NIPER/BDM-0327

Topical Report

MODAL AND GEOSTATISTICAL ANALYSIS OF PHYSICAL PROPERTIES: ALMOND FORMATION TRANSGRESSIVE SHORELINE BARRIER FACIES, SOUTH-CENTRAL WYOMING

for

Management and Operating Contract for the Department of Energy's National Oil and Related Programs

by

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BDM Petroleum Technologies
Under Contract to BDM-Oklahoma, Inc.

September 1997

Work Performed Under Contract No.
DE-AC22-94PC91008

Prepared for
U.S. Department of Energy
National Petroleum Technology Office

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Table of Contents

1.0 INTRODUCTION 1

2.0 GEOLOGICAL SETTING 3

3.0 PART 1

RESULTS OF MODAL THIN SECTION ANALYSIS 5

3.1 Methods 5

3.2 Sandstone Composition 7

3.3 Measures of Packing (Compaction) 11

3.3.1 Grain Contacts and Compaction 11

3.3.2 Porosity Loss Equations and Analysis 13

4.0 PART 2

GEOSTATISTICAL ANALYSIS OF OUTCROP DATA – TIDAL DELTA FACIES 17

4.1 Introduction 17

4.2 Reservoir Characterization 17

4.3 Limitations in Reservoir Characterization 18

4.4 Statistics and Geostatistics 19

4.4.1 Variogram 19

4.4.2 Nugget Effect 21

4.4.3 Range 21

4.4.4 Sill 21

4.4.5 Variogram Models 22

4.4.6 Spherical Model 22

4.4.7 Isotropy and Anisotropy 23

4.5 Data Analysis 23

4.5.1 Conventional Statistical Analysis 24

4.5.2 Assessment of Predictability 35

4.5.3 Variogram Analysis and Scalability 37

5.0 CONCLUSIONS 43

6.0 REFERENCES **45**

Tables

1 Correlation Coefficients" for Relationships Between Petrographic and Petrophysical Properties of Almond Samples 9

2 Trends in Selected Petrographic, Petrophysical, and Compactional Properties and Indices for All Facies From Outcrop G 15

3 Univariate Statistics of Porosity Data at Scale 0 25

4 Univariate Statistics of Permeability Data in Horizontal Direction Scale 0 27

5 Univariate Statistics of Permeability Data in Vertical Direction Scale 0 27

6 Univariate Statistics of Permeability Data in Two-Dimensional Scales 28

7 Univariate Statistics of Log-Permeability Data in Horizontal Direction Scale 0 31

8 Univariate Statistics of Log-Permeability Data in Vertical Direction Scale 0 31

9 Univariate Statistics of Permeability Data in Two-Dimensional Scales 32

10 Variogram Models for Log-Permeability 41

Figures

1 A and B. The study area is located on the eastern margin of the Rock Springs Uplift, Wyoming. C. Topographic base of Section 33, T16N, R102W showing the location of Outcrops G and V 1

2 Relationship Between Porosity and Permeability for All Plugs Collected at Outcrop G ... 5

3 Permeability Histogram and Cumulative Percent Curve for All Samples From Outcrop G 5

4 Porosity Histogram and Cumulative Percent Curve for All Samples From Outcrop G 5

5 Multiple, optically continuous thin quartz cement overgrowths (QOG) are common on quartz and silty lithic fragments but are not volumetrically significant. Kaolinite (K) and other possible clays post-date the quartz overgrowths. Width of image is approximately 69.2 μm. 6

6 Relationship between point count-derived porosity and helium porosity. Helium porosity represents total porosity and is significantly greater then point count porosity for lower values because of the effect of microporosity. 8

7 Variations in the proportions of contacts for increasing depth in the shallow subsurface of Core Hole #2. 12

8 Example of lateral variations in the proportions of grain contacts from tidal channel facies at Outcrop G. 12

9 Example of lateral variations in the proportions of grain contacts from the tidal delta facies at Outcrop G. 12

10 Comparison of the lateral variations in CI and percentage of clay cement from tidal channel unit 6 at Outcrop G. Note a roughly inverse relationship. 12

11 Comparison of the lateral variations in CI and percentage of total cement from tidal channel unit 6 at Outcrop G. Note a roughly inverse relationship. 12

12 Comparison of the lateral variations in CI and percentage of clay cement from tidal delta at Outcrop G. Note a very crude inverse relationship between the two parameters. 12

13 Comparison of the lateral variations in CI and percentage of total cement from tidal delta at Outcrop G. Note a very crude inverse relationship between the two parameters.12

14 Comparison of the lateral variations in CI, TPI, percentage of clay cement, and total cement from tidal channel at Outcrop G. Note that the CI and TPI trend essentially parallel to each other with only a minor offset. 13

15 On the left is the relationship between COPL and CEPL for samples from Outcrop G. On the right is the same relationship for facies from the shallow subsurface in Core Hole #2. See text for explanation. 14

16 Mean and Median of Experimental Variogram Bin Data 20

17 Experimental Variogram Bin Data Prior to Averaging 20

18 Parameters of a Typical Variogram Plot and Theoretical Model 21

19 Tidal Delta Samples, Outcrop G 23

20 Tidal Delta Samples, Outcrop V 23

21 Histogram of Porosity Data at Scale 0, Y = 0 ft (Outcrop G) 26

22 Histogram of Porosity Data at Scale 0, Y = -5 ft (Outcrop G) 26

23 Histogram of Porosity Data at Scale 0, Y = 0 ft (Outcrop V) 26

24 Histogram of Porosity Data at Scale 0, Y = -5 ft (Outcrop V) 26

25 Histogram of Porosity Data at Scale 0, X = 800 ft (Outcrop G) 26

6 Histogram of Entire Porosity Data at Scale 3 (Outcrop G) 26

27 Histogram of Entire Porosity Data at Scale 3 (Outcrop V) 26

28 Probability Plot of Porosity Data at Scale 0, Y = 0 ft (Outcrop G) 26

29 Probability Plot of Porosity Data at Scale 0, Y = -5 ft (Outcrop G) 26
30 Probability Plot of Porosity Data at Scale 0, Y = 0 ft (Outcrop V) 26
31 Probability Plot of Porosity Data at Scale 0, Y = -5 ft (Outcrop V) 26
32 Probability Plot of Porosity Data at Scale 0, X = 800 ft (Outcrop G) 26
33 Probability Plot of Entire Porosity Data at Scale 3 (Outcrop G) 26
34 Probability Plot of Entire Porosity Data at Scale 3 (Outcrop V) 26
35 Histogram of Permeability Data at Scale 0, Y = 0 ft (Outcrop G) 30
36 Histogram of Permeability Data at Scale 0, Y = -5 ft (Outcrop G) 30
37 Histogram of Permeability Data at Scale 0, Y = 0 ft (Outcrop V) 30
38 Histogram of Permeability Data at Scale 0, Y = -5 ft (Outcrop V) 30
39 Histogram of Permeability Data at Scale 0, X = 800 ft (Outcrop G) 30
40 Histogram of Permeability Data at Scale 1, Sub 1 (Outcrop G) 30
41 Histogram of Permeability Data at Scale 1, Sub 2 (Outcrop G) 30
42 Histogram of Permeability Data at Scale 1, Sub 3 (Outcrop G) 30
43 Histogram of Permeability Data at Scale 2 (Outcrop G) 30
44 Histogram of Permeability Data at Scale 3 (Outcrop G) 30
45 Histogram of Entire Permeability Data at Scale 3 (Outcrop G) 30
46 Histogram of Entire Permeability Data at Scale 3 (Outcrop V) 30
47 Probability Plot of Permeability Data at Scale 0, Y = 0 ft (Outcrop G) 34
48 Probability Plot of Permeability Data at Scale 0, Y = -5 ft (Outcrop G) 34
49 Probability Plot of Permeability Data at Scale 0, Y = 0 ft (Outcrop V) 34
50 Probability Plot of Permeability Data at Scale 0, Y = -5 ft (Outcrop V) 34
51 Probability Plot of Permeability Data at Scale 0, X = 800 ft (Outcrop G) 34
52 Probability Plot of Permeability Data at Scale 1, Sub 1 (Outcrop G) 34
53 Probability Plot of Permeability Data at Scale 1, Sub 2 (Outcrop G) 34
54 Probability Plot of Permeability Data at Scale 1, Sub 3 (Outcrop G) 34
55 Probability Plot of Permeability Data at Scale 2 (Outcrop G) 34
56 Probability Plot of Permeability Data at Scale 3 (Outcrop G) 34
57 Probability Plot of Entire Permeability Data at Outcrop G 34
58 Probability Plot of Entire Permeability Data at Outcrop V 34
59 Log-Permeability vs. Porosity Plot at Scale 0, Y = 0 ft (Outcrop G) 36

60 Log-Permeability vs. Porosity Plot at Scale 0, Y = -5 ft (Outcrop G) 36
61 Log-Permeability vs. Porosity Plot at Scale 0, Y = 0 ft (Outcrop V)..... 36
62 Log-Permeability vs. Porosity Plot at Scale 0, Y = -5 ft (Outcrop V) 36
63 Log-Permeability vs. Porosity Plot at Scale 0, X = 800 ft (Outcrop G) 36
64 Log-Permeability vs. Porosity Plot at Scale 1, Sub 1 (Outcrop G) 36
65 Log-Permeability vs. Porosity Plot at Scale 1, Sub 2 (Outcrop G) 36
66 Log-Permeability vs. Porosity Plot at Scale 1, Sub 3 (Outcrop G) 36
67 Log-Permeability vs. Porosity Plot at Scale 2 (Outcrop G) 36
68 Log-Permeability vs. Porosity Plot at Scale 3 (Outcrop G) 36
69 Log-Permeability vs. Porosity Plot of Entire Data at Scale 3 (Outcrop G)..... 36
70 Log-Permeability vs. Porosity Plot of Entire Data at Scale 3 (Outcrop V)..... 36
71 Experimental and Model Variogram of Log-Permeability at Scale 0, Y = 0 ft (Outcrop G)37
72 Experimental and Model Variogram of Log-Permeability at Scale 0, Y = -5 ft (Outcrop G)37
73 Experimental and Model Variogram of Log-Permeability at Scale 0, Y = 0 ft (Outcrop V)37
74 Experimental and Model Variogram of Log-Permeability at Scale 0, Y = -5 ft (Outcrop V)37
75 Experimental and Model Variogram of Log-Permeability at Scale 0, X = 800 ft (Outcrop G)..... 38
76 Experimental and Model Variogram of Log-Permeability at Scale 0, y = 0 ft, Part 1 (Outcrop G)..... 38
77 Experimental and Model Variogram of Log-Permeability at Scale 0, y = 0 ft, Part 2 (Outcrop G)..... 38
78 Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 1 (Outcrop G) 38
79 Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 2 (Outcrop G) 38
80 Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 3 (Outcrop G) 38
81 Experimental and Model Variogram of Log-Permeability at Scale 2 (Outcrop G) 38
82 Experimental and Model Variogram of Log-Permeability at Scale 3 (Outcrop G) 38

ABSTRACT

This report presents a detailed modal thin section analysis combined with statistical and geostatistical analysis of porosity and permeability data obtained from outcrops of Almond formation. The purpose of the study is to characterize the petrophysical properties of the various facies within the outcrops in particular, and the spatial variability of the parameters in the outcrops in general. This study will allow researchers to better understand the oil fields that tap oil from a reservoir with properties similar to the outcrops being investigated.

Recent work focused on characterizing the lateral variability of permeability and porosity within the tidal delta facies at two outcrops from the eastern margin of the Rock Springs Uplift in south-central Wyoming. Statistical and geostatistical analysis of porosity and permeability of outcropping tidal delta sandstones have been used to demonstrate the statistical distribution, characterize the variability, and assess the lateral predictability and scalability of the petrophysical properties. Data from the tidal channels and the foreshore facies have been included in the petrographic analysis; however, these data not been considered in the geostatistical analysis presented in this report. Once the statistical analyses of all these facies have been completed, the developed data and model can be used to provide realistic, geologically driven constraints on upscaling processes so that both intrafacies and interfacies variations of petrophysical properties can be honored.

The petrophysical analysis was done by collecting more than 1,600 plugs of 1-inch diameter from the outcrops. Seventy-eight (78) dyed, epoxy-impregnated thin sections oriented perpendicular to the bedding were then point counted for composition and packing parameters, including grain contact types and indices. Modal thin section analysis provided information on the sandstone composition, measures of packing, grain contacts, and compaction. Based on the outcome of the modal analysis, it was observed that the tidal delta and tidal channel facies have very similar overall compositions. Analysis of grain contacts and compaction showed that there are small, but consistent differences in packing indices between the tidal delta and tidal channel sands. Proportions of grain contact types, or of contact and tight packing indices resulted in predicting very poor relationships between contact index and other petrophysical and petrographic parameters. Grouping data by intergranular volume, however, significantly aided the proper interpretation of porosity in upper Almond outcrop sandstones, whereas grouping by permeability did not provide significant correlation.

