Significant volumes of oil and gas occur in reservoirs that are inferred to have been formed by ancient river deltas. This geologic setting has implications for the spatial distribution of rock types (e.g., sandstones and mudstones) and transport properties (e.g., permeability and porosity). In particular, alternations between mudstones and sandstones may form baffles and trends in rock body permeability can influence productivity and recovery efficiency. In addition, diagenetic processes such as compaction, dissolution, and cementation can alter flow properties. A better understanding of these properties and improved modeling methods will allow improved reservoir development planning and increased recovery of oil and gas from deltaic reservoirs.

Surface exposures of ancient deltaic rocks provide a high resolution, low uncertainty view of subsurface variability. Patterns and insights gleaned from these exposures can be used to model analogous reservoirs, for which data is much sparser. This approach is particularly attractive when reservoir formations are exposed at the surface. The Frontier Formation in central Wyoming provides an opportunity for high resolution characterization. The same rocks exposed around the Tisdale anticline are productive in nearby oil fields, including Salt Creek. Many kilometers of good-quality exposure are accessible, and the common bedding-plane exposures allow use of shallow-penetration, high-resolution ground-penetrating radar. This study combined geologic interpretations, maps, vertical sections, core data, and ground-penetrating radar to construct high-resolution geostatistical and flow models for the Wall Creek Member of the Frontier Formation. Strata-conforming grids were used to reproduce the progradational and aggradational geometries observed in outcrop and radar data.

A new, Bayesian method integrates outcrop-derived statistics, core samples, and radar amplitude and phase data. The proposed method consistently propagates measurement uncertainty and yields an ensemble of models for features including calcite concretions. These concretions significantly affect flow. Furthermore, neither geostatistical data from the outcrops nor geophysical data from radar is sufficient: models which integrate these data have
significantly different flow responses. This was demonstrated both for an exhaustive two-
dimensional reference image and in three dimensions, using flow simulations. The new
method to model diagenetic features, integrating geostatistical and geophysical data, was
proven to have significant modeling benefits. This method is simple to implement within
widely available geostatistics packages.

This project wholly supported one PhD student and part of the education of an addi-
tional MS and PhD student. It helped to sponsor 6 refereed articles and 8 conference or
similar presentations, on topics including flow simulation, geostatistics, and high–resolution
X-ray image reconstruction. Later students have continued related work under competitive
industrial and government sponsorship.
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Chapter 1

Executive Summary

Improved models for the stratigraphy and transport properties of fluvial–deltaic reservoirs are needed to help reservoir geoscientists predict and improve oil and gas recovery. These improved models can also support predictions of hazardous waste isolation or migration, water resources deliverability, and other applications that rely on geomodels to analyze flow through sediments or rocks. Several challenges were addressed in this study:

- Although there are many outcrop data sets extant in the geosciences literature, the density of data, properties measured, representations of geometry, and reporting format are commonly not appropriate for geomodeling. In this study, the outcrop and associated ground–penetrating–radar (GPR) surveys were tailored for geomodeling.

- Much of geostatistics is based on regular rectangular modeling geometry, or voxels. Because these methods are ill–suited to the complex clinoform and channel geometries observed in fluvial–deltaic deposits. This problem is efficiently addressed by using a surface–based (or cornerpoint) representation for both geostatistical and flow modeling.

- Even multiple, mutually nonparallel outcrop faces do not give a true three–dimensional image of the deposits. This study combines high–resolution 3D GPR with even higher resolution outcrop photomosaics, in addition to logs and samples from wells within the study area.

- Such diverse data are difficult to integrate due to indirectness of measurement and scale differences. The proposed approach is Bayesian, which systematically propagates uncertainty and can address scale of support.
The integrated geomodeling approach in this study has several key components:

- Explicit use of surface models derived from 3D GPR surveys
- Systematic integration of outcrop, wellbore, and geophysical data
- Probabilistic identification of diagenetic concretions using cluster analysis
- Flow models validate the geostatistical approach and identify key sensitivities

This study is of interest to petroleum engineers and geoscientists aiming to do tightly coupled geologic and flow modeling, especially if the effects of inclined strata, concretions, and depositional facies are deemed important to include.

The lists of students supported and papers published are included in Appendix A.
Chapter 2

Introduction

2.1 Scope

This report discusses geostatistical and flow modeling for the Wall Creek member of the Cretaceous–age Frontier Formation in central Wyoming, U. S. A. The geologic and geophysical results are reported separately, either in the report submitted to the Department of Energy (Bhattacharya and McMechan 2005) or in the references cited in sections 3, Geologic Setting and 4, which describes the data used.

2.2 Outline of Material

In this section, the motivation of the research will be sketched, followed by a survey of previous work, goals of the current research, and the approach taken. The most significant concepts, innovations and results are highlighted in section 1, Executive Summary. The Geologic Setting is briefly discussed, with appropriate references, in section 3. Available Data are discussed in section 4. The data integration approach is described in section 5, Geostatistical Methods, and feature impact is examined in section 6, Flow Modeling. These technically detailed sections are followed by section 7, Discussion, and section 8, Remarks and Conclusions. Supporting materials are included as appendices.

The principal graduate research sponsored by this grant is presented in a dissertation (Tang 2005), which is available from the Louisiana State online Theses and Dissertations site, http://etd.lsu.edu/docs/available/etd-07032005-090208/.
2.3 Motivations

Fluvial-deltaic reservoirs comprise a major reservoir type, both in U. S. fields such as Prudhoe Bay (Begg et al. 1996) and internationally. Many studies have indicated that significant volumes of oil and gas remain unrecovered in deltaic reservoirs. For example, Tyler (1988) estimated that 24 to 69 percent of oil is bypassed in such reservoirs. This translates to as much as 15 billion barrels of mobile, bypassed oil in the United States. Many geoscientists believe that a large portion of the bypassing of oil is caused by low-permeability baffles or variability in permeability (Tyler and Finley 1992; Bhattacharya and Willis 2001).

The combination of a significant target and a complex cause motivates detailed study. However, large, integrated, high-resolution studies of deltaic studies are rare, and data with a three-dimensional component are rarer yet. Most studies use only quasivertical, variably oriented cliff faces (White and Willis 1999; Willis et al. 1999; Willis and White 2000; Jackson, Hampson, and Sech 2009; Sech, Jackson, and Hampson 2009). These studies are very useful, but both the geological description and flow modeling are incomplete: a sequence of two-dimensional views is not a three-dimensional data set or model.

A number of recent studies have used a combination of multiple outcrop exposures and three-dimensional ground-penetrating radar surveys to improve inference and modeling. Corbeanu et al. (2001) derived geometric and facies models for such systems. More recently, these three-dimensional interpretations have been used to create models for shale continuity and assess flow effects using reservoir simulators; the models and flow effects are significantly different from those derived from two-dimensional studies (e.g., Li and White 2003).

In addition to depositional features such as mudstone drapes, diagenetic features may have a significant effect on flow. At least in two dimensions, these features may be very significant for tidal reservoirs similar to the subject site (White et al. 2001; Dutton et al. 2002; White et al. 2003).

Together, these factors motivate examination of three-dimensional data, integration with outcrop and borehole data, formulation of geostatistical methods for surface construction and property estimation, and assessment of feature effects using designed simulation (White and Royer 2003).

2.4 Previous Research

Various researchers have used ground-penetrating radar as part of an integrated geologic characterization study, including flow simulation. Several relevant studies are discussed below, highlighting both accomplishments and need for additional study.

