Populating a PSDM created earth model with PSTM predicted seismic properties

Arnaud Huck[1], Matthijs De Rooij[1], Paul De Groot[1], Christian Henke[2], and Stephan Rauer[2] address a key issue in quantitative seismic prediction.

When an earth model is constructed from depth migrated seismic data and porosity is predicted from time migrated data, we are confronted with spatially inconsistent information. To use the predicted porosities in the earth model the data needs to be converted to depth and re-positioned. In this case study, we present a pragmatic approach in which porosity trace positions were shifted after depth conversion to their correct x/y positions followed by a vertical depth-to-depth transformation to correct the remaining misfit. The x/y shifts were calculated by image ray map migration in the earth model. Porosity was predicted from 3D time migrated data by acoustic impedance inversion followed by pseudo-well modelling and neural network inversion.

With the increasing popularity of pre- and post-stack depth migration more and more earth models are constructed from horizons mapped on depth migrated data. Populating such models with seismically derived (reservoir) properties is not a trivial task, because properties are usually predicted from seismic data in two-way time. Seismic inversion and forward modelling techniques require a seismic wavelet. In depth, the concept of a seismic wavelet does not exist, as the wavelet is distorted by the time-depth transformation. This problem is often solved by changing the depth migrated volume back to time by a vertical depth-to-time transformation and using the resulting time volume for further quantitative analysis. Transforming the predicted properties back to depth is the way to populate the earth model. However, this procedure assumes that amplitudes have been preserved by the depth migration and subsequent depth-to-time transformation processes. This is questionable, which is why many quantitative interpretation specialists prefer to predict seismic properties from conventional time migrated data. Using the predicted seismic properties in a depth migrated earth model poses another problem: the properties are not predicted at the correct spatial positions, hence need to be corrected before they can be used to populate the earth model.

Data set and geological setting

We base our analysis on a case study of a gas storage facility onshore Germany that has been operational since the 1970s. Gas is stored and retrieved from a chalky limestone called 'Lithothamnienkalk' at some 2900 m depth. The Lithothamnienkalk main reservoir unit is approx. 45 m thick and has porosities in the 10-20% range. The reservoir is sealed vertically by the so-called 'Sannois-Fischschiefer' at the top, a marly shale interval overlying the Lithothamnienkalk and laterally by juxtaposition against impermeable formations. When the storage facility is at full capacity it is believed to be filled near to spill point, which is to the north of the structure, Fig. 1.

A study was initiated to investigate the influence of horizontal wells on the capacity of the gas storage. To improve the quality of directional drilling through the narrow upper part of the reservoir additional 3D seismic data was highly recommended. A 3D seismic data was acquired in 2003. The vibroseis dataset covers an area of approx. 75 km^2 with 25 x 25m bin spacing. The data were processed to different volumes including pre- and post stack depth and time migrated products. Eventually the pre-stack depth migrated data were selected for mapping the structural framework for the earth model and a time migrated volume - especially processed for optimal preservation of the seismic amplitudes - was used for further quantitative analysis.

Twenty wells are located within the seismic survey area, 14 of which are located inside the gas storage facili-

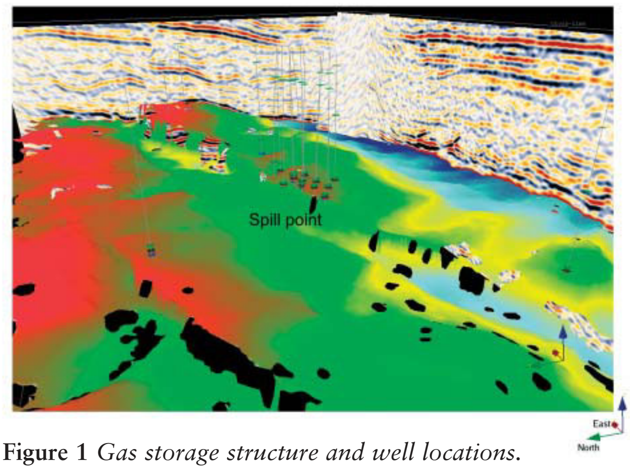

Figure 1 *Gas storage structure and well locations.*

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ty area. Only two wells have complete logging suites with sonic, density, vshale, porosity, and water saturation. To complete the well log database, neural networks were trained to predict missing and incomplete logs (Ligtenberg and Wansink, 2002). In order to obtain reliable results, the prediction of a log was based on several other logs, preferably three or more. Since the database was used to predict and calibrate seismic properties, we required that one of the input logs must be either sonic or density. Wells with neither sonic nor density were not considered for further work. Neural networks were trained per geological interval to complete the database that eventually consisted of 13 wells with complete logging suites over the relevant interval, Fig. 2.

