SOFT COMPUTING-BASED MODELING FOR INTELLIGENT RESERVOIR CHARACTERIZATION AND GEOSCIENCES APPLICATIONS

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Soft Computing-Based Modeling for Intelligent Reservoir Characterization and Geosciences Applications

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Abstract: Reservoir characterization plays a crucial role in modern reservoir management. It helps to make sound reservoir decisions and improves the asset value of the oil and gas companies. It maximizes integration of multi-disciplinary data and knowledge and improves the reliability of the reservoir predictions. The ultimate product is a reservoir model with realistic tolerance for imprecision and uncertainty. Soft computing aims to exploit such a tolerance for solving practical problems. In reservoir characterization, these intelligent techniques can be used for uncertainty analysis, risk assessment, data fusion and data mining which are applicable to feature extraction from seismic attributes, well logging, reservoir mapping and engineering. The main goal is to integrate soft data such as geological data with hard data such as 3D seismic and production data to build a reservoir and stratigraphic model. While some individual methodologies (esp. neurocomputing) have gained much popularity during the past few years, the true benefit of soft computing lies on the integration of its constituent methodologies s rather than use in isolation

1 Introduction

With oil and gas companies presently recovering, on the average, less than a third of the oil in proven reservoirs, any means of improving yield effectively increases the world's energy re-

serves. Accurate reservoir characterization through data integration (such as seismic and well logs) is a key step in reservoir modeling & management and production optimization.

There are many techniques for increasing and optimizing production from oil and gas reservoirs:

- precisely characterizing the petroleum reservoir
- finding the bypassed oil and gas
- processing the huge databases such as seismic and wireline logging data,
- extracting knowledge from corporate databases,
- finding relationships between many data sources with different degrees of uncertainty,
- optimizing a large number of parameters,
- deriving physical models from the data
- Optimizing oil/gas production.

This paper address the key challenges associated with development of oil and gas reservoirs. Given the large amount of by-passed oil and gas and the low recovery factor in many reservoirs, it is clear that current techniques based on conventional methodologies are not adequate and/or efficient. We are proposing to develop the next generation of Intelligent Reservoir Characterization (IRESC) tool, based on Soft computing (as a foundation for computation with perception) which is an ensemble of intelligent computing methodologies using neuro computing, fuzzy reasoning, and evolutionary computing. We will also provide a list of recommendations for the future use of soft computing. This includes the hybrid of various methodologies (e.g. neural-fuzzy or neuro-fuzzy, neural-genetic, fuzzy-genetic and neural-fuzzy-genetic) and the latest tool of "computing with words" (CW) (Zadeh, 1999, Zadeh and Kacprzyk, 1999a and 1999b, and Zadeh and Nikravesh, 2002). CW provides a completely new insight into computing with imprecise,

qualitative and linguistic phrases and is a potential tool for geological modeling which is based on words rather than exact numbers.

The Role of Soft Computing Techniques: Soft computing is bound to play a key role in the earth sciences. This is in part due to subject nature of the rules governing many physical phenomena in the earth sciences. The uncertainty associated with the data, the immense size of the data to deal with and the diversity of the data type and the associated scales are important factors to rely on unconventional mathematical tools such as soft computing. Many of these issues are addressed in a recent books, Nikravesh et al. (2003a, 2003b), Wong et al (2001), recent special issues, Nikravesh et al. (2001a and 2001b) and Wong and Nikravesh (2001).

Intelligent techniques such as neural computing, fuzzy reasoning, and evolutionary computing for data analysis and interpretation are an increasingly powerful tool for making breakthroughs in the science and engineering fields by transforming the data into information and information into knowledge.

In the oil and gas industry, these intelligent techniques can be used for uncertainty analysis, risk assessment, data fusion and mining, data analysis and interpretation, and knowledge discovery, from diverse data such as 3-D seismic, geological data, well log, and production data. It is important to mention that during 1997, the US industry spent over $3 billion on seismic acquisition, processing and interpretation. In addition, these techniques can be a key to cost effectively locating and producing our remaining oil and gas reserves. Techniques can be used as a tool for 1) Lowering Exploration Risk, 2) Reducing Exploration and Production cost, 3) Improving recovery through more efficient production, and 4) Extending the life of producing wells.

Artificial Neural Network: Although Artificial neural networks (ANN) were introduced in the late fifties (Rosenblatt, 1962), the interests in them have been increasingly growing in recent years. This has been in part due to new applications fields in the academia and industry. Also, advances in computer technology (both hardware and software) have made it possible to develop ANN capable of tackling practically meaningful problems with a reasonable response time. Simply put, neural networks are computer models that attempt to simulate specific functions of human nervous system. This is accomplished through some parallel structures comprised of non-linear processing nodes that are connected by fixed, variable or fuzzy weights. These weights establish a relationship between the inputs and output of each "Neuron" in the ANN. Usually ANN have several "hidden" layers each layer comprised of several neurons. If the feed-forward (FF) network (FF or concurrent networks are those with unidirectional data flow). The full technical details can be found in Bishop (Bishop, 1995). If the FF network is trained by back propagation (BP) algorithms, they are called BP. Other types of ANN are supervised (self organizing) and auto (hetro) associative networks.

Neurocomputing represents general computation with the use of artificial neural networks. An artificial neural network is a computer model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. It is an adaptive, parallel information processing system which is able to develop associations, transformations or mappings between objects or data. It is also the most popular intelligent technique for pattern recognition to date. The major applications of neurocomputing are seismic data processing and interpretation, well logging and reservoir mapping and engineering. Good quality seismic data is essential for realistic delineation of reservoir structures. Seismic data quality depends largely on the efficiency of data processing. The processing step is time consuming and complex. The major appli-

cations include first arrival picking, noise elimination, structural mapping, horizon picking and event tracking. A detailed review can be found in Nikravesh et al. (2003a).

Feature extraction from 3D seismic attributes is an extremely important area. Most statistical methods are failed due to the inherent complexity and nonlinear information content. Neural networks can be used for segmenting seismic characters thus deducing information on the seismic facies and reservoir properties (lithology, porosity, fluid saturation and sand thickness). A display of the level of confidence (degree of match) between the seismic character at a given point versus the representative wavelets (centers of clusters) is also shown. Combining this information with the seismic model derived from the well logs while perturbing for different properties gives physical meaning of different clusters.

Neurocomputing has also been applied to reservoir mapping. In Wong et al.(1997) the authors applied a radial basis function neural network to relate the conceptual distribution of geological facies (in the form of hand drawings) to reservoir porosity. It is able to incorporate the general property trend provided by local geological knowledge and to simulate fine-scaled details when used in conjunction with geostatistical simulation techniques. are limited to two-point statistics (e.g. variograms) and simple objects (e.g. channels).

Fuzzy Logic: In recent years, it has been shown that uncertainty may be due to fuzziness rather than chance. Fuzzy logic is considered to be appropriate to deal with the nature of uncertainty in system and human error, which are not included in current reliability theories. The basic theory of fuzzy sets was first introduced by Zadeh (1965). Unlike classical logic which is based on crisp sets of "true and false", fuzzy logic views problems as a degree of "truth", or "fuzzy sets of true and false" (Zadeh 1965). Despite the meaning of the word "fuzzy", fuzzy set theory is not

one that permits vagueness. It is a methodology that was developed to obtain an approximate solution where the problems are subject to vague description. In addition, it can help engineers and researchers to tackle uncertainty, and to handle imprecise information in a complex situation. During the past several years, the successful application of fuzzy logic for solving complex problems subject to uncertainty has greatly increased and today fuzzy logic plays an important role in various engineering disciplines. In recent years, considerable attention has been devoted to the use of hybrid neural network-fuzzy logic approaches as an alternative for pattern recognition, clustering, and statistical and mathematical modeling. It has been shown that neural network models can be use to construct internal models that capture the presence of fuzzy rules. However, determination of the input structure and number of membership functions for the inputs has been one of the most important issues of fuzzy modeling.

Fuzzy logic provides a completely new way of modeling complex and ill-defined systems. The major concept of fuzzy logic is the use of a *linguistic variable*, that is a variable whose values are words or sentences in a natural or synthetic language. This also leads to the use of *fuzzy if-then rules*, in which the antecedent and consequents are propositions containing linguistic variables.

In recent years, fuzzy logic, or more generally, fuzzy set theory, has been applied extensively in many reservoir characterization studies. This is mainly due to the fact that reservoir geology is mainly a descriptive science which uses mostly uncertain, imprecise, ambiguous and linguistic information. Fuzzy set theory has the ability to deal with such information and to combine them with the quantitative observations. The applications are many, including seismic and stratigraphic modeling and formation evaluation.

In Nikravesh and Aminzadeh (2001), the authors applied a neural-fuzzy approach to develop

an optimum set of rules for nonlinear mapping between porosity, grain size, clay content, P-wave velocity, P-wave attenuation and permeability. The rules developed from a training set were used to predict permeability in another data set. The prediction performance was very good. The study also showed that the integrated technique discovered clear relationships between P-wave velocity and porosity, and P-wave attenuation and clay content, which were useful to geophysicists.

Genetic Algorithms: Evolutionary computing represents computing with the use of some known mechanisms of evolution as key elements in algorithmic design and implementation. A variety of algorithms have been proposed. They all share a common conceptual base of simulating the evolution of individual structures via processes of parent selection, mutation, crossover and reproduction. The major one is the genetic algorithms (GAs) (Holland, 1975). Genetic algorithm (GA) is one of the stochastic optimization methods which is simulating the process of natural evolution. GA follows the same principles as those in nature (survival of the fittest, Charles Darwin). GA first was presented by John Holland as an academic research. However, today GA turn out to be one of the most promising approaches for dealing with complex systems which at first nobody could imagine that from a relative modest technique. GA is applicable to multi-objectives optimization and can handle conflicts among objectives. Therefore, it is robust where multiple solution exist. In addition, it is highly efficient and it is easy to use.

Another important feature of GA is its ability to extract knowledge in terms of fuzzy rules. GA is now widely used and applied to discovery of fuzzy rules. However, when the data sets are very large, it is not easy to extract the rules. To overcome such a limitation, a new coding technique has been presented recently. The new coding method is based on biological DNA. The DNA coding method and the mechanism of development from artificial DNA are suitable for

knowledge extraction from large data set. The DNA can have many redundant parts which is important for extraction of knowledge. In addition, this technique allows overlapped representation of genes and it has no constraint on crossover points. Also, the same type of mutation can be applied to every locus. In this technique, the length of chromosome is variable and it is easy to insert and/or delete any part

of DNA. Today, genetic algorithm can be used in a hierarchical fuzzy model for pattern extraction and to reduce the complexity of the neuro-fuzzy models. In addition, GA can be use to extract the number of the membership functions required for each parameter and input variables, and for robust optimization along the multidimensional, highly nonlinear and non-convex search hyper-surfaces.

GAs work by firstly encoding the parameters of a given estimator as chromosomes (binary or floating-point). This is followed by populating a range of potential solutions. Each chromosome is evaluated by a fitness function. The better parent solutions are reproduced and the next generation of solutions (children) is generated by applying the genetic operators (crossover and mutation). The children solutions are evaluated and the whole cycle repeats until the best solution is obtained.

The methodology is in fact general and can be applied to optimizing parameters in other soft computing techniques, such as neural networks. In Yao (1999), the author gave an extensive review of the use of evolutionary computing in neural networks with more than 300 references. Three general areas are: evolution of connection weights; evolution of neural network architectures; and evolution of learning rules.

Most geoscience applications began in early 1990s. Gallagher and Sambridge (1994) presented an excellent overview on the use of GAs in seismology. Other applications include geochemical analysis, well logging and seismic interpretation.

In Huang et al.(1998), the authors used GAs to optimize the connection weights in a neural network for permeability prediction from well logs. The study showed that the GA-trained networks (neural-genetic model) gave consistently smaller errors compared to the networks trained by the conventional gradient descent algorithm (backpropagation). However, GAs were comparatively slow in convergence. The same authors initialized the connection weights in GAs using the weights trained by backpropagation. The technique was also integrated with fuzzy reasoning, which gave a hybrid system of neural-fuzzy-genetic (Huang et al., 1998). This improved the speed of convergence and still obtained better results.

Another important feature of GAs is its capability of extracting fuzzy rules. However, this becomes unpractical when the data sets are large in size. To overcome this, a new encoding technique has been presented recently, which is based on the understanding of biological DNA. Unlike the conventional chromosomes, the length of chromosome is variable and it is flexible to insert new parts and/or delete redundant parts.

Hybrid Systems: So far we have seen the primary roles of neurocomputing, fuzzy logic and evolutionary computing. Their roles are in fact unique and complementary. Many hybrid systems can be built. For example, fuzzy logic can be used to combine results from several neural networks; GAs can be used to optimize the number of fuzzy rules; linguistic variables can be used to improve the performance of GAs; and extracting fuzzy rules from trained neural networks. Al-

though some hybrid systems have been built, this topic has not yet reached maturity and certainly requires more field studies.

