Intelligent Reservoir Characterization and Modeling

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A stract **Reser oir characteri ation plays a crucial role in modern reser oir management. It helps to ma e sound reser oir decisions and impro es the asset alue of the oil and gas companies. It ma imi es integration of multi-disciplinary data and nowledge and impro es the reliability of the reser oir predictions. The ultimate product is a reser oir model with realistic tolerance for imprecision and uncertainty. Soft computing aims to e ploit such a tolerance for sol ing practical problems. In reser oir characteri ation these intelligent techni ues can be used for uncertainty analysis ris assessment data fusion and data mining which are applicable to feature e traction from seismic attributes well logging reser oir 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 reser oir and stratigraphic model. hile some indi idual methodologies esp. neurocomputing ha e gained much popularity during the past few years the true benefit of soft computing lies on the integration of its constituent methodologies rather than use in isolation**

I. 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 reserves. 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, 1996, 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.

II. 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) and recent papers by Nikravesh et al. (2001c) and Nikravesh and Aminzadeh (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.

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. Although 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.

III. INTELLIGENT RESERVOIR CHARACTERIZATION

Figure 1 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.

IV. EXAMPLE

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. 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. 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. 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**). Clustering was based on three different techniques, k-means (statistical), neural network, and fuzzy c-means clustering. 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 1**, 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.

Figure 2 was generated using IRESC techniques (**Figure 1**). **Figure 3** 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 4 through 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.

V. 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 uncertainty 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 hydrocarbon 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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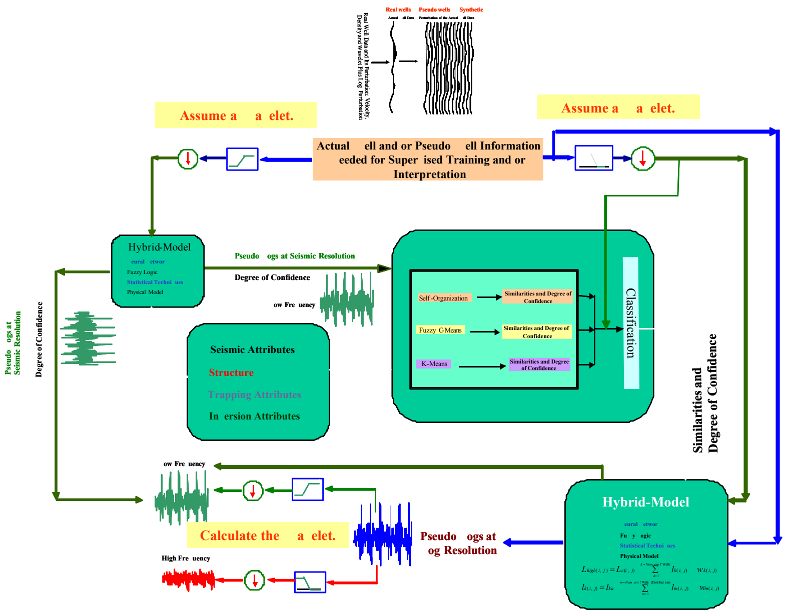


Figure 1. Technique used in IRESC Software

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
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 of iso 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