Quantitative seismic analysis

In this study several quantitative interpretation workflows were applied for different objectives. Some workflows are fast and aimed at increasing our understanding of the seismic response, others are more laborious and aimed at predicting properties with uncertainties. All workflows make use of modelled pseudo-wells (de Groot, 1995). In the context of this study a pseudo-well is a high-resolution one-dimensional model of the earth that consists of geological layers with attached well log properties but which does not have a spatial location. Pseudo-well logs are used to synthesize seismic traces. Depending on a study's needs the seismic response can be synthesized as pre-stack gathers for AVO analysis, or by convolution for post-stack analysis as is the case in this study. Pseudo-wells are modelled in GDI, dGB's quantitative interpretation system. Wells (real and pseudo) in GDI are blocked, and each blocked layer has a unique identifier in terms of an integration framework. This allows us to identify, analyze, and manipulate log data at different geological scale units. Here we conducted three applications of pseudo-well modelling: sensitivity analysis, seismic patterns analysis, and rock property inversion.

Sensitivity analysis

In sensitivity analysis we study the effect on the seismic response caused by controlled variations in the geological or petrophysical model. In this case we changed the thickness of all reservoir units one at a time, and we studied the impact of varying water saturation in the Lithothamnienkalk. We learned that the seismic response at reservoir level was controlled by variations in thicknesses of reservoir sub-units and of porosities, but that water saturation effects are negligible. Fig. 3 shows the results when we vary porosity in the reservoir unit from one-fifth of the average porosity to nine-fifth of the average porosity. The basis of this modelling is Well L, one of the two wells that had complete logging suites. The un-altered well L is shown in Fig. 3 at the position marked in red. For display purposes only 21 seismic traces out of 101 models are displayed.

Pattern analysis

A set of real wells is rarely statistically representative for the full area of interest. For example, if all wells are drilled

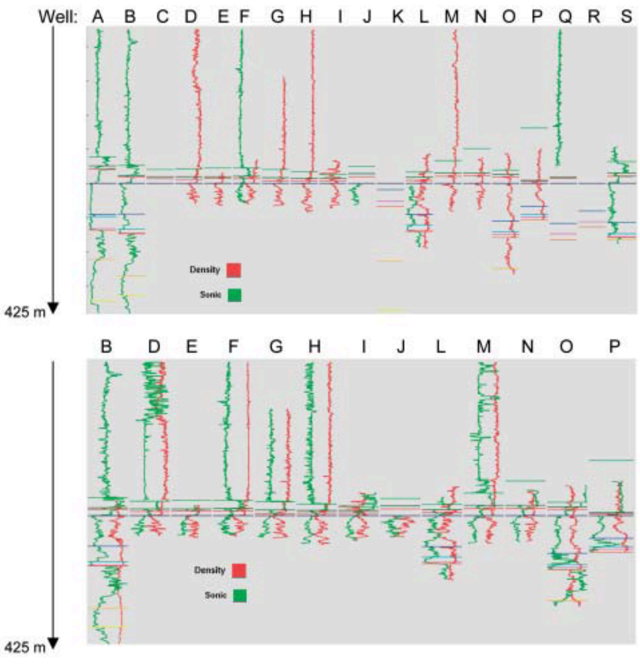

Figure 2 *Sonic and density logs before (top) and after (bottom) neural network infilling.*