2.4.1 Ground Penetrating Radar: Background and Results

Ground-penetrating radar (GPR) surveys propagate electromagnetic waves in the range of approximately 25 to 1000 MHz into the earth. The timing and attenuation of returns can be used to infer the electromagnetic properties of the earth materials. Tang (2005) provides a brief overview of GPR, suitable for engineers who use GPR data but do not design, acquire, or interpret surveys. Fundamentally, the primary tradeoffs are (1) resolution versus depth
of investigation, because resolution increases with radar frequency whereas penetration decreases; and (2) trace and line spacing versus data volume, because tighter spacing improves imaging and enables 3D interpretations, but adds greatly to dataset size and time requirements (Neal, Richards, and Pye 2003). Typically, studies of ancient rocks use frequencies below 100 MHz, which gives resolutions of between 1 dm and 1 m. Neal, Richards, and Pye reported resolutions as good as 2 cm, but that was at a frequency of 900 MHz, shallower than needed for outcrop characterization and with low loss materials like gravel.

Persistent GPR reflections can be used to construct stratal models of reservoir architecture (Corbeau et al. 2001). There will be strong contrasts in electromagnetic properties (especially the permittivity, $\varepsilon$, and permeability, $\mu$; Powers 1997) across many lithofacies contacts. Particularly for the arid setting in the Ferron (Corbeau et al. 2001) and Frontier (Lee et al. 2005) studies, many of the laterally continuous stratal reflectors will be related to mudstone-sandstone contacts. These contacts are commonly strong reflectors because of higher water content and conduction losses in the mudstones, which typically contain clays with high cation exchange capacities (Olhoeft 1998). Depending on the spacing of the survey and the desired flow model size, it may be necessary to interpolate or smooth the surface. Li and White (2003) have presented methods based on trend surfaces and kriging the residual, with additional details presented in an MS thesis (Li 2002); this yields a stationary variable for geostatistical analysis, matches observations exactly, and is easy to implement; results are satisfactory (Fig. 2.1). Compared to nearby outcrop exposures, GPR surveys appear to allow reasonable, 3D interpretation of stratal geometry, at least at scales coarser than 1 m and depths less that 15 m. The frameworks derived with this approach appear to be geometrically reasonable for the marine-influenced distributary bar imaged at Corbula Gulch (Corbeau et al. 2001; Novakovic et al. 2002; Fig. 2.2).

GPR attributes such as instantaneous phase and amplitude may discriminate between different rock types or help assign rock properties, because differences in composition and density will affect both flow and radar transport properties. Based on this principle, cluster
Figure 2.2: Example of kriged surfaces. The framework (two views in A and B) appears adequately smooth. The permeability estimates (C, D) differ for the two strata and were assigned by cluster analysis. From Novakovic et al. (2002).

analysis was used to predict fluid permeability of fluvial–deltaic rocks in the Cretaceous–age Ferron sandstone (Corbeanu et al. 2002; Hammon III et al. 2002), and the results were used in flow models (Li and White 2003; Novakovic et al. 2002). These models for permeability were deterministic, using maximum likelihood without retaining uncertainty information.

Using the deterministic permeability estimate without an uncertainty model makes data integration problematic (Gelman et al. 2003). Moreover, integration with spatial data is needed in these cases, because the data are more discontinuous than reasonable, \textit{a priori} models of property variation suggest (Fig. 2.2 A, B). The model for shale occurrence used by Li and White (2003) uses spatial models (in the form of covariances or variograms), but the classification of a surface as shale-draped or shale-free at each radar trace is deterministic; statistical methods are used only to interpolate between traces and obtain the high-resolution flow model. Besides complicating integration, treating estimates as deterministic makes stochastic simulation \textit{seem} unnecessary and restricts the range of models that can be investigated in a sensitivity, uncertainty, or inversion study. Estimation methods that include error estimates, allow data integration, and foster uncertainty estimation are needed for GPR data.
Figure 2.3: Lateral correlations in geology. Geologic features show persistent lateral correlation, which must be included in realistic reservoir models. From Li and White (2003).

2.4.2 Geostatistical Methods

As noted in the previous section, data integration methods should consistently propagate errors, weighting diverse measurements by their uncertainty. Unfortunately, previous studies did not develop the tools to accomplish this. However, they did contribute many useful concepts.

Previous interpretations (Corbeau et al. 2002; Hammon III et al. 2002) used cluster analysis to identify facies or estimate properties; this approach can be modified to yield probabilistic rather than deterministic estimates. Similarly, the deterministic cutoff applied to map shales by Li and White (2003) can be modified to an indicator method, or probability of feature occurrence. Earlier studies have also demonstrated that low-noise, reliable variograms can be computed for object indicators using outcrop data. For examples, shale indicators show significant correlation and thus the regionalization of this variable is important to model (Fig. 2.3). The shale variograms can be combined with GPR observations and trend curves (the proportion of shale tends to increase upward in channel deposits) to prepare images of shale occurrence on a particular (nonhorizontal) stratal surface (Fig. 2.4). As will be discussed later, all models are represented in a stratigraphic, cornerpoint framework – layers may be locally absent, as shown in Figure 2.4.

This review indicates that we have the basic data (GPR, wellbores, and outcrop analogs) and tools (cluster analysis, kriging, and geostatistical simulation) to undertake more systematic data integration.
2.4.3 Flow Modeling and Response Analysis

Previous work has used commercial reservoir simulators (Schlumberger Technology Co. 2004) with cornerpoint grids (Ponting 1989), and used ideal tracer flow as a model displacement (Novakovic et al. 2002; Li and White 2003; White et al. 2003). This approach appears adequate; cornerpoint grids faithfully reproduce stratal geometries and are widely used for this reason (White and Willis 1999; King and Mansfield 1999). The resulting models are efficient, and flow displacements largely conform to strata, as predicted and observed in the field (Fig. 2.5). The importance of various features can be assessed using experimental design and associated methods (Myers and Montegomery 1995), which is widely used in reservoir modeling (White and Royer 2003). Previous detailed geologic studies have used this approach to varying degrees (e.g., Novakovic et al. 2002; White et al. 2003; Li and White 2003). This analysis typically includes factorial analysis and $t$-tests, and may require principal components analysis.

2.5 Goals

In light of the accomplishments of previous research, several goals were set for this research.

1. Express all observations and computations in a probabilistic framework, giving most likely (or mean) estimates and error estimates (or standard deviations). In many cases, this will require reformulation.
2. Design methods to use probabilistic property or category estimates from geospatial models, wellbore data, and geophysical data (GPR) simultaneously. The method must consistently weight the data by their precision, and should be unbiased.

3. Compare the new property and category estimates with those obtained with lesser integration. There are two challenging aspects to this problem: first, the comparison should be based on flow responses, which are much more difficult to compute than static model statistics; second, rigorous statistical tests should be used rather than arguments of reasonableness.

4. Apply the new methods to determine the importance of various features observed at the study site. The importance should be verified statistically.

5. Provide a method to estimate properties of interest, including upscaled permeability.

2.6 Approach

This section links to previous work and required extensions.

The cluster analysis technique of categorization will be applied to get probabilistic estimates of facies; principally, this will be used to model low-permeability calcite concretions which are common in the subject sandstone body. In addition, a Bayesian classification scheme for all facies is formulated, implemented and applied (Tang and White 2008; Tang 2005).

These probabilistic estimates will be used in conjunction with outcrop observations. The outcrop data provide facies trends and indicator variograms for concretion occurrence. Wellbore observations of concretions will be treated deterministically. These data will be combined using a modified sequential Gaussian simulation method (Deutsch and Journel 1998).

