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Reservoir Characterization of an Unconventional Reservoir by Integrating Microseismic, Seismic, and Well Log Data

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Abstract

Varied data types including geophysical data as well as well logs have been used frequently in the past to characterize reservoirs. However, the use of microseismic data as a potential source of useful information and its integration with conventional seismic data for reservoir characterization is an area of opportunity where properties predicted from the microseismic data can be used as a vital source of information which can then be tied with the overall characterization scheme in a seamless manner.

In this paper we discuss the characterization scheme followed for an unconventional reservoir associated with a promising geothermal prospect. The field involves microseismic data acquisition being done continually as part of the field monitoring operations and extensive well control due to the presence of large number of injection and production wells and finally a 3D conventional seismic survey done to try and better define the reservoir. We have applied an integrated approach with these data sources in order to better characterize the reservoir in question using novel data analysis schemes where necessary to get optimum results.

The approach shared in this paper can be applied to any type of reservoir setting with microseismic, seismic and well log data being available. What we present is a workflow to integrate these data types to generate useful property predictions including important rock property estimates with the aim of obtaining useable reservoir property maps to aid in reservoir development. This approach shows how a modest data acquisition program can still lead to useful characterization of reservoirs particularly with the inclusion of microseismic data in the workflow. We have used novel methods as part of our workflow including multi-attribute analysis, geostatistical techniques and soft computing techniques such as ANN[1] based property prediction and mapping which are discussed in brief.

Keywords: reservoir, characterization, microseismic, seismic, well logs, ANN, fracture

Introduction

Passive seismic as a tool for monitoring reservoirs has become fairly common in recent years. Some of the more common uses include development of unconventional reservoirs such as geothermal reservoirs, tight gas or oil reservoir systems which require hydrofracing, monitoring of injection wells (CO_2 injection, steam flooding, etc) among others. The use of conventional seismic data for reservoir characterization is also a fairly well understood area of study with multi attribute analysis and integrated methods being used extensively in recent years for reservoir characterization. While conventional seismic data is seldom used in small unconventional reservoir developments, the use of passive seismic monitoring seems to be limited to better understanding of the fracturing process and is not used for reservoir property estimation. We have used seismic as well as microseismic data along with well logs to better predict the reservoir properties and try and analyze the reservoir for improved fracture mapping. Figure 1 shows a basic workflow outlining the various parts of the integrated analysis scheme to provide an overview of the methods used.

This article first discusses Micro-earthquake (MEQ) data analysis followed by Seismic data characterization including use of well logs as outlined in figure 1. This is followed by integrated data analysis techniques with shared results and preliminary interpretation. Finally the discontinuity and fracture mapping based on our interpretations are summarized.

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[1] Artificial Neural Network

Passive seismic data analysis

Passive seismic array is used to continuously monitor the operations of the field. The data acquisition array includes 5 recording stations which record 3 component data. The sensors are placed in boreholes and the record continuous data. Figure 2 shows the workflow used for the microseismic data analysis in our study.

The triggered data is run through an advanced ANN based autopicker (Aminzadeh 2011) and the picks obtained are used to generate phase cards for use with inversion algorithms for both location and velocity. HypoDD (Waldhauser 2001) is used to obtain hypocentral locations using the event arrival times based on generated phase data as well as initial crustal model obtained from Southern California Earthquake Center. The hypocenters obtained are then used to generate better velocity models by using SimulPS inversion algorithm (Thurber 1993) which uses the phase information along with preliminary velocity model estimates and progressively iterates over all of the phase data available to provide final velocity estimates. Figure 3a shows the phase data with the hypocentral locations in a 3D location plot close to an operational injection well while Figure 3b shows the final velocity estimate map (grid data) obtained from one of the SimulPS runs.

After adequate iterations involving removal of bad phase data and improving coverage by considering adequate events based on known sensor array spread, the final velocity models are obtained and used as a baseline estimate for the area of interest. We then use SGEMS[2] to populate the study area by using ordinary kriging technique. Figure 4a and 4b show the phase velocity (V_p and V_s) estimates obtained which are then used as the basis for estimating rock properties based on well understood physical models.

The compressional and shear wave velocities can be related to elastic rock properties including Bulk modulus, Shear modulus and Poisson's ratio and these properties can be used to estimate zones of interest using available frameworks to relate the geophysical and geomechanical properties with reservoir attributes such as fractures (Tokosoz 1981). We know that compressional and shear velocities can be used to derive Lame's parameters as follows:

$$\mu = \rho \times V_s^2$$

$$\lambda = V_p^2 \times \rho - 2 \times \mu$$

The Lame's parameters can in turn be used to estimate the inertial properties of the rock using the following relationships:

$$K = \lambda + \frac{2 \times \mu}{3}$$

$$E = \frac{9 \times K \times \lambda}{3 \times K + \mu}$$

$$\sigma = \frac{\lambda}{2 \times (\lambda + \mu)}$$

Here ρ is the bulk density, K is the bulk modulus, E is the Young's Modulus and σ is the Poisson's Ratio. Figures 5a, 5b and 5c show estimated V_p/V_s and Lame's parameters for a selected depth while figures 6 shows estimated inertial properties.

We can further calculate estimates of stress directly using Vp and Vs estimates (figure 7) obtained earlier to do fracture mapping (Tokosoz 1981) as shown below:

$$V_E^2 = \frac{V_s^2 \times \left(3 \times V_p^2 - 4 \times V_s^2\right)}{\left(V_p^2 - V_s^2\right)}$$

$$V_K^2 = V_p^2 - \frac{4}{3} \times V_s^2$$

There are a number of observations which can be made using these property estimates. Closing of small fractures due to increasing pressure with depth or cementation effects should cause an increase in seismic velocity. Fracturing, chemical alteration and extreme temperature gradients, etc can cause a reduction in seismic velocities. Fluid saturation tends to reduce Vs and enhances Vp/Vs and Poisson's ratio. For highly fractured zones we can generally expect low Vp and Vs values.

[2] Stanford Geostatistical Modeling Software

Conventional seismic data analysis

Conventional seismic survey over the area of interest is used to first identify major discontinuity features and then combined with property estimates from passive seismic data to better understand the subsurface. Figure 8 shows sectional view of the data with well track inserts for reference. Figure 9 gives a brief overview of the workflow used for 3D seismic data analysis. Seismic attribute analysis is the most important feature of the workflow including working with multiple attributes individually as well as in combination.

Well logs have been used to obtain seismic to well ties to do a preliminary time-depth conversion after undertaking the initial data processing and conditioning steps. Due to the absence of sonic logs in most wells, pseudo sonic logs are generated using resistivity log data. Two wells with sonic data available are used to obtain a generalized relationship between sonic travel time and resistivity and the relation is used with other wells to obtain pseudo sonic logs (Rudman 1975). The logs obtained are then combined with density data to generate impedance logs. The reflection coefficients obtained are then convolved with a selected seismic wavelet to obtain a synthetic seismic trace. The synthetic trace is compared with the actual seismic trace extracted from a volume around the actual well track and major reflectors are matched. Figure 10 shows the workflow used in this process including a sample "tie" obtained at one of the wells.

The final seismic volume and logs obtained are then used together to predict reservoir properties such as porosity and density maps using an ANN based approach. Seismic attributes (Chopra 2007) are calculated from the actual seismic data and these attributes are used as inputs in a supervised ANN autopicking algorithm which tries to match for the desired property as the output. Figure 11 shows sample property maps estimated using this method. These properties are useful in analysis and they also help in obtaining elastic properties from velocity data (as mentioned in the previous section dealing with microseismic data). The most prominant tool for reservoir property prediction from conventional seismic data involves the use of colored inversion algorithm (Lancaster 2000) to convert seismic data to acoustic impedances which is then followed by using ANN mapping to predict rock properties (porosity, density, etc) using data along well tracks for supervised training and prediction. Impedance is independently calculated first using colored inversion workflow where a single inversion operator is derived that optimally inverts the data and honors available well data in a global sense. Since this requires sonic travel time data, only those control wells (2 in number) with sonic data are used in this inversion scheme. Independently, Impedance is also calculated using data from all the wells by using pseudo sonic logs generated from resistivity log data using Faust’s relationship (Faust 1953) assuming consolidated sandstones. The impedance maps obtained are then matched as a basis for validating the pseudo-sonic logs generated and used for property predictions and the ANN mapping undertaken to predict properties (figure 11). This process helps in validating the choice of attributes for mapping as well as the validity of the overall workflow (figure 12).

Apart from direct property predictions using well control, seismic attribute analysis techniques can be used to independently identify reservoir properties as well. A number of these methods are in use today for various reservoir characterization schemes (Chopra 2007). We use specific attributes for analyzing the basic discontinuity mapping of the subsurface. The aim is to obtain a baseline fault map which can then be integrated with other properties to identify zones of interest. Comparing these maps with well tracks also provide useful information regarding possible future targets. Laplacian (edge enhancement methods) and Amplitude variance (Edge preserving methods) filters (figure 13a and 13b) are used for baseline discontinuity mapping. While detailed discussion on the working of these algorithms is out of the scope of this article, the basic algorithms can be found from the work done by Bakker et al. (Bakker 1999). Laplacian edge enhancement used in our work involves dip steered 2^{nd} order spatial derivative of the data (Jahne 1993). Attribute maps such as those shared in figure 13 are combined using an ANN approach to detect possible discontinuities particularly when all of the features may not show up with any one attribute.