In order to make full use of soft computing for intelligent reservoir characterization, it is important to note that the design and implementation of the hybrid systems should aim to improve prediction and its reliability. At the same time, the improved systems should contain small number of sensitive user-definable model parameters and use less CPU time. The future development of hybrid systems should incorporate various disciplinary knowledge of reservoir geoscience and maximize the amount of useful information extracted between data types so that reliable extrapolation away from the wellbores could be obtained.

2 Intelligent Reservoir Characterization

In reservoir engineering, it is important to characterize how 3-D seismic information is related to production, lithology, geology, and logs (e.g. porosity, density, gamma ray, etc.) (Chawathe et al. 1997; Schuelke et al. 1997; Monson and Pita 1997, Aminzadeh and Chatterjee, 1985). Knowledge of 3-D seismic data will help to reconstruct the 3-D volume of relevant reservoir information away from the well bore. However, data from well logs and 3-D seismic attributes are often difficult to analyze because of their complexity and our limited ability to understand and use the intensive information content of these data. Unfortunately, only linear and simple nonlinear information can be extracted from these data by standard statistical methods such as ordinary Least Squares, Partial Least Squares, and nonlinear Quadratic Partial Least-Squares. However, if *a priori* information regarding nonlinear input-output mapping is available, these methods become more useful.

Simple mathematical models may become inaccurate because several assumptions are made to simplify the models in order to solve the problem. On the other hand, complex models may become inaccurate if additional equations, involving a more or less approximate description of phenomena, are included. In most cases, these models require a number of parameters that are not physically measurable. Neural networks (Hecht-Nielsen 1989) and fuzzy logic (Zadeh 1965) offer a third alternative and have the potential to establish a model from nonlinear, complex, and multi-dimensional data. They have found wide application in analyzing experimental, industrial, and field data (Rogers et al. 1992; Nikravesh et al. 2003a, 2003b, 2001a, 2001b, 2001c, Wong and Nikravesh, 2001, Wong et al. 2002, 1997). In recent years, the utility of neural network and fuzzy logic analysis has stimulated growing interest among reservoir engineers, geologists, and geophysicists. In a recent study, Nikravesh and Aminzadeh (2001) used an artificial neural network to further analyze data. It was concluded that to find nonlinear relationships, a neural network model provides better performance than does a multiple linear regression model. Neural network, neuro-fuzzy, and knowledge-based models have been successfully used to model rock properties based on well log databases. Nikravesh et al. (1999 and 2001c) applied artificial neural networks and neuro-fuzzy techniques successfully to find the relationships between 3-D seismic attributes and well logs and to extrapolate mapping away from the well bore to reconstruct log responses.

Adams et al. (1999a and 1999b), Levey et al. (1999), Nikravesh et al. (1999 and 2001c) showed schematically the flow of information and techniques to be used for intelligent reservoir characterization (IRESC) (**Figure 1**). The main goal will be to integrate soft data such as geological data with hard data such as 3-D seismic, production data, etc. to build a reservoir and stratigraphic model. Nikravesh et al. (1999 and 2001c) were developed a new integrated meth-

odology to identify a nonlinear relationship and mapping between 3-D seismic data and production-log data and the technique was applied to a producing field. This advanced data analysis and interpretation methodology for 3-D seismic and production-log data uses conventional statistical techniques combined with modern soft-computing techniques. It can be used to predict: 1. mapping between production-log data and seismic data, 2. reservoir connectivity based on multi-attribute analysis, 3. pay zone recognition, and 4. optimum well placement. Three criteria have been used to select potential locations for infill drilling or recompletion (Admas et al., 199b, Nikravesh et al., 1999 and 2001c): 1. continuity of the selected cluster, 2. size and shape of the cluster, and 3. existence of high Production-Index values inside a selected cluster with high Cluster-Index values. Based on these criteria, locations of the new wells were selected, one with high continuity and potential for high production and one with low continuity and potential for low production. The neighboring wells that are already in production confirmed such a prediction (**Figure 2**).

Although these methodologies have limitations, the usefulness of the techniques will be for fast screening of production zones with reasonable accuracy. This new methodology, combined with techniques presented by Nikravesh et al. (1999 and 2003c) and Nikravesh and Aminzadeh (2001) can be used to reconstruct well logs such as DT, porosity, density, resistivity, etc. away from the well bore. By doing so, net-pay-zone thickness, reservoir models, and geological representations will be accurately identified. Accurate reservoir characterization through data integration is an essential step in reservoir modeling, management, and production optimization.

Figure 1 shows schematically the flow of information and **Figure 3** shows techniques to be used for intelligent reservoir characterization (IRESC). The main goal is to integrate soft data such as geological data with hard data such as 3-D seismic, production data, etc. to build reservoir and

stratigraphic models. In this case study, we analyzed 3-D seismic attributes to find similarity cubes and clusters using three different techniques: 1. k-means, 2. neural network (self-organizing map), and 3. fuzzy c-means. The clusters can be interpreted as lithofacies, homogeneous classes, or similar patterns that exist in the data. The relationship between each cluster and production-log data was recognized around the well bore and the results were used to reconstruct and extrapolate production-log data away from the well bore. The results from clustering were superimposed on the reconstructed production-log data and optimal locations to drill new wells were determined.

3 Intelligent Reservoir Characterization (IRESC)

Our example is from a field that produces from the Red River Reservoir. A representative subset of the 3-D seismic cube, production log data, and an area of interest were selected in the training phase for clustering and mapping purposes. The subset (with each sample equal to 2 msec of seismic data) was designed as a section passing through all the wells as shown in **Figure 4**. However, only a subset of data points was selected for clustering purposes, representing the main Red River focus area. This subset covers the horizontal and vertical boreholes of producing wells. **Figure 5** shows a schematic diagram of how the well path intersects the seismic traces. For clustering and mapping, there are two windows that must be optimized, the seismic window and the well log window. Optimal numbers of seismic attributes and clusters need to be determined, depending on the nature of the problem. **Figure 6** shows the iterative technique that has been used to select an optimal number of clusters, seismic attributes, and optimal processing windows for the seismic section shown in **Figure 4**. Expert knowledge regarding geological parameters has also been used to constrain the maximum number of clusters to be selected. In this

study, seventeen seismic attributes, five inversion attributes, six pseudo log attributes in seismic resolution and seven structure/trapping attributes, equaling a total of 35 attributes have been used (**Table 1**).

Figures 7 through **10** show typical representations of these attributes in our case study. Pseudo logs shown in **Figure 10** are calculated/predicted based on techniques presented in **Figure 3**. For details regarding how this techniques can be used to predict pseudo logs from seismic traces refer to the following references (Nikravesh et al. 2003a, 2003b, 2001a 2001b, Wong and Nikravesh 2001, and Wong et al. 2002). **Table 2** shows the quantitative result for prediction of pseudo logs. In this study, seven classes are used for classification purpose (**Figure 11**). A window of five samples was used as the optimal window size for the seismic traces, and a window of seven samples was used for the pseudo logs. Seismic traces have been averaged based on nine-points neighboring as shown in **Figure 11,** with the center point as location of the averaged data. Software was developed to do the qualitative analysis and it was run on a personal computer using Matlab™ software. Clustering was based on three different techniques, k-means (statistical), neural network, and fuzzy c-means clustering (**Figure 3**). Different techniques recognized different cluster patterns and one can conclude that the neural network predicted a different structure and patterns than the other techniques. Finally, based on a qualitative and quantitative analysis given the prediction from high resolution data using the technique presented in **Figure 3**, specific clusters that have the potential to include producing zones were selected. In this sub-cluster, the relationship between production-log data and clusters has been recognized and the production-log data has been reconstructed and extrapolated away from the wellbore. Finally, the production-log data and the cluster data were superimposed at each point in the 3-D seismic cube.

Figures 12 through 14 show the prediction of a high-potential and a no-potential producing D-zone (Averaged time sliced over entire D-zone) based on a conventional statistical technique (K-mean clustering techniques only) with a degree of confidence (error bar at each point) based on 1) seismic attributes only, 2) seismic attributes, inversion attributes, pseudo logs at seismic resolution, and 3) seismic attributes, inversion attributes, pseudo logs at seismic resolution and structure/trapping information. Comparing **Figures 12** through **14**, one can conclude while the changes on prediction is not significant, the degree of confidence increases by using more attributes and information in this case study (It is important to note that this is not always the case). **Figure 15** shows the prediction of high- and no-potential producing D-Zone using IRESC model (**Figure 3**). Again, even though the prediction did not changed significantly, the confidence level increased drastically compared to previous cases as shown in **Figures 12** through **14**. **Figure 15** is generated using IRESC techniques (**Figure 3**) and based on all the attributes presented in **Table 1**, seismic attributes, inversion attributes, pseudo logs at seismic resolution and structure/trapping information. It is important to note that while each color represents a certain clusters and each cluster is represented by all seven classes, it is possible that two same classified classes may not have the same distribution of these seven classes. **Figure 16** shows while one can classify a point in space either as Abrahamson or Hanson, there are several possible distributions for Abrahamson or Hanson. This representation and information can be used to calculate a better degree of confidence regarding prediction of know classes. Therefore, a better accuracy on critical decision making processes and risk assessment analysis can be achieved. Often time in the initial phase of production (or during exploration phase), the number of observation wells or producing wells are very small which makes the process of decision making and extrapolation from around the wellbore to away from the wellbore very difficult and less reliable. To over-

come this problem, one can used both expert knowledge (knowledge about similar fields) with physical knowledge to create a so-called Virtual/Pseudo wells. **Figure 17** shows a schematic diagram how one can generate the virtual well by perturbing the existing well logs and using physical model of the earth (field). Details of this process are given in a book edited by Nikravesh et al. (2003a). **Figure 18** was generated using IRESC techniques (**Figure 3**) and using techniques presented in **Figure 17** (expansion of the number of the wells using a Virtual/Pseudo well generator using expert knowledge). Comparing the results in **Figure 15**, one can conclude that both the prediction and the degree of confidence changed and increased significantly. **Figure 19** shows both qualitative and quantitative analysis of the performance of the proposed technique. In this study, we have been able to predict the D1-Zone thickness whose its presence is very critical to production from D-Zone. D1-Zone thickness it is in the order of 14 feet or less and it is not possible to be recognized using seismic resolution information which is usually in the order of 20 feet and more in this area.

Figures 20 through **22** show the performance of the IRESC technique for the prediction of classes (potential for production of high and no potential) and also the prediction of Phi*Dh which is a representative of the production zone in Red Reviver reservoirs. We have also been able to precisely predict not only the D-zone which is in the order of 50 feet, but both D1-zone which is in the order of 15 feet and D2-Zone which is in the order of 35 feet. The technique can be used for both risk assessment and analysis with high degree of confidence. To further use this information, we use three criteria to select potential locations for infill drilling or recompletion: 1. continuity of the selected cluster, 2. size and shape of the cluster, and 3. existence of high Production-Index values inside a selected cluster with high Cluster-Index values. Based on these criteria, locations of the new wells can be selected.

4 Future Trends and Conclusions

This paper addressed the key challenges associated with development of oil and gas reservoirs, given the large amount of by-passed oil and gas and the low recovery factor in many reservoirs. We are proposed the next generation of Intelligent Reservoir Characterization (IRESC) tool, based on Soft computing (as a foundation for computation with perception) which is an ensemble of intelligent computing methodologies using neuro computing, fuzzy reasoning, and evolutionary computing. The IRESC addresses the fundamental problems of current complex problems and its significant technical features are:

- Data Fusion: Integrating data from different sources
- Data Mining: Discovery of Knowledge
- Knowledge Engineering or Acquisition: Mapping the set of knowledge in a particular problem domain and converting it into a knowledge base
- Knowledge Management: Incorporating subjective information and knowledge
- Uncertainty Management: Quantifying and handling risk and uncertainty
- Scaling: Effective use of data orders of magnitude scale differences
- Economy: Time requirements to build models and update them

We have also discussed the main areas where soft computing can make a major impact in geophysical, geological and reservoir engineering applications in the oil industry. These areas include facilitation of automation in data editing and data mining. We also pointed out applications in non-linear signal (geophysical and log data) processing. And better parameterization of wave equations with random or fuzzy coefficients both in seismic and other geophysical wave propagation equations and those used in reservoir simulation. Of significant importance is their use in data integration and reservoir property estimation. Finally, quantification and reduction of uncer-

tainty and confidence interval is possible by more comprehensive use of fuzzy logic and neural networks. The true benefit of soft computing, which is to use the intelligent techniques in combination (hybrid) rather than isolation, has not been demonstrated in a full extent. This section will address two particular areas for future research: hybrid systems and computing with words.

Computing with Words: One of the major difficulties in reservoir characterization is to devise a methodology to integrate qualitative geological description. One simple example is the core descriptions in standard core analysis. These descriptions provide useful and meaningful observations about the geological properties of core samples. They may serve to explain many geological phenomena in well logs, mud logs and petrophysical properties (porosity, permeability and fluid saturations).

