Extending reservoir property prediction with pseudo-wells

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Abstract

We discuss a procedure called the 'Hit Cube' which assigns spatial positions to stochastically simulated pseudo-wells, i.e., 1D stratigraphic columns with attached well logs, with the aim of quantifying probable reservoir properties and their quality throughout a seismic data volume. We generated two sets of pseudo-wells ('hit targets', e.g., gas-filled units; and 'false hits', e.g., brine-filled units) using real well data, geological knowledge and Monte Carlo statistics. From these models, we constructed scaled synthetic seismic traces using a composite statistical wavelet extracted from the seismic data. We then matched the models with the real traces throughout the seismic volume. At any given location within the seismic cube, we assume that the rock properties defined in the pseudo-wells are similar to those represented by the seismic data if the similarity between the real and synthetic traces satisfies a predefined hit criterion. Final results of this process are likelihood cubes, which can easily be interpreted or used for further analysis. We have used this technique to correctly predict hydrocarbon presence and distribution within a deltaic sequence containing gas-filled and brine-filled channel sand deposits.

Introduction

The integration of multi-disciplinary data and prior knowledge reduces uncertainties associated with the exploration, development, and management of hydrocarbon reservoirs. The integration process, known as reservoir characterization when applied to a reservoir interval, combines information from a wide range of sources including seismic data and/or attributes, well tests, well logs and cores, and any other data that can be correlated, directly or indirectly, to reservoir properties such as porosity, permeability, saturation, thickness, and lithofacies. However, the number of wells in a study area often limits the integration of seismic data and seismic-derived attributes with reservoir properties obtained from well data. Where only a few wells have been drilled, which is the case at the early, mid, and sometimes even the late stages of most oil/gas field developments, the statistical requirements for such integration are not satisfied. To compensate for the paucity of real wells penetrating reservoirs to be characterized, the use of stochastic (e.g., de Groot, 1995; Oldenziel et al., 2002) and deterministic (e.g., Spikes and Dvorkin, 2004) pseudo-wells has been demonstrated.

Our emphasis throughout this paper is on stochastic pseudo-wells. In general, information from simulated wells ensures better statistical representation than can be achieved with only real wells (e.g., Nakayama and Hou, 2002). The fundamental assumption is that the units seen in any well within a study area are not standalone columns, but have spatial petrophysical and stratigraphic relationships with other units in the area. By analysing the petrophysical and stratigraphic relationships between lithological units in the real wells, and using our knowledge of the depositional system, we construct an integration framework which defines characteristics and relationships between units and sub-units that serve as building blocks for all real and pseudo-wells. A schematic illustration of a stratigraphic integration framework for a particular case study is shown in Figure 1. Based on the integration framework, we then construct the pseudo-wells using Monte Carlo simulation (Mardia et al., 1979; Deutsch and Journel, 1992). Figure 2 shows sample logs from pseudo-wells showing the top and base of the reservoir in each case.

Since the simulated pseudo-wells represent the stratigraphic sequence and probable rock physics properties at locations within a study area, it is possible to directly correlate rock properties defined by these wells to the seismic signature at spatial positions within a seismic cube. The Hit Cube algorithm assigns spatial positions to stochastically generated pseudo-wells with the aim of predicting possible reservoir properties and/or quality, together with relative uncertainties throughout the seismic cube.

We have generated two pseudo-well groups based on the same integration framework. The first group, called the 'hit targets', consists of stratigraphic units with desirable reservoir properties (e.g., high net-to-gross, hydrocarbon-filled channel sands), while the 'false hits' are statistically equally possible stratigraphic units with undesirable reservoir properties (e.g.,