1 -22 In ersion Attributes

23-2 Pseudo ogs Attributes

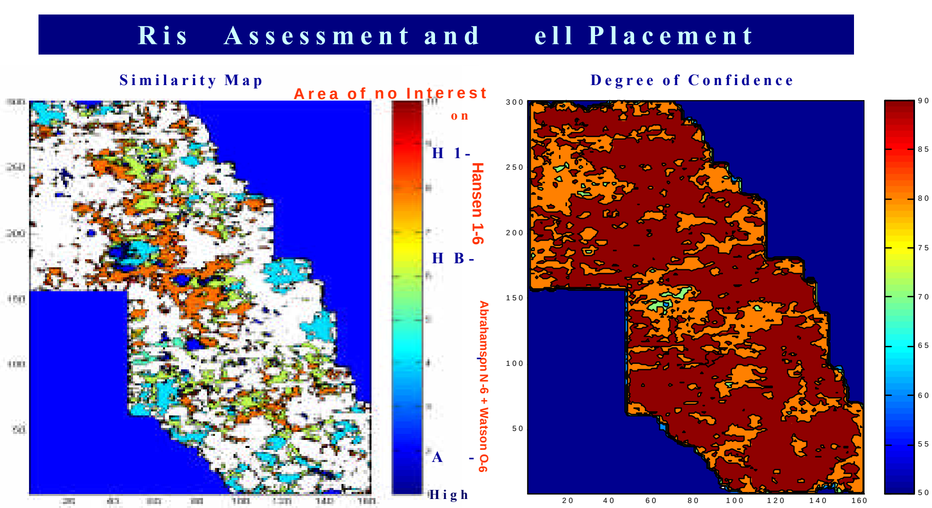
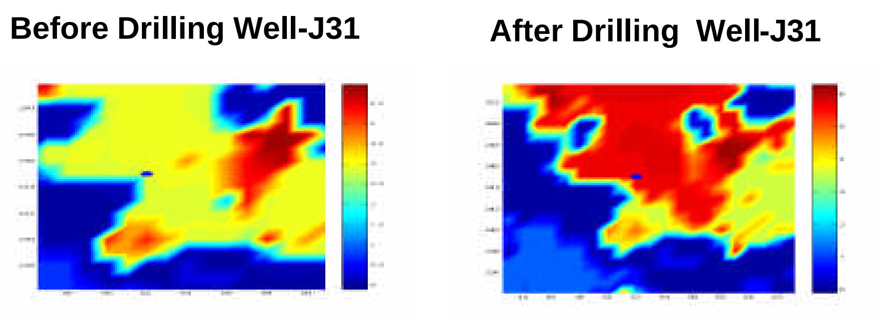


Figure 2. Performance of IRESC technique for prediction of the high-potential and no-potential producing D-Zone based on virtual logs



Actual		Cutoff		Delta Depth
	.	1 .	12.	
D Phi-h	.4	5. 12	4.537	5 .
D1 phi-h	1. 11	1.5 1	1.171	15.
D2 phi-h	4.	4.311	3.3	3 .

Actual		Cutoff		Delta Depth
	.	1 .	12.	
D Phi-h	.4	5. 12	4.537	5 .
D1 phi-h	1. 11	1.5 1	1.171	15.
D2 phi-h	4.	4.311	3.3	3 .

Predicted		Cutoff		Delta Depth
	.	1 .	12.	
D Phi-h	4.7	4.351	3. 2	53.5
D1 Phi-h	. 44	.724	.5	1 .5
D2 Phi-h	3. 4	3. 27	3.2 4	31.5
	.	. 2	.7 7	2.5
	.12	. 4	.111	3.5
	.73	.7 3	. 17	2.5

Predicted		Cutoff		Delta Depth
	.	1 .	12.	
D Phi-h	.7	.137	5.5 1	52.
D1 Phi-h	1.575	1.2 7	1. 54	14.
D2 Phi-h	5.1	4. 7	4.537	35.
	.11	.111	.1 5	.354
	. 3	. 32	. 33	.315
	. 1	. 7	. 72	.253

Figure 3. Qualitative and quantitative analysis and performance of IRESC technique for prediction of the high-potential and no-potential producing D-Zone