Moreover, porosity, density and impedance maps (figure 12) obtained earlier using ANN property prediction schemes are tied later on with these discontinuity maps to detect possible fracture zones (fault associated fracturing). This also involves using stress maps obtained from passive seismic data analysis and is discussed in the next section.

Integrated reservoir characterization

Regional discontinuity maps can be created using multi-attribute analysis techniques available in the literature and as per our discussion in the previous section. An ANN framework is trained using manual ‘expert’ fault zone identification and subsequent training/ testing and the generated volume is used as the baseline fault cube for our analysis. Figure 14 shows the output obtained from the ANN workflow (both fault cube as well as a two selected horizon maps).

The property estimates obtained from microseismic data analysis as well as those obtained from 3D seismic data using ANN – well log property prediction workflow can be combined based on the expected fracture zone observations such as high porosity, low density and low impedance values. Moreover, elastic rock properties as well as stress map observations can also be used to interpret possible zones of fracturing. Low V_p/V_s anomalies and low V_p anomalies can be considered to be fracture induced anomalies. Moreover, low extensional stress anomalies indicate open fracture zones ((Berge 2001) and (Martakis 2006)). Each of these individual properties in itself may not be indicative of fracturing with high degree of certainty however they are combined together into what we refer to as fracture zone probability maps. While there could be many ways of designing such an attribute, we use a simple relationship defined as follows for our preliminary studies:

$$FZP = \frac{\phi_n \times V_{sn}}{{V_{pn}}^2 \times \rho_n \times V_{En} \times Z_n}$$

Where ϕ_n is the porosity, V_{pn} and V_{sn} indicate the phase velocities, ρ_n is the density, Z_n is the impedance and V_{En} is the extensional stress (all attributes are normalized). This normalized attribute is shared in figure 15 where high values should indicate possible zones of interest in two randomly selected depth levels (1000m and 1500m).

Figure 16 shows an integrated display with both fracture probability map and discontinuity map shown together for the two selected depths as a means of highlighting possible zones of fault induced fracturing and other potential areas of interest. It is observed that in some cases, the mapped fracture zone shows higher probability close to the flanks of major discontinuities while some discontinuities do not seem to have major fracturing close to them which could be an indication of the type and condition of the discontinuities in question. With the number of wells available, a specific zone of interest known before hand to be prolific with fracture dominated flow is checked against the FZP and discontinuity maps at the depth of interest to validate the FZP mapping with actual observation (Figure 17a). Due to the sparse nature of available microseismic data, the fracture probability map of the closest evaluated horizon is selected for analysis. Figure 17b shows stress ratio map at the depth of interest Indicating a high value as is expected for regions with relatively high fracture density. The use of stress ratio mapping as an indicator of fracture zones as described above allows us to visually verify the location of the current wells compared with the stress anomalies (figure 18) and this indicates that most of the wells developed in the field do fall in the zones showing high degree of stress anomalies. A better classification based on classification of isolated compartments using injection/ production data and discontinuity maps is planned for the future.

Summary

The proposed workflow includes using well logs, conventional seismic and microseismic data together to characterize fault induced fractures in the reservoir. We identify the zones of interest based on our analysis and also validate the method using available information for a particular well. This method can also be applied for other unconventional reservoir settings and valuable information obtained from microseismic data can be of use to characterize the reservoir in question. While we have developed a framework for fracture zone identification, this method can easily be used for other types of characterizations including lithology and fluid type, etc. Moreover, additional information such as fluid flow (based on flow models) and geologic models can also be integrated as additional constraints. The microseismic data acquisition scheme is of vital importance in this workflow. Adequate number of stations and a good station array design is important to best constrain the data and obtain good velocity and subsequent property estimates.