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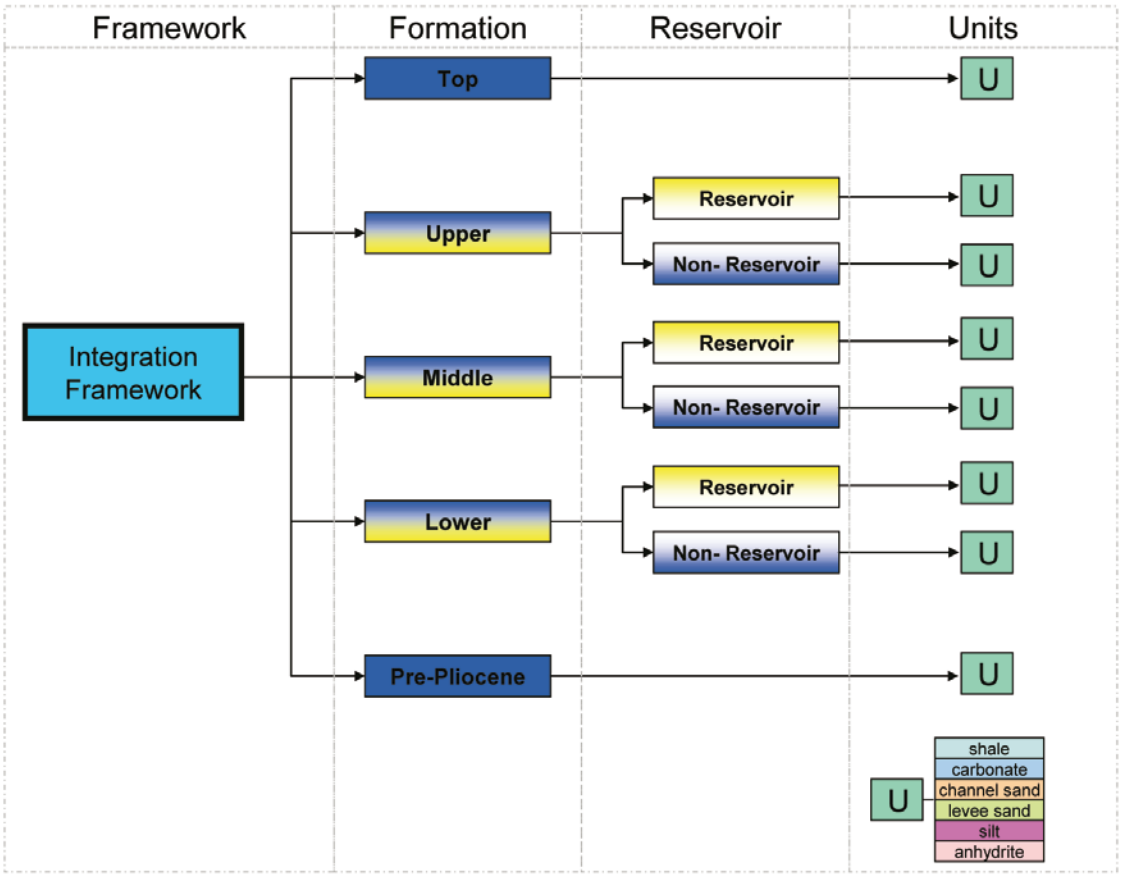

Figure 1 *Schematic illustration of a stratigraphic integration framework showing different levels of interpretation and integration of the framework units. Each column represents components of different hierarchies of integration. The illustration is for the case study discussed later in this article, and depends on the particular stratigraphic environment being studied.*

low net-to-gross hydrocarbon or brine-filled channel sands), which may or may not have similar seismic characteristics to the target units. We then constructed synthetic seismic traces, scaled to the real seismic amplitudes, for each set of pseudo-wells using the same statistical wavelet extracted from the seismic data and matched them with the real traces throughout the seismic volume. A 'hit' exists when the similarity between the model and real seismic traces exceeds a predefined threshold. If this hit criterion is satisfied, we assume that the rock properties defined by both the real and synthetic traces are similar within the limits of the predefined uncertainty criterion. Outputs from this procedure include cubes of the number of hits, 'scores' (cumulative similarity coefficient) and 'winner wells' (models with highest similarity) at each sample position. By comparing the hit-target and false-hit outputs at each point, we obtain an estimate of the likelihood that the properties of our targets are indeed present at those points. Likelihood cubes are obtained as a ratio of the hits (and scores) of the targets to those of the false hits throughout the cube.