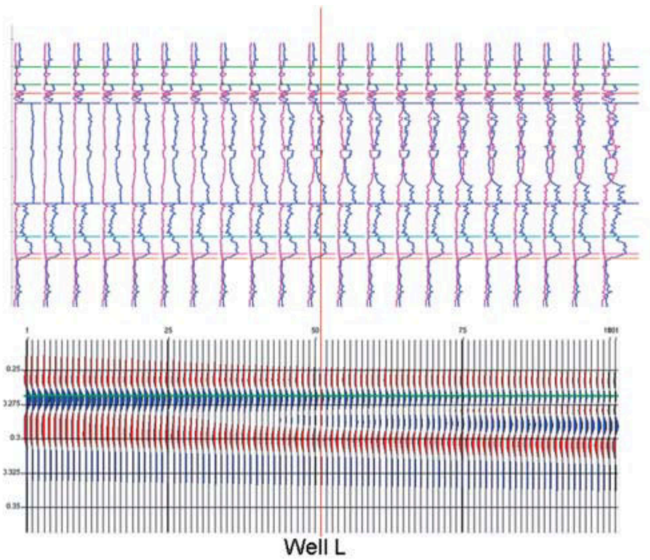

Figure 3 *Sensitivity analysis showing the impact of porosity changes on the seismic response. Porosities are varied from 1/5th to 9/5th the average porosity of the Lithothamnienkalk at Well L (red line).*

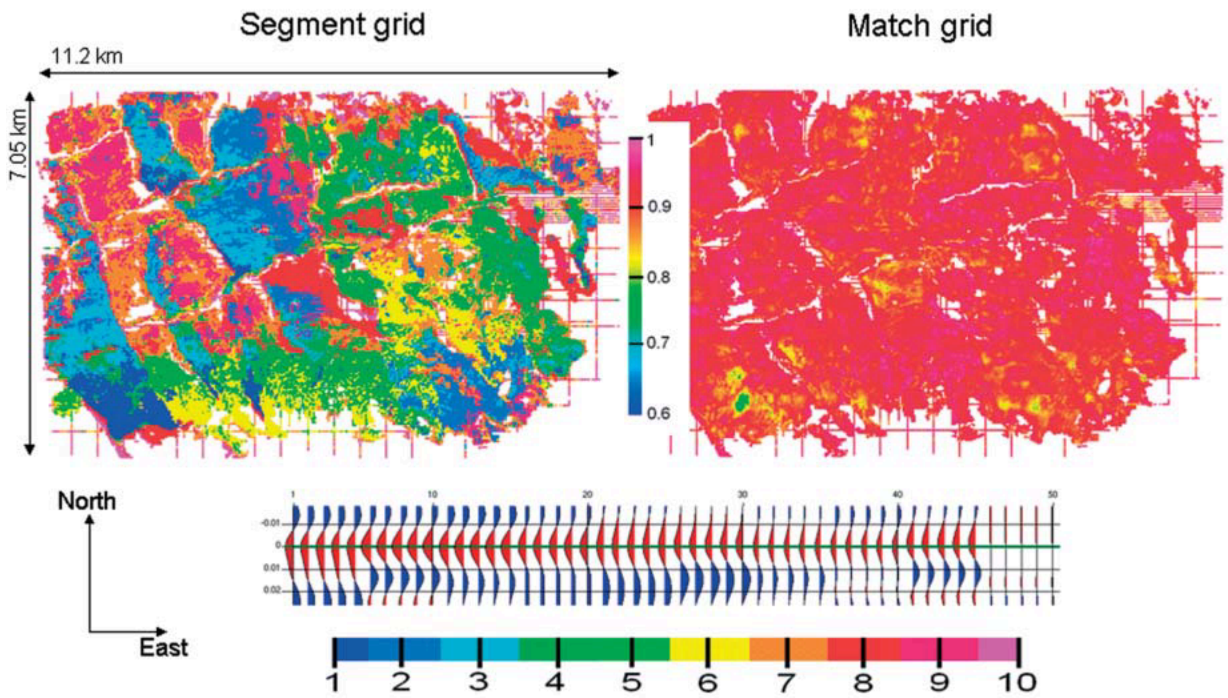

Figure 4 *Waveform segmentation at Top Lithothamnienkalk in time gate [-18,26] into 10 classes. Top left seismic pattern grid, top-right match (or confidence) grid and bottom cluster centres.*

on high amplitudes and a relationship exists between amplitude and porosity, it is likely that all wells will have similar porosities. Consequently, if these real wells are used to predict porosity, e.g., by training a neural network, the established relationship is only valid in areas with high amplitudes. Generating a pseudo well database may overcome this problem. In the simulator we can create pseudo-wells that cover the entire range of expected porosities with corresponding seismic responses. Training a network on such a well database will thus yield a relationship that is valid over a much wider range.

