Case Study of a Cadomin Gas Reservoir (Leland) in the Deep Basin: From Deterministic Inversion to Neural Network Analysis*

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Abstract

This paper provides a case study of a 3D seismic survey in the Leland area of the Deep Basin, where neural network analysis was used in an effort to refine the interpretation of the reservoir properties derived from deterministic inversion. In this case study, identifying the gas sands within the Bluesky, Gething and Cadomin Formation of the lower Cretaceous was the primary interpretive focus. Data for the project consist of 47 wells and one 3D seismic survey. First, petrophysical analysis of the well logs was performed in order to provide a trustworthy set of logs that could be used for inversions and multi-attribute analysis and to determine petrophysical relationships that can be useful on seismic data interpretation. Secondly, we ran AVO analysis and deterministic inversions of the AVO attributes. The P impedance and S impedance volumes were used to estimate rigidity and incompressibility (Goodway et al., 1997) that are very good indicators for lithology and fluids in the target formations of our study. Finally, neural network analysis was performed on logs and pre- and post-stack seismic attributes. Neural network estimation of reservoir properties (e.g. P impedance, S impedance and density) has proven effective in significantly improving accuracy and vertical resolution in the interpretation of the reservoir. In addition to the rigidity and incompressibility maps, we derived porosity maps calculated from density, in an effort to delimit the reservoir and find new opportunities for field development. This methodology helped in discriminating gas intervals and in drilling new locations, derived from this work that encountered new gas charged reservoir.

Introduction

The data consist of a 3D seismic volume, which ties 47 wells. The primary target is the Gething and Cadomin formation of the lower Cretaceous. The reservoir occurs at about 3000 m. The objective of the project is to delineate the porous sands. It is well known and accepted by the industry that inversion is a necessary step in imaging and interpreting the reservoir and there is a continuous struggle to improve the resolution of the inverted volume. In this project, we used probabilistic neural network analysis (PNN) for estimating new seismic volumes by integrating well information and existing seismic volumes (e.g. deterministic inversion results). The seismic volumes were processed through a model-based inversion algorithm to produce P impedance, S impedance and density volumes. These volumes were used as attributes in the neural network analysis.

Method

Petrophysical analysis was performed on all the wells in order to provide a trustworthy set of logs for inversions and multi-attribute analysis. The analysis included edits and corrections for poor-quality log (mainly the density). Missing curves (e.g. shear sonic and density) were estimated using either the specific mud-rock line for the zone of interest or the multi-attribute analysis that allows us to estimate logs from existing logs. Cross-plots of several properties over the target interval show a good separation between gas sand, shale and coals.

AVO analysis was performed using Fatti's equation and a velocity model derived from the correlated wells and seismic. Attributes resulting from this analysis include P-wave and S-wave impedance reflectivities that were inverted to P impedance and S impedance. Simultaneous inversion was later performed on pre-stack time migrated gathers to derive P impedance, S impedance, density and Vp/Vs followed by the calculation of rock properties (Goodway et al., 1997) such as rigidity and incompressibility.

By training a neural network with a statistically representative population of the targeted log responses (P impedance, S impedance or density) and the multiple seismic attribute volumes available at each well, a nonlinear multi-attribute transform was computed to produce P impedance, S impedance and density volumes. Neural network analysis has four steps: 1. perform a multi-attribute step-wise linear regression and its validation, 2. train neural networks to establish the nonlinear relationships between seismic attributes and reservoir properties at well locations, 3. validate results on the wells withheld from the training, 4. apply trained neural networks to the 3D seismic data volume. The multi-attribute analysis was performed for 38 wells using seismic impedances and reflectivities and a seven-point operator. Using the ranking process in commercially available software and, after checking the errors, the attributes for training the network were selected. The same attributes were used in PNN analysis.

Case Study

Deterministic inversion and neural network analysis were applied to a 3D in the Leland area, a Cadomin gas reservoir in the deep basin, in an attempt to get a better definition of the gas sands and to better differentiate between gas sands and coals in the Lower Gething.

In this paper, we discuss how neural network analysis for estimating P impedance and density volumes improved the results from deterministic inversion. The resulting logs from petrophysical analysis were used in the neural network analysis. Only the well ties with good correlations were used on the analysis. As a result, 38 out of 47 wells were used on the analysis. Validation analysis was used to ensure that the neural network (and the multi-attribute) analysis was not over predicted (Hampson et al., 2001).