Flow will be simulated on a cornerpoint grid using a commercial reservoir simulator. Responses will be validated using two-dimensional reference images from outcrop panels, and
then flow will be examined in three dimensions. This will require some permeability upscaling from the fine, GPR-trace grid to a manageable flow simulation model. All responses will then be tested for significant sensitivities, and upscaling procedures outlined using designed experiments and statistical analysis (White and Royer 2003; Kalla et al. 2007).
Chapter 3

Geologic Setting

The subject of this study is a sandstone body within the Wall Creek Member of the Frontier Formation. The Wall Creek is late Cretaceous in age (the late Turonian to early Coniacian; Merewether, Cobban, and Cavanaugh 1972). The study location is within the Powder River Basin in north-central Wyoming (Fig. 3.1).

Some general characteristics of fluvial deltaic reservoirs, the regional setting, and the

Figure 3.1: Location of the study area, highlighting Frontier outcrops. From Bhattacharya and Willis (2001).
3.1 Fluvial-Deltaic Reservoirs in General

Deltas occur where rivers enter large, relatively quiescent bodies of water. The deceleration of flow decreases the sediment transport capacity of the water, and sediments settle to the bottom of the quiescent body of water. Because fine particles settle more slowly, they remain in suspension longer; in general, the sediments deposited near the river mouth (proximally) are coarse, sand-rich, and provide better-quality reservoirs compared with sediments deposited further offshore (distally).

Classically, deltas have been classified as tide-, wave-, or river-dominated. However, it appears that the subject of this study appears to be mixed-influence (Giosan and Bhattacharya 2005). Nonetheless, large-scale delta morphology is determined by the degree of fluvial, wave, and tidal influence.

Delta systems have a complex pattern of deposition: they commonly prograde, creating a series of basinward-inclined depositional packages, each of which coarsens away from the basin; although successive meter-scale packages commonly coarsen upward, sediments within packages may fine upward (White et al. 2004b) because of localized autocyclic processes. This variation of water velocity and the gauge of deposited sediments can cause large, localized contrasts in transport properties such as facies, grain size, and permeabilities (Fig 3.2). For this reason, deltas, especially mud rich deltas, present particular challenges for reservoir characterization, modeling, and management.

Figure 3.2: Rock quality trends in deltas. Variations in depositional energy as the delta progrades and offlaps cause contrasts in grain size, permeability, and rock type. From White et al. (2004b).
Figure 3.3: Frontier type section. The Wall Creek Member is just below the Cody Shale, at the top of the Cretaceous Frontier Formation. From Bhattacharya and Willis (2001).

3.2 Regional Setting

The Frontier Formation (Fig. 3.3) is an upper Cretaceous clastic wedge deposited in an eastward migrating foreland basin. The clastic wedge of the Frontier Formation prograded to the southeast into the seaway; the Powder Basin Frontier is interpreted to have been deposited during a lowstand because of its extreme basinward position (Willis et al. 1999; Bhattacharya and Willis 2001). The coeval proximal deposits were deposited farther west and comprise a thick succession of nonmarine facies (Hamlin 1996).

The Frontier formation contains at least three unconformity-bounded members. From oldest to youngest, these are the Cenomanian Belle Fourche Member, the Emigrant Gap Member of middle Turonian age, and the late Turonian to early Coniacian Wall Creek Member (Merewether, Cobb, and Cavanaugh 1972).

Laterally extensive bentonite (volcanic ash-fall) deposits (Fig. 3.3) provide valuable constraints for regional correlation and absolute dating horizons. This helps to constrain
Table 3.1: Facies classification for the Wall Creek Member.

<table>
<thead>
<tr>
<th>Facies</th>
<th>Description</th>
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<tbody>
<tr>
<td>F1</td>
<td>Marine Mudstone</td>
</tr>
<tr>
<td>F2</td>
<td>Thin bedded siltstone and mudstone</td>
</tr>
<tr>
<td>F3</td>
<td>Decimeter to meter-thick sandstone beds</td>
</tr>
<tr>
<td>F4</td>
<td>Bioturbated siltstone and sandstone</td>
</tr>
<tr>
<td>F5</td>
<td>Intensely bioturbated gray-white sandstone</td>
</tr>
<tr>
<td>F6</td>
<td>Cross-bedded pebbly sandstone</td>
</tr>
<tr>
<td>F7</td>
<td>Amalgamated flat-stratified sandstone</td>
</tr>
<tr>
<td>F8</td>
<td>Unidirectional cross-bedded sandstone</td>
</tr>
<tr>
<td>F9</td>
<td>Tidally-influenced cross-bedded sandstone</td>
</tr>
<tr>
<td>F10</td>
<td>Wavy parallel centimeter-scale bedded sandstone</td>
</tr>
</tbody>
</table>

our picture of the regional geology and makes the Wall Creek Member an especially fine candidate for a detailed characterization study.

3.3 The Raptor Ridge Locality

The subject of this detailed study, the Raptor Ridge sandstone (sandstone 6; Bhattacharya and McMechan 2005) is the uppermost parasequence of the Wall Creek Member (Fig. 3.3). Sandstone isolith maps indicate that it is a shore-parallel elongated delta lobe. River- and tide-dominated facies with a subordinate wave-dominated facies are observed. Sandstone 6 is interpreted as mix-influenced, top-truncated delta, because of its mix of bedding structure, ichnofacies, and package geometry.

The Wall Creek comprises multiple upward-coarsening sandstone bodies containing or capped by pebble conglomerate beds and separated by bentonitic mudstones. Ten facies have been defined as the building blocks of the Wall Creek Member (Table 3.1). The facies succession of the topmost parasequence grades upward from laminated sandy mud to heterolithic strata, then to flat stratified sandstones cut by channelized sandstone and locally overlain by heterolithic cross-stratified sandstones, and finally to crossbedded sandstone.

The Raptor Ridge data set is discussed in greater detail in section 4, Available Data.
Chapter 4

Available Data

The geoscience data include outcrop observations (vertical succession and photomosaics), wellbore data (logs and core analyses), and ground penetrating radar surveys. Samples included several 2- and 3D GPR surveys, ten wells, and several outcrop faces in this area (Fig. 4.1; wider-area map, Fig. 3.1). Core samples were taken from the boreholes, and used for petrophysical analysis including permeability and radar calibration.

4.1 Outcrop Observations

4.1.1 Interpreted Photomosaic

Digital photographs were stitched together to create continuous images of the outcrop exposure at the Raptor Ridge Locality. The photograph (Fig. 4.2, top) is printed on a large-format printer, and the facies interpretations, bedding, shale traces, and concretions are mapped on this base (Fig 4.2, lower) in the field. The photomosaic is warped using photoediting software so that distances between sections and vertically are consistent, using total station surveying data (Bhattacharya et al. 2002). The facies, sedimentologic structures, and permeability were measured on seven quasivertical sections (lines on Fig. 4.2; section 4.1.3). The lines, facies polygons, shale segments, and concretion polygons were mapped using the methods outlined by Willis and White (2000). The most important of these rules are

1. Lines must not double back; surfaces are single-valued functions of $x$, which is parallel to the projection plane of the outcrop and horizontal.

2. All bedding lines must either (a) extend beyond the outcrop or (b) terminate on another bedding plane.

3. All shales must lie on bedding planes.

4. Facies will be assigned by the frontmost (visible) polygon enclosing a gridblock center. Cement is considered to be a facies for this assignment.

Several observations can be made from inspection of the photomosaic (Fig. 4.2).
Figure 4.1: Maps of Raptor Ridge site. The coarse, 2-D sites are shown as cross-hatches, indicating line spacing (a). Raptor 2 is west of the canyon, Raptor 1 is the 2-D survey on the east. There is also a large, dense 3D survey (Raptor 3) at lower left corner of the northeastern 2D, b), a long orientation line (intersecting the northeastern survey) and a very small dense survey (Raptor 4) around well 10. Circles indicate well locations. From Bhattacharya et al. (2003).

