AEOLIAN AND FLUVIAL DEPOSITIONAL SYSTEMS DISCRIMINATION IN WIRELINE LOGS: UNAYZAH FORMATION, CENTRAL SAUDI ARABIA

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ABSTRACT

The objective of this study is to discriminate between aeolian and fluvial deposits of the Permian Unayzah formation in Central Saudi Arabia by using wireline logs. The analysis is conducted on wire-line logs (field data): Density, sonic, gamma, and neutron, from two vertical wells (U1 and U2) in Central Saudi Arabia. Core data are available at well location U1 but not at U2. We apply an automated neural-network method to the wireline data for facies discrimination. Our analysis has been applied to the logs of well U2 after training the method on U1 logs using available core information. Results indicate that the Unayzah formation at well location U2 consists mainly of fluvial deposits (about 90%), which is consistent with previous studies and is supported by surface seismic images.

We also investigate an analysis method based on the Fourier transform. We study the decay of the energy spectrum in the frequency domain and estimate the associated power-law exponent (i.e., the slope of the decay) for each depositional system. Analysis on the porosity logs (density, neutron, sonic, and shear), which are highly influenced by deposition composition and texture, has shown that the exponent is about the same for fluvial deposits at both well locations, while it is different for aeolian deposits.

INTRODUCTION

Borehole geophysics studies the physical properties of the stratified Earth around a hole penetrating the subsurface. Tools are used to measure certain physical properties (e.g., density, resistivity, velocity (sonic), etc.) and generate wire-line logs for the subsurface.

Wireline logs provide continuous recording of formation parameters versus depth that can be useful for geologic applications, ranging from simple well-to-well correlation through stratigraphic information to the study of entire reservoirs. The three fundamental geological parameters—composition, texture, and structure—can be related in some manner to the response of well-logging sensors. The fact that different deposits and environments may manifest different characteristics (hence different log responses), wireline logs are intensively used for lithology discrimination. The application of wireline logs to lithology determination has been discussed extensively (e.g., Asquith and Gibson, 1982; Serra, 1989; Ransom, 1995; Schlumberger, 1991; Bigelow, 1992).

The emergence of sciences such as neural networks, geostatistics, and multiresolution signal representations, has opened the door to a new class of research that could be helpful in the interpretation process of wireline logs. Several studies have attempted to incorporate such techniques in wireline logs (see Wolff and Pelissier-Combescure, 1982; Busch *et al.,* 1987; Delfiner *et al.,* 1987; Baldwin *et al.,* 1990; Rogers *et al.,* 1992; Herrmann, 1999; Saggaf and Nebrija, 1999).

In this paper, we approach the problem of identifying both lithologic and depositional facies from well logs through the use of neural networks that perform vector quantization of input data by competitive learning. This technique has provided successful lithology classification in marine environments (Saggaf and Nebrija, 1999). Here, we apply such an unconventional method to a more complex area (in terms of lateral heterogeneity) where we discriminate between different continental depositional systems or the lithology of the Unayzah formation, in Central Saudi Arabia. The neural network method, via competitive learning, is simple, compute-efficient, and inherently well suited to classification and pattern identification.

The geology of Central Saudi Arabia is discussed in many publications (e.g., Powers *et al.,* 1966; Murris, 1980; Ayres *et al.,* 1982; Bois *et al.,* 1982; Alsharhan and Kendall, 1986; Beydoon, 1991; McGillivray and Husseini, 1992). The geology of the Unayzah formation is discussed in detail by Al-Laboun, (1987), McGillivray and Husseini (1992), Al-Jallal (1996), and Evans *et al.* (1997). In our work, two sets of wire-line logs (field data)—density, sonic, gamma, resistivity, and neutron, are used from two vertical wells from Central Saudi Arabia. Our objective is to discriminate between the aeolian and the fluvial deposits of the Unayzah formation from the wireline logs. Aeolian sand in Central Saudi Arabia is an excellent reservoir aquifer for hydrocarbon accumulation with excellent reservoir properties, such as porosity and permeability. The characteristics of the deposits for both environments have been discussed previously (e.g., Pettijohn *et al.,* 1987; Walker and James, 1992; Boggs, 1995; Emery and Myers, 1996; Reading, 1996; Selley, 1996). Conducting our analysis on datasets from different well locations (U1 and U2) provides useful information about the validity of this technique to distinguish between both geological settings. Furthermore, neural net implementation allows us to incorporate additional information that we may collect about the local geology.

Finally, an additional method based on the Fourier transform is investigated to assist in conducting our analysis. In this case, we study the decay of the energy spectrum in the frequency domain and estimate the associated power-law exponent (i.e., the slope of the decay) for each depositional system in the log-log domain. This technique is based on ideas which are adopted from multi-fractal and multi-scale analyses (e.g., Wornell, 1996; Herrmann, 1999) that are yet to be studied in wireline logs as a tool to discriminate between depositional systems.

STUDY AREA AND DATA

The Usaylah field is located 175 km south of Riyadh, Central Saudi Arabia (Figure 1). It is the first stratigraphic trap to be discovered in Central Saudi Arabia. Hydrocarbon is produced from the top of the Unayzah formation with a hydrocarbon column of about 35 ft. The trap is an updip pinch-out of an Upper Unayzah formation along the eastern flanks of a north-south anticline of the Hawtah trend. The seal is the basal shale and siltstone of the Khuff (upper seal) and Unayzah (lateral seal) formations (Evans *et al.*, 1997). The source rock is the Qusaibah Shale, deposited during the Early Silurian sea level rise following the deglaciation of Gondwana (Beydoon, 1991; Mahmoud *et al.*, 1992; McGillivray and Husseini, 1992).

The Unayzah formation is of early-to-late Permian age (about 250 Ma), which resulted from a complex succession of continental clastics (Al-Laboun, 1987; Evans *et al.*, 1997; McGillivray and Husseini, 1992) and is one of the most important producing formations in Central Saudi Arabia. It consists mainly of two depositional systems: Aeolian (dunal and interdunal) and fluvial (braided-channel and flood-plain) deposits. Figure 2 shows a geological cross section of Central Saudi Arabia illustrating the general structure and stratigraphy of the area. Note that the Unayzah formation is quite heterogeneous laterally, as we expect from continental deposits. At well U1, the Unayzah formation consists of aeolian deposits which are concentrated in the top 50 feet (Al-Jallal, 1996). The rest of the formation at well U1 is fluvial (Al-Jallal, 1996). The Unayzah formation rests unconformably on the Qusaibah Shale of the Lower Silurian age and is overlain by the Late Permian Khuff Formation.