Computing with words (CW) aims to perform computing with objects which are propositions drawn from a natural language or having the form of mental perceptions. In essence, it is inspired by remarkable human capability to manipulate words and perceptions and perform a wide variety of physical and mental tasks without any measurement and any computations. It is fundamentally different from the traditional expert systems which are simply tools to "realize" an intelligent system, but are not able to process natural language which is imprecise, uncertain and partially true. CW has gained much popularity in many engineering disciplines (Zadeh, 1996, 1999, Zadeh and Kacprzyk, 1999a and 1999b, and Zadeh and Nikravesh, 2002). In fact, CW plays a pivotal role in fuzzy logic and vice-versa. Another aspect of CW is that it also involves a fusion of natural languages and computation with fuzzy variables.

In reservoir geology, natural language has been playing a very crucial role for a long time. We are faced with many intelligent statements and questions on a daily basis. For example: "if the porosity is high then permeability is likely to be high"; "most seals are beneficial for hydrocar-

bon trapping, a seal is present in reservoir A, what is the probability that the seal in reservoir A is beneficial?"; and "high resolution log data is good, the new sonic log is of high resolution, what can be said about the goodness of the new sonic log?"

CW has much to offer in reservoir characterization because most available reservoir data and information are too imprecise. There is a strong need to exploit the tolerance for such imprecision, which is the prime motivation for CW. Future research in this direction will surely provide a significant contribution in bridging reservoir geology and reservoir engineering. Given the level of interest and the number of useful networks developed for the earth science applications and specially oil industry, it is expected soft computing techniques will play a key role in this field. Many commercial packages based on soft computing are emerging. The challenge is how to explain or "sell" the concepts and foundations of soft computing to the practicing explorationist and convince them of the value of the validity, relevance and reliability of results based on the intelligent systems using soft computing methods.

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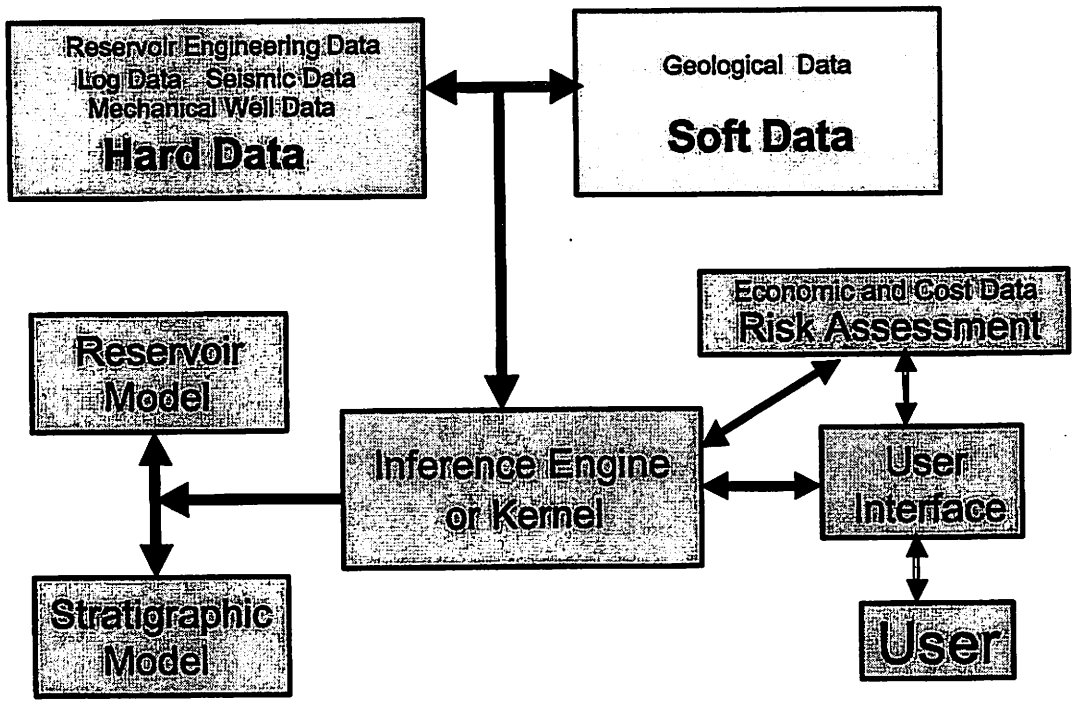


Figure 1. Integrated Reservoir Characterization (IRESC).

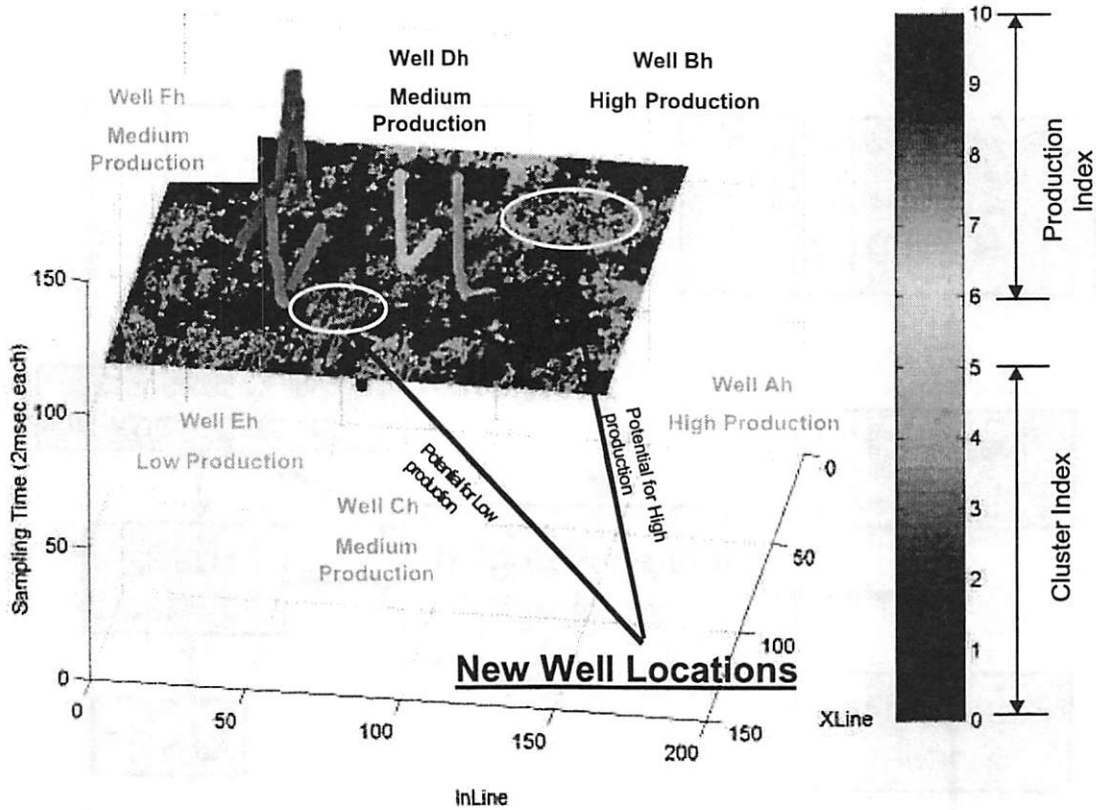


Figure 2. Optimal well placement (Nikravesh et al., 1999a and 1999b).

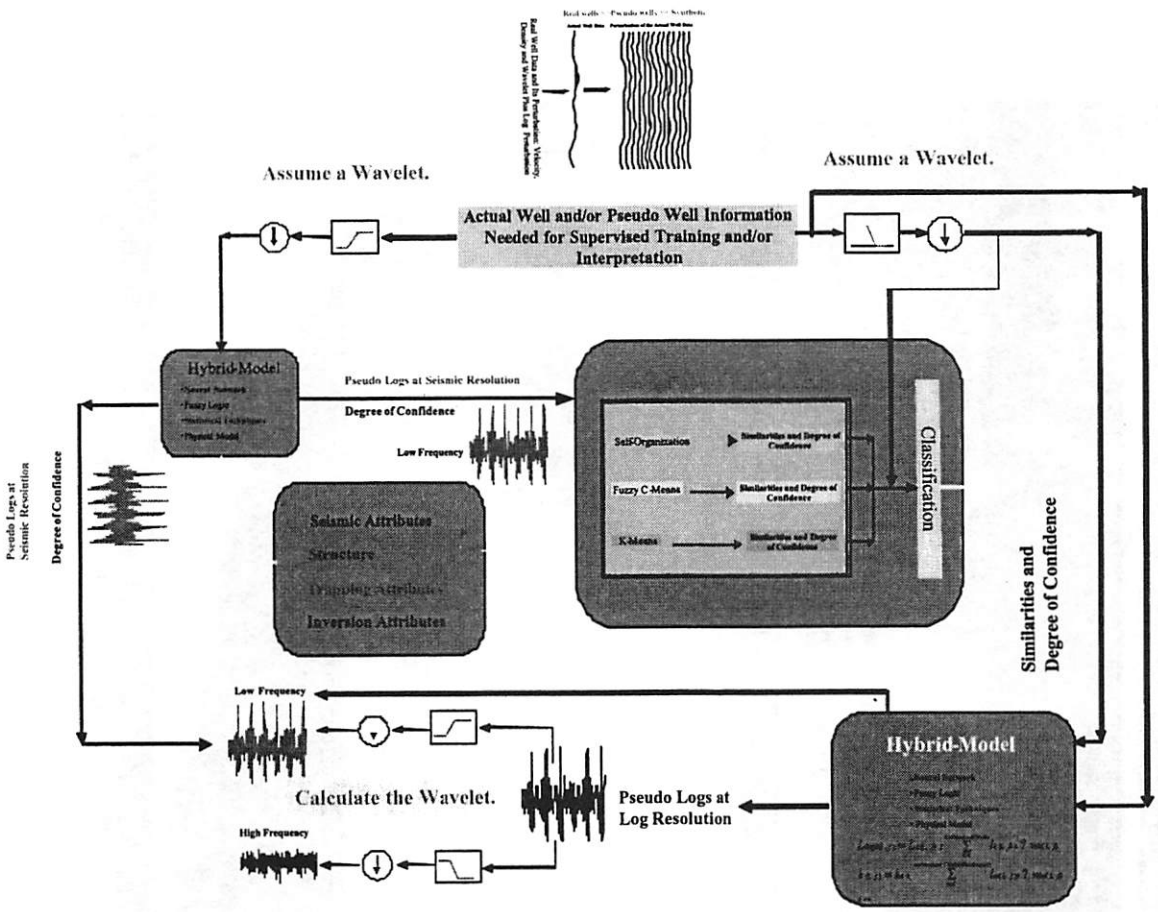


Figure 3. Technique used in IRESC Software

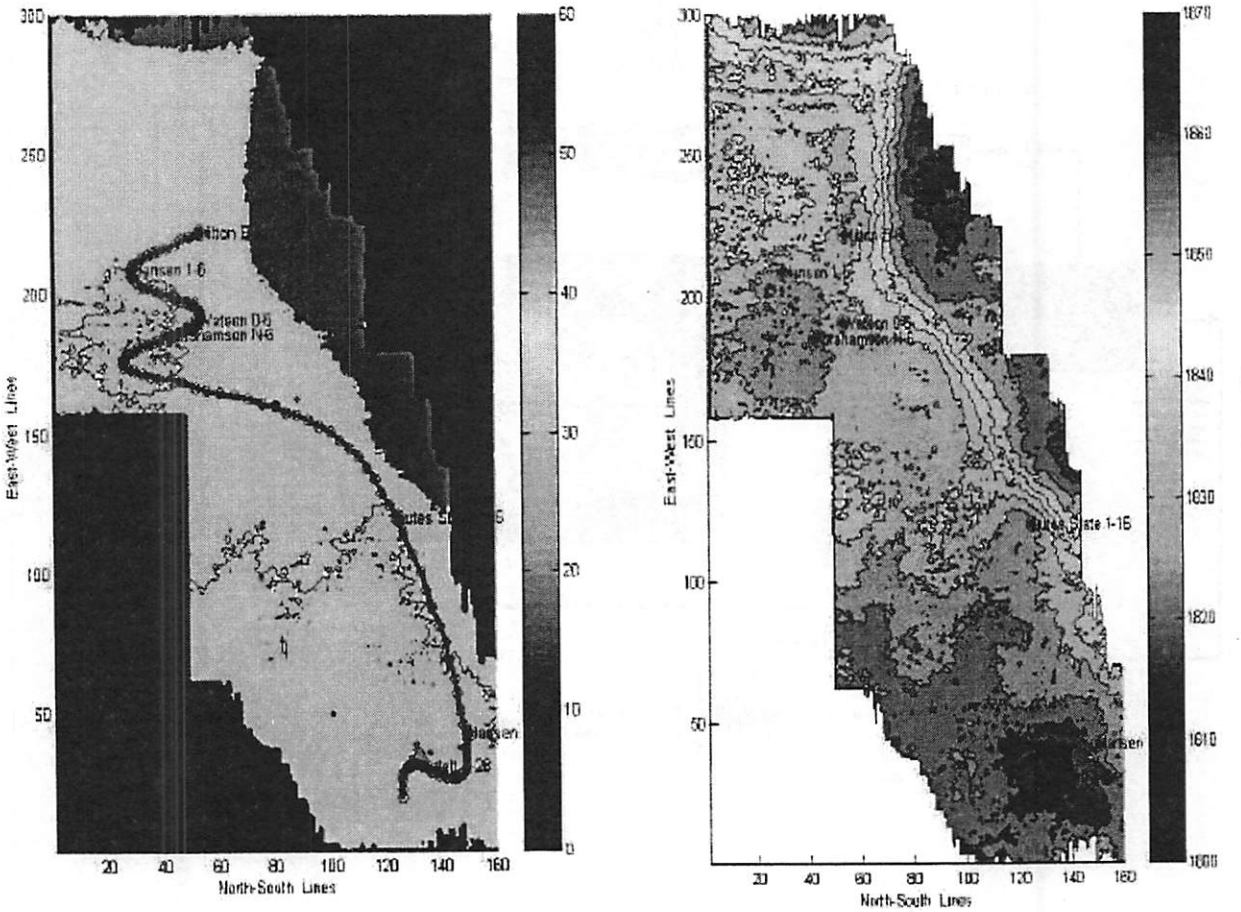


Figure 4. Seismic section passing through all the wells with structure map of the field.

