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Estimation of Flow Zone Indicator Distribution by Using Seismic Data: A Case Study from a Central Iranian Oilfield

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Abstract

Flow unit characterization plays an important role in heterogeneity analysis and reservoir simulation studies. Usually, a correct description of the lateral variations of reservoir is associated with uncertainties. From this point of view, the well data alone does not cover reservoir properties. Because of large well distances, it is difficult to build the model of a heterogenic reservoir, but 3D seismic data provides regular sampling that can improve reservoir spatial description.

In this study, seismic attribute analysis was used to predict flow zone indicator (FZI) values of a carbonate reservoir by using seismic and well log data. First, a 3D acoustic impedance volume was created as an external attribute for seismic data analysis. To improve the ability of FZI prediction, the maximum number of attributes from multiattribute analysis was computed by using a step-wise regression technique. To verify the results of multiattribute technique, the cross plot analysis of multiattribute method was performed. It was found that the R^2 value of the correlation between the predicted and actual FZI is as high as 0.859 with an average error value of 2.34 μm. The analysis of the results of multiattribute technique showed that it was an effective technique for FZI prediction in hydrocarbon reservoirs. Such accuracy in building a 3D distribution of FZI provides a good insight into reservoir production zones. The results clearly indicate that the methodology proposed herein can successfully be used to specify the locations of new wells for the purpose of future production or injection plans.

Keywords: Multiattribute Analysis, Seismic Attribute, Well Log Data, Flow Zone Index, Acoustic Impedance Volume

1. Introduction

Mapping properties of the reservoir is an important step in the assessment and development of hydrocarbon reservoirs. Numerous authors introduced empirical correlations of multivariate linear regression between seismic attributes and well log data for the prediction of physical properties such as porosity, permeability, etc. in a reservoir (Schultz et al., 1994a,b; Brown, 1996; Russell et al., 1997; Hampson et al., 2001; Leiphart and Hart, 2001; Calderon and Castagna, 2007). Multiattribute analysis is an effective method to hybridize well logs and seismic data for estimating well log properties from the seismic responses. In this paper, the prediction of FZI logs from seismic attributes was examined using multiattribute method. Permeability and FZI determination has importance in different stages of evaluation, completion, and optimization of enhanced oil recovery methods, reservoir modeling, and

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reservoir management. For this reason, different methods with different applications have been introduced by petroleum engineers and geologist for permeability evaluation (Kozeny J, 1927; Amaefule at al., 1993; Abbaszadeh and Fujii, 1996; Fahad and Stephen, 2000; Prasad, 2003; Kazemzadeh at al., 2008).

In this study, seismic attribute analysis was utilized to predict FZI in one of the southwest oil fields of Iran. For seismic attribute analysis, acoustic impedance volume as an external attribute was created and the internal attributes were computed from seismic data. Stepwise regression method was used to find the best set of attributes. Seismic attributes were applied to multiattribute analysis to predict flow zone index. The attribute map from multiattribute analysis was used to interpret reservoir properties related to spatial distribution of the oil bearing carbonate layer.

Data for the current study consists of petrophysical data from three wells, a 3D seismic data cube, and structurally interpreted data of one of the south-west oil fields of Iran. Firstly, the petrophysical interpretation of the well logs was carried out in order to provide an appropriate set of data that could be chosen for inversion process and multiattribute analysis. Meanwhile, they were used to determine petrophysical relationships that could be useful in seismic data interpretation. The wells used in this work to build a three dimensional distribution of FZI are shown in Figure 1. As can be seen, it illustrates the permeability calculated from Stoneley-flow zone index (ST-FZI) method against the core permeability (third column from the right) and effective porosity (second column from right) together with fluid and lithology of the formation (first column from right). Reservoir facies with color representation are shown in the left column for all the three well logs. Reservoir characteristics of each facies are listed in Table 1.

Table 1
Reservoir characteristics of reservoir facies

Name	Color	Porosity (v/v)	Permeability (mD)
Facies_6	Red	0.189	2030
Facies_5	ORANGE	0.166	613.925
Facies_4	Olive-Drab	0.116	46.709
Facies_3	Green	0.076	0.9
Facies_2	Deep-Sky-Blue	0.023	0.011
Facies_1	Blue	0.014	0.002

2. Methodology

This study focuses on the application of multiattribute analysis to the prediction of Asmari reservoir FZI data by using seismic attributes. For the purpose of this study, post stack 3D seismic data and available well log data of three wells were used (Figure 1). Density, porosity, sonic, and FZI logs were available for the all the wells, but check shot data were only available for one well.

In order to produce the 3D model of FZI the following procedure was used:

- ✓ Acoustic impedance model was created by using model-based inversion. It was used as an external attribute for the creation of a 3D FZI model;
- ✓ Since acoustic impedance has a close correlation with FZI, it was utilized in the creation of the 3D model. To this end, the equation for correlating seismic attributes to FZI log was determined for any wells in the field being used to construct the model.

This equation is then used to estimate the corresponding FZI log among distances of all the wells.

