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3D Seismic Data Interpretation, Attribute Analysis and Acoustic Impedance Inversion for Prediction of Reservoir Properties for the Purpose of Field Development, A Case Study Balkassar Oil Field, Central Indus Basin, Pakistan

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Abstract

The Eocene and Paleocene Reservoirs including Chorgali, Sakesar and Lockhart formations, in the Balkassar Oil field, which is present on the southern flank of the Soan syncline in Central Potwar are considered the main targets for a source of hydrocarbons in the Potwar Sub basin. The balkassar structure consists of an elongated, fault bounded, salt cored anticlinal pop up structure which trends Northeast- Southwest and mainly formed because of the compressional forces in the area. This study is intended to estimate reservoir properties through Porosity, Volume of clay and Fluid content prediction using the Artificial Neural Network. Artificial Neural Networks have gained a substantial amount of attention over the past few years, among different linear and non linear prediction tools such as curve fitting, regression etc. In this study, 3D seismic data and well logs of the Balkassar Oil field are used for the prediction of reservoir properties. To achieve this, the 3D seismic data was inverted through Probabilistic neural networks (PNN) to obtain acoustic impedance volume which was then used as part of seismic attribute study applied to the data set. Multi attribute analysis was performed in order to analyze the effectiveness of specific attributes for training the PNN. A total of seven attributes were found to provide the best training results, after stepwise regression and validation testing. These attributes proved to show a substantial amount of correlation and thus Porosity, Volume of clay and Fluid content volumes were predicted. Horizon maps for three potentially prospective formations Chorgali, Sakesar and Lockhart were extracted from these volumes, to analyze the spatial extent of these attributes, on the basis of which, potentially prospective zones were defined by a probability analysis termed as Poor, Fair and Good based on Low to High prospectivity.

Introduction

Balkassar is considered a mature oilfield, discovered in the mid 90's and producing hydrocarbons since then. The discoveries primarily were made on the basis of structural studies carried out on the balkassar structure (figure 1). The seismic amplitude data which has been used since 1945 for the purpose of Exploration and Development in this oilfield has now less significance towards delineating any further prospective zones. Acoustic impedance which is the product of Velocity and density, usually estimated from Sonic and density logs, mainly because of which these seismic reflections occur, can prove a helpful tool for the purpose of Field development.

Seismic Inversion is the method through which amplitude data can be transformed back into acoustic impedance but now on a larger scale than well logs, filling the inter well region. This acoustic impedance volume can then be used for the prediction of reservoir properties including Porosity, Lithology, Fluid saturation etc. which are ultimately utilized for demarcating the prospective hydrocarbon zones.

Research Methodology

The Objective of this research is to integrate 3D seismic and well log data to establish a relationship between reservoir properties and seismic attributes, mainly impedance, through multivariate statistics and neural network, for demarcating any further prospective zones present in the inter well region and analyzing over pressured and under pressured zones by carrying out pore pressure analysis. To predict the reservoir properties including Lithology, Porosity and Water saturation, the seismic data will be inverted to Acoustic impedance using Probabilistic Neural Network technique. This inverted acoustic impedance cube will then be linked to reservoir properties estimated at wells by Multi attribute analysis and training a Neural Network.

The resulting volumes displayed as maps, will then be used for marking the prospective zones in their order of prospectivity in the Inter well region. A probabilistic neural network based approach is used for Predrill estimation of pore pressure from seismic data. Pore pressure information not only guides the development of mud schedule, casing program, rig selection and well head ratings but also helps in understanding geological influences on hydrocarbon accumulation. For instance it is usually preferred to drill on the flanks of a structure than its highest point, reason being that higher pressure within the gas cap may source complexity in drilling.