Acknowledgement

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Figures

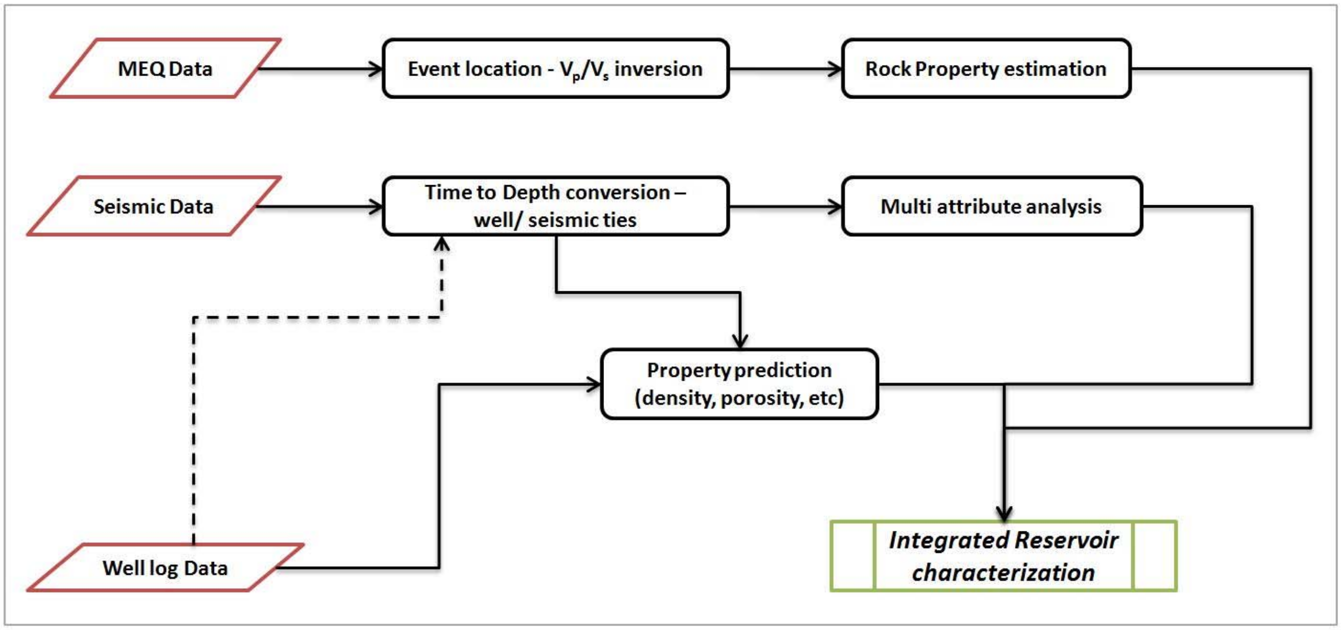


Figure 1- Integrated workflow for reservoir characterization - outline

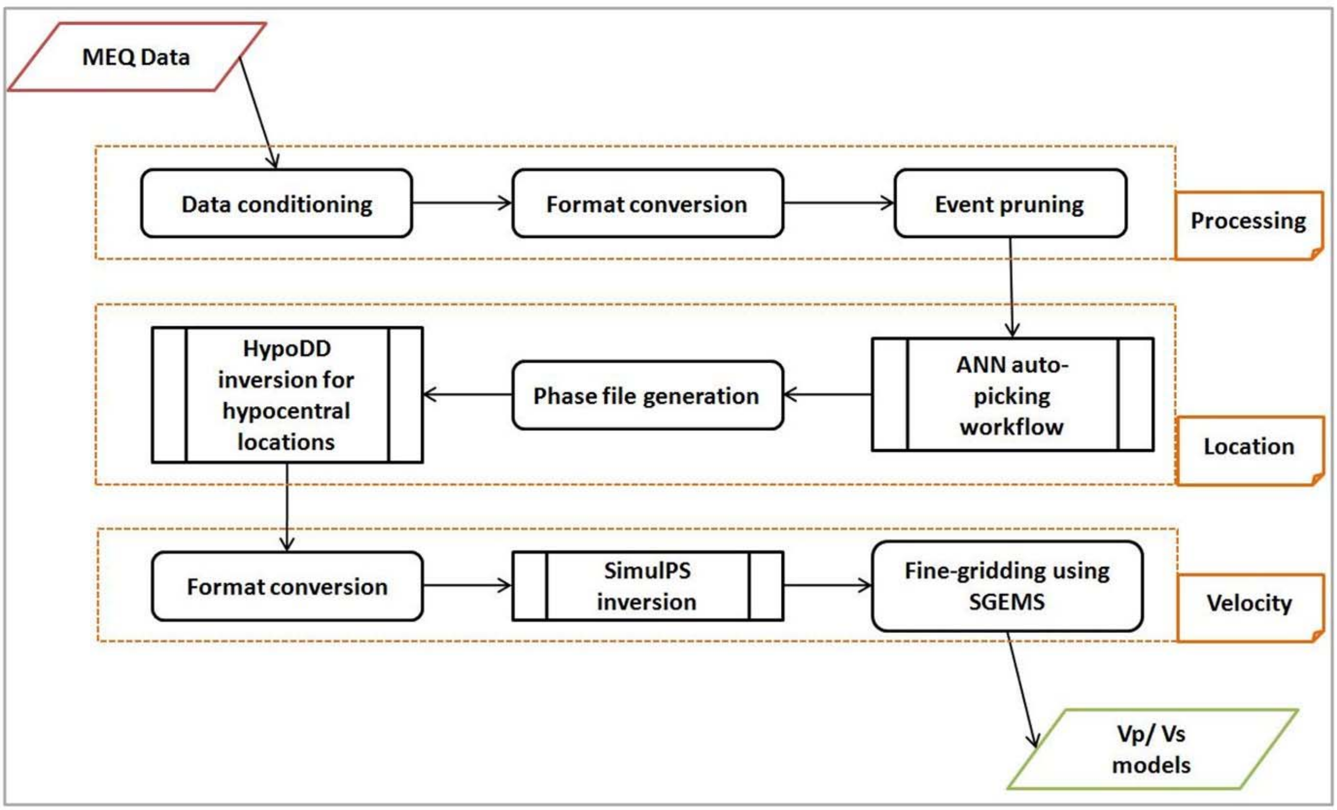
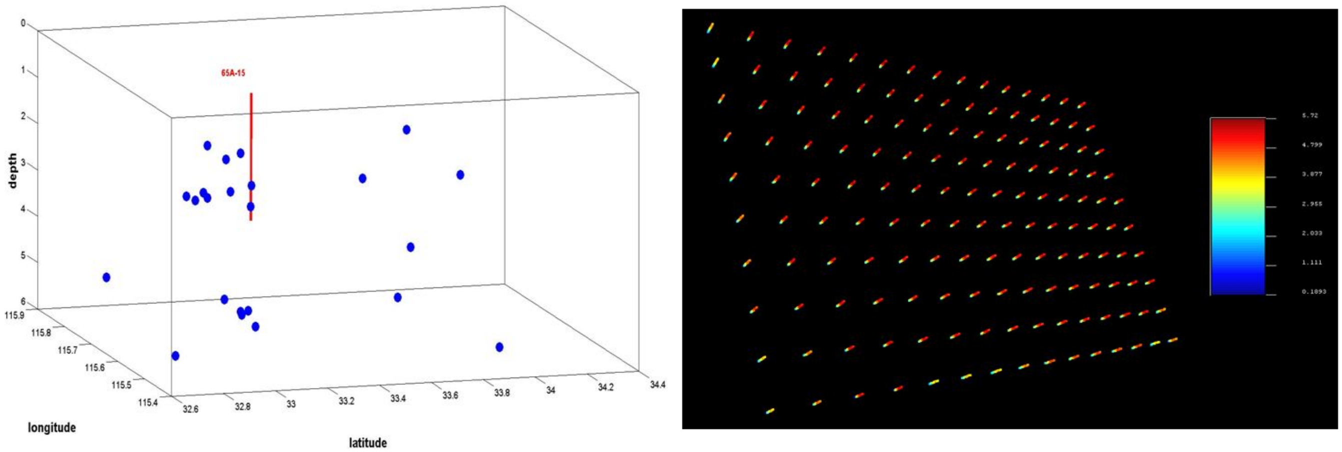


Figure 2- Velocity model generation workflow using passive seismic data



(a) (b)

Figure 3- (a) MEQ event locations from HypoDD run and (b) SimulPS result (gridded velocity estimates)

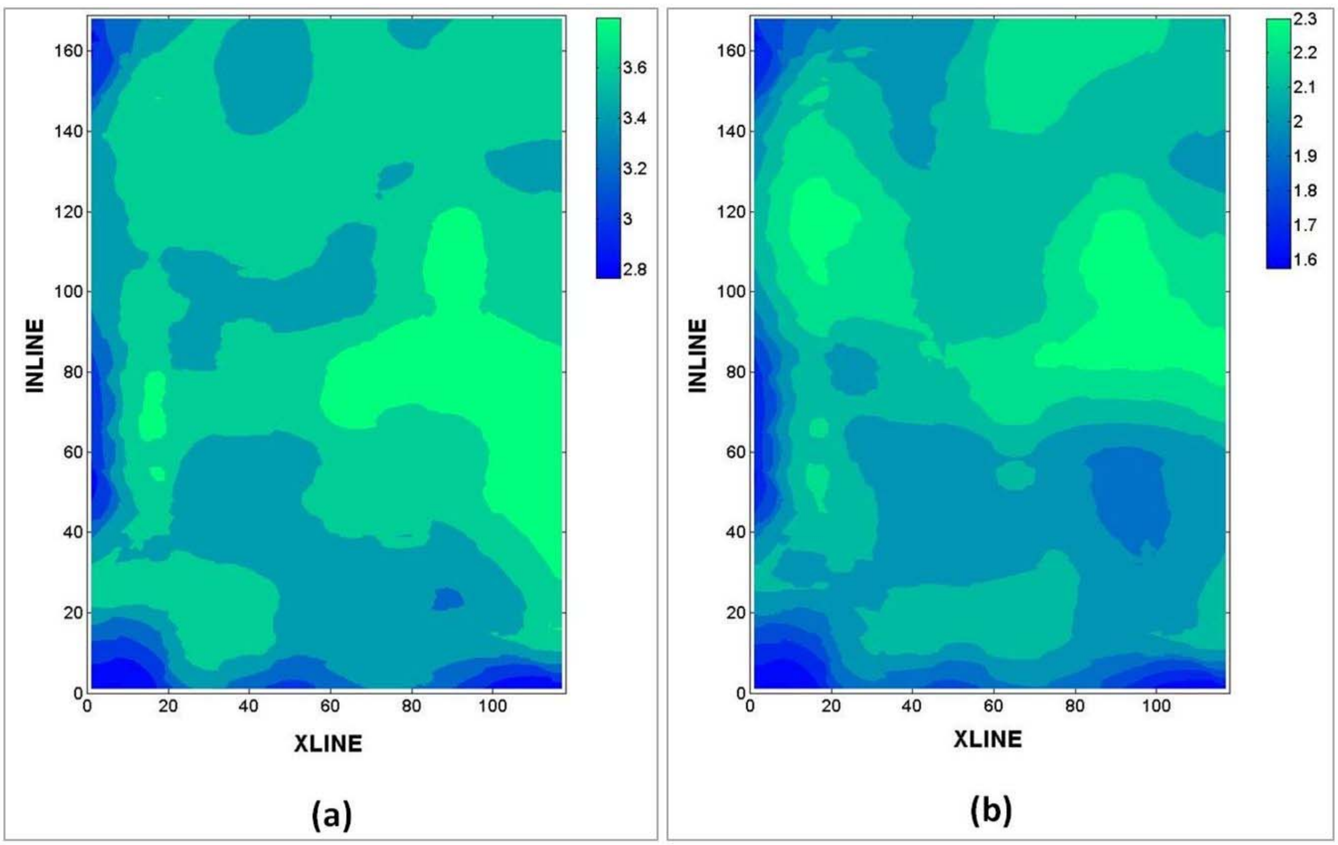


Figure 4- (a) Vp map and (b) Vs map from selected depth (1000 meters) obtained with fine-gridding using SGEMS

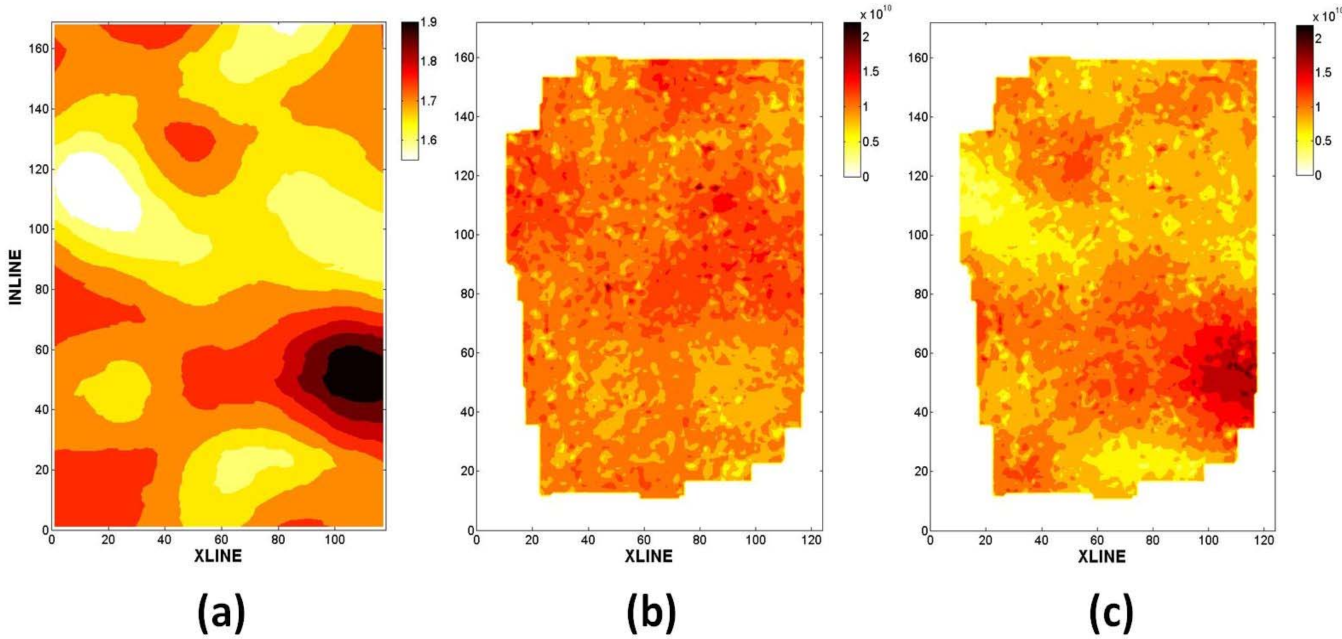


Figure 5- (a) Vp/Vs ratio, (b) Lame's parameter 'μ' and (c) Lame's parameter 'λ'