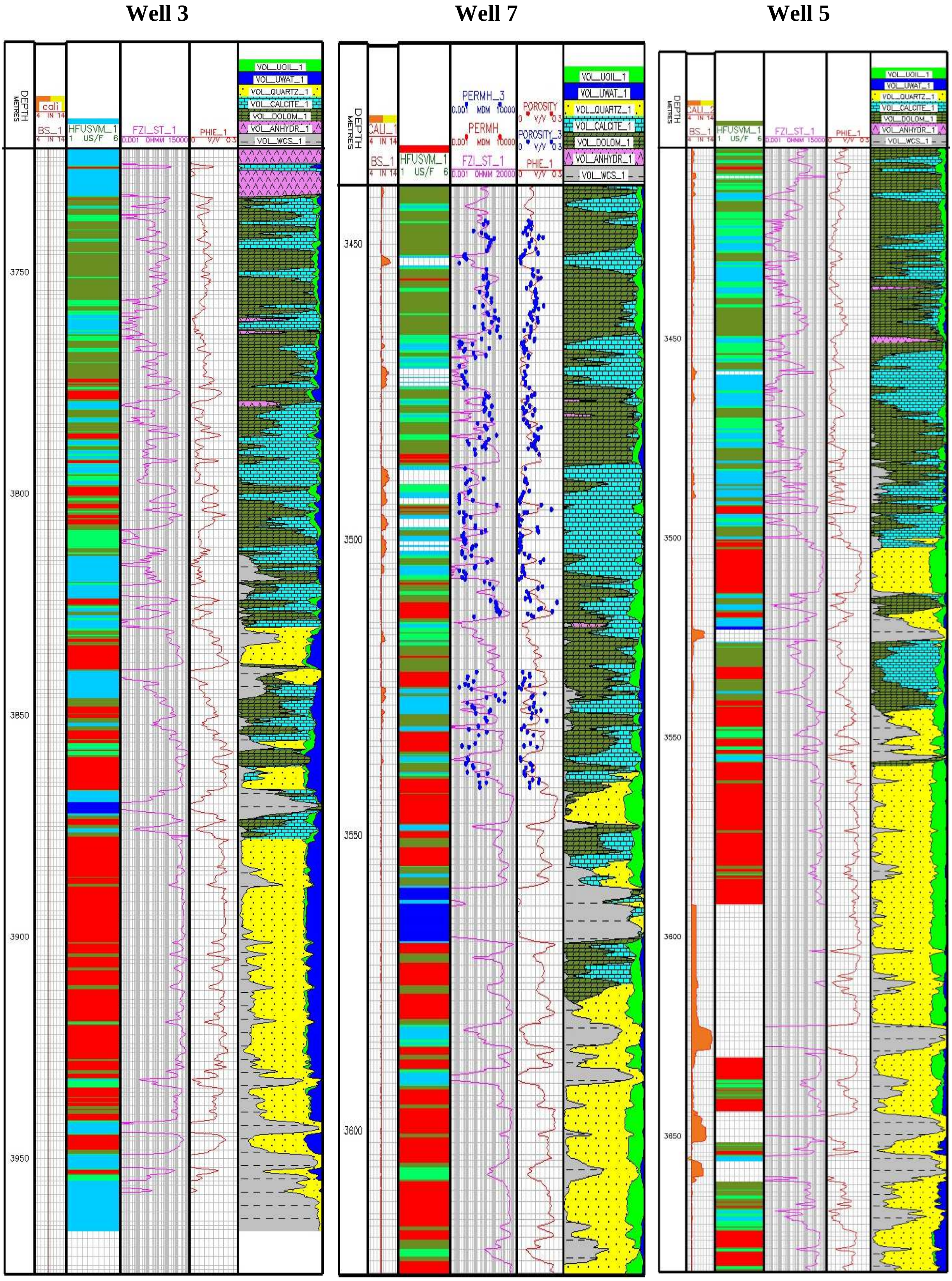

Figure 1
Wells used in this study to build a 3D distribution of FZI

2.1. Model-based inversion

It is widely accepted by many researchers that seismic inversion is a preliminary study in reservoir characterization. Accordingly, there is a continuous effort to optimize the inversion algorithm and improve the resolution of the inverted volume. The amplitude-based seismic data were processed through a model-based inversion algorithm to produce acoustic impedance volume (Cooke & Schneider, 1983; Geohorizone, 2002). This volume was used as an external attribute in the multiattribute analysis.

In order to perform the model-based inversion, a geological model was compared to seismic data. Then, the result of comparison between the real and modeled data is used to iteratively update the model to find a better match. This method is very applicable since it does not use the direct inversion of the seismic data (Haghighi et al., 2006). On the other hand, the model performing well in training data will not necessarily work on testing sample points. There are two ways in which some controls and quality checks may be used. One way is to consider the additional information as a soft constraint, meaning that the initial impedance is a separate piece of information which is added to the seismic trace with some weighing of two. This approach is called “stochastic”. The second method is to consider additional information as a hard constraint that sets absolute boundaries on how far the final answer may deviate from the initial model. This approach is called “hard constraint.” In this study, the second method was implemented. In the model-based inversion algorithm, average block size and the number of iterations are of prime importance. Using average block size greater than seismic sample interval is necessary to consider (Haghighi et al., 2006). The logic behind the recommendations is the assumption that there might be some false recorded readings from interferences in the surrounding environment mixed with the data. A larger number of iteration sets equates to better accuracy, but it requires greater investment in time. By investigating 3D seismic data from Asmari formation, the following results were obtained; constraint limit was 25%, average block size was 4 ms, and number of iterations was set to 10.

The results of model-based inversion are displayed in Figure 2. As it can be seen, this type of modeling can clearly identify the geological layers under consideration.