The geostatistical analysis of the porosity and permeability data was performed to supplement the petrophysical analysis using modal thin sections. The study was limited to the tidal delta facies of two outcrops of the Almond formation from which data have been extensively sampled. This report presents a brief review of the importance and methods of the geostatistical analysis to provide a justification and basis of the study. Data were analyzed for assessment of

predictability, variability, and scalability of the porosity and the permeability within the tidal delta facies with the goal of obtaining a single, widely applicable model that could represent the spatial continuity of the parameters. Because of the limited variation in porosity, a single average value was found sufficient to represent this parameter over the entire facies. The permeability data indicated both heterogeneity and anisotropy within the facies. The data also showed a very high degree of spatial variability. Using a logarithmic transform of the permeability was necessary to assess predictability and scalability, and to perform variogram analysis. From the analysis, researchers concluded that the two parameters do not have any significant correlation and that knowledge of the magnitude of one provides no conclusive evidence of the magnitude of the other. However, statistically, higher values of permeability have been found to be moderately associated with higher values of porosity. The results of the variogram analysis showed that it is possible to derive a single, widely applicable theoretical model for the experimental variogram estimates in the horizontal direction. However, more data need to be collected to obtain a conclusive model for the vertical direction.

EXECUTIVE SUMMARY

Petroleum reservoir characterization requires a detailed description of the geological and physical properties of the porous media. Availability of critical interwell scale reservoir data is often very limited. Information is generally only available from a limited number of well logs present in the area. Furthermore, the well logs provide a good picture of the vertical variability of properties such as porosity and permeability of the reservoir material. However, the lateral variability of these properties are often conceptualized through the limited information available via the well log data.

Accurate prediction of field performance necessitates a thorough knowledge of the spatial distribution of porosity and permeability. Because of a lack of data on the interwell scale, outcrop analogs have been studied to define the spatial distribution of the petrophysical properties in 2D and 3D to gain insight into what to expect on a reservoir scale. The information obtained from an outcrop study may not be directly translated to determine reservoir properties, yet it allows analysis of the continuity of formations and investigation of in-situ vertical and horizontal variations in properties. It also facilitates finer sampling of data points which is necessary for a detailed description of the pore-scale to facies-scale components of reservoir characterization.

The main objective of this report is to describe the lateral variations in petrophysical properties based on closely spaced samples from Almond formation outcrops. An attempt is made to relate these trends in petrophysical properties to natural processes in order to predict their distribution. To achieve these objectives, plug samples have been collected from the tidal delta, tidal channel, and foreshore facies of excellent outcrops of the formation in Rock Springs, Wyoming. The tidal delta data collected from two outcrops (G and V) of the formation have been used to compare the variational properties of the parameters relevant to a lateral flow, as would be analogous to an oil field which taps oil from a reservoir with properties similar to the outcrops under study. A detailed modal thin section analysis has been performed on the tidal delta, tidal channels, and foreshore facies of the outcrops to characterize the petrophysical and petrographic properties of the outcrop. Preliminary statistical and geostatistical analysis of the parameters of outcropping tidal delta sandstones have been used to demonstrate their statistical distribution, correlation, and variability, and to assess the lateral predictability and scalability of the petrophysical properties.

More than 1,600 plugs of 1 inch in diameter were collected from the outcrops for petrophysical analysis. From the samples collected, 78 dyed, epoxy-impregnated thin sections oriented perpendicular to the bedding were cut and point counted to determine the composition and the packing parameters. From the results of the modal analysis, it was found that the tidal delta and tidal channel facies have very similar overall compositions. Tidal delta sands have an average

framework grain composition of Q 55.7, F 20.5, R 23.9 (where Q, F, and R represent normalized percent quartz, feldspar, and lithics, respectively). The tidal channel sands' average composition is Q 56.8, F 22.9, R 20.1, and so are slightly more feldspathic and contain slightly less lithics. The point count analysis was used to distinguish primary and secondary porosity in the thin sections. It was observed that the Almond sandstones locally contain a significant amount of primary intergranular microporosity between clay particles and secondary intraparticle microporosity in finely leached feldspars and rock fragments. Two types of packing parameters were quantified in this study. First, the change in fabric with increasing compaction can be related to types of grain contacts in thin section, which is often quantified by factors known as the contact index (CI) and the tight packing index (TPI). The second method of evaluating compaction using thin sections is based on calculating the percent intergranular volume (IGV). Analysis of CI and TPI shows that there are small but consistent differences in packing indices between the tidal delta and tidal channel sands. These in turn relate to slight differences in the lithology between the facies. A very poor relationship was obtained between CI and other petrographic and petrophysical parameters whereas, qualitatively, they should provide strong correlational properties. Using the IGV method to evaluate compaction, it was observed that the porosity loss in tidal channel sands was owing to both compaction and cementation, whereas the loss in tidal delta sands was mainly because of compaction. Grouping data by IGV has been found to significantly aid in the interpretation of porosity in upper Almond outcrop sandstones. Unfortunately permeability does not correlate as well with intergranular volume as porosity does. Based on the results of modal analysis of outcropping Almond sandstones, permeability is not simply a function of compaction or cementation. With additional work, the comparison of compaction and cementation parameters may also provide the basis for an improved method to predict lateral permeability distribution within facies. Compaction can play a major role in creating lateral variations in heterogeneity on the interwell scale. This line of investigation should be continued during FY 1998.

Statistical and geostatistical analysis of the tidal delta facies of the two outcrops in the formation was used to assess the predictability, variability, and scalability of the porosity and the permeability within the facies. Both 1D and 2D analyses were included in the study to visualize the similarities of the properties in different scales and to assess the translation of the variograms obtained from the geostatistical analysis between scales. A geostatistical software package called GEO-EAS (Geostatistical Environmental Assessment Software) was used to analyze the data.

The results obtained from the conventional statistical analysis revealed that the porosity distribution is on average uniform over the entire facies, and the coefficient of variance of the data is very small. Hence it was concluded that the average porosity value is representative of the entire tidal delta facies. The statistics of the permeability data, on the other hand, indicated a very high coefficient of variation within the facies and also between the two facies which were studied. The mean permeability between the facies of the two outcrops, G and V, varied between 1.5 to 3 times in magnitude. Whereas outcrop G provided a homogeneous permeability

distribution, outcrop V indicated layered heterogeneity within the facies. The facies were also found to be moderately anisotropic with the average permeability in the vertical direction being 1.17 times higher than that of the horizontal direction. The distribution of the permeability data was found to be very skewed in both facies.

A log transformation of the permeability data was deemed necessary to dampen the variance and normalize the data for geostatistical analysis and assessment of predictability. The porosity and the log-permeability data indicated very poor correlation structure at all scales. It was concluded that the predictability of one data from the other was trivial. However, the trend in the orientation of the statistically best fit line amongst the data clusters of porosity versus permeability plots indicated that higher porosity was associated with higher permeability and vice versa. A detailed geostatistical analysis of the log-permeability data was performed, and theoretical models were fitted to the experimental variogram estimates obtained from the study. The variogram analysis was also done for different scales of sample data to assess scalability of the theoretical variogram models. The applicability of the variogram model within the facies was inconclusive for small samples that were smaller than the range of the theoretical variogram. However, for large samples, a single, widely applicable (*unique*) model could possibly be defined in the horizontal direction. The variogram analysis in the vertical direction did not provide any statistically significant results because of lack of sufficient measurements in the data samples. Two major conclusions were reached from the entire geostatistical analysis: (1) additional data needs to be collected to obtain a unique variogram estimate for the tidal delta facies, and (2) a better method to estimate the experimental variogram needs to be used to obtain more reliable results from the analysis.

The geostatistical analysis presented in this report considers only a single facies, the tidal delta. In order to understand the complete system, future work must first concentrate on a more complete analysis of the tidal delta facies with better estimates of the geostatistical parameters using cutting edge methodologies and more data samples. Second, the methods need to be extended to the other well-sampled depositional facies in the outcrop in order to obtain a complete picture. Additional input on facies architecture is needed in order to evaluate the 3D distribution of reservoir properties. The variogram models obtained need to be cross-validated by obtaining kriged estimates of the parameters in the outcrop. A detailed analysis of the covariance of the porosity and permeability data over the entire outcrop and within each facies is critical to obtain improved kriged estimates, to upscale the parameters, and to use inverse models for predicting the parameters accurately. The complete analysis will provide a thorough quantitative, interdisciplinary characterization of the outcrop and facilitate reliable transfer of the methods to subsurface reservoirs.

1.0 INTRODUCTION

Variation in petrophysical properties, notably porosity, with depth has often been reported for formations and specific reservoirs (e.g., Loucks, Dodge, and Galloway 1984; Wilson and McBride 1988; Higley and Schmoker 1989; McBride, Diggs, and Wilson 1991; Dutton 1993; Brasher and Vagle 1996; Toupin et al. 1997). In addition, experimental compaction models have been used to predict the effect of compaction on porosity with increasing depth (Pittman and Larese 1991). Keighin, Law, and Pollastro (1989) reported the expected decreasing trend of porosity with depth for the Almond formation in the eastern portion of the Greater Green River Basin noting that sandstones shallower than approximately 9,000 ft (2743 m) have porosity ranging from 8% up to 22% in conventional reservoirs, whereas porosity from deeper sandstones ranges from 3.5% to 8% in primarily unconventional reservoirs. Yin, Liu, and Surdam (1992) found that in outcrop and shallow wells (<8,000 ft) most Almond porosity values range from 8% to 25% and permeability values ranged up to 100 md, whereas in deeper wells (>8,000 ft) most porosity ranges from 1% to 15%, and permeability is generally less than 1 md. Yin, Liu, and Surdam also noted that gas and oil have been produced from the shallower, more permeable sandstones, but only gas has been produced from the deeper, tight sandstones. Almond production data tabulated by Martinsen and Christensen (1992) are generally consistent with the conclusions of Yin, Liu, and Surdam (1992).

Ranges of porosity and permeability for various facies recognized in outcrop and subsurface upper Almond formation were illustrated (Szpakiewicz et al. 1991; Schatzinger et al. 1992; Chang, Guo, Schatzinger, and Lawson 1994). Few researchers, however, have documented the lateral variability of petrophysical properties within and between facies or attempted to define the processes controlling lateral variations of "reservoir properties" among equivalent sandstones. This paper's main goal is to describe the lateral variations in petrophysical properties based on closely spaced samples from Almond formation outcrops and to relate these trends to petrographic properties so that causative processes can be determined.

The current analysis focuses on characterizing lateral variability of permeability and porosity within the tidal delta facies at two outcrops from the eastern margin of the Rock Springs Uplift (Fig. 1).

Figure 1 **A and B: The Study Area Is Located on the Eastern Margin of the Rock Springs Uplift, Wyoming. C: The topographic base of Section 33, T16N, R102W showing the location of outcrops G and V.**

Excellent outcrops of Almond formation that exhibit lateral relationships between depositional facies are located immediately north of Highway 430 in the SE 1/4, SW 1/4, Sec. 33, T16N,

R102W, approximately 32 mi southeast of Rock Springs, Wyoming. This area is called outcrop G. Additional petrophysical properties were determined for tidal delta sandstones at outcrop V, which is located in the western half of SW 1/4, NE 1/4, Sec. 33, approximately 0.8 mi north of outcrop G. Outcrop V is easily recognized as a planar bedded to planar-tabular cross bedded prominent white sandstone at the base of the outcrop, and is visible from outcrop G. Core samples were collected from the tidal delta, tidal channels, and foreshore facies of outcrop G, whereas samples were collected from only the tidal delta facies of outcrop V.

The tidal delta data collected from the two outcrops have been used to compare the variational properties of the parameters relevant to a flow situation in the lateral direction as would be found in a vertical well in an oil field which taps the oil from a reservoir that has properties similar to the outcrops under study. Statistical and geostatistical analysis of porosity and permeability of outcropping tidal delta sandstones have been used to demonstrate their statistical distribution, characterize the variability, and assess the lateral predictability and scalability of the petrophysical properties. Data from the tidal channels and the foreshore facies are included in the petrographic analysis; however, the data are not considered in the geostatistical analysis presented in this report. Once the statistical analysis of all these facies has been completed, the developed data/model can then be used to provide realistic, geologically driven constraints on upscaling processes so that both intrafacies and interfacies variations of petrophysical properties can be honored.

2.0 GEOLOGICAL SETTING

The Almond formation forms the uppermost part of the Mesaverde Group in the Washakie and Great Divide basins of the eastern part of the Greater Green River Basin (see Figure 1). In the area of the studied outcrops the Almond overlies the Canyon Creek Member of the Ericson formation and in turn interfingers with and is overlain by the Lewis shale. The Almond produces oil and gas in normally pressured, shallow (<5,000 ft depth) reservoirs east of the Rock Springs Uplift (Table Rock, Patrick Draw field). At least seventeen Almond reservoirs have produced more than one trillion cubic feet of gas from overpressured tight gas sands from reservoirs at depths greater than 9,000 ft in the eastern portion of the Greater Green River Basin (Horne and Scott, 1996).

Almond sediments consist of an informally named lower section deposited as estuarine to nonmarine alluvial plain facies and an upper unit transitional to the marine Lewis Shale. The upper Almond was deposited as facies ranging from estuarine to marine shoreface and mesotidal shoreline barrier sands located at the head of the Rock Springs Embayment during the last major eustatic sea level rise of Cretaceous. The samples were collected from the upper Almond inlet-dominated shoreline barrier sands.