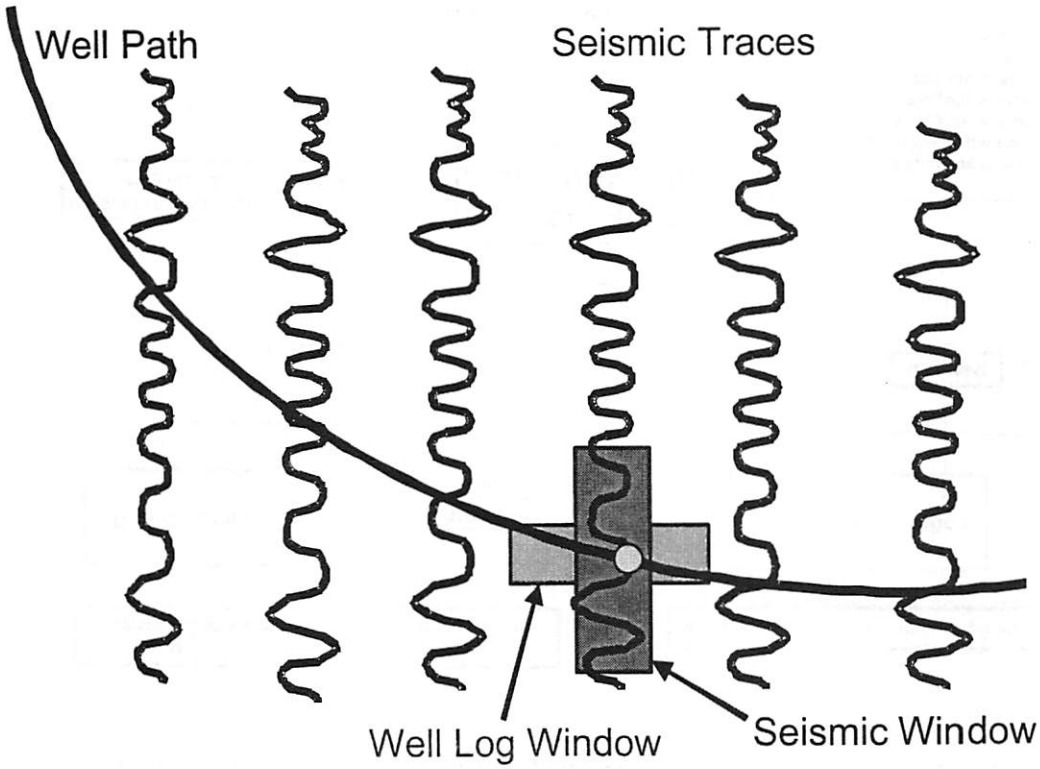


Figure 5. Schematic diagram of how the well path intersects the seismic traces.

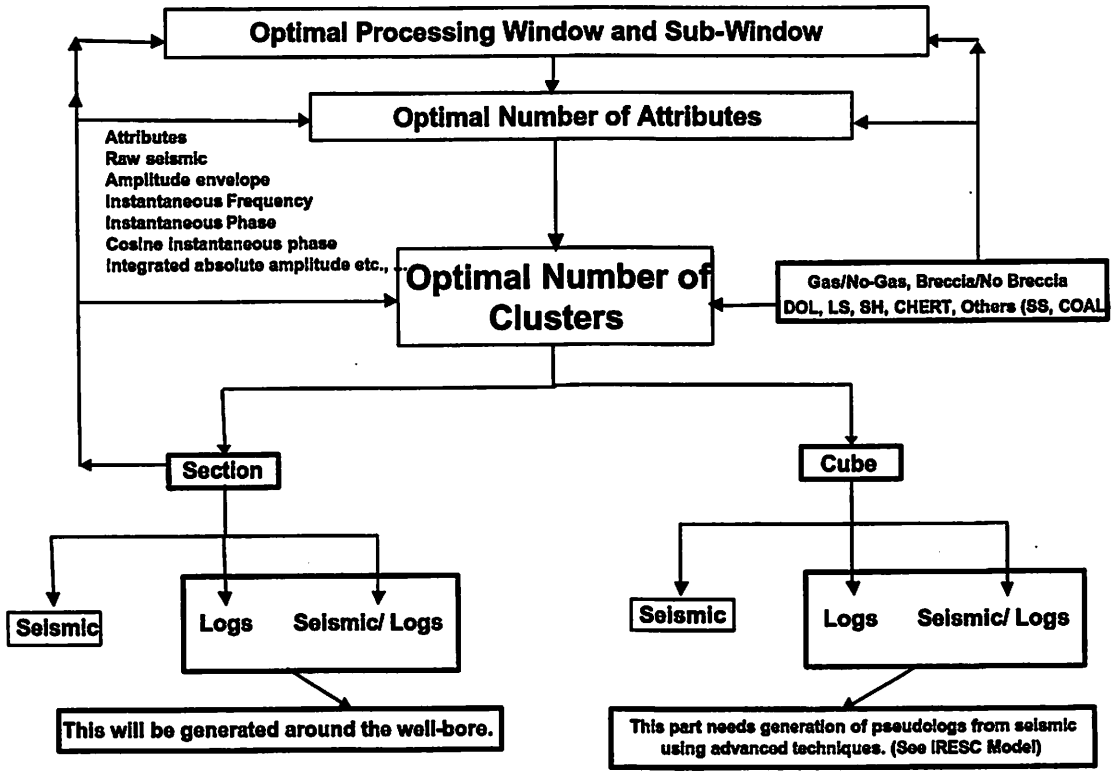


Figure 6. Iterative technique to select an optimal number of clusters, seismic attributes, and optimal processing windows.

Table 1. List of the attributes calculated in this study.

1.Amplitude envelope
2.Amplitude weighted cosine phase
3.Amplitude weighted frequency
4.Amplitude weighted phase
5.Apparent polarity
6.Average frequency
7.Cosine instantaneous phase
9.Derivative instantaneous amplitude
8.Derivative
10.Dominant Frequency
11.Instantaneous Frequency
12.Instantaneous Phase
13.Integrated absolute amplitude
14.Integrate
15.Raw seismic
16.Second derivative instantaneous amplitude
17.Second derivative
18. Acoustic Impedance
19. Low Frequency of 18.
20. Reflectivity Coefficients
21. Velocity
22. Density
23. computed_Neutron_Porosity
24.computed_Density_Porosity
25. computed_Pwave
26. computed_Density
27. computed_True_Resistivity
28. computed_Gamma_Ray

1-17; Seismic Attributes

Structure and Trapping Attributes.

Six horizons and with four attributes out of seven attributes..

Column A: line identifier
Column B: trace or cross-line identifier
Column C: easting in feet
Column D: northing in feet
1 Column E: horizon time in msecs
2 Column F: time_resd, first order residual of horizon time, negative is high or above plane
3 Column G: aspect, angle of updip direction at horizon (present day)
Column H: next deeper horizon time (used for calculation ofiso values)
4 Column I: iso, incremental time to next horizon
5 Column J: iso_resd, first order residual of iso time, negative is thinner (faster) than plane
6 Column K: iso_aspect, angle of updip direction (at time of burial)
7 Column L: cum_iso_resd, cumulative iso_resd from Winnipeg to this horizon

18-22; Inversion Attributes

23-28; Pseudo Logs Attributes

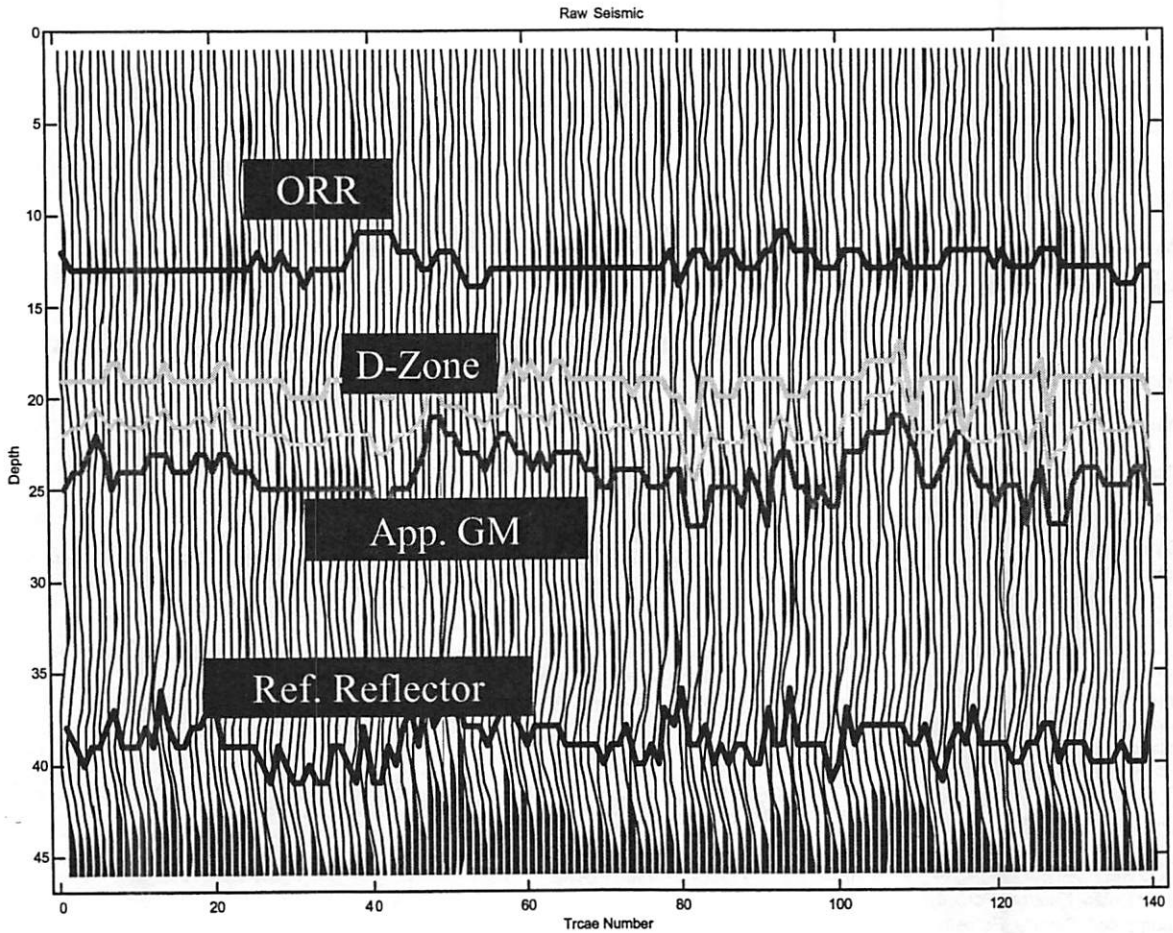
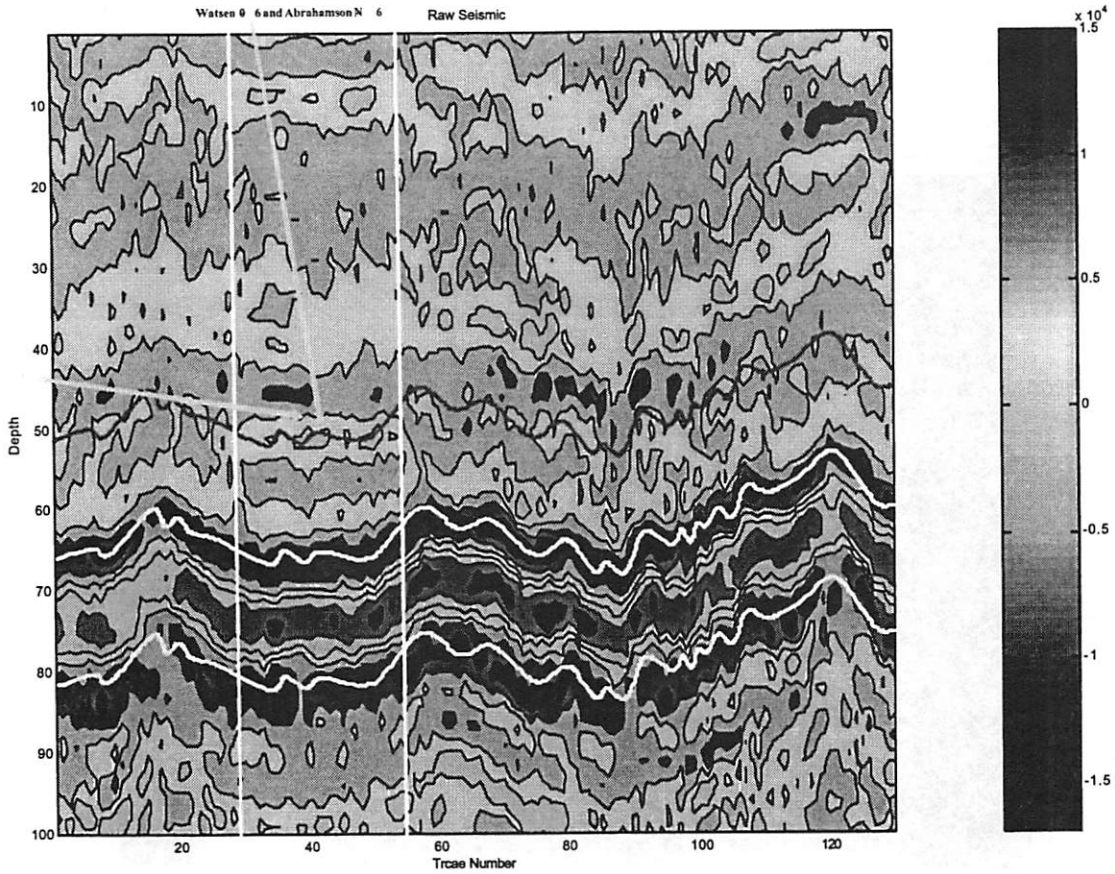