- The succession is generally richer in Facies 5 (bioturbated white sandstone; Table 3.1).
- After correcting for a slight basinward structural dip, the beds generally incline basinward (south).
- The concretions are most commonly embedded in Facies 5.
- The shape of the concretions is complex, suggesting they may be aggregations rather than simple nucleations.

### 4.1.2 Concretion Character

The concretions have various sizes and shapes. Based on measurements of dip directional cliff face, the major concretions range from 0.7 m to 5.5 m in length, and from 0.2 m to 0.6 m in height. Two concretions are greater than 10 m long. The concretions have various
Figure 4.2: Photomosaic of an intensely studied outcrop at Raptor Ridge. This display bedding diagram with shales traced in red, a map of concretions (bright orange) and facies, and the stitched photomosaic. Color bar is the facies key. Location is given in Fig. 4.1. The detailed photomosaic and outcrop parallels the area from W9-W10 (Fig 4.1b). Fine lines in top figure element indicate measured sections (e.g., LE4). From Bhattacharya and McMechan (2005).
shapes ranging from “almond shape (nearly spherical but with flattened edges), to long, thin ellipsoids, to short, thick ellipsoids, to coalesced” (Nyman 2004).

Accurate estimation of concretion dimensions must consider measurement biases. Inference of concretion dimensions from finite-extent samples can be approached using geometric probability. Because the concretion observations are lower-dimensional than the population, objects with large extents lateral normal to the exposure are over-represented. The normal biases are removed using the Abel integral equation (Wicksell 1925) and lateral length bias can be removed using an Erlang model (White and Willis 1999). Based on Wicksell’s method, eighty percent of concretions are between 0.4 and 2.7 m in length and 0.08 and 0.60 m in thickness. White et al. argued that Wicksell’s method is more realistic for bodies like concretions. The debiased cumulative probability distribution has 80 percent of concretions by number between 0.4 and 2.7 m in length and between 0.08 and 0.6 m in thickness. To capture flow responses of the concretions, the geostatistical modeling grid dimension should be smaller than the minimum significant (in terms of flow) concretion sizes. On a volume basis, 80 percent of the concretion range between 2.5 and 15.5 m in length.

Outcrop profiles in this study are from southwest facing (approximately dip aligned; Fig. 4.1) and southeast facing (approximately strike) cliffs. The concretions are outlined by polygons on the interpreted photomosaics (Fig. 4.2). The interpreted drawing is then transformed to a dense pixel grid, where cement occurrence is assigned 1 and 0 if no cement occurs. Similarly, different facies polygons are converted into a sequence of grids. The grid size is 1000 horizontally by 800 vertically, and individual pixels are approximately 8 cm long by 2.5 cm thick. The concretion proportion is almost stationary horizontally in contrast with vertical trend. The cement fraction increases vertically from 0-3 percent in the bottom 5 meters to 18-20 percent in the middle 4 meters; and no concretion occurs in the top 2 meters. The trend of cement abundance is obvious from photomosaic.

Routine plug permeability, pulse decay permeability, and minipermeameter profiles from well cores have been measured. Permeability values in most concretions are reported as 0–0.2 mD, which is considered “tight” cement. Cement zones with comparatively higher permeability are probably partially cemented and called “light” cement (Bhattacharya et al. 2004). The average cement permeability values are about 1-2 md for facies 5 and facies 4.

These geometric and facies data will be combined with petrophysical data, gridded, and used in flow simulations in later sections.

4.1.3 Petrophysical Data from Outcrop

Facies were identified for the sedimentary rocks exposed at the Raptor Ridge and surrounding locations. Approximately 20 sedimentologic logs with total gamma ray (measured by handheld gamma ray scintillometer) were measured (Bhattacharya et al. 2003). These profiles are correlated with a regional subsurface database over the entire Power River Basin and used for facies modeling locally. Vertical logs and a bedding diagram of 250 m long cliff facies were collected. Bedding diagrams of the cliff faces (both perpendicular and parallel to depositional strike) extend down to the centimeter scale; these include bedding maps, facies maps, cement/concretion maps, and shale indicators. Extensive minipermeater data were also obtained on the outcrop.
4.2 Ground-Penetrating Radar Data

GPR propagates waves into the earth; for GPR, they are electromagnetic rather than sound waves. These signals reflect and refract in the earth, and the time series of signal returns can be used to characterize geologic units. The GPR survey is reconciled with outcrop and borehole measurements to correlate depositional surfaces, which are then transformed into flow grids. Furthermore, two GPR attributes, instantaneous frequency $\omega$ and instantaneous amplitude $A$ are correlated with lithology and concretion observations from cores from on-site well bores. Deterministic and statistical relationships can thus be used to predict concretion occurrence. Core material from the boreholes was used to get a calibration data set for concretion occurrence as it correlates to frequency and amplitude.

Several one–, two– and three–dimensional GPR surveys have been obtained in the Raptor Ridge area (Fig. 4.1). The 2D surveys were $100 \times 300$ m and $160 \times 200$ m at a nominal frequency of 50 MHz. The 3D surveys were $30 \times 80$ m, and $12.5 \times 12.5$ m at 50 MHz and 100 MHz, respectively.

GPR resolution increases with frequency, although the transmitted radar energy (and depth of penetration) decreases with increasing frequency. In practice, the balance of resolution and depth of penetration is determined by the objective of research. Sedimentary surface correlation needs relatively low resolution but moderate depth of penetration, justifying low frequency. Identification of small-scale geobodies like concretions or subsurface pipelines requires higher resolution, and thus high frequencies and an implied lower depth of penetration. In the study area, a 50 MHz 2D radar grid is used to build local sedimentary surfaces. A 100 MHz 3D radar grid helps to identify the effects of calcite concretions on GPR.
Chapter 5

Geostatistical Methods

The fundamental challenge is to combine observed spatial correlation structure (here, observed in outcrop exposures) with noisy but spatially dense 3D GPR data, with the goal of predicting facies and especially concretion occurrence. In addition, we wish to impose any observed spatial vertical trend in concretion proportion. We accomplish this by treating a kriged estimate of a Gaussian proxy for concretion occurrence; we update using the conditional probabilities of GPR attributes given concretion occurrence, inferred from cluster analysis of core data. The formulation of the prior and truncation method closely follow published work (Novakovic et al. 2002; White et al. 2003; Li and White 2003), but the inclusion of the amplitudes using cluster analysis is novel. This also required a new discrete Bayesian categorical model.

This chapter only presents model formulation and inference; geostatistical and flow models results are presented in section 6.

5.1 Model Formulation

The goal is to simulate concretion occurrences that honor outcrop correlation and GPR data. We will formulate this as a Bayesian sampling problem, and draw from the posterior distribution. The occurrence of cement at any location is indicated as

\[ i(x) = \begin{cases} 
0 & \text{if not cemented} \\
1 & \text{if cemented}
\end{cases} \]  

(5.1)

where \( x \) is a vector giving spatial location. The concretion indicators can be computed directly from the pixelized outcrop data at approximately 8 cm horizontal and 2.5 cm vertical resolution (section 4.1.2, earlier; section 5.2, later).