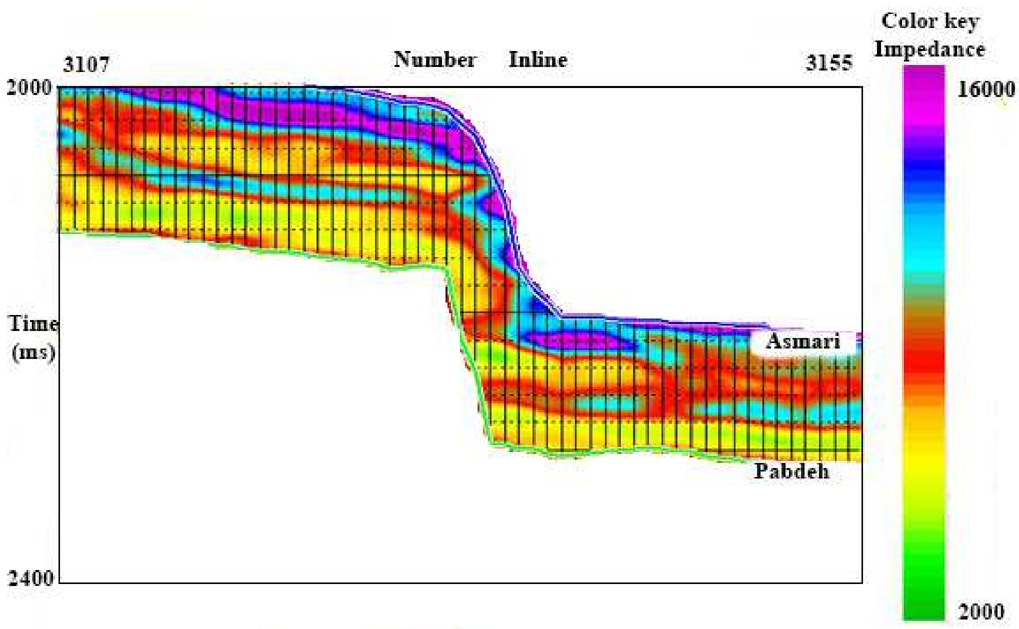

Figure 2
Broadband acoustic impedance inversion based on model

2.2. Constructing a 3D model of FZI

In order to create a 3D FZI model in inter-well spaces throughout the studied field, seismic attributes were taken into consideration. In this regard, acoustic impedance was calculated through the inversion of processes and post stack seismic data. In this particular FZI modeling, seismic attributes were extracted utilizing mathematical equations. EMERGE is to predict a well log property using the attributes of the seismic data. EMERGE analyzes the seismic attributes, not the seismic traces.

To improve the predictive power, a set of seismic attributes with strong geological basis were used. Hopefully, an optimal set of seismic attributes will combine to extract subtle features from well logging data. Since EMERGE was to correlate the target log with seismic data, the proper depth-to-time conversion was considered. Check shot data were applied to initial time to depth conversion. Through the construction of synthetic seismograms, well logs were correlated to seismic data.

In the second stage, seismic attributes relating to FZI were selected utilizing stepwise regression analysis and cross validation techniques. The utilized dataset were divided into two groups (Soubotcheva and Stewart, 2004), namely a training dataset (original wells, in black) and a validating dataset (predicted data, in red). As shown in Figure 3, the horizontal axis represents the number of attributes used in the prediction procedure. The vertical axis is the root-mean-squared prediction error for that number of attributes. From this figure, it can be seen that it is worth using only 4 attributes to avoid greater prediction errors. By analyzing the illustrated curve, it is not recommended using more than four attributes, since for the fifth attribute there is no improvement in the validation error.

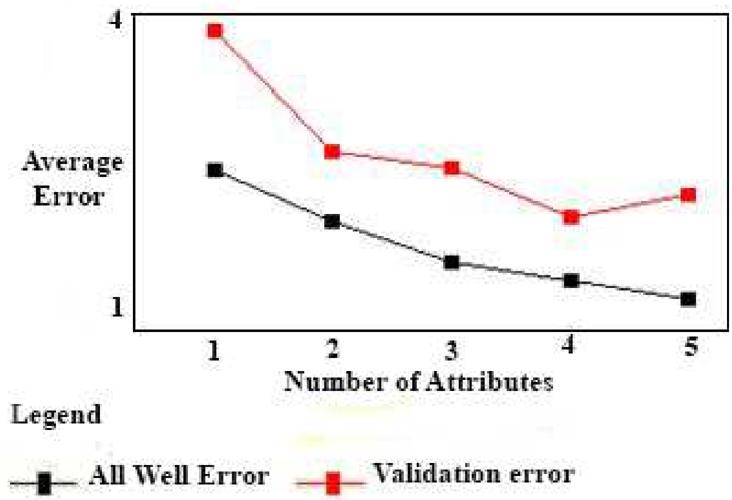

Figure 3

The multiattribute analysis showing the average RMS and validation error; the optimum number of attributes is equal to 4.

Since the frequency content of the target log is much higher than that of the seismic attribute, obtaining convolution operator was used to resolve the difference. In this case, each target sample was predicted using an average weight of a group of samples on each attribute. The parameter operator length determines the length of the convolution operator. In this case, the optimum value of operator length was obtained to be as high as 10 (Figure 4).

As shown in Figure 4, through the application of an operator length equal to 9, the number of attributes to be used in the intelligent model reaches 4.