Neural network analysis for P impedance used the calculated P impedance logs as target logs and the migrated seismic volume and the P impedance volume. The attributes determined to be of value for estimating the P impedance within the reservoir were:

1. P impedance from deterministic inversion,
2. amplitude weighted phase of the migrated stack,
3. amplitude weighted cosine phase of the migrated stack,
4. integrated absolute amplitude of the migrated stack and
5. instantaneous phase of the migrated stack.

The correlation was 86% on the validation of the neural network analysis.

P impedance results from model-based inversion (Figure 1a and Figure 2a) are compared with the P impedance results from neural network analysis (Figure 1b and Figure 2b). Inserted in color in Figure 1 is the P impedance log from a poor well. P impedance results from neural network analysis show a better correlation with the log and have a better definition of the Mannville coals. P impedance values at the horizon slice Cadomin+6ms are lower on the neural network analysis and correlate much better with well information. Refining the P impedance with neural network analysis is a necessary step in improving the rock physics results (e.g. rigidity and incompressibility).

Density is a useful property in differentiating porosity within sands. Neural network analysis for density used the petrophysical analysed density logs as target logs and six seismic volumes available from AVO and inversion in a similar approach as presented in a previous paper (Dumitrescu et al., 2005). The attributes used to estimate density within the reservoir were:

1. P impedance,
2. S impedance,
3. amplitude envelope of the P-wave impedance reflectivity,
4. integrate absolute amplitude of the S-wave impedance reflectivity,
5. filter 35/40-45/50 of the migrated stack,
6. integrate of the S-wave impedance reflectivity and
7. instantaneous frequency of the P-wave impedance reflectivity.

Figure 3 presents some density results from (a) simultaneous inversion and (b) neural network analysis, at one seismic line that intersects a good well. Density volume from simultaneous inversion is just a first approximation of the density volume. Since we have only up to 29 degrees on the angle gathers the density results are based on the relationship derived between density and P impedance on the petrophysical work. The density results from the neural network analysis correlate better with wells available on the 3D even if the wells have not been used for the analysis. By this method, density can be estimated from data, which does not have enough offsets for three term AVO.

The density volume from neural network analysis was used to estimate the porosity using a standard linear-density relationship (Figure 4). The horizon slice at Cadomin+6ms on the computed porosity volume shows good definition of the reservoir. It is clear that the estimated seismic volumes from neural network analysis provide meaningful information in identifying the gas sands. It is a good idea to compare the physical property maps with maps obtained from other attributes. In Figure 5, we present a comparison between (a) semblance and (b) porosity on a horizon slice at Cadomin+6ms. Semblance is an attribute calculated from the migrated stack and is a good indicator of structural features.

Conclusions

We presented a case study for improving the resolution of different seismic volumes (e.g. P impedance and density obtained from deterministic inversion) by using neural network analysis. The derived neural network results show strong correlation with the target logs, both at training well locations and for the rest of the wells suggesting that rock properties can be accurately estimated with neural network analysis when deterministic inversion results are used as external attributes in training the network. The results of this analysis have correlated well with recent drilling making the neural network analysis part of the workflow for future projects.