Conclusions and Results

This study was intended towards predicting reservoir properties in the Inter well regions, and identifying prospective zones on the 3D seismic data using the technique of artificial neural networks. Seismic data was tied to well data through Synthetic seismograms and the Horizons of interest Chorgali, Sakesar and Lockhart were marked on to the seismic data (figure 2, 3 & 4). A statistical zero phase wavelet with 200 ms wavelength, 4 ms sample rate, was extracted from surface seismic data and used to tie seismic to well logs (figure 5 & 6). Oxy-01 showed 80% correlation between seismic and well and Oxy-02 showed 71% correlation (figure 7 & 8). This seismic to well tie, horizon information and seismic amplitude data itself were used to construct a background impedance model in order to recover the low frequencies lost due to acquisition and processing artifacts. Neural network analysis using this background model showed a cross correlation of 0.914464 with average error of 3300.2 [(ft/s)*(g/cc)] and after validation, the cross correlation was 0.894665 with average error 3644.03 [(ft/s)*(g/cc)] among impedance logs estimated at wells and impedance predicted on seismic . This result which included three attributes as well was used for training the PNN and the P-impedance volume was computed for the whole 3D data (figure 9, 10 & 11). Petrophysical analysis was performed for the wells and petrophysical properties were estimated with average values of porosity=, Volume of clay=, Water saturation=. These properties were estimated using the well logs Neutron, Density, Sonic, Spontaneous potential, Resistivity and Gamma ray (figure 12 & 13). Shear wave was also computed using the Gardner’s equation. Multi attribute analysis was performed for estimating the best attributes in order to train the PNN for porosity prediction. A total of 28 attributes including Raw seismic, P-impedance, Amplitude weighted cosine phase, Integrate, Derivative etc. The cross correlation for predicting porosity was 0.991612 with an average error of 0.121191 and after validation, the cross correlation became 0.770736 with an average error of 0.0576725. This result was then applied to train the PNN and the porosity volume was predicted (figure 14 & 15).

Volume of clay and Water saturation were predicted through PNN by a number of external attributes that were fed into the PNN, those include S-impedance, P-impedance, Lambda rho, Mu rho (figure 16 & 17). Internal attributes included Amplitude weighted cosine phase, integrate, derivative, time etc. The logs computed for Volume of clay and water saturation were used to train the PNN and the results were applied accordingly. The volume of clay was predicted with a cross correlation 0.989697 and average error of 0.333634 [v/v]. Water saturation was predicted with a cross correlation of 0.985319 and average error of 0.034341 [v/v] (figure 18, 19 & 20). After predicting these reservoir properties, horizon maps of these properties were constructed to spatially define the behavior of each reservoir property and define zones with high prospectivity and low risk of well failure in sense of hydrocarbon production. Porosity maps for the three formations have been analyzed by marking zones with naming as Poor, fair and Good based on Low to High porosity values. Volume of clay maps are analyzed by marking zones with name “Clean zones”. The water saturation maps are marked in terms of Low Sw zones identified on the maps, based on the fact that zones with less water saturation will have more hydrocarbon saturation (figure 21, 22 & 23). These maps and the zones identified on them, along with the analysis can be a great means of developing the balkassar oil field.

References

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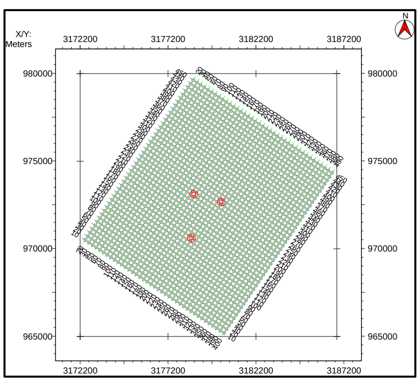

Figure.1. Base map of the 3D seismic of Balkassar

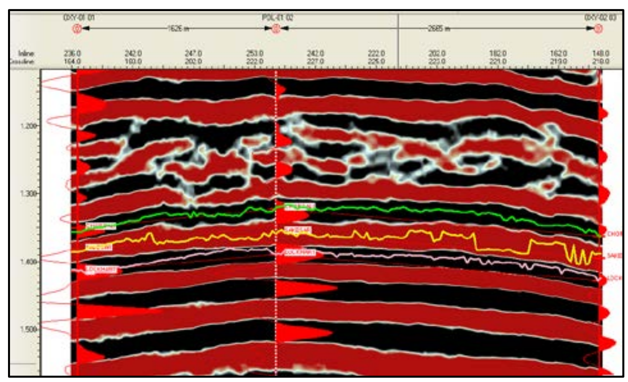

Figure 2. Arbitrary line across all three wells showing synthetic matching with eismic data