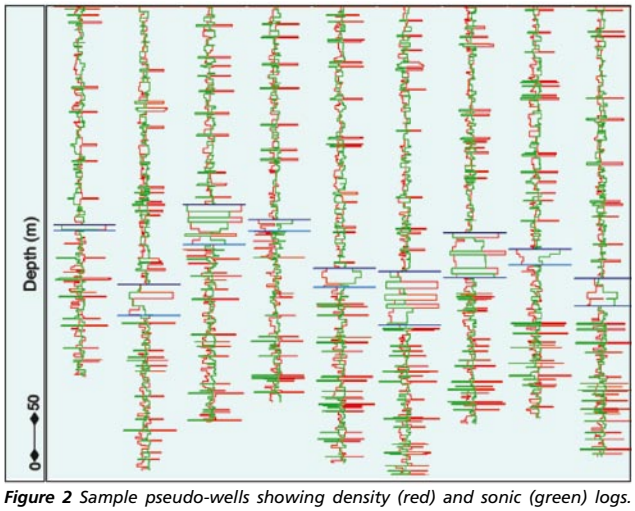

Figure 2 *Sample pseudo-wells showing density (red) and sonic (green) logs. The blue markers in each well show the top and base of the stratigraphic unit being studied.*

In the following sections, we summarize this procedure and show some results from the investigation of reservoir presence and distribution in a deltaic setting.

The workflow

Stochastic pseudo-wells are generated using information from the real wells and geological knowledge of a study area defined in a stratigraphic integration framework using

Figure 3 *An illustration of the main data types (yellow boxes) and processes (red boxes) used to generate the synthetic and scaled real seismic traces (blue boxes) required in the matching process.*

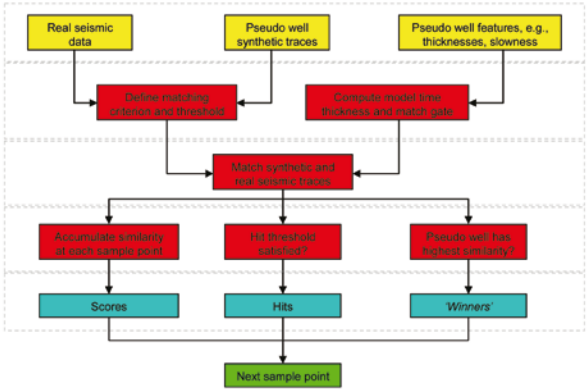

Figure 4 *Hit cube algorithm showing the input parameters (yellow boxes), processes (red boxes), and final outputs (blue boxes).*

Markov chain analysis and Monte Carlo statistics (de Groot et al., 1996). An understanding of geological setting and the construction of a robust integration framework are fundamental preliminary steps to obtaining reliable models which actually represent the geological possibilities in the area being studied. The available information, with their different dimensions and widely varying scales and accuracies, are combined into a single consistent generic framework. Each framework unit (stratigraphic and lithological building block) is assigned to a category (e.g., 'seal', 'reservoir' or 'waste') and values are specified for its physical properties (e.g., acoustic impedance, thickness, porosity, permeability). The framework units form the building blocks for describing different geological models, which in our application are real or simulated wells.