For convenience in imposing trends (White et al. 2003), we convert the indicator variable \( i(x) \) into an equivalent Gaussian variable (and associated autocovariance computed from the...
indicator; Matheron et al. 1987). The transformation to the Gaussian proxy is given by

\[ i(x) = \begin{cases} 
0 & \text{if } y(x) \leq t(x) \\
1 & \text{otherwise} 
\end{cases} \quad (5.2) \]

where \( y \) is the Gaussian variable and \( t(x) \) is the trend model (simply a constant if the concretion proportion is stationary). Kriging gives us the mean and variance of the proxy \( y \), from which we compute the prior probability of a concretion as

\[ P(C_c) \sim N(t - m, s) \quad (5.3) \]

where dependence of \( t, m, \) and \( s \) on \( x \) has been suppressed; \( m \) is the kriged mean and \( s \) is the kriging estimate of the variance; the \( \sim N \) indicates a normal distribution. The notation used is that \( C_k \) indicates the \( k^{th} \) category. The \( c \) subscript indicates concretion versus uncemented; for all categories \( k, k \in \{c[oncretion], u[ncemented]\} \).

Next, the conditional probability of attributes given concretions (or likelihood) is computed from a cluster analysis, here assuming multivariate Gaussian distributions, with distinct mean and variance, within each cluster. That is,

\[ P(a|C_k) \sim N(a - \mu_k, C_{ak}) \quad (5.4) \]

in which \( a \) is the the vector of attributes at the point to be simulated, here \( a = (\omega, A) \), and \( \mu_k \) and \( C_{ak} \) are the mean and covariance for the \( k^{th} \) cluster, respectively.

The penultimate step is to combine the prior and likelihood using the discrete form of Bayes’ rule

\[ P(C_k|a) = \frac{P(a|C_k)P(C_k)}{\sum_{\ell \in \{u,c\}} P(a|C_\ell)P(C_\ell)} \quad (5.5) \]

Finally, we draw a random number to assign the point to the cemented or uncemented set. This gives \( i \); to obtain the Gaussian surrogate at this point we choose a random number in the appropriate interval of probability,

\[ y = N^{-1}(P(C_k|a); t, s) \quad (5.6) \]

with the random draw \( r \) given by

\[ r = \begin{cases} 
0 & \text{if concretion} \\
1 & \text{otherwise} 
\end{cases} \quad (5.7) \]

We then add the point \( y(x) \) to the conditioning data, and proceed with a sequential geostatistical simulation (Deutsch 2002).

5.2 Model Inference

The trend and variogram will be inferred by a fine pixelization of outcrop photomosaics (circa 8 cm horizontally by 2.5 cm vertically; Fig. 4.2); the clusters are analyzed from wellbore data.
5.2.1 Trend

The photomosaic concretion map is converted to a binary set of indicators, and cement proportion is computed globally, and also for horizontal and vertical trends. The vertical trend is used directly as \( t(x) \); it does not depend on \( x_1 \) or \( x_2 \).

Figure 5.1: Vertical and horizontal trends in concretion proportion. The trends are computed from binary versions of the outcrop photomosaic. There is a pronounced vertical trend and a negligible horizontal one.

5.2.2 Variogram for Prior

The indicator variogram for concretion is computed in the traditional way (Deutsch 2002). It is then converted point–by–point to the equivalent Gaussian variogram using the methods outlined by Matheron et al. (1987), Figure 5.2. The variogram model parameters (Table 5.1) verify vertical–horizontal anisotropy and low noise (zero nugget).

5.2.3 Clusters for Likelihood

GPR radar attributes — especially instantaneous amplitude and frequency — have been demonstrated to be correlated to sedimentary fabric (Corbeanu et al. 2002). That relationship is exploited here to formulate a likelihood expression for \( P(a|C_k) \), the conditional probability of attributes \( a \) given that the point is known to be cemented (\( k = c \)) or not (\( k = u \)).

The amplitude and frequency of the wellbore samples were plotted with point type indicated (Fig. 5.3). Cluster analysis was done by minimizing intracluster variance and maximizing between cluster contrast. Concretions and non-concretions have large overlap because they cover large ranges of lithofacies and transport properties. The cluster analysis results (Table 5.2) shows that the clusters are only weakly informative for bar deposits (similar cluster centers, although variances are very different), whereas the discrimination is better in the channels, despite their lower amplitudes.

The GPR information about concretions is weak and noisy, but in combination with the variograms and trends it will be seen to improve model performance.
Figure 5.2: Strike, dip, and vertical Gaussian variograms. The large, dense data set provides excellent estimates of correlation with negligible nugget. Horizontal anisotropy is mild.

Table 5.1: Model variogram parameters. The nugget effects for both directions are 0; the internal ranges from semivariogram models are about 3.6 m. The dampened distance for hole effect is 10 m. The dip angle of the major axis is measured right-oriented downward to major axis.

<table>
<thead>
<tr>
<th>Structure</th>
<th>Dip Direction Range (m)</th>
<th>Strike Direction Range (m)</th>
<th>Vertical Range (m)</th>
<th>Dip (degrees)</th>
<th>Variance component</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exponential</td>
<td>1000.0</td>
<td>8.0</td>
<td>0.5</td>
<td>4.0</td>
<td>0.2</td>
</tr>
<tr>
<td>Spherical</td>
<td>2.0</td>
<td>13.0</td>
<td>0.03</td>
<td>4.0</td>
<td>0.4</td>
</tr>
<tr>
<td>Hole</td>
<td>4.0</td>
<td>3.5</td>
<td>0.1</td>
<td>4.0</td>
<td>0.4</td>
</tr>
</tbody>
</table>
Figure 5.3: The concretions in bar deposits (left) are more scattered than those in channel deposition (right). Because of attenuation, amplitude of bar deposition is larger than amplitude in channel deposition. The 95 percent posterior areas for concretion and nonconcretion are computed by adjusting the clusters parameters to maximize the well bore prediction.

Table 5.2: Centers and covariances for cluster analysis.

<table>
<thead>
<tr>
<th></th>
<th>Bar Deposites</th>
<th>Channel Deposits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Covariance Matrix</td>
<td>Cluster Center</td>
</tr>
<tr>
<td>Conc</td>
<td>A: 0.40 F: 0.08</td>
<td>8.13 8.20</td>
</tr>
<tr>
<td>Non-Conc</td>
<td>A: 4.00 F: 0.05</td>
<td>8.97 8.36</td>
</tr>
</tbody>
</table>
Chapter 6

Geostatistical and Flow Modeling

Both 2D and 3D flow models are presented. The two dimensional results are used for geostatistical method validation, whereas the 3D results are of greater practical interest.

The concretions are modeled with a modified sequential Gaussian simulation method (Deutsch and Journel 1998). By adjusting modeling choices such as variogram parameters, conditional wells, secondary data and factors of trends, different scenarios can be modeled. Geostatistical realizations combined with designed flow simulation can be used to analyze uncertainty or sensitivity of flow responses caused by different modeling factors. Furthermore, understanding the relationship between flow responses and modeling factors can guide the production history match and help validate the geologic models. For example, by understanding the outcrop flow responses modeled with dense data, we can develop theories to help predict geological factors of underground reservoir from flow responses.

6.1 Two-Dimensional Validation Runs

Two–dimensional models constructed for the outcrop are useful for validation, for several reasons:

1. The facies maps, shales, and concretion locations are known to high resolution.
2. A high–resolution model can be build and run at acceptable computational cost without upscaling.
3. Comprehensive visualization is simpler.

Of course, no GPR data are available for the outcrop face; these models rely on trend and variograms only. Static features such as variogram dip and range, and concretion proportion are compared.

The variogram and trend, along with a single conditioning “well,” were used to simulate concretion distributions. Geostatically simulated concretion distributions appear similar
to observations from cliff faces. The geostatistical simulation appears to capture the main characteristics of concretion distribution, such as concretion range, dip angle, proportion and trends (Fig. 6.1). However, the vertical trend is not aligned with bedding. This may be caused by using a simplified trend function to model the vertical trend that does not vary with dip. A more detailed trend may improve the results. Furthermore, some post-processing algorithms such as simulated annealing or multipoint statistics can be utilized to improve the geostatistical simulation (White et al. 2003).