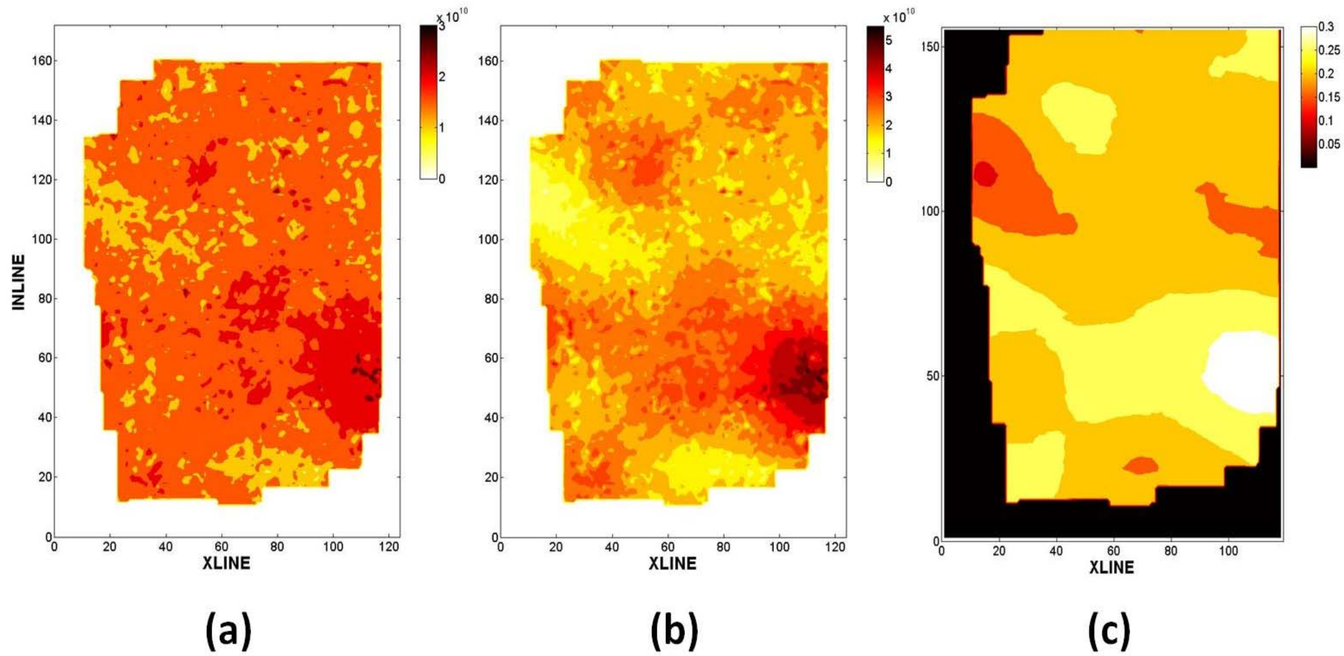


Figure 6- (a) Bulk Modulus and (b) Young's Modulus and (c) Poisson's Ratio maps at selected depth interval

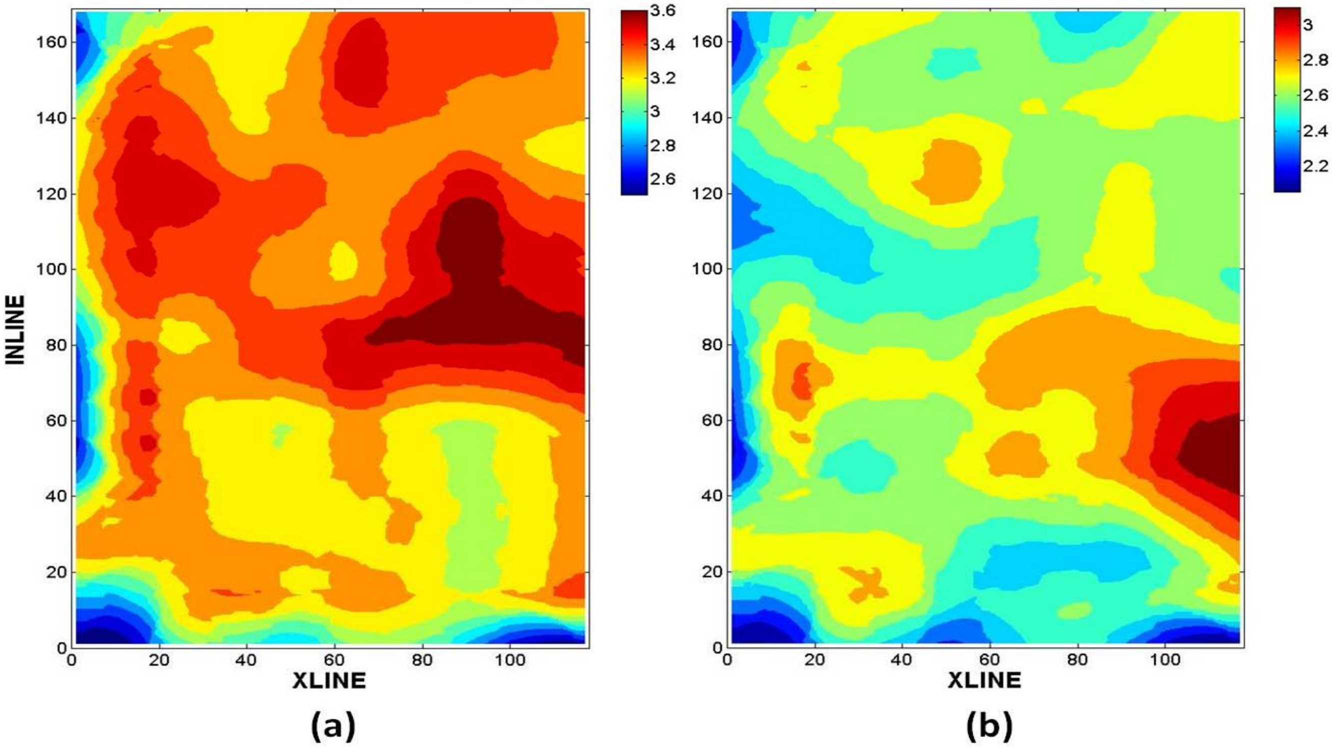


Figure 7- a) Extensional and (b) Hydrostatic stress maps at selected depth interval (relative values)