The pseudo-well simulator gets its input from real well statistics and regional geological information. Real well data is analysed to get correlations, statistical distributions, rock-physics relationships, and optionally Markov chains to capture lithology stacking patterns. Geological information is supplied in the form of rules, or by modifying the statistical input to create pseudo-wells that were not yet sampled by the wells. Whereas in sensitivity analysis only one parameter is changed at a time, in a stochastic simulation several parameters are changed simultaneously, resulting in many non-unique seismic responses. In this case we generated 300 stochastically simulated pseudo-wells in which all present logs were randomly varied. The pseudo-well database was used for analyzing waveform segmentation results and served as input for predicting a porosity volume from inverted acoustic impedance and seismic reflectivity volumes.

Waveform segmentation (Aminzadeh and de Groot, 2004) is a popular technique for visualizing seismic patterns pertaining to a certain horizon slice. The technique requires a good-quality mappable event to extract the analysis window and works best in conformable settings. Seismic waveforms (two-way time windows extracted around the mapped event) are segmented (clustered) by a neural network into a user-defined number of clusters. The cluster centres are found in a separate step by training the network on a representative subset of all waveforms. This technique generates three outputs: 1) a seismic pattern map, 2) a seismic match (or confidence) map, and 3) a display of the cluster centres.

The seismic pattern map shows us which areas have similar seismic response and the cluster centres reveal what the seismic response in each area looks like. The match grid tells us how similar the seismic response at each location is to the cluster centre. What the seismic patterns mean in terms of geological or petro-physical variations is not revealed and remains to be interpreted. This is where pseudo-well modelling can help. The workflow is as follows: we create a pseudo-well database by stochastically varying relevant properties and we synthesize the seismic response for each of these pseudo-wells. Next we extract the seismic waveform (i.e. the two-way

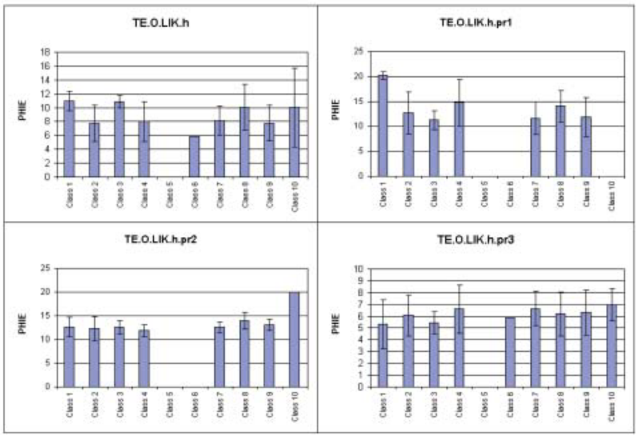

Figure 5 *Segmentation analysis: histograms and standard deviation of porosity for members of the Lithothamnienkalk reservoir. Note, that no pseudo-wells were collected in clusters 5 and 6.*

time window) and feed this to the trained neural network. The network compares the waveform with each of the cluster centres and assigns the pseudo-well to the cluster with the most similar waveform. In this way the entire pseudo-well database is split into N clusters, where N is the number of clusters the network was trained to recognize. Finally we analyze each of the resulting pseudo-well groups for variations in relevant reservoir properties in the hope of establishing what each seismic pattern means in terms of reservoir property variations. Fig. 4 shows a waveform segmentation result. An example for the analysis of porosity variation is given in Fig. 5. All 300 simulated pseudo-wells were clustered into 10 clusters. Due to the non-uniqueness of the seismic method the results are not un-ambiguous but it can be observed that some clusters are prone to higher porosities in the uppermost reservoir unit (e.g cluster 1 for unit TE.O.LIK.h.pr1).