Figure 7. Typical time slice of Raw Seismic and Auto selection of the tops/Horizons (ORR, D-zone, App. GM, and Red River Ref. Reflector)



D-Zone

Figure 8.a Typical time slice of Seismic Amplitude

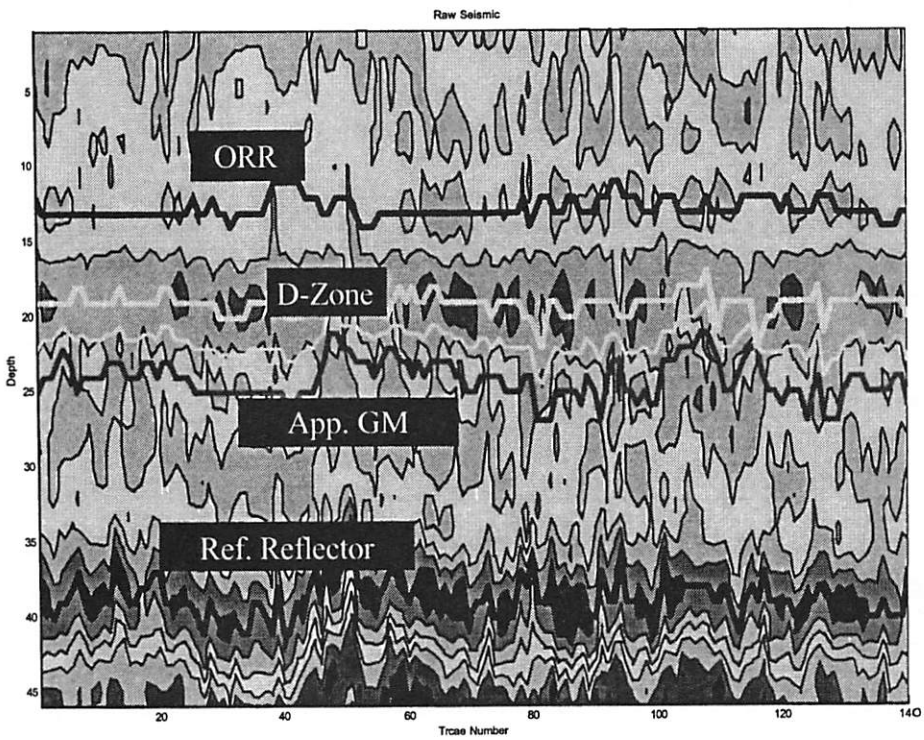


Figure 8.b. Typical time slice of Seismic Amplitude (Magnification of Figure 8.a)

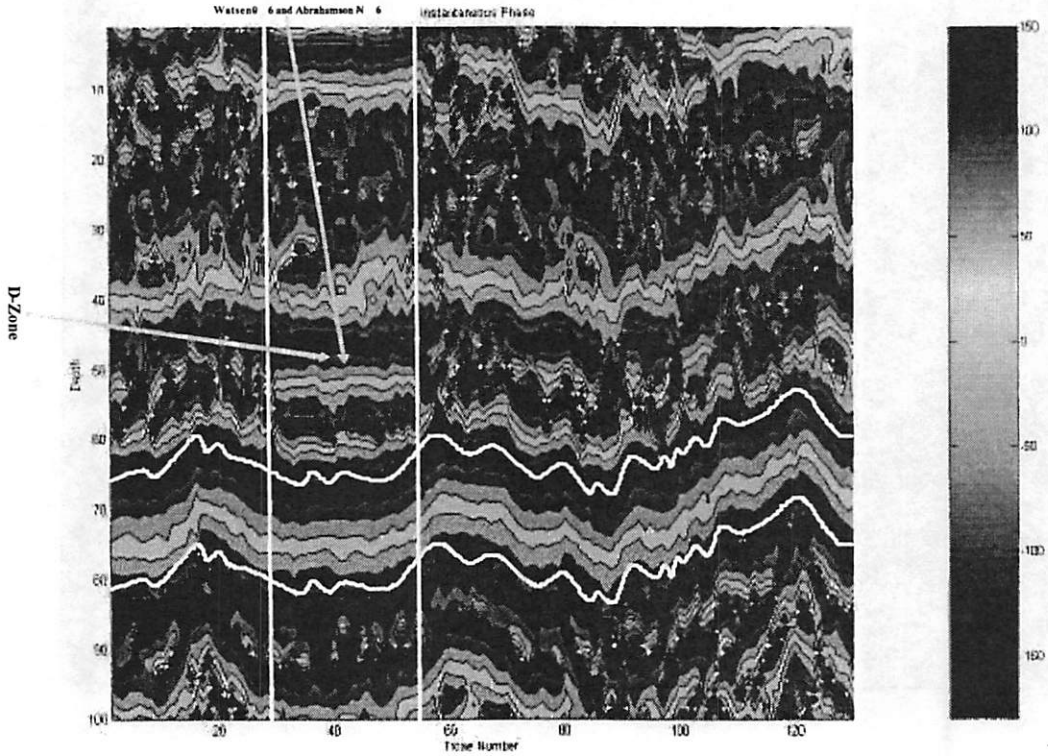


Figure 9. Typical time slice of Instantaneous Phase

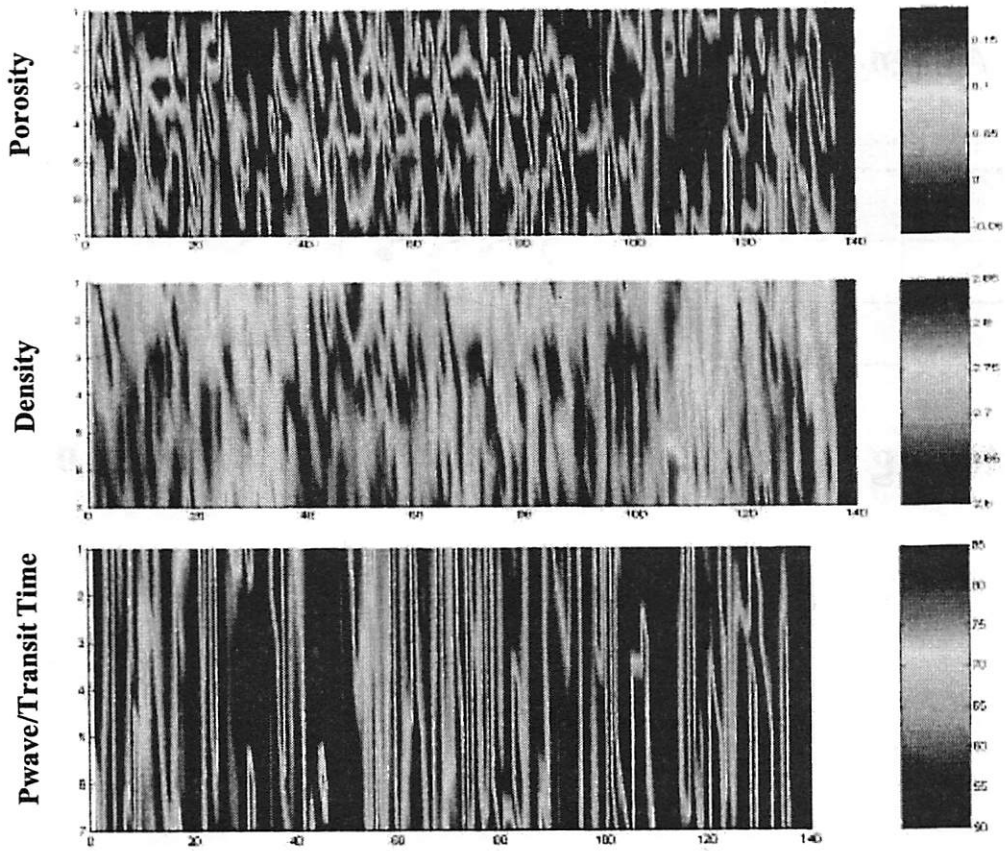


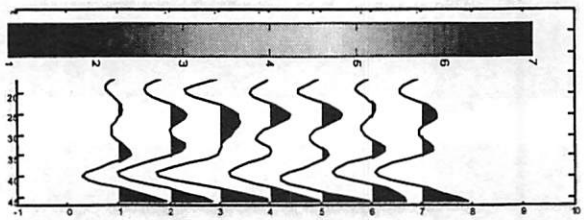
Figure 10. Typical time slice of Pseudo logs a) porosity, b) Density, and c) Pwave/Transit Time predicted in Seismic resolution

Classifications Based on Known Well Information

Assign Classes (Wells) to the Clusters.

Figure 1. Coordinate of the Traces Extracted around the Wellbore (Trace Number 5)

7	8	9
6	Well	4
1	2	3



Clustering

Classification

Well Name	InLine-Xline Data	
1. 'Jett 1-28';	31	138
2. 'Hansen 1-21';	43	150
3. 'Lutes State 1-16';	120	125
4. 'Abrahamson N-6';	186	42
5. 'Watson 0-6';	191	53
6. 'Hansen 1-6';	209	30
7. 'Hilton B-6';	222	54

Figure 11. Classification for Seven Classes

Table 2. Pseudo logs predicted at different location using techniques described in **Figure 3**.