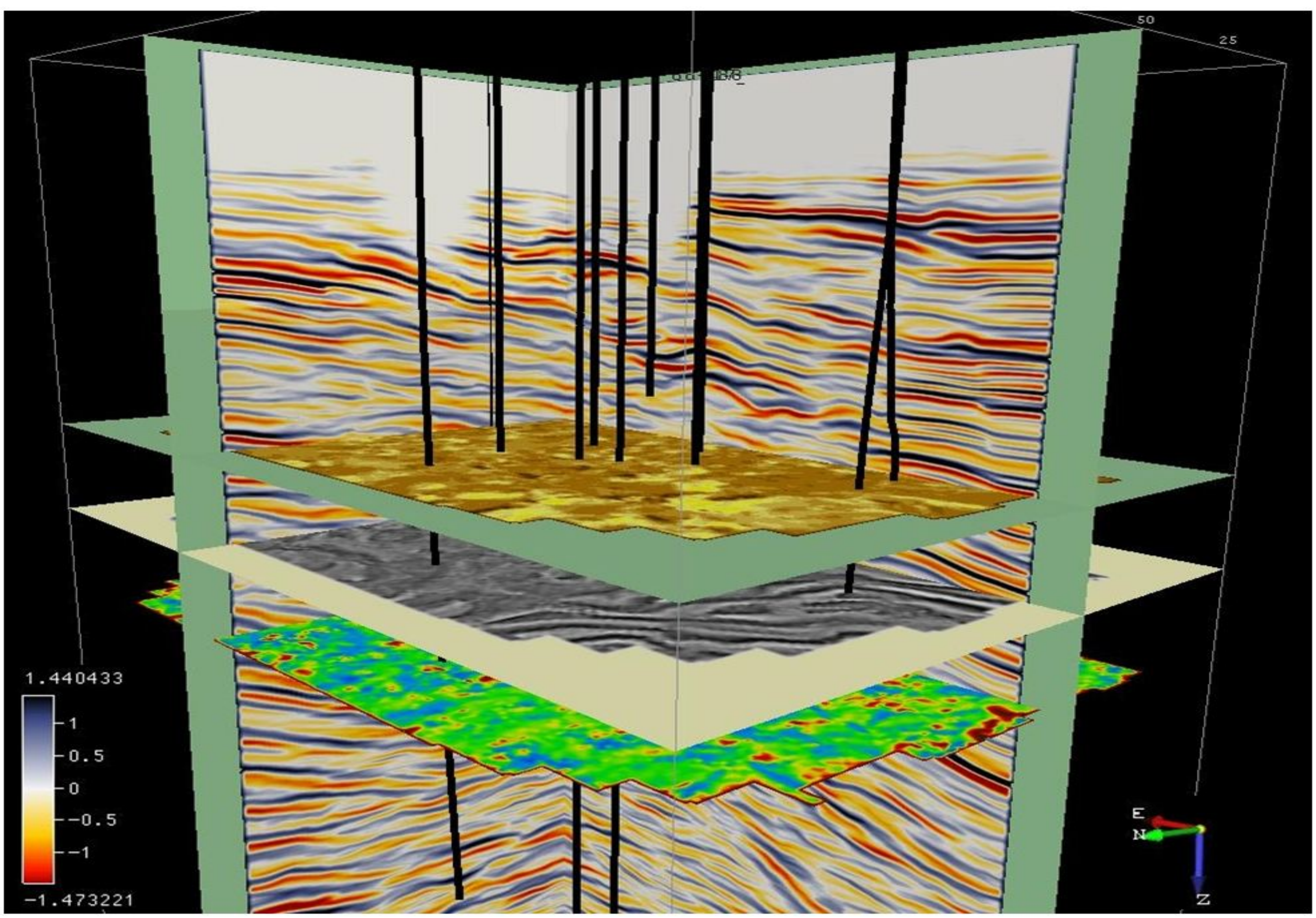


Figure 8- Processed seismic data (sectional view) with available well control and sample seismic attribute maps

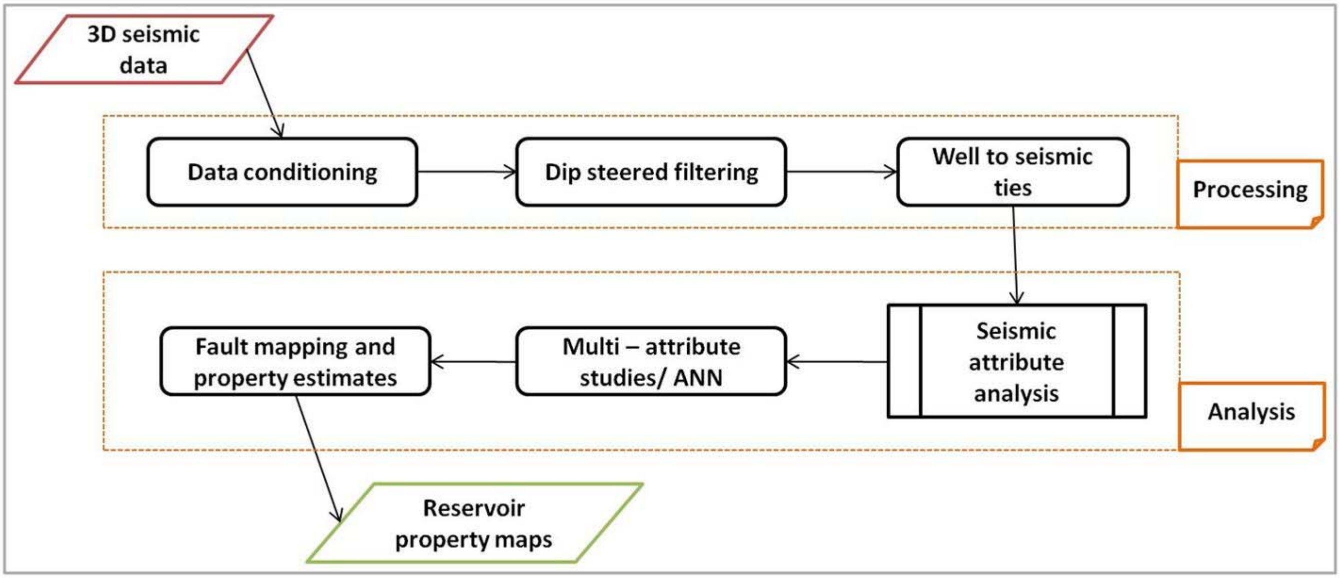


Figure 9- Workflow for seismic attribute studies (multi-attribute analysis/ ANN based mapping, etc)