3.0 PART 1: RESULTS OF MODAL THIN SECTION ANALYSIS

More than 1,600 1-inch diameter plugs were cut from the outcrop and analyzed for petrophysical properties. The distribution of porosity and permeability for all the plugs from all depositional facies is shown in Figures 2, 3, and 4. From the samples collected, 78 dyed, epoxy-impregnated thin sections which were cut oriented perpendicular to bedding and then point counted for composition and packing parameters that included grain contact types and grain contact indices.

Figure 2 **Relationship between Porosity and Permeability for All Plugs Collected at Outcrop G**

Figure 3 **Permeability Histogram and Cumulative Percent Curve for All Samples from Outcrop G**

Figure 4 **Porosity Histogram and Cumulative Percent Curve for All Samples from Outcrop G**

Compactional indices, including compactional porosity loss, index of compaction, and cementation porosity loss, were also calculated based on the original point counts and the results of separate semi-automated point counts of the thin sections which were undertaken to derive grain size. Trask sorting coefficient (determined from grain size modal analysis) was used to derive the original porosity, a value that is critical in determining the compactional indices.

3.1 Methods

Point count modal analysis of thin sections used for compactional studies must contain unambiguous grain and intergrain classes (Ehrenberg 1995). The method used to accomplish this was to subdivide the cement categories into intra- and intergrain components. Thus, for example, quartz cement occupying primary intergranular settings could be distinguished from quartz precipitated within moldic spaces, calcite cement reducing primary interparticle porosity could be distinguished from calcite cement within cement-reduced moldic oysters, and interparticle clay rims could be distinguished from fine clay cement infill within degraded

feldspars. Genetic types of porosity recorded in outcropping Almond sandstones include simple intra- and interparticle porosity, interparticle microporosity, moldic porosity, and fracture porosity. Each of these categories could easily be separated into "grain" and "intergrain" categories. Microporosity (arbitrarily less than 5 μm diameter pores), particularly within loose aggregates of authigenic clay, is difficult to determine. However, by using a high power objective (40X), by carefully determining the specific object under the cross hairs, and by focusing only on the upper surface of the thin section, the uncertainty in optically quantifying microporosity has, one hopes, been minimized. The system used here allows microporous cements or microporosity itself to be easily and accurately assigned to intergranular areas or intragranular areas.

It is believed that the primary difference between point-counted porosity and conventional helium porosity in the data set is because of microporosity and, of course, counting statistics. In a study of petrophysical properties of the Almond formation in the Washakie Basin, Yin, Liu, and Surdam (1992) determined that micropores in outcrop and shallow wells (above 6,900 ft) comprise only a small proportion of the conventional porosity compared to more deeply buried Almond sandstones. This study of outcropping sandstones, in contrast, indicates that microporosity may contribute a significant amount of the total porosity, particularly in samples with high total clay content.

Although recognition of various paragenetic phases is necessary for a meaningful analysis, it is critical to recognize and record the relative positioning of the various authigenic phases for compaction studies. Cover slips applied with glycerin over polished thin sections and examined in plane and cross-polarized light allowed researchers to distinguish overgrowths from host grains most effectively. Similar results were reported by Ehrenberg (1990). Thin section quality, recrystallization and replacive textures may obscure such observations, but these effects were considered minimal in this study. Point counting with cathodoluminescence was determined to be impractical. Scanning electron microscope (SEM) images indicate that very fine to extremely finely crystalline, discontinuous quartz overgrowths were common but were generally not distinguished in the thin sections (Fig. 5). Here, however, the amount of quartz overgrowth cement not recognized in the thin section point count analyses should be volumetrically insignificant.

Figure 5 Multiple, Optically Continuous Thin Quartz Cement Overgrowths (QOG) Are Common on Quartz and Silty Lithic Fragments but Are Not Volumetrically Significant. Kaolinite (K) and other possible clays post-date the quartz overgrowths. Width of image is approximately 69.2 μm.

A minimum of 250 points were counted from each thin section based on a predetermined grid where spacing between points was greater than grain diameters (oversize grains and pores excluded). Lithological/mineralogical and grain contact type point counts were conducted

simultaneously until 200 points had been tabulated for contact type. At that point the mineralogical/textural point count was evaluated to determine whether additional points were needed to bring the total to 250. By this methodology researchers frequently counted significantly more than 250 points for the lithological analysis.

Thin sections with more than 5% clay matrix were eliminated from the modal analysis, as were samples with poor sorting. Lundegard (1992) recommended disregarding samples with more than 10% clay matrix, but because of the abundance of clay-rich lithics in the Almond formation, it was decided to use a more conservative matrix limit. In addition, based on comments in Houseknecht (1987), Lundegard (1992), and Ehrenberg (1995) oversize or undersize grains, large micas, and highly elongate grains were not counted. Sand-sized lithic grains were included in the count despite their ductility because they constitute a large percentage of the rock volume in Almond sand and were typically not significantly "squashed." The role played by sand size lithoclasts during compaction was critical to researchers' interpretations. For this reason, particular care was taken to distinguish lithoclasts (those with little volume reduction and minor distortion) from pseudomatrix (distorted and volume reduction had made the origin ambiguous) and true depositional matrix. Pseudomatrix (which was rarely encountered) was grouped with true matrix for modal analysis to avoid overcalculating compaction.

Grain contacts include floating, tangential or point, long, concavo-convex or embayed, and sutured categories were originally defined and illustrated by Taylor (1950). Mean values were calculated for floating grains as a percent of the 200 counted grains, and mean values for point, long, embayed, and sutured contacts were calculated as a percent of the total number of contacts.

Grain size analysis was accomplished by semi-automated petrographic image analysis of all samples. Early experience with fully automated image analysis for determining grain size was disappointing. The system could not distinguish certain features that should not be counted, such as overtly compacted lithics and highly elongate grains, "clumps" of cement, or grain clusters with matrix or clay cement fill between grains. Mean values of largest apparent grain diameters from 300 grains per thin section were recorded. Trask sorting coefficient was calculated for each thin section from the cumulative grain size frequency data and is considered more reliable than results using the visual comparator method of Beard and Weyl (1973). Other grain size statistical parameters (median, mode, range, skewness, kurtosis, etc.) were determined but are not reported here.

3.2 Sandstone Composition

Ninety-eight percent of the samples that were subjected to modal analysis fall within the range of feldspathic litharenites and lithic arkoses (classification of Folk 1968). Tidal delta and tidal

channel facies have very similar overall compositions. Tidal delta sands have an average framework grain composition of Q 55.7, F 20.5, R 23.9 (where Q, F, and R represent normalized percent quartz, feldspar, and lithics, respectively). The tidal channel sands' average composition is Q 56.8, F 22.9, R 20.1, and so are slightly more feldspathic and contain slightly less lithics.

Porosity types determined by point count analysis can be used to distinguish primary and secondary porosity. However, quantitative estimates of thin section-derived porosity are subject to error brought about by the presence of pores at or below the minimal resolution of the light microscope (less than a few μm diameter). Almond sandstones locally contain significant proportions of primary intergranular microporosity between clay particles and secondary intraparticle microporosity in finely leached feldspars and rock fragments. Comparison of helium-derived porosity and thin section, point counted porosity (Fig. 6) from the data demonstrates that helium (total) porosity is essentially always greater than point count-derived porosity, and that the helium (total) porosity comprises an even greater proportion of the porosity at lower absolute values.

Figure 6 **Relationship between Point Count-Derived Porosity and Helium Porosity. Helium porosity represents total porosity and is significantly greater than point count porosity for lower values because of the effect of microporosity.**

For this reason, both point counted and helium derived porosity values were considered when reporting the relationships between petrographic and petrophysical properties in Table 1.

Table 1 Correlation Coefficients for Relationships between Petrographic and Petrophysical Pro

	Quartz	Feldspar	Lithics	Ma-trix	Cal Cem	Dol Cem	Sider Cem	Tot Carb Cem	Clay Cem	Tot Clay	CI	IGV	COPL
Feldspar	0.63												
Lithics	0.34	0.51											
Matrix	0.13	0.04	0.08										
Cal Cem	0.23	0.13	0.13	0.01									
Dol Cem	0.07	0.06	0.01	0.01	0.06								
Sider Cem	0.05	0.28	0.41	0.04	0.47	0.07							
Tot Carb Cem	0.14	0.16	0.42	0.01	0.85	0.09	0.65						
Clay Cem	0.2	0.55	0.41	0.14	0.15	0.09	0.03	0.17					
Tot Clay	0.34	0.28	0.07	0.01	0.47	0.18	0.35	0.47	0.58				
CI	0.01	0.32	0.41	0.23	0	0.29	0.01	0.02	0.51	0.2			
IGV	0.22	0.08	0.39	0.17	0.41	0.06	0.29	0.42	0.25	0.16	0.43		
COPL	0.25	0.07	0.39	0.13	0.41	0.06	0.3	0.42	0.25	0.14	0.41	0.97	
XCOM	0.13	0.29	0.55	0.12	0.55	0.12	0.4	0.57	0.34	0.03	0.43	0.74	0.49
CEPL	0.11	0.36	0.62	0.12	0.57	0.06	0.42	0.63	0.38	0.01	0.5	0.69	0.72
K	0.09	0.17	0.36	0.16	0.73	0.14	0.58	0.72	0.04	0.34	0.29	0.2	0.23
□ Gas	0.28	0.07	0.27	0.05	0.8	0.08	0.42	0.74	0.28	0.42	0.28	0.23	0.27
□ PC	0.08	0.2	0.18	0.07	0.37	0.36	0.21	0.47	0.02	0.01	0.17	0.21	0.18

Abbreviations: Cal = calcite, Dol = dolomite, Sider = siderite, Tot = total, Cem = cement, CI = contact index, IGV = intergranular volu
loss, XCOM = index of compaction, CEPL = cementational porosity loss, K = permeability (md), □ Gas = helium porosity, □ PC = p

3.3 Measures of Packing (Compaction)

Packing parameters reflect the alterations of fabric that results from compaction. For this study it was convenient to distinguish between mechanical and chemical compaction using the operational definitions of Houseknecht (1987, p. 634) where:

- *Mechanical compaction* is the bulk volume reduction resulting from processes other than framework grain dissolution. Mechanical compaction is characterized by the reorientation and repacking of brittle grains and by plastic deformation of ductile grains. Mechanical compaction characteristically reduces only intergranular volume.
- *Chemical compaction* is the bulk volume reduction caused by the dissolution of framework grains at points of contact. Chemical compaction affects porosity by reducing framework grain volume as well as intergranular volume.

Two types of packing parameters were quantified in this study. First, the change in fabric with increasing compaction can be related to types of grain contacts in thin section. Taylor (1950) used the average number of grain contacts, now known as the contact index (CI), to demonstrate the effects of compaction on fabric. Grain contacts can also be used to tabulate what Wilson and McBride (1988) called the tight packing index (TPI) which is the average per grain abundance of long, embayed, and sutured contacts.

The other, more popular method of evaluating compaction using thin sections is based on the calculation of the percent intergranular volume (IGV). Although significant discussion has been published about the details and significance of the parameters chosen for calculation (see especially Houseknecht 1987; Lundeguard 1992; and Ehrenberg 1995) the evaluation essentially uses IGV and original porosity (OP) to calculate the compactional porosity loss (COPL) and the porosity loss because of cementation (CEPL).

3.3.1 Grain Contacts and Compaction

The number of contacts per grain (CI) and the types of contacts between grains were shown to change systematically with depth for Mesozoic sandstones in Wyoming (Taylor 1950). Similarly the CI and the TPI were shown to increase with depth in Pliocene sandstones from the Ventura Basin even though both parameters have a broad range of values at any given depth (Wilson and McBride 1988). In Wilcox and Carrizo sandstones of the Gulf Coast, McBride, Diggs, and Wilson (1991) found that CI and TPI increased and intergranular porosity and pre-cement porosity decreased logarithmically with burial depth. Therefore, the relationship between increased CI, TPI, and compaction has been well established.

In the current study, the proportion of grain contacts in outcropping tidal channel and tidal delta facies may be compared to the relative variation in grain contacts from the very shallow subsurface (Figs. 7 through 9), located 1/4 mi down dip of outcrop G.

Figure 7 **Variations in the Proportions of Contacts for Increasing Depth in the Shallow Subsurface of Core Hole No. 2.**

Figure 8 **Example of Lateral Variations in the Proportions of Grain Contacts from Tidal Channel Facies at Outcrop G.**

Figure 9 **Example of Lateral Variations in the Proportions of Grain Contacts from the Tidal Delta Facies at Outcrop G.**

The range and proportion of grain types are essentially the same between outcropping tidal channel and tidal delta facies. Surprisingly, the shallow subsurface samples (Fig. 7) have a significantly increased amount of tangential grain contacts. This indicates that the shallow subsurface samples have actually been less compacted than the outcrop samples. While this appears counter-intuitive, it can be explained by the presence of greater amounts of total cement, particularly carbonates, in the shallow subsurface samples. The high permeability of the outcrop sands (tidal delta sands at outcrop G average about 1,000 md) may have been attained by carbonate (particularly from oyster shells) and other mineral species having been partially dissolved and their byproducts redistributed into the shallow subsurface by the flux of atmospheric-derived waters after the sands became exposed. Evidence of leaching is abundant in thin sections from the outcrop.

Typical lateral variation in contact index in the tidal channel and the tidal delta are illustrated in Figures 10, 11, 12, and 13, respectively.