We study well logs from two vertical wells—U1 and U2—that are 2 km apart. The logs available at well U1 are: Density, compressional sonic, gamma, and neutron porosity. Well U1 is a key well since we have a detailed lithology description at that location. However, prior to this study there was no geology information and interpretation for well U2. Figure 3 shows the wireline logs at well location U1 and its facies which are determined from cores and cuttings data. Facies 1 and 2 correspond to dunal and interdunal aeolian deposits, respectively. Facies 3 and 4, on the other hand, correspond to channel and flood-plain fluvial deposits, respectively. Figure 4 shows the wireline logs at well location U2 that need to be characterized.

APPROACH

Before attempting to analyze the data and solve the problem, we must establish a basic understanding of both depositional environments from a sedimentology prospective. The characteristics of the deposits for both environments have been discussed in many publications (e.g., Pettijohn *et al.*, 1987; Walker and James, 1992; Boggs, 1995; Emery and Myers, 1996; Reading, 1996; Selley, 1996). It is obvious that these characteristics will manifest some signatures on wireline logs that may allow us to distinguish between the two environments from wireline logs.

In fluvial environments we expect the channel deposits to contain a wide range of grain sizes, from fine to coarse or conglomerate, poorly sorted, with some cement, silt and shales, and relatively small cross bedding with ununiform dips azimuths (i.e., paleocurrent). Flood-plain deposits should contain very fine grains with a relatively large amount of shalyness or clay, and cementation. In aeolian environments, we expect the dunal deposits to have well sorted grain sizes, from fine to medium grain size, with no significant cementation or shalyness (clay), and large cross bedding with uniform paleocurrent. Interdunal deposits should contain fine grains with some silt and small cementation, and laminated bedding.

The above characteristics provide some differences in the responses of wireline logs for both environments. For example, fluvial deposits will have higher gamma log responses with more variability than aeolian deposits. Furthermore, we should expect the log responses to indicate relatively higher density, higher velocity (lower sonic), and lower porosity for fluvial deposits, compared to those for aeolian deposits. Finally, the fact that both environments have different paleocurrent signatures, the response from the dip-meter (micro-resistivity measure) would be an important signature to look for in distinguishing between both environments. In fact, the responses from both the gamma log and the dip-meter are often used to distinguish between fluvial and aeolian deposits (Selley, 1996).

WHY NEURAL NETWORKS?

Several techniques have been implemented to conduct the analysis, starting by focusing on simple statistical properties (e.g., mean and standard deviation), going through Fourier-based methods (e.g., instantaneous frequency and phase), and ending with the neural network via competitive learning.

Looking at the characteristics of both depositional environments, we notice that there is no clear boundary between the two environments. They have a lot in common in that some logs can easily produce similar responses for both environments (see Tables 1 and 2). Table 1 shows data statistics for aeolian deposits and Table 2 shows deposits for fluvial at well location U1. According to the log responses combined with data

Measurement	Mean	St. Dev.	Min	Max
Sonic (ft/s)	83.26	8.25	69.01	97.12
Density (gm/cc)	2.34	0.07	2.23	2.48
Gamma (API)	39.7	5.47	29.31	49.27
Neutron (%)	15.92	3.28	8.5	22.23

Table 1: U1 - Aeolian deposits stats.

Measurement	Mean	St. Dev.	Min	Max
Sonic (ft/s)	81.45	9.13	69.35	99.64
Density (gm/cc)	2.44	0.1	2.26	2.6
Gamma (API)	92.86	27.66	29.81	143.25
Neutron (%)	13.89	4.46	8.2	23.24

Table 2: U1 - Fluvial deposits stats.

obtained from cores and cuttings, aeolian deposits exist in the first 50 ft of the Unayzah formation at well U1. Notice that beside the gamma log response, and to some extent the density log, the rest of the logs show similar responses and a large amount of overlap in the measurements that make the distinction between the two environments, based on statistics only, at well U1 unreliable.

Recall that the dip-meter log, which has been used as a key deposition discriminator between those environments, is not available in this case. This makes our task more challenging, especially considering the fact that the amount of our information (data) to conduct the study is rather limited.

Because well logs are nonstationary, conventional methods that obtain the frequency attributes (e.g., instantaneous frequency and phase) tend to fail in characterizing such signals. In addition, the fact that we have no *a priori* knowledge about the second well (U2), we need an intelligent method that can incorporate what we know about the locality from well U1 (the key well in this study). As a result, our main objective would be to apply such automated methods to characterize the depositional environment from the wireline logs at unknown location (U2). Obviously, looking at one log at a time (e.g., conventional interpretation) or two logs at a time (e.g., cross plots) is quite tedious and time-consuming and should be avoided if possible.

Considering all the above factors, we would like a technique that is easy but smart, fast, and most importantly can incorporate what we know about the locality. Neural networking allows us to accomplish these characteristics. As we will see later, neural networking uses all the logs simultaneously to perform discrimination efficiently.

Before discussing results from the data analysis, we next briefly discuss the idea and implementation behind the neural network method.

SUPERVISED NEURAL NETWORK VIA COMPETITIVE LEARNING

Lithology classification using neural networks can be carried out by two different ways of competitive learning: unsupervised and supervised. In this study, we apply the supervised method. Figure 5 is a flow chart of the algorithm.

The objective of supervised competitive-network analysis is to identify the types of lithologies present in a certain well by making use of lithologies identified in a nearby well. This mode, often called guided or directed classification, is implemented by a two-layer neural network. The first layer is a competitive network that preclassifies the input into several distinct subclasses. It takes the various well logs as input and classifies each depth interval into its corresponding facies category. This competitive layer has a predetermined number of neurons that are mapped into the known number of classes (facies). The size of the network is thus dictated by the number of classes. The network is initialized by setting each neuron to be in the middle of the interval spanned by the input. Individual neurons are considered class representatives, and they compete for each input vector. Each input vector is compared to the neuron vectors by computing the distance d_i between the input vector and the ith neuron. This distance is usually computed as the l_2 norm. The learning rule is modified such that the winning neuron is moved closer to the input vector only if the subclass defined by that neuron belongs to the target class of the input vector. Otherwise, the neuron is moved away from the input vector. Thus, competitive neurons move closer to the input vectors that belong to the classes of those neurons, and away from those that belong to other target classes. After some iterations, the network stabilizes, with each neuron in the competitive layer at the center of a cluster. The second layer is a linear network that maps the subclasses produced by the competitive layer into the final target classes to determine the target class where the input vector belongs. A more detailed information about the methodology is given in Saggaf and Nebrija (1999).