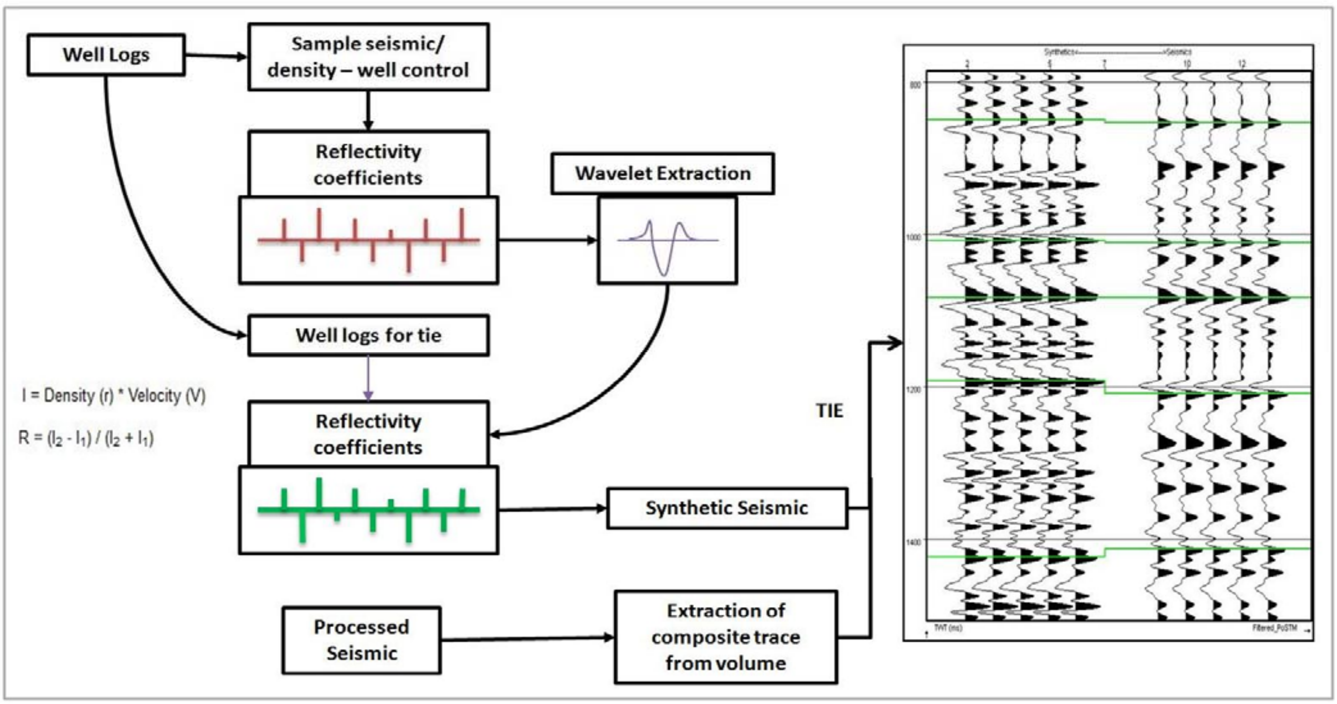


Figure 10- Seismic to well tie for Time-Depth correction

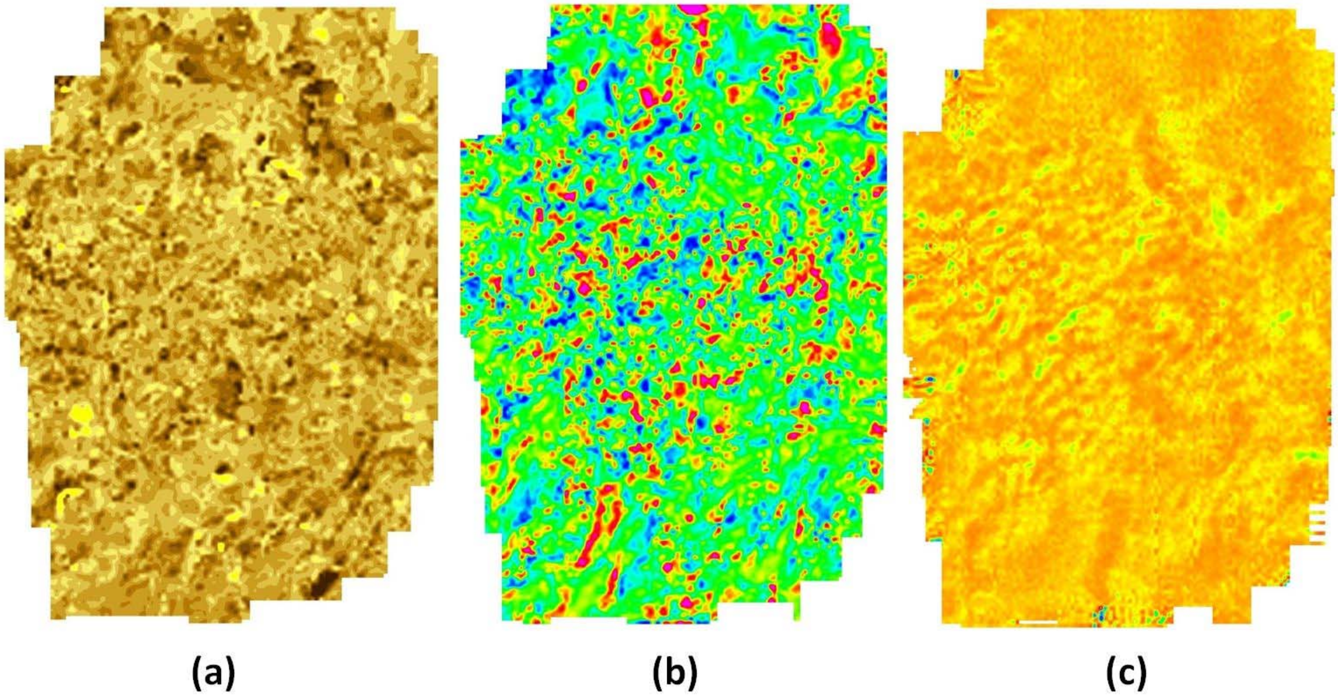


Figure 11- (a) Density, (b) Porosity and (c) impedance maps at selected depth level generated from well logs and seismic attribute data using supervised ANN property prediction workflow

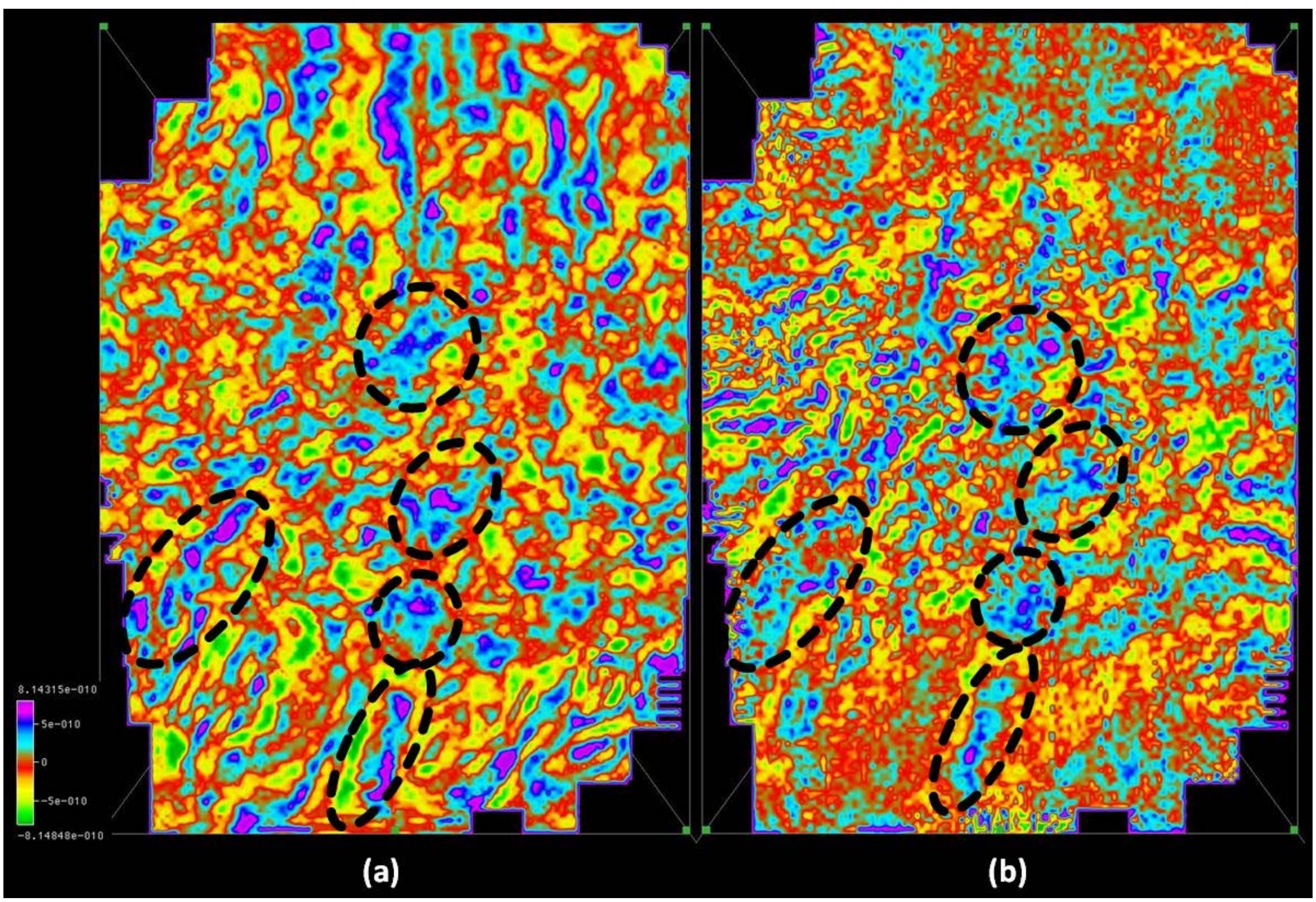


Figure 12- Impedance maps generated using (a) colored inversion with 2 sonic logs (actual) and (b) with all sonic logs (pseudo logs). The figure shows appreciable match obtained between the two indicating the validity of the pseudo logs

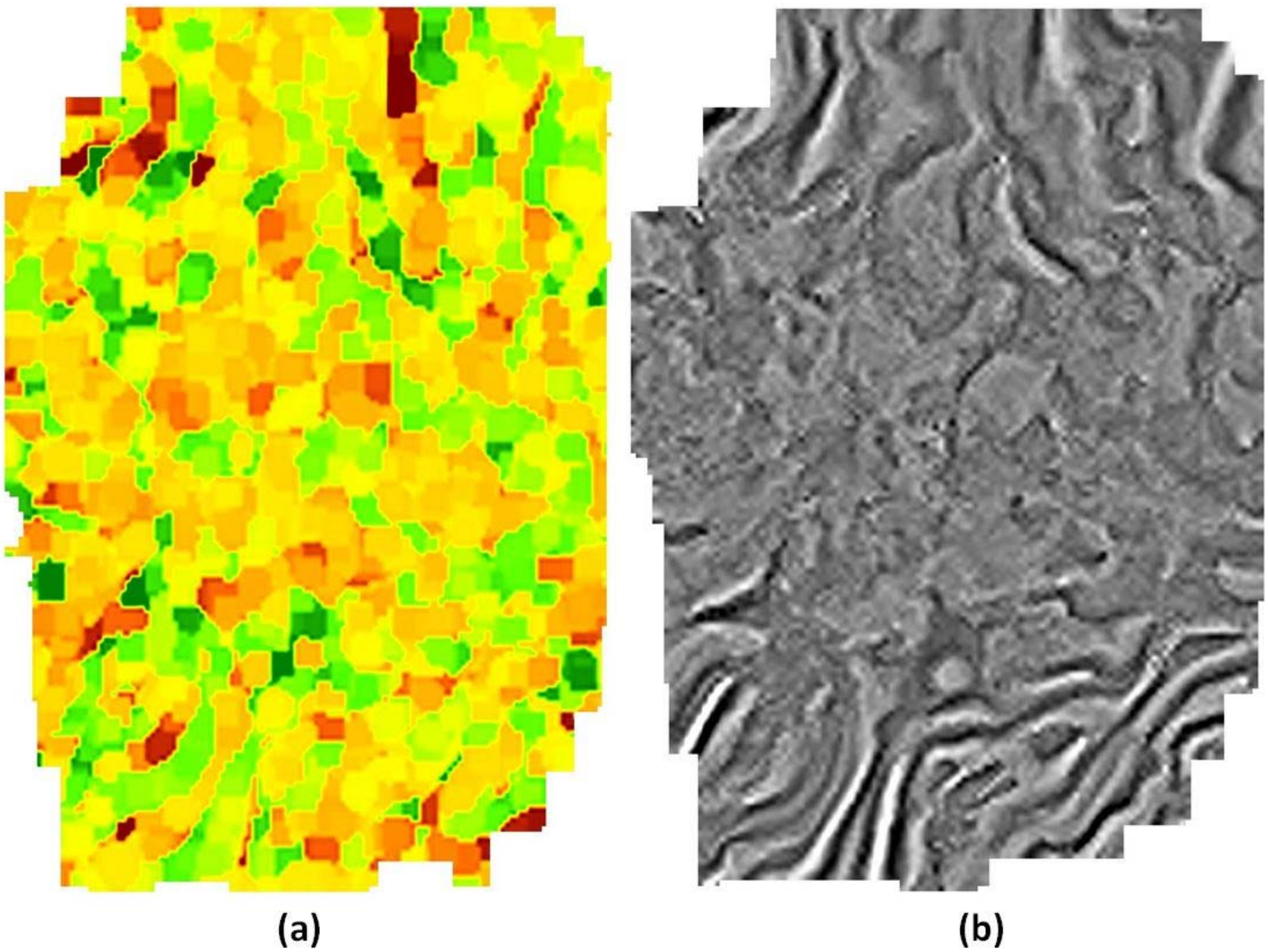


Figure 13- (a) Edge preserving and (b) Edge enhancement filters for sample depth interval