Figure 10 **Comparison of the Lateral Variations in CI and Percentage of Clay Cement from Tidal Channel Unit 6 at Outcrop G. Note a roughly inverse relationship.**

Figure 11 **Comparison of the Lateral Variations in CI and Percentage of Total Cement from Tidal Channel Unit 6 at Outcrop G. Note a roughly inverse relationship.**

Figure 12 **Comparison of the Lateral Variations in CI and Percentage of Clay Cement from Tidal Delta at Outcrop G. Note a very crude inverse relationship between the two parameters.**

Figure 13 **Comparison of the lateral variations in CI and percentage of total cement from Tidal Delta at Outcrop G. Note a very crude inverse relationship between the two parameters.**

CI tends to behave inversely to the amount of cement present, but appears to be more sensitive to the amount of carbonate than clay cement. TPI trends parallel those of CI but have slightly reduced indices (Fig. 14).

Figure 14 **Comparison of the Lateral Variations in CI, TPI, Percentage of Clay Cement, and Total Cement from Tidal Channel at Outcrop G. Note that the CI and TPI trend essentially parallel to each other with only a minor offset.**

The summary of counting statistics indicates that for an equal number of analyzed samples (n = 38) tidal delta samples have slightly lower average CI and TPI (mean values 2.65 and 2.21) than those from the tidal channel (mean CI is 3.0, mean TPI is 2.53). The range in values is also less in the tidal delta (CI range of 1.55, TPI range of 1.35) as compared to the tidal channel facies (CI range 2.28, TPI range 2.30).

Analysis of CI and TPI shows that there are small but consistent differences in packing indices between the tidal delta and tidal channel sands. These in turn relate to slight differences in the lithology between the facies. Thin section point count analysis was used to show that the tidal channel sands contain, on average, less rock fragments (20.1 normalized %), less total clay (14.3%) and clay cement (6.4%), but significantly more total carbonate (10.4%), most of which is contributed by calcite cement, than the tidal delta facies, which contain the following average values: rock fragments (23.8%), total clay (19.7%), and total carbonate (0.05%) in the form of calcite cement.

The major problem with using proportions of grain contact types or contact and tight packing indices from the data is the very poor relationship between contact index and other petrographic or petrophysical parameters as indicated by the correlation coefficient (Table 1). The relationship between tight packing index and petrographic/petrophysical properties is similar to that presented for contact indices. Thus, although the qualitative petrographic evidence suggests a relationship, researchers are unable to demonstrate a statistically significant relationship between grain contact types (or packing indices derived from grain contact types) and petrophysical properties in the upper Almond sandstones of the tidal delta and tidal channel facies.

3.3.2 Porosity Loss Equations and Analysis

Increasing compaction results in relative increase in the percent framework grains and relative decrease in the intergranular volume (IGV). As noted by Ehrenberg (1990), the IGV method of calculating the amount of compaction has become more popular than the grain-to-grain contact method, primarily because IGV can be directly related to porosity. In contrast, grain contact type indices can be difficult to measure, subjective, and can be complicated by variable amounts of cement overgrowths that may not be recognized during thin section modal analysis.

Several important compaction indices may be calculated for evaluating the degree of porosity loss because of compaction and cementation. These parameters are essentially based on the relationships between original porosity (OP) (porosity present at about the time of deposition) and current intergranular volume. Researchers chose to use the terminology set forward by Ehrenberg (1995) where:

$$\text{CompactionalPorosityLoss} \quad (\text{COPL}) = \text{OP} - \frac{(100 \cdot \text{IGV}) - (\text{OP} \cdot \text{IGV})}{(100 - \text{IGV})} \tag{1}$$

Porosity loss because of cementation (CEPL), referring to the same original porosity, is

$$\text{CEPL} = (\text{OP} - \text{COPL}) \cdot \frac{\text{CEM}}{\text{IGV}} \tag{2}$$

where CEM is the volume percent intergranular cement determined along with IGV by modal analysis of thin sections. It should be noted that all these values are reported in percentage of the rock volume.

The percentage of total porosity loss because of compaction (essentially the compaction index) XCOM is derived:

$$\text{XCOM} = \frac{100\text{COPL}}{(\text{COPL} + \text{CEPL})} \tag{3}$$

When COPL is compared to CEPL (Fig. 15), a line with a slope of one radiating from the origin defines the fields where porosity loss was dominated by compaction versus that dominated by cementation. Data points that plot farther from this line are successively more controlled by pure compaction or pure cementation porosity loss.

Figure 15 **On the Left Is the Relationship between COPL and CEPL for Samples from Outcrop G. On the right is the same relationship for facies from the shallow subsurface in Core Hole no. 2 as explained in the text.**

For outcrop samples, the tidal delta facies porosity was moderately to strongly controlled by compaction processes, whereas the tidal channel sandstones were about equally controlled by compaction and cementation processes. Because the original porosity for both of these facies, calculated as a function of sorting (not grain size!) is similar, researchers can also determine that both facies have lost similar proportions of porosity since deposition.

Comparison of COPL and CEPL for the shallow subsurface (Fig. 15) also indicate that the porosity loss in tidal channel sands was due both to compaction and to cementation, and that porosity loss in tidal delta sands was dominated by compaction.

It is difficult, however, to relate the compactional parameters such as XCOM, COPL, and CEPL to petrographic properties (such as cement types). The correlation coefficients for the relationships between compaction parameters and petrographic properties (Table 1) are low, indicating low predictive values.

Researchers have discovered, however, that if petrographic and petrophysical properties are first sorted according to intergranular volume (Table 2), then with increasing intergranular volume there is an increase in calcite cement, siderite cement, total cement, and CEPL. Note that the data were first sorted according to IGV category.

Table 2 **Trends in Selected Petrographic, Petrophysical, and Compactional Properties and Indices for All Facies from Outcrop G**

	IGV=0–20%	IGV=20–25%	IGV=25–30%	IGV=30–35%	IGV=>35%
Number of Samples	10	14	30	14	3
Skeletal Grains	73.8	64.9	61.1	60.3	54.3
Relative % Feldspar	17.6	22.3	23.6	20.9	23.6
Relative % Lithics	27.0	21.6	21.0	20.3	16.8
Clay Cement, %	3.7	7.9	8.6	7.1	10.9
Total Clay, %	16.3	18.3	17.9	1530	15.0
Iron Oxides, %	0.9	3.0	3.7	2.8	5.3
Calcite Cement, %	0.2	2.8	3.7	4.8	9.5
Siderite, %	0.0	1.3	1.7	1.5	3.2
Total Carbonate, %	1.2	4.2	5.3	8.1	12.3
Total Cement, %	5.7	15.5	18.6	19.1	31.2

Contact Index	3.19	2.90	2.78	2.45	2.37
Tight Packing Index	2.57	2.46	2.37	2.06	2.10
COPL	27.3	21.6	16.7	11.1	3.5
CEPL	2.1	6.6	8.7	11.5	21.4
XCOM	92.2	76.8	66.5	52.8	15.7
POR*	10.3	11.2	14.1	17.2	15.1
XPOR	25.9	28.3	35.7	43.3	37.8
Porosity, %	30.3	29.2	30.	27.3	19.6
Permeability, md	867.0	629.0	651.0	602.2	126.9

In contrast, with increasing intergranular volume, porosity, compactional porosity loss (COPL), XCOM, contact index, and the relative amount of lithics decrease. Compactional porosity loss, index of compaction, and cementational porosity loss then provide not only significant assistance in determining the relative effects of diagenetic events on sand quality, but help provide some explanation for lateral distribution of porosity. The calculation of COPL, XCOM, and CEPL are geared toward describing porosity. The functional connectivity between pores can be taken as a definition of permeability.

Grouping data by intergranular volume has been found to significantly aid in the interpretation of porosity in upper Almond outcrop sandstones. Unfortunately, permeability does not correlate as well with intergranular volume as porosity does. Based on the results of modal analysis of outcropping Almond sandstones, permeability is not simply a function of compaction or cementation. With additional work the comparison of compaction and cementation parameters may also provide the basis for an improved method to predict lateral permeability distribution within facies.

4.0 PART 2: GEOSTATISTICAL ANALYSIS OF OUTCROP DATA—TIDAL DELTA FACIES

4.1 Introduction

Reservoir heterogeneity is a major challenge for enhanced oil recovery. Improper reservoir evaluation often results in failures related to unexpected baffles of flow, permeability heterogeneity, or wrong appreciation of the residual oil distribution. In order to predict accurate fluid flow within a reservoir, variability in the rock properties at all scales relevant to the specific depositional environment needs critical consideration. Almond formation data collected over the past several years through outcrop studies of analogs of subsurface reservoirs can be used to advantage because various types of heterogeneity can now be quantified.

Reservoir heterogeneities should be quantified to a level sufficient to design a reservoir model. Measured data and statistical models based on analog outcrop or reservoir observations can be combined into prototype models. Geostatistics offers a comprehensive method to characterize the permeability variation within the outcrop facies and provides a model to generate data that are needed to model an equivalent reservoir. Current geostatistical methods for reservoir characterization are well suited for integrating static data such as cores, logs, and spatial statistics. Outcrop analogs offer laterally continuous data whose variability is critical to understanding the nature of equivalent subsurface reservoirs and which facilitates modeling of fluid flow to enhance recovery from subsurface reservoirs.

The present work uses rock variability information collected from the outcrop studies of outcrops V and G of the Almond formation located on the eastern flank of the Rock Springs Uplift, Wyoming (Fig. 1). Geostatistical and statistical analyses have been used to understand the statistical distribution, characterize the variability, and assess the predictability and scalability of porosity and permeability parameters. In this section the main concern is with the lateral variability of petrophysical properties within the tidal delta facies, the source of the greatest amount of outcrop data.

4.2 Reservoir Characterization

Reservoir characterization can be defined as an identification of reservoir formations which show distinctive properties of lithology, permeability, porosity, and thickness. Reservoir characterization is an important step in designing primary production and subsequent

enhanced oil recovery processes. In many cases, insufficient characterization of reservoirs was the cause of inefficient completion, infill drilling, and stimulation operations.

Heterogeneity can be described as spatial variation in reservoir properties. Heterogeneity is a common feature in many reservoirs and one of the most important factors controlling fluid flow. Major indicators of reservoir heterogeneity include variations in permeability, porosity, formation thickness, fluid saturations, and existence of different facies, faults, and fractures. Reservoir characterization helps analyze the degree of heterogeneities in these indicators created by complex depositional processes over geologic time.

The complex nature of reservoir characterization study requires a close collaboration among members of various disciplines such as geologists, geophysicists, reservoir engineers, production engineers, petrophysicists, exploration managers, production managers, team leaders, service company personnel, and research scientists. A unified, cross-disciplinary approach is essential for the most reliable predictions of reservoir size, quality, productivity, and economics.

The goal of reservoir characterization study is to develop a model that maximizes the utilization of professional power in analyzing vast amounts of technical data. A well developed model can drastically accelerate field development, minimize costs, optimize oil recovery, maximize profitability, and generate models for application in other areas. Case studies of multidisciplinary applications allow the professionals to benefit from the best practices found in the industry.

4.3 Limitations in Reservoir Characterization

It is critical to have sufficient data for accurate reservoir characterization. In many cases, spatial distribution of porosity and permeability is very little known. Available data are often limited to well logs, cores, and well tests. Yet, wells may occupy only a billionth of the total reservoir volume. Seismic and other geophysical methods may cover larger aerial and volumetric fractions of the reservoir. However, they may not discriminate the reservoir formations effectively because of low resolution. Production history and other dynamic data sources such as tracers can provide vital information. However, there will be always some lack of data preventing the professionals from describing a unique model of the reservoir. Finding other sources of data are imperative for a successful reservoir characterization. These sources could include sedimentological analysis, geological basin studies, and outcrop studies. Geostatistical predictions provide relief in many cases for the missing data.

An outcrop study is a useful tool for reservoir characterization because it allows studying the continuity of formation in 2D and 3D, and investigating in-situ vertical and horizontal property variations (Kasap 1995). The data from an outcrop study may be transferred to subsurface

conditions by simple modifications, thus providing a powerful tool to analyze the formations in 3D, and allowing investigation of vertical and horizontal variations in reservoir properties. Another important benefit of outcrop studies is that it helps closely spaced lateral and vertical sampling which is critical for detailed rock description in a reservoir characterization study. This detail can be used to design and plan improved production processes in analogous subsurface reservoirs.

4.4 Statistics and Geostatistics

Conventional statistics are based on random, independent variables which assume zero continuity and do not allow any extension of each data value. This makes it theoretically impossible to estimate porosity and permeability in individual grid blocks in a reservoir. Geostatistics, on the other hand, takes the opposite approach to conventional statistics. It assumes that the neighboring points have continuity and spatial correlation which can be measured and then used for the grid block estimates. The study of such a correlation is usually called *variogram modeling*. After variogram modeling, predictions are made at unsampled locations by using kriging or conditional simulations.

Outcrop geostatistics is an important step for reservoir characterization because it gives a chance to study the continuity of formation properties in 2D and 3D, thus making it possible to investigate the vertical and horizontal variations. Continuous sampling can easily be done on outcrops for detailed rock description which is not feasible on subsurface structures. Results of geostatistical analysis on outcrops can be transferred to subsurface reservoir structures by analogy.