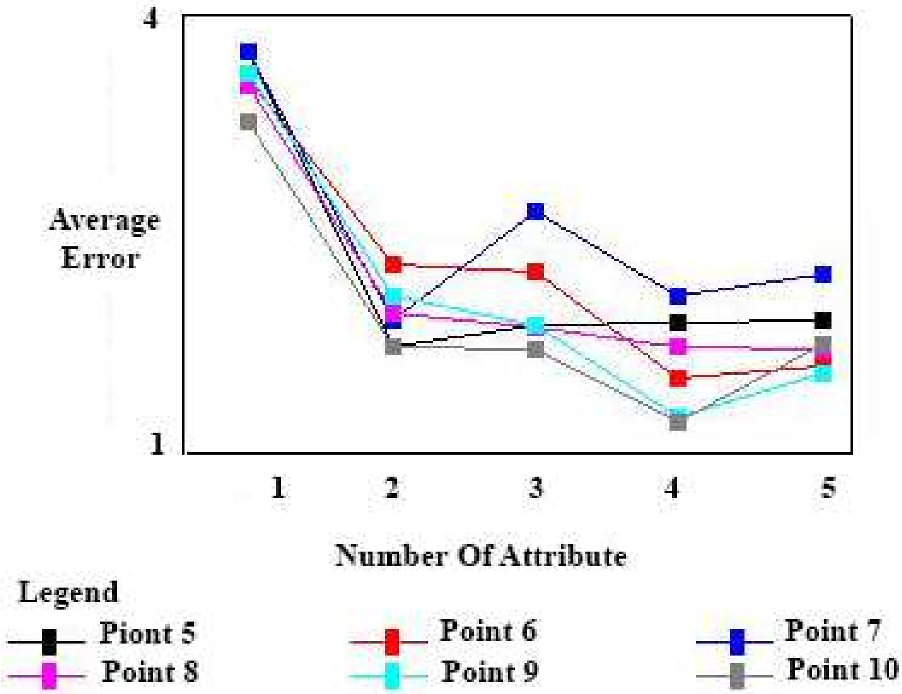

Figure 4
The multiattribute analysis result shows the average RMS error; the optimum operator length is equal to 10.

The list of seismic attributes used along with corresponding prediction errors and correlation coefficients are shown in Table 2.

Table 2
Multiattributes extracted for predicting the FZI

Target	Final Attribute	Training Error (μm)	Validation Error (μm)
FZI	Acoustic Impedance	3.155	4.172
FZI	Quadrature Trace	2.773	3.285
FZI	Amplitude Envelope	2.484	3.171
FZI	Cosine Instantaneous Phase	2.340	2.803

3. Results and discussion

In this study, the seismic attributes including acoustic impedance, quadrature trace, amplitude envelope, and cosine of instantaneous phase were used to estimate flow zone indicator. Table 3 displays the results of multiattribute analysis. Each row corresponds to a particular multiattribute and each successive row accumulates all the attributes above it. The value of amplitude envelope attribute is dependent on phase and correlated directly with the change in acoustic impedance. Moreover, the instantaneous phase indicator represents the continuation of the layers. The instantaneous phase is an effective attribute in highlighting discontinuities on seismic and detection of reflectors, faults, pinch-outs, angularities, and bed interfaces.

Table 3

The results of the multiattribute analysis

	Train Data		Validation Data	
Volume type	**Correlation**	**Error**	**Correlation**	**Error**
FZI	0.859	2.34 µm	0.8	2.8 µm

Acoustic impedance (AI) provides information about reservoir properties such as porosity, permeability, and FZI. There is an inverse relationship between AI and FZI. The FZI is defined as the relation between the volumetric proportions of pore space to its geometric distribution. Accordingly, acoustic impedance is a function of both density and velocity. The velocity increases with depth because the deeper layers are harder and denser. The porosity and saturating fluid reduces the wave velocities and density leading to acoustic impedance decrease. Such a correlation can be improved by applying the residual time-shift between the target FZI logs and the seismic data.

As shown in Figure 5, for the 4^{th} attribute and a nine-point convolutional operator, the correlation between the predicted FZI log and the target log is 85% and the RMS error decreases up to 2.34 µm (Figure 5).

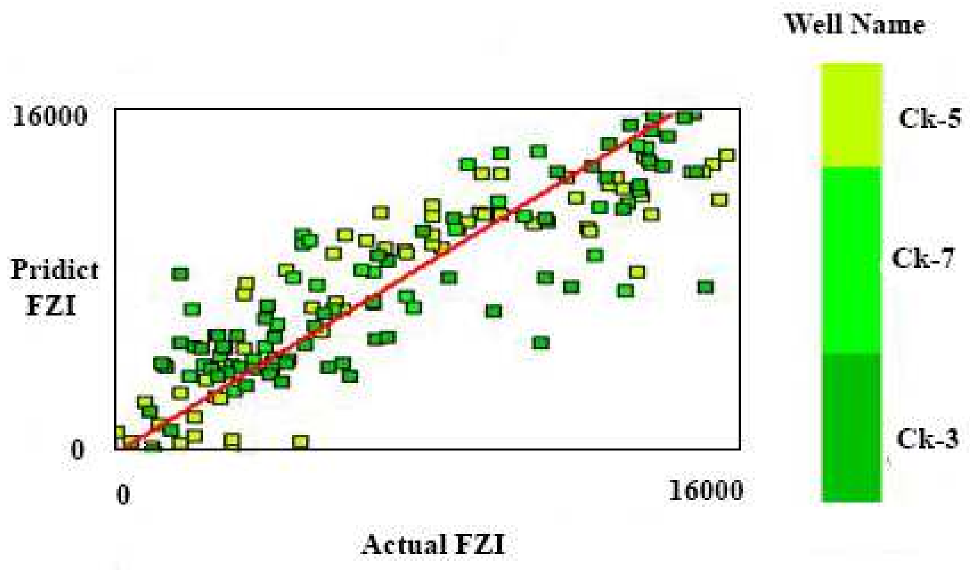

Figure 5

X-plot illustrating the relationships between the real and estimated FZI; cross correlation is 0.859.