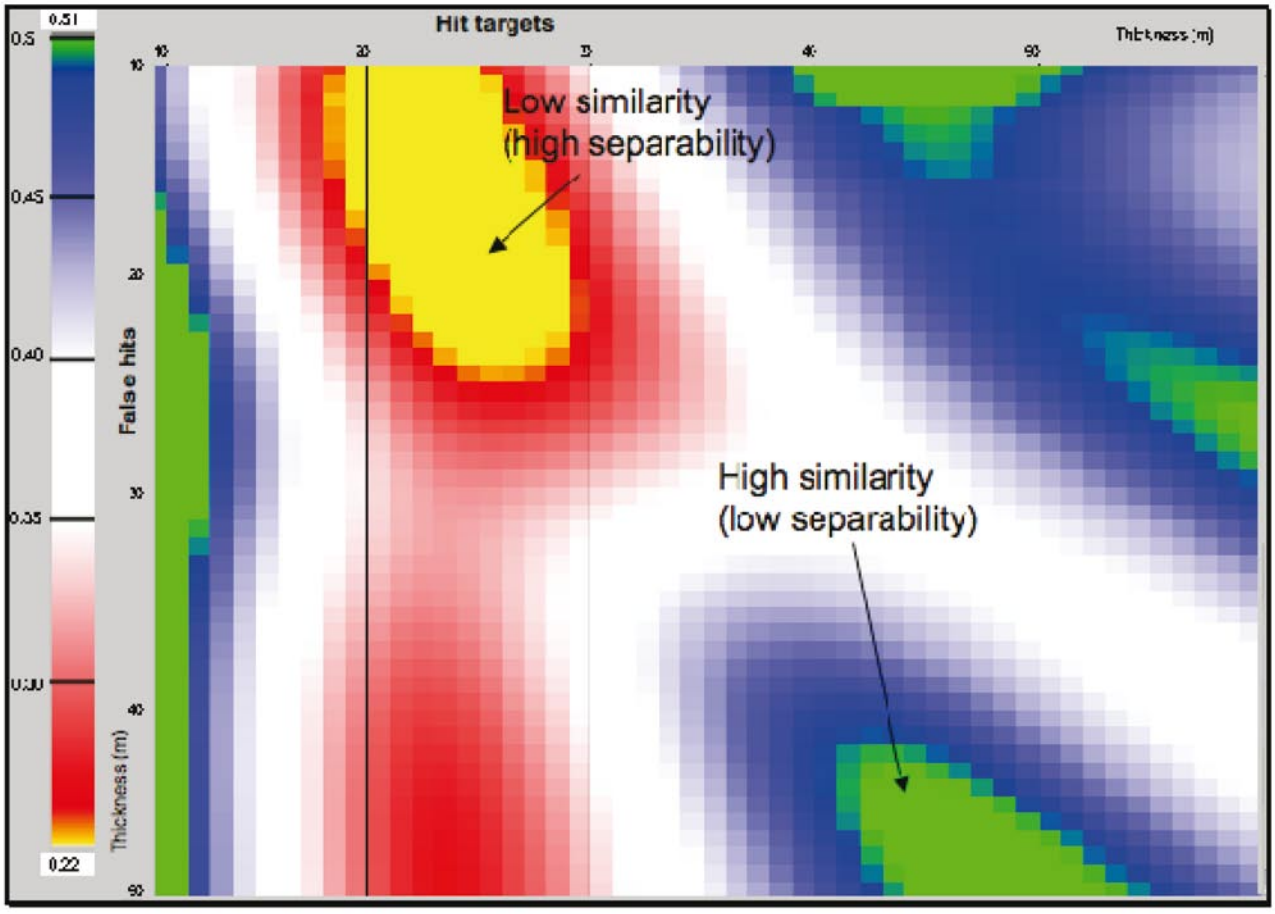

Figure 5 *Similarity field for a simple wedge-shaped sand-shale model. The hit targets are hydrocarbon-filled sand units overlain by shale, with the only variable in each group being the thickness of the sand units. Zones of high similarity (green) cannot be well separated by this procedure, while those with low similarity (yellow) can easily be separated. In this example, a similarity threshold greater than 0.51 is sufficient to separate most models in the two sets.*

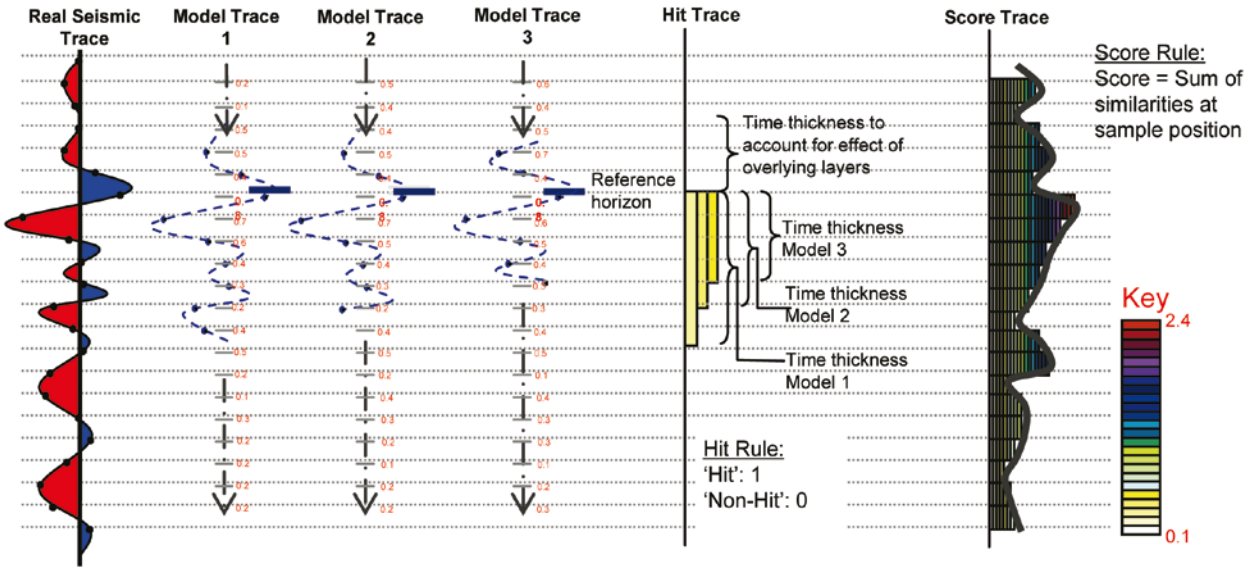

Figure 6 *Schematic illustration showing how the hit and score traces are computed.*