4.4.1 Variogram

The variogram (or its equivalent, the covariance) underpins all of geostatistics. A variogram is used to quantify the spatial correlation between two values. It is intuitively known that two values in space that are close together tend to be more similar than two values farther apart. Thus, the variogram is expected to be smaller as the distance between values becomes closer in space. The variogram of a property such as permeability or porosity measured on different points on the same outcrop is estimated by

$$\gamma(h) = \frac{1}{2n(h)} \sum_{\iota=1}^{n(h)} \left[Z(x_\iota) - Z(x_\iota + h) \right]^2 \tag{4}$$

where $\gamma(h)$ is the semi-variance or variogram, n(h) is the total number of pairs in the summation, h is the lag distance between a pair of data, and Z is the parameter for which the variogram is being determined. The value of $\gamma(h)$ in Equation 1 is an arithmetic mean of the summation of the squared difference of lagged pairs of data for which the experimental variogram is being obtained. Sometimes the arithmetic mean provides high oscillation in the estimated variogram values, thus making it difficult to obtain a theoretical variogram (to be discussed later in this section). An alternate way to estimate experimental variograms is to take the median estimate instead of the arithmetic mean as

$$\gamma(h) = \frac{1}{2}\,\mathrm{med}\left[\sum_{\iota=1}^{n(h)}\left[Z(x_\iota) - Z(x_\iota + h)\right]^2\right] \tag{5}$$

The variogram obtained by Equation 4 or 5 from data is also called the experimental variogram, which is plotted on an x-y plot with the x- axis being the lag distance h and with $\gamma(h)$ on the y-axis as shown in Figure 16.

Figure 16 Mean and Median of Experimental Variogram Bin Data

The experimental variogram estimates of Figure 16 are obtained from the bins of the computed values of $[Z(x_i)-Z(x_i+h)]^2$ which are shown in Figure 17.

Figure 17 Experimental Variogram Bin Data Prior to Averaging

These values were computed from the permeability data obtained from the tidal delta facies of the outcrop. The reason for the high oscillations seen in the mean estimates of the experimental variogram in Figure 16 can be well understood from the orders of magnitude in variability of the data within each bin shown in Figure 17. It is important to use the right variogram estimate to obtain a reliable theoretical model from the analysis.

A variogram is in fact a vectoral value with direction and distance. Variograms for various directions may be obtained from a 2D or 3D data set. Typical directions in variogram calculations are N-S, E-W, NE-SW, and NW-SE. In geostatistics, E-W is represented conventionally by 0° and N-S as 90°. Similarly, NE-SW is equivalent to 45° and NW-SE is -45°. However, sampled data are often irregularly spaced and scattered in various directions, thus choosing a precise direction becomes an impossible task. Therefore, allowable deviations and tolerance from these directions are often used if the data are not on a regular grid. The bigger the tolerance, the more pairs of data are included in the variogram calculations. Regardless of

direction, a tolerance of ±90□ will incorporate all the data in variogram calculations, referred to as *omnidirectional variogram* in geostatistics.

To calculate a variogram, a lag increment needs to be defined. A lag increment can be equal to spacing between any two points in a regular sample pattern. In general, at smaller lag distances, the value of the variogram is smaller because values separated by small distances tend to be more similar compared to values separated by a larger distance.

If the data are irregularly spaced, a lag tolerance needs to be defined. Lag tolerance is normally taken to be half the lag increment. For instance for a lag increment of 50 ft, the lag tolerance would be ±25 ft, or simply all pairs of data separated by 50 ft ± 25 ft are included in the calculation. This provides enough pairs of data points for a particular lag distance. When the variogram is plotted, the lag distance is taken as the average of all the distances between pairs falling within lag tolerance. The bigger the tolerance, the more pairs can be defined and the smoother the variogram looks.

Scattered data points on Figure 18 show an experimental variogram for a set of permeability data from the Almond tidal delta outcrop.

Figure 18 Parameters of a Typical Variogram Plot and Theoretical Model

The experimental variogram is an estimate of the local variogram. This is in turn an approximation of the theoretical variogram which extends over infinite number of pairs over an infinite field. Every variogram can be described by three parameters: nugget effect, range, and sill.

4.4.2 Nugget Effect

The value of the variogram for h = 0 is theoretically 0, however, several factors, such as sampling error and short scale variability, may cause sample values separated by very small distances to be different. This manifests itself as a discontinuity at the origin of the variogram. The sudden leap from 0 value at the origin to a variogram value at small separation distances is defined as the nugget effect.

4.4.3 Range

As the lag distance increases, the variogram also increases. Eventually, the variogram reaches a plateau level at a distance called range. The range is also the distance at which the covariance becomes zero, so it shows the limits of the zone of influence of a single sample. At lag distances greater than the range, any two pairs of values are no longer correlated and are independent.

4.4.4 Sill

Sill is the value of the variogram corresponding to the range. The variogram stabilizes around the sill which is theoretically the sample variance.

4.4.5 Variogram Models

Variogram models are theoretical expressions which fit the experimental variograms. There are three groups of models:

1. With a sill
2. Without a sill
3. Nested

With a Sill. Models with a sill stabilize around the sill value and have a finite variance and covariance. The spherical model, the exponential model, the gaussian model and the hole effect model are the ones often used in this group.

Without a Sill. Models without a sill are used when the variogram rises without leveling off. This may indicate drift if the variance is crossed. The models without a sill result from a random fluctuation with unlimited capacity for dispersion. The de Wij's model and the power model are often used in this group.

Nested. Nested Models are ones in which two or more of the theoretical models are combined to fit the experimental variogram. Variances are positive and additive. The total variance is the sum of theoretical model variances.

The discussion related to the models just described can be found in Isaaks and Srivastava (1989). At this point, the spherical model, which is by far the most widely used of all variogram models, will be briefly introduced.

4.4.6 Spherical Model

The spherical model is linear at the origin, indicating good continuity. The equation is:

$$\gamma(h) = \begin{cases} C\left[\dfrac{3h}{2a} - \dfrac{h^3}{2a^3}\right] + C_0 & \forall h < a \\ C + C_0 & \forall h \geq a \end{cases} \tag{6}$$

where C_o is the nugget effect (Sill-C), $\gamma(h)$ is the semivariance, a is the range, and h is the distance between assays (lag distance).

The sill is estimated by the assay variance, and the nugget by the interception on the vertical axis. The tangent at the origin (usually the line through the first 2 or 3 points) intersects the sill at a distance of 2a/3. If this tangent does not agree with 2a/3, then nesting may be present. The spherical variogram shown in Figure 18 has a = 20, C_o = 0.65, and sill = 1.08.

4.4.7 Isotropy and Anisotropy

Variograms with different directions can be constructed at orientations of N/S, E/W, NW/SE, and NE/SW. Then a rose diagram of ranges in the different directions is plotted. The anisotropy ratio is found by dividing the smallest range by the biggest range, which are at right angles to each other. A ratio of 1.0 marks an isotropic variogram i.e. same variogram in all directions. If anisotropy is present and is reflected by the same sill but different ranges of the same model, then the anisotropy is geometric. For example, in a tidal delta facies, permeability might have a larger range in the horizontal direction than in the vertical direction. Geometric anisotropy can be removed by a distance transformation of the coordinates.

If the variograms indicate different models or different sills, then anisotropy is zonal. For example, a variogram in a vertical wellbore typically shows a bigger sill than a variogram in the horizontal direction. Removal of zonal anisotropy is complex and not discussed here. Some variograms can be a combination of both geometric and zonal anisotropies. Anisotropies can be accounted for using anisotropic variograms.

4.5 Data Analysis

The location from which the tidal delta field samples were collected for quantitative analysis is shown in Figure 19 for outcrop G and Figure 20 for outcrop V. Permeability and porosity of the core samples were measured at the locations shown in the figures.

Figure 19 Tidal Delta Samples, Outcrop G

Figure 20 Tidal Delta Samples, Outcrop V

The data were analyzed for assessing predictability, variability, and scalability. The complete analysis of the variability consists of:

- Statistical analysis of the data

- Assessment of the predictability of the parameters for both the outcrops
- Variogram analysis and subsequent development of a theoretical model

Data were analyzed to assess both 1D and 2D variability of porosity and permeability. A rough measure of scalability is to verify whether the variograms obtained from various scales of data extend from a lower to a higher scale. To verify scalability, the data from outcrop G were analyzed in four different scales:

- *Scale 0* is the 1D horizontal and vertical analysis at specific locations
- *Scale 1* is the analysis of 2D data from a small section of the entire facies. Three small sections were chosen from the facies for the scale 1 analysis because of high density of data points in these areas:
    - *Scale 1 Sub 1* between x (750, 765) and y (0, 5) comprised of 134 data points
    - *Scale 1, Sub 2* between x (910, 925) and y (0, 5) comprised of 127 data points
    - *Scale 1, Sub 3* between x (1,010, 1,025) and y (0, 5) comprised of 137 data points
- *Scale 2* between x (650, 1,050) and y (0, 5) comprised of 52 data points evenly spaced at a distance of 50 ft in the x-direction and 1 ft in the y-direction.
- *Scale 3* between x (650, 1,000) and y (-5, 25) comprising of 56 data points evenly spaced at a distance of 50 ft in the x-direction and 5 ft in the y-direction.

Analysis of the tidal delta facies of outcrop V was limited to scale 0. It is important to note here that the entire data set of outcrop V is comparable in size to scale 1 of outcrop G. Hence, it is assumed that the conclusions derived from the scale 1 analysis of outcrop G will apply to the entire data sample of outcrop V.

The GEO-EAS (Englund and Sparks 1991) software was used for the statistical and the geostatistical analyses. GEO-EAS is a collection of interactive software tools for performing geostatistical analyses of spatially distributed data. Programs are provided for data file management, data transformations, univariate statistics, variogram analysis, cross validation, kriging, contour mapping, post plots, and line/scatter graphs. The package can be run on a PC having at least 512 Kb of RAM and a CGA/EGA graphics card with or without an arithmetic coprocessor. Standard geostatistical software libraries such as the GSLIB (developed at Stanford University) uses GEO-EAS data structure formats. The results of the quantitative analyses obtained from the outcrop data are presented next.

4.5.1 Conventional Statistical Analysis

Conventional statistical analysis is required to justify the use of a certain parameter for development of any geostatistical model. Univariate statistics of both permeability and porosity data were analyzed to gain an understanding of the distribution of the data, to find similarities

between different outcrops or at different locations of an outcrop, and to seek any visual trends or extremities. The analysis included a comparison of data statistics, histograms, and probability plots to accomplish the goals of this study. The univariate statistics of the porosity at y = 0 ft and y = -5 ft of outcrops G and V and those for x = 800 ft for outcrop G are summarized along with the statistics of the complete data from both outcrops in Table 3.

Table 3 Univariate Statistics of Porosity Data at Scale 0

Statistics	Y=0 (G)	Y=-5 (G)	Y=0 (V)	Y=-5 (V)	X=800 (G)	Outcrop G	Outcrop V
Number of Data	119	13	61	60	11	573	265
Minimum Value	27.62	29.9	28.67	29.849	29.8	27.62	28.67
Mean	31.69	31.27	30.89	31.178	31.605	31.55	31.502
Median	31.685	31.5	30.89	31.14	31.6	31.52	31.509
Maximum Value	34.9	33.3	33.373	34.386	33.486	37.8	34.73
Range	7.28	3.4	4.703	4.537	3.686	10.18	6.06
Standard Deviation	1.131	0.996	0.98	0.737	0.981	0.945	1.033
CV (%)	3.512	3.185	3.173	2.364	3.104	2.99	3.28
Skewness	-0.12	0.337	0.068	1.26	0.12	0.7	0.03

It is evident from Table 3 that the mean porosity values are approximately 31% for any location of outcrops G and V. This is also reflected in the statistics of the entire data in outcrops G and V. The mean range of variation of porosity is approximately 5.7%, and the median porosity is almost equal to the mean porosity values. The coefficient of variation of the data at any location is approximately 3%. This suggests that there is no significant variability of the porosity distribution, although the geographic location of the data collected within the facies of the outcrops vary significantly, such as 425 ft horizontally and 30 ft vertically in outcrop G and 60 ft horizontally in outcrop V. The coefficient of skewness shows a wide variation depending upon the specific location being analyzed or the entire data from the facies. Visual plots of histograms and probability distribution suggest that the data in any location at scale 0 or even at the scale of the facies is approximately normal. Plots of the histograms are provided in Figures 21 through 27, and plots for the probability distributions are provided in Figures 28 through 34.