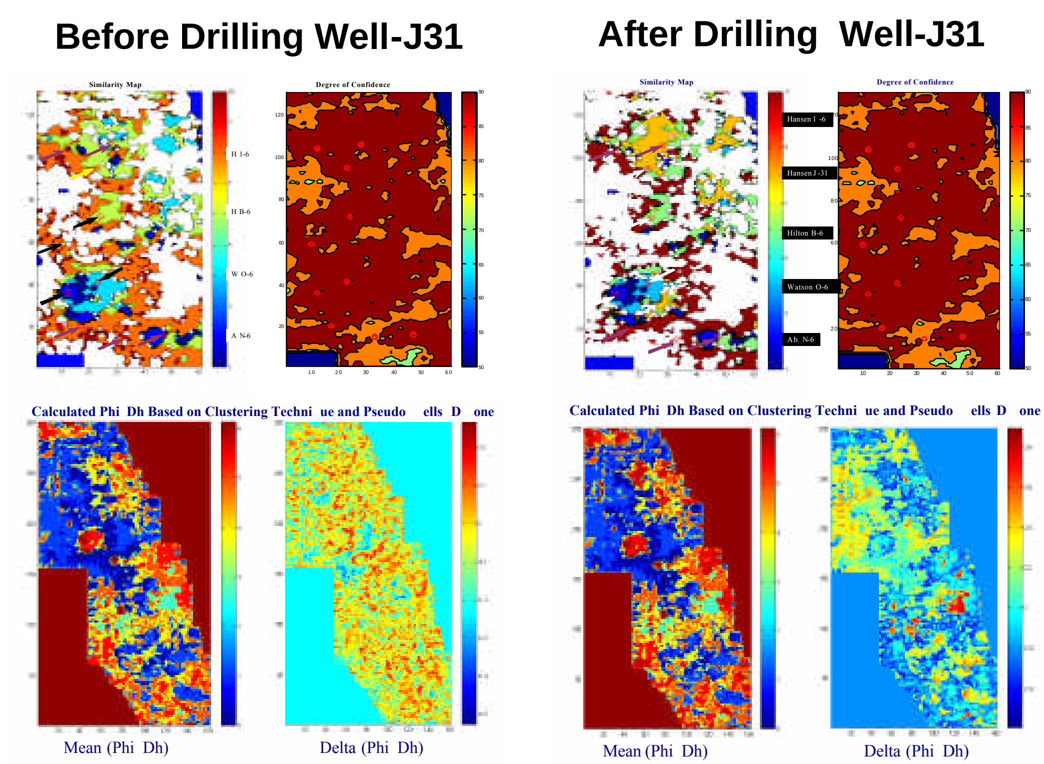


Figure 4. Qualitative and quantitative analysis and performance of IRESC technique for prediction of D-Zone and Phi Dh