Rock property prediction

Acoustic impedance is a required input for predicting porosity. Especially the low-frequency part of the acoustic impedance volume is important for calibrating the absolute values of the predictions. Therefore, band-limited acoustic impedance inversion is not a suitable method for subsequent quantitative rock property predictions. In this case full bandwidth acoustic impedance was created with Strata software using the constrained model based inversion method.

The same stochastic pseudo-well database was then used to train a supervised neural network to predict porosity

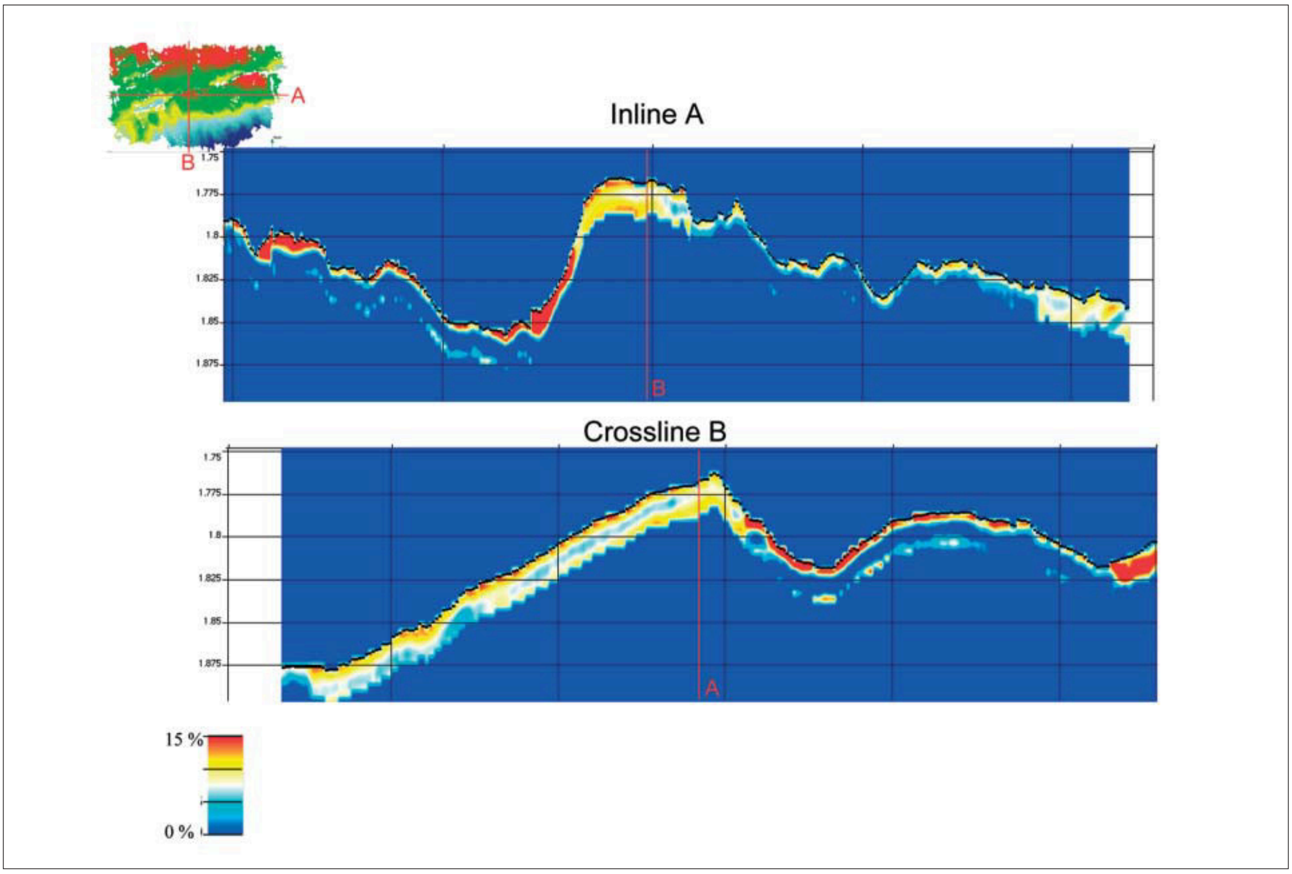

Figure 6 *Predicted porosity on an inline (top) and a cross-line (bottom) centred on the storage area.*