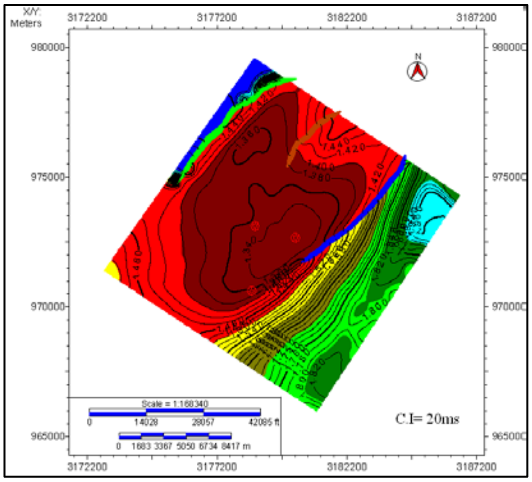

Figure 3. Time contour map on Top Chorgali Formation

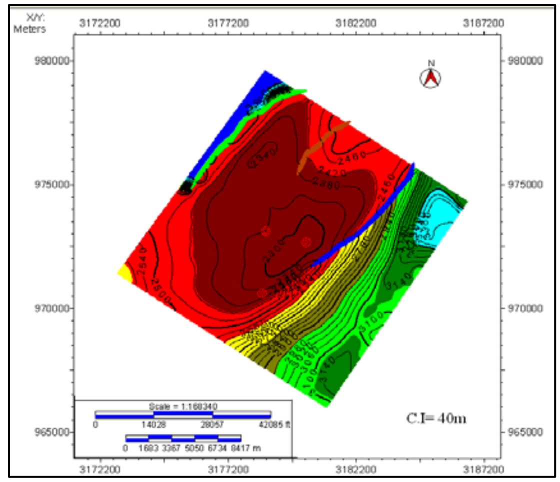

Figure 4. Depth contour map on Top Chorgali Formation

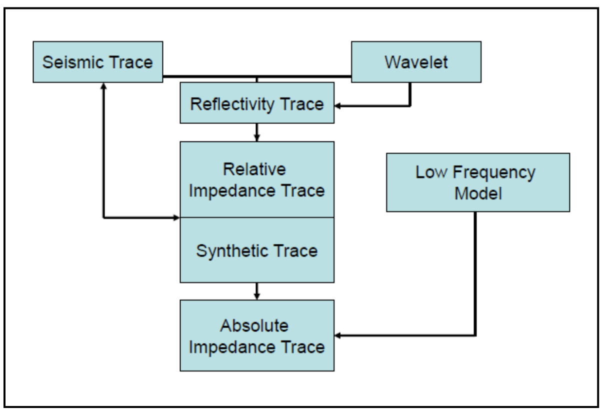

Figure 5 Workflow of the seismic inversion procedure.

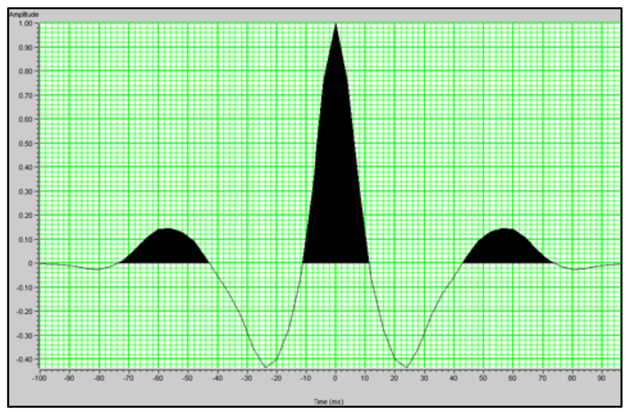

Figure 6. A zero phase wavelet extracted from surface seismic data, with its amplitude spectrum

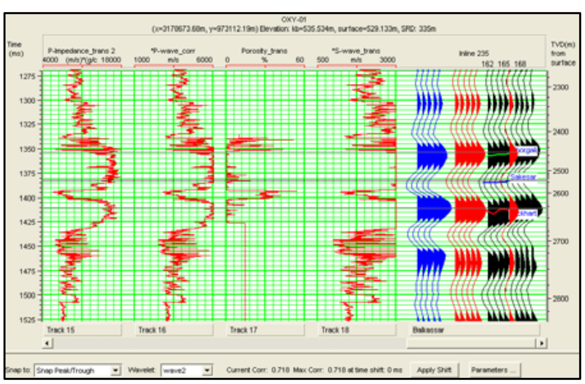

Figure 7.Seismic to well tie for Oxy-01 well.