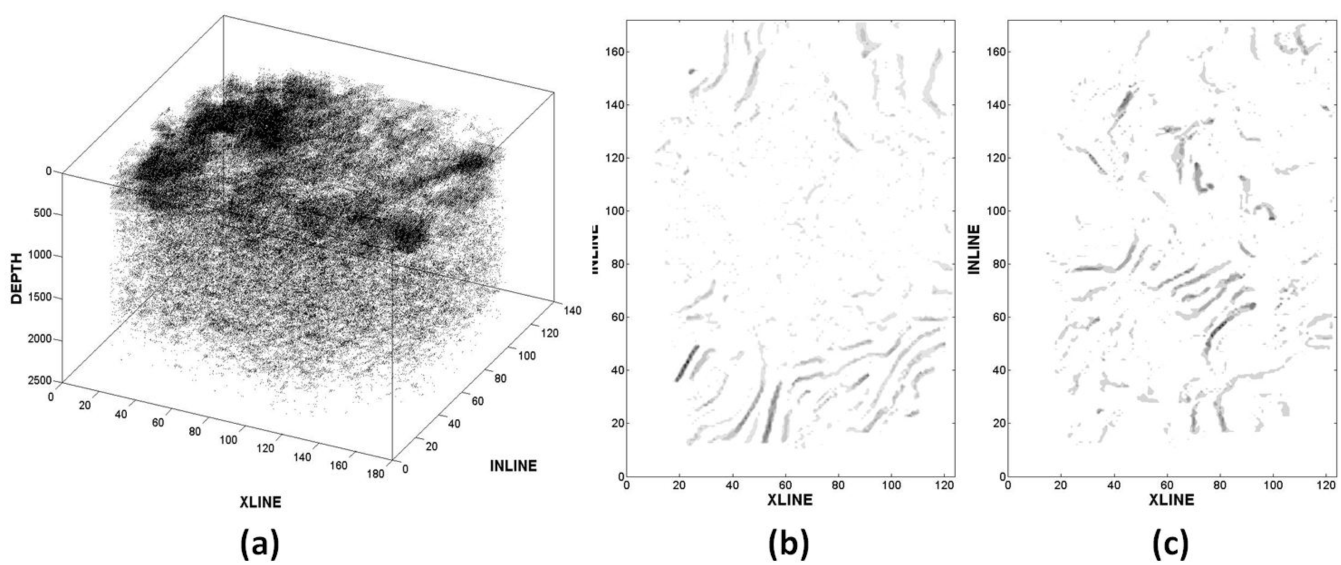


Figure 14- (a) ANN derived discontinuity cube, (b) Discontinuity map at 1000m and (c) at 500m

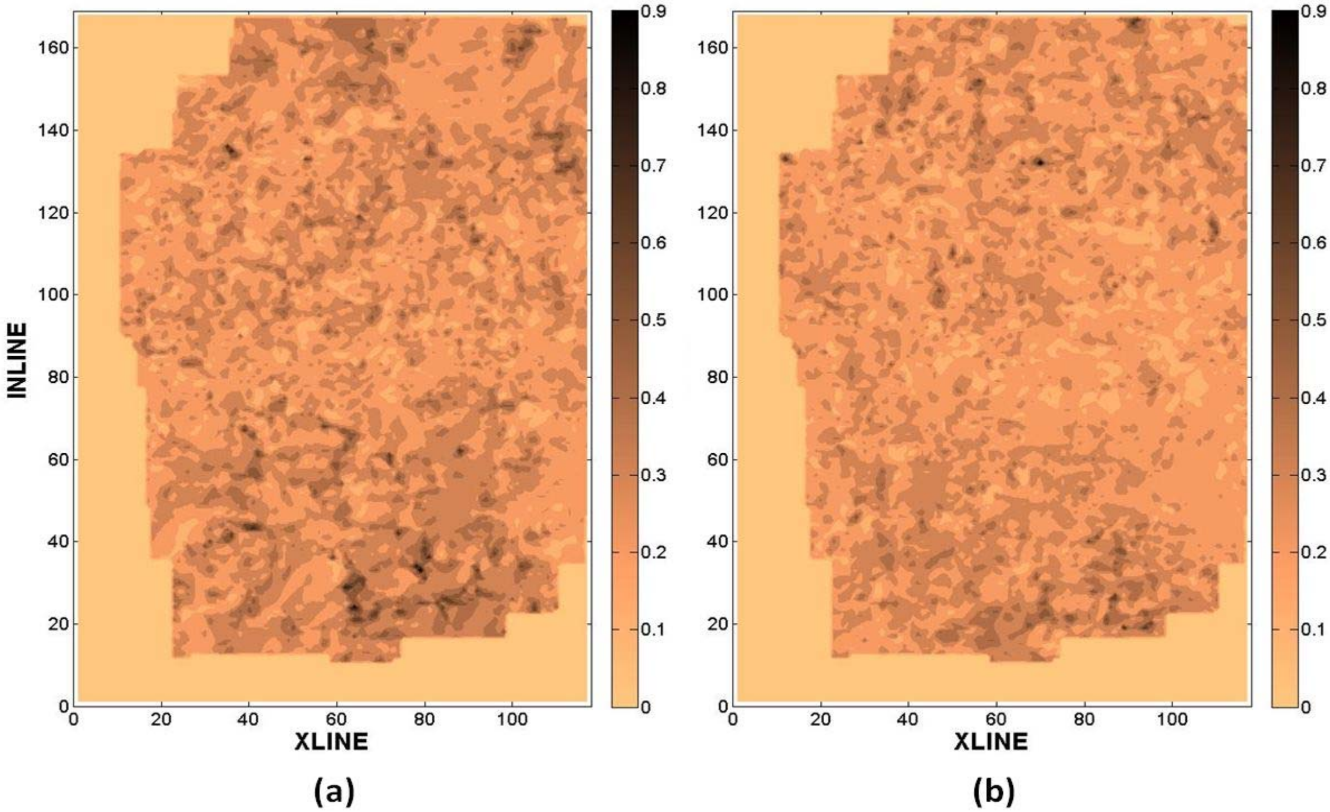


Figure 15- (a) FZP map at 1000m and (b) 1500 m depth with high values giving higher probability of fracturing/ faulting

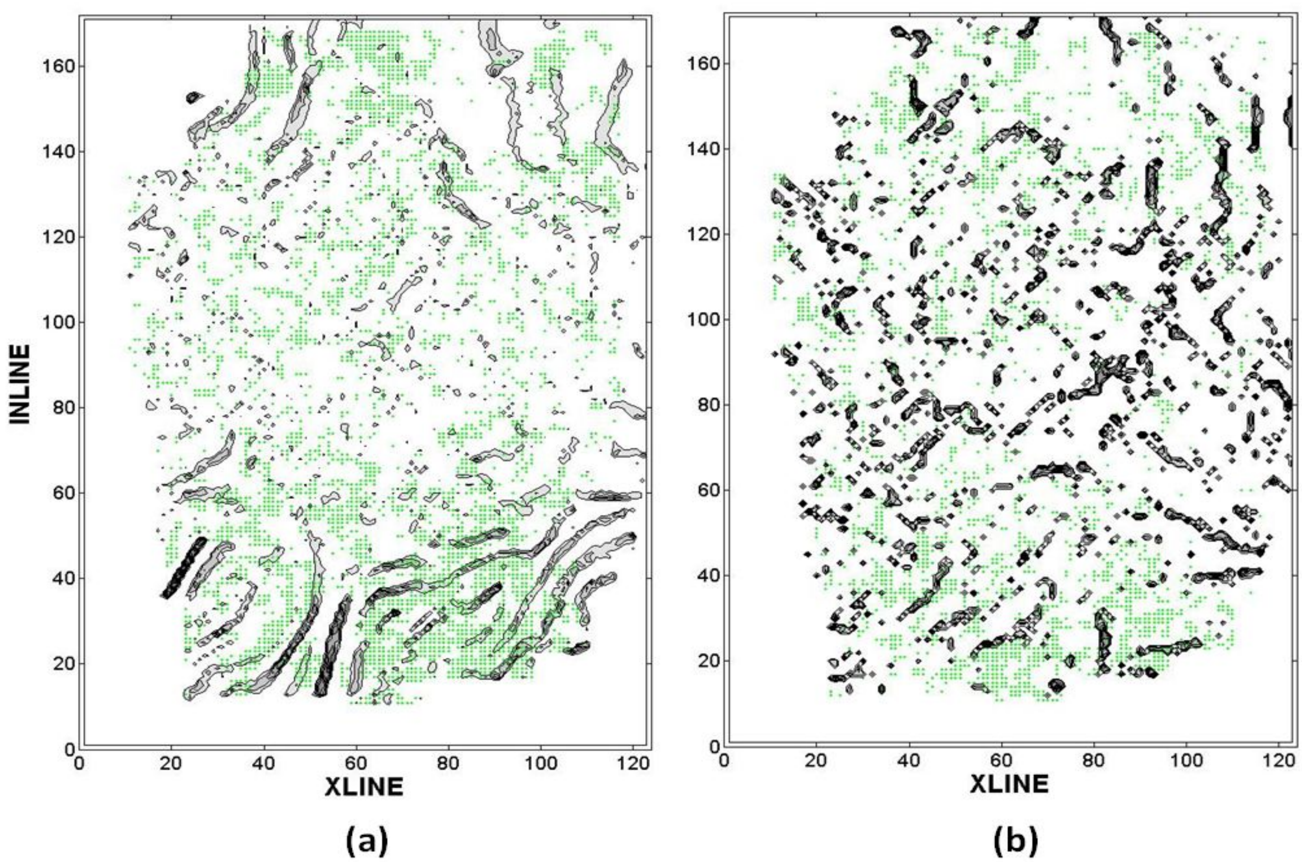


Figure 16- Integrated display of discontinuity map and FZP at (a) 1000m and (b) 1500m