Figures 6 and 7 display the target log for each well along with the “predicted” log using the selected attribute data and derived regression curve for training and validation data respectively. The plot shows the target logs in black with the “predicted” logs in red. Through the establishment of the relationship between multiattribute features and the target logs, the model was employed to estimate FZI from the entire 3D seismic volume.

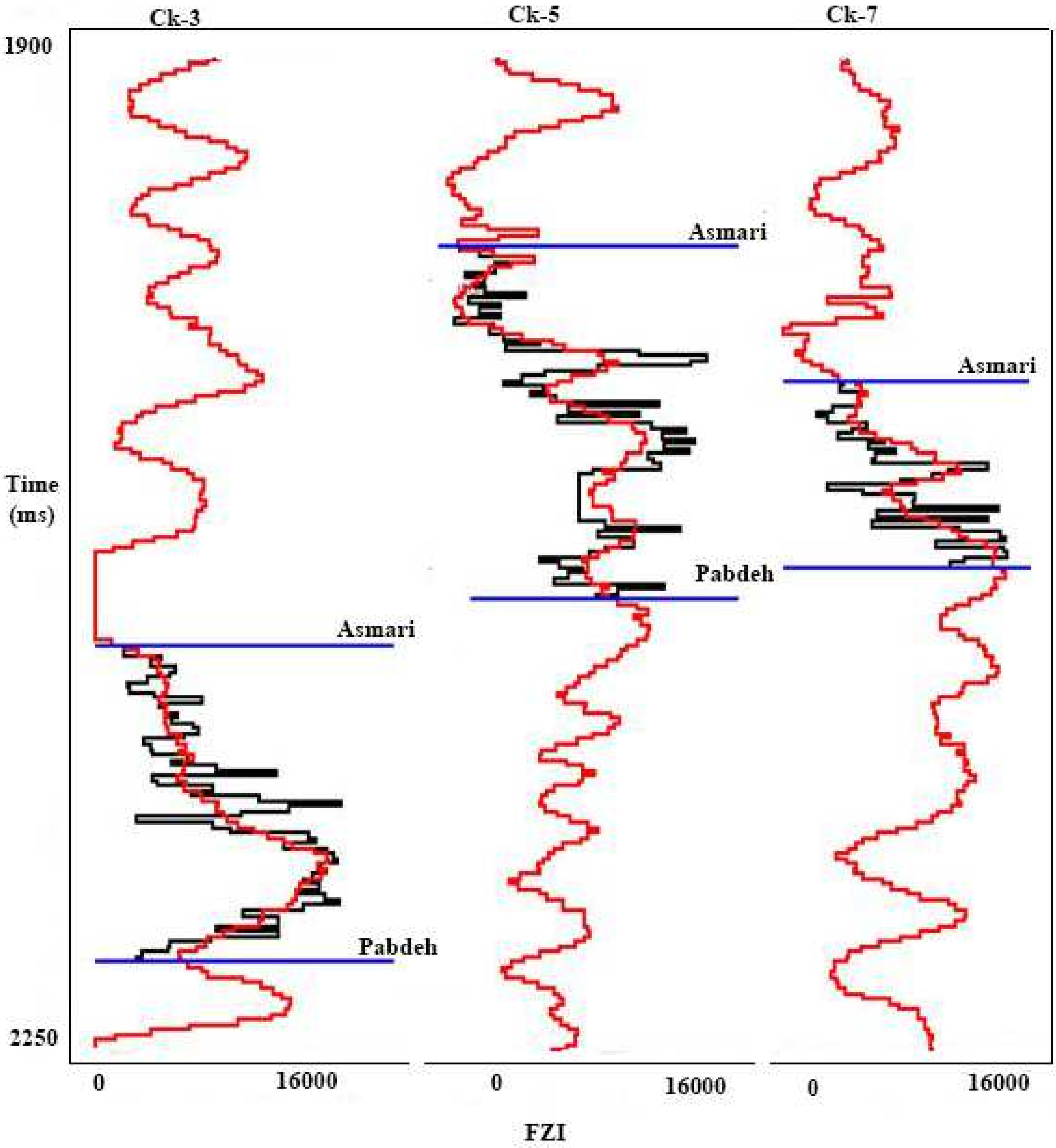

Figure 6
Measured FZI logs (in black) and the predicted ones from the multiattribute analysis (in red); the correlation of the training data is 0.859.