Figure 21 **Histogram of Porosity Data at Scale 0, Y = 0 ft (Outcrop G)**

Figure 22 **Histogram of Porosity Data at Scale 0, Y = -5 ft (Outcrop G)**

Figure 23 **Histogram of Porosity Data at Scale 0, Y = 0 ft (Outcrop V)**

Figure 24 **Histogram of Porosity Data at Scale 0, Y = -5 ft (Outcrop V)**

Figure 25 **Histogram of Porosity Data at Scale 0, X = 800 ft (Outcrop G)**

Figure 26 **Histogram of Entire Porosity Data at Scale 3 (Outcrop G)**

Figure 27 **Histogram of Entire Porosity Data at Scale 3 (Outcrop V)**

Figure 28 **Probability Plot of Porosity Data at Scale 0, Y = 0 ft (Outcrop G)**

Figure 29 **Probability Plot of Porosity Data at Scale 0, Y = -5 ft (Outcrop G)**

Figure 30 **Probability Plot of Porosity Data at Scale 0, Y = 0 ft (Outcrop V)**

Figure 31 **Probability Plot of Porosity Data at Scale 0, Y = -5 ft (Outcrop V)**

Figure 32 **Probability Plot of Porosity Data at Scale 0, X = 800 ft (Outcrop G)**

Figure 33 **Probability Plot of Entire Porosity Data at Scale 3 (Outcrop G)**

Figure 34 **Probability Plot of Entire Porosity Data at Scale 3 (Outcrop V)**

It is easily noted from Figures 26 and 27 that the porosity distribution of the samples from the entire facies of outcrops G and V are normally distributed, which is also confirmed from Figures 33 and 34. The scale 0 plots shown in Figures 21 through 25 and Figures 28 through 32 almost conform to a normal distribution. The ones that visually look skewed are because of extreme values or outliers. The extreme values might be a result of measurement error or because of the presence of local macropores. Although the coefficient of skewness values in Table 3 suggest a non-normal distribution of porosity at any scale, it must be noted that skewness is the third moment of the sample data and is highly sensitive to very high or low values in the sample. With such a compact range of porosity data in both the outcrops and a normally distributed data sample, no further analysis is needed to assess the spatial variability of the porosity values. Hence, the following discussion will concentrate analyzing the permeability data in the tidal delta facies of the outcrops being studied.

The statistics of the raw permeability data collected from the tidal delta facies of outcrops G and V are provided in Tables 4, 5, and 6 for the various scales being analyzed.

Table 4 Univariate Statistics of Permeability Data in Horizontal Direction Scale 0

Statistics	Y = 0 (G)	Y=-5 (G)	Y=0 (V)	Y=-5 (V)
Number of Data	123	18	61	60
Minimum Value	167.4	138.8	496.1	2078.98
Mean	1100.74	1165.81	1510.66	3129.85
Median	1092.02	1305	1488.88	3146.08
Maximum Value	4814.2	2004.8	2337.45	4160.68
Standard Deviation	454.7	612.81	386.1	496.94
CV (%)	41.31	52.56	25.558	15.87
Skewness	4.39	-0.486	0.0066	0.087

Table 5 Univariate Statistics of Permeability Data in Vertical Direction Scale 0

Statistics	X=700 (G)	X=800 (G)	X=900 (G)	X=1000 (G)
Number of Data	11	11	12	11
Minimum Value	622.7	748.6	626.9	174.5
Mean	1151.7	1623.3	1273.3	1248.43
Median	1008.6	1152.3	1012.9	1050.1
Maximum Value	2004.8	4814.2	2534.6	2744.95
Standard Deviation	453.6	1152.43	700.27	821.82
CV (%)	39.38	70.99	54.99	65.83
Skewness	0.945	2.12	0.888	0.45

Table 6 Univariate Statistics of Permeability Data in 2D Scales

Statistics	Scale 1, Sub 1	Scale 1, Sub 2	Scale 1, Sub 3	Scale 2	Scale 3	Outcrop G	Outcrop V
Number of Data	131	126	136	51	56	582	264
Minimum Value	294.34	696.06	552.11	174.5	334.7	138.8	496.1
Mean	1036.07	1027.81	999.27	989.77	1515.04	1098.33	2841.78
Median	977.51	1023.59	1008.98	929.4	1301.7	1024.39	3066.56
Maximum Value	2601.48	1613.44	1522.1	4814.2	4814.2	5311.57	5465.3
Standard Deviation	299.27	143.06	177.17	600.28	777.32	447.2	907.7
CV (%)	28.88	13.92	17.73	60.65	51.31	40.72	31.94
Skewness	1.563	0.54	-0.12	5.11	1.6	3.66	-0.385

The statistics of the permeability data show a remarkable difference at scale 0 within the same facies and also between the samples collected at the different outcrops as seen from Tables 4 and 5. The mean permeability is approximately 1,130 md horizontally and 1,320 md vertically in outcrop G, which suggests that the degree of anisotropy in outcrop G is approximately 1.17. The sample also suggests that on average there is no vertical layered heterogeneity in outcrop G, whereas heterogeneity exists in the horizontal direction as is evident from Table 5. The mean permeabilities in outcrop V varies significantly with location. A difference of 5 ft in elevation almost doubles/halves the mean permeability value. Also, the mean permeability between outcrops G and V in the horizontal direction differs by almost 1.5 to 3 times in value. The coefficient of variation in the permeability values range between 16% to almost 53% in the horizontal direction and 40% to 71% in the vertical direction. The sample data are all significantly skewed except for the permeability data in outcrop V. The range of variability of data is at least two orders of magnitude, except for the y = –5 ft in outcrop V. In summary, outcrop G is homogeneous horizontally with a moderate heterogeneity in the vertical direction but anisotropic with a skewed sample distribution. Whereas, outcrop V is heterogeneous with a nearly normal sample distribution. The actual sample values have several orders of magnitude difference in variability.

Table 6 summarizes the statistics of higher scales with a comparison of the entire data sample from outcrops G and V. It must be stated here as a reminder to the reader that the different scales of analysis are confined to outcrop G only because of the larger area of samples collected from this outcrop alone. The mean estimates obtained at scale 1 are comparable to the estimates obtained for scale 0 in outcrop G shown in Table 4. The coefficients of variance (CV), however, are low in comparison to those of scale 0 in outcrop G. These values are very close to the CV

values obtained for the scale 0 of outcrop V, shown in Table 4. This observation is of great significance because it has been stated before that the entire data samples collected from outcrop V is comparable to scale 1 of outcrop G. The results obtained above suggest that the data variation is very small at small scales, although the mean estimates of permeability are significantly different. It should be noted that the scale 0 of outcrop G in Table 4 covered a length of 425 ft, whereas the horizontal dimension of scale 1 in Table 6 is only 15 ft. Thus, the difference in variability arises from the length factor over which the statistical estimates are obtained. It can be noted from Table 5 that the CV values increase significantly for scales 2 and 3. These values are close to the ones obtained for scale 0 in Table 4 for outcrop G. The CV value of the sample collected from the entire outcrop V shown in Table 6 is close to those obtained from scale 1 in Table 6 and scale 0 of outcrop V in Table 4. This result confirms the observation made previously and will be very important in the geostatistical analysis. All the samples in Table 6 are highly skewed, which might pose problem for obtaining kriged estimates.

Figures 35 through 46 are the plots of the histograms for the permeability samples of the different scales of analysis in outcrops G and V.

Figure 35 Histogram of Permeability Data at Scale 0, Y = 0 ft (Outcrop G)

Figure 36 Histogram of Permeability Data at Scale 0, Y = -5 ft (Outcrop G)

Figure 37 Histogram of Permeability Data at Scale 0, Y = 0 ft (Outcrop V)

Figure 38 Histogram of Permeability Data at Scale 0, Y = -5 ft (Outcrop V)

Figure 39 Histogram of Permeability Data at Scale 0, X = 800 ft (Outcrop G)

Figure 40 Histogram of Permeability Data at Scale 1, Sub 1 (Outcrop G)

Figure 41 Histogram of Permeability Data at Scale 1, Sub 2 (Outcrop G)

Figure 42 Histogram of Permeability Data at Scale 1, Sub 3 (Outcrop G)

Figure 43 Histogram of Permeability Data at Scale 2 (Outcrop G)

Figure 44 Histogram of Permeability Data at Scale 3 (Outcrop G)

Figure 45 Histogram of Entire Permeability Data at Scale 3 (Outcrop G)

Figure 46 Histogram of Entire Permeability Data at Scale 3 (Outcrop V)

The histogram for y = 0 ft in outcrop G (Fig. 35) shows a highly skewed distribution with a significant outlier value. Without the outlier, the data are presumably normal. Figure 36 almost resembles a uniform distribution rather than a normal distribution. However, with such small number of data samples, nothing can be conclusively inferred from the distribution. The histograms in Figures 37 and 38 show a distribution that is close to the normal distribution. This is also evident from the small skewness values associated with the sample data in Table 4.

Figure 39 has been included as a sample histogram in the vertical direction at scale 0. It does not provide any visual evidence of normal data distribution. Rather it shows a high positive skewness which is evident from the statistics listed in Table 5. The samples in the vertical direction of scale 0 have very few data points and, hence, the results are statistically insignificant. All the histograms of scale 1 are approximately normal as seen from Figures 40 through 42 (except for a few outliers in Figures 40 and 41). From the statistics in Table 6, it is evident that the mean and the median values of the scale 1 samples are very close. The same observation is also true for the scale 0 samples of outcrop V in Table 4. The results obtained emphasize the notable similarities between small-scale samples of the same facies in different outcrops. The histogram of scale 2 in Figure 43 is highly skewed except for the single outlier value without which the data could have been normally distributed. However, Figure 44 provides a very different picture of the distribution. It is evident that the data are highly skewed at a higher scale. The reason could be because of the presence of distinct bedset boundaries within the facies which provides multimodal or highly skewed data distributions. Both of the histograms in Figures 45 and 46 are significantly skewed and do not correlate to any similarities that have been observed before, except that it is interesting to note that the modes of these distributions are significantly different. The distribution of outcrop G data in Figure 45 has a mode around 1,000 md, whereas that of outcrop V has a possibility of two modes—one being at about 1,500 md and the other at about 3,000 md These observations are concurrent with the statistics obtained in Table 3 which show a big difference in the mean estimates of permeability depending upon the location within outcrop V and also between the two outcrops.

The wide variability and inconsistency of the data samples for the permeability data necessitates an alternative analysis of the samples. Conventionally, the natural logarithms of the permeability data have been used for modeling and analysis because the degree of fluctuation in the data is grossly dampened by this transformation. A list of statistics for the log-permeability values of outcrops G and V are presented in Tables 7 and 8 for scale 0 and Table 9 for the higher scales. Table 9 also supplies a comparison of statistics for the full data from both outcrops.

Table 7 Univariate Statistics of Log-Permeability Data in Horizontal Direction Scale 0

Statistics	Y=0 (G)	Y=-5 (G)	Y=0 (V)	Y=-5 (V)
Number of Data	123	18	61	60
Minimum Value	5.12	4.933	6.21	7.64
Mean	6.93	6.83	7.285	8.036
Median	6.99	7.173	7.306	8.054
Maximum Value	8.47	7.603	7.756	8.333
Standard Deviation	0.407	0.818	0.28	0.164
Coefficient of Variance (CV), %	5.87	11.97	3.84	2.041
Skewness	-1.7	-1.077	-0.92	-0.468

Table 8 Univariate Statistics of Log-Permeability Data in Vertical Direction Scale 0

Statistics	X=700 (G)	X=800 (G)	X=900 (G)	X=1000 (G)
Number of Data	11	11	12	11
Minimum Value	6.43	6.62	6.44	5.16
Mean	6.98	7.24	7.02	6.85
Median	6.92	7.05	6.92	6.95
Maximum Value	7.60	8.48	7.84	7.92
Standard Deviation	0.37	0.53	0.51	0.90
CV, %	5.3	7.32	7.26	13.14
Skewness	0.4	1.115	0.516	-0.85

Table 9 Univariate Statistics of Permeability Data in 2D Scales

Statistics	Scale 1, Sub 1	Scale 1, Sub 2	Scale 1, Sub 3	Scale 2	Scale 3	Outcrop G	Outcrop V
Number of Data	131	126	136	51	56	582	264
Minimum Value	5.68	6.54	6.31	5.16	5.81	4.933	6.21
Mean	6.90	6.925	6.89	6.80	7.21	6.938	7.887
Median	6.885	6.931	6.92	6.83	7.17	6.932	8.028
Maximum Value	7.86	7.38	7.33	8.48	8.48	8.577	8.606
Standard Deviation	0.28	0.14	0.2	0.45	0.49	0.36	0.40
CV, %	4.06	2.02	2.9	6.62	6.8	5.2	4.95
Skewness	-0.45	-0.11	-0.78	-0.59	-0.08	-0.76	-1.2

From Table 7 it is immediately observed that the mean values at any outcrop location for scale 0 in the horizontal direction vary between slightly less than 7 and about 8. Hence, the fluctuation in the mean values have been dampened significantly. The median value of the samples are not significantly different from the mean values of the log-permeabilities, suggesting that the samples are almost normally distributed. This is also evident from the near-zero values of the coefficient of skewness, although all of the values are negative. The coefficients of variation of the data at all locations have been drastically reduced from very high values such as 52% down to almost 11%. Table 8 lists the log-permeability statistics of the scale 0 vertical samples of outcrop G. The mean values are almost equal to each other at any location, and the CVs have been significantly reduced because of the transformation. All the samples are positively skewed except for the sample at location of x = 1,000 ft. This anomaly is because of the scarcity of statistically significant data samples in the vertical direction at scale 0. The statistics of the higher scale samples in Table 9 have a very uniform mean value for any scale which is approximately 7.0. This uniformity was not observed in the nontransformed statistics of Table 6.