DATA ANALYSIS

Let us apply the supervised technique to characterize the depositional environments at well U2 (the logs are given in Figure 4). The training of the neural network is accomplished by using the input in Figure 3. Notice that we incorporate the lithology distribution we have learned from the local geology, cores, cutting, etc. Note that classes 1 and 2 (i.e., facies of Figure 3) correspond to the aeolian deposits, dunal and interdunal, respectively. Fluvial deposits, on the other hand, are represented by classes 3 and 4, which correspond to channel and flood-plain deposits, respectively. Figure 6 shows the result of supervised analysis for the lithology distribution at well U2. The Unayzah formation at well U2 consists mainly of fluvial deposits (i.e., about 90% fluvial and 10% aeolian). This result is consistent with published information and what we see in the seismic images (Figure 7), as given by Evans *et al.* (1997). We should realize, however, that 10% of aeolian deposits are not necessarily erroneous, especially considering the seismic resolution that can easily mask the aeolian feature. It is important to emphasize the fact that neural networking is data-size dependent. Hence, we should expect further improvement in the results as the data volume increases.

POWER-LAW ANALYSIS

We next discuss an additional (and to some extent complementary) method which has shown promising results in differentiating between the depositional systems. It is based on ideas which are adopted from multi-fractal and multi-scale analyses (e.g., Wornell, 1996; Herrmann, 1999), which are yet to be incorporated in wireline log analysis.

An enormous and varied collection of natural phenomena exhibit a power-law relationship in their power spectra. Geophysical time series, such as variation in temperature and rainfall records, and flood level variation exhibit such behavior (Wornell, 1996). In sedimentary geology, recent research shows that sedimentation rate exhibits a power-law relationship with respect to the number of cycles (beds) (Grotzinger, pers. comm.). Here, we attempt to study such phenomena in wireline logs and seek its feasibility to discriminate between the depositional systems.

We start by computing the energy spectrum for the wireline log that corresponds to a particular depositional system:

$$\xi(k) = |fft[x(j)]|^2 = |\sum_{j=1}^{N} x(j) \exp^{-2\pi i(j-1)(k-1)/N}|^2 ,$$

where $x(j)$ is the log data, k is the spatial frequency, and N is the number of data points.

Wireline logs exhibit fractal phenomena in which the power spectra decay linearly in the log-log domain (i.e., $\log \xi(\log k) = \alpha \log k + \beta$). This indicates that the energy spectrum is governed by a simple power law, as shown in the following, after recasting:

$$\xi(k) = ck^{\alpha} ,$$

where α is the power-law exponent (i.e., the slope of the power spectrum in the log-log domain) and c is a constant.

As a result, we can estimate the power-law exponent (α) by measuring the slope after fitting the power spectrum in a least-square sense to a straight line in the log-log domain. The objective now is to apply this analysis to wireline logs for both depositional environments.

Figure 8 shows the results of the power-law estimation for density logs at both well locations and for both depositional systems. Notie that the aeolian section is separated from the fluvial one of the Unayzah formation at well location U1. The Unayzah formation at well location U2 is assumed to be exclusively fluvial deposits, as neural network results (Figure 6) and seismic images (Figure 7) indicate. Table 3

Measurement	U1-Eol	U1-Flv	U2-Flv
Density	−3.2	−2.6	−2.6
Neutron	−2.1	−2.3	−2.3
Sonic	−1.9	−2.0	−2.0
Shear	−2.1	−1.8	N/A

Table 3: Power-law exponent estimation for aeolian and fluvial deposits at well U1 and U2.

shows a summary of the results for the porosity logs at both well locations. Note that the slopes in the log-log domain (i.e., the power-law exponent) for the porosity logs is about the same for fluvial deposits at both well locations, while it is different for aeolian deposits.

It is important to mention that we need to be careful before generalizing such empirical observations to other geological settings. On the other hand, we should emphasize the strength of the methodology and the fact that it shows promising results. Analyzing more data will establish statistical measures for the slopes (i.e., the mean and standard deviation) for both, and perhaps other depositional environments.

DISCUSSION AND CONCLUSIONS

We have approached the problem of identifying both lithologic and depositional facies of the Unayzah formation, Central Saudi Arabia, from well logs through the use of neural networks that perform vector quantization of input data by competitive learning. We have also discussed an additional (and to some extent complementary) method which has shown promising results in differentiating between the depositional systems by examining the power-law exponent that governs the power spectra in wireline logs. This idea is adopted from multi-fractal and multi-scale analyses that are yet to be studied in wireline log-interpretation (analysis).

Two sets of wire-line logs (field data): Density, sonic, gamma, and neutron, from two vertical wells (U1 and U2), in Central Saudi Arabia, were used to conduct the analysis. Our objective was to discriminate between the aeolian and fluvial deposits of the Unayzah formation. Unlike well location U2, a detailed stratigraphy is already in place at well location U1. Thus, our main goal was to discriminate between both geological settings at the unknown location (U2). Conventionally, the gamma and dipmeter logs, supported by borehole images, core-sample analysis and seismic, are used to perform such discrimination. To achieve our objective with limited data, we applied an automated neural-network method which is well suited for data classification. Most importantly, it allowed us to incorporate existing geologic information from well U1. Results indicate that the lithology distribution of the Unayzah formation at well U2 consists mainly of fluvial deposits (i.e., about 90% fluvial and 10% aeolian). This result is quite consistent with the published information and is supported by the seismic images.

Depositional Systems Discrimination in Wireliine Logs

We discovered that wireline logs exhibit fractal phenomena in which the power spectra decay linearly in the log-log domain. This indicates that the energy spectrum of a wireline log is governed by a simple power law in which the exponent may be used as a parameter to distinguish between different depositional systems. The idea is adopted from multi-fractal and multi-scale analyses that have not yet been applied to wireline log-interpretation. In fact, the power-law exponent estimation has demonstrated promising results in differentiating between both depositional environments. Analysis on the porosity logs (density, neutron, sonic, and shear), which are highly influenced by the deposition composition and texture, show that the slope (i.e., the power-law exponent) in the log-log domain is about the same for fluvial deposits at both well locations, and different for the aeolian deposits. However, it is difficult to generalize such empirical observations based on only two well locations. Further data analysis is necessary to establish a statistical measure for the slopes (i.e., the mean and standard deviation) for both and other depositional environments, as well. Both techniques, neural networking and power-law exponent analysis, are data-size dependent. Hence, we should expect improvement in the results as data volume increases. We recommend that further tests be performed to consolidate the empirical results obtained by the power-law exponent analysis before incorporating such results into unconventional/automated methods, such as the supervised neural network, to discriminate between different depositional systems or lithology.