A review of some practical geological considerations in the construction of geological frameworks was given by de Groot et al. (1996). In the simulation procedure, the pseudo-wells are constructed one-by-one, unit-by-unit, and variable-by-variable. Therefore, it is possible to determine at any time whether a variable must be simulated and which constraints should be satisfied. As mentioned above, we have simulated two well groups:

- Hit targets – pseudo-wells with desirable properties (e.g., thick gas-filled units)
- False hits – pseudo-wells with undesirable properties (e.g., brine-filled units)

After accounting for fluid effects, synthetic seismic traces are generated for all pseudo-wells using an effective wavelet that is extracted statistically from the seismic data. We invoke the convolutional model and assume that the effective wavelet is invariant throughout the segment of the seismic volume being studied. Finally, the real and synthetic seismic traces are scaled to similar amplitude ranges before the matching proceeds. This workflow (Figure 3) may be repeated for different sets of pseudo-wells to study specific reservoir properties which are incorporated into the simulation procedure.

The algorithm

In the algorithm, the synthetic traces are matched with real traces at every sample point throughout the seismic volume with the assumption that the seismic data contain minimal noise. It is also assumed that the seismic processing is true-amplitude and that the convolutional model used to generate the synthetics is valid.

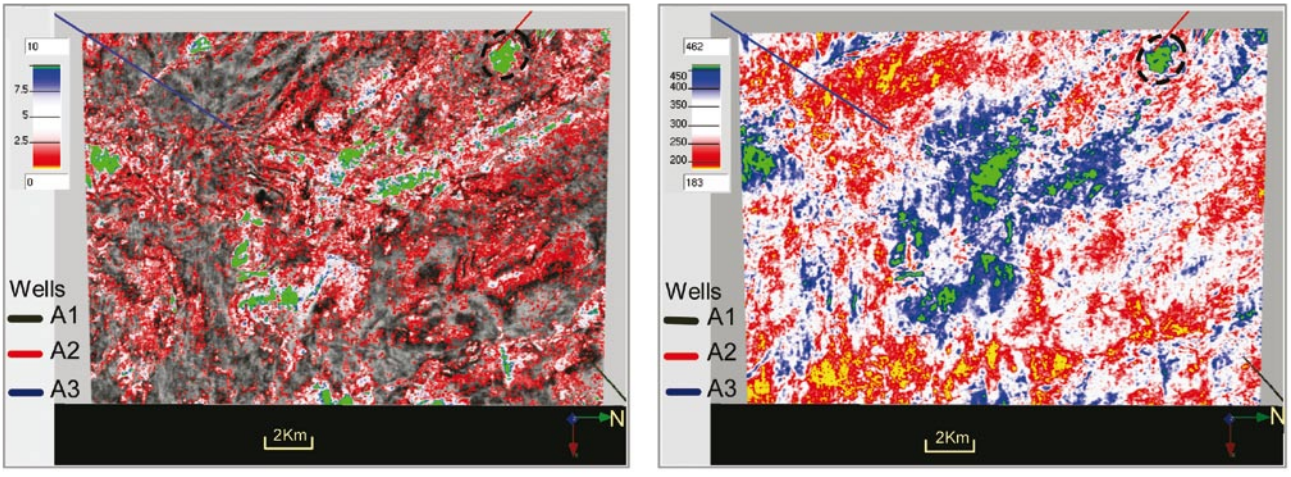

Figure 7 *Time slice showing (a) hits overlying real seismic data (greyscale) and (b) scores for the hit targets in the case study. In both figures, green indicates zones with high hits/scores, while yellow and red indicate zones with low hits/scores. The hits are clipped at 0.2 to show the real seismic data. The red, blue, and black lines indicate the three well locations.*