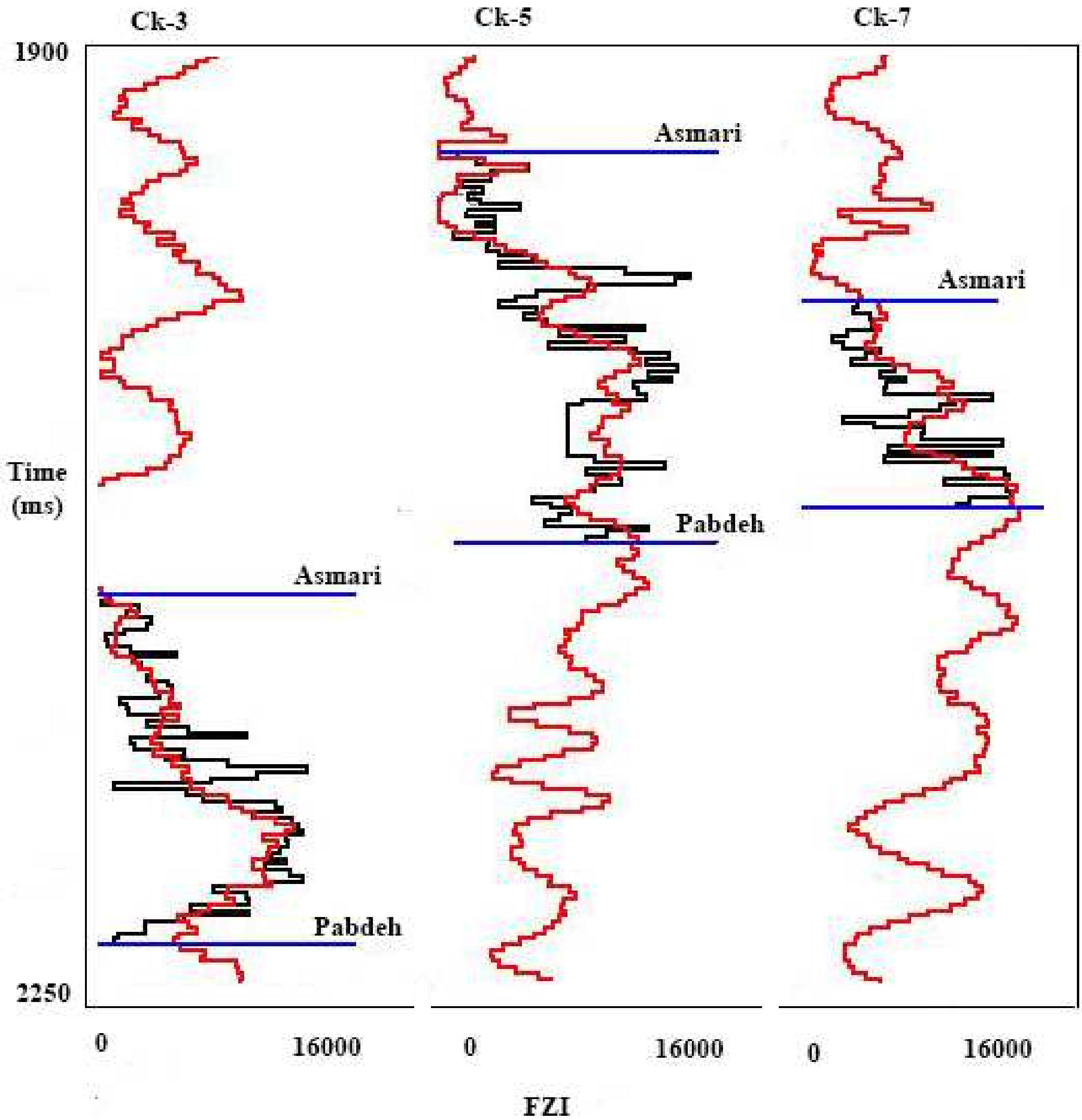

Figure 7
Measured FZI logs (in black) and predicted ones (in red); the correlation of validation data is 0.80.

It is worth comparing the physical property maps with those obtained from the other seismic attributes. A comparison between FZI and acoustic impedance by using multiattribute analysis is presented in Figures 8, 9, and 10. As can be seen, an increase in acoustic impedance decreases the flow zone index and vice versa.