ACKNOWLEDGMENTS

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REFERENCES

Al-Jallal, I.A., 1996, Usaylah-1, *Saudi Aramco Special Report No. 7.*

Al-Laboun, A.A., 1987, Unayzah Formation: A new Permian-Carboniferous unit in Saudi Arabia, *AAPG Bull., 71*, 29–38.

Alsharhan, A.S. and Kendall, C.G., 1986, Precambrian to Jurassic rocks of Arabian Gulf and adjacent areas: Their facies, depositional settings, and hydrocarbon habitat, *AAPG Bull., 70*, 977–1002.

Asquith, G. and Gibson, C., 1982, Basic well log analysis for geologists, *AAPG* .

Ayres, M.G., Bilal, M., Jones, R.W., Slentz, L.W., Tartir, M., and Wilson, A.O., 1982, Hydrocarbon habitat in main producing areas, Saudi Arabia, *AAPG Bull., 66*, 1–9.

Baldwin, J.L., Bateman, R.M., and Wheatley, C.L., 1990, Application of a neural network to the problem of mineral identification from well logs, *The Log Analyst, 3*, 279–293.

Beydoon, Z.R., 1991, Arabian plate hydrocarbon geology and potential—a plate tectonic approach, *AAPG Studies in Geology, 33,* Tulsa, OK.

Bigelow, E.L. (ed.), 1992, Introduction to wireline log analysis, Western Atlas International.

Boggs, S., Jr., 1995, *Principles of Sedimentology and Stratigraphy,* Prentice-Hall.

Bois, C., Bouche, P., and Pelet, R., 1982, Global geologic history and distribution of hydrocarbon reserves, *AAPG Bull., 66*, 1248–1270.

Busch, J.M., Fortney, W.G., and Berry, L.N., 1987, Determination of lithology from well logs by statistical analysis, *SPE Formation Evaluation, 2*, 412–418.

Delfiner, P., Peyret, O., and Serra, O., 1987, Automatic determination of lithology from well logs, *SPE Formation Evaluation, 2*, 303–310.

Emery, D., and Myers, K.J., 1996, *Sequence Stratigraphy,* Blackwell Science.

Evans, D.S., Baharbi, B.H., and Al-Otaibi, A.M., 1997, Stratigraphic trap in the Permian Unayzah Formation, Central Saudi Arabia, *GeoArabia, 2*, 259–278.

Herrmann, F.J., 1999, Multi- and mono-scale attributes for well and seismic data, *MIT Borehole Acoustics and Logging/Reservoir Delineation Consortia, Annual Report,* 6-1–6-58.

Mahmoud, M.D., Vaslet, D., and Husseini, M.I., 1992, The Lower Silurian Qulibah Formation of Saudi Arabia: An important hydrocarbon source rock, *AAPG Bull., 76*, 1491–1506.

McGillivray, J.G. and Husseini, M.I., 1992, The Paleozoic petroleum geology of Central Arabia, *AAPG Bull., 76*, 1473–1490.

Murris, R.J., 1980, Middle East: Stratigraphic evolution and oil habitat, *AAPG Bull., 64*, 597–618.

Pettijohn, F.J., Potter, P.E., and Siever, R., 1987, *Sand and Sandstone,* Springer-Verlag.

Powers, R.W., Ramirez, L.F., Redmond, C.D., and Elberg, E.L., 1966, Geology of the Arabian Peninsula, sedimentary geology of Saudi Arabia, *USGS Professional Paper 560-D.*

Ransom, R.C., 1995, *Practical Formation Evaluation,* John Wiley and Sons.

Reading, H.G., 1996, *Sedimentary Environments: Processes, Facies, and Stratigraphy,* Blackwell Science.

Rogers, S.J., Fang, J.H., Karr, C.L., and Stanley, D.A., 1992, Determination of lithology from well logs using a neural network, *AAPG Bull. 76*, 731–739.

Saggaf, M.M, and Nebrija, E.L., 1999, Estimation of lithofacies and depositional facies from wireline logs, MIT Borehole Acoustics and Logging/Reservoir Delineation Consortia, Annual Report, 2-1–2-24.

Schlumberger, 1991, Log interpretation principles & applications, Schlumberger Educational Services.

Selley, R.C., 1996, *Ancient Sedimentary Environments and Their Sub-Surface Diagnosis,* Chapman and Hall, London.

Serra, O (Ed.), 1989, Sedimentary environments from wireline logs, Schlumberger Educational Services.

Walker, R.G. and James, N.P., 1992, Facies models response to sea level change, Geological Association of Canada.

Wornell, G.W., 1996, *Signal Processing With Fractals a Wavelet-Based Approach,* Prentice-Hall, Inc.

Wolff, M. and J. Pelissier-Combescure, 1982, FACIOLOG: Automatic electrofacies determination, SPLWA Annual Logging Symp., Paper FF, 6–9.