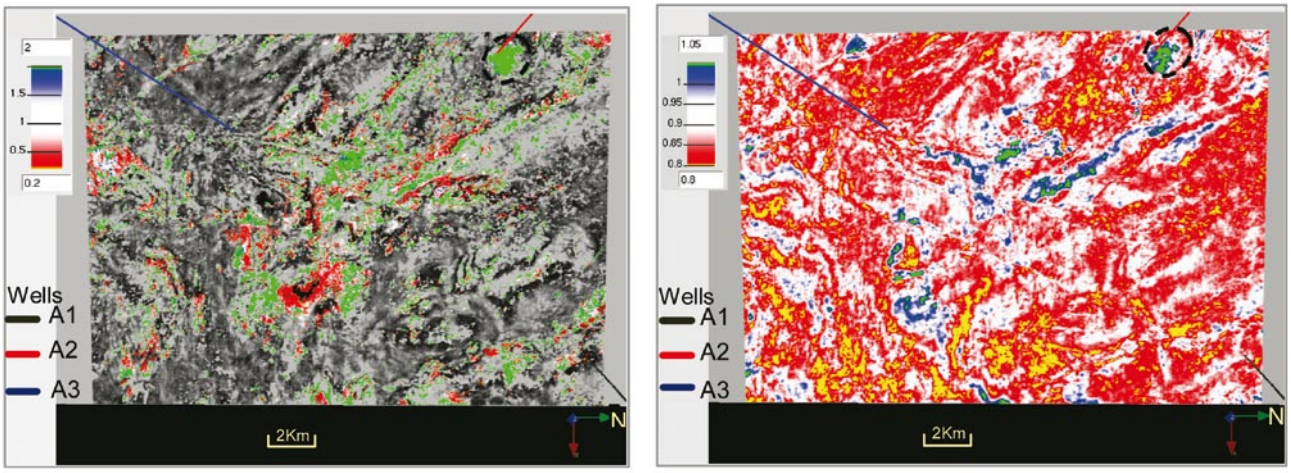

Figure 8 *Time slice showing (a) likelihood of hydrocarbon presence and (b) likelihood scores. In both figures, green indicates zones with high hits/scores, while yellow and red indicate zones with low hits/scores. The likelihood of hydrocarbon presence is overlain on the real seismic data (greyscale) and is clipped at 0.2. The three well locations are indicated by the red, blue, and black lines.*

The similarity coefficient, s, is defined as

$$s = 1 - \frac{|v_1 - v_2|}{|v_1| + |v_2|}, \quad (1)$$

where v_1 and v_2 are the two trace segments being compared. The trace segments used in the matching process are defined by the time-thickness of the unit computed from the simulated well logs plus half the period corresponding to the dominant frequency in the seismic wavelet. If the similarity between the real and synthetic traces exceeds a specified threshold, rock properties defined by both are considered similar and a hit is recorded. The algorithm structure is shown in Figure 4. The desired minimum useable similarity threshold is determined as the degree of separability of the pseudo-well models which could be assessed either by cross-matching all the hit targets and false hits and/or by using the composite similarity plots for a wide range of possible rock property changes. Figure 5 shows the similarity field for a simple wedge-shaped model.