IRESC

Abrahamson N_6

Density	Porosity	Pwave/Transit Time
2.7766	0.0127	50.5136
2.7067	0.0877	50.9988
2.6626	0.1049	51.7845
2.7093	0.0161	52.8786
2.7500	0.0701	53.8430
2.6316	0.0942	54.3527
2.6403	0.0810	54.5897

Watson O_6

Density	Porosity	Pwave/Transit Time
2.8289	0.0219	57.9844
2.6653	0.0882	57.2391
2.6425	0.1362	56.3522
2.6784	0.0613	55.6178
2.6841	0.0426	55.1912
2.6831	0.0447	54.7947
2.6931	0.0653	54.4988

Hansen 1_6

Density	Porosity	Pwave/Transit Time
2.7513	0.0004	55.0493
2.7505	0.0073	57.7750
2.7021	0.0042	62.0145
2.7200	0.0019	67.7557
2.7231	0.0011	74.4667
2.7243	0.0016	77.1229
2.7253	0.0146	77.2692

Hilton B_6

Density	Porosity	Pwave/Transit Time
2.7624	0.0038	56.8415
2.7504	0.0465	55.9862
2.7694	0.1221	54.5060
2.7563	0.0194	53.5931
2.7287	0.0313	80.9843
2.7113	0.0161	80.6559
2.6347	0.1544	80.7769

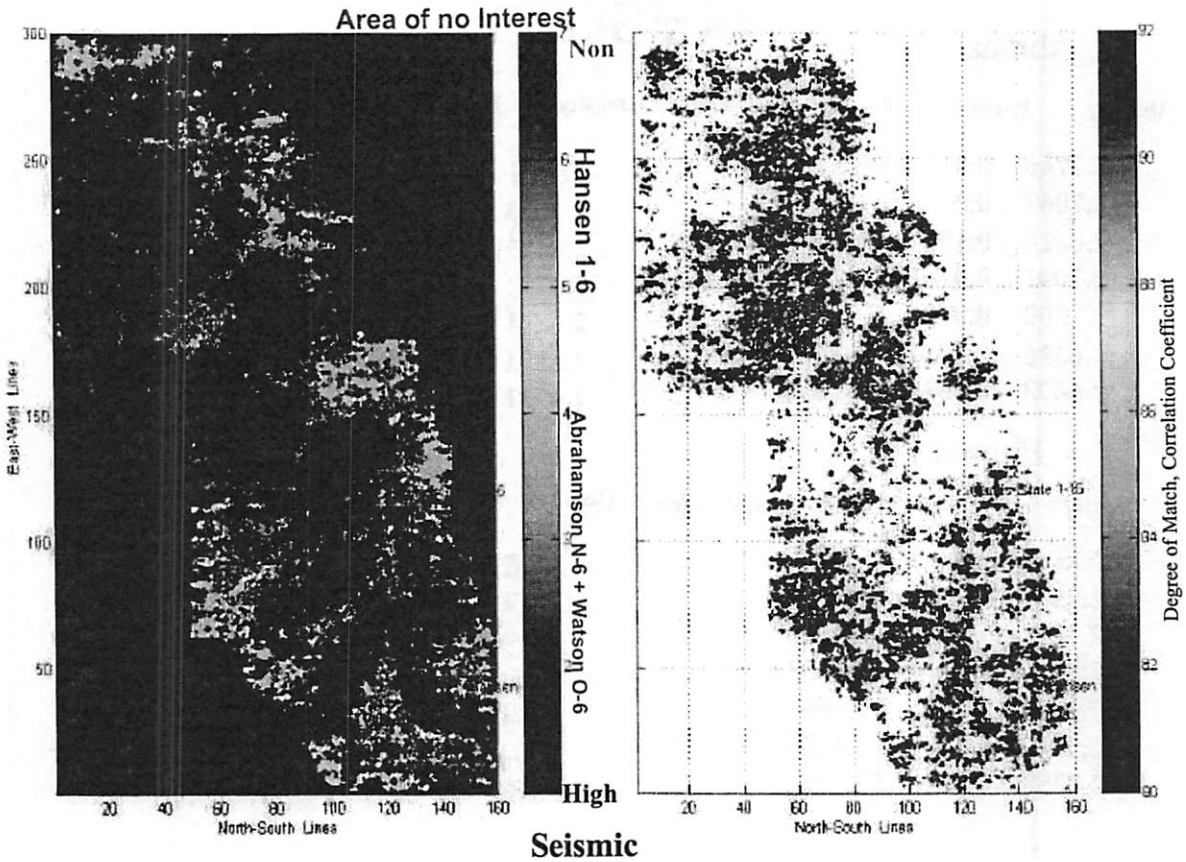


Figure 12. Performance of K-Mean clustering technique for prediction of the high-potential and no-potential producing D-Zone with degree of confidence based on seismic attributes

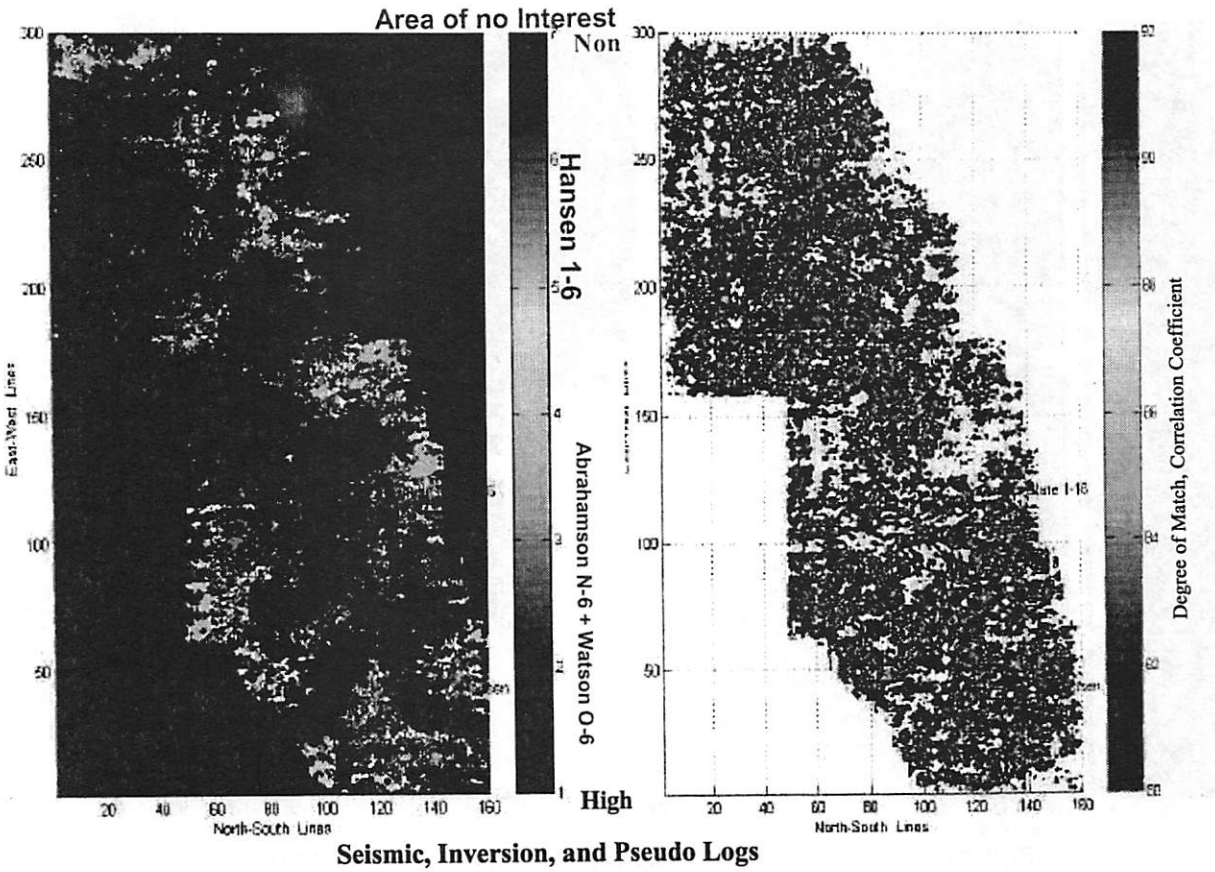


Figure 13. Performance of K-Mean clustering technique for prediction of the high-potential and no-potential producing D-Zone with degree of confidence based on seismic attributes, inversion attributes and pseudo logs

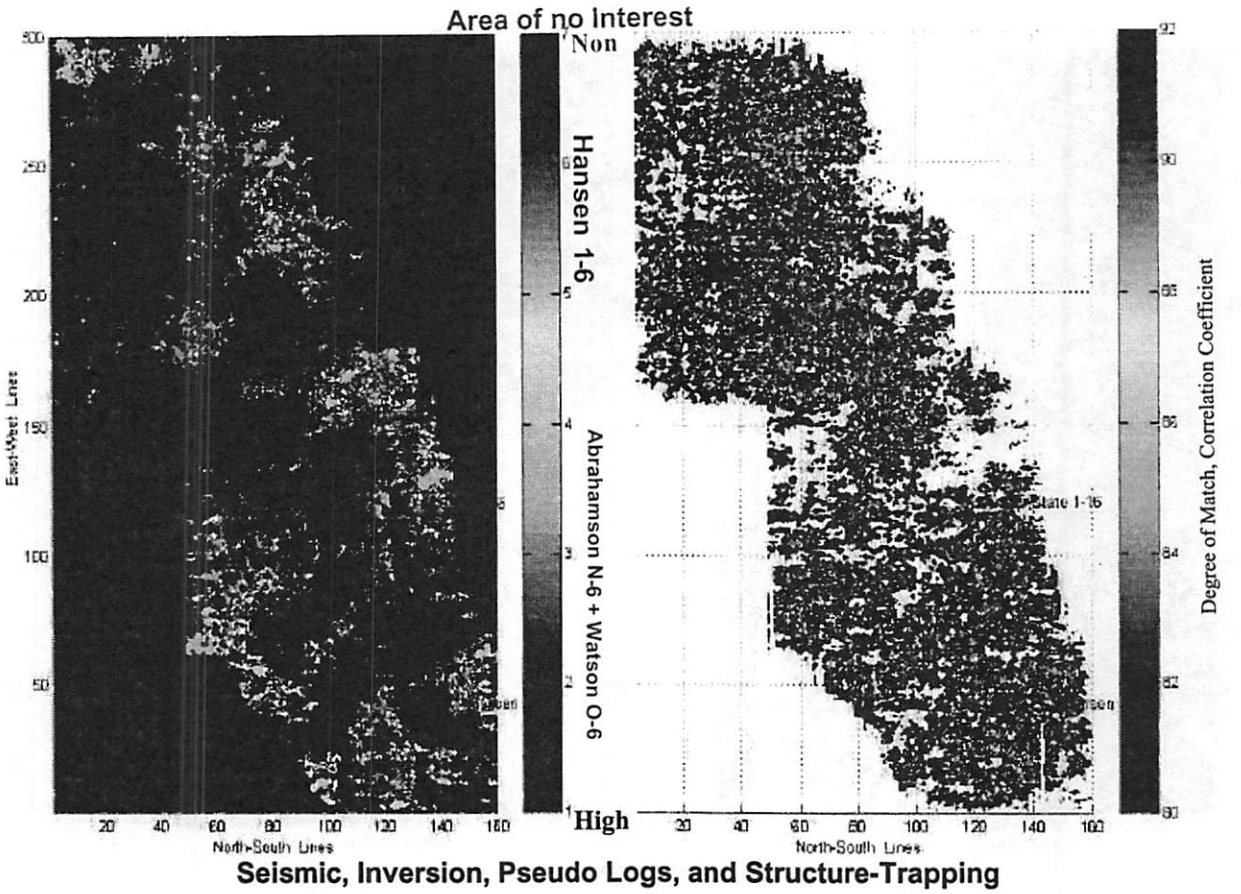


Figure 14. Performance of K-Mean clustering technique for prediction of the high-potential and no-potential producing D-Zone with degree of confidence based on seismic attributes, inversion attributes, pseudo logs, and structure/trapping attributes

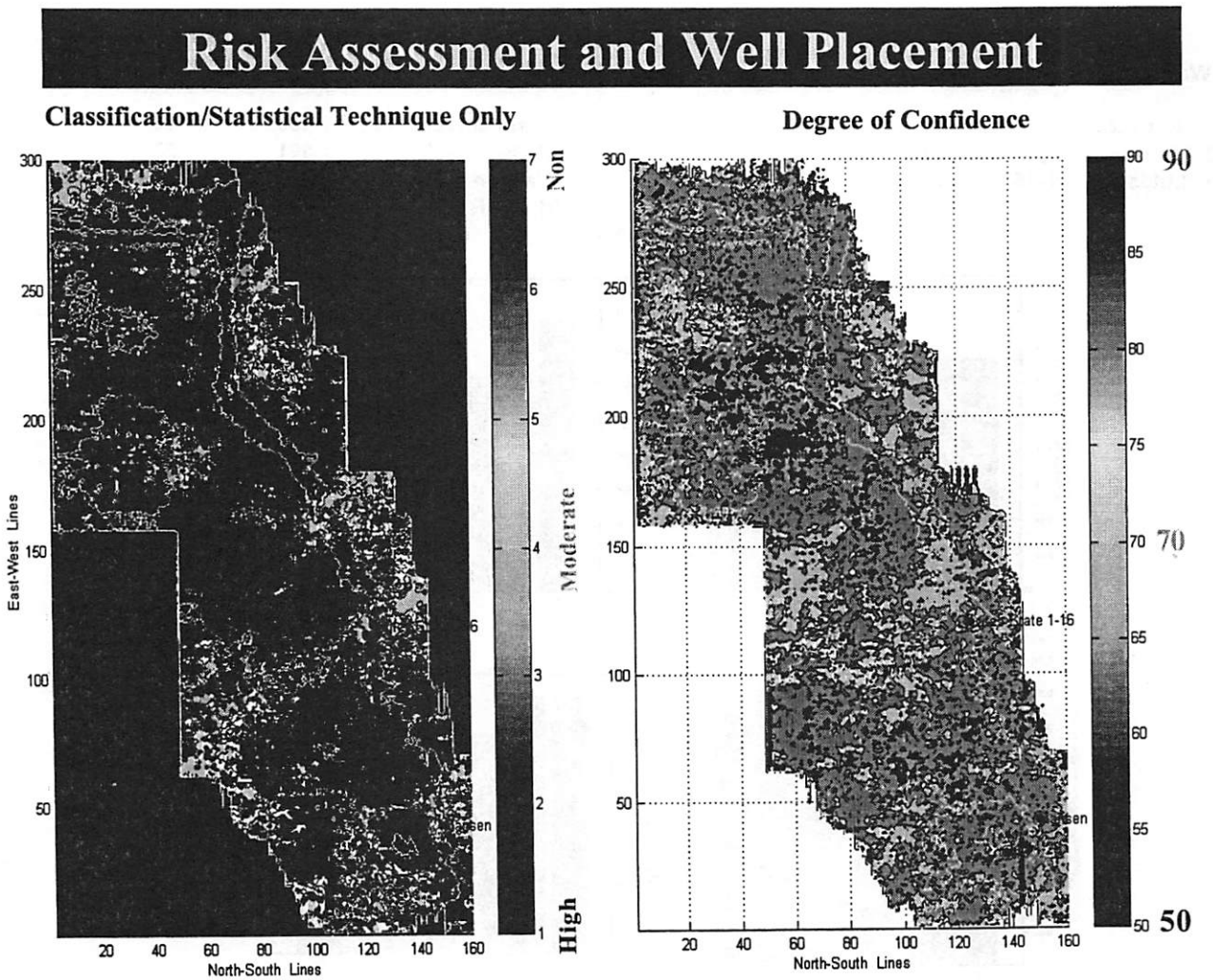


Figure 15. Performance of IRESC technique for prediction of the high-potential and no-potential producing D-Zone