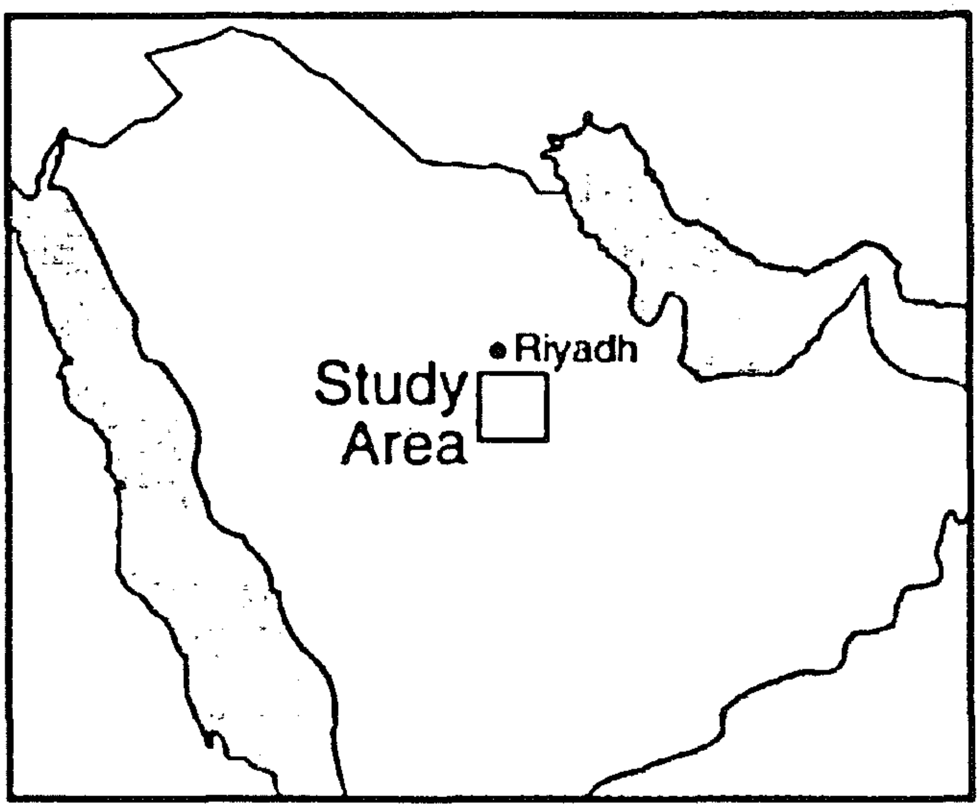

Figure 1: Geographic map of Saudi Arabia with the location of the study area highlighted.

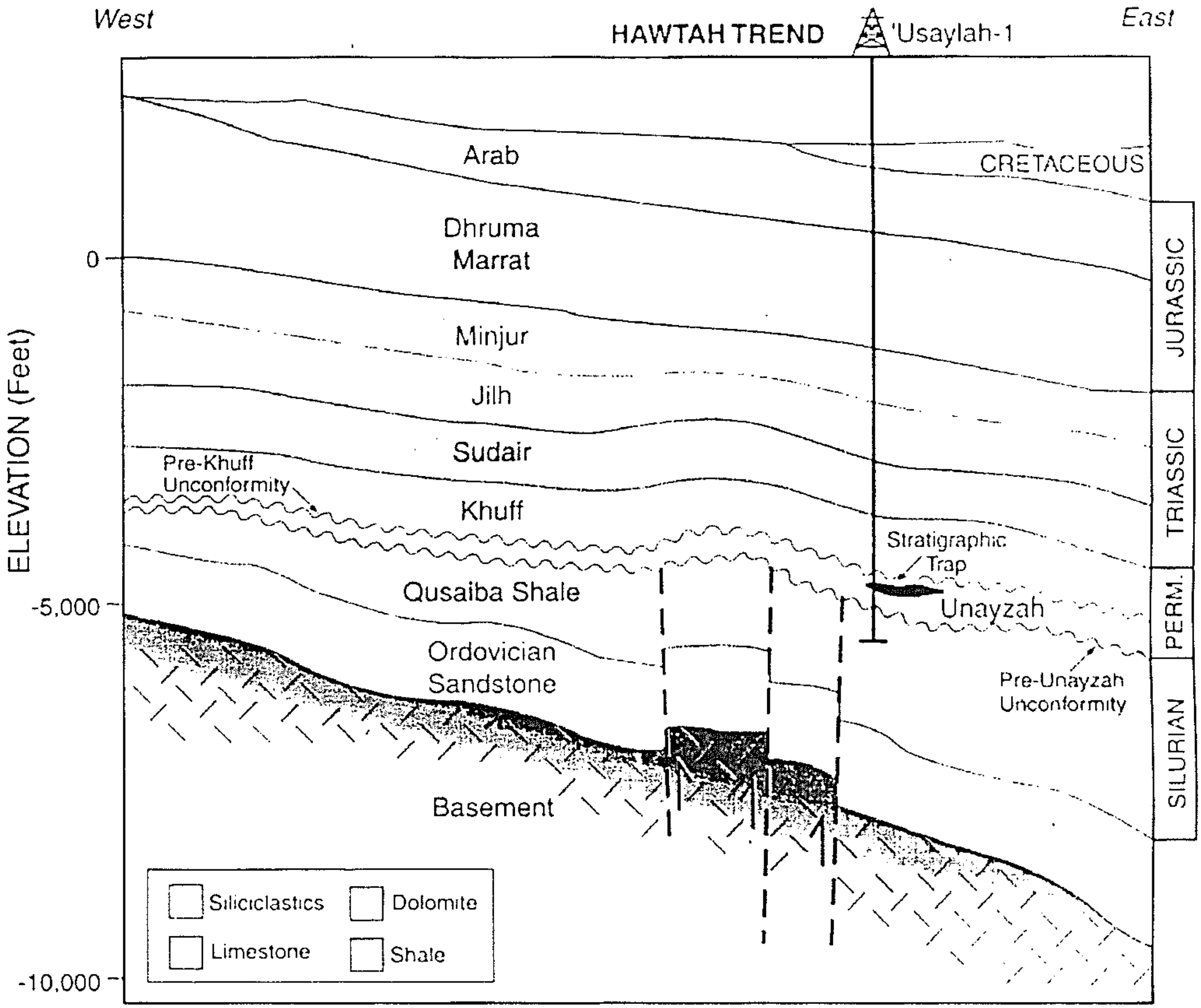

Figure 2: A west-east geologic section highlighting the general structure and stratigraphy of the study area.