![Figure 6.1: Realizations of concretions for an outcrop face. Various geostatistical and structural parameters have been varied.](image)

The parsimonious parametric representation of concretion heterogeneity allows straightforward sensitivity analysis and consideration of clearly different flow models.

But does the geostatistical model reproduce fluid flow? Flow simulations using a single-phase ideal tracer system were used to examine flow behavior (Fig. 6.2). The shunting effect of the concretions is immediately apparent. There appears to be a good qualitative match; we now assess the match statistically.

First, 6 replicates of the base-case geostatistical model were created by varying the random number seed. Flow was simulated through each realization; the mean and variance of the computed responses can be used to critique the model (Table 6.1). The mean of the simulated responses is generally within $\pm 1\sigma$ of the flow model based on the outcrop directly, which cannot falsify the null hypothesis that the simulated and outcrop models are drawn from the same population. This failure to falsify supports the modeling approach.

Second, we address the question of sensitivity. The good match of mean response is meaningless if the geostatistical parameters do not affect flow significantly. A 16-run orthogonal design (Kalla et al. 2007) with 6 factors – variogram range $R$, dip angle $D$, cement fraction $F$, trend $T$, conditioning wells $C$, and flow direction $O$ — was used to assess sensitivity (Table 6.2).
Figure 6.2: Comparison of concretion prediction for 2D fluid flow. (a), (b) are the concretion images; (a) is the observed facies and concretion structure. The blue blocks represent concretions, different colors represent different permeability (reddish is higher). (c) is the geostatistical simulation. (b) is the tracer flow front at breakthrough time for the observed concretions, (a). (d) is the flow simulation for the geostatistically simulated concretion distribution. Red represents injected tracer, blue represents original tracer. The simulation captured the characters of the trend, range, dip angle, and proportion of concretion, (a) and (c), as well as qualitative flow behavior, (b) and (d).

Table 6.1: Comparison of observed and base geostatistical flow. The digitized facies and concretions were used directly for the “observed” model, and six replicated geostatistical simulations for the “simulated” cases.

<table>
<thead>
<tr>
<th>Response</th>
<th>Observed</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k$, md</td>
<td>41.2</td>
<td>38.5</td>
</tr>
<tr>
<td>$\sigma_k$, md</td>
<td>6.2</td>
<td></td>
</tr>
<tr>
<td>$\tau_{BT}$</td>
<td>0.740</td>
<td>0.749</td>
</tr>
<tr>
<td>$\sigma_{\tau_{BT}}$</td>
<td>0.042</td>
<td></td>
</tr>
<tr>
<td>$N_{pD}$</td>
<td>0.887</td>
<td>0.887</td>
</tr>
<tr>
<td>$\sigma_N$</td>
<td>0.019</td>
<td></td>
</tr>
</tbody>
</table>
Table 6.2: Factors used in factor sensitivity. These factors were varied to assess sensitivity of flow responses to variation in model parameters using an experimental design.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Levels</th>
<th>Number of Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Semivariogram range(^a) (R)(^b)</td>
<td>0.5 1 1.5</td>
<td>3</td>
</tr>
<tr>
<td>Cement Dip angle (^a) (D)(^b)</td>
<td>0 1 1.5</td>
<td>3</td>
</tr>
<tr>
<td>Cement fraction (^a) (F)(^b)</td>
<td>1.5 1.0 0.5</td>
<td>3</td>
</tr>
<tr>
<td>Cement trend (^a) (T)(^b)</td>
<td>Yes  No</td>
<td>2</td>
</tr>
<tr>
<td>Conditioning wells (^a) (C)(^b)</td>
<td>1 2 3</td>
<td>3</td>
</tr>
<tr>
<td>Flow direction (^a) (O)(^b)</td>
<td>South to North North to South</td>
<td>2</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>20</td>
</tr>
</tbody>
</table>

\(^a\) the multiplier of observed concretion parameters. Similarly, the dip angle and the cement fraction are less, equal and larger than the observed values.

\(^b\) the symbols of factors and levels are used in experimental design

The concretion fraction \((F)\) is the average concretion coverage at a given depth.

The flow same three flow responses were analyzed as previously, and modeled using a weighted least squares response surface. An analysis of variance indicates that many of the geostatistical factors do indeed significantly affect responses (Table 6.3). Statistically replicating the mean when there is significant sensitivity provides further support for the geostatistical approach.

6.2 Three-Dimensional Simulations

Ultimately, methods must be applied in three dimensions. This will also allow incorporation of the radar data, which are not available at the outcrop face. However, the growth in model size with dimensionality makes direct flow simulation of the geomodels prohibitively expensive, which necessitates the complication of upscaling.

6.2.1 Model Construction

A 3D flow grid is established using 14 radar-interpreted surfaces (Fig. 6.3). These are treated deterministically. The 14 layers are interpolated guided by the geological model. For exam-
Table 6.3: ANOVA of 2D responses. The various responses are significantly sensitive to geostatistical model parameters.

<table>
<thead>
<tr>
<th>Flow Response</th>
<th>Upscaled Permeability (md)</th>
<th>Breakthrough Time (PV)</th>
<th>Sweep Efficiency (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Factors</strong></td>
<td>Coeff.</td>
<td>Significance</td>
<td>Coeff.</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.984</td>
<td>0.861</td>
<td>0.959</td>
</tr>
<tr>
<td>R</td>
<td>0.005</td>
<td>*</td>
<td>-0.113</td>
</tr>
<tr>
<td>D</td>
<td>0.012</td>
<td>*</td>
<td>0.096</td>
</tr>
<tr>
<td>F</td>
<td>-0.148</td>
<td>***</td>
<td>-0.338</td>
</tr>
<tr>
<td>T</td>
<td>-0.061</td>
<td>***</td>
<td>-0.112</td>
</tr>
<tr>
<td>R*C</td>
<td>0.030</td>
<td>***</td>
<td>-0.180</td>
</tr>
<tr>
<td>R*R</td>
<td>0.000</td>
<td>***</td>
<td>0.212</td>
</tr>
<tr>
<td>D*C</td>
<td>0.014</td>
<td>***</td>
<td>0.166</td>
</tr>
<tr>
<td>D*R</td>
<td>-0.001</td>
<td>**</td>
<td>-0.143</td>
</tr>
<tr>
<td>F*C</td>
<td>0.024</td>
<td></td>
<td>0.033</td>
</tr>
<tr>
<td>F*R</td>
<td>0.022</td>
<td>***</td>
<td>0.180</td>
</tr>
<tr>
<td>F*D</td>
<td>-0.008</td>
<td>*</td>
<td>-0.078</td>
</tr>
<tr>
<td>F+F</td>
<td>-0.007</td>
<td></td>
<td>0.074</td>
</tr>
<tr>
<td>T*D</td>
<td>0.021</td>
<td>**</td>
<td>-0.084</td>
</tr>
<tr>
<td>T+F</td>
<td>-0.144</td>
<td>***</td>
<td>-0.354</td>
</tr>
</tbody>
</table>

**R^2**: 0.815  0.951  0.833  0.877  0.831  0.937  
**R^2_adjust**: 0.812  0.950  0.830  0.874  0.828  0.936

From: To  Code  Interpretation
0 - 0.001  ***  Highly significant
0.001 - 0.01  **  Significant
0.01 - 0.05  *   Significant
0.05 - 0.1   o    Insignificant

The upper part of the delta sediments is interpreted as bar sediments of a top truncated low-stand delta (Bhattacharya and Willis 2001), which implies that the interpolated layers should retain that character. The lower part of the subject sandstone body is interpreted as channel deposits, which are interpolated proportional to the thickness to reproduce the sub-parallel, prograding geometry. Based on flow simulation of The flow grid uses cornerpoint geometry (Schlumberger Technology Co. 2004). The cornerpoint grid preserves the complex geological geometry more accurately and requires fewer grid blocks than a Cartesian grid, which saves computation time (Li and White 2003).