Well Name	InLine-Xline Data		Well Name	InLine-Xline Data	
1. 'Jett 1-28';	31	138	4. 'Abrahamson N-6';	186	42
2. 'Hansen 1-21';	43	150	5. 'Watson 0-6';	191	53
3. 'Lutes State 1-16';	120	125	6. 'Hansen 1-6';	209	30
			7. 'Hilton B-6';	222	54

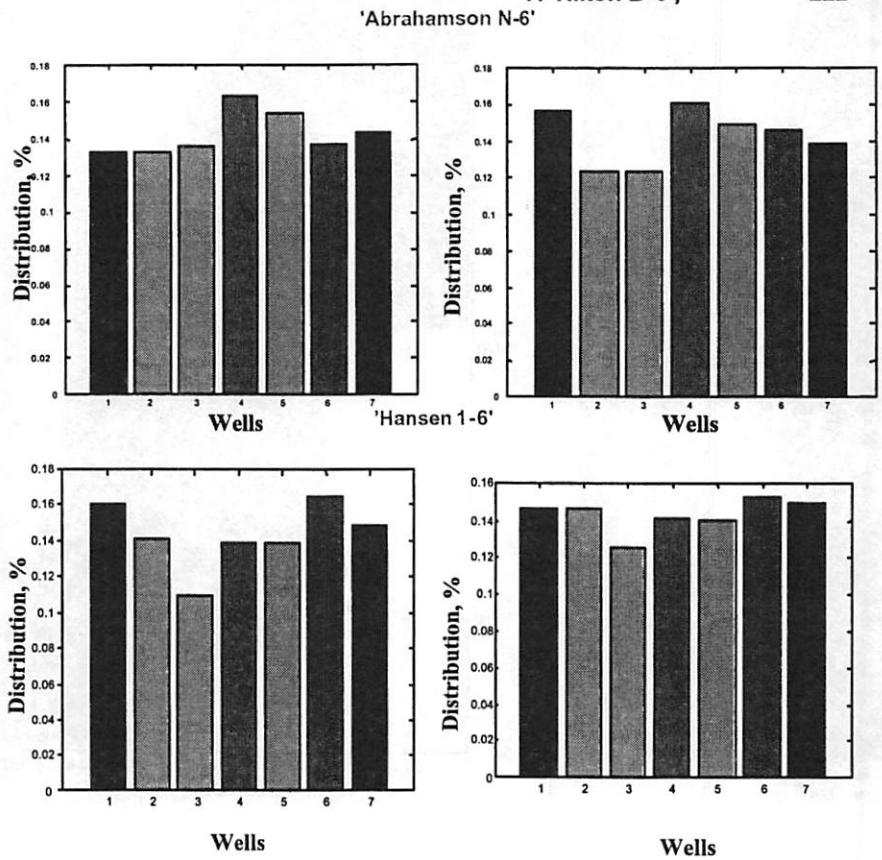


Figure 16. Each point in space in **Figure 14** can be represented by seven classes as defined in **Figure 11.**

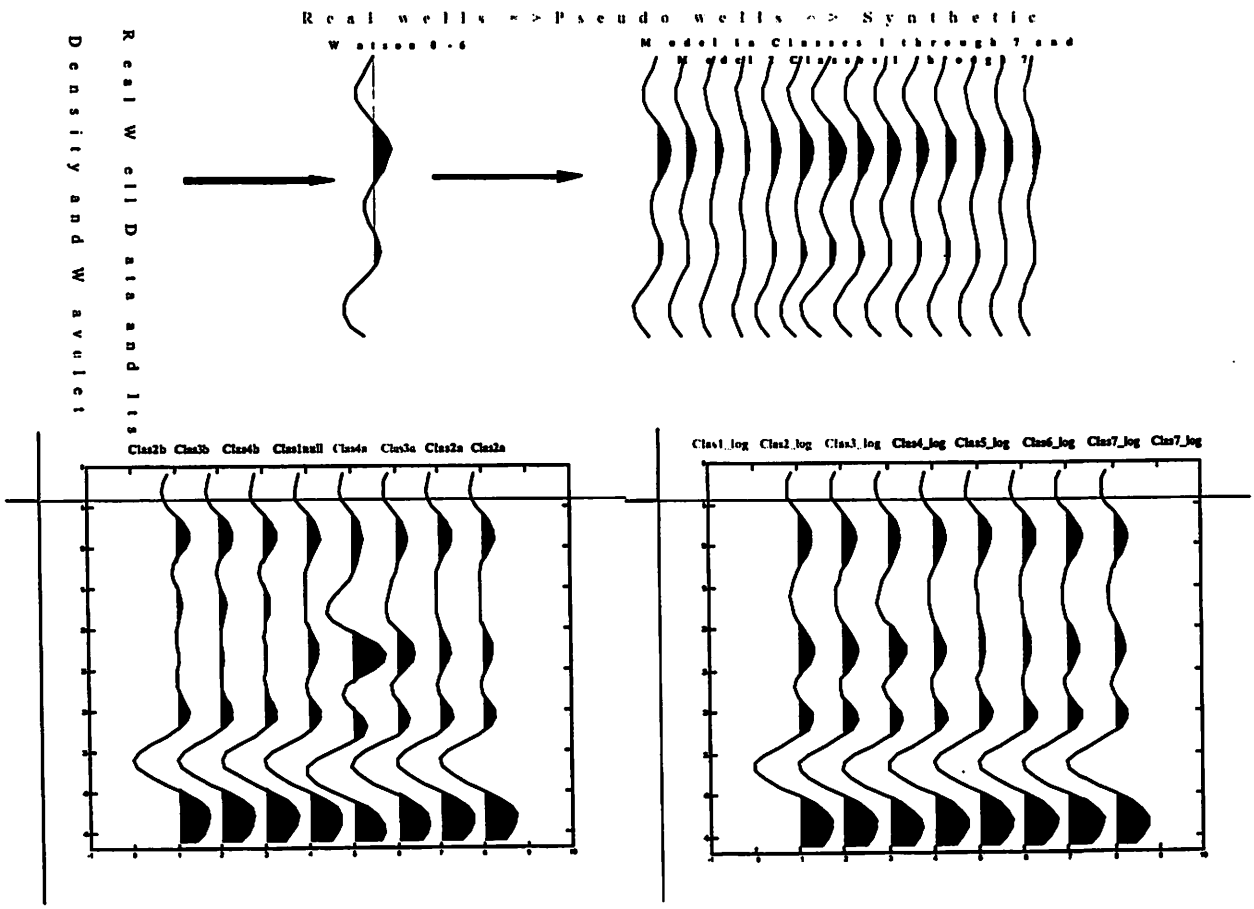


Figure 17. A schematic diagram to generate virtual well by perturbing existing well logs

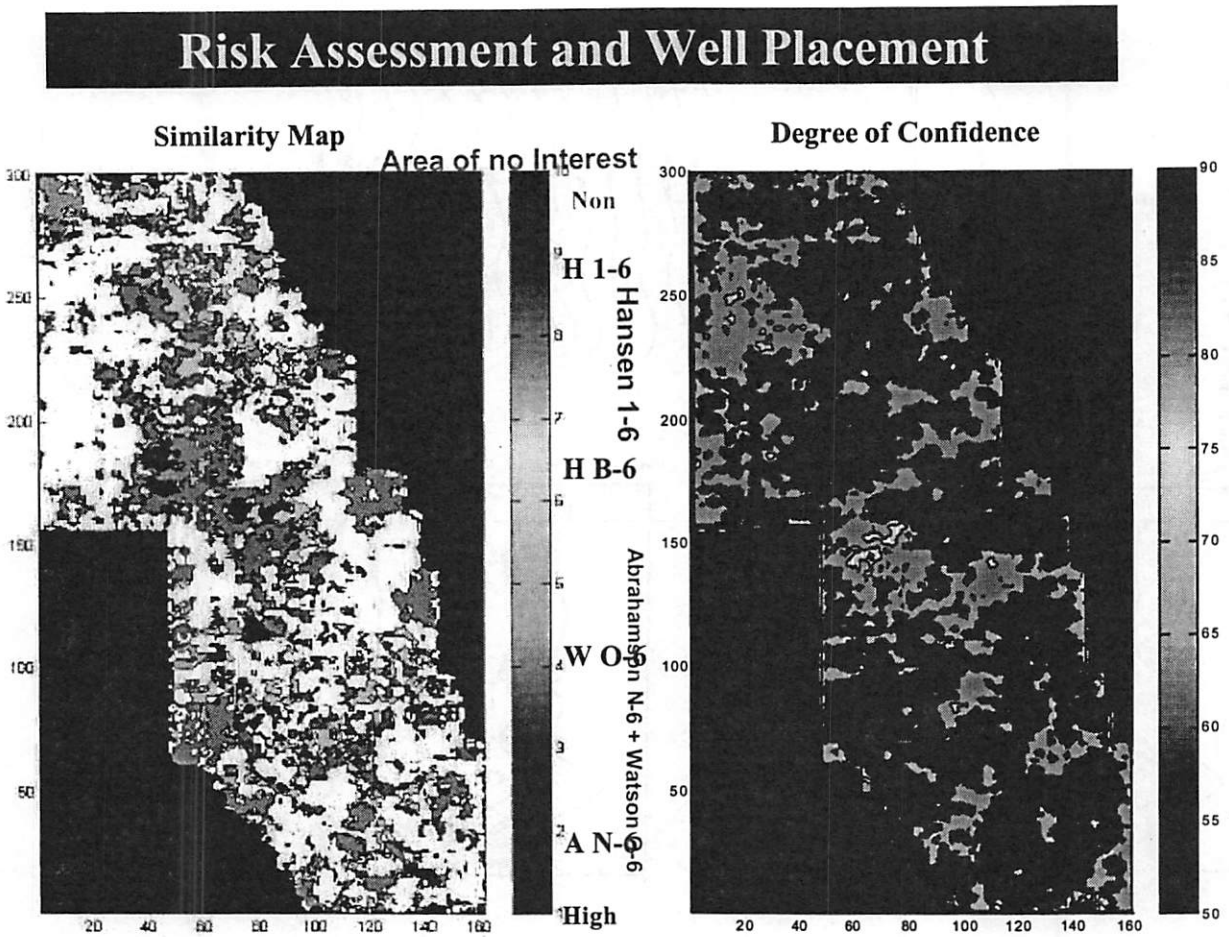
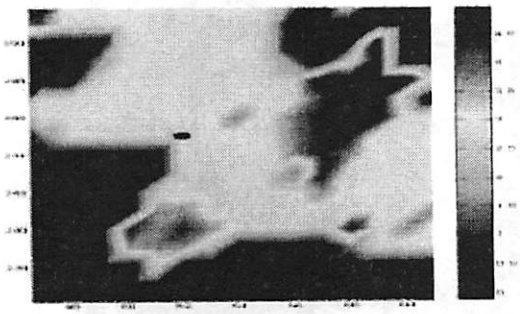


Figure 18. Performance of IRESC technique for prediction of the high-potential and no-potential producing D-Zone based on virtual logs

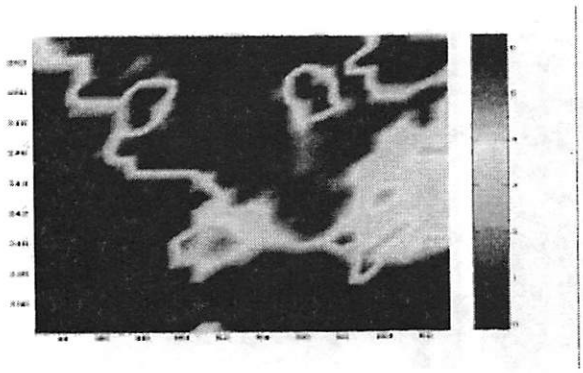
Before Drilling Well-J31



Actual	Cutoff			Delta(Depth)
	8.000	10.000	12.000	
D Phi-h	6.480	5.812	4.537	58.000
D1 phi-h	1.811	1.501	1.171	15.000
D2 phi-h	4.669	4.311	3.366	38.000