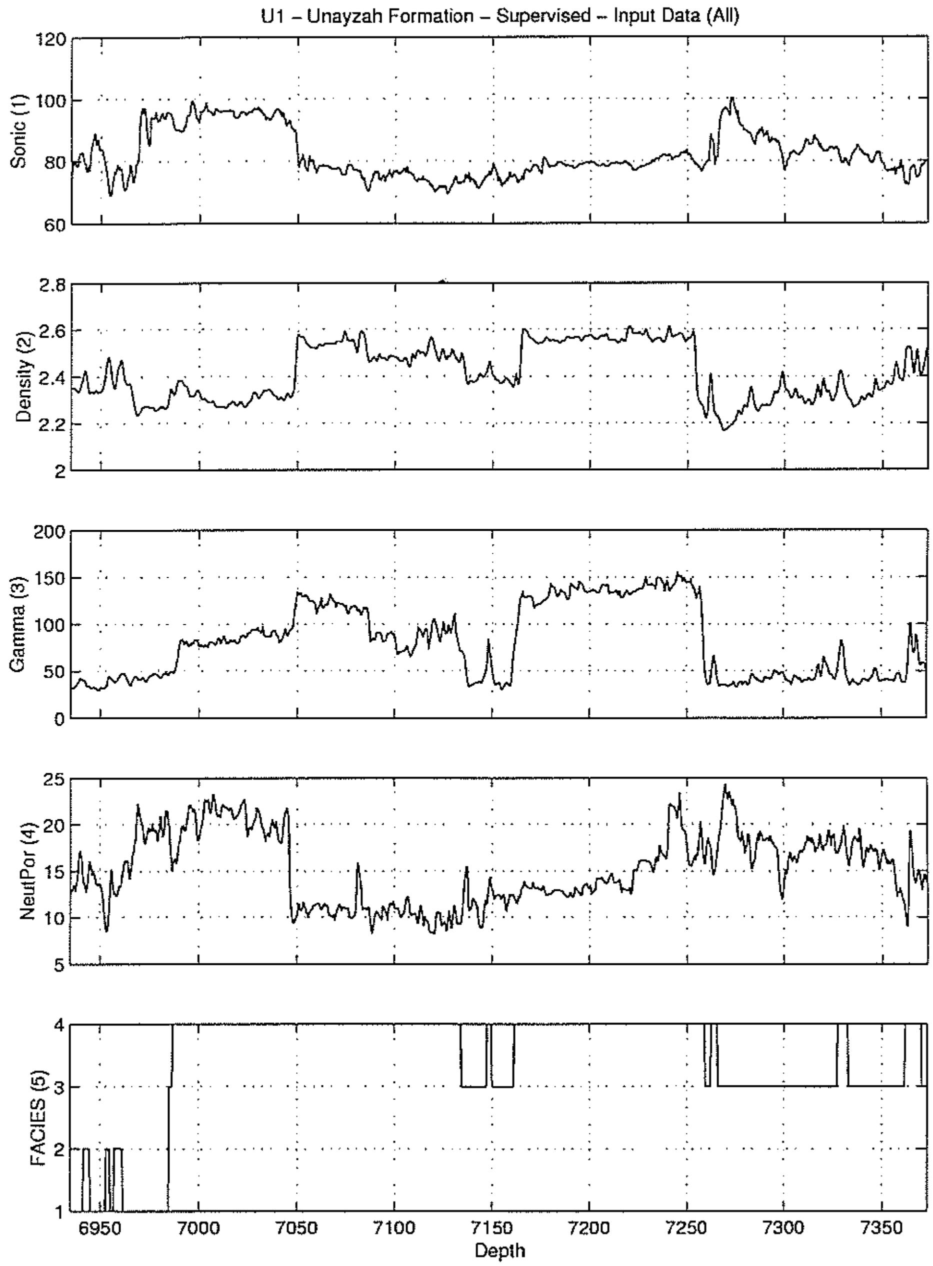

Figure 3: Input logs for Unayzah formation at well location U1 (Usaylah-1) and the lithology (facies). Depth is given in feet.

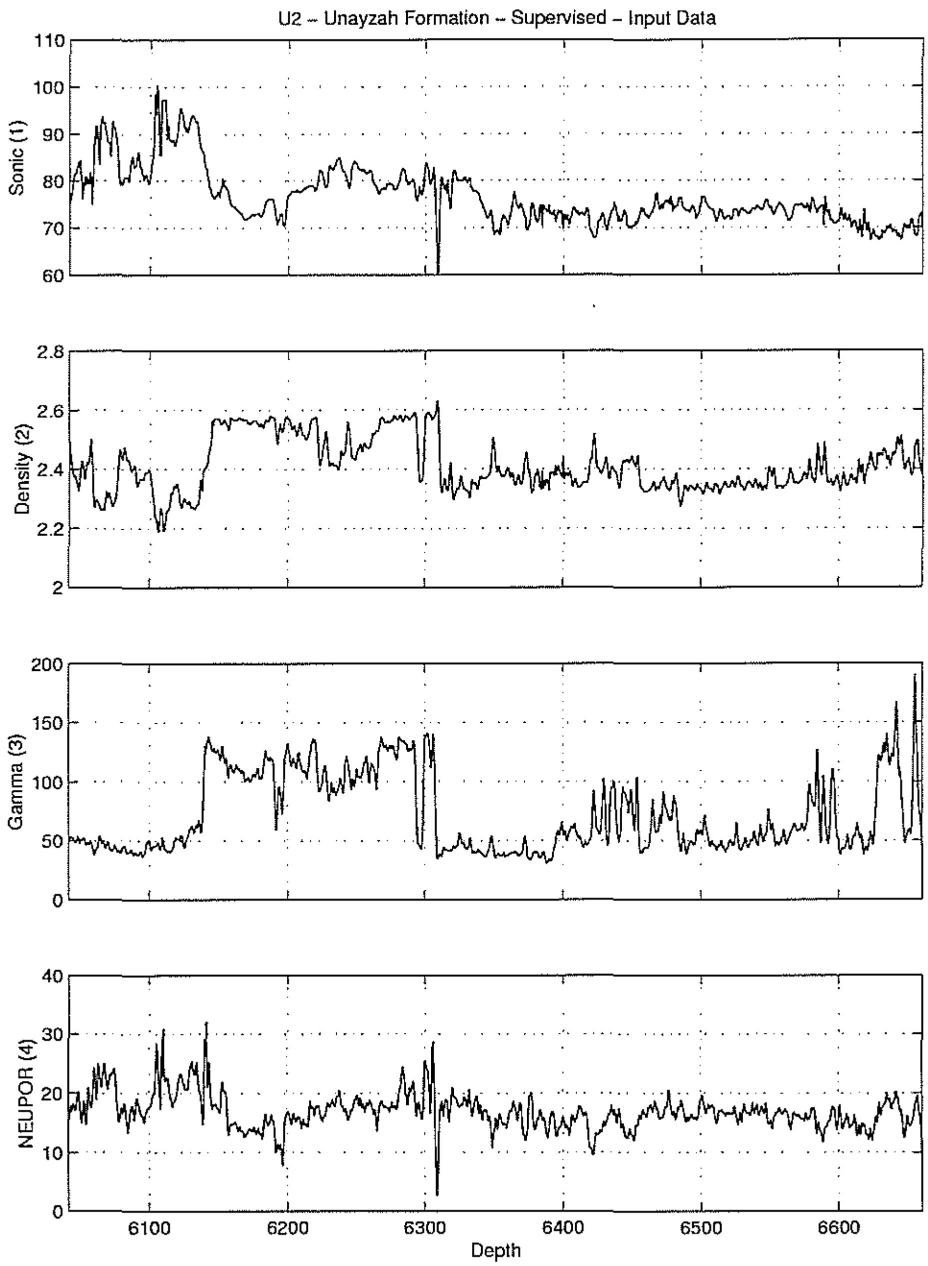

Figure 4: Wireline logs at well location U2 (Usaylah-2). Depth is given in feet.