Acknowledgement

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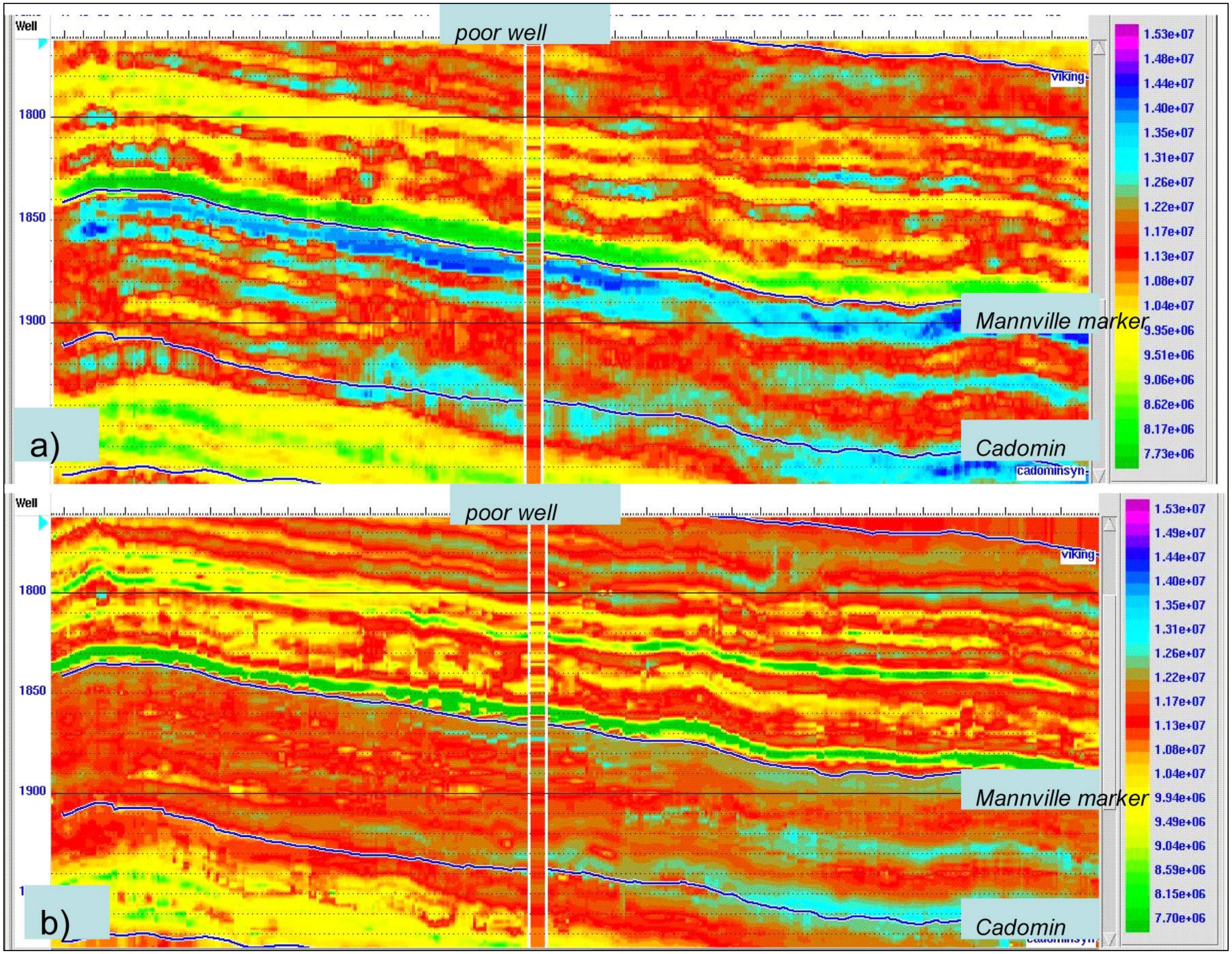

Figure 1. P impedance results from (a) model based inversion and (b) neural network analysis. Inserted in color is the P impedance log that correlates much better with neural network results.