Predicted	Cutoff			Delta(Depth)
	8.000	10.000	12.000	
D Phi-h	4.790	4.351	3.882	53.500
D1 Phi-h	0.944	0.724	0.588	10.500
D2 Phi-h	3.846	3.627	3.294	31.500
±	0.609	0.620	0.707	2.500
	0.129	0.084	0.111	3.500
	0.738	0.703	0.817	2.500

After Drilling Well-J31



Actual	Cutoff			Delta(Depth)
	8.000	10.000	12.000	
D Phi-h	6.480	5.812	4.537	58.000
D1 phi-h	1.811	1.501	1.171	15.000
D2 phi-h	4.669	4.311	3.366	38.000

Predicted	Cutoff			Delta(Depth)
	8.000	10.000	12.000	
D Phi-h	6.760	6.137	5.591	52.000
D1 Phi-h	1.575	1.267	1.054	14.000
D2 Phi-h	5.186	4.870	4.537	35.000
	0.119	0.111	0.105	0.354
	0.039	0.032	0.033	0.315
	0.081	0.079	0.072	0.253

Figure 19. Qualitative and quantitative analysis and performance of IRESC technique for prediction of the high-potential and no-potential producing D-Zone

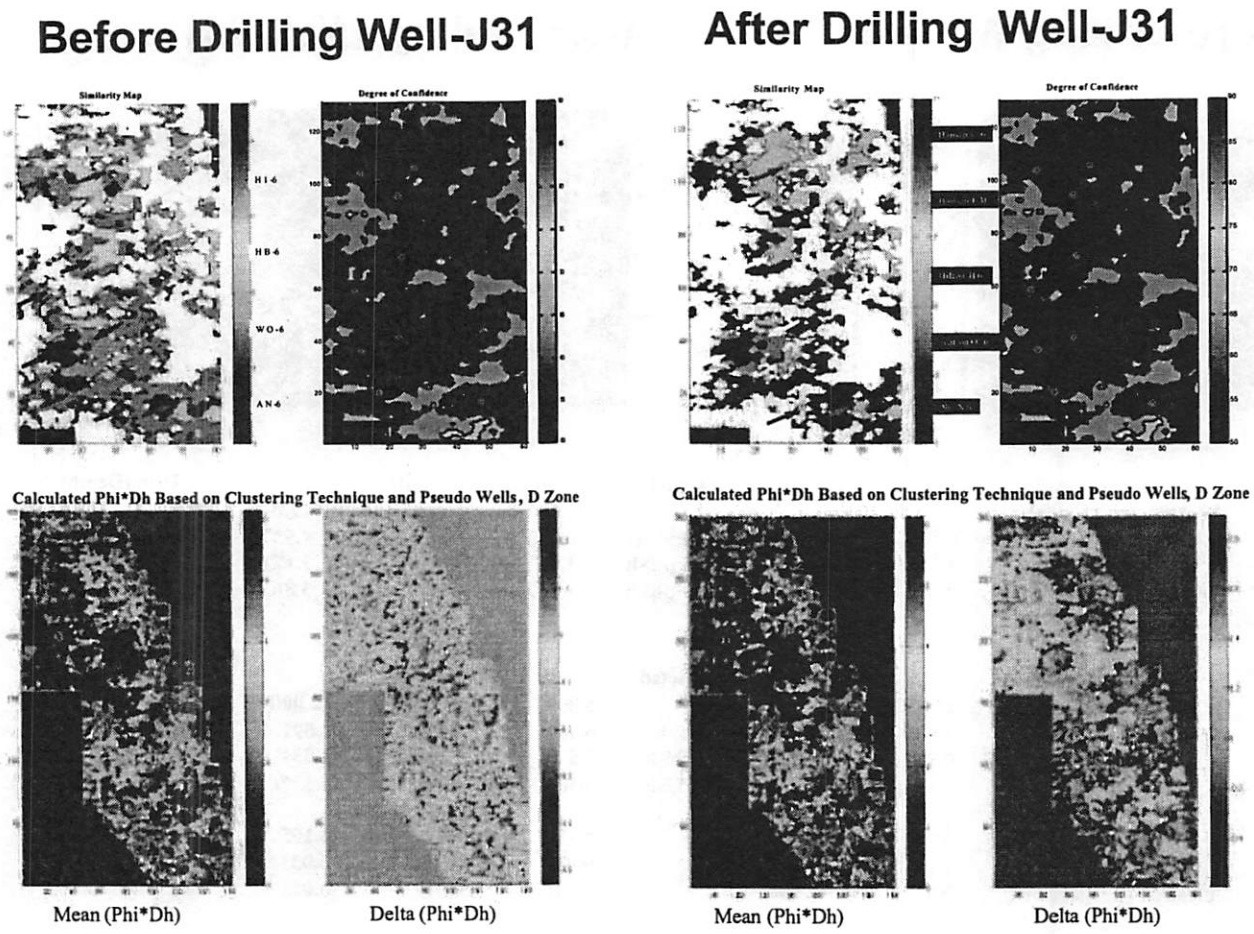


Figure 20. Qualitative and quantitative analysis and performance of IRESC technique for prediction of D-Zone and Phi*Dh

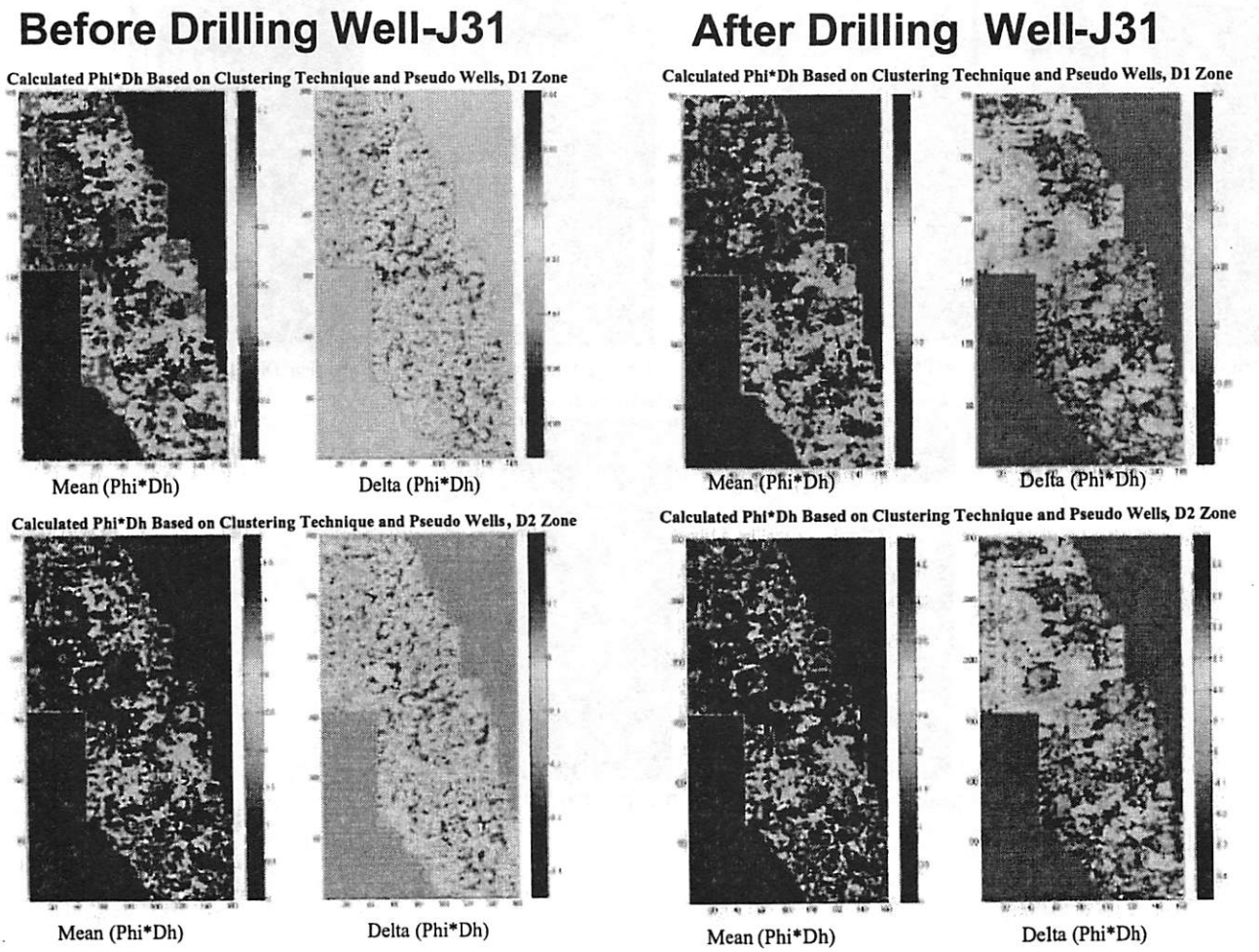


Figure 21. Performance of IRESC technique for prediction of Phi*Dh for D1-Zone and D2-Zone

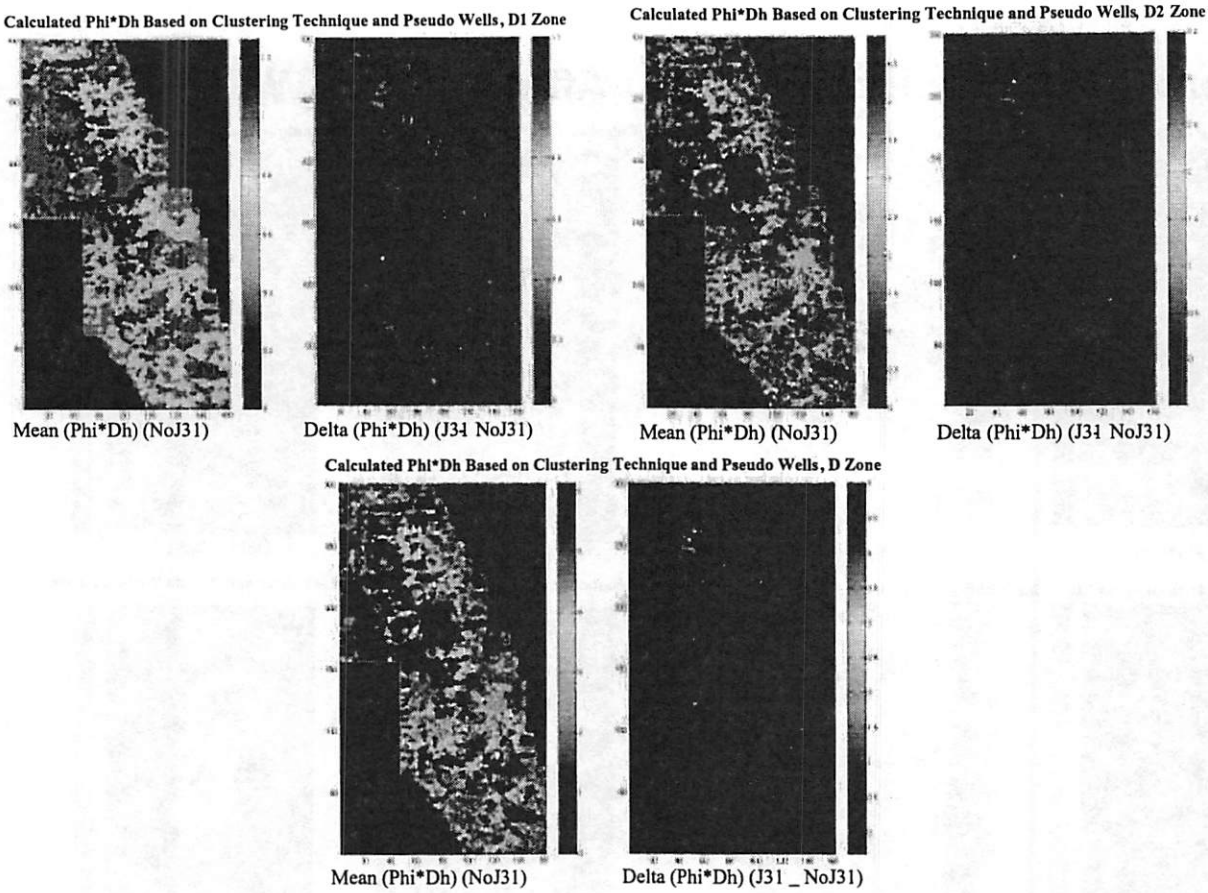


Figure 22. Performance of IRESC technique for prediction of Phi*Dh for D-Zone, D1-Zone and D2-Zone and error bar at each point before and after drilling a new well