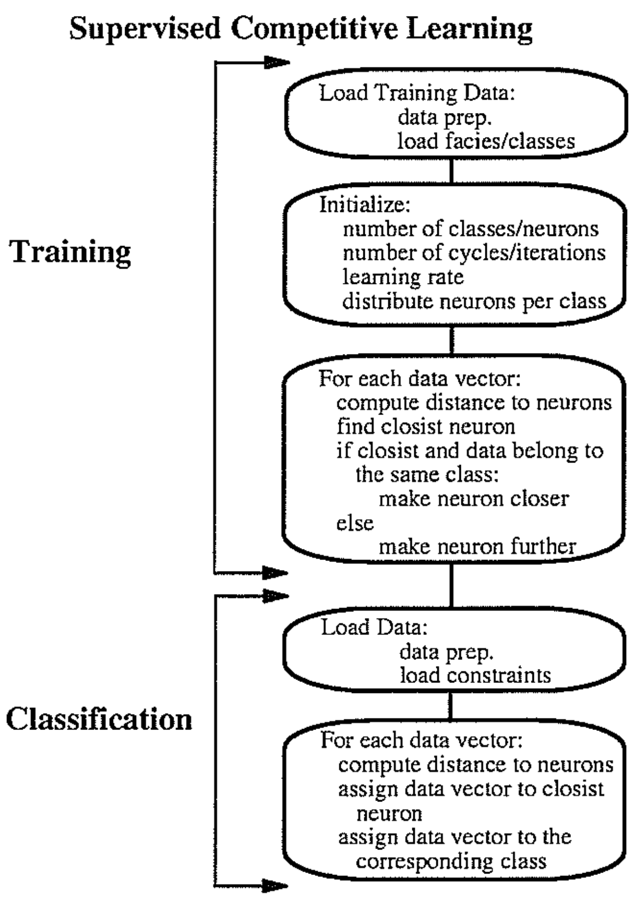

Figure 5: Flow chart of the algorithm for the supervised competitive networking.

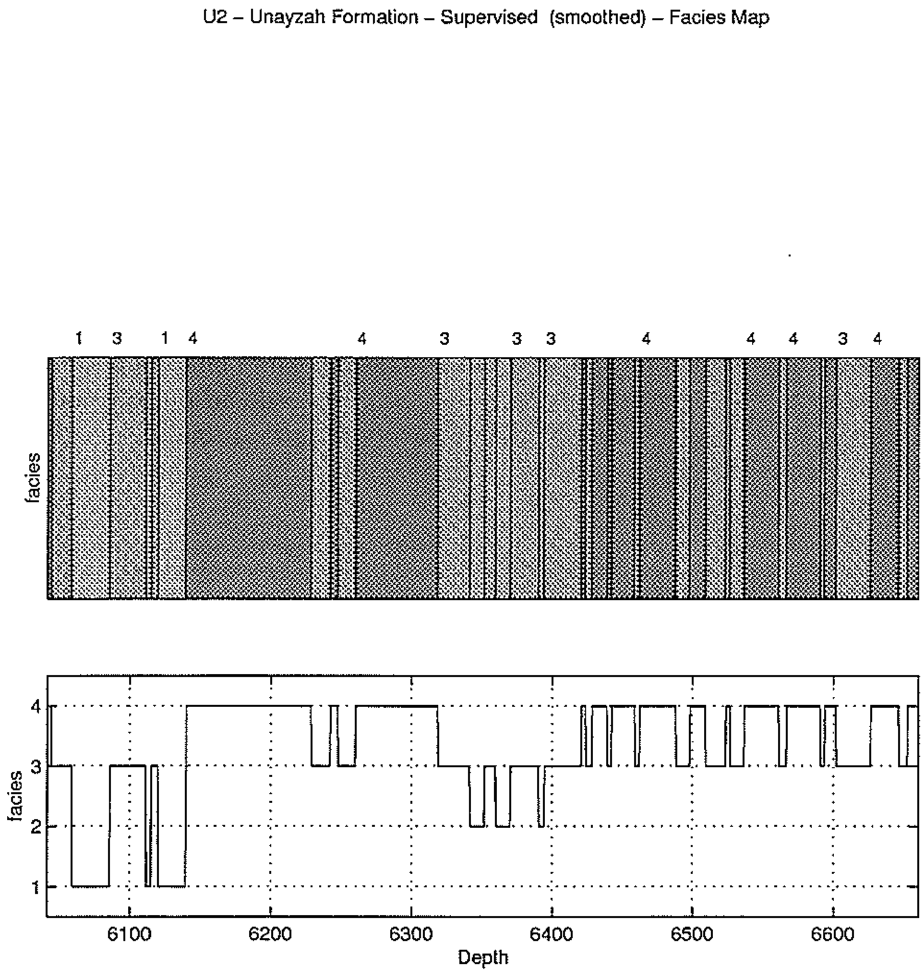

Figure 6: Data classification at well location U2 based on the supervised method and using information from well U1.