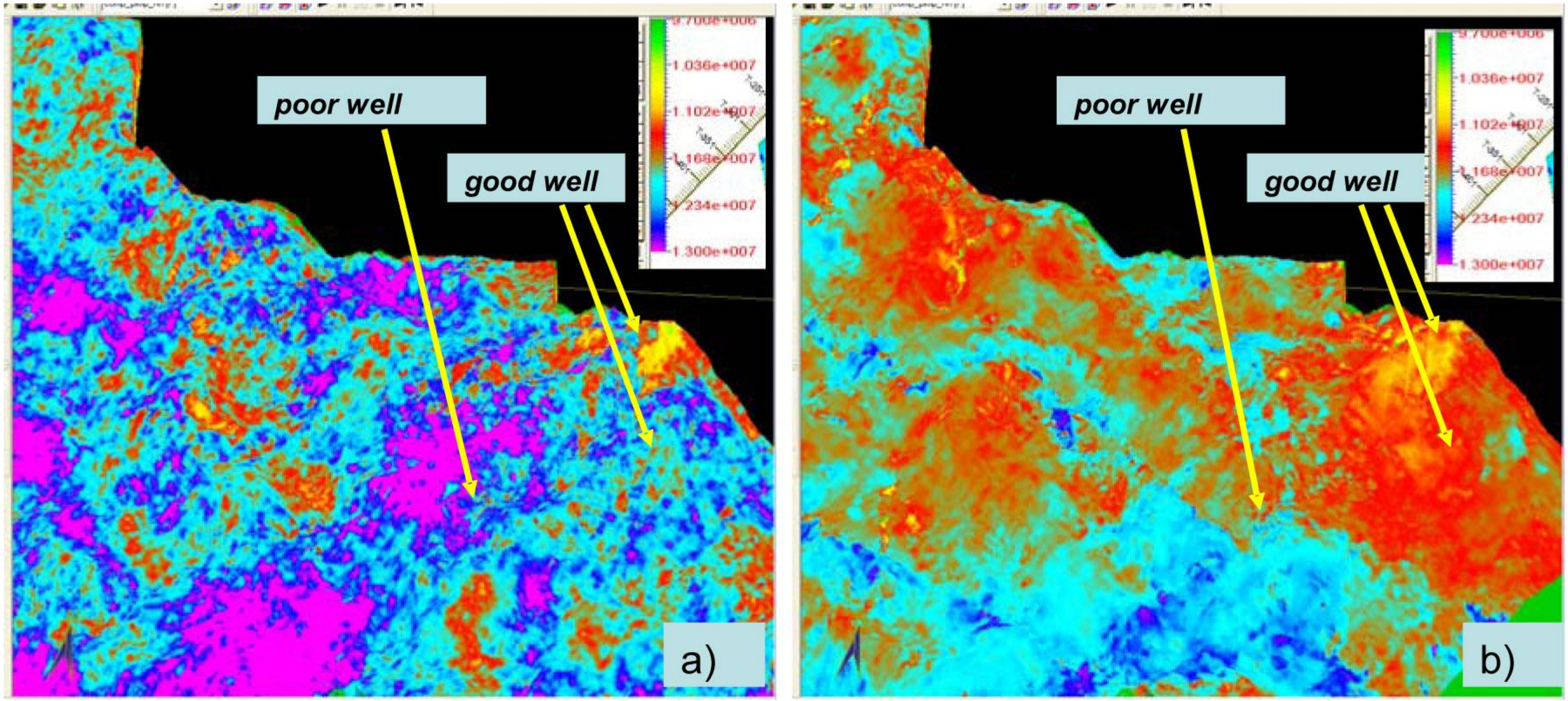

Figure 2. Horizon slice at Cadomin+6ms of P impedance results from (a) model based inversion and (b) neural network analysis.