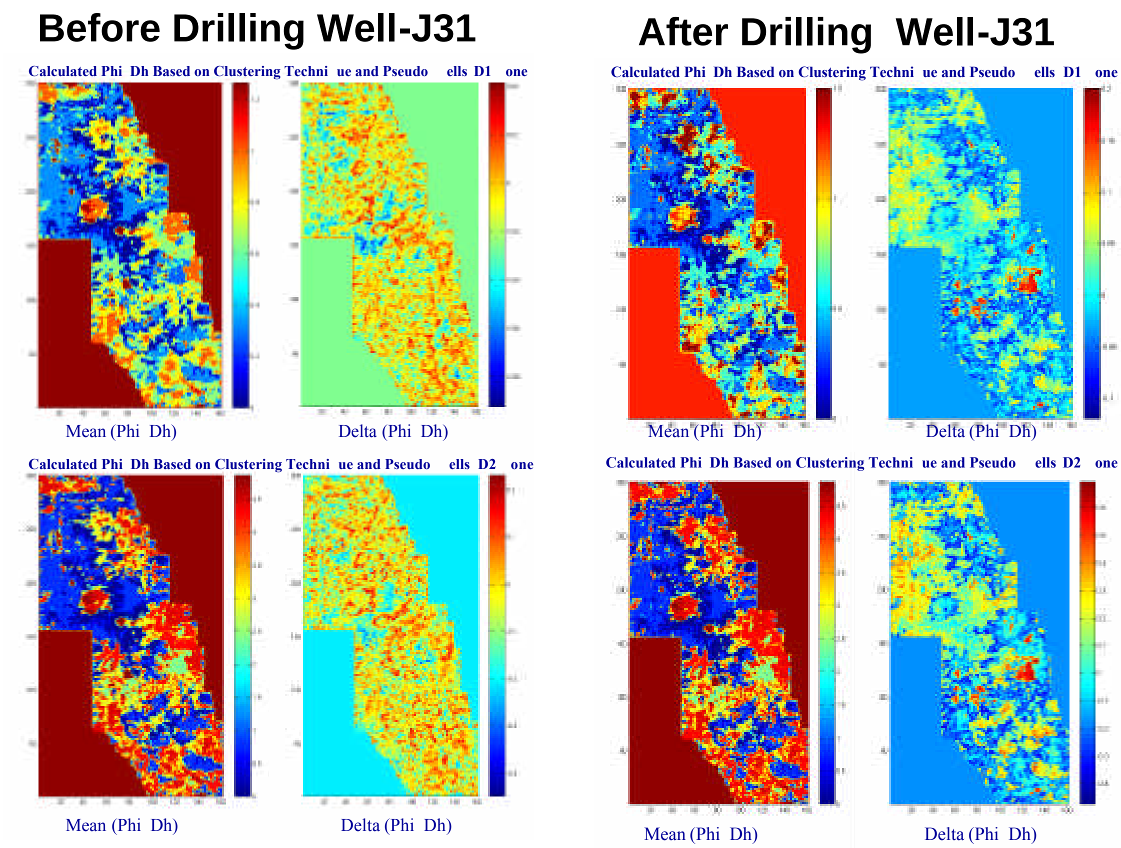


Figure 5. Performance of IRESC technique for prediction of Phi Dh for D1-Zone and D2-Zone

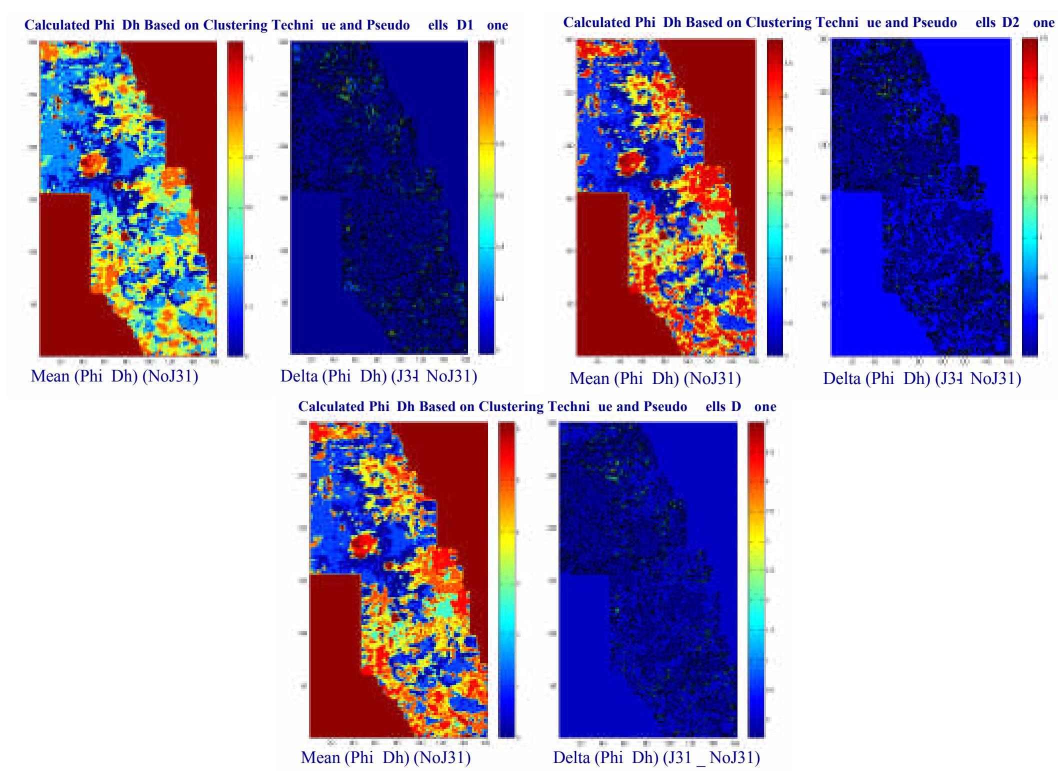


Figure . Performance of IRESC technique for prediction of Phi Dh for D-Zone, D1-Zone and D2-Zone and error bar at each point before and after drilling a new well