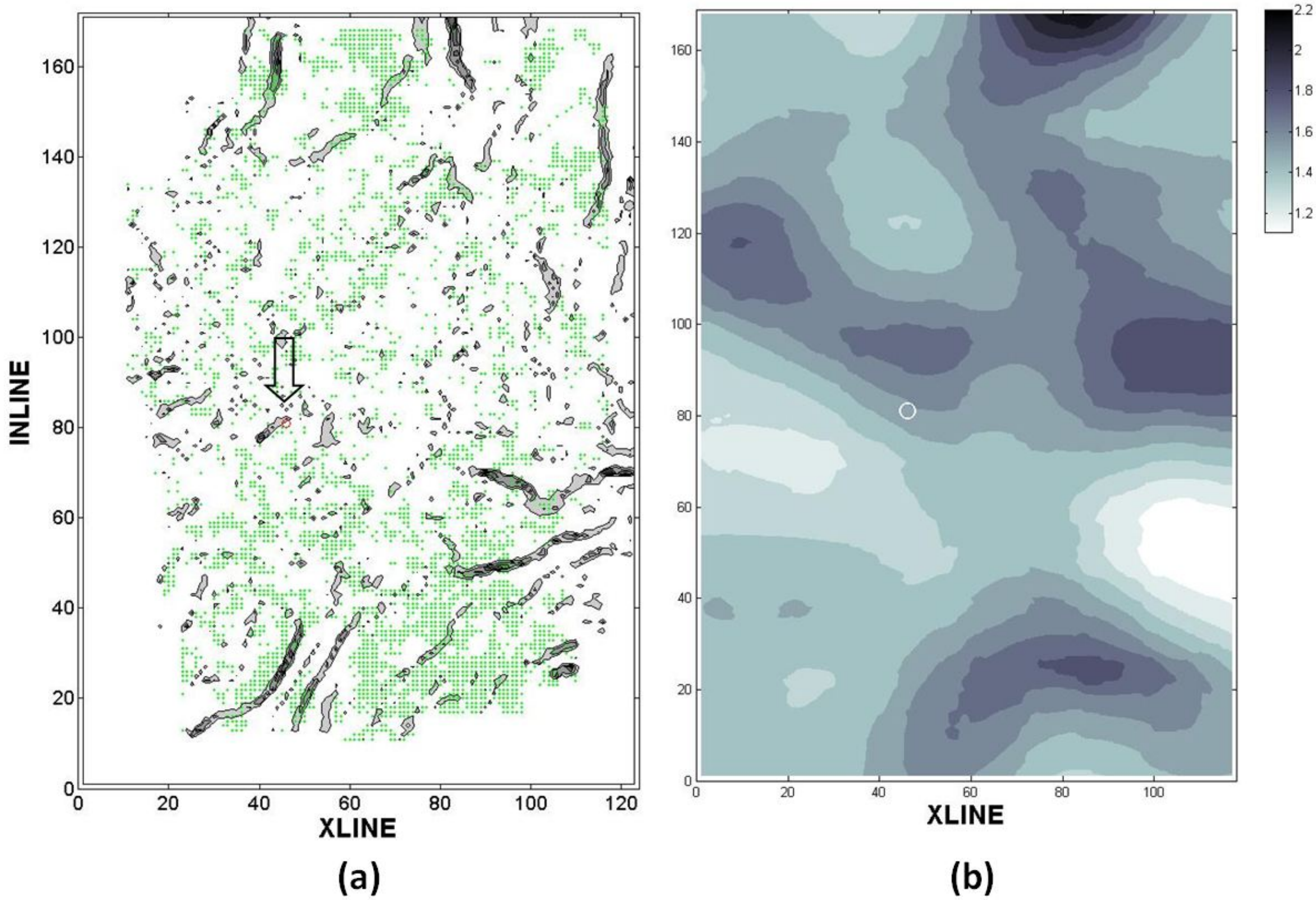


Figure 17- (a) Integrated map at Zone of interest and (b) V_E/V_K ratio indicating zone of interest also showing sample well with high production with identified discontinuity and possible fracturing

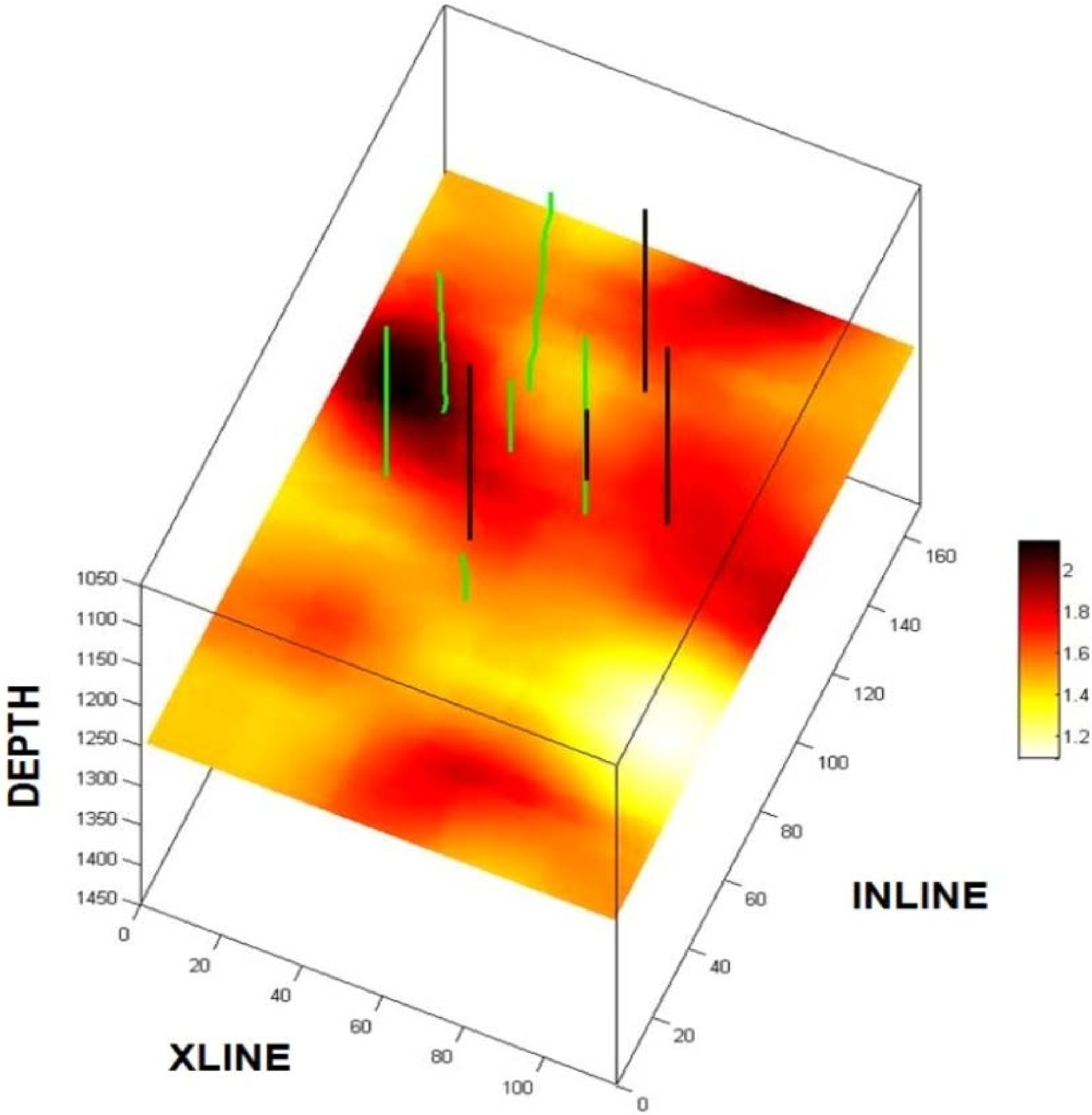


Figure 18- Stress ratio (V_E/V_K) indicating zones of interest superimposed with well tracks (green - injection & black - production) for reference