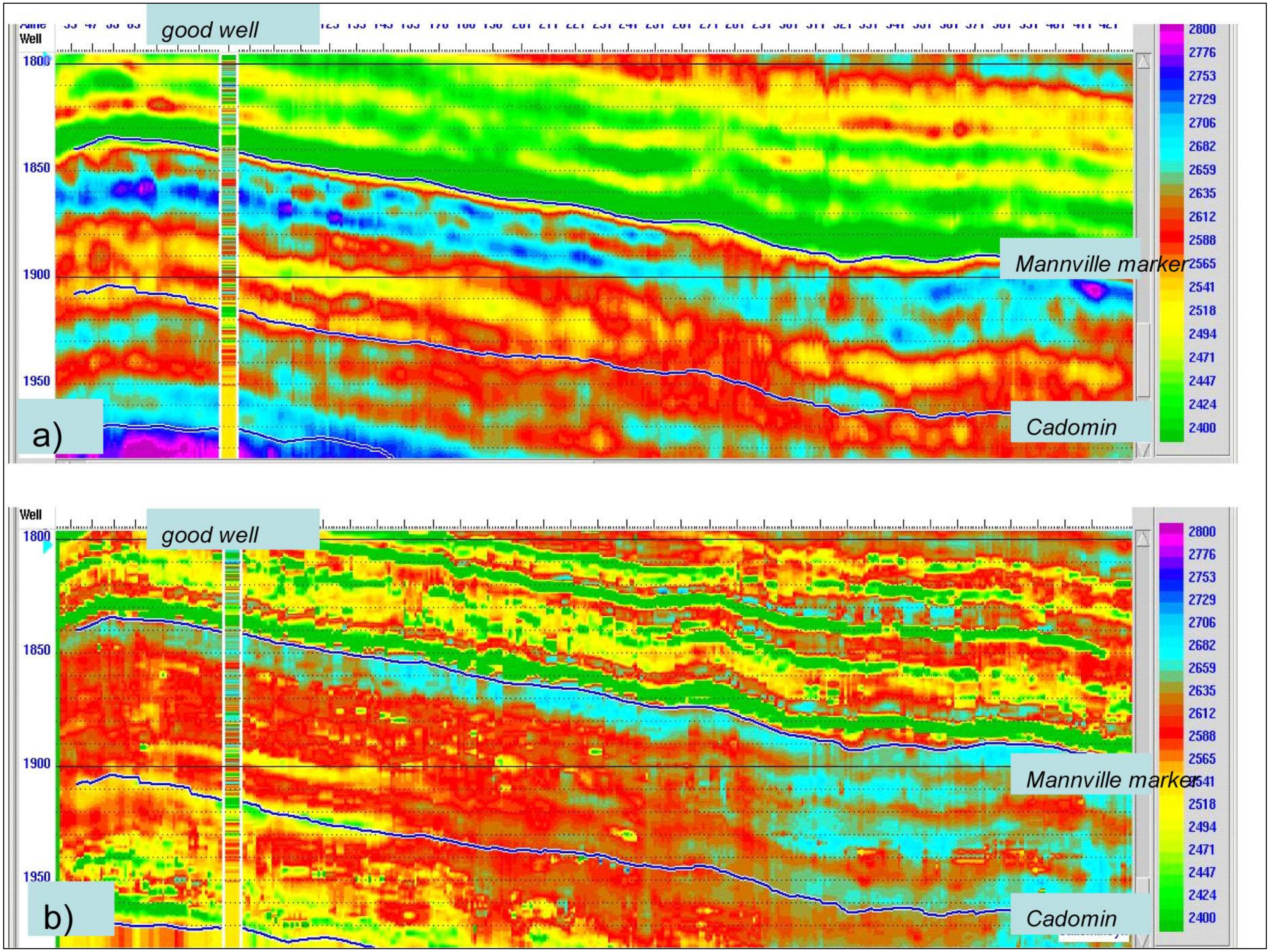

Figure 3. Density results from (a) simultaneous inversion and (b) neural network analysis. Inserted in color is the density log, which correlates much better with neural network results.

