogous reservoirs that do not have such fine-scale data. The correlation of reflector amplitude to flow barrier may be useful in other contexts, for example using seismic data to study flow barriers. The variogram-based cornerpoint grid might be used for construction of complex models for reservoirs, just as it was used for this reservoir analog.
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VITA

Hongmei Li was born in Zaoyang, Hubei Province, China, on October 28th, 1972. She entered the Jianghan Petroleum College in September 1990 where she obtained the degree of Bachelor of Science in Exploration Geology in July 1994. After graduation, she continued her study in the Department of Geosciences of University of Petroleum (Beijing). She got the degree of Master of Science in July 1997. Then she worked as a geologist in the Exploration and Production Research Institute of China Petrochemical Company. In August 2000, she was admitted to the Graduate School of Louisiana State University for the master’s program in the Craft & Hawkins Department of Petroleum Engineering. She will receive the degree of Master of Science in Petroleum Engineering in August 2002.