The CVs are significantly reduced for all scales and are at least comparable or lower than the CV of scale 0 in Table 7. It is important to note that all the samples are negatively skewed in Table 9. A similar result was obtained for the scale 0 samples in Table 7. This might suggest that either the data variability is significantly influenced in the horizontal direction, or there are very few data samples in the vertical direction to statistically influence the variability of the data samples at a scale higher than the scale 0.

The probability plots of the log-permeability distributions of the samples from different scales are shown in Figures 47 through 58.

Figure 47 Probability Plot of Permeability Data at Scale 0, Y = 0 ft (Outcrop G)

Figure 48 Probability Plot of Permeability Data at Scale 0, Y = -5 ft (Outcrop G)

Figure 49 Probability Plot of Permeability Data at Scale 0, Y = 0 ft (Outcrop V)

Figure 50 Probability Plot of Permeability Data at Scale 0, Y = -5 ft (Outcrop V)

Figure 51 Probability Plot of Permeability Data at Scale 0, X = 800 ft (Outcrop G)

Figure 52 Probability Plot of Permeability Data at Scale 1, Sub 1 (Outcrop G)

Figure 53 Probability Plot of Permeability Data at Scale 1, Sub 2 (Outcrop G)

Figure 54 Probability Plot of Permeability Data at Scale 1, Sub 3 (Outcrop G)

Figure 55 Probability Plot of Permeability Data at Scale 2 (Outcrop G)

Figure 56 Probability Plot of Permeability Data at Scale 3 (Outcrop G)

Figure 57 Probability Plot of Entire Permeability Data at Outcrop G

Figure 58 Probability Plot of Entire Permeability Data at Outcrop V

Visual inspection of Figures 49 and 50 reveals that the samples are close to normal distribution, although the data in Table 7 shows that they are slightly skewed to the left. The plots from the scale 0 of outcrop G in Figures 47, 48, and 51, however, have a different trend in their characteristics. Figure 47 shows a normally distributed data at the middle block of the sample but deviates from the normality at both the ends. In fact, if the maximum point on the curve is ignored, then two different straight lines with different slopes can fit the lower end and the

upper bulk of the data set. This is also true for the other two plots in the scale 0 of outcrop G. This could stem from the difference in the permeability patterns between bedsets within the facies. Further analysis needs to be done in order to obtain any conclusive evidence of these characteristics. Without the knowledge of these bedsets, the data in all three figures do not concur to a normal distribution.

Log-permeability distributions of the scale 1 samples shown in Figures 52 through 54 are evidently normal. It must be noted here that the scale 0 distributions of outcrop V samples were also distinctly normal in Figures 49 and 50, which once again shows the strong similarity of small scale sample distributions even though the data have been transformed to a natural logarithmic scale. Probability distributions of samples from scale 2 and 3 are shown in Figures 55 and 56, respectively. The distributions shown in the figures can be treated as normal, except for the slight deviation obtained in Figure 55 for extreme data values. The distributions of the entire data samples of outcrops G and V are definitely not normal, as is evident from Figures 57 and 58. This non-normality was also observed in the histograms of the samples plotted in Figures 45 and 46. Comparing Figures 47, 48, and 55, it can be observed that the distributions obtained from these three samples are very similar. This possibly suggests that the distribution of samples in outcrop G is influenced by the horizontal data distribution and that the bedset boundaries observed in the facies do influence the data variability within the facies. A similar statement could be made about the distribution of the entire data of outcrop V, which is that the non-normality of the data distribution results from significant deviations in the permeability values at short distances in the vertical direction. Henceforth, the logarithms of the permeability values will be considered in the predictability assessment and the geostatistical analysis, because the data have a low CV at all scales and also are nearly normal in distribution.

4.5.2 Assessment of Predictability

The prediction of permeability from the porosity value or vice versa is important in characterizing a reservoir and subsequently for reservoir management. Normally, high porosity is associated with high permeability values in a natural formation. However, because of the depositional history and genesis of the reservoir and also because of the action of external physical processes, the predictability of one parameter from the other is often trivial. Figures 59 through 70 are the plots of porosity versus log-permeability for the different scales of samples being studied.

Figure 59 Log-Permeability vs. Porosity Plot at Scale 0, Y = 0 ft (Outcrop G)

Figure 60 Log-Permeability vs. Porosity Plot at Scale 0, Y = -5 ft (Outcrop G)

Figure 61 Log-Permeability vs. Porosity Plot at Scale 0, Y = 0 ft (Outcrop V)

Figure 62 Log-Permeability vs. Porosity Plot at Scale 0, Y = -5 ft (Outcrop V)

Figure 63 Log-Permeability vs. Porosity Plot at Scale 0, X = 800 ft (Outcrop G)

Figure 64 Log-Permeability vs. Porosity Plot at Scale 1, Sub 1 (Outcrop G)

Figure 65 Log-Permeability vs. Porosity Plot at Scale 1, Sub 2 (Outcrop G)

Figure 66 Log-Permeability vs. Porosity Plot at Scale 1, Sub 3 (Outcrop G)

Figure 67 Log-Permeability vs. Porosity Plot at Scale 2 (Outcrop G)

Figure 68 Log-Permeability vs. Porosity Plot at Scale 3 (Outcrop G)

Figure 69 Log-Permeability vs. Porosity Plot of Entire Data at Scale 3 (Outcrop G)

Figure 70 Log-Permeability vs. Porosity Plot of Entire Data at Scale 3 (Outcrop V)

The plot of x = 800 ft in outcrop G was considered a representative sample in scale 0 of vertical direction and is shown in Figure 63.

All the figures show an insignificant correlation in the predictability of the log-permeability values given any porosity value. In other words, the value of the log-permeability is almost constant with the change in porosity. The slopes of all the best fit lines through the cloud of data

are very small. Figure 63 shows a negative slope of the best fit line. This observation is statistically insignificant because of the very small number of data points in this sample and presence of outliers which influence the best fit line drawn through the plot. All other plots definitely show a trend of higher permeabilities being associated with higher values of porosity and vice versa. A detailed regression analysis is needed to fully understand the predictability. However, it is evident from the observed plots that the permeability and the porosity data in the tidal delta facies are not significantly correlated. Because of this demonstrated statistical independence of the two parameters, a variogram obtained from the permeability data alone could be used independently to obtain kriged estimates of the parameter within the facies.

4.5.3 Variogram Analysis and Scalability

Statistical analyses of the data in samples do not reflect any evidence of spatial correlation. However, it is necessary to understand the degree of data variability in order to construct a suitable variogram model. Skewed data sets especially are difficult to model for variograms and provide erroneous kriged values. A detailed discussion on the variogram analysis is presented by Isaaks and Srivastava (1989). Without dwelling further on the justification of the variogram analysis and the methodology, the results and associated discussion are presented for the samples of outcrops G and V at the different scales under consideration.

The most important parameter in a reservoir characterization is the permeability. An accurate assessment of the variability or the spatial dependence of this parameter can aid in better understanding the fluid flow process in the reservoir. The spatial correlation in the tidal delta facies might help in extrapolating the model to an actual reservoir where such rock structure and architecture exists in the subsurface.

Figures 71 through 82 show the results of the variogram analysis of the log-permeability at the different scales for outcrops G and V with fitted theoretical models as appropriate.

Figure 71 **Experimental and Model Variogram of Log-Permeability at Scale 0, Y = 0 ft (Outcrop G)**

Figure 72 **Experimental and Model Variogram of Log-Permeability at Scale 0, Y = -5 ft (Outcrop G)**

Figure 73 **Experimental and Model Variogram of Log-Permeability at Scale 0, Y = 0 ft (Outcrop V)**

Figure 74 **Experimental and Model Variogram of Log-Permeability at Scale 0, Y = -5 ft (Outcrop V)**

Figure 75 **Experimental and Model Variogram of Log-Permeability at Scale 0, X = 800 ft (Outcrop G)**

Figure 76 **Experimental and Model Variogram of Log-Permeability at Scale 0, y = 0 ft, Part 1 (Outcrop G)**

Figure 77 **Experimental and Model Variogram of Log-Permeability at Scale 0, y = 0 ft, Part 2 (Outcrop G)**

Figure 78 **Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 1 (Outcrop G)**

Figure 79 **Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 2 (Outcrop G)**

Figure 80 **Experimental and Model Variogram of Log-Permeability at Scale 1, Sub 3 (Outcrop G)**

Figure 81 **Experimental and Model Variogram of Log-Permeability at Scale 2 (Outcrop G)**

Figure 82 **Experimental and Model Variogram of Log-Permeability at Scale 3 (Outcrop G)**

The experimental variogram for the vertical direction in outcrop G is presented in Figure 75 as a representative variogram in the vertical direction. The model parameters for the fitted variograms are shown in Table 10.

The scale 0 and the higher scale variograms need separate discussion at this point. However, later on a comparison needs to be made with respect to the scalability of the variogram models.

The experimental variograms of Figures 71 and 72 are distinctly different, despite the fact that they are computed from the same outcrop G. A reason for this difference can be attributed to the lack of statistically significant data in outcrop G for scale 0, y = –5 variogram. The value of sill of the fitted model in Figure 72 is in close correspondence with the variance value obtained from the data statistics shown in Table 7. However, the range of the model is significantly higher than any other model listed in Table 10. Thus, no further discussion of the variogram and the fitted model in Figure 72 is deemed necessary because the results are inconclusive. The experimental variogram shown in Figure 75 for scale 0 in the vertical direction of outcrop G shows a nugget effect alone. In other words, no theoretical model can be fitted through the cloud of variogram estimates obtained from this data. This suggests that more data needs to be sampled in the vertical direction of the outcrop in order to obtain any conclusive model from the variogram analysis.

Figures 73 and 74 for scale 0 of outcrop V variograms show that the experimental and theoretical models are similar. The value of the sill obtained from the fitted models, however, are very different in magnitude despite their concurrence with the statistical variance computed from the data samples. The reason for this difference in variance is because of the difference in the data samples collected at the particular locations. As stated before, outcrop V is very heterogeneous over a short interval of space. Hence, a difference in the variance of the data is expected. By assuming that the average sill value of 0.07 is representative of a unique theoretical model for the scale 0 of outcrop V, the similarity in the range of data correlation as obtained from the fitted models and shown in Table 10 can be justified. An average range of 21 with a sill of 0.07 could possibly describe the spatial variability of the scale 0 log-permeability data in outcrop V appropriately. Comparing the average model of outcrop V with the one obtained from Figure 71 for scale 0 data of outcrop G, it can be observed that there is a distinctive dissimilarity between the two. The latter model has a sill of 0.174 and a range of 80. Recognizing the fact that the data spread in scale 0 of outcrop G is 425 ft, whereas that of outcrop V is only 60 ft, the results obtained are not surprising. Also, the scale 0 data of outcrop G has bedset boundaries intersecting the horizontal line (y = 0) over which the data samples of permeability were collected. The bedset boundaries might possibly depict different variational properties across the bedset boundaries. Hence, it is necessary to analyze the data from each side of the point where the bedset boundary has intersected the y = 0 line.

The data of scale 0, y = 0 of outcrop G was subdivided into two parts for a finer analysis and without including the bedset boundary intersect in the data. The subdivisions were named scale 0, y = 0/part 1 which extends over x = 625 ft through x = 775 ft and scale 0, y = 0/part 2 which extends over x = 775 ft through x = 1,050 ft. The experimental variogram and the fitted models are presented in Figures 76 and 77 for parts 1 and 2, respectively. Although the experimental variograms look very scattered as compared to the ones shown in Figures 73 and 74, the fitted theoretical models have a great deal of similarity with the models obtained from the scale 0 outcrop V analysis. The average sill obtained from Table 10 for both parts is 0.18 and the range is 25. The average model for outcrop V was a sill of 0.07 with a range of 21. This suggests that a

range of data correlation between 21 and 25 with a sill of approximately 0.13 will adequately describe a semivariogram model in the scale 0 of the tidal delta facies.

The variogram analysis is incomplete without considering the experimental variogram estimates in 2D. Researchers must keep in mind that the data in vertical direction is limited and is statistically insignificant as discussed previously. However, there might be a considerable influence of the vertical data while analyzing the variograms in 2D space. The omnidirectional variogram and the variograms obtained from the x- and y-directions in the 2D space of scale 1 of outcrop G are plotted together in Figures 78 through 80. In general, it can be observed that the omnidirectional variogram falls in between the unidirectional variograms, suggesting that there is a degree of anisotropy existent in the data samples at this scale. The sills of the fitted models of the unidirectional variograms are different in all three cases, which indicates zonal anisotropy of the data at this scale. One key observation made of the models shown in the figures is that the omnidirectional variogram has a strong similarity to the x-directional variograms. This is evident because of the sparsely populated data samples in the y-direction, as well as the smaller range of data collection in the vertical direction from the facies. It must be stated here for the reference of the reader that the horizontal length of the sample at scale 1 is 15 ft, whereas the vertical length is only 5 ft and that the data collection is more populated in the horizontal direction as compared to the vertical direction.