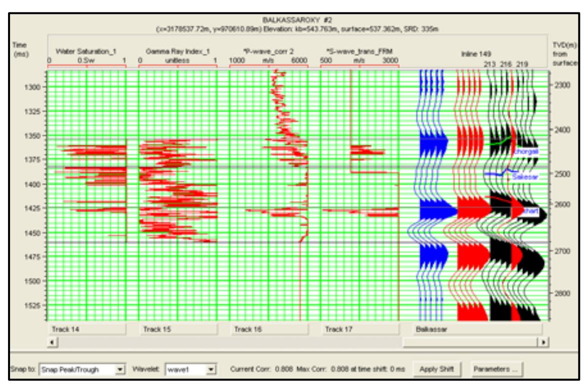

Figure 8.Seismic to well tie for Oxy-02 well.

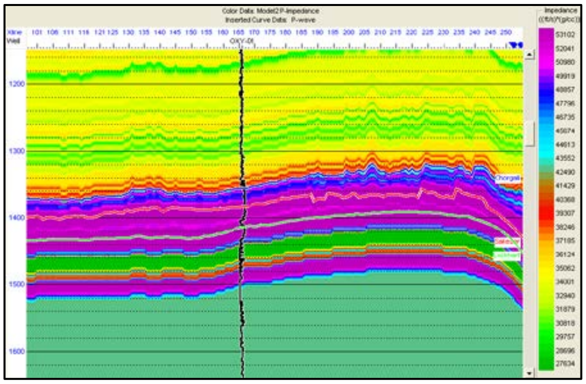

Figure 9.Model P-impedance with P-wave inserted curve

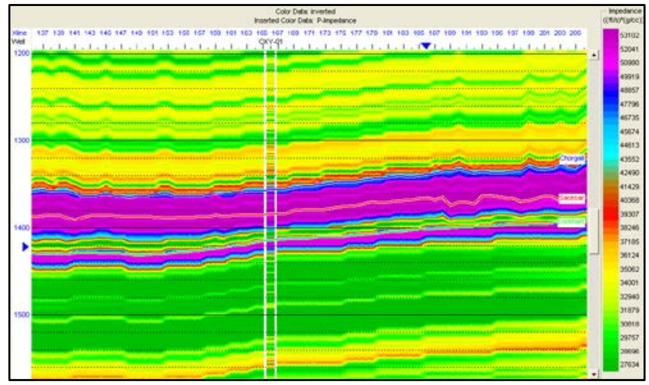

Figure 10.Computed impedance at Inline 235 with inserted well Oxy-01based computed P-impedance

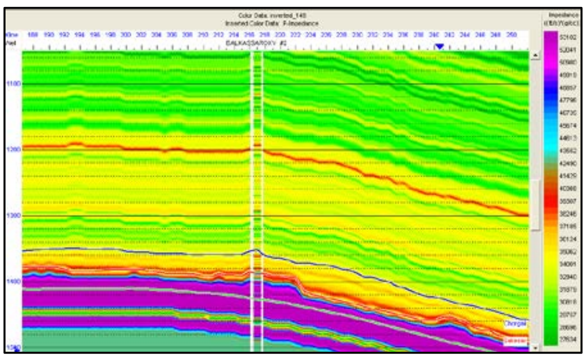

Figure 11. Computed impedance at Inline 149 with inserted well Oxy-02 based computed P-impedance

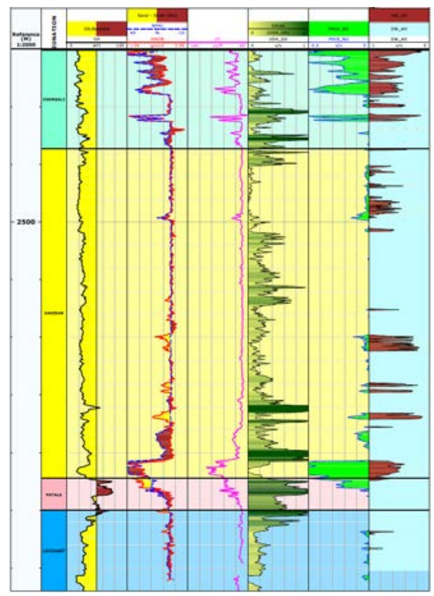

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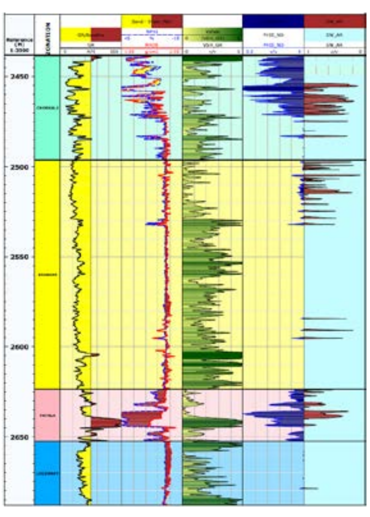
Figure 12.Petrophysical analysis results of Oxy-01 well.