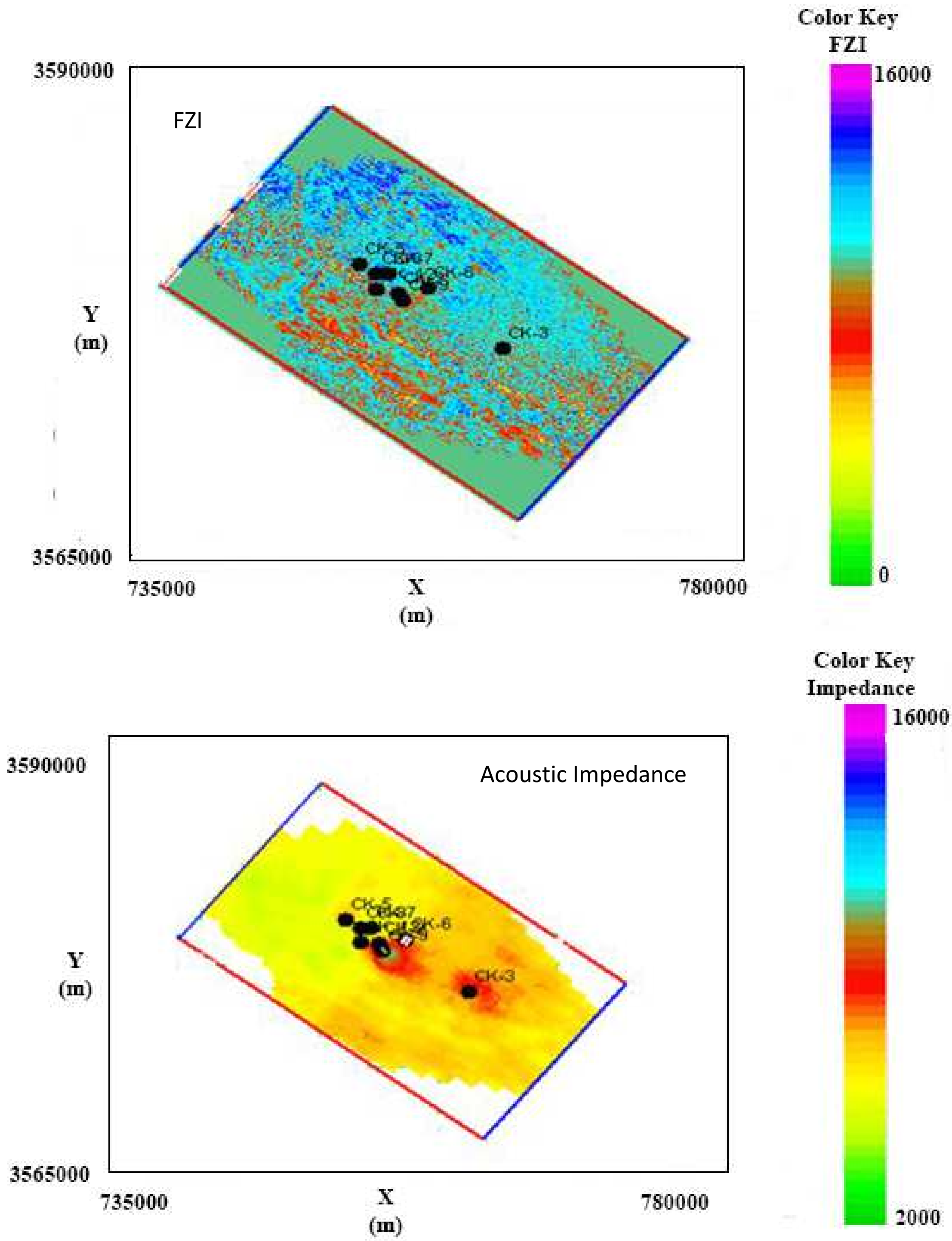

Figure 8
FZI and acoustic impedance volume slice below Asmari horizon +15 ms

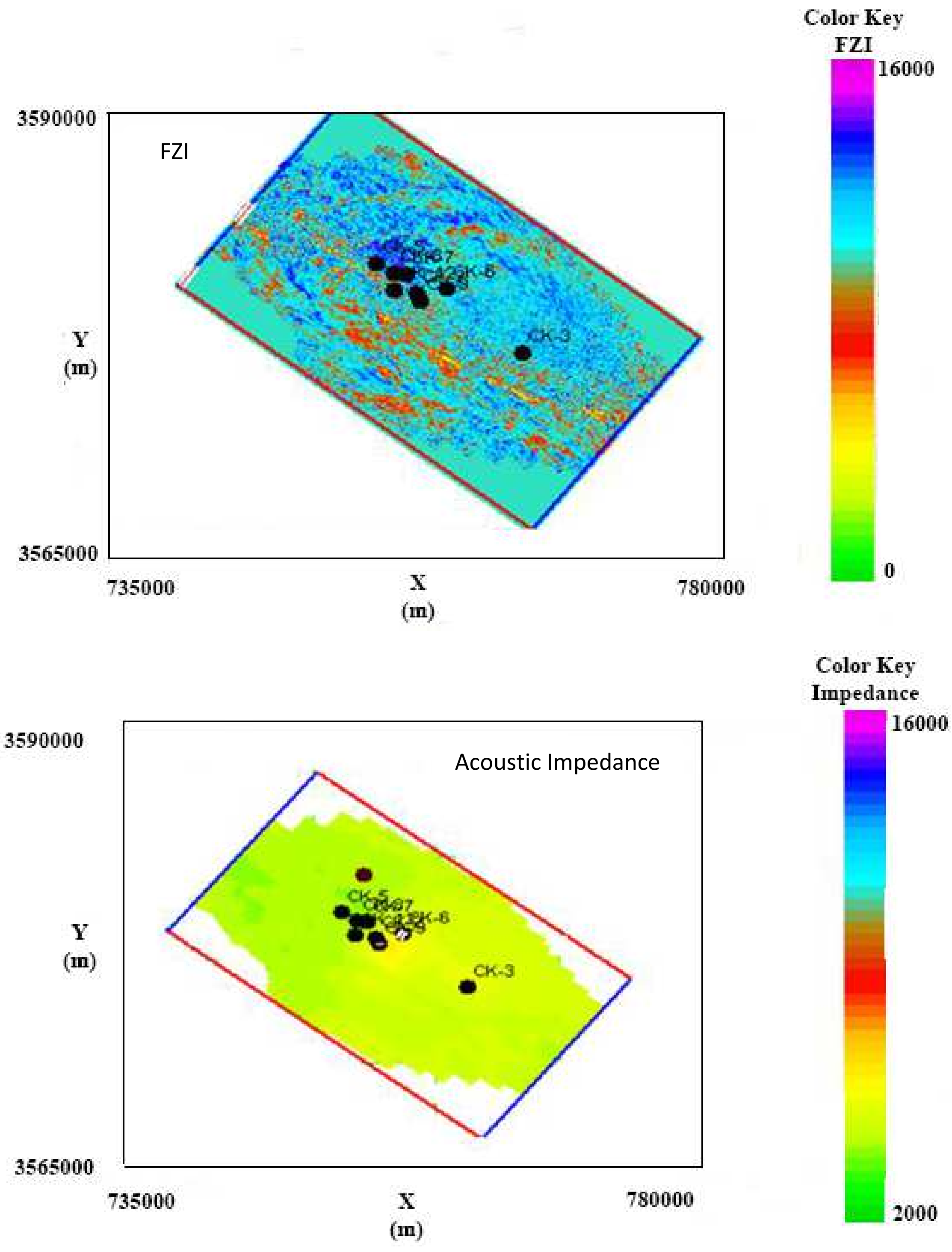

Figure 9
FZI and acoustic impedance volume slice below Asmari horizon +60 ms

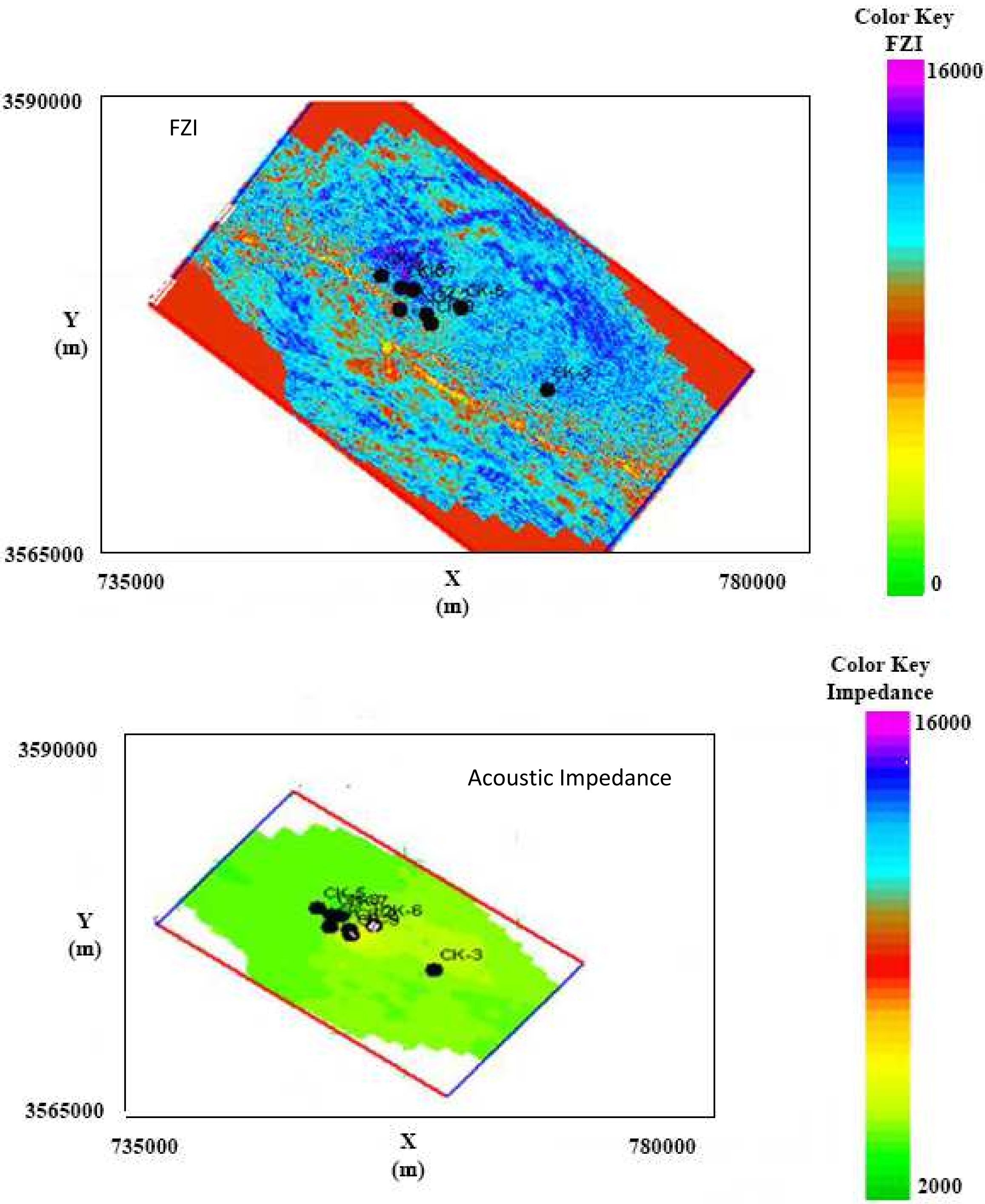

Figure 10
FZI and acoustic impedance volume slice, below Asmari horizon +100 ms

4. Conclusions

Multiattribute analysis was successfully used to predict FZI log from seismic attributes. In the present case study, the predicted FZI log is in good agreement (85%) with the calculated data from the core analysis. The methodology was effectively used to a quick evaluation of the reservoir characteristics through the integration of core data, well logs, and seismic attributes.

The resulting 3D FZI indicates high FZI anomalies, which is correlating well with the petrophysical properties of oil producing wells in the area of study. The intelligent model was applied to inter-well spaces, where well logs and core data were not available. As FZI depends on the geological properties of subsurface rocks, it provides information regarding the locations of future production wells and successful implementation of reservoir stimulation and perforation programs.

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Nomenclature

FZI	Flow zone indicator

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