The models obtained from the scale 1 analysis of the x-direction variograms in outcrop G have a range varying between 3.0 and 10.0 and an average sill of 0.04. As compared to the average model obtained for the scale 0 variogram with a sill of 0.13 and a range between 21 and 25, the model obtained from scale 1 in the x-direction is obviously underestimating both parameters of the variogram. The variogram models of the y-direction have an average sill of 0.06, and an average range of 4.67. It must be noted that the data collection in the y-direction at this scale is limited to only 5 ft. Hence, a range of similarity of 4.67 ft of the data in the vertical direction suggests that the variogram analysis needs to be done over a longer length at least in the vertical direction. The values of sill obtained from the fitted models in both x- and y-directional variograms are in close correspondence with the variance of the data at this scale. The omnidirectional variogram models are strongly influenced by the data variability in the x-direction. However, because of the difference in the variogram estimates in horizontal and vertical directions of scale 1, the omnidirectional variogram model is meaningless, unless more data are analyzed in the vertical direction to obtain a better variogram estimate, or the variogram analysis is extended to a scale higher than scale 1.

The experimental variograms and the fitted models for the x- and y-direction of scale 2 and scale 3 analysis is presented in Figures 81 and 82. Because of the scarcity of data points in the y-direction, the experimental variograms obtained may not be statistically significant. Also, the nugget effect obtained in the fitted models for the y-directional variogram in both the figures suggest that more data needs to be included in the y-direction in order to obtain a reliable estimate of the variograms in this direction. The ranges of the fitted models in the y-direction

obtained for scale 2 and scale 3 are 5 ft and 25 ft, respectively. However, the data length in the y-direction for the above scales are also 5 ft and 25 ft, respectively. This renders the models in the y-direction inadequate for the variograms under consideration. The models obtained from the x-directional variograms have a range of 80 ft in both scale 2 and scale 3. This is also the range obtained in scale 0, y = 0 for outcrop G. It has already been shown previously that the bedset boundaries influence the variogram range significantly. Hence, it can be concluded that the variogram analysis for outcrop G should be done for different bedsets separately to obtain any conclusive evidence of a single, widely applicable theoretical model for the tidal delta facies. Without procuring further data from the field and from the analysis of various scales of data samples, it can be safely concluded that a single, widely applicable model can be used to represent the variogram of the tidal delta facies with a range of about 23 ft and a sill of 0.13 for the log-permeability data distribution within individual bedsets of the facies. It can also be stated that data samples of the order of scale 1 are inadequate for variogram analysis, despite the fine sampling of data points at this scale.

Table 10 Variogram Models for Log-Permeability

Scale	Model	C_0	C	Sill $C+C_0$	Variance	Range
Scale 0,Y=0 (G)	Spherical	0.11	0.064	0.174	0.166	80
Scale 0,Y=-5 (G)	Spherical	0.15	0.73	0.88	0.67	230
Scale 0,Y=0 (V)	Spherical	0.04	0.06	0.10	0.08	25
Scale 0,Y=-5 (V)	Spherical	0.00	0.037	0.037	0.03	17.6
Scale 0, Y=0 (G)/Part 1	Spherical	0.17	0.09	0.26	0.166	25.0
Scale 0, Y=0 (G)/Part 2	Spherical	0.04	0.06	0.10	0.166	25.0
Scale 0,X=800 (G)	-	-	-	-	-	-
Scale 1, Sub 1 (X)	Spherical	0.0	0.06	0.06	0.055	3.0
Scale 1, Sub 1 (Y)	Spherical	0.045	0.06	0.105	-	4.0
Scale 1, Sub 1 (Omni)	Spherical	0.00	0.08	0.08	0.078	2.0
Scale 1, Sub 2 (X)	Spherical	0.01	0.01	0.02	0.055	10.0
Scale 1, Sub 2 (Y)	Spherical	0.0	0.023	0.023	-	3.0
Scale 1, Sub 2 (Omni)	Spherical	0.012	0.008	0.02	0.078	7.0
Scale 1, Sub 3 (X)	Spherical	0.018	0.018	0.036	0.055	7.0
Scale 1, Sub 3 (Y)	Spherical	0.018	0.035	0.053	-	7.0
Scale 1, Sub 3 (Omni)	Spherical	0.018	0.02	0.038	0.078	4.0
Scale 2 (X)	Spherical	0.0	0.2	0.2	0.235	80.0
Scale 2 (Y)	Spherical	0.1	0.1	0.2	0.28	5.0
Scale 3 (X)	Spherical	0.0	0.25	0.25	0.235	80.0

Scale 3 (Y)	Spherical	0.1	0.21	0.22	0.28	25.0

5.0 CONCLUSIONS

Grain contact types and packing indices (CI and TPI) can be successfully used to document lateral variations in compaction within the sandstones studied here. The biggest problem with packing indices encountered during this study is that these methods do not provide a significant correlation between the porosity and the permeability. This problem might largely stem from the fact that the total porosity in many Almond samples is largely dependent on the microporosity. Essentially, the microporosity is located within the grains and the interparticle cements, particularly clays. Calculation of packing indices can give a good estimation of remaining interparticle porosity, if microporosity is not significant. Researchers in general feel that this technique should not be expected to produce good estimates of permeability (which is independent of pore volume) in a lithic rich, clay cemented, or matrix-rich sandstone because the CI and TPI are only related to pore volume.

Researchers working on the Almond formation have found that porosity loss in Almond sands since the time of deposition is accurately accounted for and can be displayed as a dual end-member system where the end members are the amount of (intergranular) porosity lost to compaction and cementation. Grouping the data according to intergranular volume allows a direct comparison of the porosity results obtained from COPL and CEPL. The controlling factors for porosity evolution in the Almond sandstones appear to be the amount of diagenetically early calcite cement, clay cement, and lithics. Lithics are especially important in the Almond because a high percentage are fine-grained sedimentary clasts that were easily deformed during compaction. Permeability cannot yet be directly predicted in Almond sandstones based on the compaction and cementation indices. However, using the concept of grouping data according to intergranular volume is a promising approach that may, with more work, lead to a technique to predict the lateral distribution of permeability.

It is evident from the results and discussion above that detailed statistical analysis is necessary (and will require additional data obtained from the field) in order to understand the spatial variability of the tidal delta facies and to obtain a unique variogram model from the geostatistical analysis. This will provide researchers with the model to perform kriging and upscaling of the data on a reservoir scale and to obtain parametric information using inverse modeling techniques for enhanced oil recovery. Hence, the following conclusions are solely based upon the available information and the analyses that have been performed on the sample data from the tidal delta facies of outcrops G and V:

- The porosity data have a very compact range of distribution within the facies with a CV of approximately 3% and a uniform mean value at any location within the facies. The data are essentially normally distributed. Hence, a detailed variogram analysis of the porosity is not necessary.

- The permeability data are however, highly skewed in distribution with a very high CV for any location and any scale of analysis. Log transformed permeability data are, however, less oscillatory and more normal in distribution. Also, the transformation reduces the CV significantly. Hence, log-transformed permeability data are more suitable for both variogram analysis and for obtaining kriged estimates using the outcome of the analysis.
- The porosity data of the tidal delta facies do not demonstrate any significant correlation with the permeability data. Hence, the predictability of one from the other is trivial. The trend of the best-fit linear model through the porosity-permeability data clusters at almost all scales of analysis provide an increase in permeability with an increase in porosity and vice versa. A detailed regression analysis of the data might provide better understanding of the correlation and covariation of the two parameters within the facies. This would offers an advantage in obtaining kriged estimates without using any conditional statistics, because the parameters are independent of each other statistically.
- Variogram analysis of samples over a scale that is smaller than the range of the theoretical variogram does not provide any conclusive evidence of uniqueness of the variogram model within the facies.
- The variograms in the x-direction for any scale of analysis are either comparable or concurrent. This shows that the continuity of permeability in the horizontal direction is preserved at any scale.
- There seems to be a single, widely applicable variogram model that could be representative of the permeability variogram of the tidal delta facies within definite bedset bounds. A unique sill of 0.13 and a range of 23 ft spherical model could adequately describe the variogram model for the tidal delta facies.
- Alternative approaches to obtain reliable variogram estimates need to be investigated. Also, further data collection could improve the reliability of the variogram estimates, particularly in the vertical direction of the facies.

6.0 REFERENCES

Beard, D. C, and P. K. Weyl. 1973. Influence of texture on porosity and permeability of unconsolidated sand. *AAPG Bulletin* 57: p. 349–369.

Brasher, J. E., and K. R. Vagle. 1996. Influence of lithofacies and diagenesis on Norwegian North Sea chalk reservoirs. *AAPG Bulletin* 80: p. 746–769.

Chang, M. M., G. Guo, R. Schatzinger, and D. Lawson. 1994. *Geological and Engineering Techniques for Prediction, Detection, and Evaluation of Reservoir Bounding Surfaces.* DOE Report No. NIPER/BDM-0053.

Dutton, S. P. 1993. Influence of Provenance and Burial History on Diagenesis of Lower Cretaceous Frontier Formation Sandstones, Green River Basin, Wyoming. *Journal of Sedimentary Petrology* 63: p. 665–677.

Englund, E., and A. Sparks. 1991. *GEO-EAS 1.2.1-Geostatistical Environmental Assessment Software-User's Guide*. USEPA Report No. EPA/600/8-91/1008, 184 p.

Ehrenberg, S. N. 1990. Relationship between Diagenesis and Reservoir Quality in Sandstones of the Garn Formation, Haltenbanken, Mid-Norwegian Continental Shelf. *AAPG Bulletin* 74: p. 1,538–1,558.

Ehrenberg, S. N. 1995. Measuring Sandstone Compaction from Modal Analyses of Thin Sections: How to Do It and What the Results Mean. *Journal of Sedimentary Research* A65: p. 369–379.

Folk, R. L. 1968. *Petrology of Sedimentary Rocks.* Austin, Texas: Hemphills Books.

Higley, D. K., and J. W. Schmoker. 1989. Influence of Depositional Environment and Diagenesis on Regional Porosity Trends in the Lower Cretaceous "J" Sandstone, Denver Basin, Colorado. *In* E. B. Coalson, S. S. Kaplan, C. W. Keighin, C. A. Oglesby, and J. W. Robinson, eds., *Petrogenesis and Petrophysics of Selected Sandstone Reservoirs of the Rocky Mountain Region*. The Rocky Mountain Association of Geologists: p. 183–196.

Horne, J. C., and A. J. Scott. 1996. Sequence Stratigraphic Influence on Reservoir Characteristics-Cretaceous Foreland Basin Deposits Southwest Wyoming, Northeast Utah, and Northwest Colorado. American Association of Petroleum Geologists Field Seminar.

Houseknecht, D. W. 1987. Assessing the Relative Importance of Compaction Processes and Cementation to Reduction of Porosity in Sandstones. *AAPG Bulletin* 71: p. 633–642.

Isaaks, E. H., and R. M. Srivastava. 1989. *Introduction to Applied Geostatistics.* New York: Oxford University Press.

Kasap, E. 1995. Reservoir Characterization: A Powerful Tool for Reservoir Management, *Turkish Journal of Oil & Gas* 1(2): p. 22–38.

Loucks, R. G., M. M. Dodge, and W. E. Galloway. 1984. Regional Controls on Diagenesis and Reservoir Quality in Lower Tertiary Sandstones along the Texas Gulf Coast. *In* D. A. McDonald and R. C. Surdam, Clastic Diagenesis. *American Association of Petroleum Geologists Memoir* 37: p. 15–45.

Lundegard, P. D. 1992. Sandstone Porosity Loss—A "Big Picture" View of the Importance of Compaction. *Journal of Sedimentary Petrology* 62: p. 250–260.

Martinsen R. S., and G. Christensen. 1992. A Stratigraphic and Environmental Study of the Almond Formation, Mesaverde Group, Greater Green River Basin, Wyoming. *In* C. E. Mullen, ed., *Wyoming Geological Association 43rd Field Conference Guidebook: Rediscover the Rockies, Casper, Wyoming*, p. 171–190.

McBride, E. F., T. N. Diggs, and J. C. Wilson. 1991. Compaction of Wilcox and Carrizo sandstones (Paleocene-Eocene) to 4420 m, Texas Gulf Coast. *Journal of Sedimentary Petrology* 61: p. 73–85.

Schatzinger, R. A., M. J. Szpakiewicz, S. R. Jackson, M. M. Chang, B. Sharma, and M. K. Tham. 1992. *Integrated Geological-Engineering Model of Patrick Draw Field and Examples of Similarities and Differences among Various Shoreline Barrier Systems.* DOE Report No. NIPER-575, April.

Szpakiewicz, M., R. Schatzinger, S. Jackson, B. Sharma, M. M. Chang, and M. Honarpour. 1991. Selection and Initial Characterization of a Second Barrier Island Reservoir System and Refining of Methodology for Characterization of Shoreline Barrier Reservoirs. DOE Report No. NIPER-484, January.

Toupin, D., P. J. Eadington, M. Person, P. Morin, J. Wieck, and D. Warner. 1997. Petroleum Hydrology of the Cooper and Evomanga Basins, Australia: Some Insights from Mathematical Modeling and Fluid Inclusion Data. *AAPG Bulletin* 81: p. 577–603.

Wilson, J. C., and E. F. McBride. 1988. Compaction and porosity evolution of Pliocene sandstones, Ventura Basin, California. *AAPG Bulletin* 72: p. 664–681.

Yin, P., J. Liu, and R. C. Surdam. 1992. Petrographic and Petrophysical Properties of the Almond Sandstone in the Washakie Basin. *In* C. E. Mullen, ed., *Wyoming Geological Association 43rd Field Conference Guidebook: Rediscover the Rockies, Casper, Wyoming,* p. 191–205.