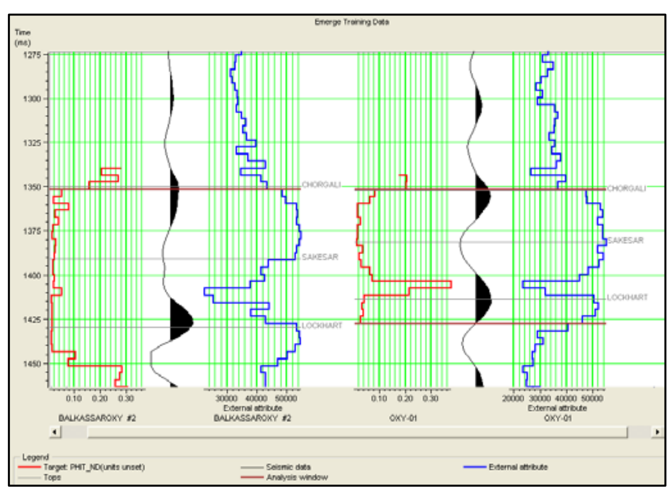


Figure 13.Petrophysical analysis results of Oxy-02 well.

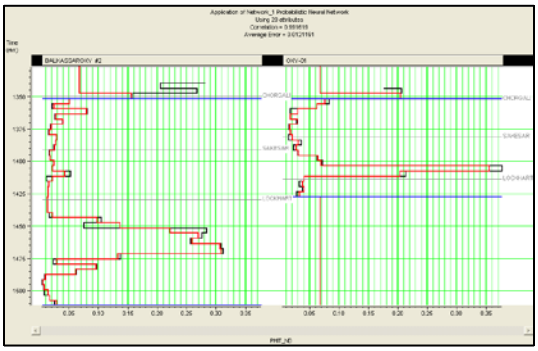


Figure 14.EMERGE PNN training data for porosity prediction using both wells Oxy-01 and Oxy-02.

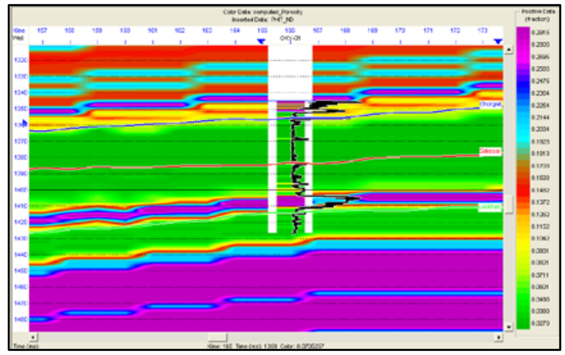


Figure 15.Application plot for PNN training for porosity prediction.

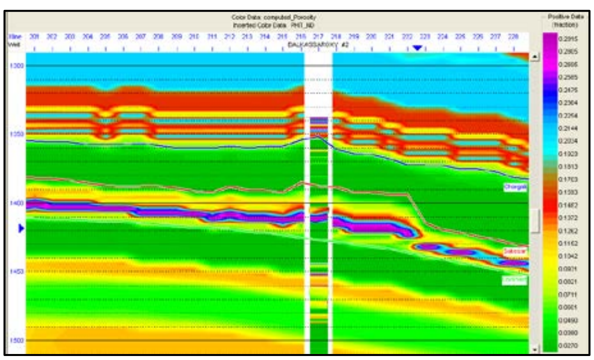


Figure 16:Showing inline 235 from porosity volume with Inserted well based porosity estimated at well Oxy-01.