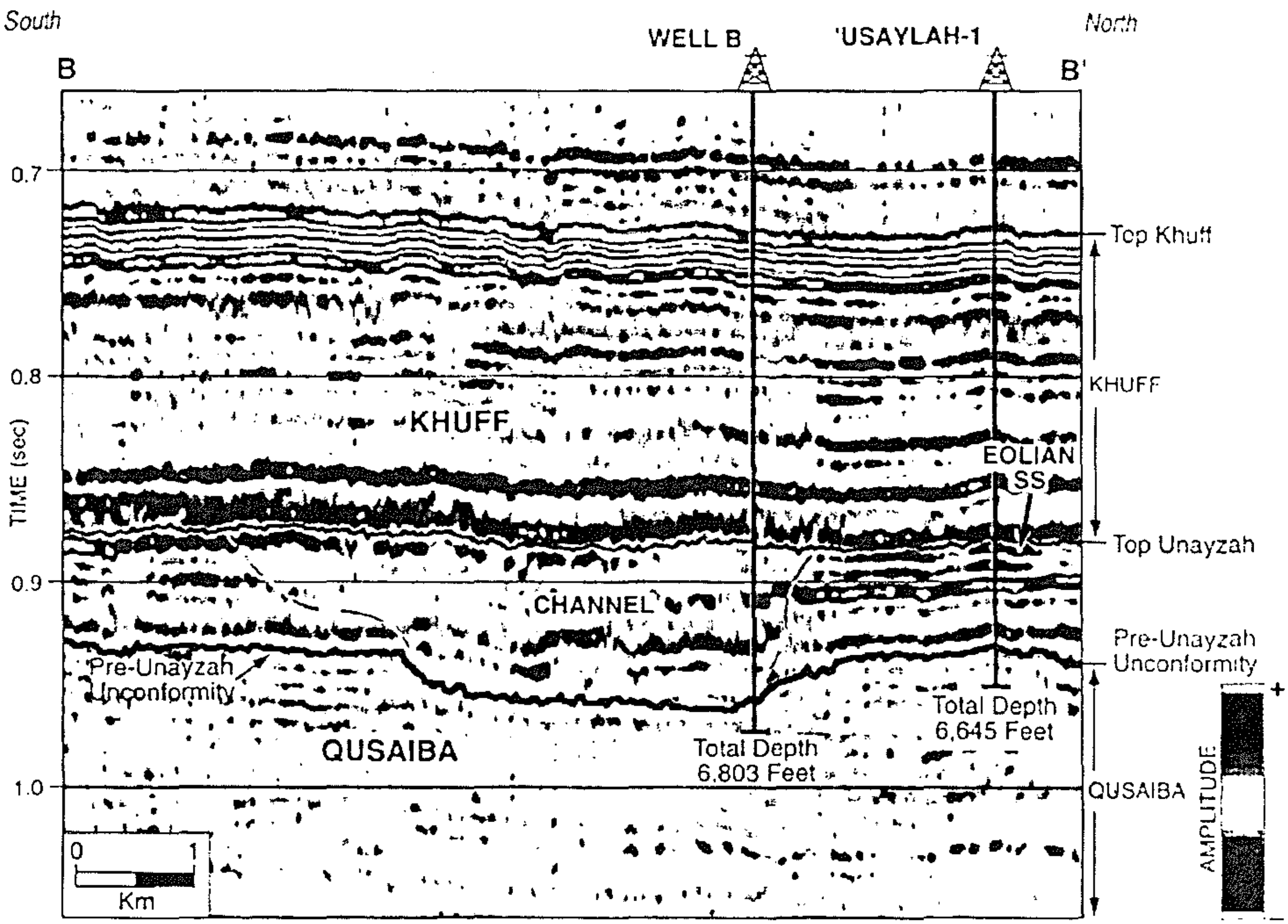

Figure 7: A South-North seismic profile with both well locations overlain (after Evans et al., 1997). It is obvious that well U2 (B) is located in an area that is characterized by a channel feature at Unayzah formation.

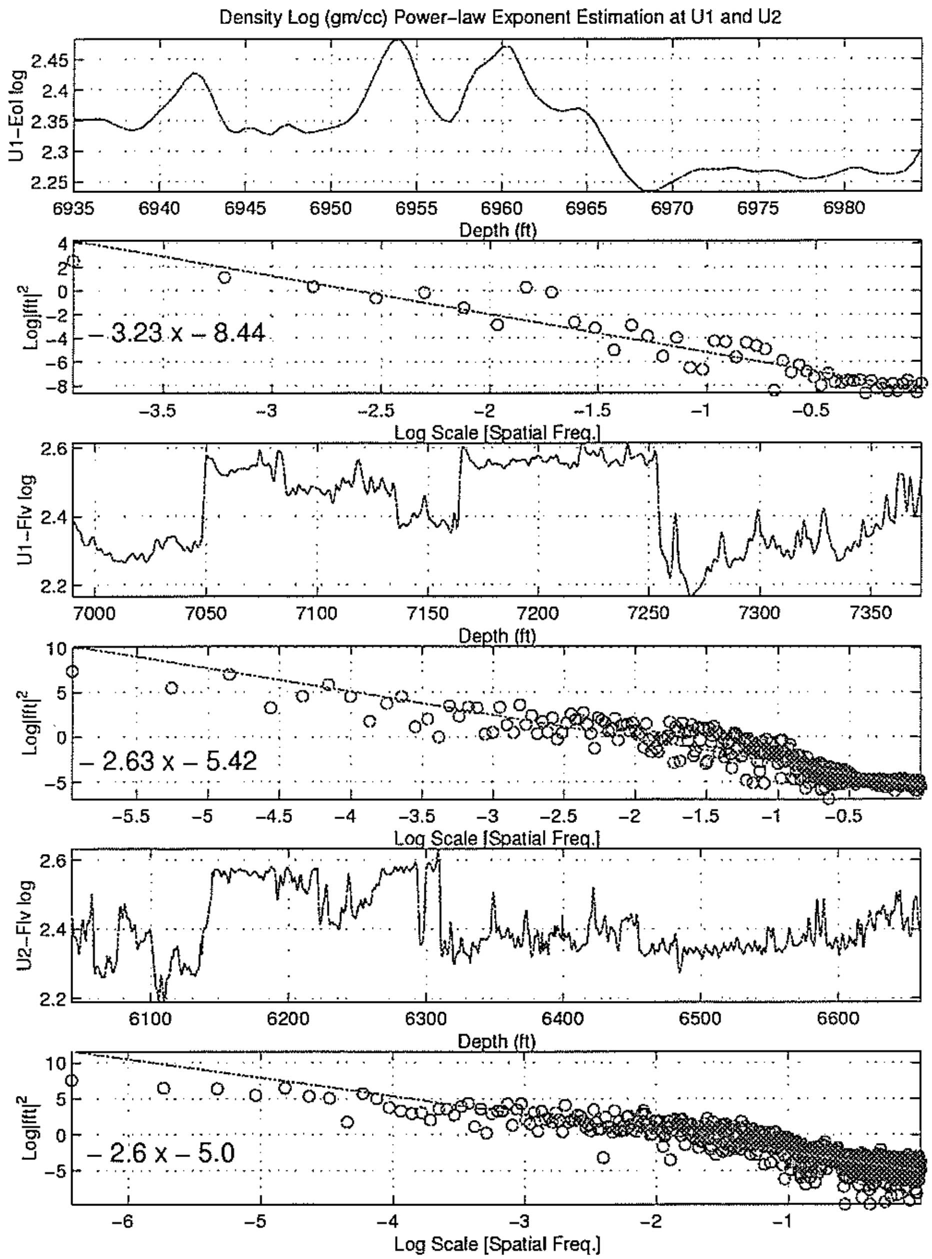

Figure 8: Power-law exponent estimation from the power spectra of the Density logs at both Well locations. The slope in the log-log domain (i.e., the power-law exponent) is about the same for the fluvial deposits at both well locations, while it is different for the aeolian deposits. Notice that the aeolian section is separated from the fluvial one at well location U1. Unayzah formation at well location U2, on the other hand, is assumed to be fluvial deposits.