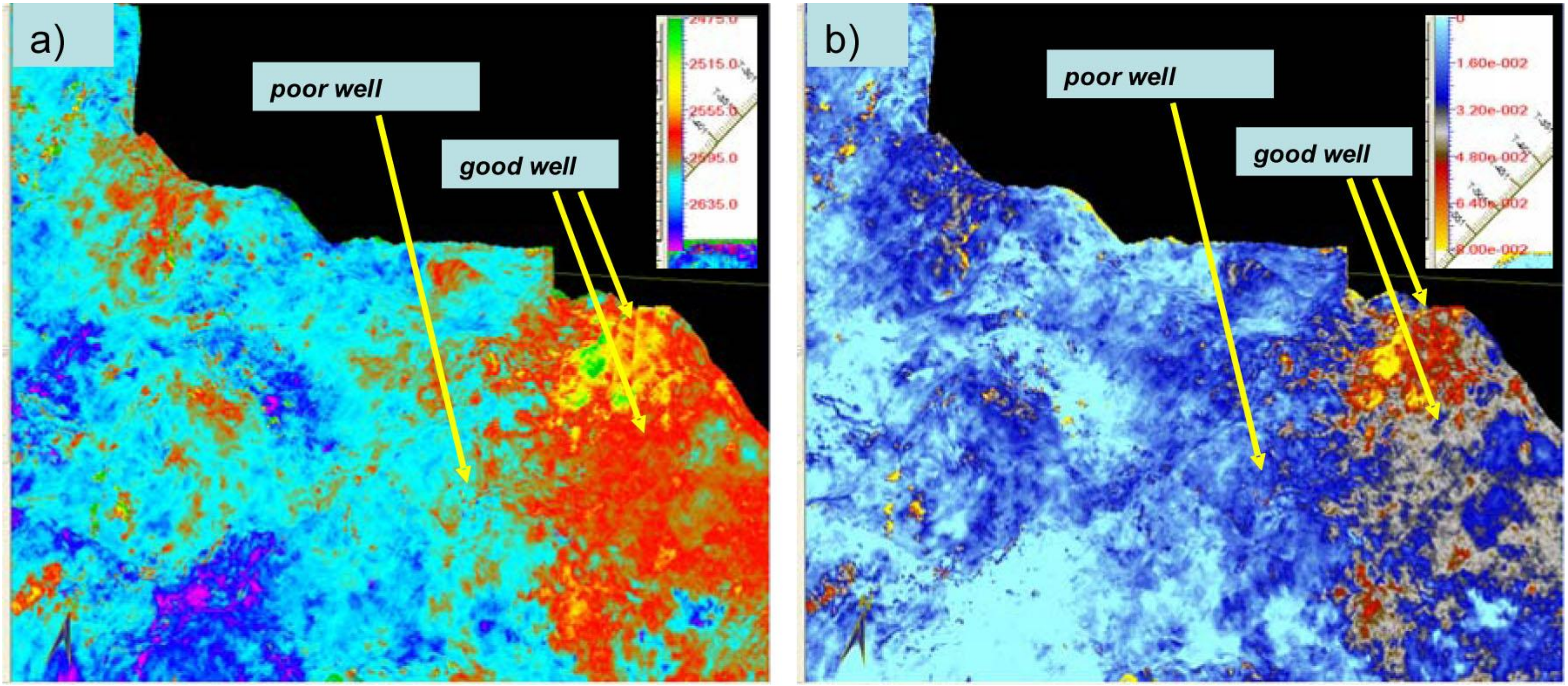

Figure 4. Horizon slice at Cadomin+6ms of the (a) density results from neural network analysis and (b) porosity results from the inverted density response using a standard linear-density relationship. Note the distinct separation of sand from silt and shale.

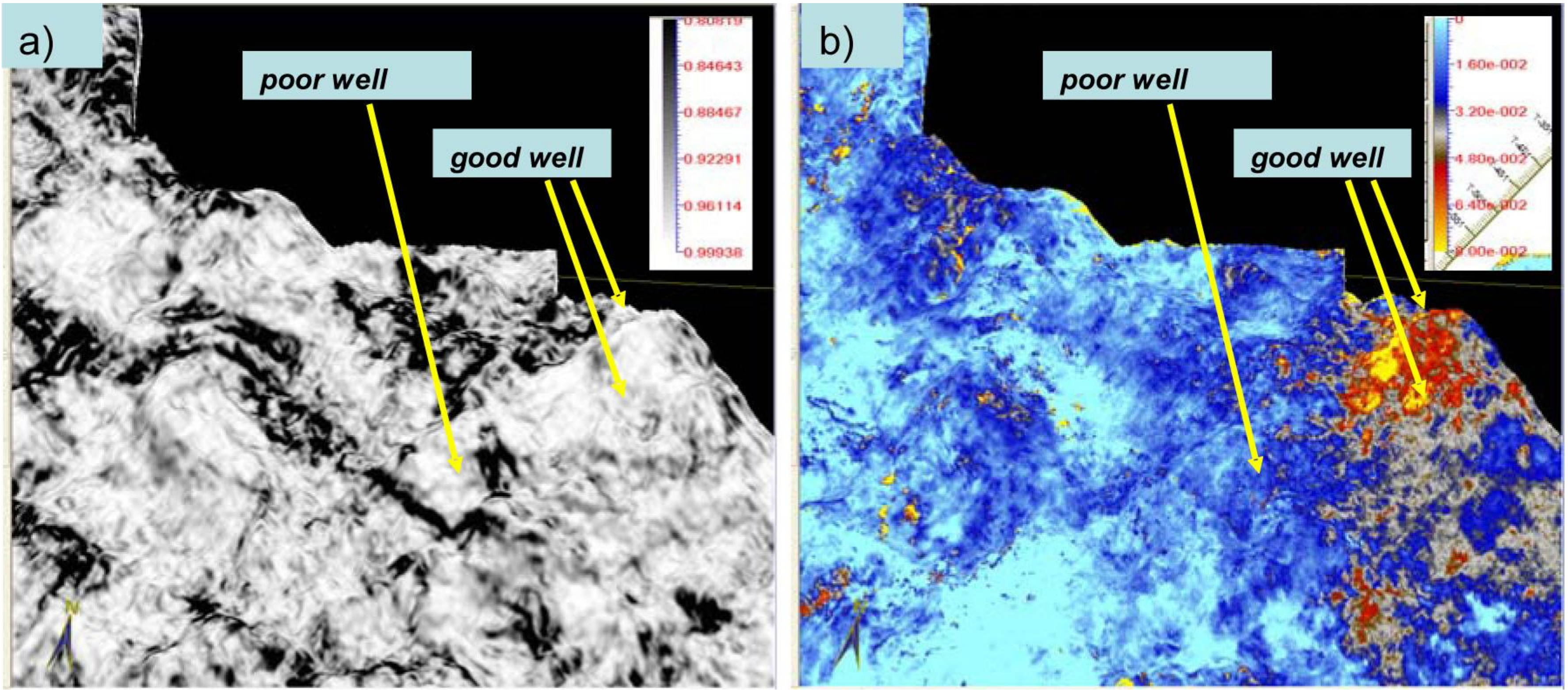

Figure 5. Horizon slice at Cadomin+6ms of the (a) semblance and (b) porosity results.