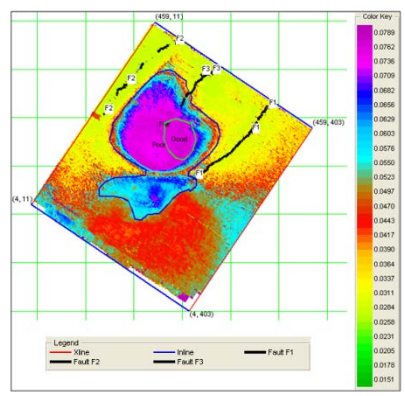


Figure 17: Showing inline 149 from predicted porosity volume With inserted well based porosity estimated at well Oxy-02

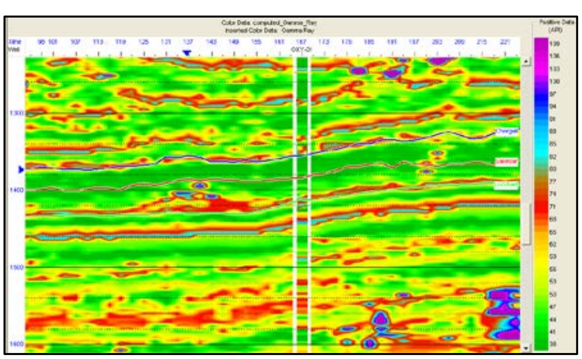


Figure 18.Porosity map of Chorgali formation plus 10ms average window above.

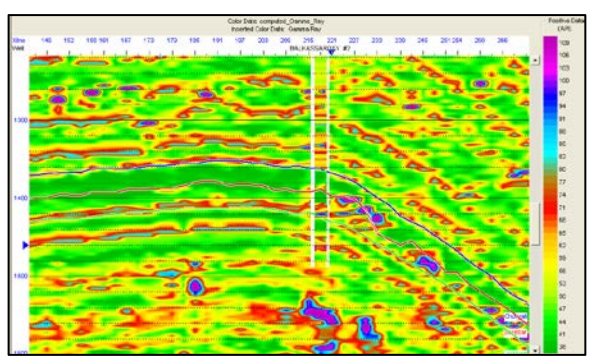


Figure 19: Showing Inline 235 from Gamma ray volume with inserted Gamma ray estimated at well Oxy-01.

Figure 20: Showing Inline 149 from Gamma ray volume with inserted Gamma ray estimated at well Oxy-02.

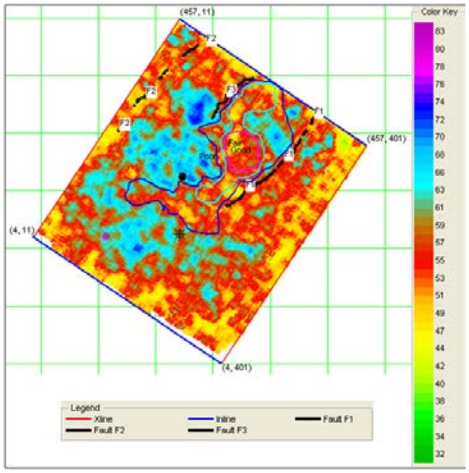


Figure 21: Gamma ray map of Chorgali

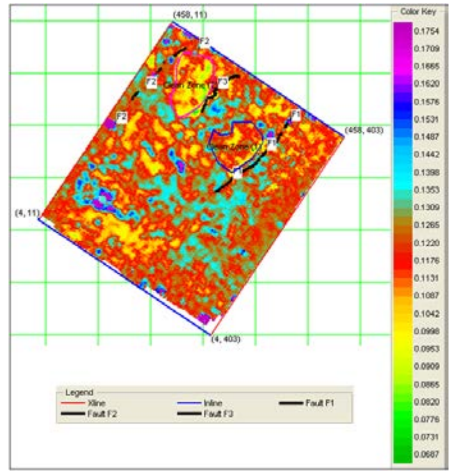


Figure 22: Volume of shale map of Chorgali plus

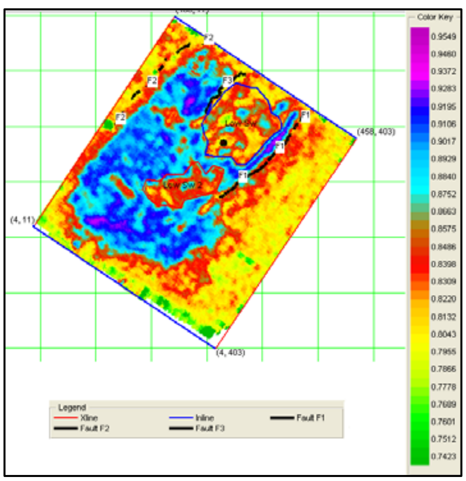


Figure 23: Water saturation map of Chorgali