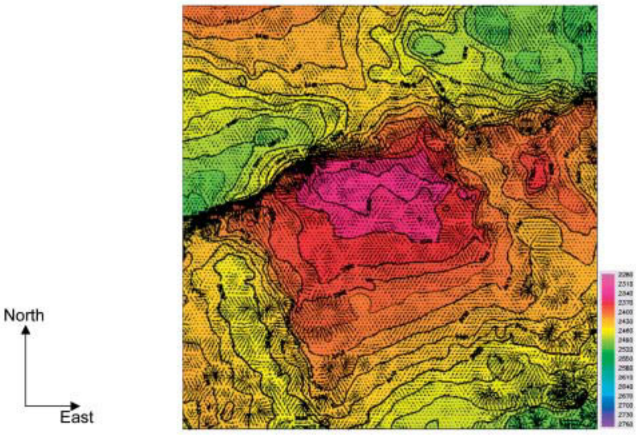

Figure 7 *Calculated shift vectors between PSDM migrated and PSTM migrated datasets at Top Lithothamnienkalk. The vectors are showing the direction and magnitude of the shift at each trace location.*

from acoustic impedance and reflectivity input. The training set was constructed by extracting input and output at every sample position over the interval of interest (Berge et.al., 2002). The trained network was applied in a horizon slice relative to the mapped Top Lithothamnienkalk. Fig. 6 shows two sections from the resulting porosity volume.

Populating the earth model

To bring the predicted porosities into the earth model we now had to solve the position problems caused by working with two different migration sets. First, we converted the porosity volume from time to depth using the final velocity model of the PSDM. The key horizons picked on the 3D time migrated data were used to apply an image ray map migration (Sattlegger and Zien, 1998) using Isp003 from AtosOrigin. Image ray migration corrects for over-migration caused by neglecting refraction in the seismic time migration process. The lateral shifting of the porosity volume in depth is based on the resulting displacement vectors in x and y direction at the Top Lithothamnienkalk. The maximum lateral shift is in the order of 80 m. Fig. 7 shows the vectors indicating the local shift at each bin.

The calculated shifts were used to re-bin the porosity traces. Some bins did not collect any porosity traces. To avoid holes in the data these positions were filled again with an inverse distance interpolation algorithm. The final step in the process was a vertical depth to depth correction to correct a remaining minor misfit. The time horizon of the PSTM interpretation was depth converted and shifted in x and y direction with displacement results from the map migration. The misfit between this depth horizon and the depth horizon mapped directly on the PSDM volume allowed us to calculate the shifts needed to arrive at the final porosity volume (Fig. 8).

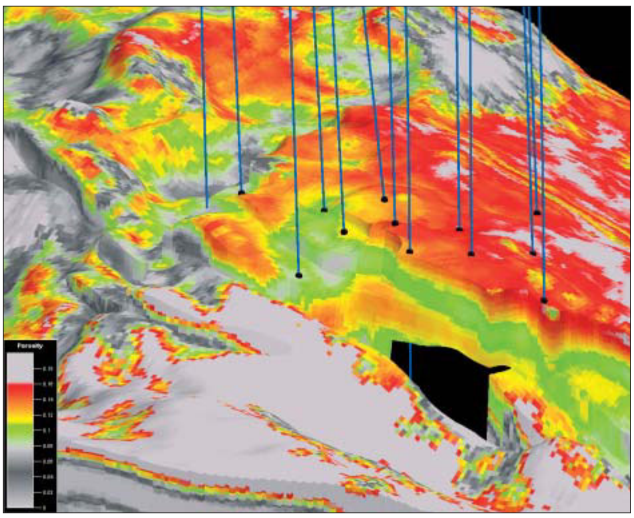

Figure 8 *Earth model with seismic porosities.*

Conclusions

Quantitative seismic predictions are usually based on two-way time volumes. To include such results in an earth model the data must be transformed from time to depth. A simple vertical time-depth conversion will do if earth model and quantitative interpretation started from the same seismic input. If on the other hand the earth model was created from depth migrated data and the predictions were based on time migrated data, the results must be re-positioned as well. In this article we discussed such a case and presented a workflow for populating the earth model correctly with predicted porosities.

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