Facies properties are assigned deterministically by interpolation within layer boundaries, using wellbore observations of properties. These could be estimated geostatistically, but an emphasis on concretions was chosen instead. This highlights their effects and the performance of radar on their estimation.

The concretions were simulated conditional to well and radar data, including outcrop–derived trends and variograms, as discussed in sections 5.1 and 5.2. Block views of realizations illustrate several interesting features (Fig 6.4). First, the radar and nonradar images (left and right, top) clearly differ. If the radar conditional probabilities were noninformative, this would not occur. Thus, information has been added to the geostatistical simulations by integrating radar geophysics. In addition, the radar appears to enforce the correct trend if it is omitted. The geostatistical images show few layering artifacts and less noise compared with
the radar conditional probabilities only (bottom of Fig. 6.4).

6.2.2 Upscaling

The flow model should resolve the concretions; that is, the flow grid sizes should be equal to or smaller than major concretion sizes. On the other hand, several factors restrict the number of gridblocks. Computational costs increase quickly with the block count, which makes the suites of flow simulations less viable. Because the permeability model is derived from radar data, there is no benefit to modeling flow properties at resolutions finer than the radar resolution. Practically, small concretions may not “baffle,” or seal the flow path as significantly as larger concretions, so that failure to resolve the smallest concretions should not make much difference in flow responses. Keeping these points in mind, three flow models with different grid dimensions examine the relationship between flow responses and grids dimensions to guide selection of a reasonable grid size. To allow consideration of very high resolutions, block dimensions are as small as 0.5 × 0.61 × 0.08 m in x, y, z. A subregion for which computation was feasible was selected as sufficiently representative of the overall volume. The subgrid has top truncation bedding, which is typical of the survey area, the geometry is proportional to original subgrid, and facies ratios and concretion fractions are typical. Finally, the subgrid has similar flow responses to the whole grid (verified subsequently).

We begin with a fine grid that we know exceeds our resolution needs for concretions, 0.2 m lateral block size, and simulate facies and concretion occurrence on this fine grid. The
Figure 6.4: Realizations of concretions in 3D. (a) Prediction without trend and 1.5 times fraction of the observation, without radar. (b) Concretion prediction using same parameters as (a) and with Bayes radar update. (c) Including trend, without radar. (d) Imposing trend, with radar update. (e) Radar conditional probability of concretion. Radar and nonradar images differ.
permeability is then upscaled using a static method (Li, Beckner, and Kumar 2001). The required grid size was computed for three different grid sizes; the areal grid sizes are 0.2, 0.5, and 1 m for the fine, intermediate, and coarse grids, respectively. Six replicates for each grid size were created by varying the random number seed in the geostatistical model. Three flow responses — upscaled permeability $\bar{k}$, sweep efficiency $N_{pD}$, and breakthrough time $T_0$, were computed from flow simulations on three grids. The results show that the intermediate grid reproduces the average permeability and breakthrough time within error bounds, but mispredicts sweep efficiency (Fig. 6.5) — perhaps due to “smearing” of low concretion permeabilities when upscaling. Nonetheless, we consider the intermediate grid sufficiently accurate for more detailed modeling, given its ten–fold advantage in speed.

Figure 6.5: Grid sensitivity of flow responses. The error bars indicate the minimum statistically significant difference (95 percent level). The intermediate grid adequately represents average permeability and breakthrough time, but underpredicts sweep. The fine grid is much more computationally expensive.

### 6.2.3 Results

Flow modeling indicates that the concretions, and including radar data, have significant effects in three dimensional flows in the Raptor model. This is qualitatively demonstrated by comparing displacements through models that include and omit GPR data and vary other ef-
fects. Otherwise identical 3D flow models with and without data have differing concretion geometry and sweep efficiency (Fig. 6.6). In this case, the models including GPR have fewer and more dispersed concretions, which improves sweep efficiency.

![Figure 6.6: Differences in 3D flow models with and without GPR data. The top subfigures (a-c) are for the radar updated case, whereas (d-f) are for the same parameters except radar. The leftmost subfigures (a,d) are fence plots of absolute transmissibility. The middle subfigures (b,d) show low-permeability regions in blue; the layer-like features in the middle are a shale, dispersed blobs are concretions. The rightmost subfigures (c, e) show regions where the tracer has not swept. The radar case (b) has fewer concretions than the no-radar case (d). Less tracer is bypassed in the radar case (c) than without radar (e).](image)

The importance of radar data is assessed using an experimental design (nearly orthogonal array; Kalla et al. 2007) of 18 runs that varied the concretion proportion trend $T$, overall proportion $F$, flow direction $O$, and – most importantly – use of radar data $G$. Briefly, analysis of the resulting response surface indicates that

**Using radar data** $G$ affects average permeability and sweep efficiency significantly (95 percent level), but no significant effect on breakthrough time.

**The geostatistical parameters** also have similar effects on responses; no effects are significantly larger than including radar data.

**Flow direction** $O$ has a very large effect; the system is notably anisotropic (Fig. 6.7).

This is further, quantitative evidence that $G$ is informative.
Figure 6.7: Tracer sweep in different directions. Anisotropy in bedding, shales, and concretion locations affects sweep, with recovery being highest along dip (b; y) intermediate vertically (c; z) and lowest along strike (a; x).
Chapter 7

Discussion

This project addresses data integration and flow modeling for fluvial deltaic systems. A new method for combining geostatistical, wellbore and geophysical data ensures consistent weighting of errors using a Bayesian formulation. The efficacy of the geomodeling method is examined using designed flow simulation and statistically sound testing. The combination of systematic uncertainty propagation, flow modeling, and statistical testing provides insights into flow in reservoirs and geomodeling needs.

The approaches used for geomodeling (section 7.1) and flow modeling (7.2) are reviewed and critiqued, before proceeding to discussion of limitations and extensions (7.3).

7.1 Geomodeling Approach

We formulate a Bayesian integration method for geostatistical, geophysical, and wellbore data. The method is internally consistent and, by avoiding deterministic (e.g., maximum likelihood) estimates enables systematic propagation of errors. The method is based on well–known approaches including kriging, proportion curves, cluster analysis, and sequential Gaussian simulation; this eases implementation.

There are a number of alternative approaches. Full inversion of the radar survey is possible, but in general neglects important intertrace property correlations (Gunning and Glinsky 2004). Multipoint methods excel at reproducing complex geometries (Strebelle 2002), but these models require a great deal of data, are difficult to integrate with geophysical data, and their incorporation of trends is less natural than in the truncated Gaussian approach taken here; moreover, their complexity precludes parametric geostatistical studies.

The proposed approach is best discussed in terms of integrated data (section 7.1.1) and model components (7.1.2). The methods and data sources are briefly described, and then linked to how they would be used in the subsurface environment to model flow in aquifers or reservoirs.
7.1.1 Integrated Data

Three distinct data types are integrated in this project: analog data, wellbore data, and geophysical data. The systematic integration of such diverse data was the principal goal of this project.