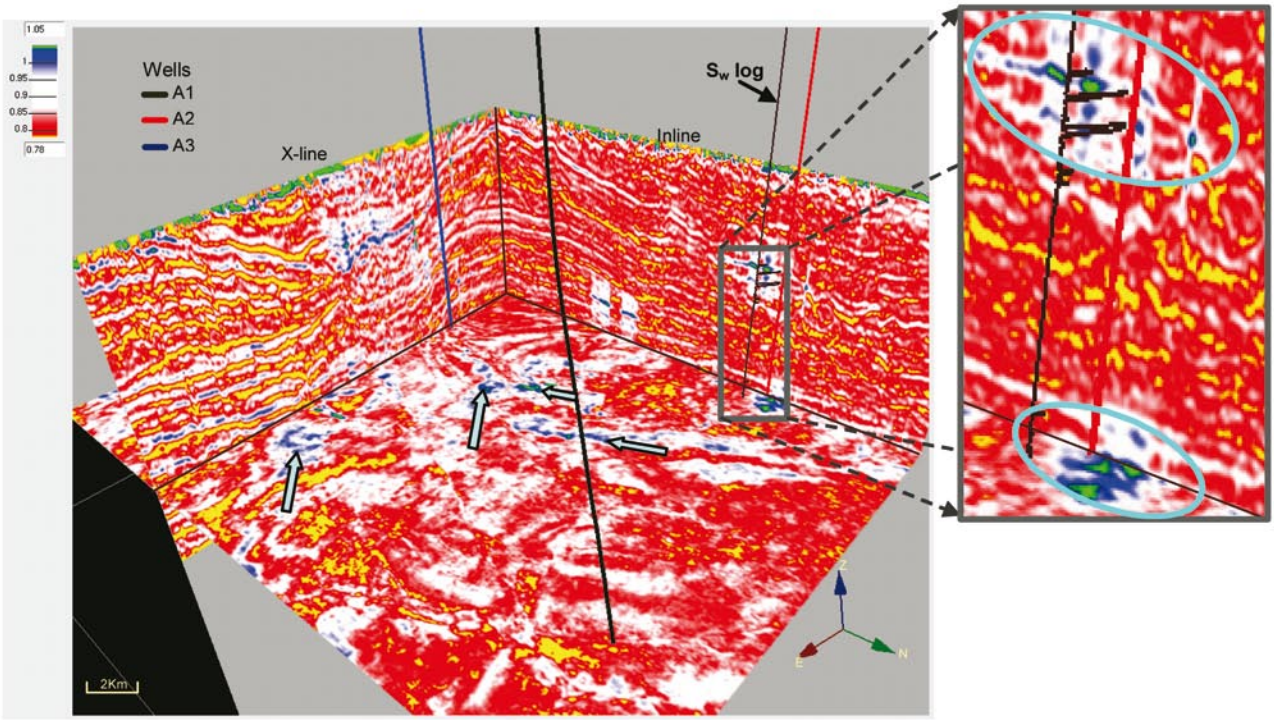

Figure 9 *Three-dimensional view of the likelihood score cube. Green and blue indicate zones of high likel hood of hydrocarbon presence, while yellow and red indicate zones of low likelihood. The highlighted spikes in the water saturation log (clearly seen in the enlarged image) in well A2 indicate locations where hydrocarbons are known to be present in the well. The blue arrows indicate channel features with high likelihood scores. Similarity threshold: 0.65.*

Outputs

The primary output cubes include:

- Hits – binary sums of equivalent time-thickness of the model
- Scores – sums of similarity coefficients of the targets over the time-thickness of the model
- Winners – models with highest similarity coefficient at each sample point

Figure 6 shows how the hit and score traces are computed. Secondary outputs include:

- Likelihood of presence – ratio of the target hits to false hits
- Likelihood score – ratio of target-hit scores to false-hit scores

Case study

Using this procedure, reservoir presence and distribution within a 3D time-migrated seismic dataset (area 20×14.4 km^2; TWT range 1400 –2800 ms) from an offshore deltaic setting were investigated using a complete suite of blocked logs (gamma, sonic, density, etc.) from three real wells (A1 to A3) being used as controls. Several maximum flooding surfaces separate different depositional bodies, the youngest of which shows fluvial-marine interaction, in the prograding Pliocene system. Fine-grained clastic sediments of Pliocene age dominate the study area, encasing sand-rich channel systems that are major hydrocarbon exploration targets.

Based on our understanding of the stratigraphic complexity, two sets of 100 stochastic models each were generated for the hit targets (high net-to-gross units with low water saturation) and false hits (low net-to-gross units with a range of water saturations and high net-to-gross units with high water saturations). The cross-matching results (not shown) suggest a minimum useable similarity threshold of 0.55. Selected hit, score, and likelihood results, at 0.65 similarity threshold, in parts of the seismic volume are shown in Figures 7 and 8. The potential gas-filled units define channel features known to be present in the study area. However, note that not all the channel features show a high likelihood of hydrocarbon presence. There is a good match between the likelihood results and water saturation logs from well A2 (Figure 9), and also from segments of A1 and A3 (not shown).

Conclusions

We have discussed a procedure that allocates spatial locations to stochastic pseudo-wells within a seismic volume. Prediction of reservoir presence and hydrocarbon distribution using this procedure has also been demonstrated. In the case study, predicted reservoir distribution defines distributary channel systems known to be present in the study area. Water saturation logs in the three real wells confirmed accurate prediction of hydrocarbon presence. Further tests and development of the concept and algorithm (e.g., to include AVO effects) are ongoing.

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