1. **Analog data** are used to estimate trend models (also known as proportion curves) and indicator variograms. Here, the analog data are very direct indeed: they come from the cliffs adjacent to the outcrop, and are spatially localized measurements (for ratio data such as permeability) or as pixels from photomosaics (for categorical data). That is, they are spatially localized scalars and categories (indicators).

In the case of a subsurface reservoir or aquifer, the analog data are not so direct. They might be obtained from outcrop studies of analogous sediments, analysis of mechanistic sediment transport simulations, carefully scaled flume experiments, or perhaps simply from conceptual geologic models.

2. **Wellbore data** are used both directly and indirectly. Directly, they are used to inform facies categories and flow properties which are then interpolated deterministically using the GPR-derived framework. Indirectly, core samples from the wells and adjacent radar traces are analyzed to obtain radar–facies relations. These are used to guide the deterministic facies mapping as well as the cluster analysis used to derive concretion probability conditional on radar attributes.

A shallow aquifer might use well data more–or–less identically, if it were within GPR range. Somewhat deeper, high–resolution seismic could be used similarly with either laboratory or wellbore assessment of acoustic properties.

3. **Geophysical data** in the form of GPR are used to guide the stratal model, help with facies assignment, and improve estimation of concretion occurrence. The dense radar grids supply abundant data to infill sparse wells. However, they are imprecise and indirect indicators of concretion occurrence, so that modeling is required to take advantage of these data (section 7.1.2).

These data are precisely analagous to seismic data; only the specific attributes are changed. Resolution may become problematic at greater depths (section 7.3).

7.1.2 Model Components

The proposed modeling scheme combines three model components

1. **An indicator covariance** (or variogram) of a category’s occurrence describes the spatial continuity of the category. Assuming stationarity (or, equivalently, scaling to ensure stationarity), it is a function only of spatial separation $(x_1 - x_2)$. In this study, it was inferred from outcrop data. Because we used dense, low–noise pixelations of interpreted outcrop photomosaics, the inferred concretion indicator variogram is both smooth and exhibits a low nugget, in contrast to noisy, high–nugget variograms often obtained from geologic data sets. It is rarely possible to infer such high–quality variograms from subsurface data due to sparsity of observations.
2. A trend model for proportion describes how occurrence frequency deterministically varies. Like the variogram, this study inferred the trend from outcrop data. For a vertical trend only, this may be inferred from well data. Such deterministic trends are commonly more important to model than the stochastic fluctuations (e.g., White et al. 2004b), so geomodelers should attempt to model trends as such — and not rely on conditioning data, simple interpolation, or geostatistical models to impose them.

If sufficient data and conceptual knowledge are available, a full 3D trend $t(x)$ can be modeled. Goovaerts (1997) states that a model with an intelligently computed trend will usually outperform universal kriging, and offers guidance in computation of trends and spatial statistics for residuals. It is this trend model $t(x)$ that is used to convert indicators $i(x)$ to a Gaussian surrogate $y(x)$.

3. A conditional probability model linking geophysical data to categories supplies spatially dense data to update the more accurate but sparse well data. In this study, the conditional probabilities were computed using cluster analysis of radar data to derive $P(a|C_k)$, where $P$ is the discrete probability of a geophysical attribute set $a$ recorded at a particular point belonging to the cluster for category $k$. This study used the instantaneous phase and amplitude, $a = (\omega A)$. Any method, and any variables, that can yield such conditional probabilities can be used for Bayesian updating as described here.

### 7.2 Flow Modeling

Flow modeling is used to assess the validity of the models and identify sensitivities. Many geostatistical studies include no flow modeling, instead resting on matching specific statistics as validation. We simulate a high-resolution reference image from the interpreted photomosaic and geostatistical model, and compare the results statistically to validate the approach and model parameters. Combined with a demonstration of sensitivity, this increases confidence in the modeling approach.

Flow modeling was done on cornerpoint grids to preserve facies and shale geometry with manageable gridblock counts. This approach is widely applied and borders on routine (King and Mansfield 1999). Even for the small area studied (about 60 m by 30 m areally), the small data support volume (from GPR and well data) implied gridblock counts in the millions. Thus, some upscaling was undertaken, which incurs some loss in fidelity. As computing speeds improve, this limitation will recede.

### 7.3 Limitations and Extensions

The clustering of the amplitudes by category was weak. This made the radar data only weakly informative. Further study might reveal that the scatter is caused by important differences in concretion types or their surrounding media. Models for multiple concretion types, or multiple concretion clusters for a given type, might be identified and used to improve the information content of the geophysical data. There are not sufficient core samples in the current data to test this hypothesis.
At typical reservoir depths, GPR cannot penetrate and seismic has insufficient resolution (typically, circa Dm); geophysics is only weakly informative below this scale. However, this project demonstrated that even weakly informative data can enhance a geomodel, and this might be true for deep seismic data as well. Alternatively, a downscaling approach (Kalla et al. 2008) or seismic inversion (Gunning and Glinsky 2004). However, it is difficult to include trace–to–trace correlation during inversion, and significant, difficult post–processing may be required (Gunning, Glinsky, and White 2007).

The stratal surfaces and facies were interpolated by hand, with radar data for guidance. The flow properties were then interpolated within this framework. It would be more reasonable to do this geostatistically. For facies and properties, is a straightforward problem that can be solved with reasonable programming effort using existing algorithms. The stratal problem is much more difficult, and is a subject of current research (Zhang, Pyrcz, and Deutsch 2009).
Chapter 8

Remarks and Conclusions

8.1 Remarks

1. Diverse data — outcrop-measured sections, outcrop interpreted photomosaics, borehole samples for radar and fluid transport properties, and ground penetrating radar surveys at various spacings and frequencies — have been integrated in a geomodel.

2. The proposed geostatistical model consists of a variogram of concretion indicators, a trend for concretion proportion, and a conditional probability model linking radar attributes to concretion occurrence. Compared to full inversion, the model is simple and efficient. Compared to multipoint statistical methods, it is parsimonious.

3. Further work on upscaling, stratal modeling, and facies models would further improve the geomodels in this study.

4. The efficacy and behavior of the proposed geomodeling approach was assessed using sets of designed flow simulations in two and three dimension.

8.2 Conclusions

1. Two-dimensional flow models demonstrate that geostatistical flow models based on variograms and trends derived from outcrops reproduce flow behavior. The mean flow responses of the geostatistical models was not significantly different from the flow response based on dense outcrop observations.

2. Suites of designed flow simulations of the two-dimensional outcrop model show that the flow responses are sensitive to geostatistical model parameters. Thus, the match of geostatistical and observed models is not serendipitous.

3. The concretions and uncremented samples cluster only weakly on radar amplitude crossplots. Nonetheless, the conditional probabilities are still informative, as demonstrated by visualizations of the conditional probability field.
4. Three-dimensional simulated flow responses in the Raptor sandstone are sensitive to geostatistical model parameters as demonstrated by statistical tests on differences between flow model responses when radar is included and omitted.

5. The sensitivity studies demonstrate that the proportion, size, and location of concretions have significant effects on permeability, recovery efficiency, and water breakthrough time. Thus, concretions should be carefully modeled in reservoirs and aquifers to obtain accurate flow predictions.
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Appendix A

Students Supported, Papers, Posters, Abstracts, and Presentations

A.1 Students Supported

**Hongmei Li, MS.** Two years support for shale modeling, partly paid from an earlier grant. Now at ExxonMobil Upstream research (after earning PhD from Stanford), Houston.


**Djuro Novakovic, PhD.** Several months support for concretion modeling and simulation, as well as shale model simulation design. Now with Chevron Technology Company, seconded to Nigeria.


**Hong Tang, PhD.** Three years support for facies, surface and flow modeling. How at Chevron Technology Company, Houston.


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